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RESEARCH ARTICLE

An Improved Fusion-Based Semantic Similarity Measure for Effective Collaborative Filtering Recommendations

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Abstract

Semantic-enhanced recommendation systems are promising approaches to overcome the sparsity and cold-start problems, which are hard to handle using the conventional collaborative filtering (CF) approaches. Further research is needed to effectively integrate ontologies into collaborative filtering recommender systems. This paper proposes an ontology-based semantic similarity measure to evaluate similarities between items and eventually generate accurate recommendations. The proposed semantic similarity measure termed fusion-based semantic similarity takes into account the semantics of ontological instances (i.e. items) inferred from a specific domain ontology, which is determined by analyzing the hierarchical relationships among the instances, as well as the features of the instances and their relationships to other instances. The new measure comprehensively captures the semantic knowledge associated with instances by exploiting all possible shared semantics between instances in a given domain ontology. Furthermore, this paper proposes a new semantic-enhanced hybrid recommendation approach as a result of combining the new semantic similarity measure with the standard item-based CF to enhance the quality of generated recommendations. In order to assess the effectiveness of our semantic-enhanced hybrid collaborative filtering method, a series of experiments were conducted to compare the performance of the proposed approach against well-established benchmark techniques. The reported experimental results consistently emphasize its superiority, demonstrating enhanced predictive abilities and a notable improvement in the quality of recommendations. More specifically, the proposed approach achieved notable 6% reduction in Mean Absolute Error (MAE) in certain cases, outperforming other benchmark techniques. Additionally, this study highlights the potential of using semantic-based similarity to enhance the performance of recommendation systems. Such enhancements address challenges within collaborative filtering, potentially leading to advancements in recommendation system design and optimization.

Keywords Semantic similarity · Ontology · Recommender system · Collaborative filtering · Personalization services

1 Introduction

With the rapid development of Internet and Web technologies, the volume of online information is increasing across various domains, such as e-commerce, e-government, and e-learning applications. Recommender Systems (RSs) have emerged as effective tools for assisting users in quickly and efficiently finding the information they need within the vast amount of content available online. In recent years, Recommender systems have gained significant importance as a crucial research area within information retrieval and decision support systems. Recommender systems employ information filtering techniques, primarily focused on predicting whether a specific user will be interested in a particular item or identifying a set of items that align with a user's preferences [1–4].

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Numerous filtering recommendation techniques have been proposed in the literature to enhance Recommendation Systems. Major recommendation techniques include Content-Based Filtering (CB), Collaborative Filtering (CF), Knowledge-Based Filtering, and Hybrid Recommendation, which is a combination of two or more recommendation techniques [1, 2]. Although CB and CF approaches are more popular in practical applications, both suffer from some limitations. For instance, the CB filtering approach tends to result in overspecialization with which the diversity in the recommendation results eventually vanishes, while the CF approach suffers from data sparsity and scalability problems. Moreover, both approaches encounter a significant challenge known as the 'cold-start problem'. This problem arises when making recommendations to new users and/or items for which the available information is limited. As a result, the recommendations offered in such cases tend to be of poor quality and lack usefulness. On the other hand, hybrid recommendation approaches can enhance recommendation quality and address the primary limitations of traditional approaches. Most hybrid recommendation approaches involve combining CF with other recommendation approaches [2, 3, 5, 6].

The quality of recommendations heavily relies on the similarity measures used to compare items or users. With respect to early recommendation techniques, similarity measures primarily relied on examining the content descriptions and user profiles, often ignoring to consider meaningful aspects that had the potential to greatly improve the accuracy of recommendations [6–10].

In recent recommendation research works, the incorporation of semantic enhancement based on semantic similarity has received increasing attention, with research findings showing promising results [4, 11–15]. Semantic-enhanced recommendation techniques have the potential to provide more accurate recommendations by integrating semantic information from user and/or item profiles into the recommendation process. These techniques mainly utilize Semantic Web technologies, including ontologies and semantic reasoning, to improve the similarity assessments used in traditional CB and CF approaches.

To address the gap between early and recent recommendation research, four primary hybridization techniques can be identified: (i) augmenting domain knowledge represented in ontologies with item-based CF to enhance similarity estimations [14, 16], (ii) enhancing the conventional user-based CF approach by incorporating semantic information from ontologies [17–20], (iii) combining user-based and/or item-based CF with semantic-enhanced Content-Based filtering [9, 13, 21], and (iv) integrating semantic user-based and/or item-based CF with semantic-enhanced CB filtering [12, 22].

Through an extensive literature review, it was observed that existing semantic similarity measures employed to enhance CF recommendations primarily rely on direct hierarchical (i.e., taxonomical) relationships among items and their semantic descriptions, as defined by ontological data type and object properties. While progress has been made in developing efficient strategies for semantic similarity estimations, limited attention has been given to reasoning about indirect relationships between ontological instances (i.e. items). Such indirect relationships have the potential to uncover hidden connections between seemingly disparate entities, enabling a richer semantic representation. This, in turn, facilitates semantic analysis of heterogeneous content, revealing valuable insights into the similarities and differences between ontological instances.

In this paper, the primary focus is the integration of semantic knowledge, represented within an ontology, into the item-based CF recommendation approach to enhance the item similarity estimations and recommendations quality. Consequently, a new ontology-based semantic similarity measure and semantic enhanced hybrid recommendation approach are proposed. The proposed approaches aim to bridge the gap between Semantic Web technologies and their practical implementation in recommendation systems. It contributes to the existing literature and offers direction for developing more effective and practical semantic-based recommendation systems.

The rest of this paper is organized as follows. Section 2 briefs the background and related work. Section 3 presents the new ontology-based semantic similarity measures along with an illustrative example. Section 4 presents the proposed semantic-based CF approach using the new SS measure. Section 5 outlines the experimental design and procedure. Section 6 demonstrates the experimental scenario results and discusses the main findings. Section 7 concludes and highlights particular future work directions.

2 Background and Literature Review

The notion of an ontology, as defined by Gruber [23], refers to an "explicit specification of a conceptualization." Subsequently, different definitions of ontology are presented, Borst [24] defined an ontology as a "formal specification of a shared conceptualization". Ontology is also defined as a "knowledge domain conceptualization into a computer processable format, which axioms" [25]. The use of ontologies allows for semantic access to information in complex environments, providing an effective means of representing and describing information at a high level of abstraction [23].

Ontologies serve as valuable tools for formally modeling the structures of domain systems based on observed relationships. One of the main goals of using ontologies is to model the information at the semantic level [26]. Consequently, ontology has a growing interest in different applications such as semantic information retrieval, information integration, semantic web service discovery and matching, text mining, e-learning as well as web-based personalized applications and recommendation systems [10, 15, 27–29].

Recommendation systems highlight the significance of ontologies as they provide a structured and clear representation of knowledge in a precisely defined format. By utilizing this valuable semantic knowledge, decision-making processes can be significantly improved. Furthermore, this approach enables us to provide more informed and precise recommendations. In essence, it empowers decision-makers with richer information, facilitating better informed choices and more accurate recommendations. [7, 11, 12, 27, 29]. Integrating ontological semantic knowledge into the recommendation process takes various forms, with a common emphasis on evaluating the semantic similarity between items or users in order to enhance recommendation accuracy [9, 12–14, 16, 18, 20, 28, 30, 31]. In the subsequent section, a comprehensive review of research studies exploring semantic similarity strategies, in alignment with the utilization of a domain ontology, is presented.

2.1 Semantic Similarity Using Ontology

Based on an extensive literature review, semantic similarity approaches for evaluating ontological concepts can be classified into three main categories: distance-based, information-theoretic (IC), and feature-based approaches [32–35].

Distance-based approaches assess concept similarity within a specific taxonomy by considering the distance or edge length between them. One well-known measure is the shortest path approach, where shorter paths indicate greater similarity [36]. Wu and Palmer [37] proposed a measure that incorporates the relative depth of concepts within a reference taxonomy. Subsequently, several distance-based similarity measures have been developed to enhance similarity calculations [32, 35, 38, 39].

Although distance-based metrics offer simplicity and computational efficiency due to their reliance on taxonomy construction, they are subject to limitations reported in the literature [29, 38–42]. Distance-based metrics heavily depend on the specific taxonomy and are influenced by subjective decisions during taxonomy engineering. Moreover, distance-based approaches exhibit limited reliability in distance calculation due to their assumption of uniform distances between edges in a taxonomy structure [43, 44].

Resnik [45] proposed the Information Content (IC) approach as an alternative to distance-based methods, aiming to address the limitations and unreliability of such metrics. The IC approach relies less on detailed taxonomy structure and instead measures conceptual similarity based on shared information between two concepts. The more shared information, the greater the similarity. Resnik [45] suggests that the concept of the Least Common Ancestor, encompassing both concepts in the ontology's taxonomy, can effectively represent this shared information. Building on Resnik's work, Jiang and Conrath [46] refined the measure by combining the IC approach with a distance-based methodology. Their approach surpasses the semantic similarity measures proposed by Resnik [45] and Rada et al. [36].

Lin [47] expanded upon Resnik's Information Content (IC) measure by introducing the concept of commonality information. Lin's enhancement suggests that the similarity between two concepts is determined by the extent to which they share information. In this approach, Lin incorporated not only the IC of the Least Common Ancestor of the compared concepts but also included the IC values of the concepts themselves in the measurement. Conventional IC methods combine hierarchical structure and usage statistics to compute IC values, which can be computationally expensive. Seco et al. [41] proposed an intrinsic measure that relies solely on the hierarchical structure (taxonomy) without involving statistics. This approach experimentally outperforms traditional IC similarity methods.

In feature-based approaches, the representation of concepts to be compared is done through a set of features. These features encompass various information elements such as the concept's neighborhood (ancestors, descendants, and siblings), synonyms, attributes, functions, and more. The utilization of such measures effectively addresses the limitations observed in previous measures [33, 43, 44, 48, 49].

In recent research endeavors, particularly in the field of recommender system applications, an increasing number of studies have embraced the integration of multiple semantic similarity approaches. The objective behind this integration is to enhance both the accuracy and efficiency of the systems. This type of combination is commonly referred to as hybrid semantic similarity. The resultant composite similarity measure typically combines two or more combinations of distance-based methodologies, IC-based approaches, and feature-based techniques, leveraging domain-specific data in diverse ways [27, 29, 30, 32, 42, 50]. A study conducted by Lastra-Díaz et al. [32] and Hussain et al. [44] provides a detailed categorization of semantic similarity measures.

2.2 Semantic Collaborative Filtering Recommendation

In the domain of recommendation systems, collaborative filtering is the most successful technique [1–4, 51]. It is based on the assumption that finding people with similar interests and recommending items that they like in an effective way to provide interesting content. Collaborative filtering works with user-item historical data, where each user rates items based on their preferences. Collaborative filtering methods require past user ratings to predict and recommend items. The prediction process involves calculating similarities between users and items using distance measures. Collaborative filtering can be categorized into user-based and item-based approaches. Both approaches use user-item rating data to compute similarity for making recommendations. However, item-based algorithms focus on exploring relationships between items rather than relationships between users, resulting in distinct prediction computations compared to the user-based approach. Despite being widely used in practice, collaborative filtering (CF) approaches have several limitations such as data sparsity and the cold-start problem for new items and users. These limitations negatively impact the quality and accuracy of recommendation predictions.

Researchers have frequently chosen to employ hybrid recommendation filtering to achieve improved recommendation quality while also mitigating the limitations associated with traditional Collaborative Filtering (CF) recommendation approaches. One stream of hybrid recommendation filtering focuses on combining CF filtering algorithms with other RSs techniques, specifically content-based filtering. Another stream of hybrid recommendation research has emerged, called semantic-based hybrid filtering, in which it focuses on incorporating the underlying semantics of users or items in the recommendation process [4, 8, 15]. Such hybrid filtering utilizes semantic Web technologies and features, specifically ontologies, as means that can allow RSs to extract useful knowledge about users or items, which ultimately leads to producing effective predictions. The focus of this study is on utilizing semantic knowledge extracted from oncology along with item-based CF, thus a review of related research studies has been conducted within this scope.

Ontology has demonstrated its effectiveness in addressing certain limitations of collaborative filtering algorithms. Its implementation has shown promising results in improving recommendation system accuracy and alleviating the challenges posed by new item cold-start problems and sparsity.

To improve the accuracy and reliability of collaborative filtering recommendations within e-commerce, Martín-Vicente et al. [17] presented a new strategy based on an ontology, which encapsulates the semantic representation of commercial goods. The exploitation of semantics enables reasoning about the data stored in the users' profiles and inferring new knowledge. Such new knowledge enhances recommendations in two ways: by refining neighborhood selection based on candidate trustworthiness and by adjusting the prediction process to value contributions from more experienced users.

Martín-Vicente, et al. [52] introduced an improved hybrid approach for recommending products in the e-commerce domain. Their hybrid approach mainly avoids selecting fake neighborhoods in collaborative filtering recommender systems with diverse products. The authors adopted a new strategy, which implements a semantic procedure for calculating the similarity between users, based on a measure of the semantic similarity between the products they have rated, aiming to enhance flexibility in similarity detection and reduce the sparsity of CF. By using the hierarchical structure of an ontology, the strategy intelligently categorizes products and determines their similarity based on how close they are to the hierarchy and how many common ancestors they have. This structure also helps to choose the best level of abstraction needed to form neighborhoods.

Tarus et al. [13] proposed a hybrid knowledge-based recommendation approach, which integrates ontology and sequential learning patterns for recommending learning resources to learners. Ontology encapsulates knowledge about learners and resources, while a sequential pattern mining algorithm is applied to discover the learner's historical sequential learning patterns. Collaborative filtering is employed to compute similarities of ratings and make predictions for a target learner. The findings of this approach show its effectiveness in addressing the cold-start problem using ontology-based domain knowledge. Additionally, it overcomes sparsity by leveraging learners' sequential patterns, ensuring accurate predictions even with a few ratings.

Kermany and Alizadeh [22] proposed a novel hybrid recommendation approach that combines ontological semantic CF filtering with user demographics in multi-criteria recommendations for movie recommendation purposes. The Jaccard metric and cosine similarity are used to compute user-based and item-based similarities for accurate predictions. The semantic similarity is computed by considering taxonomy-based relations between movie items. The data sparsity problem is tackled by blending these similarities with optimized weights obtained through a gradient descent algorithm.

Nilashi et al. [14] proposed a hybrid recommendation approach by integrating CF and dimensionality reduction. An ontology is used in order to describe the semantic relations between concepts. Only the taxonomy-based relations are considered to compute semantic similarity between items. Their approach was tested in the movie recommendation domain, showing enhanced recommendation accuracy.

A new hybrid recommendation approach proposed by Bagherifard et al. [12] uses ontology to improve new item suggestions. It combines collaborative and content-based filtering, refining ontology structure and semantic similarity measurement for better accuracy. The refined semantic similarity measure is enhanced by removing uniformity in hierarchical relationships between concepts in item ontology. The similarity is computed by Enhanced clustering driven by ontology reduces search needs for similar clusters and users.

According to Chew et al. [21], they discovered that incorporating ontology significantly boosted the accuracy of the matrix factorization model. This enhancement was achieved by merging item-based and user-based collaborative filtering techniques to enrich the user-item matrix with additional data. This enriched dataset combined semantic similarity with user ratings, addressing the "cold start" problem in recommender systems, where there's limited data for new users/items.

The noticeable features so far of related research studies are focused on incorporating semantic knowledge along with CF in different aspects. Some research studies combine knowledge of content (i.e. items) with the traditional item-based CF approach as in [16, 17, 19]. Other research studies incorporate semantic knowledge of items with the user-based CF approach [19, 20, 22, 30, 52, 53]. Moreover, combining user-based or item-based CF approaches with semantic-enhanced CB filtering was adopted as effective research in recommender systems [9, 12]. Lastly, other streams of studies focus on combining semantic knowledge along with CF and data mining models [13, 14, 21].

While the incorporation of semantic knowledge has certainly enhanced the recommendation techniques previously mentioned, its utility remains relatively limited and the research in this area is still open. This is mainly because the ontological connections between instances are not always effectively addressed, and only a few research endeavors have tackled this issue.

While existing studies have incorporated semantic knowledge with CF in various aspects [16, 17, 19], and different streams of research explore combinations of user-based or item-based CF with semantic-enhanced content-based filtering [9, 12], our work introduces a novel fusion-based semantic similarity measure. This measure, integrated with item-based CF, aims to evaluate item similarities within a specific domain ontology, addressing gaps in the current literature regarding the effective handling of ontological relationships between instances. The proposed approach enhances the depth of semantic assessment, focusing on explicit hierarchical relationships among items, shared attributes, and implicit item relationships.

Our research contributes to the state-of-the-art by introducing an innovative fusion-based semantic similarity measure and integrating it with the standard item-based Collaborative Filtering (CF) similarity. By leveraging refined semantic similarity measures offered by ontology, our hybrid recommendation approach aims to provide more accurate and high-quality recommendations.

In the following sections, we will provide a thorough explanation of both the semantic similarity measure and the hybrid recommendation approach.

3 The Proposed Semantic Similarity Measure

This section presents the proposed semantic similarity measure, motivated by Resnick's 1995 assumption of semantic similarity, which suggests: "the more information two concepts share in common, the more similar they are". To achieve this assumption, the proposed semantic similarity measures focus on exploring all possible shared information between items that are defined in the considered domain ontology, to effectively estimate their similarity. The proposed measure, entitled "fusion-based semantic similarity measure", takes into account three kinds of semantic knowledge: (i) taxonomy-based knowledge, (ii) content-based knowledge, and (iii) inference-based (i.e., implicit) knowledge. The taxonomy-based knowledge is utilized to compute the similarity of items based on their hierarchical positions in the considered taxonomy of specific domain ontology. The content-based knowledge is utilized to compute the similarity of items based on their common semantic description as defined in the considered domain ontology using OWL datatype properties. The implicit-based knowledge is utilized to compute the similarity of items through reasoning extensively their semantic description (i.e. object properties) to infer hidden relationships that might be useful for computing similarity.

Beyond these kinds of semantic knowledge, the proposed semantic similarity measure consists of three types of similarity measures including (i) hierarchical-based similarity (ii) attribute-based similarity, and (iii) inferred-based similarity. The proposed semantic similarity measure is termed a fusion-based semantic similarity measure.

To illustrate the proposed fusion-based semantic similarity measure and its comprised metrics, this section first introduces a formal description of the ontology model and definition and then describes the proposed semantic similarity measure.

3.1 Ontology Model Definition

An ontology is defined as "a set of representational primitives that are relevant for modeling a domain of knowledge or discourse. These primitives typically consist of a set of concepts or entities within a domain, relationships among these concepts, and attributes that distinguish each concept" [23]. A formal definition of ontology structure, as introduced by Maedche and Zacharias [31]:

Definition 1 (*Ontology*) An ontology structure is a six-tuple $O := < C, P, A, H^c, prop, att >$, where C represents the concept set defined in O; P is a set of relationships defined in O, each ($p \in P$) has a domain and range which are at least one concept of the set C; A is a set of attributes defined in O; H^c is a directed transitive relation $H^c \subset C \times C$ which is also called concept taxonomy, $H^c(c_2, c_1)$ means c_2 "*is-a*" c_1, or c_2 is a sub-concept of c_1; *prop* is a function, i.e. $prop : P \rightarrow C \times C$, that relates concepts non-taxonomically, e.g. the function $prop(p_1) = (c_1, c_2)$ means that the concept c_1 is related to the concept c_2 through p_1; and *att* is a function, i.e. $att : A \rightarrow C$, that relates concepts with literal values such as string, integer, Boolean, etc.

In OWL domain ontology, concepts are linked either directly through asserted relationships or indirectly through implicit relationships. Asserted relationships are explicitly defined by ontology developers within a specific domain. Implicit relationships, on the other hand, are generated through reasoning based on asserted relationships, aiming to formulate valuable knowledge about the domain. Asserted relationships encompass two primary types: taxonomical (hierarchical) and non-taxonomical relations. Taxonomical relations denoted as H^C in Definition 1, establish hierarchical links among all concepts within a particular domain. These relations are often represented in a hierarchical tree structure, where one class is identified as a subclass of another. Conversely, non-taxonomical relations are explicitly established using OWL properties for each concept, describing their various characteristics, attributes, interconnections, restrictions, and other logical assertions available within the OWL ontology.

A detailed description of semantic similarity measures is presented in the subsections below.

3.2 Hierarchical-Based Similarity

The hierarchical-based Similarity aims to compute the similarity between instances in a domain of ontology with respect to the concepts that they belong to in the hierarchical structure H^c. The hierarchical structure H^c is generated using semantic reasoning. In this study, Protégé editor is employed as a platform to develop OWL ontology for the considered domain (i.e. recommending movies). Under this platform, Pellet descriptive logic reasoner is used to generate class hierarchy by automatically classifying whether or not one class is a subclass of another class, it uses the description of the classes to determine if a super-class/subclass relationship exists between them [54].

Hierarchical-based similarity computes the similarity between ontology instances based on their positions within the taxonomy structure (H^c) representing concepts. This study incorporates the similarity metric proposed by [55], which was originally extended based on the work done by Seco, et al. [41], to assess instances' similarity. Thus, for two instances I_x and I_y, their hierarchical-based similarity, denoted as $Sim_H(I_x, I_y)$, is calculated as follows:

$$Sim_H(I_x, I_y) = IC\left(LCA_{I_x,I_y}\right), \tag{1}$$

where $IC(LCA_{I_x,I_y})$ denotes intrinsic IC of given two instances I_x and I_y, which is obtained with regard to their Least Common Ancestor (LCA) of concepts that subsumes them in the considered H^c. Considering the fact that the instances in OWL ontology may have more than one parent concept, we define LCA_{I_x,I_y} as the most informative LCA for I_x and I_y, which is the pair of parent concepts that has the highest IC. For example, if the parent set of two given instances I_x and I_y is $\{c_1, c_2\}$ and $\{c_3\}$, respectively, the LCA_{I_x,I_y} can be expressed as follows:

$$max\left(IC\left(LCA_{c_1,c_3}\right), IC\left(LCA_{c_2,c_3}\right)\right), \tag{2}$$

The IC of a concept can be calculated as follows:

$$IC(c) = 1 - \frac{\log(hypo(c) + 1)}{\log(max_{cons})}, 0 \leq IC(c) \leq 1 \tag{3}$$

where c is a concept in H^c, *hypo* is a function that returns the number of hyponyms[1] of a given concept c and max_{cons} is the number of concepts that exist in the taxonomy under consideration H^c.

[1] *Hyponymy* involves specific instantiations of a more general concept. On another word, the hypo of a concept c denotes the number of its direct subclasses.

3.3 Attribute-Based Semantic Similarity Metric

Attribute-based semantic similarity measures the similarity among ontology instances based on their shared attributes, defined using OWL datatype properties. These properties connect individuals to data values like strings, integers, Booleans, times, and dates. For example, in the Movie dataset ontology, we have properties like "movie's name," "movie's audience," and "movie's actors."

In OWL ontologies, instances can have literal datatype values, which come in various types like interval-scaled, binary, nominal, ordinal, ratio, or mixed. Each data type requires a different approach when calculating similarity. In this study, detailed similarity metrics for each data type are explored, and the Jaccard coefficient, as outlined in [56], is employed to compute the attribute-based semantic similarity.

For two instances I_x and I_y, N is the set of their common datatype properties, their attribute-based similarity, denoted as $Sim_{attr}\left(I_x, I_y\right)$, is defined formally as follows:

$$Sim_{attr}\left(I_x, I_y\right) = \frac{\sum_{p_{i\in N}} AttrSim_{p_i}\left(I_x, I_y\right)}{N}, \tag{4}$$

where $p_i \in N$ denotes each datatype property p_i belongs to the set of common datatype properties N, $AttrSim_{p_i}(I_x, I_y)$ function represents the attribute similarity between instances I_x and I_y concerning the datatype property p_i. It is important to note that formula (4) yields a result of zero when both instances do not have any shared datatype properties.

The similarity function in Formula (4), $AttrSim_{p_i}\left(I_x, I_y\right)$, varies based on the data type of the property p_i. In the considered case study, which is the Movie dataset, we focus on nominal (categorical) datatype properties, which generalize binary data by allowing multiple values. Thus, we employ the Jaccard coefficient [56], a commonly used measure for asymmetric information on binary and non-binary variables, to calculate attribute-based similarity between instances sharing common datatype properties.

3.4 Inferred Attribute-Based Semantic Similarity Metric

Inferred attribute-based semantic similarity aims to measure similarity between instances within a specific domain ontology by examining their shared OWL object properties. Object properties, as described in Definition 1, establish connections between instances of different concepts. These connections create chains of linked instances within a given OWL domain ontology. Starting with a particular instance in a chain, we can infer other instances by following the links along the entire chain. Consequently, exploring object properties among instances along the entire chain helps reveal implicit semantic relationships, which can effectively contribute to computing semantic similarity between instances. For example, in the considered Movie domain ontology, it is important to note that tracing any movie, as illustrated in, using any of its object properties could lead to the discovery of new movies that may share common information (i.e., data and object properties).

As an example, the similarity between "The Good Dinosaur" with "Rio2" movies is computed by comparing their datatype and object properties. Regarding the datatype property, the two movies are compared by comparing their values of each datatype property using Formula 4. Accordingly, three datatype properties will be compared, these properties include "hasAudience", "hasExperience" and hasPlotAspect". While object properties of two movies are compared based on their instances that are linked through the same object property. As shown in Fig. 1, three object properties are common between "The Good Dinosaur" with "Rio2" movies, including "isDirectedBy", "hasStar" and "hasGenre" object properties. As can be seen in Fig. 1, both movies have in common "hasStar" object property, "Steve Zahan", who is a star in "The Good Dinosaur" movie also a star in "Escape from Planet Earth" movie. While "George Lopez" is a star in "Rio" movie and he is also a star in "Escape from Planet Earth" movie. This indicates that new information, in this case, the "Escape from Planet Earth" movie, extracted by tracing the object property named "hasStar" could contribute to the total similarity between "The Good Dinosaur" and "Rio" movies. Further comparison between "The Good Dinosaur" movie and "Rio" movie will be carried out for the other object properties including the "isDirectedBy" and "hasGenre" to calculate the overall object properties similarities.

The inferred-based semantic similarity, denoted as $Sim_{infer}\left(I_x, I_y\right)$, for given two instances I_x and I_y, is defined formally as follows:

$$Sim_{infer}\left(I_x, I_y\right) = \frac{\sum_{i=1}^{M} Sim_{objpr_i}\left(I_x, I_y\right)}{M} \tag{5}$$

where M denotes the number of common object properties that are shared by I_x and I_y, $Sim_{objpr_i}\left(I_x, I_y\right)$ is the similarity between I_x and I_y with regards to the i^{th} object property ($i = 1,2, \ldots, M$) and is calculated as follows:

$$\begin{aligned} &Sim_{objpr_i}\left(I_x, I_y\right) = \\ &\frac{1}{L_i} \sum_{I_{x_l} \in R\left(obj\,\mathrm{Pr}_i, I_x\right), l=1}^{l=L_i} \left(\frac{1}{K_i} \sum_{I_{y_k} \in R\left(obj\,\mathrm{Pr}_j, I_y\right), k=1}^{k=K_i} \left(Sim_H\left(I_{x_l}^i, I_{y_k}^j\right) \right.\right. \\ &\left.\left. + Sim_{att}\left(I_{x_l}^i, I_{y_k}^j\right) + Sim_{\inf er}\left(I_{x_l}^i, I_{y_k}^j\right) \right)/3 \right), \end{aligned} \tag{6}$$

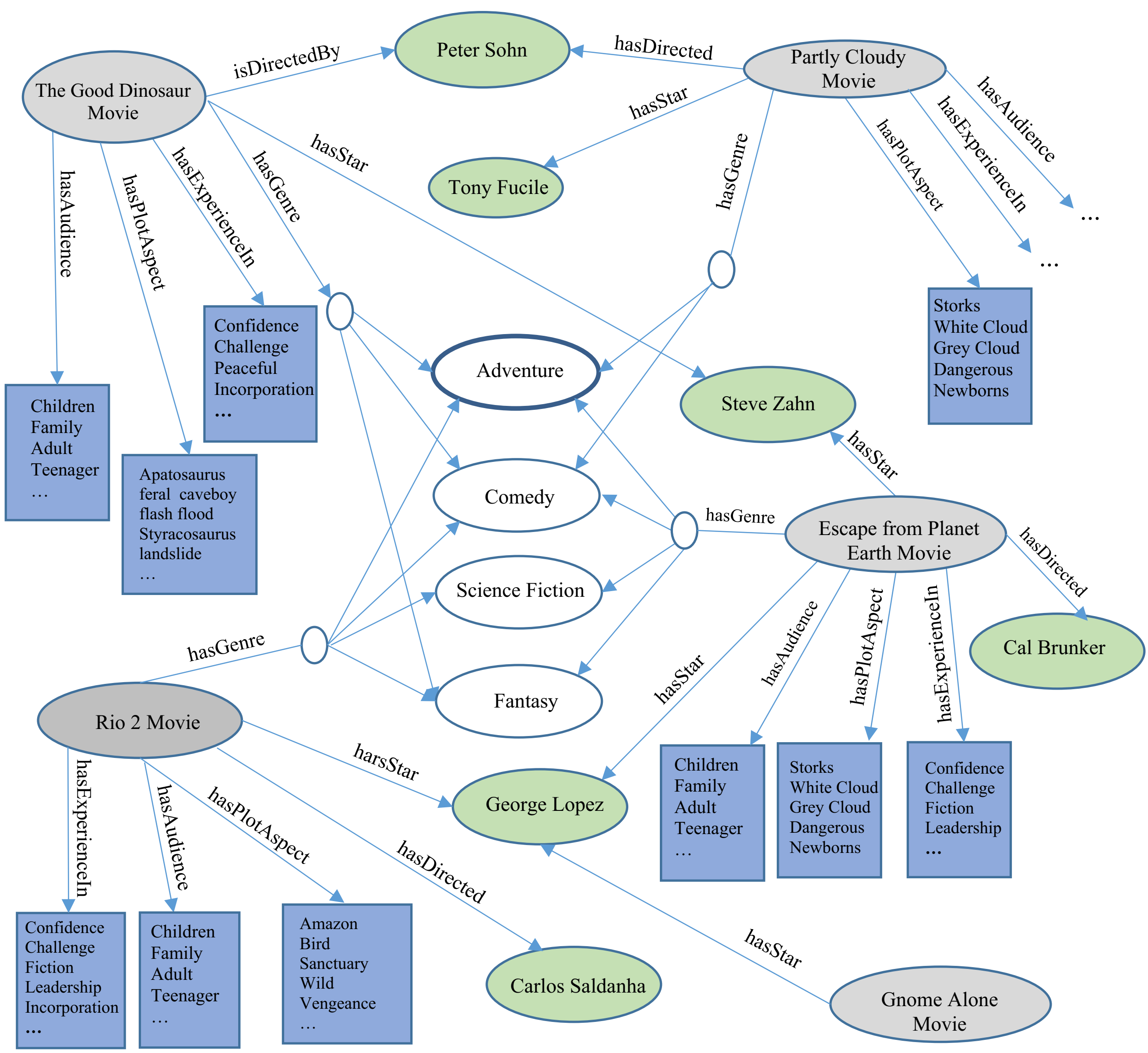


Fig. 1 Sample of the utilized the MovieLens ontology

where $R(objPr_i, I_x)$ and $R(objPr_i, I_y)$ denote the set of instances (i.e. object property range) for I_x andI_y, respectively. L_i denotes the number of instances in the range of I_x ($R(objPr_i, I_x)$) and K_i is the number of instances in the range of I_y ($R(objPr_i, I_y)$).

The calculation procedure of computing Inferred-attribute-based SS between a given two instances in specific domain ontology consists of the following steps:

Step 1: retrieve the instances that connected with I_x and I_y via object property range $objPr_i$, Suppose $\{I_x^1, I_x^2, ..., I_x^l\}$ and $\{I_y^1, I_y^2, ..., I_y^k\}$ sets are retrieved as $R(objPr_i, I_x)$ and R, respectively. Then, a set of elements, denoted as "*pair-instances-set*", is formed. Each element in this set represents a pair of corresponding instances from both mentioned sets, i.e. $\{(I_x^1, I_y^1), (I_x^1, I_y^2), ..., (I_x^1, I_y^k), \ldots, (I_x^l, I_y^1), (I_x^l, I_y^2), \ldots, (I_x^l, I_y^k)\}$.

Step 2: evaluate each pair of instances that formed the "*pair-instances-set*". For example, starting with the first pair of instances (I_x^1, I_y^1), the evaluation is performed by computing their hierarchical-based similarity and attribute-based similarity, as well as further evaluation is performed recursively on their corresponding common object properties. The evaluation of the respective pair, i.e. (I_x^1, I_y^1), continues till identical instances or instances with no common object properties are reached (i.e. to prevent infinite computation a maximum recursion depth is defined).

Step 3: The resulting computed similarity measures of the pair of instances $\left(I_x^1, I_y^1\right)$ are aggregated, as shown in Formula 7, along with the inferred similarity result of each traversed element in the "*pair-instances-set*".

Step 4: Repeat steps 1, 2 and 3 for all M common object properties between the instances I_x and I_y, as defined in Formula 6.

Step 5: calculate the final result of the Inferred-based SS measure between I_x and I_y, using Formula 6, as the average of inferred similarity measures obtained as a result of traversing all common object properties.

The inferred attribute-based similarity measure depends on a semantic reasoning strategy in which it recursively traverses each common object property between two compared instances. Such reasoning leads to infer all possible instances that might share similar properties; the more inferred instances the more similar the compared instances would be.

3.5 Fusion-Based Semantic Similarity Measure

In this study, a Fusion-based semantic similarity measure is developed to effectively evaluate similarity between instances. It aims to capture rich semantic knowledge of instances by exploiting all possible shared semantics between instances in a given domain ontology, in line with Resnik's principle that suggests "the more shared information between concepts, the greater their similarity". Accordingly, the Fusion-based semantic similarity measure integrates all the utilized semantic similarity metrics for calculating the semantic similarity between instances. Thus, it targets significant sources of semantic knowledge to define the similarity between instances, including their structural information, direct content knowledge that is defined using datatype properties, and implicit knowledge that is inferred using object properties.

The Fusion-based semantic similarity measure between a given two instances,I_x and I_y is computed as the proportional rate of three similarity measures including hierarchical-based similarity, attribute-based similarity, and inferred attribute-based similarity to a variable $\mathscr{F}$ named weight factor. The weight factor $\mathscr{F}$ indicates how much the similarity of each involved measure contributes to the similarity measure. The Fusion-based semantic similarity between I_x and is defined as follows::

$$FusionSim\left(I_x, I_y\right) = \frac{\gamma Sim_H\left(I_x, I_y\right) + \beta Sim_{attr}\left(I_x, I_y\right) + \lambda Sim_{\inf er}\left(I_x, I_y\right)}{\mathcal{F}}, \tag{7}$$

where γ, β, and λ are semantic parameters determined by the contribution of each involved similarity measure in total similarity using Formula 7. Semantic parameters γ, β, and λ are set to a constant value one. The weight factor $\mathscr{F}$ is assigned to summation values of semantic parameters γ, β, and λ. The $Sim_{Hier}(I_x, I_y)$ measure denotes the hierarchical-based similarity and is calculated using Formula 1, $Sim_{attr}\left(I_x, I_y\right)$ measure denotes the attribute-based similarity and is calculated using Formula 4 and $Sim_{infer}(I_x, I_y)$ measure denotes the inferred attribute-based similarity and is calculated using Formula 6. The fusion similarity of two instances ranges from 0 to 1, with higher similarity yielding values closer to 1.

4 The Proposed Semantic-Based CF Recommendation Approach

In this paper, we correspondingly proposed a new hybrid recommendation method called the "Fusion-based Semantic CF" approach. This approach combines traditional item-based collaborative filtering with fusion-based semantic similarity measures to enhance recommendation quality. This integration offers several advantages; it improves item similarity by incorporating ontology-based semantic knowledge alongside item ratings. It also addresses common issues in collaborative filtering, such as sparsity and cold-start items. Ultimately, this approach holds the promise of significantly boosting prediction accuracy in recommendations.

The framework of the proposed semantic-based improved collaborative filtering approach is presented in Fig. 2. It consists of four main phases. The first phase constructs the ontology repository of the considered domain. The other three phases form the computational procedure that is required to generate top-*N* recommendations. The procedure phases of the proposed Fusion-based semantic collaborative filtering are demonstrated in detail as follows:

4.1 Phase 1: Ontology Construction and Items Ratings Extraction

To empower a recommendation system, ontology construction and item ratings extraction must be undertaken. Using the Protégé editor, ontology repository, a structured knowledge base encompassing related concepts, relationships, and attributes, are constructed. We acknowledge the inherent complexity involved in constructing ontologies, and its feasibility within this context relies on well-defined domain ontology. This includes the utilization of appropriate tools, understanding dataset characteristics, and aligning with the primary goal of enhancing the recommendation system. The involvement of

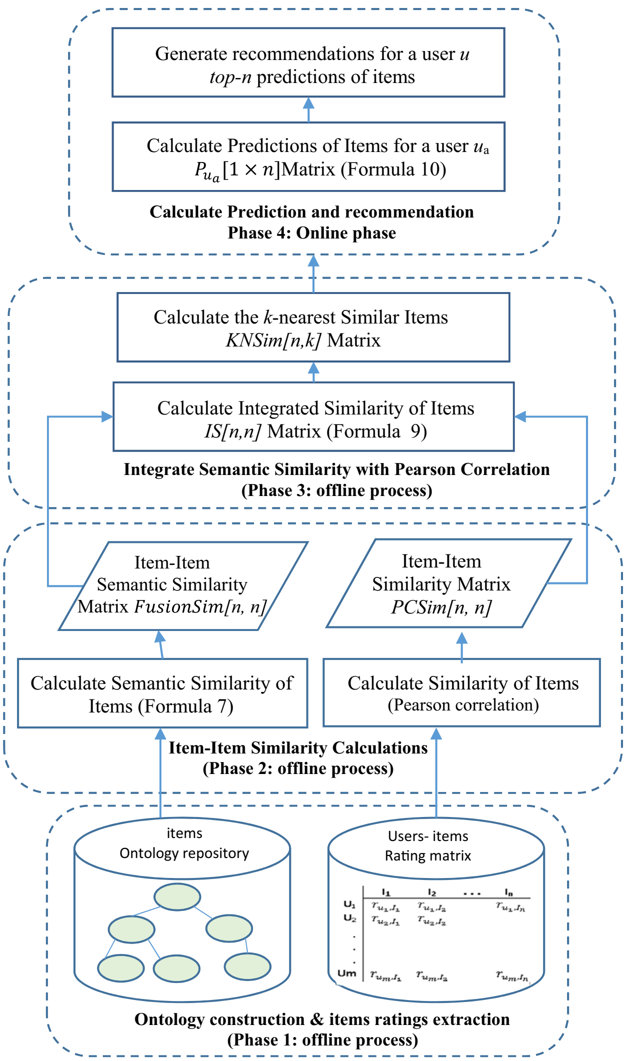


Fig. 2 The introduced framework of the proposed semantic-based improved collaborative filtering approach

domain experts becomes principal in ensuring the accurate representation of intricate relationships within the ontology. The knowledge repository, shaped by domain expertise, plays a pivotal role in enabling our system to comprehend the intricate connections within its designated domain. This process lays a robust foundation essential for generating context-aware recommendations.

Furthermore, the extraction of item ratings from the dataset under consideration is a crucial step in our proposed framework. This process involves creating users' ratings on items, which are then organized into a user-item rating matrix R[m×n] with m users and n items. These ratings play a pivotal role in collaborative filtering calculations, serving as a foundational component of our recommendation framework.

4.2 Phase 2: Calculate the Similarity of Items Including Semantic Similarity

This includes:

First, calculate item similarity using the Pearson correlation coefficient

In this step, we compute pairwise item similarities for all items in the dataset. In item-based CF, the similarity between items is computed according to users' ratings on items R $[m \times n]$. This study uses the Pearson Correlation PC coefficient to compute items' similarities, as it demonstrates its superiority in performance compared to other similarity measures. Suppose $U = \{u_1, u_2, \dots, u_m\}$ be the set of all users,$I = \{I_1, I_2, \dots, I_n\}$ be the set of all items, and U_{ij} be the set of users who rated items I_i and I_j together. The item-based CF similarity between a pair of items I_i and I_j using Pearson Correlation, denoted as $Sim_{PC}(I_i, I_j) : I \times I \to [-1, 1]$, is given in the following formula:

$$Sim_{PC}(I_i, I_j) = \frac{\sum_{u=1}^{|U_{ij}|}(r_{u,I_i} - \bar{r}_{I_i})(r_{u,I_j} - \bar{r}_{I_j})}{\sqrt{\sum_{u=1}^{|U_{ij}|}(r_{u,I_i} - \bar{r}_{I_i})^2}\sqrt{\sum_{u=1}^{|U_{ij}|}(r_{u,I_j} - \bar{r}_{I_j})^2}}, \quad (8)$$

where r_{u,I_i}andr_{u,I_j} represent the rating of user u on items i and j separately, and $\bar{r}_{I_i}$and$\bar{r}_{I_j}$ is the average ratings of all users $u \in U_{ij}$ on the i^{th}andj^{th} item, respectively. Thus, this step computes the similarity of each pair of items using users' opinions (ratings) and stores items' similarities resulting in a similarity matrix named $SimPC[m \times m]$.

Second, calculate semantic similarity with the proposed fusion-based SS measure

Unlike the first step which is used to find the similarity of each pair of items with regard to users' opinions (i.e. ratings), this step aims to compute similarity using the proposed Fusion-based semantic similarity measure. The semantic similarity degrees between each pair of items are calculated using Formula 7. The obtained similarities of pairwise items are stored in the item-item semantic similarity matrix denoted as $SimSem[m \times m]$.

4.3 Phase 3: Integrate Semantic Similarity with Pearson Correlation

In this step, the obtained similarities from the previous two steps of each pair of items are integrated linearly to create a combined similarity. An integrated similarity matrix, called $SemPCSim$[m × m], is created to store the combined similarity results of pairwise items. The integrated similarity of a pair of items I_i and, denoted as $TotalSim(I_i, I_j) : I \times I \to [-1, 1]$, is defined in the following formula:

$$IntegrSim\left(I_i, I_j\right) = \alpha \times FusionSim\left(I_i, I_j\right) + (1 - \alpha) \times Sim_{PC}(I_i, I_j), \tag{9}$$

where α is a semantic combination parameter specifying the weight of similarity measure in the integrated total similarity. If $\alpha = 0$, then the total similarity between I_i and I_j is attributed to the PC similarity, whereas, if $\alpha = 1$, then the total similarity between I_i and I_j is attributed to semantic similarity. Determining the optimal α value is dataset-dependent, and a sensitivity analysis is needed to select the best α value.

4.4 Phase 4: Generate Recommendations

This phase aims to suggest the most relevant items for users' interests and preferences. In recommendation systems, several prediction methods are used to compute predictions of users' ratings for unseen items (i.e. rating values between 1 and 5). However, the weighted sum method is employed in this study for computing the prediction of items' ratings, since it is commonly used in recommender systems research.

Considering the weighted sum method, the prediction of a user's rating for each un-rated item is calculated first by selecting the most similar items set to a target item I_i. Next, the intersection set between the set of rated items by the active user u_a and the most similar items set to the target item I_i is retrieved, this set is denoted as K_i. Finally, the prediction of a rating value is computed by summing up the ratings given by the active user to all those items in the intersection set, where each rating is weighted by the corresponding similarity between the target item I_i (which is un-rated) and the others rated items in the intersection set. The prediction value of an active user u_a on a target item denoted as P_{u_a,I_i}, is defined using the weighted sum method as shown in the following Formula:

$$P_{u_a,I_i} = \frac{\sum_{q=1}^{K_i} r_{u_a,I_q} \times TotalSim(I_i, I_q)}{\sum_{q=1}^{K_i} TotalSim(I_i, I_q)}, \tag{10}$$

where the item $I_q \in K_i$, K_i denotes the set of the most similar items to the target item I_i and is rated also by the active user u_a, r_{u,I_q} denotes the rating of an item I_q by the user u_a, $TotalSim(I_i, I_q)$ denotes the combined similarity value of the target item I_i and I_q which is calculated by Formula 9. The predicted rating values of unseen items for the user u_a are stored as a vector in the prediction matrix $P_{u_a}[1 \times n]$.

Based on the matrix $P_{u_a}[1 \times n]$, all unseen items will be sorted in descending order according to their predicted rating values and then the top-N items will be generated as the most relevant recommendations for the given user.

5 Experimental Design and Procedures

To evaluate the proposed Fusion-based Semantic CF approach, we present the experimental design, which includes details about the utilized dataset, evaluation metric employed, and parameter settings. Moreover, the experimental procedures are illustrated.

5.1 Utilized Dataset

This study employs the MovieLens benchmark dataset, accessible at https://grouplens.org/datasets/movielens/. Specifically, the academic and research dataset is utilized, comprising a randomly selected sample. This sample consists of a user-item rating matrix with 600 rows representing users and 1000 columns representing movie items, totaling approximately 35,000 ratings. The density of the user-item rating matrix of the utilized dataset is around 5%. It indicates the proportion of non-zero entries that are actually rated by users to the total entries in the utilized Movielens dataset. Users included in this dataset have provided a minimum of 20 ratings within this matrix, each user's entry represents a rating score on a scale from 1 to 5, with 5 indicating high interest and 1 indicating low interest. Entries may also be null, indicating that the corresponding users have not rated those items. This resulting matrix is subsequently employed for computing item similarity using Pearson Correlation Formula 8 and making predictions for unrated items using Formula 10. Benchmark IMdb dataset (https://datasets.imdbws.com/) is used to construct the semantic description of movie items (i.e. instances) and their properties values. In this regard, a preprocessing of the Movielens enriched with the IMdb dataset was performed, where the required data of movie features and user ratings are firstly extracted from the available dataset files and then imported into protégé. The OWL ontology, named Movie Recommender (MovieRec) ontology, is constructed to represent semantic knowledge for the considered domain. The MovieRec ontology provides a detailed semantic description of movie-related concepts and their corresponding instances. It includes a formalized description of a set of concepts (i.e. classes), e.g. movies, genres, actors, actresses, etc., with their hierarchal relationships and properties. Such a formalized description is then utilized to meet the purpose of this study. In this regard, the semantic knowledge embedded in the constructed MovieRec ontology is exploited for computing movie item similarities using the proposed semantic similarity measures.

5.2 Evaluation Metric

This study employs the Mean Absolute Error metric (MAE) to evaluate the proposed recommendation approach, as it is

Table 1 The integrated SS measures with item-based CF

Semantic similarity (SS) measure	The integration of SS formula and CF formula	Semantic combination parameter
Hierarchical-based Formula (1)	$\gamma Sim_H(I_x, I_y) + (1-\gamma)Sim_{PC}(I_x, I_y)$	γ
Attribute-based Formula (4)	$\beta Sim_{attr}(I_x, I_y) + (1-\beta)Sim_{PC}(I_x, I_y)$	β
Inferred-based SS Formula (5)	$\lambda Sim_{infer}(I_x, I_y) + (1-\lambda)Sim_{PC}(I_x, I_y)$	λ

one of the most commonly used metrics in recommendation research [19, 57, 58]. The MAE basically measures the accuracy of generated recommendations. It measures the deviation of prediction values of items from their actual rating values over all predicted items in the test dataset:

$$MAE = \frac{\sum_{i,j}^{n} \left| a_{i,j} - p_{i,j} \right|}{n}, \tag{11}$$

where n is the total number of predicted ratings over all users, $p_{i,j}$ is the predicted rating for user i on item j, and $a_{i,j}$ is the actual rating for user i on item j. The lower the MAE, the more accurate the prediction made by the recommendation approach.

5.3 Parameters Settings

In this study, we must emphasize two critical parameters that significantly impact prediction accuracy: neighborhood size (K) and the semantic combination parameter (α). These parameters play pivotal roles in shaping the performance and outcomes of the evaluation and thus warrant careful consideration and adjustment during the experimentation process. The neighborhood size K parameter represents the number of the most similar movie items for a given movie item as presented in phase 4, Sect. 4. It is utilized to compute the prediction values of unseen movie items. On the other hand, the semantic combination parameter α used to specify the weight of semantic similarity in the combined similarity measure as described in Phase 3, Sect. 4.

On the other hand, the data density, defined by the training/test ratio, significantly impacts prediction accuracy, as discussed by [59]. For our subsequent experiments aimed at determining optimal values for parameters 'K' and 'α', we select a training/test ratio of 0.9. To ensure statistical robustness, we conducted tenfold cross-validations, randomly partitioning the user ratings dataset into 90% for training and 10% for testing in each fold. All reported results in this study represent averages over these 10 folds. It is worth noting that the training dataset was utilized to construct movie item-item similarity models, while the testing dataset was used to evaluate predicted accuracy for unseen items.

5.4 Experimental Procedure

In conducting the experimental evaluation, we implemented the utilized semantic similarity measures and their integration, both individually and alongside the item-based CF approach, using the Java NetBeans platform. Additionally, we included other competing approaches for evaluation purposes. To facilitate communication between the OWL ontology of the MovieLens dataset (generated as an OWL file by the Protégé editor) and the Java NetBeans platform, we employed OWLModel and Jena OntModel.

The effectiveness of the proposed semantic similarity measures in enhancing the performance of item-based CF is investigated. The evaluation involves three key comparison scenarios. First, we individually evaluate the influence of each semantic similarity measure on the recommendation accuracy in conjunction with the item-based CF approach, and the obtained results are analyzed. Second, we examine the impact of the proposed Fusion-based SS measure on recommendation accuracy when used alongside item-based CF. Finally, we investigate the highest recommendation accuracy attained by the aforementioned experimental scenarios relative to other benchmark methods, focusing on predictive accuracy, sparsity, and new item problems.

6 Experimental Results and Discussion

6.1 First Experimental Scenario

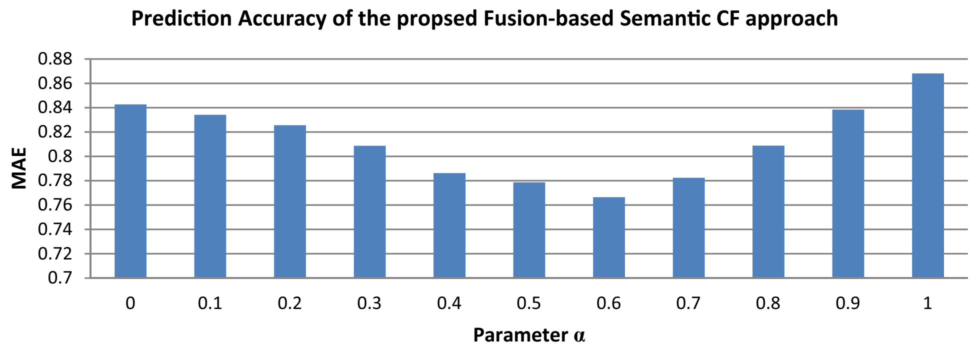
The objective of this experimental Scenario is to investigate how the proposed semantic similarity measures influence the accuracy of recommendations. To achieve this goal, each of the proposed semantic similarity measures is incorporated into the standard item-based CF approach, resulting in an integrated formula for computing item similarity. This integrated similarity measure is then applied to compute predictions using Formula 10. Table 1 presents the semantic similarity (SS) measures under consideration, which encompass the Pearson correlation coefficient, resultant integrated similarity formulas, and the associated semantic combination parameters.

The sensitivity of semantic combination parameters, presented in Table 1, is investigated in order to determine

Table 2 Parameters values that achieved the best prediction accuracy results

Integrated SS measure with item-based CF approach	Best MAE	Optimal value of k	Optimal value of semantic combination parameter
Hierarchical-based SS	0.81144	60	0.4
Attribute-based SS	0.8038	50	0.6
Inferred-based SS	0.77823	60	0.4

Fig. 3 Prediction accuracy of the integrated Fusion-based SS with Item-based CF approach



the impact of each integrated similarity measure with the item-based CF approach on prediction accuracy. The MAE metric (Formula 11) is used to compute the accuracy of prediction. Accordingly, a number of experiments were performed when the values of γ, βandλ varied from 0 to 1, with an increment of 0.1. For each distinct value of these parameters, further experiments were run over different values of K. The neighborhood parameter, i.e. K, takes values between 10 and 80 with an increment of 10. Based on the obtained results, the minimum value of MAE has been conducted for each involved approach as well as the corresponding values of each semantic parameter and K parameter, as shown in Table 2. For instance, the integrated hierarchical-based SS with item-based CF approach achieved the lowest MAE when semantic parameter γ equals 0.4 and K parameter equals 60. As can be seen in Table 2, the best-achieved result of MAE (i.e. 0.77823) is obtained by the integrated Inferred-based SS with Item-based CF approach; this result is achieved when the K parameter equals 60 and semantic parameter λ equals 0.4.

6.2 Second Experimental Scenario

This experimental Scenario aims to investigate the impact of integrating the proposed Fusion-based semantic similarity measure with item-based CF on recommendation accuracy. It also aims to validate its effectiveness against other semantic similarity measures listed in Table 2.

Accordingly, a set of experiments has been conducted to examine the sensitivity of semantic combination parameter α on the prediction accuracy. Items similarities are computed using the proposed integrated similarity as in Formula 9. The prediction accuracy has been computed using the prediction metric (Formula 10). The experiments were performed when the value of α varied from 0 to 1, in an increment of 0.1, and parameter K takes values from 10 to 80 in an increment of 10. Each experiment was run at a distinct value of α and different values of K. For each different combination of K parameter and α parameter, the MAE is computed. Figure 3 shows the MAE of the proposed integrated Fusion-based semantic similarity with the Item-based CF approach. As can be seen in Fig. 3, each plotted value of the MAE represents the minimum achieved value at specific K (i.e. nearest neighbors of items) for each distinct value of parameter α. To sum up, the minimum value of MAE is (0.766433) and is achieved when parameter α is 0.6 and the size of the K parameter is 60. Note that the obtained results for using different values of K are not reported here due to space availability.

As shown in Fig. 3, note that when $\alpha = 0$, the prediction accuracy of the proposed recommendation approach is weak as the MAE value is quite high. In this case, the semantic similarity is not taken into account to generate recommendations and only the Item-based CF approach is considered (see Formula 9). In contrast, when $\alpha = 1$, the proposed recommendation approach has made worse predictions because the semantic similarity is only considered to generate recommendations. This indicates that integrating the proposed semantic similarity with the item-based CF leads to improved recommendation outcomes. Nevertheless, the parameter α exhibits a positive influence on prediction accuracy, especially within the range of 0.2 to 0.8, where recommendation accuracy shows improvement.

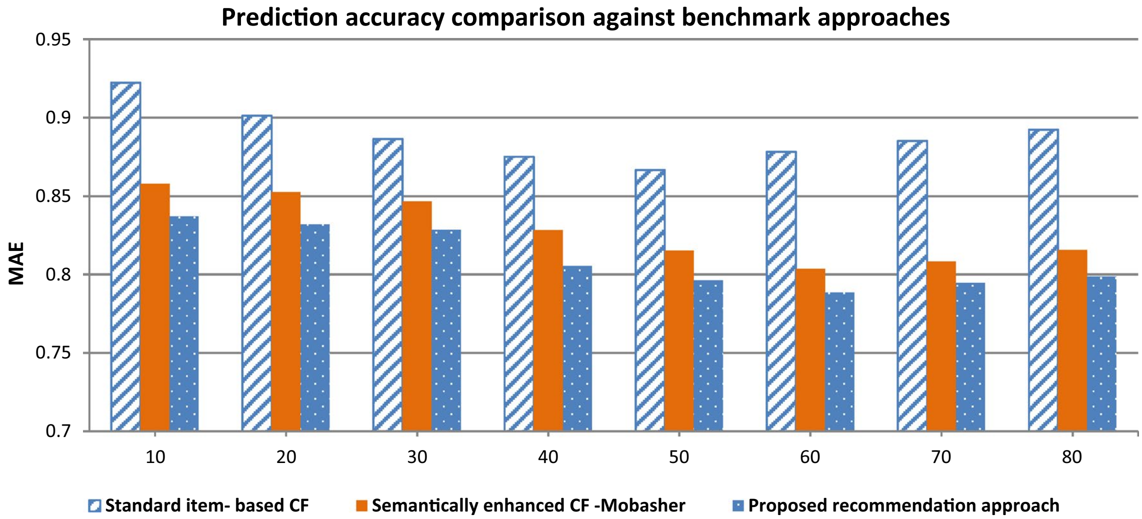


Fig. 4 Prediction accuracy of the proposed approach in comparison to benchmark approaches

The optimal accuracy is achieved when α is set to 0.6. The experimental findings emphasize the enhancing effect of the parameter on prediction accuracy. Additionally, the effect of both similarity measures yields advantageous outcomes, emphasizing the essential integration of users' ratings data with the proposed Fusion-based semantic similarity measure.

It is important to mention that, the semantically enhanced CF approach proposed by Mobasher (2003) is sensitive as well to parameter alpha as it linearly combines the item-based CF similarity and the semantic similarity. The combined similarities are used to generate predictions of unseen items. The parameter alpha is tested by following the same procedure as explained above used to test our approach. Based on the running experiments, the achieved optimal value of parameter alpha was 0.4 and K was 60.

6.3 Third Experimental Scenario

In terms of comparing the performance of the proposed Fusion-based semantic CF recommendation approach with other benchmark approaches, we have implemented two approaches proposed in the field of RSs. These approaches include the standard item-based CF proposed by Sarwar et al. [59] and the advanced semantically enhanced CF approach proposed by Mobasher et al. [16]. Standard item-based CF relies solely on users' ratings for recommendations, while semantically enhanced CF aims to boost accuracy by addressing sparsity and new item problems. It combines item descriptions from web-based ontologies with users' ratings to make predictions. Consequently, several experiments were conducted to investigate the effectiveness of the proposed Fusion-based Semantic CF recommendation approach compared to other benchmark approaches. The results of these experiments are outlined below.

6.3.1 Enhancement in Predictive Accuracy

The impact of the proposed Fusion-based semantic CF recommendation approach is evaluated against other benchmark approaches. A number of experiments are performed at different values of parameter K which varies from 10 to 80 with an increment of 10 and the parameter α is set to its optimal value for our proposed approach and semantically enhanced-CF approach proposed by Mobasher et al. [16] as illustrated in the second previous experiment. Figure 4 shows the MAE improvement of the proposed approach against other competing approaches according to the K parameter. It shows that the proposed approach achieves substantially better results in terms of prediction accuracy compared to the other competing approaches. As Fig. 4 shows, when the size of the K parameter is higher than 60, the MAE value tends to gradually increase for all compared approaches. The underlying rationale can be attributed to the diminished capacity for accurate predictions by all approaches as the neighborhood size for each item expanded, intensifying the differences between items. The minimum MAE achieved by the proposed approach is 0.788661 and obtained when K is 60, thus this value is selected as the optimal value of the K parameter for the given dataset. Further, the minimum achieved MAE values for the standard item-based CF and semantically enhanced CF competing approaches are 0.866752 and 0.803506, respectively. However, the proposed approach result indicates effective improvement in prediction accuracy for all K parameter values when compared with other competing approaches.

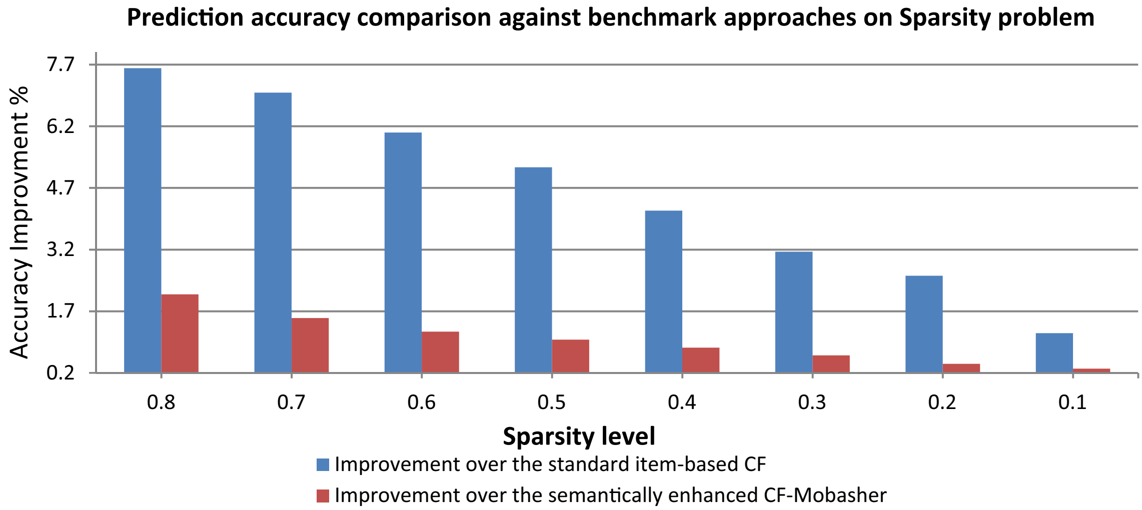


Fig. 5 Prediction accuracy comparison on sparsity problem

6.3.2 Improvement Extent for Sparsity Problem

In this experiment, the effectiveness of the proposed approach in handling the sparsity problem is investigated and examined against other considered benchmark approaches. Sparsity is one of the main problems that negatively influence the prediction accuracy of CF recommendation approaches. It occurs once the entire ratings of a dataset are few compared to the total number of the items, e.g. sparsity level of the considered MovieLens dataset in this study is 94.23%, which denotes the proportion of the non-zero entries that were actually rated by users to the total entries in the given dataset.

A number of experiments were carried out using the proposed approach and competing benchmark approaches considering different sparsity levels. For all conducted experiments using the involved recommendations approaches, parameters K and α were set to their optimal values. For each sparsity level, the MAE result of each approach was recorded. Then, the improvement in the prediction accuracy of the proposed recommendation approach against other competing benchmark approaches is calculated using the following formula:

$$Accuracy_{imp} = \frac{\left|MAE_{appr1} - MAE_{appr2}\right|}{MAE_{appr1}},$$

where MAE_{appr_1} and MAE_{appr2} is the MAE value of approach 1 and approach 2, respectively. Note that, approach 1 is considered the proposed recommendation approach in this study.

Figure 5 shows the accuracy improvement of the proposed recommendation approach over all other competing approaches for all sparsity levels. The results reveal that the MAE of the proposed approach achieves a significant improvement over the traditional item-based CF and a better improvement against the semantically enhanced CF approach at all sparsity levels.

Moreover, as depicted in Fig. 5, while the overall improvement in recommendation accuracy decreases for all approaches as the sparsity is increased, the proposed approach achieves larger improvements than the other approaches. As expected, this improvement starts to converge to 0 for very sparse datasets as shown in Fig. 5. The observed phenomenon is attributed to the inherent limitations posed by extremely sparse data, where neither approach is capable of producing accurate recommendations. Nonetheless, up to a training/test ratio of 40%, the proposed approach demonstrates a notable enhancement, the proposed approach provides improvement that exceeds 4.1459% in accuracy over the standard item-based CF approach and 1.0% over the other approach. These results indicate the effectiveness of our proposed fusion-based semantic CF approach to generate more accurate predictions at all sparsity levels.

6.3.3 Extent of Improvement for New Item Problem

The standard item-based CF recommendation approach suffers from generating accurate recommendations for new items because high-quality recommendations can only be obtained with sufficient data ratings. The effectiveness of the proposed recommendation approach in dealing with the new items problem is evaluated only against the semantically enhanced CF approach proposed by Mobasher et al. [16]; where the item-based CF approach is excluded from the experiments as it cannot make recommendations for new items.

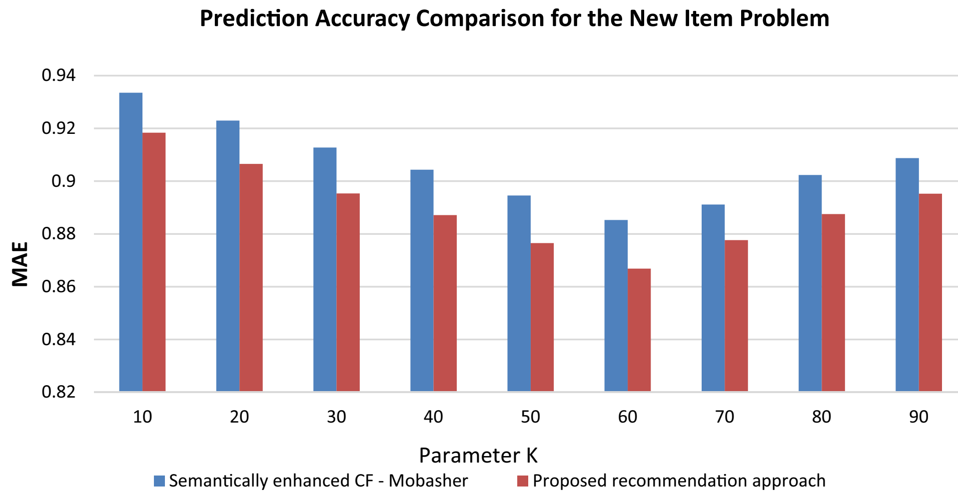


Fig. 6 Prediction accuracy comparison for the new item problem

Accordingly, the experiments are only conducted on the items that have been actually rated once in the considered MovieLens dataset. These items are considered to be new items, which have no ratings. Using this dataset, a number of experiments were conducted in which the K parameter is varied from 10 to 80 and parameter α being the corresponding optimal value for both the proposed recommendation approach and the other competing semantically enhanced CF benchmark approach. Figure 6 shows the obtained MAE results for both compared approaches. It can be observed that the obtained results of prediction accuracy for new items by the proposed approach have performed better in comparison to the other competing approach (i.e.) at all values of parameter K. The minimum MAE value achieved by the proposed recommendation approach is 0.86683 at neighborhood size equals 60. Whereas the minimum MAE for the competing approach equals 0.885263 and is reached when the neighborhood size K parameter equals 60. Therefore, our proposed approach demonstrated its effectiveness in making more accurate predictions for new item problems.

7 Conclusion

This paper introduces a hybrid semantic recommendation approach designed to address the limitations of existing recommendation methods, with a particular focus on issues such as sparsity and cold-start items that significantly affect recommendation accuracy. To achieve this, our proposed approach enhances the recommendation quality by integrating the semantic similarity of items with the item-based CF approach. Additionally, this paper introduces a semantic-based similarity measure that takes into account various components, including hierarchical relations, instance features, as well as implicit relationships. Limited attention has been given to exploring implicit ontological relationships, despite their potential for richer semantic representations. Thus, the proposed measure effectively captures shared semantic knowledge between instances as conceptualized in any given domain ontology. Implicit relationships can greatly enhance the semantic analysis of heterogeneous content, offering valuable insights into the similarities and differences between ontological instances in recommendation systems.

We demonstrated the effectiveness of our proposed Fusion-based semantic CF approach and the semantic similarity measure through comprehensive experiments. The results consistently outperformed other benchmark techniques, achieving a significant reduction in Mean Absolute Error. Our research highlights the pivotal role of integrating semantic knowledge in recommendation systems. By addressing the 'cold-start problem' and improving recommendation quality, our findings offer promising pathways for optimizing recommendation system architectures.

Future research in the field of recommendation systems is promising, particularly in the exploration of hybrid semantic similarity measures applied to dynamic ontologies. Dynamic ontologies are constantly evolving, and current studies largely focus on static ontologies, which overlook the potential changes and updates that real-world ontologies undergo. Addressing this research gap by developing adaptive approaches could lead to more robust and flexible similarity measures, enhancing the effectiveness and relevance of recommendation systems. Moreover, we intend to broaden our experimental evaluation by incorporating diverse datasets from various domains. This expansion aims to enhance the external validity of our findings. Subsequently, we plan to assess the proposed approach against other advanced similarity approaches for recommender systems, providing valuable insights into its effectiveness and adaptability across real-world scenarios.

Author Contributions Conceptualization, MA, and BA; methodology, EA and AA; writing original draft preparation, MA, AA, and AR; experiment, MA, EA, and BA; data, MA, AA and AR; project administration, MA and BA. All authors have read and agreed to the published version of the manuscript.

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Availability of Data and Materials This study utilizes the MovieLens benchmark dataset, which is available at https://grouplens.org/datasets/movielens/.

Declarations

Conflict of Interest The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Adomavicius, G., Tuzhilin, A.: Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Trans. Knowl. Data Eng.Knowl. Data Eng. **17**, 734–749 (2005)
2. Burke, R.: Hybrid web recommender systems. In: The adaptive web: methods and strategies of web personalization, pp. 377–408. Springer (2007)
3. Cacheda, F., Carneiro, V., Fernández, D., Formoso, V.: Comparison of collaborative filtering algorithms: limitations of current techniques and proposals for scalable, high-performance recommender systems. ACM Trans. Web **5**, 1–33 (2011)
4. Roy, D., Dutta, M.: A systematic review and research perspective on recommender systems. J. Big Data **9**, 1–36 (2022)
5. Su, X., Khoshgoftaar, T.M.: A survey of collaborative filtering techniques. Adv. Artif. Intell. **2009**, 1–9 (2009)
6. Mbaye, B.: Recommender system: collaborative filtering of e-learning resources. Presented at the The International Association for Development of the Information Society (IADIS) International Conference on e-Learning, Madrid, Spain, (2018)
7. Agarwal, A., Mishra, D.S., Kolekar, S.V.: Knowledge-based recommendation system using semantic web rules based on learning styles for MOOCs. Cogent Eng. **9**, 2022568 (2022)
8. Ko, H., Lee, S., Park, Y., Choi, A.: A survey of recommendation systems: recommendation models, techniques, and application fields. Electronics **11**, 141 (2022)
9. Blanco-Fernández, Y., Pazos-Arias, J.J., Gil-Solla, A., Ramos-Cabrer, M., López-Nores, M., García-Duque, J., et al.: Exploiting synergies between semantic reasoning and personalization strategies in intelligent recommender systems: a case study. J. Syst. Softw.Softw. **81**, 2371–2385 (2008)
10 Eirinaki, M., Mavroeidis, D., Tsatsaronis, G., Vazirgiannis, M.: Introducing semantics in web personalization: the role of ontologies. In: European web mining forum, pp. 147–162. Springer (2005)
11. Ibrahim, M.E., Yang, Y., Ndzi, D.L., Yang, G., Al-Maliki, M.: Ontology-based personalized course recommendation framework. IEEE Access **7**, 5180–5199 (2018)
12. Bagherifard, K., Rahmani, M., Nilashi, M., Rafe, V.: Performance improvement for recommender systems using ontology. Telemat Inform. **34**, 1772–1792 (2017)
13. Tarus, J.K., Niu, Z., Yousif, A.: A hybrid knowledge-based recommender system for e-learning based on ontology and sequential pattern mining. Futur. Gener. Comput. Syst.. Gener. Comput. Syst. **72**, 37–48 (2017)
14. Nilashi, M., Ibrahim, O., Bagherifard, K.: A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques. Expert Syst. Appl. **92**, 507–520 (2018)
15. George, G., Lal, A.M.: Review of ontology-based recommender systems in e-learning. Comput. Educ.. Educ. **142**, 103642 (2019)
16. Mobasher, B., Jin, X., Zhou, Y.: Semantically enhanced collaborative filtering on the web. In: European web mining forum, pp. 57–76. Springer (2003)
17. Martín-Vicente, M.I., Gil-Solla, A., Ramos-Cabrer, M., Blanco-Fernández, Y., López-Nores, M.: Semantic inference of user's reputation and expertise to improve collaborative recommendations. Expert Syst. Appl. **39**, 8248–8258 (2012)
18. Sieg, A., Mobasher, B., Burke, R.: Improving the effectiveness of collaborative recommendation with ontology-based user profiles. In: Proceedings of the 1st International Workshop on Information Heterogeneity and Fusion in Recommender Systems, pp. 39–46 (2010)
19. Tarus, J., Niu, Z., Khadidja, B.: E-learning recommender system based on collaborative filtering and ontology. Int. J. Comput. Inform. Eng. **11**, 256–261 (2017)
20. Middleton, S.E., Shadbolt, N.R., De Roure, D.C.: Ontological user profiling in recommender systems. ACM Trans. Inform. Syst. (TOIS) **22**, 54–88 (2004)
21. Chew, L.J., Haw, S.C., Subramaniam, S., Ng, K.W.: A hybrid ontology-based recommender system utilizing data enrichment and SVD approaches. J. Syst. Manag. Sci. **12**, 139–154 (2022)
22. Kermany, N.R., Alizadeh, S.H.: A hybrid multi-criteria recommender system using ontology and neuro-fuzzy techniques. Electron. Commer. Res. Appl.Commer. Res. Appl. **21**, 50–64 (2017)
23. Gruber, T.R.: Toward principles for the design of ontologies used for knowledge sharing? Int. J. Hum. Comput. Stud.Comput. Stud. **43**, 907–928 (1995)
24. Borst, W. N.: Construction of engineering ontologies for knowledge sharing and reuse. Philosophy (1997)
25 Taniar, D., Rahayu, J.W.: Web semantics & ontology. Igi Global (2006)
26. Guarino, N., Oberle, D., Staab, S.: What is an ontology? In: Handbook on ontologies. Springer (2009)
27. Schwering, A., Kuhn, W.: A hybrid semantic similarity measure for spatial information retrieval. Spat. Cogn. Comput.Cogn. Comput. **9**, 30–63 (2009)
28. Wang, R.-Q., Kong, F.-S.: Semantic-enhanced personalized recommender system. In: 2007 International Conference on Machine Learning and Cybernetics, pp 4069–4074 (2007)

29. Sánchez, D., Batet, M., Isern, D., Valls, A.: Ontology-based semantic similarity: a new feature-based approach. Expert Syst. Appl. **39**, 7718–7728 (2012)
30. Liu, P., Nie, G., Chen, D.: Exploiting semantic descriptions of products and user profiles for recommender systems. In: 2007 IEEE Symposium on Computational Intelligence and Data Mining, pp 179–185 (2007)
31. Maedche, A., Zacharias, V.: Clustering ontology-based metadata in the semantic web. In: Principles of Data Mining and Knowledge Discovery: 6th European Conference, PKDD 2002 Helsinki, Finland, August 19–23, 2002 Proceedings 6, pp. 348–360 (2002)
32. Lastra-Díaz, J.J., García-Serrano, A., Batet, M., Fernández, M., Chirigati, F.: HESML: a scalable ontology-based semantic similarity measures library with a set of reproducible experiments and a replication dataset. Inf. Syst. **66**, 97–118 (2017)
33. Sathiya, B., Geetha, T.: A review on semantic similarity measures for ontology. J. Intell. Fuzzy Syst. **36**, 3045–3059 (2019)
34. Meng, L., Huang, R., Gu, J.: A review of semantic similarity measures in wordnet. Int. J. Hybrid Inform. Technol. **6**, 1–12 (2013)
35. Elavarasi, S.A., Akilandeswari, J., Menaga, K.: A survey on semantic similarity measure. Int. J. Res. Advent Technol. **2**, 389–398 (2014)
36. Rada, R., Mili, H., Bicknell, E., Blettner, M.: Development and application of a metric on semantic nets. IEEE Trans. Syst. Man Cybern.Cybern. **19**, 17–30 (1989)
37. Wu, Z., Palmer, M.: Verb semantics and lexical selection. arXiv preprint cmp-lg/9406033 (1994)
38. Poorna, B., Ramkumar, A.S.: Semantic similarity measures: an overview and comparison. Int. J. Adv. Res. Comput. Sci.Comput. Sci. **9**, 100 (2018)
39 Gan, M., Dou, X., Jiang, R.: From ontology to semantic similarity: calculation of ontology-based semantic similarity. Sci. World J. **2013**, 1–11 (2013)
40. Meymandpour, R., Davis, J.G.: A semantic similarity measure for linked data: an information content-based approach. Knowl.-Based Syst..-Based Syst. **109**, 276–293 (2016)
41. Seco, N., Veale, T., Hayes, J.: An intrinsic information content metric for semantic similarity in WordNet. In: Ecai, p 1089 (2004)
42. Zhang, X.-G., Sun, S., Zhang, K.-J.: An information content-based approach for measuring concept semantic similarity in WordNet. Wireless Pers. Commun.Commun. **103**, 117–132 (2018)
43. Formica, A., Taglino, F.: An enriched information-theoretic definition of semantic similarity in a taxonomy. IEEE Access **9**, 100583–100593 (2021)
44. Hussain, M.J., Bai, H., Wasti, S.H., Huang, G., Jiang, Y.: Evaluating semantic similarity and relatedness between concepts by combining taxonomic and non-taxonomic semantic features of WordNet and Wikipedia. Inf. Sci. **625**, 673–699 (2023)
45. Resnik, P.: Using information content to evaluate semantic similarity in a taxonomy. arXiv preprint cmp-lg/9511007 (1995)
46. Jiang, J. J., Conrath, D. W.: Semantic similarity based on corpus statistics and lexical taxonomy. arXiv preprint cmp-lg/9709008 (1997)
47. Lin, D.: An information-theoretic definition of similarity. In: Icml, pp 296–304 (1998)
48 AlMousa, M., Benlamri, R., Khoury, R.: Exploiting non-taxonomic relations for measuring semantic similarity and relatedness in WordNet. Knowl. Based Syst. **212**, 106565 (2020)
49. Priya, M., Ch, A.K.: A novel method for merging academic social network ontologies using formal concept analysis and hybrid semantic similarity measure. Lib. Hi Tech **38**, 399–419 (2020)
50 Bai, Y., Gao, D., Peng, L.: HAZOP ontology semantic similarity algorithm based on ACO-GRNN. Processes **9**, 2115 (2021)
51. Xu, Y., Guo, X., Hao, J., Ma, J., Lau, R.Y., Xu, W.: Combining social network and semantic concept analysis for personalized academic researcher recommendation. Decis. Support. Syst.. Support. Syst. **54**, 564–573 (2012)
52. Martín-Vicente, M.I., Gil-Solla, A., Cabrer, M.R., Pazos-Arias, J.J., Blanco-Fernández, Y., Nores, M.L.: A semantic approach to improve neighborhood formation in collaborative recommender systems. Expert Syst. Appl. **41**, 7776–7788 (2014)
53. Cantador, I., Bellogín, A., Castells, P.: Ontology-based personalised and context-aware recommendations of news items. In: 2008 IEEE/WIC/ACM international conference on web intelligence and intelligent agent technology, pp 562–565 (2008)
54. Horridge, M., Jupp, S., Moulton, G., Rector, A., Stevens, R., Wroe, C.: A practical guide to building owl ontologies using protégé 4 and co-ode tools edition1.2. In: The university of Manchester, vol. 107 (2009)
55. Al-Hassan, M., Lu, H., Lu, J.: A semantic enhanced hybrid recommendation approach: a case study of e-Government tourism service recommendation system. Decis. Support. Syst.. Support. Syst. **72**, 97–109 (2015)
56. Han, J., Kamber, M., Mining, D.: Concepts and techniques. Morgan Kaufmann Publishers (2006)
57. García-Sánchez, F., Palacios, R.C., Valencia-García, R.: A social-semantic recommender system for advertisements. Inf. Process. Manag.Manag. **57**, 102153 (2020)
58. Schafer, J.B., Frankowski, D., Herlocker, J., Sen, S.: Collaborative filtering recommender systems. In: Brusilovsky, P., Kobsa, A., Nejdl, W. (eds.) The adaptive web, pp. 291–324. Springer Verlag Berlin Heidelberg (2007)
59. Sarwar, B., Karypis, G., Konstan, J., Riedl, J.: Item-based collaborative filtering recommendation algorithms. In: Proceedings of the 10th international conference on World Wide Web, pp 285–295 (2001)