Analysis on College Students' Extracurricular Learning Interests Based on Their Book Borrowing Behaviours

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Abstract—Extracurricular reading can broaden the horizons of college students. Exploring the patterns of students' extracurricular learning and analyzing the relationships between extracurricular learning interests and book borrowing behaviours and the intervention mechanism of book borrowing can provide scientific guidance and basis for the comprehensive development of college students. Most of the existing learning interest analysis models have ignored other feedbacks generated in learner's behaviours, and there are very few studies on learning interests based on book borrowing behaviours. Therefore, this paper conducts an analysis of college students' extracurricular learning interests based on book borrowing behaviours. Based on the data of college students' book borrowing behaviours obtained from the service terminal of the library management system, an extracurricular learning interest model for learners was constructed, and the extracurricular learning interest degrees of college students were calculated based on the borrowing time and the number of borrowing times. A multi-layer interest model based on knowledge graph was also constructed to further improve the accuracy of the analysis results of learners' extracurricular learning interests.

Keywords—book borrowing behaviours, students' learning interests, extracurricular learning interests

1 Introduction

Books are the "intellectual food" for college students [1-6]. Unlike in senior high school, college students have more extracurricular study time, and reading is their most important extracurricular activity [7-11]. Extracurricular reading can broaden college students' horizons, cultivate their minds and relax their bodies. Besides, colleges and universities are currently aiming to cultivate interdisciplinary talents through the integrated development of multiple majors, so college students are more motivated to integrate their majors and social needs with their own learning interests [12-15]. Therefore, it is necessary to explore the patterns of students' interdisciplinary extracurricular learning and analyze the relationships between college students' extracurricular learning interests and their book borrowing behaviours and the intervention mechanism of book borrowing, so as to provide scientific guidance and basis for colleges and universities in the comprehensive development of college students and the cultivation of high-level talents.

With the rapid development of science and technology, interdisciplinary talents have become the target of talent cultivation and technological innovation, and thus college students' interdisciplinary learning interests have become more and more important. Zhang et al. [16] analyzed the book borrowing data of 14,600 students in Northwest Normal University using the complex network method and constructed an interdisciplinary learning interest network with disciplines as the nodes. It discussed the topological properties of the weighted network. and the importance of nodes, and divided students' learning interest communities using the hierarchical clustering algorithm. Liang et al. [17] proposed a method based on reading behaviours to capture users' interests in online learning systems, which requires pre-defined topic ontology as the reference for constructing user's interest model. It used a behaviour matrix and a weight matrix to calculate the user's interests in each leaf topic in the topic ontology. The user's interest in the topic ontology can be extended by the support factor. Takano and Li [18] proposed a prototype of an adaptive learning book system based on users' learning behaviours. The learner's learning history and behaviours are stored in the learning archive database through the monitoring function of smart phones, and their learning interests are extracted in the form of a weighted term set, so that the learning content can be adaptively provided according to users' learning interests in a series of learning opportunities. Ohsawa et al. [19] applied a chance discovery method to ID-free RFID tag data obtained in the experimental library, and proposed that the patterns obtained from the RFID tag data be regarded as the log of the learning behaviours of the learner group. The preferences of learners converge to the interests latently shared by the group in the extension of each customer's behaviours when they pick items looking at the scenario maps.

The theoretical methods for studying students' learning interests with the use of big data have provided some new ideas for the analysis of college students' extracurricular learning interests based on book borrowing behaviours in this paper. Most of the existing learning interest analysis models only sequentially model students' online learning behaviours, while ignoring other feedbacks generated in such behaviours, resulting in the lack of consideration of learners' personalized learning in the learning interest analysis models, and what is more, there are very few studies on the analysis of learning interests based on book borrowing behaviours. To this end, this paper conducts an analysis of college students' extracurricular learning interests based on their book borrowing behaviours. Section 2 presents the process of how the learner interest degree model is established. It collects and extracts the book borrowing behaviours data of college students from the service terminal of the library management system, constructs an extracurricular learning interest model for learners, and calculates the extracurricular learning interest degrees of college students based on their borrowing time and number of borrowing times. Section 3 establishes a multi-layer interest model based on knowledge graph to improve the accuracy of the analysis results of learners' extracurricular learning interests. The experimental results prove the feasibility of the proposed model for analysis of the extracurricular learning interests of college students.

2 Extracurricular learning interest model and calculation of interest degrees

The extracurricular learning interest model for college students proposed in this paper needs to be established based on the borrowing behaviours of learners in the library management system after learner and book sets are formed. Figure 1 shows the construction process of the learners' interest degree model. Considering the analysis of the extracurricular learning interests needs to cover different types of college students, it is necessary to collect complete data on their book borrowing behaviours. In this paper, such data were obtained from the service terminal of the library management system, and then the information on the interests of learners was extracted. Based on the data of the extracurricular learning interests of learners obtained from the analysis, the extracurricular learning interest model for learners was further established.

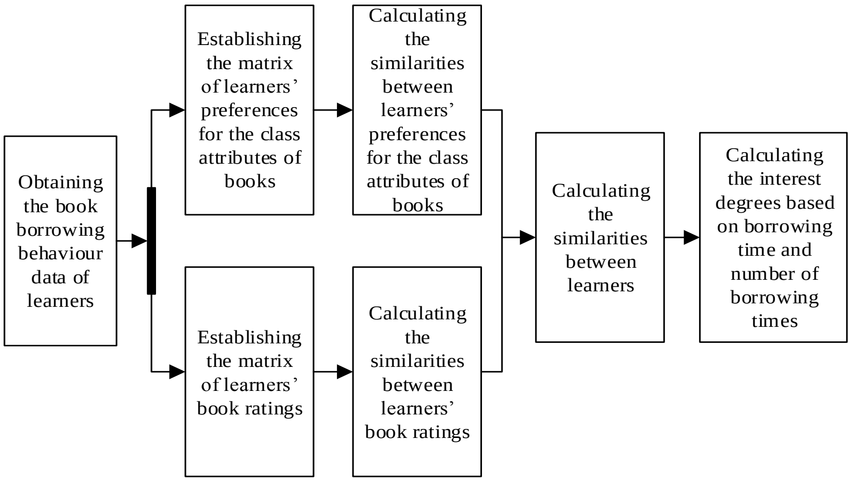


Fig. 1. Construction process of the learners' interest degree model

2.1 Modelling

The book borrowing behaviours data of learners include information on book browsing, inquiry, borrowing and rating. Learner's book ratings reflect their preferences for the books they have finished reading. If different learners have very similar preference for a certain book, it indicates that their extracurricular learning interests are similar. Assuming that learner v's rating for book i is represented by $E_{v,i}$, the following matrix of $A \times B$ can be constructed:

$$E=\begin{bmatrix} E_{1,1} & \cdots & E_{1,i} & \cdots & E_{1,B} \\ E_{2,1} & \cdots & E_{2,i} & \cdots & E_{2,B} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ E_{A,1} & \cdots & E_{A,i} & \cdots & E_{A,B} \end{bmatrix} \tag{1}$$

In the matrix, there are A learners and B books, so the elements in the matrix are the learners' ratings for the books they have read, ranging from Level I to V. If a learner has not read a certain book, the learner's rating for the book will be 0. A learner's interest in a book can be represented by the rating given by the learner for the book. Suppose that the rating of learner x for book i is represented by $E_{x,i}$, that the rating of learner y for book i by $E_{y,i}$, and that the set of books that have been rated by both learner x and learner y is represented by $EQ_{x,y}$. Eq.(2) shows how to calculate the similarity between the ratings given by learner x and learner y:

$$SIM_{PJ}\left(x,y\right)=\frac{\sum_{j\in EQ_{xy}}\left(E_{x,i}-\overline{E_x}\right)\left(E_{y,i}-\overline{E_y}\right)}{\sqrt{\sum_{j\in EQ_x}\left(E_{x,i}-\overline{E_x}\right)^2}\sqrt{\sum_{j\in EQ_y}\left(E_{y,i}-\overline{E_y}\right)^2}} \tag{2}$$

If learner x and learner y have similar extracurricular learning interests, they will have similar preferences for book types. One book can have multiple class attributes. Assuming that the class attributes of the book are represented by Y_j, Eq. (3) shows the expression of the class attribute set of the book:

$$Y=\left\{Y_1,Y_2,...,Y_j,...,Y_m\right\},1\le j\le m \tag{3}$$

Each book corresponds to a two-dimensional matrix of class attributes. When the value of the matrix element $X_{i,j}$ is 1, it means that book i falls within the book class attribute j. When the value of the matrix element $X_{i,j}$ is 0, it means that book i does not fall within the book class attribute j. The extracurricular learning interest degree of a learner shows how much this learner prefers a certain type of extracurricular books. The more times a learner borrows a certain type of books, the more interested this learner is in this type of books. The interest degree of learner x in book class attribute j can be calculated by Eq. (4):

$$INT_{x,j}=\frac{M_{x,j}}{M_x} \tag{4}$$

Suppose that the total number of times learner x has borrowed books of class attribute j is denoted as $M_{x,j}$ and that the total number of times this learner has borrowed books of all class attributes is denoted as Mx.

Suppose that the preference of learner x for books of class attribute j is represented by $EQ_{x,j}$, that the preference of learner y for books of class attribute j by $EQ_{y,j}$, and that the total number of book class attributes by m. Learner x's preference set $INT_{x,j}$={$EQ_{x,1}$,

$EQ_{x,2},...,EQ_{x,j},...,EQ_{x,m}\}$ for books of all class attributes can be calculated by Eq.(4), and the similarity $SIM_{INT}(x,y)$ between learner x and learner y can be calculated by Eq.(5):

$$SIM_{INT}(x,y)=\frac{\sum_{j=1}^{m} EQ_{x,j}\times EQ_{y,j}}{\sqrt{\sum_{j=1}^{m} EQ^2{}_{x,j}}\sqrt{\sum_{j=1}^{m} EQ^2{}_{y,j}}} \tag{5}$$

Suppose that the balance between the similarity of the learners' ratings of books $SIM_{PJ}(x,y)$, and the similarity of the learners' preferences for book class attributes $SIM_{INT}(x,y)$ is represented by δ, whose value ranges between [0,1]. Based on $SIM_{PJ}(x,y)$ and $SIM_{INT}(x,y)$, the similarity $SIM(x,y)$ between learners can be calculated. Substitute $SIM_{PJ}(x,y)$ and $SIM_{INT}(x,y)$ into the weighted calculation to obtain $SIM(x,y)$:

$$SIM_{(x,y)}=\delta * SIM\left(x,y\right)+\left(1-\delta\right)* SIM_{INT}\left(x,y\right) \tag{6}$$

2.2 Calculation of interest degree based on borrowing time and number of borrowing times

Through analysis of the scaling laws of learners' book borrowing behaviours, it can be found that the patterns of learners' book borrowing behaviours are related to borrowing time. Suppose that a learner's extracurricular learning interest degree corresponding to the borrowing time is ET_o, and that the actual borrowing time O, calculate the extracurricular learning interest degree of every two intervals, and there are:

$$\begin{aligned} ET_o &= \frac{O-O_{min}}{O_{max}-O_{min}}\left(0\le ET\le 1\right)\\ &=\begin{cases} ET_1,\left(0< ET_1\le 2\right)\\ ET_2,\left(2< ET_2\le 4\right)\\ ET_3,\left(4< ET_3\le 6\right)\\ ET_4,\left(6< ET_4\le 8\right)\\ ET_5,\left(8< ET_5\le 10\right)\end{cases}\end{aligned} \tag{7}$$

$$O=\begin{cases} O_{min}, O_i\le O_{min}\\ O_{min}, O_{min}< O_i\le O_{max}\\ O_{max}+1-O_i/O_{max}, O_{max}< O_i\le 2O_{max}\\ O_{min}, 2O_{max}< O_i\end{cases} \tag{8}$$

where, when $O_{max}<O_i\le 2O_{max}$, $O=10\times(O_{max}-O_{max})/(O-O_{max})$.

According to the definition of extracurricular learning interests, the more times a learner borrows books of a certain class attribute, the more interested this learner is in the knowledge presented in books of such class attribute, and the higher the learner's extracurricular learning interest degree is. The preferences for a certain type of books are divided by the number of times Y such books have been borrowed. With the maximum number of times $Y_{\_max}$ the books have been borrowed by learners majoring in a certain discipline as the benchmark, Y is divided into 5 levels, from Level I to V, and there is:

$$Y=\begin{cases}\mathrm{I}, 0<Y_i<Y_{max}/5\\ \mathrm{II}, 1Y_{max}/5\le Y_i<2Y_{max}/5\\ \mathrm{III}, 2Y_{max}/5\le Y_i<3Y_{max}/5\\ \mathrm{IV}, 3Y_{max}/5\le B_i<4Y_{max}/5\\ \mathrm{V}, 4Y_{max}/5\le Y_i<Y_{max}\end{cases} \tag{9}$$

Through averaging of the interest degrees related to borrowing time and number of borrowing times, the comprehensive extracurricular learning interest degree is $ELI=[ET_o+Y]/2$. Through the above operations, a rating matrix SM of learner-book-extracurricular learning interest degree can be formed based on the book borrowing behaviours data of learners, as shown in Eq. (10), where the number of rows and that of columns of SM correspond to the number of learners n and the number of books m, the student set is $r=\{r_1, r_2,...,r_m\}$, the book set is$\tau=\{\tau_1, \tau_2,..., \tau_n\}$, and the extracurricular learning interest degree set of learners is $SR=\{SR_{11},SR_{2,1},...,SR_{n,m}\}$, and there is:

$$SM=\begin{pmatrix} & \tau_1 & \tau_2 & \tau_3 & \cdots & \tau_m\\ r_1 & SR_{1,1} & SR_{1,2} & SR_{1,3} & \cdots & SR_{1,m}\\ r_2 & SR_{2,1} & SR_{2,2} & SR_{2,3} & \cdots & SR_{2,m}\\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots\\ r_n & SR_{n,1} & SR_{n,2} & SR_{n,3} & \cdots & SR_{n,m}\end{pmatrix} \tag{10}$$

3 Construction of the multi-layer interest model based on knowledge graph

The structure of the multi-layer interest model based on knowledge graph is shown in Figure 2. The users' records of books that the users have finished reading are linked to their deep-level extracurricular learning preferences on the book knowledge graph, such as book types, content and authors, etc. At the same time, the attributes of learners are incorporated to find out the relationships between the users' reading behaviours and attributes.

The analysis algorithm for the extracurricular learning interests of learners with the knowledge graph as auxiliary information can not only improve the accuracy of the analysis results of learners' extracurricular learning interests, but also interpret the analysis results to some extent. The book-based knowledge graph has integrated the multi-source heterogeneous data of book borrowing behaviours to accurately characterize the extracurricular learning interests of learners and in this way, the extracurricular learning interests of learners can be extracted at a deep level. Based on the above analysis, the model was constructed as follows. Figure 3 shows the book set and learner attribute generation model, and Figure 4 presents the mining model for deep–level extracurricular learning interests.

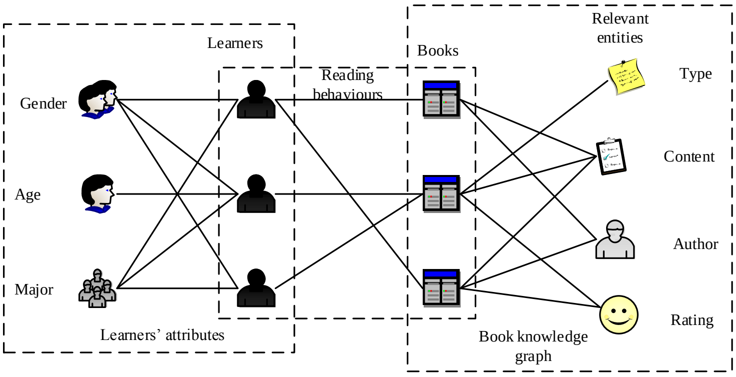


Fig. 2. Structure of the multi-layer interest model based on knowledge graph

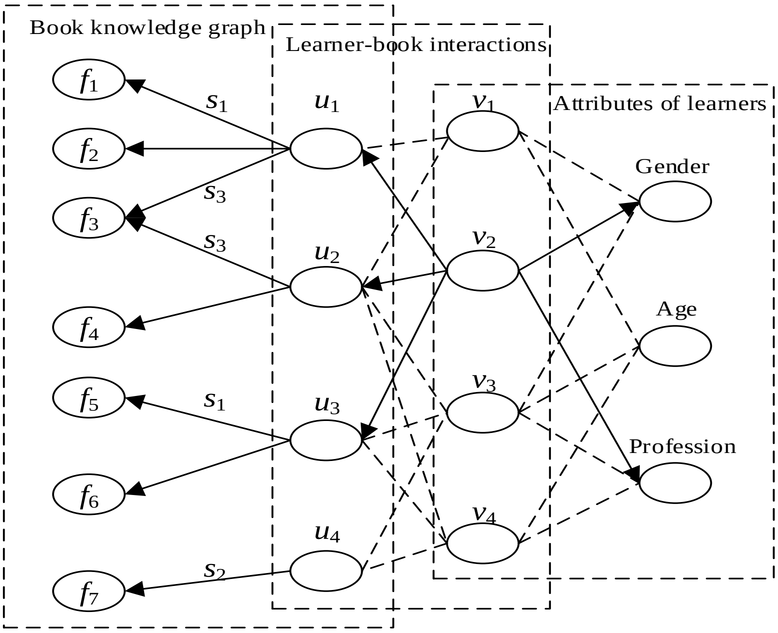


Fig. 3. Book set and learner attribute generation model

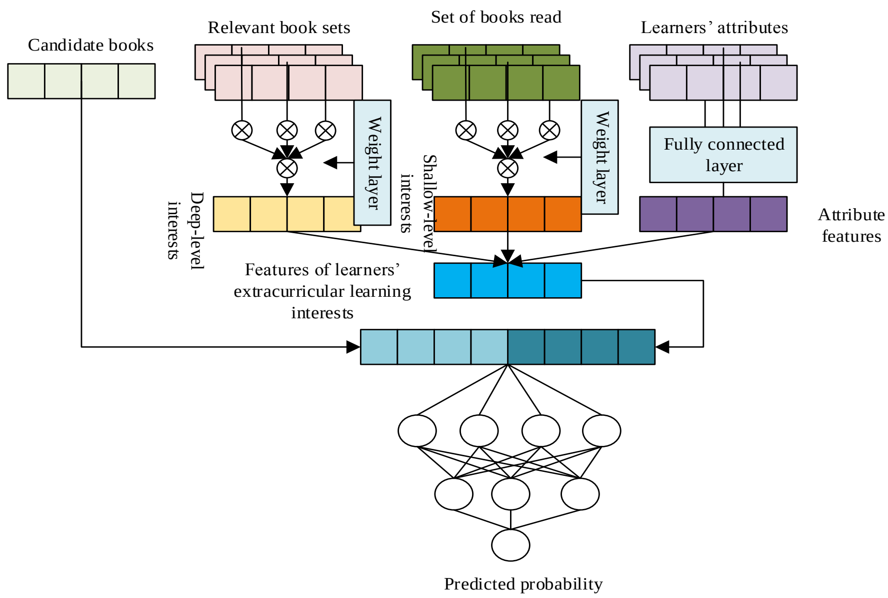


Fig. 4. Mining model for deep-level extracurricular learning interests

Suppose the book borrowing behaviour record of learner v is β_v, Since the relevant entities of the constructed knowledge graph match the books, the vector representation $u_i \in \mathbb{R}^p$ corresponding to the book $u_i(i=1, 2,...,M_i)$ can be obtained through knowledge representation learning. In order to construct the multi-layer learner interest model based on knowledge graph fusion for the extracurricular learning interests of learner v, first directly average the features of the books that the learner has read, and then assign uniform weights to all the books that have been read according to the following formula:

$$v = \frac{1}{M_i} \sum_{i=1}^{M_i} u_i \tag{11}$$

Assuming that the weight factor in the adaptive weighting is represented by ξ_i, based on the candidate books $u_j \in R^p$, assign a different weight to each u_i in the book set β_v that learner v has finished reading, and perform the weighted average operation to further obtain the representation of the shallow-level interests of learner v:

$$v_F = \frac{1}{M_i} \sum_{i=1}^{M_i} \xi_i u_i \tag{12}$$

The correlation between the given books u_i and u_j can be fitted in the form of an inner product based on the function G', and then converted into the weight factor in the above formula through the *softmax* function:

$$\xi_i = softmax\left(G'\left(u_i;u_j\right)\right) = \frac{exp\left(G'\left(u_i;u_j\right)\right)}{\sum_{i=1}^{M_i} exp\left(G'\left(u_i;u_j\right)\right)} \tag{13}$$

The book knowledge graph contains massive information on the knowledge of the books. Analyzing the correlations in knowledge between different books can help extract the deep-level extracurricular learning interests of learners. Given the book knowledge graph H, taking the books β_v that the learner v has finished reading as the head entity, the triplet set R_v of other related book entities and those that have been read can be obtained by links along the book knowledge paths. Suppose the tensor representation of the book knowledge relation is $s_i \in R^{p \times p}$, and that the vector representation of the head entity matched by the books is $f_{gi} \in R^p$. Based on the inner product function G'', the weight factor δ_i of the candidate book u_j and the triple (f_{gi},s_i,f_{oi}) to the head entity f_{gi} under the relationship s_i can be calculated:

$$\delta_i = softmax\left(G_2\left(u_i; f_{g_i}, s_i\right)\right) = \frac{exp\left(G_2\left(u_i; f_{g_i}, s_i\right)\right)}{\sum_{\left(f_{g_i}, s_i, f_{o_i}\right) \in R_v} exp\left(G_2\left(u_i; f_{g_i}, s_i\right)\right)} \tag{14}$$

After the calculation of the relevant weight factors of all triples in R_v is completed, link the learner to the book entities and calculate the weighted sum, which can be used to characterize the learner's deep-level extracurricular learning interests:

$$v_O = \sum_{\left(f_{g_i}, s_i, f_{o_i}\right)} \delta_i f_{o_i} \tag{15}$$

4 Experimental results and analysis

In order to build a model with better analysis performance, the relevant parameters of the model were checked, including the embedded dimension and the weight of the regularization term in the knowledge graph, with the results shown in Figures 5 and 6. It can be seen that the accuracy, recall rate and F1 value gradually increase with the increase of the embedded dimension. However, if the embedded dimension is too large, the model training will be over-fitted, and the three performance indicators will all decline. The weight of the regularization term in the knowledge graph should be neither too large nor too small; otherwise it will not be able to provide regularized constraints or make the objective function more focused on the optimization of the knowledge graph. In this paper, the embedded dimension of the model was set at 16, and the weight of the regularization term in the knowledge graph was set at 0.01, to obtain better model analysis performance.

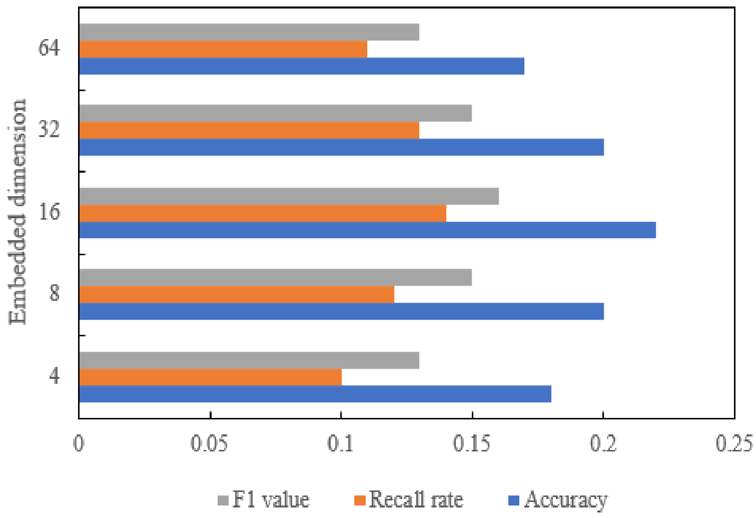


Fig. 5. Embedded dimension check

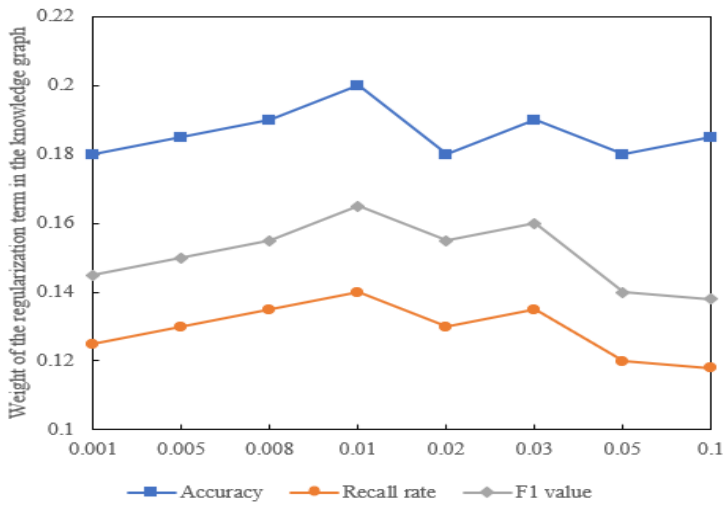
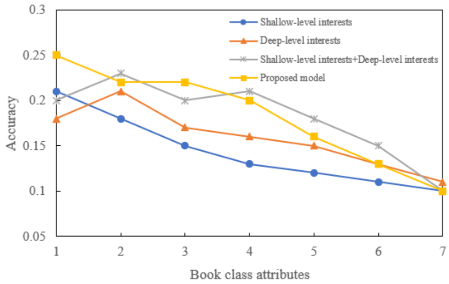


Fig. 6. Check of the weight of the regularization term in the knowledge graph

In order to discuss the effects of the number of book class attributes on the extracurricular learning interests of college students, an ablation experiment was carried out to compare and verify the proposed model with the shallow-level interest model, the deep-level interest model, and the model combining the two levels of interests. The number of book class attributes was set at 1, 2, 3, 4, 5, 6 and 7. Figure 7 (1), (2) and (3) show the changes in accuracy, recall rate, and F1 value with the different numbers of book class attributes, respectively. It can be seen that the recall rate of the deep-level extracurricular learning interest model based on knowledge graph mining significantly improved. Compared with the shallow-level interest model and the deep-level interest model, the combined model showed greater performance in all 3 performance indicators, indicating that the fusion of the two levels of interests can improve the analysis accuracy of the model to a certain extent. The proposed model introduced the extracurricular learning interest features of learners on the basis of the combined model, which greatly improved its performance and made it outperform the other models in all indicators. Table 1 shows the results of the ablation experiment for the model.



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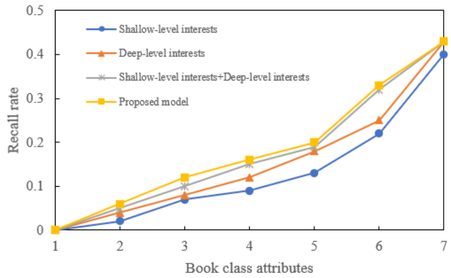

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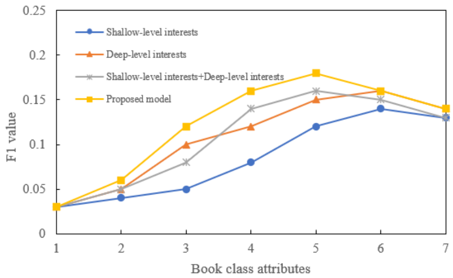

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Fig. 7. Performance of the model with different numbers of book class attributes

Table 1. Results of the ablation experiment for the model

Model	Shallow-level interest model	Deep-level interest model	Shallow-level + deep-level interest model	Proposed model
Accuracy	0.258	0.182	0.192	0.214
Recall rate	0.085	0.135	0.147	0.128
F1 value	0.113	0.148	0.159	0.172

5 Conclusion

This paper conducted an analysis on the extracurricular learning interests of college students based on book borrowing behaviours. Based on the book borrowing behaviours data of college students extracted from the service terminal of the library management system, an extracurricular learning interest model for learners was constructed, and based on the borrowing time and the number of borrowing times, the extracurricular learning interest degree of college students were calculated. Then, a multi-layer interest model based on knowledge graph was established to further improve the accuracy of the analysis results of learners' extracurricular learning interests. In order to build a model with better analysis performance, the embedded dimension of the model and the weight of the regularization term in the knowledge graph were checked. After that, the performance of the model with different numbers of book class attributes was discussed, showing that the proposed model can perform better than the other ones in terms of all three indicators, and that the analysis performance of the model has been effectively improved.

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