

Construction of Higher Vocational Teaching Quality Evaluation System based on the Combination of Work and Study

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Abstract. To improve reasonability and accuracy of higher vocational teaching quality evaluation, higher vocational teaching quality evaluation system based on optimized deep neural networks of intelligent water drop algorithm (IWD) is put forward. Firstly, make use of on-line student evaluation system widely adopted by certain vocational technical college to perform evaluation index design, and aimed at nonlinearity existing among these indexes, make use of deep neural networks to perform higher vocational teaching quality evaluation system construction. Then utilize second order parameter optimization form to perform Hessian matrix solution, and realize simplification of training process of deep network learning. Finally, verify effectiveness of algorithm mentioned through experiment simulation.

1. Introduction

Popularization of higher education continuously extends school operation scale of higher learning institution, which causes relative shortage of teacher strength, and makes teaching quality problem more and more obvious with time going by. Aimed at this problem, Ministry of Education organizes relevant experts to perform teaching level evaluation to each higher learning institution in batch. Therefore, how to improve teaching quality has become primary task of colleges and universities at present and in the future for school operation. To improve teaching quality, comprehensive management to teaching quality must be enhanced, especially evaluation to teaching quality of teacher.

Teaching is mutual activity between teacher and student. Teaching process consists of various factors, factors affecting teaching quality are numerous, and therefore contents needing to be evaluated are relatively numerous. There are mainly 3 kinds of traditional teaching evaluation methods: ①evaluate teaching effect of a teacher through simple arithmetical operation to various evaluation indexes, such as addition, subtraction, multiplication and division; ② perform fuzzy comprehensive evaluation through fuzzy mathematic theory; ③Markov chain evaluation method. Obvious disadvantages exist in these evaluation methods, former two methods cannot get rid of direct effect of human factor on evaluation result and the third method performs evaluation merely from single aspect, i.e. student score, and great one-sidedness exists.

2. Teaching Quality Evaluation Example

Certain vocational technical college widely adopts on-line student evaluation system, expert lecture attendance system of teaching quality management committee and mutual lecture attendance and score evaluation system of teacher, attaching much importance to teaching quality. 16 evaluation indexes adopted are as follows, respectively represented as x_1, x_2, \dots, x_{16} , of which x_1 represents work enthusiasm and spirited energy; x_2 represents classroom organization condition; x_3 represents carefulness degree when giving a lecture; x_4 represents after-class tutorship question answering patience; x_5 represents correctness of teaching content and proper volume and speed;

x_6 represents scientificity, logicity and systematicness emphasis in teaching content; x_7 represents being able to confirm key point and difficult point with proper handling; x_8 represents linking theory with practice; x_9 represents enlightening innovative thinking; x_{10} represents homework assignment and correction condition; x_{11} represents adopting different methods according to teaching demand; x_{12} represents application condition of multimedia teaching measure; x_{13} represents normative and vivid teaching language and clear and reasonable blackboard-writing; x_{14} represents educating student by combining with teaching content and classroom discipline etc.; x_{15} represents condition of following discipline by teacher; x_{16} represents general impression on teacher.

Value range of evaluation index is confirmed as [0,100]. Result as shown in table 1 is gained after marking aimed at 14 teachers of computer major of our institute from student, expert and teacher is summarized. Seen from analysis to table 1, relationship between evaluation object (i.e. teaching effect) and each evaluation index is relatively complex and nonlinear. What is the relationship between them? To solve the problem, we construct mathematical model of evaluation system by utilizing deep neural networks.

Table 1. Summary of Teaching Quality

Sample	Evaluation Index																Object
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	Average X	
1	88	91	89	89	87	86	80	83	85	84	84	89	87	86	84	84	86
2	87	86	84	84	84	89	86	81	84	82	85	84	84	85	86	81	87
3	85	84	85	86	81	85	82	84	84	85	86	81	82	83	87	86	84
4	84	87	81	85	82	87	86	81	89	89	85	82	86	81	84	89	80
5	89	82	83	87	86	84	83	82	87	81	89	82	83	86	89	85	86
6	91	84	82	89	87	85	81	86	89	83	83	85	82	84	91	83	85
7	92	86	87	82	89	87	86	87	84	82	89	84	85	87	92	85	84
8	96	81	80	83	85	82	92	86	87	87	86	85	82	86	96	84	85
9	85	82	86	81	84	86	84	82	89	80	85	83	82	83	82	86	89
10	86	86	85	89	84	83	84	87	85	86	87	82	85	89	86	82	85
11	81	85	84	87	85	81	89	84	83	89	85	87	88	82	87	86	84
12	82	87	85	89	83	80	86	86	85	85	82	82	89	87	89	85	92
13	83	85	86	86	82	85	87	82	89	84	82	86	86	85	89	87	96
14	86	88	82	85	85	85	87	86	84	84	84	89	85	89	84	85	82

3. Dynamic Planning Design of Deep Learning Network IWD

3.1. Deep Network Learning

Deep neural network (DNN) is basic structure of deep network learning encoding, mainly implementing feature extraction and dimensionality compression process. On the basis of increasing hidden layer between input and output layer of traditional neural network, DNNs realizes improvement of network structure, of which node number of hidden layer in the middle shall be lower than that of input layer (encoder) and output layer (decoder). Common feature mapping of input and output of learning model can be constructed by utilizing network parameter training process. Main data dimensionality compression method is principal component analysis (PCA), but it is concluded that deep encoding learning method is more excellent than PCA encoding in experiment of literature [13].

To perform effective learning training to DNNs network, literature [5] designs learning training method of non-supervision form and realizes greedy-parameter tuning of non-supervision form layer by layer to solve partial unsatisfactory extreme value existing in deep training model. Different from above method, perform Hessian matrix solution and realize simplification of deep network learning training process by utilizing second order parameter optimization form. DNNs

structure is as shown in Fig. 1.

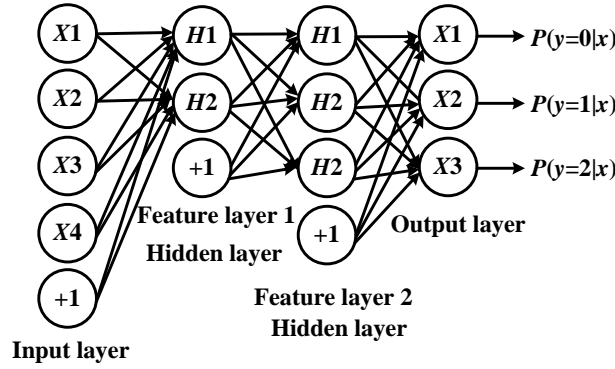


Figure 1. DNNs Structure

Fig.1 is DNNs structure, slightly different from traditional neural network structure. At least one layer of hidden layer structure is attached here to perform learning, and the structure can improve recognition algorithm performance of network structure obviously.

3.2. Heuristic Dynamic Planning of DNNs

Heuristic dynamic planning (DNNs-HDP) algorithm based on object expression is new reinforcement learning mechanism evolved from adaptive dynamic planning method (ADP) recently. It needs 3 functional approximation networks: object network, judgment network and action network. The 3 networks are constructed by adopting deep neural networks. Learning function of evaluation network is similar to cost function of Bellman equation. Action network learns to generate control strategy, and maximally reduces approximate cost of evaluation network; object network provides an adaptive internal reinforcement signal. Specifically, definition of functional cost function is as follows:

$$J[x(i), i] = \sum_{t=i}^{\infty} \gamma^{t-i} U[x(t), u(t), i] \quad (1)$$

Where, $x(t)$ is state vector of system, $u(t)$ is control law, and U is utility function and γ is discount factor. In this paper, all 3 networks realize 3-layer nonlinear structure by utilizing neural network of one hidden layer. However, learning rule can also be promoted to any functional approximation by implementing proper counterpropagation rule.

Step1: (object network training) performance cost of system can be shown with a compact form. Objective of dynamic planning is to choose control sequence $u(t)$ and minimize cost function J , and its form is as follows:

$$J^*(x(t)) = \min_{u(t)} \{U(x(t), u(t)) + \gamma J^*(x(t+1))\} \quad (2)$$

Based on the structure, J can be estimated through following formula:

$$\|E_h\| = \frac{1}{2} \sum_t [J(t) - r(t) - \alpha J(t+1)] \quad (3)$$

As for all moments t , $E_h = 0$, and following formula can be gained:

$$J(t) = r(t) + \alpha J(t+1) \quad (4)$$

Following formula can be gained after iteration step by step:

$$J(t-1) = r(t-1) + \alpha J(t) \quad (5)$$

Minimum form of objective function in object network of formula (13) and (14) is:

$$\begin{cases} e_g(t) = \alpha J(t) - [J(t-1) - r(t-1)] \\ E_g(t) = \frac{1}{2} e_g^2(t) \end{cases} \quad (6)$$

Counterpropagation path of high layer concept is:

$$\frac{\partial E_g(t)}{\partial \omega_g(t)} = \frac{\partial E_g(t)}{\partial J(t)} \frac{\partial J(t)}{\partial s(t)} \frac{\partial s(t)}{\partial \omega_g(t)} \quad (7)$$

As for deep neural networks used, connection weight adjustment from input layer to hidden layer and from hidden layer to output layer is as follows:

$$\begin{cases} \Delta \omega_{g_i}^{(2)} = \eta_g(t) \left[-\frac{\partial E_g(t)}{\partial \omega_{g_i}^{(2)}(t)} \right] \\ \omega_{g_{i,j}}^{(1)} = \eta_g(t) \left[-\frac{\partial E_g(t)}{\partial \omega_{g_i}^{(1)}(t)} \right] \end{cases} \quad (8)$$

Step2: (evaluation network training) once object network outputs signal, it will be used as input of evaluation network and used to define error function to realize evaluation network parameter adjustment, and form is as follows:

$$\begin{cases} e_c(t) = \alpha J(t) - [J(t-1) - s(t)] \\ E_c(t) = \frac{1}{2} e_c^2(t) \end{cases} \quad (9)$$

Counterpropagation path is:

$$\frac{\partial E_c(t)}{\partial \omega_c(t)} = \frac{\partial E_c(t)}{\partial J(t)} \frac{\partial J(t)}{\partial \omega_c(t)} \quad (10)$$

From hidden layer to output layer, adjustment to evaluation network weight input by hidden layer is as follows:

$$\begin{cases} \Delta \omega_{c_i}^{(2)} = \eta_c(t) \left[-\frac{\partial E_c(t)}{\partial \omega_{c_i}^{(2)}(t)} \right] \\ \Delta \omega_{c_{i,j}}^{(1)} = \eta_c(t) \left[-\frac{\partial E_c(t)}{\partial \omega_{c_{i,j}}^{(1)}(t)} \right] \end{cases} \quad (11)$$

Step3: (action network training) network action in the structure is adaptive adjustment, similar to reverse error communication method of typical ADP, which makes evaluation network output U_c approximate to final objective J . When U_c signal is strengthened, it represents that network action is effective. Therefore, error adjustment function of network action parameter is as follows:

$$e_a(t) = J(t) - U_c(t), \quad E_a(t) = \frac{1}{2} e_a^2(t) \quad (12)$$

Because action network is connected to object network and evaluation network, counterpropagation path form is as follows:

$$\begin{cases} \frac{\partial E_a(t)}{\partial \omega_a(t)} = P_{a,c}(t) + P_{a,g}(t) \\ P_{a,c}(t) = \frac{\partial E_a(t)}{\partial J(t)} \frac{\partial J(t)}{\partial u(t)} \frac{\partial u(t)}{\partial \omega_a(t)} \\ P_{a,g}(t) = \frac{\partial E_a(t)}{\partial J(t)} \frac{\partial J(t)}{\partial s(t)} \frac{\partial s(t)}{\partial u(t)} \frac{\partial u(t)}{\partial \omega_a(t)} \end{cases} \quad (13)$$

In action network, from hidden layer to output layer, adjustment to weight input by hidden layer is as follows:

$$\begin{cases} \Delta \omega_{a_i}^{(2)} = \eta_a(t) \left[-\frac{\partial E_a(t)}{\partial \omega_{a_i}^{(2)}(t)} \right] \\ \Delta \omega_{a_{i,j}}^{(1)} = \eta_a(t) \left[-\frac{\partial E_a(t)}{\partial \omega_{a_{i,j}}^{(1)}(t)} \right] \end{cases} \quad (14)$$

Procedure of higher vocational evaluation system is as follows:

Step1: Action network receives index data $\bar{\omega}$ gained from statistics and uses it to generate evaluation result data P_{esd} .

Step2: Object network generates internal strengthening signal $s(t)$ by utilizing external strengthening signal $r(t)$ and index data $\bar{\omega}$.

Step3: Evaluation network estimates cost function J on the basis of internal strengthening signal $s(t)$, index data $\bar{\omega}$ and evaluation result data P_{esd} .

Step4: Object network updates its weight according to formula (21~23) until conforming to

stopping criterion.

Step5: Evaluation network updates its weight according to formula (24~26) until conforming to stopping criterion.

Step6: Action network updates its weight according to formula (27~29) until conforming to stopping criterion.

Step7: Repeat implementing above processes until algorithm convergence.

3.3. Intelligent Water Drop Algorithm

Adopt intelligent water drop algorithm to perform weight optimization to above deep neural networks and specific steps are as follows:

Step 1: supposed that population size of water drop algorithm is NP, and dimensionality is D, supposed that initial soil quantity in water drop is $ini_soil(i, j)$ and its initial flow velocity is ini_vel_{IWD} , and execution cycle of partial automatic zoom of space is NC, and supposed that initial domain of intelligent water drop algorithm is $[l^0, u^0]$, and initialize evolution algebraic value $s = 1$.

Step 2: in above defined initial search domain $[l^0, u^0]$, generate population P_1 with NP scale through random way, and calculate individual fitness degree.

Step 3: if termination restriction is followed, stop evolution and perform result output.

Step 4: if current value of algebra s is integral multiple of automatic zoom setting period NC, steps in section 3.2.2 will be followed to perform renewal process to $[l^{t-1}, u^{t-1}]$, $[l^t, u^t]$ and P_1 .

Step 5: update evolution algebra $s = s + 1$ and return to step 3.

In implementation process of algorithm, oversize increasing of period parameter NC is unbeneficial to embodiment of automatic zoom advantage while undersize will increase computational expense correspondingly. This paper selects period parameter NC=10 according to experiment condition.

3.4. Complexity Analysis

Main complexity of algorithm is from learning of deep network. In training process of imprecise information machine, complexity P is proportional to $(1/\varepsilon)^{n/r}$:

$$P \propto (1/\varepsilon)^{n/r} \quad (15)$$

In formula (20), ε is permissible error of machine training; n is problem solution scale, and if it is approximation process, n can be regarded as its independent variable; r is smoothing factor, the smaller r is, the coarser it will be, and that is to say that the more complex function will be. In DNNs model training, because acquisition number of sample is limited, and it will be affected to uncertainty of noise, deep training complexity is concerned with uncertain complexity of sample information, which can be analogized as:

$$P' \propto (1/\varepsilon)^{n/R} \quad (16)$$

In formula (21), ε is permissible error of machine training; n is node number of network input layer; R is relevance of sample or approximation function, i.e. smoothing factor. At the same time, with increasing of network complexity, its problem solution capacity will be enhanced correspondingly. The capacity can be measured with dimensionality capacity index d_{vc} , and its estimated lower limit can be shown as:

$$d_{vc} \geq 2 \left\lceil \frac{H}{2} \right\rceil n \quad (17)$$

In formula (13), H is total node number of hidden layer network; n is input dimensionality. The network construction requires that index d_{vc} matches with data information complexity. If merely single node output (k=1) is involved, then formula (3) can be approximated to:

$$d_{vc} \geq (n+1)H \quad (18)$$

Following formula can be gained after summary:

$$C_R = \varepsilon [(n+1)H]^{R/n} \quad (19)$$

In the formula, C_R is concerned with problem solution complexity index R, error ε and total node

number H of hidden layer.

4. Model Test

Perform training to network model, perform test with the last 4 groups of data, and inspect whether error between output evaluation object and actual evaluation object conforms to requirement. Value of the last 4 groups of data in Table 1 after normalization is listed in Table 2.

Table 2. Test Value after Normalization

Sample	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	Average X	Object
1	0.92	0.73	1.02	0.92	0.68	0.80	1.02	0.65	0.54	0.54	0.61	0.72	0.52	0.62	0.63	0.92	0.92
2	0.71	0.53	0.52	0.91	0.75	0.7	0.89	.52	0.15	0.72	0.59	0.46	0.18	0.24	0.61	0.83	0.83
3	0.35	0.19	0.16	0.57	0.57	0.52	0.78	0.53	0.28	0.63	0.81	0.28	0.24	0.38	0.56	0.21	0.21
4	0.50	0.37	0.80	0.69	0.69	0.53	0.69	0.65	0.65	0.82	0.43	0.93	0.71	0.73	0.46	0.46	0.46

Output result after calculation of neural network is: 0.9434, 0.9335, 0.1251 and 0.3628. Compare evaluation object gained from the result after normalization processing with actual evaluation object, and test error of network can be gained, which is as shown in table 3 Result from test is quite approximate to original data, and that is to say that the model can confirm teaching effect quite accurately according to each evaluation index.

Table 3. Test Error

Actual Output	Network Output	Error
93	92.34	-0.63
92	92.56	0.27
84	83.64	-0.68
86	85.97	0.01

5. Conclusion

This paper constructs comprehensive evaluation model of teaching quality of teacher in universities and colleges by utilizing deep neural network algorithm, finds global optimum network parameter and overcomes low construction precision defect in traditional neural network model. Experiment verifies that the method is an effective comprehensive evaluation method, which adds new content for teaching management work of computer and has certain application value in teaching quality evaluation of universities and colleges.

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