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Construction and Training Application of Intelligent Sports Teaching Knowledge Graph

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Abstract In this paper, a knowledge graph construction scheme integrating deep learning and lightweight architecture is proposed for intelligent sports teaching scenarios, focusing on solving the three major problems of fuzzy entity recognition, computational redundancy, and low efficiency of knowledge fusion in the sports domain. We design a BERT-BiLSTM-CRF entity recognition model enhanced by attention mechanism, and combine it with TF-IDF weighting + alias dictionary matching strategy to improve the entity linking accuracy. The DeLighT module is then introduced to optimize the Transformer, and the parameter distribution is dynamically adjusted through the expansion-scaling mechanism, which significantly reduces the computational redundancy while maintaining the performance. Finally, based on the ontology “seven-step approach” to build the knowledge system of physical education courses, using Neo4j graph database to realize the efficient storage of ternary groups. The BERT-BiLSTM-CRF head entity detection model has an F1 value of 91.03%, with a compressed number of model parameters after optimization by the DeLighT module, and a composite score of 92.13%, which is an improvement of 14.19 points from the baseline. Teaching empirical evidence shows that the system significantly improves the training effect, the experimental group of students' physical health indicators are better than the control group in all aspects, lung capacity is improved by 12.1% (3,142.75ml and 2,803.64ml), the 50-meter run is accelerated by 0.84 seconds (8.01s and 8.85s), and the standing long jump is increased by 11.2% (211.95cm and 190.72cm). In the dimension of sports learning interest, positivity increased by 45.5% (4.73±0.59 and 3.25±1.25) and negativity decreased by 71.5% (1.09±0.35 and 3.82±1.06), which verified the effectiveness of knowledge graph-driven intelligent teaching in personalized training instruction and learning motivation.

Index Terms intelligent sport teaching, BERT-BiLSTM-CRF, knowledge graph, entity recognition, DeLighT

I. Introduction

With the enhancement of the awareness of national fitness and a strong sports nation, physical education has received more and more attention. At present, the physical education teaching model has insufficient attention to students' individual characteristics, and the pull of differences between students has increased; delayed feedback of sports movements leads to the solidification of erroneous movements; insufficient integration of interdisciplinary (biomechanics, etc.) educational resources; and the lack of multimodal data leads to a decline in the scientific nature of training [1]-[4]. These deficiencies urge physical education to become intelligent.

Information technology has profoundly changed the way human beings learn, affecting the existing learning mode and educational form, and educational intelligence is increasingly becoming a trend [5]. Knowledge graph describes the complex relationships between concepts and entities in the objective world in a structured form, or expresses the information on the Internet into a form closer to the human cognitive world, providing a way to better organize, manage and understand the massive information on the Internet [6]. By extracting conditions such as entity relationships, events, labels, models, rules, etc., a graph-based data form is formed, which can not only reflect events with data, but also reflect the connections between events [7], [8].

The use of knowledge mapping to display the complex knowledge domain through data mining, information processing, knowledge measurement and graphical drawing, revealing the dynamic development law of the knowledge domain, used to solve the problems on teaching and learning such as teaching content management, learning path recommendation, error correction and cross-disciplinary education has become an inevitable part of educational research [9]-[12]. In physical education, knowledge mapping provides scientific physical education testing by integrating physical education teaching resources, visual presentation of physical education training performance, provides personalized physical education training suggestions for students, further optimizes the classroom knowledge content of physical education teachers, meets the needs of students in the new era for physical education and health knowledge and physical education and sports skills, realizes the scientific nature of physical education training, improves the quality of physical education and teaching, and assists in intelligent physical education teaching [13]-[15].

This paper focuses on the key technology system of knowledge graph construction and proposes an innovative solution that integrates deep learning and lightweight architecture, aiming at solving the three core problems of fuzzy entity recognition, redundant model computation and inefficient knowledge fusion in the sports domain. Firstly, a Q&A system based on sports knowledge graph is designed, with entity recognition and linking at the core. An attention mechanism-enhanced BERT-BiLSTM-CRF model is used to achieve high-precision entity recognition. the BERT layer extracts semantic context features, BiLSTM captures sequence dependencies, the attention mechanism optimizes long sequence processing, and the CRF layer constrains the probability of label shift. Secondly, for the entity ambiguity problem in sports domain, the entity linking strategy of TF-IDF weighting + alias dictionary matching is proposed to enhance the knowledge base alignment accuracy by lexical filtering and alias template expansion of entity references. In order to improve the efficiency of the model, DeLighT Optimized Transformer is introduced, which dynamically adjusts the width and depth of the module through the expansion-scaling mechanism to address the problems of large number of parameters in the original model and high consumption of computational resources for long sequences. The expansion phase maps the inputs to a high-dimensional space, and the reduction phase compresses the dimensionality by group linear transformation (GLT), which is combined with lightweight FNN to reduce the number of parameters, while retaining the multi-head attention mechanism. The method achieves comparable performance to Transformer with lower computational cost. Finally, the engineering construction of knowledge graph is completed. Based on the ontology “seven-step approach” to establish the conceptual system of physical education courses, define entity relationships and attribute constraints. Using Neo4j graph database to achieve ternary storage and visualization, and batch importing through LOAD CSV to adapt to small and medium-sized sports teaching data, to ensure the efficiency and scalability of knowledge fusion.

II. Research on key technology of knowledge map construction for intelligent physical education

II. A. Design of a Q&A system based on the Sports Knowledge Graph

II. A. 1) Entity naming recognition

In this paper, we train the BERT-BiLSTM-CRF model with the addition of an attention mechanism for named entity recognition.The BERT-BiLSTM-CRF model is a deep learning-based text classification algorithm that combines the strengths of BERT and BiLSTM-CRF.The BERT has excellent entity feature extraction capability, and the BiLSTM-CRF is excellent in word feature acquisition. BERT has excellent performance in word feature acquisition, BiLSTM-CRF has excellent performance in word feature acquisition, and the introduction of the attention mechanism makes the model more accurate and focused in entity recognition. The structure of the model is shown in Fig. 1, which consists of four parts, including the BERT pre-training module, bi-directional long and short-term memory (BiLSTM), the attention mechanism and the conditional random field (CRF) module.

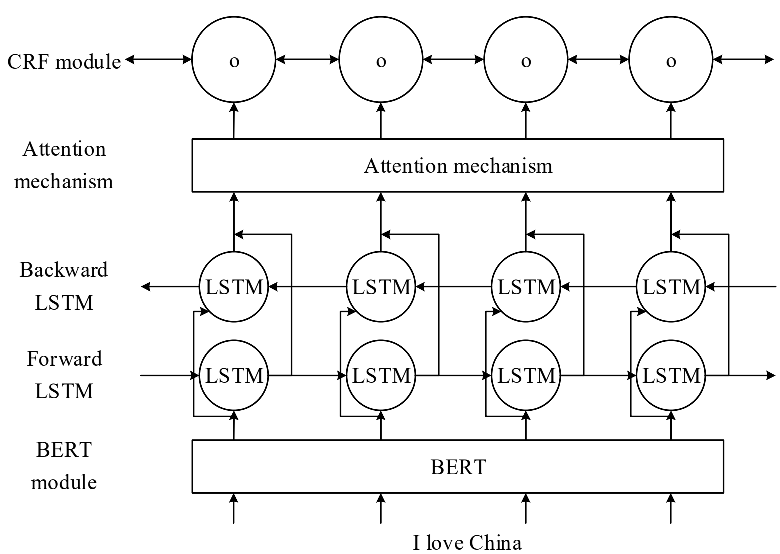

Figure 1: Named entity recognition algorithm model

The natural language question is input into the model, and the input is processed by the BERT model, which transforms the text into word vectors and obtains rich contextual information.The BERT model cares more about semantic changes than the traditional word vector acquisition method or random word vectors.In this paper, we mask nearly twenty percent of the semantic information in the training of the named entity recognition model, and we learn by predicting the masked information, and obtain the expression meaning of the same word in different contexts. The BERT model transforms unstructured natural language interrogative sentences into word vectors, which can utilize the interrelationships between words to effectively extract features from the text.

At the BiLSTM level, the word vectors obtained by the BERT model are used as inputs, and the BiLSTM calculates the current state values of the hidden layer and synchronously updates the corresponding parameters of the forgetting gate, the memory gate and the output gate. The updated output values are further passed to the CRF module for subsequent processing. In view of the fact that the BERT model supports input to text sentences, the model performance may be significantly affected when BiLSTM is faced with very long sequences output from the BERT module. To address this issue, an attention mechanism is introduced into the BiLSTM architecture, which helps to alleviate the limitation of BiLSTM's over-reliance on internal fixed-length vectors, and optimizes the model's performance to a certain extent when dealing with long sequence inputs. After the attention mechanism, the output of BiLSTM is shown in Equation (1):

$$S_t = f(S_{t-1}, y_{t-1}, c_t) \tag{1}$$

where f represents the LSTM, y_{t-1} is the label at the moment $t-1$, S_t is the output of BiLSTM at the moment t, and S_{t-1} is the output of BiLSTM at the moment $t-1$, while c_t is computed as shown in Eq. (2):

$$c_t = \sum_{j=1}^{Tx} a_{ij} h_j \tag{2}$$

where h_j refers to the output of the jth input in BiLSTM and a_{ij} represents the weights, which are computed as shown in equation (3):

$$a_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})} \tag{3}$$

BiLSTM lacks the ability to capture the transfer features between output labels, and the outputs are independent, so CRF is introduced to overcome this limitation.CRF not only predicts the corresponding state sequences based on the inputs, but also incorporates both the input features of the current state and the transfer features between various types of output labels, thus optimizing the accuracy of the prediction. And the score $Score(X, y)$ of the sentence X output label sequence y is calculated as shown in Eq. (4):

$$Score(X, y) = \sum_{i=0}^{n} A_{y_i, y_{i+1}} + \sum_{i=1}^{n} P_{i, y_i} \tag{4}$$

where P is the matrix of LSTM outputs, $P_{i,j}$ is the score assuming from the ith word to the jth word as a named entity; and A is the transfer matrix, which serves to quantify the probability of transferring between different states, and thus guides the model to efficiently change the state during the prediction process.

II. A. 2) Entity links

In the field of natural language processing, entity linking plays a key role in associating named entities (e.g., people, places, organizations, etc.) in a text with entities in a knowledge base, thus providing richer semantic information for the text. In Q&A system, entity linking is to link the entities in the question sentence to the corresponding entities in the knowledge base, and to obtain all the entities corresponding to the entities in the question sentence in order to accurately retrieve the relevant answers. Obtaining the entities in the question sentence as well as the candidate entities has a significant impact on the performance of the whole system. Entity linking is a complex process that needs to consider several factors, such as lexicality, named entities and their weights. For example, lexicality plays an important role in determining whether a word is a keyword or not; verbs emphasize actions, adjectives emphasize states, and nouns describe objects, so nouns are more suitable as keywords than verbs and adjectives, and named entities are more likely to be key sports entities in natural language problems. However, traditional entity dictionary matching methods are less efficient in distinguishing entities in the sports domain.In this paper, we score the recognized noun entities by TF-IDF model to screen the candidate entity word sets.TF-IDF model is a common model used to measure the importance of words in text.The detailed steps are:

(1) Segmentation and lexical labeling;

(2) Use for named entity recognition;

(3) Sort the list of words in descending order by TF-IDF score;

(4) Iterate over each word in the question and check whether its lexicality is legal, if the lexicality is legal, continue to determine whether the word is a named entity, if it is a named entity, select the word as a keyword.

Next, this paper can construct an alias dictionary based on Sports Knowledge Graph for obtaining information about entities related to named entities, and by traversing these entities, their aliases or synonyms can be extracted. In this paper, we adopt the template matching method to extract the alias information from the knowledge graph and match the attributes with alias meaning. An attribute of an entity is used as its alias when it can match the following templates:

(1) Ending with “name”: Chinese name, foreign name, alias, etc. (ranking and similar attributes do not belong to this category);

(2) Ending in “name”: alias, pronoun, abbreviation, old name, etc;

(3) End with “name”: official name, English name, Chinese name, other names, etc.

By using these templates, this paper extracts the alias information related to the entity, and then enriches the reference mode and diversity of the entity.

II. B.DeLight Optimization

The performance of the Q&A system built based on the above entity recognition and linking techniques is highly dependent on the efficiency of the underlying representation learning model. In order to reduce the computational overhead and adapt to long sequence sports text processing, this section introduces the DeLighT module to lighten the Transformer.

Connection and normalization module, the final output layer is connected to the previous Transformer without a direct connection path, the layer normalization module is generally located between the two residual link module, so the layer normalization module will make the top gradient flow block, if the number of layers is more, there will be the problem of the disappearance of the top gradient. Moreover, the Transformer framework has too many parameters and the model is too complex, which consumes more computational resources for long sequence tasks.

For the existing sequence modeling task, in order to improve the overall performance, more Transformers are usually stacked to expand the model, however, the significant increase in the model parameters leads to more complex learning and more difficult operation and training. In order to improve the performance of Transformer-based networks, this paper uses DeLighT to optimize the Transformer, and proposes a deeper-network, lightweight Transformer model that is applied to sequence modeling tasks with fewer operations and better model performance. DeLighT, a parameter-based attention structure, allows for easier scaling and deepening of the model, more efficient assignment of parameters in each Transformer module, and the new approach provides similar or better performance compared to Transformer with significantly fewer model parameters.

In this paper, DeLighT Transformations, the core of DeLighT, is used to optimize the Transformer module in the DAM model framework used to improve the performance of the sequence model.

The normal transformer framework mainly applies the DeFINE module, while the optimization of the module by the Expansion-Reduction (Expansion-Reduction) method to change the width and depth in the module, after the module scaling and expansion can be efficiently assigned to the parameters, the optimization is called the DeLighT module, the width of the module is shown schematically in Fig. 2, and the overall module depth are all N.

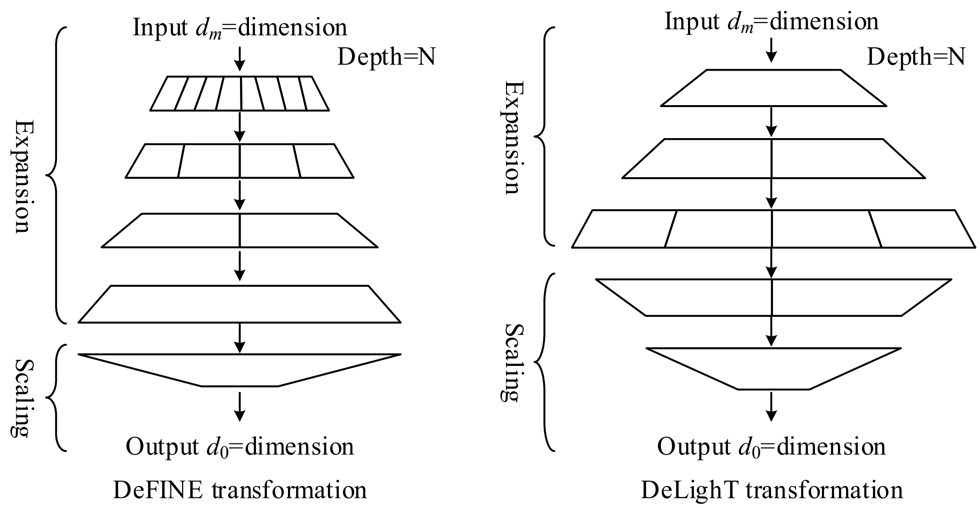

Figure 2: Illustration of DeFINE and DeLighT transformation

The usual way to enhance the expressive power and capacity of a transformer module is by increasing the dimensionality of the input d_m, but this linear increase tends to increase the complexity of the module's operations. DeLighT, on the other hand, deals with this by increasing the depth and width of the intermediate transformations of the module through an expansion-shrinkage phase, which results in fewer DeLighT operations and allows for the computation of attention using smaller dimensions.

The overall DeLighT transformation is mainly controlled by five configuration parameters: the depth N of the GLT layer, the width multiplier w_m, the input dimension d_m, the output dimension d_o, and the maximal group $g_{\max}$ in GLT. Where GLT stands for Group Linear Transformation, which can learn local information by input specific parts, which is better than linear transformation, and secondly to ensure the learning of global representation, DeLighT also uses the shared information of features in Group Linear Transformation. Different colors in the image are used to represent groups in GLT, DeLighT transformation makes learning wider representation by using more group linear transformations and less parameters are used in comparison, the performance is not much different from the pre-transformation one, with sports as follows.

In the expansion phase, the DeLighT transform module maps the input dimension d_m input to a higher dimensional space, $d_{\max} = m_w d_m$, with a linear layer of $\frac{N}{2}$.

In the reduction phase, the DeLighT transform maps the $d_{\max}$-dimensional vectors to the d_o-dimensional space output for the remaining $\left(N-\frac{N}{2}\right)$ GLT layers, and the output Y for each layer l is shown below, where the number of groups on l is calculated as shown in equation (5):

$$g^l = \begin{cases} \min\left(2^{l-1}, g_{\max}\right) & 1 \le l \le \frac{N}{2} \\ g^{N-1} & Other \end{cases} \tag{5}$$

Therefore, in this paper, the DeLighT transform is utilized to optimize it based on block scaling, which in turn reduces the depth of each head attention dot. And the lightweight FNN proposed in DeLighT similar to the FNN in the original transformer module is utilized to reduce the parameters of the model. Unlike the overall DeLighT model, the attention mechanism utilized in this paper is still the multi-head attention mechanism, just borrowing the idea of DeLighT's module scaling for optimization, in which the scaled dot product attention mechanism is calculated as shown in Eq. (6), scaled according to the output dimension.

$$\text{Attention}(K,Q,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_0}}\right)V \tag{6}$$

where Q, K, V represent query, key, and value respectively, and d_0 represents the output dimension.

Finally the specific implementation parameters of the transformer_decoder applied in this paper apply the multi-head attention mechanism, which makes the layer of the transformer deeper but the width becomes narrower by changing the parameters of hn and head_num.

II. C.Knowledge graph construction process

The optimized deep learning model provides technical support for knowledge extraction, while ontology modeling and storage problems still need to be solved for how to systematically organize sports teaching knowledge. Accordingly, this section develops the knowledge graph construction process, defines the knowledge framework through ontology design, and realizes efficient integration with the help of graph database.

II. C. 1) Modeling the course ontology

In the current research on knowledge graph construction methods, ontology modeling is often used to construct the schema layer of knowledge graph. The term ontology originates from the field of philosophy, which mainly refers to abstracting and generalizing the objective things in the real world while revealing and reflecting their essence. The derived meaning of ontology in the field of computer science is a shared conceptual model for describing domain knowledge. An ontology contains not only the basic concepts within a subject area, which delineates the categories and levels in which the concepts are located, but also defines the relationships between different concepts and the basic properties of the concepts, and can be regarded as a collection of recognized terms within a specific domain.

Ontology serves as the logical basis for the construction of most domain knowledge graphs, and there is an inseparable relationship between the two. Ontology defines the concept types, relationship types and attribute types in the domain by defining the metadata in the domain. If the whole knowledge graph is regarded as a knowledge tree, ontology is the trunk of the tree, which restricts the “growth range” of the domain knowledge, describes the overall structure of the trunk, and at the same time, it provides the “branches” and “leaves” in the knowledge tree, which can be used as the basis for the construction of the knowledge graph. At the same time, it defines the “branches and leaves”, i.e., relationships and attributes, which are the basis and constraints for the construction of the knowledge graph. When the ontology modeling is completed, only then can we populate the instantiated entity data that focuses on the actual business, and at the same time determine the relevant attributes of the entities and the relationships with other entities based on the attribute categories and relationship categories defined in the ontology model, so as to integrate the massive data into a knowledge graph or knowledge base that completely covers the domain knowledge. We can regard ontology as the upper level model of knowledge graph and the constructed knowledge graph as the figurative representation of the ontology model. In this paper, we model the Python course ontology based on the “seven-step approach” proposed by Stanford University. First, we determine the coverage of the research domain, then define the concept types, inter-concept relationship types, and concept attribute types based on the existing knowledge system or thesaurus in the domain, and finally populate the constructed ontology model with instantiated entity information.

II. C. 2) Knowledge integration

In this paper, the graph database tool Neo4j is used to achieve the storage of Python course knowledge point ternary and the visual display of course knowledge graph. At present, the commonly used ternary data import neo4j graph database has a variety of import methods, commonly used import methods LoadCSV method, the use of batch import tool import method, the use of Cypher Create statement will be the ternary data import and so on.

The Load CSV method requires that the ternary data be converted into a CSV format data file with specific table headers in advance, and then the entities, relationships, and entity attributes can be imported at one time through the data import statement in the neo4j interface.The Load CSV method is commonly used for storing local file data with a small amount of data (under ten million). The method of using batch tools to import is based on the neo4-import tool officially provided by neo4j graph database, which is commonly used to import large datasets and can be used to store local or remote file data. Another commonly used import method is to use Cypher Create statement to import ternary data, generally through the Py2neo library installed in Python to realize the connection with the graph database to create entities and relationships between entities. It is relatively slow compared to the first two import methods.

After comparing the characteristics of the above three graph database storage methods, and taking into account that the amount of ternary data acquired in this paper for physical education teaching courses is small and locally stored data, this paper adopts the LOAD CSV method for batch ternary data import to complete the construction of the physical education course knowledge graph.

III. Experimental analysis of DeLight optimization-based Q&A model for sports knowledge graphs

Based on the above fusion of BERT-BiLSTM-CRF entity recognition, TF-IDF weighted linking strategy, and DeLighT optimized Transformer lightweight architecture, this paper constructs the core engine of a knowledge mapping Q&A system for sports teaching. In order to comprehensively verify the effectiveness of this optimization model in the sports knowledge quizzing task and its enhancement of knowledge mapping accuracy, exhaustive comparative experiments are designed and implemented in this chapter.

III. A. Experimental setup

III. A. 1) Data sets

In order to comprehensively evaluate the effectiveness of the SBERT_QA model in performing single-hop user question-to-knowledge graph mapping, experiments are conducted using a Chinese assessment dataset about physical education teaching based on knowledge graph-based Q&A KBQA, which consists of an encyclopedic knowledge base about physical education knowledge and a Q&A dataset.

Each row of the data in the knowledge base is a triple, where the parentheses after the header entity are the disambiguation terms of the entity; the Q&A dataset is in json format, and each row is a question-answer pair that contains a triple of questions and answers. For header entity detection experiments, the questions and entities in the Q&A dataset are converted to BIO's data annotation format; In the candidate ternary detection experiments, the ternary data including entities, predicates, tail elements, and disambiguation information in the knowledge base are stored in bulk to the Elasticsearch index, which facilitates the rapid retrieval of candidate ternaries in the knowledge base after detecting the problematic head entities; in the training of the candidate ternary ranking model based on SBERT, a segmented sampling strategy is adopted, and finally 732374 training sets and 21382 validation sets and 20046 test sets are prepared. 732374 training sets, 21382 validation sets and 20046 test sets.

III. A. 2) Experimental parameters

BERT-BiLSTM-CRF is adopted as the base model when performing head entity detection model training, which is pre-trained using a standard Chinese corpus with 12 layers of Transformer and a hidden layer size of 812. The number of training rounds for fine-tuning is set to 50, and an early-stopping mechanism is used to avoid overfitting, and the training is stopped when there is no performance improvement in 10 iterations. When performing the training of the Delight-based optimized model, the pre-training dataset is suitable for capturing complex relationships between words in similarity assessment by employing full-word masking and extended pre-training dataset. The number of training rounds is set to 5 due to the high efficiency of the model and the simplicity of realizing the similarity training task, which requires only very few rounds of fine-tuning for fast convergence.

III. A. 3) Assessment of indicators

In the head entity detection task, the accuracy Precision, the recall Recall, and the F1 value are used as evaluation metrics.

In the optimized model testing, the evaluation metrics of exact matching EM and similarity matching SIM are used to evaluate the accuracy of predicting the head entity S, predicate P, and tail element O of the obtained triad, respectively. SIM measures the similarity of two texts by the longest common subsequence, a method that not only takes into account the degree of matching of characters in the text, but also ensures that the results are normalized by length normalization.

Finally, the EM accuracy for exact matching of the tail elements of the triad and the SIM accuracy for similarity matching are combined to obtain the final score of the model's quizzing effectiveness.

III. B. Comparative Analysis of Physical Detection Models

III. B. 1) Experimental results and analysis of head entity detection models

Comparison experiments were conducted to compare the head entity detection effect of word2vec-BiLSTM-CRF model, BERT-BiLSTM-CRF model and BERT -CRF model used in this study, respectively, and the results of the experiments are shown in Figure 3 below.

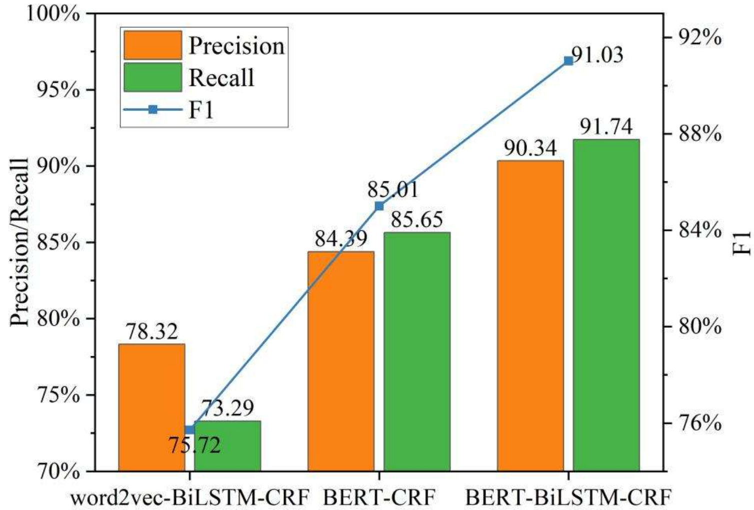

Figure 3: The results of the comparison experiment for head body detection

From the experimental results, it can be seen that the word2vec-BiLSTM-CRF method is the worst for head entity detection, with insufficient feature extraction and context capturing ability, and the F1 is only 75.72%; after using BERT as a feature extractor, the accuracy and recall are significantly improved, and the BERT-CRF model achieves head entity detection with F1 reaching the 85.01% level; BERT-BiLSTM-CRF, as the most general entity recognition model, has the best performance when applied to this head entity detection task, with an accuracy of 90.34%, a recall of 91.74% and an F1 of 91.03%.

III. B. 2) Experimental results and analysis after improved modeling

The improved model in this paper is optimized by introducing DeLight module on the optimal entity recognition model BERT-BiLSTM-CRF. In order to evaluate the performance of the optimized model in this paper for the user problem to knowledge graph mapping task, it is compared with several benchmark models in the last 5 years, which are briefly described.

NER-SIM: This model first fine-tunes the BERT to achieve the entity recognition task, and then fine-tunes the BERT to splice the question with the relation for sentence binary classification to determine whether the question should ask for the attribute or not.

GKRE: This model is an end-to-end generative knowledge graph Q&A model that views the knowledge graph Q&A task as a sentence-completion task, and the complete task consists of: entity recognition, relation recognition, and entity linking.

Seq2Seq + Prefix Tree: only positive samples are needed to train the Seq2Seq model, which interacts the target sentence with the input sentence at the Token level, and also utilizes the prefix tree to constrain the decoding process and ensure that the generated results are in the database.

The results of the knowledge graph quizzing experiments for each model are shown in Table 1.

Table 1: The experimental results of knowledge graph question answering

Model	Score	EM				SIM			
		EM-S	EM-P	EM-O	EM-ALL	SIM-S	SIM-P	SIM-O	SIM-ALL
NER-SIM	83.20	86.41	83.68	83.5	80.99	89.85	86.78	83.56	85.41
GKRE	80.58	80.11	79.41	78.02	78.55	86.41	85.8	81.96	82.61
Seq2Seq + prefix tree	86.76	89.88	86.87	86.19	79.76	94.79	90.37	88.08	93.76
BERT-BiLSTM-CRF	77.94	85.88	83.1	82.96	77.78	85.75	80.15	76.83	78.09
BERT-BiLSTM-CRF-DeLight	92.13	91.39	89.45	87.48	88.91	96.32	93.71	90.88	95.34

As shown in Table 1, the BERT-BiLSTM-CRF-DeLight optimized model significantly outperforms all baseline models in the knowledge graph quizzing task with a combined score of 92.13, which is a 14.19-point improvement over the original BERT-BiLSTM-CRF model's score of 77.94, which verifies the effectiveness of the DeLight lightweight design. Specifically, on the exact matching (EM) performance, the optimized model outperforms the baseline model in the accuracy of 91.39% for the head entity EM-S, 89.45% for the predicate EM-P, and 87.48%

for the tail element EM-O, where the EM-O is improved by 10.52% compared to the original model, which indicates that the optimized model is better at capturing the complete structure of the ternary. On similarity matching (SIM), the optimized model has a SIM-ALL index of 95.34%, which is 1.58% higher than the 93.76% of the second-place Seq2Seq+ prefix tree model. In particular, it excels in the tail element similarity SIM-O of 90.88%, reflecting its greater robustness to semantic variants of user questions.

As for other models, the NER-SIM model performs moderately well in EM-S (86.41%) and SIM-S (89.85%), but lower in EM-ALL (80.99%), which shows that its global inference ability is insufficient; Seq2Seq+ prefix tree is ahead of the optimization model in SIM-S (94.79%), but lags behind the optimization model in EM-O (86.19%) by 1.29%, proving that there is an exact matching shortcoming in the generative approach; the GKRE end-to-end model is at the bottom of the list in all indicators (total score 80.58), highlighting the limitations of generative architectures in complex tasks.

Overall, DeLight optimization significantly improves the knowledge mapping efficiency through parameter compression and attention mechanism improvement with SIM-ALL of 95.34% while maintaining the strong representation capability of BERT-BiLSTM-CRF, providing a high-precision and low-redundancy solution for physical education Q&A system.

IV. Empirical Research on Teaching and Learning with an Intelligent Physical Education Teaching Knowledge Mapping System

The experimental results show that the DeLight-optimized BERT-BiLSTM-CRF model exhibits significant performance advantages in the sports knowledge graph quizzing task. In order to deeply explore the application value of this intelligent sports teaching knowledge mapping system in real teaching environments and its contribution to students' learning effectiveness, this chapter further carries out a semester-long teaching control experiment in a university sports course.

IV. A. Experimental setup

IV. A. 1) Objects of study

A total of 111 students in Physical Education 1 class (56 students) and 2 class (55 students) of 2024 will be the subjects of this experiment. Through the preexperimental understanding, the experimental subjects in the teaching experiment before the situation of each base consistent, and in the attitude of physical exercise, learning interest and special physical quality there is no significant difference. For this reason, the two classes were divided into the experimental group and the control group for the actual physical education teaching by using the teaching mode based on knowledge mapping and the traditional teaching mode respectively.

IV. A. 2) Experimental methods

After a semester-long teaching period, a comparative analysis was conducted on two aspects of students' institutional health and their interest in learning physical education. The aspect of students' institutional health was carried out through specific sports tests, including lung capacity, seated forward bending, 50m running, 1000m running for male students, 800m running for female students, standing long jump, push-ups (for male students) and sit-ups (for female students). Interest in physical education learning was analyzed by distributing the questionnaire “Interest in Physical Education Learning of College Students”. The questionnaire was centered on five aspects of physical education learning positivity, physical education learning negativity, physical education skill learning, physical education after-school activities, and physical education concern, and students filled out the questionnaire according to the Likert 5-point rating scale (1-5) interest degree from none to some degree.

IV. B. Analysis of students' physical fitness test data before and after the experiment

At the end of the semester-long 16-week experiment, students in the experimental and control groups were tested for basic physical health indicators. The comparison of each test index between the two groups after the experiment is shown in Table 2.

Table 2: Comparison of each test index between the two groups after the experiment

Test indicators	Gender	Experimental group	Control group	T	P
Vital capacity (ml)	Male	3940.38	3629.32	4.87	0.000***
	Female	2345.13	1977.97	6.01	0.000***
	All	3142.75	2803.64	3.45	0.001***
Sit forward Bend (cm)	Male	11.25	8.96	5.23	0.000***
	Female	18.75	13.72	4.56	0.000***
	All	14.78	11.79	4.78	0.000***
50m running (s)	Male	7.24	8.58	3.21	0.002***
	Female	8.58	9.07	4.95	0.000***
	All	8.01	8.85	5.34	0.000***
1000m running (min)	Male	3.93	4.60	6.12	0.000***
800m running(min)	Female	3.69	4.52	7.45	0.000***
Standing long jump (cm)	All	228.15	200.57	4.89	0.000***
	Male	195.74	180.87	6.78	0.000***
	Female	211.945	190.72	2.34	0.022***
Pull-ups	Male	5.08	4.52	3.56	0.001***
Sit-ups	Female	52.79	46.71	4.87	0.000***

As can be seen from Table 2, the experimental group using the knowledge mapping teaching mode was significantly better than the traditional teaching control group in all physical fitness indicators (p<0.05), which verified the practical effectiveness of the intelligent sports teaching system. Specifically, cardiorespiratory function was improved: the overall mean value of lung capacity in the experimental group (3142.75 ml) was 12.1% higher than that of the control group (2803.64 ml) (t=6.01, p<0.001), with boys improving by 8.6% (3940.38 ml→3629.32 ml) and girls improving by 18.6% (2345.13 ml→ 1977.97ml), reflecting the effect of the system's personalized guidance on endurance training.

Speed and flexibility advantage: 50m running performance of the experimental group 8.01s significantly faster than the control group 8.85s (t=4.95, p<0.001), the difference between the boys amounted to 1.34s (7.24s→8.58s); seated forward bends of the experimental group 14.78cm compared with the control group 11.79cm 25.3% improvement (t=4.56, p<0.001) In the experimental group, the improvement was 36.6% (18.75cm→13.72cm). Strength quality breakthrough: standing long jump experimental group as a whole 211.95cm far more than the control group 190.72cm (t=6.78, p<0.001), boys improved 13.7% (228.15cm→200.57cm). The most significant difference was found in the strength program, where the number of pull-ups improved by 12.4% for boys (5.08 → 4.52, t=2.34, p=0.022) and sit-ups by 13.0% for girls (52.79 → 46.71, t=3.56, p=0.001).

By accurately analyzing students' physical fitness data and providing dynamic training programs, such as long-distance running pace optimization and flexibility-specific training, the knowledge mapping system significantly improves the teaching effect-especially in traditionally weak areas such as the female group (lung capacity +18.6%, flexibility +36.6%) and strength quality (pull-ups +12.4%) A breakthrough has been made.

IV. C. Comparative Analysis of Interest in Physical Education Learning

IV. C. 1) Comparative analysis of physical education learning interest of the experimental group before and after the experiment

The comparative analysis of the experimental group's interest in physical education learning before and after the experiment is shown in Table 3. In order to show the specific scores of each index more clearly, the specific scores of the violin diagram about the evaluation of the student questionnaire of these five dimensions were drawn as shown in Figure 4.

Table 3: Analysis of Physical Education learning Interest in the experimental group

	Before the experiment	After the experiment	T	P
The enthusiasm for physical education learning	3.25±1.25	4.73±0.59	7.283	0.000***
The negativity of physical education learning	3.82±1.06	1.09±0.35	5.242	0.000***
Learning of sports skills	3.36±1.16	4.47±0.96	4.574	0.000***
After-school sports activities	3.67±1.19	4.62±0.65	3.490	0.000***
Sports attention	3.07±0.92	4.65±0.62	6.392	0.000***

As shown in Table 3, after adopting the knowledge mapping teaching model, students in the experimental group showed statistically significant increases in all interest dimensions (p<0.001). Positivity jumped from 3.25±1.25 to 4.73±0.59, an increase of 45.5%, t=7.283, reflecting that students' willingness to take the initiative to participate increased dramatically; negativity plummeted from 3.82±1.06 to 1.09±0.35, a decrease of 71.5%, t=5.242, indicating that learning resistance was significantly alleviated; interest in skill learning increased by 33.0%, and the average score was 3.36 before the experiment, and increased to 4.47 after the experiment. The average score of 3.36 before the experiment was raised to 4.47 after the experiment, t=4.574, reflecting the increased confidence in the mastery of specialized techniques; the participation in extracurricular activities increased by 25.9%, and the score was raised from 3.67±1.19 to 4.62±0.65, t=3.490, indicating that the habit of independent exercise outside the classroom has been formed; the increase in the degree of concern for physical education amounted to 51.5% (3.07±0.92→ 4.65±0.62→5.490), indicating a significant alleviation of learning resistance. 4.65±0.62, t=6.392), verifying the effect of the system on the promotion of sports culture.

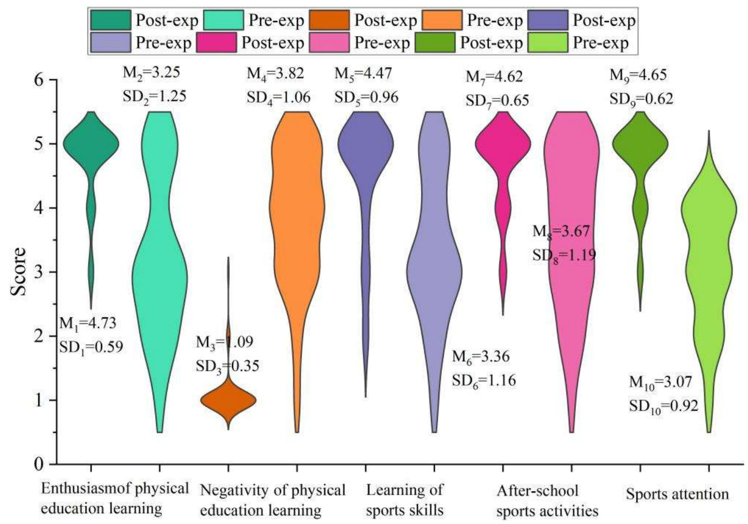

Figure 4: Analysis of Physical Education learning Interest in the experimental group

The knowledge mapping system comprehensively stimulates students' internal motivation for physical education learning through personalized training feedback, real-time action correction, and training plan adaptation, especially for the improvement of negative emotions, with a drop of 71.5%.

IV. C. 2) Comparative analysis of physical education learning interest of the control group before and after the experiment

The comparative analysis of physical education learning interest of the control group before and after the experiment is shown in Table 4, and the violin plot is shown in Figure 5.

Table 4: Analysis of Physical Education learning Interest in the control group

	Before the experiment	After the experiment	T	P
The enthusiasm for physical education learning	3.47±1.21	3.85±0.91	2.383	0.033***
The negativity of physical education learning	3.64±1.13	2.53±1.30	4.294	0.004***
Learning of sports skills	3.67±1.26	3.95±0.99	1.836	0.081**
After-school sports activities	3.60±1.21	4.02±1.05	2.294	0.036***
Sports attention	3.22±1.26	3.89±1.18	2.027	0.020***

The traditional teaching mode brought only a limited and uneven increase in interest. Positivity increased by only 11.0% (3.47±1.21→3.85±0.91, t=2.383, p=0.033), an increase of less than 1/4 of that of the experimental group; negativity decreased (3.64±1.13→2.53±1.30, t=4.294, p=0.004), but the residual value (2.53) was still 1.09 2.3 times; no significant change in interest in skill acquisition (3.67±1.26→3.95±0.99, t=1.836, p=0.081), exposing the lack of incentives for skill acquisition in traditional teaching; weak enhancement in after-school activities (+11.7%) and attention (+20.8%) with large standard deviations (1.05-1.18), reflecting the high degree of dispersion of students' engagement .. Traditional instruction failed to systematically address interest differentiation, and skill acquisition (p=0.081) and after-school activities (p=0.036) were weakly elevated, highlighting the limitations of uniform instruction.

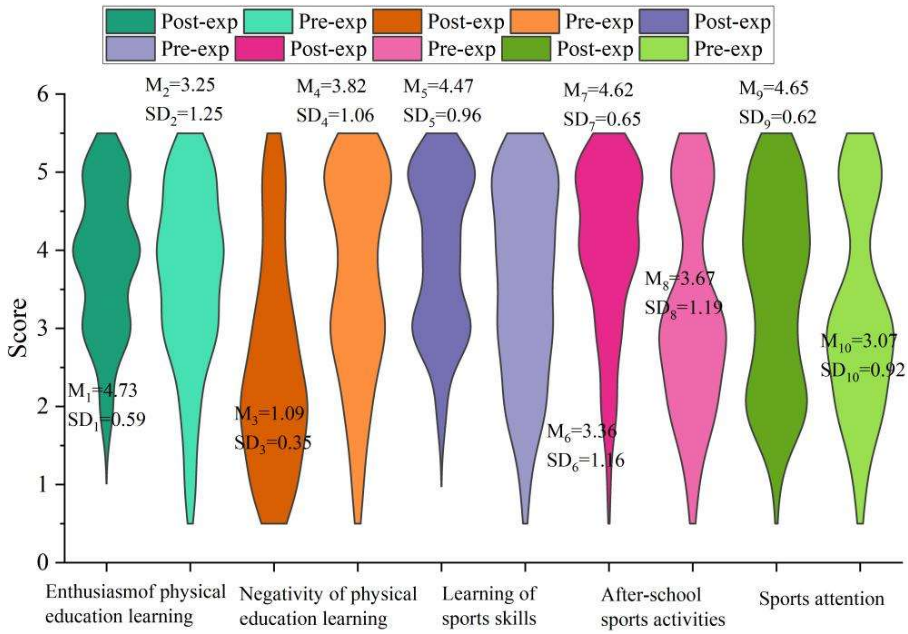

Figure 5: Analysis of Physical Education learning Interest in the control group

IV. C. 3) Comparative Analysis of Gymnastics Learning Interest between Experimental Group and Control Group after the Experiment

The comparative analysis of learning interest in gymnastics between the experimental group and the control group after the experiment is shown in Table 5.

Table 5: Analysis of gymnastics learning Interest between two groups

	Experimental group	Control group	T	P
The enthusiasm for physical education learning	4.73±0.59	3.85±0.91	8.328	0.000***
The negativity of physical education learning	1.09±0.35	2.53±1.30	12.754	0.000***
Learning of sports skills	4.47±0.96	3.95±0.99	2.694	0.016***
After-school sports activities	4.62±0.65	4.02±1.05	2.925	0.009***
Sports attention	4.65±0.62	3.89±1.18	3.693	0.000***

The experimental group crushed the control group across the board on the interest dimension (p<0.05) and had better data stability, standard deviation ≤0.96), the largest gap in positivity regarding interest in physical education learning (4.73 vs 3.85, t=8.328, p<0.001), with the experimental group leading by 22.9%; a significant advantage of negativity control (1.09 vs 2.53, t=12.754, p<0.001), with a 56.9% reduction in negative affect in the experimental group; a 13.2% lead in interest in skill acquisition (4.47 vs. 3.95, t=2.694, p=0.016), corroborating the role of personalized instruction in shaping technical confidence; and a significant advantage in participation in after-school activities (4.62 vs. 4.02, t=2.925, p=0.009) and attention (4.65 vs. 3.89, t=3.693, p<0.001) were 14.9% and 19.5% higher, respectively, reflecting the system's long-lasting effects on sports habits.

The knowledge mapping system has a revolutionary advantage in eliminating negative emotions (difference of 1.44 points) and enhancing participation initiative (difference of 0.88 points) through dynamic learning path planning.

V. Conclusion

In this paper, we propose a knowledge graph construction method integrating lightweight deep learning architecture for intelligent sports teaching scenarios, and verify the effectiveness of the system through technological innovation and teaching empirical evidence.

The proposed BERT-BiLSTM-CRF+attention mechanism model significantly improves the performance of entity recognition in the sports domain, and the F1 value reaches 91.03%. The BERT-BiLSTM-CRF-DeLight model optimized by introducing the DeLighT module reconstruction Transformer reaches a comprehensive score of 92.13%

in the sports knowledge quiz task, which is 14.19 points higher than the original model, with the tail element matching accuracy (EM-O) improved by 10.52% and the similarity matching (SIM-ALL) up to 95.34%, providing efficient solutions for teaching scenarios with limited resources.

The effect of knowledge graph-driven teaching is remarkable, and the core indexes of lung capacity (3142.75ml vs 2803.64ml, +12.1%), 50m run (8.01s vs 8.85s, +10.5%) and standing long jump (211.95cm vs 190.72cm, +11.2%) of the students in the experimental group are significantly better than those of the control group, which verifies the scientific nature of the personalized training program; the sports training program of the experimental group is also more effective than that of the control group. The scientific nature of the individualized training program was verified. The experimental group showed a 45.5% increase in the positivity of physical education learning (4.73±0.59 vs. 3.25±1.25), a 71.5% decrease in the negativity (1.09±0.35 vs. 3.82±1.06), and a systematic increase in the interest in skill learning (+33.0%), participation in after-school activities (+25.9%) and other dimensions.

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