ISSN 2616-7433 Vol. 6, Issue 3: 66-72, DOI: 10.25236/FSST.2024.060310

Multi-dimensional Model of Python Resources Based on Portrait Technology: Research on Building and Optimizing Recommendation Services

Ju Zhou[a,*], Hong Li[b]

Yunnan Normal University, Kunming, China
[a]2798380239@qq.com, [b]651035658@qq.com
[*]Corresponding author

Abstract: *In the digital era, various types of online learning resources have emerged, covering comprehensive fields, providing learners with the opportunity to conveniently access learning resources and flexibly arrange their study time. However, this has also led to drawbacks such as network resource overload and information disorientation, with uneven quality of online resources and little attention to personalized learner needs. As Python has become a popular choice for many beginners and professionals, how to personalize the vast amount of Python learning resources available online has become an urgent issue. This article, based on the advantages of user portraits in resource recommendation services, reviews the shortcomings of current educational resource recommendation services. Taking Python learning resource users as an example, it proposes strategies for optimizing resource recommendation platform services through the process of constructing multi-dimensional Python resource user portraits. The strategies include improving resource quality, personalizing recommended content, diversifying resource formats, speeding up resource recommendations, promptly handling user feedback, establishing a sound protection mechanism, and safeguarding user privacy.*

Keywords: *user portrait, Python, model construction, personalized recommendation services*

1. Introduction

Educators should pay attention to the different characteristics and personalized features of students to implement targeted teaching. Since ancient times, Confucius advocated the method of adjusting teaching strategies to suit individual students, demonstrating the importance of catering to each student's unique needs. To support the personalized and adaptive development in education, the country has issued a series of policy documents from a top-level architecture perspective. The "Education Informatization 2.0 Action Plan" released by the Ministry of Education in 2018 proposed to "explore typical approaches to achieving differentiated teaching, personalized learning, refined management, and intelligent services under informationized conditions[1]." In 2019, the "China Education Modernization 2035" issued by the Central Committee of the Communist Party of China and the State Council emphasized leveraging modern technologies to accelerate talent development mode reform and achieve an organic combination of large-scale education and personalized training[2]. The "Work Points of the Ministry of Education in 2022," released on February 8, 2022, also included the implementation of the "education digitalization strategic action" to promote education digital transformation and intelligent upgrading[3]. This highlights the significant importance of digitalization for the development of the education industry, where online education has evolved into a new educational model. However, in the long-term practice of education, given the students' unique individual differences, diverse learning outcomes, and dynamically changing learning states, educators face a daunting task: they need to overcome the challenge of comprehensively and accurately understanding students' educational resource needs while addressing the unique learning requirements of different students, providing personalized, tailored educational resource recommendation services[4]. With the rapid development of information technologies such as "Internet+" and big data, various online learning resources have emerged, providing more possibilities for personalized education. How to accurately capture the required information in the ocean of information has become a challenging issue. User portraits can through effective analysis of user data, precisely grasp users' learning needs, making them a key technology for personalized educational resource recommendations. This article

ISSN 2616-7433 Vol. 6, Issue 3: 66-72, DOI: 10.25236/FSST.2024.060310

explores the application advantages of user portrait technology in recommendation service platforms, establishes the intrinsic connection between user learning needs and personalized recommendation services using portrait technology, constructs a multi-dimensional user model for Python learning resources, and proposes strategies for optimizing educational resource recommendation platform services based on this.

2. Overview of User Portraits

Research on user portraits started earlier abroad and has formed relatively mature ideas. It is generally believed that the concept of user portraits was first proposed by Alan Cooper[5], the father of interaction design, in 1999. It refers to using a fictional yet uniquely specific user to represent the target user. Alan Cooper believes that user portraits categorize users into different types based on their behaviors, motivations, and other attributes, extracting common features of each type of user and describing them with elements such as names, photos, and scenarios. Research in this field in China started later compared to overseas but has also achieved numerous results. From the annual publication trends on CNKI, research on user portraits in China can be roughly divided into three stages. The first stage, from 2010 to 2013, was the budding period. During this stage, there were only 1-2 publications per year, with very few literature. In 2010, Zheng Baoxin[6] published a study on "Mobile Game Product Promotion Based on User Portraits and Signaling Mining Technology," which was the first literature in China explicitly focusing on user portraits as a research topic. They proposed a new approach to promoting mobile game products combining user portraits with signaling mining technology, which was nearly 50 times more effective than traditional marketing methods. Since then, China has embarked on the research path centered around user portraits. The second stage, from 2014 to 2015, was the period of rising development. The number of publications slightly increased during this stage, showing a growing trend, but the overall number of literature was still very limited. The third stage, from 2016 to the present, is the period of vigorous development. The number of publications during this stage grew rapidly and was quite substantial. The number of publications in 2016 was four times that of 2015, while the number of publications in 2021 was seven times that of 2016. Although the number of publications in 2022 was slightly lower than that in 2021, there was still a growth trend in 2023. This indicates that research on user portraits in China is flourishing.

Different scholars have varying understandings of "user portraits" at different times and in different disciplinary fields, but their basic connotations are similar. User portraits mainly include three elements: user attributes, user characteristics, and user labels. User attributes can be divided into static attributes and dynamic attributes. Static attributes refer to users' basic information (such as name, gender, age, major, etc.) and other relatively stable attributes. Dynamic attributes refer to users' behavioral information (such as viewing frequency, duration, likes, bookmarks, etc.) and other dynamically changing attributes. User characteristics are common features extracted from user attributes through certain means and methods. User labels refer to expressing user characteristics in concise and easy-to-understand language, semanticizing and labeling user features[7].

3. Overview of Personalized Recommendation Service Research

3.1 Overview of personalized recommendation technology research

Personalized recommendation technology is a technique that collects, integrates, and analyzes users' interests, hobbies, professions, and other information to actively recommend information that meets their needs or interests through a recommendation system[8]. Research on personalized recommendation technology started earlier abroad, especially in the United States, and its application is very mature. Personalized recommendations initially appeared in the form of collaborative filtering. The earliest proposal was in 1992 when Goldberg[9] and others created the Tapestry System, a rudimentary collaborative filtering system used for email filtering and news recommendations. In 1997, Resnick and Varian[10] defined personalized recommendation systems in the e-commerce field in their article "Recommender Systems." According to their definition, a personalized recommendation system is a software system that analyzes customers' individual needs and purchasing characteristics, providing them with product information and suggestions that meet their needs on e-commerce websites. The goal of such systems is to simulate the process of personal sales, provide customers with a personalized shopping experience, and help them make better purchasing decisions. This definition is considered the most original and classic definition of personalized recommendation systems and is widely cited.

ISSN 2616-7433 Vol. 6, Issue 3: 66-72, DOI: 10.25236/FSST.2024.060310

Research on personalized recommendation technology in China started relatively late, and it was not until the early 21st century that formal research on personalized recommendation technology began. In 2000, Lu Haiming[11] and others published an article titled "Personalized Network Information Recommendation Based on Multi-Hybrid Intelligence," which drew significant attention from domestic experts and scholars in related fields to personalized recommendation technology. Subsequently, more and more research institutions joined the research in this field, leading to rapid development of personalized recommendation technology. Significant achievements have been made in intelligent data mining, data analysis and processing, as well as the application of recommendation systems.

3.2 Overview of personalized recommendation research in educational resources

The integration of personalized concepts into traditional educational systems has given rise to personalized learning resource recommendation systems, which can provide learners with a more tailored and efficient learning experience that meets their individual needs. Overseas research on personalized recommendation of learning resources has primarily focused on aspects such as tag-based recommendations and learners' learning styles. As early as the 1990s, the Educational Technology Experiment Center of the Open University of the Netherlands pioneered the exploration of personalized education recommendations as an independent research focus, and it continues to refine related technologies to this day. In China, personalized recommendation technology was also introduced relatively early into the research on learning resource recommendations. As early as 2002, Ding Lin and Wu Changyong[12] proposed the use of data mining technology to establish a model for personalized services in distance education. This document represents an early application of personalized recommendation technology in the field of online distance education in China. With the widespread use of cutting-edge technologies such as artificial intelligence and big data, the application of personalized recommendation technology on online education platforms has seen even greater development potential. However, existing recommendation technologies still have certain shortcomings and limitations. The following discussion will address these from the perspectives of user characteristics and the learning process.

3.2.1 Insufficient understanding of user characteristics and overall knowledge structure, leading to low level of personalization in recommendations

In the field of education, recommendation technology has become an effective means to address issues such as information overload and knowledge navigation in online learning environments, with various learning platforms emerging. However, existing recommendation technologies still have some shortcomings, with the most significant being the low level of personalization in recommendation systems and insufficient understanding of user characteristics and overall knowledge structure. This hinders the recommendation systems' ability to promote learners' reflection on learned knowledge and accurately predict and adjust learners' learning paths.

3.2.2 Inadequate focus on the coherence and systematicity of learning, leading to problems such as knowledge navigation and topic drift

Although recommendation systems can help learners find content that aligns with their learning goals and interest preferences, difficulties still exist in maintaining the coherence and systematicity of learning as it progresses. Over time, these issues can lead to problems such as knowledge navigation, topic drift, and declining learning interest, which ultimately impact learning outcomes and motivation. Therefore, it is crucial to further enhance personalized learning resource recommendation technologies to meet learners' higher-level personalized needs. Introducing user profiling techniques into recommendation systems has emerged as a new approach to improving recommendation system accuracy.

4. Building a Multi-Dimensional Python User Profile Model

In order to meet the diverse learning needs of users, before recommending personalized learning resources to users, the resource recommendation system needs to comprehensively and multi-dimensionally obtain users' personal attributes and extract their personalized features. This study takes learning users as an example to learn Python programming language, as shown in Figure 1, to obtain users' learning needs from three aspects and build user profiles.

ISSN 2616-7433 Vol. 6, Issue 3: 66-72, DOI: 10.25236/FSST.2024.060310

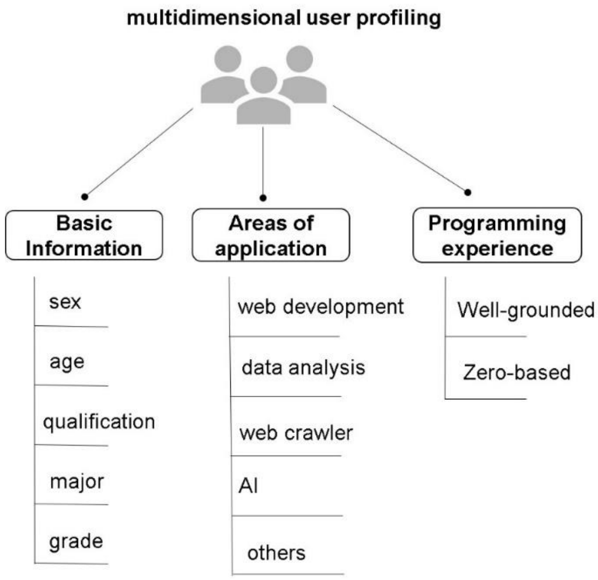

Figure 1: Multidimensional Python user profiling structure

4.1 Analysis of attribute dimensions for Python learners

4.1.1 Basic information

The basic information of Python learners includes personal attributes such as gender and age, as well as educational background, major, grade, and other information related to learning foundations. Educational background, major, and grade influence the level of learners' demand for learning resources and can provide preliminary insights into users' proficiency levels. Based on users' basic information, the system can initially categorize users based on similarity levels.

4.1.2 Application fields

Python language, as a lightweight syntax programming language adapted to the new technological era, possesses powerful capabilities. It can be used for various purposes such as data analysis, web scraping, web development, artificial intelligence, and more. Given the diverse functionalities, it is important to understand users' learning needs and objectives.

4.1.3 Programming experience

Python, being an easy-to-learn programming language, has become the top choice for many beginners and professionals. Beginners may start from the most fundamental knowledge as programming novices. On the other hand, professionals, regardless of their expertise in other programming languages or Python itself, already possess a certain knowledge base in programming languages. Consequently, their learning resource requirements may involve more complex and systematic knowledge. By combining the dimensions of basic information such as educational background, major, and grade, we can gain a more accurate understanding of users' programming language experience and their learning abilities in Python.

4.2 Construction of Python Learner's Portrait Model

4.2.1 Data Mining and Processing

The construction of user portraits consists of three steps: data mining, data processing, and model building. To build user portraits, it is necessary to first obtain data on users' basic attributes, behavioral characteristics, learning preferences, and other information. Subsequently, this data needs to be cleaned and preprocessed to remove duplicates, handle missing values, correct erroneous data, and transform it into analyzable and effective data. Finally, personalized features are extracted from this effective data and labeled to generate user portrait models. Common methods for data collection include web scraping, surveys, log file analysis, and database queries. Depending on the specific requirements and scenarios, suitable methods should be chosen to collect data. The Python learner portrait model developed in this study involves three dimensions, requiring the collection of basic information,

ISSN 2616-7433 Vol. 6, Issue 3: 66-72, DOI: 10.25236/FSST.2024.060310

learning objectives, and programming language experience of Python learners. These pieces of information are quite intuitive and can be directly obtained through surveys.

4.2.2 Multi-dimensional model construction

The basic information dimension is divided into five sub-dimensions: gender, age, education level, major, and grade. The application field dimension includes five sub-dimensions: web development, data analysis, web scraping, artificial intelligence, and others. The programming experience dimension is divided into two sub-dimensions: basic and zero-based. Detailed values are listed for each sub-dimension, representing personalized feature labels. Surveys are designed to collect detailed information on each sub-dimension, extract personalized labels for each user, group users with consistent labels into categories, thereby constructing group portraits.

4.3 Resource recommendation system based on portrait technology

Introducing user portrait technology in the recommendation service platform can accurately understand and fulfill users' needs and interests, providing students with more precise and personalized educational resource recommendation services that align with their learning goals and preferences. This promotes students' proactivity and enthusiasm while improving learning outcomes.

4.3.1 Alleviating issues of information overload and knowledge confusion in the current online learning environment

A recommendation system is an effective tool for addressing users' difficulty in quickly and efficiently obtaining desired information from a vast amount of data. By analyzing user historical behavior data, interest preferences, and other information, personalized recommendation services that meet users' needs are implemented using algorithms and technologies. For personalized recommendation techniques, understanding user characteristics is crucial to ensure accurate comprehension and satisfaction of user requirements. User portraits involve mining and analyzing a significant volume of authentic and valuable user data, extracting user features, and semantically labeling these features to construct user portrait models. Combining user portraits with algorithms in the resource recommendation approach enhances the personalization of recommendation services, thereby alleviating problems such as information overload and knowledge confusion in the current online learning environment.

4.3.2 Saving time in resource retrieval, enhancing students' learning abilities and efficiency

A resource recommendation system designed and developed based on learners' personalized characteristics effectively helps students save significant time in resource retrieval. Furthermore, different learners may retrieve distinct learning resources for the same problem, catering to their personalized learning needs. This greatly enhances users' learning efficiency and subsequently improves learners' abilities.

5. Optimization Recommendations for Resource Recommendation Services

5.1 Emphasis on resource quality, recommending resources that meet personalized user needs

Typically, various online resource platforms do not monitor and manage the quality of online resources, leading to varying levels of quality on these platforms. Firstly, educational application platforms should conduct thorough audits and controls on the quality of resources when collecting and recommending educational resources. Resources that do not meet quality standards should not be included or recommended. Secondly, educational application platforms should prioritize user learning experiences, focusing on learners' characteristics and needs to provide personalized learning resources that align with their fundamental requirements. Furthermore, resource recommendation systems should promptly track changes in user needs to better refine user portraits.

5.2 Diversify content formats, recommend a variety of resource formats

Firstly, learners have diverse learning preferences and needs; some prefer reading text, while others prefer watching videos or listening to audio. Therefore, providing a variety of resource formats can better cater to different learners' preferences and meet the diverse learning needs of various users. Secondly, by offering resources in various formats such as text, video, audio, etc., learners can gain a

ISSN 2616-7433 Vol. 6, Issue 3: 66-72, DOI: 10.25236/FSST.2024.060310

deeper understanding of knowledge from different perspectives, enhancing learning outcomes. Moreover, diverse resource formats can enrich the learning experience, stimulate learners' interest in learning, and increase engagement and motivation. To achieve a diversified range of resource formats effectively, the recommendation system should integrate various types of learning resources, including written materials, video courses, audio lectures, etc., ensuring that learners can choose their preferred learning methods. Based on learners' preferences and study habits, the recommendation system can intelligently select suitable learning resource formats for learners, thereby improving the accuracy of recommendations and user satisfaction.

5.3 Enhancing recommendation speed, accelerating system response and cache speed

Fast system response and recommendation speed can reduce user waiting time, enhance user experience, and make users more willing to continue using the recommendation system. Increasing user trust in the system, improving user stickiness and loyalty, and facing a large number of visiting users, the system can also effectively meet users' learning needs. Firstly, the system can use user profiles to accurately capture users' potential needs, predict and meet users' learning needs in real-time to accelerate the speed of recommendations. Secondly, based on users' historical behavioral data, the system can cache popular resources or frequently used data, improve data retrieval speed, reduce database access times, thus speeding up recommendation response times.

5.4 Establishing a monitoring system, timely handling user feedback

Firstly, the resource recommendation platform should establish a monitoring system to real-time monitor the system's operation status, performance metrics, and any anomalies. Secondly, the resource recommendation platform should set up dedicated user feedback channels to promptly receive user opinions and suggestions, and quickly respond to and address user feedback to enhance user satisfaction and experience. Furthermore, the resource recommendation platform should regularly analyze user feedback data and monitoring metrics, identify user pain points and needs, and make timely adjustments to system strategies and algorithms. Finally, based on users' historical learning behaviors, the resource recommendation platform should promptly optimize and update user profiles, comprehensively understand users' learning needs, and recommend resources that better align with their needs and learning preferences, thereby enhancing user satisfaction.

5.5 Establishing a sound protection mechanism, safeguarding user privacy

In the context of the internet, there is a significant risk of user information leakage. Logging into registration platforms requires user-related information, and constructing multidimensional user profiles also involves personal information, which can potentially lead to privacy breaches. Therefore, the resource recommendation platform must avoid the risk of violating laws protecting user data privacy, protect user privacy, clearly define rules for collecting, using, and storing user data, thereby enhancing user trust in the system, increasing user retention rates, and loyalty. Firstly, when collecting user information, the platform should seek full consent from users and must not change or use user information without authorization. Secondly, when collecting user information, the focus should be on the user's learning needs, avoiding involvement with the user's private information. Furthermore, when using user information, it should comply with relevant laws and regulations, and establish strict data access permissions and control mechanisms. Finally, the construction of user profiles should adhere to standards and norms, effectively address users' learning difficulties, and meet their learning needs.

6. Conclusion

In the context of big data, user profiling can derive valuable user information through the analysis and processing of a large amount of user data, extracting personalized characteristics and creating profiles. This process aims to address the current issues of knowledge confusion and low levels of personalization in recommendation systems. Therefore, integrating user profiling with recommendation technologies in personalized recommendation systems can interpret user needs extensively, provide personalized recommendations and precise services based on user characteristics, thus solving the problems of information overload and resource confusion. This approach not only saves time in resource retrieval for users but also enhances students' learning abilities and efficiency. Research on user profiling and personalized recommendation systems has made significant progress and

ISSN 2616-7433 Vol. 6, Issue 3: 66-72, DOI: 10.25236/FSST.2024.060310

achievements, leading to the emergence of various learning resource recommendation platforms. However, these studies and platforms still have some shortcomings, such as insufficient personalization, cold start issues, and room for improvement in capturing user feature information. With the continuous enrichment of online learning resources, the demand for personalized recommendations for online learning resources is becoming increasingly urgent. Therefore, research on personalized recommendations for learning resources continues to receive widespread attention from scholars.

References

[1] Ministry of Education. Notice on the Implementation of the "Action Plan for Education Informatization 2.0" [J]. Bulletin of the Ministry of Education of the People's Republic of China, 2018(04): 118-125.
[2] CPC Central Committee and State Council. "China's Education Modernization 2035" [N]. People's Daily, 2019-02-24 (001).
[3] Ministry of Education. Key Points of Work in 2022 [J]. Bulletin of the Ministry of Education of the People's Republic of China, 2022(05): 11-21.
[4] Yin Tingting, Gong Siyi, Zeng Xianyu. Research on Personalized Recommendation Services for Educational Resources Based on User Profiling Technology [J]. Journal of Digital Library Forum, 2019(11): 29-35.
[5] Cooper A, Reimann R R, Cronin D. About Face 3: The Essentials of Interaction Design [M]. New Jersey: Wiley Publishing Inc., 2007: 19-22.
[6] Zheng Baoxin, Zhou Xues ong, Li Bin, et al. Promotion of Mobile Game Products Based on User Profiling and Signaling Mining Technology [C]. Proceedings of the Guangdong Communication Society. Excellent Papers Collection of the 2010 Guangdong Communication Youth Forum [Publisher unknown], 2010: 4.
[7] Song Meiqi, Chen Ye, Zhang Rui. Review of User Profiling Research [J]. Journal of Information Science, 2019, 37(04): 171-177. DOI: 10.13833/j.issn.1007-7634.2019.04.027.
[8] Yang Yan, Sun Tieli, Qiu Chunyan. Research on Personalized Recommendation Technology [J]. Journal of Information Engineering University, 2005(02): 84-87.
[9] Goldberg D, Nichols D. Using collaborative filtering to weave an information tapestry [J]. Communications of the ACM, 1992, 35(12): 61-70.
[10] Resnick P, Varian H R. Recommender systems [J]. Communications of the ACM, 1997, 40(3): 56-58.
[11] Lu Haiming, Lu Zengxiang, Li Yanda. Personalized Network Information Recommendation Based on Multi-Agent Hybrid Intelligence [J]. Computer Science, 2000(07): 32-34.
[12] Ding Lin, Wu Changyong. Application of Data Mining in Personalized Services for Distance Education [J]. E-education Research, 2002(09): 43-46. DOI: 10.13811/j.cnki.eer.2002.09.011.