

Improvement of Learning Process in E-Learning Environment Using Learning Styles Recognition Approach

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Abstract—Providing adaptive tutoring system which can adapt its layout and material based on the preferred learners' learning style is an effective way to improve the outcome of the learning process and help students to improve their performance. In this research, the web-based tutoring system offered by author collect the learner click behavior during the education and uses a machine learning algorithm in order to classify each individual learner based on their learning style. Research presented learners who participate in web-based tutoring system uses different methods in order to learn. This research applies machine learning algorithm on e-learning environment and is conducted among 50 students of Multimedia University in Malaysia who take part in web-based curriculum.

Index Terms- Learning style recognition, Felder-Silverman learning style, Neural network.

1 INTRODUCTION

By the advent of technology everything is transforming. One of the aspects of society that has been transforming is the ways that people learn and the method of teaching. In the recent years, there has been exponential development of web-based learning. Learners are capable to participate in many tutorial curriculums in anywhere and anytime.

Learners are identified by various learning styles that they have, focusing on various kinds of information and the process of this information in different ways. One of the desirable features of a distance learning or eLearning system is that the entire learner can learn through web-based application in spite of their different learning styles. In most of the application that was designed for e-learning student, the user profile are similar for all learners, but each learner has different performance, goals, experience, abilities and needs. Learners have their own unique way and the learning process is different for each learner to another one. The aim of this research is to use of machine learning algorithm in order to recognize of the learner's style, because the learning style influences your level of learning success.

2 LEARNING STYLE

Learning style is recognition of treats, emotional

and mental behaviors that provide quite fixed indicators of the way learners understand, how they interact and respond to learning environments [9]. In the recent years, numerous learning style prototypes have been suggested [6].

A fundamental study of learning styles, exploring their credibility, reliability and effect for pedagogy, can be found in [2]. Also, investigation studies on the use of learning styles in web-based learning provides support for the view that learning process can be improved through the performance of resources that are consistent with a learner's specific learning style [1]. For instance, in many researches it has been shown that the performance of learners in a Web-based learning environment related to their self-reported learning preference [5].

There was a study that shows the learning style is not relevant to traditional learning but it is essential in the e learning systems and the research shows the better effect would achieve in the learning process where learners have assimilated and converging learning style [7].

3 Felder-Silverman model

Many researches have used the model proposed by Felder and Silverman (1988) for education,

which categorizes learners based on their position on numerous measures that estimate how the learners process and perceive information:

-Perception: What kind of information do the learners favorably perceive: including sensory (external) like sights, audio, physical feelings, or intuitive (internal) such as options, visions, emotions?

Sensing learners: these learners prefer exact data, facts and self-experiences. They are attracted toward more procedural information and concrete, practical, and are oriented towards facts. In the problem solving, these students are patiently dealing with details and do not like to be surprised. Thus, they react to the problems with a slower pace, but they normally render a better result [4].

Intuitive learners: these learners are attracted more in theoretical methods and principles. They are not interested in details and do not like to solve the difficulties and problem in mechanical. These types of learners are interested in innovation. They basically do not go into the details and try to get an instant result. They tend to be fast but on the other hand vulnerable against mistakes errors, as a result it lowers their work quality [4].

- Input: there are a number of ways by which the information is conveyed to the learners namely: visual such as images, statistical charts, sketch or verbal for example recordings and pictured videos.

Visual learners: the information in the form of pictures and graphs is more likely to be memorized and understood by this kind of learners. They prefer graphics, timelines, drafts, plans, presentations and some other visual stuff to other forms of information.

Verbal learners: it has been proved by scientists that written words are converted to verbal equivalent and analyze them in a similar way with spoken words [3]. Therefore these learners are good at memorizing the written works as well as spoken form of information.

-Processing: generally there are two types of students first are the ones who actively take part in the group activities and the second one are those who prefer to react and are reflective.

Active learners: these learners appear more active and enthusiastic in dynamic situations. They tend to be good in team works and involve in each problem voluntarily. They want to go through any

problems they face using the receive information.

Reflective learners: these learners have a desire to deeply analyze the situation and they use the information in their own way of thinking. They are not good in team works and prefer to do things individually.

-Understanding: they are usually two types of approach towards understanding: sequentially in constant pace, or global learners that progress in large jumps.

Sequential learners: these learners usually track a fixed way of rationale when dealing with problems; they are interested to proceed in a direct way. Their learning achievement would improve if the difficulties and problems come in a linear form.

Global learners: global learners go through the problems based on their instinct and may not be able to describe it in detail. They prefer to think about the difficulties as a whole and do not elaborate. These groups of learners want to get the big picture of the problem.

4 PROPOSED APPROACH

The process of analyzing data was conducted, in accordance with the objectives and goals of the research and the research questions, in an attempt to implement an effective and productive analysis of the data. To find the answers to the questions, in the same manner as the studies that have been conducted before, the web-based application was used. 50 students took part in the survey and the web-based course was examined. Taking some assistance from Matlab, this research conducted a descriptive analysis in order to analyze the quantitative data that has been gathered with the help of web-based application.

The web-based application that collects data from student has shown in Fig 1. The web-based application gathers needed data from interaction between the students and application. The collected data will be saved in database and then are transferred to Matlab in order to process on the foundation of learning styles, the web-based was usually used with the purpose of collecting user click behavior. Furthermore, in this study, the mutual action of the learner, time, the order of some behavior and action is gathered. Then, the data is transformed into an area between 1 and 3 in

order to set out the power of each dimension. As stated before the percentage of each pattern behavior computed and used as an input to the algorithm. The information of those students who spent less than 10 minutes on each part of their lesson was thrown away due to the fact according to the teacher's timeline the studying time for each part should be at least 10 minutes and these students didn't have the test's requirements.

Learning style values for each dimension were separated into three distinctive categories. For instance, there are global, balanced and sequential preferences based on Felder and colleagues suggestion. So based on their recommendations and with regards to arranging reduction of question for expanding reliability, these groups were built. The suggested thresholds by Felder are reasonable because maximum three questions were deleted as a result of reliability reasons.

Values which are 1 are indicated the lowest preference in that dimension, those which are 3 indicate a preference for the other pole and finally, the values which are 2 points to a balanced learning style.

TABLE 1: THE ARRANGEMENT OF CHANNELS

Global/Sequential	Active/Reflective	Sensing/Intuitive	Visual/Verbal
G.S-outline-click	Ch-exercise-click	Ch-abs-click	Ch-forum-visit
G.S-seq-click	Ch-exercise-time	Ch-example-click	Ch-txt
Overview-click	Ch-forum-post	Ch_more	Ch-pdf-dl
	Ch-sa-click	Ch-exercise-ans-time	Ch-pic-mov
	G.S-outline-time	Ch-sa-click-afterle	
	Ch-example-time	Ch-sa-time	
		Ch-exercise-time	
		Ch-forum-post	
		Ch-exercise-click-afterle	
		Ch-example-time	

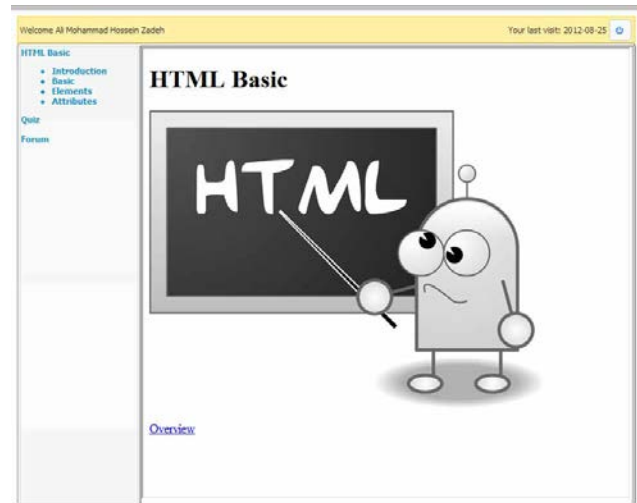


Fig. 1. Magnetization as a function of applied field.

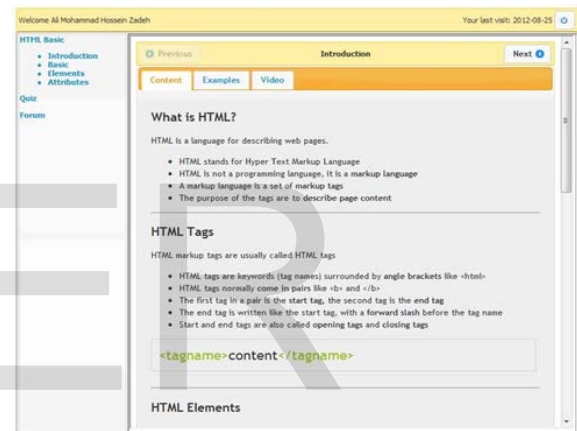


Fig 2: sample of introduction page

5 THE RESULT BASED ON MULTILAYER FEED FORWARD NEURAL NETWORKS

The process of Training the neural network in order to achieve the accurate outputs based on the proposed inputs is a repetitive that the network is trained with several samples and the actual outputs are compared with the target and then, the weights are adjusted to produce better prediction and results. In this research, there are 50 students who participated in a web-based tutorial system and we divided them into training and test sample. After collecting data and calculating the preference of each dimension, the data are transferred to Matlab. Each of the 23 inputs has specific information about learning styles. The MFNN receives input and use activation function in order to classify learner based on learning style.

Each layer is represented as Fig 3 based on their

neuron.

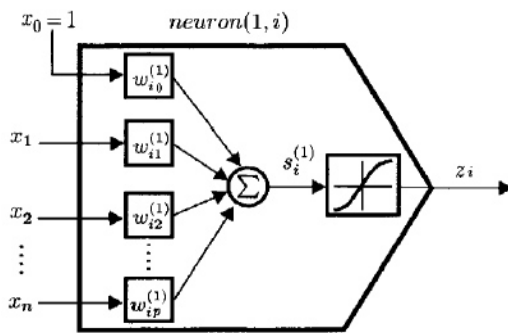


Fig 3: main structure of first layer in MFNN

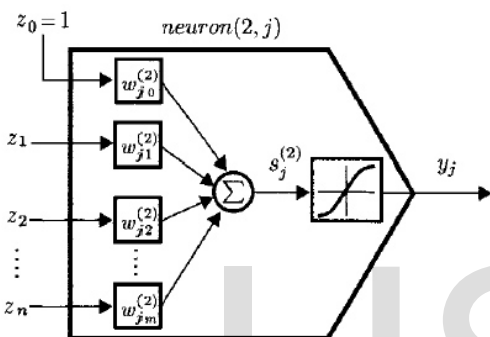


Fig 4: main structure of second layer in MFNN

The input and output of each layer are:

$$\begin{aligned}
 \text{neuron}(1, i) \text{ (input layer)} & \left\{ \begin{aligned} s_i^{(1)} &= \sum_{k=0}^n w_{ik}^{(1)} x_k \\ z_i &= \sigma(s_i^{(1)}) \\ i &= 1, 2, \dots, p \end{aligned} \right. \\
 \text{neuron}(2, j) \text{ (output layer)} & \left\{ \begin{aligned} s_j^{(2)} &= \sum_{q=0}^m w_{jq}^{(2)} z_q \\ y_j &= \sigma(s_j^{(2)}) \\ j &= 1, 2, \dots, m \end{aligned} \right.
 \end{aligned}
 \tag{1}$$

In order to learn network 34 of the samples were chosen and 8 samples for validation and the rest of them for testing.

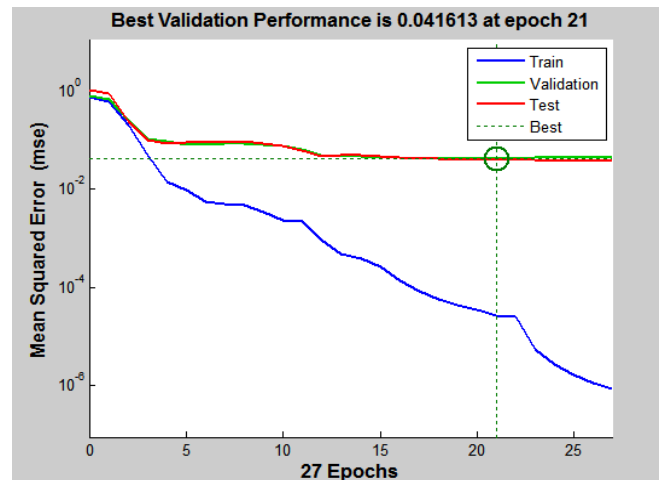


Fig 5: Best Validation Performance in 10 neurons

As illustrated in Fig 5, the numbers of Hidden Neurons are 10, but in order to decrease the rate of Error, several tests by changing the number of Neurons were implemented. In addition, in the proposed model 15% of samples were selected as a validation set and the number of Early-Stopping model was applied. Finally, by choosing 6 for the number of Neurons the lowest rate of error achieved (Fig 6).

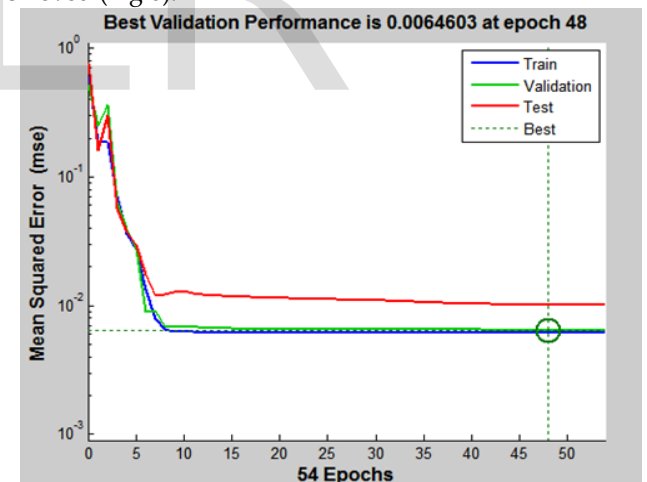


Fig 6: Best Validation Performance in 6 neurons

6 THE RESULT BASED ON RADIAL BASIS FUNCTION NEURAL NETWORK

Radial basis function (RBF) networks generally consist of three layers: 1- Input layer, 2-hidden layer with a non-linear RBF activation function 3-linear output layer.

We selected RBF neural network because of its

simplicity of structure and learning efficiency that is very important. The RBF neural network is able to predict in various ways. In order to test RBF neural network we have to load the input to Matlab. Based on the input, the RBF neural network learns how to classify learner. The inputs of the network are features that extracted from the web-based application. For instance, the amount of click on example, the total number of the click on self-assessment test, the sequence of clicking on exercise after learning the each part of the lecture. In addition, the RBF has 12 outputs that mean each of the dimensions is divided into 3 parts.

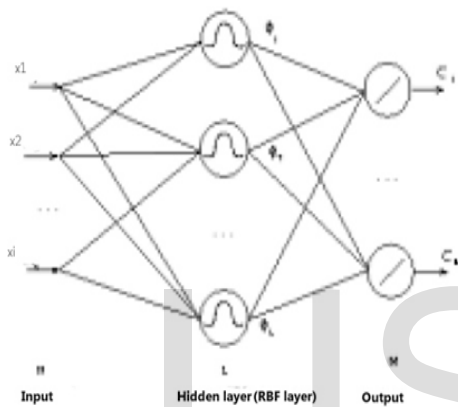


Fig 7: Main component of RBF

A class of functions form Radial functions which could be used in any sort of model such as linear or nonlinear and any sort of network like single-layer or multi-layer [8] . In order to use train RBF neural network, 35 data were chosen as samples and 15 of the input were used as test input and the following result were achieved. For spread=1 the mse error was around 0.3358 that is not satisfying and it is maybe due to the selection of test and training data. Table 2 shows the analysis of mse item and indicates the rate of error, based on different spread.

Tabel2: mse on various spread in RBF

Spread	mse
0.05	0.3333
0.1	0.3333
0.2	0.3333
0.5	0.3333
0.7	0.3334
0.8	0.3336
0.9	0.3343
1	0.3358
2	0.3537
3	0.3854
4	0.4027
50	0.6627
500	0.5372
1000	0.5461
5000	0.5462

Then, we used 10 samples as a test data which have been chosen among the all of data and the rest of them for training the network. As illustrated in Table 3 the result is better than the previous running but the percentage of the error is more than MFNN neural network.

Table 3: mse for 10 samples

spread	mse
0.05	0.3255
0.01	0.3333
0.09	0.3001
1	0.3023
2	0.3375
3	0.3461
4	0.3440
5	0.3462
50	0.3506
10	0.3463
20	0.3496
500	0.3508
5000	0.3429
By comparison of the output it can be achieved that the results when spread=500 are better than the previous test then it is better to run the tests around this variance.	
550	0.3508

The examination showed that the neural network with 6 Neurons are more precise than RBF. For instance, there are different answers in one of the prediction (Table 4).

Table 4: misclassification of learning style

1.0000	1
0.0000	0
0.0000	0
0.0000	0
0	0
1.0000	1
0.1920	0
0.3841	0
0.8080	1
1.2250	0
0.4500	0
0.2250	0

Based on the result, there is misclassification in one row of RBF in Table 4. In order to estimate the efficiency of the MFNN we run the test data on MFNN.

Finally, the answer of the MFNN is predicted match to target.

The MFNN can be employed in order to recognize a learner's learning style that lead to produce user interfaces based on their specific learning style in the learning environment.

```
>> round(out)
ans =
1 1 0 1 1 0 0 0 1 1
0 0 0 0 0 1 1 0 0 0
0 0 1 0 0 0 0 0 1 0 0
0 0 0 1 0 1 1 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0
1 1 1 0 1 0 0 1 1 1 1
1 0 1 1 0 1 0 0 0 0 0
0 0 0 0 1 0 0 1 1 1 0
0 1 0 0 0 0 1 0 0 0 1
0 0 0 0 1 1 1 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0
1 1 1 0 0 0 0 1 1 0
```

Fig 8: Output of the network with 6 neurons

y_10 =

1	1	0	1	1	0	0	0	1	1
0	0	0	0	0	1	1	0	0	0
0	0	1	0	0	0	0	1	0	0
0	0	0	1	0	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0
1	1	1	0	1	0	0	1	1	1
1	0	1	1	0	1	0	0	0	0
0	0	0	0	1	0	0	1	1	0
0	1	0	0	0	0	1	0	0	1
0	0	0	0	1	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0
1	1	1	0	0	0	0	1	1	0

Fig 9: Target of the MFNN

The MFNN and RBF neural network make it possible to recognize automatically the preferred learning styles of learners. In other word, the behavior and interaction between learner and web-based application indicate the learning style. As a result, this learning style can help the web developer to design intelligent web-based application that is able to adapt itself to each individual learner. This result showed that 46% of students who participated are active learners that means they are interested to involve in learning process by posting in forums, doing self-assessment test and spending time on exercise. As mentioned in chapter 2 the active learners prefer to try thing out by themselves. Furthermore, 32% of them are reflective learners and 22% of them are balanced learners. Furthermore, by the analysis of answers, 44% of participants were visual learners who prefer to study in a picture/video based learning material. In addition, the result has discovered 48% of participants were verbal learner whose preference were text-based material and used PDFs in order to study and finally, 8% of them were balanced learner they study in both modes. In the Global/Sequential area, the research shows that 50% of students were global who were interested to get a big picture of lessons in order to learn better and 50% of them were sequential who prefer to study based on the structure designed by the lecturer and follow the course step by step in a sequential mode.

7 CONCLUSION

This study essentially uses two algorithms of machine learning in order to classify learners based on preferred learning style and compared them. The methods to perform classification, as well as finding out the features that have the most impact on classification are important. In other words, which attributes are more effective in learning style recognition? According to the characteristic of each dimension and related activity, each student is put in a specific dimension. The collected data are transferred to Matlab software and are trained to the MFNN and RBF neural network in order to achieve the result. This chapter mainly focuses on the result that gained from the classification algorithm in order to get the conclusion.

This study has investigated several features which have an impact on the learning style recognition. The result of this study can be used in order to make the tutoring system more flexible based on the Felder-Silverman learning style model. For example, learners who are verbal more often used PDF and written material and therefore the web-based system usually offers the lecture in a text mode. In addition, the aim of the tutoring system established in this research is to extract learner click behavior patterns in learning environment in order to develop an adaptive tutoring system. This adaptive learning system can improve the learning process and outcome via the use of convenient way of learning match to individual students. To attain the goal of this research, some of important actions which are effective in recognizing learning style dimensions based on other research learning had been selected. This pattern behavior is based on the Felder-Silverman theory and then using the characteristics and machine learning algorithm to classify learning style. Finally, this research examines two algorithms and tries to reduce the error in classification and analyses the relevant pattern and the percentage of students that have the same dimension.

REFERENCES

- [1] Budhu, M. "Interactive Web-Based Learning Using Interactive Multimedia Simulations." Paper presented at the International Conference on Engineering Education (ICEE 2002), 2002.
- [2] Coffield, F., D. Moseley, E. Hall, and K. Ecclestone. "Learning Styles and Pedagogy in Post-16 Learning: A Systematic and Critical Review." Learning and Skills Research Centre London, 2004.
- [3] Felder, R.M., and R. Brent. "Understanding Student Differences." *Journal of engineering education* 94, no. 1 (2005): 57-72.
- [4] Felder, R.M., and L.K. Silverman. "Learning and Teaching Styles in Engineering Education." *Engineering education* 78, no. 7 (1988): 674-81.
- [5] Felder, R.M., and J. Spurlin. "Applications, Reliability and Validity of the Index of Learning Styles." *International Journal of Engineering Education* 21, no. 1 (2005): 103-12.
- [6] Kolb, D.A. "Experiential Learning: Experience as the Source of Learning and Development." (1984).
- [7] Manochehr, N.N. "The Influence of Learning Styles on Learners in E-Learning Environments: An Empirical Study." *Computers in Higher Education Economics Review* 18, no. 1 (2006): 10-14.
- [8] Orr, M.J.L. "Introduction to Radial Basis Function Networks." *Center for Cognitive Science, Scotland, UK* (1996).
- [9] Yau, J.Y.K., and MS Joy. "Context-Aware and Adaptive Learning Schedule for Mobile Learning." (2006).

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