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A Semantic Enrichment Framework for Scientific Literature Retrieval Systems: Design and Practice (Postprint)

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Abstract

【Purpose】To enhance the service functions and effectiveness of scientific literature retrieval systems by employing methods such as semantic recognition and knowledge relationship computation, enabling them to present richer knowledge-based semantic information and display more knowledge points and knowledge relationships to users.

【Methods】Apply data mining and relationship computation tools to deeply identify and extract semantic knowledge from scientific literature, analyze, compute, and construct semantic relationships, and establish a multi-dimensional semantic index tree from the obtained semantic knowledge and relationships, designing a new data organization and presentation model.

【Results】Develop a demonstration system for semantic enrichment retrieval that fully reveals semantic information during the application process of scientific literature retrieval, enriching the retrieval experience.

【Limitations】The selected experimental dataset is not sufficiently comprehensive, lacking application comparisons across other domains.

【Conclusion】The model design in this paper provides users with more knowledge-level associations, revelations, and navigation, enhancing the retrieval system experience. Simultaneously, it analyzes the shortcomings of the design model and explores improvement methods.

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Full Text

Design of a Semantic Enrichment Framework for Scientific Literature Retrieval Systems

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Abstract

[**Objective**] This study aims to enhance the service functions and effectiveness of scientific literature retrieval systems through semantic recognition and knowledge relationship computing, enabling the presentation of richer knowledge-based semantic information and revealing more knowledge points and relationships to users. [**Methods**] We applied data mining and relationship calculation tools to deeply identify and extract semantic knowledge from scientific literature, analyzed and computed semantic relationships, constructed multidimensional semantic index trees from the extracted knowledge and relationships, and designed a new data organization and presentation model. [**Results**] We developed a semantic enrichment retrieval demonstration system that fully reveals semantic information during the retrieval process and enriches the user experience. [**Limitations**] The experimental dataset was insufficient, and comparative applications in other domains were lacking. [**Conclusions**] The proposed model design provides users with more knowledge-level associations, revelations, and navigation, thereby improving the retrieval system experience. The paper also analyzes the limitations of the design model and explores potential improvements.

Keywords: Semantic Enrichment; Semantic Knowledge Organization; Semantic Relation Presentation; Multidimensional Index
Classification Number: TP391

With the rapid development and application of semantic technologies, knowledge graphs, and ontology technologies in scientific literature, discovering and revealing semantic relationships among scientific documents and fully utilizing and demonstrating the value of knowledge have become key focuses of contemporary scientific literature retrieval. Users are no longer satisfied with traditional "keyword + retrieval list" systems and instead hope to discover scientific literature through semantic approaches, with retrieval systems presenting richer content such as knowledge points and knowledge relationships. The design goal of a semantic enrichment framework is to improve existing single-keyword-oriented retrieval systems by reorganizing various types of semantic knowledge [1] and the rich associative relationships between knowledge elements using data mining and presentation technologies, thereby fully revealing deep information during the scientific literature retrieval process.

2. Current State Analysis and Research Significance of Semantic Enrichment

Current semantic search engines based on knowledge graphs [2], such as Google Knowledge Graph [3], utilize knowledge graphs to improve the presentation methods of traditional search engines, analyze user input to generate relevant encyclopedic knowledge, and assist in organizing multi-type semantic knowledge with multimedia displays, significantly enhancing user retrieval experience. Well-known intelligent semantic search engines like WolframAlpha [4] and Kngine [5] present semantic search as an intelligent knowledge Q&A approach. Based on powerful encyclopedic knowledge bases and knowledge graphs, these search engines intelligently parse user questions, search, and present relevant knowledge graphs. However, they only perform semantic enrichment on user input and reveal existing knowledge in knowledge graphs, failing to discover potential knowledge within scientific literature itself. During literature discovery, they still employ traditional retrieval architectures and present relevant documents in list format. In contrast, research applications on the SindiceTech [6] platform have implemented intelligent methods such as deep text data decomposition and semantic relationship calculation, representing massive text data entirely in RDF triples [7] to discover potential knowledge in texts.

3.2 Semantic Indexing

Semantic indexing constructs a multidimensional semantic index system from the literature clues, text content, knowledge objects, and object relationships obtained through semantic computation, organically organizing data from various dimensions to facilitate revelation and application by semantic enrichment retrieval systems. As shown in the lower half of [Figure 1: see original paper], semantic indexing consists of three parts: (1) **Literature Index**: Indexes basic descriptive metadata of articles and sentence fragments after text segmentation, ensuring the mapping relationship between articles and their sentence fragments for literature metadata query, browsing, and text fragment organization and presentation. (2) **Knowledge Object Index**: Used for retrieval, querying, and classification display of knowledge objects, identifying and standardizing user input keywords, and associating knowledge objects with literature text to locate which literature and specific sentences contain the knowledge objects. (3) **Knowledge Relationship Index**: The semantic annotation work yields both semantic and syntactic relationships, which the text index collectively refers to as knowledge relationships, both expressed in S-P-O triple format. The knowledge relationship index is built upon these triples to enable knowledge association navigation and discovery of potential knowledge relationships.

4. Semantic Computing Framework

The workflow of the semantic computing framework is shown in [Figure 2: see original paper]. Referring to the MeSH thesaurus [19], we divided medical domain knowledge objects into 16 top-level categories, 134 secondary classifications [20], and 30 types of predicate semantic relationships (these numbers and structures vary according to annual NLM updates). We selected title and abstract text data from medical literature as experimental materials and used SemRep and MetaMap [21] tools to annotate and extract important knowledge objects from the experimental text data. We employed MetaMap and ClausIE tools to implement semantic relationship computation.

4.1 Content Semantic Annotation

(1) Semantic Annotation of Literature Content
We preprocessed 200,000 scientific literature records using StanfordTagger [22] and ClausIE syntactic parsing tools for sentence segmentation; used dTagger [23] for part-of-speech tagging; and utilized MetaMap, developed by the U.S. National Library of Medicine based on the UMLS Metathesaurus, to split sentences into meaningful phrase fragments. For example, processing the title "Effectiveness of behavioural management on migraine in adult patients visiting family practice clinics: a randomized controlled trial" yields five phrases (A-E), with specific annotation examples shown in [Figure 3: see original paper].

(2) Semantic Recognition of Knowledge Objects
The semantic annotation results were mapped to the UMLS Metathesaurus using SemRep to identify semantic types of each term and extract reliable semantic relationships. Using the same example from Figure 3, SemRep analysis of the above title identified 10 entities and semantic relationships, detailed in . Through semantic recognition, we achieved identification and mapping of important knowledge objects to the 16 top-level categories and 134 secondary classifications of the MeSH thesaurus.

4.2 Semantic Relationship Calculation and Recognition

We used MetaMap to calculate and recognize semantic relationships, identifying knowledge object relationships as 30 standardized relationships; ClausIE was used to identify syntactic tree relationships. The semantic relationship data identified by both MetaMap and ClausIE were merged and integrated, with reference to the 30 standardized relationships selected by MetaMap for normalization and correction of the experimental data.

The completed data organization and standardization work included: (1) Implementing semantic relationship annotation of knowledge objects within literature, extracting 30 types of semantic relationships from scientific literature using SemRep and MetaMap tools to mine potential knowledge relationships between knowledge objects. (2) Implementing syntactic relationship annotation of literature content, extracting syntactic relationships (S-P-O) from scientific literature using ClausIE to discover potential associative relationships between knowledge objects (keywords, terms). (3) Integrating semantic and syntactic relationship annotations, extracting S-P-O relationships from 1,116 literature abstracts, totaling 50,204 relationships, including 41,590 semantic relationships and 8,614 syntactic relationships.

4.3 Solutions to Key Problems

(1) Mapping Annotation Content to MeSH Thesaurus
The SemRep processing results are shown in . Taking the first row as an example, the red field (e.g., "qlco" in the example) represents semantic relationship abbreviations for the 134 secondary classifications. This paper completed the collection and organization of English full names, English abbreviations, and Chinese names corresponding to the 16 top-level categories and 134 secondary classifications of the MeSH thesaurus. Through the red field association, we established mapping relationships between text-identified terms and the MeSH thesaurus, thereby solving the correspondence problem between SemRep processing results and the MeSH thesaurus.

(2) Correspondence Between ClausIE-Extracted Subjects (S), Predicates (P) and UMLS Metathesaurus
ClausIE-extracted triples based on syntactic relationships cannot completely match entities extracted by SemRep; meanwhile, SemRep can only extract semantic verbs, ignoring other verbs. For the first case, we used fuzzy matching to ensure entity correspondence; for the second case, we extracted verbs from MetaMap and then performed matching to ensure the standardization and consistency of experimental data.

5. Construction of Semantic Index System

The design goal of semantic indexing is to reveal knowledge objects and various semantic relationships between them, changing the current single-dimension indexing approach by using multiple index trees working collaboratively to present semantic content multidimensionally. As shown in [Figure 4: see original paper], semantic indexing takes knowledge objects as the core, following the user workflow: starting from retrieval keywords, performing semantic recognition and disambiguation through the knowledge object index; then navigating and filtering required associated knowledge by traversing the knowledge network through the knowledge object relationship index; determining the sentences and paragraphs where knowledge objects are located through bridging indexes; and finally querying and displaying literature information containing relevant knowledge content through the literature index.

5.1 Functions and Organizational Structure of Semantic Indexing

Based on the above four steps, the index is divided into four functional components:

(1) Knowledge Object Index
- Knowledge Object Index: Converts user input keywords into relevant knowl-

edge objects, achieving a shift to semantic retrieval. Retrieves and displays various attributes of knowledge objects, identifies keywords with semantic conflicts, and implements semantic disambiguation.
- Dependency Relationship Index: Indexes the locations where knowledge objects exist (e.g., specific sentences in articles) for rapid query and positioning of literature containing the knowledge points.

(2) Knowledge Relationship Index
- Semantic Relationship Index: Indexes semantic relationships between knowledge objects appearing in text (the semantic relationships obtained from the above semantic computation, standardized using the STKOS knowledge organization system [24]), enabling retrieval and analytical presentation of semantic relationships.
- Syntactic Relationship Index: Indexes syntactic relationships between knowledge objects appearing in text (syntactic relationships are based on NLP [25] syntactic analysis), used to distinguish retrieval and analytical presentation of semantic and syntactic relationships.

(3) Co-occurrence Statistical Index
- Object-Co-occurrence Relationship Index: Implements indexing records of knowledge objects appearing in the same literature for analyzing and revealing co-occurrence relationships of semantic knowledge objects.
- Object-Co-paragraph Relationship Index: Implements indexing records of knowledge objects appearing in the same paragraph for analyzing and revealing co-paragraph relationships of semantic knowledge objects.
- Object-Co-sentence Relationship Index: Implements indexing records of knowledge objects appearing in the same sentence for analyzing and revealing co-sentence relationships of semantic knowledge objects.

(4) Literature Index
- Metadata Index: Indexes metadata description information of literature for displaying literature description information.
- Fragment Sentence Index: Indexes article text content and sentences for displaying literature content and highlighting relevant knowledge objects.

Based on the selected dataset, this experiment indexed 1,116 literature records, 4,023 paragraphs, 7,684 sentences, and 4,935 knowledge objects, with 50,204 knowledge relationships indexed.

5.2 Key Problems and Solutions

(1) Mapping Input Keywords to Knowledge Objects
During the experiment, user input keywords might not completely match knowledge objects in the index, preventing accurate mapping to knowledge objects; alternatively, a single keyword might contain multiple meanings, causing semantic recognition ambiguity and preventing clear mapping to specific knowledge objects. For the first problem, we used fuzzy matching to select the knowledge object with the highest matching score and listed the top 5 matching items to

notify users for manual semantic recognition correction. For the second problem, we prompted users about knowledge objects with different meanings, allowing them to select and correct for semantic disambiguation.

(2) Statistical Revelation of Association Relationships Between Knowledge Objects
All knowledge object relationships are indexed in Apache Solr using S-P-O triples. How to use Solr' s retrieval faceting mechanism to statistically reveal association relationships between knowledge objects is a challenge. This paper adopted the method of adding redundant fields in triple indexing, with the index structure shown in . When retrieving the subject (S), we facet on the predicate-object (P+O) combination field; when retrieving the object (O), we facet on the subject-predicate (S+P) combination field. By faceting on (P+O) and (S+P) when retrieving any knowledge object, we can reveal the TopN associated knowledge objects by frequency in the retrieval result set, helping to discover potential knowledge.

6.1 Data Organization of the Experimental System

To implement the semantic enrichment retrieval demonstration platform, the system organizes data into four dimensions, as shown in [Figure 5: see original paper].

The first dimension is the literature description layer, revealing basic metadata such as article titles, authors, abstracts, and publication dates. The second dimension is the text fragment layer, splitting abstracts into paragraphs and sentences and revealing their associations. The third dimension is the knowledge relationship layer (Figure 5 collectively refers to knowledge objects and their relationships as facts), used to express and reveal knowledge association relationships. The fourth dimension is the knowledge object layer, revealing knowledge objects identified in the text.

From a bottom-up perspective, the third and fourth dimensions decompose scientific literature into knowledge objects and knowledge association relationships, forming a semantically enriched scientific literature knowledge network for semantic querying and association navigation. The first and second dimensions combine basic literature information with text fragments to organically associate and organize knowledge with literature for knowledge presentation and assisted literature retrieval reading.

6.2 Implementation of Demonstration Platform Functions

The semantic enrichment demonstration platform centers on users' knowledge application needs, with the retrieval workflow designed as: input recognition and interpretation, knowledge relationship presentation, potential knowledge association discovery, and semantic-assisted browsing. The semantic enrichment demonstration platform implements these four functions.

(1) Recognizing and Interpreting User Input
The first step of the demonstration system identifies corresponding knowledge objects based on user input keywords, interpreting and presenting specific knowledge content. As shown in [Figure 6: see original paper], when entering the retrieval keyword "Headache," the system identifies knowledge objects related to "Headache," which belongs to the category of "Signs or Symptoms." It also provides encyclopedia entries and related images about Headache and lists related knowledge objects for user selection.

Compared with traditional literature retrieval, this function can standardize user input, transforming simple keyword matching retrieval into knowledge object retrieval with semantic features, making semantic enrichment retrieval more accurate. Simultaneously, the semantic recognition function can indicate the category of knowledge objects, assisting users in semantic disambiguation and avoiding semantic deviations common in traditional keyword retrieval.

(2) Graphical Presentation of Knowledge Relationships
The knowledge relationship revelation function takes the retrieved knowledge object as the center and reveals related knowledge objects, relationships, and article fragments in the retrieval results through graphical presentation, as shown in [Figure 7: see original paper].

Similarly, S-P-O semantic relationships and syntactic relationships are revealed through faceting, using predicate+object (knowledge object) faceting statistics to reveal potential semantic and syntactic relationships. As shown in the lower half of [Figure 8: see original paper], when retrieving "Headache," syntactic relationship revelation discovers articles on deep professional domain knowledge such as child treatment (PROCESS_{OF} Child) and adolescent treatment (PROCESS_{OF} Adolescent), and reveals research papers on related therapeutic drugs (followed Eplepsy) through syntactic relationships, providing researchers with clear knowledge relationship inspiration and guidance.

These knowledge elements and association relationships are displayed graphically using points and edges, with different colored points representing different types of knowledge objects and different shapes representing different types of relationships. Through a "click-associate-present" navigation operation, users can select any knowledge point appearing on the graph to display surrounding knowledge contexts and deeply discover needed knowledge.

The demonstration system can present knowledge relationships in retrieval results, greatly helping researchers judge whether the content meets their retrieval needs. This paper argues that a knowledge-discovery-oriented retrieval approach that views full-text literature through knowledge object associations is more helpful for improving semantic retrieval accuracy than traditional keyword retrieval.

(3) Discovery of Potential Knowledge Relationships
The potential knowledge relationship discovery function takes the retrieved knowledge object as the center and uses the "co-occurrence relationship index" to

statistically identify knowledge objects that co-occur, co-appear in paragraphs, and co-appear in sentences within retrieval result literature. It also implements faceted browsing of associated knowledge objects, facilitating researchers to discover valuable content from potentially associated knowledge objects and providing navigation functions to filter these scientific literature. As shown in the upper half of [Figure 8: see original paper], when querying "Headache," co-occurrence relationships, co-sentence relationships, and co-paragraph relationships reveal Migraine Disorders, Clinical Research, etc., providing inspiration for researchers.

The faceted navigation function of the demonstration system reveals knowledge co-occurrence relationships and semantic/syntactic relationships based on statistical analysis of existing literature data, helping to discover implicit knowledge association information within literature, assisting researchers in discovering new potential knowledge relationships, exploring new research points in interdisciplinary fields, expanding research ideas, and supporting scientific research.

(4) Semantic-Assisted Reading of Single Literature

As shown in [Figure 9: see original paper], the semantic-assisted reading function can highlight and display knowledge objects and relationships when viewing single literature. The tree list on the left displays semantic knowledge objects in the literature, grouped by type and marked with different colors. The central main section shows the literature' s text information; when a certain type of knowledge object is selected, the text information in the center highlights that object with its color, marking its location in the literature for easy user reference. The right side displays the semantic and syntactic relationships calculated for the literature, also allowing users to view the specific sentence and paragraph locations of knowledge relationships in the text.

The semantic-assisted reading method provided by the demonstration system helps users directly view knowledge points, locate their specific positions, and guides readers to prioritize reading paragraphs and sentences dense with relevant knowledge, thereby improving reading efficiency of full-text literature content.

This paper proposes a design model for a semantic enrichment framework and further demonstrates its advantages and feasibility through building a demonstration system, improving literature retrieval effectiveness in four aspects: (1) Semantic recognition technology transforms keyword matching retrieval into knowledge object retrieval with semantic features, improving retrieval accuracy, assisting users in semantic disambiguation, and avoiding semantic deviations in keyword retrieval. (2) Using precise semantic expression of relevant knowledge objects and relationships instead of list-based retrieval result presentation helps researchers judge whether retrieval content meets their needs. (3) Semantic association navigation functions help discover implicit knowledge association information, assisting researchers in discovering new knowledge associations, exploring interdisciplinary fields, and expanding research ideas. (4) Semantic-assisted reading highlights knowledge point locations, guides readers to prioritize reading knowledge-dense paragraphs, and improves literature content reading efficiency.

During the experiment, some shortcomings were identified for future improvement: (1) S-P-O triple relationships obtained from syntactic analysis were not completely mapped to the 30 standardized predicates provided by MetaMap. Unstandardized predicates impact association navigation discovery to some extent; subsequent work will consider constructing predicate standardization thesauri and modifying predicate semantic recognition algorithms. (2) Knowledge relationship revelation frequently associates with broad and frequent hypernyms, which are not conducive to helping professional domain researchers. Future work will attempt to filter frequent and broad hypernyms using weighted calculation methods such as TF-IDF to improve knowledge association navigation effects. (3) The experimental dataset was small, lacking application testing on large datasets and comparative evaluation experiments outside the medical domain.

References

[1] U.S. National Library of Medicine. Semantic Knowledge Representation [EB/OL]. [2016-01-13]. https://skr3.nlm.nih.gov/.
[2] Wikipedia. Knowledge Graph [EB/OL]. [2016-02-10]. https://en.wikipedia.org/wiki/Knowledge_{Graph}.
[3] Google Inside Search [EB/OL]. [2016-02-10]. https://www.google.com/intl/es419/insidesearch/features/sear
[4] Wolframalpha. Computational Knowledge Engine [EB/OL]. [2015-03-10]. https://www.wolframalpha.com/.
[5] Kngine. The Most Intelligent Engine [EB/OL]. [2015-03-10]. http://www.kngine.com/.
[6] SindiceTech. Enterprise Knowledge Graphs [EB/OL]. [2015-03-10]. http://www.sindicetech.com/overview.html.
[7] W3C Semantic Web. RDF [EB/OL]. [2015-06-05]. https://www.w3.org/RDF/.
[8] SindiceTech. FreeBase Distribution [EB/OL]. [2015-03-10]. http://www.sindicetech.com/freebase-distribution.html.
[9] Apache Solr [EB/OL]. [2015-06-05]. http://lucene.apache.org/solr/.
[10] PubMed [EB/OL]. [2015-10-11]. http://www.ncbi.nlm.nih.gov/pubmed.
[11] U.S. National Library of Medicine. SemRep [EB/OL]. [2015-10-22]. https://semrep.nlm.nih.gov/.
[12] Del Corro L, Gemulla R. ClausIE: Clause-Open Information Extraction[C]//Proceedings of the 22nd International Conference on World Wide Web. 2013:355-366.
[13] Merrill M D. Knowledge Objects[R]. USA: CBT Solutions, 1998: 1-11.
[14] U.S. National Library of Medicine. Unified Medical Language System (UMLS) [EB/OL]. [2016-01-13]. https://www.nlm.nih.gov/research/umls/.
[15] Wang Ying, Zhang Zhixiong, Li Chuanxi, et al. The Design and Implementation of Open Engine System for Scientific & Technological Knowledge Organization Systems[J]. New Technology of Library and Information Service, 2015(10): 95-101.
[16] UMLS. Semantic Relationships [EB/OL]. [2015-10-17]. https://www.nlm.nih.gov/research/umls/new_{use
[17] Chakraborty A, Munshi S, Mukhopadhyay D. Searching and Establishment of S-P-O Relationships for Linked RDF Graphs: An Adaptive

Approach[C]//Proceedings of International Conference on Cloud & Ubiquitous Computing & Emerging Technologies (CUBE). 2013.
[18] Matthews P H. Syntactic Relations: A Critical Survey[M]. University of Cambridge Press, 2007: 3-10.
[19] U.S. National Library of Medicine. Medical Subject Headings (MeSH) [EB/OL]. [2015-06-05]. https://www.nlm.nih.gov/mesh/.
[20] U.S. National Library of Medicine. MeSH Category Tree View [EB/OL]. [2015-06-05]. https://meshb.nlm.nih.gov/#/treeSearch.
[21] MetaMap - A Tool For Recognizing UMLS Concepts in Text [EB/OL]. [2015-06-20]. https://metamap.nlm.nih.gov/.
[22] The Stanford Natural Language Processing Group. Stanford Part of Speech Tagger [EB/OL]. [2015-08-24]. https://nlp.stanford.edu/software/tagger.shtml.
[23] SPECIALIST dTagger [EB/OL]. [2015-06-20]. https://specialist.nlm.nih.gov/dTagger/.
[24] Sun Tan, Liu Zheng. Methodology Framework of Knowledge Organization System for Scientific & Technological Literature[J]. Library & Information, 2013(1): 2-7.
[25] Rindflesch T C, Fiszman M. The Interaction of Domain Knowledge and Linguistic Structure in Natural Language Processing: Interpreting Hypernymic Propositions in Biomedical Text[J]. Journal of Biomedical Informatics, 2003, 36(6): 462-477.

Author Contributions

Xie Jing: Designed the semantic enrichment retrieval model and demonstration system framework, developed the system, and primary author of the paper.
Wang Jingdong: Performed data processing, semantic annotation, and relationship computing, and author of the semantic computation chapter.
Wu Zhenxin: Organized paper structure and edited/revised the text.
Zhang Zhixiong: Proposed ideas for semantic computation and semantic indexing design.
Wang Ying: Designed the demonstration system data organization and graphical presentation scheme.
Ye Zhifei: Developed the graphical presentation module of the demonstration system.

Conflict of Interest Statement

All authors declare no conflict of interest.

Supporting Data

Supporting data is self-archived by the authors, E-mail: xiej@mail.las.ac.cn.
[1] Xie Jing, Wang Jingdong. pubmed_{paper}.csv. Experimental literature data extracted from PubMed open access.
[2] Xie Jing, Wang Jingdong. mesh_{object}.csv. Medical knowledge object data extracted and standardized from MeSH.

[3] Xie Jing, Wang Jingdong. stkos_{object}.csv. Standardized medical domain knowledge object data extracted from STKOS.
[4] Wang Jingdong, Xie Jing. semrep_{anno}.csv. SemRep knowledge object annotation results.
[5] Wang Jingdong, Xie Jing. semrep_{spo}.csv. Knowledge relationship computation results based on SemRep.
[6] Wang Jingdong, Xie Jing. clausIE_{spo}.csv. Knowledge relationship computation results based on ClausIE.
[7] Xie Jing. solr_{{{semantic}}_{{index}}}.rar. Solr-based semantic index data.

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