A Deep Reinforcement Learning-based Algorithm for Balanced Allocation of Teaching Resources in International Economics

WENXI XU
School of Economics,
Hefei University of Technology,
Hefei, Anhui, 230601,
CHINA

Abstract: - The rapid development of online education technology and the increasing demand for international education require a more flexible and intelligent allocation of teaching resources to adapt to the constantly changing teaching environment and student needs. Therefore, a balanced allocation algorithm of international economics teaching resources based on deep and strong learning is proposed. That is, the joint allocation scheme of international economics teaching resources is designed by using deep reinforcement learning, and the balanced allocation algorithm of international economics teaching resources is generated, thus realizing the balanced allocation of teaching resources. The experimental results show that the RF service rate of the designed in-depth reinforcement learning balanced allocation algorithm for international economics teaching resources is low, which proves that the designed balanced allocation algorithm for teaching resources has good performance and reliability, the research results of this paper not only provide new ideas and methods for the allocation of teaching resources in international economics but also provide valuable experience and inspiration for the allocation of teaching resources in other fields, which will help promote the optimization and efficient utilization of educational resources and promote the sustainable development of the education industry.

Key-Words: - Deep learning, Reinforcement learning, International economics, Teaching resources, Balanced allocation algorithm, Multi-layer hidden neural network, Critical network; Assign tasks.

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1 Introduction

International economics is very important to national economic development, not only can it better understand the operation of the global economy, including the commercial and financial exchanges between different countries, [1]; but it can also understand the laws and regulations of different countries, and solve the major poverty problems of the modern economy. In recent years, international economics has gradually developed in the direction of trade liberalization, financial internationalization, and sustainable development, involving a great variety of teaching resources and increasing teaching difficulty. Balanced distribution of teaching resources for international economics is the key to ensuring the quality and fairness of teaching, which can break the unbalanced distribution of educational resources, cultivate high-quality talents, and improve the quality of education. Therefore, we can study the algorithm of balanced allocation of teaching resources for international economics according to the differences in economic development between regions and the allocation of teaching resources.

The algorithm for balanced allocation of teaching resources can analyze and calculate a large amount of data, improve the efficiency of resource utilization by considering multiple factors, and maximize the benefits of limited resources. When designing the algorithm, it is necessary to determine the types and quantities of teaching resources, collect data related to the allocation of teaching resources, including the basic information of regions, schools, and students, as well as the quantity, quality, and distribution of resources, and then carry out linear planning and multi-objective optimization to complete the dynamic adjustments, and the relevant researchers have designed several conventional algorithms of balanced allocation of teaching resources given the characteristics of the allocation of teaching resources. Reference [2] analyze the learning needs of students and teachers by considering the vision of teaching and adjusting them in combination with the changes of external conditions, which is more flexible, but the method involves a large number of subjective factors, such as educational concepts, practical needs, etc., which makes it difficult to measure and the algorithm's performance is poor. Reference [3] based on self-regulated learning for self-directed adjustment, the learner is actively involved in the learning process, recording learning progress feedback, improve the relevance of the algorithm, but its emphasis on personalized adaptation, difficult to develop a unified evaluation standard, distribution uncertainty is high. Reference [4] combines the bilingual motivational self-perspective to establish a self-motivation system, improve the identity of learning goals and learning meanings, and ensure the algorithm's distributional motivational effect, but its total cost is higher. Reference [5] use the bootstrap plan to adjust the expected allocation factor to realize diversified allocation, but its optimization difficulty is high and does not meet the balanced allocation requirements of the algorithm. To improve the performance of comprehensive resource allocation, this paper designs an effective balanced allocation algorithm for international economics teaching resources based on deep reinforcement learning. This paper utilizes deep reinforcement learning techniques to process and analyze a large amount of data related to the allocation of teaching resources, including basic information about regions, schools, and students, as well as the quantity, quality, and distribution of resources. Through continuous trial and error and feedback optimization, resource allocation strategies can be dynamically adjusted to adapt to changes in the teaching environment and student needs. This adaptive ability enables algorithms to quickly respond to unexpected situations or environmental changes, ensuring a balanced allocation of teaching resources.

2 Design of a Deep Reinforcement Learning-based Algorithm for Balanced Allocation of Teaching Resources in International Economics

2.1 Designing a Joint Allocation Program for Teaching Resources in International Economics based on Deep and Intensive Learning

Deep reinforcement learning is an AI perception decision-making method, which can classify teaching resources according to their higher-order characteristics, realize automatic recognition, and meet the real conditions for teaching resource allocation. Therefore, this paper designs a joint allocation scheme of international economics teaching resources based on deep reinforcement learning. First, MDP modeling is carried out for the optimization of balanced resource allocation to judge the discrete state of continuous state space, and the problem of continuous action variables, [6], [7], [8], [9], [10], is solved by deep reinforcement learning. First, the balanced parameters X of teaching resource allocation need to be calculated, as shown in Eq. (1):

$$X = \frac{\sum_{r=1}^{m} x_r}{m} \tag{1}$$

In equation (1), x_r represents the resource initialization constant, m represents the resource loading constant, at this time, the teaching resources to be allocated can be driven to process, [11], [12], [13], [14], [15], and the obtained resource allocation driving model f is shown in Eq. (2):

$$f = \frac{\sqrt{\sum_{j=1}^{m}(x_r - X_j)}}{m} \quad (2)$$

In equation (2), X_j represents the virtualization constant of resource allocation, when using reinforcement learning to deal with the problem of balanced allocation of teaching resources, it is necessary to carry out Markov decision-making transformation, [16], [17], [18], [19], [20], mapping the elements of balanced allocation of resources to the above model, and completing the drive in a unified way, which is driven by the process with the help of the resource allocation drive scheme shown in Figure 1:

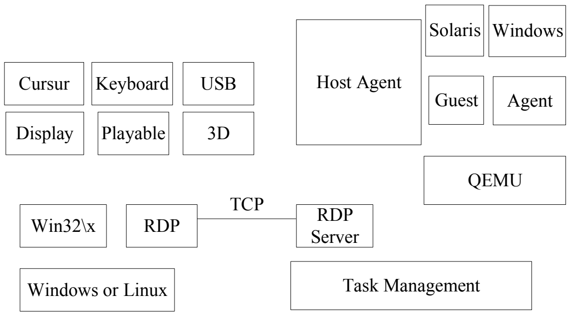

Fig. 1: Balanced Distribution of Teaching Resources Program

It can be seen from Figure 1 that in the process of random allocation of teaching resources, the MDP search process needs to be split, the resources to be allocated are regarded as part of the environment, the depth learning dimension is adjusted, and resampling is carried out. At this time, the space s_t to be allocated of teaching resources is shown in Eq. (3):

$$s_t = \{o, \tau, \varepsilon\} \quad (3)$$

In equation (3), o represents the action space, τ represents the reward function, ε represents the recursive parameter, the balanced allocation of teaching resources using the above-designed scheme can effectively deal with the interference in the process of resource allocation and realize intelligent perception.

2.2 Generating an Algorithm for the Balanced Allocation of Teaching Resources for International Economics

The stability of the conventional teaching resource balanced allocation algorithm is low, it is difficult to control continuous variables, and the set diversion coefficient also has some deviation. To solve this problem, this paper uses the Critical network to optimize the algorithm and conduct Actor training. At this time, the greedy scheduling and allocation process is shown in Figure 2:

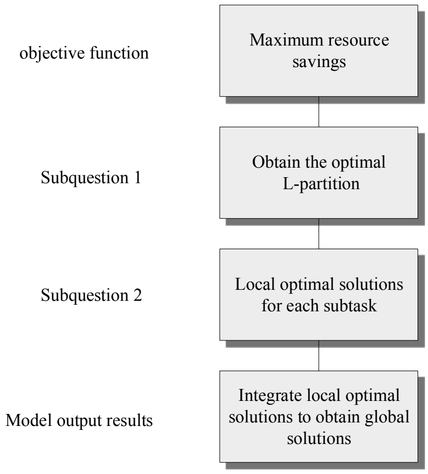

Fig. 2: Greedy scheduling allocation process

As can be seen in Figure 2, at the initial stage of teaching resource scheduling, it is necessary to perform scheduling ordering by each scheduling node, obtain the scheduling sub-problem, generate the matrix model, [21], [22], [23], and then look for the increased scheduling nodes in the scheduling matrix and switch the subtasks until the assignment task is completed, at which time the value ΔT of the scheduling resources, as shown in Eq. (4):

$$\Delta T = \left[\sum_{l=1}^{L}(b_l - c_l - M_0 \cdot \alpha)\right]^2 \quad (4)$$

In equation (4), b_l represents the number of resource allocation nodes, c_l represents the total number of nodes to be allocated, M_0 represents the resource allocation transformation value, α represents the allocation coefficient. Different sizes of teaching resources and balanced allocation of tasks corresponding to different allocation times, can be optimized using the integrated scheduling matrix, [24], at this time, the optimization of the average time ΔT_i is shown in Eq. (5):

$$\Delta T_i = \sum_{le}^{Vt} (d_{le} \cdot k_{le}) - M_0 \cdot \alpha \quad (5)$$

In Eq. (5), d_{le} represents allocation overhead. k_{le} represents the allocation delay. Based on this, we can use the strategy gradient algorithm to update, observe the original Ornstein Uhlenbeck random allocation process, and generate an effective optimization algorithm $u(k+1)$ for balanced allocation of teaching resources is shown in Eq. (6):

$$u(k+1) = \sum_{j=1}^{n} \mu(n) f(i) \quad (6)$$

In equation (6), $\mu(n)$ represents the amount of instructional resources controlled at different moments in time, [25], $f(i)$ represents the linear combination of coefficients, using this algorithm can be implemented differentially to meet the requirements of the allocation gradient, minimize the overhead of resource allocation, and improve the reliability of resource allocation.

3 Experiment

To verify the comprehensive performance of the designed balanced allocation algorithm of teaching resources for international economics based on deep reinforcement learning, this paper sets up an effective experimental environment and compares it with the balanced allocation algorithm of teaching resources based on self-regulated learning and the balanced allocation algorithm of teaching resources that combines the second-language motivational self-perspective, as follows.

3.1 Experimental Preparation

In combination with the experimental requirements for the balanced allocation of teaching resources, this paper selects the WINNER II platform as the experimental model, sets up several different scenarios for the allocation of teaching resources, and the parameters of the experimental model are shown in Table 1.

It can be seen from Table 1 that the experimental model has set up a multi-layer hidden neural network, with the number of neurons being 100\50, and the Actor-network is connected to the Critical network to ensure the output Q value of resource allocation. To meet the restriction requirements of the diversion coefficient, this paper uses the sigmoid activation function to update the RMSProp parameters and adjust the experimental learning rate to 0.0001. In this experiment, the D3QN unit is used as the Adam optimizer. Its network learning rate is 0.005 and the soft update parameter is 0.001. Before the experiment, 10000 rounds of training are carried out continuously for energy efficiency evaluation to ensure that it meets the requirements of real network resource allocation state changes.

Table 1. Parameters of the Experimental Model

Parameter	Numerical value
Balanced allocation of teaching resources and the number of users	8
Bandwidth of different teaching resource blocks	180kHz
Teaching resource allocation carrier frequency	2GHz
D2D pair quantity	{8,16,24,32,40}
Allocation of teaching resources and user transmission power	23dBm
D2D transmission power	[0,23] dBm
noise power	-114 dBm
Energy collection efficiency coefficient	0.8
D2D circuit power consumption	20 dBm
Resource allocation user signal-to-noise ratio threshold	3 dB

During the experiment, a large amount of teaching resource data is involved, which requires the use of Dennard's principle for multi-power processing and parallel development of experimental instructions. The composition of the Intel Sandy Bridge processor is shown in Figure 3:

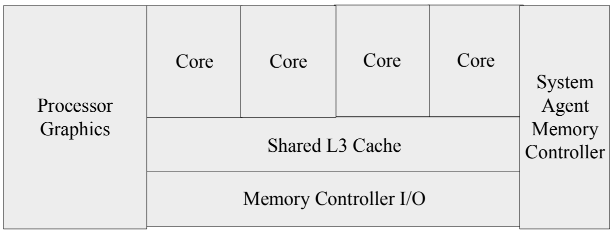

Fig. 3: Composition of Intel Sandy Bridge Processor

It can be seen from Figure 3 that the Intel Sandy Bridge processor chip contains four identical cores, which complete data conversion in parallel, and then input the resource allocation calculation results into the value Inetl memory. The structural characteristics of the memory are shown in Table 2:

Table 2. Inetl Memory Structure Features

Codename	L1 Cache	L2 Cache	L3 Cache	Number of processor cores
P5	32 KB	N/A	N/A	1
P6	32 KB	256KB	N/A	1
Core	64 KB	8MB	16MB	4
Penryn	64 KB	12MB	16MB	4
Nehalem	64 KB	256KB	12MB	8
Westmere	64 KB	256KB	30MB	10

It can be seen from Table 2 that the above data storage characteristics meet the experimental requirements for a balanced allocation of teaching resources. This paper selects Windows XP as the experimental client, ping and tracert as the application server, and mysql5.0 as the database server. The software architecture of the experimental platform is shown in Figure 4.

As can be seen from Figure 4, the above software architecture is mainly divided into three layers, through the business center, operation center, and other parallel storage of experimental data, the output of the final balanced allocation of teaching resources to verify the performance of the experimental results.

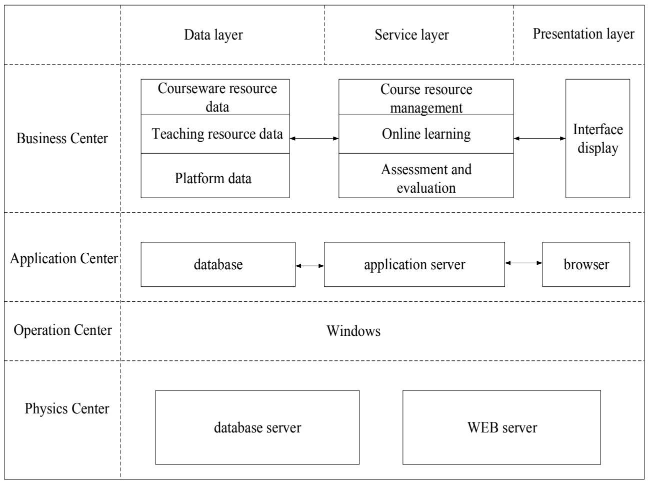

Fig. 4: Software architecture of the experimental platform

3.2 Experimental Results and Discussion

According to the above experimental preparation, this paper sets up several different teaching resource allocation users and adjusts QoE scores according to resource allocation requirements. At this time, we use the international economics teaching resource balanced allocation algorithm based on in-depth reinforcement learning designed in this paper, and the teaching resource balanced allocation algorithm based on self-regulation learning, as well as the balanced allocation algorithm of teaching resources from the perspective of two language motivation self, the VLC tool is used to calculate the RF service rate of the three algorithms. The experimental results are shown in Table 3 (Appendix).

It can be seen from Table 3 (Appendix) that under different QoE scores, the RF service rate of the balanced allocation algorithm of international economics teaching resources designed in this paper based on deep reinforcement learning is low, the service mechanism is simplified, and the RF service rate of the balanced allocation algorithm of teaching resources based on self-regulated learning and the balanced allocation algorithm of teaching resources from the perspective of second language motivation is relatively high, complex scheduling mechanism is required, which proves that the algorithm designed in this paper can reduce the service difficulty of resource allocation and save bandwidth resources. At this time, HIFs software is used to output the resource allocation benefits of the three algorithms. Resource allocation efficiency "is one of the important indicators for evaluating the performance of teaching resource allocation algorithms, which covers multiple aspects such as allocation efficiency, fairness, value creation, stability, and reliability. The experimental results are shown in Table 4 (Appendix).

It can be seen from Table 4 (Appendix) that the allocation time and random of the teaching resource allocation algorithm designed in this paper are low, and credit, welfare, and ca are high. The other two teaching resource allocation algorithms have higher allocation time and random, and credit, welfare, and ca are low. The above experimental results prove that the balanced allocation algorithm of international economics teaching resources designed in this paper based on deep reinforcement learning has good allocation performance and high allocation value. This is because the algorithm designed in this paper aims to achieve balanced allocation by optimizing resource allocation strategies to reduce RF service rates and improve resource utilization efficiency. This strategy helps reduce resource waste and conflicts, ensuring fair and effective utilization of teaching resources.

4 Conclusion

With the deepening development of globalization, the flow and sharing of educational resources on a global scale have become possible, and at the same time, the problem of imbalance in the distribution of educational resources has arisen. Factors such as the level of economic development, policy orientation, and cultural background of different countries and regions will lead to differences in the distribution of educational resources, and this imbalance is especially obvious in international economics education. Some developed countries or regions have abundant teaching resources, such as excellent teaching teams, advanced teaching equipment, abundant library materials, etc., while some developing countries or regions are facing the difficulties of lack of teaching resources. Therefore, how to achieve a balanced distribution of teaching resources for international economics in the context of globalization has become an urgent problem. International economics is a special discipline to provide international economic and trade talents, which mainly studies international investment, exchange rate changes, balance of payments, and so on, and involves more types of teaching resources, therefore, this paper designs an effective algorithm for balanced allocation of teaching resources in international economics based on deep reinforcement learning. The experimental results show that the designed balanced allocation algorithm has good performance, has a certain application value, and contributes to the development of international economics teaching.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The author contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The author has no conflicts of interest to declare.

APPENDIX

Table 3. RF Resource Allocation Service Rate Experiment Results

Method	Teaching resource allocation users	Collection of teaching resources	QoE score	Target latency(slots)	RF service rate(packets\slot)
The balanced allocation algorithm of international economics teaching resources based on deep reinforcement learning designed in this paper	RVLC1	CART0-a	1.5	0.1213	1.8542
	RVLC2	CART0-b	2.0	0.1225	1.1423
	RVLC3	CART0-c	2.5	0.1156	1.8574
	RVLC4	CART0-d	3.0	0.1235	1.2562
	RVLC5	CART0-e	3.5	0.1574	1.8413
A balanced allocation algorithm for teaching resources based on self-regulated learning	RVLC1	CART0-a	1.5	10.5441	3.6862
	RVLC2	CART0-b	2.0	12.2454	4.5465
	RVLC3	CART0-c	2.5	15.7235	4.3233
	RVLC4	CART0-d	3.0	11.8412	3.5248
	RVLC5	CART0-e	3.5	12.6523	3.4878
A Balanced Allocation Algorithm for Teaching Resources from the Perspective of Second Language Motivation Self	RVLC1	CART0-a	1.5	14.8465	3.2563
	RVLC2	CART0-b	2.0	16.9872	4.2225
	RVLC3	CART0-c	2.5	13.1465	4.7458
	RVLC4	CART0-d	3.0	15.2338	3.3658
	RVLC5	CART0-e	3.5	13.8546	4.4148

Table 4. Resource Allocation Benefits

Algorithm for Balanced Allocation of Teaching Resources	round	time	credit	random	welfare
The balanced allocation algorithm of international economics teaching resources based on deep reinforcement learning designed in this paper	1	2.51E+12	9.15E+25	2.55E+15	7.32E+21
	2	2.41E+12	8.42E+24	2.24E+14	7.12E+24
	3	1.25E+13	9.36E+22	2.32E+12	7.32E+25
	4	2.35E+15	8.58E+26	2.53E+13	6.85E+22
	5	1.35E+14	7.52E+25	2.45E+15	7.68E+23
A balanced allocation algorithm for teaching resources based on self-regulated learning	1	7.22E+25	1.55E+12	6.55E+21	2.55E+12
	2	6.55E+24	2.44E+15	6.44E+25	3.86E+14
	3	7.44E+22	1.88E+14	6.26E+22	2.43E+15
	4	7.51E+23	2.64E+16	7.62E+23	2.65E+13
	5	8.32E+25	2.25E+13	6.53E+26	2.24E+15
A Balanced Allocation Algorithm for Teaching Resources from the Perspective of Second Language Motivation Self	1	6.56E+22	2.62E+15	7.88E+25	3.38E+11
	2	7.55E+24	1.53E+14	8.64E+26	2.52E+14
	3	8.48E+21	1.75E+12	7.36E+28	2.43E+12
	4	7.26E+22	2.65E+15	6.55E+24	2.26E+16
	5	8.33E+23	2.88E+14	7.22E+22	3.38E+15