Application and Implementation of Word Vector Semantic Expansion Technology in Library Intelligent Consultation Systems (Postprint)

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Abstract

[Purpose/Significance] To address the deficiencies in semantic expansion of current automatic question answering systems, this paper proposes a word vector-based semantic expansion technique, and designs and implements an intelligent consultation system for libraries.

[Method/Process] Using Word2vec-based word vector semantic expansion technology combined with Chinese word segmentation and co-occurrence word matching techniques, an intelligent Q&A engine is designed. By integrating the collaborative office management concept, the construction of the library intelligent consultation system is realized, and statistical analysis is conducted on the system's operational data.

[Results/Conclusion] The system satisfactorily meets the design requirements in terms of working hours, consultation effectiveness, and backend management, providing a reference for the construction of intelligent information consultation systems in libraries.

Full Text

Preamble

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Application and Implementation of Word Vector Semantic Extension Technology in Library Intelligent Consulting Systems

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Abstract: [Purpose/Significance] To address the deficiencies in semantic extension within current automatic question-answering systems, this paper proposes a semantic extension technology based on word vectors and designs and implements an intelligent consulting system for libraries. [Method/Process] Using Word2vec-based word vector semantic extension technology combined with Chinese word segmentation and co-occurrence word matching, an intelligent Q&A engine was designed. Integrated with the collaborative office management concept, the construction of the library intelligent consulting system was realized, and the system's operational data was statistically analyzed. [Result/Conclusion] The system satisfactorily meets design requirements in terms of working hours, consultation effectiveness, and backend management, providing a reference for the construction of intelligent library information consulting systems.

Keywords: word vector; semantic extension; Word2vec; intelligent consultation; library
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To better provide information consulting services for users, libraries have offered various web-based service methods, such as virtual consulting systems and automatic Q&A systems. However, due to deficiencies in semantic extension, the effectiveness of information consultation has been unsatisfactory. With the development of word vector technology in artificial intelligence natural language processing, new approaches have emerged for the design and construction of library intelligent consulting systems. This paper provides a reference for domestic library intelligent consulting system construction through the development and operational analysis of a Word2vec-based word vector semantic extension intelligent consulting system.

2 Literature Review

With the application of digital technology and network technology, information consulting services—the core value of libraries—have achieved leapfrog development. Traditional face-to-face consultation models have gradually been replaced by network-based digital reference services. In terms of consultation response modes, early digital consultations used real-time communication tools for manual services, such as video conferencing software, Twitter, or Facebook. With the rapid development of artificial intelligence technology, the application of intelligent information consulting systems has gradually emerged in the library field. Abroad, the University of Hamburg Library was the first to use an intelligent Q&A system to address the low efficiency and slow response of traditional manual services. In China, libraries at Tsinghua University, Shanghai Jiao Tong University, Nanjing University, and Beijing Technology and Business University have successively built their own automatic Q&A systems using different platforms and technologies. However, most of these systems remain in the improvement and testing stages, with few being deployed in real library scenarios.

The basic workflow of library intelligent information consulting systems involves analyzing user questions upon receipt, extracting keywords, and then searching and matching in existing corpora or knowledge bases to return answers to users. Early automatic Q&A systems employed keyword-based retrieval models, including question analysis, keyword extraction, information retrieval, and answer verification processes. This approach used direct matching between keywords and answers. However, in practical applications, Chinese semantics can often be expressed through multiple text strings, while data and keywords in databases exist independently without mutual association. Consequently, this single-keyword matching model suffers from low answer matching rates due to its lack of semantic extension capability for natural language synonyms. Subsequent research found that using synonym dictionary-based semantic extension during retrieval could effectively improve answer matching rates in Chinese information retrieval. This method involves comparing question keywords with words in synonym dictionaries to extract related words for semantic extension. Later, scholars attempted to apply knowledge organization models such as knowledge ontologies, linked data, and knowledge graphs to optimize database associations and provide semantic understanding mechanisms for information retrieval. The problem with these approaches is that construction and maintenance are extremely complex, and operational efficiency is low with large databases.

With the development of word vector technology in natural language processing, better solutions for semantic extension have emerged. Word vector technology was invented to represent natural language words and their corresponding vectors using mathematical models, and to quantify and classify semantic similarity between linguistic items. Statistical natural language word vector models such as n-gram, neural networks, and Word2vec have emerged successively. Their characteristic is that through corpus training, matching effects can be continuously optimized. They are currently widely used in natural language processing tasks such as semantic similarity calculation, machine translation, and text matching.

3 Word2vec-Based Word Vector Semantic Extension

The main difficulty in implementing intelligent Q&A systems lies in accurately identifying user questions and returning appropriate answers. Semantic extension of keywords extracted from questions is key to improving answer matching effectiveness. Word2vec-based word vector semantic extension technology can effectively solve this problem. The core idea of Word2vec is to obtain vectorized representations of words through their context. Using training samples for training and learning, words in sentences are mapped into multi-dimensional word vectors, and the semantic similarity between words is determined by the distance between vectors. Its advantage is that it does not require complex processing of sample data and can directly conduct word vector training. Based on this characteristic, effective Q&A pairs accumulated in library information consulting services can be conveniently added as training samples. Through continuous vector training, the accuracy of word vectors can be improved without manual intervention.

The Word2vec-based word vector semantic extension process first involves training word vectors on the sample library to obtain a word vector table. Then, using the trained word vector table, the cosine value between query words and extension words is calculated to determine their similarity. After obtaining the query results, a certain threshold is set. If the value exceeds the set threshold, the word is judged as a similar word and added to the query word's extension set, preparing for subsequent Q&A matching.

4 System Design and Related Technologies

Southeast University Library has successively used virtual consulting, QQ, and automatic Q&A robots in the informatization and intelligentization of information services. During application, several issues requiring resolution were identified: Q&A robot systems based on keyword retrieval lack semantic extension capability, resulting in inaccurate consultation answers. Manual information consulting services cannot meet user demands in terms of service time. Repetitive transactional questions account for a large proportion of consultation inquiries, such as questions about library location, service terms, and working hours, leading to excessive workload for consulting librarians. Professional consultation content from library users requires multi-department cooperation to answer, necessitating a convenient internal collaborative processing work model to improve response timeliness and quality. Based on these issues, Southeast University Library designed and constructed an intelligent consulting engine and maintenance management platform based on Word2vec.

4.1 Requirements Analysis for Library Intelligent Consulting System

Functional requirements for the library intelligent consulting system are mainly summarized into the following two aspects:

4.1.1 User Consultation Requirements The intelligent consulting system provides library information consultation, collection catalog retrieval, and other services to faculty and students 24 hours a day through multi-terminal presentation methods such as WeChat and web interfaces. The system supports users consulting questions through natural language and keywords. Based on Word2vec word vector semantic extension, combined with Chinese word segmentation and co-occurrence word answer matching technologies, an intelligent Q&A engine is implemented to analyze user questions and provide associated recommended answers. When the intelligent Q&A engine cannot answer faculty and student questions, manual service connection is provided. For unanswered user questions, after administrators answer and submit them to the intelligent consulting system in the backend, the system supports question push functionality.

4.1.2 Backend Management Requirements For backend system operators, hierarchical and role-based management functions based on collaborative work are provided, with different permissions granting different backend operation functions for roles such as subject librarians, student librarians, Q&A knowledge base administrators, and operation and maintenance personnel. The system supports statistical analysis of relevant data according to different dimensions and produces statistical reports for visual display. Administrators with operation permissions can add and modify new question-answer pairs in the knowledge base, supporting single or batch data update operations synchronized to relevant databases.

4.2 Business Process of Library Intelligent Consulting System

The business process of the library intelligent consulting system (hereinafter referred to as "the system") is as follows: After users send consultation questions through the system, the system processes and searches for answers through the intelligent Q&A engine. If answers exist, they are returned to users; if no matching answers are found, they can be transferred to manual services for backend maintenance and management platform processing. Consulting librarians complete manual services, collaborative work, and system management tasks through the maintenance and management platform. As shown in Figure 1 [Figure 1: see original paper]:

4.3 Technical Architecture of Library Intelligent Consulting System

The architecture design of the library intelligent consulting system (see Figure 2 [Figure 2: see original paper]) adopts a layered design concept, dividing the services required by the intelligent information consulting system into the data layer, business logic layer, application layer, and presentation layer according to function. Each layer subsystem interacts with upper and lower layer subsystems through specific subsystem access interfaces. Subsystems at different layers provide corresponding interfaces. For example, the data layer not only stores the business database for intelligent Q&A but also provides multiple data interfaces to facilitate access to data sources from other library business modules. Internally, the subsystem adopts modular design, with each module being relatively independent and capable of flexible addition according to future library information consulting service needs, such as electronic resource retrieval, citation verification, and other application layer modules. Based on library user information acquisition habits, the system provides multi-terminal service interfaces based on web and WeChat, while reserving interfaces for the introduction of physical robots.

4.4 Design of Word2vec-Based Intelligent Q&A Engine

4.4.1 Intelligent Q&A Engine Operation Flow The basic technical principle of the intelligent Q&A engine is to preprocess statements, use Word2vec to train word vectors, perform semantic extension on keywords from user questions using the word vector table, and finally implement answer matching through sentence co-occurrence word similarity calculation. The operation flow of the intelligent Q&A engine is shown in Figure 3 [Figure 3: see original paper]: When the Q&A engine receives a user question, it first performs word segmentation and stop-word removal preprocessing based on a Chinese dictionary and stop-word dictionary to obtain a processed candidate word group. Second, the obtained candidate word group is compared with the trained word vector library, and several words with high similarity to the feature word group are extracted as semantically extended feature word groups. Finally, the extended feature word group is matched with questions in the built Q&A knowledge base based on sentence co-occurrence word similarity. The answer with the highest matching value is selected and returned to the user, while unmatched answers are provided with manual services.

4.4.2 Statement Preprocessing Statement preprocessing includes Chinese word segmentation and stop-word filtering. Stop-word filtering uses comparison with a stop-word dictionary. Before this, Chinese word segmentation processing is required to convert user questions into effective word representations. This system applies a maximum matching word segmentation algorithm based on dictionary segmentation. Extensions of maximum matching segmentation mainly include forward maximum matching and backward maximum matching algorithms. After comparative analysis, since English words are separated by spaces, forward maximum matching algorithm achieves higher efficiency and word list hit accuracy for English word segmentation. Due to the complex structure of Chinese vocabulary, backward maximum matching algorithm is more accurate. Therefore, this system selects the backward maximum matching algorithm (see Figure 4 [Figure 4: see original paper]).

The process of the backward maximum matching algorithm for word segmentation in the intelligent consulting engine is: When the sentence to be segmented is S1, first set the maximum word length "MaxLen value" as m, where m is set to the maximum length of valid words in the segmentation dictionary. Take m characters from right to left in S1 as the candidate string denoted as "W," and search the existing dictionary to match "W." If the match is successful, output the string as a word to the segmentation result set "S2." If the match is unsuccessful, remove the rightmost character from the string and use the remaining characters as a new string for re-matching until all words are segmented. Finally, output the segmentation result set "S2."

4.4.3 Word Vector Training and Semantic Extension Based on Word2vec The training sample library must first select a word vector training model. Word2vec mainly has two training models: the Continuous Bag-of-Words (CBOW) model and the Skip-gram model. The CBOW model predicts the center word based on surrounding words, then uses the Gradient Descent method to adjust the vectors of surrounding words according to the prediction results of the center word, thereby obtaining word vectors for all words in the entire text. The Skip-gram model, conversely, predicts surrounding words based on the center word and uses the prediction of surrounding words to adjust the center word's vector, requiring processing of all characters in the text. From the training patterns, CBOW has higher training efficiency but lower accuracy in semantic analysis than the Skip-gram model. Taking the trigram of the sentence "如何能借图书馆的书" (How to borrow library books) as an example, using sequential training can only yield four trigrams: "如何能借" (How can borrow), "能借图书馆" (can borrow library), "借图书馆的" (borrow library's), and "图书馆的书" (library's books). The sentence itself expresses the meaning "如何借书" (How to borrow books), but none of these four trigrams accurately express the sentence's meaning. Using the Skip-gram model allows skipping words, enabling the formation of multiple trigrams from non-adjacent words, as shown in Table 1 :

Table 1 Skip-gram Training Word Set Example

Skip-gram training yields: "如何能借""如何能图书馆""如何能的""如何能书""能借图书馆""能借的""能借书""借图书馆的""借图书馆书""借的书""图书馆的书""如何借图书馆""如何借的""如何借书""能借图书馆""能借的""能借书""图书馆的书"

As shown in Table 1, when using the Skip-gram model for corpus training, all semantic combinations can be covered, and the actual meaning to be expressed, "如何借书" (How to borrow books), is included. Word vectors can better reflect the true text semantics. Therefore, the Skip-gram model is more suitable for semantic analysis, and this system selects the Skip-gram model as the word vector training model. The mathematical formula for Skip-gram model word vector training can be expressed as:

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-m\leq j\leq m, j\neq 0}\log P(\omega_{t+j}|\omega_t)$$

In formula (1), T represents the position of the window center word, and m represents the sliding window size. In actual training, taking "如何能借图书馆的书" as an example, when calculating to the word "借" (borrow) and setting m=2, the probabilities of this word with the two adjacent words before and after need to be calculated respectively: P(如何 | 借), P(能 | 借), P(图书馆 | 借), and P(的 | 借). It can be seen that if the sliding window is too large or too small, it will affect the model training effect. After testing the sample library, the sliding window value was set to 4 in actual training.

The specific method for keyword semantic extension is: In the trained word vector table, query words with cosine values close to the keyword. Set the comparison threshold to 0.8; if greater than this value, the word is judged as a similar word and used as an extension word for the query term. In actual calculation, many words may exceed this value. Considering system computational precision, the top 3 words with the highest similarity are selected as extension words for the current word and added to the extended word set, preparing for subsequent Q&A matching.

4.4.4 Answer Matching Based on Co-occurrence Word Similarity

The answer matching method of the intelligent consulting engine is: The extended word set is matched with questions in the knowledge base based on co-occurrence word similarity calculation. The answer with the highest matching value is selected and returned from the FAQ database. The basic principle of the co-occurrence word similarity matching algorithm is to compare the number of co-occurring vocabulary in two statements; the more co-occurring words, the higher the similarity between the two statements. The similarity calculation formula can be expressed as:

$$Similarity(S_i, S_j) = \frac{|\{w_k | w_k \in S_i \cap w_k \in S_j\}|}{\log(|S_i|) + \log(|S_j|)}$$

In formula (2), S_i and S_j represent the two sentences to be compared, and W_k represents words in the sentences. The numerator represents the number of words appearing in both sentences simultaneously. The denominator uses logarithms to offset the impact of length differences when comparing sentences of significantly different lengths.

4.5 Maintenance and Management Platform Design

The maintenance and management platform mainly includes four sub-modules: Q&A management, system management, data statistics, and knowledge base management. The Q&A management process design adopts the collaborative office concept, adding question assignment and Q&A review mechanisms. The specific approach is: On-duty librarians assign questions to relevant department staff based on question types. After review by department heads, answers are replied to readers, and the knowledge base is updated simultaneously. The system management module includes user management and login log management. User management adopts hierarchical role management: administrators, subject administrators, subject librarians, and operation and maintenance staff, supporting query, add, edit, and delete operations for users at different permission levels. The data statistics module provides statistics and visualization of intelligent consulting system operations and user behavior, supporting statistical analysis and visual display from different dimensions. The knowledge base management includes overall import and export of new knowledge bases, and add, modify, and delete operations on existing knowledge base corpora. To ensure data security, only subject administrators can perform review, storage, and deletion operations on corpora, while subject librarians can only edit and view corpora.

5 System Implementation

Based on the above system design and algorithms, the library intelligent consulting system was implemented. The system environment configuration is as follows:

- Programming Language: Frontend pages use Vue+React, core algorithms use C++.
- Database: MySQL 5.6.
- Runtime Environment: Server operating system uses Windows 2008, Web server uses Tomcat 5.5.

5.1 Implementation of Intelligent Q&A Engine

5.1.1 Chinese Word Segmentation The engine uses the backward maximum matching algorithm to perform Chinese word segmentation on obtained questions. The system selects the jieba word segmentation dictionary and a self-built library FAQ segmentation dictionary, outputting segmented word strings. The specific pseudocode is:

```
VectorWordSegment(String sentence, Dict wordList)
var maxLen = 7 // Maximum phrase length
var result // Output word string
var index = 0
while (sentence.length() > 0) {
    var word = sentence[index:maxLen]
    while (1) { // Inner loop
        if (wordList.find(word)) { // Check dictionary to see if word is in dictionary
            result.append(word)
            index = index + word.length() // Update cursor
            break // Exit inner loop
        } else { // word not in dictionary
            if (word.length() == 1) { // Only one character left
                result.append(word)
                index = index + word.length()
                break // Exit inner loop
            }
            word = word.pop_{back}(), // Remove rightmost character
            sentence = sentence[index:] // Remove matched word from left side of sentence
        }
    }
}
return result // Return result [word1, word2, word3, ...]
```

5.1.2 Stop-word Filtering The word string obtained after Chinese word segmentation undergoes stop-word filtering to remove unnecessary words, outputting a filtered effective word string. The stop-word list uses the Baidu stop-word list and a custom word list, outputting the segmented word string wordList. The specific pseudocode is:

```
VectorStopWordsFilter(Vector words, Dict stopWordList)
Var result
var index = 0
while (index < words.length()) {
    var word = words[index]
    index += 1
    if (stopWordList.find(word)) { // In stop-word dictionary
        continue // Skip
    }
    result.append(word) // Not in stop-word dictionary
}
return result // Return result [word1, word2, word3, ...]
```

5.1.3 Word Vector Training Based on Word2vec The system uses Python's gensim as the training tool, employing Southeast University Library's common FAQ knowledge base, library facilities, and regulation knowledge base as training samples. Key parameters are set as: -train=trainfile; -output=FAQ.vec; -cbow=0 (training model selection: Skip-gram); -size=200 (vector dimension); -window=4 (sliding window). Partial word vector training results are shown in Figure 5 [Figure 5: see original paper].

After training is completed, using "延期" (extension) as the input word, comparison and calculation with the trained word vector library yields a set of words similar to "延期" and their similarity values, as shown in Figure 6 [Figure 6: see original paper].

5.1.4 Semantic Extension Based on Word Vectors The trained word vector library is used to perform semantic extension on preprocessed effective word strings, taking the top 3 words with the highest similarity to the input word as the current word's extension words. The specific pseudocode is:

```
VectorWordFilter(Vector words, Model word2VecModel)
Var result
Var index = 0
var topn = 3 // Take top 3 word vector extensions
while (index < words.length()) {
    var word = words[index]
    index += 1
    w2v = word2VecModel.most_{similar}(word, topn)
    result.append(word) // Original word
    for (w in w2v) { // In stop-word dictionary
```

```
        result.append(w) // Semantic extension word
    }
}
return result // Return result [word1, word2, word3, ...]
```

Where input: words are the words after stop-word filtering, word2VecModel is the word vector model. Output: semantically extended words.

5.1.5 Sentence Similarity Matching Based on Co-occurrence Words

According to the similarity algorithm, sentence similarity matching is performed to calculate the similarity value. The specific algorithm pseudocode is:

```
double SentenceSimilarity(String sen1, String sen2)
counter = 0
for word in sen1: // Co-occurrence word calculation
    if word in sen2:
        counter += 1
double similarity = counter / (log(len(sen1)) + log(len(sen2))) // Similarity calculation
return similarity
```

5.2 Implementation of User and Management Ends

The user end provides web and WeChat versions. The intelligent consulting system supports two types of users: anonymous consultation and authenticated users. Authenticated users can access manual services. The WeChat version provides account binding service—after one-time binding of WeChat ID and student ID, users can conveniently leave messages and receive manual replies without logging in. The user interface and manual service interaction interface of the WeChat version are shown in Figure 7 [Figure 7: see original paper].

The intelligent analysis and management platform provides web-based management interfaces for library staff, including Q&A management, site data analysis, knowledge base management, and system management functions. The overall implementation page is shown in Figure 8 [Figure 8: see original paper].

Due to space limitations, the following only demonstrates the implementation of the collaborative workflow for different librarian roles in Q&A management, specifically manual services and storage operations as designed in Section 4.5.

When a user submits the question "Is the school cafeteria open to the public?", after the intelligent consulting engine finds no matching answer, the subject librarian obtains the unanswered question in the backend. Clicking on the relevant question, the system jumps to "Online Message Processing" to perform answer operations, as shown in Figure 9 [Figure 9: see original paper].

After the answer is pushed to the user, the system pushes the question, answer, and operator information to the subject administrator and enters the pending review status. The subject administrator reviews whether the Q&A meets storage standards—those meeting standards are stored, while non-compliant ones are rejected and deleted, as shown in Figure 10 [Figure 10: see original paper].

After the subject administrator reviews and stores the Q&A, when the intelligent consulting system receives the same question from users again, the intelligent Q&A engine system can directly provide answers. As shown in Figure 11 [Figure 11: see original paper].

6 Operation of Library Intelligent Consulting System

The Southeast University Library intelligent consulting system began trial operation in October 2019 and had been running for three months by January 2020. The following analyzes usage through system data statistics.

6.1 User Usage Analysis

The intelligent consulting system accumulated a total of 4,634 visits and 4,420 queries, with an average daily visit volume of approximately 51 visits/day. Working hours were set as 8:30-17:00, with other times considered non-working hours. As shown in Figure 12 [Figure 12: see original paper], users accessing the intelligent consulting system during non-working hours accounted for 29.3% of total visitors, and user consultation questions accounted for 31.1% of total consultations, indicating that Southeast University Library users have significant demand for library information consulting services during non-working hours.

In terms of consultation content, routine questions about library regulations accounted for approximately 51% of questions, while collection catalog retrieval accounted for about 36%. Meanwhile, the number of manual service replies using the Southeast University Library official account and online tools has significantly decreased, especially for routine library questions. As shown in Figure 13 [Figure 13: see original paper].

6.2 System Operation Effectiveness

During the early system testing phase, some synonyms had no matches. Testing revealed this was due to the Skip-gram model's sensitivity to corpus quantity and the initially set overly high matching threshold. By lowering the threshold and accumulating the corpus, more ideal matching effects were achieved. Additionally, pushing similar question links was applied to improve consultation effectiveness and user friendliness. Taking the question "Book overdue return rules" as an example, consulting with semantically similar questions such as "My book is overdue," "Overdue return," "What to do if overdue," and "Book expired" all yield relevant library rule replies about "Book overdue return," while similar questions are pushed to users. See Figure 14 [Figure 14: see original paper].

During system operation, the system received 1,927 information consultation questions, of which the intelligent consulting engine automatically replied to

1,436 questions (approximately 74.5%), and 99 unanswered questions were submitted to backend processing through manual services. This represents a significant improvement compared to the current library's keyword-based automatic Q&A robot, which has a response rate of less than 50%. Analysis of questions that could not be automatically replied to revealed that the main reason is the system currently only accesses the library domain knowledge base, while user consultation questions exceed this scope. With continuous expansion of the knowledge base content, the response rate of the intelligent Q&A engine should be able to improve further.

6.3 Maintenance and Management Platform Usage

In actual system usage, the collaborative work effect is relatively ideal. When on-duty librarians receive manual service requests, they quickly forward relevant questions to responsible librarians through the management system, reducing communication time, lowering response delays, and improving reply quality. Regarding knowledge base expansion, the role-based hierarchical management model and storage review mechanism establishment have improved the quality and security of knowledge base storage.

Conclusion

Through research and application of Word2vec-based word vector semantic extension technology, Southeast University Library has effectively solved the semantic extension deficiencies in automatic Q&A systems and implemented an intelligent library information consulting system. The intelligent consulting system satisfactorily meets library information consulting needs in terms of extending consultation service hours, improving consultation effectiveness, reducing consulting librarians' workload, and enabling librarian collaborative work. However, there are some shortcomings. The next steps will strengthen system construction in the following three aspects: Provide more consultation service terminals and functions, such as integrating voice recognition, developing WeChat mini-program clients, and integrating physical robot systems to further enhance user experience. Strengthen system knowledge base construction by providing expansion of knowledge bases beyond the library domain for the intelligent Q&A system through network downloads or access, such as chat databases, while paying attention to content review and management. Strengthen research on popular artificial intelligence technologies, such as combining deep learning and part-of-speech tagging technologies to actively determine user intentions, further enhancing the intelligence level of library consulting systems.

References

[1] Zheng Hongjing. A Comparative Study of Reference Consultation Services between China and the US in the Past Decade[J]. University Library Work, 2012(6): 75-78.

[2] Liu Qinghua, Tan Hongying. A Brief Discussion on Foreign Reference Consultation Service Forms[J]. Information Science, 2002(6): 590-594.

[3] Guo Yajun, Meng Jia, Hu Yayue. A Comparative Study of Mobile Services in First-class University Libraries between China and the US[J]. Library and Information Service, 2019, 63(11): 43-51.

[4] Yao Fei, Ji Lei, Zhang Chengyu, et al. A New Attempt at Real-time Virtual Reference Consultation Services - Intelligent Chatbot at Tsinghua University Library[J]. Data Analysis and Knowledge Discovery, 2011(4): 77-81.

[5] Sun Yi, Li Bao, Qu Jianfeng. Design and Implementation of Library Intelligent IM Consultation Robot[J]. New Technology of Library and Information Service, 2011(5): 88-92.

[6] Shen Kuilin, Shao Bo, Zhao Hua. Building Library Intelligent Q&A System Using WeChat[J]. Library Science Research, 2015(8): 75-80.

[7] Zhang Changheng, Huang Fang. Technical Implementation of Building University Library APP Using WeChat Public Platform[J]. Library and Information Service, 2015, 59(4): 37-43.

[8] Li Dan. Practice and Reflection on Library WeChat Platform Construction[J]. New Technology of Library and Information Service, 2016(4): 104-110.

[9] Han Rubing, Ye Dexue. Research on Chinese Word Segmentation Algorithm for Q&A Systems[J]. Digital Technology and Application, 2012(5): 114-115.

[10] Ou Shiyan, Hu Shan, Zhang Shuai. Ontology and Linked Data-driven Semantic Integration Method for Library Information Resources and Its Evaluation[J]. Library and Information Service, 2014, 58(2): 5-13.

[11] Du Wenhua. Research on Ontology Construction and Its Application in Digital Libraries[D]. Wuhan: Wuhan University, 2005.

[12] MCCORMICK C. Applying word2vec to Recommenders and Advertising[EB/OL]. [2020-01-18]. http://mccormickml.com/2018/06/15/applying-word2vec-to-recommenders-and-advertising.

[13] Liu Chenmao, Qi Li Yan, Zhu Xiaomang, et al. Research on Application of Intelligent Response System in University Informatization Services[J]. China Education Informatization, 2019(3): 43-45.

[14] Zhou Chengyuan, Zhu Min, Yang Yun. Research on Chinese Word Segmentation Algorithm Based on Dictionary[J]. Computer & Digital Engineering, 2009(3): 68-71, 87.

[15] MIKOLOV T, CHEN K, CORRADO G, et al. Efficient Estimation of Word Representations in Vector Space[EB/OL]. [2020-01-18]. https://arxiv.org/abs/1301.3781.

[16] Xu Chengzhi. Research and Design of Chinese Web Intelligent Q&A System Based on Word2vec[D]. Chengdu: University of Electronic Science and

Technology of China, 2018.

Note: Figure translations are in progress. See original paper for figures.