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Exploration and practice of teaching reform of automotive mechanical system course based on information technology

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--***ABSTRACT***--
The course of automotive mechanical system is the cornerstone course of automotive related majors,it plays an important role in cultivating students' professional quality.However,in the face of the rapid development of the automobile industry and the continuous renewal of educational ideas, the traditional teaching mode in this course has exposed many problems and can no longer meet the needs of students' learning and teaching. This article uses modern information technology to establish a knowledge map teaching resource for the course, introduces advanced intelligent technology to assist personalized learning for students, combines online teaching tools for knowledge reconstruction and meets the needs of students' independent learning. By implementing these reform measures, the aim is to improve the quality of course teaching and cultivate high-quality talents with innovative spirit, practical ability and solid professional knowledge for the automotive industry.

Key words： *Automotive mechanical system;Knowledge map teaching resource;Advanced intelligent technology;Knowledge reconstruction*

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Ⅰ. Introduction

The course of the automobile mechanical system occupies a fundamental and crucial position in the automotive engineering education system [1],it is an important prerequisite for students to deeply understand the working principles of automobiles, master car maintenance skills, and engage in subsequent professional course studies [2].With the rapid evolution of automotive technology towards intelligence, electrification, networking and sharing, as well as the continuous improvement of talent training quality in the education field[3], the traditional teaching mode has become difficult to meet the demands of the new era. In-depth exploration of teaching reform paths and innovative teaching methods and means have become urgent tasks facing the teaching of automobile construction courses at present.

The problem of imbalance between theory and practice teaching: the traditional automobile structure course focuses too much on the explanation of theoretical knowledge, and the practical teaching part is relatively weak and lacks systematic planning. Classroom teaching mainly revolves around theoretical lectures based on textbook content, while laboratory courses often only serve as a simple verification of theoretical knowledge, failing to form an organic synergistic effect between the two. This teaching model leads to students being unable to effectively apply their theoretical knowledge to analyze and solve practical car problems, resulting in a serious lack of hands-on ability and practical operational experience [4].

The automobile industry, as an important representative of modern manufacturing, isundergoing unprecedented technological changes[5]. However, the current curriculum for automotive engineering lags behind the pace of industry development, still mainly focusing on the construction and technology of traditional fuel vehicles. Knowledge related to emerging fields such as new energy vehicles and intelligent connected vehicles is rarely covered in textbooks, leading to a significant gap between what students learn in class and actual industry applications. As a result, they are unable to timely access and master cutting-edge technologies and development trends in the automotive industry, making it difficult to meet future career development needs[6].

Ⅱ. Design of knowledge map of automotive teaching resources

As a modern teaching resource, the knowledge map of the automobile mechanical systems can significantly improve the quality and efficiency of course teaching[7]. Its unique advantage mainly lies in the systematic integration of complex and fragmented knowledge, which enhances students' interest in learning.

The systematic integration of knowledge is one of the core values of knowledge graph[8]. It organizes the complex information about car structures, including component functions, fault diagnosis processes, maintenance skills, etc., in a structured way to form a clear and logical knowledge network. This integration not only facilitates students to comprehensively and orderly master professional knowledge but also enables teachers to design teaching plans more systematically and efficiently.

The knowledge graph is a new method of modeling knowledge in the form of a graph and structurally expressing the relationships between various knowledge in the world[9]; it is a knowledge network formed by connecting entities and entities or entities and attributes through their associative relationships [10]. It is a graph structure used to represent knowledge and its interrelationships, with nodes representing entities (such as people, places, things) and edges representing relationships between entities (such as "author-writing-book"). The knowledge graph systematically represents the various components of an engine and their relationships through a graph structure [11], helping students establish a comprehensive knowledge framework for the engine's crankshaft connecting rod mechanism and valve mechanism; using visualization tools to display the knowledge graph, helping students understand the structure and principles of the engine concretely; recommending personalized learning paths based on the knowledge graph [12].

Ⅲ. Knowledge graph technology architecture

Knowledge fusion refers to the integration of knowledge from different sources, formats, and domains to form a more complete and accurate knowledge graph. This process requires addressing issues such as entity alignment, relationship matching, and data conflict resolution. The technical framework for constructing a knowledge graph is shown in Figure 3-1.

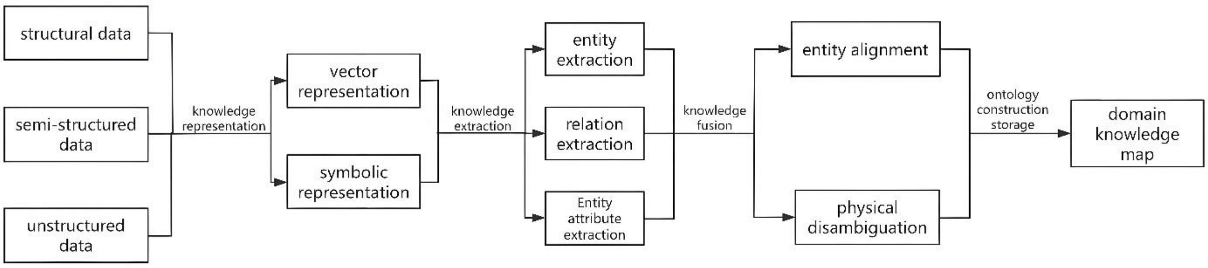

Figure 3-1 Technical architecture of the knowledge graph

3.1 Research on named entity recognition model based on BERT-BILSTM-CRF

The project utilizes the pre-trained BERT (Bidirectional Encoder Representations from Transformers) model to build an efficient Chinese NER (Named Entity Recognition) system. By integrating BERT's semantic information into the BILSTM-CRF model, we are able to effectively capture the semantic and sequential information in the text, thereby improving the performance of NER tasks. In the future, we can further explore techniques such as incorporating graph embeddings to enhance the model's ability to model relationships between words.

BERT Model and Semantic Understanding: BERT is a pre-trained language model based on the Transformer architecture. Unlike traditional word embedding methods, BERT can capture bidirectional semantic information of words in context. Through pre-training on a large-scale corpus, BERT learns rich language knowledge and can map each word to a vector space containing rich semantic information. In this project, we use the pre-trained Chinese BERT model (chinese_L-12_H-768_A-12) as the foundation and utilize it as an embedding layer to generate contextually relevant word vectors for each word in the input text. Specifically, we first need to appropriately preprocess the input text, including tokenization, removing stop words, adding special tokens (such as CLS and SEP), etc., to meet the input requirements of the BERT model.

After preprocessing, the text data will be fed into the Chinese BERT model. Since the training of BERT model is based on two tasks: "MLM" (Masked Language Model) and "NSP" (Next Sentence Prediction), it is able to understand and generate bidirectional semantic representations for each input word. This means that the representation of each word is not only based on its preceding words, but also on its following words, effectively capturing the true semantics of the word in a specific context. The obtained word vectors will be used as feature inputs for various NLP (Natural Language Processing) models. In named entity recognition tasks, the vector of each word can be directly used to identify and classify specific entities in the text, such as names of people, places, organizations, etc.

In addition, fine-tuning the BERT model is also an important step. Although the pre-trained BERT model has gained extensive language understanding capabilities, fine-tuning on specific task data can help the model better adapt to particular application scenarios. This step usually involves adjusting the last few layers of the model to enable it to learn more task-specific features, thereby improving task execution efficiency and accuracy. BERT not only provides us with a powerful language representation method but also greatly advances the ability of machines to understand and generate natural language.

In order to better utilize the semantic information of BERT for NER, we constructed a BERT-BILSTM-CRF model with the following architecture:

1) BERT embedding layer: A pre-trained BERT model is used to generate a context-dependent word vector for each word in the input text.

2) Two-way LSTM layer (BILSTM): The BILSTM layer captures the sequential relationship between words in a sentence. The word vector generated by BERT is input into the BILSTM layer, Context-sensitive feature representations are further extracted.

3) Conditional random field layer (CRF): The CRF layer is used to sequence label the output of the BILSTM layer, it learns the dependencies between labels, this ensures that the final predicted label sequence is legal and consistent.

4) Model evaluation and training process visualization：To evaluate model performance, we evaluated the trained BERT-BILSTM-CRF model using the test set data, the accuracy rate, recall rate and F1 value are calculated **Error! Reference source not found.**.

Bert-bilstm-crf model integrates the semantic information learned by BERT model into BILSTM (Bidirectional Long Short-Term Memory) and CRF (Conditional Random Field) models.BERT model learns semantic information of text through pre-training, Graph embedding technology maps words to vector space to capture semantic information, The Bert-BilstM-CRF model integrates the semantic information of BERT model into BILSTM-CRF model, the performance and accuracy of the model in sequence labeling tasks are improved.

This project utilizes Kashgari, an efficient and flexible NLP framework based on PyTorch. Kashgari offers a rich set of tools and pre-trained models designed to accelerate the development and research of natural language processing tasks.In this project, we primarily focus on the task of Named Entity Recognition (NER). For the model, I employed the fit method for training and specified the training set, validation set, number of epochs and batch size. Upon completion of the training process, we saved the model to a file and utilized the evaluate method to compute performance metrics on the test set.

Finally, the variations of the loss function and accuracy are illustrated in a single chart, as shown in Table 3-2.

Table 3-2 Model training parameters

Parameter Name	Numeric
epoch	10
Batch_size	512
Sequence_length	38

3.2 Analysis of experimental results

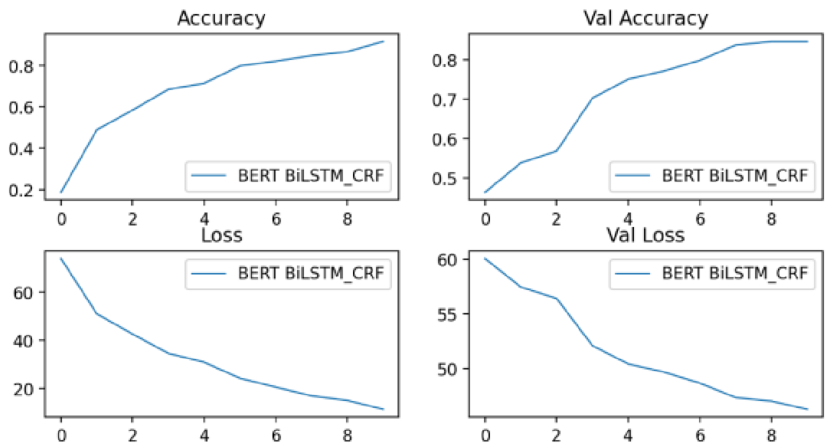

Figure 3-3 Model experiment results

As shown in Figure 1-2, the loss function and Accuracy curve in the training process of BERT-BILSTM-CRF model. The BERT-BiLSTM-CRF model training curve shown in the picture provides an intuitive understanding of the model performance and training process for this design, including accuracy and

Val Accuracy, Loss, Val Loss.In the training process, the accuracy and loss value of the model are the key indicators to evaluate its performance. As can be seen from the figure, both the training accuracy and validation accuracy remain at a high level, about 0.8, which indicates that the model not only performs well on the training data, but also maintains stable performance on the unseen validation data, which is an important sign to avoid overfitting. The curve of the loss value shows that the model's losses on both the training set and the validation set gradually decrease as the training progresses, which means that the model is effectively learning the patterns in the data, and the optimization algorithm is helping the model to reduce the prediction error.The performance changes of the model over 10 training cycles were recorded in detail. Typically, each cycle represents one complete training iteration of the model over the entire training set. It can be observed from the figure that with the increase of the cycle, the accuracy curve steadily rises and the loss curve gradually decreases, which shows the gradual improvement and steady improvement of the model during the training process.

In addition, the stability of the model training is also an important aspect to evaluate its performance. As can be seen from the figure, both accuracy and loss value, the curves are relatively stable, and there is no drastic fluctuation, which indicates that the model training process is stable, and there is no problem caused by training instability or improper parameter updating.

3.3 Visualization of automotive knowledge graph based on Neo4j

First, through the collection of knowledge, and then the construction of the knowledge map. The construction of knowledge graph first creates nodes for each entity. Then create edges for relationships between entities and attach relationship attributes; finally, the knowledge fusion integrates data from different sources, eliminates duplication and conflicts, and forms a unified knowledge map.The knowledge points of engine crank connecting rod mechanism and valve mechanism are sorted out, the nodes and relations are created, and the knowledge points of knowledge graph are fused. See Figure 3-4.

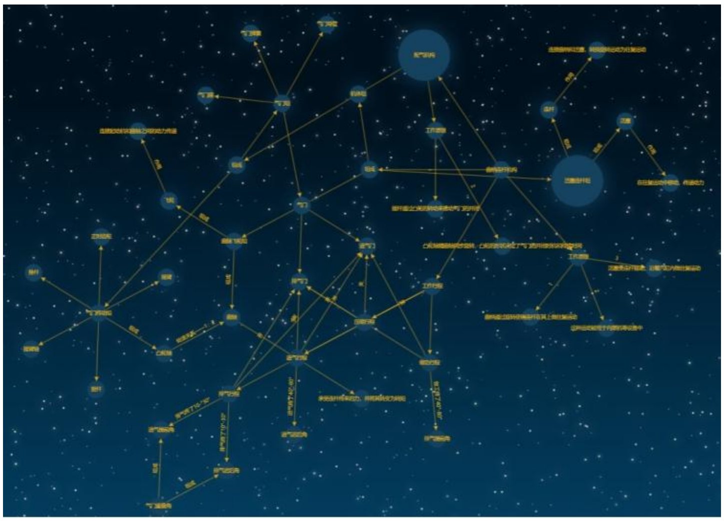

Figure 3-4 Completion result

In order to make the rendering of the atlas more vivid and vivid, the completed 2D atlas is further optimized and converted into 3D atlas. Compared with 2D knowledge graph, 3D knowledge graph can represent more information types and relationships, including multi-dimensional information such as time, space and attribute, which enables 3D knowledge graph to better represent complex knowledge and relationships in the real world, improve students' understanding of knowledge points, and be visually more beautiful and three-dimensional.See Figure 3-5.

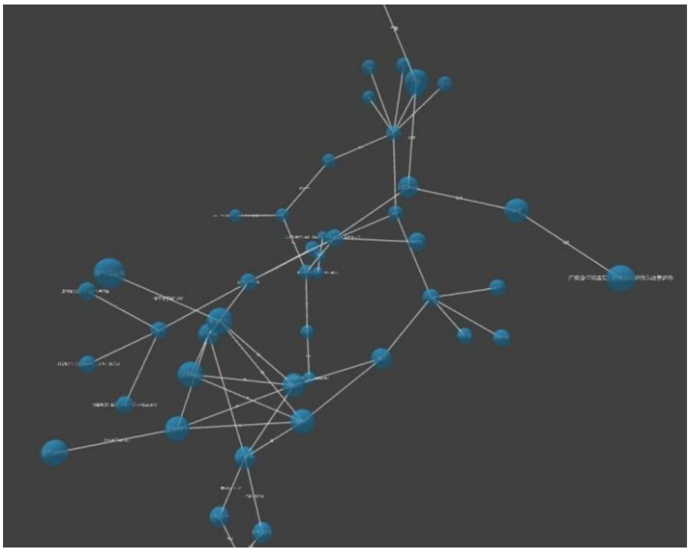

Figure 3-5 Three-dimensional diagram.

3.4 Other functions

The website used to make the knowledge graph is NRDStudio, which has other practical functions besides the functions applied to the design. Such as multi-person collaboration, just generate the invitation link, you can edit and use online at the same time, and work efficiency is greatly improved. According to the production node for statistical analysis, more clear. Export file format variety, for people to choose.

Through knowledge extraction, the triplet data is obtained in this design, as shown in Table 3-6.

Table 3-6 triplet format examples

Head entity	Relation	Tail entity
Automotive undercarriage	Make up	Power train
Automotive undercarriage	Make up	Running system
Automotive undercarriage	Make up	Brake system
Excessive water temperature	Fault condition	Non-rotation
Lack of power	Fault condition	Weak starting
Tire balance weight loss	Fault cause	Shiver

Through knowledge extraction, the triplet data was obtained in this design, as shown in Table 2-2 above. Neo4j graph database was used to store the data. Neo4j is a native graph database that stores and manages data through nodes, relationships and attributes in graph theory, rather than using tables to organize data as traditional relational databases do. The biggest feature and advantage of Neo4j is that it can efficiently deal with highly interconnected data. In relational databases, it is inefficient to query complex relationships by using multiple tables. By using graph structure, Neo4j can traverse nodes and relationships at a very fast speed, easily dealing with complex query requirements, especially for dealing with social networks, recommendation systems, knowledge graphs and other relational network scenarios that need to analyze massive associated data. In addition, Neo4j uses a flexible property graph model that makes it easy to model real-world entities and relationships. It supports ACID transactions to ensure data consistency and reliability. At the same time, Neo4j provides a powerful query language Cypher, and the syntax is simple and easy to understand, convenient for users to query and analyze graph data.

There are several ways to import "CSV" (Comma-Separated Values) data into a Neo4j database, each with advantages and disadvantages in terms of efficiency and complexity:

1）Read and import CSV data line by line using the py2neo library's create method, which is easy to understand but less efficient and suitable for small data volumes.
2）Data can be imported in batches using the run method of the py2neo library combined with the LOAD CSV statement of Cypher. This is more efficient, but requires knowledge of Cypher syntax.
3）The neo4j-admin import command can convert CSV data into the Neo4j import format and import it directly into the database. This method is the most efficient, but the operation is relatively complex and requires the user to understand the internal mechanism of Neo4j.

This paper uses py2neo library to import csv. Py2neo provides simple and easy to understand API, which makes the interaction with Neo4j database very intuitive. Whether it's creating nodes and relationships, performing Cypher queries, or graph traversal, Py2neo provides a clear interface for developers to get started quickly. At the same time, you can easily create, modify, and delete nodes and relationships, and build complex graph structures.Using the py2neo.bulk module, you can efficiently import large amounts of data into Neo4j databases. Importing the data, we get a partial visualization of the WEB interface of the Knowledge graph as shown in Figure 3-7:

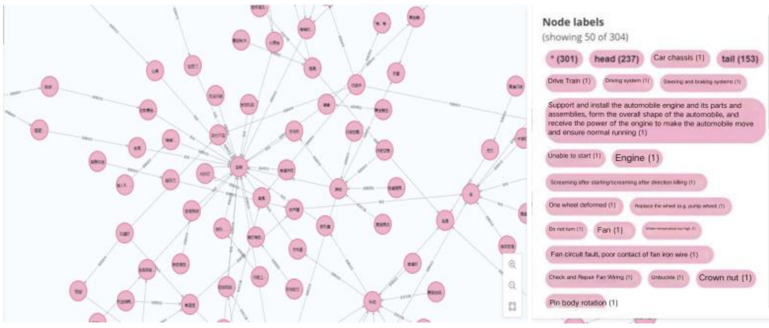

Figure 3-7 Diagram visualization

Ⅳ. Conclusion

To sum up, knowledge graph has important application value and positive research conclusion in the teaching of automotive mechanical system. Through the collection of knowledge and the construction of knowledge graph, the teaching efficiency and accuracy can be improved, the integration and expansion of knowledge can be promoted, and the students' independent learning ability and innovative thinking can be cultivated to adapt to the development trend of modern educational technology. In the future teaching of automotive mechanical system, we should further strengthen the application research of knowledge graph, and constantly explore more effective teaching methods and means to improve the teaching quality and level.

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