2025 International Conference on Intelligent Computing
July 26-29, Ningbo, China
https://www.ic-icc.cn/2025/index.php

BERT-PointerNet: A Unified Framework for Cross-Sentence Entity-Relation Extraction in Chinese Computer Science Texts

ChuCheng Wu[1] and YunQi Huang[1] and TuanXiong Ni[2(✉)] and ShiDeng Ma[3]

[1] Guangdong Neusoft Institute, Foshan GuangDong 528225, China
[2] Guangdong Neusoft Institute, Foshan GuangDong 528225, China
[3] Guangdong Neusoft Institute, Foshan GuangDong 528225, China
ntx1024784355@outlook.com

Abstract. This study presents an innovative text annotation framework for constructing knowledge graphs in the Chinese computer science domain, addressing challenges such as nested entity resolution and implicit relation extraction in Chinese technical texts. The proposed method integrates relation extraction into named entity recognition (NER) via a novel CS+R+BMES tagging schema, which extends the BMES (Begin-Middle-End-Single) approach to encode both entity boundaries and relation types. By appending a fully connected layer to the BERT model, we generate domain-specific word embeddings that align with the CS+R+BMES annotation space. These embeddings are then fed into a BERT-BiLSTM-CRF-PointerNet architecture, where a Pointer Network decodes CRF-generated labels into structured triples, dynamically resolving nested entities and implicit relations through cross-attention mechanisms. Experimental results demonstrate a 4.19% F1 score improvement over baseline models, with the proposed model achieving 93.7% F1 for entity-relation extraction. Ablation studies confirm the critical role of BERT's contextual encoding and the Pointer Network's capability to handle complex linguistic phenomena. Notably, this framework exhibits strong generalizability, enabling cross-domain adaptation to fields like software engineering by adjusting entity/relation categories. The constructed knowledge graph provides a scalable foundation for educational applications in computer science.

Keywords: Knowledge Graph Construction , Named Entity Recognition Tasks, BERT Models, PointerNet, Ternary Extraction Tasks

This work was supported by the following grants:
Guangdong Provincial University Achievement Transformation Center under the Characteristic Innovation Research Project of Universities in Guangdong Province (Grant No. 2022DZXX02), titled "Collaborative Motion Control of Agents (Robots) in Edge Computing Mode";Guangdong Higher Education Institutions Research Platform and Project (Grant No. 2024KQNCX140), titled "Intelligent Inspection Research and Application Based on Error-Cause Reconstruction Algorithm".

1 Introduction

This paper presents BERT-PointerNet, a unified framework for cross-sentence entity-relation extraction in Chinese computer science texts. To address challenges such as nested entity resolution and implicit relation extraction in Chinese technical texts, it uses the CS+R+BMES tagging schema which integrates relation extraction into named entity recognition, appends a fully connected layer to the BERT model to generate domain - specific word embeddings, and applies a BERT - BiLSTM - CRF - PointerNet architecture. The Pointer Network decodes CRF - generated labels into structured triples through cross - attention mechanisms. Experiments show that the model achieves an F1 score of 93.7% for entity - relation extraction, with a 4.19% improvement over baseline models. Ablation studies confirm the importance of BERT's contextual encoding and the Pointer Network's capabilities. This framework also shows strong generalizability and can be adapted to other fields, and the constructed knowledge graph provides a basis for educational applications in computer science[1].

This study presents three key innovations. First, it introduces the CS+R+BMES ("CS+R+BMES" is a labeling method specifically proposed for text processing in the field of computer science.) Text Processing Strategy, tailored to the unique challenges of Chinese text processing in the computer science domain, particularly the lack of clear word separation. This method enables precise entity recognition and relationship annotation, offering a fresh framework for text analysis in this field. Second, the study optimizes the BERT model by adding a fully connected layer and adapting it to the CS+R+BMES system, ensuring accurate mapping to the BMES categories (B, M, E, S) and enhancing the model's performance. Finally, the study applies knowledge graphs to education, utilizing complex datasets that combine text and images. Unlike previous research, which focused on plain text, this approach addresses the complexities of entity recognition and relationship extraction in educational documents, offering a novel solution for this domain. Together, these innovations drive advancements in text processing, model optimization, and knowledge graph applications in education.

2 Related Work

2.1 Knowledge Graph Construction strategy

The development of domain-specific knowledge graphs like CS-KG, spearheaded by Danilo Dessí and collaborators, marks a significant advancement in leveraging natural language processing (NLP) techniques for extracting entities and relationships from extensive corpora of research papers[5]. By integrating entity and relationship processing modules, CS-KG reduces redundancy and noise, delivering high-quality and structured data that has proven invaluable for academic research. However, despite its technical sophistication and contributions to the academic field, CS-KG's potential applications in other critical areas, such as education, remain underexplored.

Education, as a domain rich in structured and interconnected knowledge, presents a unique opportunity to extend the utility of such methodologies[7]. Unlike academic papers, educational materials like textbooks and instructional documents require tailored approaches to handle their domain-specific content effectively. These resources, characterized by technical precision and contextual nuances, demand advanced techniques capable of accurately identifying, classifying, and extracting entities and their relationships. To bridge this gap, our study aims to adapt the methodological advancements of CS-KG to the practical needs of educational knowledge extraction [8][10]. By doing so, we enable the systematic construction of structured knowledge frameworks, supporting intelligent processing and enhancing pedagogy.

2.2 Model Selection and NER Tuning

BERT model

The BERT model, known as Bidirectional Encoder Representations from Transformers, was developed by the Google Brain team [11]. BERT learns bi-directional representations of language by pre-training deep bi-directional converters, which makes it possible to utilize unlabeled text data for efficient language understanding tasks. The success of BERT is due to its simple yet powerful concept and new state-of-the-art results on a variety of natural language processing tasks [13].

BiLSTM-CRF model

BiLSTM - CRF is a combination where the bidirectional feature extraction ability of BiLSTM is combined with the label dependency modeling of CRF [12]. This combination is specifically designed for sequence tagging tasks, allowing it to analyze the sequential nature of text data effectively.

A BiLSTM-CRF model based on the BERT word embedding

In order to further improve the accuracy of the named entity recognition task, some research teams have adopted the BiLSTM-CRF model based on the BERT word embedding [14]. The advantage of this model is that it combines the BERT pre-trained language representation model, which provides a language representation model for large-scale unlabeled corpora, with the traditional BiLSTM-CRF architecture, which excels in handling sequence annotation tasks. When combining the two, the performance of the NER task can be improved by leveraging the latter's powerful sequence annotation capabilities [15].

2.3 Challenges in Chinese Named Entity Recognition and Our Contribution

Existing research on knowledge graph construction for the computer science domain has primarily focused on English-language resources, with limited attention to the unique challenges posed by Chinese texts. Unlike English, Chinese lacks explicit word segmentation, making it inherently difficult to identify entity boundaries and relationships. This issue is compounded by the complex grammatical structures and frequent use of implicit references in Chinese technical writing, which often lead to **entity folding** (overlapping entities expressed as a single surface form) and **hidden entity mentions** (entities referenced indirectly through pronouns or ellipsis). For example, the phrase "基于深度学习的自然语言处理模型" contains nested entities ("深度学习", "自然语言处理", "模型") that require fine-grained segmentation and semantic analysis.

3 Methodology

3.1 Overall framework of the model

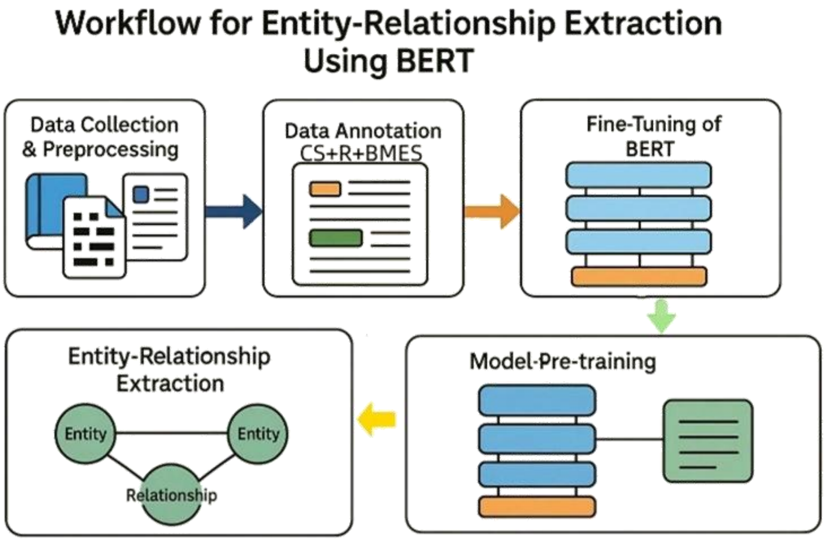

Fig. 1. Workflow for Entity-Relationship Extraction Using BERT

The experimental steps in this paper are roughly divided into the following steps:

Data collection and preprocessing

Obtain educational CS books from an open source data center, extract text via OCR and merge with plain text data to form an initial data set.

Data annotation

Employ a semi-automated multi-model collaboration approach with the CS+R+BMES annotation method for detailed annotation on the initial data set.

Fine-tuning of BERT
Add a fully connected layer behind BERT's output layer for classification to make it fit the text annotation method used.

Model pre-training
Input labeled data into the BERT model for pre-training to make its output closer to the features of the annotated text and obtain suitable word embedding vectors.

Entity-relationship extraction
A BERT-BiLSTM-CRF-PointerNet architecture is proposed for end-to-end triple extraction. The CRF layer generates CS+R+BMES labels encoding entity/relation boundaries, which are then decoded by a Pointer Network into structured triples $\{(s1, e1, s2, e2, r)\}$using BERT's semantic features. This pipeline directly constructs an educational domain knowledge graph without heuristic post-processing.

3.2 BERT model adjustment

The pre - trained BERT model consists of multiple Transformer encoder layers, which can capture rich contextual information from text. This structure models text semantic relations, boosting task adaptability. Given a sequence of input tokens $x = [x_1, x_2, \cdots, x_n]$, BERT first embeds these tokens into a low - dimensional vector space. The input embeddings E are composed of three types of embeddings: token embeddingsE_{token}, segment embeddings$E_{segment}$, and position embeddings $E_{position}$

$$E = E_{token} + E_{segment} + E_{position}$$

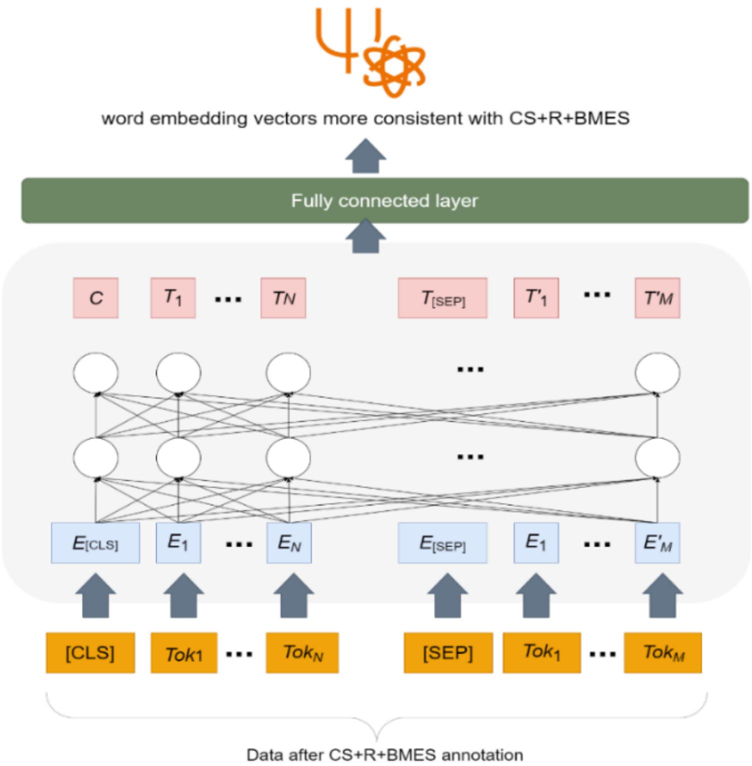

Fig. 2. BERT Model Architecture Adapted for CS+R+BMES Annotation

Insert $[\boldsymbol{CLS}]$at the sequence start, whose embedding $\boldsymbol{E}[\boldsymbol{CLS}]$captures global sequence features.

Use $[\boldsymbol{SEP}]$at sentence boundaries. Let $\boldsymbol{EN}$and $\boldsymbol{EM}'$denote token embeddings in the sentence; $\boldsymbol{T}[\boldsymbol{SEP}]$and $\boldsymbol{TM}'$

represent [SEP]and model - output feature vectors. This design ensures BERT accurately processes non - conventional labeling, mapping outputs to BMES categories like *B*, *M*, *E*, *S*for entity boundary identification.

3.3 BiLSTM-CRF model based on BERT word embedding vector

The diagram presents the processing flow from input to output: the text is first encoded by the BERT Encoder, then features are integrated through the Fully Connected layer and Attention mechanism, followed by the extraction of sequential contextual information using BiLSTM, and finally, the annotations are generated through decoding with CRF to achieve the task of entity relation extraction.

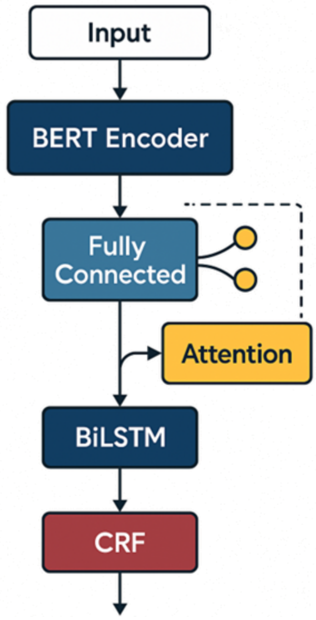

Fig. 3. The architecture diagram of the entity relationship extraction model based on BERT-BiLSTM-CRF.

Pointer Network for Structured Triple Extraction

This study introduces a Pointer Network architecture to address the challenges of nested entity resolution and implicit relation detection in Chinese computer science texts, overcoming the limitations of traditional sequence labeling approaches. The Pointer Network operates as a post-processing module that leverages dynamic attention mechanisms to decode CRF-generated labels and BERT contextual embeddings into structured triples.

The core innovation lies in the cross-attention decoding mechanism, which computes attention weights $\alpha_{i,j} = \mathrm{softmax}(W_a h_i + U_a l_j)$ by integrating BERT semantic vectors h_i with CRF labels l_j. This allows the model to capture spatial correlations between entity tags (e.g., B-Technology) and relation tags (e.g., B-R-Develops), enabling precise alignment of entities and their relationships.

To handle nested entities, the Pointer Network employs a hierarchical span selection strategy. By maximizing:

$$\mathrm{Span}(s, e) = \arg\max_{s<e} \sum_{t=s}^{e} \alpha_{t,\mathrm{EntityTag}}$$

the model dynamically identifies entity boundaries while respecting hierarchical structures (e.g., distinguishing B-Technology containing B-Method). This attention-based localization ensures accurate parsing of overlapping entities without relying on heuristic rules.

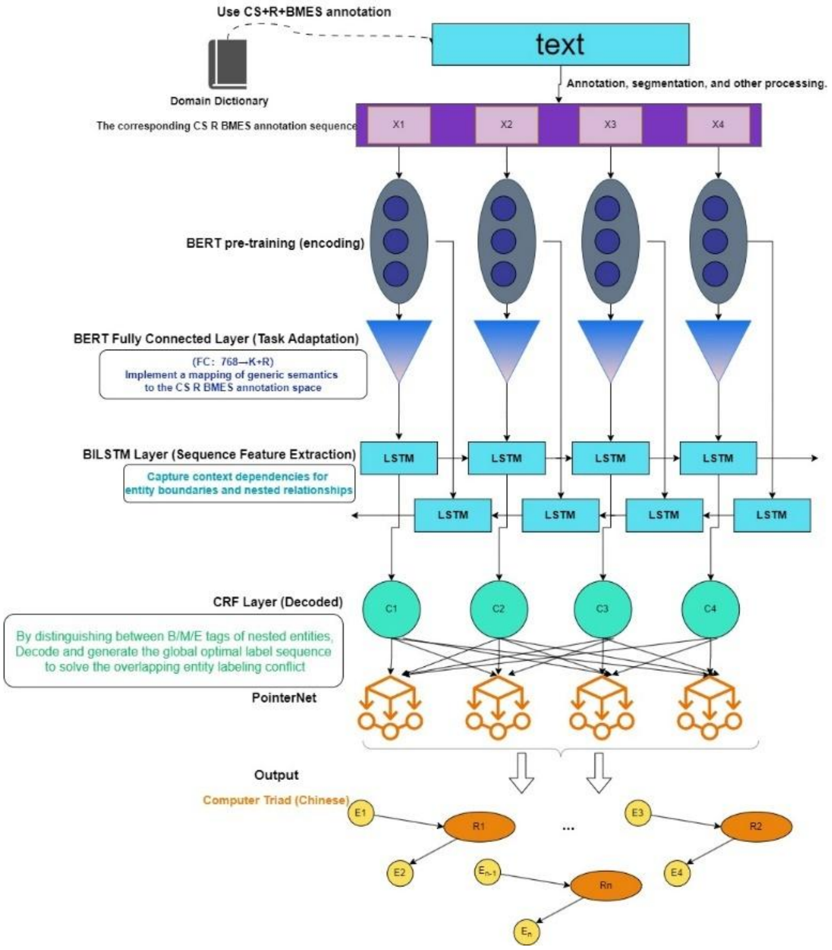

Fig. 4. The overall operational data flow of the BERT-BiLSTM-CRF-Pointer Network model.

The character positions are based on the BERT tokenization results, with each token corresponding to one character.The end-to-end architecture (as shown in Fig.4) directly converts raw text into triples such as {(0,5,7,12,Supports)} from the input "基于深度学习的自然语言处理模型", demonstrating its capability to handle complex linguistic phenomena. By eliminating intermediate post-processing steps, the Pointer Network reduces error propagation and improves extraction efficiency while maintaining computational scalability.

4 Experiments

4.1 Data processing work

Th This experiment downloads computer science PDF teaching books from open-source datasets, parses PDF structures to extract and convert text into TXT files, addressing the limitation that existing NER/RE methods underperform on complex computer science texts due to their unique structural and semantic complexities. To solve this, the study introduces the CS+R+BMES annotation approach, which integrates BMES entity boundary tags (B/M/E/S) with relation-specific tags to encode both entity details and relational semantics in a unified sequence labeling framework, streamlining extraction for diverse computer science entity classes and improving annotation consistency/accuracy for high-quality input in subsequent experiments.

Table 1. ENTITY TABLE

Entity List	Description
Technology	Specific technologies or tools that form the basis for implementing computer science theories and applications.
Theory	Areas such as algorithm theory and computational theory, which are the foundations of computer science.
Person	Scientists and engineers who have made significant contributions to computer science.
Publication	Important media for disseminating knowledge and research findings in computer science.
Event	Important events or discoveries in the history of computer science.
Area	Different research areas within computer science.
Component	Hardware or software components that make up computer systems.
Structure	The organizational structure within computer systems.
Problem	Specific problems that arise in the field of computer science.
Algorithm	Specific steps and methods for solving problems.
Method	Methods for implementing specific functions or solving specific problems.
Effect	The results or impacts after the implementation of technologies or methods.
Performance	The efficiency and speed at which computer systems, software, or hardware components perform tasks.
Metric	Specific numerical values or standards for measuring and assessing performance, effects, or quality.

As shown in Table 1, the classification system is based on the characteristics of the computer science domain and divides the entity categories, aiming to reflect the generalization of the various types of entities within the domain. Table 2, on the other hand, demonstrates the relationship categories, which cover the various connections that may exist between entity categories. Table 3 presents the BMES annotation system, explaining in detail the specific meaning of the four different annotations in the system.The method comprehensively considers the characteristics of the computer science domain,

Table 2. RELATIONSHIP TABLE

Relationship List	Description
Develops	The development relationship of technology or theory.
Belongs_to	The relationship that a technology is part of a larger technology or area.
Publishes	The publication relationship of academic works or findings.
Solves	The relationship where a theory or technology addresses a problem.
Improves	The relationship where one technology or theory is an improvement over another.
Influences	The impact of one theory, technology, or person on another.
Implements	The implementation of an algorithm or technology in specific hardware or software.
Depends_on	The dependency of a technology or system on another technology or component.
Optimizes	The use of one technology or method to enhance the performance of another.
Measures	The use of a metric to assess the performance of a technology or system.
Contributes_to	The contribution of a person to a technology, theory, or field.
Related_to	The correlation between two areas, technologies, or problems.
Prerequisite_for	One technology or theory being a prerequisite for another.
Integrates	The incorporation of a technology or component into a larger system or platform.
Follows	The adherence of a technology or method to a specific theory or standard.
Extends	The expansion of one technology or theory beyond another.
Replaces	One technology or method replacing an outdated one.
Supports	The support of one technology or system for another technology or application.
Affects	The impact of one technology or method on the effects or outcomes.

Table 3. BMES TAGGING TABLE

BMES Tagging	Description
B	Start of an entity or relationship
M	Middle part of an entity or relationship
E	End of an entity or relationship
S	Single character entity
O	Character that does not belong to any entity or relationship

and provides a solid foundation for subsequent natural language processing tasks through fine-grained entity recognition and relational labeling.

After data pre-processing, the initial open-source e-book data was converted into computer-readable text data, a process that is crucial as it ensures the readability and usability of the data. Subsequently, we adopted the CS+R+BMES annotation method.

First, we performed some manual annotation to generate example text data (about 135 copies) that had been labeled by the CS+R+BMES method.

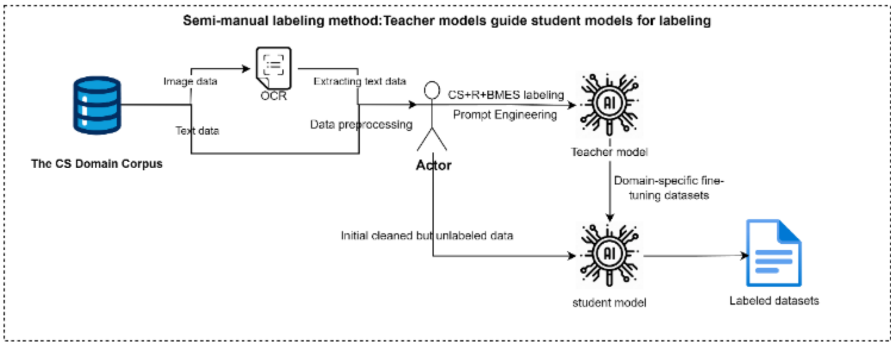

Fig. 5. Semi-Manual Labeling Workflow: Teacher-Student Model for Dataset Annotation in CS Domain.

In previous research, many scholars have proposed various multi-model collaboration strategies aimed at improving the efficiency and accuracy of annotation tasks.One such strategy involves using a “teacher model” with a large parameter scale to guide other smaller, more specialized “student models”[20]. These student models usually focus on specific types of data or tasks, and by drawing on the knowledge and capabilities of the teacher model, they can improve overall task performance[20].

4.2 Exploiting Multi-Task Learning in BERT Model Pre-Training

This step aims to process CS+R+BMES-annotated text through a BERT pre-training model and add a fully-connected layer after BERT's output layer to generate word vectors aligned with the annotated corpus. Using a multi-task learning approach in pre-training, the model incorporates Masked Language Model (MLM) and Next Sentence Prediction (NSP) tasks to enhance downstream task performance. After pre-training BERT on CS+R+BMES-labeled text to obtain corresponding word vectors, these vectors are input into a BiLSTM layer for semantic encoding and decoded via a CRF layer to output the most probable label category for each character.

4.3 BiLSTM-CRF neural network model with the CRF output

In the experiments, the BERT-BiLSTM-CRF model fixes BERT parameters while updating those of the BiLSTM-CRF part to leverage BERT's pre-trained semantic capabilities and optimize contextual information extraction and tag sequence generation via BiLSTM-CRF. Comparative studies with BiLSTM-CRF and CNN+BiLSTM+CRF models are conducted to evaluate performance. Through parameter tuning, optimal configurations are determined: batch size 128 (balancing memory and efficiency), sequence max_length 512 (handling long texts without resource waste), dropout rate 0.2 (preventing overfitting), learning rate 0.01 (controlling weight update steps), and 256

LSTM units (capturing complex sequence dependencies efficiently), enabling excellent training performance and validation results.

4.4 Pointer Network for Structured Triple Extraction

To address the limitation of traditional sequence labeling approaches in directly generating structured triples, this study introduces a Pointer Network as a post-processing module following the CRF layer. The Pointer Network is designed to decode the CRF-generated label sequences and BERT-derived contextual embeddings into explicit entity-relation triples, thereby bridging the gap between sequence annotations and knowledge graph construction.

5 Results and Discussion

5.1 Method for assessing the model performance

We have chosen the BiLSTM-CRF and CNN+BiLSTM+CRF models as benchmarks. By comparing the performance of these models on the aforementioned evaluation metrics, we are able to gain an in-depth understanding of the advantages and potential room for improvement of the models proposed in this study with respect to existing techniques.

This paper introduces the following evaluation indexes to evaluate the final classification effect of the classifier:

precision:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

F1 Evaluation value:

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

5.2 Interpretation of result

In order to evaluate the performance of the proposed model, this study designed a series of comparison experiments to compare the performance of this model with two existing models:BiLSTM-CRF and CNN+BiLSTM+CRF[19][18].

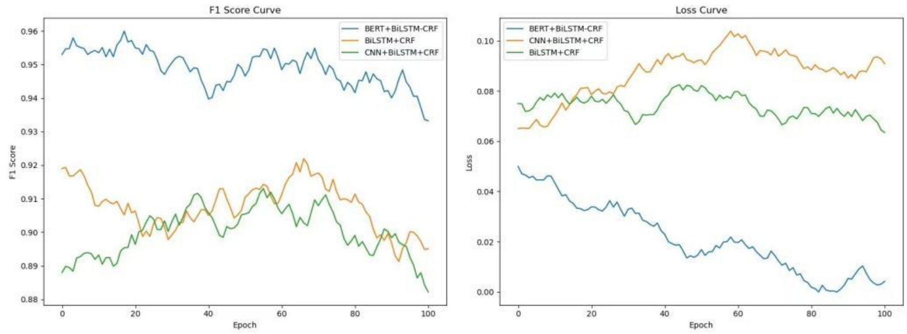

Fig. 6. Comparison of ternary group extraction test results for three models

Data analysis shows the BERT-BiLSTM-CRF model achieves 93.9% precision, 93.5% recall, and 93.7% F1 score in entity-relation extraction, outperforming traditional BiLSTM+CRF and CNN+BiLSTM+CRF models: the CNN-based model sees an F1 drop to 88.1% (precision 87.3%, recall 88.9%), while integrating BERT into BiLSTM-CRF boosts F1 by 4.19 percentage points, indicating BERT enhances the model's ability to capture text relationships and semantic understanding effectively.

Table 4. Predictive results of the BERT-BiLSTM + CRF model for the principal entities and their relationships

Relationship List	Precision/%	Recall/%	F1 -score/%
Develops	97.30	95.32	95.63
Belongs_to	93.36	92.11	92.73
Publishes	98.07	96.72	97.39
Solves	89.67	89.65	89.66
Uses	86.63	84.30	85.45
Improves	96.23	94.74	95.48
Influences	89.49	80.74	84.89
Implements	98.64	96.72	97.67
Depends_on	91.47	84.21	87.69
Optimizes	90.99	87.44	89.18
Measures	95.44	93.09	94.25
Contributes_to	97.14	93.75	95.37
Prerequisite_for	83.12	72.41	77.38
Integrates	81.34	80.05	80.69
Follows	89.24	86.96	87.63
Extends	91.73	84.96	88.17
Replaces	88.59	85.73	87.13
Supports	92.73	90.69	91.69

5.3 Ablation experiment

In order to gain a deeper understanding of the function of each module in the BERT-BiLSTM-CRF model and its contribution to the model performance, we designed a series of ablation experiments. These experiments were conducted by removing the key components of the model one by one, the bidirectional long and short-term memory network layer (BiLSTM layer) and the BERT-based word embedding layer, to observe the impact of these changes on the model's performance in entity recognition and "Problem" named entity and 'Solves' relationship co-extraction task. Specifically, we ran the BiLSTM-CRF model and the BERT-BiLSTM model on the test set and compared their performance with the full BERT-BiLSTM-CRF model. The experimental results (see Table 6) show that removing the BiLSTM layer has a relatively small impact on the joint extraction task, with the F1 value dropping only slightly from 93.56% to 90.83%, while the impact on the entity recognition task is even more limited. In contrast, when the BERT-embedding layer was removed, the BiLSTM-CRF model showed a significant decrease in performance on both tasks. This result emphasizes the importance of BERT models in providing rich semantic information about word vectors, which is consistent with what we observed in our ternary extraction experiments. These findings further confirm the critical role of the Chinese language model BERT in enhancing the model's ability to learn the mapping relationships between characters, symbols and entity naming, and relational labels in utterances in the field of computer science, which steadily improves the overall performance of the model.

Table 5. Predictions of different models

Task	Evaluationindex	BiLSTM +CRF	BERT-CRF	BERT-BiLSTM	BERT-BiLSTM+CRF
Entity recognition	Accuracy rate /%	72.82	98.30	93.57	95.54
	Recall rate /%	79.25	94.85	97.50	98.30
	F_1 score /%	75.86	96.52	95.45	96.87
Entity recognition and relationship joint extraction	Accuracy rate /%	59.86	91.94	91.19	93.78
	Recall rate /%	65.12	89.88	91.37	93.34
	F_1 score /%	62.38	90.83	91.28	93.56

5.4 Construction of Knowledge Graph

In this paper, after completing the validation process, the entities and their relationships in the collected data were parsed and extracted. Subsequently, these data were stored in the form of triples in the Neo4j graph database using the Cypher query language. Specifically, Cypher's LOAD CSV functionality was utilized in this paper. This process first involves exporting the parsed entity nodes and relationship data to CSV format files respectively, and storing them in the import directory of the Neo4j database. Next, the Nodes and Relationships are imported into the database by executing the LOAD CSV command. In this way, the connections between entities are effectively stored in the Neo4j graph database, which in turn constructs a knowledge graph for the computer science (CS) domain, as shown in Figure 7.

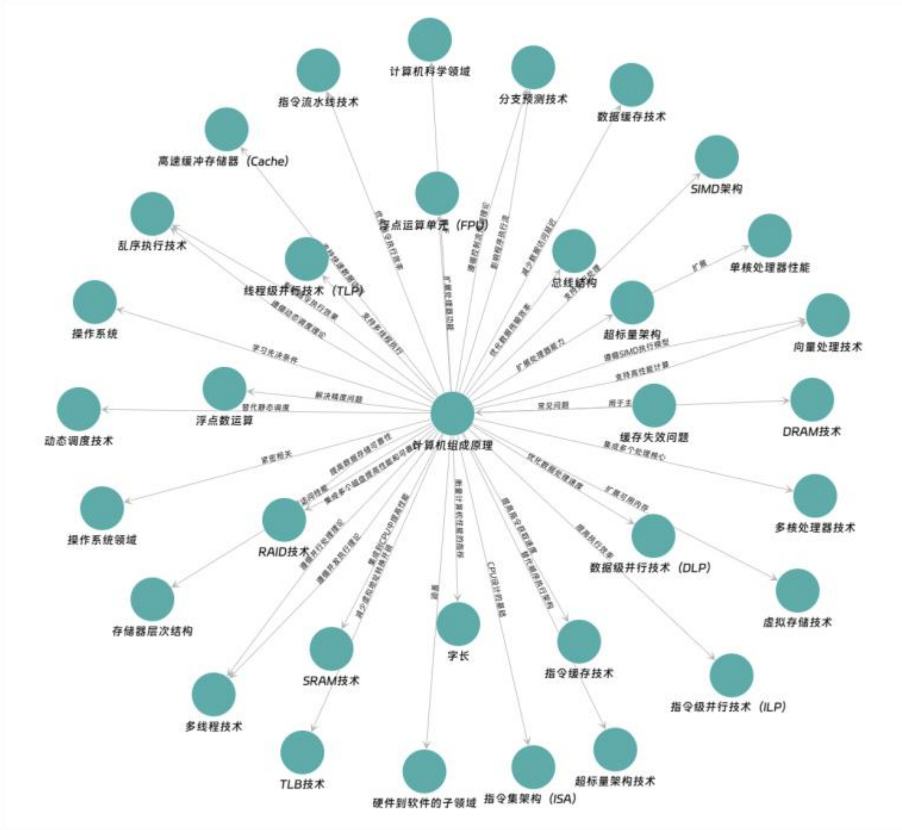

Fig. 6. Chinese Knowledge Graph in Computer Science (Partial)

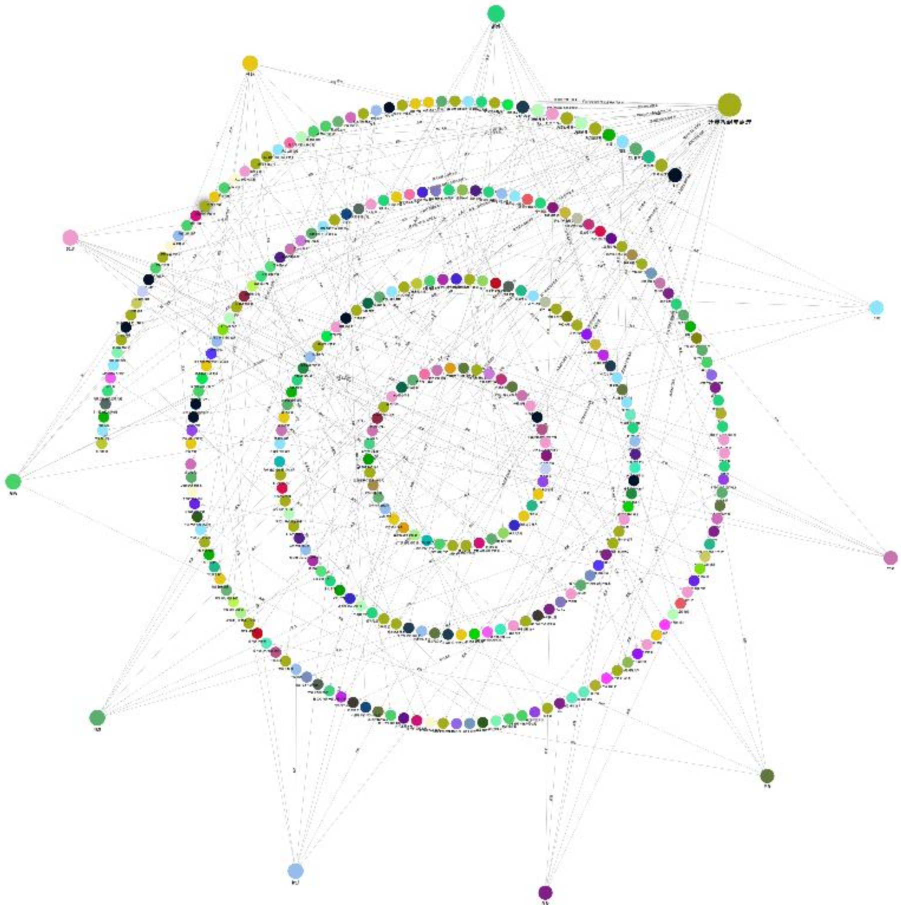

Fig. 8. Chinese Knowledge Graph in Computer Science (Global Perspective)

Fig. 8 , visually encapsulates the comprehensive structure of the constructed computer science domain knowledge graph. The graph employs a multi-colored node system, where each node represents distinct entity categories defined in the CS+R+BMES schema. These nodes are interconnected by directed edges labeled with predefined relationships, explicitly mapping the semantic connections extracted via the Pointer Network's cross-attention mechanism.

5.4 Discussion

Overall, the innovative annotation method proposed in this study significantly improves the model's ability to understand entities in the computer science (CS) domain. By optimizing the BERT model, the method further enhances the model's adaptability to new annotation strategies, resulting in better output results.

From a methodological point of view, this study proposes an innovative annotation method specifically for CS domain texts, accompanied by a complete set of processing flows. These methods and processes provide valuable references for future scholars conducting entity extraction research in the CS domain.

As far as the results are concerned, the present method shows obvious superiority over traditional methods in the CS domain. However, in terms of entity recognition under fuzzy conditions, although the labeling method is able to recognize most of the entities, there is still room for improvement in the performance of the model when dealing with overlapping entities and complex relationships. This suggests that although the labeling approach has achieved some success in recognizing entities, the model still needs further optimization and improvement when facing more complex entities and relationships. Notably, the proposed annotation scheme and model architecture demonstrate strong generalizability—by adjusting entity categories and relation types, this framework can be readily adapted to other technical domains such as software engineering or data science, offering a scalable solution for cross-domain knowledge graph construction.

References

1. Chaudhri, V., Baru, C., Chittar, N., Dong, X., Genesereth, M., Hendler, J., ... & Wang, K. (2022). Knowledge graphs: introduction, history and, perspectives. AI Magazine, 43(1), 17-29.
2. Bellomarini, L., Fakhoury, D., Gottlob, G., & Sallinger, E. (2019, April). Knowledge graphs and enterprise AI: the promise of an enabling technology. In 2019 IEEE 35th international conference on data engineering (ICDE) (pp. 26-37). IEEE.
3. Li, Y., Zhao, J., Yang, L., & Zhang, Y. (2019). Construction, Visualization and Application of Knowledge Graph of Computer Science Major. Proceedings of the 2019 International Conference on Big Data and Education. Presented at the ICBDE?19: 2019 International Conference on Big Data and Education, London United Kingdom. https://doi.org/10.1145/3322134.3322153
4. D'Souza, J., & Auer, S. (2022, November). Computer science named entity recognition in the open research knowledge graph. In International Conference on Asian Digital Libraries (pp. 35-45). Cham: Springer International Publishing.
5. Dessí, D., Osborne, F., Reforgiato Recupero, D., Buscaldi, D., & Motta, E. (2022). CS-KG: A Large-Scale Knowledge Graph of Research Entities and Claims in Computer Science. In The Semantic Web – ISWC 2022,Lecture Notes in Computer Science (pp. 678–696). https://doi.org/10.1007/978-3-031-19433-7_39
6. Sun, J., Zhang, Z., & He, X. (2024, August). LLM4EduKG: LLM for Automatic Construction of Educational Knowledge Graph. In 2024 International Conference on Networking and Network Applications (NaNA) (pp. 269-275). IEEE.
7. Zhao, H., Pan, Y., & Yang, F. (2020). Research on information extraction of technical documents and construction of domain knowledge graph. Ieee Access, 8, 168087-168098.
8. T. Wang, Y. Wang and C. Tan, "Construction and Application of Knowledge Graph System in Computer Science," 2018 International Conference on Security, Pattern Analysis, and Cybernetics (SPAC), Jinan, China, 2018, pp. 169-172, doi:

10.1109/SPAC46244.2018.8965547. keywords: {Data modeling;Neo4j;GSON stream;knowledge graph},
9. Meng, Y., Li, X., Sun, Z., & Li, J. (2019). Query-Based Named Entity Recognition. arxiv preprint arxiv:1908.09138.
10. Chiu, J. P., & Nichols, E. (2016). Named entity recognition with bidirectional LSTM-CNNs. Transactions of the association for computational linguistics, 4, 357-370.
11. Zhang, Y., & Zhou, J. (2000, October). A trainable method for extracting Chinese entity names and their relations. In Second Chinese Language Processing Workshop (pp. 66-72).
12. Davletov, A. A., Gordeev, D. I., Rey, A. I., & Arefyev, N. V. (2020). Renersans: Relation extraction and named entity recognition as sequence annotation. In Computational Linguistics and Intellectual Technologies (pp. 187-197).
13. Devlin, J. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arxiv preprint arxiv:1810.04805.
14. Yang, G., & Xu, H. (2020). A residual bilstm model for named entity recognition. Ieee Access, 8, 227710-227718.
15. Guan, G., & Zhu, M. (2019, July). New research on transfer learning model of named entity recognition. In Journal of Physics: Conference Series (Vol. 1267, No. 1, p. 012017). IOP Publishing.
16. Fábio, & Souza (2020). Chinese Entity Recognition Based on BERT-BiLSTM-CRF Model.
17. Zhu, B., & Pan, W. (2023, December). A Text Classification Model Based on BERT and Attention. In 2023 4th International Conference on Computers and Artificial Intelligence Technology (CAIT) (pp. 90-95). IEEE.
18. Devlin, J. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arxiv preprint arxiv:1810.04805.
19. Hu, X., Zhang, H., & Hu, S. (2022, June). Chinese named entity recognition based on BERT-based-BiLSTM-CRF model. In 2022 IEEE/ACIS 22nd International Conference on Computer and Information Science (ICIS) (pp. 100-104). IEEE.
20. Sun, Q., Yin, Z., Li, X., Wu, Z., Qiu, X., & Kong, L. (2023). Corex: Pushing the boundaries of complex reasoning through multi-model collaboration. arxiv preprint arxiv:2310.00280.