Design of a Visual Training System for Software Engineering Education Based on Knowledge Graphs

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Abstract—With the increase of the content and difficulty of software engineering education courses, software engineering education visual training system came into being, but the technology is not mature at present, and the representation learning algorithm part of the visual training system needs to be optimized. In order to solve this problem, the research proposes to optimize the take model by using the trans representation algorithm, and embed the optimized knowledge map into the new software engineering education visual training system. The performance of TEKEE model is verified by comparing TEKEE model with Trans E model, Trans D model and TEKED model. The experimental results show that the MR value of the optimized TEKEE model is 62, Hits@10 The value is 0.92, which is better than the other three representation learning models. In terms of the bearing capacity test of the visual training system, the response time of the business operation of the research and design training system is 1.22 seconds, and the CPU occupancy of the application server is 12.5%, all of which are normal. The experimental results show that the performance of the optimized TEKEE model has indeed been greatly improved, and the visual training system composed of the optimized knowledge map has a very good carrying capacity, which can provide a new idea for the software engineering education and training system.

Keywords—knowledge mapping, TEKEE model, trans R model, software engineering education, visualization

1 Introduction

Current traditional software engineering courses are usually taught by teachers using scattered examples [1]. This approach does not have complete examples, resulting in students not developing a holistic view of software development and low learning outcomes [2]. With the rapid development of digitalization, more new education and training methods are used in teaching [3]. However, there is no new education and training system in software engineering education at present. In order to improve the teaching efficiency of teachers and the learning efficiency of students, it is of great value to explore a new visual training system for Software Engineering Education [4]. Knowledge mapping technology is a theory that combines theoretical and analytical methods from multiple disciplines to present the overall knowledge structure of a discipline using visual images, which can provide a valuable reference for disciplinary research [5]. Therefore, the study optimizes the knowledge mapping technology and applies the optimized knowledge mapping technology to the software engineering education visualization training system to improve the inefficiencies in the software engineering education curriculum.

2 Related works

With the popularity of knowledge mapping, it is widely used in various fields. Aiming at the problem that it is difficult to evaluate systematic financial risks, FL et al. Proposed a method combining scientific measurement and knowledge map to analyze and evaluate systematic financial risks. The results show that this method can accurately evaluate financial risks and predict their trends, providing a new idea for systematic research on financial risks [6]. To explore the different resources and capabilities related to the integration of the silver economy and ICT, Butt S A's team proposed to create a knowledge map on the Protégé model and use it to integrate key knowledge resources. The results show that the method can be good for integrating resources and is useful for exploring the relationship between the silver economy and ICT integration [7]. Esfahani et al. propose a comprehensive knowledge map in the field of energy security measurement in order to address the problem of insufficient methods for analyzing the field of energy security, and use this knowledge map to explore the relationship between relevant the articles were collected and analyzed, and the results showed that the knowledge map can be used to accurately analyses energy security and obtain reliable conclusions, which is of great practical importance [8]. Chen's team proposed a visual analysis method based on the knowledge map in order to analyses the current state of application of network meta-analysis in the field of Chinese medicine, and the results showed that Lin et al. used knowledge graphs to visualize the collected Chinese and English literature in order to analyze the research progress of the medicinal food chicory. The analysis of the literature concluded that chicory has high economic and medicinal value and its food nutrition and medicinal activity will be the main direction of future research [10].

There are also numerous methods used in educational training methods. the Klehm team, in order to solve the problem of inadequate field safety instruction for student training in archaeology, proposed to draw on the experience of graduate students and professors working in the field for instruction and refer to domestic and foreign projects for improved training. the results showed that the method greatly improved the effectiveness of field archaeology training and provided a guarantee for safe archaeology for students [11]. Zhang et al. addressed the problem of poor teaching quality and effectiveness of anatomy by proposing a teacher-student anatomy-assisted teaching system based on the results of our digital visual human research and anatomical knowledge points, and the results showed that the teaching system covered several teaching aspects and was an important supplement to traditional anatomy teaching. The system has been applied and promoted in most medical schools in China and has played a positive role in ensuring the effectiveness and quality of anatomy teaching [12]. Huang W's team proposed a teaching system based on a digital platform and mobile devices for the visualization of human acupuncture points in order to solve the problem of insufficient teaching resources in acupuncture teaching. The system uses a mobile learning approach to present acupuncture knowledge. Fourteen common clinical conditions can be systematically displayed on selected anatomical teaching models of human acupuncture points. The results show that the system enables modern digital teaching and application of traditional acupuncture theory, provides an intuitive and dynamic teaching method, and alleviates the challenge of insufficient resources for teaching acupuncture [13]. li addresses the problem of low learning efficiency of students in English learning and proposes a virtual reality technology based on artificial intelligence and machine learning for university English immersion the results showed that the classes using the method were more effective than those using the method. The results showed that the average English score of the class using the method was 2.8 points higher than that of the control group, which indicated that the teaching method could indeed improve students' English proficiency [14].

The above studies illustrate that knowledge mapping techniques have been successfully applied in a number of fields, and a variety of approaches have been found to be used in teaching and training. However, few studies have combined knowledge mapping technology with teaching and training. Therefore, the study will design a software engineering education visualization training system based on knowledge mapping to provide a new way of learning in software engineering education.

3 Research on a visual training system based on knowledge graphs

3.1 Knowledge mapping

A knowledge graph is essentially a semantic network that serves to reveal relationships between things and can describe real things and the connections between things [15]. Knowledge graphs are generally represented by the three-dimensional vector set (h, r, t). If the set E is used to represent the set of all objects in the knowledge graph, then E contains all pre-objects h and post-objects t; the set R is used to represent the set of all relations, then R contains all relations r; and the set S is used to represent the set of all three-dimensional vector groups (h, r, t). A uniquely determined ID is generally used to correspond to each object in the knowledge graph [16]. There are now more mature knowledge graphs in many fields. One of the more complex knowledge graphs about countries and regions among themselves is shown in Figure 1.

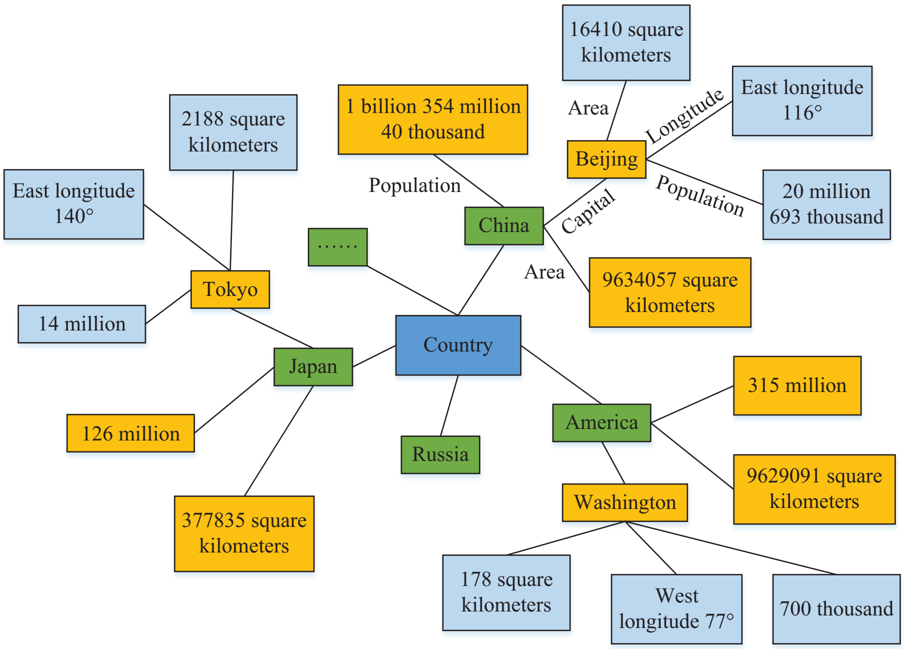


Fig. 1. Complex knowledge map between countries and regions

A complete knowledge map mainly includes entity nodes, concept nodes, content nodes, attribute nodes, relationships and other elements [17]. An entity node is a concrete thing such as China and Beijing in the diagram, while a relationship is a connection between different things such as Beijing is the capital of China; an attribute node is usually a specific attribute value of a thing such as the longitude of Beijing is 116 degrees East, a concept node is a collection of things with many identical characteristics such as China, the United States, Russia and Japan are all one country, and a content class nodes refer to the names of specific things or the names of the concepts to which they belong. Knowledge graphs are divided into two categories: general knowledge graphs and industry knowledge graphs. Generic Knowledge Graphs are larger in scale than Industry Knowledge Graphs, but they are less accurate than Industry Knowledge Graphs. The content of the generic knowledge map is domain-wide, while the industry knowledge map is domain-specific and has richer data types. As software engineering education is a fixed domain, a more suitable industry knowledge map was chosen for the study. With the rapid development of artificial intelligence, knowledge graphs are receiving more and more attention, and there is already a more complete technical architecture, which is shown in Figure 2.

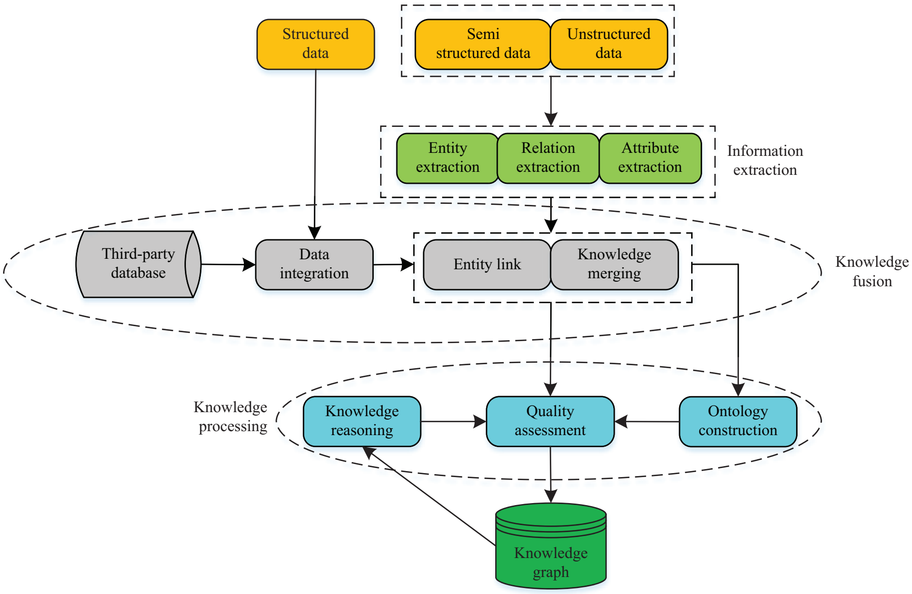


Fig. 2. Specific structure of knowledge map

It can be seen from Figure 2 that the construction process of knowledge map is mainly composed of three modules, namely, information extraction module, knowledge fusion module and knowledge processing module. Among them, the main function of the information extraction module is to extract the classified data, obtain structured entity, relationship and attribute information, and express knowledge on them. As the information extracted by the information extraction module is not logical and of low value, it needs to be passed through the knowledge fusion module, where knowledge linking and merging techniques are used to eliminate incorrect expressions in the extracted information and obtain correct factual expressions. The other module, the knowledge processing module, mainly reasoned with the factual expressions derived from the knowledge fusion module, supplemented them with the missing information and relationships, then evaluated the supplemented facts and, if qualified, output the completed knowledge map, which could be used for visualization, Q&A, etc. The study applies the constructed software engineering knowledge graphs to visualization and education and training. The knowledge graph-based software engineering education and visualization training system uses Spring to unify the file configuration and division model, and Spring MVC to interact with the data in the front and back. The overall architecture consists of four layers: the infrastructure layer, the data resource layer, the application business layer and the system user layer. The specific system architecture is shown in Figure 3.

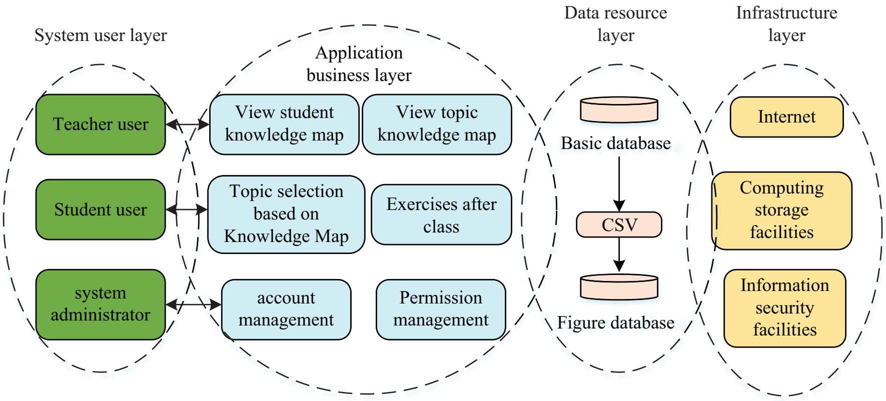


Fig. 3. Specific system architecture

As shown in Figure 3, the infrastructure layer of the system includes Internet, server, system and other infrastructure, which is mainly used to ensure the normal operation of the whole system. The main function of the data resource layer is to provide different data for the system according to different needs. The system user layer includes three kinds of users, namely teachers, students and system administrators. The application business layer mainly includes the business functions of three users in the system user layer, among which the teacher user has the function of viewing the student knowledge map and the topic knowledge map, and the student user function includes exercise exercises and topic selection based on the knowledge map.

3.2 Knowledge graph representation learning algorithm optimization

The most common knowledge representation algorithm in knowledge graphs at present is the Trans E model, which has the advantages of simple and easy-to-understand principles and simple computations, and can achieve good results when dealing with large-scale knowledge graphs with many values [18]. However, the Trans E model is prone to output different independent individuals with certain correlation as the same entity when dealing with complex relationships [19]. For example, if three independent individuals, Li Bai, Du Fu and Li Shimin, all belong to the Tang Dynasty, the vectors obtained by the Trans E model after training the three individuals are not very different, they will be considered as the same entity by the model, resulting in false identification. Therefore, knowledge atlas can be applied to software engineering education to improve the quality of software engineering online education. In addition, the Trans E model learns the representation of the knowledge graph through the graph structure, so the size of the knowledge graph affects the performance of the model [20].

The performance of the model is more significantly affected in specific domains where the size of the knowledge graph is small. Aiming at the problems that the Trans E model is prone to error in dealing with complex relationships and the low performance of the knowledge map when the scale is small, a text enhanced representation learning algorithm (TEKE) is proposed, which expands the semantic structure of the knowledge map by using the rich information of the text corpus. The specific text augmentation approach is shown in Figure 4.

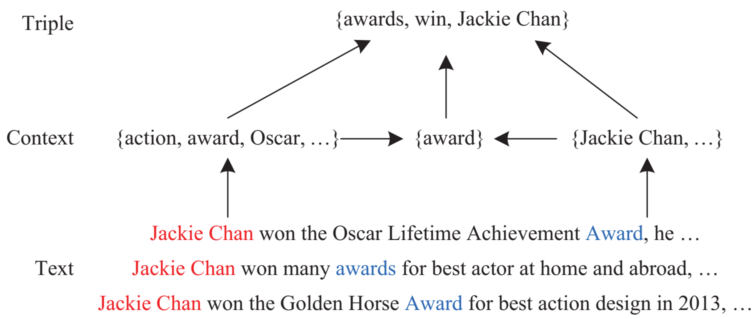


Fig. 4. Text enhancement method

As shown in Figure 4, the textual context shows that "Jackie Chan" is an actor and awards refers to a variety of awards, and it can be inferred from the common entity contextual text that the relationship of this triad should be win. In the TEKE representation learning algorithm, given the knowledge graph to be presented and the corresponding text corpus, first A network should be constructed to link the knowledge graph with the textual information. Then, on the basis of this network, the contexts of entities and relations in the text are defined and combined with the knowledge graph structure. Finally, the vectors of entities and relations are modelled using the training means of traditional models. The Trans E learning algorithm treats the common part of the textual context of the preceding and following entities of a triad as the relations of that triad, and in this way the problem of modelling complex relations between them can be better handled. The study integrates the algorithm into each triad entity and relationship, greatly ensuring the accuracy of the output vector. For a given knowledge graph and text corpus D, the TEKE model is to learn vector representations of entities and relations with the 3D vector group expression (h, r, t), where h denotes the pre-entity, t denotes the post-entity, and r denotes the relation between the pre-entity and post-entity. TEKE representation learning model mainly includes four modules: entity annotation, text context embedding, representation learning modeling based on text enhancement, and model training. The specific framework of the TEKE representation learning model is shown in Figure 5.

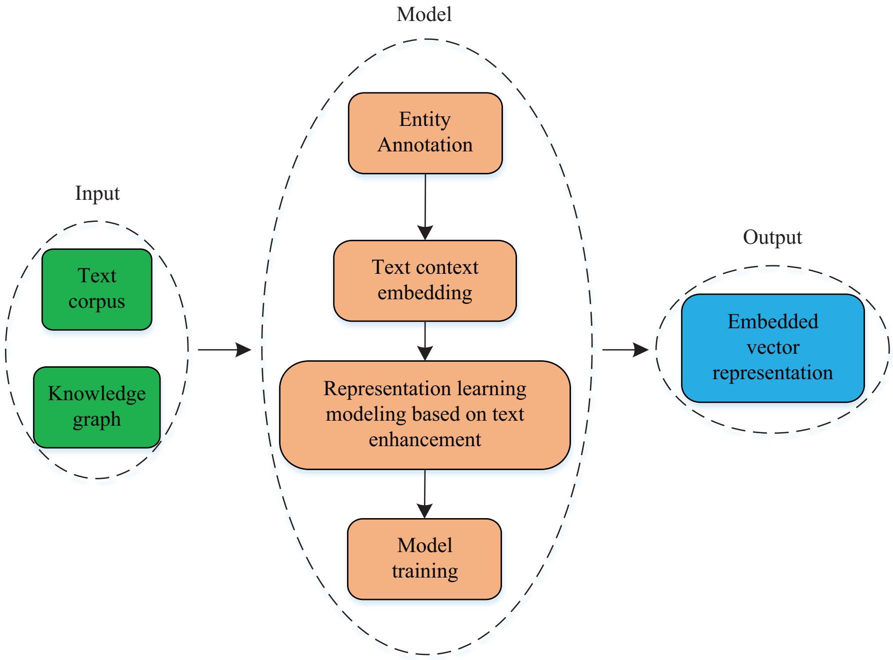


Fig. 5. TEKE shows the specific framework of the learning model

In the entity annotation step, the text corpus D is a set of text documents with the expression shown in equation (1).

$$D = \langle w_1, w_2, \ldots, w_m \rangle \tag{1}$$

In equation (1) $w_i (1 \le i \le m)$ denotes the individual entities and m denotes the number of entities in the text corpus D. In order to cover more entities in the knowledge graph, Wikipedia was selected as the text corpus for the study. For the selected text corpus D, the entities in the knowledge graph were tagged using the entity linking tool to obtain the entity annotated corpus D', whose expression is shown in equation (2).

$$D' = \langle z_1, z_2, \ldots, z_{m'} \rangle \tag{2}$$

In Equation (2) $z_i (1 \le i \le m')$ corresponds to the entities in the text corpus D and m' indicates the number of entities in the text corpus D' after entity annotation. The length of the corpus D' m' is smaller than the length of the corpus D m because multiple words can be tagged as the same entity during the entity annotation process. In the textual contextual embedding step, a co-occurrence network G is constructed in order to combine the knowledge graph and textual information, and the expression is shown in equation (3).

$$G = (X, Y) \tag{3}$$

The expression X in equation (3) denotes the set of all nodes in the co-occurrence network and is shown in equation (4).

$$X = \left\langle x_1, x_2, \ldots, x_i \right\rangle \tag{4}$$

In equation (4) x_i denotes the nodes in the co-occurrence network, while Y in equation (3) denotes the set of co-occurrence frequencies between any two nodes in the co-occurrence network, whose expression is shown in equation (5).

$$Y = \left\langle y_{12}, y_{13}, \ldots, y_{ij} \right\rangle \tag{5}$$

In equation (5) y_{ij} represents the co-occurrence frequency of node x_i and node x_j. The co-occurrence network can connect words and entities, and then use text information to express and learn them on the knowledge map. Contextual information of node x_i is defined as $n(x_i)$, and the expression of $n(x_i)$ is shown in equation (6).

$$n(x_i) = \left\{ x_j \middle| y_{ij} > \theta \right\} \tag{6}$$

In equation (6),θ is the threshold value, if the co-occurrence frequency of the neighboring nodes is lower than θ, it will be discarded. Generally, the proximity information of two nodes in a text can suggest the relationship between them, so the paired contextual information of two nodes is defined as $n(x_i,x_j)$, which is calculated as shown in equation (7).

$$n(x_i, x_j) = \left\{ x_k \middle| x_k \in n(x_i) \cap n(x_j) \right\} \tag{7}$$

In addition, word2vec word vectors were trained on individuals from the corpus D'. Since the nodes of the co-occurrence network were directly derived from the corpus D', the vectors obtained from the word vector training corresponded to each node in the co-occurrence network. The text vector of node x_i can be represented by $v(x_i)$ if the weighted average of each node vector of the contextual information $n(x_i)$ of node x_i is $v(x_i)$. $v(x_i)$ The formula for this is given in equation (8).

$$v(x_i) = \frac{1}{\sum_{x_j \in n(x_i)} y_{ij}} \sum_{x_j \in n(x_i)} y_{ij} v_j \tag{8}$$

In equation (8) v_j represents the vector representation at the node x_j. If $n(x_i)$ has no content, then $v(x_i)$ is represented as a zero vector. Similarly, the paired text-based vector representation of $n(x_i,x_j)$ is denoted as $\mathrm{v}(x_i,x_j)$ and the computational representation is shown in equation (9).

$$v(x_i, x_j) = \frac{1}{Z} \sum_{x_k \in n(x_i, x_j)} \min(y_{ik}, y_{jk}) v_k \tag{9}$$

In equation (9) v_k represents the vector representation at the node x_j and Z is the sum of the weight values of each node of $n(x_i,x_j)$, the expression of which is shown in equation (10).

$$Z = \sum_{x_k \in n(x_i,x_j)} \min(y_{ik}, y_{jk}) \tag{10}$$

The common neighbor between every two nodes x_k takes the smallest of y_{ik} and y_{jk} if $n(x_i,x_j)$ has no content, then $v(x_i,x_j)$ is also a zero vector. The core of the TEKE representation learning model is text-enhanced representation learning modelling based on the traditional Trans E model selected for the basic vector representation model at this step, setting the model vector to (h, r, t), the vector representations of h and t $v(h)$ the linear transformations of $\hat{h}$ and $\hat{t}$ $v(t)$ as the text-enhanced text-based representation of the pre-entity and post-entity vector representations. The expression for $\hat{h}$ is shown in equation (11).

$$\hat{h} = v(h)A + h_b \tag{11}$$

In equation (11), A represents the weights of $v(h)$ and $v(t)$, and h_b is the bias vector. $v(t)$ The formula for the linear transformation of $\hat{t}$ is shown in equation (12).

$$\hat{t} = v(t)A + t_b \tag{12}$$

In equation (12) h_b is the bias vector. The linear variation $\hat{r}$ of the paired vector representation $v(h, t)$ of the former entity h and the latter entity t is used as the vector representation of the relationship r based on text enhancement, which is calculated as shown in equation (13).

$$\hat{r} = v(h, t)B + r_b \tag{13}$$

In equation (13) B represents the weight of $v(h, t)$ and r_b is the bias vector. TEKE represents the expression of the score function of the learning model as shown in equation (14).

$$f(h,r,t) = \left\|\hat{h} + \hat{r} - \hat{t}\right\| \tag{14}$$

The TEKE model combines the textual contextual embedding vectors $v(h)$, $v(t)$ and $v(h, t)$ in the process, which can better solve the problem of small size of the knowledge graph. Moreover, the different pre- and post-entities in the complex relationships are represented by the corresponding $v(h, t)$, which improves the performance of the model when dealing with complex relationships. The expression of the training function L selected in the training step of the TEKE model is shown in equation (15).

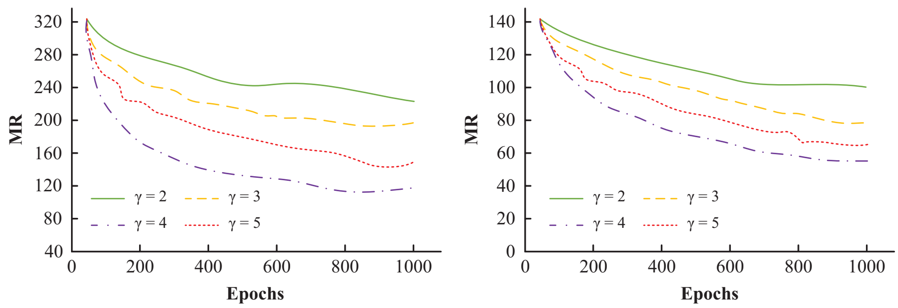
$$L = \sum_{(h,t,r)\in s} \max(0, \gamma + f(h,r,t) - f(h',r,t')) \tag{15}$$

In equation (15) γ denotes the interval distance parameter with a value greater than 0 and $f(h, r, t)$ denotes the model specific score function.

4 Comparison of algorithm performance and analysis of system results

4.1 Representation learning algorithm parameter determination and performance comparison

To determine the optimal γ value for the TEKEE model, the study trained the representation learning algorithm model at γ 2, 3, 4 and 5, setting the number of training sessions to 1000. Fb15k and wn18 are subsets of the free base and word net knowledge bases respectively, which were first introduced by Bordes et al. in 2013. Because the accuracy of experiments can be improved by using these two data sets in knowledge atlas research, fb15k and wn18 data sets are widely used in knowledge atlas research. Figure 6 shows the MR index changes of the learning algorithm on fb15k and wn18 data sets, MR represents the average of correct entity score ranking.



(a) Tekee model in WN18 mean rank learning curve **(b) Tekee model in FB15k mean rank learning curve**

Fig. 6. Different γ value corresponding to mean rank learning curve

From Figure 6, the TEKEE model converges to the Mean Rank evaluation metric after 1000 training sessions in both datasets when γ is 2, 3, 4 and 5, with the smallest convergence value for Mean Rank when γ = 4. The optimal value of γ was determined to be 4 for both the FB15K and WN18 datasets. After determining the optimal value of γ, in order to compare the performance of the TEKEE model, the Trans E model, the Trans D model, the TEKED model and the TEKEE model were trained on both the FB15K and WN18 datasets, and the results are shown in Figure 7, hit@10 Indicates the proportion of the correct entities in the test set in the top ten entities with the highest scores.

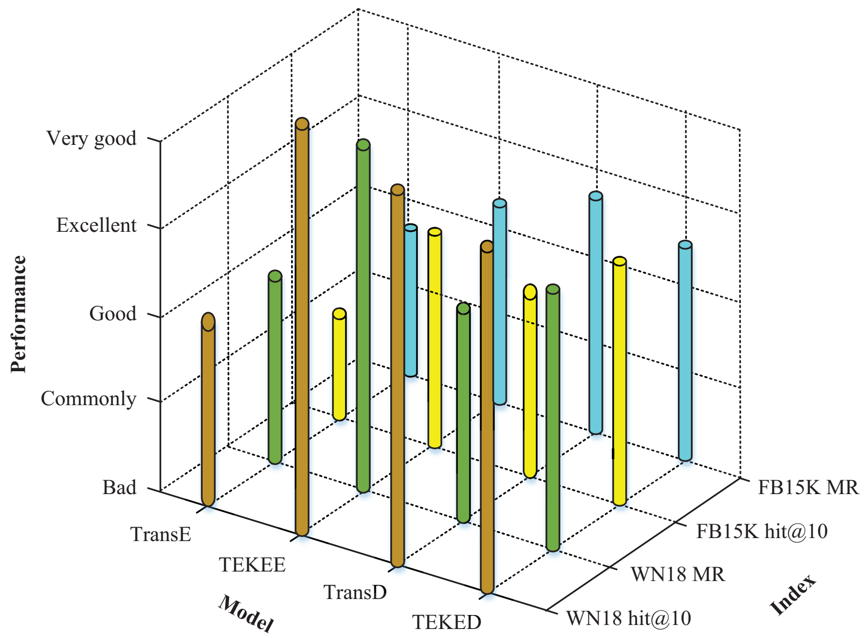


Fig. 7. Performance comparison of four models

As can be seen from Figure 7, a comparison of the metrics on the WN18 dataset with those on the FB15K dataset reveals that all the performance metrics on the WN18 dataset are better than those on the FB15K dataset, indicating that the WN18 dataset is more suitable for determining performance metrics. On the WN18 dataset, both MR and Hits@10 of the TEKEE model outperformed the other models. This result indicates that the TEKEE model outperforms the Trans E model, Trans D model, and TEKED model on the WN18 dataset. In addition, it can also be found that the optimized TEKEE model has improved metrics compared to the traditional Trans E model on both the FB15K and WN18 datasets. This result indicates that the performance of the optimized TEKEE model has indeed been improved. To further compare and analyses the performance of the four models, the study also compared the learning curves of MR values and Hits@10 for each of the four models under the two datasets, where the comparative analysis of the learning curves for MR values is shown in Figure 8.

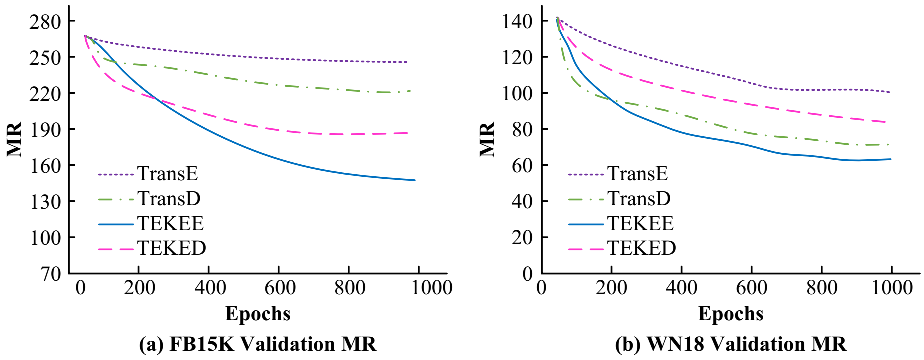


Fig. 8. Mean rank learning curve of four models under two data sets

The learning curve of the MR values of the four models on the FB15K dataset is plotted in Figure 8 (a), and it can be seen from Figure (a) that the TEKEE model has a lower stable MR value than the other models after training, at 148. The lower MR value indicates the better performance of the learning model, and this result indicates that the TEKEE model outperforms the Trans E model, Trans D model and TEKED model. In Figure 8 (b), the learning curves of the four models on the WN18 dataset are plotted. In addition, the comparative analysis of the learning curve of Hits@10 for each of the four models under the two datasets is shown in Figure 9.

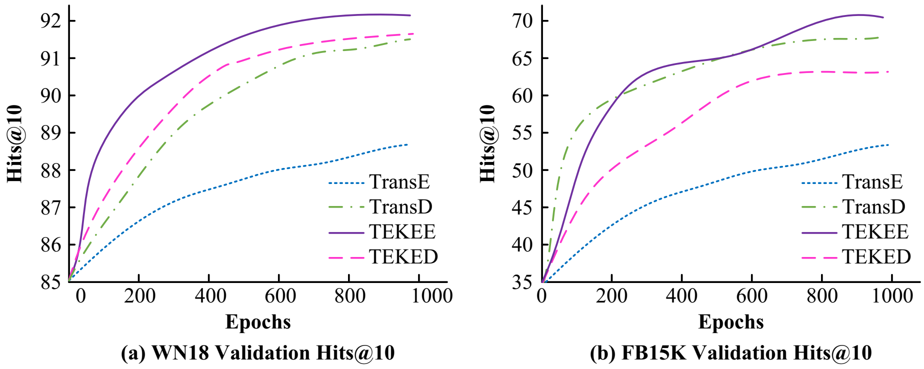


Fig. 9. Hits@10 learning curve of four models under two data sets

Figure (a) in Figure 9 shows the application of four models on wi18 dataset Hits@10 From Figure (a), we can see that TEKEE model is stable after training Hits@10 Higher than other models, 92. Among the four models, the traditional Trans E model Hits@10 The lowest is 88. In the representation learning model, Hits@10 The higher the index value, the better the performance of the model. Therefore, it can be concluded that the performance of TEKEE model optimized in wi18 data set is far better than that of traditional Trans E model. Figure (b) in Figure 9 shows the application of four models on fb15k data set Hits@10 Learning curve of. As can be seen from Figure (b), among the four models, TEKEE means that the learning model is stable after training Hits@10 The value is higher than other models, which is 70. Among the four models Hits@10 The model with the lowest value is the traditional Trans E model, which is 52. The results show that in fb15k data set, the performance of TEKEE learning model is better than the other three models, and the performance of Trans E model is the lowest among the four models. Based on the above results, it can be concluded that among the four representation learning models, the performance of the optimized representation learning model TEKEE is better than that of other learning models. This model can enhance the performance of the knowledge map when used in the knowledge map, and has high use value.

4.2 Analysis of the results of the visualization training system tests

After assembling the software engineering education visualization training system design, the study conducted system carrying capacity testing experiments on the system in order to confirm the stability as well as reliability of the system. The study recorded the business execution, memory, server, CPU and other data of the system at 100, 500 and 1000 concurrent users of the system respectively. The specific experimental data recorded is shown in Table 1.

Table 1. System bearing capacity test results

Index		Number of Visits		
		100	**500**	**1000**
Business execution	Average login response time (second)	0.34	0.63	0.91
	Maximum login response time (second)	0.81	0.95	1.22
	90% user login response time(second)	0.22	0.61	0.81
	Number of login response failures	0	0	1
Application server system resource usage	CPU utilization (%)	6.1	9.6	12.5
	Occupied memory (MB)	888	923	1258
	Disk Time (%)	0.853	1.238	3.276
Data server system resource occupancy	CPU utilization (%)	3.2	6.8	10.3
	Occupied memory (MB)	592	718	943
	Disk Time (%)	1.153	1.226	3.837

As can be seen from Table 1, when the concurrent users are 100, the average response time and the maximum response time of the training system for business operations are 0.34 seconds and 0.81 seconds respectively; The CPU occupation rate of the application server is 6.1%, and the memory occupation is 888MB; The CPU occupation rate of the database server is 3.2%, and the memory occupation is 592mb. When the concurrent users are 500, the average response time and the maximum response time of the training system for business operations are 0.63 seconds and 0.95 seconds respectively; The CPU occupation rate of the application server is 9.6%, and the memory occupation is 923MB; The CPU occupation rate of the database server is 6.8%, and the memory occupation is 718mb. When the number of concurrent users is 1000, the average response time and the maximum response time of the training system for business operations are 0.91s and 1.22s respectively, the CPU occupation rate of the application server is 12.5%, and the memory occupation is 1258mb; The CPU occupation rate of the database server is 10.3%, and the memory occupation is 943mb. According to the above results, when the concurrent users are 100–1000, the response time of the system for business operations is 1.22 seconds at the highest, the CPU occupation rate of the application server is 12.5%, and the memory occupation is 1258mb at the highest. The CPU occupation rate of the database is 10.3%, and the memory occupation is 943mb at the highest. These data are all normal. According to the results, the software engineering education visual training system designed by the research can support 1000 users to use it at the same time and operate normally.

5 Conclusion

With the development of technology, the knowledge system of software engineering subject content is constantly updated, which leads to the teaching task of teachers becoming heavier and heavier, the teaching efficiency is not high, and the learning efficiency of students is constantly reduced due to the increase of knowledge difficulty. Aiming at the problem of reducing the efficiency of teachers and students in the teaching course of software engineering, a visual training system for software engineering education is proposed. This paper studies the text enhancement and optimization of the representation and learning algorithm of knowledge map in the system, Trans E, to get the TEKEE model, and compares the performance of the optimized model with the traditional representation and learning algorithm models, Trans E, transd and TEKED. The results show that the MR value of TEKEE model on wn18 data set is 62, Hits@10 The value is 0.92; The MR value of TEKEE model on fb15k data set is 148, Hits@10 The value is 0.70, which is better than the other three models. In order to determine the stability of the training system, the bearing capacity of the system is tested. The results show that the response time of the training system for business operation is up to 1.22 seconds, the CPU occupation rate of the application server is up to 12.5%, the memory occupation is 1258mb, the CPU occupation rate of the database is 10.3%, the memory occupation is 943mb, and all indicators are at a normal level.

The above results show that the visual training system has good performance and carrying capacity. However, the representation learning model proposed in the study can be further optimized by integrating knowledge reasoning and other contents to achieve better performance. How to integrate other relevant contents on the current model to improve performance is the follow-up research direction.

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