Analysis and Prediction of the Trend Features for Teaching Development Based on Knowledge Discovery

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Abstract—The existing research on teaching development of teachers fails to effectively quantify the teaching development trend. This paper deeply mines the evaluation data on the teaching quality of college teachers, before analyzing and predicting the trend features for teaching development of college teachers based on knowledge discovery. Firstly, the knowledge features of the teaching development trend of college teachers were examined. Next, the fluctuation features of the time series on the teaching quality development of college teachers were described based on chaotic time series. In addition, a prediction model for teaching development of college teachers was established for weighted first-order chaotic time series, and used to simulate the nonlinear features of the time series on the teaching quality development of college teachers. The prediction model was proved effective through experiments.

Keywords—knowledge discovery, college teachers, teaching development, trend feature analysis, trend prediction

1 Introduction

To improve the quality of higher education, the first step is to better the teaching quality of college teachers [1-3]. As early as the end of the 20th century, the United States, Britain, Switzerland, Canada and other Western countries, as well as Japan began to attach importance to the teaching development of teachers. China did not pay attention to and research the teaching development of college teachers until the 21st century [4-9]. In 2011, the education departments at central and local levels circulated their opinions on the teaching reform of higher education, highlighting the importance of enhancing the teaching ability of young college teachers. This kicked off in-depth and extensive domestic research into teaching development of college teachers [10-13].

Aiming to promote personal and organizational development, the teaching development of young college teachers mainly involves college training, college consultation, and teaching reform. Feng and Zhao [14] regarded the application of mobile Internet as an important component of teaching development, which is mainly manifests in the personalized training, consultation, and evaluation of the teaching process, and predicted that mobile Internet will motivate teaching design, classroom teaching, and teaching reflection comprehensively. Gurevich et al. [15] tracked the changes in the choice of technology tools and attitudes towards technology use of young college teachers in three stages of their professional development, and elaborated the benefits of new teachers' emphasis on technology in teaching: improving learning, motivating students, and making courses more effective. Tasić et al. [16] believed that teaching ability development, as the key area of academic assessment and self-assessment, covers teaching planning and preparation, and the evaluation of other teaching tasks and teaching realization. Besides, Tasić argued that teachers must improve their knowledge, skills and competencies, and understand the necessity of long-term training on professional development. The training could be organized for a group of teachers or individual teachers. Pellegrino et al. [17] developed a system that integrates the progresses of educational research, teaching practice, and information technology, and provides accessible knowledge. The system is expected to support the development and deployment of education courses, seminars, and resources for college teachers, and provide the core elements to teaching development programs for teachers.

With the fast development of the big data and artificial intelligence (AI), the application of data analysis system in the education industry has become mature. Starting with the big data on education, this paper deeply mines the evaluation data on the teaching quality of college teacher, and analyzes and predicts the trend features for teaching development of college teachers based on knowledge discovery. The prediction results of our model were obtained through experiments, revealing that our model is highly effective.

2 Knowledge feature analysis

During the knowledge discovery of the teaching development trend for college teachers, it is necessary to solve several key issues: the data composition, trend description, and scientific discovery flow for the time series on the teaching quality development of college teachers. When it comes to the data mining of the time series on the teaching quality development of college teachers, the development trend usually depicts the change direction of the collected data in a fixed period. Thus, the time series need to be divided into multiple segments. Let $a_{j,K}$ and $a_{i,S}$ be the start and end values of segment j, respectively; $\psi_j=\tau_{j,S}-\tau_{j,K}$ be the time span of segment j; l be the number of sub-series of the entire time series. It is assumed that $a_{1,K}=a_1$, $a_{l-1,S}=a_{l,K}$, and $a_{l,S}=a_m$. Then, the time series data X can be divided into several sub-series by:

$$A=\left\{\left(a_{1,K},...,a_{1,S}\right),\left(a_{2,K},...,a_{2,S}\right),...,\left(a_{j,K},...,a_{j,S}\right),...,\left(a_{l,K},...,a_{l,S}\right)\right\} \tag{1}$$

Figure 1 gives examples of time series of different development trends. It can be observed that the long-term trend of teaching development for college teachers is the long-term development direction of the time series on the teaching quality development of college teachers, and an organic combination of several trend elements corresponding to multiple sub-series. Table 1 lists the symbols of the trend elements.

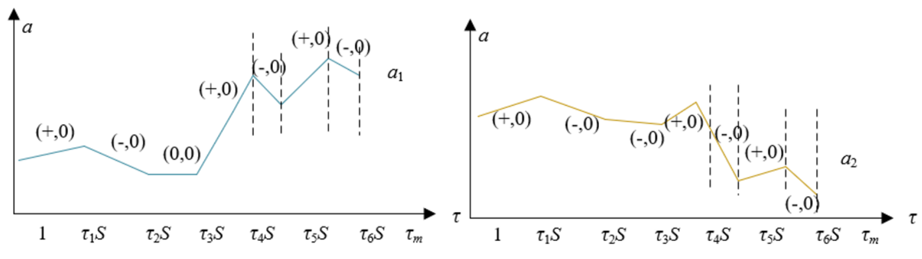

Fig. 1. Examples of time series of different development trends

Table 1. Differences in learning engagement

Slope \ Range of mean	$[a_{min},a_{min+\gamma}]$	$[a_{min+\gamma},a_{min+2\gamma}]$	$[a_{min+2\gamma},a_{min}]$
<0	υ_1	υ_2	υ_3
=0	υ_4	υ_5	υ_6
>0	υ_7	υ_8	υ_9

After the time series on the teaching quality development of college teachers is divided into l segments, the trend series obtained through trend recognition and transformation can be expressed as $C\_TD=(c_1^{TD}>c_2^{TD}>...>c_j^{TD}>\ldots>c_l^{TD})$, where $c_j^{TD} \in (\upsilon_1,\upsilon_2,\upsilon_3,\upsilon_4,\upsilon_5,\upsilon_6,\upsilon_7,\upsilon_8,\upsilon_9)$. According to the modality variation of the teaching development trend series for college teachers, we have:

$$C\_TD=\left(c_1^{TD}>c_2^{TD}>...>c_j^{TD}>...>c_l^{TD}\right)=\left(C_1^{TD}>C_1^{TD}>...>C_v^{TD}>...>C_r^{TD}\right)$$
$$=\begin{cases}\left(c_1^{TD}>c_{1,2}^{TD}>...>c_{1,i_1}^{TD}>...>c_{1,r_1}^{TD}\right)\\ \left(c_{2,1}^{TD}>c_{2,2}^{TD}>...>c_{2,i_2}^{TD}>...>c_{2,r_2}^{TD}\right)\\ \vdots\\ \left(c_{v,1}^{TD}>c_{v,2}^{TD}>...>c_{v,i_v}^{TD}>...>c_{v,s_v}^{TD}\right)\\ \vdots\\ \left(c_{r,1}^{TD}>c_{r,2}^{TD}>...>c_{r,i_r}^{TD}>...>c_{r,\psi_r}^{TD}\right)\end{cases} \tag{2}$$

As shown in formula (2), the teaching development trend series for college teachers is divided into r segments, where $C_v^{TD}=(c_{v,1}^{TD}>c_{v,2}^{TD}>\ldots>c_{v,iv}^{TD}>\ldots>c_{v,sv}^{TD})$, i.e., segment v contains s_v trend elements. s_v is not necessarily equal to s_{v+1}, that is, the number of trend elements may vary between segments of the time series. In addition, $c_{v,sv+1}^{TD}=c_{v+1,1}^{TD}$, $c_{r,sr}^{TD}=c_l^{TD}$, and $c_{1,1}^{TD}=c_1^{TD}$.

Trend similarity measurement is a key link of trend knowledge discovery. To facilitate the trend knowledge discovery of multiple time series on college teachers' teaching development, it is important to develop an effective method for trend similarity measurement of teaching development for college teachers. This paper introduces the dynamic pattern matching. In the traditional pattern matching strategy, the distance can be calculated by:

$$e\left(c_i, c_j\right) = \begin{cases} 0, c_i = c_j \\ 1, c_i \neq c_j \end{cases} \tag{3}$$

The trend similarity measurement of the time series on the teaching quality development of college teachers is established on the segmented modeling of that time series. Formula (3) is not applicable, because it cannot effectively resist short-term local noise. Hence, this paper chooses the dynamic time warping distance, which supports asynchronous similarity comparison.

Let $W=\{w_1,w_2,...,w_m\}$ and $V=\{v_1,v_2,...,v_n\}$ be two time series. The distance matrix between the data points of the two time series can be denoted as $E_{m\times n}=\{e(1,1)\}_{m\times n}$, with $1\leq i\leq m$, and $1\leq j\leq n$. The value of $e(i,j)$ depends on the square of the Euclidean distance between w_i and v_j, i.e., $e(i,j)=(w_i-v_j)^2$. In other words, E stores the distance between the data of W and V at different time points. In matrix E, the dynamic time warping distance is represented by one path:

$$SA_D\left(W,V\right) = min_o\left(\frac{1}{r}\sum\nolimits_{k=1}^{r} o_k\right) \tag{4}$$

The shortest path from the start position to the end position can be recorded by a cumulative matrix $S=\{s(i, j)\}_{m\times n}$:

$$s\left(i, j\right) = e\left(i, j\right) + min\begin{cases} s\left(i, j-1\right) \\ s\left(i-1, j-1\right) \\ s\left(i-1, j\right) \end{cases} \tag{5}$$

where, $s(0,0)=0$; $s(i, 0)=s(0, j)=\infty$. Finally, the dynamic time warping distance between W and V can be expressed as cumulative distance: $SA_{DTW}=(W,V)=s(m,n)$.

Furthermore, the dynamic pattern matching is constructed based on the pattern matching between trend elements. Let $B'=\{c'_1, c'_2, ..., c'_j, ..., c'_l\}$ and $B''=\{c''_1, c''_2, ..., c''_i, ..., c''_u\}$ be two trend series formulated through segmented modeling. The two trend series are not necessarily of equal length. The distances between the element forms of the two trend series form a distance matrix $E_{l\times u}=\{e(j,i)\}_{l\times u}$, where $1\leq j\leq l$, and $1\leq i\leq u$. Let $e(j,i)=e(c_i, c_i)$. be the pattern matching distance between c_{1j} and c_{2i}. Then, the resulting pattern matching distance matrix can be obtained as $E_{l\times u}=\{e(j,i)\}_{l\times u}=\{e(c_i,c_i)\}_{l\times u}$.

Following the solving process of dynamic time warping distance, the optimal path can be found by recording the shortest path from the start position to the end position in the cumulative matrix $S_{DD}=\{s_{DD}(j,i)\}_{l\times u}$:

$$s_{DD}(j,i)=e(c_i,c_j)+min\begin{cases}s_{DD}(j,i-1)\\ s_{DD}(j-1,i-1)\\ s_{DD}(j-1,i)\end{cases} \tag{6}$$

where, $s_{DD}(0,0)=0$; $s_{DD}(j,0)=0$; $s_{DD}(0,i)=\infty$. Finally, the dynamic pattern matching distance $SA_{DD}(B',B'')$ between B' and B'' can be described by the cumulative distance $SA_{DD}(B',B'')=s_{DD}(l,u)$.

3 Teaching trend prediction

The foregoing analysis indicates that the time series on the teaching quality development of college teachers fluctuates cyclically over time. This phenomenon is very similar to the chaotic time series in nonlinear systems. Thus, this paper adopts chaotic time series to depict the fluctuation features of the time series on the teaching quality development of college teachers. The crux of reconstructing the chaotic time series on the teaching development of college teachers is to acquire the chaotic features of the original time series on the teaching quality development of college teachers. Based on phase space reconstruction theory, this paper constructs a prediction model for teaching development of college teachers for weighted first-order chaotic time series, and simulates the nonlinear features of the time series on the teaching quality development of college teachers.

The correct choice of delay time is very important for phase space reconstruction. C-C algorithm is a lightweight, easy-to-operate, and noise-resistant estimation method for phase space delay time. The algorithm relies on correlation integral method to compute the delay time t and the time window t_n. The embedding dimension n of the reconstructed phase space can be derived from t_n by $t_n=(n-1)t$. Let N be the number of sampling points after phase space reconstruction; δ_{ij} be the Euclidean distance between two points in the phase space; u be the radius of the neighborhood; $F(\omega)$ be the Heaviside step function. Then, the correlation integral can be defined as:

$$OU(u)=\frac{2}{N(N-1)}\sum_{1\le i\le j\le N}F(u-\delta_{ij}) \tag{7}$$

$F(\omega)$ can be defined as:

$$F(\omega)=\begin{cases}1,(\omega>0)\\ 0,(\omega>0)\end{cases} \tag{8}$$

The time series on the teaching quality development of college teachers$\{a(\tau),\tau=1,2,..., M\}$ can be processed by:

$$R(n,N,u,\tau)=\frac{1}{\tau}\sum_{r=1}^{\tau}\left[OU_r(n,M/\tau,u,\tau)-OU^n{}_r(1,M/\tau,u,\tau)\right] \tag{9}$$

Let N and J be the dimension and number of embeddings after phase space reconstruction, respectively. Then, the mean of all $R(n,M,u,\tau)$ in the time series on the teaching quality development of college teachers can be solved by:

$$\overline{R} = \frac{1}{N \cdot J} \sum_{n=1}^{N} \sum_{j=1}^{J} R\left(n, u_j, \tau\right) \tag{10}$$

The maximum bias $\triangle R(n,\tau)$ of u can be calculated by:

$$\Delta R\left(n, \tau\right) = max\left\{R\left(n, u_j, \tau\right)\right\} - min\left\{R\left(n, u_j, \tau\right)\right\} \tag{11}$$

Let ϕ be the standard deviation of the time series on the teaching quality development of college teachers. Drawing on the concept of asymptotic distribution function, and taking n=3, 4, 5, 6, $u_j=i_{\phi/2}$, and i=1, 2, 3, 4:

$$\overline{R} = \frac{1}{18} \sum_{n=3}^{6} \sum_{j=1}^{4} R\left(n, u_j, \tau\right) \tag{12}$$

$$\Delta \overline{R} = \frac{1}{5} \sum_{n=3}^{6} \Delta R\left(n, \tau\right) \tag{13}$$

$$R^{*} = \Delta \overline{R}\left(\tau\right) - \left|\overline{R}\left(\tau\right)\right| \tag{14}$$

Statistically speaking, the results of formulas (12) and (13) both reflect the autocorrelation of the time series on the teaching quality development of college teachers.

The teaching development of college teachers is a gradual process. To realize the multi-step prediction of teaching development for college teachers, it is necessary to improve the traditional model prediction method, whose system error accumulates with the growing number of prediction steps. To predict the teaching development of college teachers, this paper proposes a prediction model for weighted first-order chaotic time series. The details of this model are explained as follows:

For the chaotic time series on teaching development of college teachers $a=\{1, 2, ..., M\}$, the embedding dimension n and delay time t of the original chaotic series are solved by the C-C method. Let $N=M-(n-1)t$ be the number of data points in the time series on the teaching quality development of college teachers after phase space reconstruction. Then, the reconstructed phase space can be expressed as $A_i=(a_i, a_{i+t}, ..., a_{i+(n-1)t})$, where i=1, 2, ..., N.

From the idea of phase reconstruction, the proposed prediction model for teaching development of college teachers adheres to the following principle: In the reconstructed phase space, (n+1) most similar data points are found relative to the datum points in the original time series on the teaching quality development of college teachers. Based on these data points, the teaching development of college teachers is predicted again for the reconstructed time series on the teaching quality development of college teachers. If n is greater than 1, and the prediction of the chaotic time series contains l steps, then the teaching development of college teachers will be predicted in l steps, following the evolution law of the (n+1) reconstructed time series in the l steps.

Let A_N be the center point; $\{A_{Ni}\}$ be the reference vector set of the reconstructed time series. After l steps of prediction, the data point set of the reconstructed time series on the teaching quality development of college teachers is converted into $\{A_{Ni+l}\}$. The first-order local linear fitting can be expressed as:

$$A_{N_i+l} = x_l d + y_l A_{Ni}, i = 1, 2, ..., w \tag{15}$$

Based on weighted least squares method, this paper solves the optimal values of x_l and y_l:

$$min = \sum_{i=1}^{w} O_i \left[\sum_{j=1}^{n} \left(a_{N_i+l}^{j} - x_l - y_l a_{Ni}^{j} \right)^2 \right] \tag{16}$$

Formula (16) is a bivariate function of parameters x_l and y_l. Finding the partial derivatives of x_l and y_l:

$$\begin{cases} \sum_{i=1}^{w} O_i \sum_{j=1}^{n} \left(a_{N_i+l}^{j} - x_l - y_l a_{Ni}^{j} \right) = 0 \\ \sum_{i=1}^{w} O_i \sum_{j=1}^{n} \left(a_{N_i+l}^{j} - x_l - y_l a_{N_i}^{j} \right) a_{N_i}^{j} = 0 \end{cases} \tag{17}$$

Formula (17) can be simplified as:

$$\begin{cases} x_l \sum_{i=1}^{w} O_i \sum_{j=1}^{n} a_{N_i}^{j} + y_l \sum_{i=1}^{w} O_i \sum_{j=1}^{n} \left(a_{Ni}^{j} \right)^2 = \sum_{i=1}^{w} O_i \sum_{j=1}^{n} a_{N_i+l}^{j} a_{N_i}^{j} \\ x_l n + y_l \sum_{i=1}^{w} O_i \sum_{j=1}^{n} a_{N_i}^{j} = \sum_{i=1}^{w} O_i \sum_{j=1}^{n} a_{N_i+l}^{j} \end{cases} \tag{18}$$

Formula (18) can be written as a matrix:

$$\begin{pmatrix} Q1 & Q2 \\ n & Q1 \end{pmatrix} = \begin{pmatrix} x_l \\ y_l \end{pmatrix} = \begin{pmatrix} d_l \\ g_l \end{pmatrix} \tag{19}$$

where,

$$Q1 = \sum_{i=1}^{w} O_i \sum_{j=1}^{n} a_{Ni}^{j},\ Q2 = \sum_{i=1}^{w} O_i \sum_{j=1}^{n} \left(a_{N_i}^{j} \right)^2, d_l = \sum_{i=1}^{w} O_i \sum_{j=1}^{n} a_{N_i+l}^{j} a_{N_i}^{j},\ g_l = \sum_{i=1}^{w} O_i \sum_{j=1}^{n} a_{N_i+l}^{j} \tag{20}$$

Formula (19) can be further converted into:

$$\begin{pmatrix} x_l \\ y_l \end{pmatrix} = \begin{pmatrix} Q1 & Q2 \\ n & Q1 \end{pmatrix}^{-1} \begin{pmatrix} d_l \\ g_l \end{pmatrix} \tag{21}$$

Finally, x_l and y_l can be expressed as:

$$\begin{pmatrix} x_l \\ y_l \end{pmatrix} = \begin{pmatrix} \sum_{i=1}^{w} O_i \sum_{j=1}^{n} a_{Ni}^{j} & \sum_{i=1}^{w} O_i B_{Ni} B_{Ni}^{T} \\ n & \sum_{i=1}^{w} O_i \sum_{j=1}^{m} a_{Ni}^{j} \end{pmatrix} \begin{pmatrix} \sum_{i=1}^{w} O_i B_{Ni} B_{Ni}^{T} \\ \sum_{i=1}^{w} O_i \sum_{j=1}^{n} a_{N_i+l}^{j} \end{pmatrix} \tag{22}$$

Substituting the x_l and y_l values into the l-step prediction formula $A_{N+l}=x_l d+y_l A_N$, the predicted value A_{N+l} for the data points in the time series on the teaching quality development of college teachers after l steps can be obtained as:

$$A_{Ni+l} = \left(a_{N+l}, a_{N+l+t}, ..., a_{N+l+(n-1)t} \right) \tag{23}$$

Element n $a_{N+l+(n-1)s}$ of A_{N+l} is the l-step predicted value $\tilde{a}_{M+l}$ of the original time series on the teaching quality development of college teachers.

4 Experiments and results analysis

Table 2 shows the descriptive statistics on the teaching quality evaluation data during the teaching development of college teachers. The central tendency of the evaluation data towards a central value is indicated by mean, median, and mode. As shown in Table 1, the time length of the collected time series on the evaluation data of teaching development quality for college teachers was 574. The mean of 79.72 was far smaller than the maximum of 92.57. Hence, there are few large evaluation data on teaching development quality. The median of 80.21 is the middle-ranking value, after the evaluation data are ranked in descending order. The mode is meaningless, because the evaluation data are not repetitive. Range refers to the gap between the maximum and the minimum of the evaluation data in the sample period. The minimum of 75.42 differed significantly from the maximum of 92.57. The standard deviation and variance measure the dispersion of the evaluation data. In the sample period, the standard deviation and variance of the evaluation data were 15.26 and 12.85, respectively, suggesting a high dispersion of the evaluation data.

The skewness of teaching quality development for college teachers was 3.152. The positive skewness indicates that the evaluation data do not obey normal distribution in the sample period. According to the skewness and kurtosis (5.68), most evaluation data were relatively small, and clustered in a narrow range.

Table 2. Descriptive statistics on teaching development of college teachers

Case number	**Maximum**	**Minimum**	**Range**	**Sum**
574	92.57	75.42	17.15	4152.24
Mean	SEM	Standard deviation	Variance	Mode
79.72	0.74851	15.26	12.85	/
Skewness	SES	Kurtosis	SEK	Median
3.152	0.215	5.68	0.152	80.21

Note: The SEM, SES, and SEK are short for standard error of the mean, standard error of skewness, and standard error of kurtosis, respectively.

The above evaluation data on teaching quality of college teachers through teaching development were converted into a trend series, through the proposed trend recognition and transform. The original time series on the teaching quality development of college teachers are high-dimensional, calling for data compression. Figure 2 shows the trend series for the teaching development increment obtained after the compression. It can be learned that the underlying forms υ_1, υ_2 and υ_3 are the main local forms of teaching development increment for college teachers. The other forms lasted for a short time, a sign of short-term effective development.

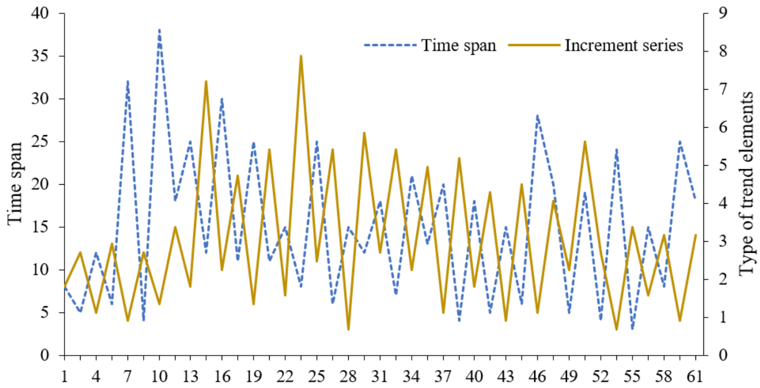

Fig. 2. Trend series and its time span

Figure 3 presents the relationship between embedding dimension and correlation dimension in the prediction model for teaching development of college teachers. With the continuous increase of embedding dimension, the correlation dimension between teaching quality evaluations in different periods tended to be stable.

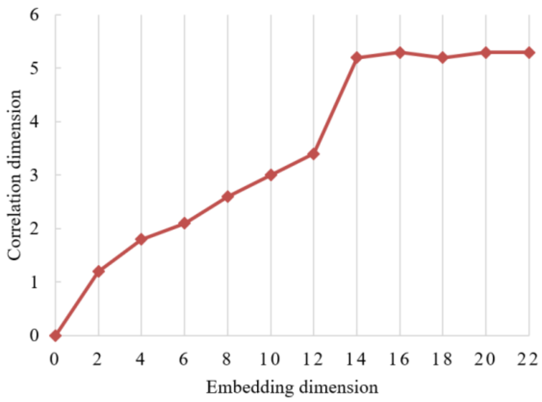

Fig. 3. Relationship between embedding dimension and correlation dimension

The prediction model for teaching development of college teachers, which was designed based on weighted first-order chaotic time series, was adopted to predict the teaching quality of 12 sampling points. The prediction results (Figure 4) show that most teaching qualities predicted by our model deviated very slightly from the true values. Thus, our model achieves an ideal prediction accuracy, and exhibits a high feasibility.

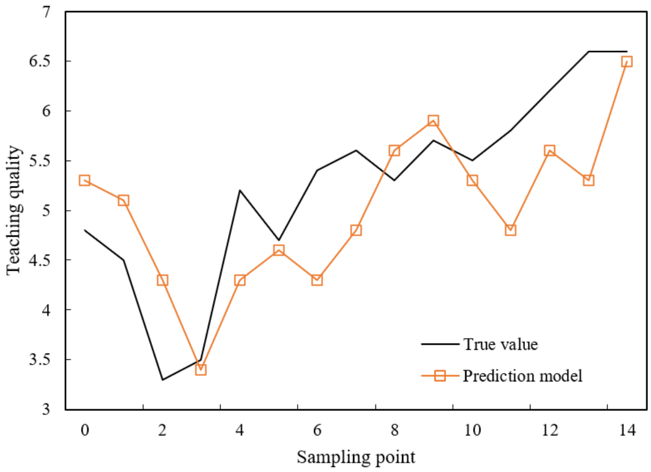

Fig. 4. Model prediction results

Figure 5 presents the trend of evaluation score on teaching development of college teachers. Overall, after taking up their jobs, young college teachers see their teaching quality growing at a medium speed within 5 years: the teaching quality is significantly improved, the teaching planning and decision abilities are clearly optimized, and the information teaching level is increased properly. Overall, young college teachers make steady progresses under personal efforts and training polices of the college. Table 3 summarizes the growth rates of teaching development levels of college teachers.

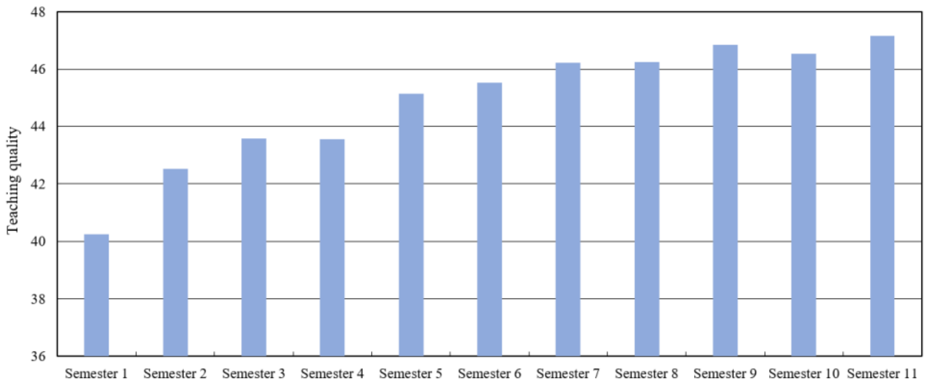

Fig. 5. Trend of evaluation score on teaching development of college teachers

Table 3. (A) Growth rates of teaching development levels of college teachers

Semester number	Level of teaching quality development	Growth rate of teaching quality development	Level of teaching planning and decision abilities
1	41.15	-0.12%	35.62
2	42.05	0.24%	40.15
3	43.26	4.26%	38.52
4	40.52	-3.26%	41.16
5	44.27	4.51%	39.27
6	43.16	8.52%	43.28
7	41.51	9.15%	34.47
8	43.27	9.85%	42.58
9	45.85	10.15%	43.26
10	43.62	11.42%	45.18
11	47.48	13.64%	46.74

Table 3. (B) Growth rates of teaching development levels of college teachers

Semester number	Growth rate of teaching planning and decision abilities	Information teaching level	Growth rate of information teaching
1	6.52%	41.18	-12.48%
2	3.21%	35.62	2.15%
3	-3.26%	37.49	0.13%
4	2.15%	44.15	-11.41%
5	7.48%	42.37	8.15%
6	-2.85%	40.55	6.74%
7	6.15%	39.58	8.49%
8	11.48%	40.17	13.62%
9	16.24%	36.28	18.49%
10	19.48%	42.51	22.57%
11	21.47%	48.62	25.16%

5 Conclusions

After deeply mining the evaluation data on the teaching quality of college teacher, this paper analyzes and predicts the trend features for teaching development of college teachers based on knowledge discovery. Firstly, the trend knowledge features of the teaching development were analyzed for college teachers, and a prediction model for teaching development of college teachers was constructed based on weighted first-order chaotic time series. The model was adopted to simulate the nonlinear features of the time series on the teaching quality development of college teachers. Through experiments, the authors gathered the descriptive statistics on the teaching quality evaluation data during the teaching development of college teachers, plotted the trend series for the teaching development increment. It was concluded that the underlying forms υ_1,

v_2 and v_3 are the main local forms of teaching development increment for college teachers. Finally, the relationship between embedding dimension and correlation dimension was discussed, and the prediction results of our model were obtained, revealing the effectiveness of the model.

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