# Prediction and Evolution of Distance Education Learners' Feedback Attitudes by a Deep Learning Approach

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**Abstract—**In recent years, the feedback attitude towards teachers has become one of the most important factors affecting learners' trust in teachers' teaching ability and changing learning plans, so the research on learners' feedback attitude has received extensive attention from experts and scholars at home and abroad. Most of the existing relevant research focuses on empirical research and behavioral research using questionnaires and scales from a theoretical point of view, which need to be further verified in terms of reliability and scientificity. Therefore, this paper conducts research on the prediction and evolution of distance education learners' feedback attitudes towards teachers based on deep learning. With the help of deep learning technology, it is easy to discover the advantages of distributed feature representation of data, and ARIMA model is combined with BP neural network model to construct a predictive model of distance education learners' feedback attitudes towards teachers. This paper makes the evolution analysis of distance education learners' feedback attitudes towards teachers, and introduces the assumptions and principles of the evolutionary analysis model in detail. The experimental results verify the effectiveness of the proposed model, and the analysis results of learner attitude evolution based on distance English learning as an example are given.

**Keywords—**deep learning, distance education, learner feedback, predictive studies, evolutionary analysis

## 1 Introduction

The advent of the mobile Internet era and the activity of distance education platforms have made online learning that breaks through the boundaries of time and space a part of learners' daily lives, providing opportunities for the masses who have entered the society to upgrade their academic qualifications [1–8]. Compared with the traditional on-campus teaching mode, learners can get more learning resources, learning communication opportunities, and learning channels, for example, online communication with teachers, online comment information of other learners, etc. when receiving distance education [9–18]. Due to its characteristics, the negative feedback attitude towards teachers has become one of the most important factors affecting learners' trust in teachers' teaching ability and thus changing learning plans [19–26], so it has received extensive attention from experts and scholars at home and abroad.

Heryadi et al. [27] proposes to sort out and explore the empirical results of sentiment analysis in the educational process, so as to extract and classify their learning views, evaluations, attitudes and emotions from learners of online learning programs. The qualitative results confirm that from the learner's perspective, the main gains of online learning are mainly the knowledge that can be gained from the program, the learning guidance, and the joy of learning from the collaborative learning by joining the learner team. Stephan [28] adopts a data-driven approach to explore the relationship between online course production quality, teaching effectiveness, and learner satisfaction with teachers. Data from the six-year online course learner assessment are evaluated and compared to the style and quality of the production of these courses. Quantitative selection course assessment questions address issues such as overall quality and satisfaction, learner learning, content, and course clarity. The findings provide valuable insights into how to best allocate time and resources for online course production. The Task-Oriented Portfolio Assessment (TOPA) model and associated software support have proven effective in engaging learners in a range of computer science education units. Modi [29] revolves around incorporating TOPA models and software tools to construct formative feedback processes by improving learners' attention and satisfaction and modifying the teachers' teaching strategies. Hooda et al. [30] examines how immediate and effective feedback and qualitative assessment impact can improve learners' learning in higher education settings. With the rise of online education, especially during this COVID-19, the role of assessment and feedback has also changed. This reference attempts to summarize the most commonly used AI and machine learning algorithms for learners' success. The results showed that I-FCN outperformed other technologies (ANN, XG Boost, SVM, random forest, and decision trees) in all measured performance indicators. The use of online peer feedback tools has grown rapidly in practice. However, the size of the effect appears to vary widely between studies, suggesting that implementation details are critical. Zong et al. [31] uses time-lagged multiple regression analysis in 13 different courses to test the received data samples. The results showed that: 1) more reviews are provided than received; 2) more long comments than short ones; 3) comments that are considered helpful for revision have a stronger relationship with task performance growth.

An analysis of existing research on learners' feedback attitudes shows that most of the research focuses on empirical and behavioral research using questionnaires and scales from a theoretical perspective. However, the results obtained by such methods need to be further verified in terms of reliability and scientificity because they are completely dependent on the scientific nature of the scale. At the same time, this type of methods measures the attitude that learners are willing to show at the current moment, and does not represent the real attitude of learners in the learning process. The above problems have limited the research on learners' feedback attitudes towards teachers, and it is easy to have inconsistencies between the real behavior of individuals and the behavior of experimental performance. Therefore, this paper conducts a research on the prediction and evolution of distance education learners' feedback attitudes towards teachers based on deep learning. In Chapter 2, this paper explores the advantages of distributed feature representation of data with the help of deep learning technology, and combines the ARIMA model with the BP neural network model to construct a predictive model of distance education learners' feedback attitudes towards teachers. In Chapter 3, this paper analyzes the evolutionary distance education learners' feedback attitudes towards teachers, and introduces the assumptions and principles of evolutionary analysis models in detail. The experimental results verify the effectiveness of the proposed model, and the analysis results of learner attitude evolution based on distance English learning as an example are given.

## 2 Learners' feedback attitude prediction

Learners' feedback attitudes towards teachers is usually reflected in the form of comments, which are simply classified into positive feedback attitude and negative feedback attitude according to their emotion or comment content, both of which can affect learners' learning attitudes and learning behaviors when choosing to learn from a teacher. Negative online comments from other learners have a more pronounced impact on learners than positive online comments. Learners' online comments also have a greater impact on teachers, who need to actively interact with learners to ensure that learners receive the desired learning gains in order to maintain their influence on learners' behavior.

In order to obtain the real attitude of learners towards teachers in the learning process, this paper uses deep learning technology to discover the advantages of distributed feature representation of data, constructs a prediction model of distance education learners' feedback attitudes towards teachers, and further analyzes the evolution of learners' feedback attitudes towards teachers.

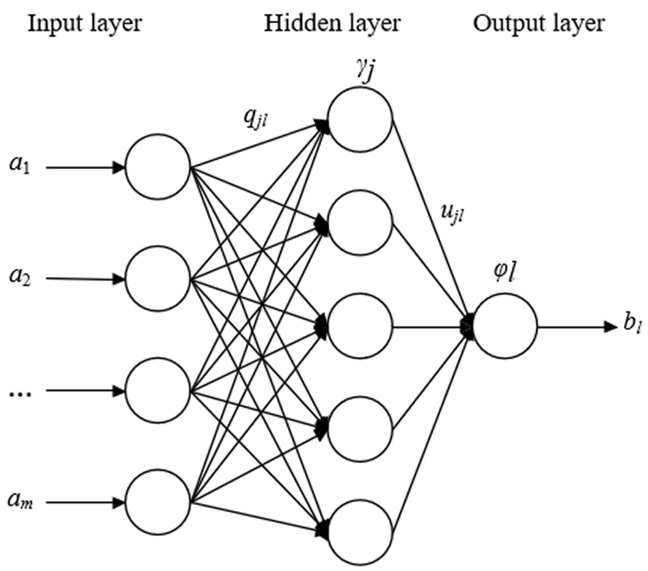


**Fig. 1.** BP neural network model architecture

This paper selects 13 influencing indicators related to the distance education learners' feedback attitudes towards teachers. Due to the large amount of online learning behavior data of learners on the distance education platform and the partial absence of some information data, the learner behavior data with a duration of more than 2 years' online learning is considered for the training of the deep learning model.

In order to obtain a more ideal prediction effect, this paper combines the ARIMA model with the BP neural network model shown in Figure 1 to construct a combined model of the ARIMA-BP neural network. In the model, it's assumed that $a \in R^m$, $g$: $R^m \to R^1$, $h_i : R^m \to R^1$, $i = 1, \ldots, o$, $f_j : R^m \to R^1$, $j = 1, \ldots, w$. The following equation gives the constraint nonlinear programming problem formulation of prediction of distance education learners' feedback attitudes towards teachers:

$$\begin{cases} \min g(a) \\ s.t.\ \ h_i(a) \le 0, i = 1, \ldots, o \\ f_j(a) = 0, j = 1, \ldots, w \end{cases} \tag{1}$$

The optimal solution for the above equation satisfies the following conditions:

Condition 1: Let $g$: $R^m \to R^1$ and $h_i$: $R^m \to R^1$, $I = 1, 2, \ldots o$, $h_i(a) = 0$, $i \in I$ are differentiable at the local optimal solution $a^*$ of the above equation, $h_i$, $i \in I(a^*)/I$ are continuous at point a*, $f_j$: $R^m \to R^1$, $j \in J$ are continuously differentiable at a*, and ∇hi (a*), i ϵ I(a*), ∇fi(a*), j ϵ J are linearly independent. Then there are two sets of real numbers $\mu^*_i$, $i \in I(a^*)$ and $\lambda^*_i$, $j \in J$, satisfying

$$\begin{cases} \nabla g(a^*) + \sum_{i \in I(a^*)} \mu_i^* \nabla h_i(a^*) + \sum_{j \in J} \lambda_j^* \nabla f_j(a^*) = 0 \\ \mu_i^* \ge 0, i \in I(a^*) \end{cases} \tag{2}$$

Condition 2: For Equation 1, if $g$, $h_i(i \in I)$ and $f_j(j \in J)$ are continuously differentiable at $a^*$, which satisfies the K-T condition and g and $h_i(i \in I(a^*))$ are convex functions, and $f_j(j \in J)$ is linear, then a* is the overall optimal solution of Equation 1.

Assuming that the ARIMA model and the BP neural network model are represented by BX and BY, the combined model can be represented by B = q1BX + q2BY. The objective function of the combined model is the mean squared error processed for the observed values of the influence index, and the corresponding nonlinear programming is expressed as follows:

$$\begin{cases} \min g(q_1, q_2) = \frac{1}{m} \sum_{i=1}^{m} (b_i - q_1 b_{Xi} - q_2 b_{Yi})^2 \\ s.t.\quad q_1 + q_2 - 1 = 0 \\ 0 < q_1 < 1 \\ 0 < q_2 < 1 \end{cases} \tag{3}$$

Assuming that $b_i$ is the real value of prediction result of the distance education learners' feedback attitudes towards teachers, and the fitting value of the combined model is represented by $q_1b_{Xi} + q_2b_{Yi}$, the nonlinear programming problem of predicting the distance education learners' feedback attitudes towards teachers can be changed in the form of the following Lagrangian function:

$$\begin{aligned} LAG(q,\mu,\lambda) = \frac{1}{m}\sum_{i=1}^{m}(b_i - q_1b_{Xi} - q_2b_{Yi})^2 + \mu_1(-q_1) + \mu_2(1-q_1) \\ +\mu_3(-q_2) + \mu_4(1-q_2) + \lambda(q_1 + q_2 - 1) \end{aligned} \tag{4}$$

After finding the partial derivation, then:

$$\begin{cases} \dfrac{\partial LAG}{\partial q_1} = -\dfrac{2}{m}\sum_{i=1}^{m}(b_ib_{Xi} - q_1b_{Xi}^2 - q_2b_{Xi}b_{Yi}) - \mu_1 - \mu_2 + \lambda \\ \dfrac{\partial LAG}{\partial q_2} = -\dfrac{2}{m}\sum_{i=1}^{m}(b_ib_{Yi} - q_2b_{Yi}^2 - q_1b_{Xi}b_{Yi}) - \mu_3 - \mu_4 + \lambda \end{cases} \tag{5}$$

The K-T condition can be further obtained, then:

$$\begin{cases} \dfrac{\partial LAG}{\partial q_1} = 0 \\ \dfrac{\partial LAG}{\partial q_2} = 0 \\ \mu_1(-q_1) = 0 \\ \mu_2(-q_2) = 0 \\ \mu_3(-q_2) = 0 \\ \mu_4(1-q_2) = 0 \end{cases} \tag{6}$$

If $\mu_1$ and $\mu_3$ are 0, the above equation can be simplified as follows:

$$\begin{cases} \dfrac{\partial LAG}{\partial q_1} = 0 \\ \dfrac{\partial LAG}{\partial q_2} = 0 \end{cases} \tag{7}$$

Let $q_1 + q_2 - 1$ be 0, then:

$$\begin{cases} q_1 = -\dfrac{\sum_{i=1}^{m}(b_{Yi}-b_{Xi})(b_{Yi}-b_i)}{\sum_{i=1}^{m}(b_{Yi}-b_{Xi})^2} \\ q_2 = -\dfrac{\sum_{i=1}^{m}(b_{Yi}-b_{Xi})(b_{Xi}-b_i)}{\sum_{i=1}^{m}(b_{Yi}-b_{Xi})^2} \end{cases} \tag{8}$$

## 3 Evolutionary analysis of learners' feedback attitudes

In the previous section, this paper makes a short-term prediction of the distance education learners' feedback attitudes towards teachers, but due to the influence of new teachers who enter the platform, the influence of teachers on learners will fluctuate or even decline. Indicators in the text, such as the number of learners and class hours of teachers, will also fluctuate or even decrease. Therefore, under the influence of the continuous development of distance education platforms, how distance education learners evaluate teachers plays a crucial role in the optimization of teachers' teaching strategies and teaching methods. Therefore, this paper then analyzes the evolution of distance education learners' feedback attitudes towards teachers, so as to provide theoretical reference for distance education learners' learning plans and teachers' teaching decisions. It's assumed that the probability of the learner having a positive feedback attitude towards the teacher is $a$, the probability of having a negative feedback attitude is $1 - a$, the probability of the teacher choosing to adjust the teaching strategy is $b$, and the probability of choosing not to adjust the teaching strategy is $1 - b$. When the learner has a positive feedback attitude towards the teacher, the expected learning gain is $V_1$, the expected learning gain for negative feedback attitude is $V_2$, and the average expected learning gain is $V^*$. The expected impact gain of the teacher who chooses to adjust the teaching strategy is $U_1$, the expected impact gain of choosing not to adjust the teaching strategy is $U_2$, and the average expected learning gain is $U^*$, then:

$$V_1 = b(B_1 + Y_{11} - O_{11} - K_1) + (1-b)(B_1 + Y_{12} - O_{12} - K_1) \tag{9}$$

$$V_2 = b(B_1 + Y_{13} - K_1) + (1-b)(B_1 - K_1^{'} - K_1) \tag{10}$$

$$V^* = aV_1 + (1-a)V_2 \tag{11}$$

Based on the above equation, a replicate dynamic equation of learners' feedback attitudes towards teachers can be obtained:

$$\begin{aligned} G(a) &= a(1-a)(V_1 - V_2) \\ &= a(1-a)\left[u(Y_{11} - O_{11}) - Y_{13} - (Y_{12} - O_{12}) - K_1^{'} + \left[(Y_{12} - O_{12}) + K_1^{'}\right]\right] \end{aligned} \tag{12}$$

Based on the evolutionary analysis matrix, there are:

$$U_1 = a(B_2 + Y_{21} - K_2) + (1-a)(B_2 - O_{21} - K_2) \tag{13}$$

$$U_2 = a(B_2 + Y_{22} - K_2) + (1-a)(B_2 - O_{23} - K_2) \tag{14}$$

$$U^* = aU_1 + (1-a)U_2 \tag{15}$$

The dynamic equation for replicating the influence of the teacher is:

$$\begin{aligned} H(b) &= b(1-b)(U_1 - U_2) \\ &= b(1-b)[a[(Y_{21} - Y_{22}) + (O_{21} + Y_{23})] - (O_{21} + Y_{23})] \end{aligned} \tag{16}$$

Let $G(a) = 0$ and $H(b) = 0$, then obtain the five equilibrium points of the system $X$ (0, 0), $Y$(0, 1), $D$(1, 1), $C$(1, 0) and $T(a^*, b^*)$; assuming that $a^* = O_{21} + Y_{23}/(Y_{21} - Y_{22}) + O_{21} + Y_{23}$ and $b^* = O_{12} - Y_{12} - K_1'/(Y_{11} - O_{11}) - Y_{13} + O_{12} - Y_{12} - K_1'$, obtain the *Jacobi* matrix, where:

$$SQ = \begin{pmatrix} \frac{\partial G}{\partial a} & \frac{\partial G}{\partial b} \\ \frac{\partial H}{\partial a} & \frac{\partial H}{\partial b} \end{pmatrix}$$

$$\frac{\partial G}{\partial a} = (1-2a)\{b[(Y_{11} - O_{11}) - Y_{13} - (Y_{12} - O_{12}) - K_1'] + (Y_{12} - O_{12}) + K_1'\} \tag{17}$$

$$\frac{\partial G}{\partial b} = a(1-a)[(Y_{11} - O_{11}) - Y_{13} - (Y_{12} - O_{12}) - K_1'] \tag{18}$$

$$\frac{\partial H}{\partial a} = b(1-b)[(Y_{21} - Y_{22}) + (O_{21} + Y_{23})] \tag{19}$$

$$\frac{\partial H}{\partial b} = (1-2b)\{a[(Y_{21} - Y_{22}) + O_{21} + Y_{23}] - (O_{21} + Y_{23})\} \tag{20}$$

Considering the position of the point $T(a^*,b^*)$, we can know that a* > 1 from the hypothesis 2 $Y_{21} < Y_{22}$, so the point $T(a^*,b^*)$ is not on the rectangular field [0,1] × [0,1], and bringing $X$, $Y$, $D$, and $C$ into the Jacobi matrix, then:

$$
\begin{aligned}
SQ(0,0) &= \begin{pmatrix} Y_{12} - O_{12} - K_1' & 0 \\ 0 & -O_{21} - Y_{23} \end{pmatrix} \\
SQ(0,1) &= \begin{pmatrix} Y_{11} - O_{11} - Y_{13} & 0 \\ 0 & O_{21} + Y_{23} \end{pmatrix} \\
SQ(1,0) &= \begin{pmatrix} O_{12} - Y_{12} - K_1' & 0 \\ 0 & Y_{21} + Y_{22} \end{pmatrix} \\
SQ(1,1) &= \begin{pmatrix} Y_{13} - (Y_{11} - O_{11}) & 0 \\ 0 & Y_{22} - Y_{21} \end{pmatrix}
\end{aligned} \tag{21}
$$

Observing the obtained values of $X$, $Y$, $D$, and $C$ points, when $O_{12} - Y_{12} < K_1'$, the final evolutionary stability strategy of the evolutionary analysis matrix is positive feedback attitude (no adjustment of teaching strategy), indicating that in the continuous evolution of distance education learners' feedback attitudes towards teachers, when learners' learning gain objectives are high and teaching teachers tend not to adjust teaching strategies, learners can only have negative feedback attitude towards teachers and choose to follow other teaching teachers to learn, in order to improve their own learning gain.

## 4 Experimental results and analysis

**Table 1.** Negative feedback attitude prediction fitting under different $q_1$ conditions

| Learning Cycle | Actual Data | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 |
|---|---|---|---|---|---|---|
| 3 | 14.4187 | 13.726 | 14.0785 | 12.6671 | 11.4902 | 10.5958 |
| 6 | 12.8876 | 14.36 | 13.9887 | 13.9483 | 12.936 | 11.9654 |
| 9 | 11.7542 | 7.02 | 12.3637 | 12.7162 | 13.0513 | 12.1742 |
| 12 | 10.7196 | 10.915 | 10.0143 | 10.7308 | 11.3896 | 12.0411 |
| 15 | 9.8253 | 9.778 | 9.9355 | 9.338 | 9.6377 | 10.2223 |
| 18 | 9.1729 | 9.056 | 9.0153 | 9.1249 | 8.665 | 8.8037 |
| 21 | 8.8071 | 8.671 | 8.6142 | 8.5371 | 8.5796 | 8.183 |
| 24 | 7.9246 | 8.615 | 8.5617 | 8.4321 | 8.3273 | 8.3096 |
| 27 | 7.1705 | 5.789 | 7.1386 | 7.5269 | 7.6277 | 7.6295 |
| 30 | 7.0957 | 6.537 | 6.0721 | 6.2265 | 6.5489 | 6.7563 |
| *MAE* | | 0.9954 | 0.4872 | 0.6317 | 0.7261 | 0.9054 |
| *MAPE* | | 0.0951 | 0.0503 | 0.0609 | 0.0672 | 0.0812 |
| *MSE* | | 2.7756 | 0.3679 | 0.6561 | 1.1682 | 1.8544 |
| *RMSE* | | 1.6667 | 0.6063 | 0.8087 | 1.0823 | 1.3625 |

**Table 2.** Prediction data of different models

| Year | Actual Data | *ARIMA* Model Forecast Data | Combined Model Forecast Data |
|---|---|---|---|
| 2010 | 14.4186 | 13.8105 | 14.2285 |
| 2011 | 12.8879 | 13.4513 | 12.6254 |
| 2012 | 11.7542 | 12.1137 | 11.8912 |
| 2013 | 10.7193 | 10.9225 | 10.8127 |
| 2014 | 9.8253 | 9.9757 | 9.8545 |
| 2015 | 9.1726 | 9.2674 | 9.1653 |
| 2016 | 8.8071 | 8.5579 | 8.7634 |
| 2017 | 7.9244 | 8.2413 | 8.0898 |
| 2018 | 7.1703 | 7.4722 | 7.0618 |
| 2019 | 7.0955 | 6.7446 | 6.9402 |
| MAE | | 0.3123 | 0.2034 |
| MAPE | | 0.0325 | 0.0153 |
| MSE | | 0.1254 | 0.0881 |
| RMSE | | 0.3511 | 0.2275 |

Based on the iterative process of the predictive model, it can be seen that determining the values of $q_1$ and $q_2$ is crucial. Because $q_1 + q_2 = 1$, only the value of $q_1$ can be discussed. Because $q_1$ is too large or too small, the results are biased towards the single model prediction value of the combined model, which is not conducive to reflecting the characteristics and evolution trend of distance education learners' feedback attitudes towards teachers. Moreover, neither the ARIMA model nor the BP neural network model is suitable for the situation of fewer training samples, and too few indicator sequences will lead to large prediction errors. Therefore, the value of $q_1$ can be preliminarily selected between 0.5~0.7. Based on the negative feedback attitude prediction fitting results given in Table 1 under different $q_1$ conditions, the value of $q_1$ can be determined according to the error evaluation criteria. Since when $q_1$ is selected as 0.5, the prediction results are the smallest under the four error evaluation criteria, so $q_1 = q_2 = 0.5$.

Table 2 shows the forecast data for single and combined models. It can be seen from the table that compared with the pre-combination prediction results, the combined model of ARIMA model and BP neural network model obtains smaller error values under four error evaluation criteria, which verifies that the prediction effect of the model obtained by *K-T* conditions is better. Therefore, the combined model can be used to predict the distance education learners' feedback attitudes towards teachers and learning gains. Figures 2 and 3 show the change in cumulative values of the fitting results of the combined model.

It can be seen from the figure that the fitting error of distance education learners' feedback attitudes towards teachers and learning gains is small. It is explained that after the combination of ARIMA model and BP neural network model, the fitting of the model is more consistent with the real situation, and the prediction effect is much better than that of a single model, so the prediction value of distance education learners' feedback attitudes towards teachers and learning gains by the combined model can be used as the final prediction result for further research.

Next, based on the evolutionary analysis principle in Section 3, this paper uses simulation experiments to analyze the evolution direction of distance education learners' feedback attitudes towards teachers. Taking English distance learning as an example, the total number of learners participating in the experiment is 500, and the number of teachers is 10 and 20. The individual learner interacts with all connected teachers repeatedly in teaching and feedback, and the connection relationship is maintained throughout the interaction. Let the initial learner's participation density in teaching activities be 0.5, and the number of interactions between the teaching and feedback be 400. With the advancement of learners' learning process, the density of learners' participation in teaching activities will show a dynamic trend. This paper selects the average participation density of the last 50 learner teaching activities as the equilibrium density of learners' teaching activities, and effectively assigns the parameters of the constructed evolutionary model.

Figures 4 and 5 show the evolution results of 10 teachers and 20 teachers, respectively. It can be seen from the figures that when there are 10 teachers, the participation density of learners in feedback attitude towards teachers tends to 0.2 after about 300 interactions between teaching and feedback, that's, the evolution direction of learners' feedback attitude towards teachers changes. After a limited number of teaching and feedback interactions, all individuals participate in the teaching activities of 10 teachers; because learners have a narrower choice from 10 teachers than 20 teachers, and are more inclined to give positive feedback to teachers.

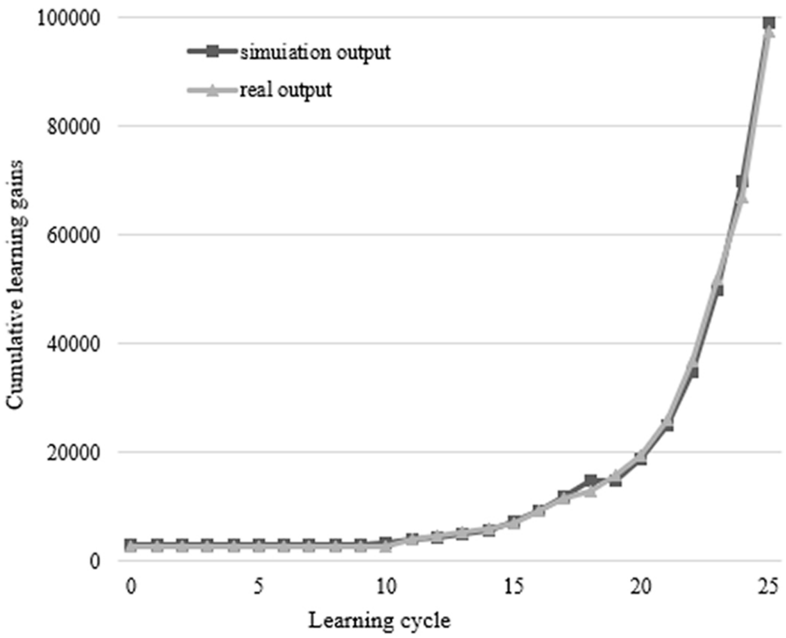


**Fig. 2.** Changes in cumulative value of learners' learning gains

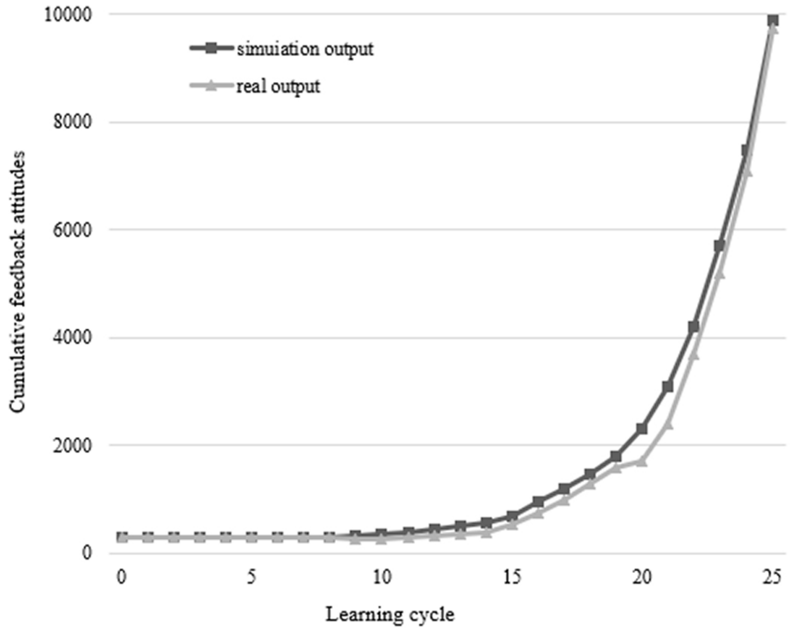


**Fig. 3.** Changes in cumulative values of learners' feedback attitudes

In case of than 20 teachers, the participation density of learners in feedback attitude towards teachers tends to 0.1 after about 100–200 interactions between teaching and feedback, that's, the evolution direction of learners' feedback attitude towards teachers changes more rapidly. This is mainly because compared with the situation of 10 teachers, after a limited number of teaching and feedback interactions, learners who participate in the teaching activities of 20 teachers are more likely to select suitable teachers through the comparison of whether the teacher's teaching strategy is suitable for themselves, that's, choose teachers who receive positive feedback attitude, and abandon teachers who receive negative feedback attitude.

Tables 3–6 shows the Jacobi matrix values corresponding to *X*, *Y*, *D*, and *C* points under different evolutionary stabilization strategies of learners and teachers in the process of evolutionary analysis. Tables 3 and 4 show the matrix values in the natural state, and Tables 5 and 6 show the matrix values under the supervision of the distance education platform.

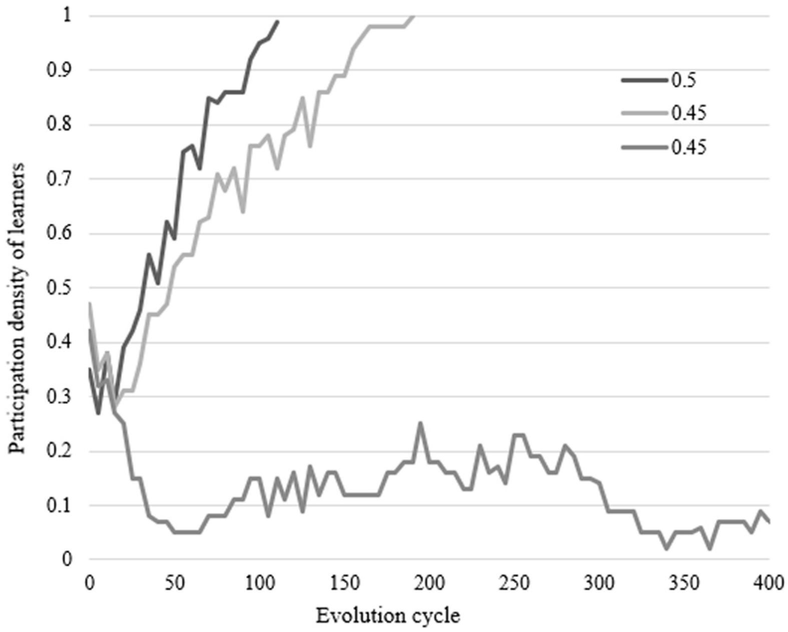


**Fig. 4.** Evolution results of 10 teachers

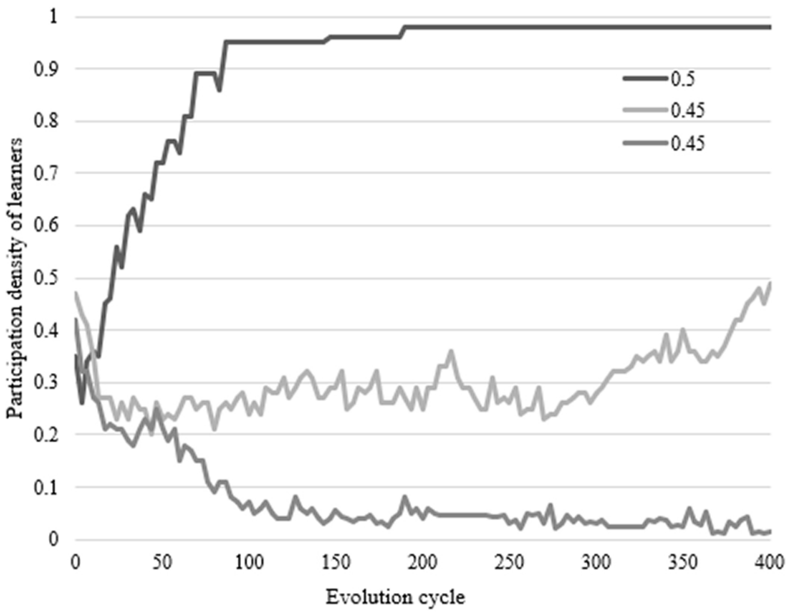


**Fig. 5.** Evolution results of 20 lectures

It is not difficult to see from the results of Tables 3 and 6 that in the natural state, due to the continuous development of distance education platforms, the number of new teachers on the platform changes, and learners' feedback attitudes towards teachers will evolve in two directions: first, learners have a positive feedback attitude towards teachers and teachers adjust teaching strategies for learners, and both parties can obtain gains; second, learners have a negative feedback attitude towards teachers and teachers do not adjust teaching strategies for learners. With the continuous development of distance education platforms, learners cannot obtain ideal learning gains, teachers also lose their influence on students, and the losses of both parties will be increasing. Therefore, in the case of the second direction, the distance education platform needs to implement intervention policies, the loss of learners and teachers can be reduced under reasonable constraint strategies, and learners' feedback attitude towards teachers can be significantly improved in a positive way.

**Table 3.** Jacobi matrix values at points in natural state (1)

| **Equilibrium** | ***det SQ*** | ***tr SQ*** | **Result** |
|---|---|---|---|
| *X*(0,0) | − | Uncertain | Saddle point |
| *Y*(0,1) | − | Uncertain | Saddle point |
| *D*(1,1) | + | + | Unstable |
| *C*(1,0) | + | + | ESS |

**Table 4.** Jacobi values at points in the natural state (2)

| **Equilibrium** | ***det SQ*** | ***tr SQ*** | **Result** |
|---|---|---|---|
| *X*(0,0) | + | − | ESS |
| *Y*(0,1) | − | Uncertain | Saddle point |
| *D*(1,1) | − | Uncertain | Saddle point |
| *C*(1,0) | + | + | Unstable |

**Table 5.** Jacobi values of points under the supervision of distance education platform (1)

| **Equilibrium** | ***det SQ*** | ***tr SQ*** | **Result** |
|---|---|---|---|
| *X*(0,0) | + | − | ESS |
| *Y*(0,1) | − | Uncertain | Saddle point |
| *D*(1,1) | + | Uncertain | Saddle point |
| *C*(1,0) | − | + | Unstable |

**Table 6.** Jacobi values of points under the supervision of distance education platform (2)

| **Equilibrium** | ***det SQ*** | ***tr SQ*** | **Result** |
|---|---|---|---|
| A(0,0) | − | − | Saddle point |
| *Y*(0,1) | + | + | Unstable |
| *D*(1,1) | + | − | ESS |
| *C*(1,0) | − | Uncertain | Saddle point |

## 5 Conclusion

This paper conducts a research on the prediction and evolution of distance education learners' feedback attitudes towards teachers based on deep learning. With the help of deep learning technology, it is easy to discover the advantages of distributed feature representation of data, and ARIMA model is combined with BP neural network model to construct a predictive model of distance education learners' feedback attitudes towards teachers. This paper makes the evolution analysis of distance education learners' feedback attitudes towards teachers, and introduces the assumptions and principles of the evolutionary analysis model in detail. Combined with prediction fitting of the negative feedback attitude under different $q_1$ conditions given by the experiment, the value of $q_1$ is determined according to the error evaluation standard. The paper gives the change in cumulative values of the fitting results of the combined model, and verifies the effectiveness of the constructed model. Taking distance English learning as an example, simulation experiments are used to analyze the evolution direction of distance education learners' feedback attitudes towards teachers. It gives the Jacobi matrix values corresponding to $X$, $Y$, $D$ and $C$ points under different evolutionary stability strategies of learners and teachers in the process of evolution analysis and compare the evolution results of 10 teachers and 20 teachers. Finally, the cause analysis is provided.

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2022 key research project of school-level education and teaching reform (HKJGZD2022-07); Hainan Provincial University Scientific Research Support Project (Hnkyzc2022-19); 2021 School-level Curriculum Reform Research Project of Hainan Vocational University of Science and Technology (EKKG2021-09); 2022 research project of school-level education and teaching reform (HKJG2022-33).

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