Research on Digital Literature Resource Content Service Recommendation Based on Ontology Rule Inference and Semantic Similarity Computation (Postprint)

Authors: Liu Jian, Bi Qiang, Liu Qingxu, Wang Fu

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Abstract

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Objective: To address the limitation of traditional content-based recommendation services for digital literature resources, which fail to fully exploit the semantic information inherent in these resources.

Method: We establish ontology reasoning rules to perform semantic expansion of user query keywords and propose a novel semantic similarity computation method to calculate content similarity among literature resources. Search results are ranked according to similarity scores, with top-ranked items recommended to target users.

Results: Experimental results demonstrate that the proposed method computes semantic similarity with relatively high accuracy and effectively recommends resources according to user requirements.

Limitations: The study is constrained by the lack of a large-scale digital resource collection and insufficient experimental cases.

Conclusion: This method fully exploits the semantic information of digital literature resources to provide effective recommendations, offering a new approach for content-based recommendation services for digital resources.

Full Text

Research on Content Service Recommendation of Digital Literature Resources Based on Ontology Rule Reasoning and Semantic Similarity Calculation

Liu Jian[1], **Bi Qiang**[1], **Liu Qingxu**[1], **Wang Fu**[1,2]
[1](School of Management, Jilin University, Changchun 130022, China)
[2](Inner Mongolia University of Technology Library, Hohhot 010051, China)

Abstract

This study aims to address the limitation of traditional content service recommendation for digital literature resources in fully exploiting semantic information. The proposed method employs ontology reasoning rules to semantically expand user query keywords and introduces a novel semantic similarity calculation method to compute content similarity among literature resources. Search results are then ranked according to similarity scores, with top-ranked documents recommended to target users. Experimental results demonstrate that the method can accurately calculate semantic similarity and effectively recommend documents aligned with user needs. However, the study is limited by the lack of large-scale digital resource collection and a relatively small number of experimental cases. In conclusion, the method successfully exploits semantic information from digital literature resources and provides a new approach for content service recommendation.

Keywords: Digital literature; Service recommendation; Ontology reasoning; Semantic similarity

Introduction

User-centered, targeted, and proactive information services tailored to individual needs represent a crucial approach for improving information service quality and resource utilization efficiency [1]. Resource service recommendation constitutes an effective means of satisfying users' pursuit of personalized value [2]. Currently, recommendation methods such as content-based filtering [3], collaborative filtering [4-6], and context-based recommendation [7-10] have achieved considerable application and promotion. However, these methods predominantly rely on keyword frequency as their computational basis, which fails to accurately capture the semantic information of digital literature resources [11], making it difficult to distinguish resource quality and style [12]. This limitation results in low structural organization of digital literature resources, constraining their effective utilization and sharing [13], and preventing the full excavation of users' latent information needs [14-15].

This paper proposes a digital literature resource recommendation method based on ontology rule reasoning and semantic similarity calculation, using ontology as a model that reflects resource attribute relationships. This approach addresses issues of semantic deficiency and low structural organization in recommendation systems [16-17], while fully excavating users'latent needs, thereby offering a novel perspective for digital resource content service recommendation.

2.1 Ontology-Based Recommendation

Ontology represents a conceptual system of knowledge structure within a specific domain, reflecting the common perspective of that domain along with a collection of explicit concepts and inter-concept relationships. It focuses on expressing terminology and term relationships at the conceptual hierarchy level, providing precise control for knowledge organization and sharing [18]. Ontology-based recommendation methods can effectively address issues of semantic deficiency and low structural organization in recommendation systems [19], making them a focal point for researchers. Currently, three main approaches exist: resource recommendation based on ontology rule reasoning, resource recommendation based on ontology semantic similarity, and resource recommendation based on ontology semantic description. The first approach combines Semantic Web ontology languages with inference engines (such as Jess, Pellet, etc.) to discover implicit semantic associations through rule setting, addition, and logical reasoning, thereby recommending highly relevant resources to target users [20-22]. The second approach integrates multi-source information by constructing domain ontologies, where the consolidated ontology attributes reflect resource characteristics. Similar resources are then identified by calculating similarity among concept node attributes and ontology network structures, improving recommendation quality [16, 23-25]. The third approach introduces ontology into recommendation systems, using OWL to describe user and item information, which is then combined with traditional models like collaborative filtering and content-based recommendation to compute similarity between user preferences and item information. This simultaneously endows users and items with semantic information, enhances the structured description level of resource information, and effectively improves recommendation recall and accuracy [26-28].

However, ontology rule reasoning-based recommendation only excavates user needs through predefined rules without fully describing resource semantic information. Ontology semantic similarity-based recommendation fails to express users' true needs due to multiple expression differences between keywords and index terms. Ontology semantic description-based recommendation suffers from low recommendation accuracy caused by traditional algorithmic issues such as user cold-start and sparse rating matrices. This paper proposes a recommendation method based on both ontology reasoning rules and semantic similarity calculation to address the inadequate mining of resource semantic information and inability to express user needs, thereby enhancing the semantic expression and processing capabilities of recommendation systems.

2.2 Ontology Rule Reasoning

Ontology reasoning can discover implicit logical relationships within ontologies, verify compatibility between ontologies and knowledge, and automatically classify instances [29]. This ensures the correctness and consistency of ontology construction, connects loosely coupled concepts, attributes, and instances to form a comprehensive knowledge base, thereby optimizing the ontology and reducing maintenance costs [30]. Hayes defined the D-entailment rule set, which derives a standard set of rules from an RDF graph [31]. Due to the incompleteness of D-entailment rules, Ter Horst supplemented them [32], creating the D* entailment rule set. This rule set allows blank nodes to appear in the predicate position of triples to ensure RDFS completeness. As an extension of RDFS, OWL resolves issues such as lack of support for cardinality constraints, Boolean class combinations, and property restrictions. Horrocks et al. integrated OWL 1 DL with rules, constructing the Semantic Web Rule Language (SWRL) based on a subset of RuleML' s Horn clauses [33]. As a Semantic Web framework, Jena also supports rule reasoning. Similar to SWRL, Jena features strict syntax rule formatting, close alignment with OWL description methods, and supports both forward and backward chaining. Therefore, this paper adopts Jena rules for conceptual expansion reasoning.

2.3 Semantic Similarity

Semantic similarity refers to the degree of similarity between two concepts [17] and has been applied in word sense disambiguation [34], automatic retrieval [35-36], image classification and annotation [37-38], information extraction [39], information retrieval [40-41], and other domains. Calculation methods can be categorized into distance-based, content-based, and attribute-based approaches. Distance-based methods quantify semantic distance between two concepts using path length in hierarchical networks [42]. Greater semantic distance (i.e., longer path length) yields lower similarity. In such networks, all directed edges are assigned a weight of 1, treating all nodes as equally important, enabling calculation of semantic distance based on the number of directed edges forming the shortest path. However, this model' s assumption of uniform edge weights overlooks factors like node position, type, and association strength that affect importance in practice. Scholars have improved upon this model; for instance, Leacock et al. considered the depth of the ontology classification tree' s impact on concept similarity, proposing an improved calculation model [43]. Content-based methods [44] posit that shared information between concepts influences their semantic similarity. In hierarchical networks, child nodes refine and specify their parent nodes, inheriting parental information content, thus enabling similarity calculation between child nodes based on the information content of their common parent.

Attribute-based methods [45] differentiate concepts through distinct attribute features—the more shared attributes, the higher the similarity. Therefore, conceptual semantic similarity can be computed via similarity between corresponding attribute sets. Nevertheless, these methods neglect ontology structural information, inadequately revealing semantic relationships between concepts and resulting in low structural precision of similarity calculations. The semantic similarity calculation method proposed in this paper incorporates three influencing factors—density, depth, and attributes—to more accurately compute conceptual semantic similarity.

3.1 Recommendation Process

The digital literature resource recommendation method based on ontology rule reasoning and semantic similarity calculation expands user-input concepts into a set of similar concepts to enable fine-grained ontology querying. It calculates semantic similarity between expanded concepts and the semantic information inherent in literature resources, recommending highly similar documents to target users and thereby providing valuable personalized resource recommendation services. The constructed recommendation process is illustrated in Figure 1 [Figure 1: see original paper]. Initially, users input keywords, which undergo conceptual set expansion through domain ontology rule reasoning in the ontology knowledge base to obtain expanded query conditions. The resource layer performs domain concept extraction and creates ontologies based on extracted domain knowledge to establish the ontology knowledge base. The computation layer maps query conditions to ontology instances (using keyword matching methods) and calculates semantic similarity between the expanded concept set and resources. Finally, recommendations are ranked by relevance score, and top-ranked digital literature is recommended to target users.

3.2 Algorithm Design and Implementation

Semantic Reasoning

Semantic reasoning employs synonymous semantic expansion with rules encompassing hierarchical relationships (hypernymy/hyponymy) and similarity relationships. RDF, as a Semantic Web ontology description language, standardizes a data model expressed in triple form. RDFS can represent simple terms and their relationships, such as class inclusion, property inclusion, and property domain/range. Inference rules described by RDF and RDFS exhibit characteristics of reversibility, transitivity, inheritance, and partiality. For example: `{v p w|p rdfs:domain u.}  v rdfs:type u. (rdfs2)`, and `{v p w|p rdfs:subPropertyOf q.}  v q w. (rdfs7)` [20].

OWL, as an extension of RDFS, resolves issues such as lack of support for cardinality constraints, Boolean class combinations, and property restrictions. OWL class and property reasoning rules specifically include `owl:sameAs`, `owl:intersectionOf`, `someValuesFrom`, and `allValuesFrom`. In OWL ontology definitions, `owl:sameAs` describes synonymous relationships, while `rdfs:subClassOf` describes hierarchical relationships, both possessing transitivity. For instance, if `(?x rdfs:subClassOf ?y)` and `(?y rdfs:subClassOf`

?z) exist, then (?x rdfs:subClassOf ?z) can be inferred. Similarly, if (?x owl:sameAs ?y) and (?y owl:sameAs ?z) hold, then (?x owl:sameAs ?z) follows. Although the relationship between x and z is not explicitly defined, the inference engine can derive their implicit relationship from these two direct definitions.

Jena, a Java framework for building ontology applications, supports parsing of ontology description languages including RDF, RDFS, and OWL, processing of RDF files and models, persistent storage of RDF models, and rule-based reasoning. Jena provides rule-based reasoners (e.g., RDFS Reasoner, OWL Reasoner) encompassing transitive reasoning, RDFS rule reasoning, OWL-Lite reasoning, as well as generic rule reasoning and third-party inference engine integration. Jena rules bind to rule reasoners, which connect to models or schemas via `bindSchema` calls [30]. Due to its comprehensive functionality, Jena is selected for reasoning with the rules defined in this paper.

The following presents partial custom production rules for computer reasoning:

```
@prefix computer: <http://www.xh.com/computer.owl#>.
@include <RDFS>.
@include <OWL>.

String rules = "[Rule1: (?x rdfs:subClassOf ?y), (?y rdfs:subClassOf ?z) -> (?x rdfs:subClas

// Create corresponding reasoner based on custom inference rules
Reasoner reasoner = new GenericRuleReasoner(Rule.ParseRules(rules));

// Create inference model containing inferred relationships based on custom reasoner
InfModel inf = ModelFactory.createInfModel(reasoner, rawData);
```

Semantic Similarity Calculation

In the ontology hierarchical network formed by domain ontologies, child nodes refine parent node concepts, with child node meanings being more specific than their parents. Consequently, deeper concept positions and greater surrounding node density indicate richer information content. When child and parent concepts share more common attributes in the network, their relationship similarity increases, warranting larger directed edge weights. Based on this principle, this paper proposes a semantic similarity algorithm as shown in Formula (1), incorporating three influencing factors: hierarchical depth, regional density, and conceptual attributes.

The semantic similarity between concepts p1 and p2 is calculated as:

$$sim(p_1, p_2) = \alpha \times \text{DepthFactor} + \beta \times \text{DensityFactor} + \gamma \times \text{AttributeFactor}$$

Where: - DepthFactor incorporates $D(Anc(p_1, p_2))$ and $\min(D(p_1), D(p_2))$ -

DensityFactor involves path length and information content $IC[Anc(p_1, p_2)]$ - AttributeFactor uses $N(attr(p_1) \cap attr(p_2))$, the number of common attributes of p_1 and p_2 - $\alpha + \beta + \gamma = 1$ are weighting parameters - N_{all} is the total number of nodes - $N_{anc}(p_1, p_2)$ is the number of common ancestor nodes of p_1 and p_2

The improved ontology-based semantic similarity algorithm is described as follows:

```
Input: Abstract concept term set ACS
Output: Literature resources to be recommended and their similarity scores

Begin:
  For each ig   abstract concept term set ACS
  Find concepts similar to term ig in the Glossary table and store them in A1, and place dig
// Glossary table contains all concepts from the ontology constructed in this paper
  While count(A1) $\neq$ 0 && count(A2) $\neq$ 0
  Retrieve one concept from array A1 and one from array A2, then calculate their similarity
  If sim(ig, ig1) > threshold
  Do: Expanded abstract concept term set EACSig = EACSig   ig
  Simvalue = Simvalue + sim(ig, ig1)
Endif
Endwhile
```

Recommendation Method Design

The recommendation method proposed in this paper can be represented by the following pseudocode:

```
Input: User query concept C
Output: Digital literature resources matching user requirements

Begin
  Obtain input concept c
  Perform semantic reasoning via Jena to obtain expanded concept set C = {c1, c2, ⋯}
  Query the resource repository for literature resources containing any concept from S(C), f
  Calculate relevance between the expanded concept set and the concept set describing litera
  Compute recommendation score using formula Recd = Simvalue / N // N represents the number
  If Recd exceeds threshold
  Do: User specifies recommended resource quantity r
Recommend r resource items to users ranked by recommendation score
Endif
```

4.1 Ontology Construction

The conceptual terminology used in the computer domain ontology constructed for this study primarily derives from the *Encyclopedia of Computer Science and Technology* [46] and the *Chinese Library Classification* [47]. The former includes comprehensive computer science terminology with broad coverage, standardized classification and definitions, and strong authority, making it an ideal reference for constructing the computer domain ontology. Using the OntoGraf function in Protégé , visual representations of the constructed ontology can be displayed. A visual association graph centered on computer science is shown in Figure 2 [Figure 2: see original paper].

The computer domain ontology constructed in this paper contains over 1,000 searchable computer domain concepts, attributes, and their interrelationships.

4.2 Algorithm Experiment

Similarity Verification

This study calculated semantic similarity for ten groups of representative concepts and conducted comparative experiments with methods proposed in literature [42-43]. Additionally, to validate experimental effectiveness, manual semantic similarity judgments were obtained through consultation. Participants included 20 master' s and doctoral students majoring in computer science and information science, who evaluated semantic similarity of the concept pairs. The evaluation range was [0,1], where 0 indicates completely different concepts and 1 indicates identical semantics. Two trials were conducted for both professional and non-professional subjects, with evaluation results averaged.

Table 1 presents the concept semantic similarity calculation results. Sim1 and Sim2 represent results calculated using methods from literature [42-43], while Sim3 shows results from the proposed method, with the final column indicating manual judgments.

Analysis of Table 1 reveals that for the first five rows, all three algorithms produce results largely consistent with human judgment. However, for concepts with high node density or numerous common attributes, existing methods yield unreasonable similarity calculations, whereas the proposed method accurately computes conceptual similarity, aligning computational results with subjective human judgment.

Recommendation Verification

To evaluate the recommendation method, 800 computer science domain documents were downloaded from CNKI as the dataset, each containing titles, abstracts, and keywords. Since keywords describe article themes, they were selected as semantic descriptors. The F-measure was used to compare recommendation effectiveness across datasets. The F-measure [48] comprises precision and recall, where higher F-values indicate better recommendation performance.

F = 2 × Precision × Recall / (Precision + Recall)

Precision and recall are calculated as:

Precision = Number of recommended digital literature resources meeting user needs / Total number of recommended digital literature resources

Recall = Number of recommended digital literature resources meeting user needs / Total number of digital literature resources

Experimental results are shown in Table 2 . The results indicate that F-values from the proposed method improve as literature quantity increases. By fully considering structural ontology features such as concept density and attributes in the ontology knowledge base, the proposed conceptual similarity calculation method more accurately reflects semantic similarity between literature resources, enriches resource semantic information, enhances semantic relevance computation, and provides effective recommendations to target users.

The study is limited by insufficient collection scale and content richness of literature resources, plus subjective user judgment of recommendation accuracy. For comparative effectiveness, recall was fixed at 0.5 without increasing with test literature quantity, contributing to lower F-values compared to existing algorithms. Therefore, improving F-values and enriching recommended literature resources represent future research priorities.

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Author Contributions

Bi Qiang: Proposed the research proposition and research methodology
Liu Jian: Paper writing, data processing, and empirical research
Liu Qingxu: English abstract writing and revision
Wang Fu: Abstract writing and paper revision

Supporting Data

Supporting data is self-archived by the authors, E-mail: tomosliu9999@126.com.
[1] Liu Jian, Bi Qiang. Glossary.csv. Ontology concept collection.
[2] Liu Jian, Bi Qiang. CNKI.resources.sql. CNKI downloaded resource database file.
[3] Liu Jian, Bi Qiang. Similarity.doc. Similarity survey form.

Conflict of Interest

All authors declare no conflict of interest.

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