College Students' Learning Decision-Making Based on Group Learning Behavior

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Abstract—In learning groups, individuals have a few similarities in terms of the regularity of learning time, requirement for learning resources, and requirement for tutoring and accompanying. Analyzing the differences and connections of the learning behavior of different groups is helpful for generating more effective, targeted, and comprehensive learning decisions, however, existing studies are not extensive or deep enough in analyzing the learning behavior of different type learning groups. For this reason, this paper attempts to explore a learning decision-making model based on the influence of group learning behavior. At first, this paper made use of the advantages of Q-learning to improve the conventional behavior tree model, constructed a new model and used it to research the group learning behavior; then, this paper combined decision-making idea with the game model, and adopted a complex network structure to explore the evolution law of group learning decision-making based on multiple games. At last, this paper used experimental results to prove the effectiveness of the constructed model.

Keywords—group learning, learning decision-making, behavior tree, multiple games

1 Introduction

In order to provide guidance to learners in making learning decisions, a necessary work is to thoroughly analyze and research the changing laws of learners' learning behavior [1-9]. This research involves professional knowledge of psychology, pedagogy, sociology, and other disciplines, through descriptive statistics on the learning behavior of different groups, it can be found that individuals in learning groups have a few similarities in terms of the regularity of learning time, requirement for learning resources, and requirement for tutoring and accompanying [10-17]. Some field scholars in the world have researched the classification of learners based on educational big data, and figured out the trends of their learning behavior [18-22]. Exploring the implicit information in the data of learners' group learning behavior and analyzing the differences and connections of the learning behavior of different groups is helpful for making more effective, targeted, and comprehensive learning decisions, and at the same time, it can also provide constructive suggestions for organizations that are in charge of making plans for teaching activities.

Zhou et al. [23] discussed the self-regulated learning ability of students and its relationship with their learning engagement behavior observed in multimodal data, in their work, the participation behavior of students with multi-level self-regulated learning ability was investigated, and the results showed that, students with different levels of self-regulated learning ability might behave differently in individual, group, and queue learning behaviors. Xia and Wang [24] constructed a six-element learner group feature model based on the learners' knowledge level, learning motivation, learning attitude, learning style, interest preference and cognition ability. Under the dual actions of learner group feature analysis and the adaptive feedback updates of user groups, this model adopted a hybrid intelligent recommendation engine constructed based on collaborative filtering algorithm and deep learning to realize visualized and personalized recommendation and customized services for users. Now collaborative learning has been widely applied in the education field. Razanakolona et al. [25] performed cluster analysis in the process of collaborative mobile learning and extracted a learning decision-making model from group profiles. Zheng et al. [26] emphasized that group formation is one of the key processes in collaborative learning, they proposed a method to attain homogeneity between groups and heterogeneity in groups, the method converted the group formation problem into a combinatorial optimization problem, and the results proved that the proposed method was effective, stable, and able to form homogeneous and heterogeneous groups. During the collaboration period, each student's teammates had a significant impact on his/her learning. Sadeghi and Kardan [27] revealed how to effectively describe problems using binary integer programming method and all the requirements behind it, so as to build linear model for optimal solution within a reasonable time; also, they introduced the concept of fairness in the context of learner group formation, and elaborated on how to quantify it and apply it to the models.

Existing studies about group learning behavior mostly focus on the relationship between behavior and effect, and their data sources are mainly questionnaires or collected behavior history data, moreover, they generally analyze the behavior of learners from an overall perspective, while in terms of the learning behavior of different type learning groups, the analysis is neither detailed or deep enough. For this purpose, this paper attempts to explore a learning decision-making model for college students based on the influence of group learning behavior. The main contents of this paper are: 1) optimize the conventional behavior tree model based on the advantages of Q-learning; 2) construct a new model based on the optimized model and use it to research the group learning behavior; 3) combine decision-making idea with the game model and use a complex network structure to explore the evolution law of group learning decision-making based on multiple games; 4) employ experimental results to verify the effectiveness of the constructed model.

2 Individual learning decision-making based on behavior tree

In learning groups, individual learners only have three learning behavior rules: leaving the group, participating in learning, and joining the group. Concerning the behavior of learning groups, this paper paid the closest attention on the aspect of the microscopic interaction patterns among individuals in the groups. Each individual in the learning group will be affected by the learning behavior of other group members, it will make corresponding learning decisions for different teaching activities, that is, the learning decision-making mechanism of individuals in learning groups is the center point for research on group learning behavior.

Figure 1 gives the structure of the learning decision-making model. The model uses the perception module to perceive the applicability, usefulness, and the degree of the ease of use of group learning, then, the model generates individual and group learning decisions, and determines individual and group learning behaviors that need to be performed through the behavior module, during the decision-making process, the information of individual learning decisions needs to be exchanged.

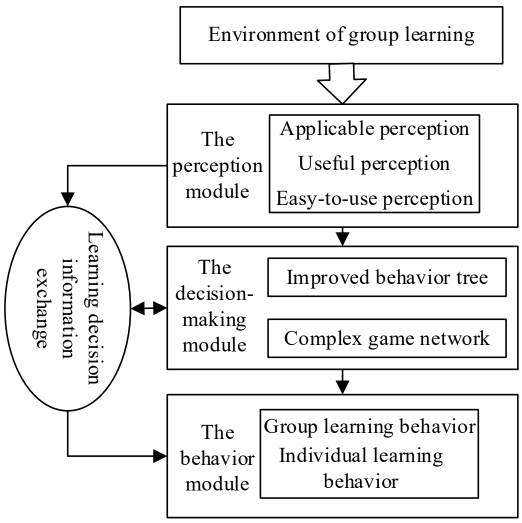

Fig. 1. Structure of the learning decision-making model

At first, this paper studied a learning decision-making model for college students based on the influence of group learning behavior. Behavior tree is a widely used decision-making model at present, so this paper adopted the behavior tree model to simulate the group learning behavior. To minimize the number of conditional nodes on the behavior tree, this paper made use of the advantages of Q-learning to improve the conventional behavior tree model, and realized automatic arrangement of the behavior tree at the same time.

2.1 The conventional Q-learning algorithm

Q-learning is a very efficient reinforcement learning algorithm with proven convergence performance. In this algorithm, the two-dimensional lookup table indexed by state-behavior pairs can be described by a function about decision and value. Assuming a represents the state, o represents the behavior, $S(x,a)=F\{s_0|a_0=a,o_0=o\}$; under state a, the probability of reaching state b by taking action o can be expressed as $FV_{ab}(o)$, and equation $D^{\varepsilon}(a)=max_o W^*(a,o)$ is satisfied, then Formula 1 gives the calculation formula of the discounted return value of Q-learning:

$$W^*(a,o)=S(a,o)+\alpha\sum_b FV_{ab}(o)D^*(b) \tag{1}$$

According to above formula, $W^*(a, o)$ is the value of the state-action pair (a, o), which is used to describe the discounted return value of taking action o under state a when the decision is optimal.

The updates performed by the Q-learning algorithm on the discounted return value are only based on the information of the next step, so it is a single-step operation. The Q(λ) algorithm integrates the Q-learning algorithm with the TD(λ) algorithm, it can update the current discounted return value based on all future information, so it is a multi-step operation. Assuming: τ represents time moment, then Formula 2 gives the update rule of the algorithm:

$$W_{\tau+1}(a,o)=\begin{cases} W_\tau(a,o)+\beta\left[f_\tau^{'}+\sum_{i=1}^{\infty}(\mu\alpha)^i\cdot f_{\tau+i}\right], if\ a=a_i, o=o_i \\ W_\tau(a,o), others \end{cases} \tag{2}$$

where, $\mu\in[0,1)$, $f_\tau=s_\tau+\alpha\cdot D_\tau(a_\tau+1)-D_\tau(a_\tau)$, $f_\tau'=s_\tau+\alpha\cdot D_\tau(a_\tau+1)-W_\tau(a_\tau,o_\tau)$.

With the increase of the number of state-behavior object pairs, using conventional combinatorial algorithms can no longer obtain the optimal solution of complex problems. The simulated annealing algorithm has the advantage of effectively avoiding solutions falling into local minimums, it determines the probability of accepting a new solution based on the Metropolis criterion. Assuming: $h(r_i)$ represents the current solution, $h(r_j)$ represents the newly generated solution, $h(a)$ represents the objective function, ψ represents the control parameter, then there is:

$$FV(r_i:=r_j)=\begin{cases} 1, h(r_i)\ge h(r_j) \\ exp\left(\dfrac{h(r_i)-h(r_j)}{\psi}\right), h(r_i)<h(r_j) \end{cases} \tag{3}$$

According to this formula, the adopted Metropolis criterion has two parts: if $h(r_i)\ge h(r_j)$, then the probability of accepting $h(r_j)$ is 1; if $h(r_i)<h(r_j)$, then $h(r_i)$ is accepted with a certain probability.

2.2 Construction of the behavior tree model improved by Q-learning

In case of object behaviors with complex logic, the constructed behavior tree will be very complex as well, and the work load of debugging the tree will be very huge. To analyze the group learning behavior, this paper introduced the advantages of Q-learning into the design of the behavior tree. Since the Q-learning algorithm needs to make a trade-off between exploration and utilization when making behavior selections, its convergence speed is relatively slow. Starting from practical problems, this chapter first improved the Q-learning algorithm, and then combined the behavior tree to generate a learning decision-making model for college students based on the influence of group learning behavior. This model can adaptively debug the behavior tree and re-sort the nodes on the original behavior tree, and it can be applied to the analysis of the learning decision-making of college students under the influence of group learning behavior.

Formula 4 gives the update rule of the adopted multi-step Q-learning:

$$W_{\tau+1}(a,o)=\begin{cases} W_\tau(a,o)+\beta\left[f_\tau^{'}+\sum_{i=1}^{l-1}(\mu\alpha)^i\cdot f_{\tau+i}\right], if\ a=a_i and\ o=o_i \\ W_\tau(a,o), other \end{cases} \tag{4}$$

where, $\lambda\in[0,1)$, $f_\tau=s_\tau+\alpha\cdot D_\tau(a_\tau+1)-D_\tau(a_\tau)$, $f_\tau'=s_\tau+\alpha\cdot D_\tau(a_\tau+1)-W_\tau(a_\tau,o_\tau)$, β represents the learning rate, $D_\tau(a_{\tau+1})$ represents the model's estimation of the value function under state $a_{\tau+1}$ at time moment τ, s_τ represents the immediate return value obtained when shifting from state a_τ to state $a_{\tau+1}$, then Formula 5 gives the update strategy of single-step Q-learning:

$$W_{\tau+1}(a_\tau,o_\tau)\leftarrow(1-\beta_\tau)W_\tau(a,o)+\beta_\tau\bullet\left[s_\tau+\alpha\bullet\max_b W_\tau(a_{\tau+1},y)\right] \tag{5}$$

In the adopted Q-learning algorithm, m represents the length of the input learning behavior sample data; $A[m]$, $X[m]$, $F[m]$ and $F'[m]$ respectively stores the state and behavior of m steps, which are denoted as f' and f.

To reach a balance between exploration and utilization, this chapter adopted the simulated annealing selection strategy to optimize the multi-step Q-learning algorithm above-mentioned. Assuming: o_s represents randomly selected behavior, o_t represents selected behavior, Formula 6 gives the formula for calculating the probability of accepting a random behavior:

$$FV(o_t=o_s)=\begin{cases} 1, W(r,o_s)\le W(r,o_t) \\ exp\left[\left(W(r,o_s)-W(r,o_t)\right)/\psi\right], W(r,o_s)>W(r,o_t) \end{cases} \tag{6}$$

When $W(r, o_s)\le Q(r, o_t)$, it chooses to accept behavior o_s and start exploration, and the performance of the algorithm can be improved by exploring non-optimal behaviors, otherwise it explores non-optimal behaviors with a probability of $exp[(W(r, o_s)-Q(r, o_t))/\psi]$. The temperature cooling strategy in the Metropolis criterion has a direct impact on the performance of the algorithm, ψ is the temperature control parameter,

ψ_0 represents the initial temperature, M represents the number of algorithm iterations, υ represents the specified heterogeneous constant, N represents the number of parameters to be inverted, then the temperature cooling strategy adopted in this paper can be described by Formula 7:

$$\psi(M)=\psi_0 exp\left(-\upsilon M^{1/N}\right) \tag{7}$$

In real applications, Formula 7 can be rewritten as:

$$\psi(M)=\psi_0 o^{M^{1/N}} \tag{8}$$

In the initial stage of the algorithm, it's necessary to set ψ with a larger value, then the obtained $FV(o_t=o_s)$ will be relatively large as well, and at this time, there is a greater probability of behavior selection. During algorithm iterations, the value of ψ will be subject to cooling processing through Formula 7, which will decrease $FV(o_t=o_s)$, and further reduce the probability of selecting non-optimal behaviors, and this is conducive to reducing the number of iterations and completing the selection of optimal behavior in the later stage of the algorithm.

Under a certain state, individuals in learning groups execute a certain learning behavior according to the behavior decision. This paper updated the discounted return value of the learned state-behavior pairs in reverse order, and introduced a dynamic reverse programming method which adopts the idea of using space to exchange time into the multi-step Q-learning algorithm to improve its convergence speed.

Assuming: an individual gets a certain reward value s after performing behavior o_τ, when the current state r_τ shifts to the next state $r_{\tau+1}$, the adjacency list of $r_{\tau+1}$ will be updated at the same time. When a state-behavior pair (r_τ, o_τ) under current state r_τ has been added into the adjacency list of $r_{\tau+1}$, then at this time, the adjacency list is $\{(r_1, o_1), (r_2, o_2),...,(r_\tau, o_\tau)\}$, and the $W(r_\tau, o_\tau)$ value of current state-behavior pair (r_τ, o_τ) will be updated by the discounted return value update function of multi-step Q-learning. Then, judging whether $W(r_\tau, o_\tau)$ is the maximum discounted return value under state r_τ, if yes, namely $W(r_\tau, o_\tau)=maxW(r_\tau, o_\tau)$ (i =1,2,...,m), then it can be judged that the adjacency list under the current state is not null. The discounted return value of the elements in the adjacency list can be updated in reverse order using Formula 9, if the discounted return value is not an optimal value or the adjacency list of the set is null, then the algorithm terminates. Assuming $W(r_l, o_l)$ is the discounted return value of (r_τ, o_τ), β is the learning rate, α is the decay factor, then there is:

$$W(r_l,o_l)=W(r_l,o_l)+\beta\left[s+\alpha W(r_\tau,o_\tau)-W(r_l,o_l)\right], l=\tau-1,\tau-2,...,1 \tag{9}$$

3 Group learning decision-making based on multiple games

The previous chapter discussed the learning decisions of individuals in learning groups, then, in order to figure out the influence of group learning behavior on the learning decision-making of other groups, this paper combined decision-making idea with the game model, and used a complex network structure to explore the evolution law of group learning decision-making based on multiple games.

This paper constructed a two-layer coupling network with an upper layer and a lower layer which were used to store different decision-making ideas and game strategies. The constructed network dynamically updates the individuals following the Monte Carlo simulation rule. In each step the network performs, an individual i is randomly selected and motivated to play games with its neighbors. Individuals who establish group relationships will get 1 point each during the game. When an individual who has already established a group relationship encounters another individual who has detached from another group, the detached individual will have an impulse to update its decision and can get 1+s, while the individual with a group relationship can only get -s; when two individuals who have both detached from group relationships meet, they will get 0 benefit each, and Formula 10 gives the benefit matrix of individuals:

$$\begin{array}{cc} & U \quad V \\ U & \\ V & \begin{bmatrix} 1 & -s \\ 1+s & 0 \end{bmatrix} \end{array} \tag{10}$$

If there is a certain correlation between the learning behavior network of learning groups and the learning decision-making idea network, and learning groups in the upper network have different learning decisions, then the game rules they follow won't change, but the games of the learning groups will follow the benefit matrix of snowdrift game, as shown in Formula 11:

$$\begin{array}{cc} & U \quad V \\ U & \\ V & \begin{bmatrix} 1 & 1-s \\ 1+s & 0 \end{bmatrix} \end{array} \tag{11}$$

Parameter s satisfies $0<s<1$. For the lower-layer network, an individual i in the learning group randomly selects a neighbor j and imitates its learning decision, and the probability of this situation is $P(i \rightarrow j)$. Assuming 1/L represents the selection intensity, then there is:

$$P_{(i \rightarrow j)} = \frac{1}{1+exp\left[\left(BE_i - BE_j\right)/L\right]} \tag{12}$$

The information exchange of individual learning decisions has a crucial influence on the learning behavior decision-making of learning groups. In order to explore the influence of individual learning decision information exchange mechanism on the evolution of group learning behavior in complex networks, this paper established a two-layer interdependent coupling network, individuals in different layers of the network can exchange their learning decision-making information. Figure 2 shows the structure of the two-layer coupling network. Orange nodes represent individuals entering the group, blue nodes represent individuals leaving the group, nodes in light colors have different decision-making update willingness; if there is a line between two nodes, then it means that there is information exchange between the them.

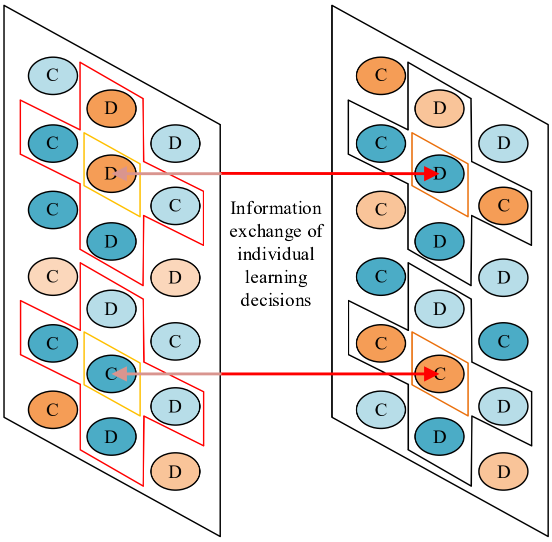

Fig. 2. Structure of the double-layer coupling network

The update of individuals' learning decision information can only be carried out between individuals in a same layer. For individuals in different layers, there is no learning decision information exchange connection between them, and the updates of learning decision information between them follow the traditional Fermi function, the individual *i* randomly selects a neighbor *j* and imitates its learning decision with probability $P_{(i \to j)}$.

When individuals in different layers are establishing their learning decision information exchange connections, the updates of their learning decisions will be affected not only by the update willingness of other individuals in the current layer, but also by the update willingness of individuals in other learning groups in the other layer and their neighbors. Assuming: q_i and w_i represent parameters that describe the degree of influence of information sharing; *mr* represents the sum of the number of individuals in other learning groups in the other layer and the number of neighbors who have the same learning decision as individual *i*, *m* represents the number of individuals in *mr* who have the willingness to change their learning decisions, then the learning decision update needs to follow the equations below:

$$P_{(i \to j)} = \frac{w_i^{\beta}}{1 + exp\left[\left(BE_i - BE_j\right) / L\right]} \tag{13}$$

$$w_i = m / mr\left(m \neq 0, mr \neq 0\right) \tag{14}$$

4 Simulation and experimental results

The prediction ability of the constructed decision-making model is determined by the length of the sample data, this value cannot be too large or too small. If the value is too small, the model will have no prediction ability; if the value is too large, the calculation complexity will be too high. In this paper, the value was determined by the comparative experiment. Figure 3 shows the experimental curves when the value of sample data length takes 15 and 25. As can be seen in the figure, the convergence speed of the two curves is similar, comparatively speaking, when the value of m is 15, the curve decreases faster, and finally, in this paper, the value of sample data length was determined to be 15.

Figure 4 shows the structure of the rearranged group learning behavior tree model. The model searches from top down and from left to right, it enters the first selection branch first, and judges whether it belongs to one of r_2, r_6, or other states in turn; if it belongs, then the learning stops, and the value of discounted return is assigned to be 9.8; if it belongs to one of r_3, r_4, or other states, then it updates the learning decision, leaves the current group, and the value of discounted return is assigned to be 8.7. Then, the model enters the second selection branch and starts searching, and judges whether it belongs to one of r_5, r_1, or other states, if it belongs, then it continues learning, and the value of discounted return is assigned to be 9.6. At last, the model enters the third selection branch and starts searching, and judges whether it belongs to one of r_1, other states, or r_2, if it belongs, then it randomly joins a group and stars learning, and the value of discounted return is assigned to be 7.4. If it belongs to one of r_1, r_2, or r_3, then it matches the learning decision and joins the new group to start learning, and the value of discounted return is assigned to be 6.9.

Figure 5 shows the relationship between decision update impulse and information exchange efficiency of learning groups of different sizes. The results showed that no matter the efficiency of learning decision-making information exchange is high or low, neither a too large learning group nor a too small learning group is conductive to group learning behavior analysis. As the impulse of decision update increases, relatively speaking, the group learning participation rate of the learning group with a size of 20 is higher.

Figure 6 shows the changes in the probability of group learning under different heterogeneous parameters. It can be seen from the figure that when the heterogeneous parameter υ is equal to 0.37, the probability of group learning reaches the maximum; as υ decreases, the probability value decreases gradually. This is consistent with the findings in existing research results.

Table 1 shows the results of regression test on the decisions of different learning groups. In terms of login time interval, the differences among different learning groups A, B, C, and D were not obvious. While in terms of the number of visits, the number of required resources, and the number of times of receiving tutoring, there're certain differences among these groups. Generally, there're significant differences between groups with extended feature and groups with similar feature.

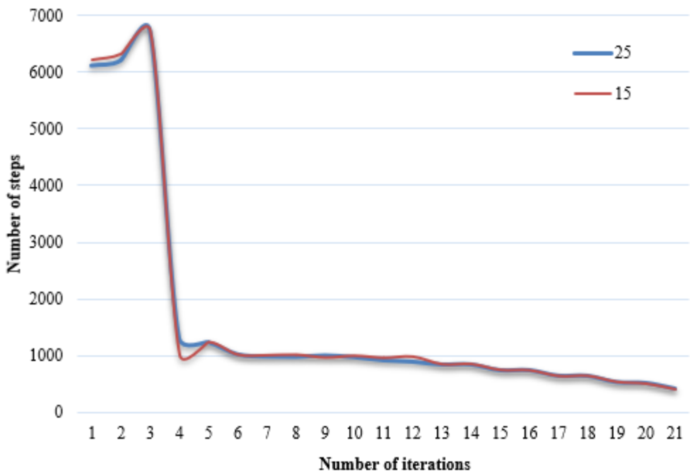

Fig. 3. Impact of sample data length on the convergence speed of the algorithm

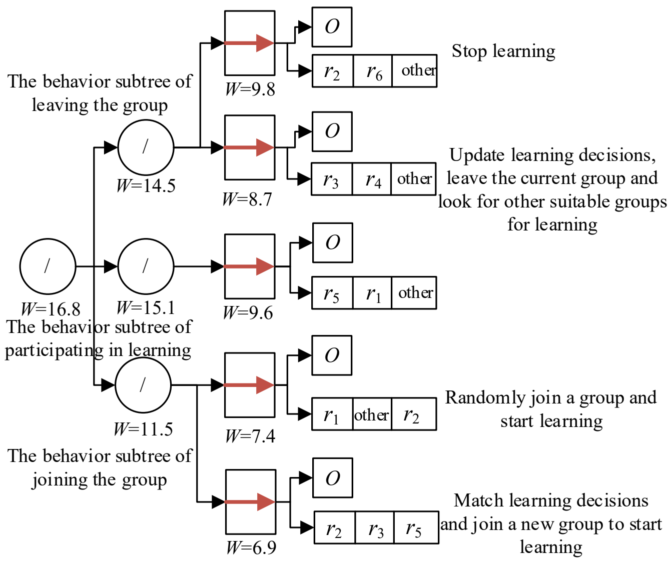

Fig. 4. Structure of the rearranged group learning behavior tree model

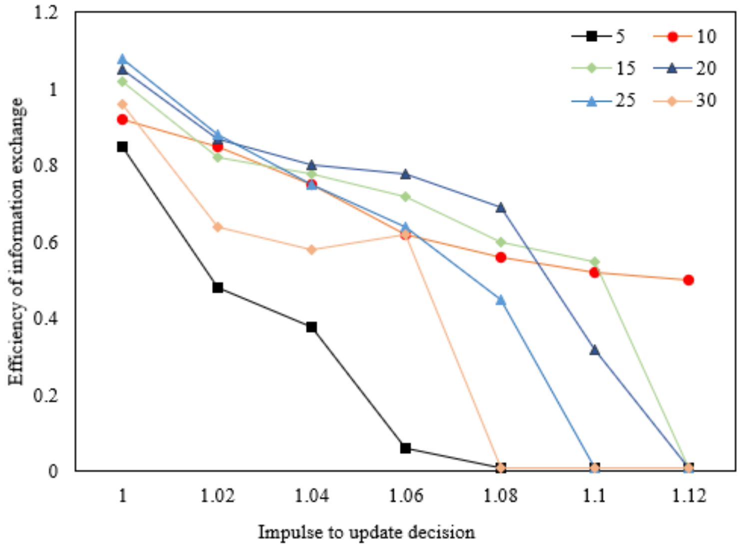

Fig. 5. The relationship between decision update impulse and information exchange efficiency

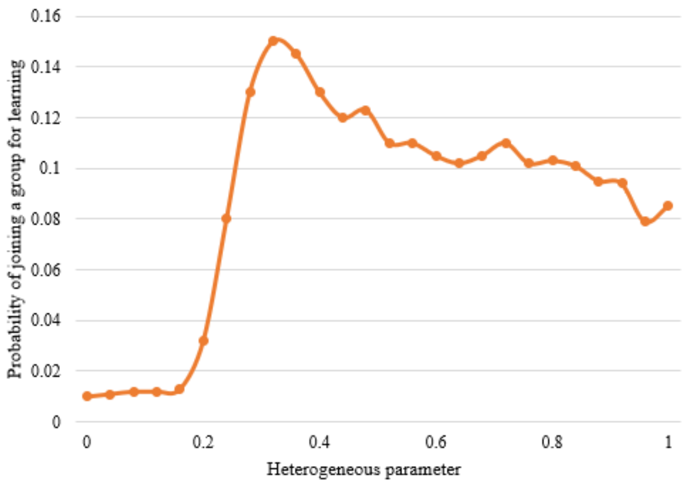

Fig. 6. Changes in the probability of group learning under different heterogeneous parameters

Table 1. Regression test on decisions of different learning groups

Learning behavior		Login interval				Number of visits				Number of required resources				Number of times of receiving tutoring			
Learning group		*B*	*A*	*C*	*D*	*B*	*A*	*C*	*D*	*B*	*A*	*C*	*D*	*B*	*A*	*C*	*D*
Significance	*B*	5.12				4.75				0.01				5.28			
	C	0.02	12			0.01	15			0.03	4.26			0.14	0.06		
	D	0.01	0.06	0.35		0.08	9.75	0.04		0.07	9.48	0.01		0.02	0.05	0.01	

5 Conclusion

This paper researched a learning decision-making model for college students based on the influence of group learning behavior. Firstly, the conventional behavior tree model was improved, and an improved behavior tree model based on Q-learning was constructed to study the group learning behavior. Then, this paper employed a complex network structure to explore the evolution law of group learning decision-making based on multiple games. After that, this paper determined the length of sample data through comparative experiment, showed the structure of the re-arranged group learning behavior tree model, gave the relationship between decision update impulse and information exchange efficiency of learning groups of difference sizes, and plotted the changes in the probability of group learning under the condition of different heterogeneous parameter values. At last, the decisions of different learning groups were subject to regression tests, and the effectiveness of the constructed model was verified.

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7 References

[1] Chang, H.C. (2010). Developing EL-RFM model for quantification learner's learning behavior in distance learning. In 2010 2nd International Conference on Education Technology and Computer, 4: V4-452. https://doi.org/10.1109/ICETC.2010.5529644
[2] Yang, L.Q. (2020). Comprehensive evaluation of music course teaching level based on improved multi-attribute fuzzy evaluation model. International Journal of Emerging Technologies in Learning, 15(19): 107-121. https://doi.org/10.3991/ijet.v15i19.17411
[3] Al-Shabandar, R., Hussain, A.J., Liatsis, P., Keight, R. (2018). Analyzing Learners behavior in MOOCs: An examination of performance and motivation using a data-driven approach. IEEE Access, 6: 73669-73685. https://doi.org/10.1109/ACCESS.2018.2876755
[4] Wang, K.C., Yan, C.K. (2020). An evaluation model for the cultivation and improvement of the innovation ability of college students. International Journal of Emerging Technologies in Learning, 15(17): 181-194. https://doi.org/10.3991/ijet.v15i17.16735
[5] Parker, M.C., Rogers, K., Ericson, B.J., Guzdial, M. (2017). Students and teachers use an online ap cs principles E-book differently: Teacher behavior consistent with expert learners. In Proceedings of the 2017 ACM Conference on International Computing Education Research, 101-109. https://doi.org/10.1145/3105726.3106189
[6] Cheng, Z., Sun, S., Kansen, M., Huang, T., He, A. (2005). A personalized ubiquitous education support environment by comparing learning instructional requirement with learner's behavior. In 19th International Conference on Advanced Information Networking and Applications (AINA'05) Volume 1 (AINA papers), 2: 567-573. https://doi.org/10.1109/AINA.2005.46

[7] Wu, B., Xiao, J. (2018). Mining online learner profile through learning behavior analysis. In Proceedings of the 10th International Conference on Education Technology and Computers, 112-118. https://doi.org/10.1145/3290511.3290560
[8] Gallagher, S.E., Savage, T. (2016). Comparing learner community behavior in multiple presentations of a massive open online course. Journal of Computing in Higher Education, 28(3): 358-369. https://doi.org/10.1007/s12528-016-9124-y
[9] Holmes, M., Latham, A., Crockett, K., O'Shea, J.D. (2017). Near real-time comprehension classification with artificial neural networks: Decoding e-learner non-verbal behavior. IEEE Transactions on Learning Technologies, 11(1): 5-12. https://doi.org/10.1109/TLT.2017.2754497
[10] Cucuiat, V. (2018). Exploring the meaning of effective exploratory learner behavior in hands-on, collaborative projects using physical computing kits. In International Conference on Artificial Intelligence in Education, 508-512. https://doi.org/10.1007/978-3-319-93846-2_95
[11] El Haddioui, I., Khaldi, M. (2012). Learner behavior analysis on an online learning platform. International Journal of Emerging Technologies in Learning (iJET), 7(2): 22-25. https://doi.org/10.3991/ijet.v7i2.1932
[12] Tseng, S.F., Tsao, Y.W., Yu, L.C., Chan, C.L., Lai, K.R. (2016). Who will pass? Analyzing learner behaviors in MOOCs. Research and Practice in Technology Enhanced Learning, 11(1): 1-11. https://doi.org/10.1186/s41039-016-0033-5
[13] Christudas, B.C.L., Kirubakaran, E., Thangaiah, P.R.J. (2018). An evolutionary approach for personalization of content delivery in e-learning systems based on learner behavior forcing compatibility of learning materials. Telematics and Informatics, 35(3): 520-533. https://doi.org/10.1016/j.tele.2017.02.004
[14] Wang, S.Y. (2021). Online learning behavior analysis based on image emotion recognition. Traitement du Signal, 38(3): 865-873. https://doi.org/10.18280/ts.380333
[15] Kizilcec, R.F., Pérez-Sanagustín, M., Maldonado, J.J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. Computers & Education, 104: 18-33. https://doi.org/10.1016/j.compedu.2016.10.001
[16] Sun, Y., Chai, R.Q. (2020). An early-warning model for online learners based on user portrait. Ingénierie des Systèmes d'Information, 25(4): 535-541. https://doi.org/10.18280/isi.250418
[17] Imai, Y., Kawanishi, C., Hattori, T., Hori, Y. (2014). Development and evaluation of learner-centric graphical educational tool for IP routing and network behavior. IEEJ Transactions on Electronics, Information and Systems, 134(11): 1634-1639. https://doi.org/10.1541/ieejeiss.134.1634
[18] Cao, D., Lan, A.S., Chen, W., Brinton, C.G., Chiang, M. (2018). Learner behavioral feature refinement and augmentation using GANs. In International Conference on Artificial Intelligence in Education, 41-46. https://doi.org/10.1007/978-3-319-93846-2_8
[19] Dwivedi, P., Bharadwaj, K.K. (2015). E-Learning recommender system for a group of learners based on the unified learner profile approach. Expert Systems, 32(2): 264-276. https://doi.org/10.1111/exsy.12061
[20] Bull, S., Al-Shanfari, L. (2015). Negotiating individual learner models in contexts of peer assessment and group learning. In CEUR Workshop Proceedings, 1432: 1-6.
[21] Sadeghi, H., Kardan, A.A. (2015). A novel justice-based linear model for optimal learner group formation in computer-supported collaborative learning environments. Computers in Human Behavior, 48: 436-447. https://doi.org/10.1016/j.chb.2015.01.020
[22] Vagale, V., Niedrite, L. (2014). Learner group creation and utilization in adaptive e-learning systems. In DB&IS, 189-202.

[23] Zhou, Q., Suraworachet, W., Cukurova, M. (2021). Different modality, different design, different results: exploring self-regulated learner clusters' engagement behaviours at individual, group and cohort activities. In CEUR Workshop Proceedings, 2902: 28-40. https://doi.org/10.35542/osf.io/u3g4n
[24] Xia, P., Wang, Z. (2021). Construction of learner group characteristics model based on network learning data perception and mining. In International Conference on Applications and Techniques in Cyber Security and Intelligence, 441-447. https://doi.org/10.1007/978-3-030-79197-1_63
[25] Razanakolona, L., Razafimandimby, J.P., Andriamiandanomenajanahry, H.C.C., Rhazali, Y. (2020). Approach model driven engineering: profiling group collaborative learner in mobile learning. Procedia Computer Science, 170: 863-868. https://doi.org/10.1016/j.procs.2020.03.143
[26] Zheng, Y.Q., Du, J.Z., Yu, H.B., Lu, W.G., Li, C.R. (2016). An improved genetic algorithm approach for optimal learner group formation in collaborative learning contexts. ICCE 2016 - 24th International Conference on Computers in Education: Think Global Act Local - Main Conference Proceedings, 76-78.
[27] Sadeghi, H., Kardan, A.A. (2015). A novel justice-based linear model for optimal learner group formation in computer-supported collaborative learning environments. Computers in Human Behavior, 48: 436-447. https://doi.org/10.1016/j.chb.2015.01.020

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