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A Knowledge Image Construction Method for Effective Information Filtering and Mining From Education Big Data

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ABSTRACT Traditionally, education resources are shared insufficiently, and updated slowly; the education data are not utilized adequately. What is worse, the conventional information filtering method cannot effectively mine desired information, if the big data has a heavy noise. This article presents an information mining method from education big data, on the basis of support vector machine (SVM), and cleans the sampled abnormal data through data integration and conversion. Besides, the authors presented a method that automatically builds education knowledge image. Based on the filtered and mined education data, a neural network was designed to retrieve the themes of classroom knowledge, and the education correlations between these notions were recognized from the evaluation data by possibility correlation rules. The results show our method achieved excellent results on teaching notion retrieval and education correlation recognition.

INDEX TERMS Knowledge mining, neural network, knowledge image, education big data.

I. INTRODUCTION

In the 21st century, social progress is mainly driven by the Internet and education. Thanks to the rich education resources on the Internet, online learning and education have been integrated with various education notions into various education models, namely, massive open online course (MOOC) and computer supported collaborative learning (CSCL), forming numerous knowledge images [1]–[3].

In the field of education, knowledge images are often adopted in course teaching. Many popular MOOCs platforms apply knowledge images visualize notions and recommend education resources. These knowledge images are usually prepared artificially by field experts [4]. However, the artificial preparation consumes too much time, and cannot be extended to many notions and correlations. Due to the explosive growth of courses and themes on MOOC platforms, it is extremely hard to artificially plot a knowledge image for each new course [5]. Besides, artificial preparation has another huge problem: Teaching research shows that every expert has his/her blind spot, that is, the same notion could be perceived differently by experts and learners. Therefore, the artificially generated knowledge images may have suboptimal effect or mislead learners [6].

Chaplot *et al.* [7] designed a data filtering algorithm from education big data. Relying on particle filters to screen and mine information, this traditional information filtering method sets a high requirement on the initial particle trajectory. Thus, this paper firstly puts forward a data mining algorithm from education big data based on support vector machine (SVM), providing good data support to the establishment of knowledge images.

Considering the growing demand and limited creation method of knowledge images in the education field, this paper also designs a system that automatically builds knowledge images fit for the teaching of school courses and online courses [8], [9]. In education knowledge images, the expected nodes represent the teaching notions of a subject or course; the education notions refer to the basic notions (e.g., the physical notion of acceleration and geographical notion of landmass formation) that must be fully understood and understood by learners [10]; the data need to be retrieved from the education field and new entity markers (e.g., people, locations, and organizations), instead of traditional markers. Since the teaching notions are often abstract and implicit, the correlations between these notions, which reflect learners'

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cognition and education process, will be difficult to determine, if the specific education data are not properly analyzed and modeled. Therefore, this paper specially chooses to identify education correlations from the data on learning evaluations and activities [11].

- This paper proposes an SVM-based data filtering algorithm from education big data. The algorithm cleans the abnormal entries in the collected data, and integrates and transforms the abnormal data, providing good data support to the creation of knowledge images.
- The authors put forward a novel and practical automatic generation system of education knowledge images. This system can retrieve teaching notions and identify important education correlations from heterogeneous data, which usually include teaching data and learning evaluation data.
- Given the education purpose of the teaching notions, the authors proposed to apply neural network to the teaching data, such as to complete the retrieval of classroom notions.
- Possibility correlation rules were mined from the notion-based learner evaluation data to derive the required correlations.

II. LITERATURE REVIEW

Knowledge image is essentially an atlas of semantic network and related knowledge. Through the new round of technology change, a series of well-known knowledge images have emerged, such as Google, DBpedia, NELL, SSCO, Baidu, etc. These knowledge images intuitively present the information about knowledge background and development history of various subjects. Early knowledge images are mainly used in scientific research [12]–[15].

Knowledge image as a teaching method takes shape with the continuous development of online information. For example, Zhang *et al.* [16] produced a tutorial video on an outsourcing website, teaching complete mathematical notions to ordinary people. Wang *et al.* [17] introduced notional graphics into the teaching process. Based on the learning notion map of education data, Chaplot *et al.* [7] established a directed notion graph of the correlation degrees between given courses, and applied the graph into teaching to reveal the implicit correlations between courses. Through graph analysis, Chen *et al.* [18] discussed the scientific learning views of learners, predicted the learning situation of learners by the activities, emotions, and attitudes of learner portraits, and proposed a new automatic learning method to qualify the contribution to the knowledge base. Nickel *et al.* [19] developed a textbook-based notional graph, which is superior to supervised learning baseline. Based on the retrieved entity correlations, Xie *et al.* [20] built up an education knowledge image, and constructed a visualization analysis platform called EduVis. With the aid of graph mining, Bordes *et al.* [21] modeled the network graphs of different types of learners, lecturers, and subjects in public education, providing a good reference for similar research.

Camacho *et al.* [42] explained how to design a knowledge management system in a rural low-knowledge school in Costa Rica, and how the participatory approach used in the design process creates a learning culture that encourages the use of knowledge management systems (KMSes). This paper contributes to the methodology of KMSes, and details three novel methods that enable KMSes developers to handle he social and technical dimensions of KMSes.

Bouton *et al.* [43] described that, although social network technology (SNT) helps to build knowledge collaboratively, recent studies in secondary schools indicate that students mainly use these tools to learn about knowledge sharing of related artifacts. Here, this discovery is extended to higher education, and two surveys are reported, which respectively summarize the SNT learning features of college students in an undergraduate program ($N = 264$) and a normal college ($N = 449$).

Despite their achievements, the previous studies have not effectively extracted the key information of education data (e.g., the knowledge points of each class hour), summarized after-class learning factors (e.g., personality, and diligence), or constructed the logic relationship between different knowledge points. To solve these problems, this paper introduces the possibility correlation rule mining to recognize the education correlations, establishes knowledge images, and experimentally verifies the effectiveness of such images.

III. DATA MINING ALGORITHM

This paper mines data with the help of the SVM algorithm [22]–[26]. First, the abnormal data were cleaned from the education big data. Then, the clean data were converted and classified, followed by integration, regularization, and transform. After that, data mining rules were set up to filter the uncorrelated information, and mine the effective information from the data, thereby enhancing the training efficiency and performance of the neural network [18], [19].

The data gathering tree was adopted for data conversion and classification. The tree can discover the correlations and dependence between data. To filter the information in the education dataset [27], the expectation of data X, exp $SN(x)$, can be defined as the support to the correlation degree of the data gathering tree of the dataset. Then, the unbiased risk of the data gathering tree can be estimated as:

$$\exp \mathrm{SN}(X) = \sum_{T_d X \wedge T_d \in D} P(X, T_d) \tag{1}$$

The solution to the standard support vector can be assumed as:

$$\min_{0 \le \alpha_i \le c} W = \frac{1}{2} \sum_{i,j=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i, x_j) - \sum_{i=1}^{l} \alpha_i + b \left(\sum_{i=1}^{l} y_j \alpha \right) \tag{2}$$

where, (x_i, x_j) is a sample. During the adjustment of the weight vector a_c, data mining is performed by the SVM to obtain a set S_s. Then, the correlation rule matrix of effective information can be expressed as:

$$Q' = \begin{bmatrix} 0 & y_1 & \ldots & y_n \\ y_1 & Q_{11} & \ldots & Q_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ y_n & Q_{n1} & \vdots & Q_{nn} \end{bmatrix} = \begin{bmatrix} 0 & y^{\mathrm{T}} \\ y & Q \end{bmatrix} \quad (3)$$

By gradually increasing/decreasing the samples, the measurable effective information can be obtained from the education data:

$$\det\left(Q'\right) = \det(Q) \cdot \left(-y^{\mathrm{T}} Q^{-1}\right) \neq 0 \quad (4)$$

The local area of education notion nodes was divided several nonoverlapping blocks with the side length of K·λ. Then, the shortest unbiased delay for data mining can be estimated by:

$$\tau = \alpha\left(1 + 2^{-\alpha/2}\right)(\alpha - 1)^{-1} + \pi 2^{-\alpha/2}(\alpha - 2)^{-1}/2 \quad (5)$$

Then, the unbiased phase of the sink node on the data gathering tree T_{DAG} of the education dataset can be derived as:

$$K = \left\lceil \left(4\beta\tau P\ell^{-\alpha}\right)^{1/\alpha} \cdot \left(2^{-\alpha/2} P\ell^{-\alpha} - \beta N_0\right)^{-1/\alpha} + 1 + \sqrt{2} \right\rceil \quad (6)$$

In each round, the SVM was adopted to mine key features of education big data, which dominates the data transmission between nodes on the knowledge image.

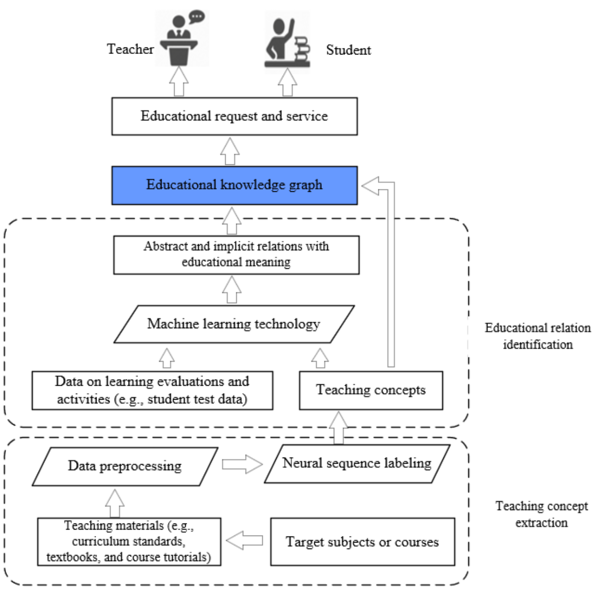


FIGURE 1. Knowledge image system.

IV. FRAMEWORK REALIZATION

Figure 1 is the block diagram of the proposed education data-oriented knowledge image system, which covers a teaching notion retrieval module (a) and an education correlation recognition module (b).

Module (a) mainly obtains the teaching notions from teaching data collected from the education field [28]. Then, the instructive notions could be retrieved by methods like neural sequence labeling. Module (b) mainly recognizes the education correlations associated with teaching notions.

The latest data mining techniques are embedded in this module, such as the mining of possibility correlation rules, due to the implicit and abstract nature of education correlations. In addition, the module uses the data on learning evaluations and activities, which can reflect the learners' cognition and knowledge acquisition process. The correlations mined by this module link up the teaching notions into the knowledge image required for education, providing support to the various requests and services of learners and lecturers.

The two modules are introduced in details below.

A. TEACHING NOTION RETRIEVAL

The nodes required in the education knowledge image represent the key teaching notions. The raw data could be in different formats, usually including texts, audios, and videos. Therefore, multiple format conversion techniques were adopted to convert them into machine readable formats. For example, many optical and speech conversion techniques were adopted to transform the original data into unified form [29], [30]. After the preprocessing, the teaching notions could be retrieved by our system.

Take the word sequence "Understand that Biden is the President of the United States" for example [31]. For notion retrieval, B-CP, Q-CP, and O were defined as the beginning, inside, and outside of a notion, respectively. Both B-CP and Q-CP are teaching notions. Table 1 shows the correct results of word sequence annotation, where $\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_\omega, \}$ is the input sequence of Chinese words, and $\beta = \{\beta_1, \beta_2, \ldots, \beta_\omega, \}$ is the corresponding output labels.

TABLE 1. Correct results of word sequence annotation.

β	O	B-CP	Q-CP	O	O	O
α	Understand	Biden	President	Is	United States	of

Unlike general entities in general knowledge image, teaching notions are usually good sources of teaching data. In particular, the teaching notions are not clearly defined [32]. Based on the sequentiality and inherent correlations of education text data, the authors designed a neural network.

In Long short-term memory (LSTM) network [33], [34], each module contains various learning paths, owing to the long-term dependency of structured learning [11].

As shown in Figure 2, the basic operations of the standard LSTM module are completed by the input gate i_t, forget gate f_t, and output gate O_t. The memory C_t of the module reflects the state of the cell, and updates (saves or forgets) the memory based on the information received from the input or forget gate. The state of the memory can be updated by:

$$\mathbf{i}_t = \sigma\left(\mathbf{W}_i \cdot (\mathbf{h}_{t-1}, \mathbf{x}_t) + \mathbf{b}_i\right)$$
$$\mathbf{f}_t = \sigma\left(\mathbf{W}_f \cdot (\mathbf{h}_{t-1}, \mathbf{x}_t) + \mathbf{b}_f\right)$$

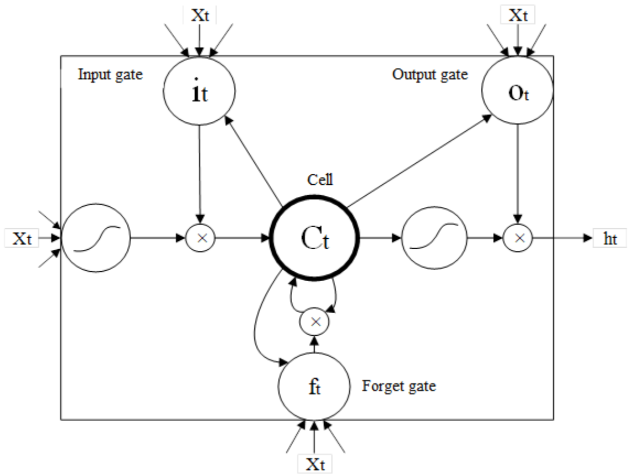


FIGURE 2. Standard LSTM module.

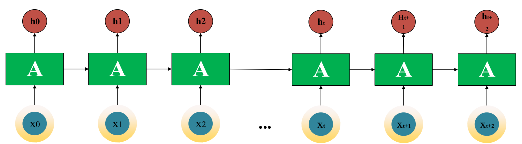


FIGURE 3. Single-layer LSTM network.

$$\begin{aligned}
\mathbf{o}_t &= \sigma\left(\mathbf{W}_o \cdot (\mathbf{h}_{t-1}, \mathbf{x}_t) + \mathbf{b}_o\right) \\
\mathbf{c}_t &= \phi\left(\mathbf{W}_c \cdot (\mathbf{h}_{t-1}, \mathbf{x}_t) + \mathbf{b}_c\right) \\
\mathbf{c}_t &= \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \mathbf{c}_t \\
\mathbf{h}_t &= \mathbf{o}_t \odot \phi\left(\mathbf{c}_t\right)
\end{aligned} \tag{7}$$

where, $\sigma(\cdot)$ is the sigmoid function; $\phi(\cdot)$ is the hyperbolic tangent function (tanh) [35]; W is the weight matrix; b is the bias; t is the time; $\odot$ is multiplication. The output h_t is treated as the input of the next module at time window $t + 1$.

Figure 4 shows the proposed multi-channel model. It is a multi-channel LSTM network stacked from multiple layers of basic LSTM modules. The depth (e.g., number of layers) of the network ensures the prediction accuracy. The prediction is performed on the last fully-connected layer. On the one hand, sparse connections were configured for each channel based on the ideal of Resnet [36] to prevent vanishing gradients. On the other hand, the jump connections enable the model to adaptively assigns different weights to different time nodes of education data, enhancing the ability of the deep neural network to capture key features [37].

Multi-to-one architecture was adopted for knowledge prediction in each step. That is, the neural network observes the number of education data in time window T and the time windows before T, and then forecasts the volume of education knowledge in the next time window T+1. During multi-point knowledge prediction, the forecast was delayed by a number of time windows, like what is done for word sequence prediction in language modeling problem. Finally, the LSTM output was transferred for prediction. To regress the loss function, one last layer was configured: the feedforward layer. This layer was activated by the mean squared error (MSE) function [38]. During the training, the activation function was used to optimize the weights of network nodes.

B. EDUCATION CORRELATION RECOGNITION

The interconnection between teaching notions could be any logical connection that can directly help learning and teaching. In the education field, many correlations are important for lecturers and learners, such as containment correlation, and causal correlation. Specifically, the prerequisite correlation between notions P and Q means that learners need to understand notion P first in order to understand notion Q. Thus, determining this prerequisite correlations will help lecturers design correct teaching strategy and help learners acquire new knowledge. For example, many learners have difficulties in learning the mathematical notion of quadratic equation; lecturers can judge the cause of this learning obstacle based on the prerequisite correlation, while learners can determine their learning sequence or adjust the topic or course sequence based on this correlation. The containment correlation means a notion is subordinate to another notion. It is often used by educators to determine the level of the course or subject. The containment correlation is easier to recognize than prerequisite correlation, because the relevant information is saved in the original structure of the textbook or tutorial [39].

After being established, the correlations between knowledge points could be identified based on prior knowledge. Thus, the interesting correlations hidden in large databases can be discovered through correlation mining by certain rules.

Let supp (A $\Rightarrow$ B) be the support of A to B, i.e., A and B occur simultaneously in the data; conf (A $\Rightarrow$ B) be the confidence of A to B, i.e., the percentage of data containing A also contain the deals in B. Under the given minimum supp and minimum conf, a correlation rule A $\Rightarrow$ B can be viewed as interesting and powerful if:

$$supp(A \Rightarrow B) \geq minsupp\ AND\ conf\ (A \Rightarrow B) \geq minconf \tag{8}$$

Taking teaching notions as projects and learner scores as deals, correlation rule mining would become a natural strategy for educators to recognize the prerequisite correlation.

If notion j is the prerequisite of notion j, then those not familiar with i cannot understand j, and those having learned j could also understand i. During correlation rule mining, notions i and j obey this prerequisite correlation, under the following pair of correlation rules:

$$P_j \Rightarrow P_i \quad AND\ \overline{P}_i \Rightarrow \overline{P_j} \tag{9}$$

Let P_i and P_j be the indicators that the learner has understood notion i and notion j, respectively; $\overline{P}_i$ and $\overline{P}_j$ be the indicators that the learner has not notion i and notion j, respectively. Then, the interest degree of the two correlation rules could be estimated by the system based on the knowledge states (whether notions i and j are understood) of multiple learners.

However, knowledge state is often a potential variable. The learner's understanding of a notion cannot always be directly observed. A common and feasible method is to derive the

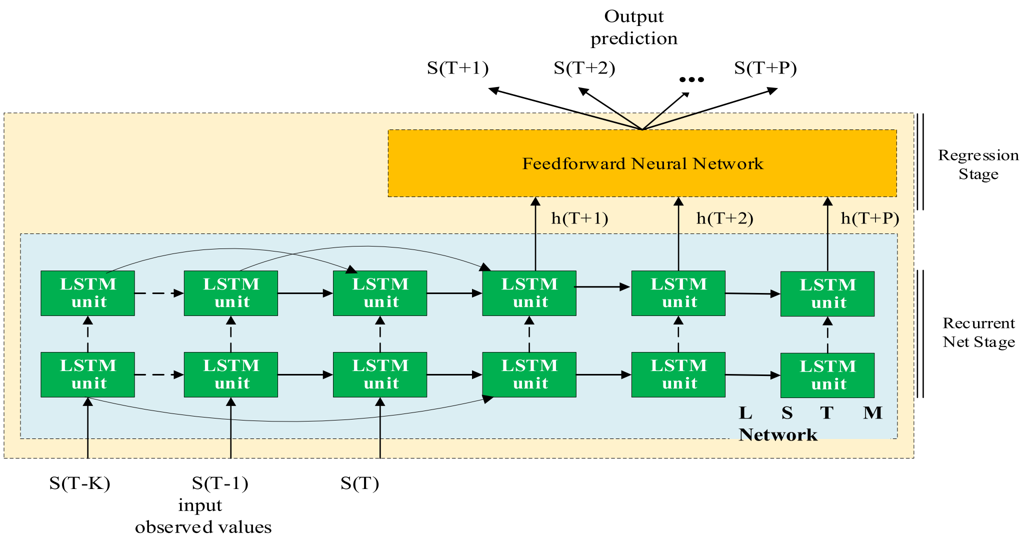


FIGURE 4. Multi-channel sparse LSTM network.

knowledge state of a learner from his/her academic (test) scores. But the test results are highly uncertain. Sometimes, learners give wrong answers to test questions (i.e., making mistakes even they have understood the relevant notions) and make guesses (i.e., making correct choices even they do not understand the relevant notions. Therefore, the learners' understanding of notions is often viewed as a stochastic variable.

The possibility correlation rule mining [40] is an extended approach to mine the correlation rules by processing the uncertainties in data. In a given possibility data, the support and confidence were treated as stochastic variables; the deterministic correlation rule $S_j \Rightarrow S_i$ was formulated as $P(S_j \Rightarrow S_i)$; if $P(S_j \Rightarrow S_i)$ is greater than the given threshold of minimum prob, then the rule is valid:

$$P(Sj \Rightarrow Si) \geq minprob. \tag{10}$$

Considering support and confidence, formula (10) can be instantiated as:

$$P\{supp(Sj \Rightarrow Si) \geq minsupp\ AND\ conf\ (Sj \Rightarrow Si) \geq minconf\} \geq minprob. \tag{11}$$

According to formula (11), both rules must be valid to determine the prerequisite correlation from notion i to notion j. Thus, it is required that:

$$P(Sj \Rightarrow Si) * P(\overline{S}i \Rightarrow -\overline{S}j) \geq minprob \tag{12}$$

To calculate the possibility in formula (12), this paper adopts the p-Apriori [41] algorithm. To sum up, the authors mainly introduced how to identify prerequisite correlations of learner test data, using probabilistic correlation rules.

V. EVALUATION AND VERIFICATION

To verify the performance of the proposed system, an exemplary mathematical knowledge image was constructed to demonstrate the teaching notion retrieval and education correlation recognition.

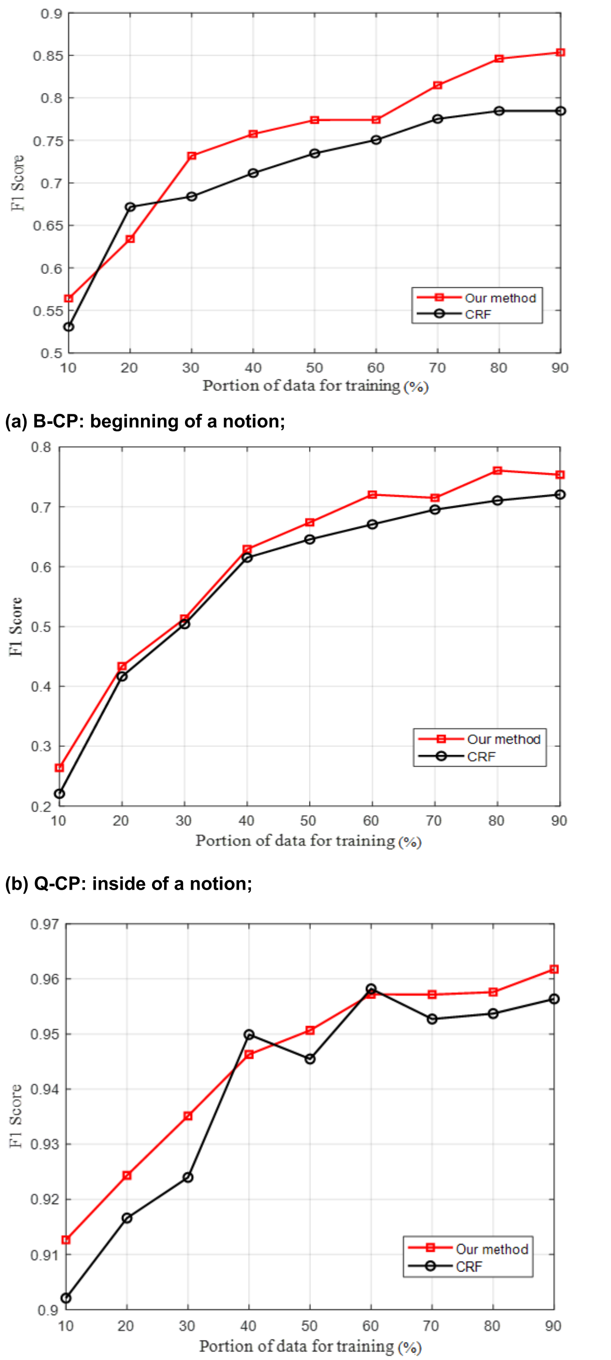
A. NOTION RETRIEVAL

The teaching notion dataset was constructed from classroom teaching and education resources, such as textbooks and reference books. Here, the main data source is the national curriculum standard for college math. The data setting was determined because the math textbooks for most college students in China are of the same version. For example, the textbook of Advanced Mathematics is compiled by Tongji University. The data extraction method ensures that our scheme is applicable to the knowledge image construction for math courses of college students across China.

During data preprocessing, texts were retrieved by Tika [7] from the formal text of the curriculum standard, and sentences were segmented by chapters, paragraphs, and punctuations. The non-text information like figure and table boundaries were deleted automatically. Next, ICTCLAS [17], an open-source library of Chinese words segmentation, was adopted to segment each sentence into words. Finally, 36,697 words in 1,847 sentences were obtained from the original dataset.

All teaching notions were listed to lay the basis for the evaluation model. A total of 4,251 words were marked as B-CP, and 969 as Q-CP. To comprehensively evaluate model performance, the proportion of training samples was gradually increased from 10% to 90%. In the LSTM-based neural network, the dimensions per module output were set to 128. The model was trained with the Adam optimizer, with the learning rate of 0.01, and the number of iterations of 1,000. For comparison, L-1 regularization was adopted for maximum likelihood estimation in the conditional random field (CRF) model.

Figure 5 compares the F1 values of CRF model and our method on B-CP, Q-CP, and O labels. With the growing



(a) B-CP: beginning of a notion;

(b) Q-CP: inside of a notion;

(c) O: outside of a notion

FIGURE 5. Evaluation results on notion retrieval.

amount of training data, every F1 value curve was on the rise. On the retrieval of B-CP, our LSTM-based neural network outperformed CRF. There was no obvious difference between the two in Figure 5a. From Figures 5b and 5c, it can be seen that the two models had similar performance on the retrieval of Q-CP and O. Comparing Figures 5a and 5b, the F1 values of Q-CP retrieval in both models were lower than that of B-CP retrieval, suggesting that Q-CP is more difficult to retrieve

TABLE 2. AUC values of different pairs of parameters.

AUC		minsupp 400	600	800	1000	1200	1400
	0.3	0.623	0.69	0.645	0.483	0.51	0.477
	0.4	0.689	0.756	0.722	0.518	0.525	0.478
	0.5	0.868	0.874	0.838	0.623	0.559	0.493
minconf	0.6	0.953	0.953	0.954	0.803	0.692	0.546
	0.7	0.836	0.836	0.836	0.84	0.84	0.688
	0.8	0.85	0.85	0.85	0.853	0.858	0.756
	0.9	0.735	0.735	0.735	0.735	0.747	0.682

TABLE 3. MAP values of different pairs of parameters.

AUC		minsupp 400	600	800	1000	1200	1400
	0.3	0.566	0.627	0.627	0.505	0.521	0.535
	0.4	0.594	0.656	0.661	0.518	0.525	0.535
	0.5	0.737	0.802	0.727	0.564	0.534	0.538
minconf	0.6	0.877	0.877	0.863	0.778	0.595	0.55
	0.7	0.818	0.818	0.818	0.816	0.766	0.66
	0.8	0.823	0.823	0.823	0.822	0.814	0.742
	0.9	0.788	0.788	0.788	0.788	0.801	0.785

than B-CP. This is confirmed by the situation of correctly labeled Q-CP and B-CP.

B. CORRELATION RECOGNITION

The test scores of 6,000 freshmen from 42 "985" project colleges in China were collected, and the relevant teaching notions were determined.

Definition 1: There is a prerequisite correlation from notion A to notion B called assertive correlation. The two notions are positively correlated in the absence of this correlation, and negatively in the presence of this correlation. Similar to traditional mining of education data, the scoring rate was adopted as the estimated possibility that a learner understands a notion. Thus, correlation rule mining treats each notion as a project, and the estimated knowledge states of the 6,000 learners as 6,000 deals. For each candidate of every prerequisite condition, the system computes its positive possibility.

The key parameters are minsupp and minconf. This paper takes the area under the curve (AUC) of receiver operating characteristic (ROC) and mean average precision (MAP) as the main metrics. Tables II and III suggest that the AUC and MAP of the minconf of (0.6, 600) and minsupp of (0.6, 800) were obviously higher than those of the other pairs of minsupp and minconf values.

Figure 6 further presents the constructed knowledge image of math. Each circle represents a notion. The solid and dotted arrows stand for prerequisite and containment correlations, respectively. In addition, the red circles are level 1 knowledge points, the green circles are level 2 knowledge points, and the yellow circles are level 3 knowledge points. Our strategy mines and identifies the deep correlations between knowledge points on different levels, revealing the potential learning and teaching paths for teachers and students.

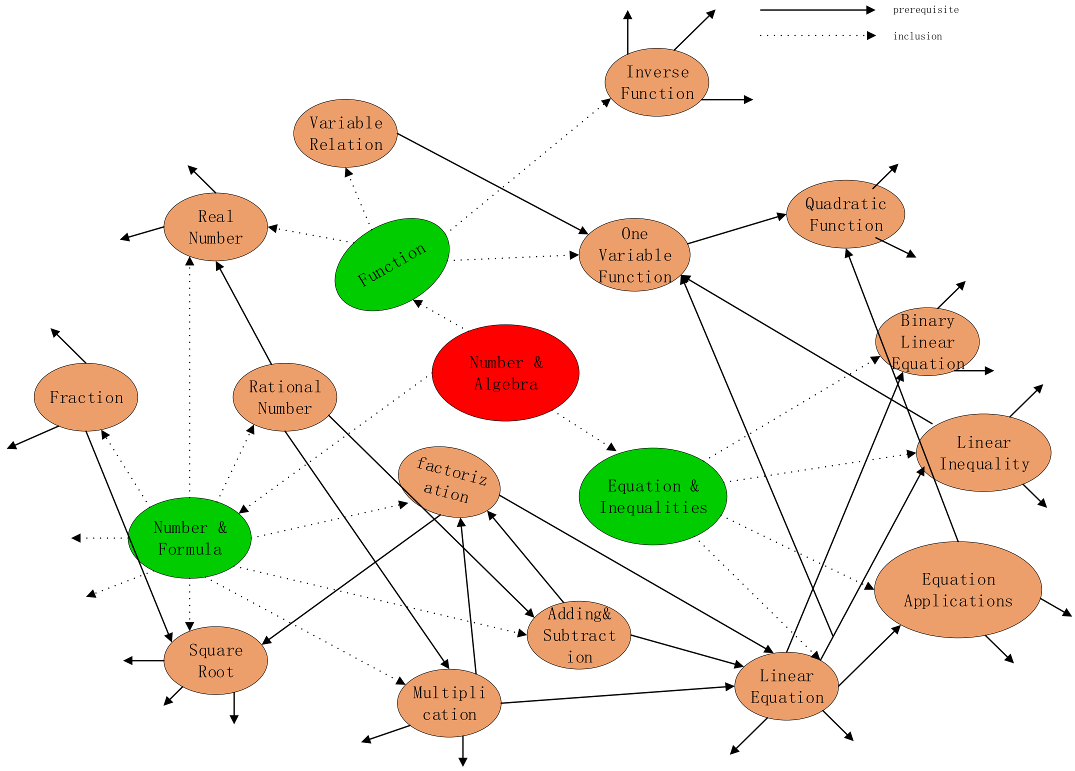


FIGURE 6. Knowledge image of math.

VI. CONCLUSION

This paper designs a neural network to retrieve teaching notions, and introduces possibility correlation rule mining to identify education correlations. Besides, an SVM-based data mining algorithm for education big data, which can rapidly process the abnormal entries in the collected data. During experimental evaluation, excellent performance was achieved by the constructed knowledge image.

However, the following issues of this work need to be solved urgently: (1) the non-uniform formats of education big data, and the massive number of knowledge notions; (2) the lack of personalized plans for student end; (3) the neglection of the causality between the knowledge notions in the construction of knowledge image.

The future research will try to deal with the following aspects: (1) effectively extracting the key information from education data; (2) further improving the personalized teaching services based on knowledge image, e.g., online diagnosis of learning disabilities, and intelligent recommendation of learning resources; (3) analyzing the causality and logic among knowledge points of different subjects and grades in education

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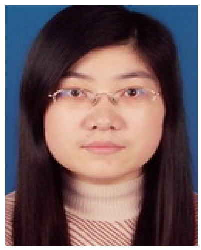

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