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Research on Improved Algorithms for Learning Path Design in French Courses Supported by Digital Resources

Ying Chen[1] and Cen Peng[1,*]
[1] School of Foreign Languages, Zhixing College of Hubei University, Wuhan, Hubei, 430011, China
Corresponding authors: (e-mail: peggyalicia@163.com).

Abstract The development of digital technology provides more possibilities for the learning of students in French courses. This paper explores the learning path design algorithm for French courses with the research purpose of personalized assisted learning. The learner portrait model is applied to the design of French courses, and the optimization and improvement of French learning paths are carried out by analyzing and combining the learning process of learners. Then, from the perspective of blended learning and the personalized learning interests of French students, we describe the parameterized representation method and process of French students' learning process data, student characteristics and knowledge point information. Combining the above data parameters, the framework of Sequence Generation Algorithm Based on Multi-Factor Combination (SGAMFC) is proposed. The algorithm processes course information, calculates user similarity, and gives a French learning path that matches user characteristics. The designed learning path modeling method provides the best performance in overall compared to similar modeling methods with 92.00%, 87.00%, and 87.00% precision, recall, and F1 values, respectively.

Index Terms sgamfc algorithm, French learning path, learner profile model, personalized learning

I. Introduction

For university students, French is difficult not only in words, but also in syntax [1]. Because French is a morphosyntactic language, while Chinese is an ideographic language, which means that the expressions in French are different from the expressions that teachers can form for a long time [2]. How to help students to solve the difficulty of learning words and grammar becomes the most difficult problem for every French teacher. The significance of the existence of French is not to make students pass the exam, but to help students solve problems in the future learning life. Many students have an aversion to French because of the French grammar problem, so teachers can eliminate this emotion through various teaching methods, so as to improve students' French ability [3], [4].

Digital teaching resources and application platform is a platform that provides teaching resources for online courses [5]. It is powerful enough to support teachers' self-built online courses, online interactive teaching, multiple modes of teaching as well as the tracking and analysis of the teaching process, and it has a wealth of teaching resources and high-quality courses for teachers and students to share [6]-[8]. Digital French teaching resources meet the needs of French education reform and bring new opportunities for networked foreign language teaching [9]. On the one hand, digital resources as the extension of classroom resources, the limited classroom time will be used for the teaching of important and difficult knowledge, face-to-face communication between teachers and students and group discussion and other activities [10], [11]. On the other hand, teachers can use the digital resource platform to generate teaching interaction with students, thus improving the interest of learning and ensuring students' concentration and participation in the French classroom [12], [13]. In order to achieve better teaching results, there is an urgent need to explore the course learning path that combines the digital resource teaching mode and traditional classroom teaching to realize the complementary teaching advantages.

This paper discusses the concept of constructing a learner portrait model and the application path in French courses in light of the teaching needs of French courses. Under the guidance of this theory, the parameterized representation of the learning process, student characteristics and knowledge information in French teaching is discussed in turn, and the group learning path model is constructed. Combining the above analyses, the SGAMFC algorithm is proposed as “processing course information - calculating similarity - optimizing recommendation - generating final recommendation”. The group learning path model is added to the SGAMFC algorithm framework to propose a French learning path model that can meet the learning needs of French users. Finally, the model's performance is examined by evaluating the readability of the recommended resources, the excellence of the learning paths, the judgment of the students' learning conditions, and the overall performance of the model.

II. Application of Learner Portrait Modeling to French Course Design

The classroom of Basic French is a place to improve language knowledge and skills, how to use different teaching methods and concepts to organize a dynamic classroom teaching? In view of the current situation that the content of the textbook is outdated but lack of better materials to replace it, how should teachers of basic French improve their teaching methods and organize classroom teaching scientifically and rationally in different parts of the different contents of the lectures? In order to guide students to explore learning from multiple perspectives and dimensions, and to achieve the purpose of enhancing the sense of fun of the times, teachers try to make efforts to create a new concept of teaching methods in various aspects. Here, this paper analyzes the characteristics of learners by constructing a learner portrait model, and develops the teaching design of French courses according to different learners' characteristics.

The learner portrait model is a labeled learner model abstracted based on the basic attributes of learners and the characteristics of the learning process. Learner portrait can be understood as the user portrait of learners in the field of education. According to related research, the process of constructing a user portrait model consists of three steps: collecting data, extracting features and labeling. Learner portrait, on the other hand, with the help of the construction principle of user portrait, labels the educational data based on learning analysis, and through the establishment of a multi-dimensional portrait label system, it deeply understands the learner characteristic information, so as to provide personalized learning support services for learners and optimize the learning experience of learners.

In the learner classification attribute module, according to the construction requirements of the learner portrait model, the data are divided into learning preference and knowledge level dimensions from the perspective of judging learning preference and estimating knowledge level. Learning preference can adequately represent the learner's individual preference differences for learning process and subject knowledge, which are further subdivided into learning style preference and subject knowledge preference, where the learning style preference attribute is subdivided into eight learning style types: intuitive or perceptual, verbal or visual, reflexive or active, global or sequential. Knowledge level, on the other hand, demonstrates the learner's mastery of knowledge in a certain domain, and the categorized attributes of the knowledge level dimension include: mastery level of basic course 1, mastery level of basic course 2, and mastery level of basic course 3, and so on.

The final learner portrait integrates learner categorization attributes and learning characteristics, and assigns scores from two dimensions: learning preference and knowledge level. On the one hand, based on the style scale and questionnaire collation, the learning preference feature vector $S=\{S_1,S_2,S_3,S_4,S_5,S_6\}$ was constructed by correlating the subject knowledge preference with the cognitive style features. Among them, S_1,S_2,S_3,S_4 each dimension is discretized from small to large by numerical transformations into 12 grades, which are represented by the numbers 1~12, respectively. For example, the information processing dimension S_3 is represented by 1~12 as a change from contemplative to active, with smaller numbers representing a greater tendency to be contemplative. Conversely, it represents the more inclined to the active type. Learning Heat Dimension S_5 uses 0 and 1 to represent low and high heat, a number of 0 means the more you prefer low heat learning resources. On the contrary, it represents the more preferred learning resources with high heat level. Learning Difficulty Dimension S_6 uses 0 and 1 to indicate low and high difficulty, and a number of 0 represents the more you like low difficulty learning resources. On the contrary, it represents the more preferred learning resources with high difficulty. On the other hand, based on the historical learning performance measure of learners' knowledge mastery, the knowledge level feature vector is constructed $L=\{L_1,L_2,L_3\dots\}$.

III. Design and Modeling of Learning Path Algorithms for the French Language

III. A. Construction of group learning path model

III. A. 1) Parametric representation of data on the learning process of French-speaking students

Data on the learning process of French students are generated from their learning records, which not only tell when and what learning behaviors were produced by French students, but also the sequence in which they were produced. The type of learning behavior is associated with the type of learning activity, and the corresponding learning behavior is generated by participating in the learning activity. The learning process data is defined as a 3-tuple structure as in equation (1):

$$LG=\{L,LB,T\} \tag{1}$$

$L=\{L_1,L_2,\dots,L_k\}$ stands for K French students, $1\le k\le K$. $LB=\{lb_1,lb_2,\dots,lb_k\}$ represents the learning behaviors of K French students, where lb_k denotes the record of learning behaviors of the French student L_k, and there are a total of Q one-dimensional vectors with which $lb_k=\{lb_{k1},lb_{k2},\dots,lb_{kq}\}$, $1\le q\le Q$, the value of lb_{kq} is a real number corresponding to the type of learning behavior produced by the French student, and Q is the total number of behaviors of the French student L_k. $T=\{t_1,t_2,\dots,t_k\}$ represents the time at which K French students produce learning behaviors, and there are a total of Q one-dimensional vectors with which $t_k=\{t_{k1},t_{k2},\dots,t_{kq}\}$, t_{kq} denotes the time when the q th learning behavior of the French student L_k is produced.

III. A. 2) Parametric representation of the characteristics of French-speaking students

French students not only have general learner characteristics, but also have their own characteristics. On the one hand, compared with other learners, French students are eager to communicate and share with others in order to get recognition, but they are isolated from their peers and lack interaction in the process of online learning, so they need to be grouped into groups to carry out collaborative learning and strengthen the connection between their peers. On the other hand, French students have poor self-control and lack of interest in learning, so the learning interest factor of French learning is considered, and group learning paths are constructed by adjusting the sequence order of knowledge points to improve French students' learning interest. French student characteristics are inferred from the learning process data, which is defined as a 3-tuple structure as equation (2):

$$LF=\{LP,LI,LH\} \tag{2}$$

$LP=\{lp_1,lp_2,\dots,lp_k\}$ represents the learning preferences of K French students, $1\le k\le K$, the value of lp_k is a real number corresponding to the type of the specific learning activity, which is deduced from the number of times of the learning behaviors of the French students and the corresponding time. time reasoning, if a French student L_k a high frequency of occurrence of a particular behavior and longer duration, it indicates that L_k prefer the type of learning activity corresponding to the behavior. $LI=\{li_1,li_2,\dots,li_k\}$ represents the learning engagement of K French students, which is inferred from the total duration of French students' learning, with longer duration indicating more engagement. $LH=\{lh_1,lh_2,\dots,lh_k\}$ represents the study habits of K French students, where $lh_k=\{lh_{k1},lh_{k2},lh_{k3}\}$ denote the probability that a French student L_k studies in the morning, afternoon and evening, respectively, reasoned from the time and frequency of his/her logins and logouts, and the magnitude of the frequency value reflects the French student's habitual preference to study during the corresponding time period. The probability values of study habits satisfy the constraints as in equation (3):

$$\sum_{i=1}^{3} lh_{ki}=1 \tag{3}$$

III. A. 3) Parameterized representation of knowledge point information

Knowledge point information contains two aspects of knowledge point logical structure and learning activities. The logical structure of knowledge points is fixed, and there are three kinds of logic: antecedent logic, subsequence logic and parallel logic. If knowledge point A is the basis of knowledge point B, and knowledge point B can be learnt only when knowledge point A is mastered, then A is the antecedent logic of knowledge point B, and B is the consequent logic of knowledge point A. If knowledge point C and knowledge point D belong to the same knowledge category, but the learning sequence of the knowledge points does not affect the efficiency of French students' mastery of the knowledge points, then C and D are juxtaposed logical knowledge points. Learning activities are preset for each knowledge point, and the learning of knowledge points is accomplished by participating in learning activities, while learning activities and learning behaviors constitute a one-to-one mapping relationship, i.e., the corresponding learning behaviors are generated only after participating in learning activities. The knowledge point information is defined as a 3-tuple structure as in equation (4):

$$KN=\{KP,KR,KA\} \tag{4}$$

$KP=\{kp_1,kp_2,\dots,kp_m\}$ stands for M to-be-learned knowledge points, $1\le m\le M$, and M is the total number of to-be-learned knowledge points. $KR=\{kr_1,kr_2,\dots,kr_m\}$ represents the logical structural relationship of M knowledge points, where $kr_m=\{kr_{m1},kr_{m2},\dots,kr_{mn}\}$ denotes the relationship between the knowledge point kp_m

and other knowledge points, $m \neq n$, if $kr_{mn} = 1$, it indicates that the knowledge point kp_m is the preorder logical knowledge point of kp_n, if $kr_{mn} = 2$, it indicates that the knowledge point kp_m is the kp_n of a subsequence logic knowledge point, and if $kr_{mn} = 3$, it indicates that the knowledge point kp_m is a concurrent logic knowledge point with kp_n. $KA = \{ka_1, ka_2, \ldots, ka_m\}$ represents the learning activities contained in M knowledge points, where $ka_m = \{ka_{m1}, ka_{m2}, \ldots, ka_{mj}\}$ indicates the proportion of each type of learning activity in knowledge point kp_m, and the larger the ka_{mj} the larger value corresponds to the higher proportion of learning activities, $0 \leq ka_{mj} \leq 1$, J is the total number of types of learning activities. The value of the proportion of learning activities of knowledge points satisfies the constraints as in equation (5):

$$\sum_{j=1}^{J} ka_{mj} = 1 \tag{5}$$

III. B. SGAMFC framework

Based on the above analysis and research on learning paths and teaching French courses, this paper proposes a Sequence Generation Algorithm Based on Multi-Factor Combination (SGAMFC), which can recommend learning paths, i.e., a series of sequential courses, for the target learners. The flow of this algorithm is shown in Fig. 1.

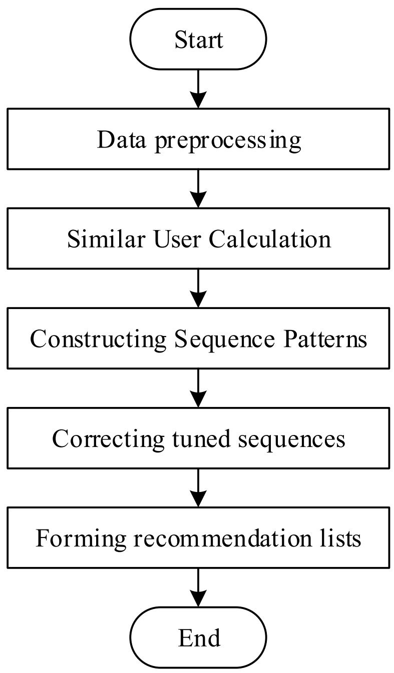


Figure 1: SGAMFC algorithm process

SGAMFC first performs data preprocessing, which focuses on the information of the course, and obtains the representative information of the course after filtering. Next, the top k learners with high similarity are obtained by synthesizing and calculating multiple similarities between the target learner and other learners. After that, the course learning records of the top k learners are used to construct the course learning sequence. Then, the course learning sequence is populated and optimized using the course association matrix. Finally, the course learning sequence is adjusted based on the initial settings and the similarity between courses to obtain the final learning path and recommend it to the target learners.

IV. Testing and Evaluation of the Model

This chapter examines the operational performance of the designed French learning path model from three perspectives: the readability of the recommended French learning resources, the excellence of the French learning path design, and the overall performance. It also statistically analyzes the French learning data of several students in its practical application to assess the reliability of the model.

IV. A. Readability of the model

In order to verify that the proposed modeling method has good readability, a learner Y is randomly selected and outputs his/her specific mastery of answering the questions covering the knowledge points (A, B, C, D, E), and the change process of the knowledge state of this learner during the learning process is shown in Fig. 2. Where the X-axis coordinates are the answer serial numbers, and the Z-axis coordinates are the degree of mastery: the bigger the value is, the stronger the mastery degree is. It can be found that with the assistance of the modeling method in this paper, the learner's mastery of all five knowledge points has been improved to a certain extent. For knowledge point A, it is even assisted to increase from 0.31 in the first answer to 0.61 at the end.

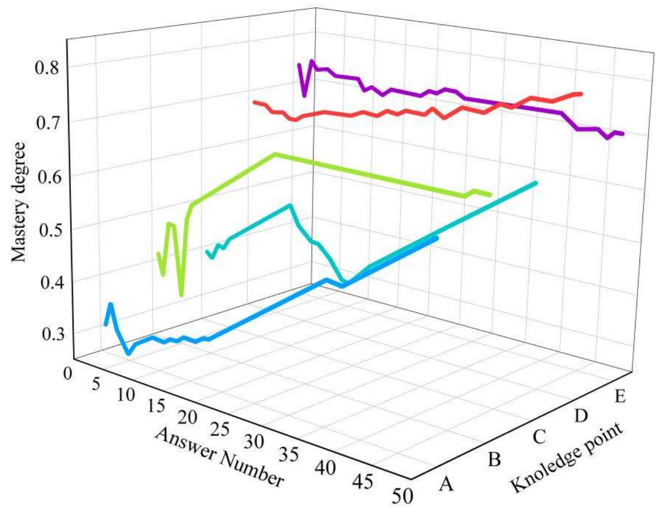
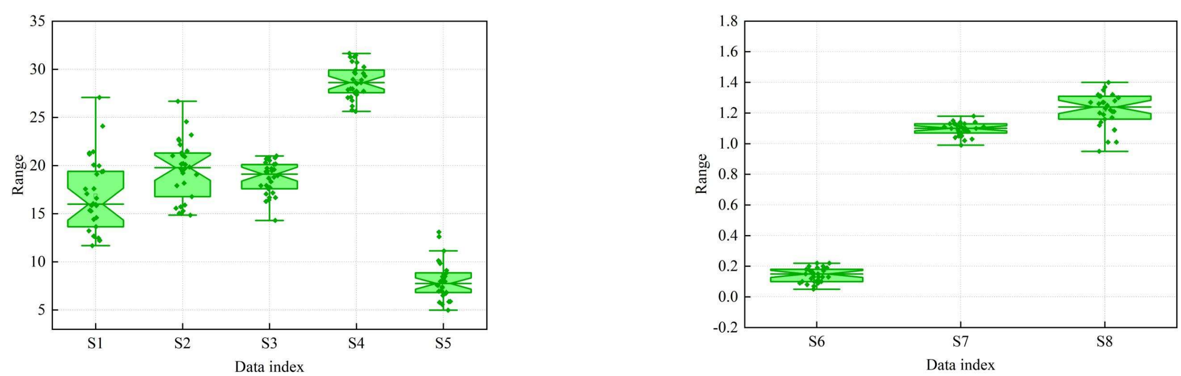


Figure 2 The process of knowledge state change of learner Y

IV. B. Analysis of video clickstream data at the time scale of the teaching week

Using the instructional week as the time scale, the 30 students recorded by the French teaching platform equipped with the learning path model designed in this paper, the video clickstream data and the student self-report data were organized as weekly data from week 1 to week 15. For the purpose of analysis, this study calculated the weekly means of the data as well as the changes in the means of each indicator on a 15-week cycle. Specifically, this study examined the clickstreams of student videos (S1) viewed, (S2) fast-forwarded, (S3) rewound, (S4) paused, (S5) interactively evaluated, (S6) pause duration ratio, (S7) watch duration ratio, and (S8) playback speed in the pre-semester (Weeks 1-5), mid-semester (Weeks 6-10), and the end of the semester (Weeks 11-15) The data were detailed and analyzed, and the data distribution of different clickstream indicators is shown in Figure 3.

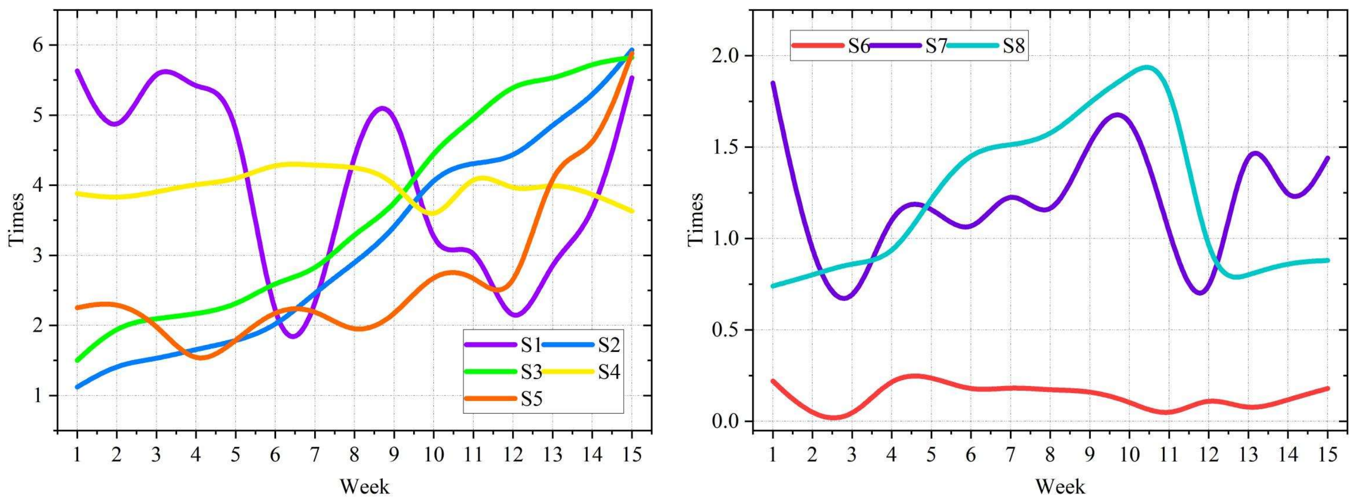


(a) Data distribution of video clickstream S1-S5 (b) Data distribution of video clickstream S6-S8

Figure 3: Analysis of Video clickstream data

As can be seen in Figure 3, students (S1) watched the videos 16.09 times per week with a standard deviation of 4.28, which indicates that students have some interest in learning videos, and at the same time, there is a significant variability in viewing behavior. The weekly means of (S2) fast-forward times and (S3) rewind times are similar (both are greater than the mean of viewing times), indicating that when students watch each video, there is an operational behavior of skipping the knowledge points or replaying to find the knowledge points, which reflects that students are more inclined to in-depth comprehension than fast browsing in the process of watching videos. (S4) The weekly average of the number of pauses is 28.97 times, indicating that pausing is an important behavior when students watch videos. (S5) The low weekly mean value of the number of interactive evaluations indicates that students are less motivated to interact and evaluate, and the level of interactive learning is low. The large difference between the maximum value (13.1) and the minimum value (4.98) of the number of interactive evaluations reflects that the interactive evaluation behavior varies among individuals. (S6) The weekly mean of the pause duration ratio is 0.13, indicating that students pause on average 13% of the time each time they watch a video. (S7) The weekly mean of the viewing duration ratio was slightly above 1, indicating that on the whole students watched the video in its entirety. (S8) The weekly mean of playback speed was 1.22, indicating that students tended to play videos at a slightly faster speed.

In order to see more clearly the students' learning trajectories in different instructional weeks, and to understand the weekly changes as well as the temporal trends of the students, the statistics of the students' average data of video clickstreams in the 15 instructional weeks are shown in Fig. 4.



(a) Data of video clickstream S1-S5 (b) Data of video clickstream S6-S8

Figure 4: Video clickstream data of students over 18 teaching weeks

Figure 4 shows the dynamic changes of the eight video clickstream indicators during the 15-week teaching cycle. Among them, the playback speed of (S8) ranges from 0.7 to 2.0, which is slow in the early part of the teaching week, accelerates in the middle, and slows down in the late part, showing a change in the learning rhythm of “first slow, then fast, then slow”. The number of (S3) rewinds and (S2) fast-forwards reached a higher value in the middle and the end of the teaching week, indicating that students needed to watch the key content several times in order to deepen their understanding in these critical phases. (S4) The number of pauses remained around 4 on average, indicating that students paused frequently during video viewing, while (S6) the ratio of pause duration was low and stable at around 0.15, showing that students' time spent on each pause was short. (S5) The number of interactive evaluations was relatively stable in the early part of the teaching week, indicating that students were less engaged in interactive evaluations in the early part of the study. However, the number of interactive evaluations increased significantly from week 13 onwards, reflecting that students' need for interaction was stronger at the end of the semester, and the frequency of their active participation in evaluations increased significantly.

IV. C. An excellent test of the French Learning Pathway

This section unfolds the center degree experimental simulation of the learning path method, using the form of comparing similar methods to verify the excellence of the method of this paper, in the figure Method1 represents the method based on BP neural network, Method2 represents the method of this paper. The knowledge graph is extracted for entities and relationships, the extraction results are processed, the knowledge points are represented by numbering (J1-J12) to facilitate data entry, and the knowledge graph of the extracted knowledge points is simplified for observation and experimentation.

The knowledge point centrality can be compared with the excellence of the learning path by calculating the depth knowledge node centrality (J1-J7) and breadth knowledge node centrality (J1-J12) respectively. The results of deep node centrality comparison are shown in Fig. 5, and the results of breadth node centrality comparison are shown in Fig. 6.

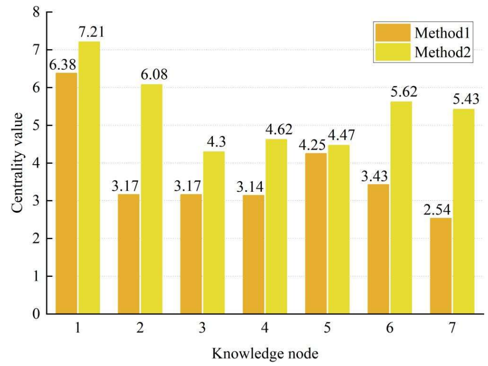


Figure 5: Comparison result of depth knowledge node centrality

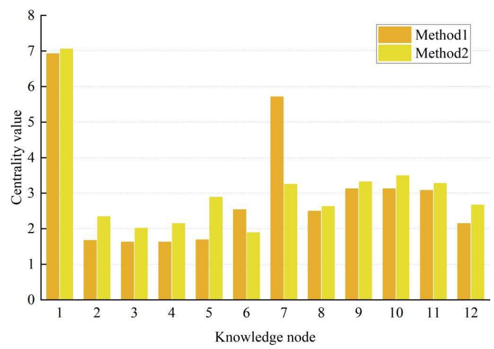


Figure 6: Comparison results of breadth knowledge node centrality

From the data in Fig. 5 and Fig. 6, it can be seen that when focusing on the depth of knowledge, the node centrality of the proposed method is not only greater than that of the node centrality of the BP neural network-based learning path method, but also in 4.00 and above, and in the knowledge node J1, it even reaches 7.21. Therefore, the longitudinal depth strategy based on the containment relationship is more practical for the knowledge graph in this paper. When focusing on knowledge breadth, the node centrality of the proposed method in this paper is mostly larger than that of the BP neural network-based learning path method, and only two nodes, J6 and J7, have smaller centrality of 1.87 and 3.25, respectively, but it does not cause a great impact in the overall recommendation.

IV. D. Demonstration of the ability to make judgments about students' academic performance

In this section, the proposed path method is used to locate the learners' zone of nearest development based on the learning data from the cognitive diagnostic evaluation. Taking the learning of a group of 12 learners on a knowledge unit with 12 knowledge points as an example, the results of the learning situation diagnosis can be visualized using the form of a heat map, where each row in the heat map represents a learner and each column represents a knowledge point. If each row and column in the diagram are sorted in ascending order according to the degree of mastery of the learning situation, then a heat map based on the sorting of the learning situation will be obtained in Figure 7, where the blue-circle area is the student's failure area, and the yellow-circle area is the guessing area.

From Figure 7, it is easy to see that the more to the left of the knowledge points the better the learning situation, that is, the higher the degree of acceptance of the knowledge points, which to a certain extent indicates that these knowledge points may belong to the basics or less difficult to be called simple knowledge points, and vice versa is called difficult knowledge points. Similarly, the lower the learners the better the learning situation, the more comprehensive and solid mastery of the knowledge points, which to some extent that these learners may have a better learning method or better learning order, called the academic excellence, and vice versa, is called the students who are struggling. The unexpectedly poorer learning situation of the academically gifted students in the easy knowledge point area may be caused by their misplay during the assessment, as shown in the circled misplay area in the figure. Unexpectedly good performance by a struggling student in a difficult area may be due to a correct guess on the assessment, as in the circled guessing area in the figure.

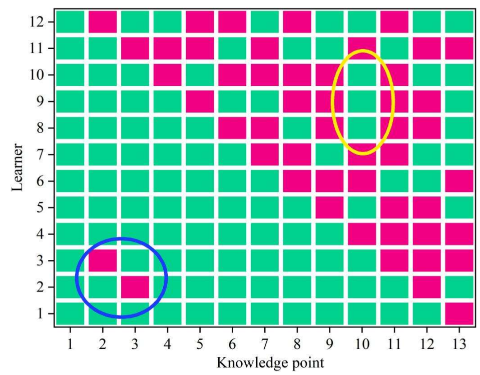


Figure 7: Zone of proximal development assessment

IV. E. *Overall Performance of Learning Path Models*

Expand (L3) The results of the comparison between this paper's model and similar models: (L1)TOP, (L2)GRU in terms of precision, recall and F1 value are shown in Table 1.In the three indexes, this paper's modeling method reaches the optimal, respectively, 92.00%, 87.00% and 87.00%. Comprehensively, it seems that the modeling method in this paper is characterized by stronger expressive ability and more flexible model structure, and with the gradual increase in the amount of sample data and the tuning of the model hyperparameters, it is also expected to obtain better generalization ability.

Table 1: Experimental result: The precision, recall and F1 score of models

Model	Accuracy rate	Recall rate	F1 value
L1	0.19	0.47	0.27
L2	0.87	0.78	0.82
L3	0.92	0.87	0.87

V. Conclusion

With the support of digitized resources, this paper proposes Sequence Generation Algorithm Based on Multi-Factor Combination (SGAMFC) as a design algorithm for French learning paths. This algorithm calculates similar users, constructs a sequence model of French learning resources, and then amends the tuning method to recommend language learning resources, thus forming an optimal French learning path recommendation.

The designed French learning path model increases from 0.31 to 0.61 at the highest in assisting learners to master the knowledge points.Compared with similar model algorithms, the recommended French resources have a depth of knowledge node centrality of 4.00 and above, and the highest is 7.21.In terms of the overall operational performance, the model precision is as high as 92.00%, and the recall rate and the F1 value are both 87.00%.

References

[1] Evens, M., Elen, J., & Depaepe, F. (2017). Effects of opportunities to learn in teacher education on the development of teachers' professional knowledge of French as a foreign language. Journal of Advances in Education Research, 2(4), 265-279.

[2] Tardieu, C. (2021). Language didactics and language teaching since 1945–the French way. European Journal of Applied Linguistics, 9(1), 21-46.

[3] Zhang, X. (2020). English as first foreign language, French as second foreign language in China: policy and practice. Journal of Education and Human Development, 9(3), 79-87.

[4] Fiagbe, F. K., Fiadzawoo, J. K., & Agbo, J. K. (2023). Systemic barriers to effective teaching/learning of French in Ghana: Policy and curriculum perspectives. European Journal of Language Policy, 15(1), 105-126.

[5] Hromalik, C. D., & Koszalka, T. A. (2018). Self-regulation of the use of digital resources in an online language learning course improves learning outcomes. Distance Education, 39(4), 528-547.

[6] Taib, N. A. M., Rahmat, N. H., Ismail, S., & Hassan, O. (2021). Teacher presence as mediator in online learning: The case for French as a foreign language. European Journal of Foreign Language Teaching, 5(5).

[7] Kuzmina, E. K., Nazarova, G. I., Nizamieva, L. R., & Leblanc, C. (2018). Innovative technologies of teaching business French. International Journal of Engineering and Technology (UAE), 7(4), 85-87.
[8] Smith, C. W. (2020). Essayons: French as a second language teacher experiences of technology-enhanced practice. Emerging Perspectives: Interdisciplinary Graduate Research in Education and Psychology, 4(2), 1-15.
[9] Zwanziger, E. (2024). Post-Pandemic Pedagogy: Multimodal Tools in French Instruction. The French Review, 98(2), 121-125.
[10] Hehir, E., Zeller, M., Luckhurst, J., & Chandler, T. (2021). Developing student connectedness under remote learning using digital resources: A systematic review. Education and Information Technologies, 26(5), 6531-6548.
[11] TOMÉ DÍEZ, M. A. R. I. O. (2020). Developing speaking skills and learning pronunciation with new technologies in the French as a Foreign Language classroom. Archivum, 70(2).
[12] Ruthven, K. (2018). Instructional activity and student interaction with digital resources. Research on mathematics textbooks and teachers' resources: advances and issues, 261-275.
[13] Strømme, T. A., & Furberg, A. (2015). Exploring teacher intervention in the intersection of digital resources, peer collaboration, and instructional design. Science Education, 99(5), 837-862.