Information Dissemination Prediction of College Students' Learning Requirements Based on Mobile Social Network

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Abstract—Starting point of this research is the information dissemination and fluctuation of the learning requirements of college students between the student individuals and the mobile learning platforms, to solve this problem, it's of certain practical value to explore the information dissemination efficiency of college students' learning requirements under different conditions and study the prediction accuracy optimization method. However, existing studies generally focus on the feasibility of applying existing methods to the prediction of college students' learning requirements, but the research on such prediction is neither sufficient nor deep enough. This paper constructed a model of college students' mobile social network based on the actual data of college students' mobile social behaviors, and innovatively proposed a novel algorithm for predicting college students' requirements for mobile learning. At last, experimental results verified the effectiveness of the constructed model and the proposed algorithm.

Keywords—college student, mobile social behavior, mobile social network, learning requirement, information dissemination, prediction

1 Introduction

Predicting college students' learning requirements is an important research aspect in the mobile education management field [1–6]. Because mobile learning is a personalized and continuous training method which is free from the limitations of time and space, so it's particularly important to make accurate predictions and good plans for college students' requirements for mobile learning [7–13]. Initiators and subjects of the mobile learning requirements are college students who conduct learning activities to acquire knowledge of the learning targets, and the mobile learning platforms are providers of learning resources to meet the learning requirements of students [14–20]. There is a service receiver-provider relationship between college students and the mobile learning platforms, so taking the information dissemination and fluctuation of learning requirements between the two parties as the starting point of research to explore the information dissemination efficiency of college students' learning requirements under different conditions and study the prediction accuracy optimization method is a research direction that is innovative and groundbreaking.

Hussien et al. [21] developed a one-stop e-learning platform which can assist graduate students in addressing their knowledge and understanding towards plagiarism. The authors used a self-designed questionnaire to survey 440 post-graduate students and adopted descriptive technique to quantitatively analyze the survey results, and their findings suggest that the developed platform could indeed serve as a guidance for students to know about plagiarism. Schulz et al. [22] pointed out that now there're increasing opportunities of digital learning and teaching in the field of higher education. The authors described the requirements of teachers in this upcoming project, especially their teaching motivation will be taken into consideration. The topic about teacher requirements involves the initial and ongoing motivation as well as the behaviors and attitudes toward current or upcoming ICT systems for education. Capuano et al. [23] argue that designing personalized courses with requirements and preferences of each learner taken into consideration is one of the most studied topics within the field of adaptive learning system, the authors developed an approach and a prototype system that can trigger potential learning requirements and automatically generating learning experiences that can meet such learning requirements. Watanabe [24] discussed the requirements of Japanese universities and learners for e-learning. The author told us that a survey carried out by the National Institute of Multimedia Education clearly shows that the requirement for on-campus courses where the faculty uses e-learning tools as a supplemental measure of classes is higher, and this mode is expected to become the most popular e-learning mode in the future since it can respond to the needs of universities and students. If universities can successfully offer courses that can meet students' potential needs, then it's possible to promote this mode.

After reviewing relevant literatures, it's found that existing studies generally focus on the feasibility of applying existing prediction methods to the prediction of college students' learning requirements, overall speaking, the research on the prediction of college students' learning requirements is yet to be deepened, possible directions might be to apply information data that can be used for the prediction of college students' learning requirements, or to build decision support systems that can forecast the information dissemination of learning requirements. This paper built a model of college students' mobile social network based on the actual data of college students' mobile social behaviors, and innovatively proposed an algorithm for predicting college students' requirements for mobile learning.

2 Modeling of the time-space information of college students' mobile social network

Figure 1 gives the structure of the learning requirement prediction model based on deep learning. Inputs of the model are the features of college students' mobile social behaviors such as learning motivation, learning attitude, cognition level, learning preference, and the awareness of learning experience sharing, etc. Outputs of the model are the learning information such as the requirement for learning materials, requirement for Q&A and exchange, requirement for simulated training, and requirement for information consultant, etc. In order to attain the accurate features of college students' mobile social behaviors, this paper modeled the time-space information of college students' mobile social network based on deep learning. Assuming: H represents the college student mobile social network planning; U represents the set of network nodes; O represents the set of network edges; A represents the eigenvector of mobile social behaviors; Q and Y are parameters to be learnt by the constructed model; $M_{(i)}$ represents the neighbor nodes of node i; f_i^l represents the embedding of the i-th node in the k-th layer; $f_i^{p'}$ represents the embedding of the i-th node within history time period p'; f^{total} represents the overall embedding of the i-th node within all time periods; β represents the weight of attention; $\beta^{<total,p'>}$ represents the assigned weight of time period p' with respect to all time periods *total*; o represents the coefficient between two embeddings; $o^{<total,p'>}$ represents the coefficient of the embedding between time period p' and all time periods; D_i^p represents the attention embedding of node i within time period p'; $\dot{f}_i^p$ represents the complete embedding of node i within time period p; $XHH()$ represents the aggregate function; $XPP()$ represents the attention function.

The algorithm proposed in this paper constructed a college student mobile social network planning $H=(U,O)$, in which the set of nodes (students) is denoted as $P=\{u_1,u_2, u_3...u_i\}$, the set of connecting edges between nodes (representing relationships between college students) is denoted as $O=\{o_1, o_2, o_3...o_i\}$; the eigenvector of college students' mobile social behaviors is denoted as $A=\{a_1, a_2, a_3...a_i\}$; features of the i-th node are denoted as a_i, such as the cognition level, major, and learning preference, etc.

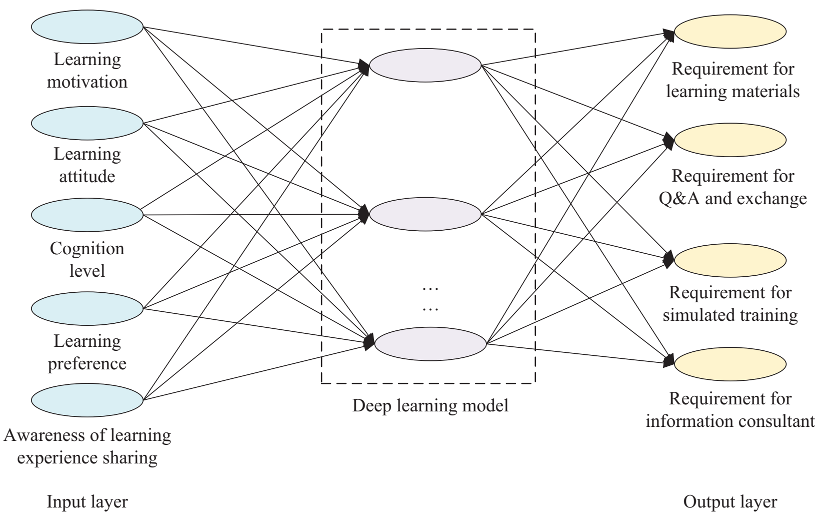


Fig. 1. Structure of learning requirement prediction model based on deep learning

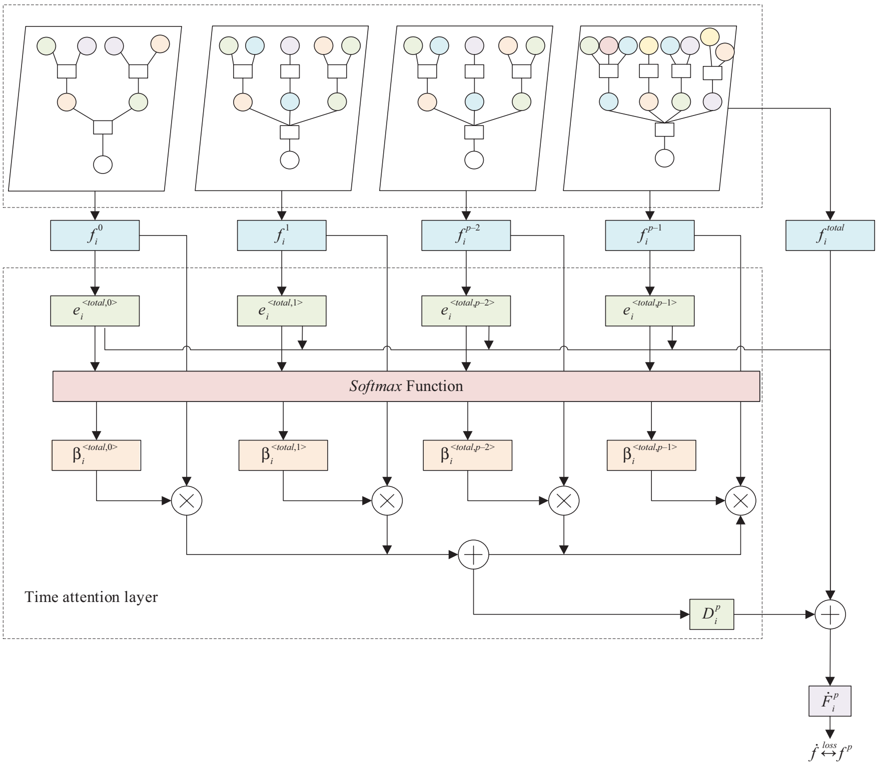


Fig. 2. Structure of the time attention neural network

With the development of the network, the nodes and connecting edges in the mobile social network of college students would change constantly, so this paper adopted a graph embedding method for space information modelling instead of the graph convolution network method, in this way, the constructed model is inductive. The algorithm proposed in this paper aggregates the neighbor features into the target node, $M_{(i)}$ represents the set of neighbor nodes within L steps from node i; f_i^{l-1} represents the embedding of the i-th node in the l-1 layer; f_j^{l-1} represents the feature embedding of neighbor node j; Q and Y are the parameters to be learnt by the constructed model which describes the importance of node i and its neighbors in the previous layer when aggregating; $f_i^{\,0}$ represents the eigenvector of node i, and its value is equal to a_i. Then, layer by layer, the information of all neighbors is aggregated, and finally, the final embedding f_i^L of the i-th node in terms of time and space is attained.

After the spatial features of the data of college students' mobile social behaviors had been aggregated, in order to capture the temporal features during the evolution of the mobile social network, this paper constructed a time attention neural network, as shown in Figure 2. At first, the global embedding f_i^{total} of each node was aggregated independently in each time slice; assuming: $f_i^{p'}$ represents the embedding of node i from the start time slice to a certain time slice of current time moment p; $f_i^0, f_i^1, \ldots, f_i^{p-1}$ represent the embeddings of node i in time slices 0, 1,…,p–1, p; p represents the time slice of the prediction target; p' represents the time slice of a certain history time moment before p; then, based on the attention mechanism, the coefficient $o^{<total,p'>}$ which describes the importance of time slice p' relative to the total embedding was calculated, and the importance of p' when the model makes predictions on p was determined.

$$o_i^{\langle total,p'\rangle} = ReLU(\beta^T[Q^{p'} f_i^{p'}, Q^{total} f_i^{total}]) \tag{1}$$

The algorithm set two training parameters $Q^{t'}$ and Q^{total} which respectively acted on $f_i^{t'}$ and f_i^{total}, and a model training parameter β which was applied after $Q_f^{p'} {}_i^{p'}$ and $Q^{total} f_i^{total}$ were connected; then, let $\beta_I^{<total,p'>}$ act on $f_i^{p'}$, and $Q_i^{p'}$ was set:

$$\beta_i^{\langle total,p'\rangle} = Softmax\left(o_i^{\langle total,p'\rangle}\right) = \frac{o^{o_i^{\langle total,p'\rangle}}}{\sum_0^p o^{o_i^{\langle total,p'\rangle}}} \tag{2}$$

Nonlinear conversion processing was realized based on the *ReLU* function, and the attention was put on node i; then, the attention weight $\beta_I^{<p,p'>}$ was generated based on the *softmax* function, and the final attention embedding D_i^p of node i is:

$$D_i^p = ELU\left(\sum_{p'=0}^{p} \beta_i^{\langle total,p'\rangle} Q_i^{p'} f_i^{p'}\right) \tag{3}$$

After the calculation of time attention was finished, the complete node embedding $\dot{f}_i^p$ was built based on the aggregation of D_i^p and f_i^{total}. The model constructed in this paper directly connected D_i^p to f_i^{total} to aggregate the effects of the two:

$$\dot{f}_i^p = \left[D_i^p, f_i^{total}\right] \tag{4}$$

The correlation between $\dot{f}_i^p$ and f_i^{total} was calculated based on dot product operation or neural network:

$$o_i^{\langle total,p'\rangle} = f_i^{p'} \cdot f_i^{total} \tag{5}$$

$$o_i^{\langle total,p'\rangle} = \sqrt{(f_i^{p'} - f_i^{total})^2} \tag{6}$$

Inspired by the multi-head attention mechanism, assuming: l represents the number of attention heads, then this paper attempted to use the formula below to replace Formula 3 to get better network performance:

$$D_i^p = ELU\left(\sum_{l=1}^{L}\sum_{p'=0}^{p} \beta_i^{\langle total,p'\rangle} Q_i^{p'} f_i^{p'}\right) \tag{7}$$

3 Prediction of learning requirement information dissemination based on clustering analysis

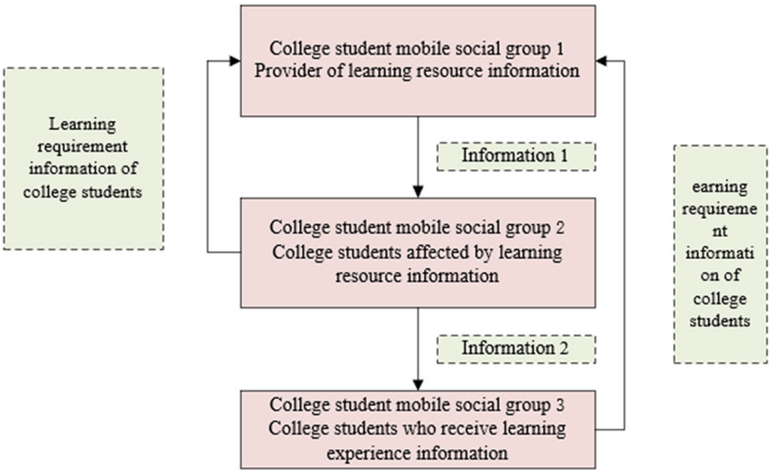


Fig. 3. The circular process of the influence of college students' mobile social information on their learning requirements

Figure 3 shows the circular process of the influence of college students' mobile social information on their learning requirements. As can be known from the figure, objects of the prediction of learning requirement information dissemination based on clustering analysis are the observed data or sample set of college students' mobile social behaviors. Using figures and tables to show the data analysis results of college students' mobile social behaviors is to visualize the actual learning requirements of colleges students for mobile learning. Assuming: there're *m* college student mobile social behavior samples composed of eigenvectors with *n* attributes, matrix *A* represents the set of samples, then there is:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \tag{8}$$

In the matrix, the *j*-th column represents the *j*-th college student mobile social behavior sample; the *i*-th row represents the *i*-th attribute of college students' mobile social behavior, and matrix element a_{ij} represents the *i*-th attribute of the *j*-th college student mobile social behavior sample.

During the clustering analysis of the prediction of learning requirement information dissemination, the set of college student mobile social behavior samples could be regarded as a collection of the nodes in the vector space of college students' mobile social network, and the Minkowski distance between nodes in the network vector space was used to describe the similarity between behavior samples. For given samples $a_i=(a_{1i},a_{2i},a_{ni})$ and $a_j=(a_{1j},a_{2j},a_{nj})$ and sample set A, $a_i,a_j \in A$, $a_i=(a_{1i},a_{2i},a_{ni})^T$, and $a_j=(a_{1j},a_{2j},a_{nj})^T$; the following formula gives the method for calculating the Minkowski distance between a_i and a_j, at this time $t \geq 1$:

$$\xi_{ij} = \left(\sum_{l=1}^{n} \left| a_{li} - a_{lj} \right|^t \right)^{\frac{1}{t}} \tag{9}$$

When $t=2$, there is:

$$\xi_{ij} = \sqrt{\sum_{l=1}^{n} \left| a_{li} - a_{lj} \right|^2} \tag{10}$$

When t=1, there is:

$$\xi_{ij} = \sum_{l=1}^{n} \left| a_{li} - a_{lj} \right| \tag{11}$$

When t=∞, extract the maximum value of the absolute values of the difference of each matrix element, then there is:

$$\xi_{ij} = \max_{l} \left| a_{li} - a_{lj} \right| \tag{12}$$

The following formula calculates the similarity coefficient between samples a_i and a_j:

$$s_{ij} = \frac{\sum_{l=1}^{n} (a_{li} - \overline{a}_i)(a_{lj} - \overline{a}_j)}{\left[\sum_{l=1}^{n} (a_{li} - \overline{a}_i)^2 \sum_{l=1}^{n} (a_{lj} - \overline{a}_j)^2 \right]^{\frac{1}{2}}} \tag{13}$$

where,

$$\overline{a}_i = \frac{1}{n} \sum_{l=1}^{n} a_{li}, \overline{a}_j = \frac{1}{n} \sum_{l=1}^{n} a_{lj} \tag{14}$$

The formula for calculating the cosine value of the angle between a_i and a_j is:

$$r_{ij} = \frac{\sum_{l=1}^{n} a_{li} a_{lj}}{\left[\sum_{l=1}^{n} a_{li}^2 \sum_{l=1}^{n} a_{lj}^2 \right]^{\frac{1}{2}}} \tag{15}$$

The classes or clusters of college students' learning requirements attained from clustering were essentially the sub-sets of the observed data samples of college students' mobile social behaviors, denoted as W, and the samples in the clusters were represented by a_i and a_j, the distance between the a_i and a_j was represented by ξ_{ij}, a threshold value P greater than 0 was preset, then for any sample a_i and a_j in W, there is:

$$\xi_{ij} \le P \tag{16}$$

Under the condition that the classification results of the observed data samples of college students' mobile social behaviors were determined, in order to get the real learning requirements of college students based on the analysis and visualization of some indicators, this paper attempted to build some discriminants that can effectively separate the sets, and the adopted method is the Fisher discriminant analysis method.

The sample $A(a_1,a_2,\dots,a_m)\in R^C$ of the mobile social behavior of college students coming from a C-dimensional space was taken as the training data of the analysis method, there're D classes of college students' learning requirements, there're n_i samples contained in the i-th class of learning requirements, and it satisfies $n_1+n_2+...+n_D=m$; assuming: R_q represents the dispersion matrix within a class, R_y represents the dispersion matrix between classes, then their expressions are given by the following formulas:

$$R_q = \sum_{i=1}^{D} \sum_{a_j \in D_i} (a_j - \lambda_i)(a_j - \lambda_i)^T \tag{17}$$

$$R_y = \sum_{i=1}^{D} n_i (\lambda_i - \lambda)(\lambda_i - \lambda_i)^T \tag{18}$$

The following formula calculates the mean vector λ_i of the i-th class of samples:

$$\lambda_i = \frac{1}{n_i} \sum_{a_j \in D_i} a_j \tag{19}$$

The following formula calculates the mean vector λ of all samples:

$$\lambda = \frac{1}{m} \sum_{i=1}^{m} a_i \tag{20}$$

The total dispersion matrix is equal to the sum of R_q and R_y:

$$R_p = R_q + R_y \tag{21}$$

To maximize the dispersion between classes and minimize the dispersion within classes, based on the Fisher discriminant criterion, the above objectives were converted to the problem of searching for a set of mapping vectors U that can ensure the maximization of the objective function:

$$SU(U) = \underset{U \in R^{C \times c}}{argmax} \frac{U^T R_y U}{U^T R_q U} \tag{22}$$

The following formula is a transformed form of the Lagrangian function of the above formula:

$$KP(U,\mu) = U^T R_y U - \mu(U^T R_q U - D) \tag{23}$$

Let the partial derivative of U be equal to 0, then the optimal solution of the above formula could be attained:

$$\frac{\partial KP(U,\mu)}{\partial U} = 2R_y U - 2\mu R_q U = 0 \tag{24}$$

At last, the generalized eigenvector μ_l corresponding to the maximum eigenvalue $\varphi(\varphi \leq D-1)$ could be attained based on the following formula:

$$R_y Q_l = \mu_l R_q Q_l \tag{25}$$

4 Experimental results and analysis

In order to ensure the universality and objectivity of the data of college students' mobile social behaviors, this paper selected 6 public datasets, and Table 1 gives the information of these datasets.

Table 1. Information of the datasets of college students' mobile social behaviors

Dataset No.	1	2	3	4	5	6
Node number	715	139	261	127	895	2362
dge number	16253	362517	1528459	85196	39681	30247
Degree value	35.29	8574.22	18247.15	958.63	72.58	37.16
Duration	17*months*	3*weeks*	7*months*	9*weeks*	12*months*	27*weeks*
Node ID	√	√	×	√	√	√
Node feature	√	×	√	×	×	×
Edge feature	×	√	√	√	√	√
Directed or not?	√	√	×	√	×	×
Transient or not?	×	√	√	√	√	√

Table 2 gives the prediction errors of college students' learning requirements based on the multi-head attention mechanism. Table 3 gives the F1-scores of the clustering of college students' learning requirements based on the multi-head attention mechanism. According to the tables, regardless of predicting the 10-th month based on data from the first month to the tenth month or predicting the 20-th month based on the data from the

11-th month to the 20-th month, the prediction model constructed in this paper gave the best MAE and MSE values. Moreover, regardless of predicting the 7-th month based on the data from the first month to the sixth month, or predicting the 8-th month based on the data from the first month to the seventh month, or predicting the 9-th month based on the data from the first month to the eighth month, the prediction model constructed in this paper gave the best F1-scores. This paper set experiments to compare the prediction effects of the single-head and multi-head attention mechanisms, and the results are shown in Figure 4a and b, according to the fitting results, the fitting degree of the multi-head attention mechanism is more satisfactory.

Table 2. Prediction errors of college students' learning requirements based on the multi-head attention mechanism

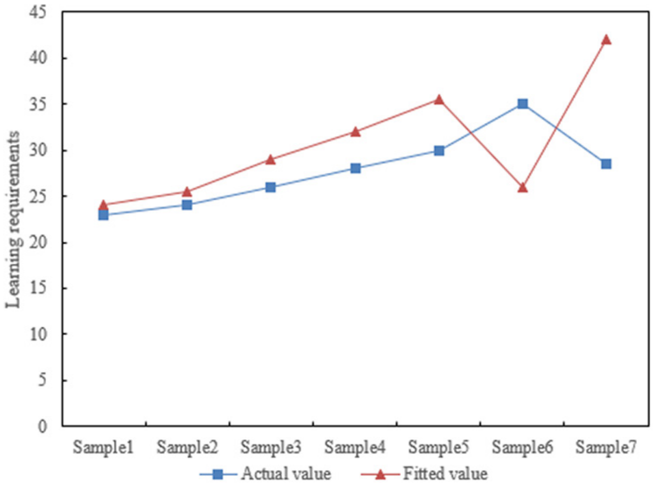
Prediction Task	Predict The 10-th Based On 1–10		Predict The 20-th Based On 11–20	
	MAE	MSE	MAE	MSE
Sample 1	2.418±0.063	8.629±0.324	1.328±0.027	6.295±0.182
Sample 2	2.951±0.184	7.153±0.051	1.629±0.032	6.392±0.041
Sample 3	2.847±0.017	7.692±0.038	1.596±0.047	5.342±0.195
Sample 4	2.598±0.042	7.418±0.235	1.302±0.067	6.597±0.027
Sample 5	2.691±0.126	6.952±0.291	1.385±0.044	5.328±0.069
Sample 6	2.507±0.081	6.854±0.274	1.258±0.059	6.912±0.175
Sample 7	2.695±0.048	7.385±0.329	1.325±0.074	6.327±0.269
Sample 8	2.147±0.069	7.518±0.315	1.582±0.058	5.833±0.214
Sample 9	2.385±0.127	9.287±0.362	2.341±0.081	7.629±0.327
Sample 10	2.859±0.035	6.385±0.249	1.352±0.048	5.184±0.021
Sample 11	2.414±0.082	6.273±0.214	1.692±0.074	5.627±0.069

Table 3. The F1-scores of the clustering of college students' learning requirements based on the multi-head attention mechanism

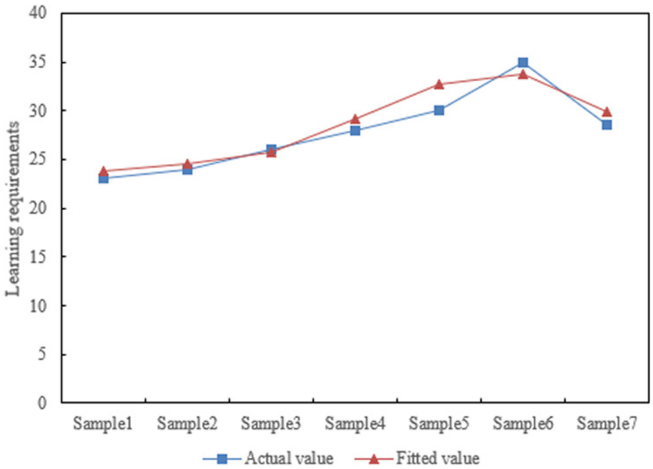
Prediction Task	Predict The 6-th Based On 1–5	Predict The 7-th Based On 1–6	Predict The 8-th Based On 1–7	Predict The 9-th Based On 1–8
	***F*1**	***F*1**	***F*1**	***F*1**
Sample 1	0.428±0.039	0.439±0.015	0.436±0.084	0.439±0.015
Sample 2	0.548±0.036	0.496±0.027	0.519±0.037	0.539±0.024
Sample 3	0.518±0.021	0.469±0.038	0.495±0.012	0.526±0.069
Sample 4	0.539±0.014	0.562±0.085	0.529±0.037	0.695±0.074
Sample 5	0.538±0.069	0.527±0.069	0.513±0.046	0.639±0.027
Sample 6	0.584±0.072	0.538±0.027	0.574±0.032	0.684±0.094
Sample 7	0.469±0.048	0.436±0.095	0.463±0.058	0.539±0.041
Sample 8	0.426±0.092	0.457±0.031	0.416±0.023	0.536±0.057
Sample 9	0.462+0.013	0.584+0.068	0.518+0.084	0.618+0.024
Sample 10	0.528+0.068	0.533+0.028	0.539+0.027	0.647+0.016
Sample 11	0.569+0.051	0.519+0.084	0.516+0.035	0.692+0.047

Figure 5 shows the distribution of attention. When the attention mechanism was not introduced and the modeling was conducted based on the time-slicing method solely, the model gave the worst performance on the sample set, and the effect of the node aggregation method was not ideal.

In a college student mobile social network that evolves over time, there're large differences in the distribution of temporal importance under different conditions and in different scenarios. Figure 5a–c gave the predictions of the dissemination of learning requirement information under the time-slicing conditions of taking a day, a week, and a month as the unit, respectively. The attention weight reflects an increasing trend pattern, that is, the decisive impact of the contributions increases. Different from the models used in other requirement prediction scenarios, in the model constructed in this paper, only considering the specific class of the prediction objects is not enough, and the prediction process of the proposed model must be proved effective via verification. Therefore, when the model outputs the prediction results of the dissemination of learning requirement information, it's necessary to show the distribution of time attention, so that the high application value of the proposed model in the scenario preset in this paper could be ensured. In this way, the mobile learning platforms can clearly understand the characteristic mechanisms behind the mobile social behaviors of college students and the logic of information dissemination of their learning requirements, and then make the ultimate analysis and judgement based on the proposed model.



(a)



(b)

Fig. 4. Prediction effects of single-head and multi-head attention mechanisms

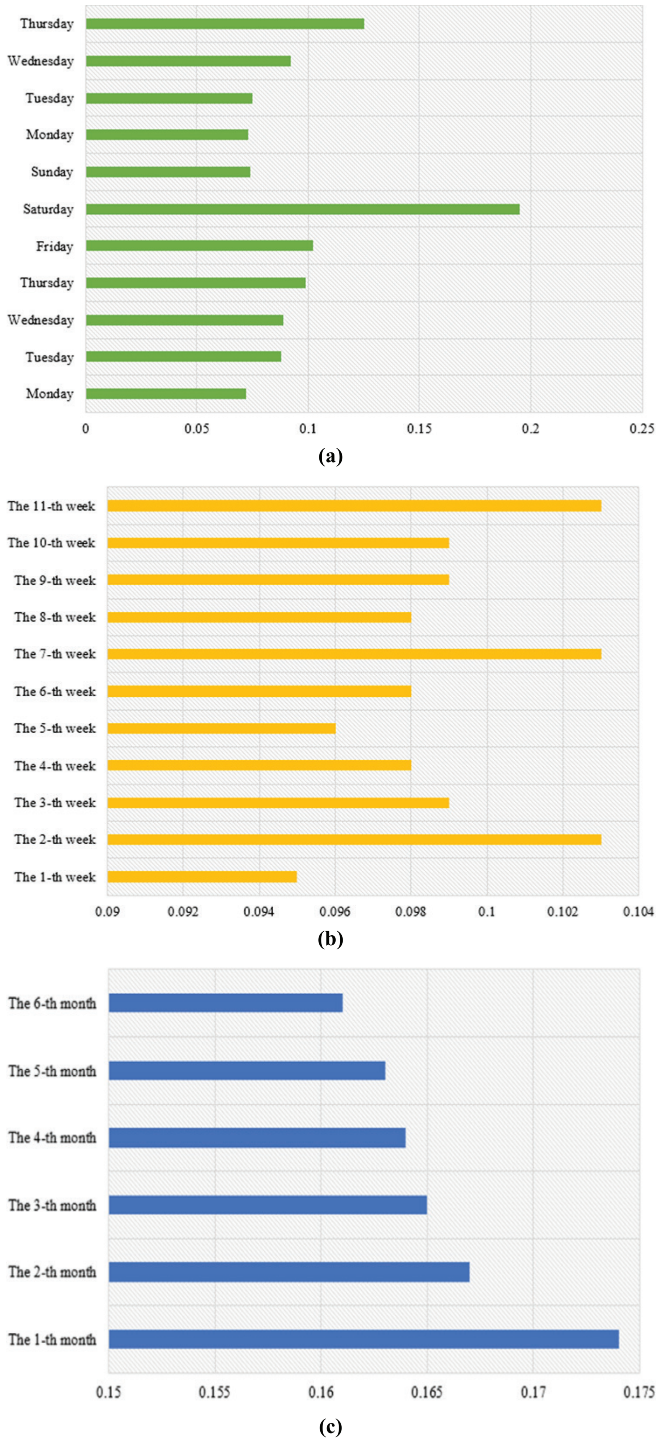


Fig. 5. Attention distribution

5 Conclusion

This paper constructed a mobile social network model of college students based on the mobile social behavior data of college students, innovatively proposed a novel algorithm for predicting college students' requirements for mobile learning, and used experimental results to verify the effectiveness of the constructed model and the proposed algorithm. In the paper, six public datasets were selected and their information was given; the prediction errors of college students' learning requirements based on multi-head attention mechanism, and the F1-scores of the clustering of college students' learning requirements based on multi-head attention mechanism were given, and the model constructed in this paper gave the best MAE and MSE values and F1 scores. Moreover, the prediction effects of the model with single-head and multi-head attention mechanisms respectively introduced were compared, and the results verified that the fitting degree of the multi-head attention mechanism was more satisfactory. At last, the attention distribution was given, which further verified the effectiveness of the introduction of attention mechanisms.

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