Design and Realization of Experiential Teaching Based on Knowledge Feature Transformation of Course Teaching

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Abstract—Experiential teaching, which combines real environment with virtual environment, helps students understand and internalize knowledge. To a certain extent, the organization and design of experiential teaching can promote the education reform in the new era. The existing studies on experiential teaching mostly emphasize theoretical applications, without paying much attention to teaching process and practical methods. Therefore, this paper designs and realizes experiential teaching based on knowledge feature transformation of course teaching. Firstly, node betweenness was selected as the reference metric for allocating the initial granularity importance to the knowledge points of physical education (PE) course teaching, and the macro-importance of the course was proportionally allocated to the known granularity of knowledge points. Next, a knowledge network was established for PE course teaching, and the named entities were identified based on course teaching knowledge features. The purpose is to extract the knowledge points of experiential PE teaching units, with class hour as the unit, and to determine their teaching sequence. After that, the design frameworks were established for experiential teaching scenarios and experiential learning activities, and the course evaluation strategy was provided for students majoring in sports dance, a professional PE course. Experimental results show that our approach achieves excellent effects on designing and implementing experiential learning activities.

Keywords—course teaching, knowledge feature transformation, experiential teaching

1 Introduction

During the actual teaching process, intense practical teaching is necessary for many courses, such as the courses of physical education (PE) and arts [1-7]. Originating from foreign training industry, experiential teaching allows students to acquire knowledge and skills in real or virtual environment [8-17]. Through experiential teaching, the real environment is integrated with virtual environment to help students understand and internalize knowledge. Hence, this teaching model depends heavily on the feature transformation of teaching knowledge, and the coherence of knowledge points in course teaching [18-23]. To a certain extent, the organization and design of experiential teaching can promote the education reform in the new era.

Practice is fundamental to the courses of any scientist, engineer, and technician. It enables students to face the real world, put their knowledge into practice, and judge the operability of knowledge. To ensure that an educational system can better meet student needs, Gourmaj et al. [24] presented a solution based on students' personal learning environment, in which the learning module of specific goals is realized through remote experiments.

The application of experiential teaching is largely limited to informal learning. Despite being occasionally introduced to classroom, experiential teaching has not substantially helped teaching or learning. After deeply examining the common problems of experiential teaching, Lv and Zheng [25] designed an experiential teaching model based on e-schoolbag, and analyzed the teaching of chemistry in a senior middle school, aiming to enrich the theories on experiential teaching, and provide more cases for experiential teaching practice.

Knowledge managers traditionally focus on knowledge sharing. Nowadays, knowledge generation has become a new focal point among knowledge managers. Benítez et al. [26] put forward two theoretical model for the generation of students' experiential knowledge in higher education: a teacher-centered generation model, and a student-centered generation model. Then, the essence of student experiential knowledge was expounded, drawing on a series of theories on knowledge management and experiential learning.

To solve information loss, the lack of salient features, and the weak generalization ability, Tang et al. [27] proposed a knowledge-based prototype network of diversity feature transformation. Chen et al. [28] constructed a model for teacher knowledge transformation in online collective teaching preparation, and analyzed the circular conversion of teacher knowledge between individuals and the collective, through specific examples. The results show that teachers internalize explicit knowledge into implicit knowledge through practice and reflection, and promote their professional development via the iterative update of knowledge.

In general, the existing studies on experiential teaching mostly emphasize theoretical applications, without paying much attention to teaching process and practical methods. Very few researchers have carried out the detailed design for knowledge feature transformation of course teaching in the context of experiential teaching. It is an urgent issue to carry out effective experiential learning activities, while ensuring the teaching quality.

Taking professional PE courses for example, this paper designs and realizes experiential teaching based on knowledge feature transformation of course teaching. Section 2 selects node betweenness as the reference metric for allocating the initial granularity importance to the knowledge points of PE course teaching, and proportionally allocates the macro-importance of the course to the known granularity of knowledge points. Section 3 sets up a knowledge network for PE course teaching, and identifies the named entities based on course teaching knowledge features, with the aim to extract the knowledge points of experiential PE teaching units, with class hour as the unit, and to determine their teaching sequence. Section 4 establishes the design frameworks for experiential teaching scenarios and experiential learning activities, and provides the course evaluation strategy for students majoring in sports dance, a professional PE course. Experimental results show that our approach achieves excellent effects on designing and implementing experiential learning activities.

2 Course knowledge importance algorithm

In our PE course teaching knowledge network, each node represents a knowledge point in course teaching. This paper selects node betweenness as the reference metric for allocating the initial granularity importance to the knowledge points of PE course teaching. That is, the macro-importance of the course is allocated to the known granularity of knowledge points, in reference to the betweenness of the knowledge points in the PE course. Let UE_l^Z be the known reference importance of PE course *l*. Then, the initial importance of knowledge point *i* in course *l* can be calculated by:

$$UE_i^Y = \frac{Y_i}{\sum_{u_j^Y \in u_l} Y_j} UE_l^Z \tag{1}$$

In practice, UE_l^Z can be determined by the distribution of credits of the PE course.

In PE course teaching, the knowledge points must be taught coherently. In other words, the antecedent nodes in the PE course teaching knowledge network must be the prior knowledge of the subsequent nodes. If the subsequent nodes are important, then the corresponding antecedent nodes must be important, too. The importance is transferred from the antecedent nodes to the subsequent nodes, and the other way round. Let FDN_i be the set of antecedent nodes of node u_i^Y; PZ_i be the set of nodes with node u_i^Y as the prior knowledge; l^{out} and l^{in} be the out-degree and in-degree of a node, respectively. Then, formula (1) can be modified into:

$$UE_i^Y(l) = \sum_{u_i^Y \in FDN_i} \frac{UE_j^Y(l-1)}{l_j^{out}} + \sum_{u_i^Y \in PZ_i} \frac{UE_i^Y(l-1)}{l_k^{in}} \tag{2}$$

Since the initial granularity importance of the knowledge point at each node cannot be fully transferred to the subsequent nodes, the importance of a node is only affected by the antecedent nodes. Then, formula (2) can be further revised into:

$$UE_i^Y(l) = \frac{\left(\sum_{u_i^Y \in FDN_i} \frac{UE_j^Y(l-1)}{l_j^{out}} + \sum_{u_i^Y \in PZ_i} \frac{UE_i^Y(l-1)}{l_l^{in}} + UE_i^Y(l-1) \right)}{2} \tag{3}$$

Formula (3) shows that, during the transfer of the granularity importance of knowledge points, every time node u_i^Y allocates the importance to subsequent nodes, it also retains the granularity importance of its own knowledge point.

Considering the shear size and complex structure of our PE course teaching knowledge network, the students will inevitably encounter dilemmas like the lack of subsequent knowledge points or the loop of knowledge points, during the knowledge feature transformation of PE course teaching. In either situation, the students need to switch to other nodes in the same chapter of the course. Let UE^R be the granularity importance of knowledge points in the chapter of knowledge point *i*, i.e.., the sum of the granularity importance of all M^R knowledge points in that chapter; λ be the probability of facing a dilemma. Following formula (3), the granularity importance of node *i* is allocated evenly to the other nodes in that chapter, based on λ. Then, we have:

$$UE_i^Y(l) = \lambda \frac{\left(\sum_{u_i^Y \in FDN_i} \frac{UE_i^Y(l-1)}{l_j^{out}} + \sum_{u_i^Y \in PZ_i} \frac{UE_i^Y(l-1)}{l_j^{Fin}} + UE_i^Y(l-1) \right)}{2} + (1-\lambda) \frac{UE^R(l-1)}{\left(M^R\right)^2} \tag{4}$$

3 Named entity identification

The data of the PE course teaching knowledge network are usually merged from preprocessed data from multiple sources. As a result, there is a high diversity of the network data in terms of network structure and node granularity. This section identifies the named entities in the proposed PE course teaching knowledge network based on course teaching knowledge features, aiming to extract the knowledge points of experiential PE teaching units, with class hour as the unit, and to determine their teaching sequence. In other words, the entities suitable for experiential PE teaching are extracted from the semi-structured teaching knowledge text, and divided into different classes.

The hidden Markov model (HMM) and conditional random field (CRF) were adopted to identify the named entities based on course teaching knowledge features. Let *M* be the total number of states for course teaching knowledge features; *N* be the number of observable states for course teaching knowledge features. Then, the set of the *M* states, and the set of the *N* states can be expressed as:

$$B = \{b_1, b_2, b_3, \cdots, b_M\}, A = \{a_1, a_2, a_3, \cdots, a_N\} \tag{5}$$

The HMM was adopted to identify the named entities based on course teaching knowledge features, such as to label every potentially observable state for course teaching knowledge features, and to recognize the unlabeled entities of course teaching knowledge features in the corpus, while predicting their classes. Among the named entities, the unlabeled entities in the corpus and their classes are forecasted based on the series of labeled observable states. The structure of the HMM is illustrated in Figure 1. According to the Markov properties, the state b_τ of variable *B* at time τ

is only affected by its state $b_{\tau\text{-}1}$ at time τ-1; the state a_τ of variable A at time τ depends on b_τ. Then, we have:

$$CG\left(A_m, B_m\right) = CG\left(b_m \mid b_{m-1}\right) CG\left(a_m \mid b_m\right) \tag{6}$$

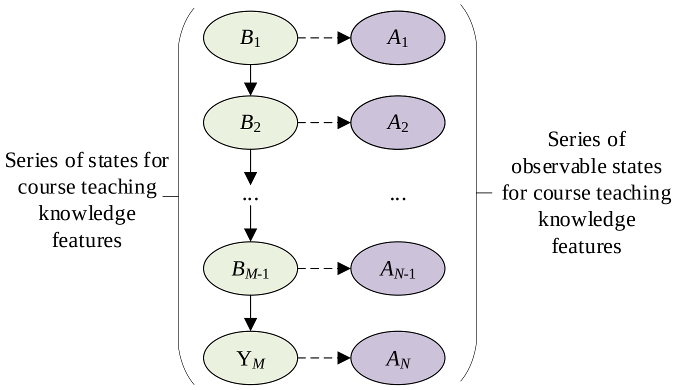

Fig. 1. Structure of HMM

The joint probability can be calculated by:

$$\begin{aligned} &CG\left(a_1, b_1, a_2, b_2, \cdots, a_m, b_m\right) = \\ &CG\left(b_1\right) CG\left(a_1 \mid b_1\right) \prod_{i=2}^{m} CG\left(b_i \mid b_{i-1}\right) CG\left(a_i \mid b_i\right) \end{aligned} \tag{7}$$

The next goal is to solve the conditional probability of each core variable, according to the potentially observable course teaching knowledge features. To this end, the CRF was employed to identify the named entities based on course teaching knowledge features. Suppose variables A and B are both random variables. In the undirected network $H(U,D)$ of course teaching knowledge composed of random variable A, any node is represented by u, and the set of all the nodes connected to node u is denoted as $m(u)$. The distribution probability of A and B must satisfy:

$$CG\left(B_u \mid A, B_{U/\{u\}}\right) = CG\left(B_u \mid A, B_{m(u)}\right) \tag{8}$$

Figure 2 shows the structure of the knowledge network for experiential course teaching. In this paper, the PE course teaching knowledge network is constructed to extract the knowledge points of experiential PE teaching units, and to determine their teaching sequence, according to the organization of course teaching knowledge features. Focusing on the meta-path, long path, and degree reasoning of the PE course teaching knowledge network, this paper derives some tasks of knowledge point extraction, and teaching sequence determination. Then, an experiential PE teaching plan is developed based on the completion state of the tasks.

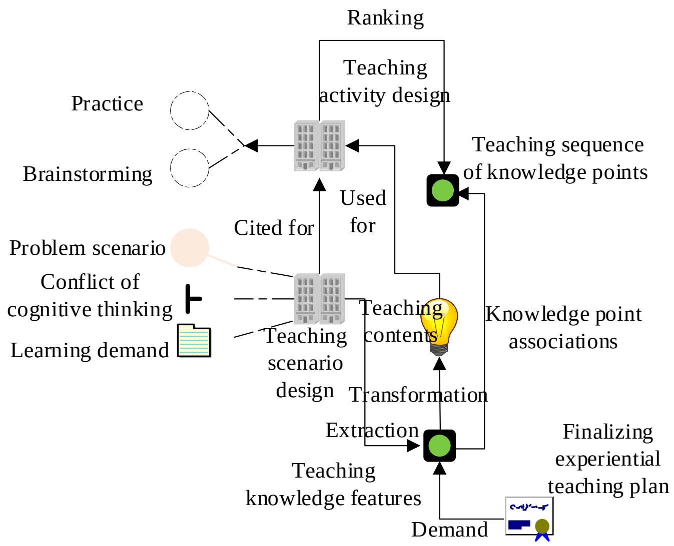

Fig. 2. Structure of experiential course teaching knowledge network

The improved event extraction method was introduced to construct the tasks for the PE course teaching knowledge network. The entities and associations were respectively modeled as course teaching knowledge points, and the associations between knowledge points; the entity extraction task and association extraction task were treated as the prediction problem of teaching sequence of experiential PE knowledge points. The teaching sequence was forecasted incrementally based on several knowledge feature transformations of course teaching. Through the transformation, named entity recognition and knowledge point association extraction were implemented alternatively to make full use of the associations between knowledge points, and to identify the knowledge points and their associations that meet the requirements of experiential PE teaching.

Let R be an input requirement on experiential PE teaching; M_W be the number of knowledge points. The series of knowledge points required by R can be expressed as $R=\{q_1,q_2,q_3,...,q_M\}$. Let u_i^q be the knowledge point vector initialized by Glove matrix; u_i^{LAB} be the eigenvector of knowledge point labels; u_i^{LSTM} be the knowledge point vector spliced by bidirectional long short-term memory (LSTM) network; MST_i be the vector of knowledge point sequence obtained by multilevel Transformer model; u_i^{DSF} be the teaching knowledge point features captured by syntactic dependency parser; u_i^{BL} be the blocking label. The above vectors can be stitched up into the vector of each knowledge point demand q_i by:

$$a_i = \left[u_i^q, u_i^{LAB}, u_i^{LSTM}, MST_i, u_i^{DSF}, u_i^{BL}\right] \tag{9}$$

This paper uses two LSTMs to encode word vector a_i, aiming to capture the knowledge point features required by experiential PE teaching. In this way, the model can obtain the associations between teaching knowledge points:

$$\overleftarrow{f}_i = LSTM_Q\left(\overleftarrow{f}_{i-1}\right) \tag{10}$$

The representation of forward LSTM can be spliced with that of reverse LSTM into a bidirectional representation:

$$f = \left[\overrightarrow{f}_i, \overleftarrow{f}_i\right] \tag{11}$$

After clarifying the associations between knowledge points, the features corresponding to the knowledge points required by experiential PE teaching are stitched up in reverse order to initialize the buffer pool for storing unprocessed knowledge points. For the stack used to store some entities, the initialization is carried out by the stacked LSTM, which can prompt the elements in the series of states for course teaching knowledge features, as a neural network. Let μ_i entity recognized during feature transfer or labeled action identification. Then, the stack state at time τ can be calculated by:

$$r_\tau = STLSTM\left[\mu_0, \mu_1, ..., \mu_\tau\right] \tag{12}$$

Then, the entities and labels are subjected to recursion based on two combinatory functions, and introduced to the knowledge feature transformation system of course teaching. Let $Q_{d,\mu}$ and $Q_{\tau,\mu}$ be the weight parameters of entity d_τ and label τ_i, respectively; k_τ^{FT} and k_τ^{FT} be the feature transformation vectors corresponding to labels and entities, respectively. Then, we have:

$$\mu_i^{trigger} = tanh\left(Q_{\tau,\mu}\left[d_\tau; k_\tau^{trigger}\right] + y_{d,\mu}\right) \tag{13}$$

The model state at time τ can be calculated by:

$$h_\tau = \left[r_\tau; e_\tau; d_\tau; \tau_i; \mu_\tau; f_\tau\right] \tag{14}$$

The teaching sequence of experiential PE knowledge points to be executed at time τ is predicted in the following manner. Firstly, state h_τ is compressed by a fully-connected layer into a low-dimensional vector n_τ. Next, the generation probability of the teaching sequence of experiential PE knowledge points is computed by softmax function. Let Q_n be the weight matrix; v_c be a weight column vector of the teaching sequence c of experiential PE knowledge points; y_c and y_n be the bias terms of that sequence; $u(R,X)$ be the set of all teaching plans for experiential PE knowledge points. Then, we have:

$$n_\tau = tanh\left(Q_n h_\tau + y_n\right) \tag{15}$$

By maximizing the generation probability of the teaching sequence of experiential PE knowledge points, the most probable sequence $CG(c_\tau|n_\tau)$ is adopted for implementing experiential PE teaching:

$$CG\left(c_\tau \mid n_\tau\right)=\frac{exp\left(v_{c_\tau}^T n_\tau+y_c\right)}{\sum_{c\in u(R,X)} exp\left(v_{c_\tau}^T n_\tau+y_c\right)} \tag{16}$$

During the actual training of the neural network, the output structure is converted into the teaching sequence of a group of experiential PE knowledge points. Let ψ be the length of the teaching sequence; ω_G be the set of parameters of the feedforward neural network; δ be the L_2 regularization term. For any transformation state of knowledge points, the negative log likelihood function can be expressed as:

$$SR(\omega)=-\frac{1}{\psi}\sum_{\tau}\log CG\left(c_\tau \mid n_\tau;\omega\right)+\frac{\delta}{2}\left\|\omega_G\right\|^2 \tag{17}$$

4 Experiential teaching design

Before designing experiential learning activities, it is necessary to determine the knowledge points, and their teaching sequence, and to allocate the available resources and tools. Once these issues are solved, it would be possible to design experiential teaching scenarios and activates based on the knowledge points. Figures 3 and 4 provide the design frameworks for experiential teaching scenarios and experiential learning activities, respectively. The specific teaching procedure covers the following steps: experience application, experience acquisition, observation and reflection, and summary. The teaching activity series involve many links, including brainstorming, practice, and evaluation.

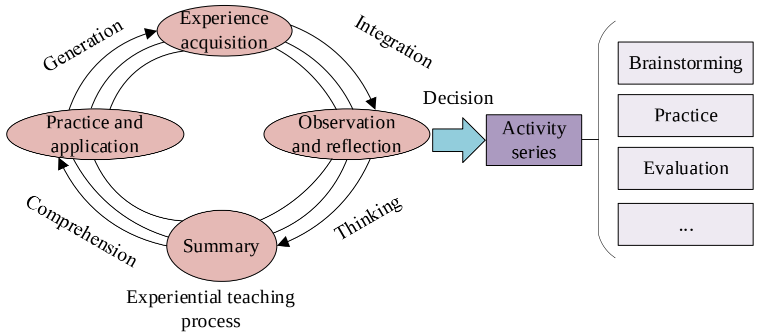

Fig. 3. Design framework of experiential teaching scenarios

Taking sports dance, a professional PE course, for example, the course evaluation strategy of students was presented as follows:

1. Basic task (70 points): The basic task covers four aspects: content understanding (10 points), movement fluidity (30 points), movement accuracy (20), and movement completeness (10 points). Specifically, content understanding (10 points) can be break down into full and clear understanding of the training task (5 points), and clear recognition of the focus of teaching (5 points). Movement fluidity (30 points) includes continuous and reasonable movements (15 points), and completeness of every movement detail (15 points). Movement accuracy (20 points) means that every movement detail is displayed correctly and completely (20 points). Movement completeness (10 points) refers to that each movement is divided clearly, and all details of the complete movement are fully understood (10 points).
2. Aesthetic expression (8 points): Aesthetic expression requires beautiful movement details, in addition to smooth completion of the training task.
3. Movement arrangement optimization (7 points): Movement arrangement optimization indicates that the most beautiful and creative plan is selected out of multiple movement arrangement plans.
4. Problem solution (15 points): Problem solution means the ability of finding the solution to problems through interaction with peers and teachers.

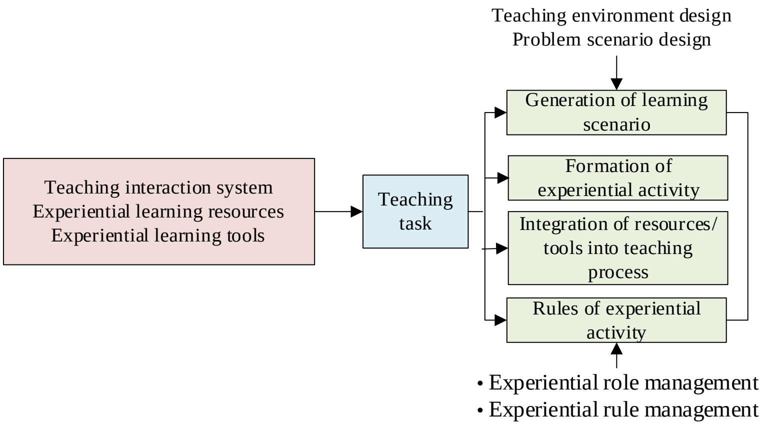

Fig. 4. Design framework of experiential learning activities

5 Experiments and results analysis

Table 1 shows the course teaching knowledge associations obtained by event extraction method. Compared with convolutional neutral network (CNN) (algorithm 1), LSTM (algorithm 2), and structured perceptron (algorithm 3), our algorithm achieved excellent results on precision, recall, and F1 on three different datasets.

During every experiential PE teaching activity, the teacher records the students' mastery of each knowledge point, and their entire thinking process of experience acquisition in the class record sheet, laying the basis for follow-up evaluation of his/her students. After the acquired evaluation data were processed and analyzed, the students' classroom evaluation was discussed in four dimensions: basic task, aesthetic expression, movement arrangement optimization, and problem solution. In this way, the teacher could know how the thinking of each group of students developed during experience acquisition through the four experiential teaching activities. The results in Table 2 show that, with the advancement of experiential teaching activities, the evaluation scores of different groups were all on the rise (Figure 5). Hence, the proposed experiential PE teaching can promote the cultivation of sports dance ability of students.

Table 1. Course teaching knowledge associations obtained by event extraction method

Algorithm number		**1**	**2**	**3**	**Our algorithm**
Dataset 1	Precision	33.6	36.9	45.2	53.5
	Recall	33.4	33.2	34.8	51.2
	F1	33.8	35.1	39.4	52.8
Dataset 2	Precision	32.6	35.8	41.5	52.5
	Recall	30.2	33.5	40.8	45.2
	F1	32.6	35.8	42.5	50.7
Dataset 3	Precision	31.5	36.2	41.8	53.2
	Recall	30.8	33.6	40.2	51.8
	F1	30.8	33.4	41.8	42.3

Table 2. Different dimensions of students' classroom evaluation

Group number		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Basic task	Activity 1	7	11	9	11	13	10	15	11	10	8
	Activity 2	9	16	14	15	13	16	13	15	12	14
	Activity 3	18	16	19	15	20	22	19	20	17	15
	Activity 4	21	25	22	24	20	21	23	25	23	26
Aesthetic expression	Activity 1	9	11	13	8	15	10	12	10	9	13
	Activity 2	19	16	18	15	17	13	16	14	20	18
	Activity 3	20	19	18	22	19	17	22	18	16	19
	Activity 4	23	25	22	20	26	23	21	22	25	23
Movement arrangement optimization	Activity 1	12	16	11	13	15	10	9	15	12	14
	Activity 2	18	22	20	19	16	22	19	20	16	18
	Activity 3	28	26	24	22	26	21	25	23	20	22
	Activity 4	32	35	30	33	30	34	31	35	32	34
Problem solution	Activity 1	8	6	9	5	9	7	10	8	11	9
	Activity 2	8	10	12	13	8	11	9	12	10	14
	Activity 3	14	16	12	10	15	12	10	16	12	17
	Activity 4	12	15	13	15	17	13	11	13	10	14
Total score	Activity 1	39	41	39	42	45	48	40	43	48	38
	Activity 2	55	66	52	63	57	62	55	63	68	64
	Activity 3	75	82	74	81	75	79	76	81	75	85
	Activity 4	91	93	95	89	86	88	90	93	95	93

Finally, this paper surveys the satisfaction of the students participating in the experiential teaching activities with our teaching design. Table 3 reports the descriptive statistics. It can be learned that the mean evaluation scores of the students for the organization of experiential teaching activities were all above 4 points (full mark: 5 points). This means most students are satisfied with the teaching contents, knowledge point selection, teaching procedure, scenario design, activity forms, and resource/tool utilization in the experiential teaching activities. As a result, this paper achieves desirable effects on the design and implementation of experiential learning activities.

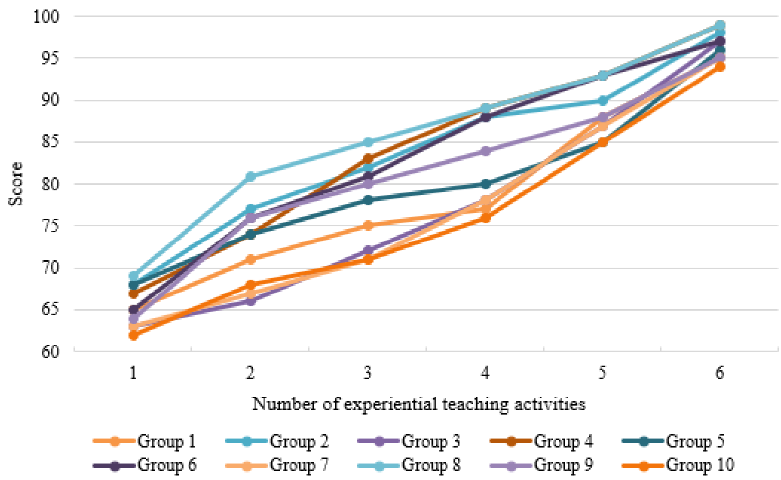

Fig. 5. Classroom evaluation scores of each group

Table 3. Student satisfaction with the organization of experiential teaching activities

Group number	5	6	7	8	9	10	11	12
N	33	34	34	33	34	34	34	33
Minimum	2	3	4	2	2	3	2	2
Maximum	6	6	6	6	6	6	6	6
Mean	4.25	4.17	4.35	4.26	4.52	4.16	4.32	4.57
Standard deviation	0.715	0.724	0.625	0.592	0.948	0.725	0.638	0.511

6 Conclusions

This paper attempts to design and implement experiential teaching based on knowledge feature transformation of course teaching. Firstly, the authors chose node betweenness as the reference metric to initialize the granularity importance of the knowledge points in PE course teaching, and proportionally allocated the macro-importance of the course to the known granularity of knowledge points. After that, a knowledge network was built up for PE course teaching, and the named entities were identified based on course teaching knowledge features, thereby extracting the knowledge points of experiential PE teaching units, with class hour as the unit, and determining their teaching sequence. Furthermore, the design frameworks were established for experiential teaching scenarios and experiential learning activities, and the course evaluation strategy was provided for students majoring in sports dance, a professional PE course. Through experiments, the course teaching knowledge associations were mined by event extraction method; our algorithm was found to outshine the other algorithms in precision, recall, and F1; the different dimensions of students' classroom evaluation were analyzed, and the student satisfaction with the organization of experiential teaching activities was surveyed, revealing that this paper achieves desirable effects on the design and implementation of experiential learning activities.

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