A Survey on Learning Path Recommendation

Fengjun Zhu[1,2], Yiping Wen[1,2](✉), and Qi Fu[1,2]

[1] School of Computer Science and Engineering, Hunan University of Science and Technology, Xiangtan, China
ypwen81@gmail.com

[2] Key Laboratory of Knowledge Processing and Networked Manufacturing, Hunan University of Science and Technology, Xiangtan, China

Abstract. With the popularization of online learning, a wide range of learning activities have occurred and produced a huge amount of related data. A learning path consists of a set of learning activities that help users achieve particular learning goals. Learning path recommendation is important in smart education applications, which can provide suitable learning resource sequences for large-scale online learners, reduce the impact of information overload on learners, and help learners realize learning goals more quickly. Besides, it is necessary to apply popular technologies such as data mining, machine learning, optimization, knowledge graph and user profile in the domain of learning path recommendation to effectively handle related personalizing learning path parameter problems. So far, a variety of learning path recommendation methods have been proposed, which can be conducted in two ways: 1) single learner-oriented recommendation and 2) grouped learners-oriented recommendation. This paper presents an overview of these methods and analyzes future research directions of learning path recommendation.

Keywords: Learning path · Learning resource · Recommendation system

1 Introduction

The COVID-19 that broke out in early 2020 accelerated the reformation process of "Internet + education", and the number of online learning users is rapidly increasing. As a by-product of the process of large-scale online teaching activities, the learning platform has accumulated a large number of relevant learning behavior data related to learners' learning behaviors from login to exit. Technological and pedagogical innovations are redefining learning. Online learning promotes the convergence of technology and pedagogical innovation. The main advantages of online learning include availability, reduced cost, improved collaboration, enhanced flexibility (learners learn at their own convenience), etc. On the other hand, information overload and knowledge fragmentation are two major challenges facing human learning in the 21st century. It is difficult for learners to find appropriate learning resources on the Internet. Many learning resource recommendation systems do not fully consider learners' learning purpose, time limitation, knowledge backgrounds, etc. The recommended learning resources are

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not suitable for learners, which increases the difficulty of learning for learners, causes learning difficulties for learners, and slows down their learning process.

Learning path recommendation helps learners select more appropriate learning resources and organize them into learning paths suitable for learners according to their personalized learning needs. Learning Path recommendations will help learners have a better online learning experience. In this paper, focusing on the two mainstream directions of the learning path is recommended: single learner-oriented recommendation and grouped learners-oriented recommendation. This paper introduces the relevant terms involved in learning path recommendation and learners' personalized parameters, analyzes the difficulties and development directions of learning path recommendation, and provides a reference for the study of recommended learning path recommendation.

2 Terminology

We refer to a modular content hierarchy [24], which is proposed by Duval & Hodgins. We propose a modular content hierarchy for some of the main terms in the learning path recommendation research, as shown in Fig. 1. The modular content hierarchy introduces the relationship between learning resources. According to the different relationships of learning resources, the modular content hierarchy is abstracted into four levels: subject, learning unit, learning topic, learning object.

2.1 Subject

Subject is the most informative level. For example, a course such as Python programming language can be viewed as a subject. Multiple courses can be represented as directed graphs. In these graphs, the vertices indicate the learning topics or the learning objects, and directed edges represent the prerequisite relations among the vertices [23].

2.2 Learning Unit

Each subject consists of some learning units, each learning unit covers a unique concept. Each learning unit covers one or more learning topics. For example, in the Python programming language, the learning units include data types, arrays, loops, functions, etc. In some researches, the learning units might be referred to as "learning chapters".

2.3 Learning Topic

In each lesson, learners study at least one learning topic. For example, the learning unit on "loops" in Python programming language covers two learning topics: "for loops" and "while loops".

2.4 Learning Object

A learning object is the smallest unit of learning content that is reusable and constructed around a certain learning goal [21, 22]. Learning objects can be presented in many different forms, such as tests, an audio, a video, a text file, etc. In some researches, learning objects might be referred to as “learning materials” or “knowledge units”.

Learning path can be understood as the sequence of the above contents (learning objects, learning topics, etc.) [25, 26], and there is a certain learning sequence relationship between these contents. Learning path recommendation is to generate learning paths that satisfy learners’ preferences and learning goals. The main goal of learning path personalization is to generate a learning path that meets the preferences and requirements of the learners [41]. The way to identify learners’ characteristics and requirements is to apply personalization parameters.

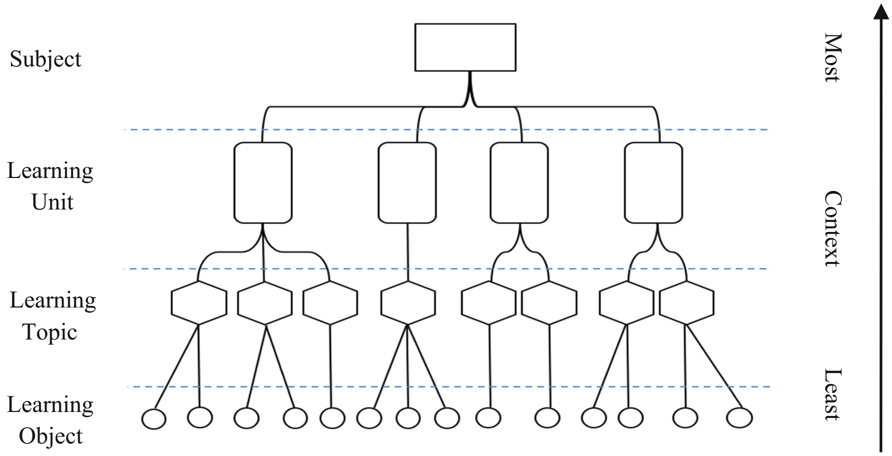

Fig. 1. Content hierarchy for learning path recommendation

3 Personalization Parameters

Personalized parameters are critical for generating personalized learning paths. Learners’ personalization parameters are used to describe learners’ characteristics and learning requirements, such as learning style, knowledge background, etc. According to the needs of learning path recommendation researches, we divide these parameters into three categories: “why to learn”, “what to learn” and “how to learn”, as shown in Fig. 2.

It is worth noting that some of the personalization parameters are dynamic, such as master ability and learning style. These values may change during the learning process. Some parameters may not be identified in advance, such as learning style, knowledge background. These parameters only are identified when learners learn through online learning platforms. It is necessary to update learners’ information based on personalized parameters modeling regularly [22, 35].

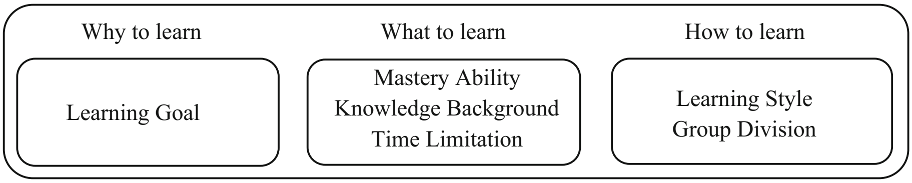

Fig. 2. Classification of personalization parameters

3.1 Personalization Parameters About "Why to Learn"

Personalization parameters about "why to learn?" can be denoted as the learning goal. The differences between learners are reflected in the personalization parameters about "why to learn". For example, a learner's goal is to master the Python programming language in two months.

Learning Goal. It refers to the level that learners hope to achieve after a period of learning. If the learning goal of a learner is to maximize his score, it is considered that the learner is a score-driven learner [23]. There also exist reward-driven learners whose learning goal is to obtain a certain learning reward [32], ability-driven learners who take improving their abilities as the learning goals [21, 33], and skills-driven learners who aim to master a certain skill in the least time [21].

3.2 Personalized Parameters About "What to Learn"

Personalized parameters about "what to learn?" allow learning path personalization with respect to the Learner's master ability, learner's knowledge background, and Learner's time limitations. For example, learners only need to pay attention to the learning paths that match their knowledge background, mastery ability, and time limitation after determining their learning goals.

Mastery Ability. Mastery ability indicates learners' mastery of the knowledge and skills required for a specific course or task [28]. This is a dynamic parameter that might change during the learning process.

Knowledge Background. This refers to the knowledge reserve of users before they accept the recommendation of the learning path. A good knowledge reserve can help learners better understand new knowledge. Knowledge background can be divided into objective knowledge background and subjective knowledge background. The objective knowledge background refers to the course grades or predicted scores of the course. Subjective knowledge background refers to learners' judgment on their current knowledge level reserve based on their judgment [13, 31].

Time Limitation. This refers to the time that learners can spend to achieve learning goals [23, 27]. If learners choose a learning path to achieve a certain learning goal, they usually need to spend a certain amount of time, and the length of time is usually fixed.

Learners may not have enough time to follow an entire learning path due to various reasons such as poor time management, inability to multi-task at the same time, and so on. Hence, The information provided by the "time limit" personalization parameter is used to generate a learning path that satisfies the learner's time limitation.

3.3 Personalized Parameters About "How to Learn"

Personalized parameters about "How to Learn" are used to describe the individual differences of learners as the manner that they deal with learning ways, including learners' learning styles, and group division. For example, a learner who plans to learn the Python programming language expects his learning materials to be in Chinese, and he also hopes to learn cooperatively in the form of a group so that he can communicate with other learners in the learning process.

Learning Style. This is an important parameter that indicates how a learner learns [22]. According to individual learning style preferences, learners can be divided into four categories: active-reflective learners, Sensing-intuitive learners, visual-verbal learners, and sequential-global learners [29, 30].

Group Division. Collaborative Learning is a learning strategy that learners form study groups and learn in groups. In the context of collaborative learning, learners are divided into study groups, in which learners with similar learning interests are normally in the same study group. Recommend similar or identical learning paths to members of the same group. Group division requires obtaining learners' preferences, alleviating preference conflicts among group members, and making the learning path recommendation results satisfy the preferences of all group members as much as possible [34].

4 Methods of Learning Path Recommendation

4.1 Single Learner-Oriented Recommendation

Methods Based on Learner Characteristics. This kind of research mainly applies the methods of data mining, machine learning, and optimization. This kind of research generates a personalized learning path according to the learning behavior and characteristics of learners in the learning process. Lin et al. [2] used the hybrid decision tree method to provide learning path recommendations for learners with different learning abilities and characteristics. Their personalized innovative learning system integrates personalized learning and game-based learning into a personalized learning plan. Based on the learner model and knowledge model, Zhao et al. [3] dynamically matched and restructured learning resources through association rule mining technology, and then realized personalized learning path recommendations. Aleksandra et al. [4] proposed a personalized learning path recommendation method based on social tags and sequential pattern mining. The method collects labels about learning resources entered by learners, then these tags are rated and used to recommend sequences of learning resources. Cheng

[5] applied ant colony optimization algorithm to generate learning path recommendation results. However, these methods do not consider the learning efficiency of learners who follow the learning path recommendation results. In order to further improve the quality of recommendation, Zhou et al. [6] proposed a full-path learning recommendation model. In this model, learners are clustered based on their feature similarity, and then learners' learning paths and learning effects are predicted by Long-Short Term Memory. Finally, a personalized learning path suitable for learners is recommended according to the prediction learning effects.

Methods Based on the Internal Relationships Between Learning Resources. This kind of research mainly uses ontology, semantic chain network, knowledge graph, and other technologies to generate recommendation results by analyzing semantic or cognitive relations among learning resources involved in learning paths. For example, Huang et al. [9] constructed the ontology-based context model and subject domain ontology library and elaborated the adaptive learning path recommendation mechanism and its implementation process based on context awareness. Yang et al. [10] proposed a learning path recommendation tool suitable for learners' learning style bias by using the semantic link network technology. Wan et al. [7] used mixed concept maps to establish the relationship between learners and learning resources, described recommendation as a constraint satisfaction problem, and applied the immune algorithm to obtain recommendation results. Zhu et al. [8] verified that learners have different preferences for learning paths in different learning scenarios, and they proposed a multi-constraint learning path recommendation algorithm based on a knowledge map. Guillaume Durand et al. [11] established a learning path recommendation model that can describe the ability dependency relationship between learning resources based on graph theory. However, these methods are not considering the diversity of the relationships between the learning resources. In order to better generate diversified learning paths that satisfy different learning needs, Shi et al. [12] used the knowledge graph to represent six main semantic connections between learning resources and proposed an interpretable and reusable learning path recommendation model based on the multidimensional knowledge graph.

4.2 Grouped Learners-Oriented Recommendation

In the domain of recommendation research, group recommendation methods are usually divided into two categories: recommendation by mixed model and recommendation by mixed recommendation results [34], which are illustrated in Fig. 3 and Fig. 4 respectively. The former kind of method is to aggregate user preferences into group preferences and then provide recommendation services to group learners. The more similar the learners' preferences in the group, the better the group recommendation effect. The latter kind of method normally takes each learner's personalized recommendation list and merges all the lists into the same list as the group recommendation results.

In order to satisfy the needs of learning paths recommendation for group learners rather than individual learners in practical applications, researchers have made active explorations, but only a few research results have been obtained. In the field of online learning, group learners usually refer to learners with similar learning interests. The

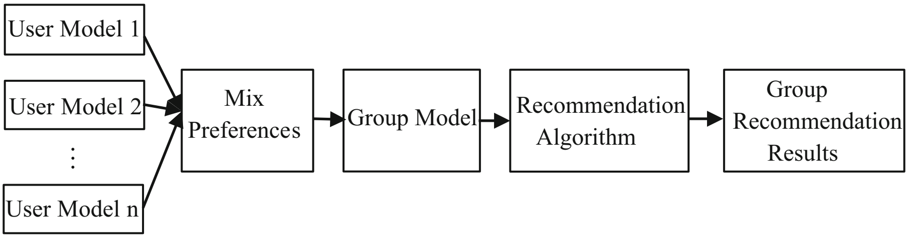

Fig. 3. Group recommendation by mixed models

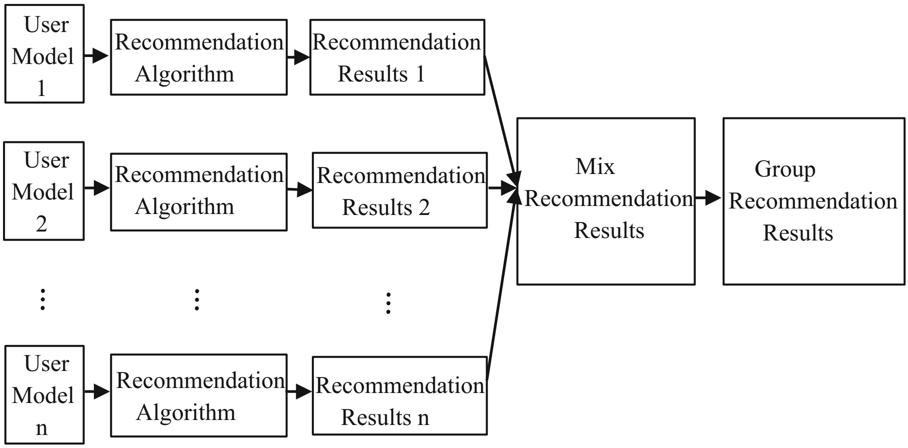

Fig. 4. Group recommendation by mixed recommendation results

explicit attributes of learners on learning resources and the implicit attributes of accessing resources, such as learning time and learning frequency, are often used together to calculate the similarity between learners [14]. Xie et al. [13] proposed a group learning path recommendation framework based on user profile to help each learner in the group efficiently learn the needed new knowledge within the time limitation, and to enable the whole group to acquire all the knowledge needed to complete the group learning task on the whole. This method considers learners' knowledge background, learning preference, and group learning task. However, the computational complexity of this method is relatively high, and it is difficult to ensure its recommendation performance when the relevant data of learners is too sparse. Because of these deficiencies, Zhu et al. [14] used the data and knowledge graph in the learner's learning history log to firstly represent the knowledge point learning of learners in different periods as personalized learning to generate a network, and then conducted cluster analysis on these personalized learning to generate a network. In this way, the group learning generation network reflecting the common characteristics of the learning group is generated. Finally, the recommendation results are generated based on the preferences of the learning group for different types of learning paths in different learning situations. However, these methods do not take into account the differences in learning behaviors of learners when they learn different courses and finish different learning tasks, and whether the recommended learning resources and paths are effective in promoting collaborative learning, which has an important impact on the overall actual learning effect of the group.

In addition, in the field of recommender system research, group recommender system, which takes into account the preferences of each user in the same group, has become a hot research topic in recent years, because of the application scenarios where multiple users watch movies, catering and tourism in a group. A large number of research results have been obtained [15–19]. Compared with the recommended method for a single user, grouped user-oriented methods recommended to consider the emotional contagion and consistency (i.e., the various user satisfaction degree can be a profound impact on others, users express opinions will influence each other) affect the performance of recommendation and other social phenomenon and recommend the accuracy and fairness of giving attention to two or more things. But in the actual group cooperative learning scene, there are also a few people who do not actively participate in cooperative learning and other similar phenomena. And, it is worth noting that some scholars have applied the characteristics of learners' learning process to recommend learning resources for group learners. For example, Xin Wan and Toshio Okamoto et al. [20] used the Markov chain model to describe the learning process of group learners and the characteristics of interaction between learners and proposed a method that can recommend learning resources for group learners. Therefore, it is necessary to learn from the existing research experience of group-oriented recommendation methods, consider and analyze the characteristics of the group collaborative learning process, to further improve the actual effect of recommending learning paths to group learners. Table 1 shows some study cases of learning path recommendations.

Table 1. Summarizing some methods of learning path recommendation

Single learner-oriented recommendation	Methods based on learner characteristics	Lin, C., et al. (2013) [2]
		Zhao, X., et al. (2016) [3]
		Klašnja-Milićević, A., et al. (2018) [4]
		Cheng, Y. (2011) [5]
		Zhou, Y., et al. (2018) [6]
	Methods based on the relationships between learning resources	Wan, S., et al. (2016) [7]
		Zhu, H., et al. (2018) [8]
		Huang, Z., et al. (2015) [9]
		Yang, J., et al. (2013) [10]
		Durand, G., et al. (2013) [11]
		Shi, D., et al. (2020) [12]
Grouped learners-oriented recommendation		Xie, H., et al. (2017) [13]
		Zhu, H., et al. (2018) [14]

5 Future Research Directions

At present, the number of research on single learner-oriented recommendation methods is more than that of group-oriented recommendation methods. In recent years, a lot of progress has been made in the research and application of learning path recommendation methods. However, many of the methods proposed by researchers still have a set of limitations and challenges with regard to these methods and these problems have led to some very significant consequences. Introducing these challenges will help researchers make breakthroughs in the current study and achieve the desired results. Not only are there several difficulties with learning path recommendation methods that we mentioned regarding learning path personalization, but there are also some pressing issues that need to be addressed. We summarized the difficulties and development directions of the following learning path recommendation:

5.1 Time Limitation

If learners cannot devote enough time to follow the learning path to learn, it will be difficult to achieve their original learning goals. For various reasons, learners spend less time learning than they expect to spend in learning. There are many reasons for this situation, the most notable part of which is: improper time management, laziness, multitasking, etc. When learners do not have enough time to study, learners are faced with two questions: can the outcome of the learning justify the time spent by learners; what are learners can learn from the learning path that they want to follow in limited time? In many studies [27, 36], the study time of the course is usually specified by experts, and the duration is the same for all learners. Antonio Garrido et al. [37] considered learners' learning background, learning environment, and time available for learning, and generated personalized learning path recommendations for learners to help learners better achieve their learning goals.

5.2 Updating Learners' Profile

The learner's master ability and the time available to reach the learning goal may change during the learning process. Sometimes the learner's knowledge background cannot be accurately identified. Therefore, taking into account the changes that may occur to the learner during the learning process, the user's configuration file should be updateable. Updating the learner's configuration file also has the following problems: how to determine under which circumstances the learner's configuration file should be updated; what information needs to be updated in the learner's configuration file. It is a difficult task to determine the updating time. It is because updating learners' profiles and frequently evaluating learners is time-consuming and sometimes unnecessary. But delaying updating learners' profiles may result in the recommendation of learning resources that are not suitable for learners, thus increasing learners' knowledge fragmentation and wasting learners' time. Do the updated learners' profiles have the same importance when generating recommendations? Is there a ranking (weight) among them? How to check the validity of updated learners' information.

5.3 Designing Course Map

In the current research, the design of the curriculum map is usually done manually by the teacher, which requires a lot of manpower and material resources and cannot be changed. It means that each learner who takes this course uses the same course map, and more importantly, the course map is teacher-centered [42]. The teacher-centered course map is not suitable for all learners because of the differences in learning goals, knowledge backgrounds, and other personalized learning parameters. Therefore, it is necessary to construct a course map from the learners' perspectives. Yu et al. [1] divided the classification and annotation of learning object concepts into two processes. First, for each curriculum concept, a pre-trained word embedding was used to calculate its most likely category. Then the three annotators in the corresponding field are required to mark whether the concept belongs to this category. For the concept category pair marked as "not belonging", select the previous sibling category as the new candidate, and put the refreshed pair in the annotation again Pool. This process effectively reduces the number of invalid comments. Although this reduces part of the manual operation, it may still cause the learning goals that learners want to achieve cannot be matched with the designed course map, thereby reducing the efficiency of learning path recommendation.

5.4 Learner Privacy and Information Security

Preference sharing and learner interaction are conducive to the improvement of the accuracy of group learning path recommendations. But at the same time, it also brings a lot of learner privacy and information security issues. At present, there are relatively little researches on the privacy issues of group recommendation [38, 39]. And there are situations where different groups have different requirements for privacy protection.

5.5 Interpretability and Validity of Group Recommendation Results

A Reasonable explanation of the group learning path recommendation results helps learners to better understand the recommendation mechanism and the preferences of other members in the group, it is easier to accept the recommendation results of the learning path, and enhance the learning effect [40]. Currently, offline evaluation methods are mainly used to measure the effectiveness of group learning path recommendation results. The more similar the learning characteristics of the learners in the group, the more effective the group recommendation will be.

6 Conclusion

In summary, learning path recommendation is a research hotspot in recent years, and a large number of research results have been obtained. In recent years, the methods for single learner-oriented recommendation have been extensively researched in depth, and the research is relatively mature. grouped learners-oriented recommendation research results are relatively few, and there is still room for improvement in the effectiveness of recommendation results.

In this paper, we have introduced the two mainstream directions of current learning path recommendation methods, and clearly explained the related terminology that will be involved in learning path recommendation methods. Finally, combined with recent research work, the future development direction of learning path recommendation research is introduced.

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