Association retrieval and recommendation of agricultural environmental sensing data based on knowledge map

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Abstract. When the current general methods are used to retrieve agricultural environmental sensing data, there is no knowledge map constructed, and there are often problems such as low recall rate, low precision rate and low retrieval efficiency. In order to retrieve agricultural environmental sensing data efficiently, accurately and comprehensively, the method of association retrieval and recommendation of agricultural environmental sensing data based on knowledge map was proposed. The NLP algorithm was used to associate knowledge concepts of various agricultural environmental sensing data to construct the knowledge map of agricultural environmental sensing data. The knowledge map was pruned and expanded to reduce the amount of related calculations, and improved the retrieval efficiency of agricultural environmental sensing data. On the basis of the knowledge map of agricultural environmental sensing data, the vector space retrieval model was further used to realize the association retrieval and recommendation of agricultural environmental sensing data. To compared with the data retrieval method based on the quantification of the product within the cluster and the agricultural environment before the optimization of the knowledge map Sensing data association retrieval and recommendation method, the relevant experimental results showed that when the number of retrieved data sets increased, the recall rate, precision rate, and retrieval efficiency of the agricultural environmental sensing data association retrieval and recommendation method based on the knowledge map optimized after the knowledge map constructed in this paper were higher than the other two retrieval methods, which had high practical applicability and development prospects.

Keywords: Knowledge Map, NLP Algorithm, Agricultural Environmental Sensing Data, Vector Space Retrieval Model, Retrieval Recommendation

1. Introduction
The agricultural environment is affected by many factors such as natural climate change, policy revisions, and major emergencies, but it still has certain laws and these influencing factors are interrelated. Therefore, the data sensed by combining various sensings and communication modules are also interrelated. When users retrieve agricultural sensing environment data, they are not only concerned about the retrieved data, but also some related data[1]. The data retrieval method that combined knowledge map and text mining proposed in this paper could enable researchers to accurately and effectively retrieve agricultural environmental sensing data to understand changes in various environmental parameters in advance and modify them. It can also recommend the relevant historical data of the current retrieved agricultural environmental sensing data for decision makers, so that researchers can track the changes in time or compare the differences in locations of this specific agricultural environmental sensing data, then agriculture can achieve more efficient and intelligent services and production[2].

At present, there were few researches on unified description and associated retrieval of agricultural environmental sensing data. In terms of other data association retrieval and association recommendation, Lv Hongwu and others proposed an octree-based data retrieval method[3]. This method used an octree scene segmentation method to store and encode data, complete data addressing, introduce the room partition constraint into data, filter data, and retrieve the filtered data. Because this method did not construct a knowledge map of the data, the recall rate and precision of the method were low. A semantic-based English phrase retrieval method proposed by Zhu Yeshuang and others[4]. This method retrieved phrases based on semantic conditions in English and had the function of automatically recommending collocations. Learners can use the automatic collocation recommendation function and phrase retrieval function of the model to improve their writing quality and efficiency. Liu Shuwei and others proposed a data retrieval method based on intra-cluster product quantization[5]. This method used a multi-layer number structure of product quantization and vector quantization to describe high-dimensional and large-scale data sets, and reduced the complexity of data retrieval through the neighbor cluster screening method based on greedy queue. The distance between the query vector and the data set vector was calculated by the surface quantization method, and the data retrieval was realized according to the calculation results. The method could not obtain the relationship between the data, which led to the long retrieval time and the low retrieval efficiency.

This paper combined knowledge co-occurrence analysis technology and search engine technology to study the related retrieval and recommendation of agricultural environmental sensing data. Firstly, a unified associated sensing data model was established, and the NLP algorithm based on statistics and corpus was used to correlate the knowledge concepts existing in agricultural environmental sensing data and calculate the co-occurrence degree[6]. Secondly, the knowledge map model was constructed by using the preprocessed data entity and its co-occurrence relationship, and the knowledge map was optimized by pruning and extension operations. Finally, based on the optimized knowledge map, the multi-objective search method and vector space retrieval recommendation model were used to realize the correlation retrieval and recommendation of agricultural environmental sensing data[7].

2. **Construction of knowledge map model of related sensing data**

Figure 1 shows the overall construction idea of agricultural environmental sensing data knowledge map, which has experienced data collection, knowledge extraction, entity alignment, data model construction and other steps[8] The construction method of knowledge map based on NLP algorithm was mainly to
improve the quality of knowledge map of agricultural environmental sensing data and optimized the retrieval model of agricultural environmental sensing data in two steps of knowledge extraction and entity alignment.

![Knowledge Map Diagram]

**Figure 1.** Ideas for the overall construction of knowledge map

### 2.1. Introduction of agricultural environmental sensing data sources

Agricultural environmental sensing data is essentially a type of dynamic data with typical nonlinear characteristics. Using its historical data to build a model can classify and predict the current data. Agricultural environmental sensing data has a variety of characteristics. Each characteristic parameter competes with each other, and there is a complete correspondence between the complementary process and the associated process.

The recognition of agricultural environmental sensing data needed to solve two problems: text mining and knowledge map analysis. Among them, the extraction step of the standard pattern of agricultural environmental sensing data text mining was the most important. According to certain learning rules, actual sample data should be excavated and summarized from practice. Some of these data were less understandable than economic market data (for example, a single transaction in sales data was a set of items). However, association rules could still be used as a basis for processing agricultural environmental sensing data, and through a certain preprocessing process for mining and analysis.

### 2.2. Text mining model of unstructured data based on NLP algorithm

Aiming at the unstructured agricultural environmental text data mentioned above, this section used the NLP algorithm based on statistics and corpus to associate the knowledge concepts existing in agricultural environmental sensing data[9].

Before mining entities and relationships, the agricultural environment sensing data needed to be processed in a regular manner, such as stemming, window sentence segmentation, etc. Let \( D \) represent the agricultural environmental sensing data set, and use window \( H \) to segment the documents \( d_i \) existing in the agricultural environmental sensing data set to obtain the relevant string \( S_{ij} \):

\[
S_{ij} = (w_j \ast H + w_j \ast H + 2w_j \ast H + 1\cdots w_j \ast H + H)
\]

(1)

In the formula, \( w_j \) represented the \( j \)-th word in the string, \( w_j' = \text{stem}(w_j) \).
After the regularization process, a sample set of clauses was obtained:

\[
T = \{S_1, S_2, \ldots, S_n\}
\]  

(2)

Assuming that there were semantic connections between words in the same sentence, the method of association retrieval and recommendation of agricultural environmental sensing data based on knowledge map used co-occurrence to measure the strength of semantic association between words in the same sentence.

Assuming that the word \( w_i \) and the word \( w_j \) existed in the string \( S \) with a window size of \( H \), the expression of the co-occurrence degree \( D_{<w_i,w_j>} \) corresponding to the phrase \( <w_i,w_j> \) was as follows:

\[
D_{<w_i,w_j>} = P(w_i,w_j)
\]  

(3)

In the formula, \( P(w_i,w_j) \) represented the joint probability corresponding to the word \( w_i \) and the word \( w_j \), and \( P \) represented the joint probability distribution corresponding to the word.

Let \( \hat{P}(a,b) \) represent the empirical distribution of the pairs of words in the actual agricultural environment sensing data set \( T \), which expression was as follows:

\[
\begin{align*}
\hat{P}(a,b) &= \frac{\text{Count}(a,b)}{\sum_{A,B} \text{Count}(a,b)} \\
\text{Count}(a,b) &= \sum_{i=1}^{N} 1^S(a,b)
\end{align*}
\]  

(4)

In the formula, \( 1^S(a,b) \) represented an indicator function whose expression was as follows:

\[
1^S(a,b) = \begin{cases} 
1 & a \odot S, b \odot S \\
0 & \text{other}
\end{cases}
\]  

(5)

In the formula, \( a \odot S \) and \( b \odot S \) respectively described whether word \( a \) and \( b \) existed in string \( S \).

When the sample set of agricultural environmental sensing data was large enough, the likelihood of word pair joint probability distribution could be described by the empirical distribution:

\[
D_{<w_i,w_j>} = P(w_i,w_j) \approx \hat{P}(w_i,w_j) \approx \frac{\text{Count}(w_i,w_j)}{\sum_{C_i[w]} \text{Count}(w_i,w_j)}
\]  

(6)

Through the above analysis, the frequency of co-occurrence word pairs was co-occurrence degree.

2.3. Construction of knowledge map of agricultural environmental sensing data based on co-occurrence

According to the co-occurrence calculated above, the connection of different entities in the agricultural environmental sensing data set was obtained, establish a map with co-occurrence relations as edges and entities as vertices, namely knowledge map or semantic association map:

\[
G = (V,E)
\]  

(7)
Among them, \( V = \{v_1,v_2,v_3,\cdots,v_n\} \) and \( E = \{e_1,e_2,e_3,\cdots,e_m\} \) respectively represented the set of vertices and edges[10].

Through the above process, the undirected map with the co-occurrence relationship as the edge and the word as the vertex was obtained, and the knowledge map of agricultural environmental sensing data was visualized by using the Neo4j graphics database, and the knowledge map was displayed from multiple dimensions such as concept, attribute and instance.

At this time, the agricultural environmental sensing data knowledge map constructed was a relational structure constructed by the basic unit of triple. The environmental data triple and the location data triple were not constructed into a network structure by knowledge fusion. This would result in lower efficiency and accuracy in subsequent data retrieval[11]. In order to further improve the user’s retrieval efficiency, this paper proposed an optimization method for the knowledge map: we traversed the set \( V \), used \( v_i \) to describe the \( i \)-th traversed vertex in the traversal process, and performed pruning and expansion operations on the vertices.

2.4. Optimization of knowledge map

(1) The pruning of the map

The correlation degree between vertices in the knowledge map was mainly affected by two factors. The first factor was the number of hops between vertices, and the corresponding correlation between vertices increased as the number of hops decreases, the second factor was the degree of co-occurrence between vertices, namely the edge weight. The degree of association between vertices increases with the increased co-occurrence degree.

Let \( r \) represented the degree of association between vertex \( v_i \) and vertex \( v_j \), the calculation formula was as follows:

\[
r = q(1-\theta) + \frac{\theta}{(p+\varepsilon)}
\]

(8)

In the formula, \( \theta \) represented a parameter that balanced the degree of co-occurrence and the number of hops, \( p \) represented the number of hops from vertex \( v_i \) to vertex \( v_j \), the main function of parameter \( \varepsilon \) was to adjust the correlation degree affected by the number of hops, \( q \) represents was the co-occurrence of vertex \( v_i \) to vertex \( v_j \).

Let \( V_{i1} \) represented the set of vertices around the vertex \( v_i \), and traversed the vertex \( v_k \) in the set. If the correlation degree \( r_{ik} \geq \alpha \) existed between vertices, the vertex \( v_k \) was added to the strong correlation set \( R_i \) of the vertex \( v_i \), if the correlation between vertices \( r_{ik} < \alpha \), the vertex \( v_k \) was subtracted, namely:

\[
V'_{i1} = V_{i1} - \{v_k\}
\]

(9)

The remaining set \( V_{i1} \) proceeded to the next step. Remember that the path between the adjacent vertex \( v'_k \) and vertex \( v_j \) in the set \( V_{i1} \) was \( p_{ik} = |i,k| \).
(2) The expanding of the map

The vertex set $V_{i2}$ was obtained by traversing all adjacent vertices of any vertex $v_k'$ in the vertex set $V_{i1}$. When the co-occurrence $r_{ik} \geq \alpha$ between vertex $v_i$ and vertex $v_l$ and $v_l \notin R_i$, vertex $v_l$ was added to the association set:

$$R_i' = R_i \cup \{v_l\}$$  \hspace{1cm} (10)

Similarly, the vertex set $V_{i2}'$ was obtained by deleting the vertices in the adjacent vertex set $V_{i2}$ which did not meet the above conditions. The path $p_{ik}$ between vertex $v_i'$ and vertex $v_k'$ in the set $V_{i2}'$ was recorded, and the path $p_{il}$ between vertex $v_i'$ and vertex $v_l$ in the set $V_{i2}'$ was recorded. The expression was as follows:

$$p_{il} = p_{ik} \oplus p_{ik} = |i,k| \oplus |l,k| = |i,l,k|$$  \hspace{1cm} (11)

The above process was repeated to expand until it was impossible to expand, and the subgraph after pruning expansion was obtained:

$$\begin{align*}
G_i &= (V',P) \\
V' &= V_{i1}' \cup V_{i2}' \cup V_{i3}' \\
P &= \{p_{ij}|i,j = 1,2,3\}
\end{align*}$$  \hspace{1cm} (12)

The minimization and maximization of the agricultural environmental sensing data knowledge map will be obtained by the above method after the pruning expansion optimization operation. The entire agricultural environmental sensing data knowledge map took time as the main index entity, which linked the location data triple and the environment data triple to complete the knowledge merging.

3. Association retrieval and recommendation method of agricultural environmental sensing data

Association retrieval and recommendation of agricultural environmental sensing data based on knowledge map focused on map mining. In order to excavate the potential relationship between agricultural environmental sensing data, a multi-objective relationship search method was proposed and a vector space retrieval recommendation model was constructed to retrieve agricultural environmental sensing data[12].

3.1. Construction of vector space retrieval model

The method of association retrieval and recommendation of agricultural environmental sensing data based on knowledge map used vector space model to associate retrieval and recommendation of agricultural environmental sensing data on the basis of knowledge map[13].

In the process of agricultural environmental sensing data retrieval, each retrieval and data set could be described by a vector composed of index units, and the degree of correlation between the query and the data set was calculated, the query and the data set was judged based according to the calculation results.
In the vector space retrieval model, it was necessary to define the corresponding meaning of the query or data set described by the vector.

Let \( \Omega: < t_1, t_2, \cdots, t_n > \) denoted the search space, where \( n \) denoted the size of the search space. \( t_i \) represented the index unit existing in query and data set.

Vector could be used to describe all data sets in retrieval space \( \Omega \):

\[
\vec{d}: < \omega_{d1}, \omega_{d2}, \cdots, \omega_{dn} >
\]

(13)

In the formula, \( \omega_{dj} \) represented a series of descriptions of the meaning of the data set. When the parameter \( \omega_{dj} \) was 1, it showed that there was an index unit \( t_i \) in the data set. When the parameter \( \omega_{dj} \) was 0, it showed that there was no index unit \( t_i \) in the data set.

Vector was used to describe the query in retrieval space \( \Omega \):

\[
\vec{q}: < \omega_{q1}, \omega_{q2}, \cdots, \omega_{qn} >
\]

(14)

When the parameter \( \omega_{qi} \) was 1, it indicated that there was an index unit \( t_i \) in the query. When the parameter \( \omega_{qi} \) was 0, it indicated that there was no index unit \( t_i \) in the query.

The method of association retrieval and recommendation of agricultural environmental sensing data based on knowledge map adopted the \( \text{tf} – \text{idf} \) formula to calculate the weight corresponding to the index unit. The \( \text{tf} – \text{idf} \) weight was usually composed of the frequency \( \text{tf} \) of the index unit in the agricultural environmental sensing data set and the frequency \( \text{idf} \) of the inversion data set.

Let \( \text{df}_j \) represented the number of data sets containing the index unit \( t_j \) in the entire agricultural environmental sensing data set. \( n \) represented the total number of index units in query and data set, namely the corresponding size of retrieval space. \( \text{tf}_{ij} \) represented the occurrence frequency corresponding to the index unit \( t_j \) in the agricultural environmental sensing data set \( d_i \). \( d \) represented the total number of data sets in agricultural environmental sensing data sets.

The formula for calculating the frequency \( \text{idf} \) of inversion dataset was as follows:

\[
\text{idf}_j = \log \left( \frac{d}{\text{df}_j} \right)
\]

(15)

Let \( \text{df}_j \) represented the weight corresponding to the element, which could be calculated by the frequency of the index unit in the entire agricultural environmental sensing data set and the frequency of the index unit appearing in the corresponding data set:

\[
\text{df}_j = \text{idf}_j \times \text{tf}_{ij}(1)
\]

The method of association retrieval and recommendation of agricultural environmental sensing data based on knowledge map used the vector angle cosine as the judgment basis in the vector space retrieval model to determine the correlation between the query and the data set[14]. Let \( \text{SC}(d,q) \) represented query the similarity between \( q \) and data set \( d \), the calculation formula was as follows:
(16) \n
\[ SC(d,q) = \sum_{i=1}^{n} (\omega_{d_i} \times \omega_{q_i}) / \left[ \sum_{i=1}^{n} (\omega_{d_i}^2) \times \sum_{i=1}^{n} (\omega_{q_i}^2) \right]^{1/2} \]

Where \( \omega_{d_i} \) and \( \omega_{q_i} \) both used tf–idf weights. According to the vector angle cosine, the associated retrieval and recommendation of agricultural environmental sensing data were realized.

4. Experiment

In order to verify the overall effectiveness and efficiency of the agricultural environmental sensing data association retrieval and recommendation method based on the knowledge map, this paper carried the following three experimental tests: (1) The test of the data retrieval method based on intra-cluster product quantization (Method 1). (2) the test the method of association retrieval and recommendation of agricultural environmental sensing data based on the knowledge map before the optimization of the knowledge map (Method 2). (3) the test the method of association retrieval and recommendation of agricultural environmental sensing data based on the knowledge map after the optimization of the knowledge map (Method 3).

4.1. Experimental Data Sets

Three types of agricultural environmental data (structured data, semi-structured data, and unstructured data) were selected as experimental test data sets:

1) Structured data: about 7200 real-time environmental data recorded by various environmental sensing devices.

2) Semi-structured data: The historical weather data and water quality data (about 1500 items), which were in JSON format and CSV format.

3) Unstructured data: collected description files of related environmental websites (about 174 documents), the format was text data described in natural language.

4.2. Evaluation Standard

In the course of the experiment, this paper mainly adopted international general standards to evaluate the results of agricultural environmental sensing data association retrieval and recommendation[15]. There were three main types of indicators:

1) Recall rate:

\[ Re_i = \frac{TP_i}{TP_i + FN_i} \]  

In the formula, \( TP_i \) represented the number of correctly retrieved results of related category. \( FN_i \) represented the number of unretrieved results of related category.

2) Precision rate:

\[ Pr_i = \frac{TP_i}{TP_i + FP_i} \]  


In the formula, \( FP \) represented the number of search results that belonged to other categories but were classified into that category, that is, the number of incorrectly retrieved results from unrelated categories.

4.3. Results and Analysis

The experimental equipment configuration environment was Windows 10 operating system, processor Intel(R) Core(TM) i7-8550U CPU @ 1.80GHz, memory 8GB, and PyCharm 2020.1 as the development environment. Three retrieval methods, Method 1, Method 2 and Method 3, were used to conduct retrieval comparison experiments on the above data sets, and the evaluation indicators of the three methods under different retrieval data sets were compared[16].

**Figure 2.** Comparison of recall rates (%) of different data retrieval methods

Figure 2 showed the comparison of the recall rates of Method 1, Method 2 and Method 3. The horizontal axis represented the relative number of retrieved data sets, and the vertical axis represented the size of the recall rate. Figure 2 showed that with the increase of the retrieval data set, the recall rate of the three methods had decreased. Among them, the decline of method 1 was about 30%. With the increase of the data set, the retrieval recall rate was less than 25%; Method 2 Compared with Method 3, the decline was not large, but the overall recall rate was lower. Method 3 had a smaller decline, and the recall rate was above 85%.

Figure 3 showed the precision of Method 1, Method 2, and Method 3. The horizontal axis represented the relative number of retrieved data sets, and the vertical axis represented the precision. It can be seen from the data in Figure 3 that the precision of three methods decreased with the increase in the number of retrieved data sets, but the decline of method 1 was obvious, and the precision of Method 3 was much higher than that of Method 1 and Method 2 under the same number of retrieval data sets.
Figure 3. Comparison of precision rates (%) of different data retrieval methods

The above test showed that the recall rate and precision rate of Method 3 were higher, because Method 3 associated knowledge concepts with NLP algorithm to construct knowledge map of agricultural environmental sensing data, and after pruning and expansion optimization operations, the agricultural environment was transmitted. Retrieving agricultural environmental sensing data on the basis of the sensing data knowledge map had improved the recall rate and precision rate.

The retrieval time was used as the test indicator to further test Method 1, Method 2 and Method 3. The test results were shown in Figure 4. The horizontal axis represented the relative number of retrieval data sets, and the vertical axis represented the retrieval time (unit: second).

Figure 4. Comparison of retrieval time of different data retrieval methods

It can be seen from Figure 11 that with the increase in the number of retrieval data sets, the retrieval time of methods 1, 2 and 3 also increased. However, by comparison, it could be seen that Method 3 took the least time to retrieve data. In summary, the retrieval precision and accuracy of the method of association retrieval and recommendation of agricultural environmental sensing data based on the knowledge map were improved, and the retrieval efficiency met the requirements.

5. Conclusion

(1) Aiming at the retrieval characteristics of agricultural environmental sensing data, the knowledge map of agricultural environmental sensing data is constructed based on NLP algorithm, and the spatial vector retrieval model is proposed, which is beneficial to improve the recall rate and retrieval time of data retrieval.
(2) By comparing the evaluation indicators of the retrieval model before and after the optimization of the knowledge map, it is found that the recall rate and accuracy of the retrieval results are relatively improved after the pruning and expansion the knowledge map of agricultural environmental sensing data. The recommended results are also optimized.

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