

Mining Formative Evaluation Rules Using Web-based Learning Portfolios for Web-based Learning Systems

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ABSTRACT

Learning performance assessment aims to evaluate what knowledge learners have acquired from teaching activities. Objective technical measures of learning performance are difficult to develop, but are extremely important for both teachers and learners. Learning performance assessment using learning portfolios or web server log data is becoming an essential research issue in web-based learning, owing to the rapid growth of e-learning systems and real application in teaching scenes. The traditional summative evaluation by performing examinations or feedback forms is usually employed to evaluate the learning performance for both the traditional classroom learning and the web-based learning. However, summative evaluation only considers final learning outcomes without considering learning processes of learners. This study presents a learning performance assessment scheme by combining four computational intelligence theories, i.e., the proposed refined K-means algorithm, the neuro-fuzzy classifier, the proposed feature reduction scheme, and fuzzy inference, to identify the learning performance assessment rules using the web-based learning portfolios of an individual learner. Experimental results indicate that the evaluation results of the proposed scheme are very close to those of summative assessment results of grade levels. In other words, this scheme can help teachers to assess individual learners precisely utilizing only the learning portfolios in a web-based learning environment. Additionally, teachers can devote themselves to teaching and designing courseware since they save a lot of time in evaluating learning. This idea can be beneficially applied to immediately examine the learning progress of learners, and to perform interactively control learning for e-learning systems. More significantly, teachers could understand the factors influencing learning performance in a web-based learning environment according to the obtained interpretable learning performance assessment rules.

Keywords:

Learning Performance Assessment, Web-based Learning, Web-based Learning Portfolio, Data Mining

Introduction

Gagnés' research on the internal process of learning has indicated that the complete learning process should assess learning performance (Gagnés, 1997). Learning performance evaluation instruments can generally be classified as summative assessment and formative assessment (Torrance & Pryor, 1998; Campbell et al, 2000). While summative evaluation is generally performed after finishing an instruction unit or class, formative assessment emphasizes the learning process. Teachers can assess the overall learning performance using summative assessments. Conversely, the use of formative assessments helps teachers obtain feedback about how well students are learning and particular difficulties they might be having. The standard summative assessment scheme at course level is to perform either an examination or an assessment form. However, these methods cannot collect all learning process information. Since the formative assessment strongly emphasizes integrating "what people learned" with "how people learned", the formative assessment occurs when teachers feed information back to students in ways that enable the student to learn better, or when students can engage in a self-reflective process. Therefore, while assessing learning performance using the portfolio has become increasingly popular, technology is facilitating its evolution and management (Torrance & Pryor, 1998;

Campbell et al, 2000; Lankes, 1995). Moreover, learning performance assessment based on the learning portfolio is a very useful concept for some fields of learning assessment, such as psychological testing, knowing how subjects take the test can be more important than their answers.

Traditional portfolio assessment relies on man-made data collection and a writing-centered learning process. Difficulties in data storage, search and management after long-term implementation have become problematic in developing and implementing portfolio assessment (Chang, 2002). In contrast, a web-based learning portfolio can be collected, stored and managed automatically by computers when learners interact with an e-learning platform. Therefore, learning performance assessment using a web-based learning portfolio has received significant attention recently (Lankes, 1995; Rahkila & Karjalainen, 1999; Wu & Leung, 2002). Rasmussen et al. (Rasmussen et al. 1997) suggested that Internet-based instruction could also allow student progress to be evaluated through participation in group discussions and portfolio development. Lankes (Lankes, 1995) stated that implementing computer-based student assessment portfolios is an innovative educational innovation owing to its ability not only to offer an authentic demonstration of accomplishments, but also enable students to take responsibility for their completed tasks. Rahkila (Rahkila & Karjalainen, 1999) also proposed using the user profiles with log data for the learning performance assessment, finding that it can be applied to interactively control learning effectively. Rahkila emphasized that the learning portfolio assessment is supported by the cognitive-constructive theory of learning (Rahkila & Karjalainen, 1999; Bruner, 1996). Zaiane (Zaiane & Luo, 2001) proposed applying web access logs and advanced data mining techniques to extract useful patterns that can help educators evaluate on-line course activities. Wang et al. (Wang et al. 2003) found that learning behavior information, commonly referred to as a learning portfolio, can help teachers understand why a learner obtained a high or low grade. Carreira (Carrira & Crato, 2004) proposed monitoring users' reading behaviors to infer their interest in particular articles.

However, developing a precise learning performance assessment scheme using web-based learning portfolio is a challenging task for web-based learning systems. Data mining, or knowledge discovery, attempts to obtain valuable knowledge from data stored in large repositories. Data mining has been considered as an appropriate method of knowledge discovery to excavate the implicit information (Dunham, 2002). This study presents a data mining approach that integrates four computational intelligence schemes, i.e., the refined K-means clustering algorithm, the neuro-fuzzy classifier (Nauck & Kruse, 1999), the proposed feature reduction scheme, and the fuzzy inference (Lin & Lee, 1996), to evaluate on-line learning behavior and learning performance. The four computational intelligence schemes are employed to logically determine fuzzy membership functions for the neuro-fuzzy classifier, discover the fuzzy rules relating to the learning performance assessment, reduce the feature dimension of the discovered fuzzy rules, and infer the learning performance using the discovered fuzzy rules based on the learning portfolio of an individual learner, respectively.

The proposed learning performance assessment scheme was implemented on the personalized e-learning system, and its effectiveness was demonstrated in a real-world teaching scenario. Experimental results show that the proposed learning assessment scheme can correctly measure learners' learning performance according to their learning portfolios as well as help teachers save a lot of time for the learning evaluation during the learning process. Significantly, the learning evaluation results were applied to help teachers examine the learning progress of learners and interactively control learning for the personalized e-learning system. The remainder of this study is organized as follow. Section 2 describes the problem description based on the gathered learning portfolios for the proposed learning performance assessment scheme. Section 3 explains the proposed learning performance assessment scheme. Section 4 presents the detailed experiments. Conclusions are drawn in Section 5.

Problem Description

Personalized E-learning System (PELS) with Learning Performance Assessment Mechanism Based on Learning Portfolios

The personalized e-learning system (PELS) based on the Item Response Theory, which includes an off-line courseware modeling process, four intelligent agents and four databases, is presented in our previous study for adaptive courseware recommendation (Chen, Lee & Chen, 2005), (Chen, Liu & Chang, 2006). However, the PELS mainly focuses on performing adaptive learning based on the difficulty parameters of courseware and learner ability of individual learner, the learning performance assessment is lacked feature in this system. In this paper, the functionalities of the PELS system are extended to include the learning performance assessment agent

in order to perform the evaluation of learning performance using the gathered learning portfolios of individual learners. The extended system architecture is shown as Figure 1.

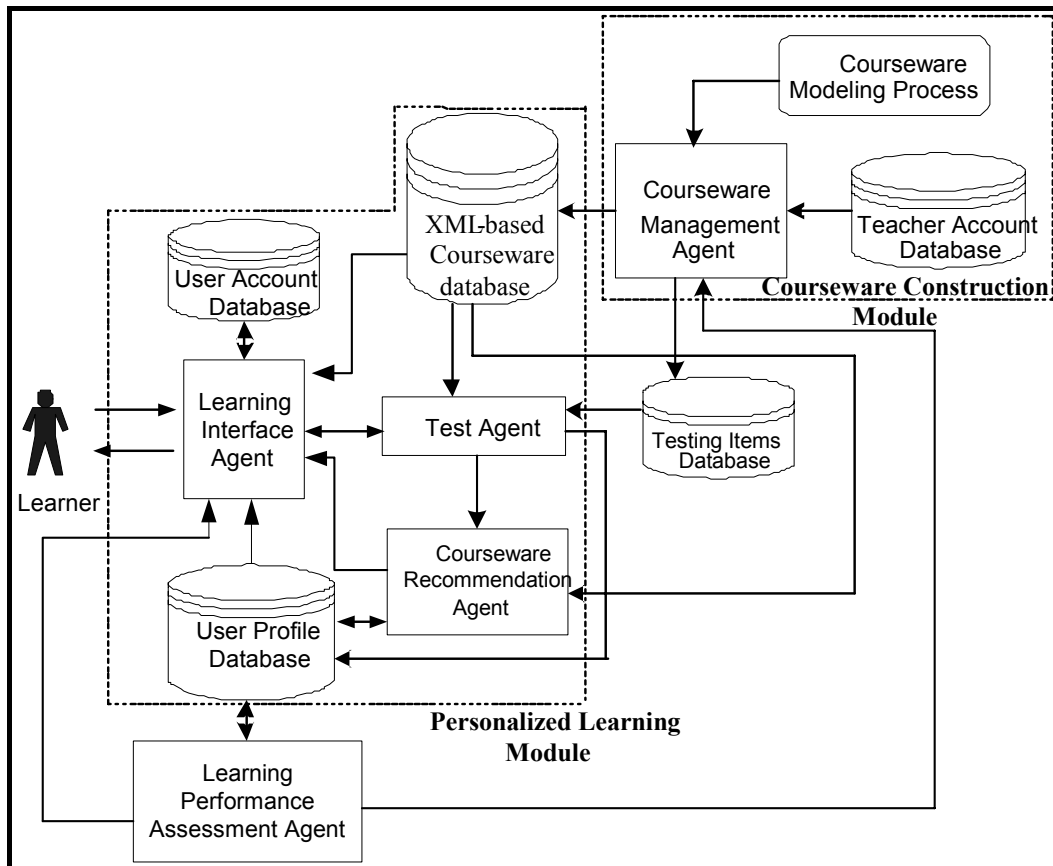


Figure 1. The system architecture

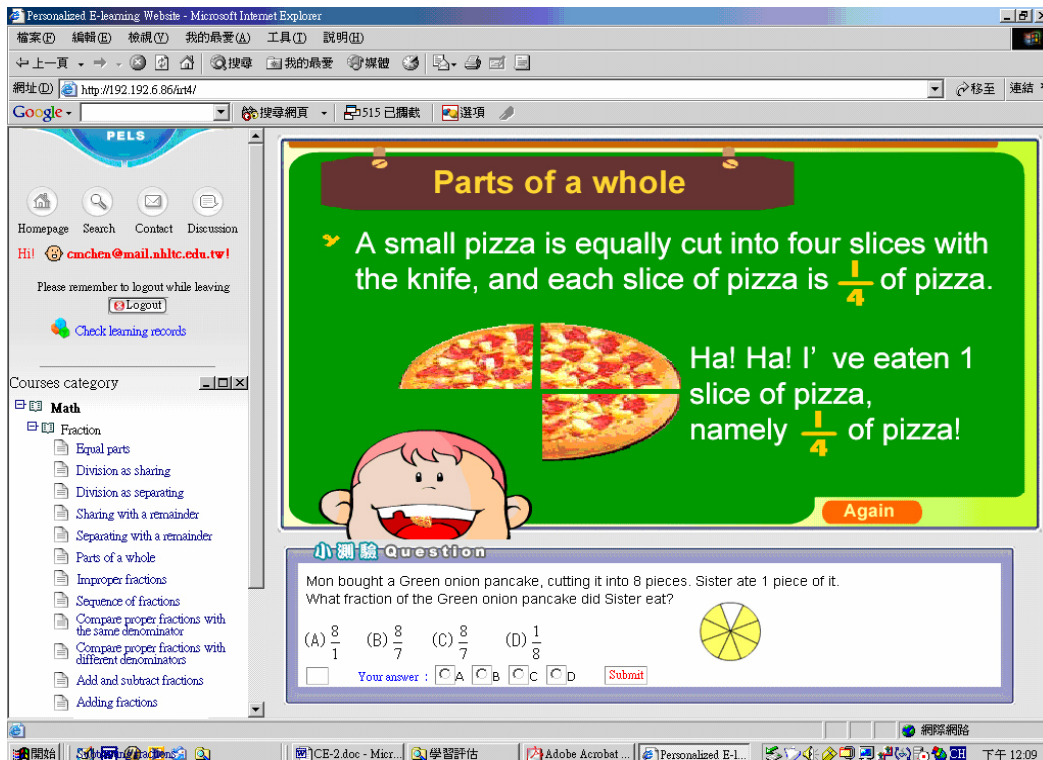


Figure 2. The learning interface for learner

Figure 2 shows the entire layout of the learning interface on PELS. In the left frame, system shows the course categories, course units and the list of all courseware in the courseware database using a hierarchical tree topology structure. While a learner clicks a courseware for learning, the content of selected courseware will be exhibited in the upper-right window. Besides, the feedback interface is arranged in the bottom-right window. The proposed system can get learner's feedback response from the interface of feedback agent through learner replies one randomly testing question related to the conveyed learning content. The answer of testing question helps system to get the learner's comprehension percentage for the recommended courseware. System passes the feedback response to the courseware recommendation agent to infer the learner's ability using the item response theory (Baker & Frank, 1992) detailed in our previous study (Chen, Lee & Chen, 2005; Chen, Liu & Chang, 2006). After a learner presses the button of "submit", this system will reveal a list of the recommended courseware based on his current ability. After the learner selects the next courseware according to the suggestion of the courseware recommendation agent for further learning, the learner can continue to learn the selected courseware. The PELS will continue to run the learning cycle until the evaluated learner ability satisfies the stop criterion. Next, the learning procedure will enter the final testing stage to perform a summative assessment through replying 25 randomly selected testing questions. The results of final testing will be used to verify the evaluation quality of the proposed learning performance assessment approach in the analysis of experimental results. Besides, the learner can also log in the discussion board on PELS to publish the learning questions of the individual self or contribute helpful ideas for the learned course unit. The PELS will automatically gather the useful learning portfolios of individual learners for the learning performance assessment during learning processes.

Considered Learning Portfolio in the User Profile Database

The IMS Global Learning Consortium defined that ePortfolios are collections of personal information about a learner that represent accomplishments, goals, experiences, and other personalized records that a learner can present to schools, employers, or other entities (<http://support.imsglobal.org/ePortfolio/>). The ePortfolio specification developed by IMS Global Learning Consortium enables the use of the Internet for personalized, competency-based learning and assessment, enhanced career planning, and improved employment opportunities. In the meanwhile, the proposed ePortfolio specification supports many kinds of portfolios, including assessment ePortfolios, presentation ePortfolios, learning ePortfolios, personal development ePortfolios, and working ePortfolios. The IMS Global Learning Consortium also summarized that ePortfolio can contain personal information about the owners, achievements, interests and values, test and examination results, and so on. Next, the learning portfolio information collected by PELS for the proposed learning performance assessment approach is presented based on the IMS ePortfolio specification. This learning portfolio information was saved into the user profile database according to the learner's interaction with PELS. Hence, the learning performance was graded according to their PELS learning portfolios. The eight gathered learning factors are described in detail as follows:

1. Reading rate of course materials (RR)

After a learner has logged onto the PELS system, the PELS automatically counts and accumulates the reading amount of the learned course materials for each learner. The learning parameter is progressively increased for each section learning process. Thus, the reading rate of course materials is defined as the rate of studying course materials in a course unit, and the notation RR is employed to represent the learning factor. Table 1 presents an example of calculating the reading rate for both the learners A and B in the learning course unit.

Table 1. A calculating example for the learning factor of reading rate

Learner	Learning path of course materials	The number of studying course materials	The total number of course materials in the learned course unit	Reading rate (RR)
A	1⇒5⇒8⇒10⇒11⇒12⇒13⇒14⇒15⇒16⇒17	11	11	1
B	1⇒5⇒4⇒6⇒7⇒8⇒9⇒10⇒(9)⇒(10)⇒11	9	11	0.82
() indicates the repeated course material during the learning process				

2. Total accumulated reading time of all learned course materials (RT)

The total accumulated reading time of each learner is calculated by summing up the reading time of all learned course materials on the PELS system, and the notation RT is used to represent the learning factor. Table 2 presents an example of calculating the total accumulated reading time for both the learners A and B in the learning course unit.

Table 2. A calculating example for the learning factor of total accumulated reading time

Learner	Learning path of course materials	Total accumulated reading time(RT)
A	1(25)⇒5(32)⇒8(33)⇒10(30)⇒11(36)⇒12(43)⇒13(47)⇒14(43) ⇒15(45)⇒16(40)⇒17(46)	420(secs)
B	1(42)⇒5(56)⇒4(50)⇒6(62)⇒7(67)⇒8(72)⇒9(79)⇒10(93) ⇒9(70)⇒10(81)⇒11(118)	790(secs)
() indicates the reading time for the learned course material		

3. Learner ability evaluated by PELS (LA)

After studying the recommended courseware, the PELS (Chen, Lee & Chen, 2005; Chen, Liu & Chang, 2006) can dynamically estimate a learner's ability according to the item response theory (Baker & Frank, 1992) by collecting the replied responses of the learner to the randomly selected testing questions in the learned course unit. The value denotes the learner's ability in the learned course unit measured by the PELS system during the learning process, and the range of learner's ability are limited from -3 (i.e. lowest ability) to +3 (i.e. highest ability). As a learner logs in this system, if the user account database does not have any history records in the selected course unit for this learner, then his initial ability will be regarded as 0. That is, the system assumes beginner's ability is moderate level. As a learner clicked the recommended courseware for learning, his/her ability in this course unit will be re-evaluated according to his/her feedback responses and the corresponding difficulty parameter of the learned courseware. The notation LA is used to represent the learning factor of learner ability in this paper.

In the PELS, the quadrature form proposed by Bock and Mislevy (Baker & Frank, 1992) was employed to approximately estimate learner's ability as follows:

$$\hat{\theta} = \frac{\sum_k^q \theta_k L(u_1, u_2, \dots, u_n | \theta_k) A(\theta_k)}{\sum_k^q L(u_1, u_2, \dots, u_n | \theta_k) A(\theta_k)} \quad (1)$$

where $\hat{\theta}$ denotes the learner's ability of estimation, $L(u_1, u_2, \dots, u_n | \theta_k)$ is the value of likelihood function at a level below their ability level θ_k and learner's responses are u_1, u_2, \dots, u_n , θ_k is the k^{th} split value of ability in the standard normal distribution, and $A(\theta_k)$ represents the quadrature weight at a level below their ability level θ_k .

In Eq. (1), the likelihood function $L(u_1, u_2, \dots, u_n | \theta_k)$ can be further described as follows:

$$L(u_1, u_2, \dots, u_n | \theta_k) = \prod_{j=1}^n P_j(\theta_k)^{u_j} Q_j(\theta_k)^{1-u_j} \quad (2)$$

where $P_j(\theta_k) = \frac{e^{D(\theta_k - b_j)}}{1 + e^{D(\theta_k - b_j)}}$, $Q_j(\theta_k) = 1 - P_j(\theta_k)$, $P_j(\theta)$ denotes the probability that learners can understand the j^{th} courseware at a level below their ability level θ_k , $Q_j(\theta_k)$ represents the probability

that learners cannot understand the j^{th} courseware at a level below their ability level θ_k , b_j is the difficulty parameter of the j^{th} courseware, and D is a constant 1.702, and U_j is the understanding or not understanding answer obtained from learner feedback to the j^{th} courseware, i.e. if the answer is understanding then $U_j = 1$; otherwise, $U_j = 0$.

4. Correct response rate of randomly selecting testing questions (CR)

After a learner has studied the recommended course material, the PELS tests the learner on his understanding by randomly selecting a relevant question from the testing item database. The rate of correct responses to test questions helps determine the learner's degree of understanding for all learned courseware, and the notation CR is used to represent the learning factor in this paper. For example, if a learner gave seven correct responses and three incorrect responses for ten randomly selecting testing questions from the testing item database, then the correct response rate is 0.7.

5. Posted amount of articles on the forum board (PN)

The PELS system can automatically count the total number of posted articles and answered questions on the forum board for each learner during the learning process. The value usually shows a learner level of participation in group discussion, and the notation PN is used to represent the learning factor in this paper. For example, if a learner posted three articles and answered five questions on the forum board, then the posted amount of articles on the forum board is eight pieces.

6. Accumulated score on the forum board (AS)

The PELS system gives various scores for the various interactive behaviors among learners on the forum board. In this study, the PELS will automatically increment a learner's score of one point when he/she logs onto the forum board, and accumulate a learner's score of two points if he/she posts an article on the forum board. The accumulated score on the forum board represents the level of useful feedback given by a learner, and the notation AS is used to represent the learning factor in this paper. For example, if a learner logged onto the forum board two times and posted three articles, then the accumulated score on the forum board will be eight points.

7. Effort level of studying course Materials (EL)

Since each course material in the PELS system is assigned a required minimum reading time by course experts based on the courseware content, the effort level is defined as the actual reading time compared with the required minimum reading time for the learned courseware, and the notation EL is used to represent the learning factor in this paper. Suppose the actual reading time of learners A and B in the learned course unit is 420 seconds and 790 seconds, respectively, and listed as Table 2. Table 3 presents an example of calculating the effort level for the learners A and B in the learned course unit. In this study, the range of the effort level is limited from 0 to 1. Restated, the value of the effort level will be assigned as 1 if the calculated value is over 1.

Table 3. A calculating example for the learning factor of effort level

Learner	Learning path of course materials	Effort level (EL)
A	1(30)⇒5(60)⇒8(75)⇒10(60)⇒11(75)⇒12(75)⇒13(60)⇒14(60)⇒15(75) ⇒16(75)⇒17(90)	420 / 735 ≈ 0.57
B	1(30)⇒5(60)⇒4(45)⇒6(60)⇒7(60)⇒8(75)⇒9(60)⇒10(60)⇒9(60) ⇒10(60)⇒11(75)	790/585 → 1
() indicates the required minimum reading time determined by course experts for the learned course material		

8. Final test grade (G)

This study measures the final test grade through the summative assessment scheme of fixed-length testing examination after the entire learning process is completed, and the notation G is used to represent the learning factor in this paper.

Mining Learning Performance Assessment Rules Based on Learning Portfolios

Flowchart of Mining Learning Performance Assessment Rules

Figure 3 shows the entire flowchart of the proposed learning performance assessment scheme. The proposed refined K-means algorithm is initially employed to logically determine the fuzzy membership functions of each learning factor based on real data distribution of learning portfolios for mining learning performance assessment rules by the neuro-fuzzy classifier (Nauck & Kruse, 1999). After the fuzzy rules for learning performance assessment are identified by the neuro-fuzzy classifier, the feature reduction scheme is employed to simplify the linguistic terms of the discovered learning performance assessment rules under keeping a satisfied accuracy rate of learning performance assessment. This procedure aims to obtain simplified learning performance assessment rules for promoting the inferring efficiency in web-based learning systems as well as discover the main learning factors that affect the learning outcomes. Finally, the fuzzy inference is employed to grade the learning performance by the simplified fuzzy rules for individual learners. The following sections give details for the proposed learning performance assessment scheme for individual learners.

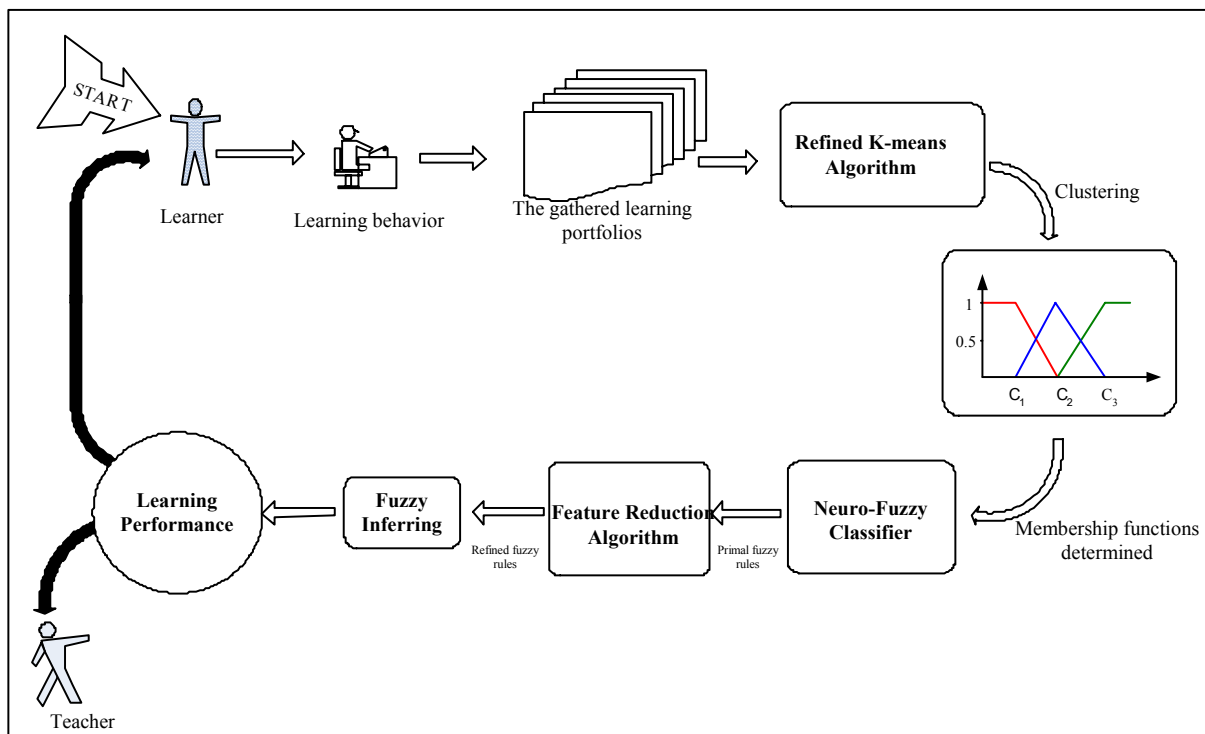


Figure 3. The flowchart of learning performance assessment

Mining Learning Performance Rules Using Web-based Learning Portfolios

Determining Fuzzy Membership Functions by the Refined K-means Algorithm for the Neuro-Fuzzy Classifier

This study employed the neuro-fuzzy classifier to discover the fuzzy knowledge rules from the learning portfolios for learning performance assessment. To identify the fuzzy knowledge rules by the neuron-fuzzy classifier, the membership functions used in the neuro-fuzzy classifier must be logically determined according to the data distribution of learning portfolios in advance. In this work, the proposed refined K-means clustering algorithm improved from the original K-means clustering algorithm (Xu & Wunsch, 2005) was employed to determine the centers of the triangle fuzzy membership functions automatically according to the data distribution

of each learning factor in learning portfolios for the neuro-fuzzy classifier herein. To obtain appropriate and interpretable learning performance assessment rules by the neuro-fuzzy classifier, this study sets the number of clusters in the refined K-means clustering algorithm as three based on the requirements of learning performance assessment in real teaching scenario. In other words, each considered learning factor contains three linguistic terms, i.e. low, moderate, and high, to describe a fuzzy rule. After that, the membership functions of the triangle fuzzy sets were automatically determined according to three cluster centers of each learning factor. Suppose the centers of three linguistic terms determined by the refined K-means clustering algorithm are respectively c_1 , c_2 , and c_3 , the membership functions for the linguistic terms “low”, “moderate”, and “high” can be formulated as follows:

- i. The membership function for the linguistic term “low”

$$\mu_{Low}(x) = \begin{cases} 1 & \text{if } x \leq c_1 \\ \frac{c_2 - x}{c_2 - c_1} & \text{if } c_1 < x < c_2 \\ 0 & \text{if } x \geq c_2 \end{cases} \quad (3)$$

- ii. The membership function for the linguistic term “moderate”

$$\mu_{Moderate}(x) = \begin{cases} 0 & \text{if } x \leq c_1 \\ \frac{x - c_1}{c_2 - c_1} & \text{if } c_1 < x < c_2 \\ 1 & \text{if } x = c_2 \\ \frac{c_3 - x}{c_3 - c_2} & \text{if } c_2 < x < c_3 \\ 0 & \text{if } x \geq c_3 \end{cases} \quad (4)$$

- iii. The membership function for the linguistic term “high”

$$\mu_{High}(x) = \begin{cases} 0 & \text{if } x \leq c_2 \\ \frac{x - c_2}{c_3 - c_2} & \text{if } c_2 < x < c_3 \\ 1 & \text{if } x \geq c_3 \end{cases} \quad (5)$$

Next, the difference of the proposed refined K-means clustering algorithm with the original K-means clustering algorithm is compared and explained herein. Suppose there are s patterns in the gathered learning portfolios, the original K-means clustering algorithm is employed to find the k centers for each learning factor, where $k \leq s$, and the set of the k cluster centers are represented as follows:

$$C_s \in \{c_1, \dots, c_l, \dots, c_r, \dots, c_k\} \quad (6)$$

where C_s is the set of the k cluster centers, c_l is the cluster center with the nearest Euclidean distance to the left boundary, and c_r is the cluster center with the nearest Euclidean distance to the right boundary.

In the proposed refined K-means clustering algorithm, the cluster centers c_l and c_r determined by the original K-means clustering algorithm are tuned by the refined value δ ; moreover, the other cluster centers are unchangeable. The refined value is computed as follows:

$$\delta = \frac{\max(\mathbf{S}) + \min(\mathbf{S})}{2} \quad (7)$$

where $\max(\mathbf{S})$ and $\min(\mathbf{S})$ represent the maximum and minimum feature values of patterns in each learning factor, respectively.

Therefore, the new cluster centers determined by the refined K-means clustering algorithm can be represented as follows:

$$C_s^{(new)} \in \{c_1, \dots, c_l - \delta, \dots, c_r + \delta, \dots, c_k\} \quad (8)$$

where $C_s^{(new)}$ is the new set of the k cluster centers.

Figure 4 gives an example to explain how to tune the membership functions by the refined value δ defined in the proposed refined K-means clustering algorithm. In Fig. 4, the circle and square notations with black and grey colors represent respectively the cluster centers determined by the K-means and refined K-means clustering algorithms. Moreover, the dotted and solid lines respectively represent the membership functions determined by the K-means and refined K-means clustering algorithms. Compared with the original K-means clustering algorithm, we find that the refined K-means clustering algorithm has benefits in terms of promoting classification ability for the boundary patterns between different classes and reducing the number of unknown patterns due to expanding the boundary range while employing the neuro-fuzzy classifier to discover the learning performance assessment rules based on learning portfolios. The later experimental results will confirm these benefits.

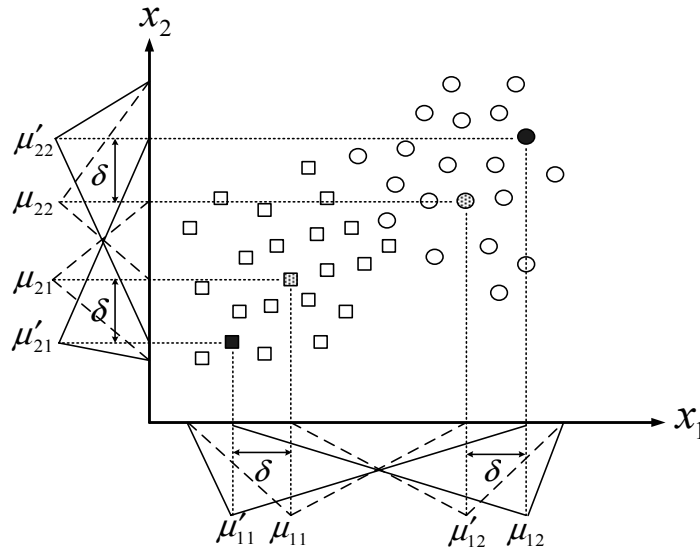


Figure 4. Tuning membership functions by the refined value δ , where the circle and square notations with black and grey colors respectively represent the cluster centers determined by the K-means clustering algorithm and refined K-means clustering algorithm, and the dotted and solid lines respectively represent the membership functions determined by the K-means and refined K-means clustering algorithms

Neuro-Fuzzy Classifier for Mining Learning Performance Assessment Rules

After the triangle fuzzy membership functions were determined by the refined K-means clustering algorithm, the neuro-fuzzy classifier proposed by Nauck (Nauck & Kruse, 1999) was employed to infer the fuzzy rules for the learning performance assessment based on learning portfolios. Figure 5 shows the learning architecture of the used neuro-fuzzy classifier which can be represented as four-layer feed-forward networks. The first layer is the input layer which consists of input neurons and each neuron corresponds to an input feature. The second layer is the fuzzification layer which consists of fuzzy set neurons and each neuron corresponds to a linguistic term, such as low, moderate, and high, and so on. The third layer is the rule layer which consists of rule neurons and each neuron corresponds to a fuzzy rule. The fourth layer is the class layer which consists of class neurons and each neuron corresponds to a class label. To explain the detailed operation procedures of the neuro-fuzzy classifier, the notations used in Fig. 5 are first explained as follows: x_k is the k^{th} input feature, μ_{kl} denotes the l^{th} membership function of the k^{th} input feature, Rule j is the j^{th} fuzzy rule, and Class i is the i^{th} output class. In addition, ar_j denotes the activation strength of the j^{th} neuron in the rule layer, and ac_i denotes the activation strength of the i^{th} neuron in the class layer. Moreover, the input layer only receives input features from the gathered learning portfolios and directly passes the input features to the fuzzification layer for computing the fired membership degrees. Each fuzzy set neuron in the fuzzification layer could connect to several rule neurons and each rule neuron only connects to one class neuron, but each class neuron could be simultaneously connected by different rule neurons since different antecedent parts of fuzzy rules could lead to the same consequent part.

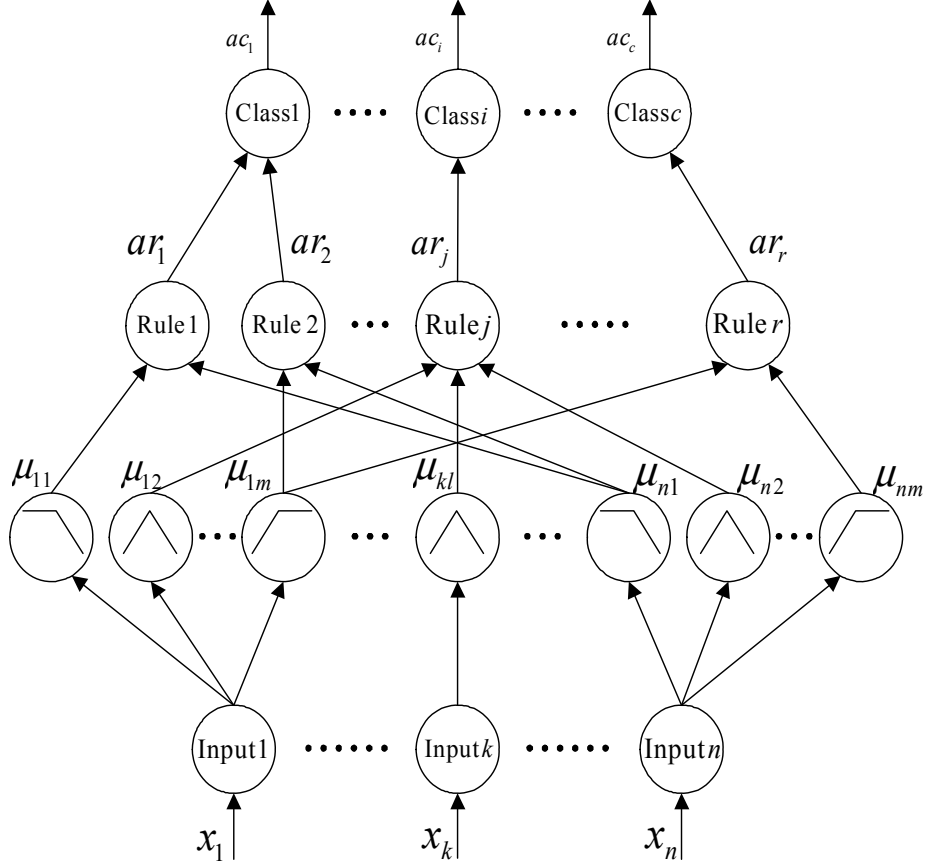


Figure. 5 Four-layer learning architecture of the employed neuro-fuzzy classifier

In this study, the employed neuro-fuzzy classifier follows six steps to generate fuzzy rules for learning performance assessment, and summarized as follows:

Step 1. Computing the activation strength of each fuzzy neuron in the rule layer by the minimum operator, and formulated as follows:

$$ar_j = \min_{k=1,2,\dots,n} \{u_k^{(j)}\} \quad (9)$$

where ar_j is the activation strength of the antecedent part of the j^{th} rule neuron, $u_k^{(j)}$ represents the membership degree of the j^{th} rule fired by the k^{th} input feature, which can be computed as $u_k^{(j)} = \max\{u_{k1}, u_{k2}, \dots, u_{km}\}$, and m is the number of the defined linguistic terms of each input feature.

Step 2. Computing the activation strength of each class neuron in the class layer by the maximum operator, and formulated as follows:

$$ac_i = \max_{j=1,2,\dots,z_i} \{ar_j^{(i)}\} \quad (10)$$

where ac_i is the activation strength of the consequent part of the i^{th} class neuron, $ar_j^{(i)}$ represents the activation strength of the i^{th} class neuron fired by the j^{th} rule which is the set member of the activation strengths of the rule neurons represented as $ar_j^{(i)} \in \{ar_1, ar_2, \dots, ar_j, \dots, ar_r\}$, and z_i is the number of the fired fuzzy rules of the i^{th} class neuron, and $z_i \leq r$.

Step 3. Computing the corresponding class register values by respectively calculating the summation of the activation strengths fired by all training patterns for each fuzzy rule, and formulated as follows:

$$t_i(j) = \sum_{p=1}^y ac_i^{(j)}(X_p), \text{ where } i = 1, 2, \dots, c, j = 1, 2, \dots, r \quad (11)$$

where $t_i(j)$ is the class register value of the i^{th} class for the j^{th} rule, $ac_i^{(j)}(X_p)$ is the activation strength of the i^{th} class neuron fired by the p^{th} training pattern for the j^{th} rule, and y is the total number of training patterns.

Step 4. Finding the class label with the largest class register value for each fuzzy rule, and formulated as follows:

$$\tau(j) = \underset{i=1,2,\dots,c}{\text{arg max}} \{t_i(j)\} \quad (12)$$

where $\tau(j)$ represents the class label with largest class register value for the j^{th} rule.

Step 5. Evaluating the performance for each fuzzy rule, and formulated as follows:

$$p(j) = t_{\tau(j)}(j) - \sum_{i=1,2,\dots,c, i \neq \tau} t_i(j) \quad (13)$$

where $p(j)$ represents the performance of the j^{th} fuzzy rule, $\tau(j)$ is the class label with the largest class register value for the j^{th} fuzzy rule.

Step 6. Collecting the fuzzy rules with the best performance in each class as the learning performance assessment rules.

Feature Reduction Scheme for Simplifying the Learning Performance Assessment Rules

To generate greater efficient and even accurate fuzzy rules, the original fuzzy rules discovered by the neuro-fuzzy classifier can be refined by the proposed feature reduction scheme. In the feature reduction process, it is assumed that there are sufficient relevant features in the original feature set to discriminate clearly between categories, and that some irrelevant features can be eliminated to improve efficiency and even accuracy. Generally, elimination of redundancy will improve efficiency without losing accuracy, and elimination of noise will improve both efficiency and accuracy (Chakraborty & Pal, 2004). In particular, the antecedent parts of fuzzy rules discovered by the neuro-fuzzy classifier always contain all features so that the main relevant features related to the classification accuracy cannot be clearly revealed as well as the inference efficiency is descended. More significantly, the antecedent parts of the fuzzy rules discovered by the neuro-fuzzy classifier containing all features will lead to over strict fired conditions so that many patterns cannot be inferred, and called as unknown patterns herein. The number of unknown patterns will obviously reduce the classification accuracy rate. Moreover, the simplified fuzzy rules for learning performance assessment are more easily interpreted by teachers, thus helping teachers to tune their teaching strategies. Based on these reasons, this study proposes a feature reduction scheme to simplify the discovered fuzzy rules. To obtain the simplified fuzzy rules, the proposed feature reduction scheme only performs the feature reduction scheme to the fuzzy rules with the best performance in each class. After that, the feature reduction is performed based on the proposed performance evaluation method for all feature combinations of the antecedent parts containing in each discovered fuzzy rule.

Figure 6 shows that the linguistic terms used in a fuzzy rule usually have overlapped intervals between two neighborhood linguistic terms, such as the intervals I_1, I_2, I_3 , and I_4 . In these overlapped intervals, a training pattern with feature value mapped in the corresponding overlapped interval will simultaneously fire the antecedent parts of two linguistic terms defined in a feature dimension and the fired strengths of two linguistic terms are different. For example, the membership degree of the linguistic term “Small” fired by a training pattern with feature value mapped in the interval I_1 is larger than the linguistic term “Moderate”. In contrast, the membership degree of the linguistic term “Small” fired by a training pattern with feature value mapped in the interval I_2 is smaller than the linguistic term “Moderate”. Based on the observation, an excellent feature combination in a discovered fuzzy rule should trigger the membership degree on the fired linguistic term as large as possible, but trigger the membership degree on the other non-fired linguistic terms as small as possible when the discovered fuzzy rule is fired by a training pattern. Herein, the fired linguistic term indicates the linguistic term with the largest membership degree fired by a training pattern, and the other linguistic terms are viewed as

the non-fired linguistic terms. This study names the difference between the membership degree of the fired linguistic term with the summation of the membership degrees of the non-fired linguistic terms as the match degree. To develop the proposed feature reduction scheme, the match degree is first defined as follows:

$$u_j^l(i) = u_{j\lambda}^l(i) - \sum_{k=1, k \neq \lambda}^n u_{jk}^l(i) \quad (14)$$

where $u_j^l(i)$ represents the match degree of the j^{th} feature of the l^{th} fuzzy rule fired by the i^{th} training pattern, $u_{jk}^l(i)$ is the membership degree of the k^{th} linguistic term of the j^{th} feature of the l^{th} fuzzy rule fired by the i^{th} training pattern, n represents the number of the defined linguistic terms in each fuzzy rule, λ indicates the linguistic term with the largest membership degree fired by the i^{th} training pattern.

After the match degree is obtained, the performance of the discovered fuzzy rule with the considered feature combination can be measured as follows:

$$v_q^l = \frac{\sum_{j=1}^{\varphi} \sum_{i=1}^t u_j^l(i)}{\varphi} \quad (15)$$

where v_q^l represents the performance of the l^{th} fuzzy rule under the q^{th} feature combination, t is the number of training patterns, φ is the number of features, $u_j^l(i)$ is the membership degree of the j^{th} feature of the l^{th} fuzzy rule fired by the i^{th} training pattern.

Moreover, the total number of feature combinations for a discovered fuzzy rule can be computed as follows:

$$g = \sum_{j=1}^p \frac{p!}{j!(p-j)!} \quad (16)$$

where g is the total number of feature combinations for a discovered fuzzy rule, p is the total number of feature dimensions, j is the number of the considered features.

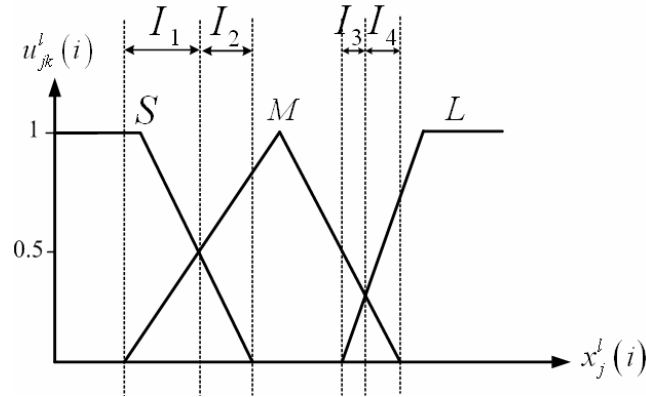


Figure 6. The overlapped regions between various linguistic terms, where $u_{jk}^l(i)$ is the membership degree of the k^{th} linguistic term of the j^{th} feature of the l^{th} fuzzy rule fired by the i^{th} training pattern, and $x_j^l(i)$ is the feature value of the i^{th} training pattern corresponding to the j^{th} feature of the l^{th} fuzzy rule

Fuzzy Inference by the Discovered Fuzzy Rules for the Learning Performance Assessment

This section explains how to infer the learning performance according to the discovered fuzzy rules by fuzzy inference. The discovered fuzzy production rules are formed by IF-THEN rules represented as follows:

$$\text{IF } X_1 = A_1 \text{ and } X_2 = A_2 \text{ THEN } Y = B$$

where X_i and Y denote linguistic variables, and A_i and B represent linguistic terms.

A defuzzification strategy aims to convert the outcome of fuzzy inference into a crisp class label. In this study, the maximum operator (Lin & Lee, 1996) is employed as the defuzzification scheme, to infer the crisp class label from the respective fired degrees of membership functions. Restated, the result of the learning performance assessment is assigned as the class label with the largest membership degree fired by a training pattern among the discovered fuzzy rules.

Experiments

The personalized e-learning system (PELS) was published on the web site <http://192.192.6.86/irt4> to provide personalized e-learning services and assess the learning performance of individual learners by web-based learning portfolios. To verify the evaluation quality of the discovered fuzzy rules for the learning performance assessment, some third-year students of Jee-May Elementary School (<http://www.jmes.tpc.edu.tw/>), who had majored in the “Fractions” course unit in elementary school mathematics, were invited to test this system. The experimental results are described as follows.

The Format of Learning Portfolio Gathered by PELS

The “Fractions” unit currently includes a total of 17 course materials with various difficulty levels, each conveying similar concepts. The system was used by 583 learners from 18 different classes of Taipei County Jee-May Elementary School (<http://www.jmes.tpc.edu.tw/>). Among the eight gathered learning factors, the final testing score G was obtained through the summative assessment scheme of fixed-length testing examination after the entire learning process is completed. Table 4 shows the format of the partial learning portfolios in the user profile database gathered by PELS.

Table 4. The format of the learning portfolio in the user profile database

Learning Factor Learning Record	G (0~100)	RR (0~1)	RT (sec)	LA (-3~+3)	CR (0~1)	PN (piece)	AS (point)	EL (0~1)
T ₁	83.24	0.630	2212	1.68	0.815	0	41	1.00
T ₂	74.17	0.600	1413	0.26	0.533	0	42	1.00
{	{	{	{	{	{	{	{	{
T583	84.81	0.436	3747	1.36	0.846	1	27	0.95

Evaluating Accuracy Rate of Learning Performance Assessment

Evaluation Method

To measure the accuracy rate of learning performance assessment for the proposed method, the score level method was used to evaluate the accuracy rate of the predicted learning performance. In this evaluation method, each learner is assessed according to one of three score levels based on the mapping membership degrees of learning factor G . For example, the score level of a learner with a final test score of 86.16 was set to moderate level if the linguistic term of moderate level has the largest mapping membership degree among all linguistic terms of the learning factor G .

Experimental Results

In our experiments, half the learning portfolios among 583 learners selected randomly were used as training data and the remaining learning portfolios were used as testing data. Table 5 illustrates the number of learning records in each grade level. To obtain simple and interpretable fuzzy rules for learning performance assessment, the number of cluster centers in the K-means algorithm is set to 3. That is, each learning factor contains three

various linguistic terms to describe a fuzzy rule, and named as “low”, “moderate”, and “high” herein. Table 6 shows the determined centers of the linguistic terms for eight learning factors by the K-means algorithm. To obtain fuzzy rules for learning performance assessment more accurately, the proposed refined K-means algorithm was employed to tune the centers of the linguistic terms listed in Table 6. Tables 7 and 8 display the revised amount of cluster centers for each learning factor and the revised centers of the linguistic terms of eight learning factors by the refined K-means algorithm, respectively. Figure 7 reveals the membership functions of triangle fuzzy sets for eight learning factors determined by the revised centers of the linguistic terms in the refined K-means algorithm. Basically, the left and right widths of triangle membership functions of the linguistic terms “moderate” for each learning factor are determined by the differences between the self-center with the left and right neighborhood centers, respectively. Moreover, the left and right widths of triangle membership functions of the linguistic terms “low” and “high” for each learning factor are determined by the difference between the self-center with the left or right neighborhood center as well as the boundary of each learning factor.

Table 5. The number of learning records in each grade level

Data set Item	Training data set			Testing data set			Whole data set		
	Low	Moderate	High	Low	Moderate	High	Low	Moderate	High
Number of patterns	51	194	47	65	188	38	116	382	85
Total number of patterns	292			291			583		

Table 6. The determined centers of the linguistic terms for eight learning factors by the K-means algorithm

Learning factor Linguistic term	G	RR	RT	LA	CR	PN	AS	EL
The centers of the linguistic term “low”	81.95	0.25	739.24	1.25	0.77	1.52	28.38	0.74
The centers of the linguistic term “moderate”	87.25	0.44	1585.02	1.58	0.87	2.61	53.88	1.05
The centers of the linguistic term “high”	90.44	0.63	3284.04	1.62	0.91	5.08	90.12	1.08

Table 7. The revised amount of cluster centers for each learning factor

Learning factor Revised amount	G	RR	RT	LA	CR	PN	AS	EL
The revised amount δ	12.5	0.5	3154	1.15	0.5	13	175	1.87

Table 8. The revised centers of the linguistic terms of eight learning factors by the refined K-means algorithm

Learning factor Linguistic term	G	RR	RT	LA	CR	PN	AS	EL
The revised center of the linguistic term “low”	69.45	-0.26	-2414.76	0.10	0.27	-11.48	-146.62	-1.13
The revised center of the linguistic term “moderate”	87.25	0.44	1585.02	1.58	0.87	2.61	53.88	1.05
The revised center of the linguistic term “high”	102.94	1.13	6438.04	2.77	1.41	18.80	256.12	2.95

Next, the neuro-fuzzy neural network with the refined K-means algorithm for logically determining membership functions was employed to discover the formative evaluation rules based on the learning portfolios of the training data set. There are totally 24 fuzzy rules discovered by the employed neuro-fuzzy neural network in our

experiment. Among all discovered fuzzy rules, there are 10, 9, and 5 rules discovered for assessing the low, moderate, and high grade levels, respectively. Table 9 shows three fuzzy rules with the best performance for assessing three different grade levels based on gathered learning portfolios. In our experiment, ten independent runs were performed to yield an average performance for the training and testing data sets. Table 10 displays the averaged accuracy rate of learning performance assessment evaluated by the discovered rules listed in Table 9. The averaged accuracy rates of learning performance assessment for the training and testing data sets are 74.3% and 71.1%, respectively.

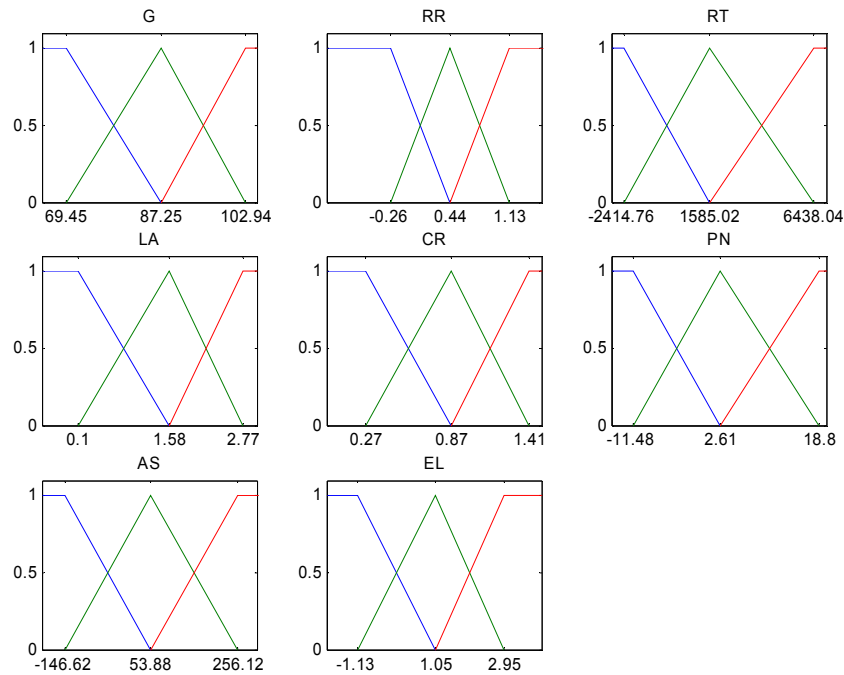


Figure 7. The membership functions of learning factors determined by the refined K-means algorithm

Table 9. The learning performance assessment fuzzy rules discovered by the neuro-fuzzy network with the refined K-means algorithm for determining fuzzy membership functions

Learning factor The discovered rule	Antecedent part							Consequent part
	RR	RT	LA	CR	PN	AS	EL	G
The rule 1	M	M	L	L	M	M	M	Low
The rule 2	M	M	M	M	M	M	M	Moderate
The rule 3	H	M	M	M	M	M	M	High

Table 10. The accuracy rate of learning performance assessment evaluated by the discovered rules listed in Table 9

Item	Data set	
	Training data set	Testing data set
Number of patterns	292	291
Number of the discovered rules	3	3
Number of the used fuzzy sets in the discovered rules	10	10
Number of patterns with correct learning performance assessment	217	207
Number of patterns with incorrect learning performance assessment	66	73

Number of patterns with unknown learning performance assessment	9	11
Averaged accuracy rate of learning performance assessment	0.743	0.711

Table 11. All combinations of seven learning factors in the antecedent parts of the discovered fuzzy rules evaluated in various training cycles

Training cycle	The combined learning factors
1~7	$x_1 \sim x_7$
8	x_1, x_2
9	x_1, x_3
10	x_1, x_4
\vdots	\vdots
125	$x_1, x_3, x_4, x_5, x_6, x_7$
126	$x_2, x_3, x_4, x_5, x_6, x_7$
127	$x_1, x_2, x_3, x_4, x_5, x_6, x_7$

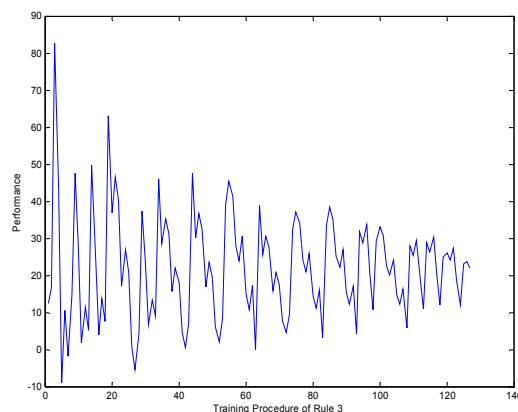


Figure 8. The performance evaluation plot of the discovered rule 1 for assessing the low score level

Although the used neuro-fuzzy classifier with the refined K-means algorithm can discover as few fuzzy rules as possible to assess the learning performance of an individual learner accurately, the obtained fuzzy rules always contain all learning factors so that the main learning factors that affect the learning performance cannot be revealed clearly. To simplify the obtained fuzzy rules, the feature reduction scheme was employed to further reduce the fuzzy rules of learning performance assessment. In the proposed feature reduction scheme, the performance index defined in Eq. (17) for all combinations of learning factors of the antecedent parts of discovered rules will be used to find the main learning factors that affect the learning performance. Table 11 lists all combinations of seven learning factors contained in the antecedent parts of the discovered fuzzy rules, where x_i represents the i^{th} considered learning factor, and their performances were respectively evaluated in various training cycles. Figures 8, 9 and 10 show the performance evaluation plots of the discovered rules 1, 2 and 3 for assessing the low, moderate and high score levels, respectively. Table 12 shows the learning factor combinations with top six excellent performances for three discovered fuzzy rules. In particular, the learning factor combination with best performance index among three discovered fuzzy rules is x_3, x_2 and x_1 . The result indicates that the third learning factor of the discovered fuzzy rule 1, i.e. learner ability (LA), is the main learning factor for assessing the learners with low score level. Similarly, the results also indicate that the second and first learning factors are the main learning factors for the discovered fuzzy rules 2 and 3, respectively. Table 13 shows the simplified learning performance assessment rules after performing the proposed feature reduction scheme. Table 14 displays the accuracy rate of learning performance assessment by these simplified fuzzy rules.

Compared with the results of learning performance assessment listed in Table 10, we find that the accuracy rate of the learning performance assessment using the simplified fuzzy rules is only slightly poor than the discovered fuzzy rules without performing feature reduction scheme. However, the simplified fuzzy rules provide benefits to teachers in terms of easily understanding main learning factors that affect learning performance for learners with various score levels (Paiva & Dourado, 2004; Mikut, Jakel & Groll, 2005). Moreover, this idea can be beneficially applied to immediately examine the learning progress of learners, and to perform interactively control learning for web-based learning systems. In the meanwhile, the simplified fuzzy rules will obviously promote the inference efficiency of learning performance assessment for web-based learning systems (Paiva & Dourado, 2004; Mikut, Jakel & Groll, 2005).

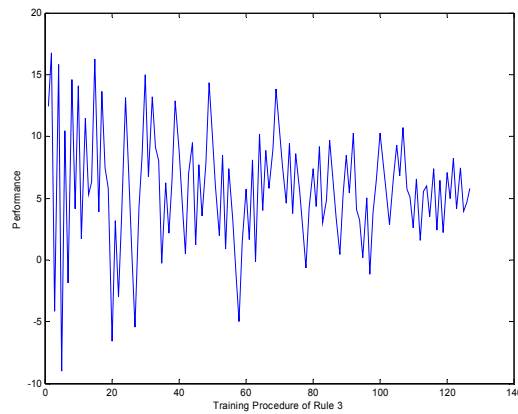


Figure 9. The performance evaluation plot of the discovered rule 2 for assessing the moderate score level

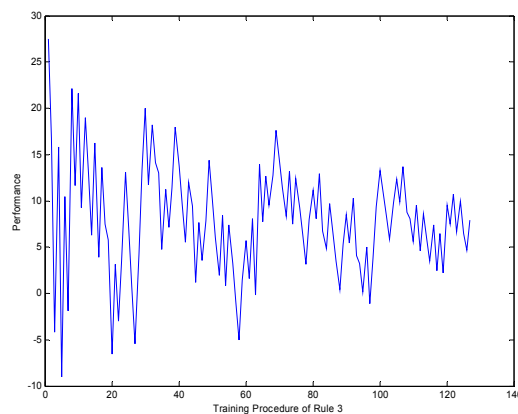


Figure 10. The performance evaluation plot of the discovered rule 3 for assessing the high score level

Table 12. The top six combined learning factors with excellent performance of learning performance assessment for three discovered rules

The discovered rule 1			The discovered rule 2			The discovered rule 3		
Training cycle	The combined learning factor	Performance index	Training cycle	The combined learning factor	Performance index	Training cycle	The combined learning factor	Performance index
3	x_3	82.71	2	x_2	16.78	1	x_1	27.50
19	x_3, x_4	62.98	15	x_2, x_4	16.29	8	x_1, x_2	22.14
14	x_2, x_3	49.75	4	x_4	15.79	10	x_1, x_4	21.65
44	x_2, x_3, x_4	47.58	30	x_1, x_2, x_4	15.00	30	x_1, x_2, x_4	20.02
9	x_1, x_3	47.57	8	x_1, x_2	14.61	12	x_1, x_6	18.98
21	x_3, x_6	46.59	49	x_2, x_4, x_6	14.34	32	x_1, x_2, x_7	18.25

Table 13. The discovered learning performance assessment rules after performing feature reduction

Learning factor The discovered rule	Antecedent part			Consequent part
	RR	RT	LA	G
The rule 1			L	Low
The rule 2		M		Moderate
The rule 3	H			High

Table 14. The accuracy rate of learning performance assessment by the simplified fuzzy rules listed in Table 13

Item	Data set	Training data set	Testing data set
	Number of patterns		292
Number of the discovered rules		3	3
Number of the used fuzzy sets in the discovered rules		3	3
Number of patterns with correct learning performance assessment		212	204
Number of patterns with incorrect learning performance assessment		80	87
Number of patterns with unknown learning performance assessment		0	0
Accuracy rate of learning performance assessment		0.726	0.701

Conclusion

This study presents an effective learning performance assessment approach which contains the neuro-fuzzy network with the refined K-means algorithm for logically determining membership functions and the proposed feature reduction scheme to discover simplified and small amount fuzzy rules for evaluating learning performance of individual learners based on the gathered learning portfolios. The proposed method can help teachers to perform precise formative assessments according to the web-based learning portfolios of individual learners in a web-based learning environment. The inferred learning performance can be applied as a reference guide for teachers and as learning feedback for learners. Such a feedback mechanism enables learners to understand their current learning status and make suitable learning adjustments. Additionally, teachers can determine the main factors affecting learning performance in a web-based learning environment according to the interpretable learning performance assessment rules obtained. These factors can be used by teachers to tune their teaching strategies. Meanwhile, teachers can devote themselves to teaching job, since they save significant time in performing learning evaluation.

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