

A quantum computing-based approach to improve the efficiency of library information retrieval

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Abstract: Since the digital information resources have been characterized by explosive growth, the traditional Bayesian algorithm has been unable to meet the demands of retrieval scenarios for large amounts of resource data. Based on the traditional Bayesian network, this paper proposes a quantum Bayesian network structure using a quantum probabilistic graph model based on the density algorithm to integrate the dispersed quantum state information. A digital library information retrieval system is designed with user request, information retrieval processing and retrieval results as the core modules. Taking the (quantum) Bayesian network as the inference machine, the user request is processed through semantic logic reasoning and extraction, and the inference and retrieval are combined with the probability estimation results. Overall, the retrieval efficiency of the library information retrieval system based on Quantum Bayesian Networks for different types of queries is consistently 80.00% and above. The quantum Bayesian network provides more levels of probabilistic reasoning based on the uniqueness of quantum computing, which effectively improves the efficiency of library information retrieval.

Keywords: quantum bayesian networks; density algorithms; library information retrieval; quantum computing

1. Introduction

With the development of modern society, lifelong learning has become a trend, and libraries have become an important place for people to learn knowledge in order to improve their personal quality [1,2]. Along with the dramatic increase in the amount of information resources, how to efficiently manage, categorize, and use the huge amount of information has become a key challenge for libraries [3,4]. Traditional retrieval techniques have provided users with basic information services in the past decades, however, the huge information resources make them no longer applicable, and the rapid development of quantum computing provides a brand new technological framework to improve the efficiency of information retrieval in libraries [5–8].

Quantum computing is a new type of computation in accordance with the theory of quantum mechanics, and in library information retrieval, the measurement-based approach of quantum computing, as well as quantum search algorithms provide the possibility to improve the efficiency of library information retrieval [9–11]. In quantum information retrieval, the measurement-based approach is a commonly used means. When specific quantum information needs to be retrieved, it can be done by performing a specific measurement operation on the system storing the quantum state, which is not arbitrary but carefully designed [12–14]. It needs to determine the measurement base based on how the quantum state is stored and the information we want to retrieve, and the accuracy and efficiency of retrieval can be improved by continuously optimizing the measurement strategy [15,16]. However, the measurement-based retrieval method has some limitations, as the measurement operation will destroy the quantum state, so generally only one retrieval can be performed, and the accurate selection of the measurement basis is not easy for complex quantum states [17–19].

And quantum search algorithms are powerful tools specialized in solving quantum information retrieval problems [20]. Among them, the most famous one is Grover's algorithm [21]. Grover's algorithm utilizes the properties of quantum mechanics to be able to quickly search for target information in a huge amount of data [22,23]. It constructs a quantum state evolution process that enhances the probability of the target state by performing a series of

rotation operations on the quantum bits [24,25]. Compared with traditional search algorithms, Grover's algorithm has an exponential acceleration advantage, which makes the quantum search algorithm has a great potential when dealing with large-scale quantum information retrieval tasks, and its application to information retrieval in libraries can effectively improve the retrieval efficiency [26–29].

Enhancing the efficiency of information retrieval in libraries plays an important role in improving the user experience, and as a method that can simultaneously process massive combinations of data, quantum computing can significantly improve retrieval efficiency. Literature [30] discusses the development of quantum computing and its potential impact on libraries, emphasizing that quantum computing has revolutionized libraries by facilitating faster and more efficient information processing and effectively enhancing information retrieval. Literature [31] describes information retrieval systems that incorporate the characteristics of quantum computing with the aim of developing a quantum-based information retrieval system with greater computational power to be able to improve accuracy and data retrieval precision. Literature [32] introduces a conceptual framework based on quantum computing and incorporates it into the design of a library system, illustrating the applicability of the framework in enhancing content retrieval, personalization and semantic interoperability through use cases. Literature [33] describes the history of the application of quantum computing in the field of information retrieval, recognizes the results achieved by existing research, and systematically reviews the research in this field with the aim of understanding its current status and exploring future directions. Literature [34] emphasized the development of education informatization and the universality of quantum computing, and explored an intelligent retrieval platform for digital resources in universities based on quantum cloud computing theory.

It can be seen that quantum computing and its related tools effectively improve the efficiency of information retrieval in libraries, while in addition to quantum computing, with the development of artificial intelligence, virtual reality technology, blockchain technology and other intelligent methods also play an important role in improving the efficiency of information retrieval in libraries. Literature [35] examined the existing intelligent information retrieval systems in university libraries and their problems, and based on the solutions of artificial intelligence, the findings verified that artificial intelligence significantly improves the comprehensive management ability of university libraries and brings better experience to users. Literature [36] pointed out the shortcomings of traditional library information retrieval methods, and proposed the construction of a library information retrieval system based on virtual reality technology, which can enhance the reader's information retrieval experience from the perception and interaction level, and improve the efficiency of information retrieval in the library. Literature [37] describes the basic concepts of artificial intelligence technology and information retrieval technology, and examines the application of artificial intelligence technology in the information retrieval link and related services in public libraries, aiming to provide reference for professionals. Literature [38] points out that the application of AI in library systems is able to improve the efficiency of information retrieval by identifying the user's information needs for content recommendation, and proposes a fuzzy model to enhance this personalized recommendation. Literature [39] investigated the application of ICT in library information retrieval systems and verified that ICT significantly improves the efficiency of information retrieval and it excels in terms of operation and cost effectiveness. Literature [40] introduced library information visual presentation technology based on analyzing the characteristics of readers' information retrieval needs, aiming at designing a visual retrieval system for library information resources, which shows the collection structure, popular books, etc. in a visual way, and facilitates the visual sharing of library information resources. Literature [41] examined the role of knowledge organization and metadata in enhancing the information retrieval process in university libraries and validated it by optimizing the information retrieval system in university libraries aiming to meet the changing needs of users. Literature [42] emphasizes the importance of artificial intelligence in information systems and aims to improve the efficiency of educational information retrieval by introducing artificial intelligence into the integrated intelligent information system "SMART TUIT". Literature [43] examined the determinants of effective research information retrieval by librarians, revealing two factors: information technology competence, and network competence through a descriptive survey. Literature [44] explored the transformative impact of the use of artificial intelligence in libraries, especially in information retrieval, while emphasizing the issues of data privacy, algorithmic bias, and other issues associated with the use of artificial intelligence. Literature [45] describes blockchain technology and its benefits for libraries, which improves the traditional library information retrieval service and enables intelligent recommendations for this service, providing intelligent and advanced knowledge services to the library's users and beneficiary groups.

Based on the traditional Bayesian network, this paper explains the content of quantum Bayesian network based on density operator, and analyzes the structure of two quantum probabilistic graphical models, Bayesian network and quantum hidden Markov model. It briefly describes the construction principle of digital library information retrieval

$$p(a, b, c) = p(c|a, b) p(b|a) p(a)$$

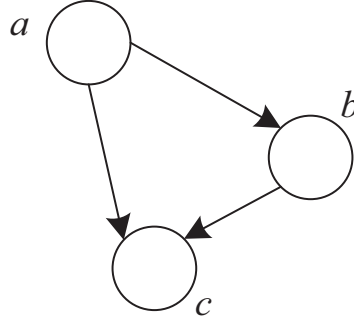


Figure 1. Simple Bayesian network

system based on artificial intelligence, on the basis of which it explores the probability estimation, inference and retrieval process of Bayesian network for digital information, so as to form the digital library information retrieval system based on Bayesian network. Multiple simulation and comparison experiments are set up to evaluate the feasibility of the proposed retrieval system in terms of overall efficiency, query response and retrieval performance.

2. Quantum Bayesian network structure

2.1. Bayesian networks

Bayesian algorithms are the basis of Bayesian networks, while Bayesian networks are an important application of Bayesian algorithms. Bayesian networks have been widely used in the fields of artificial intelligence and data mining. With the help of Bayesian networks, people can extract meaningful knowledge from complex data and deeply understand and analyze complex stochastic systems. On this basis, accurate predictions can be carried out so that informed decisions can be made.

Bayesian networks are divided into two main components: nodes and edges. Nodes represent random variables, which can be discrete or continuous. Edges represent dependencies between variables, with directed edges representing causal relationships and undirected edges representing correlations. Each node contains a conditional probability table for that node, and the probability distribution for that node is computed given its parent.

The simple Bayesian network is shown in Fig. 1, a , b , and c are the nodes, a is the parent node of b , a and b are the parent nodes of c , $p(a)$, $p(b|a)$, and $p(c|a, b)$ are the conditional probabilities of a , b , and c in that order, and then the joint distribution of probabilities of a , b , and c is equation (1):

$$p(a, b, c) = p(c|a, b) p(b|a) p(a) \quad (1)$$

2.2. Quantum Bayesian networks based on density operators

2.2.1. Basic concepts

Quantum Bayesian networks based on density operators are to be based on the following four assumptions. First, many identical quantum states are needed as a large data set in the first place. Second, there is no noise or coupling to the unknown external environment when the quantum state receives the quantum operator. Third, there is no feedback in the system. Then, the definition of the inputs and outputs of each operator is obvious, and the graph is acyclic, i.e., it is a directed acyclic graph. Fourth, the 1qubit in both quantum systems merges into a joint state by tensor product. Similarly, the 2qubit quantum state splits into two 1qubit quantum states is by tracking the particle paths in each dimension. That is, if they merge or separate the operation destroys the quantum entangled state.

There are four kinds of operation operators in the quantum probabilistic graphical model: the measurement operator, the you operator, the merger operator and the separation operator. Their representation is shown in Fig. 2.

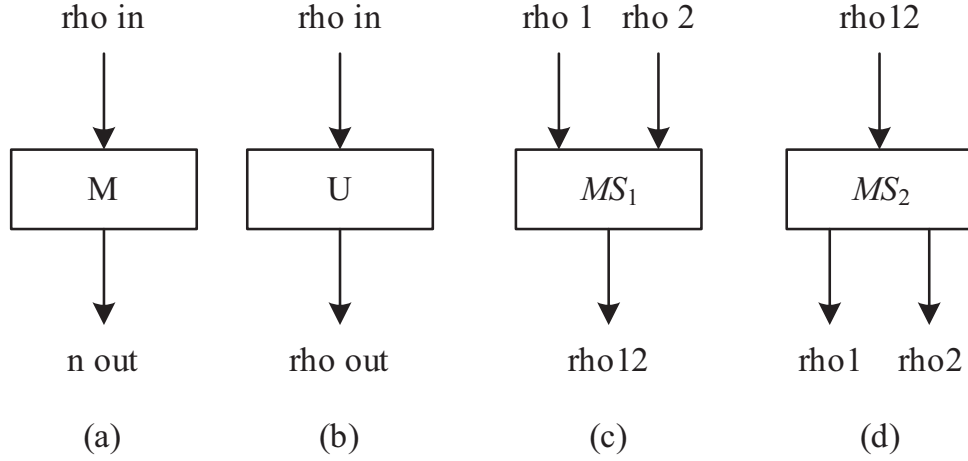


Figure 2. The operation operators of quantum probabilistic graphical models

The joint probability of the quantum probabilistic graphical model is determined by all the quantum states and measurements. The probability of output $\vec{n}$ under the condition of hidden state ρ with measurement operator M shown in Fig. 2(a) is equation (2):

$$P(\vec{n}|M, \rho) = \prod_{i=1}^d \langle \varphi_i | \rho | \varphi_i \rangle^{n_i} \quad (2)$$

where $\{\varphi_i\}_{i=1}^d$ includes a series of orthogonal bases of M and n_i , and n_i is the i th component of vector $\vec{n}$.

The density matrices of the input and output of the You operator are determined. Figure 2(b) Then the conditional probability of the output You matrix can be expressed as equation (3):

$$P(\rho_2|U, \rho_1) = \delta(\rho_2, U\rho_1 U^+) \quad (3)$$

where if $x_1 = x_2$, then $\delta(x_1, x_2) = 1$; otherwise $\delta(x_1, x_2) = 0$.

A merger operator is the transformation of two quantum states in lower dimensions into one quantum state in higher dimensions. According to Assumption IV, the uncoupled joint state is the tensor product of the two inputs. As in Fig. 2(c), the conditional probability can also be expressed as Eq. (4):

$$P(\rho_{12}|MS, \rho_1, \rho_2) = \delta(\rho_{12}, \rho_1 \otimes \rho_2) \quad (4)$$

Conversely, a separation operator divides a quantum state into two states. According to Assumption IV and the opposite operation of the tensor product, the density matrix of each quantum state is the trace of the joint density matrix particle, which is a subspace of the other edge state. The conditional probability of Fig. 2(d) is represented as Eqs. (5)- (6):

$$P(\rho_1|MS, \rho_{12}) = \delta(\rho_1, tr_2(\rho_{12})) \quad (5)$$

$$P(\rho_2|MS, \rho_{12}) = \delta(\rho_2, tr_1(\rho_{12})) \quad (6)$$

From Eq. (4)-Eq. (6), the joint probability of the quantum probabilistic graphical model is given by Eq. (7):

$$\begin{aligned} L = & \prod_{U \in V_U} \delta(\rho_{U_{out}}, U\rho_{U_{in}} U^+) \\ & \cdot \prod_{MS \in V_{MS_1}} \delta(\rho_{MS_{12}}, \rho_{MS_1} \otimes \rho_{MS_2}) \\ & \cdot \prod_{MS \in V_{MS_2}} \delta(\rho_{MS_1}, tr_2(\rho_{MS_{12}})) \delta(\rho_{MS_2}, tr_1(\rho_{MS_{12}})) \\ & \cdot \prod_{M \in V_M} \prod_i \langle \varphi_{M_i} | \rho_M | \varphi_{M_i} \rangle^{n_{M_i}} \end{aligned} \quad (7)$$

where $\rho_{U_{in}}$ and $\rho_{U_{out}}$ denote the density matrices of the input and output You operators U , V_{MS_1} and V_{MS_2} are the sets of separation and merger operators, $\rho_{MS_{12}}$ is the joint state, ρ_{MS_1} and ρ_{MS_2} are the corresponding edge states, ρ_M is the measurement operator M of the input quantum state, n_{M_i} is the i th output of the measurement operator M , and φ_{M_i} is the i th basis of the measurement operator M .

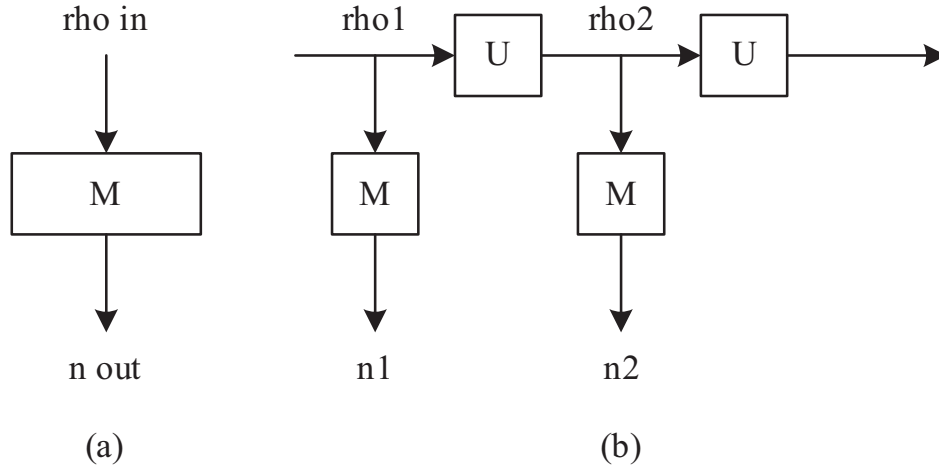


Figure 3. Quantum Bayesian network

2.2.2. Structure of Quantum Bayesian Networks

Based on the principle of probabilistic reconstruction, graphical models have a corresponding quantum graph model. Two examples are briefly described below. Since quantum probabilistic graphical models mainly include quantum Bayesian models and quantum Markov random fields (QMRF).

(1) A binary measurement of a quantum state: a quantum Bayesian network is shown in Fig. 3, where Fig. 3(a) is the simplest quantum Bayesian network: a measurement of a 1 qbit quantum state. The input is the density matrix of the measurement operator M and the output vector $\vec{n} = (n_0, n_1)$ is the result of the binary measurement. M includes two orthogonal bases $|\varphi_0\rangle$ and $|\varphi_1\rangle$.

(2) Quantum Hidden Markov Model (QHMM): a quantum hidden Markov model is a type of quantum Bayesian network, all directed acyclic graphs. Unlike classical systems, it is measured using a set of basis vectors, but is not sufficient to determine a quantum state. In order to adequately characterize a quantum state, it is represented by a series of cascaded You operators. This is the quantum Markov model shown in Fig. 3(b). Its likelihood function is equation (8):

$$L = \prod_k |\varphi_k \rho_1 | \varphi_k \rangle \cdot \left[\prod_l \delta(\rho_{l+1}, U_l \rho_l U_l^\dagger) \cdot \prod_k |\varphi_k \rangle \rho_{l+1} | \varphi_k \rangle^{n_{l+1,k}} \right] \quad (8)$$

3. Bayesian Networks-based Information Retrieval System for Digital Libraries

3.1. Digital library information retrieval system

At present, the realization and application of digital library information retrieval function based on artificial intelligence technology usually adopts the logic of building a multi-point interconnected information retrieval model in accordance with the library semantic network, and the data recognition and analysis can be technically guaranteed in the process of system driving. From the existing digital library information system operation level to analyze, when the information is retrieved or borrowed, the library information retrieval service system should be based on the user's instructions, according to the classification of information retrieval and processing. In the whole data processing mode, information retrieval needs to be realized according to specific benchmarks. The correlation between the user and the library information system in the process is the information retrieval model. In the information retrieval process, the information is processed by different modules to ensure that the user's request is accurately matched with the retrieval driver. Users enter keywords into the information retrieval system to send requests to the information retrieval module, and then the resource library completes the creation of the ontology and retrieves relevant information based on the data model. Then, through the reasoner-driven semantic query and extraction and other functions, to retrieve the information corresponding to the keywords in the database, and synchronized to complete the feedback of the information retrieval results. Figure 4 gives the digital library information retrieval model based on artificial intelligence.

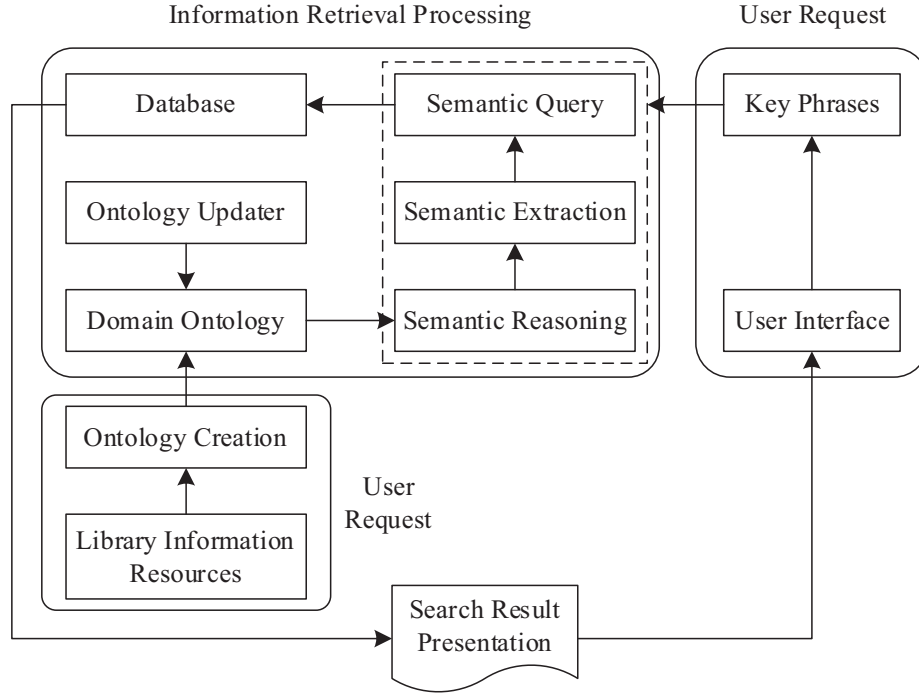


Figure 4. Digital library information retrieval system based on artificial intelligence

3.2. Bayesian network inference and retrieval

3.2.1. Extended Bayesian Networks

A dual term layer is selected to reflect the associations within the term nodes. Let R and R_i denote the original term layer as well as the term nodes respectively, all term nodes R_i existing within the original term layer R are copied, and the acquired term nodes R'_i are used to build a new term layer, denoted by R' . The pointing of arcs between term nodes within different layers is obtained using ontology-based association between term nodes, which is performed as follows:

(1) Setting the correlation between term R_i and term R'_i to 1 gives $R'_i \rightarrow R_i$, which means that the arc moment of term R'_i pointing to term R_i exists.

(2) When there is an ontology correlator relationship between term R_i and term R_j , $Srd(R_i, R_j)$ is used to denote the ontology correlation between the terms, and the correlation between the two is set to be greater than a certain threshold, at which time $R'_i \rightarrow R_j$, $R'_j \rightarrow R_i$, i.e., the arc of term R'_i pointing to term R_j , and the arc of term R'_j pointing to term R_i , exist at the same time.

The set of parent nodes of term R_i is denoted by $pa(R_i)$. The set of values of the term variable R'_i , which exists within the term layer R' , is $\{\bar{r}', r'\}$, which is a term binary random variable, where it is denoted by $\bar{r}'$ when the terms are irrelevant and by r' when the terms are relevant.

3.2.2. Probability estimates

Let T'_i be a randomly existing root term node, the edge probability associated with this root term node needs to be clarified, and by setting the probability of all term nodes within a given set to be the same, the edge probability associated with the root term node can be obtained as equation (9):

$$P(r') = 1/M \quad (9)$$

where M denotes the total number of term nodes in the set.

The root term node irrelevance probability is as in equation (10):

$$P(\bar{r}'_i) = 1 - P(r'_i) \quad (10)$$

The parent node of the node within the Bayesian network determines the probability of the random non-root node, let R_i be the random non-root term node within the set, and the combination of correlated and uncorrelated values of the term variables within $pa(R_i)$ is also represented by $pa(R_i)$. In this way, we obtain the general regular model probability function as in Eq. (11):

$$P(r_i|pa(R_i)) = \sum_{R_j \in pa(R_i), r_j \in pa(R_i)} v_{ij} \quad (11)$$

where v_{ij} denotes the weight of term R'_j affecting term R_i .

When there are many parent nodes for term R_i , the weight v_{ij} can be obtained as equation (12):

$$v_{ij} = \begin{cases} \eta, & 0.5 \leq \eta \leq 1.0, i = j \\ \frac{1-\eta}{MaxSrd} Srd(R_i, R'_j), & i \neq j \end{cases} \quad (12)$$

where η and Srd denote the regulation parameters and the sum of term ontology associations within the set of term nodes, respectively.

The maximum value of the sum of term ontology correlations is equation (13):

$$MaxSrd = \max \left(\sum_{R_j \in pa(R_i)} Srd(R_i, R'_j) \right) \quad (13)$$

The sum of the effects of term-related terms on the term is less than the effect of the term on itself, which is evident when $i = j, 0.5 \leq \eta \leq 1.0$.

Let B_j denote the document that exists within the set to get its conditional probability as equation (14):

$$P(b_j|pa(B_j)) = \sum_{R_i \in B_j, r_i \in pa(B_j)} w_{ij} \quad (14)$$

where $pa(B_j)$ and w_{ij} denote the combination of relevant and irrelevant values of each term variable in $pa(B_j)$ and the weight of index term R_j of document B_j , respectively. The above formulas need to satisfy $w_{ij} \geq 0 (\forall i, j)$, $\sum_{R_i \in B_j} w_{ij} \leq 1 (\forall j)$. When $r_i \in pa(B_j)$, it means the sum of the weights of the related terms in $pa(B_j)$.

The correlation probability value of B_j is higher when there are more correlated terms in $pa(B_j)$ the document. The TF-IDF algorithm is selected to calculate w_{ij} as in equation (15):

$$w_{ij} = \gamma^{-1} \frac{rf_{ij} \times ibf_i^2}{\sqrt{\sum_{R_k \in B_j} rf_{kj} \times ibf_k^2}} \quad (15)$$

where γ is a specification constant at $\sum_{R_i \in B_j} w_{ij} \leq 1$ and satisfies $\forall B_j \in B, rf_{ij}$ and ibf_i denote term frequency and backward document frequency, respectively.

3.2.3. Reasoning and retrieval

Let Q be the user query as well as the submitted information, and the relevance $P(B_j|Q)$ denotes the conditional probability of obtaining the document B_j at the time of query Q . The steps to obtain the relevance are as follows:

- (1) The edge probability belonging to the term Q is instantiated when the user submits the query information Q . When $R'_j \in Q$ as well as $R'_j \notin Q$, the results are obtained as $P(R'_j|Q) = 1$ and $P(R'_j|Q) = 1/M$, respectively.
- (2) The a posteriori probability of a random term R_i within a term layer R is obtained based on equation (16):

$$P(R_i|Q) = \sum_{R_j \in pa(R_i)} v_{ij} P(R'_j|Q) \quad (16)$$

- (3) Calculate the correlation $P(B_j|Q)$ between query information Q and document B_j , i.e., the final a posteriori probability of document B_j , through equation (17):

$$P(B_j|Q) = \sum_{R_i \in pa(B_j)} w_{ij} P(R_i|Q) \quad (17)$$

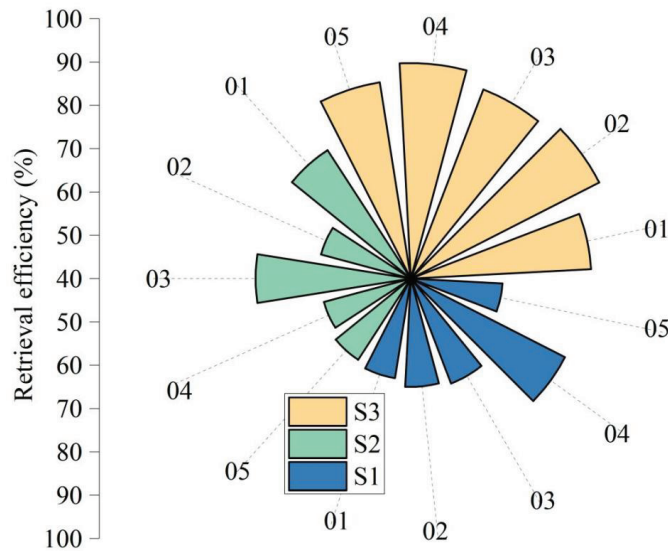


Figure 5. Comparison of retrieval efficiency among different methods

Acquired and query information Q the highest degree of relevance of the document B_j that is the most relevant information with the user query document, that is, the user needs the document, through the above process to realize the library information retrieval.

4. Multi-dimensional examination of the performance of retrieval systems based on quantum computing

4.1. Overall efficiency

Using (S1) multi-agent technology-based library retrieval system, (S2) cognitive style-based library retrieval system as a control, set up five different subject resources retrieval tasks (sequentially numbered 01-05), unfolding the retrieval efficiency of the retrieval system proposed in this paper compared with (S3) is shown in Fig. 5. (S3) The retrieval efficiency of the retrieval system proposed in this paper for the five kinds of subject resources are in the range of 80.00% and above, and the retrieval efficiency gap between different topic resources is small, and the overall performance is the best among the three retrieval systems. (S2) Although the retrieval efficiency of the cognitive style-based library retrieval system can reach up to 75.92%, the performance of the retrieval efficiency for different subject resources varies greatly and is not stable. (S1) The library retrieval system based on multi-agent technology is relatively more stable, but the overall retrieval efficiency is lower, mostly concentrated at 70.00% and above.

4.2. Query response

This section examines the operational performance of a digital library information retrieval system based on quantum computing based on Boolean queries and vector queries. Where Boolean query is a query that uses Boolean logical conjunctions to join word items together, vector query focuses on the connection between the query and the contextual meaning associated with the data entries.

4.2.1. Boolean queries

A total of 862 digital resources from the digital library of University E were randomly selected as the experimental document data, with a total of 2015 terms appearing in their titles, 597 terms with document frequency >2 , and 643 pairs of related terms with a term number of 2 (the number of documents with related terms appearing in their titles >2). There were 445 pairs of related terms with a correlation of less than 1 calculated using the assumption of interterm independence, where the correlation is the number of documents in which both terms appear in the title. Most of the related terms were proper nouns.

When the user query is 5 terms and the terms are all frequent itemsets, a total of 306 frequent itemsets are calculated. Using (S3) the retrieval system proposed in this paper calculates that there is an average of 5.91 number of useful documents, an average of 5.68 number of actual useful documents, and (S4) an average of 2.128 number of documents under the assumption that the terms are independent of each other. Arbitrarily selected 15 of the same type

Table 1. The number of documents when the query is for five terms

Query	Number of documents		
	S1	Actually useful	S4
1	5	5	2.93
2	7	6	0.18
3	7	7	2.51
4	6	5	2.62
5	8	7	1.49
6	5	3	0.48
7	9	7	2.32
8	6	5	0.16
9	6	5	2.67
10	7	7	1.75
11	7	6	1.78
12	9	8	1.96
13	8	8	1.82
14	7	6	2.33
15	9	7	1.39

Table 2. The number of documents and average similarity

Query	Number of documents			Average similarity		
	S1	Actually useful	S4	S1	Actually useful	S4
1	32.58	30	9.4	0.73	0.76	0.69
2	30.51	25	0.12	0.74	0.75	0.69
3	29	20	2.85	0.84	0.84	0.61
4	27.32	27	8.31	0.75	0.76	0.64
5	12.85	9	7.11	0.81	0.82	0.70
6	28.45	25	15	0.79	0.80	0.62
7	28	28	20.88	0.84	0.86	0.63
8	33	30	10.46	0.79	0.80	0.66
9	17.06	15	13	0.79	0.80	0.62
10	44.13	40	34.24	0.74	0.74	0.64
11	28	27	2.79	0.84	0.84	0.67
12	26.13	23	7.01	0.72	0.72	0.61
13	32	29	7.86	0.71	0.70	0.67
14	27.93	26	4.87	0.8	0.82	0.69
15	24	22	9.11	0.78	0.80	0.63

of query calculation results are shown in Table 1, overall (S3) the proposed retrieval system calculates the number of documents closer to the actual number of useful documents, the difference is controlled in [0,3].

4.2.2. Vector Queries

Set the critical value of similarity between user query and document as 0.7, select 12 identical queries and compare the engine usefulness computed by (S1) the systematic approach of this paper and (S4) the engine usefulness computed under the assumption of mutual independence between terms are shown in Table 2. (S3) The retrieval system proposed in this paper not only calculates the same number of documents as the actual number of useful documents, but also maintains the average similarity at 0.70 and above, up to 0.86, which shows greater feasibility in vector queries.

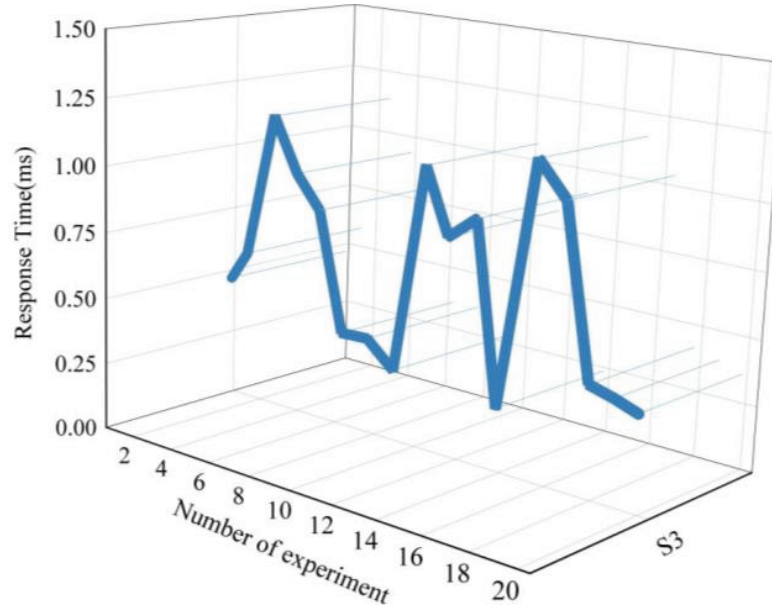


Figure 6. Operational efficiency assessment

4.3. Retrieval performance

4.3.1. Response time

To further test the response performance of the proposed retrieval system, 20 retrieval experiments are conducted using (S3) the proposed retrieval system in this paper, and its response time performance is shown in Fig. 6. In the 20 retrieval experiments, the retrieval system in this paper has certain fluctuations, but the overall response time is more ideal, controlled in the [0,1.25] ms interval, and in the 13th experiment is as low as 0.24 ms, which has a high retrieval efficiency, and shows excellent applicability in practical scenarios.

4.3.2. Search accuracy

The overall Chinese literature resources of the digital library of university E were used as the test data, which contained a total of 350,000 literature data in economy, agriculture, industry, and medicine, according to which eight search terms were selected: (Q1) trade, (Q2) finance, (Q3) edible fungus, (Q4) wheat, (Q5) electric power, (Q6) communication, (Q7) biomaterials, and (Q8) ultrasound, and were still used as the control by (S1) a multi Agent technology-based library retrieval system, (S2) cognitive style-based library retrieval system as a control. The accuracy of the search results of the three retrieval systems in the digital library of university E is shown in Fig. 7.

The accuracy of the retrieval results of (S3) the retrieval system proposed in this paper was consistently 96.00% and above on the search terms of eight different domains, and the retrieval accuracy of (S2) the cognitive style-based library retrieval system was slightly inferior to that of (S3) the retrieval system proposed in this paper, with the highest retrieval results of 95.00%. In contrast, (S1) Multi-Agent technology based library retrieval system has the worst retrieval accuracy (<90.00%). (S3) The retrieval system proposed in this paper not only has the highest retrieval accuracy, but also floats less, which is the best among the three retrieval systems. Thanks to the incorporation of quantum Bayesian network, (S3) the retrieval system proposed in this paper has lower computational complexity and thus higher retrieval accuracy on rich types of resources.

4.3.3. Search time and search volume

Using the same search term, (S1) a library retrieval system based on multi-agent technology, (S2) a library retrieval system based on cognitive style. Setting up 20 experiments, the retrieval time is incremented in frequency of 3 s. The retrieval time and the number of retrieved documents for the three retrieval systems are shown in Fig. 8. When the retrieval time is the same, the number of documents retrieved by (S3) the retrieval system proposed in this paper (>140) is always significantly more than that by the other retrieval models (80~120). When the retrieval time reaches 51s, the results of all retrieval systems tend to stabilize, and the number of retrieved documents

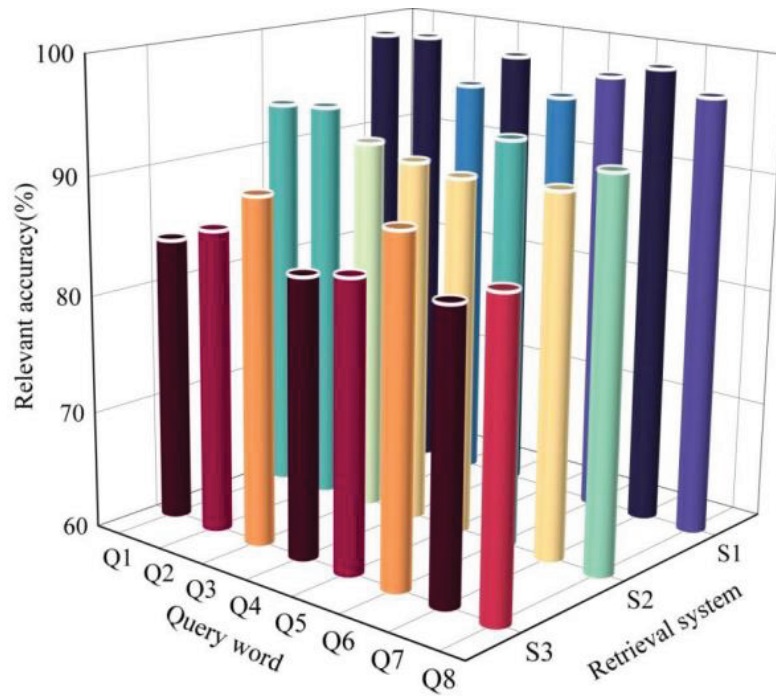


Figure 7. The retrieval accuracy of the three retrieval systems

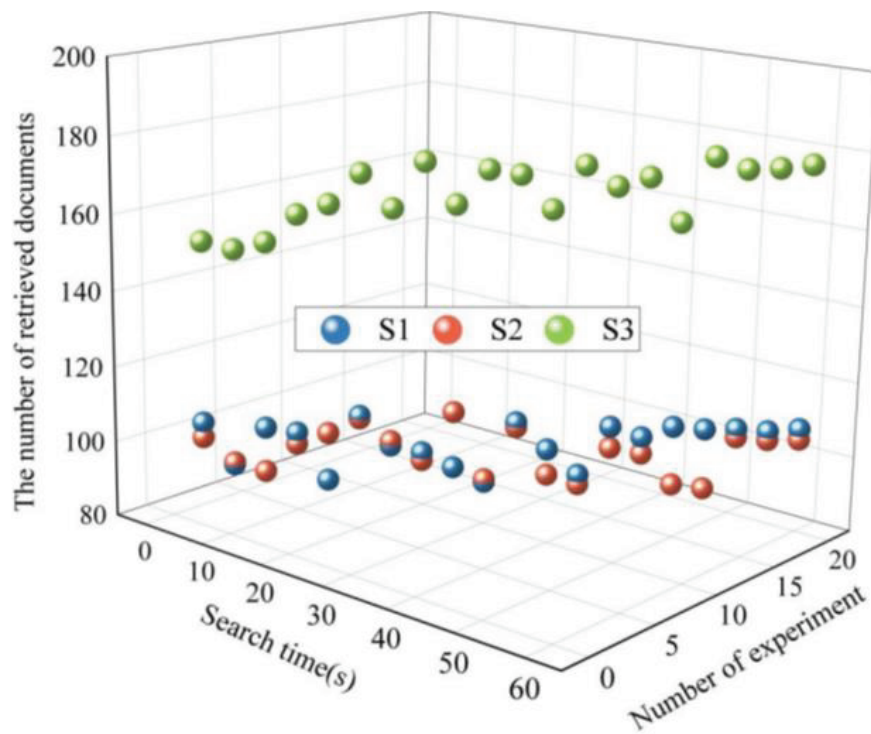


Figure 8. The retrieval time and quantity of the three models

of (S3) the proposed retrieval system is also stabilized at about 175, which is far beyond the other two retrieval systems.

5. Conclusion

This paper establishes and explores Bayesian networks at the quantum level, transforms classical probability distributions into quantum states, and applies them to the probabilistic relationship processing of digital library information retrieval. With the support of quantum Bayesian network, the retrieval efficiency of digital library information retrieval system for multiple subject resources is stabilized at 80.00% and above. In the Boolean query response, the

difference between the number of computed documents and the actual number of useful documents is controlled in [0,3), and the average similarity of the number of computed documents in the vector query response is maintained at 0.70 and above, and the maximum can be up to 0.86. In the retrieval experiments, the response time is controlled in the interval of [0,1.25] ms, and the accuracy of the retrieved words in eight different domains is maintained at 96.00% and above. Compared to similar retrieval systems, the maximum number of retrieved documents (>140) is always maintained in the same time.

Quantum Bayesian network provides a new probabilistic representation, which enhances the efficiency and accuracy of probabilistic computation and processing of library information retrieval system, thus promoting the double improvement of retrieval speed and quality.

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