

Analysis of Influences of memory on Cognitive load Using Neural Network Back Propagation Algorithm

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Abstract-Educational mining used to evaluate the learner's performance and the learning environment. The learning process are involved and influenced by different components. The memory is playing vital role in the process of learning. The long term, short term, working, instant, responsive, process, recollect, reference, instruction and action memory are involved in the process of learning. The influencing factors on these memories are identified through the construction analysis of Neural Network Back Propagation Algorithm. The observed set of data represented using cubical dataset format for the mining approach. The mining process is carried out using neural network based back propagation network model to decide the influencing cognitive load for the different learning challenges. The learners' difficulties are identified through the experimental results.

I.INTRODUCTION

The data mining techniques are applicable to all domains according to the need of applications. The data

mining technology phases are majorly having preprocess analysis and pattern generation. The data mining technology is attempted to integrate the learning system of learners and their cognitive behavior using predict approach. The Data mining technology is supported to determine the unknown values from available values. In this work, the predictive approach is used to identify the relationship of learner's performance and their cognitive load using Neural network approach and its optimized based on back propagation algorithm.

II.REVIEW OF LITERATURE

The review of literature covers basic concept of the data mining and the applications. The data mining tool and its techniques are highlighted. The Educational Data Mining process and its applications reviewed and presented in table 1. The Learner difficulties are identified and attempted to resolve.

Table 1: Describes Various Research Work Done Related To The Use Of Data Mining In The Context Of Education.

| S. No. | Year | Author | Work |
|--------|------|--|---|
| 1 | 2000 | Ma, Y., Liu, B., Wong, C. K., Yu, P. S., Lee, S. M | Presented a real life application of data mining to find weak students |
| 2 | 2001 | Luan J. | Introduced a powerful decision support tool, data mining, in the context of knowledge management |
| 3 | 2002 | Luan J. | Discussed the potential applications of data mining in higher education & explained how data mining saves resources while maximizing efficiency in academics. |
| 4 | 2005 | Delavari et al | Proposed a model for the application of data mining in higher education. |
| 5 | 2006 | Shyamala, K. & Rajagopalan, S. P. | Developed a model to find similar patterns from the data gathered and to make predication about students' performance. |
| 6 | 2006 | Sargenti et al | Explored the development of a model which allows for diffusion of knowledge within a small business university. |

III. ROLE OF MEMORY MODEL IN LEARNING PROCESS

In the learning process, memory model is playing vital role from the observation, reorganization, understating and learning. In learning process memory classified as working memory , short term memory, long term memory and sensor memory . Working memory is where thinking gets done. The working memory is dual coded with a buffer for storage of verbal/text elements.sensory memory that those experiences get introduced into working memory. Once an experience is in working memory, the person can then consciously hold it in memory and think about it in context. The short-term memory acts in parallel with the long-term memory.According to the analysis of memory , the learning process is involved in the following memory process such as Long Term Memory, Short Term Memory, Working (Calculation) Memory , Instant Memory ,Responsive Memory ,Processing (Search Content) Memory ,Recollecting Memory ,Reference Memory ,Instruction Memory , Action Memory These memory performances are consider as a process unit and the neural network model designed . The real time learners performances are observed using NASA workload scaling process.

IV.NEURAL NETWORK –BACK PROPAGATION MODEL

Neural Networks are analytic techniques modeled after the (hypothesized) processes of learning's in the cognitive system and the neurological functions of the brain and capable of predicting new observations (on specific variables) from other observations (on the same or other variables) after executing a process of so-called learning from existing data. Neural Networks is one of the Data Mining techniques to determine and optimize the factors.

A. Neural Network

Artificial neural networks simulate the biological structure of neural networks in brains in a simplified way to endow computers with the very considerable abilities of biological neural networks: the ability of learning from examples, pattern classification, generalization and prediction.

B. Back Propagation Algorithm

As per the adopted back propagation neural network model, the observed data is mapped and the model is constructed. The adopted algorithm concept converted as a step by step executable concept and presented below

Step 1 :

Normalize the I/P and O/P with respect to their maximum values. For each training pair, assume that in normalized form there are ℓ inputs given by $\{ I \}_I$ and $\ell \times 1$ outputs given by $\{ O \}_O$
 $n \times 1$

Step 2 :

Assume that the number of neurons in the hidden layers lie between $1 < m < 10$. because the ten memory attributes are consider for this network construction.

Step 3:

Let $[V]$ represents the weights of synapses connecting input neuron and hidden neuron. Let $[W]$ represents the weights of synapses connecting hidden neuron and output neuron. Initialize the weights to small random values usually from -1 to +1;

$$[V]^0 = [\text{random weights}]$$

$$[W]^0 = [\text{random weights}]$$

$$[\Delta V]^0 = [\Delta W]^0 = [0]$$

For general problems λ can be assumed as 1 and threshold value as 0.

Step 4:

For training we need to present one set of inputs and outputs. Present the pattern as inputs to the input layer $\{ I \}_I$ then by using linear activation function, the output of the input layer may be evaluated as.

$$\{ O \}_I = \{ I \}_I t \times 1 \quad t \times 1$$

Step 5 :

Compute the inputs to the hidden layers by multiplying corresponding weights of synapses as

$$\{ I \}_H = [V]^T \{ O \}_I$$

$$m \times 1 \quad m \times \ell \quad \ell \times 1$$

Step 6 :

Let the hidden layer units, evaluate the output using the sigmoidal function as 1

$$\{ O \} =$$

$$(1 + e^{-(HI)})$$

$$m \times 1$$

Step 7 :

Compute the inputs to the output layers by multiplying corresponding weights of synapses as

$$\{ I \}_o = [W]^T \{ O \}_H$$

$$n \times 1 \quad n \times m \times 1$$

Step 8 :

Let the output layer units, evaluate the output using sigmoid function as

$$1 / (1 + e^{- (I_{oj})})$$

Note : This output is the network output

Step 9 :

Calculate the error using the difference between the network output and the desired output as for the j th training set as E^p

Step 10 :

Find a term $\{ d \}$ as

$$\{ d \} = (T_k - O_{ok}) O_{ok} (1 - O_{ok})$$

$$n \times 1$$

Step 11 :

Find $[Y]$ matrix as

$$[Y] = \{ O \}_H \{ d \}$$

$$m \times n \quad m \times 1 \quad 1 \times n$$

Step 12 :

$$[\Delta W]^{t+1} = \alpha [\Delta W]^t + \eta [Y]$$

$$m \times n \quad m \times n \quad m \times n$$

Step 13 :

$$\{ e \} = [W] \{ d \}$$

$$m \times 1 \quad m \times n \quad n \times 1$$

$$(O_{Hi}) (1 - O_{Hi})$$

$$\{ d^* \} = e_i$$

$$m \times 1 \quad m \times 1$$

Find $[X]$ matrix as

$$[X] = \{ O \}_I \{ d^* \} = \{ I \}_I \{ d^* \}$$

$$1 \times m \quad \ell \times 1 \quad 1 \times m \quad \ell \times 1 \quad 1 \times m$$

Step 14 :

$$[\Delta V]^{t+1} = \alpha [\Delta V]^t + \eta [X]$$

$$1 \times m \quad 1 \times m \quad 1 \times m$$

Step 15 :

$$[V]^{t+1} = [V]^t + [\Delta V]^{t+1}$$

$$[W]^{t+1} = [W]^t + [\Delta W]^{t+1}$$

Step 16 : Find error rate as

$$\text{Error rate} = \frac{\sum E^p}{n_{\text{set}}}$$

Step 17 : Repeat steps 4 to 16 until the convergence in the error rate is less than the tolerance value.

The Back propagation algorithm is converted for Education process

V. BACK PROPAGATION NEURAL NETWORK MODEL TO IDENTIFY INFLUENCES OF MEMORY ON COGNITIVE LOAD

In neural network, multilayer perceptron (MLP) architecture consists more than 2 layers; A MLP can have any number of layers, units per layer, network inputs, and network outputs such as fig 1 models. This network has 3 Layers; first layer is called input layer and last layer is called output layer; in between first and last layers which are called hidden layers. Finally, this network has three network inputs, one network output and hidden layer network. This model is the most popular in the supervised learning architecture because of the weight error correct rules. It is considered a generalization of the delta rule for nonlinear activation functions and multilayer networks. In a back-propagation neural network, the learning algorithm has two phases. First, a training input pattern is presented to the network input layer.

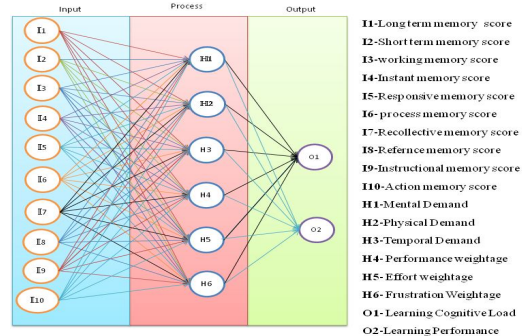


Figure1 : Neural network model

VI RESULT ANALYSIS

All external observation attributes are considered for the input. I1 to I10 represents the input variable which presents the score of the each exercise which carried out different memory learning process such as long term, short term, working, instant, responsive, process, recollect, reference, instruction and action memory. The cognitive loads are treated as process neuron of hidden layer. The H1 to H6 presents the mental, physical, temporal, performance, effort and frustration cognitive loads.

According to the observed values, the neural network process is made. The student exercise values for different memory and are presented 5, 7, 10, 7, 10, 6, 8, 10, 10 and 8. The process values weightage is presented as a matrix.

Table 2: Initial assignment I-> H

| | | | | | |
|---|--------|--------|--------|--------|--------|
| Initially Assigned Input to Hidden layer values are | | | | | |
| 0.1159 | 0.7452 | 0.7667 | 0.3303 | 0.5616 | 0.0683 |
| 0.6439 | 0.4698 | 0.0191 | 0.2963 | 0.8009 | 0.6156 |
| 0.2143 | 0.5475 | 0.2102 | 0.3169 | 0.1742 | 0.4353 |
| 0.9549 | 0.5177 | 0.1248 | 0.0150 | 0.7018 | 0.2846 |
| 0.4923 | 0.1257 | 0.9708 | 0.0489 | 0.7574 | 0.9536 |
| 0.0792 | 0.3202 | 0.8221 | 0.3629 | 0.9702 | 0.0913 |
| 0.1030 | 0.4678 | 0.0615 | 0.0294 | 0.1558 | 0.3777 |
| 0.6844 | 0.4638 | 0.3015 | 0.5345 | 0.3129 | 0.2956 |
| 0.8698 | 0.8769 | 0.1957 | 0.9274 | 0.4688 | 0.0399 |
| 0.1469 | 0.6540 | 0.3309 | 0.5981 | 0.0100 | 0.3490 |

Table 3: Initial Assignment H-> O

| | |
|--|--------|
| Initially Assigned Hidden layer to Output values are | |
| 0.9532 | 0.4718 |
| 0.0451 | 0.0943 |
| 0.1912 | 0.4462 |
| 0.5433 | 0.1154 |
| 0.6347 | 0.8885 |
| 0.8214 | 0.0804 |

From the initial values, each level obtained output is recalculated and assigned as a input and reduced the error level. Initially the output is estimated for 81 for the learning cognitive and 95 for the learning performance. The initial assigned neuron process produced 96 for the cognitive load and 89 for the learner performance. While obtaining this process, -62.048 error is produced. The iterative process implemented and obtained the final value in zero level error. The final weight age values are presented below

Table 4: Obtained weight I-> H

| | | | | | |
|--|--------|--------|--------|--------|--------|
| Final Input to Hidden layer values are | | | | | |
| 0.2318 | 1.4905 | 1.5335 | 0.6605 | 1.1232 | 0.1366 |
| 1.2879 | 0.9397 | 0.0382 | 0.5926 | 1.6019 | 1.2313 |
| 0.4286 | 1.0950 | 0.4204 | 0.6338 | 0.3484 | 0.8705 |
| 1.9099 | 1.0355 | 0.2495 | 0.0300 | 1.4036 | 0.5692 |
| 0.9846 | 0.2514 | 1.9416 | 0.0979 | 1.5147 | 1.9072 |

| | | | | | |
|--------|--------|--------|--------|--------|--------|
| 0.1583 | 0.6403 | 1.6442 | 0.7259 | 1.9405 | 0.1825 |
| 0.2060 | 0.9356 | 0.1229 | 0.0587 | 0.3116 | 0.7554 |
| 1.3687 | 0.9276 | 0.6030 | 1.0690 | 0.6258 | 0.5912 |
| 1.7397 | 1.7538 | 0.3913 | 1.8548 | 0.9375 | 0.0799 |
| 0.2938 | 1.3080 | 0.6618 | 1.1962 | 0.0200 | 0.6980 |

Table 5 Obtained weight H->O

Final Hidden to output layer values are

| | |
|--------|--------|
| 0.9532 | 0.4718 |
| 0.0451 | 0.0943 |
| 0.1912 | 0.4462 |
| 0.5433 | 0.1154 |
| 0.6347 | 0.8885 |
| 0.8214 | 0.0804 |

While processing the network model, the high value of mental effort is influenced at the maximum level of 95.32 percentage and least level of physical at 4.51 percentage.

The advantage of this model is less number of iteration and better performance compare with standard back-propagation model. To evaluate this algorithm, the MATLAB coding designed and executed .The learning performance is inclined to performance factor of the cognitive load to obtain as expected result. The entire model is presented according to the load along with the learning performance with the controlled weight. The load is differ one with another according to the different learning process. Mental, physical, temporal, effort, frustration is less while performance is high.

VII. CONCLUSION

The back propagation model could be designed and evaluation with multiple learning domains. A knowledge repository could be created for different learning objectives with available and adoptable technologies. The cognitive load six factors may be increased with environmental, socio-economic level of Learners as continuation of this research work.

VIII. BIBLIOGRAPHY

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