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Research on Dynamic Mathematical Resource Screening Methods Based on Machine Learning

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Abstract

The current digital educational resources are of many kinds and large quantities, to solve the problems existing in the existing dynamic resource selection methods, a dynamic resource selection method based on machine learning is proposed. Firstly, according to the knowledge structure and concepts of mathematical resources, combined with the basic components of dynamic mathematical resources, the knowledge structure graph of mathematical resources is constructed; according to the characteristics of mathematical resources, the interaction between users and resources is simulated, and the graph of the main body of the resources is identified, and the candidate collection of mathematical knowledge is selected; finally, according to the degree of matching between mathematical literature and the candidate collection, machine learning is utilized, and the mathematical resources are screened.

Keywords

Machine Learning, Dynamic Resource Filtering, Knowledge Structure Graph, Resource Interaction

1. Introduction

Digital educational resources refer to the digitized information and multimedia content produced by computers or other related devices in a network environment that can be used by users. Reasonable utilization of these digital educational resources can effectively improve learning efficiency [1]. With the development of Internet technology and intelligent devices, the variety and quantity of digital educational resources are increasing, leading to a sharp increase in the amount of data of relevant educational content on the Internet, and a large number of computational tasks that require the use of a large number of computational resources. Dynamic mathematical resources, as a kind of interactive educational resource, are loved by teachers and students for their interactive teaching characteristics and strong interest. With the rising number of users and resources, the quality of the resources varies, and for the dynamic mathematical resources under the specified categories, it is difficult to find out how to filter out the “correct resources” that meet the conditions of the categories and the “correct resources” that do not meet the conditions of the categories. For dynamic math resources under a given category, it is necessary to distinguish between “correct resources” that meet the category conditions and “dirty resources” that do not meet the category conditions. At present, there are problems such as large amounts of data, complex data types, incomplete data, and bad learning effects in the selection method of dynamic educational resources, which limit the application of dynamic educational resources in teaching. How to quickly and effectively conduct the selection of mathematical computing resources to ensure efficient and reliable results is a common concern in the fields of computers and mathematics. For the selection of digital educational resources, there are generally two ways: one is based on the user’s demand, and the user’s actual demand is used as an input vector, and the selection of resources is realized through the calculation of the user’s demand vector [2]. This approach is more common in the selection of educational resources, but it has some problems, such as a large amount of data information needs to be provided by the user during the calculation process, which leads to high complexity of the system’s computation; in some cases, the user may ignore some important information; and the system can’t make adjustments promptly when the user’s needs change. Another approach is based on dynamic educational resource selection, i.e., the selection of educational resources is dynamically adjusted according to changes in user needs. This approach has certain advantages: it can constantly make dynamic adjustments to educational resources according to user needs; it can effectively avoid problems such as bad learning effects due to the lack of information in a certain part of the system. However, this approach also has some problems: because users may be affected by their own needs or external factors when choosing educational resources, the application of this method is also subject to certain limitations. To solve this problem, this paper proposes a dynamic mathematical resource screening method based on machine learning based on the analysis of existing problems in dynamic resource selection methods. With a machine learning algorithm as the core, the paper uses machine learning to automatically classify dynamic mathematical resources by mining users’ behavior habits in using digital educational resources. According to the classification results, different types of dynamic mathematics resources are screened to provide users with personalized learning services [3].

2. Constructing a Knowledge Structure Map of Math Resources

Mathematical resources are abstractions and generalizations of mathematical phenomena and laws based on a certain knowledge system. The knowledge structure and concepts of mathematical resources are gradually established in the process of using mathematical resources [4]. To provide learners with easy access to relevant mathematical resources, we will construct a knowledge structure diagram as the basis of mathematical resource screening to provide learners with effective knowledge services. In a knowledge structure graph, there is a node that represents content, and the nodes are connected with dotted lines to indicate the relationship between different kinds of content. In this study, we mainly consider the relationship between contents. Because mathematical resources are knowledge systems formed by abstracting and generalizing mathematical phenomena, laws, etc., the following two aspects were mainly considered in constructing the knowledge structure diagram: 1) the relationship between different kinds of contents; the case where there is a correlation between different kinds of contents: when learning mathematical concepts and theorems, it is necessary to compare concepts with theorems and to prove them. In this study, we mainly consider the following kinds of relationships: a) there is a connection between concepts and concepts; b) there is a connection between concepts and theorems; c) there is a connection between theorems and theorems. 2) Cases in which there is a connection between different kinds of content. There is a connection between different kinds of content: when learning mathematical knowledge, you need to apply the knowledge to real life, for example: when learning linear algebra, you need to transform algebraic problems into geometric problems to solve; when learning probability statistics knowledge, you need to transform probability problems into probabilistic problems to solve [5].

Interrelationship between different kinds of contents: When learning mathematical knowledge, you need to apply the knowledge to real life, for example, when learning higher mathematics, you need to apply higher mathematics to daily life. Based on the above three considerations, we divide mathematical resources into different levels according to their structure: 1) knowledge units; 2) knowledge points; 3) combinations of knowledge points. According to the method of constructing the knowledge structure graph of mathematical resources, we first analyze the relationship between the main graph of resources and the candidate set. A knowledge unit is a special form of unit formed by organizing mathematical knowledge in a certain way. In this study, we take the knowledge unit as the smallest unit of knowledge in the knowledge structure graph. For example, when learning higher mathematics, it is necessary to organize the contents of higher mathematics about algebra, geometry, trigonometry, calculus, etc. to form a knowledge unit [6]. In the process of construction, a) first determine the scope and goal of the knowledge structure map: before constructing a knowledge structure map of mathematical resources, it is first necessary to clarify its scope and goal. For example, whether it is for a specific knowledge point or for the whole mathematics subject, and what is the goal of constructing the structure map, whether it is to help students understand mathematical concepts or to show the connection between different knowledge points. Collecting and organizing mathematical resources: Based on the scope and objectives identified, collect relevant mathematical resources, including textbooks, reference books, online resources, etc. Organize and analyze the collected resources to filter out the content related to the objectives. b) Construct a preliminary knowledge structure map: based on the collected mathematical resources and the results of organizing them, use graphic software (e.g. Visio, MindManager, etc.) or online tools (e.g. MindMeister, etc.) to construct a preliminary knowledge structure map. At this stage, key concepts, theorems, formulas, etc. from the mathematical resources can be added to the structure map and the connections between them can be indicated using arrows, connecting lines, etc. c) Dynamic updating and optimization: the initially constructed knowledge structure map is only a basic framework, and with deeper learning and deeper understanding, the structure map needs to be constantly updated and optimized. For example, new knowledge points can be added, duplicated content deleted or merged, and correlations adjusted. d) Interactivity and dynamic realization: in order to make the knowledge structure diagram more vivid and interactive, some dynamic display techniques or tools can be used. For example, programming languages such as JavaScript or Python can be used to write interactive animation effects, or some online tools (e.g. Lucidchart, Edraw Max, etc.) can be used to realize dynamic display. e) Evaluation and feedback: after the construction of the dynamic math resource knowledge structure map is completed, evaluation and feedback are needed. Peers or experts can be invited to conduct evaluation and make comments and suggestions. Necessary modifications and improvements are made according to the evaluation results to make it more in line with practical needs. f) Publishing and using: finally, the constructed dynamic math resource knowledge structure map is published to the appropriate platform or environment for students or other people in need to use. In the process of using, pay attention to the actual effect and user feedback for further improvement and refinement. The knowledge structure diagram of dynamic mathematical resources established in this paper is shown in **Figure 1** below.

In this study, we divide knowledge points into several knowledge points. For example, when learning probability statistics, it is necessary to organize knowledge points such as random variables and probability distribution in probability statistics to form a knowledge point; in the study of higher mathematics, it is necessary to organize the knowledge points about derivatives and integrals in higher mathematics to form a knowledge point. For example, when studying advanced mathematics, it is necessary to organize the content about differential equations, integral transformations, etc. in advanced mathematics to form a knowledge point; when studying probability statistics, it is necessary to organize the content about random variables, probability distributions, etc. in probability statistics to form a knowledge point. The number of nodes in the knowledge structure graph determines the knowledge volume of dynamic mathematical resources, and according to the knowledge volume of dynamic mathematical resources, combined with practical needs, the number of nodes is set to range

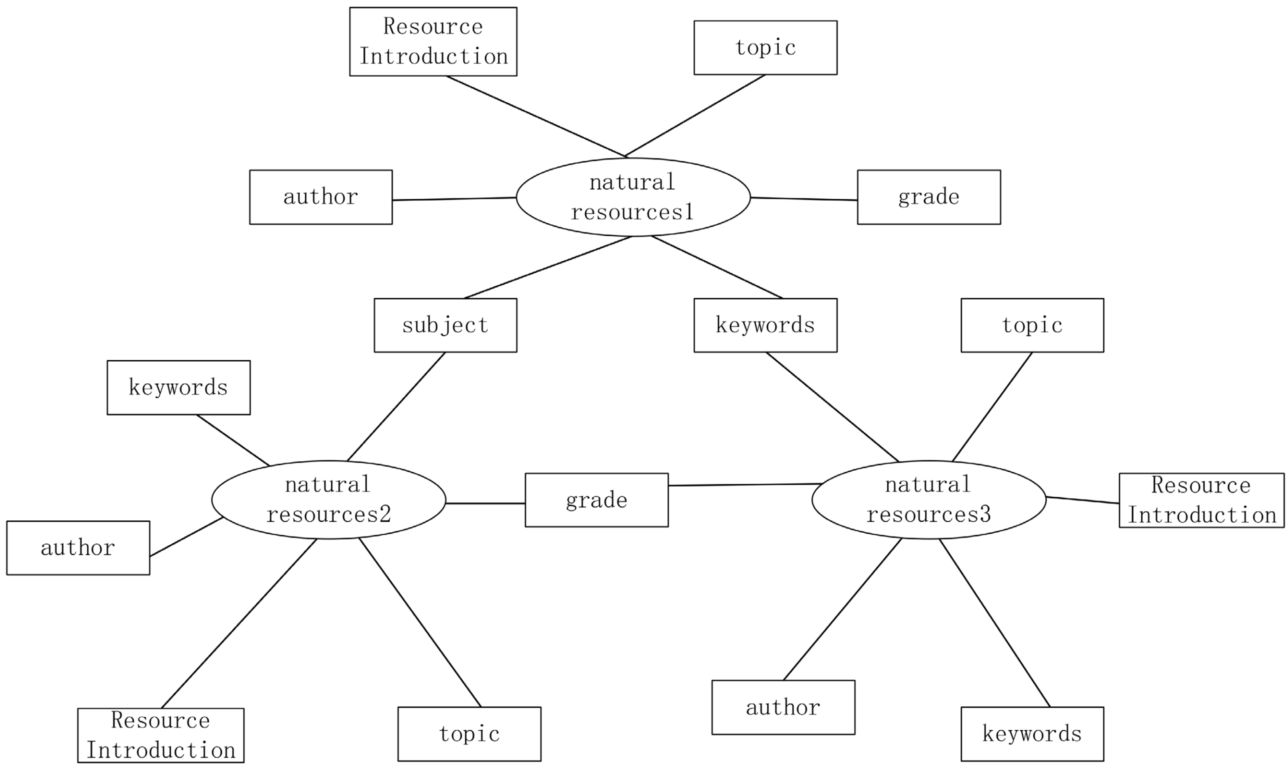

Figure 1. Knowledge structure of dynamic mathematical resources.

from 1 to 100 [7]. The construction of the mathematical knowledge structure graph is the basis for the screening of dynamic digital educational resources using machine learning technology. Mathematical knowledge structure map mainly includes mathematical subject knowledge structure map and mathematical teaching resources structure map, in which mathematical subject knowledge structure map refers to the mathematical knowledge network composed of different units, which shows different types of mathematical knowledge in the form of points, lines, and surfaces, etc.; while mathematical teaching resources structure map mainly refers to the teaching resources network composed of different types of resources in the form of point types of teaching resources. Using machine learning technology, dynamic digital educational resources can be screened and those resources that do not meet the requirements can be eliminated from the dynamic digital educational resources database. First, when constructing the dynamic mathematical knowledge structure map, the static mathematical knowledge is dynamically transformed by analyzing and categorizing the mathematical knowledge in the dynamic digital education resource base, and the corresponding knowledge structure map is constructed according to different types of resources. Secondly, different types of teaching resources are identified according to the mathematical subject knowledge structure map and teaching resources structure map. Through the above selection process of features of dynamic mathematical resources, it can be seen that feature selection reflects the closeness of the connecting relationship between dynamic mathematical resources and their knowledge structure diagrams from the whole, and after a certain amount of feature information is extracted, dynamic mathematical resources are classified according to the extracted feature information. When classifying dynamic mathematical resources, it is necessary to consider whether the classification result is reasonable and whether the classification result meets the practical needs.

3. Selection of Dynamic Math Resource Characteristics

Dynamic mathematical resources become more complex after providing interactive functions, and the feature extraction of this kind of resources is also known as a difficult problem, to address this problem, this chapter proposes a dynamic mathematical resources feature extraction DMRFE method, which mainly mines the geometric element information, image information, and hidden text information to complete the feature extraction work. Dynamic mathematical resources, as a kind of classical interactive resources in the field of mathematics, provide users with human-computer interaction functions, which are more interesting and inspiring in the teaching process of mathematics compared with traditional static resources. Dynamic mathematical resources provide users with different interaction methods according to the different contents of teaching and learning, and users can customize the operation through the buttons and drag-and-drop elements provided in the resources so that the obscure and difficult-to-understand geometric contents can be displayed in a more vivid form under a series of scrolling and panning. However, the increase in interactive functions makes the resources more complex and puts forward higher requirements for feature extraction of dynamic mathematical resources, so this chapter proposes a dynamic mathematical resource feature extraction method [8]. First, the background storage file of the resource is analyzed to extract the element information, the static elements are directly used for the construction of element features, and the dynamic-related elements are used to generate the interaction sequence to assist the software in completing the automation of interaction and record the video to save it; then, the contour extraction of the main graphic in the video sequence frames is accomplished by using the moving object detection technology, and the graphic recognition is accomplished by the OpenCV graphic detection technology to construct the graphic features; finally, the Chinese word segmentation technique and the Chinese word recognition technique are used to extract the graphic features. Finally, the text features are constructed by using Chinese word segmentation technology and the LDA topic model. The overall flow chart of the DMRFE method is shown in the following **Figure 2**.

Feature selection of dynamic mathematical resources is to extract the features of dynamic mathematical resources by using machine learning algorithms, and the extracted feature information is an important basis for the selection of dynamic mathematical resources. The factors affecting the selection of dynamic mathematical resources mainly include: the number of nodes in the knowledge

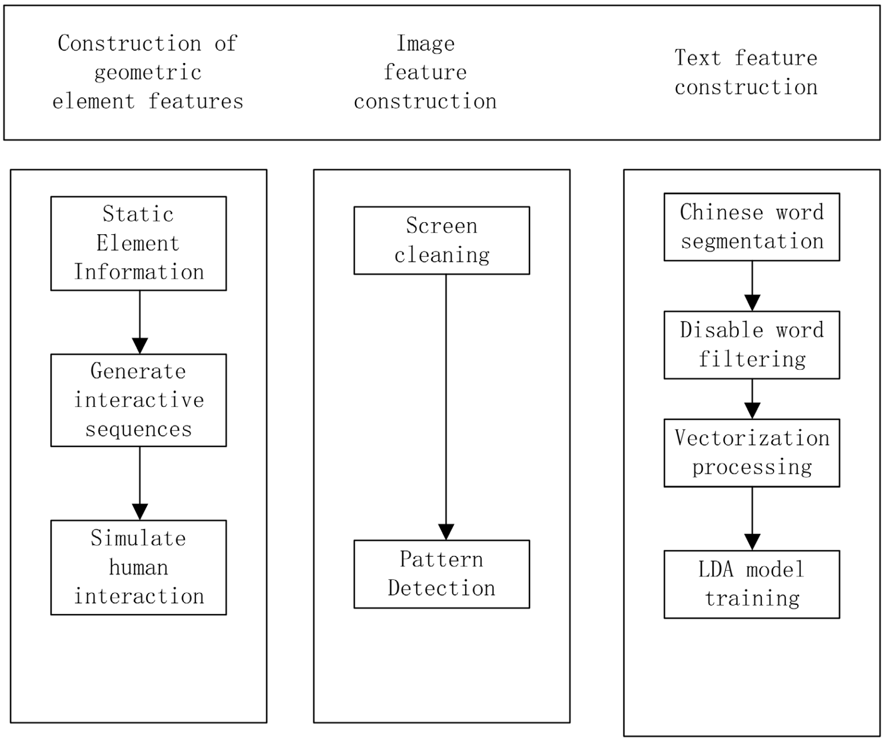

Figure 2. Dynamic mathematical resource feature extraction process.

structure graph and the number of edges between nodes, in which the number of nodes in the knowledge structure graph determines the number of nodes in the knowledge structure graph of dynamic mathematical resources, and the number of edges between nodes determines the number of edges in the knowledge structure graph of dynamic mathematical resources [9].

For the extraction of geometric elemental information, elemental information is subdivided into two parts: static elemental information and dynamic interaction information, the former uses the number of elements as feature values to construct geometric elemental features, and the latter is mainly used to generate interaction sequences, which are simulated by automated software and saved in videos as the object of extracting image information; dynamic mathematical resources have a high convenience and interactivity when displaying dynamic geometric problems, but many educational resource platforms at home and abroad provide the creation environment for this type of resources, but the respective characteristics of platforms lead to the standardization. and interactivity, many educational resource platforms at home and abroad provide an environment for the creation of these types of resources, but the platforms have their characteristics, resulting in different standards, to fully explore and extract the information of the basic elements of the resources, the dynamic mathematical resources need to be defined in a unified way. In dynamic geometry problems, the basic elements such as points, lines, and surfaces are mainly used as motion carriers to study the geometric and quantitative relationships between graphical objects that appear under the motion modes of translation, rotation folding, etc.

Therefore, from the definition of dynamic geometry problems, dynamic mathematical resources can be abstracted as the basic unit of elements:

$$\text{DMR} = \left(\text{id}, \text{E-static}, \text{R-dynamic}\right) \quad (1)$$

In the above equation, id the number of resources in the platform, according to the unique number can locate the specified resource. E-static is the set of all static elements in the resource, and the suffix reflects the static character of the element when there is no interaction. At the same time, there are interactive elements in dynamic math resources, and the hidden information needs to be accessed through dynamic interaction, and the suffix reflects the dynamic characteristics of such elements. The differences in the content of dynamic educational resources under different categories lead to the differences in the basic components and interaction forms between the resources, and the geometric element information is extracted from the static components and dynamic interactions in the following sections.

4. Machine Learning Based Resource Screening

This method uses machine learning algorithms to classify and filter dynamic educational resources, which includes three dimensions of learning interest, knowledge demand, and behavioral performance as follows:

1) Learning interest dimension. When users learn through digital educational resources, the system can make personalized recommendations for them based on their interests. In the interest dimension, the data can be clustered and analyzed using the K-mean clustering algorithm to determine the classification and screening of digital educational resources [10].

2) Knowledge demand dimension. When users use digital educational resources, they will select resources for them according to their knowledge needs. The system determines the classification and screening criteria of dynamic math resources by calculating the user's learning interest degree and knowledge demand degree to guide the selection and screening of dynamic educational resources. Machine learning is a kind of artificial intelligence system built based on statistical data that can automatically discover unknown laws and make predictions, and the method of machine learning is used in the selection of digital educational resources to effectively solve the problem of screening math resources. The method first extracts features from the dynamic educational resources submitted by users, and processes and classifies them with features. Then, machine learning algorithms are used to screen and classify dynamic math resources using multiple classification algorithms. In this paper, we propose a dynamic mathematical resource screening method based on machine learning, which first simulates the interaction between users and resources, identifies the main graph of resources, and selects the candidate set of mathematical knowledge by constructing the structure graph of mathematical knowledge and the basic constituent elements of mathematical resources; and then, based on the interaction between users and resources and the attributes of mathematical

knowledge, combined with the basic constituent elements of dynamic mathematical resources, we utilize the machine learning method that filters the dynamic mathematical resources.

Machine learning is a scientific rule that uses computers to learn data and acquire new knowledge and technology by transforming data into useful information. In this paper, backward propagation is adopted. In the process of machine learning, the structure of neural network is shown in the following Figure 3.

Artificial neural network based on machine learning is a statistical learning algorithm inspired by biological field. A backward propagation neural network consists of forward and backward propagation of input layer, hidden layer and output layer. In detail, backward propagation means that the input signal comes from the input layer, passes through the hidden layer and passes to the output layer. If the output layer obtains the expected results, the algorithm will end. Otherwise, the wrong result will be propagated back to the output layer through the original connection path, and will continue to loop to get the error that minimizes the cost function. Before these steps, in order to calculate the activation value, activation parameters should be set between the input layer and the hidden layer, and between the hidden layer and the output layer. The relevant calculation formula is as follows:

$$f(x) = \frac{1}{1 + \mathrm{e}^{-\theta x}} \tag{2}$$

$\mathrm{e}^{-\theta x}$ represents the training accuracy in the activation process, and the activation function is monotonically increasing and continuous and smooth. By setting parameters, the function can balance the relationship between linearity and nonlinearity, and the function is differentiable, which is very important for the calculation of error back propagation. The number of hidden layers is determined by the number of input layers and output layers. Gradient descent algorithm is used to mediate the minimum error sum of squares, which is a common method to train back propagation neural networks.

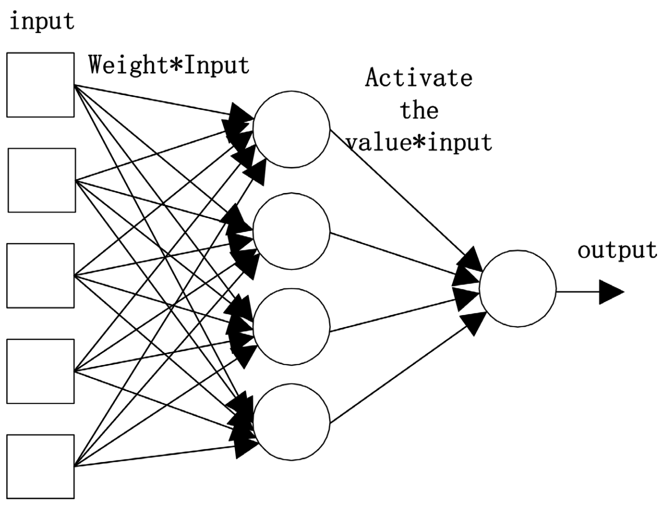

Figure 3. Structure of back propagation neural network.

The dynamic mathematical resource screening method based on machine learning mainly includes three parts: the first part is to construct the mathematical knowledge structure diagram; the second part is to identify the subject graph of mathematical knowledge according to the interaction between users and resources; the third part is based on the interaction between users and resources, using machine learning to screen dynamic mathematical resources. The dynamic digital educational resources screening method based on machine learning first establishes the mathematical knowledge structure graph and the candidate collection and then screens the candidate collection according to the user-resource interaction situation and relevant attributes. The machine learning-based dynamic mathematical resources screening method takes mathematical knowledge as the entry point and divides mathematical knowledge into basic concepts, basic ideas, basic methods, basic skills, and applications. Among them, the basic concepts include "number", "operation of the number", "numerical representation", "symbols and operations", "geometry and operations", "mathematics", "mathematics", "mathematics", "mathematics", "mathematics", "mathematics", "mathematics", "mathematics", "mathematics", "mathematics", "mathematics", "mathematics" and "mathematics". The basic ideas include: the creation and development of numbers is the foundation of human society, mathematical knowledge plays an important role in the development of human society, and mathematical knowledge has its systematic nature; the basic methods include: geometric intuition, reasoning and argumentation, and logical deduction; basic skills include: symbolic arithmetic ability, spatial imagination ability, and logical thinking ability, etc.; applications include: solving practical problems, discovering new problems and innovative thinking. Based on the mathematical knowledge structure diagram, dynamic mathematical resources are divided into basic mathematical resources, higher mathematical resources, and applied mathematical resources, of which, the basic mathematical resources refer to "numbers" and "operations of numbers" in elementary number theory and "numbers and operations" in geometry and algebra. The basic math resources refer to "number", "operation of the number" in elementary number theory, and "number and shape" in geometry and algebra; the higher math resources refer to "number" in elementary number theory, and "number and shape" in geometry and algebra; and the application includes: solving practical problems, discovering new problems and innovative thinking. The application includes: solving practical problems, discovering new problems, and innovative thinking. Since different types of digital educational resources have different characteristics, it is necessary to screen the candidate collection according to the characteristics of different types of digital educational resources in the process of dynamic digital educational resources screening, to realize the optimization of the dynamic digital educational resources selection process.

Dynamic mathematical resource screening can be classified into a data mining problem, where resources are categorized and relevant classification rules are inferred from a database with no rule order. In this process, a decision tree algorithm is utilized for analysis and prediction, and nodes in different regions are divided according to the different levels of the tree. A decision tree is a tree structure similar to a flowchart, and the tree structure mainly includes root nodes, branch nodes, and leaf nodes. The decision tree structure established in the screening approach of this paper is shown below in **Figure 4**.

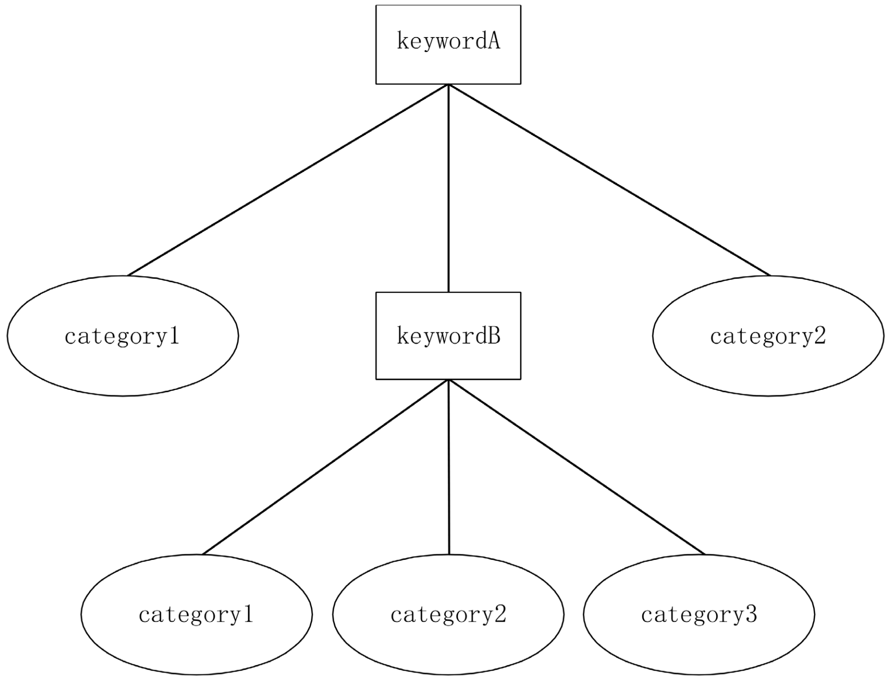

Figure 4. Schematic diagram of the decision tree in the screening methodology.

In the decision tree algorithm, the keyword A is the root node, representing the entire set of resource data, and of the two categories obtained through the keyword A, both can be regarded as data subsets, which are also called leaf nodes in the decision tree. Keywords A and B are non-leaf nodes, a path from the beginning of keyword A to the leaf nodes, that corresponds to a prediction rule in retrieval, the entire decision tree corresponds to a set of retrieval rules.

In the dynamic resource screening method designed in this paper, when an attribute in the sample set in the decision tree is uniformly distributed in all categories, then the mutual information of the categories is 0. At this point, it indicates that there is a weak relationship between the retrieved attribute and the category, and there is a significant difference. The correlation between retrieved attributes and dynamic resource types is calculated as:

$$I(x,y) = \log \frac{p(x_i, y_j)}{p(x_i)p(y_j)}' \tag{3}$$

Among them, $p(x_i)$ indicates the probability that a dynamic resource screening attribute is *i*, $p(y_i)$ indicates the probability that the sample category y is *j*, and $p(x_i, y_i)$ indicates the probability that the attribute x is i and the sample category y is j. In the actual screening calculation process, it is necessary to consider the distribution probability between the above relevant variables and add the weighting factor C^{-1} in the calculation process, and the calculation formula is:

$$C_i^{-1} = \exp\left(-\frac{n_i}{\sum n_i}\right) m_0 \tag{4}$$

where, n_i denotes the amount of data of attribute i in the retrieval process, and m_0 denotes a constant, the value of which is fine-tuned according to the actual database situation acquisition. The final retrieval sorting partition mutual information calculation formula between categories and attributes is defined as:

$$MI(x) = C^{-1} \sum_{i,j} p(x_i, y_i) \log \frac{p(x_i, y_j)}{p(x_i) p(y_j)}, \tag{5}$$

According to the above calculation process, it can be seen that the greater the correlation between the attributes and categories in the decision tree, the better the performance in the process of retrieval sorting segmentation. The decision tree model allows for the categorization and sorting of data in the screening method, the screening process is shown in Figure 5 below.

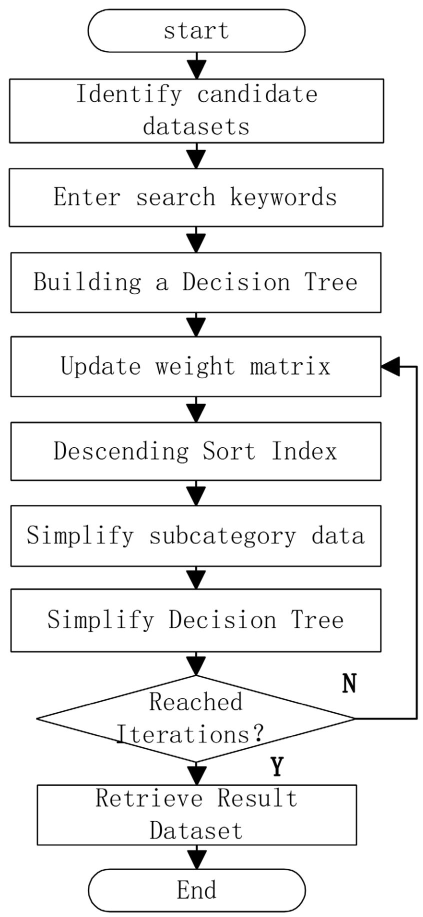

Figure 5. Schematic diagram of the dynamic math resource screening process.

With the above screening process, the greater the correlation between the retrieval attributes and the sample categories, the more useless data will be removed. The irrelevant information will be greatly reduced in the obtained retrieval results, improving the efficiency of the retrieval method. This completes the study of intelligent retrieval methods of library literature resources based on decision trees.

5. Discussion of the Significance and Contribution of This Paper

By applying machine learning technology, this paper can extract and classify the characteristics of dynamic mathematical resources, which is helpful to quickly and accurately identify and screen out resources that meet specific requirements. Compared with traditional manual screening methods, this method has higher efficiency and accuracy. Secondly, the practical significance of dynamic mathematics resource screening method is that it can promote the popularization and improvement of mathematics education. By screening out high-quality dynamic mathematics resources, students can better understand and master mathematics knowledge and improve their learning effect. At the same time, it also helps teachers to better design mathematics teaching and improve teaching quality. In addition, the dynamic mathematical resource screening method based on machine learning can also promote the sharing and reuse of mathematical resources. By sharing the screened high-quality resources, more people can benefit from these resources and promote the popularization and development of mathematics education. The contribution of this method is that it can promote the application and development of machine learning technology in the field of education. By applying machine learning technology to the selection of mathematical resources, it can further promote the popularization and application of machine learning technology in the field of education and contribute to the development of educational informationization and intelligence. To sum up, the dynamic mathematics resource screening method based on machine learning has important practical significance and contribution, which can promote the popularization and improvement of mathematics education, promote the sharing and reuse of mathematics resources, and also promote the application and development of machine learning technology in the field of education.

6. Concluding Remarks

In this paper, the current selection method of digital educational resources is studied. Through the construction of the knowledge structure diagram of digital educational resources, the basic constituent elements of mathematical resources can be represented, thus providing a theoretical basis for the design of the selection method of mathematical resources. By identifying the knowledge structure diagram of dynamic mathematical resources, the knowledge contained in dynamic mathematical resources can be screened. Through the identification of the main body graph in the dynamic mathematical resources, the mathematical literature can be matched with the candidate collection, thus providing a reference for the design of the dynamic mathematical resources selection method. However, because the current research on digital educational resources is still in the exploratory stage, its research results are not perfect, especially the dynamic digital educational resources are constantly updated and developed, so there are still many problems to be solved in the next research. For example, how to better construct the knowledge structure graph of dynamic mathematical resources, how to more accurately identify the subject graph of dynamic mathematical resources, and how to effectively use machine learning to screen dynamic digital educational resources need to be further studied.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] Lin, J., Ma, X., Lin, S.C., Yang, J.H., Pradeep, R. and Nogueira, R. (2021) Pyserini: A Python Toolkit for Reproducible Information Retrieval Research with Sparse and Dense Representations. *Proceedings of the* 44*th International ACM SIGIR Conference on Research and Development in Information Retrieval*, July 2021, 2356-2362. https://doi.org/10.1145/3404835.3463238

[2] Duvaud, S., Gabella, C., Lisacek, F., Stockinger, H., Ioannidis, V. and Durinx, C. (2021) Expasy, the Swiss Bioinformatics Resource Portal, as Designed by Its Users. *Nucleic Acids Research*, **49**, W216-W227. https://doi.org/10.1093/nar/gkab225

[3] Pereira, V. and Bamel, U. (2021) Extending the Resource and Knowledge Based View: A Critical Analysis into Its Theoretical Evolution and Future Research Directions. *Journal of Business Research*, **132**, 557-570. https://doi.org/10.1016/j.jbusres.2021.04.021

[4] Li, Y., Ma, J. and Zhang, Y. (2021) Image Retrieval from Remote Sensing Big Data: A Survey. *Information Fusion*, **67**, 94-115. https://doi.org/10.1016/j.inffus.2020.10.008

[5] Gao, H., Duan, Y., Shao, L. and Sun, X. (2021) Transformation-Based Processing of Typed Resources for Multimedia Sources in the IoT Environment. *Wireless Networks*, **27**, 3377-3393. https://doi.org/10.1007/s11276-019-02200-6

[6] Yan, J.C. (2022) Preliminary Exploration of Machine Learning Solutions for Combinatorial Optimization Problems: Taking the Research Progress of Graph Matching Problems as an Example. *China Basic Science*, 6.

[7] Li, L., Xue, Y., Gao, Y., *et al.* (2022) Research on Exploration and Development Data Quality Control Methods Based on Machine Learning. *Computer Applications in the Petroleum Industry*, 030

[8] Boukhari, K. and Omri, M.N. (2023) DL-VSM Based Document Indexing Approach for Information Retrieval. *Journal of Ambient Intelligence and Humanized Computing*, **14**, 5383-5394. https://doi.org/10.1007/s12652-020-01684-x

[9] Rogers, A., Gardner, M. and Augenstein, I. (2023) Qa dataset explosion: A taxonomy of nlp resources for question answering and reading comprehension. *ACM Computing Surveys*, **55**, 1-45. https://doi.org/10.1145/3560260

[10] Yang, Z., Gan, Z., Wang, J., Hu, X., Lu, Y., Liu, Z. and Wang, L. (2022) An Empirical Study of GPT-3 for Few-Shot Knowledge-Based VQA. P*roceedings of the AAAI Conference on Artificial Intelligence*, **36**, 3081-3089. https://doi.org/10.1609/aaai.v36i3.20215