ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR STUDENT ALLOCATION IN COOPERATIVE EDUCATION

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Abstract
This paper presents an Adaptive Neuro-Fuzzy System (ANFIS) for student allocation in Cooperative Education. The objective is to properly match internship positions with cooperative education students. It integrated an ANFIS for learning and inferring outcome based on knowledge of cooperative education experts. The input data includes average grade, English score and skill proficiency (Informational skill or Interpersonal skills etc.) obtained from a readiness test system. Then they were processed with a Sugeno type Adaptive Neuro-Fuzzy inference system whose membership functions were suggested by cooperative education experts. Our experiments were conducted with a group of 4th year students in a Hospitality Industry Management major. The result showed that the proposed method can suggest a proper job position to each student which is 97.5% similar to the human experts.

Keywords: Student Allocation, Cooperative Education, Adaptive Neuro-Fuzzy Inference System.

Introduction

Internationally, cooperative education is well known as a high efficiency work integrated learning program to improve the quality of higher education students around the world. Work Internship Placements (WIP) is a transversal program of enterprise internships for the students of which is focused on quality improvement, academic control and satisfaction of collaborating enterprises (Garcia & Puig, 2010). Today, over 4,000 Work Integrated Learning programs (WIL) are available worldwide.

The process of selection of student for appropriate job positions in cooperative education programs is an overloaded and difficult task for academic institutes. The placement requires experts and takes time which is similar to the job matching. From literature, there were many attempts to develop expert systems to deal with this issue.

We found two major types of expert systems which are related to our work. One is rule-based expert system and another is case-based reasoning. The rule-based system represents an information in the form of rules (Shu-Hsien Liao, 2005, Garcia & Puig, 2010, Siting, Wenxing, Ning, & Fan, 2012). For example, Work Internship Placements system (WIP) (Garcia & Puig, 2010) is the rule-based application for matching between students and enterprises. Other rule-based systems for job recommendation are Content-based Recommender, Collaborative Filtering Recommender, Reciprocal Recommender, CASPER and Bilateral People-job recommender (Siting, Wenxing, Ning, & Fan, 2012). In case of case-based reasoning, it recommends the best candidate suitable with the job requirement using similarity measurement (Siraj et al, 2011). To improve the quality of job matching, genetic algorithm was used and presented in the allocation of short-term jobs to unemployed citizens (Chen, Huang, Chung, & Hsu, 2011). Unfortunately all systems above cannot perform matching if the decision rules are approximate which is the real situation for job recruitment from industries. In other words, to recruit a person, the industry always uses various factors and rules. These rules are normally approximate and overlapped and have no direct relationship with the input factors. To tackle this problem, we focus on the fuzzy inference technique which is a better alternative to deal with approximate decision rules.

The fuzzy expert system combined with neural networks to match an unemployed person with an offered job was presented by A.Drigas (Drigas, Kouremenos, Vrettos, Vrettaros, & Kouremenos, 2004). Inspired by this work, A. Wongwan (Adisorn & Surapong, 2012) proposed a combination of rule-based system and fuzzy inference system to improve the system's performance. However, there is still a gap of decision accuracy.

Therefore, in this paper, we propose an Adaptive Neuro-Fuzzy Inference System for cooperative education to improve the decision accuracy. Instead of using user's evaluation for training data, we used cooperative education expert to define score marks to train data and reduce the error between the real and the desirable output in the same condition at our experiment.

Methodology

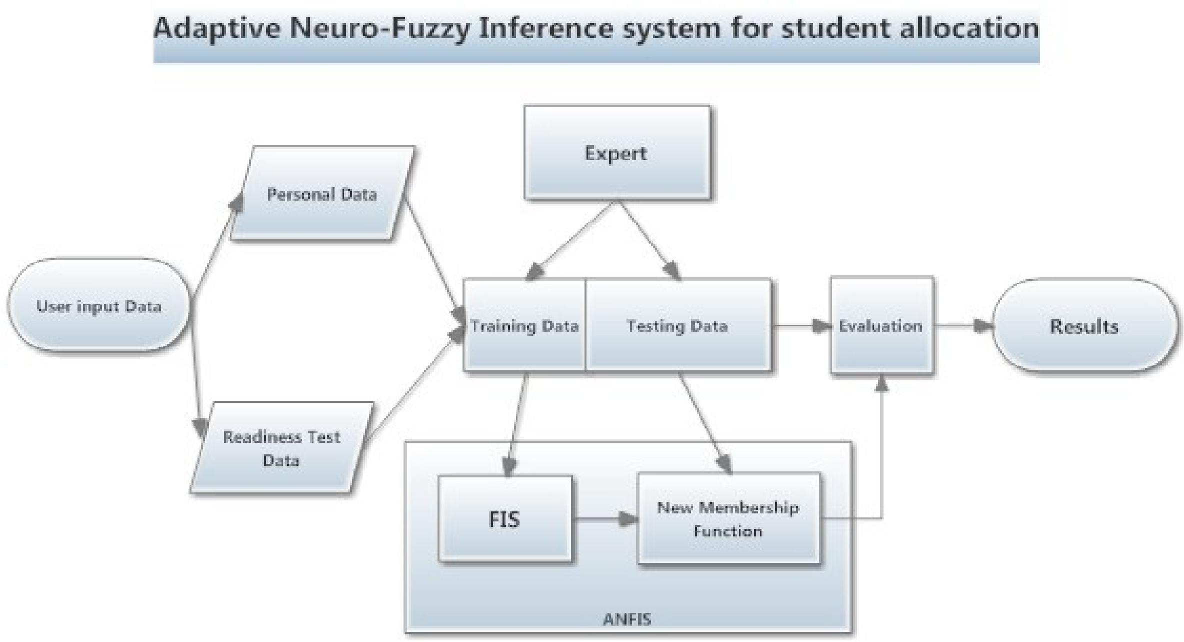

Figure 1 Proposed Adaptive Neuro-Fuzzy Inference System

Step 1 Students input all personal data in five fields: student identification, sex, age, major and cumulative grade point average (GPAX).

Step 2 The system retrieves grades (variable range between A-D) from University registration system in two subjects which are English for Communication and Management Information Technology.

Step 3 Student performs a Readiness test. It is a psychology test to identify their career characteristics. A higher result of readiness test indicates more self-esteem and generalized self-efficacy (Hirschi, 2011). The test focuses on three skills i.e. Informational skill, Mechanical skill and Interpersonal skill in three levels namely “High”, “Moderate” and “Poor”. Then both personal data and readiness test results are prepared for training data.

Step 4 We generate the membership function of the fuzzy inference system suggested by cooperative education experts. In this step we select Gaussian as a membership function type.

Gaussian (x; C, σ) = μ = $e^{\frac{-1}{2}\left(\frac{x-c}{\sigma}\right)^2}$

Then we create rules of FIS as demonstrated in Figure 2.

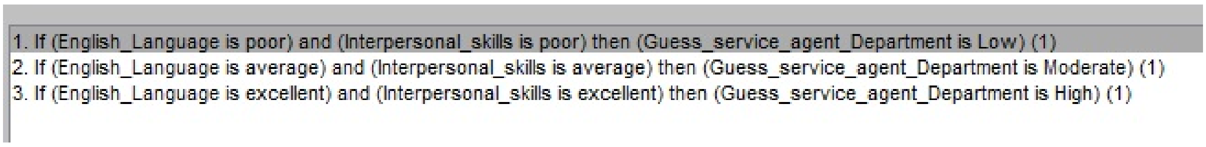
1. If (English_Language is poor) and (Interpersonal_skills is poor) then (Guess_service_agent_Department is Low) (1)
2. If (English_Language is average) and (Interpersonal_skills is average) then (Guess_service_agent_Department is Moderate) (1)
3. If (English_Language is excellent) and (Interpersonal_skills is excellent) then (Guess_service_agent_Department is High) (1)

Figure 2 Example of rules of FIS

Step 5 We start Adaptive neuro-fuzzy inference system (ANFIS) and feed training data. After that the parameters associated with the membership function change through the learning process.

Step 6 The testing data are entered to the system and we measure the accuracy of the results comparing to the expert’s evaluation.

Results

We conducted our experiments with a group of 4th year students in a Hospitality Industry major who are going to have internship. At first to experiment on proposed system. We used training data from 20 internship students and testing data from 14 internship students.

After training data in ANFIS with 40 epochs, we found that the initial membership functions were modified. Their shapes were changed and adapted to fit the data as seen in Figure 3 and Figure 4.

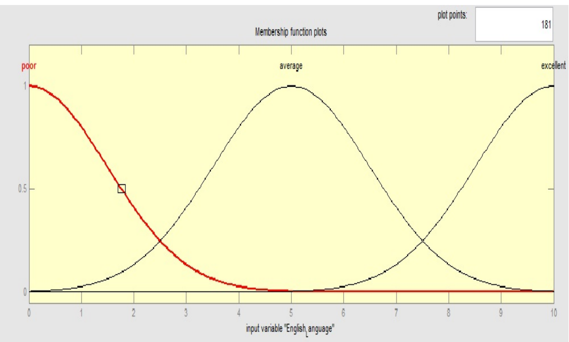

Figure 3 Membership function before training data

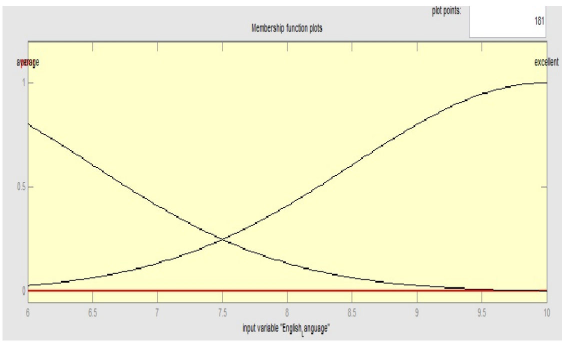

Figure 4 Membership function after training data

When the new membership function was created, we tested 14 example cases to the proposed system and the result is 97.5 percent similar to expert's result. The number is calculated from the average absolute value of a difference between the system's output and the expert's result.

In experiment of the conventional method by using Rule-based System and Fuzzy Inference System with FIS 6 rules. We used the same examples to perform the test and it generated a result with 93.14 percent similar to expert's result.

The last experiment was performed through Sugeno type Neuro-Fuzzy Inference System with FIS 3 rules and conducted with the same examples. This system performed 88.64 percent similar to expert's result.

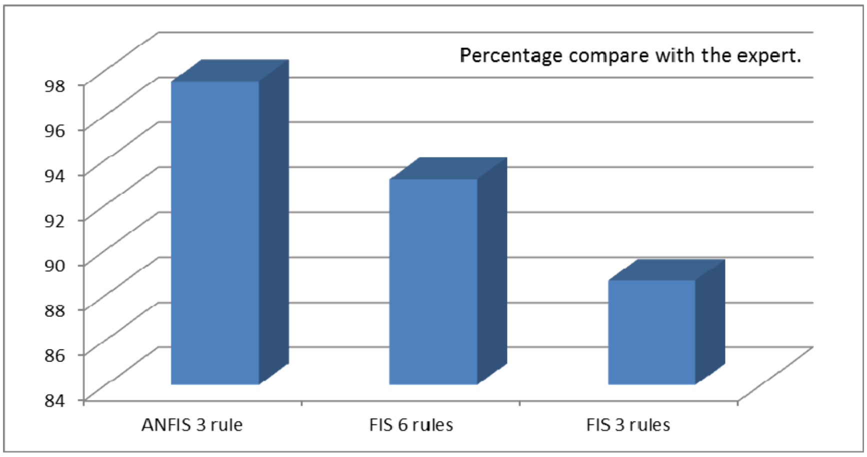

Figure 5 The results from experiment

The results from Figure 5 show that the proposed system, ANFIS (FIS 3 rules) gives result that is very close to the result from the expert. It was around 97.5 percent similar to expert's result. In addition the proposed system can perform 4.63 percent better than conventional method the Rule-based System and Fuzzy Inference System (FIS 6 rules) which is performed at 93.14 percent. Furthermore the proposed system also performed 9.95 percent better than the Sugeno type Neuro-Fuzzy Inference System (FIS 3 rules).

Discussion and Conclusion

We have proposed a system for internship job matching based on an Adaptive Neuro-Fuzzy inference system. The accuracy of the proposed system is around 97.5 percent comparing to the experts. We expect to further improve the system's accuracy, allow students to have self test, and integrate automatic membership function extension to adjust the system's efficiency.

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