# **Constructing a Knowledge Graph for the Chinese Subject Based on Collective Intelligence**

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# **ABSTRACT**

Knowledge graphs are a valuable tool for intelligent tutoring systems and are typically constructed with a focus on objectivity and accuracy. However, they may not effectively capture the subjectivity and complex relationships often present in the humanities. To address this issue, a dynamic visualization of subject matter knowledge graph was developed using a collective intelligence approach that integrates the individual intelligence of learners and considers cognitive diversity to construct and evolve the knowledge graph. The approach resulted in the construction of 722 knowledge associations and the evolution of 584 triples. A survey assessed the effectiveness and user-friendliness, revealing that this approach is effective, easy to use, and can improve subject matter knowledge ontology. In conclusion, combining individual and collective intelligence is a promising approach for building effective knowledge graphs in subject areas with subjectivity and complexity.

#### **Keywords**

Knowledge Graph, Knowledge Ontology, Ontology Construction, Ontology Evolution, Subject Matter Learning Cell

#### **INTRODUCTION**

Knowledge is a cornerstone of intelligent tutoring systems, and an ontology provides the foundation for organizing and understanding complex knowledge structures. However, previous studies have focused on constructing ontologies based solely on the principles of objectivity and clarity while overlooking the subjective and situational nature of humanistic knowledge. Ontologies constructed on the principles of "clarity and objectivity" tend to be stable and objective but fail to capture the

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ambiguity and uncertainty inherent in humanistic knowledge. Learners' understanding of knowledge and its relationships are closely tied to the expression of that knowledge and influenced by the environment or context. For example, in response to the question "What becomes of snow when it melts?" some students may answer "spring," which shows the diversity of humanistic knowledge. Thus, the situated, subjective, and generative features of knowledge should be considered when constructing ontologies.

This paper presents a method using collective intelligence to address the subjectivity and situational nature of humanistic knowledge in ontology construction. By leveraging the visualization capabilities of knowledge graphs and the support provided by the Learning Cell platform, a collective knowledge graph activity was designed to promote the construction and evolution of Chinese subject matter ontology through the participation of learners. One approach to addressing this issue is to analyze and investigate the process of learners' participation in learning activities using collective intelligence. Collective intelligence arises from communication, collaboration, competition, brainstorming, and similar activities and can be more powerful and wise than the sum of individual contributions. Scholars have recognized the value of collective intelligence in many fields, such as public decision-making, voting activities, social networking, and crowdsourcing (Yu et al., 2018). By incorporating collective intelligence into the ontology construction process, we can better capture the richness and complexity of humanistic knowledge. By embracing the subjectivity, generativity, and situatedness of knowledge, we can create more effective and relevant ontologies that are applicable to a wider range of contexts.

The essay is structured as follows:

- 1. A systematic literature review was conducted on "ontology and knowledge graph," "ontology construction and evolution," and "ontology construction and evolution ideas" based on collective intelligence.
- 2. An ontology evolution activity based on a collective knowledge graph was proposed. Following this proposal, an experiment was conducted to verify the findings, demonstrating how collective intelligence can improve the ambiguity and uncertainty present in knowledge.
- 3. Finally, the contributions, limitations, and future research directions of this paper are discussed.

In summary, the study demonstrates the potential of collective intelligence in ontology construction and evolution. The incorporation of learners' knowledge, experiences, and perspectives can enrich the ontologies produced, resulting in a more complete and accurate representation of knowledge. Future research could explore additional methods to enhance and refine the proposed collective knowledge graph activity for ontology construction.

## **RELATED RESEARCH**

## **Ontology and Knowledge Graph: Foundations and Applications**

An ontology provides a systematic approach to structuring and categorizing knowledge. It enables the reuse and sharing of key knowledge, leading to improved effectiveness in various fields, such as intelligent tutoring systems. As technology advances, an ontology is likely to play an increasingly important role in facilitating knowledge management across different domains. An ontology is a philosophical concept originating from metaphysics, which involves the analysis and categorization of "what there is" (Poli & Seibt, 2010). It provides a systematic description of the fundamental attributes of objects in daily life (Kripke, 1981). With the development of artificial intelligence since the 1960s, the computer science community recognized the importance of knowledge ontology in structuring information (McCarthy, 1980), leading to a more standardized definition of an ontology. Today, most definitions of an ontology within computer science align with Gruber's (1995:199)

definition: "An ontology is an explicit specification of a conceptualization." An ontology consists of five components: concepts, relations, attributes, axioms, and instances (Gómez-Pérez et al., 2006), making it possible to represent structured knowledge.

On the one hand, an ontology establishes a hierarchical and structured knowledge model based on relationships between different knowledge elements. On the other hand, it enables dynamic updates and association of generative content through reasoning and annotation of relational attributes.

The main function of an ontology is realizing the reuse and sharing of key knowledge. For instance, in intelligent tutoring systems, Sun and Li (2009) use a subject ontology, knowledge concept ontology, and learning material ontology to represent domain knowledge according to the properties of the teaching materials, thereby improving the sharing and reusing of materials and incorporating multimedia materials obtained from the web to enhance the teaching effects. Therefore, an ontology not only introduces a formal, explicit, shareable, and reusable knowledge representation but also potentially adds new knowledge to the applied domain (Wang et al., 2021).

In the field of computer science, a knowledge graph is a structured semantic knowledge base. It was initially introduced by Google as a way to represent knowledge databases. The primary difference between a knowledge graph (KG) and a knowledge base (KB) is that the data within a knowledge graph can be structured and visualized (Hassanien et al., 2021; Ji et al., 2021). In recent years, due to the vigorous development of the internet, there has been increasing demand for ontologies and knowledge graphs, which have been widely applied in healthcare, finance, education, and other fields.

In the field of education, Chi et al. (2018) assessed learning behaviors using a curriculum knowledge graph to help teachers optimize Massive Open Online Course (MOOC) teaching effects. Dang et al. (2019) adopted an acknowledged educational ontology to model online learning resource knowledge and constructed a MOOC-related knowledge graph to improve the utilization of online learning resources. Al-Aswadi et al. (2022) explained how an ontology serves as a foundation layer for a knowledge graph. A knowledge graph is an extension of an ontology and can be considered a network knowledge base formed by entities with attributes linked by relations.

It consists of two layers: The schema layer serves as the core underlying layer of the knowledge graph, employing concepts, axioms, rules, and constraints to standardize and connect knowledge. The data layer primarily stores and organizes relevant concepts, relations, attributes, and instances of the domain in a graph database using triples, forming an extensive network of knowledge relations (Liu et al., 2016).

#### **Ontology Construction and Evolution: Methods and Challenges**

Current research on ontology mainly focuses on two aspects: one is the technology and method of ontology construction; the other is the study of ontology evolution for new knowledge, which evolves with the change of situation after the completion of ontology construction.

#### *Ontology Construction*

The research and practice of ontology construction have contributed to the formulation of principles and methods for building ontology knowledge bases. The five-principle method is widely adopted for ontology construction (Gruber, 1995). Based on this, Perez & Benjamins (1999) proposed ten principles for ontology construction: clarity and objectivity, completeness, coherence, maximum monotonic extendibility, minimal ontological commitments, ontological distinction principle, diversion of hierarchies, minimal modules coupling, minimization of semantic distance between sibling concepts, and standardization of names whenever possible.

Regarding ontology construction methods, several approaches have been developed, including the skeleton method (Fernandez, 1999), the Term Oriented Vocabulary for the Enterprise method (TOVE, Gruninger, 1995), the Knowledge Acquisition and Conceptualization for Task Understanding and Synthesis method (KACTUS, Bernaras et al., 1996), the Methodology for Ontology Engineering method (METHONTOLOGY, Fernández-López et al., 1997), Semi-Automatic Methodology for

Developing Ontologies from Natural Language Text (SENSUS, Swartout et al., 1996), the Integrated Definition for Ontology Description Capture Method (IDEF5, Benjamin, 1994), the activity-first method (Mizoguchi, 1995), and the seven-step method (Noy & McGuinness, 2001). These methods provide methodological guidance for ontology construction (Shang, 2012).

At a more detailed level, manual approaches using visualization tools like Protégé and OntoEdit (Du et al., 2006) are adopted for constructing knowledge ontologies with small domains and limited content. Moreover, for domains with vast and complex knowledge that undergo frequent content changes, the construction of ontologies heavily relies on automated or semiautomated approaches. Machine-based ontology construction typically involves four basic processes: knowledge extraction, knowledge fusion, knowledge processing, and knowledge updating (Zhu et al., 2017).

Knowledge extraction aims to extract concepts, relations, and attributes from professional websites or encyclopedias using techniques such as web scraping, entity recognition, and natural language processing. Knowledge fusion focuses on disambiguating the extracted concepts, attributes, and relations and integrating them with existing knowledge bases. Techniques such as entity linking, entity disambiguation, and relation disambiguation continue to play a crucial role in this process. Knowledge processing involves validating the formed knowledge through similarity calculations and inference before incorporating it into the ontology. This step ensures that knowledge is coherent with the existing ontology and is accurate. Knowledge updating primarily focuses on representing newly acquired knowledge that emerges over time. This involves incorporating new data into the existing ontology and performing updates to reflect any changes or additions.

In summary, knowledge extraction, fusion, processing, and updating are critical steps to building an ontology. These steps enable researchers to efficiently acquire, integrate, validate, and update ontological knowledge, leading to a more complete and effective representation of domain-specific knowledge. Continued advances in natural language processing, machine learning, and related technologies will likely further improve these processes and lead to even more sophisticated methods for building high-quality ontologies.

## *Ontology Evolution*

Once an ontology database has been constructed, its content will evolve with changes in domain knowledge and evolving situations. This is particularly critical for humanities-based ontologies, where ensuring continuous evolution during the application process is essential. Ontology evolution methods include the following approaches:

- 1. Ontology mapping (Martins et al., 2012) involves constructing diversified ontologies for different dimensions in a specific domain. To realize the fusion of multiple ontologies in the domain, multiple ontologies can be mapped based on the same concept, attribute, and relation in different ontologies.
- 2. Bridge ontology (Maedche et al., 2003) maps ontologies based on the same concept, attribute, and relation in different domains to associate ontologies in different domains and facilitate evolution based on bridge ontology.
- 3. Data/file mining (Cao et al., 2007) utilizes machine learning techniques such as support vector machines to automatically discover knowledge based on an ontology knowledge framework. This newly discovered knowledge is then integrated into the original ontology to facilitate ontology evolution (Sumathi et al., 2021).
- 4. Ontology evolution based on deep learning involves transforming user sessions and interactions for a specific domain into vectors using word2vec processing tools. Subsequently, vector similarity calculations are carried out according to the corpus to realize ontology evolution.
- 5. Coevolution involves the idea of collective intelligence wherein evolution tasks are assigned to internet users as a group activity and crowdsourcing task to realize ontology evolution (Gendarmi & Lanubile, 2006).

Ontology mapping and bridge ontology methods integrate ontologies for ontology evolution from the perspective of domain experts, and data/file mining and deep learning evolution are realized by machine learning domain and other related algorithms, while coevolution promotes ontology evolution from the new perspective of collective intelligence.

#### **Ontology Construction and Evolution: Leveraging Collective Intelligence**

Currently, ontology construction primarily relies on manual approaches involving domain experts or machine-based automatic approaches. However, these methods may fail to reflect learners' personalized understanding of knowledge or address different situations in the learning environment (Soleša-Grijak & Soleša, 2015). To address knowledge representation differences, the utilization of collective intelligence becomes crucial. Crowdsourcing, initially proposed by *The Rise of Crowdsourcing* (Howe, 2006), is one strategy for applying collective intelligence on the internet. It involves dividing large tasks into smaller, independent subtasks that individuals can complete quickly. Through collaborative convergence, these subtasks can be efficiently accomplished. Collective intelligence has already solved various problems, such as facilitating massive image recognition and annotation on the internet (Von Ahn & Dabbish, 2008).

Given this, some researchers have proposed integrating ontology construction and evolution into users' business processes through the use of "collective intelligence" (Stojanovic & Motik, 2002). This approach allows users to finish their work while simultaneously promoting ontology construction and evolution using collective intelligence (Liu, 2013). For example, users can embed the construction process of subject matter knowledge ontology into a situated learning environment, which allows them to interact with ontology content through thematic inquiries or other teaching strategies. Feedback on these activities can then promote ontology construction and evolution.

Incorporating collective intelligence through crowdsourcing into ontology construction and evolution is an efficient, cost-effective, and collaborative approach to meet the personalized understanding of knowledge. It harnesses the power of the crowd to promote knowledge sharing and facilitate continuous improvement of ontology knowledge bases. These methods generate more current and accurate ontologies that better reflect changes over time or shifts in understanding.

## **Enlightenment on the Study**

Prior studies have shown that knowledge graphs can enhance learners' comprehensive understanding of learning materials and improve their learning efficiency and effectiveness (Haase et al., 2019). As the foundation of a knowledge graph lies in the ontology database, any actions performed by learners on the visual knowledge graph will be reflected in changes to the ontology. By designing learning activities that leverage the learners' knowledge graph, two significant benefits can be achieved. Firstly, it facilitates the realization of structured knowledge as learners actively contribute to the improvement of the knowledge graph. This type of active participation fosters a deeper understanding of the subject matter as learners work collaboratively to create new content and improve upon existing knowledge graph elements. Secondly, leveraging the collective knowledge graph enables the incorporation of more context-specific and personalized new knowledge into the subject matter knowledge ontology. As learners add new information or perspectives, this process accelerates the evolution of the ontology itself.

Designing learning activities that leverage the power of knowledge graphs and ontologies enables learners to actively participate in continually improving the ontology, which further promotes structured knowledge acquisition. It also allows for the incorporation of context-specific and personal knowledge and accelerates the evolution of the ontology, leading to more complete and effective representations of domain-specific knowledge.

# **DESIGN OF ONTOLOGY EVOLUTION ACTIVITY BASED ON COLLECTIVE KNOWLEDGE GRAPH**

#### **Introduction to the Learning Cell Platform and Its Semantic Framework**

The Learning Cell is a new organizational form of learning resources and is generative, open, interconnected, coherent, evolvable, intelligent, miniaturized, and self-tracking. Its rich background semantic system enables the Learning Cell platform to support intelligent and adaptive learning and teaching services. As shown in Figure 1, the semantic system of the Learning Cell is divided into five layers according to the different representations of knowledge in the flow process, as described below:

- 1. **Storage layer:** This layer stores three types of knowledge ontologies: domain knowledge ontology, domain organization ontology, and domain teaching ontology through Jena Transportation Database, Graph Database, and Owlfile storage. The data encapsulation layer contains knowledge organization relationship (knowledge and outline), teaching content description relationship (knowledge and resources), and concept logic relationship, and realizes extraction of ontology knowledge in the storage layer in the form of triples.
- 2. **Knowledge processing layer:** This layer involves two processes: in the first process, the application data from the application layer are converted into triples and stored in the data storage layer; and in the second process, the triples extracted from the storage layer are reencapsulated into user data required by the application layer.
- 3. **Layer of knowledge graph visualization service:** This layer realizes the visualization of application data extracted from the knowledge processing layer to visually output the application data to the user.
- 4. **Presentation layer:** This layer realizes the operation of the knowledge by the user through terminals, such as a tablet, mobile phone, and Personal Computer (PC), and acts as the entrance for the interaction between the user and the underlying data of the platform.
- 5. **Knowledge control layer:** The knowledge control layer plays the role of knowledge control through quality control, version control, and evolution control to promote the orderly evolution of knowledge ontology. The above four layers realize the complete business process of knowledge from database to user interaction. The control of knowledge is essential due to the subjective operation of knowledge by the user and the lack of a quality control mechanism for group ontology construction.

Based on this five-layer ontology architecture, this study designs and implements a collective knowledge graph activity in which the users collaboratively participate, providing the guarantee for ontology construction and evolution based on collective intelligence.

## **Design of Collective Knowledge Graph Activity**

The basic idea of learning activity design based on the collective knowledge graph is explained as follows: Due to differences in learners' individual, cognitive, and situational factors, their understanding of the same learning content always varies in the learning process, resulting in the formation of different individual knowledge graphs. The collective knowledge graph, which integrates individual knowledge graphs, allows for the coexistence of individual knowledge graphs with cognitive differences, thereby facilitating the construction and evolution of situated and subjective subject matter knowledge ontologies. To this end, the design process of a collective knowledge graph activity should highlight the following three elements. Firstly, structured knowledge centered on the learning content should be presented to learners to provide personalized learning guidance. Secondly, learners should be enabled to supplement and modify the existing knowledge graph individually during the learning process, thus constructing their situated and personalized individual knowledge graphs. And



#### **Figure 1. Five-Layer architecture of the semantic system of the learning cell**

thirdly, the individual knowledge graphs of different learners should be integrated and summarized to form a knowledge graph of group learners, which can provide better support for situated learning.

Based on the above, and as shown in Figure 2, the basic process of a collective knowledge graph activity is described below:

- Create the collective knowledge graph activity;
- Assign tasks for the activity (i.e., assign collective knowledge graph construction and improvement tasks as learning activities for learners to participate in the online learning process);
- Participate in the activity and improve the knowledge graph (users learn online and participate in the activity; learners can improve their individual knowledge graphs during the learning process and add content to the collective knowledge graph by referring to the established collective knowledge graph);
- Conduct quality control and audit of knowledge graphs generated by users;
- Cluster the individual knowledge graph and the collective knowledge graph.

# **Design of Collective Knowledge Graph Activity by Taking** *A Song of Liangzhou* **as an Example**

#### *Create the Collective Knowledge Graph Activity*

The collective knowledge graph activity can be created in two ways: one is to be created by the teacher, and the other by the system.

The teacher-created activity aims for online learning organized by a teacher. As shown in Figure 3, the teacher first creates the learning cell for the teaching content, then creates a knowledge graph



#### **Figure 2. Workflow of using knowledge graph to promote the evolution of subject matter knowledge ontology**

activity based on the teaching needs, and uses the knowledge graph improvement activity as a tool to aid learners in learning.

Based on the knowledge points associated with the learning cell, the system can cluster related concepts, attributes, relations, and instances from the ontology database of the Learning Cell platform to form an initial knowledge graph. Taking *A Song of Liangzhou* as an example, the teacher first creates a collective knowledge graph activity in the learning cell of *A Song of Liangzhou*. The system then extracts the triple <A, R, B> of *A Song of Liangzhou* from the ontology knowledge base of the storage layer and transforms the subject A and object B of the triple into nodes, and the predicate R into the relation edge, forming an initial knowledge graph about *A Song of Liangzhou*. The initial knowledge graph describes the existing knowledge and resource structure related to *A Song of Liangzhou* in the subject matter knowledge ontology, as shown in Figure 4, including the author, category of the poem, and the emotion expressed. When the learner clicks on the author Wang Zhihuan or the poem category (frontier poetry), the learner can start learning guided by the knowledge graph. In this way, a knowledge graph with the current learning cell as the center and relevant content and resources as the

#### **Figure 3. Activity creation**



Send to: Select the target user ,all users by default Click to select the target

network is established, through which learners not only can view the existing knowledge structure of the content but can also edit and supplement the content based on their personalized understanding.

The automatic creation of a knowledge graph by the system aims to promote self-organizing learning in online courses. This method involves generating a knowledge graph for the learning activities of popular topics and knowledge that have sparse relations in the ontology. This approach facilitates the continuous improvement of corresponding knowledge ontologies. First, the system automatically extracts the most recent hot words and tags on a regular basis. Then, knowledge lacking relations in the ontology database is determined by the number of knowledge associations. In this way, knowledge cells used for activity creation can be identified. The system then automatically publishes a collective knowledge graph activity for this knowledge point and pushes it to the learners of the course or learning cell.

#### *Assign Tasks of the Activity*

After the activity is created by the teacher, the teacher needs to decide the participation time and participants to publish it. For the activity automatically created by the system, the system will automatically push it to the learners of all courses, learning cells according to the courses, and learning cells associated with the activity.

#### *Participate in the Activity and Improve the Knowledge Graph*

Once an activity is published, the learner's personal learning space will receive a notification about the activity. In the case of an activity created and assigned automatically by the system, the learner is not obligated to participate, whereas, for course learning activities created by the teacher, participation in those activities is required as part of the course curriculum. The learner can click on the notice to enter the learning cell, participate in the activity, and begin learning, guided by the initial knowledge graph generated by the system.

During the learning process, users can add new associations to the initial knowledge graph based on their understanding of the content, thus improving their individual knowledge graphs. As seen in Figure 5, Learner A added the poem "Chu Sai" (On the Frontier) and other related content, including poems related to war and willows. This reveals Learner A's understanding of relevant knowledge as it relates to *A Song of Liangzhou*, thereby contributing to improving their individual knowledge graph. These poems will be regarded as nodes in the knowledge graph, connected to one another through relations of different poems and poets. To store this kind of information, the triple notation <subject,



#### **Figure 4. Initial knowledge graph of A Song of Liangzhou**

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#### **Figure 5. Knowledge graph constructed by Learner A**



predicate, object> is utilized to extract the subject, predicate, and object elements in the knowledge graph, converting them into triples, and storing them in the ontology database.

Regarding the formation of the collective knowledge graph, all individual knowledge graphs constructed by learners merge into the collective knowledge graph of *A Song of Liangzhou*. As depicted in Figure 6, the resulting collective knowledge graph reflects each learner's understanding of *A Song of Liangzhou* from various perspectives. The tree structure adopted follows the basic principle of connectionism, which emphasizes that learning is not just an individual activity but also involves optimizing the learner's internal and external networks. The approach takes individual learners as the basic unit and creates a complex learning network with other individual members in the social network (Siemens, 2017), thus facilitating the improvement and evolution of knowledge ontology. The personalized knowledge triples generated by learners are stored in the process knowledge base and contribute to the continuous expansion and updating of the collective knowledge graph.

## *Quality Control and Audit of User-Generated Knowledge Graph*

Judging the quality of user-constructed knowledge graphs is essential to ensure their accuracy and authority. Individual users generate triple data in the process of constructing the knowledge graph, which can affect the overall quality of the content. Some triples may have a higher level of confidence and authority than others. To address this issue, this study adopted an algorithmic approach to controlling triple confidence levels to maintain content quality. This approach involves both machine computation and user voting of confidence levels. Through this method, high-quality content is

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**Figure 6. Overall knowledge graph of the learning cell (a partial screenshot)**

identified by computing the contribution score of each triple generated by users according to the relevance and importance of triple elements. Additionally, users are allowed to vote on the confidence levels of triples through rating or commenting, thereby further enhancing their accuracy and reliability.

• **Quality Control Based on Machine Computation:** Quality control based on machine computation involves three main components: dependency parsing, word to vector (word2vec), and paragraph vectot (doc2vec) . The first component, dependency parsing, judges the logic of the syntactic structure of a sentence by generating its grammatical structure. The second component, word2vec, determines whether the content of the sentence is logical, while the third component, doc2vec, evaluates the likelihood of a sentence's existence. Through comprehensive evaluation of these components, the quality of generated content can be assessed.

The specific process of this quality control method follows these steps: First, the generated triple  $\langle S, R, P \rangle$  is extracted, and the three elements, S, R, and P, are concatenated into a sentence. For example, for the triple <*A Song of Liangzhou*, Author, Wang Zhihuan>, the sentence "The author of *A Song of Liangzhou* is Wang Zhihuan" is generated. Second, the sentence is segmented to obtain the subject S', predicate R', and object P', which are then combined to create a new triple. Finally, the rationality of the sentence composed of the new triple is judged using the following criteria: 1) Dependency parsing is conducted on the sentence using the Stanford Parser tool (returning false if unreasonable) to obtain the dependency syntax tree; 2) The system checks whether the center word (i.e., the predicate) of the dependency syntax tree exists and is equal to the relation R in the original triple <S, R, P>. If it does not exist or is not equal, the system returns false; and 3) If the center word exists and is consistent with the relation R, the system checks whether the subject and object in the syntax tree are equivalent to S and P in the original triple. If they are, the score for this part is marked as 1; otherwise, the similarity between them is returned as f1 (triple).

Then, word2vec is used to assess the association between the subject S and object P. By training on a specific corpus, word2vec simplifies text content and transforms it into a K-dimensional vector, which facilitates text computation in the form of a space vector. In this process, the individual understandings of learners generate the triple  $\langle S, R, P \rangle$  as input. Then, word2vec matches vector similarities to obtain the related vocabulary W {w1, w2, …, wn} associated with subject S in the triple. If P in the triple (i.e., the object) exists in the vocabulary W, the output result of this part marked as f2(triple) is 1; otherwise, it is 0.

Finally, doc2vec processes the triple  $\langle S, R, P \rangle$  generated by learners. The sentence concatenated by the triple <S, R, P> in the first part gets extracted first. Then, a set of *n* sentences {Sentence1, Sentence2, …, Sentence*n*} related to the sentence in the corpus is generated using doc2vec. The sentence having the highest similarity to Sentence in the sentence set is queried and marked as Sentence'. Lastly, the similarity between Sentence and Sentence' is assessed. If the similarity exceeds the system's set threshold value of 0.5, the output result of this part marked as f3(triple) is 1. Otherwise, the output result is the similarity itself.

After completing judgments in these three links, the final confidence level  $F(triple) = (f1 + f2)$ + f3) / 3 can be obtained.

• **Quality Control Based on User Vote of Confidence:** Although quality control based on machine computation can judge the confidence level of generated knowledge and reduce the burden of expert intelligence, it is difficult for machines to accurately evaluate all generated triples due to the limited existing corpus and mathematical robustness of algorithms. Thus, experts or related users need to evaluate the quality of the generated knowledge. In the evaluation method based on user voting, each user has a trust score w  $(wI[0,1])$  for specific learning content in the system. For each generated triple requiring user feedback, the user can express their opinion V (1 for pro and –1 for con). The collective trust score of users for the triple is accumulated to determine if the triple meets the quality requirements. The evaluated triple's trust score is calculated as follows:

 $Trust (triple) = (\sum wi * Vi)$ 

The trust score of a generated triple by learners, expressed as Trust(triple), is calculated based on the confidence degree of individual users (wi) and their vote scores for the given triple (Vi). Vi is assigned a value of 1 for pro and –1 for con. If Trust(triple) exceeds the preset threshold set by the system, it denotes that the new triple is reliable and can be added to the semantic database. In cases of disagreement among users, where some support the semantic information while others oppose it, *n* people vote on the triple, but Trust(triple) does not meet the threshold set by the system, *n* reaches the preset value of the system (such as 10 users), then the semantic information requires review by domain experts. The experts will evaluate whether the semantic information meets the quality requirements before it is stored in the database.

#### *Update Individual Knowledge Graph and Cluster Collective Knowledge Graph*

Once the triple is generated by learners, it undergoes quality control via machine computation or expert authority before being stored in the formal ontology library. Any triples that fail quality control are marked as failed. At the end of the process, knowledge nodes that pass the quality audit in the knowledge graph constructed by learners will be highlighted, while others will be displayed in gray to provide feedback for individual learner knowledge construction. The system automatically clusters all individual knowledge graphs constructed by the learners to form a collective knowledge graph representing the current state of knowledge. This collective knowledge graph depicts the complete structure of learners' knowledge acquisition across different contexts and situations. It facilitates learners' understanding of knowledge from multiple angles and promotes the evolution of knowledge.

# **CASE IMPLEMENTATION**

## **Experimental Process**

After completing the logic design of the activity, the collective knowledge graph activity was developed based on the Learning Cell platform of Beijing Normal University (<http://lcell.bnu.edu.cn/>). In this experiment, 40 Grade 5 students from a primary school in Shenzhen participated in a learning activity focused on Wang Zhihuan's *A Song of Liangzhou* in the fifth-grade Chinese course. Given the unique characteristics of the Chinese subject, the teacher seamlessly integrated the collective knowledge graph activity with the Chinese course curriculum, allowing individual knowledge graphs based on personal understanding. Additionally, learners were able to view the knowledge graphs of other students. As a result, a stable structure of *A Song of Liangzhou* was formed, and improved by all learners. Figure 7 depicts the flow of the experiment.

The experiment involved the following steps:

- Participants logged into the Learning Cell knowledge graph platform ([http://lcell.bnu.edu.cn/](http://lcell.bnu.edu.cn/lcontology/mobile) [lcontology/mobile](http://lcell.bnu.edu.cn/lcontology/mobile)).
- Based on their understanding of the content, learners constructed their own knowledge structure graph, known as their personal knowledge graph.
- Learners modified and improved their personal knowledge graph by viewing the knowledge graphs created by the group and other individuals. Ultimately, they formed a stable knowledge graph structure about *A Song of Liangzhou*, while the system clustered the knowledge graphs of all learners to form an authoritative collective knowledge graph.
- A questionnaire survey was conducted on learners to gauge their technology acceptance towards the collective knowledge graph activity.
- The triples generated in the collective knowledge graph activity were counted.



#### **Figure 7. Application of collective knowledge graph**

# **Data Analysis**

#### *Technology Acceptance Analysis of Collective Knowledge Graph Activity*

Technology acceptance in this experiment was measured using a 5-point Likert scale, with "1" representing "strongly disagree" and "5" indicating "strongly agree." The questionnaire comprised questions from Venkatesh et al.'s (2000) research. It aimed to evaluate the usability and effectiveness of knowledge graph functions in the learning process.

The study had 40 participants, out of which 38 valid questionnaires were collected, indicating an effective rate of 95%. The average score of each question exceeded 3.8. This indicated that the collective knowledge graph activity was easy to use and promoted learners' learning.

#### *Promote the Construction and Effect of Subject Matter Knowledge Ontology Based on the Knowledge Graph*

At the end of the experiment, researchers extracted and analyzed the triples constructed by learners from the database. Analysis revealed that 40 learners, each constructing unique individual knowledge graphs, generated 722 knowledge associations, 263 knowledge nodes, and 584 high-quality evolvable triples. These results demonstrated that learners generated novel knowledge points throughout the process of creating and improving the knowledge graph while also extending the existing knowledge content related to *A Song of Liangzhou*. Specifically, 584 triples evolved into ontology, showcasing how collective intelligence contributed to the construction of the collective knowledge graph and promoting the evolution of ontology.

Lu et al.(2022) also proposed Universal Information Extraction (UIE) in Association for Computational Linguistics Conference(ACL), which unifies modeling tasks, such as entity extraction, relationship extraction, event extraction, and emotion analysis, showcasing strong migration and generalization capabilities across different tasks with state-of-the-art performance. Building upon this research, PaddleNLP developed and released the first Chinese general information extraction model, UIE, based on the Enhanced Representation through kNowledge IntEgration (ERNIE) 3.0 knowledgeenhanced pretraining model. The UIE model allows for the extraction of key information without limitations on industry fields or extraction objectives, supports a fast cold start without requiring a large number of samples, demonstrates exceptional performance in fine-tuning with limited data, and enables quick adaptation to specific extraction objectives.

To evaluate the usefulness of the PaddleNLP model, this study employed the model to extract entity objectives from 36 teaching design cases of *A Song of Liangzhou*. Subsequently, 770 triplet relationships were selected from the crowdsourced knowledge graph for comparison, and the similarities and differences of the included subjective knowledge were analyzed and presented in Table 1.

Most of the knowledge extracted by UIE corresponds to information extracted from text based on inherent contexts. If the text fails to contain any relevant knowledge, no new knowledge will appear in the extraction results. However, the knowledge graph relationship network obtained through crowdsourcing is more complex and includes new subjective knowledge, such as "farewell" and "pipa," beyond *A Song of Liangzhou*.

Moreover, experiments may generate ambiguous and uncertain humanistic knowledge, reflecting its inherent ambiguity and uncertainty. While most knowledge is extracted based on the implicit context in the text during UIE extraction, there are instances of fuzziness or uncertainty. This fuzziness may stem from semantic ambiguity, contextual ambiguity, or information gaps in the text. For instance, the text describing the story, events, or emotions of "Liangzhou" may ambiguously express the characters' emotional states or specific event details. Additionally, different texts may express information differently, which might lead to some degree of uncertainty in the extracted knowledge.

The generation of ambiguous and uncertain knowledge through experiments is critical for understanding the complexity and diversity of the humanistic domain. It reflects the subjectivity





and polysemy of human knowledge, enabling the knowledge graph to simulate human cognition and semantics more realistically. In the field of education, learners can interact and explore this ambiguous and uncertain knowledge, enhancing their reasoning and judgment abilities while developing their adaptability to uncertain situations.

In summary, the implementation of collective knowledge graph activities facilitates the improvement of learners' structured knowledge and subject matter knowledge ontology while also generating ambiguous and uncertain humanistic knowledge. This enriches the content of the knowledge graph, better reflecting the complexity and diversity of human knowledge. Moreover, it provides learners with abundant learning resources and challenges, fostering cognitive development and intelligence enhancement when faced with complex and uncertain situations.

# **CONCLUSION**

Currently, subject matter knowledge ontology construction primarily relies on expert presupposition and machine generation, limiting its adaptability to dynamic situations and the needs of diverse learners. To overcome these limitations, this study proposed an ontology construction and evolution method based on collective knowledge graph activity enabled by the Learning Cell platform. Learners can construct their individual knowledge graph based on their own understanding of the knowledge while also learning under the guidance of the system's preset knowledge graph. Finally, the individual knowledge graphs constructed by all learners are clustered into a collective knowledge graph about current knowledge that promotes the dynamic construction and continuous evolution of subject matter knowledge ontology.

The questionnaire revealed that the collective knowledge graph activity was easy to use and useful in promoting learners' learning. With respect to promoting the construction and evolution of subject matter knowledge ontology, the 722 knowledge associations and 584 evolvable triples related to *A Song of Liangzhou* constructed by learners demonstrated the crucial role of collective knowledge graph activity in supporting knowledge ontology construction.

In future research, collective knowledge graph activity will be applied to more subjective disciplines to promote the construction and evolution of subject matter knowledge ontology. The emphasis will be on finding a reliable method for guaranteeing ontology evolution quality through machine automation.

# **AUTHOR NOTE**

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