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Research on the Construction of Knowledge Map Technology Framework of Core Curriculum within the "AI+" Context

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Abstract

With the deep integration of artificial intelligence into education, core courses face challenges like the need for strong interdisciplinary knowledge, complex content, and a lack of adaptability in teaching. As a result, this research utilizes "AI+" as the technological framework, constructing a knowledge graph based on a three-tier architecture-"data layer, schema layer, application layer"-utilizing the Protege tool for ontology construction and standardized coding. By combining the Bert model, precise extraction of entity relationships is possible, which facilitates knowledge storage and the development of a visual interface via the Neo4j graph database. This knowledge graph ensures quality through a closed-loop mechanism of "construction-evaluation-optimization-application" supporting intelligent applications such as personalized learning recommendations, smart question-answering, and teaching decision-making support. It effectively mitigates the fragmentation of interdisciplinary knowledge, drives educational model innovation, and provides a technical paradigm and practical reference for implementing "AI+Education".

Keywords

Artificial Intelligence; Knowledge Graph; Core Courses.

1. Introduction

With the advancement of next-generation artificial intelligence technologies such as knowledge graphs and deep learning, the era of "Internet Plus Education" is progressively transitioning into the era of "Intelligent Education". In 2022, the report of the 20th National Congress of the Communist Party of China first incorporated "digital education" into its agenda. In 2025, the Outline of the Plan for Building China into a Strong Nation in Education (2024-2035), issued by the Central Committee of the Communist Party of China and the State Council, explicitly called for leveraging digital education to pioneer new development pathways and forge new competitive advantages. This initiative aims to harness artificial intelligence to drive educational transformation and innovate talent cultivation models. Education, as a vital foundation for cultivating future societal builders and innovators, now confronts unprecedented transformative opportunities. The curriculum knowledge graph, through its visualized knowledge representation and relational modelling, represents the evolution and advancement of the symbolist research paradigm in the era of big data and artificial intelligence[1]. It constitutes a crucial foundation for AI's progression from "perceptual intelligence" to "cognitive intelligence" [2], thereby providing new enabling capabilities for teaching and learning in the Education Informatisation 2.0 era.

Although course knowledge graphs have achieved certain results in educational applications, the utilization of technologies such as deep learning during knowledge graph construction is markedly insufficient, hindering both the efficiency of graph development and the

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advancement of their intelligence levels. Concurrently, the continuous emergence of emerging technologies such as big data, cloud computing, and artificial intelligence is profoundly transforming the operational models and risk management mechanisms of financial services. This presents new challenges for talent cultivation in higher education institutions, demanding timely updates to educational content and methodologies to reflect the latest theoretical and practical advancements. Traditional financial education models, constrained by inherent limitations, struggle to meet industry development needs, necessitating educational innovation to enhance quality and effectiveness. Consequently, constructing a knowledge map for core courses has become particularly crucial. This paper employs artificial intelligence technologies to structurally represent the interconnected knowledge points, concepts, theories, and practical operations within the discipline. Establishing a knowledge map for core courses provides educators and learners with a comprehensive, in-depth, and dynamically updated knowledge framework[3]. This framework supports future personalized and precision-oriented education, holding profound implications for advancing the reform and development of education.

2. Analysis of Teaching Difficulties in the Course

2.1. Fragmented Knowledge Structures and Dispersed Learning Resources

The core curriculum involves numerous and interconnected knowledge points, with students frequently encountering fragmented learning that hinders the formation of systematic knowledge frameworks. Simultaneously, learning resources remain scattered across textbooks, courseware, academic papers, and other formats, lacking unified classification labels and associative indexes. Students must expend significant effort filtering resources rather than focusing on the internalization and practical application of the knowledge itself.

2.2. Lack of Personalized Teaching Methods and Insufficient Teaching Feedback

The traditional “one-size-fits-all” lecture model fails to meet individualized development needs of students, resulting in teaching interactions that remain superficial. Furthermore, feedback mechanisms exhibit significant shortcomings, with conventional approaches relying heavily on delayed methods such as homework assignments and final assessments. And it prevents the real-time identification of learning gaps of students. Teachers also find it difficult to accurately gauge each student's level of knowledge mastery, leading to instructional adjustments that lack data support and hindering the implementation of “teaching according to individual needs.”

2.3. Insufficient Application of Educational Technology

Although advances in educational technology offer new possibilities for financial education, its practical implementation remains inadequate. Most current applications are primarily used as tool replacements and do not deeply integrate with the specific features of core course. This creates challenges in aligning with the “technology-driven” development process, leading to a generational gap between students' skills and industry practices.

3. The Construction of technical framework of Knowledge Graphs for Core Courses

This research utilizes a tiered architecture system, breaking down the entire process into three main modules: the data layer, schema layer, and application layer. This enables the systematic completion of the entire process from multi-source data collection to the intelligent application development of knowledge graphs. The overall technical architecture is illustrated in Figure 1. Based on this foundation, the theoretical framework and ontology model for the core

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curriculum were developed by thoroughly analyzing the knowledge system and educational goals.

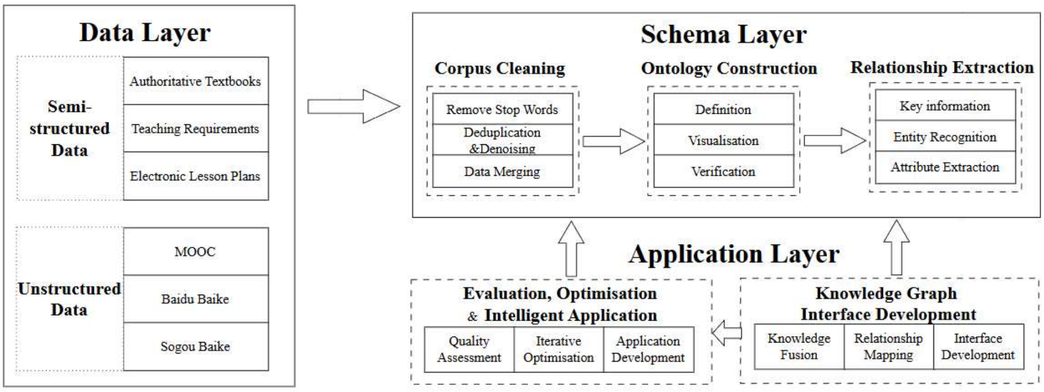

Figure 1. Overall Construction Framework

3.1. Data Layer

The data layer serves as the essential base for building knowledge graphs, tasked with integrating diverse and pre-processed data from multiple sources.

3.1.1. Multi-source Data Collection

The data for this research are primarily divided into two types. Initially, semi-structured data comprises crucial educational resources such as primary textbooks, course syllabi, and online teaching materials. The data naturally includes organized features like chapter hierarchies and directory indexes, which aid in breaking down initial knowledge units to identify essential concepts and frameworks. The second category comprises unstructured data, including course video subtitles and explanatory texts from the China University MOOC platform, alongside featuring course video captions and explanatory materials from the China University MOOC platform, as well as entries on fundamental concepts from online encyclopedias like Baidu Baike and Sogou Baike. This data offers rich content and flexible formats, providing crucial supplementary material for expanding knowledge graph content and extending its dimensions.

3.1.2. Data Preprocessing

Data preprocessing is a critical step in ensuring the quality of knowledge graph construction. The subsequent primary operations are executed as follows:

Remove Stop Words: Use tools such as the Python jieba library to systematically eliminate common words that hold no significance for extracting entities and relationships from the text, thereby achieving precise refinement of the corpus content.

Deduplication & Denoising : Standardize multi-source data to handle redundant information and conflicting content, such as repeated knowledge points and varying expressions of the same concept. This unifies term representation and simultaneously cleans noise data from the text, such as special characters, garbled code, and irrelevant advertisement information.

Data Merging: Integrate cleaned semi-structured and unstructured corpora to construct a high-quality, standardized unified raw corpus, serving as input for the schema layer.

3.2. Schema Layer

The Schema Layer (also known as the Ontology Layer) serves as the core logical center of the knowledge graph, undertaking the functions of defining and formalizing the organizational rules of the knowledge graph. Its core tasks focus on two major modules: ontology construction

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and relation extraction, providing a unified knowledge representation framework for the structured corpus of the data layer.

3.2.1. Ontology Construction

Ontology construction aims to formally define the knowledge system. Using the processed data from the corpus, Stanford University's open-source Protégé software is employed, along with the logical framework of the course knowledge, to construct a conceptual model of the core curriculum. This standardizes the description of the core conceptual system, including its attributes, relationships, and rules. The ontology construction is illustrated in Figure 2. The specific implementation of ontology construction is as follows:

First, Define Entities, Relationships, and Attributes. According to the basic teaching requirements of the core courses and input from authoritative textbooks and renowned course instructors, the application scope of the ontology research domain is determined, and relevant knowledge and terminology are defined. Through semantic analysis and concept clustering, core course concepts are extracted, forming entity category sets such as “concepts”, “models”, and “applications”. Based on logical coherence and practical applicability, a hierarchical knowledge structure for core courses is proposed. This involves refining entity relationships and attributes within the ontology, while specifying the valid value ranges and constraint rules for entity attributes.

Second, Ontology Visualisation. Employing ontology engineering methods, the organised concepts and relationships are formalized into computer-interpretable structures, such as standard languages like OWL or RDF, ensuring that the ontology structure can be effectively processed by computer systems.

Third, Ontology Verification and Iterative Optimisation. Through collaboration with domain experts, the ontology undergoes verification across three dimensions: knowledge coverage completeness, logical consistency, and pedagogical suitability, ensuring its accuracy and practicality. The ontology is continuously refined based on expert feedback to improve its hierarchical structure, semantic association strength, and attribute definitions. This enhances both the breadth of coverage and depth of representation within the knowledge system, guaranteeing the ontology's academic rigour and practical applicability.

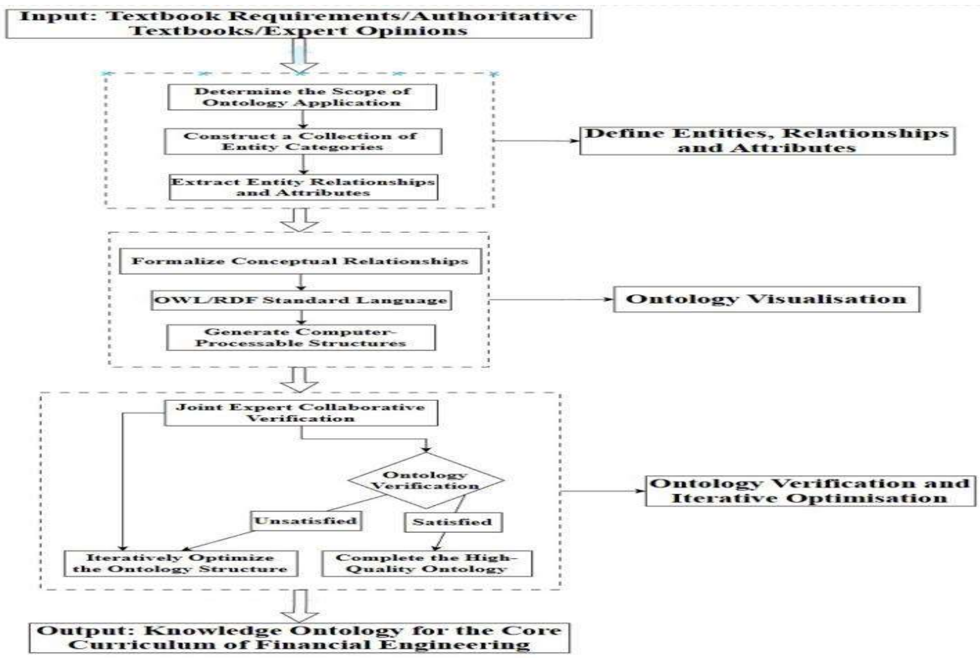

Figure 2. Ontology Construction Framework

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3.2.2. Relation Extraction

As the core task of the schema layer, relation extraction focuses on mining semantic associations between knowledge units and extracting specific knowledge facts from a standardized corpus, providing fundamental support for constructing the associative network of knowledge graphs. Given the relatively limited scale of domain-specific corpora for core courses, this study adopts an adaptive strategy of "pre-trained models + domain data fine-tuning" to achieve precise implementation of entity recognition and relation extraction. The relation extraction is illustrated in Figure 3. The specific process is as follows:

First, Data Collection and Preprocessing. Teaching syllabuses, textbooks, case studies, and supplementary materials from core courses were systematically gathered. Building upon the initial data preprocessing, additional steps involved noise reduction, format unification, and terminology alignment to create a domain-specific standardized training corpus encompassing essential knowledge areas[4].

Second, Key Information Extraction. Utilize Natural Language Processing (NLP) techniques to annotate the effective corpus, which is then divided into training and test sets. A pre-trained Chinese BERT model encodes input text into word vectors, utilizing bidirectional long short-term memory networks to capture contextual and positional information within the text [5]. Attention mechanisms concentrate on essential semantic details, improving the efficiency of core feature extraction.

Third, Entity Recognition and Extract Entity Relationships. The classifier receives key information and maps it to corresponding categories, obtaining relationships or labels between entities. The model is fine-tuned using the training set[6]. The resulting entities and relationships undergo manual screening and organization to yield high-quality triples: "entity-relationship-entity" and "entity-attribute-value". This model exhibits strong scalability, enabling real-time entity recognition and relation extraction for newly added corpora, thereby providing technical support for the dynamic updating of knowledge graphs.

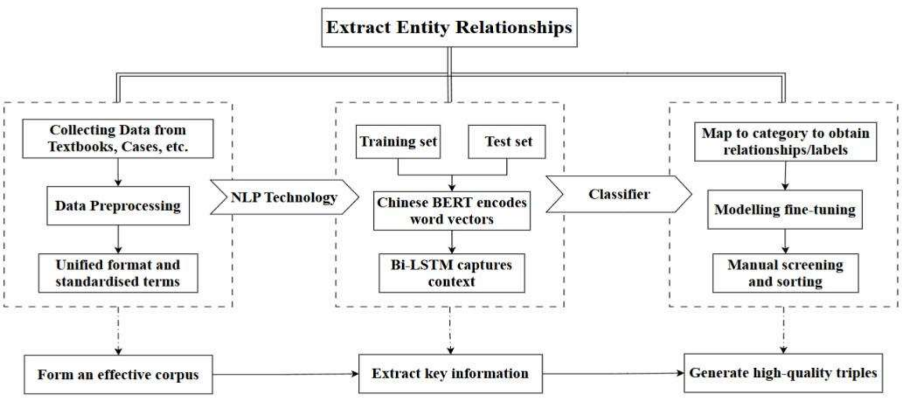

Figure 3. Relation Extraction Framework

3.3. Application Layer

As the core for transforming the value of the knowledge graph, the application layer integrates and optimises knowledge outputs from the pattern layer to ultimately deliver intelligent services tailored for education scenarios.

3.3.1. Knowledge Graph Interface Development

(1)Knowledge Fusion. Integrates multi-source triples extracted through relational mining. Utilises entity disambiguation and co-reference resolution techniques to accurately link entities to their counterparts in the knowledge base, resolving homonymy and polysemy issues.

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Ensures entity uniqueness and correctness, enhancing the accuracy and usability of the knowledge graph.

(2)Entity-Relationship Mapping. Map extracted knowledge points to corresponding nodes within the knowledge graph. Construct relationships between entities based on ontology definitions, ensuring the knowledge graph accurately reflects the intrinsic connections and knowledge structure of the financial discipline.

(3)Storage and Interface Development. Employ Neo4j graph database as the core storage medium. Leveraging its efficient relational query capabilities and topological structure visualization, achieve structured storage and dynamic management of entity, attribute, and relationship data. Simultaneously develop a user-friendly visual interface offering knowledge node retrieval, association path tracing, hierarchical structure browsing, and other functionalities. By providing intuitive exploration tools, users can effectively utilize the knowledge graph.

3.3.2. Evaluation, Optimisation & Intelligent Application

Establish a closed-loop mechanism of Construction-Evaluation-Optimisation-Application to drive continuous iteration and value enhancement of the knowledge graph.

(1)Knowledge Graph Quality Assessment. Construction is an iterative process. Establish a suite of evaluation metrics to assess the accuracy, completeness, consistency, and usability of the knowledge graph, ensuring its quality and providing feedback for subsequent optimization and application.

(2)Knowledge Graph Iterative Optimization. Based on evaluation outcomes and user feedback, iteratively refine the knowledge graph to enhance its quality and user experience. This ensures it meets education and research requirements while continuously improving its academic rigour, usability, and contextual adaptability.

(3)Exploration and Development of Intelligent Applications. Investigate diverse intelligent applications of the knowledge graph in education, such as: Intelligent question-answering systems supporting natural language interaction to accurately address queries on course content and model principles; decision-support tools assist educators by linking teaching design to knowledge and identifying learning weaknesses, amongst other applications. Leveraging artificial intelligence technologies elevates the intelligence of education, transforming the knowledge graph into tangible educational assets. This provides educators and students with rich resources and tools, enabling the intelligent application of knowledge.

4. Application of the Core Curriculum Knowledge Graph

The intelligent construction of the Core Curriculum Knowledge Graph employs artificial intelligence technologies, particularly natural language processing and machine learning, to form an ontology model comprehensively reflecting the discipline's core concepts, theories, methodologies, and practical case studies. This standardizes the core conceptual framework of attributes, relationships, and rules. Through automated entity recognition and relationship extraction, it enhances both the efficiency and quality of knowledge graph construction. The application of this knowledge graph will yield significant positive outcomes across both teaching and practical dimensions.

4.1. Intelligent Educational Applications

At the teaching level, exploring knowledge graph applications in core course instruction, case analysis, and simulated trading activities provides educators and students with rich educational resources and tools. Examples include personalized learning recommendations, intelligent question-answering systems, and decision-support tools, thereby enhancing the quality of financial education and fostering innovation in talent cultivation models.

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Simultaneously, considering the characteristics of disciplines and educational objectives, alongside multidimensional factors such as the difficulty, importance, practicality, and interdisciplinary nature of knowledge points, the knowledge graph effectively addresses the challenge of fragmented knowledge in traditional teaching by visualizing and structurally linking knowledge points across core courses. Students can intuitively grasp the intrinsic connections between different core courses, thereby constructing a multi-layered, multidimensional classification system for knowledge.

4.2. Application in Practical Competency Development

At the practical level, this knowledge graph guides students through structured knowledge networks to undertake comprehensive, systematic practical training across diverse application scenarios. This not only deepens students' comprehension of theoretical knowledge but also proactively cultivates their engineering-oriented thinking paradigms and systematic problem-solving capabilities for tackling complex challenges. Consequently, the application of the Core Curriculum Knowledge Graph effectively facilitates the transformation of fragmented theoretical knowledge into an organic, evolvable knowledge application system. It establishes a core paradigm for shifting education from “knowledge transmission” to “capability development”, providing crucial support for cultivating high-calibre, multidisciplinary financial engineering professionals. This holds significant value for teaching practice and disciplinary advancement.

5. Conclusion

The construction and application of the core knowledge graph align with the developmental context of “Artificial Intelligence + Education”. It has achieved a preliminary transition from static knowledge repositories to dynamic intelligent cognitive entities, providing valuable insights for higher education teaching reform initiatives. This effectively supports the digital transformation and development within the education sector. Concurrently, it must be acknowledged that the framework established in this study remains exploratory. Future endeavours should involve rigorous controlled experiments and long-term tracking studies to empirically validate and continually refine the integration of artificial intelligence with knowledge graph construction.

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