Research Scholar Interest Mining Method based on Load Centrality

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Abstract In the era of big data, it is possible to carry out cooperative research on the research results of researchers through papers, patents and other data, so as to study the role of researchers, and produce results in the analysis of results. For the important problems found in the research and application of reality, this paper also proposes a research scholar interest mining algorithm based on load centrality (LCBIM), which can accurately solve the problem according to the researcher's research papers and patent data. Graphs of creative algorithms in various fields of the study aggregated ideas, generated topic graphs by aggregating neighborhoods, used the generated topic information to construct with similar or similar topic spaces, and utilize keywords to construct one or more topics. The regional structure of each topic can be used to closely calculate the weight of the centrality research model of the node, which can analyze the field in the complete coverage principle. The scientific research cooperation based on the load rate center proposed in this paper can effectively extract the interests of scientific research scholars from papers and corpus.

Keywords interest mining; data mining; load centrality; graph aggregation; research scholar

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The mining of scholars' interests can not only reflect the field of scholars' research, but also analyze the research direction of scholars. It has great prospects in the construction of scholar portraits, academic exchanges and cooperation, and analysis of scientific research results. For example, in the construction of scholar portraits, the scientific and technological information and technological needs that scholars are interested in can be recommended according to the scholar portraits. In terms of academic cooperation, a network of scholars can be constructed to analyze similar scholars to discover possible potential partners. In terms of analysis of scientific research results, it is possible to analyze scholars' fields based on data published by scholars, such as papers and patents, to analyze scholars' influence in this field, and to reveal the development process of scholars' research fields.

In order to mine the interests of scientific researchers, the existing methods are mainly studied from the aspects of vocabulary-based interest mining, topic-based interest mining and network-based interest mining. However, there are not many methods for mining the interests of scholars at present, and the papers and patent information published by scholars are not well utilized. This paper proposes a load centrality-based research and scholar interest mining algorithm (LCBIM), which continuously optimizes the graph structure by constructing and continuously optimizing the graph structure through a series of methods such as semantic similarity, so as to obtain a multi-node graph structure, and use the load centrality to calculate the weight of the graph nodes. And then dig out the areas of interest of scholars.

The main contributions of this paper include two aspects:

1) A research scholar's interest mining algorithm based on load centrality is proposed, which can continuously optimize the quality of the graph according to the vertices of the constructing elements, so that the structure of the graph is more streamlined, and the rough graph is optimized into a more discriminative graph.

2) Through the collected academic keyword information, it is possible to better and more accurately analyze the scholar's field from the scholar's dissertation data.

1 Related work

Interest mining of scientific research scholars has a very wide range of applications in the academic field. By mining the interests of scholars, it can be used to analyze
similar scholars, recommend scientific and technological data in corresponding research fields, and potential cooperative teams. At present, there are three main categories of research directions for the extraction of areas of interest of scientific researchers. The first research direction is vocabulary-based interest mining, that is, how to extract corresponding vocabulary to describe the interest direction of scholars [1][2][3]. In the early days, questionnaires, word frequency statistics, etc. were used for extraction, and then this method was highly subjective and could not well describe the field of interest of scholars [4]. Due to the rise of artificial intelligence, it was developed to use machine learning [5] for extraction, because the computing power of the computer can make use of a variety of scientific and technological resources [6][7][8]. Tang et al. [9] based on the AMiner platform to label the scholars' data with keywords and entities from various websites, and extract the scholars' interest fields through models such as CRF. Sugiyama et al. [10] also considered the number of scholar papers and impact factors when judging the importance of words, which made the extracted scholar fields more accurate. The second research direction is to extract the interests of scholars based on topics. Compared with vocabulary, topics contain richer semantics [11][12][13], which can well represent scholars' interest areas. Guan et al. [14] added the life cycle to the research on the field of interest, and used the model to obtain the field distribution of scholars at different time stages [15]. Daud [16] proposed a temporal-based topic model for scholars, which perfectly integrated the temporal model with the dynamic topic model. This direction can also be used to mine dynamic models of scholars’ interests [17][18][19][20]. The third research direction is network-based interest mining, which can present scholars’ interests through co-occurrence networks [21][22]. Ba [23] et al. The research interest similarity measurement method is introduced into the network to express a wider range of scholars' interests. Ying et al. [24] constructed a hierarchical network by identifying the hierarchical information of scholars' interest.

2 Proposal of interest mining algorithm for scientific research scholars based on load centrality

2.1 Construction of interest map of scientific research scholars

Convert the text to a directed graph, let \( G = (V, E) \) denote a graph consisting of a set of vertices \( V \) and a set of edges \( E \), which are ordered pairs with weights on \( E \). Let \( D \) denote an ordered set of documents consisting of tokens \( \{ t_1, \ldots, t_n \} \). A potential approach to regular document building graphs is to simply observe word co-occurrences. When two words appear together, they are used as edges. When traversing a given corpus, for each element \( t_i \), its successors \( t_{i+1} \), along with the given element, form a directed edge \( (t_i, t_{i+1}) \in E \). These edges are weighted according to the number of times they appear in a given corpus. At the same time, because there are professional terms in some fields that can better represent the field of scholars, in order to better extract the field of scholars, these field nouns will also be appropriately weighted. Therefore, after traversing a given corpus, the constructed graph consists of all local neighborhoods, merged into a joint structure. At the same time, the global context information is also kept intact through the weight information.

The meta-vertex construction steps are as follows: Let \( V \) denote the vertex set, as defined above. A meta vertex \( M \) consists of a set of vertices that are elements of \( V \), \( M \subseteq V \). Let \( Mi \) denote the meta vertex. Constructs a given such \( M_i \), that for each \( u \in M_i \), the initial edges of \( u \) (before merging them into metavertices) are reconnected to the newly added ones \( M_i \). Note that these edges connect to \( M_i \) vertices that do not belong. Therefore, the number of vertices and edges is greatly reduced. This function is achieved through the following specific process:

1) Meta vertex candidate identification: Edit distance and word length distance are used to determine whether two words should be merged into one meta vertex (the more expensive edit distance will only be calculated if the length distance threshold is met).

2) Meta vertex creation: as a generic identifier, use the stemmed version of the original vertex, if there are multiple resulting stems, select the vertex with the highest centrality value in the graph from the identified candidates and stem it. Versions are introduced as new vertices (meta vertices).

3) The edges of the words contained in the meta-vertices are next reconnected to the meta-vertices.
4) Remove the original words from the graph except as meta-vertices.

5) Repeat the process for all candidate pairs.

2.2 Calculate word weights using load centrality

After completing the graph construction, the concept of load centrality is used to estimate the importance of the vertices in the graph. Load centrality, i.e. the load centrality of a vertex, belongs to the family of centralities, and these centralities are defined based on the number of shortest paths through a given vertex \( v \), calculated as formula (1):

\[
c(v) = \sum_{t \in V} \sum_{s \in V} \frac{\sigma(s, t | v)}{\sigma(s, t)} ; t \neq s
\]  

\( \sigma(s, t | v) \) the number of shortest paths \( \sigma(s, t) \) from vertex \( s \) through \( v \) to vertex \( t \), and represents the number of all shortest paths between \( s \) and \( t \). The load centrality metric considered is slightly different from the well-known betweenness centrality; suppose that each vertex sends a packet to the other vertices it is connected to, and its routing is based on a priority system: the input of a given flow \( x \) reaches vertex \( v \) with With a destination \( v' \), \( v \) distributes the minimum shortest path of \( x \) to the destination's neighbors equally among all nodes. The total flow through a given \( v \) through this process is defined as \( v \)'s load. The edge weighted correlation of node \( v \) is obtained according to formula (2).

\[
R(v_i) = (1 - d) \cdot W(v_i) + d \cdot W(v_i) \cdot \sum_{j:i \neq v_j} \frac{w_{ij}}{\sum_{k:v_k} w_{jk}} R(v_j)
\]  

\( d \) is the damping factor representing the probability of jumping from one node to the next, usually set to 0.85. \((1 - d)\) represents the probability of jumping to a new node. \( W(v_i) \) is the weight of the current node \( v_i \). \( w_{ij} \) is the weight from the previous vertex \( v_j \) to the current edge. Represents \( R(v_j) \) the dependencies of nodes \( v_j \).

2.3 Mining the interests of scientific research scholars according to the big data of science and technology

Load centrality maps from vertex set \( V \) to actual values, respectively. This section identifies the vertices of the graph with the highest load centrality as key vertices in a given network. These vertices are good descriptions of the keywords. Therefore, ranking vertices produces a prioritized list of potential keywords. According to the order of potential keywords and the weighted ranking of the keywords in the subject area, the interests of scientific researchers can be mined through the paper and patent corpus.

\[\text{Figure 1: Research and Scholars Interest Mining Algorithm Based on Load Centrality (LCBIM)}\]

3 Algorithm steps of interest mining of scientific research scholars based on load centrality

Constructed from the given documents, resulting in a generally very sparse graph, with most words rarely occurring at the same time, and the graph can be optimized by defining meta vertices. After the build is complete, load centrality is calculated for each vertex. At this time, if the top \( k \) vertices are considered by load centrality, only a single keyword will appear. If in order to extend the selection to 2-grams and 3-grams, do the following:

1. **2-gram keyword**: A keyword consisting of two terms is constructed as follows. First, first-order keyword pairs (all tokens) are computed. A token pair is considered a potential 2-gram keyword if the calculated keyword score (i.e. the number of 2-gram keyword occurrences) is higher than the single token keyword score. The load
center value of the two tokens is averaged, that is:

\[
c_v = \frac{c_1 + c_2}{2}
\]  

(3)

The obtained keywords are considered together with the calculated score for the final selection.

3-gram keywords: For the construction of 3-gram keywords, the obtained 2-gram keywords will be further expanded as follows. For each candidate 2-gram keyword, two expansion scenarios are considered: the first scenario expands the 2-gram from the left, and the left-labeled neighborhood is treated as a potential expansion for the given keyword. The ranking of such keyword candidates is calculated by averaging the centrality scores in the same way as in the 2-gram case. The second scenario expands the 2-gram from the right, but unlike the previous point, all connections to the rightmost vertices are treated as potential expansions. As above, the candidate keywords are ranked by the average load center to obtain a set of (keyword, score) pairs, and finally the set is sorted in descending order according to the score, and the first k keywords are taken as the result as the scholar’s interest point.

Algorithm 1: LCBIM

Input: Document D, containing n tokens\{ t_1, t_2, ..., t_n \}, the number of extracted keywords k, the minimum token length \( \mu \); edit distance threshold \( \alpha \); token length difference threshold \( l \); distance length \( p \); w-gram frequency threshold \( f \).

Output: keyword set \( K \)

1: Generate Graph based on token
2: for \( t_i \in D \) do
3: ( \( t_i, t_{i+1} \) ) \rightarrow edge
4: if edge not in Graph and len ( \( t_i \) ) \( \geq \mu \) then
5: add edge to Graph;
6: end
7: Update the weights of the graph
8: end
9: Generate meta vertex optimization graph
10: Calculate load centrality and generate token score
11: If calculating 2-gram and 3-gram, then update the token score according to the rules
12: \( K = \) getKeywords [ : \( k \) ]

4 Experimental results and analysis

Table 1 Keyword extraction dataset

| data set       | number of documents | Gold Keywords Average | Standard deviation | average document length |
|----------------|---------------------|-----------------------|--------------------|------------------------|
| 500N-KPCrowd-v1.1[25] | 500               | 48.92                | 1.00               | 408.33                 |
| citeulike180[26]       | 180               | 18.42                | 0.86               | 4796.08                |
| Schutz2008[27]         | 1231              | 44.69                | 0.94               | 3901.31                |
| wiki20[28]             | 20                | 36.5                 | 0.22               | 6177.65                |

As shown in Table 2, the performance of LCBIM on each dataset is compared with other methods, and the F1@10 value is used for evaluation. It can be seen that on the following five datasets, the proposed LCBIM method is generally better than other methods. The method is better, because other methods do not use load centrality to calculate the weight of each node, so it is difficult to reflect the importance of the corresponding node, so the effect is not as good as the proposed LCBIM.
Figure 2 Comparison of LCBIM and other algorithms on P@10 and R@10 indicators/dataset GAData.

Shown in Figure 2, under the comprehensive comparison of the GAData dataset, the LCBIM algorithm outperforms other algorithms in both P@10 and R@10. It is proved that optimizing the graph structure and using load centrality to extract keywords is effective. Through the optimized graph structure, the experimental effect is also better than the other two graph-based extraction algorithms (PageRank, TextRank). While KEA is a supervised keyword extractor, it can be seen that the proposed unsupervised LCBIM algorithm has the same effect as KEA on the overall data set, which also proves the effectiveness of the proposed LCBIM algorithm and shows that the graph structure is effective.

Figure 3 Comparison of LCBIM and other algorithms on P@10 and R@10 metrics/dataset 500N-KPCrowd-v1.1

Figure 3, the LCBIM algorithm outperforms other algorithms in P@10 and R@10 under the comprehensive comparison of the 500 N-KPCrowd-v1.1 dataset. It also shows the stability of the LCBIM algorithm, indicating that the optimized graph structure can better tap the interests of scientific researchers.

Figure 4 Comparison of LCBIM and other algorithms on P@10 and R@10 metrics/dataset citeulike180

Figure 4, in the comprehensive comparison of the citeulike180 dataset, the LCBIM algorithm outperforms other algorithms in P@10 and R@10. This is because the algorithm proposed in this paper can effectively use the load centrality to calculate the weight.

Figure 5 Comparison of LCBIM and other algorithms on P@10 and R@10 metrics/dataset Schutz008

Figure 5, in the comprehensive comparison of the Schutz008 dataset, the LCBIM algorithm outperforms other algorithms in P@10 and R@10. It shows that the proposed LCBIM algorithm reasonably optimizes the graph structure, and can accurately calculate the weight of nodes by using the load centrality, which also shows the stability of the LCBIM algorithm.

Figure 6 Comparison of LCBIM and other algorithms on P@10 and R@10 metrics/dataset wiki20

From Figure 2 to Figure 6 that the LCBIM algorithm
outperforms other algorithms in both P @10 and R@10 under the comprehensive comparison of the five datasets. It is proved that optimizing the graph structure and using load centrality to extract keywords is effective. Through the optimized graph structure, the experimental effect is also better than the other two graph-based extraction algorithms (PageRank, TextRank). While KEA is a supervised keyword extractor, it can be seen that the proposed unsupervised LCBIM algorithm performs on par with KEA on the overall dataset. Even on some datasets, such as 500N-KPCrowd-v1.1 and Schutze 2008, the effect is outstanding. It is shown that a more powerful keyword extraction algorithm is proposed from the graph structure than learning a classifier.

5 Conclusion

This paper proposes an interest mining algorithm for scientific researchers based on load centrality, and explores it from three aspects: vocabulary-based interest mining, topic-based interest mining and network-based interest mining. This paper proposes the use of lexical semantic similarity, part-of-speech similarity and other methods to continuously construct the meta-vertex optimization graph to make it more discriminative. The weight of the vertices in the graph is calculated by the load centrality, and the threshold is set to obtain the field keyword extraction of the researcher. The experimental results verify the effectiveness of the proposed algorithm from multiple dimensions. Compared with other methods, the algorithm proposed in this paper can more effectively tap the research interests of scholars.

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