Research on Online Teaching Method of Equation Solving Based on Transfer Learning

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Abstract. In order to improve the online teaching effect of equation solving, an online teaching method of equation solving based on transfer learning is designed. First of all, integrate the online teaching resources in the Internet, then the data conversion and classification processing, and finally build the learner behavior and knowledge resources relationship model, to recommend the relevant teaching content to learners, so as to achieve online teaching. The experimental results show that the online teaching method of equation solving based on transfer learning has high accuracy, short classification time and high student performance. It is proved that the online teaching method in this study can effectively improve the online teaching effect.

Keywords: Transfer learning · Online teaching · Data flow classification · Knowledge resource modeling

1 Introduction

With the advent of the information age, how to make better use of computer technology to assist classroom teaching has become a hot issue in the teaching reform of various courses. Equation solving is a basic course of Mathematics for information and computing science, which plays an important role in the whole professional system [1]. Because of the combination of theory and practice, through the teaching of this course, students can not only learn professional theoretical knowledge, but also improve their ability to solve practical problems by using mathematical knowledge, and cultivate their insight, creativity and imagination. Therefore, in order to improve the efficiency of classroom teaching, the design of the online teaching method of equation solving has become a hot issue in the teaching reform of constant equation [2].

In the face of the great challenges in the era of big data, the core technologies of intelligent fields such as data mining and machine learning have been widely concerned and developed rapidly. Therefore, the online teaching method of equation solving can be improved by using machine learning. However, the limitations of traditional machine learning methods begin to show. Among them, the most important problems include: the source of training and test data is inconsistent; the distribution of training data and test data is different; the training task and test task change [3]. Traditional machine learning can achieve good results. The main premise is to avoid the emergence of the

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above three situations, but in practical application, this premise is difficult to meet. In order to effectively solve a series of problems faced by traditional machine learning, transfer learning came into being. The core technology of transfer learning is to build bridges between different fields, so as to realize the cross domain transfer of knowledge and skills. Based on the idea of transfer learning, an online teaching method of equation solving based on transfer learning is designed. On the basis of data integration of teaching resources, the data in the original data table are standardized and classified according to the purification rules. By constructing the association model between learners' behavior and network resources, transfer learning is used to provide relevant teaching resources to learners. So as to realize the online teaching of equation solving.

2 Integration of Online Teaching Resources

With the increasing popularity of the Internet, the Internet can be closely linked with the teaching and learning activities of the Internet, including the increasing relationship with the Internet and the use of Internet technology. Equation solving course can make use of network resources for teaching, make classroom teaching more in line with the requirements of the times, and improve the quality of online teaching. The use of modern education means and internet teaching can broaden the channels of students' learning knowledge, expand the space–time scope of traditional teaching, and effectively solve the innovation of teaching methods. The Internet effectively strengthens the effect of network teaching, makes students easily understand and master knowledge, guides students from passively accepting knowledge to actively exploring knowledge, and effectively improves the learning effect.

Firstly, the mobile learning method is used to allocate the database resources in the network, and the parameters in the database are graded under the support of the mobile learning architecture. The following is the specific calculation process.

step1: According to the average number of database requests per second, it can be divided into three types: large, medium and small;
step2: Mobile learning is used to manage and schedule a large number of network connected computing resources [4]. According to the key factors affecting the consumption of database load resources, the request complexity is calculated.

$$\mathrm{Km} = \frac{\mathrm{p} \rightarrow \mathrm{o}}{\sum_{\mathrm{m}} \mathrm{j} \times \mathrm{m}} \tag{1}$$

In formula (1), $\mathrm{p} \rightarrow \mathrm{o}$ represents that p and o request a teaching resource at the same time, j represents the database request complexity, m represents the consumed database resources, and Km represents the request complexity level.

- step3: Check the corresponding time of the database, and view the time required from the submission of the request to the completion of the execution and return to the client;

- step4: The number of database connections, which represents the maximum number of connections established when a user makes a request.

According to the type of physical resources to be allocated. According to the amount of user access resources and the amount of resources available in the database, select the server to allocate resources [5]. Suppose there are m system databases on server i in the ideological and political resources, The number of connections available to the k system database is $SDGH_j(j \in 1, m)$, The database schema that can be assigned to users is $AADG_j(j \in 1, m)$, There is a q system mode in the j system database, Then the data assigned to users in the n database is expressed as $ASA^j_{qm}(n \in 1, q)$; The problem to be solved is to select which server to allocate database resources for users according to the amount of database resources required by users and the available resources of servers. When the database object to be allocated is a database schema [4], formula (2) is used to represent the number of modes that can be allocated to the database.

$$S = \sum_{k=1}^{i} ak \times V \tag{2}$$

In formula (2), S is the system database traffic, a is the number of connections accessed by users, and V is the database object to be allocated.

According to the above process, the data integration of online equation solving teaching resources is completed.

3 Data Stream Classification of Online Teaching Resources Based on Equation Solving

Because the data formats excavated are different, the data in the database needs to be converted to extensible markup language (eXtensible Markup Language, XML) documents, while the received XML documents are converted to the data in the database for data exchange between virtual data centers and heterogeneous databases. When the database corresponds to different application systems, the corresponding data representation methods should be different. Therefore, in the face of heterogeneous data from different data sources, we must transform the corresponding data format. XML, a heterogeneous data exchange model based on XML, can not only describe irregular data, but also include data from multiple applications in the same XML file, so as to integrate different source data. In terms of the field name and specification type of the attribute value, the data in the virtual data table is different from that in the original data table. Therefore, the data in the original data table should be normalized according to the purification rules, as shown in Fig. 1.

After the process data transformation in Fig. 1, the resources are obtained according to the user's needs, and the resources in the library database are integrated on the unified platform. Local accuracy is often used in dynamic classification selection methods. This method assumes that the classification accuracy of each base classifier is different around the samples to be classified, so the base classifier with the highest local accuracy

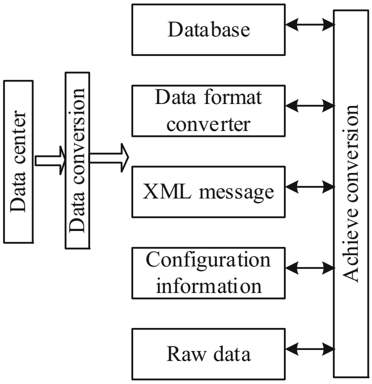

Fig. 1. Data conversion process

is selected, and the output of the classifier is taken as the output of the whole classifier combination system. At present, local precision can be divided into category independent and category dependent methods. The index proposed in this paper is based on the category independent method and its definition is shown in formula (3).

$$\mathrm{L} = \sum_{\mathrm{i}=1}^{\mathrm{k}} \frac{\mathrm{I}(\mathrm{f_j} \times \mathrm{pritect}(\mathrm{x_i}) = \mathrm{y_i})}{\mathrm{e}} \tag{3}$$

In formula (3), $\mathrm{x_i}$ is the feature of the classified sample, k is the number of samples in its field, and $\mathrm{f_j}$ is the feature and real class of the i th sample in the field.

On this basis, the distance between the sample and the classification sample is analyzed, and the Euclidean distance is used for processing. The processing formula (4) is.

$$\mathrm{I(x)} = \begin{cases} 1x = true \\ 0x = false \end{cases} \tag{4}$$

In formula (4), I(x) is the indicator function.

On this basis, the classifier is selected and updated.

$$\mathrm{f : y = sign}\left(\alpha_1 \prod\left(\mathrm{w_s^T x_t}\right) + \alpha_{3\mathrm{t}} \prod(\mathrm{w_s^T x_t}\right) - \frac{1}{2} \tag{5}$$

In formula (5), α_1 and $\alpha_{3\mathrm{t}}$ are the weights of the source domain classifier and the target domain classifier, respectively,f stands for weighted combined component class, $\mathrm{x_t}$ represents the new sample, $\mathrm{w_s^T}$ represents the weight vector of the classifier with the highest local classification accuracy selected from the classifier set, and $\prod$ is a compression function.

Based on the above process, the teaching content of equation solving is discretized and reorganized, and all contents are grouped according to the degree of difficulty or content relevance.

4 Knowledge Recommendation of Equation Solving Learning Based on Transfer Learning

Data mining and machine learning have made remarkable achievements in many knowledge engineering fields, including classification, regression, clustering and so on. However, many machine learning methods work on a common assumption: training and testing data come from the same feature space and satisfy the same distribution. When the distribution changes, most statistical models need to re collect training data from the beginning and reconstruct them. In many real-world applications, the cost is expensive or it is impossible to re collect the training data needed. If the processed data can be used in other task fields to help improve the completion of other tasks, the cost of data collection will be greatly reduced and the learning accuracy will be improved [6]. In this case, knowledge transfer between domains will play a significant role. The differences and connections between transfer learning and traditional machine learning are shown in Fig. 2.

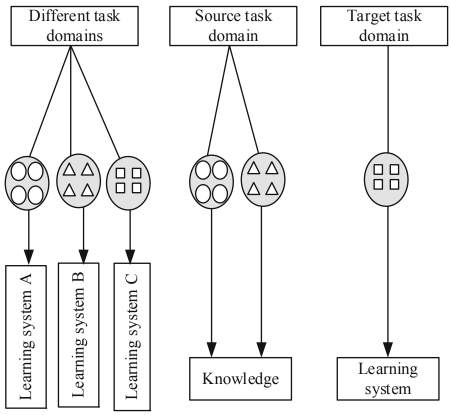

Fig. 2. Transfer learning

With the knowledge knowlege of the Internet, there are many resources such as topics, videos and handouts. Knowledge resources belong to a number of different feature domains, the better recommendation effect will be obtained by dividing the knowledge resources into domains and then recommending knowledge according to the fields [7]. However, learners' learning behavior patterns in one domain can also be applied to other similar domains to a great extent. And because human learning behavior itself has the ability to "transfer" and "draw inferences from one instance". It is also very important to use the transfer learning method to use its learning characteristics in one field to help learn knowledge in other fields.

4.1 Internet Knowledge Resource Modeling

Based on the above analysis, in order to solve the problem of disorderly and uneven quality of knowledge resources in the field of knowledge learning, and to prepare for the next step of knowledge recommendation, the first problem to be solved is the construction of learner model, knowledge resource model and the model of relationship between learners and knowledge resources.

1) Feature selection of learners and knowledge resources: by analyzing the basic information filled in by learners and the learning records of learners, the characteristics used to construct the learner model and knowledge resource model are selected. The characteristics of this part include two aspects. One is the explicit characteristics such as learning time and homework completion On the other hand, it is difficult to get the level of the current learners directly from the hidden characteristics of learners [8–10].
2) Quantifying the selected features, constructing learner model and knowledge resource model: after completing the feature selection of learners and knowledge resources, it is necessary to quantify the selected features, because the influence of each feature on learners' learning behavior is different. It is necessary to establish a model by using features, and use the model to represent the learning behavior pattern and knowledge resources of learners.
3) The construction of the relationship model between learners and knowledge resources: learners and knowledge resources are closely related. After the construction of the learner model and knowledge resource model, the relationship model between learners and knowledge resources is constructed, which can be the evaluation matrix of learners on knowledge resources. The bipartite graph model for learners to learn knowledge resources can also be a more complex Bayesian belief network model. The construction of the relationship model between learners and knowledge resources plays an important role in the following knowledge recommendation methods.

At present, in the Internet learning environment, learners and the organization of knowledge resources are chaotic. Only through these data, we can not determine the learners' preferences, the current level of learning and learning behavior patterns. Therefore, before knowledge recommendation, it is necessary to preprocess the learners' past learning records and knowledge resources [11].The process of constructing the relationship model between learners and knowledge resources is shown in Fig. 3.

The construction of learner model: Learners' learning preference, learning behavior often with certain characteristics. Before knowledge recommendation, it is necessary to model learners. The feature vector of learners mainly includes four aspects: Learners' basic information, learners' learning preferences in various fields, learners' learning feature sets in specific learning fields and learners' current learning level sets in various fields. These four aspects and their construction methods are described in detail below.

(1) The basic information about learners includes the learners' age, gender, hobbies, major and current educational background, and more basic information can be covered according to actual needs. Learners' basic information generally reflects learners' learning level and learning tendency at the present stage. This part of information is often obtained by the way of active filling in by learners, and learners may default the part of information, so it should only play an auxiliary role in the process of knowledge recommendation.

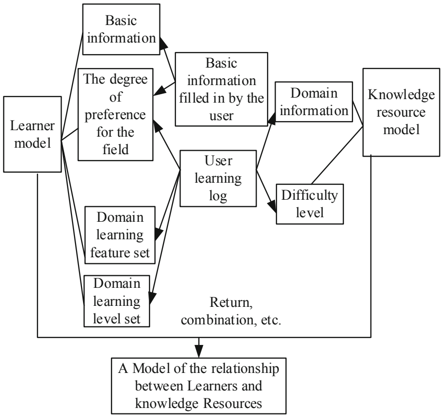

Fig. 3. The relationship model between learner behavior and knowledge resources

(2) At present, the knowledge in the Internet learning environment includes the knowledge of various fields and disciplines. However, the degree of learners' learning preference in different fields is quite different, which is closely related to the feature selection of knowledge resources. This part of information can be provided by learners, and more importantly, it can be obtained by analyzing learners' past learning records and quantifying them.

(3) Learners in various learning areas of learning characteristics set [12], learners will invest a lot of time and energy in their preferred learning field, the learning characteristics of learners in this field is particularly important. On the one hand, it can provide some more easily acquired features, such as learning time, visiting times, learning feedback and so on. In addition, there are many hidden features that can not be directly obtained, so the unsupervised learning method in feature selection field can be used for feature selection. Since learners may be interested in multiple learning fields, learners' learning characteristics in specific learning areas will form a set to represent the learning characteristics of learners in various fields.

(4) The collection of learners' learning level in various fields at the present stage is mainly obtained through the level of knowledge resources learned by learners and learning feedback. Define the function $h(x) \rightarrow R.(R)$ as an ordered set, such as a nonnegative integer, or a range of real numbers) for two learners. If $h(x_i) \geq h(x_j)$ indicates that x_i's current level of learning in a given field is higher than that of x_j. If the learners have learned the knowledge resources at a high level in a certain field, and give positive learning feedback, it can be considered that the learners' learning level in this field is high at the present stage. Learners' learning level in various fields is changing with their learning situation.

The construction of knowledge resource model: the characteristics of knowledge resources are closely related to learners' knowledge learning process. Learners are very interested in a certain field, so the possibility of learning knowledge resources related to this field is much higher than that of other fields. Therefore, the corresponding characteristics of knowledge resources will be combined in the process of knowledge recommendation. Therefore, the feature selection of knowledge resources is equally important. The characteristics of knowledge resources mainly include two aspects: domain information and difficulty. The following two aspects and their construction methods are described in detail.

(1) Domain information, domain information is the basic information of knowledge resources, including the subject field, subject direction, number of learners, learning duration and so on. The domain information of knowledge resources can be selected by manually marking a part of knowledge resources [13]. Automatic classification is performed by supervised learning domain classification methods such as linear classification, vector space model, word structure representation and semantic based representation.
(2) The degree of difficulty and the difficulty of knowledge resources are closely related to whether they are suitable to be recommended to a learner [14]. It is necessary to combine the level of learners and the difficulty of knowledge resources for knowledge recommendation to achieve good results. In this paper, we define a function $g(x) \rightarrow R.(R)$ as an ordered set. If $g(x_i) \geq g(x_j)$, the difficulty level of x_i is not lower. On the one hand, the definition of this function is related to the number of learners and learning time of knowledge resources, and also related to the learning order and learning feedback of learners.

4.2 The Construction of the Relationship Model between Learners and Knowledge Resources

The model of the relationship between learners and knowledge resources is an important model to reflect learners' learning behavior patterns [5]. Through the construction of the relationship model between learners and knowledge resources, we can get the learning interest of learners and the current learning situation of learners. Reasonable relational model will greatly simplify the difficulty of knowledge recommendation in the next stage [15]. There are two main models of the relationship between learners and knowledge resources.

(1) Evaluation matrix model, evaluation matrix model is to synthesize the characteristic information of learners. The evaluation matrix R and $R_{u,j}$ obtained from the characteristic information of knowledge resources indicate the comprehensive evaluation of knowledge resources i by learners u. the higher the evaluation value, the more suitable for learning.
(2) The bipartite graph model uses the form of bipartite graph to represent the relationship between learners and knowledge resources [16]. U is the learner set, I is the set of knowledge resources. If learner u has learned knowledge resource i, there is an edge E_{ui} between u and i.

4.3 Learning Knowledge Recommendation

The knowledge recommendation of collaborative filtering is based on the common learning behavior of other learners similar to learners [17–19]. The expression (6) is as follows:

$$\mathrm{sim}(x, y) = \frac{\sum_{s \in S_{xy}} \left(r_{x,s} - \bar{r}_y\right)\left(r_{y,s} - \bar{r}_y\right)}{\sqrt{\sum_{s \in S_y} \left(r_{x,s} - \bar{r}_x\right)} \sqrt{\sum_{s \in S_{yj}} \left(r_{y,s} - \bar{r}_y\right)^2}} \tag{6}$$

In formula (6), S_{xy} represents the knowledge resources that learner x and learner y have learned together.

In general, the feature space of learners is large in the knowledge recommendation problem. In order to make the algorithm run more effectively, formula (7) is used to deal with the similarity calculation between learners.

$$u(c, s) = \alpha \bar{r}_c + \beta \frac{\sum_{x \in c_y} \mathrm{sim}(u, x) \times \left(r_{x,s} - \bar{r}_x\right)}{\sum_{x \in c_N} \mathrm{sim}(u, x)} \tag{7}$$

In formula (7), α and β are adjustable parameters, s represents knowledge resources and c represents learners. Based on the streaming of teaching resource data and the construction of the relationship model between learners and knowledge resources based on transfer learning, the online teaching of equation solving is improved.

5 Experimental Comparison

In order to verify the effectiveness of the online teaching method of equation solving based on transfer learning, the experimental comparison is carried out. In order to ensure the preciseness of the experiment, the traditional online teaching method (reference [3] method) is compared with the teaching method of this study. In this paper, the experiment is carried out on the dataset, which is the real mathematics test scores of a school for many times in succession, including 1340 students, 92 test questions, 28 knowledge points and 291 scoring data. Online learning behavior data: login time, browsing teaching resources, forum data, online notes, homework completion and online test results. 80% of the data set is used as training data set, and 20% of the data set is divided into target training data set and test data set. In the experiment, we select the accuracy of knowledge splitting, classification time and test scores as indicators to compare the online learning effect of the traditional method and this method.

5.1 Accuracy Comparison of Learning Knowledge Classification

In this process, five kinds of teaching resources (text resources, image resources, audio resources, video resources, integrated resources) are classified, and the classification accuracy is shown in Fig. 4.

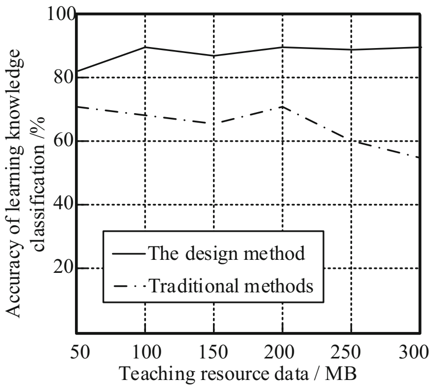

Fig. 4. Comparison of learning knowledge classification accuracy

It can be seen from Fig. 4 that in the experiments with different amounts of data, the classification accuracy of the online teaching method of equation solving based on transfer learning is 80% in dividing five types of teaching resources, which is less affected by the number of classification events. However, the accuracy of traditional learning knowledge classification is poor. With the increase of classification data, the classification accuracy generally shows a downward trend, and the classification accuracy rate is lower than 73%. Because this method normalizes the data in the original data table before classification, so it improves the classification accuracy of the method.

5.2 Comparison of Classification Time

The online teaching method based on transfer learning and the traditional online teaching method are respectively used to classify the data. Data is divided into six types: text resource (1321 data), image resource (529 data), audio resource (762 data), video resource (566 data) and integrated resource (872 data). The comparison results are shown in Fig. 5.

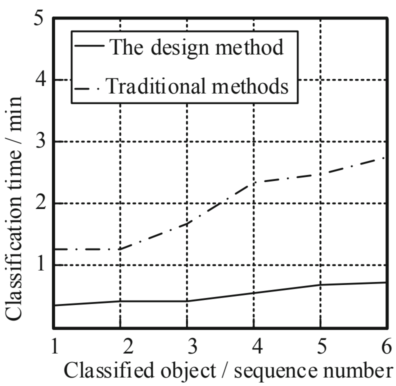

Fig. 5. Comparison of classification time

It can be seen from Fig. 5 that the traditional classification method takes a long time to classify related information, and the longest time is 2.8 min. However, the classification time of this research method is short, and the classification time is less than 1 min in the experimental process. This method selects the base classifier with the highest local accuracy, and takes the output of the classifier as the output of the whole classifier combination system. Furthermore, the time of resource classification is shortened.

5.3 Comparison of Teaching Effect

In order to further verify the effectiveness of the design of the online teaching method, the students' learning results after using the two methods are tested. 40 students in the same grade were randomly divided into two groups, one group accepted the traditional teaching method, the other group accepted the teaching method of this design. After learning, six tests were conducted with one day interval. The results of teaching effect comparison are shown in Fig. 6.

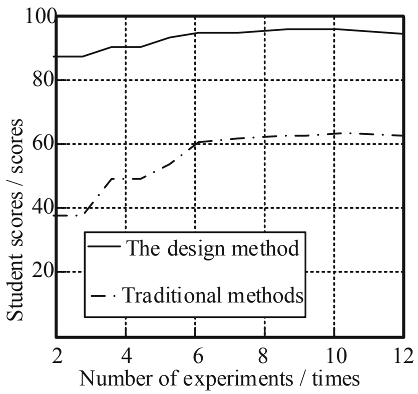

Fig. 6. Comparison of teaching effect

The analysis of Fig. 6 shows that after learning the online teaching method of equation solving based on transfer learning, the average score of students is higher than 80 points, and the score increases steadily with the increase in test times. However, the average score of students using traditional method does not reach the pass level (60 points). The comparison shows that the effect of the method designed in this paper is better than the traditional teaching method. Because this method constructs the association model between learners' behavior and network resources. Then transfer learning is used to provide relevant equation teaching resources for learners, which improves the recommended hardcover degree of resources and promotes the improvement of learners' academic performance.

6 Conclusion

An online teaching method of equation solving based on transfer learning is designed, and the effectiveness of the research method is verified by experiments. Through this research method can improve the teaching effect of students, and improve the classification effect of learning resources. However, due to the limitation of research time, there are still some deficiencies in the online teaching method of this study, and further research is needed in the follow-up study to solve the existing problems. The data show that the design method can meet the personalized learning needs of students, effectively guide students to learn knowledge in accordance with their own characteristics, and has a certain guiding and promoting role. Therefore, it is of great theoretical significance and research value to deeply analyze the guiding role of learning style in online learning guidance system, design specific algorithm and function model, and develop online learning system with strong recommendation and guidance function.

In the future research, expand the number of users of this method. In the later stage, we should constantly enrich learning resources, shorten the update time of design method resources, publicize and promote the system through multi-channel and multi-channel, and constantly collect users' suggestions on the method, and strive to improve.

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