Generation and Optimization of Teaching Decision Generation Under a Smart Teaching Environment

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Lei Shi[1], Xiaoling Wu[2](✉)
[1] Department of Music, Shijiazhuang Preschool Teachers College, Shijiazhuang, China
[2] College of Music, Handan University, Handan, China
wuxiaoling_handan@163.com

Abstract—Teaching decisions need to be optimized to guide learners to stick to the right learning method, and maintain learning interests. However, the existing evaluation systems for college teachers' teaching decision ability cannot adapt to online teaching decision-making. What is worse, the previous studies on college teachers' teaching decisions rarely consider online teaching decision-making. Therefore, this paper attempts to optimize college teachers' teaching decision under the smart teaching environment. Specifically, the roadmap of teaching decision generation and optimization was presented, the teaching decision bases were specified for different teaching decision scenarios, and a teaching decision model was established under the smart teaching environment. In addition, teaching decisions were generated based on deep reinforcement learning algorithm, and optimized by certain rules under the experience replay mechanism. The proposed algorithm was proved effective and feasible through experiments.

Keywords—smart teaching, teaching decision generation, decision optimization

1 Introduction

The development and application of smart teaching platforms are promoted by various new smart devices and advanced techniques [1-9]. Online learning is highly susceptible to interference from other factors. Online teaching must be dominated by teachers, and teaching decisions must be optimized based on the data of the smart teaching platform, so as to guide learners to stick to the right learning method, and maintain learning interests [10-15]. Traditional teaching decision-making methods are usually only suitable for specific teaching environments. It is difficult for them to adapt to dynamic, uncertain, complex decision environments [16-21]. Based on artificial intelligence (AI), adaptive decision-making provides a new solution to complex decision-making problems.

So far, most teachers have relied on summative evaluation items as the benchmark for measuring student learning and making teaching decisions. However, these items may not necessarily provide comprehensive evidence for the actual learning process, especially in an online learning environment. After that, it is impossible for them to monitor students' online learning patterns over time. Kaliisa et al. [22] discussed how teachers understand students' learning process through social learning analysis, and thus make smart teaching decisions during course operation. Mceachron and Torres [23] measured the application value of educational decision support system in the field of education, and its impact on the educational environment. Through a case study on 26 British teachers, Webb and Cox [24] investigated various aspects of the teaching reasoning process, including the beliefs and knowledge used, examined the reasoning behind decisions related to the utilization of information and communications technology (ICT), developed a teaching practice framework related to different types and usages of ICT, and applied the framework to real cases to illustrate ICT-related teaching practices. Salcedo et al. [25] developed a knowledge-based distance education system, which plans teaching strategies through a neural network, and described various issues, including the motivation for creating the platform, the theoretical basis of the platform, the services provided by the system, and the operating results of the system. Kwok et al. [26] optimized and validated a prototype of a smart decision support system for teaching task assignments, and tested the algorithm on a real dataset from a secondary school. The algorithm results were compared with the manually collected results of the school president, revealing that the algorithm is highly feasible.

Domestic and foreign scholars have probed deep into college teachers' teaching decisions. In foreign countries, the existing evaluation systems for college teachers' teaching decision ability concentrate on decision-making on college or school level, and cannot adapt to online teaching decision-making. In China, the research into college teachers' teaching decisions mostly stop at evaluating the decision values, paying little attention to the decision practice in online teaching. Taking music teaching for example, this paper attempts to optimize college teachers' teaching decision under the smart teaching environment. The main research contents are as follows: Section 2 presents the roadmap of teaching decision generation and optimization, specifies the teaching decision bases for different teaching decision scenarios, and builds a teaching decision model under the smart teaching environment. Section 3 generates teaching decisions based on deep reinforcement learning algorithm. Section 4 optimize the generated decisions by certain rules under the experience replay mechanism. The proposed algorithm was proved effective and feasible through experiments.

2 Modeling

Figure 1 explains the roadmap of teaching decision generation and optimization, and presents the basis for teaching decision-making under different scenarios, including decision of teaching plan, that of teaching interaction, and that of teaching effect reflection. For online and offline teaching, the decision of teaching plan is affected by teaching goal, teaching content, and teaching method, and based on learning situation, teaching environment, teaching style, textbook, and school requirements. The decision of teaching interaction is influenced by method selection, and strength/weakness analysis, tool determination, and affectivity improvement, and based on highlighting student subjectivity, technology update, and classroom feedbacks. The decision of teaching effect reflection is impacted by teaching evaluation, and teaching results, and based on learning results, mutual evaluation results, and subjective experience of teachers.

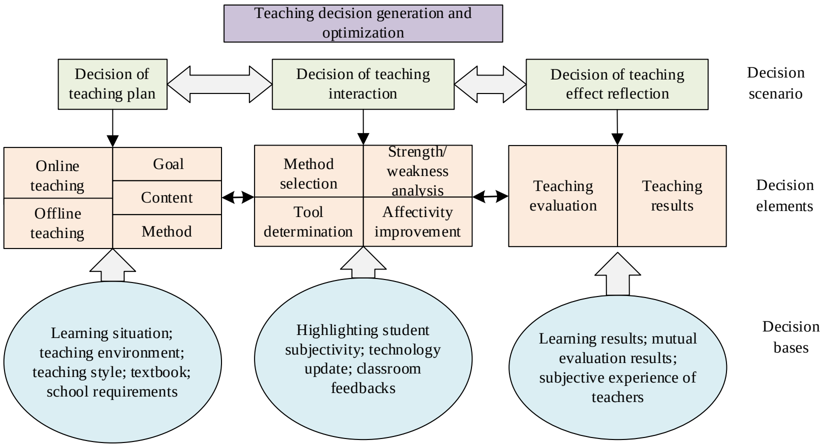

Fig. 1. Roadmap of teaching decision generation and optimization

Based on the above roadmap, a teaching decision model was established for college teachers under the smart teaching environment (Figure 2). Specifically, a decision is generated and optimized through the following steps: (1) collecting and sorting out the data on teaching decision elements; (2) processing the existing data, judging the current teaching state, and estimating the teaching state; (3) generating the teaching decision based on deep reinforcement learning, and optimizing the generated decision by certain rules, following the experience replay mechanism; (4) implementing the decision, and evaluating the effectiveness of the decision. The generation and optimization of teaching decisions are detailed below.

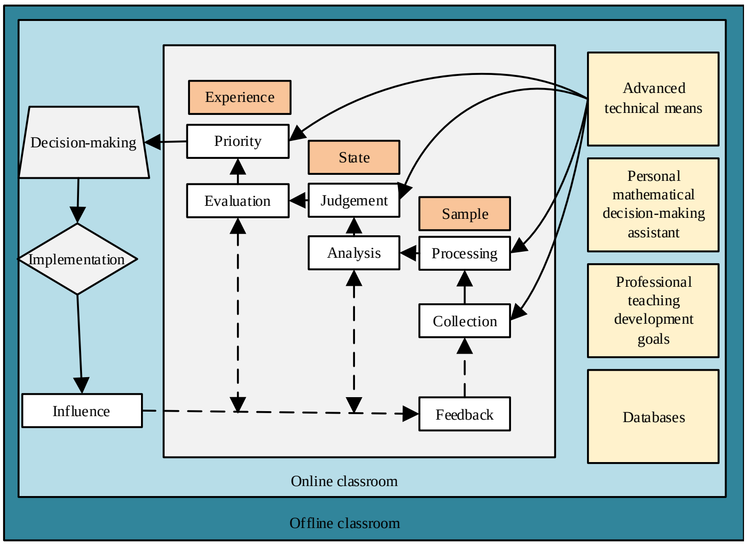

Fig. 2. Architecture of teaching decision model under the smart teaching environment

3 Decision generation

Model-free deep reinforcement learning has been applied in finance and intelligent control, thanks to its capability of realizing many automated decision and control tasks. However, the algorithm faces problems like high computing cost and unideal convergence, which bottleneck its adaptivity to complex decision environments. To overcome these problems, this paper generates each college teachers' teaching decision by an improved maximum entropy reinforcement learning algorithm, and maximizes the expected reward and entropy of the decision. The improved algorithm boasts a strong exploration ability and a high robustness.

The training goal of traditional reinforcement learning is to maximize the cumulative expected reward of the decision:

$$\varepsilon^* = arg\max_{\pi} \sum_{\tau=0}^{\psi} F_{(r_\tau, o_\tau)\sim\sigma_\pi}\left[s(r_\tau, o_\tau)\right] \tag{1}$$

The training goal of maximum entropy reinforcement learning can be expressed as:

$$\varepsilon^* = arg\max_{\pi} \sum_{\tau=0}^{\psi} F_{(r_\tau, o_\tau)\sim\sigma_\pi}\left[s(r_\tau, o_\tau) + \beta E(\varepsilon(\cdot \mid r_\tau))\right] \tag{2}$$

Comparing formulas (1) and (2), the maximum entropy reinforcement learning has one more entropy term than the traditional reinforcement learning. In maximum entropy reinforcement learning, the cumulative expected reward of the decision and the entropy of decision implementation should be maximized at the same time. Let β be the relative importance of the entropy term relative to expected reward. Then, the entropy can be expressed as:

$$\beta E(\varepsilon(\cdot \mid r_\tau)) = \sum_{\tau=0}^{\psi} \varepsilon(\cdot \mid r_\tau) log\, \varepsilon(\cdot \mid r_\tau) \tag{3}$$

Formula (3) shows that the stochasticity of the optimal decision can be adjusted by regulating β. Through maximum entropy reinforcement learning, the probability of decision implementation is scattered as much as possible, rather than focusing on one decision only.

To solve the optimal decision through dynamic programming, the basic maximum entropy reinforcement learning was derived from the angle of policy iteration. The derivation process includes decision evaluation and decision improvement.

Decision evaluation aims to compute the size of decision ε based on the goal of maximum entropy learning. For a fixed strategy, the state transfer probability is expressed as FV, the state value function as $D(r_{\tau+1})$, and the Bellman operator as ψ^ε. Then, the soft Q value can be solved iteratively from any function W: $R\times X\rightarrow U$, which satisfies $W^{l+1}=\psi^\varepsilon W^l$:

$$\psi^\varepsilon W(r_\tau, o_\tau) \stackrel{\Delta}{=} u(r_\tau, o_\tau) + \alpha F_{r_{\tau+1}\sim t}\left[D(r_{\tau+1})\right] \tag{4}$$

As $l \rightarrow \infty$, function W^l will converge to the soft Q value of decision ε. The soft state value function $D(r_\tau)$ can be expressed as:

$$D(r_\tau) = F_{o_\tau \sim \varepsilon}\left[W(r_\tau, o_\tau) - log\varepsilon(o_\tau \mid r_\tau)\right] \tag{5}$$

Let ε_N and ε_O be the new and old values of decision ε, respectively. During decision improvement, the decision in each state can be updated by:

$$\varepsilon_N = arg\min_{\varepsilon \in \Pi} RB_{LK}\left(\varepsilon'(\cdot \mid u_\tau) \| \frac{exp\left(W^{\varepsilon_O}(u_\tau, \cdot)\right)}{C^{\varepsilon_O}(u_\tau)}\right) \tag{6}$$

where, $C^{\varepsilon old}(r_\tau)$ is responsible for normalizing decision distribution. This term can be neglected, because it does not significantly affect the gradient of the new decision.

The above algorithm can only be executed in exact form under discrete conditions. To overcome the limitation, this paper constructs a decision optimization network based on Soft Actor-Critic algorithm. The soft Q value of the algorithm is characterized by a function approximator. The evaluation and improvement links are performed alternatively until convergence.

The established decision optimization network consists of two Q networks and two state value networks. The Q networks are expressed as $W_\omega(r_\tau,o_\tau)$, responsible for outputting the value of the selected decision. The two state value networks are expressed as $D_\Phi(r_\tau)$ and $D_{\Phi'}(r_{\tau+1})$, responsible for outputting the value r_τ of the current state, and that $r_{\tau+1}$ of the next state, respectively. The decision network can be expressed as $\varepsilon_\Omega(o_\tau|r_\tau)$, responsible for outputting the decision implementation under the current state.

The quadratic sum of the residual function is minimized by training the state value function of the network. Let RB be the replay buffer. Then,

$$XL_D(\Phi) = F_{r_\tau \sim RB}\left[\frac{1}{2}\left(D_\Phi(r_\tau) - F_{o_\tau \sim \varepsilon_\Omega}\left[W_\omega(r_\tau, o_\tau) - log\varepsilon_\Omega(o_\tau \mid r_\tau)\right]\right)^2\right] \tag{7}$$

The gradient of formula (7) can be calculated by:

$$\hat{\nabla}_\Phi XL_D(\Phi) = \nabla_\Phi D_\Phi(r_\tau)\left(D_\Phi(r_\tau) - W_\omega(r_\tau, o_\tau) + log\varepsilon_\Omega(o_\tau \mid r_\tau)\right) \tag{8}$$

According to the current decision, the decision implementation is sampled. Then, the soft Q function is trained to minimize the Bellman residual:

$$XL_W(\omega) = F_{(r_\tau, o_\tau) \sim RB}\left[\frac{1}{2}\left(W_\omega(r_\tau, o_\tau) - W^*(r_\tau, o_\tau)\right)^2\right] \tag{9}$$

where, $W^*(r_\tau,o_\tau)$ can be given by:

$$W^*(r_\tau, o_\tau) = s(r_\tau, o_\tau) + \alpha F_{r_{\tau+1} \sim t}\left[D_{\Phi'}(r_{\tau+1})\right] \tag{10}$$

Introducing the objective value network $D_{\Phi'}$ to perform stochastic gradient optimization of formula (9):

$$\hat{\nabla}_{\omega} XL_W(\omega) = \nabla_{\omega} W_{\omega}(o_{\tau}, r_{\tau})(W_{\omega}(r_{\tau}, o_{\tau}) - u(r_{\tau}, o_{\tau}) - \alpha D_{\Phi'}(r_{\tau+1})) \tag{11}$$

The decision network parameter for Kullback-Leibler (KL) divergence can be minimized by:

$$XL_{\varepsilon}(\Omega) = F_{r_{\tau} \sim RB}\left[RB_{KL}\left(\varepsilon_{\Omega}(\cdot \mid r_{\tau}) \parallel \frac{exp(W_{\omega}(r_{\tau}, \cdot))}{C_{\omega}(r_{\tau})}\right)\right] \tag{12}$$

Let ρ_τ be the noise. During the selection of decision implementation, ρ_τ is introduced to satisfy a certain distribution. The actual strategy ε_Ω is defined as g_Ω. Then, decision implementation o_τ can be expressed as:

$$o_{\tau} = g_{\phi}(\rho_{\tau}; r_{\tau}) \tag{13}$$

By sampling from a fixed distribution, formula (12) can be converted into:

$$XL_{\varepsilon}(\Omega) = F_{r_{\tau} \sim RB, \rho_{\tau} \sim M}\left[log\,\varepsilon_{\Omega}(g_{\Omega}(\rho_{\tau}; r_{\tau}) \mid r_{\tau}) - W_{\omega}(r_{\tau}, g_{\Omega}(\rho_{\tau}; r_{\tau}))\right] \tag{14}$$

The gradient of formula (14) can be calculated by:

$$\begin{aligned} &\hat{\nabla}_{\Omega} XL_{\varepsilon}(\Omega) = \nabla_{\Omega} log\,\varepsilon_{\Omega}(o_{\tau} \mid r_{\tau}) \\ &+ (\nabla_{o_{\tau}} log\rho_{\Omega}(o_{\tau} \mid r_{\tau}) - \nabla_{o_{\tau}} W(r_{\tau}, o_{\tau}))\nabla_{\Omega} g_{\Omega}(\rho_{\tau}; r_{\tau}) \end{aligned} \tag{15}$$

Soft Actor-Critic algorithm relies on two Q networks to effectively reduce the deviation produced in decision improvement, and accelerate network training, especially under complex decision environments. In the above analysis, the gradient of state value and that of decision can be characterized by the minimum values of the two Q functions.

4 Decision optimization

Experience replay is the most crucial link in the implementation of deep reinforcement algorithm. Figure 3 explains the principle of experience replay mechanism for teaching decision optimization: the teaching experiences are randomly and repeatedly sampled from the historical music teaching samples in experience replay buffer, and used to optimize the teaching decision. Different teaching experiences in the buffer are of different importance in the optimization of the generated teaching decision. To differentiate the teaching experiences by importance, this paper introduces the priority experience replay into Soft Actor-Critic algorithm.

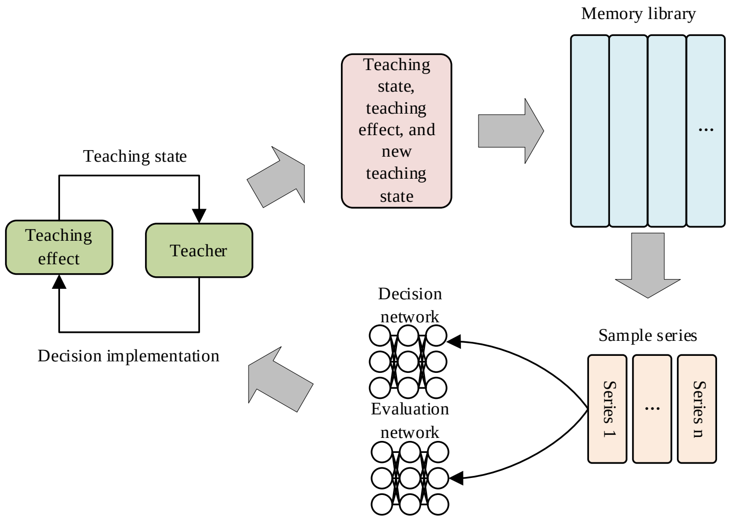

Fig. 3. Principle of experience replay mechanism for teaching decision optimization

Here, the experience value is evaluated by a special index: the estimation error *TD-error* of the experience states corresponding to different time points. Since the algorithm has two *Q* networks, the absolute value of experience state estimation error of the algorithm equals the mean absolute value of the experience state estimation errors of the two networks:

$$|\xi| = \frac{1}{2}\sum_{k=1}^{2}\left|u + \alpha D_{\Phi\text{-}OB}(r') - W_{\omega,k}(r,o)\right| \tag{16}$$

On the right side of formula (16), the first term $s+\alpha D_{\Phi\text{-}OB}(r')$ is the goal network of *W*, and the second term $W_{\omega,k}(r,o)$ is the current estimate of the network of the k-th *W*.

Random sampling was employed to prevent the lack of sample diversity, which arises from the utilization of the priority of experience state estimation error. The probability of sampling experience *i* can be calculated by:

$$FV(i) = \frac{h_i^{\beta}}{\sum_l h_l^{\beta}} \tag{17}$$

Let *rank*(*i*) be the rank of experience *i* in replay buffer. Taking the absolute value of experience state estimation error as the criterion, priority h_i=1/*rank*(*i*) is greater than zero. Parameter β controls the degree of utilization of h_i. β=0 and β=1 correspond to even sampling and greedy sampling, respectively.

If the decision prefers to play back the experiences with high experience state estimation errors frequently, the state access frequency will change. Then, the network training will oscillate or diverge. Therefore, this paper adopts importance sampling weights. Let M be the scale of the playback buffer; $FV(i)$ be the probability of sampling experience i. Then, we have:

$$\theta_i = \left(\frac{1}{M}\cdot\frac{1}{FV(i)}\right)^{\lambda} \tag{18}$$

where, λ controls the degree of correction. If λ=0, it is not necessary to implement importance sampling; if λ=1, regular importance sampling will be performed. As network training approaches the end, the λ value must approximate 1.

Suppose the current update phase needs to cyclically take L mini batch data from the replay buffer. For the l-th update, the samples are collected evenly from the latest u_l data points. Then, we have:

$$u_l = max\left\{M\cdot\gamma^{l\frac{1000}{L}}, u_{min}\right\} \tag{19}$$

where, $\gamma\in(0, k]$ is a hyperparameter determining the importance attached to the recent data. If γ=1, even sampling will be performed; if γ<1, the sampled number will gradually decrease with the growing number of updates. Let u_{min} be the minimum threshold of u_l. By controlling u_l, it is possible to avoid collecting samples from the few recent samples of music teaching. Therefore, this paper performs even sampling in the first update. The γ value condition for the last update can be expressed as:

$$\gamma^{L\frac{1000}{L}} = \gamma^{1000} \tag{20}$$

During network training, this paper optimizes γ value with simulated annealing (SA) algorithm. Let ψ be the total time step of network training; γ_0 and γ_{END} be the initial and final values of γ, respectively. If γ_{END}=1, even sampling will be performed. Then, the γ value corresponding to the time step τ can be calculated by:

$$\gamma_\tau = \gamma_0 + (\gamma_{END} - \gamma_0)\cdot\frac{\tau}{\psi} \tag{21}$$

When the collected music teaching samples are sufficient, L mini batch updates are carried out. Let EMu_l be the u_l most recent experience data samples in the replay buffer. Then, the probability of sampling a single data sample can be calculated by:

$$FV(i) = \frac{h_i^\beta}{\sum_j h_j^\beta}, i, j \in EM_{u_l} \tag{22}$$

5 Experiments and results analysis

This paper carries out a chi-squared test on the combination between each of the three teaching decision scenarios and each of the corresponding teaching decision elements. Table 1 summarizes the approximate power of the Pearson chi-square test of each decision element. It can be seen that the decision of teaching plan has a significant correlation with teaching goal, teaching content, and teaching method; the decision of teaching interaction has a significant correlation with method selection, strength/weakness analysis, tool determination, and affectivity improvement; the decision of teaching effect reflection has a significant correlation with teaching evaluation and teaching result. The results confirm the scientific nature of the selected decision elements.

Table 1. Chi-squared test results of different decision elements

	Decision of teaching plan	Decision of teaching interaction	Decision of teaching effect reflection
Teaching goal	0.001	0.241	0.275
Teaching content	0.002	0.251	0.314
Teaching method	0.001	0.082	0.145
Method selection	0.137	0.001	0.118
Strength/weakness analysis	0.263	0.000	0.208
Tool determination	0.241	0.002	0.185
Affectivity improvement	0.182	0.001	0.183
Teaching evaluation	0.215	0.128	0.003
Teaching result	0.136	0.172	0.001

This paper looks for the optimal solution of model training, using Adam optimizer and gradient descent optimizer, respectively. Repeated experiments were carried out under online teaching and offline teaching scenarios. The mean number of training steps was obtained as each algorithm completes decision-making. The results of traditional Soft Actor-Critic algorithm are compared with those of our algorithm in Table 2. The comparison shows that the Soft Actor-Critic algorithm with priority experience replay achieved higher training efficiency, stronger stability, faster convergence, and better robustness than the original Soft Actor-Critic algorithm.

The ROC curves of different types of decision optimization obtained by our algorithm can be found in Weka software. Figure 4 divides the ROC curves into categories like excellent, poor, and general. These curves reflect the relationship between true positive and false positive. As shown in Figure 4, the optimization performance of different categories ranked as excellent, poor, and general. Hence, the excellent teaching decision generated by our algorithm has the best optimization effect.

Table 2. Training steps of different algorithms in decision-making

Algorithm		Traditional Soft Actor-Critic algorithm	Our algorithm
Online teaching	Adam optimizer	361	32
	Gradient descent optimizer	163	25
Offline teaching	Adam optimizer	525	42
	Gradient descent optimizer	325	29

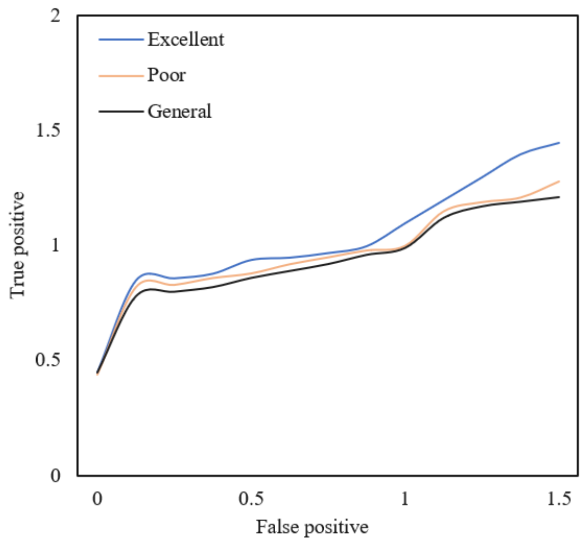

Fig. 4. Receiver operating characteristic (ROC) curves of different types of decision optimization

Through comprehensive analysis of the performance of the teaching decisions generated by each teaching decision element, it is possible to clarify the direction of improving the implementation effect of teaching decisions, e.g., highlighting student subjectivity, stressing affectivity improvement, learning situation analysis, teaching environment creation, interaction tool determination, and modern teaching technology update. Whether online teaching or offline teaching, teaching decision-making must focus on learning motivation, learning interests, as well as the learning state of students with learning difficulties. This paper collects music teaching samples, which cover such aspects as music theory, sight singing, singing, instrumental music, and music appreciation. Figure 5 shows the error percentage of teaching effect of different samples after the execution of teaching decisions. It can be seen that the teaching effect of the generated teaching decision deviated from the target teaching effect by less than 7%. This means our teaching method is highly effective.

The sources of unideal teaching effect were discovered after preliminary analysis of the existing samples of music teaching. In addition, the authors collected the teaching states of student problems and teaching plan problems, which are evaluated based on music teaching samples. The specific problems include unstable performance, uneven distribution of performance, inaccurate grasp of key difficulties, deviation of teaching contents from teaching goals, etc. This paper uses a fishbone diagram (Figure 6) to illustrate the existing data on music teaching samples and the evaluated teaching states, aiming to disclose the deep-seated reasons of unideal teaching effect, and to help teachers find the right solution.

As shown in Figure 6, the current teaching state was sorted out, and the causes of unreal teaching effect were mined from two aspects: student problems, and teaching plan problems. Teachers should make a solution in view of the personal learning needs of students in the class, from both dimensions of students and teaching plan.

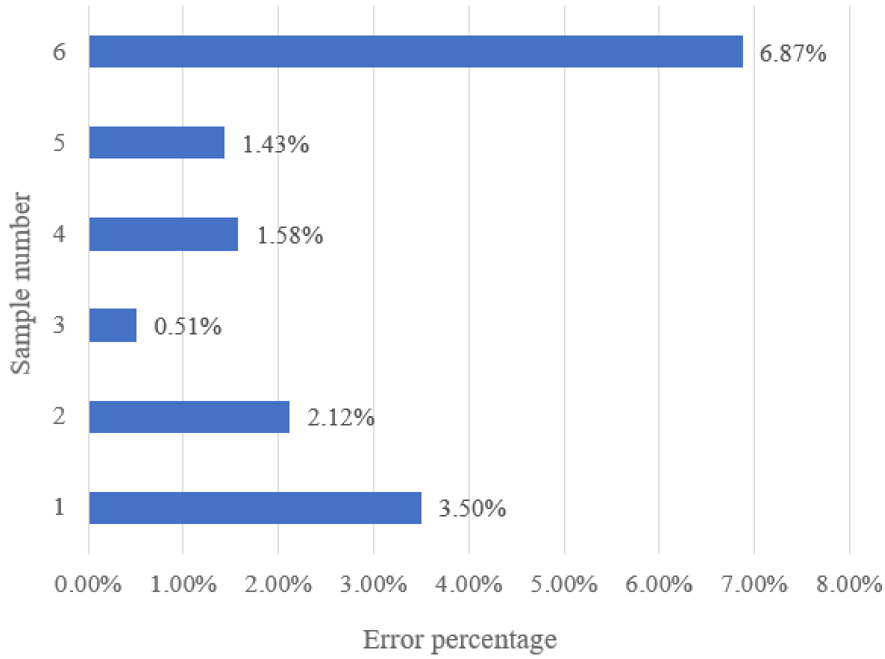

Fig. 5. Error percentage of teaching effect of different samples

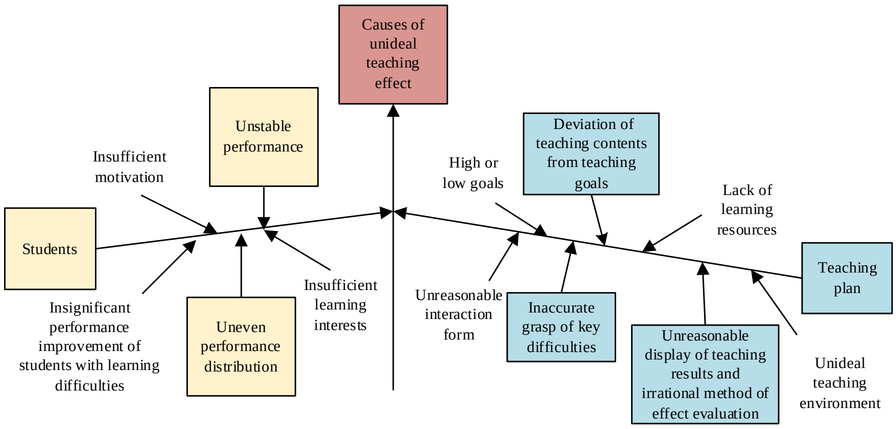

Fig. 6. Fishbone diagram

6 Conclusions

This paper explores the optimization of college teachers' teaching decision under the smart teaching environment. Firstly, the roadmap of teaching decision generation and optimization was presented, and the teaching decision bases were specified for different teaching decision scenarios. Next, a teaching decision model was established under the smart teaching environment, and teaching decisions were generated based on deep reinforcement learning algorithm. The generated decisions were optimized by certain rules under the experience replay mechanism. After that, a chi-squared test was performed on the combination between each of the three teaching decision scenarios and each of the corresponding teaching decision elements. The test results confirm the scientific nature of the selected decision elements. Then, the training steps of different algorithms in decision-making were compared, revealing that our algorithm achieved higher training efficiency, stronger stability, faster convergence, and better robustness than the original Soft Actor-Critic algorithm. Further, the authors drew the ROC curves of different types of decision optimization, and computed the error percentage of teaching effect of different music teaching samples. It was learned that the excellent teaching decision generated by our algorithm has the best optimization effect. Finally, fishbone diagram analysis was conducted, and suggestions were given on how to prepare a solution to teaching problems.

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8 Authors

Lei Shi, was born on November 1980 in Shijiazhuang City, Hebei Province, China. She received B.A. Degree in Musical Education of Hebei Normal University in 2002 and M.A. Degree in Music Performance of Monash University, Australia in 2012. She started her teaching career in 2002 in School of Film and Television Arts of Hebei University. At present, she is the Associate Professor of Arts School of Shijiazhuang Preschool Teachers College and the Judge of the Piano Grade Test Committee of Hebei Provincial Musician Association. Since 2002, She has authored than 6 papers in musical education and arts student management. In 2014, She compiled the piano college textbook "Learning Piano Starts Here". As the art director, In July 2013, she led the Hebei Children's Choir to participate in the 7th Vienna World Peace Chorus Festival in Austria, and won the group gold medal and the individual "Best Piano Performance Award". In June 2016, they went to Hungary to participate in the 21st Kodaj Zoldan International Children's Chorus Festival and won the "Best Nursery Rhyme Performance Award". In April 2018, they won the first prize of the group in the "Sing of Moscow" International Art Festival held in Russia (email: shilei@syty.edu.cn).

Xiaoling Wu, was born in Jilin, China, in 1978. From 1998 to 2002, she studied in Hebei Normal University and received her bachelor's degree in 2002. Her major research is vocal performance. From2005 to 2008, he studied in Hebei University and received her Master's degree in 2008.She mainly studies music performance and music theory, including Chinese and foreign music history, Chinese folk music, and postmodern music. From 2008 to 2020, she worked in Handan University of Art Department. Currently, she has published six papers, one of which has been indexed by SCI. During her work, she once worked as a counselor for three years, and won the title of "Advanced Individual of Moral Education" and "The most Beautiful Instructor" at the university level. In 2017, she won the first prize in the whole school teaching competition, and hosted and participated in several projects at all levels. At present, she teaches two courses, vocal music skills and Chinese folk music.

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