A New Method of Teaching 'Software Operation' by a Knowledge Sharing Oriented to Practice Teaching Approach

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Qiong Ding(✉)
College of Arts, Jiaozuo University, Jiaozuo, China
dingqiong20180302@163.com

Abstract—The practice teaching of software operation emphasizes operation practice and practical experience, and it lays special attention on the interactions among students and teachers and teaching in accordance with aptitude. As a typical knowledge sharing platform, question-and-answer (Q&A) community is developing fast and can be taken as an assistant teaching method for the practice teaching of software operation to facilitate the teaching knowledge sharing between teachers and students. Most existing studies consider the attention mechanism of the correlation between questions and answers based on the similarity of word vectors, which has resulted in unsatisfactory accuracy and interpretability of the answers given by the model, in view of this matter, this paper studied a new method of teaching knowledge sharing oriented to the practice teaching of software operation. At first, this paper elaborated on the idea of knowledge sharing, and proposed a knowledge answer selection model for practice teaching of software operation based on the aggregation of features and attention to solve the problem with conventional studies which generally focus on the weighting of attention of a single sentence. Comparing the word granularity of sentence sequences to be matched and aggregating the comparison results have solved the problem with conventional methods in ignoring the interaction between the sentence sequences to be matched. At last, experimental results verified the effectiveness of the proposed method.

Keywords—software operation, practice teaching, teaching knowledge, knowledge sharing

1 Introduction

Practice teaching emphasizes operation practice and practical experience, it lays special attention on the interactions among students and teachers and teaching in accordance with aptitude [1–7]. Practice teaching often involves the knowledge and skills of multiple disciplines, and the knowledge sharing during teaching process can help students master practical skills more quickly and avoid misoperations [8–11]. In the meantime, the knowledge sharing between teachers also helps to improve the design level of teaching methods and practical projects. The knowledge sharing that is oriented to practice teaching can encourage communication and exchange among teachers and students and assist teachers to know about students' operations in a timely manner, so that the instructions could be provided to students in a targeted manner [12–19].

In recent years, as a typical knowledge sharing platform, Q&A community is developing fast and can be taken as an aid for practice teaching of software operation, thereby facilitating the teaching knowledge sharing between teachers and students. Through such Q&A community platforms, students can quickly get answers for their questions, obtain the professional knowledge, or share their own opinions, while teachers can answer to the questions proposed by students, moreover, students can help each other out and improve their learning effect [20–24].

Wang and Liu [25] argue that physical education, skill training and other related courses with physical exercises and experience training as the main means are suitable for teaching with virtual reality technology, and formulating teaching knowledge sharing strategies can promote the sharing of virtual practical teaching resources among students. The authors studied a teaching knowledge sharing method of virtual practice teaching and constructed a BiLSTM-Attention relation extraction model to recognize named entities of teaching knowledge resources in virtual practice teaching, to record the information of knowledge points involved in teaching knowledge resources, and to explore the information hidden in knowledge resources more deeply. Almujally et al. [26] studied the knowledge management in institutions of higher education, aiming to figure out the academics' perceptions about the sharing of teaching-related knowledge within Saudi universities. Their research suggests that, researchers have clear ideas about several potential benefits of managing teaching-related knowledge, despite the challenges they have faced when managing their knowledge using existing knowledge management approaches. The effective network-based knowledge management approach they developed holds a considerable promise and it fits the academics' needs. Wang et al. [27] drew on the social capital theory to propose that knowledge seeking behaviors lead to knowledge contribution behaviors through online users' social capital which is accumulated as a result of knowledge seeking. Based on the data of more than 1000 online users' knowledge sharing activities in the Zhihu Community in China, their study provided an empirical support for the proposed model. Cai et al. [28] employed the social cognitive theory and performed a decision tree analysis to predict the knowledge-sharing intentions of social question-and-answer (Q&A) community members based on a multitude of environmental and individual factors, including a sharing culture, motivations, and individual characteristics. The authors collected data from 1007 users and built a regression tree model using the R package rpart, and their research results showed that high levels of knowledge-sharing intentions occur among those who strongly enjoyed sharing and who perceived fairness within the community. For those who had a moderate or low level of enjoyment, their willingness to share knowledge was jointly affected by the sharing culture and extrinsic motivations.

To ensure the quality of knowledge answers of software operation practice teaching in Q&A communities, and facilitate students' sharing and retention of the knowledge, world field scholars generally choose to combine natural language processing technologies with deep learning to build professional Q&A matching models with faster response, however, existing models mostly consider the attention mechanism of the correlation between questions and answers based on the similarity of word vectors, while ignoring the influence of objectivity, interpretability, and persuasiveness on the quality of the answers, which can result in unsatisfactory accuracy and interpretability of the answers given by the model. In view of this matter, this paper studied a new method of teaching knowledge sharing oriented to the practice teaching of software operation. In the second chapter, this paper elaborated on the idea of knowledge sharing; then the third chapter proposed a knowledge answer selection model for practice teaching of software operation based on the aggregation of features and attention to solve the problem with conventional studies which generally focus on the weighting of attention of a single sentence. Comparing the word granularity of sentence sequences to be matched and aggregating the comparison results have solved the problem with conventional methods in ignoring the interaction between the sentence sequences to be matched. At last, experimental results verified the effectiveness of the proposed method.

2 The idea of knowledge sharing for practice teaching of software operation

Figure 1 shows the function structure of a software operation practice teaching platform, as can be seen from the figure, the platform offers a variety of functions to students including to select learning projects, to display the course content, and to provide the service of online virtual lab. Figure 2 gives the flow of software operation practice teaching.

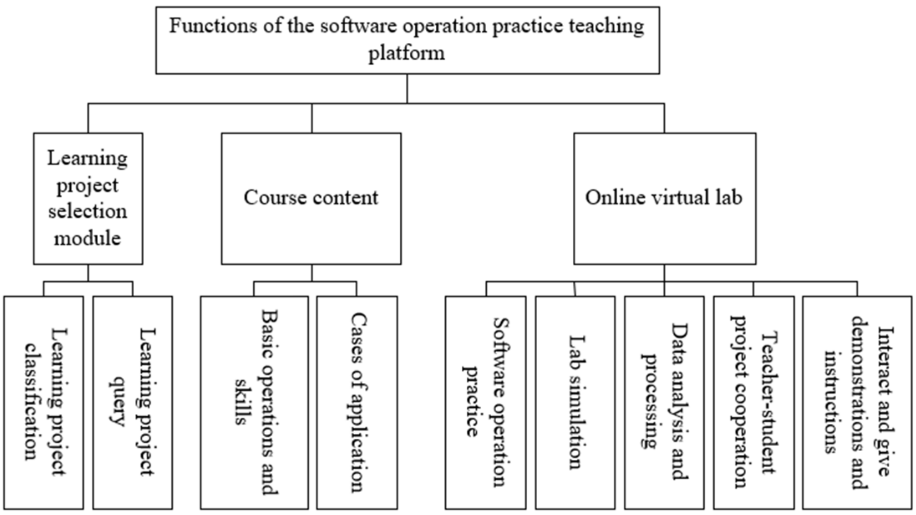

Fig. 1. Function structure of a software operation practice teaching platform

At first, teachers give a brief introduction to the objective, content, and learning requirement of the course, this can help students understand the basic situation of the course so that they could make preparations for subsequent learning. Students need to install the software and configure the environment. Teachers need to provide detailed installation tutorials or videos to make sure that students could install the software and configure the environment successfully. Then, teachers explain to students about basic concepts, tools, and operations of the software through video or text tutorials. After students learn about the basic concepts and operations, they need to do exercises. Teachers can design some actual cases to let students consolidate what they have learned in practice. After students have finished the exercises which are then modified by teachers or the platform and uploaded to the cloud, they can ask questions about the teaching content, and the platform will assign a suitable teacher or other students to answer the questions. Teachers or the platform can refine the learning content based on the Q&A of students. If students encounter problems during practice, they can also ask for help from teachers or other students through the Q&A community. Meanwhile, teachers can organize regular online discussions to share experiences and skills and encourage students to learn from each other, also, they can assign homework and ask students to complete certain design tasks. After students submit their work, teachers will evaluate the work, give feedback and suggestions, and help students know about their progress and shortcomings.

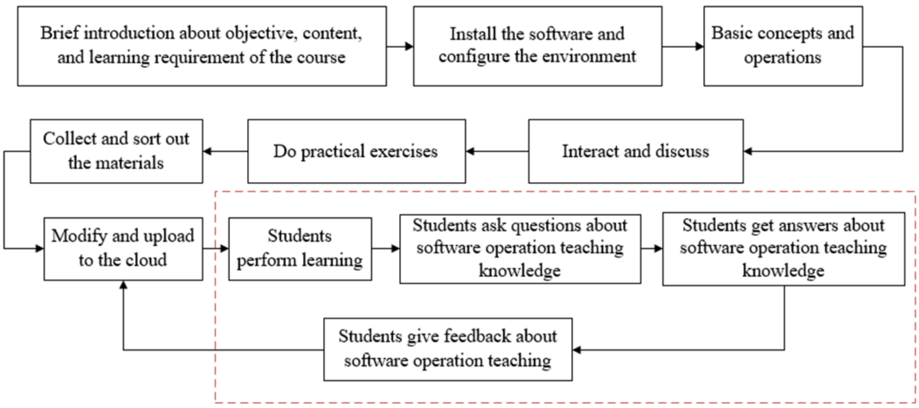

Fig. 2. Flow of software operation practice teaching

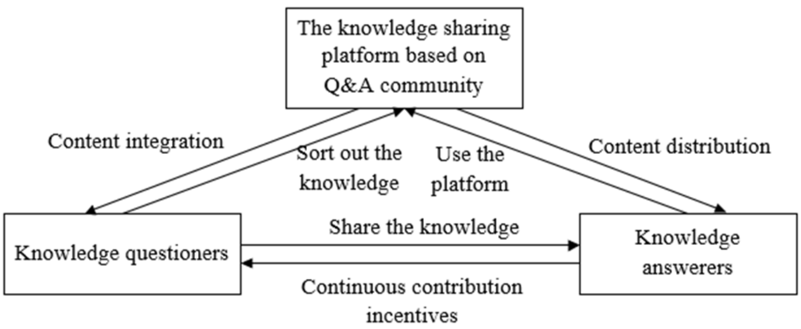

Fig. 3. Knowledge sharing principle of software operation practice teaching

Figure 3 illustrates the knowledge sharing principle of software operation practice teaching. In the knowledge sharing scenarios of software operation practice teaching studied in this paper, main subjects involved include three aspects: knowledge questioners, knowledge answerers, and the knowledge sharing platform based on Q&A community, wherein knowledge questioners share their questions about the knowledge of software operation practice teaching on the knowledge sharing platform, the platform integrates this part of knowledge about software operation practice teaching and releases to other knowledge answerers, knowledge answerers give answers to the questions through the continuous contribution incentive mechanism, in this way, the entire knowledge sharing process of software operation practice teaching could be completed.

3 Knowledge sharing of software operation practice teaching based on features and comparative aggregation

In the course of practice teaching of software operation, students' understanding of the meaning of knowledge words is inseparable from their semantic environment, so the teaching context of these knowledge words must be considered when selecting answers. Moreover, when analyzing the semantics of the sentences in the questions proposed by students, more attention is required for words or phrases that can affect the semantics of the sentences. The task of selecting answers is essentially a problem of semantic matching, in order to solve the problem with conventional studies which generally focus on the weighting of attention of a single sentence, this paper proposed a knowledge answer selection model for practice teaching of software operation based on the aggregation of features and attention. In the following texts, the structure of the proposed model will be introduced in detail.

To attain the meaning of words in question sentences proposed by students (for knowledge about practice teaching of software operation) in different contexts, the model set a word embedding layer which could attain word embedding of question sentences based on *BERT*, the following formula describes the process for attaining word vectors:

$$P = BERT(a_1, a_2, ..., a_m) \tag{1}$$

Assuming: a_m represents words in question sentences, p_i represents the related word embedding of teaching context of each word $P = (p_1, p_2, ..., p_m)$.

In order to describe the influence of different words in question sentences on sentence meaning and pay attention to the content related to sentence sequences of questions and answers to be matched, the proposed model set an attention layer that adopts two kinds of attention mechanisms: multi-head self-attention, and two-way attention. Figure 4 shows the adopted attention mechanisms for matching questions and answers.

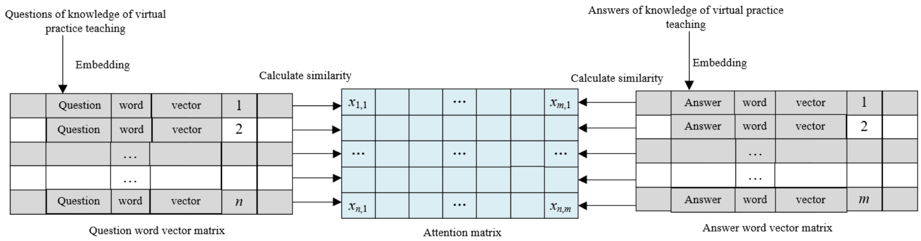

Fig. 4. Attention mechanisms for matching questions and answers

The calculation of multi-head self-attention of word embedding of question sentences was completed by the encoder in the *Transformer* model. Assuming: p represents the word embedding output by *BERT*; e_l represents the dimension; W, L, U respectively represent the query vector matrix, key vector matrix, and value vector matrix of all words in question sentences; Q_i^W, Q_i^L, Q_i^U, and Q^T represent the parameter matrices; $DV()$ represents vector splicing; N represents the final multi-head attention output vector, then the multi-head attention of question sentences can be calculated by the following formula:

$$Attention(W,L,U) = soft\max\left(\frac{W \times L^T}{\sqrt{e_l}}\right)U \tag{2}$$

$$US_i = Attention(WQ_i^W, LQ_i^l, UQ_i^u) \tag{3}$$

$$N = DV(US_1,...,US_m)Q^T \tag{4}$$

Assuming: a represents the input vector of the feed-forward neural network; Q_1 represents the weight matrix of the first linear transformation; y_1 represents the bias of the first linear transformation; max represents the maximum value function; Q_2 represents the weight matrix of the second linear transformation; y_2 represents the bias of the second linear transformation; then the feed-forward neural network layer output in the *Transformer* coding unit can be calculated by the following formula:

$$FFN_{out} = \max(0, aQ_1 + y_1)Q_2 + y_2 \tag{5}$$

To prevent the vanishing gradient problem and speed up model training, this paper introduced residual connection and normalization operations into the *Transformer* module, and the calculation formula is given below. Assuming: IP represents the input vector of the upper layer; IP_{GX} represents the output vector of the multi-head attention layer; OP represents the output vector calculated by residual connection; a_i represents the input vector of the normalization layer; λ_K represents the mean of the last dimension; β and γ represent bias parameters for compensating the information lost by the normalization operation, and a parameter ρ is set to prevent a variance of 0, then there are:

$$OP = IP + OP_{GX} \tag{6}$$

$$KM(a_i) = x \times \frac{a_i - \lambda_K}{\sqrt{\varepsilon_K^2 + \rho}} + \gamma \tag{7}$$

The first step of two-way attention calculation is to multiply the word embedding of questions and answers to create an interaction matrix; and the second step is to respectively calculate the attention weights of word embedding of questions and answers based on the interaction matrix. Assuming: p_{ij} represents an element in the interaction matrix; w_i and x_j represent the word embedding of question and answer sentences attained by *BERT*; k represents the sentence length; w_i represents the weighted sum of x_j; then there are:

$$p_{ij} = w_i^O x_j \tag{8}$$

$$w_i = \sum_{j=1}^{k_x} \frac{\exp(p_{ij})}{\sum_{l=1}^{k_x} \exp(p_{il})} x_j \tag{9}$$

$$x_i = \sum_{j=1}^{k_x} \frac{\exp(p_{ij})}{\sum_{l=1}^{k_x} \exp(p_{lj})} q_i \tag{10}$$

For solving sequence matching problems such as an answer selection task, the conventional methods generally calculate the similarity between two sequences based on the coding vector of the sentence sequences to be matched, while ignoring the interaction between them during the coding process. To solve this problem, this paper chose to use the word granularity of the sentence sequences to be matched to make comparisons and aggregate the comparison results, thereby attaining the final sequence matching output.

Assuming: R_w and R_x represent the output of the question sentence and answer sentence after going through the *Transformer* encoder; O_w and O_x represent the output of the question sentence and answer sentence after going through two-way attention; "–" represents the substraction of elements; D^X represents the matching feature matrix after comparing R_w with O_x; D^X represents the matching feature matrix after comparing R_w with O_w, then the formulas for comparing the word granularity of sentence sequence to be matched are:

$$D^W = R_w - O_x \tag{11}$$

$$D^X = R_x - O_w \tag{12}$$

The aggregation of comparison results was realized based on the average pooling layer. Assuming: D represents the matching feature matrix, D_i represents an eigenvector in the matrix, then the calculation method is:

$$S^{W} = YW - PQ(D^{W}) \tag{13}$$

$$S^{X} = YW - PQ(D^{X}) \tag{14}$$

$$YW - PQ(D) = \frac{1}{M}\sum_{i \in M} D_i \tag{15}$$

At last, the cosine function was adopted to calculate the matching score of a question sentence W and an answer sentence X:

$$b = \text{consine}(S^{W}, S^{X}) \tag{16}$$

The answer selection model constructed in this paper predicted the matching scores of each candidate answer and question about the knowledge of software operation practice teaching, and the model was trained by minimizing the mean variance. The following formula gives the loss function of the model:

$$LOSS = \frac{1}{m}\sum_{i=1}^{m}(b_i - \dot{b}_i)^2 \tag{17}$$

where, b_i represents the actual matching value; $\dot{b}_i$ represents the matching value predicted by the model, m represents the total number of samples of questions and answers adopted for model training.

4 Knowledge sharing of software operation practice teaching based on answer fine-tuning

To fine-tune the attained answers of the knowledge sharing of software operation practice teaching, this paper introduced a *MVLSTM* layer into the pre-training model and added semantic information between questions and answers so that the model could better adapt to the answer selection task. The answer selection model based on fine-tuning is composed of four parts: input layer, encoding layer, *MVLSTM* layer, and output layer. The text below gives a detailed introduction to the structure of the answer selection model, and Figure 5 shows the knowledge sharing model of software operation practice teaching based on answer fine-tuning.

In the input layer, assuming: $A = \{a_1, ..., a_n\}$ and $B = \{(b_1, ..., b_m)\}$ respectively represent the question sentence and the answer sentence, according to the input format of *BERT* model, the question and answer sentence sequence was spliced by [*STA*] and [*END*], and the format of the generated spliced sequence is given by the following formula:

$$SS = \{[STA], a_1, ..., a_n, [END], b_1, ..., b_m, [END]\} \tag{18}$$

The encoding layer encodes each character in *SS*, then a vector *R* could be attained based on the word vector, segment vector, and position vector generated by the encoding. Assuming: $f \in R^{k \times e}$, k represents the length of sequence *SS*, f_0 represents the vector representation of token [*STA*], f_i represents the teaching context-related vector of the i-th character in *SS*, then the following formula gives the encoding matrix of question and answer sentence sequence to be matched attained from the encoding of R by *BERT*:

$$f = \{f_0, f_1, ..., f_{k-1}\} = BERT(R) \tag{19}$$

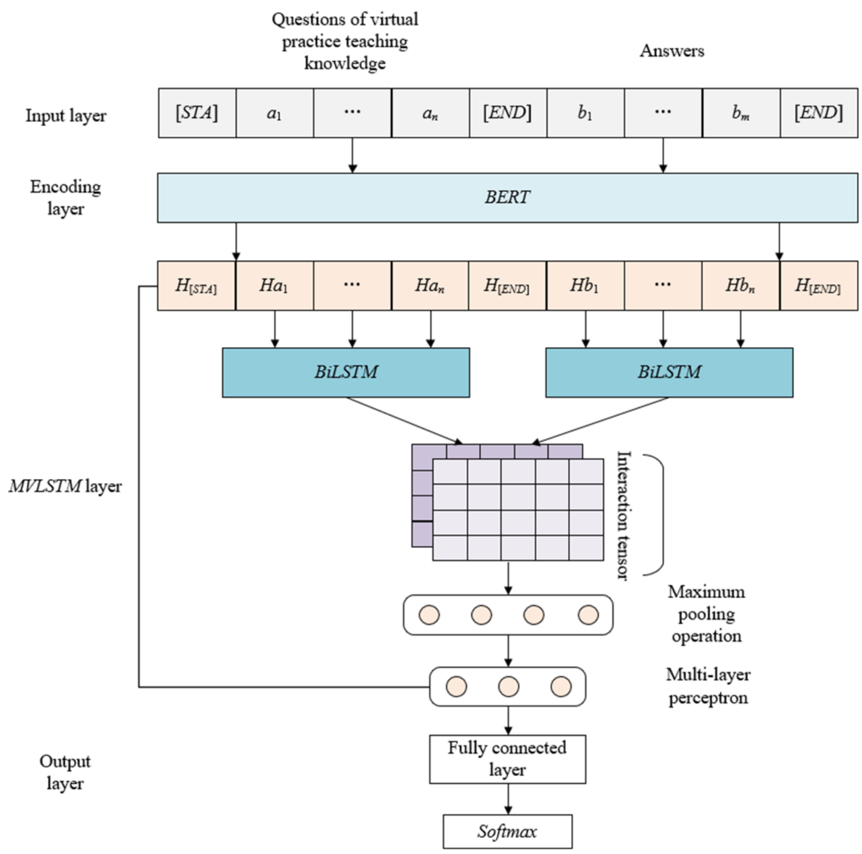

Fig. 5. Knowledge sharing model of software operation practice teaching based on answer fine-tuning

The calculation process of the *MVLSTM* layer includes two steps: first, get the teaching context matrix of *SS* based on *BERT*; second, mask the teaching context matrix to get word vector matrices O_a and O_b of the question and answer sentences. The vector expressions of the question and answer sentence sequence at each position could be attained by inputting O_a and O_b into the *BiLSTM* network layer. Assuming: v_o represents the vector expression of question sentence A at position o in the *BiLSTM* layer, u_o represents the vector expression of answer sentence B at position o in the *BiLSTM* layer, then the output of each position of *BiLSTM* can be calculated as:

$$v_o = [\overrightarrow{BL}_{O_a}; \overleftarrow{BL}_{O_b}] \tag{20}$$

$$u_o = [\overrightarrow{BL}_{O_a}; \overleftarrow{BL}_{O_b}] \tag{21}$$

The vector expressions of different positions of the question and answer sentence sequence to be matched were interacted in pairs. Assuming: *v* and *u* represent the output vector of the question and answer sentence sequence to be matched at a certain position in *BiLSTM*; $N^{[1:d]}$ represents the slices of the tensor; $Q_{v,u}$ represents the parameter matrix in linear calculation; *y* represents the bias parameter; *g* represents the nonlinear function; *r* represents the vector attained after interactive calculation, then the formula of interactive calculation is:

$$r = g\left(v^T N^{[1:d]} u + Q_{vu} \begin{bmatrix} v \\ u \end{bmatrix} + y \right) \tag{22}$$

$$g(c) = \max(T, c) \tag{23}$$

Through the interactive calculation of the above formula, an interactive tensor with rich information about the matching of question and answer sentences could be attained. Further, in the *MVLSTM* layer of the model, the first *l* largest values of each slice in the interactive tensor were extracted and spliced; at last, based on the multi-layer perceptron, the expression of the semantic relationship of the sentence sequence to be matched could be attained. Assuming: Q_s represents the parameter matrix, y_s represents the bias parameter, *w* represents the vector after the maximum pooling operation of the *MVLSTM* layer, then the formula for calculating the output *s* of the *MVLSTM* layer is:

$$s = Q_s w + y_s \tag{24}$$

The output of above formula and the vector of token [STA] were spliced and the result was delivered to the fully connected layer, then processed by the *Soft* max function of the fully connected layer to attain the similarity probability of sentence sequence to be matched. Assuming: Q_Z represents the parameter matrix, y_Z represents the bias, *Z* represents the token probability distribution predicted by the model, the calculation formulas are:

$$z = [s : f_0] \tag{25}$$

$$Z = Soft\max(Q_z \times z + y_z) \tag{26}$$

The update of model parameters was realized by minimizing the cross-entropy loss function. Assuming: *M* represents the total sample number, b_i represents the real token of sample *i*, z_i represents the value of the sample predicted by the model, then the expression of the cross-entropy loss function is:

$$LOSS^* = \frac{1}{M} \sum_{i=1}^{M} -[b_i \log(z_i) + (1 - b_i) \log(1 - z_i)] \tag{27}$$

5 Experimental results and analysis

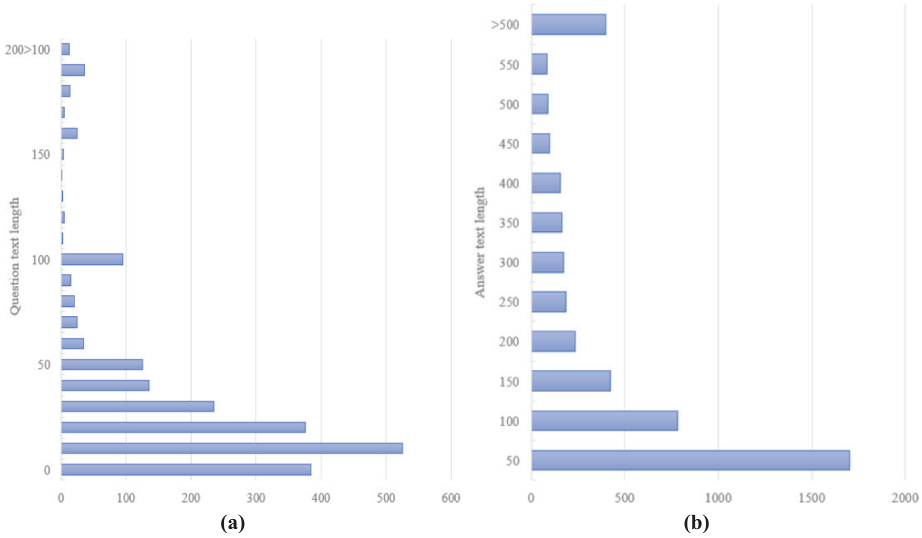

Fig. 6. Data text length distribution

The length of question and answer texts input into the constructed knowledge sharing model needs to be kept consistent. However, in real cases, the answer texts are generally much longer than the question texts, so a maximum length needs be set for the question and answer texts. Figure 6 shows the data text length distribution. According to the figure, the maximum length of question texts is less 100 words, and the maximum length of answer texts is less 200 words, therefore, in this paper, the maximum length of question texts was set to 100, and the maximum length of answer texts was set to 200, such setting could cover most questions and answers about the knowledge of software operation practice teaching.

Table 1. Experimental results on sample sets of different learning projects

Model No.	Sample Set of Learning Project 1		Sample Set of Learning Project 2	
	Accuracy	*F*1 Score	Accuracy	*F*1 Score
1	72.63	73.96	71.06	73.62
2	71.42	72.81	70.51	70.29
3	76.29	73.68	73.62	75.18
4	70.52	70.15	79.52	73.69
5	74.53	63.92	70.58	70.51
6	76.92	72.51	82.36	85.37

In this paper, experiments were carried out to compare the performance of different models on different learning project sample sets, and the results are given in Table 1. Model 1 is a model without the attention module and the word granularity aggregation module; Model 3 is a model that introduced the multi-head self-attention; Model 5 is a model established based on feature and attention aggregation; Models 2, 4, and 6 are respectively models that added the *MVLSTM* module based on Models 1, 3, and 5. In this paper, all models were subjected to 10-fold cross validation, and the results showed that compared with other models, Model 6 performed the best in terms of accuracy and F1 value, and its success rate of question and answer matching of knowledge sharing was higher. The model's performance on the sample sets corresponding to different learning projects was the best. Compared with Model 5 which hadn't added the *MVLSTM* module, the Model 6 with a *MVLSTM* module showed obvious improvement in accuracy. At the same time, the fluctuation of the experimental results of Model 6 was smaller, and the data dispersion was smaller as well.

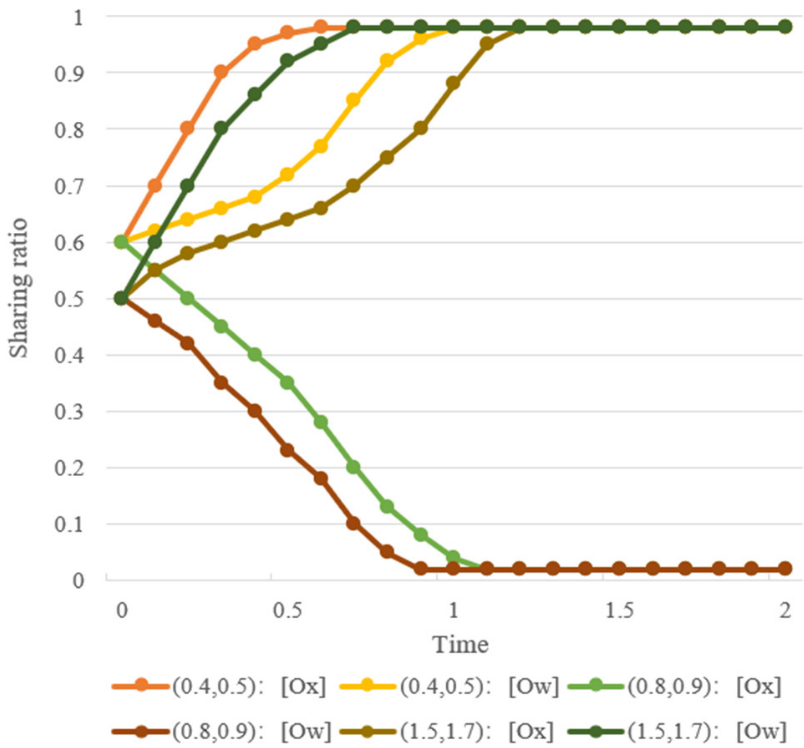

Fig. 7. Influence of knowledge transformation degree of knowledge sharing answers

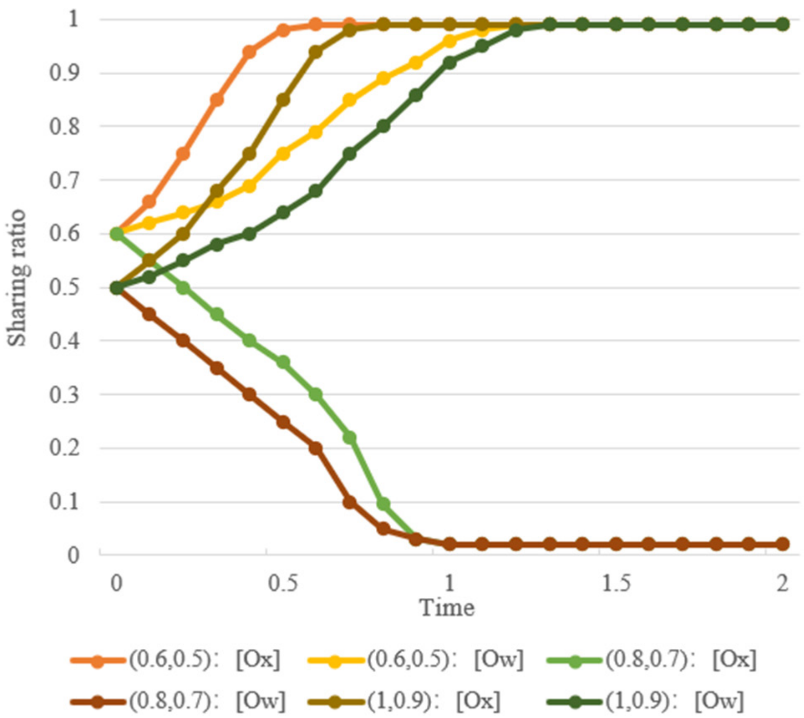

Fig. 8. Influence of knowledge expression degree of knowledge sharing answers

In order to verify whether the constructed model can fine-tune the knowledge sharing answers, the knowledge transformation degree and knowledge expression degree of the knowledge sharing answers of learning projects 1 and 2 were changed during experiment, and the simulation results are given in Figures 7 and 8. When knowledge transformation degree and knowledge expression degree take a small value, the slope of the curves is less than 0, the curves gradually approach to the origin and tend to be stable, indicating that at this time, the success rate of knowledge sharing of learning projects 1 and 2 is not high. When the value of knowledge transformation degree and knowledge expression degree increases, the slope of the curves is greater than 0, the curves approach to (1.1) and reach stable, indicating that at this time, the success rate of knowledge sharing of learning projects 1 and 2 is high. Then, it can be known that, when the value of knowledge transformation degree and knowledge expression degree grows, the evolution speed of the learning projects of software operation practice teaching to high success rate knowledge sharing gets faster; when the value of knowledge transformation degree and knowledge expression degree decreases, the evolution speed slows down, indicating that knowledge transformation degree and knowledge expression degree have a positive effect on the knowledge sharing behavior of software operation practice teaching.

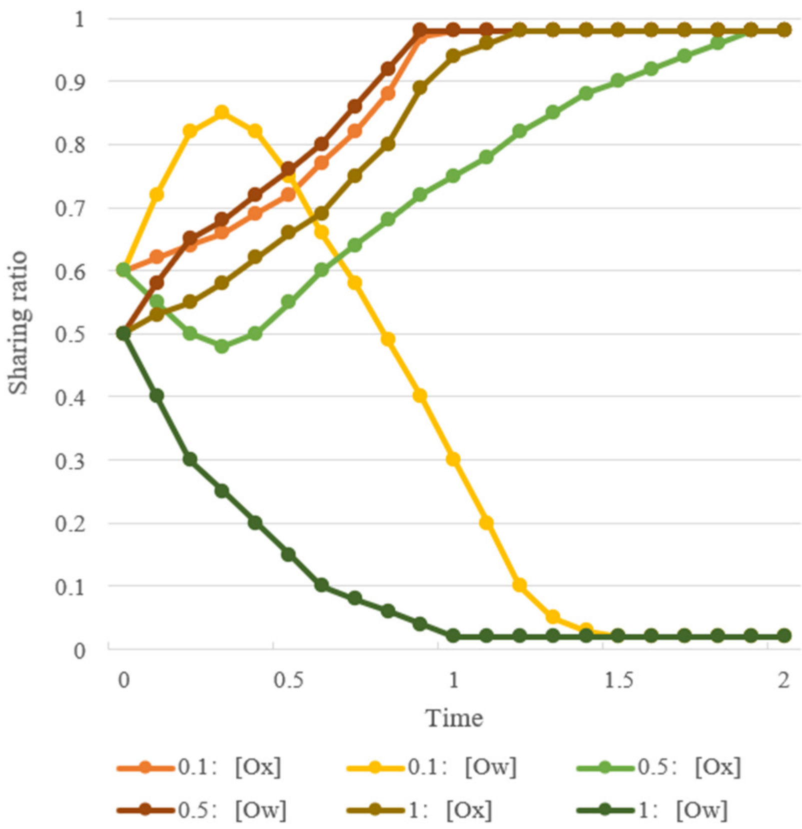

Fig. 9. Influence of knowledge sharing benefit of knowledge sharing answers

To verify the influence of knowledge sharing benefit ratio of the knowledge sharing answers, the said ratio was changed during experiment, and the simulation results are shown in Figure 9. When the knowledge sharing benefit ratio is small, the slope of all curves is less than 0, the curves gradually approach to the origin and tend to be stable, indicating that at this time, the success rate of knowledge sharing of learning projects 1 and 2 is not high. When the knowledge sharing benefit ratio increases, the slope of the curves is greater than 0, the curves approach (1.1) and reach stable, indicating that at this time, the success rate of knowledge sharing of learning projects 1 and 2 is high. That is, knowledge questioners would still propose questions when the knowledge sharing benefit is less. Besides, for the knowledge sharing benefit ratio, there is a threshold that makes the slope of the curve reach the maximum, indicating that at this time, the success rate of knowledge sharing of learning projects 1 and 2 evolves toward the direction of higher success rate.

6 Conclusion

This paper studied a knowledge sharing method of software operation practice teaching. At first, the paper elaborated on the idea of knowledge sharing, proposed a knowledge answer selection model for practice teaching of software operation based on feature and attention aggregation to solve the problem with conventional studies which generally focus on the weighting of attention of a single sentence. Comparing the word granularity of sentence sequences to be matched and aggregating the comparison results have solved the problem with conventional methods in ignoring the interaction between the sentence sequences to be matched. Combining with experiment, this paper gave the distribution of data text length, determined suitable lengths for questions and answers, compared the performance the different models on different learning project sample sets, and gave the corresponding experimental results, which verified that Model 6 performed the best in terms of accuracy and F1 value, its success rate of knowledge sharing question and answer matching was higher, the fluctuation of experimental results was smaller, and the data dispersion was smaller as well. Simulation experiment was performed by changing the knowledge transformation degree, knowledge expression degree, knowledge stock, the trust degree of questioners for answerers, and the knowledge sharing benefit of knowledge sharing answers of learning projects 1 and 2, and the results had verified the effectiveness of the fine-tuning made by the constructed model to the knowledge sharing answers of software operation practice teaching.

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8 Author

Qiong Ding, lecture and director of the Teaching Research Office of the School of Fine Arts in Jiaozuo University, graduated from he School of Fine Arts of Xuchang University in 2012 and graduated from the School of Design and Art of Shaanxi University of Science and Technology in 2015. Email: dingqiong20180302@163.com, https://orcid.org/0009-0000-2567-8449

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