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Discrete dynamic modeling analysis of intelligent teaching based on big data mining

Na Wei[1,*]

[1] College of education, Yunnan University, Kunming 650091, Yunnan, China

SUMMARY: *In order to analyze the discrete dynamic modeling of intelligent teaching based on big data mining, a deterministic learning theory is put forward based on the research on the continuous excitation characteristics of radial basis function (RBF) neural network. Firstly, the hierarchical analysis framework of dynamic generative data in intelligent teaching is introduced. Then, the modeling /identification based on temporal data is discussed, and the similarity definition and fast identification method of temporal data sequence are studied. Finally, numerical experiments are carried out.The key to realize the local accurate modeling of discrete system dynamics lies in the satisfaction of some continuous excitation conditions, the exponential convergence of discrete linear time-varying systems, and the convergence of some neural network weights along the regression trajectory. These elements reveal the nature of deterministic learning for discrete dynamic systems. The local accurate modeling of discrete system dynamics can be used to time invariant representation of temporal data sequences. Numerical experiments on the fast recognition of temporal show that the error generated by the test mode* $\left\|e_1^3(k)\right\|_{l_1}$ *is smaller than that of the other two when compared with the third training mode. The test temporal is most similar to the third training temporal.*

KEYWORDS: *big data mining; Intelligent learning; Discrete dynamics; Modeling analysis; temporal data*

1 Introduction

With the rapid development of new technologies such as cloud computing, big data and human-computer interaction, collecting and analyzing the data of learners and their activity situations has increasingly become one of the focus issues (Korenchenko, Vorontsov, Gel'Chinskiy, 2016). Online learning environments such as learning management system, social media, Mu class and smart class contain richer data, which makes it possible for us to have a deeper understanding of students' learning process (Safaee, Janipour, Karami, 2015). Although it is relatively easy to collect the data of learners and their behavior, it is difficult for users to effectively process and interpret these rich data data mining and processing technical knowledge. The research on data analysis methods and mechanisms, the application of data visualization analysis technology, and the automatic provision of graphical analysis results by the system are the key issues in the field of learning analysis (Korenchenko, Vorontsov, Gel'Chinskii, 2016). With the increasing popularity of smart classroom, a large number of dynamic generative data. Existing studies have proposed solutions for the collection and storage of the above data, but it still needs to be fully mined and applied with the help of

*thumbweina@163.com
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interactive visual analysis technology (Bakhtiari-Nejad, Nazemizadeh, 2016). On the one hand, the previous data analysis largely stayed at the analysis level of the original learning behavior attribute itself, only carried out simple summary statistics and comparative analysis, with poor comprehensibility and lack of whole process and relevance analysis (Bayram, Uzlu, Kankal, Dede, 2015). On the other hand, due to the singleness and limitations of analysis methods, even if there are rich learning process data, it is difficult to mine the data value to the greatest extent, and there is a lack of visual analysis based on human-computer interaction (Satzoda, Trivedi, 2015).

This paper puts forward the human-computer interaction visual analysis method based on cognitive model, introduces time-space data and multi-dimensional data visualization technology, and studies the visual analysis method of intelligent teaching data, transforming metaphorical knowledge into graphics and images that are easy for educational users to accept and recognize (Agarwal, Kachroo, Contreras, 2016). The most fundamental challenge faced by education big data analysis is to condense comprehensible knowledge from data, and use data fusion technology to aggregate multi-dimensional and multi-granular relationships among data, information and knowledge fragments, so as to realize knowledge interaction at more levels. Taking knowledge discovery activities as the core, build a cognitive model and intervention engine for human-computer interaction visual analysis, so as to form the establishment process of new knowledge (Zeng, Zhang, Kusiak, 2015). For example, the analyst can explicitly establish links through interactive operations such as annotation. The computer updates the new knowledge links created by the analyst, and updates the domain knowledge base through syntax and semantic analysis to provide an intervention engine for interactive visual analysis (Li et al., 2015). The knowledge generation model is the core to realize the visual analysis of human-computer interaction. It analyzes the different types of dynamic generative data of intelligent teaching, and puts forward the knowledge generation model in the visual analysis of dynamic generative data, as shown in Figure 1 (Li et al., 2015).

Data mining processes a large amount of data and excavates hidden and valuable rules and knowledge information. The task of mining is shown in the following aspects: Concept description by finding out the internal information of the discovered data, extracting and generalizing the same characteristics and differences between them, and then generating the characteristic description with the same characteristics of the data set. Then generate a description of the differences in the different characteristics of the category. Classification and prediction this task is mainly divided into two cases: one is to establish data model standards to represent the pre-set logical data set or conceptual data set; The other is to select categorization through established models and established normative patterns. Prediction is to build a prediction model by learning sample data and then evaluate the information content contained in the unknown data. Association rules discover regular connections between key relational information or attributes in a data set. In other words, there is a close correlation between attributes, and the change of one or more attributes will lead to the change of other attributes. Its analysis aims at finding hidden relationships in large data sets and mining unfamiliar knowledge. The analysis of association rules is to find out the regularity in time or sequence of events that occur and lead to other events. Cluster analysis is mainly used to discover unknown object classes in a large amount of data. The process of facing the source data directly and dividing the data into classes, so that there are similarities between classes and differences between classes. Cluster analysis is to classify data according to some similarity and analyze the process of these components.

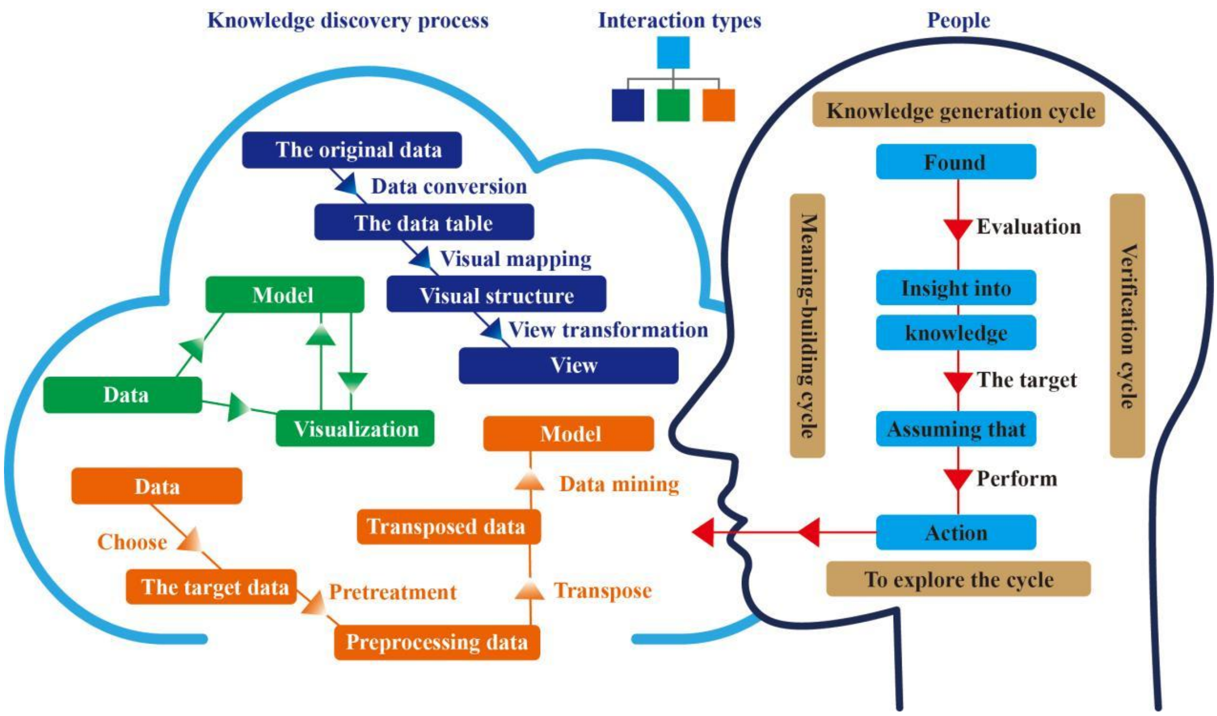


Figure 1: knowledge generation model in dynamic generative data visualization analysis

2 Literature review

Aiming at this study, KH Kim and others solved the sequence prediction problem by using the method of context tree through the research on MOOC platform forum, so as to recommend useful information to students (Kim, Yoon, Lee, 2020). Li, S and others analyzed and applied the perceptual learning technology. They collected and analyzed the facial expression data and body motion characteristics of students when reading books and watching videos through the method of supervised learning (Li, Zhang, Cui, 2019). Liu, H. L and others collected students' eye movement data and extracted features during learning, and studied students' absentmindedness during learning by using Bayesian network model (Liu et al., 2017). Kachroo, P and others conducted corresponding education big data analysis through the collection of campus classroom data (Kachroo et al., 2015). Choi, C. S and others collected the learning data of 196 students in 10 classes and studied the students' ability and learning rate by using the individualized-slope additional factors model (i AFM) and individualized Bayesian knowledge tracing (i BKT) (Choi, Baccelli, Veciana, 2019). D venkatramanan and others developed different gauges for dynamic evaluation in the intelligent tutor system (Venkatramanan, John, 2019). Asif and others evaluated students' learning activities through a series of visual analysis tools (Asif, Md, 2017). Borujeni, M. S and others used data in reputation system to provide feedback for learners to learn knowledge in informal learning environment (Borujeni et al., 2017). Liu, y and others developed Tell Me More application for business language learning (Liu et al., 2020). Askari, E and others constructed an analysis and task model to understand students' cognitive participation in complex literacy tasks by tracking different types of knowledge and different levels of mastery (Askari et al., 2015). Golestan, S and others proposed a visual analysis tool based on interactive technology by using people's perception and cognitive ability, which enables users to more effectively understand the value of deep-seated data (Golestan et al., 2015).

At present, the main difficulties faced by the research and application of education big data are as follows: first, in terms of the focus of research objects, whether to study big data in education or education problems under the background of big data, the research objectives and ideas are not clear, and often stay at the concept and concept level of education big data. The focus on the application of big data in education and solving practical problems in education is not enough. Even the research on application is mainly on the aspects of education quality monitoring and education macro. Second, in the collection of educational data, most of them adopt the form of filling in. For example, teachers need to fill in students' social practice, physical examination and some data related to students' morality for the evaluation of students' comprehensive quality. Under this data collection method, whether teachers and students use paper or information equipment to fill in, the main behavior of users is to report data rather than actual teaching, which is difficult to realize the real-time and normalization of education big data collection. Third, in the modeling and analysis of education data, at present, it mainly focuses on the establishment of theoretical model and qualitative analysis, and lacks the specific analysis and model construction of education and teaching process and teaching and learning behavior, that is, the research on establishing mathematical model and mining analysis based on real data is rare.

In view of the above problems, we can see that in the analysis and application of educational big data mining, it is very necessary to focus on a professional application field, closely follow the specific problems in education and teaching, collect real data based on actual use, and build models and process and analyze them. Based on the current study, this paper studies the problems of knowledge acquisition (modeling), expression and reuse (identification, control) in unknown dynamic environment by using the concepts and methods of adaptive control and nonlinear dynamic system.Comparing the nonlinear function and local learning of the system, it can be clearly seen that the neural network can approach the nonlinear function of the system in the region along the system trajectory. The key to realize the local accurate modeling of discrete system dynamics lies in the satisfaction of some continuous excitation conditions, the exponential convergence of discrete linear time-varying systems, and the convergence of some neural network weights along the regression trajectory. The results in this paper provide a systematic research method.

3 Method

3.1 Hierarchical analysis framework of dynamic generative data in Intelligent Teaching

Based on the hierarchical framework of dynamic generative data collection in smart classroom teaching, a hierarchical analysis framework of dynamic generative data in smart classroom teaching is constructed from the perspective of computer automatic processing. According to different types of analysis methods provided for the behavior layer, event layer, activity layer and target layer of data collection, combined with frequent pattern and periodic pattern mining, a dynamic generative data mining model is proposed. On the basis of data analysis, it provides teachers, students, educational managers and other users with visual charts such as teaching activity sequence diagram and learning result statistical diagram in different dimensions, so as to transform complex knowledge into dynamic graphics that are easy for educational users to accept and recognize. For different analysis requirements of description layer, diagnosis layer and application layer, it provides prediction analysis, cluster analysis, relationship mining, pattern discovery and other analysis methods (Tan et al., 2016).

(1) Description layer

The description layer extracts and analyzes the data of teaching behavior, learning behavior and learning performance, so as to realize the basic statistics and feature description of the data of one or more courses. The data can be described from the aspects of teachers' and students' learning performance, behavior sequence, behavior duration, specific behavior parameters, etc. for the classroom data marked with teaching event information, the description layer provides the behavior type and duration of each type of teaching event. The description and analysis of the article includes: the description and analysis of students' learning performance. The description of multi class data taught by the same teacher focuses on "teachers' behavior habits of using technology. And the description of classroom data in the same class focuses on students' learning behavior and performance (Ma et al., 2017).

(2) Diagnostic layer

The diagnosis layer provides relevant descriptions of teaching and learning characteristics, such as technology application level (the technology here includes software and hardware, content and services, etc.), learning effect analysis, attention to generative content, etc.

Technology application level

Technology plays an important role in classroom teaching. However, technology itself cannot change the essence of classroom teaching unless teachers can make rational use of technology in classroom teaching. From the perspective of teaching, reasonably analyze the proportion of teachers' classroom management and resource use, organization of evaluation activities, use of learning situation analysis, sharing and evaluation of students' activities in their technology application behavior, and determine the level of technology application. Combined with further analysis, the teaching mode and style of teachers' wisdom classroom are obtained.

Analysis of learning effect

With the help of S-P table analysis, this paper provides the analysis of the abnormal degree, abnormal coefficient, learning stability and learning stability coefficient of classroom exercises and classroom tests. The S-P table records each student's answers to each question and each option. If a wrong choice is chosen by most students, it can be considered that students do not master the knowledge of the problem, have misunderstandings or have ambiguity. If a few students choose the wrong option, the strategy that teachers can choose is to give individual guidance to the wrong students after class (Kish, Lehn, 2016).

Focus on generative content

Generative content includes teachers' blackboard writing, students' evaluation results and learning works. Attention to generative content is reflected in "resource use", "work display" and "classroom evaluation" (Islam, Nakai, Onodera, 2017).

(3) Suggestion layer

The ultimate goal of learning analysis is to improve the effectiveness of learning and teaching. Therefore, effective intervention according to the results of data analysis is very important. According to the analysis results of the description layer and the diagnosis layer, the suggestion layer provides guidance and help for teachers to deepen the technical application level, students to understand their personal classroom learning status, parents to master students' learning status, and education managers to view teachers' classroom teaching status.

3.2 Modeling of temporal data: Problem Description

The system state $Y(K)$ is uniformly bounded, $Y(K) \in \Omega \subset R^n$, The system state trajectory is a periodic trajectory or a more general regression trajectory. In this paper, the temporal data sequence is defined as the data sequence generated by the discrete dynamic system (1), including periodic, quasi periodic, quasi periodic and chaotic, which is collectively referred to as the regression data sequence. The regression data sequence can describe most of the various trajectories generated by the discrete nonlinear system. Our goal is to design a dynamic RBF neural network model for the regression φ_ζ to identify and model the unknown dynamics of discrete system (1): $f\left(y(K-1),\ldots,Y(k-M);P\right)$, and use the modeling results to express the regression data sequence φ_ζ.

3.3 Determining learning design

The weight learning rule of neural network is designed as follows:

$$\hat{W}_i(K+1)=\hat{W}_i(K)+\Gamma S_k \upsilon_i(K) \tag{1}$$

Due to the existence of z_{ik}, υ_{ik} cannot be calculated directly. The following equivalent algorithm is adopted:

$$\begin{aligned} &\upsilon_{ik} = y_{ik} - \hat{y}_{ik} + \hat{y}_{ik} - z_{ik} = \\ &y_{ik} - \hat{y}_{ik} - \left[\hat{W}_i^T(k+1) - \hat{W}_i^T(k)\right] S_k = \\ &y_{ik} - \hat{y}_{ik} - S_k^T \Gamma S_k \upsilon_{ik} \end{aligned} \tag{2}$$

Therefore:

$$\upsilon_{ik} = \frac{y_{ik} - \hat{y}_{ik}}{1 + S_k^T \Gamma S_k} \tag{3}$$

Formula (1) is used instead of formula (2), the learning algorithm (3) can be realized.

3.4 Similarity and fast recognition of temporal data sequences

The simplest way to identify temporal data sequences is to directly compare the differences of the corresponding elements of the two sequences, but this method is obviously not suitable for many practical application requirements. For two temporal data sequences, sometimes we are more concerned about whether the internal laws hidden by the two sequences are consistent. For example, the internal dynamics of two seemingly different temporal data sequences generated by chaotic system are the same, but the difference is only a small difference in the initial state. This section studies the mechanism of identifying temporal data sequences based on the internal dynamic similarity of temporal data sequences. We first propose a similarity definition for temporal data sequences. Then, a fast recognition method for temporal data sequences is proposed.

Here, an important problem is how to define the distance, so that this definition can be used to measure the similarity of two temporal data sequences with different lengths and different noise levels. According to the qualitative analysis of nonlinear dynamic systems, the similarity of the two dynamic behaviors depends on the topological similarity between the dynamics of the system generating dynamic behaviors. In fact, temporal data sequence is also a description of dynamic behavior. Therefore, similar to continuous dynamic system, the similarity of temporal data sequence depends on the difference between the internal dynamics of discrete dynamic system generating temporal data sequence. In this way, referring to the similarity definition of dynamic patterns generated by continuous dynamic systems, the similarity definition of temporal data sequences is proposed.

Definition 1: if the temporal data sequence φ_ζ is maintained in a nearby area of the temporal data sequence φ_ζ Ω and the dynamic difference between the corresponding two systems in this area is very small, that is:

$$\max_{Y\in\Omega} \left| f_i'(\cdot; p_i') - f_i(\cdot; p_i) \right| < \varepsilon_i^*, i = 1,\ldots,n \tag{4}$$

Among them, $\varepsilon_i^* > 0$ is a small constant. We say that the temporal data sequence φ_ζ is similar to the sequence φ_ζ, and call ε_i^* the similarity measure of the two patterns.

Since the internal dynamics of the two systems in the above definition are unknown quantities, and their similarity measurement cannot be obtained, we have the following definition by using the modeling of the internal dynamics of the sequence φ_ζ. When the test temporal data sequence φ_ζ is maintained in the local area $\Omega_{\varphi\zeta}$.

Definition 2: if the temporal data sequence φ_ζ is maintained in the vicinity of the temporal data sequence φ_ζ $\Omega_{\varphi\zeta}$ and the dynamic difference between the corresponding two systems in this region is very small, that is:

$$\max_{Y\in\Omega_{\varphi\zeta}} \left| f_i'(\cdot; p_i') - \overline{W}_i^T S_k \right| < \varepsilon_I^* + \xi_I^*, i = 1,\ldots,N \tag{5}$$

where, ε_i^*, $\xi_i^* > 0$ are two small constants, we say that temporal data sequences φ_ζ is similar to temporal data sequences φ_ζ.

Considering that the temporal data sequence φ_ζ is a test temporal, our goal is to quickly identify the sequence most similar to the test temporal φ_ζ from this group of training temporal data sequences φ_ζ^s. According to the similarity definitions 1 and 2 of temporal data sequences, we propose the following fast recognition mechanism. For the training temporal φ_ζ^s, the constant RBF network $\overline{W}^{sT} S_k$ is used to construct a dynamic model as its dynamic expression:

$$\overline{Y}^s(K) = -a\left(y(K-1) - \overline{Y}^s(K-1)\right) + \overline{W}^{sT} s_K \tag{6}$$

where, $\overline{Y}^s(K) = \left[\overline{y}_1^S(K),\ldots,\overline{y}_N^S(K)\right]$ is the state of the dynamic estimation model and $S_k = S\left(y(k-1),\ldots,Y(K-M)\right),\left[y(K-1),\ldots,y(K-m)\right]$ is the test temporal φ_ζ. Comparing the test temporal data sequence φ_ζ with this set of dynamic models (13), the following identification error system is obtained:

$$\begin{aligned} &e_i^s(k) = a_i e_i^s(k-1) + \left(f_i'(\cdot; p_i') - \overline{W}_i^{sT} S_k\right), \\ &i = 1,\ldots,n \end{aligned} \tag{7}$$

Among them, $e_i^s(k) = y_i(k) - \overline{y}_i^s(k)$.

Next, we will show that there is no need to model the temporal data sequence φ_ζ. By comparing the dynamic matching between the dynamic model and the test system in the identification error system, the error of the identification error system $e_i^s(k)$ will be approximately proportional to the dynamic difference $\left| f_i'(\cdot; p_i') - \overline{W}_i^{sT} S_k \right|$. Therefore, the error

$e_i^s(k)$ can be regarded as a measure to quickly judge the similarity of temporal data sequences.

4 Results and analysis

4.1 Numerical experiment of modeling effect

We use the following He non system to show the modeling effect of deterministic learning on temporal data sequences:

$$\begin{aligned} X_1(K+1) &= X_2(K)+1-AX_1^2(K) \\ X_2(K+1) &= BX_1(K) \end{aligned} \tag{8}$$

The system parameters are a = 1.3, b = 0.2. Assuming subsystem x_1 is unknown, figure 2 shows the state sequence generated by the system.

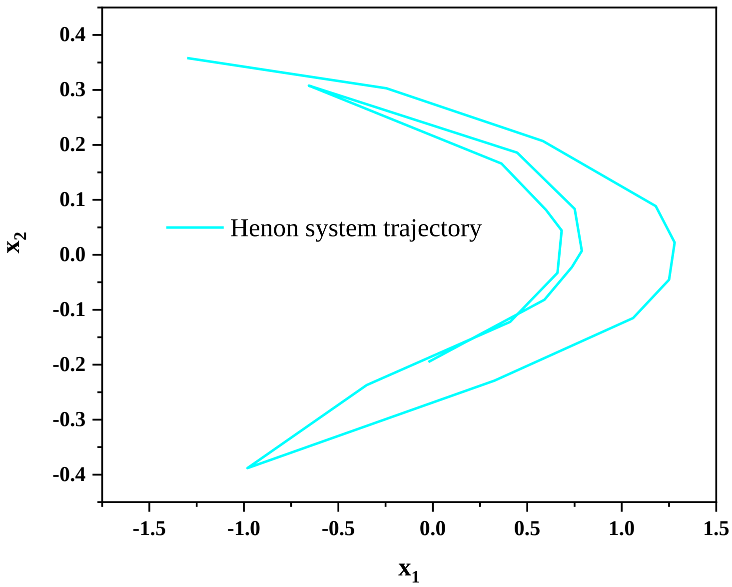


Figure 2: Trajectory of Henon system

Neurons is used to learn the nonlinear function of the first subsystem $x_2(k)+1-ax_1^2(k)$ (as shown in Figure 3).

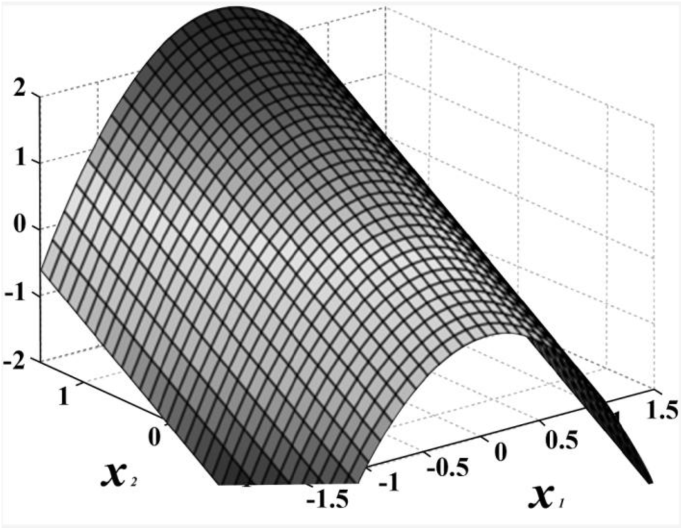


Figure 3: System nonlinear function

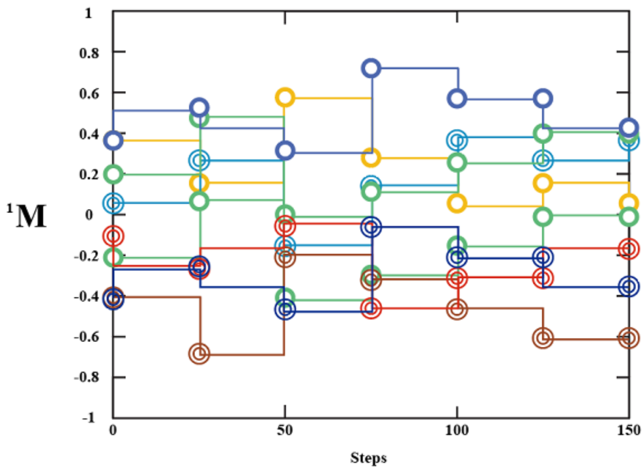


Figure 4: Convergence of some neuron weights

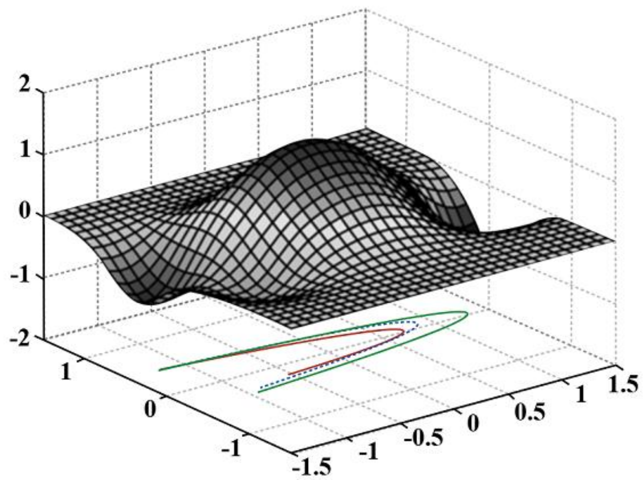


Figure 5: Local accurate approximation of system nonlinear function

Neurons are evenly distributed in the region [- 1.5, 1.5] × [- 1.5, 1.5], and $\eta = 0.2$. The parameters of the neural network identifier are selected as follows: $a_1 = 0.5.\Gamma = 2$. The weight convergence and local learning of the neural network are shown in Figure 4 and Figure 5 respectively. Comparing Figure 3 and Figure 5, it can be clearly seen that the neural network can approach the nonlinear function of the system (15) $x_2(k)+1-ax_1^2(k)$ in the region along the system trajectory.

4.2 Numerical experiment of fast recognition of temporal data sequence

It is still considered that He non system (15) generates three groups of temporal data sequences respectively when a = 1.1, a = 1.2 and a = 1.4 (as shown in Figure 6-11). Consider another test data sequence generated by He non system (15) at a = 1.38 (as shown in Figure 10-11).

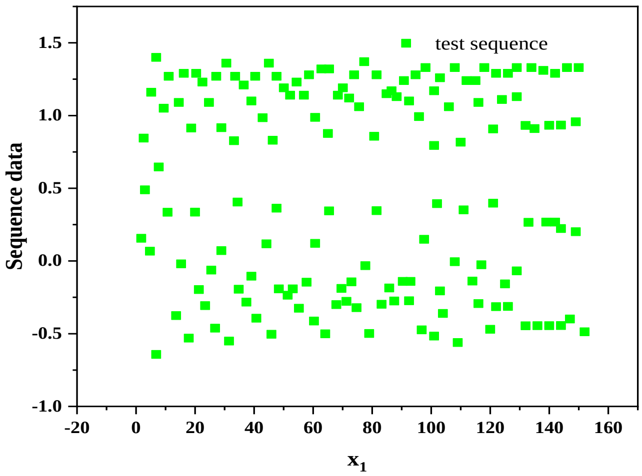


Figure 6: x_1 *in training sequence* φ_ζ^1

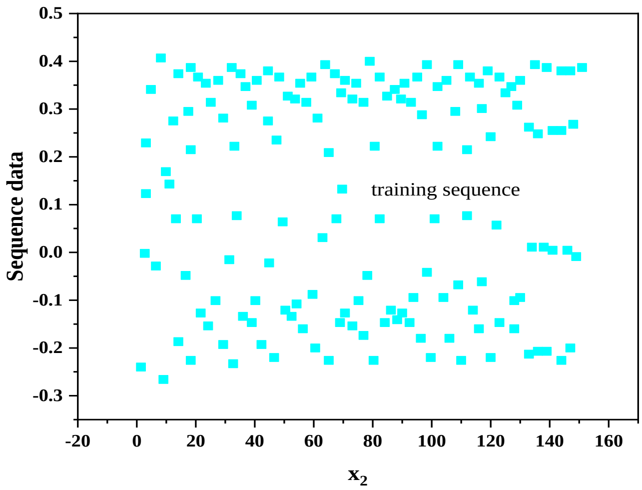


Figure 7: x_2 *in training sequence* φ_ζ^1

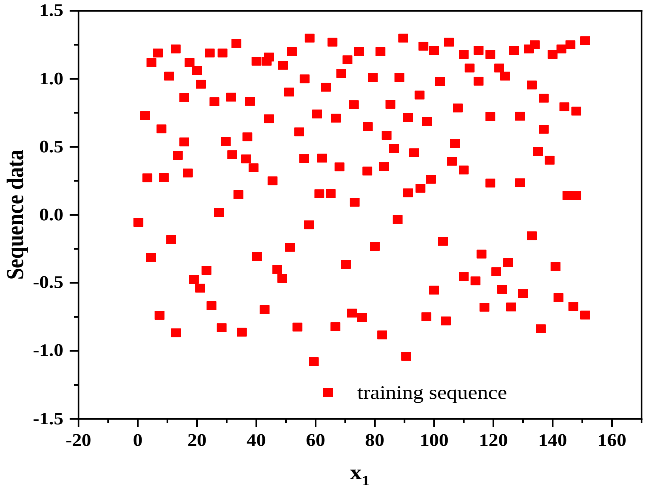


Figure 8: x_1 *in training sequence* φ_ζ^2

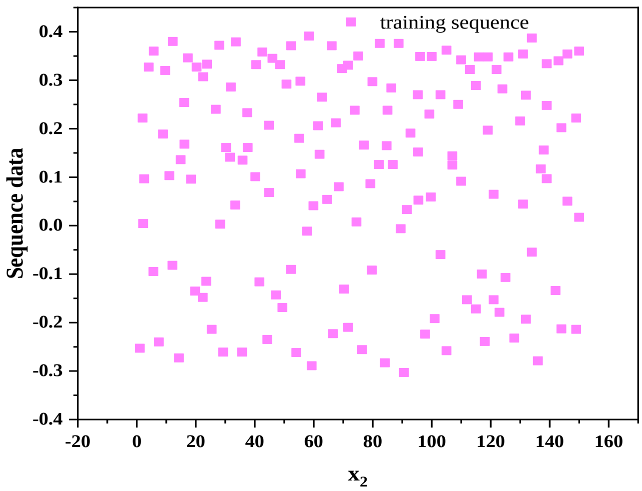


Figure 9: x_2 *in training sequence* φ_ζ^2

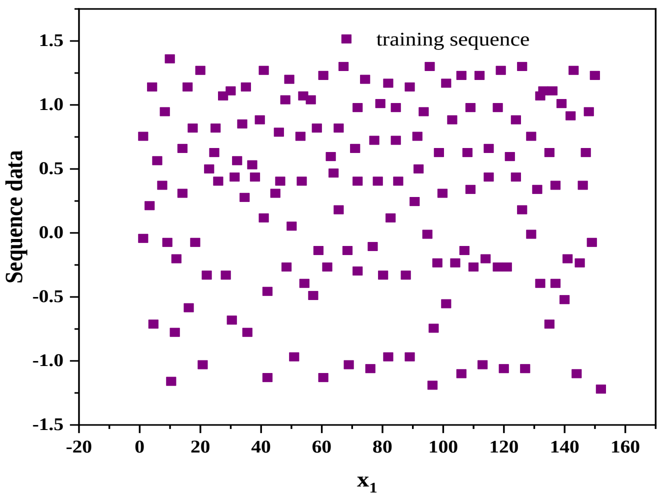


Figure 10: x_1 *in test sequence* φ_ζ^3

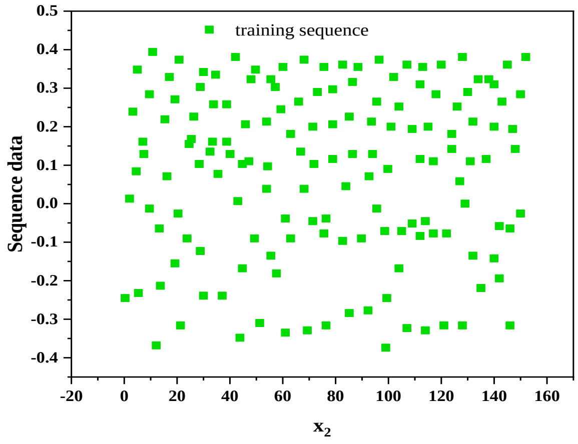


Figure 11: x_2 *in test sequence* φ_{ζ}^{3}

Using these three constant valued neural networks, three dynamic models are constructed according to equation (13), and three identification errors are generated. The system obtains three groups of errors $\left\|e_1^s(k)\right\|_{l_1}, s = 1,2,3$, as shown in Figure 12-13.

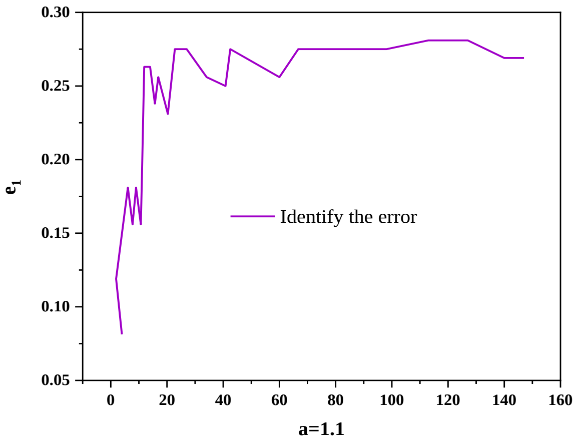


Figure 12: Identification error when a = 1.1

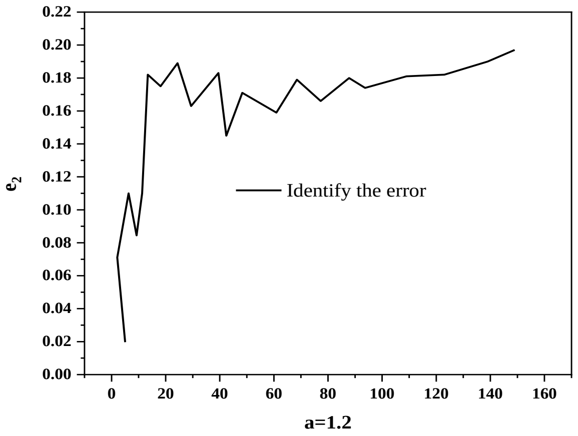


Figure 13: Identification error when a = 1.2

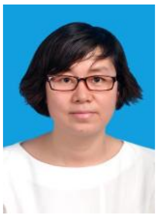
5 Conclusion

In this paper, the discrete dynamic modeling problem of intelligent teaching based on big data mining is proposed and analyzed. Using the stability analysis of discrete dynamic system, the deterministic learning theory for discrete dynamic system is extended, and a method for modeling, similarity characterization and fast recognition of temporal data series is proposed. This paper studies not only the stability of neural network modeling, but also the convergence of neural network weights based on meeting some PE conditions and the local accurate neural network approximation of system dynamics. The work of this paper provides a new idea for the research of temporal data mining, and provides a possible way for data-based modeling and control. Focusing on the normalized application of smart classroom, it is of practical significance to conduct empirical research on education big data analysis based on smart classroom. The next research work will form the simulation data and the visual analysis report formed in the real user application according to the system simulation user interaction, collect the user's opinions on the data acquisition indicators and visual report.Put forward the optimization strategy of the acquisition and analysis method, and explore the general law of data visual analysis in the application process, so as to form an ecosystem supporting process data interaction analysis and dynamic evolution. This article systematically introduces the application of discrete dynamic modeling in intelligent teaching, analyzes the main problems and limitations currently existing, and explores new methods and technologies based on big data mining. Through in-depth research and innovation, this article aims to promote the further development of modeling technology in the field of smart education, providing theoretical support and technical paths for achieving personalized teaching and improving educational quality.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this article.

About the Author



Na Wei was born in FuKang, Xinjiang, P.R. China, in 1978. She received the Master degree from Yunnan University, P.R. China. Now, she works in College of Education, Yunnan University. Her research interests include Teacher education, teacher training.
E-mail: thumbweina@163.com

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