

Retraction

Retracted: Mind Map Construction for English Grammar Teaching Based on Knowledge Map

Scientific Programming

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Q. Fu and S. Kuang, "Mind Map Construction for English Grammar Teaching Based on Knowledge Map," *Scientific Programming*, vol. 2021, Article ID 4921825, 10 pages, 2021.

Research Article

Mind Map Construction for English Grammar Teaching Based on Knowledge Map

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The analysis of the frontier issues of the English language teaching method in China is of great guidance for English language teaching. Based on the ontology model of English teaching domain, the knowledge map of English teaching in colleges and universities is constructed by fusing heterogeneous English subject data from multiple sources. Firstly, we obtain domain knowledge from relevant websites and existing documents through web crawlers and other techniques and clean the data based on BERT model; then, we use Word2Vec to judge the similarity between the research directions of characters and solve the entity alignment problem; based on the scientific knowledge map theory, we count the frequency of keywords in each year and analyze them to describe the association and union between keywords. It can explain the current situation and trend, rise and fall, disciplinary growth points, and breakthroughs of ELT. Through keyword analysis, the hot issues mainly revolve around ELT, English teaching, college English, grammar-translation method, curriculum reform, and so forth, to realize the quick query and resource statistics of ELT basic data, in order to promote the subsequent English discipline assessment work to be completed more efficiently.

1. Introduction

Since the birth of English in the 17th century, discussions, reforms, and researches on teaching methods have been in full swing [1]. At the same time, English teaching theory has been greatly enriched. Since the reform and opening up, the situation of English teaching in China has undergone great changes [2]. The traditional grammar-translation method has been broken, and some new teaching methods from abroad have been introduced and brought in, which has injected vitality into English teaching. English teaching workers have been actively involved in the reform, research, and practice of English teaching methods, and the face of English teaching has become a new one. However, many English teachers also reflect that while they are encouraged by the good situation of English teaching since the reform and opening up, they are always “circling” around the foreign teaching methods, resulting in, to some extent, some misunderstandings in the research and practice of English

teaching methods. In order to make the reform of English teaching to get out of the misunderstanding and go further and really receive effective results, it is necessary to make a serious analysis and comparison of English teaching methods, so as to provide scientific guidance for English teaching [3]. Knowledge mapping is an emerging research field developed on the basis of citation analysis theory and information visualization technology. It displays the development process and structural relationship of scientific knowledge in a visual way by visualizing the complex scientific knowledge field through data mining, information processing, knowledge measurement, and graphical drawing, reveals scientific knowledge and its activity law, and shows the knowledge structure relationship and evolution law. Through scientific knowledge mapping, the authors, keywords, abstracts, and references contained in the literature are analyzed in two-dimensional horizontal and vertical time, and the research development path of the field and its frontier hot issues are visually analyzed [4].

In recent years, the problem of information visualization has received more and more attention [5]. People want to analyze a large amount of data at a deeper level and have no way to do so, so people want to analyze it at a deeper level in order to make better use of it. Knowledge mapping can graphically display the overall image, affinity, and evolution law of frontier fields that are difficult to obtain by personal experience alone and has become an important tool for grasping the development dynamics of disciplines, the direction of disciplinary research, and assisting scientific and technological decision-making. The study in [6] introduced CiteSpace to China, which has rapidly created a boom in related research. CiteSpace is a Java application for identifying and visualizing new trends and developments in scientific research in the scientific literature and has become an influential information visualization software application in the field of information analysis.

Competition among universities is mainly based on discipline competition, and the strength of a discipline can represent the level of the institution to some extent. The assessment of disciplines can help in effectively and comprehensively understanding the current status of discipline construction, and, through the correct assessment of disciplines, problems in construction can be identified, so as to further clarify the direction of the discipline and achieve better development [7]. Since the results of discipline construction involve many aspects, storing and displaying information about the discipline in the form of scattered documents and web resources cannot show the correlation between all data comprehensively, and it is difficult to dig out the information statistics and potential relationships, which is not conducive to the subsequent evaluation work.

As a new and efficient knowledge organization method in the era of big data, knowledge map can fuse and correlate heterogeneous data from multiple sources based on graphs [8]. In this paper, we apply the knowledge map technology to the field of English teaching in colleges and universities; firstly, we obtain the domain knowledge related to English teaching from the resource-rich data sources such as knowledge networks, university official websites, and discipline assessment documents through the method of web crawlers and rule mapping. With the possible problem of impurity data, a fine-tuned BERT (Bidirectional Encoder Representations from Transformers) model is used to classify the data. By searching the keywords of ELT and the frequency of occurrence by year and analyzing them, the association and combination between the keywords are described, which can explain the current status and trends, the rise and fall of ELT research, the growth points, and breakthroughs of the discipline. Visualization mapping can clearly show the changes of ELT method in a certain time period and the process of its change.

2. Related Knowledge and Research Ideas

The concept of knowledge map was first introduced by Google in 2012, with the aim of improving the quality of search engine results and enhancing the user search experience. According to the different coverage, the knowledge

map can be divided into general knowledge map and domain knowledge map. Among them, the general knowledge map has a wider coverage, covering a lot of common knowledge in the real world, and some well-known large-scale general knowledge maps are DBpedia, Wikidata, Freebase, and so forth [9, 10]. These knowledge maps are very large in scale, but the quality of extracted knowledge is not strict, and the structure of the knowledge of each domain is simple, so they do not perform well when applied to specific domains. Domain knowledge maps are built for specific domains and have very strict requirements on the accuracy and depth of knowledge in the domain and can provide good support for the upper layer applications in the target domain. Knowledge maps have been used in medical, e-commerce, and legal fields, such as chatting bots based on knowledge maps for users to learn about healthcare and drugs [11] and designing inference rules to provide reference for sentencing in similar cases based on the constructed knowledge maps of legal documents of theft cases [12].

The knowledge map model is based on the graph structure $G=(V,E)$ in graph theory, where V is the set of vertices and E is the set of edges. The knowledge map can be perceived as a factual knowledge, which can be represented as a triple (H, r, t) , where h is the head entity, t is the tail entity, and r is the relationship between the two entities. In constructing the knowledge map, there are two main ways to construct the knowledge map, top-down and bottom-up. The top-down approach refers to extracting the relevant ontology and pattern information directly from the high-quality dataset, while the bottom-up approach refers to extracting the resource patterns from the collected large amount of data and then selecting the ones with high confidence as the basis for the subsequent knowledge map construction [13]. For some more mature domains with complete knowledge systems, the top-down approach is usually adopted; that is, the schema ontology is defined first, and then knowledge is extracted using supervised, semi-supervised, and unsupervised methods, and finally the domain knowledge map is improved by combining knowledge fusion and knowledge inference mechanisms.

The general construction process of knowledge map is as follows: firstly, we determine the knowledge representation model; then we select different technical means to acquire knowledge according to different sources of data and import it into the knowledge map database; then we make comprehensive use of knowledge fusion, knowledge inference, and knowledge mining technologies to improve the scale and quality of the constructed knowledge map; finally, we design effective knowledge access and presentation channels according to different requirements of target scenarios, as shown in Figure 1, such as human-computer interaction and Q&A, graph visualization and analysis, and similar recommendation.

3. ELT Ontology Construction

Ontology defines the class set, relationship set, attribute set, and so forth of the knowledge map, which mainly emphasizes the relationship between concepts and is the

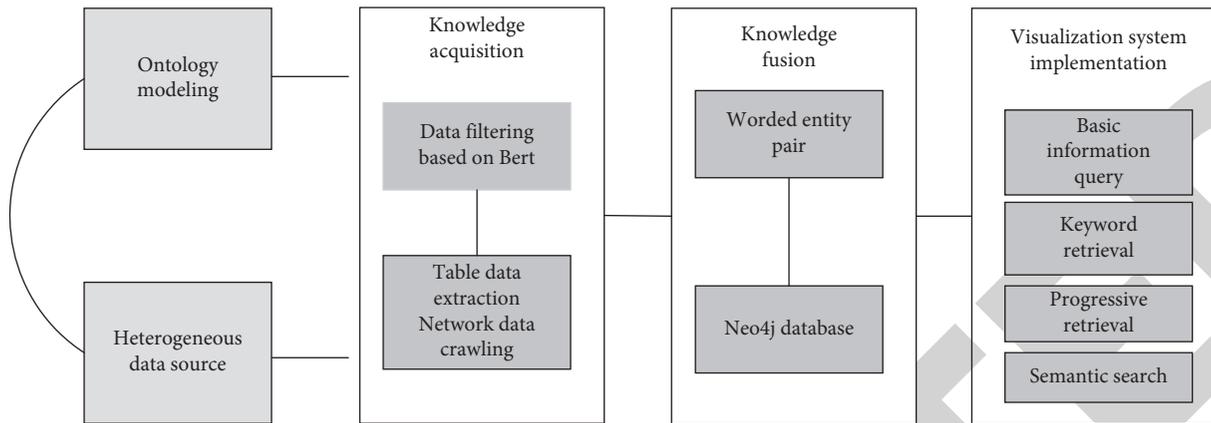


FIGURE 1: Overall build process.

management of the schema layer of the knowledge map. By constructing an ontology model, entities, relationships, and entity attributes can be constrained and standardized as a guide for subsequent knowledge extraction and organization [14]. In this paper, we use the ELT Computer Science and Technology 4th round discipline assessment brief as the main knowledge source, combine with specific ELT domain related websites, use OWL language as the ontology description language, and use Protégé ontology development tool to complete the construction of ELT ontology in universities.

The concepts included in the ELT ontology and the structure of their relationships are shown in Figure 2 using the OntoGraf tool in Protégé. In this ontology model, there are 10 categories: teachers, alumni, students, foreign students, institutions, national projects, provincial projects, journal papers, conference papers, and patents, and the subcategories are related to each other through various relationships. The ontology represents the relationships between concepts as semantic relationships, which are also called object attributes in Protégé, including generic semantic relationships and custom semantic relationships [15]. The ontology constructed in this paper contains a variety of custom semantic relations, and the related concepts and their detailed descriptions are shown in Table 1.

4. ELT Knowledge Mapping Construction

4.1. Knowledge Acquisition. In the process of knowledge map construction, data is a very important underlying support, and only by obtaining a large amount of data in the research domain can we build a good quality knowledge map. Generally, the knowledge sources used to build the knowledge map can be structured data, semistructured data, unstructured data, IoT sensors, and artificial crowdsourcing [16]. It is found that the data in the field of English teaching in universities are mainly distributed in electronic documents and various websites, such as subject evaluation documents, university official websites, and national knowledge infrastructures, which cover different types of subject area data, including teachers' information, papers, patents, and research projects, respectively. Therefore, this

paper mainly obtains domain knowledge from the sources shown in Table 2.

For the structured data stored in the form of table documents, such as the English teaching assessment profile, a mapping-based information extraction method can be used; that is, first establish a one-to-one mapping between the table header fields to be extracted and the data attributes in the subject ontology constructed above, and then use the vocabulary defined in the ontology to describe the extracted structured information, thus preventing the occurrence of synonymy between attribute names; complete the extraction of data from the target table cell.

In order to crawl the data stored in the Internet web pages, the content organization of different web pages varies greatly, so it is necessary to develop specific crawling methods according to different target websites. Requests downloads a web page through an initial URL, parses the content of the tags contained in it with a web page parsing library, and obtains a new URL to crawl in turn [7]. Selenium, on the other hand, runs directly in the browser by simulating user actions, such as clicking buttons and typing text, to achieve the correct jumping between web pages [17]. The different implementation principles also determine the advantages and disadvantages of each type of crawler and their respective scenarios: Requests is fast, but the crawl is interrupted when the URL of the jumped page is not available, so it is suitable when the target URL is available; when the target URL is not available directly, Selenium can be used for page jumping, but it has the disadvantage that it needs to wait for the browser to open and load. When the target URL is not available, Selenium can be used for page jumping.

In this paper, we propose a web crawler algorithm that can flexibly invoke the above two tools according to the different forms of web page organization to obtain the target data while improving the crawling efficiency as much as possible. The specific crawler workflow is shown in Figure 3.

The algorithm needs to determine the organization of the jump URLs on the web page after the crawling starts. For example, for the official website of a university, the faculty list page usually contains the URL of the faculty details page, so we can crawl it by the following steps: (1) Starting from

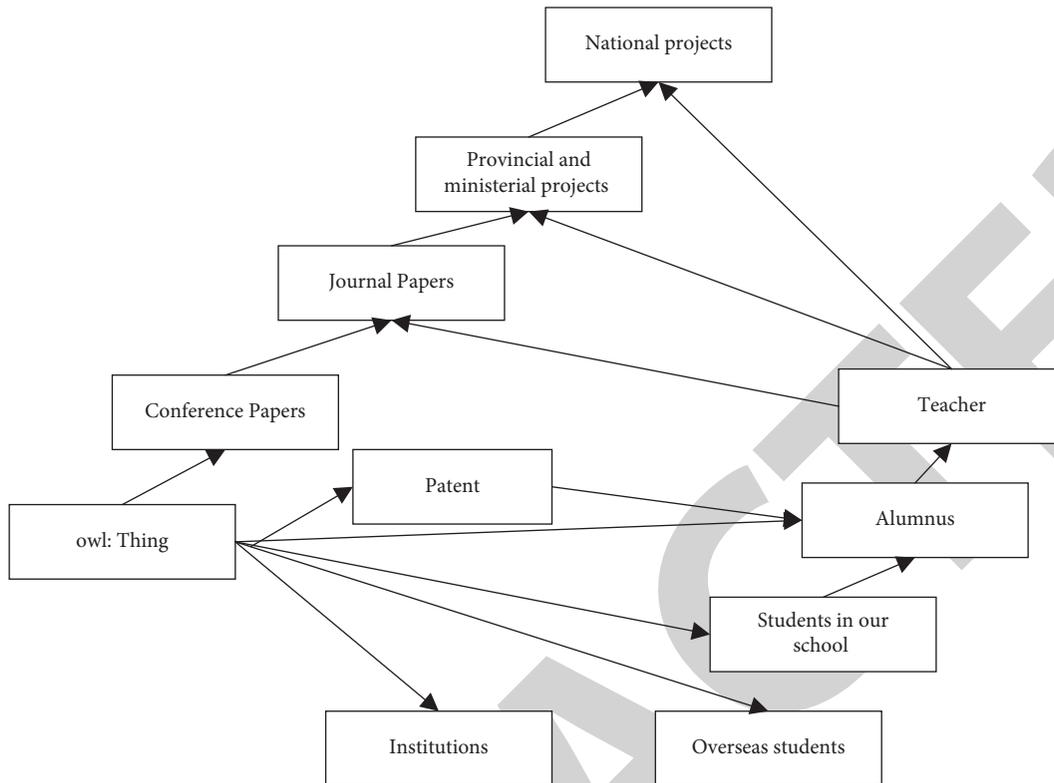


FIGURE 2: Ontology model of subject knowledge mapping.

TABLE 1: Table of custom semantic relations.

Association concept	Semantic relation	Associated concept	Semantic relation description
Teacher	Teach in	Institutions	Teach at
Teacher	Graduated from	Institutions	Graduated from
Alumnus	Graduated from	Institutions	Graduated from
Students in our school	Study in	Institutions	Study in
Overseas students	Study in	Institutions	Study in
Teacher	Author in	Journal papers	Publish one's thesis
Teacher	Author in	Conference papers	Publish one's thesis
Teacher	Lead	National projects	Host the project
Teacher	Lead	Provincial and ministerial projects	Host the project
Teacher	Participate in	National projects	Participation project
Teacher	Participate in	Provincial and ministerial projects	Participation project
Teacher	Inventor in	Patent	Invention patent

TABLE 2: Statistics of various data volumes before and after cleaning.

Data category	Before cleaning	After cleaning
Paper	3297	3208
Patent	1189	1150
Teacher	87	89
Institutions	35	36

the URL of the faculty list page, we obtain the content of the page through Requests library. (2) According to the defined page extraction rules, we extract the URL of the faculty details page and put it into the URL queue to be crawled. If the URL is incomplete, the missing fields are added according to the URL construction of similar pages. (3) Download the details page according to the queue of URLs to be crawled, extract the target data from it, and save it to

the data storage file. (4) The whole process is executed cyclically until all URLs in the queue are crawled [18]. For some websites that cannot get the URL of the jump page directly, such as China Knowledge Network, the Selenium tool can be chosen to crawl, and the process is as follows: (1) Configure the URL address and related parameters, and call Selenium's web driver to open the browser page. (2) Wait for the page to finish loading, locate the search box and button

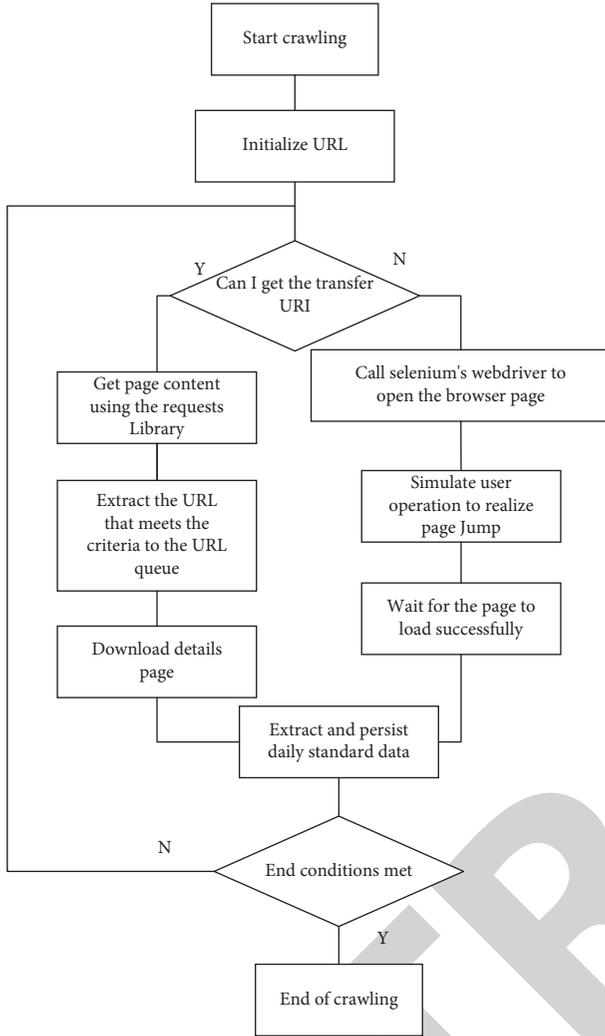


FIGURE 3: Crawler workflow.

elements, and, after completing the input of search conditions, simulate. (3) After the page is loaded successfully, use XPath to extract the target data and perform the data persistence operation. (4) Repeat the previously mentioned process until the number of crawlers is satisfied or all pages are crawled.

4.2. Knowledge Integration. When fusing knowledge from different sources, the problem of instance heterogeneity may arise; that is, entities with the same name may point to different objects, while entities with different names may point to the same object. Therefore, if so, construct corresponding alignment relationships between the entities to complete the knowledge fusion. In the process of constructing the knowledge map, the ambiguity of characters may arise in the process of collecting data related to English teaching in universities from data sources such as Knowledge Network and SooPAT. For example, the research results published by university teachers at different time points, such as papers and invention patents, are determined as different person

entities due to job transfer, or the teachers with the same name in the same university are incorrectly pointed to the same entity, resulting in incorrect statistics of research results. Therefore, in order to build an accurate knowledge map of English teaching in universities, we need to design a suitable entity alignment algorithm to solve the above problems.

The algorithm firstly extracts the renamed characters from multiple data sources to obtain the set of entities to be aligned; then, the basic information of the characters, including gender, ethnicity, date of birth, and other attributes that cannot be easily changed, is used for preliminary screening; finally, based on the set of keywords in the published papers or patent applications of the characters, the corresponding word vectors are obtained using Word2Vec and the cosine similarity between the word vectors is calculated [19]. If the similarity exceeds a defined threshold, it can be considered that both of them have the same research direction and refer to the same entity.

In order to determine the similarity threshold, the following experiment is designed to investigate. Firstly, we select some university teachers' papers as the original data, and each teacher randomly selects 3 papers' keywords to form his or her research keyword set, and suppose that the length of a teacher's research keyword set is m ; then the set can be expressed as

$$\{K_{s1}, K_{s2}, \dots, K_{sm}\}. \quad (1)$$

The remaining papers of the faculty member are then compared with this set, and the set of keywords for comparison is assumed to be n if the remaining papers contain n keywords:

$$\{K_{t1}, K_{t2}, \dots, K_{tn}\}. \quad (2)$$

After that, the Word2Vec model is used to obtain the word vector of the keyword set, and the word vector of the keyword set in the research direction is represented as

$$\{K_{s1}, K_{s2}, \dots, K_{sm}\}. \quad (3)$$

The word vector of the set of contrasted keywords is represented as

$$\{K_{t1}, K_{t2}, \dots, K_{tn}\}. \quad (4)$$

Finally, the mean value of the cosine of the word vector between the two sets of keywords is calculated as the similarity between the paper and the corresponding faculty research direction:

$$\text{similarity} = \frac{\sum_{j=1}^n \sum_{k=1}^m \cos(V_{sk}, V_{tj})}{n \times m}. \quad (5)$$

The cosine function $\cos(\bullet)$ between two word vectors is defined as

$$\cos(V_s, V_t) = \frac{V_s \cdot V_t}{\|V_s\| \times \|V_t\|} = \frac{\sum_{i=1}^L V_s^i V_t^i}{\sqrt{\sum_{i=1}^L (V_s^i)^2} \sqrt{\sum_{i=1}^L (V_t^i)^2}}, \quad (6)$$

where L is the dimension of the word vector obtained by Word2Vec and V_i is the i -th component of the word vector.

In this paper, a total of 2400 sets of test data were randomly selected, and the final distribution of the keyword similarity values is shown in Figure 4. From Figure 4, we can see that the keyword similarity of papers with the same research direction is above 0.5, so the similarity threshold is set to 0.5 in the entity alignment algorithm.

In order to verify the feasibility of the algorithm, several teachers with the same name but different research directions were selected and their published papers were crawled from the Internet, and the set of keywords of papers of the same teacher was taken as the positive data and the set of keywords of papers of different teachers was taken as the negative data. Then 200, 400, 600, and 800 pieces of data were randomly selected and the accuracy was analyzed and calculated with the results of manual annotation [20]. The experimental results are shown in Table 3. The accuracy rates of the four random tests are above 90%, which indicates that the Word2Vec-based character entity alignment method identifies less erroneous data and can be used in the knowledge fusion scenario of university subject areas.

4.3. Knowledge Storage. After cleaning and aligning the data, its content and format have met the requirements of subject knowledge map construction, and the next step is to import the data into the underlying database. Neo4j is a high-performance nonrelational graph database that stores data on a very large network, which is very suitable for storing knowledge maps based on graph structures [21]. In this paper, we import various types of data into Neo4j in the form of nodes and edges by using the operations provided by the Py2Neo third-party library supported by Python and can perform corresponding operations such as adding, deleting, and checking.

The data scale statistics of the finalized subject knowledge map are shown in Table 4. The various types of knowledge in the map for a large and complex multi-relationship network are helpful for the subsequent implementation of various functions and performance optimization.

5. Visualization System Implementation

In this paper, we develop a visualization system for teaching English in higher education based on the above knowledge mapping, which is implemented in a B/S (Browser/Server) front-end and back-end model and built with Python's Flask framework. In the front end, ECharts tool is used to visualize the data [22], and the subject domain knowledge is visualized in various forms such as text and force-oriented diagrams.

5.1. System Functions. The functions of this visualization system mainly include basic information query, keyword search, and progressive search and semantic search, which can complete the search and display of knowledge from

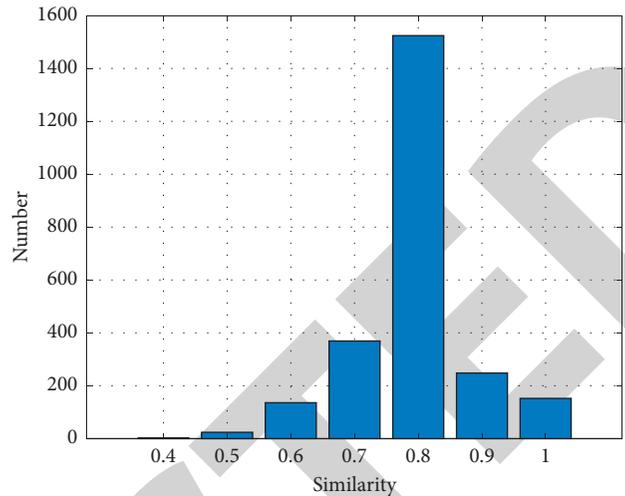


FIGURE 4: Keyword similarity distribution.

TABLE 3: Character entity alignment test results.

Number of data pieces	Number of correct classifications	Accuracy (%)
200	189	94.50
400	367	91.75
600	560	93.33
800	741	92.63

TABLE 4: ELT knowledge mapping data statistics.

Element	Type	Total quantity
Entity	10	3504
Relationship	24	4668
Attribute	39	22584

multiple dimensions such as entities, attributes, and relationships.

The purpose of the basic information query function is to count all entities and relationships related to the queried entity and then represent the entity relationships in the form of a force-oriented graph through a graphical interface. At the same time, a recommendation algorithm conforming to the storage structure of the graph database is used to select some similar entities with the highest similarity to the queried entity as recommendations that may be of interest to the user.

This function consists of two main data processing modules: direct query and similar recommendation. In the direct query module, the corresponding matching paths are constructed based on the user input [5], and then all the related entities and their relationships are found from the Neo4j graph database by Cypher statements. In the similar recommendation module [23], we first construct the multihop matching path “(qe:Stype)-[r1]-(e)-[r2]-(me:Stype),” where qe refers to the queried entity, me refers to the matched entity, Stype indicates that they are of the same data type, and r1, r2, and e represent the relationships and entities that do not make specific requirements. After that, all the matched entities and their

corresponding paths are counted and ranked in descending order, and the top- k entities are selected as similar recommendations (the value of k in this paper is 3; i.e., at most 3 similar entities are recommended). Finally, the node and link types and label values are determined from the obtained data attribute values and passed to the drawing function of ECharts to complete the drawing and display of the graph.

Figure 5 shows the results of the information search by entering “English teaching,” which includes a description of the nodes of the various entities directly related to this entity and the relationships between them and also suggests the most relevant entities of the same type for the user: “English test,” “English teachers,” and “New Oriental.” The force-oriented diagram supports zooming in and out and moving the graph, and when clicking on the category tabs at the top of the interface, all entity nodes in that category can be hidden or reproduced, making it easy for users to observe and count.

The keyword search function displays all entity nodes related to the input keywords and supports the task of multikeyword search. The system first uses the HIT LTP language processing tool to annotate the user input keywords with lexical types, including people, time, and nouns, and then constructs the corresponding regular expressions based on the lexical distribution to find the eligible entities from the knowledge map [24].

For example, when multiple keywords are entered as “neural network,” “recognition,” and “2019,” the LTP lexical annotation module labels them as “n,” “v,” and “nt,” and the corresponding regular expressions are “(? = . * [god] [warp] [net] [network] . * ,” “(? = . * [knowledge] [other] . * ,” and “(? = . * [2] [0] [1] , [8] . * .” These regular expressions are then used as attribute fields to form a Cypher statement to retrieve the entities that satisfy the conditions, and the final result is shown in Figure 6.

Semantic search can be used to match the user’s real intention by mining the semantic meaning behind the input question. In the process of semantic search, the input questions and defined question templates are first divided by using the LTP word division tool, which usually may overdivide the entities and concepts in the proprietary domain [25] and cause troubles in the subsequent search. Then, each question template and the input question are combined to perform one-hot coding to obtain the word vector representation of this template and the input question, and the highest similarity is selected as the type of the input question by calculating the cosine similarity between the two word vectors. Finally, the relevant data based on the template and the question keywords are returned to the front-end interface for integration and display.

Figure 7 shows the search results of the question “the coauthored journal papers of Ms. Zheng Qiumei and Ms. Huang Tingpei,” and the interface shows the coauthored journal papers and the collaboration between the two teachers through graphical drawings, which achieves the goal of semantic search [26, 27].

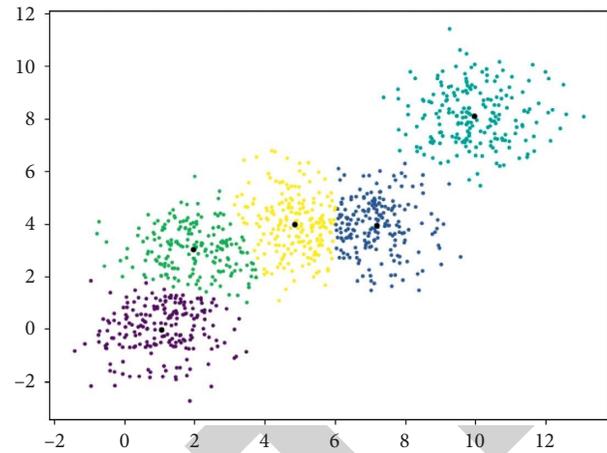


FIGURE 5: Results for “English Language Teaching.”

5.2. System Performance Evaluation. In order to verify whether the performance of the system can meet the requirements of users, a dozen of English teaching staffs were invited to test the system after it was built. The testers participating in the testing process were divided into two groups according to the different testing methods: one group adopted the α -testing method; that is, the participants were given certain instructions and instructions on how to use the system, mainly to verify the reliability of the visualization system; the other group adopted the β -testing method, in which the participants were allowed to explore the functions of the system on their own without any guidance and help, mainly to verify the robustness and ease of use of the system. The overall feedback from the α -testing group was that the system had a wide range of data coverage and was user-friendly and reliable, while the overall feedback from the β -testing group was that the system was easy to use and operate, and no anomalies were generated. As shown in Figure 8, the average satisfaction rate of all test participants was 91.67%.

Chinese foreign language teaching has made remarkable achievements, but the traditional English major training mode aims to create tool-oriented talents, and such English talents can no longer meet the demand for English talents in today’s social development. Therefore, the curriculum of English majors must be reformed, and the new training objectives and training mode should be based on the cultivation of complex English talents with innovative quality. A foreign language university in northeast China has reformed the CBI curriculum for college English majors. Content-dependent teaching reform is guided by the content-dependent teaching theory, and a curriculum system that integrates content-dependent courses and skill-based course in the basic stage of English majors has been built. After the curriculum reform, students’ competencies were significantly improved, and experimental studies showed that content-dependent teaching achieved better results in terms of language knowledge teaching, language skill development, and subject knowledge transfer compared to language skill-oriented teaching and better achieved the overall teaching objectives specified in the national syllabus [1].

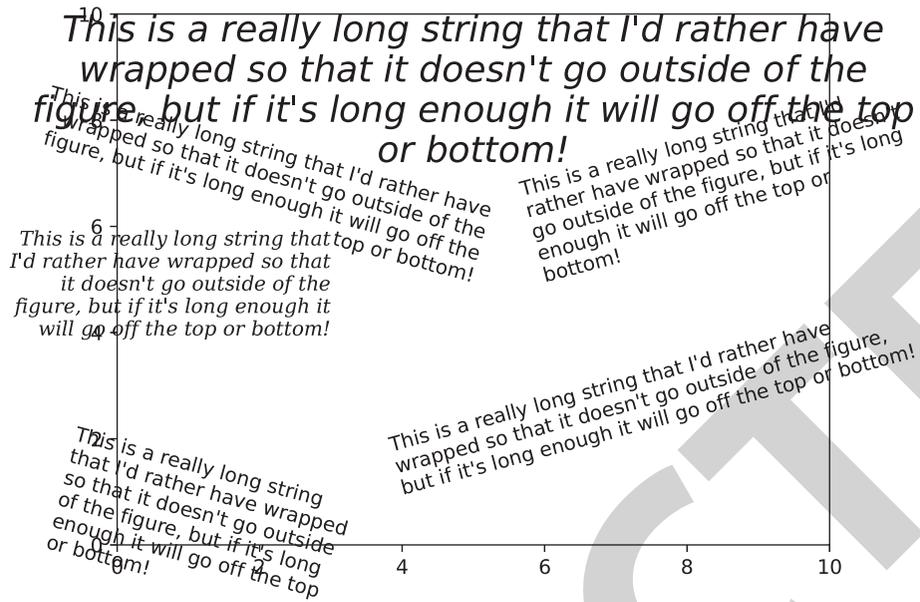


FIGURE 6: Multikey word search results.

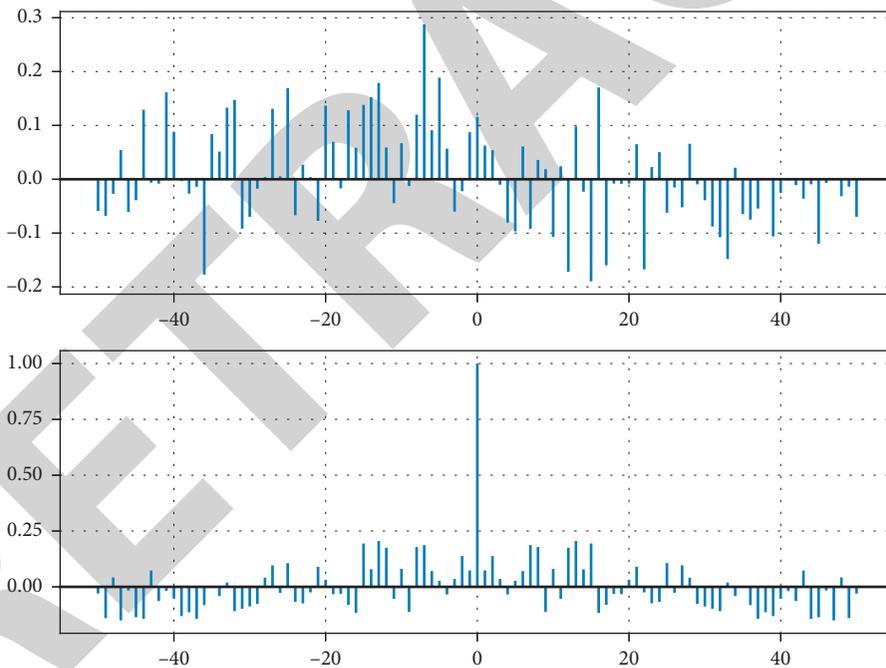


FIGURE 7: Semantic search results.

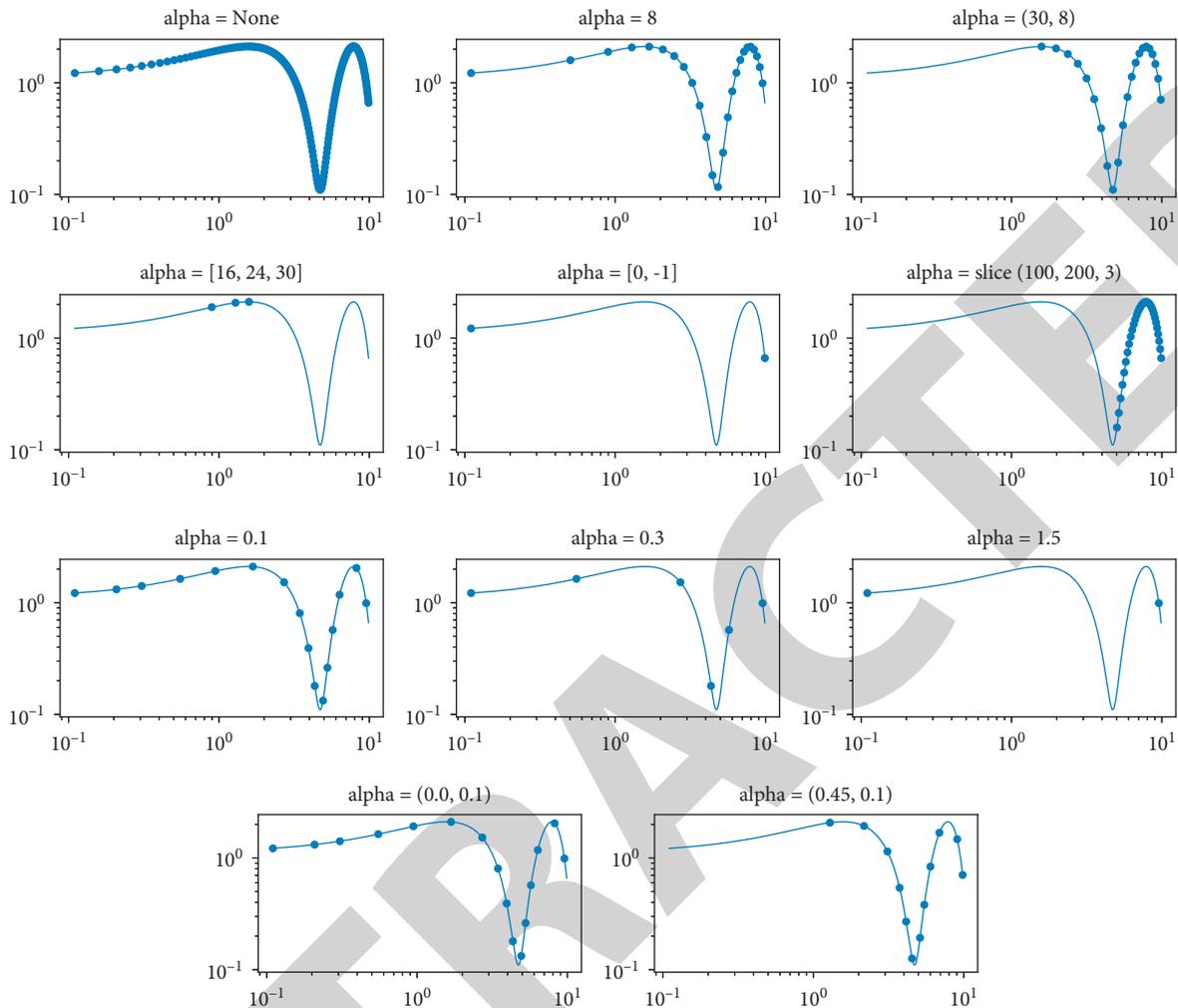


FIGURE 8: System performance with different alpha settings.

6. Conclusions

In this paper, we present a complete domain knowledge map construction scheme in the field of English teaching in colleges and universities and demonstrate the usability of the scheme through experimental results. For multisource heterogeneous domain data, we design a data acquisition method based on a combination of rule-based mapping and improved web crawlers and then use a BERT classification model after fine-tuning to clean and filter the data. In the fusion of knowledge from different sources, a Word2Vec-based entity alignment method is proposed to effectively solve the data conflict problem in the fusion process. Finally, knowledge is imported into Neo4j graph database for storage, and the implementation of English teaching visualization system is completed based on this knowledge map, which provides convenient and fast resource query and relationship display services for future discipline assessment work. Since the data sources of ELT include some unstructured data, the knowledge extraction method of unstructured text will be improved in the follow-up work to make the constructed subject knowledge map more comprehensive.

Data Availability

The datasets used in this paper are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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