A Hierarchical Architecture for Ontology-based Recommender Systems

Fábio Augusto Procópio de Paiva[1], José Alfredo Ferreira Costa[2], Cláudio Rodrigues Muniz Silva[3]
[1] Department of Electrical Engineering, Universidade Federal do RN, Natal, Brazil, fabiopaiva@yahoo.com
[2] Department of Electrical Engineering, Universidade Federal do RN, Natal, Brazil, jafcosta@gmail.com
[3] Department of Communications Engineering, Universidade Federal do RN, Natal, Brazil, claudio.rmsilva@gmail.com

***Abstract* — There is no doubt that the World Wide Web has made easier the task of searching for information on the Internet. The amount of information obtained (some of them irrelevant ones) increases day after day and creates opportunities for a new breed of systems named "Recommender Systems". These systems have emerged as one successful approach to tackle the problem of information overload. Traditional recommender systems suggest research items using well-known text mining techniques, however they fail when there are no identical keywords to match searches. In order to overcome this and other limitations, several studies have been made in order to verify the benefits of ontology-based approaches to create what is known as ontology-based recommender systems. This paper analyzes several ontology-based recommender systems and discusses some classification criteria in order to define a common architecture for these special types of recommender systems. The architecture presented is discussed in details and recommended as basis architecture for other ontology-based recommender systems.**

Keywords— recommender systems; ontology; user profile; recommendation algorithm

I. INTRODUCTION

Every day, Internet users and their applications create approximately 2.5 quintillion bytes of data (one followed by 18 zeros in USA and Canada). This is so much that some estimate that 90% of the data in the world today has been created in the last two years alone [1]. This data comes from everywhere: file uploads, sensors used to gather climate information, posts to social networks, digital pictures and videos, purchase transaction records, and GPS navigation info, just to name a few. In this context, one of the main challenges of a web user within this "ocean" of resources is to identify those ones that meet his/her needs and preferences. This is why personalized recommendation services have become necessary and urgent [31] and have been widely used in several areas such as services, e-commerce, entertainment and other areas. These services may be provided by the recommender systems.

Recommender Systems has emerged as one successful approach to tackle the problem of information overload. They are special applications that provide personalized advice to users about products or services they might be interested in. Recommender systems are becoming a part of everyday life. They are helping people efficiently manage content overload and handle a long tail of content discovery. This social prevalence may be evidenced by the increasing demand for personalized radio, television, video and on-line shopping in several different domains. Traditional personalized recommender systems suggest items using text mining techniques considering term frequencies or similarity measures based on statistical methods [3]. However, these recommendation systems fail when there are no identical keywords although there is a semantic relationship between them [31]. To minimize this problem, in latest years, several studies [23-37] have proposed the use of ontologies as a way to increase the performance of recommender systems.

An ontology is a formal explicit description of concepts in a domain of discourse (classes or concepts), properties of each concept describing various features and attributes of the concept (properties), and restrictions on slots (facets or role restrictions). Ontologies are considered one of the pillars of the Semantic Web, since they are used to share common understanding of the structure of information among people or software agents, enable reuse of domain knowledge, make domain assumptions explicit, to separate domain knowledge from the operational knowledge and analyze domain knowledge. Sharing common understanding of the structure of information among people or software agents is one of the more common goals in developing ontologies [3][4]. The Semantic Web is well recognized as an effective infrastructure to enhance visibility of knowledge on the Web. They use ontologies to provide a rich conceptualization of the domain of an organization, representing the main concepts and relationships of the work activities.

Ontologies help extend recommender systems to a multi-class environment, allowing knowledge-based approaches to be used alongside classical machine learning algorithms. Moreover, they have been used routinely in recommender systems in combination with machine learning, statistical correlations, user profiling and domain specific heuristics. Commercial recommender systems generally either maintain simple product ontologies that they can then utilize via heuristics or have a large community of users actively rating content suitable for collaborative filtering [1].

This paper analyzes the main works that apply an ontology-based approach to some aspect of a traditional recommender system. In section II, a brief background about recommender systems is provided to reader; in section III, the main criteria that are going to be used to compare the different approaches that have been selected; in section IV, these criteria are identified in the analyzed works; in section V, a generic hierarchical architecture is presented in details and

978-1-4799-3194-1/13 $31.00 © 2013 IEEE
DOI 10.1109/BRICS-CCI-CBIC.2013.67

recommended as basis for ontology-based recommender systems; and finally, in section VI, the final considerations are presented to conclude the work.

II. Recommender Systems

The main objective of a Recommender System (RS) is automatically to identify items (e.g., movies, services or news) which meet the preferences of a particular user and also display these items appropriately.

Presently, the field of recommender systems has attracted the attention of many researchers because [12][14]: a) it plays a relevant role in important websites such as Amazon.com, Youtube, Netflix, Yahoo, Tripadvisor, and IMDb; b) there are dedicated conferences and related workshops to this field; c) there have been several special issues in academic journals covering research and developments in this field as well.

An ontology-based system can be used not only to improve the precision of search/retrieval mechanism but also to reduce search time [9]. For these reasons, as in [10], ontology-based approaches will likely be the core technology for the development of a next generation of semantically enhanced Knowledge Management solutions.

III. Main Criteria of Ontology-Based RS

This work aims to discover a common hierarchical architecture for the ontology-based recommender systems. This objective drives the survey questions that will be used to define the analysis of used criteria. In order to define this architecture the criteria were chosen according to the common functionalities suggested in [28]. The resulting of the criteria set is easily related to specific questions presented below:

- Ontology: *Which models were used and shared?*
- User Profile: *How it was used and managed?*
- Discovery: *How the user's interest was discovered?*
- Algorithm: *Which algorithm was used?*

A. *Ontology*

Although its origin is in Philosophy, currently the use of ontology plays an important role in other knowledge spheres such as [5]: a) knowledge engineering, b) object-oriented analysis, c) knowledge representation, d) information retrieval and extraction, e) database design, and others.

The ontology models are the basis for the ontology-based recommender systems. They mainly concerns building context model from both user and knowledge sides. Building an ontology model from scratch is a task which demands several resources, it does not tap the full potential of existing domain-relevant knowledge sources and therefore it is important to consider the possibility of reusing ontologies. Ontology reuse can be defined as the process in which available knowledge is used as an input to generate new ontologies [20][21]. This process has several advantages [22] because a) it reduces human labor during the building of an ontology from scratch; b) it increases the quality of new ontologies because the components have been tested previously and; c) it facilitates the mapping of shared components between two ontologies.

B. *User Profile*

The information about the user, including his/her preferences, is usually stored in a personal data structure known as user profile [37], which can be constructed considering direct feedbacks from the user either in explicit or implicit form.

It is difficult to obtain sufficient and representative feedback from a population of users when it is explicit [17] because the user's interest is updated frequently and, for this reason, he/she is reluctant to report the system his/her new preferences. In the explicit form, the system can request, e.g., the user's opinion on an item or that he/she answers questions from a questionnaire. On the other hand, the system which extracts implicit feedback observes the user's behavior and utilizes his/her interactions with the system to infer his/her interests.

C. *Discovery*

The use of profiles to represent the user's long-term information needs and interests is a key concern to a recommendation system [28]. An inadequate profile may lead to low quality and irrelevant user recommendations. The criteria discovery is used to improve the user ontology and to find the user's potential interests necessary to a specific application. These criteria can be also associated with rules for the recommendation engine use. Those rules consist normally of three sorts: main rules, constraint rules and newly-added rules defined by an administrator user. Moreover, they could be mined out from the query log data by the means of several data mining technologies (rules engines, clustering systems, etc).

D. *Algorithm*

In this paper, the combination which is formed by the recommendation techniques and the similarity measures has been named *recommendation algorithm*.

A variety of recommendation techniques have been proposed as the basis for recommender systems and they are classified in six different classes [13]:

1. Collaborative: this technique suggests items to users who have similar interests and preferences according to their ratings in the past;
2. Content-based: the system learns to recommend items that are similar to the ones that the user liked in the past;
3. Demographic: this technique classifies people based on demographic attributes and recommends items according to the user's demographic profile [15];
4. Knowledge-based: the system suggests items based on inferences about the user's needs and preferences [13];
5. Community-based: this technique recommends items based on the preferences of the user's friends [14] and;
6. Hybrid recommender systems: these systems are those that combine two or more recommendation techniques.

There are different ways to compute the similarity between users. Here we present two commonly used methods: Cosine Index [39] and Jaccard's Coefficient [40].

In the Cosine Index a user u is represented by a vector $\bar{u}$. Thus, the similarity between user i and user j is measured by computing the cosine of the angle between normalized vectors $\bar{\imath}$ and $\vec{\jmath}$, as in (1):

$$sim(i,j) = \cos(\bar{\imath}, \vec{\jmath}) = \frac{\bar{\imath} \cdot \vec{\jmath}}{\|i\| \, \|j\|} \tag{1}$$

The Jaccard's Coefficient is defined as the quotient between the intersection and the union of the pairwise compared variables among two objects A and B:

$$sim(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{2}$$

IV. Ontology-Based Recommender Systems

In this section, some works related to the ontology-based recommender systems field are presented. These works are grouped according to recommendation techniques and finally, the main criteria of these works are compared in Table I.

A. Collaborative

Naudet et al. [23] proposed a recommender system which suggests TV contents to mobile devices users. The authors developed a set of ontologies which allows the matchmaking between the user and content at different levels, based on three means to define the user's interests: according to categories (or themes of interests), content description, or any combination of concepts defined in an ontology. The user's ontology is inspired by different user's models, among them GUMO (General User Model Ontology), TV-A (TV-Anytime) Ontology and others.

Lin et al. [24] presented an algorithm of a User's Interest Model based on ontology which focus not only on the user's interest quality, but also the difference between long-time and short-time. The user's interest model is based on many aspects of interest called Interest-Points (IP). To define the user's interest quality, the authors divided them in long-time interest and short-time interest. Long-time interest is based on principle the partial similarity to a particular user's IP and short-time interest is based on the user's experience. The proposed system is used to recommend e-books.

Yuan et al. [25] proposed an ontology-based method for the user's modeling and a similarity algorithm called Simi-New to suggest web pages. The algorithm calculates the similarity based on a) closeness of the scores of common resources and b) angle between two vectors related to these scores. The user's model was built following three steps: a) obtaining the access score vector on leaf nodes in ontology tree, b) obtaining the access score vector on non-leaf nodes in ontology tree and c) combination of access score vector on leaf nodes and access score vector on non-leaf nodes to generate the user's interest model.

Zhenglian et al. [26] presented a representation model of user's interest which uses Spreading Activation Theory algorithm to update incrementally the user's interest degree in relation to associated concepts to his/her profile. The User Interest Model (UIM) is represented by *UIM=(PI, C, D, S)*, where a) PI is personal information, b) C is the collection of all the concepts in the user's interest ontology, c) D is the collection of all the user's interest degrees and d) S is a matrix containing all semantic similarity degrees between pairwise concepts in set C. The proposed system can be used to recommend movies.

B. Content-based

Proactive [27] is an adaptive job recommender system, which helps job seekers to find relevant opening jobs in multiple ways. Based on recommendation taxonomy [38], Proactive designs and deploys four different kinds of interfaces: Most Recent Jobs, Advance Search, Recommended Jobs and Preferred Jobs. Proactive uses two kinds of ontology defined by Yahoo! HotJobs.

Gao et al. [28] proposed an approach to recommendation system of information which combines user's ontology and spreading activation model in order to enhance the capability of discovering of user's potential interests. The user's interest model is implemented in two stages: a) the construction of Domain Semantic Network which is a graph and b) user's interest discovery algorithm based on Spreading Activation Model which is used in order to enhance the capability of discovering of user's potential interests.

A framework for integrating semantic information to Web Usage Mining process was proposed by Salin and Senkul [29] in order to recommend e-books and web pages. These semantic information was obtained from extraction of frequent navigation patterns as ontologies instances. In the access patterns generation phase, log file items are associated with the ontology instance. The authors performed an adaptation of the SPADE algorithm to mine sequential association rules.

Athena [30] is an extension to the existing Hermes framework, which is used to build a news personalization service. The proposal presents a new method for building a user's extended profile, which is used to support the growth of the user's interest for certain concepts that are not part of his/her profile, although they are related. Athena stores concepts found in read news by the user during his/her navigation on the Web. Athena reuses the ontology defined in Hermes framework.

Kang and Choi [31] presented a personalized recommendation system of e-books. For this fact, they built two ontologies: a domain and another preference. The first one represents conceptual relationships between documents and the second one represents concepts preferences weights. By monitoring the visited web pages, the system constructs the user's preference ontology from associated weights to his/her preferences for long-term and short-term.

Mohanraj and Chandrasekara [32] proposed a method for detecting Greatest Common Subsequence which is used to discover navigation profiles that contain patterns that possibly are interesting to users. The method compares the similarity between pages of discovered Navigation Profile and the pages contained in current Live Session Window (LSW), which is a set of visited pages by the user in an active session. All similar pages findings are classified according to the concept score and recommended to the user as Imminent Browsing Pattern (IBP). The system classification module acts on the Navigation

Profile implementing Greatest Common Subsequence Detection for discovering subsequences which can be considered the user's IBP.

C. Hybrid Systems

Yingchen et al. [33] presented an approach which captures dynamically and updates the user's historical preferences according to a decay factor and a time window. Content-based and Demographic are the recommendation techniques used in this paper to suggest names of restaurants. The user's preferences are mapped into the domain ontology in order to create User Dynamic Preference Ontology. The domain ontology utilizes Service Relationship Ontology.

Pan et al. [34] proposed a hybrid strategy which reuses the Ontology Movie and applies Content-based and Knowledge-based techniques in order to resolve some of the key issues related to personalized recommendations: a) New Item, b) New User and c) Overspecialization. The recommendation module is based on an approach of multi-agent personalization and consists of three elements: a) Random Selection Agent which is responsible for avoiding the overspecialization problem, b) Semantic Discovery Agent aims to solve the problems of overspecialization and New Item and c) Data Mining Agent which is responsible for resolving the New User problem. Let U be the set of all users and for each user u_i the system keeps users' past rating as a set of 4-tuple data: *PR=(UserID, MovieID, RatingScore, RatingDate)* in which the *RatingScore* belong to the range [-1, 1]. Moreover, the user's Category Preferences are maintained to emphasize his/her preferences.

Zhen et al. [35] presented a model of an inner-enterprise knowledge recommender system which is based on semantic matching on context information. The system architecture is divided into three layers such as: 1) Context model and elicitation, 2) Rules for recommendation, and 3) Recommendation engine. The hybrid system uses Collaborative and Knowledge-based techniques. The proposed system recommends inner-enterprise knowledge.

Ge et al. [36] proposed the development of a personalized recommender system framework which is used to suggest movies. A domain ontology is used to integrate multi-source and heterogeneous data. Collaborative and Content-based techniques were used during recommendation process. Analysis of user's demographic characteristics, information about his/her personal preferences, and his/her browsing behavior were used to create an interest ontology.

SigTur/E-Destination [37] is a recommender system in tourism area which provides to the user leisure possibilities according to his/her profile, and also facilitates travel planning. This proposal uses a domain ontology to generate recommendations and to infer the relation between the user profile and available items. The system also associates an interest degree for each recommendation and analyzes the user's preferences from processes that make bottom-up and top-down propagation of the preferences over the concepts of the ontology. SigTur/E-Destination uses Content-based and Collaborative techniques to recommendation and reuses the Tourism Ontology.

TABLE I. COMPARISON OF ONTOLOGY-BASED RECOMMENDER SYSTEMS

Reference	Analyzed Criteria											
	Ontology				User Profile		Discovery	Algorithm				
								Technique				Similarity Measure
	User	*Dom* [a]	*Reused*	*Shared*	*Imp*	*Exp*		*C* [b]	*Cb* [c]	*D* [d]	*Kb* [e]	
Naudet et al. (2008)	●	●	●		●	●	Rules set	●				(customized) [f]
Lin et al. (2008)	●	●			●		Neighbors with partial similarity	●				Interest Point (customized) [f]
Yuan, Zhang & Ni (2010)	●	●			●		Score vector on tree nodes	●				Simi-New (customized) [f]
Zhenglian et al. (2011)	●	●			●		Ontology KNN	●				Euclidean Dist.
Lee & Brusilovsky (2007)		●	●		●	●	(customized) [f]		●			(customized) [f]
Gao et al. (2008)	●				●	●	Spreading activation model		●			(customized) [f]
Salin & Senkul (2009)		●		●	●		Seq. Assoc. Rules		●			(customized) [f]
IJntema et al. (2010)	●		●		●		Supervised learning		●			Binary Cosine and Jaccard
Kang & Choi (2011)	●	●				●	Long and short-term preference		●			Cosine and Jaccard
Mohanraj & Chandrasekara (2011)		●			●		Graph partitioning		●			Cosine
Yingchen et al. (2009)	●	●	●	●	●		Association rules		●	●		Jiang & Conrath
Pan et al. (2010)		●	●			●	Semantic association		●		●	Blanco-Fernández et al.
Zhen, Huang & Jiang, (2010)	●	●		●	●	●	Rules set	●			●	Concept Semantic
Ge et al. (2012)	●	●	●	●	●	●	Association rules	●	●			Ge & Qiu
Moreno et al. (2013)	●	●	●		●	●	K-Means	●	●			Yager, Dujmovic & Nagashima

[a] Domain, [b] Collaborative, [c] Content-based, [d] Demographic, [e] Knowledge-based, [f] Customized approach by the authors

V. The Proposed Architecture

It has been identified that the observed functionalities in the related works may be organized in layers, which interact with one another to implement the whole recommendation process. In this study, four layers were clearly identified such as Context Layer, Discovery Layer, Recommendation Layer and Ontology Layer. Fig. 1 presents a generic hierarchical architecture for ontology-based recommender systems.

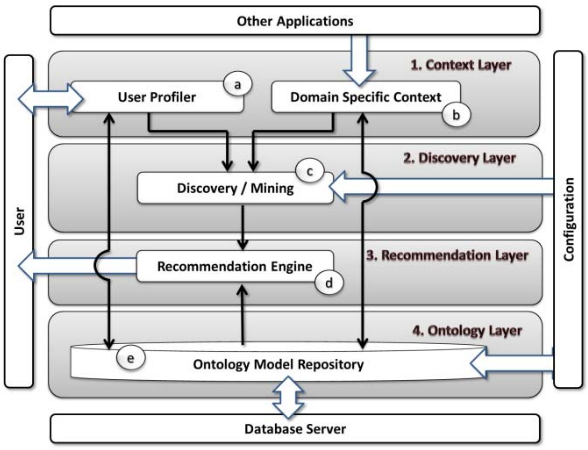

Fig. 1. Hierarchical Architecture for Ontology-based RS

These layers have their own internal components, functionalities and relationships. Each component may differ among the implementations presented in the previous sections, however we could describe then as follows:

1. Context Layer — the User Profile (Fig. 1a) represents the related data to the user and the function of Domain Specific Context (Fig. 1b) is to represent the set of concepts used in a specific domain. Here, the ontology models used in the related works are populated and used, generally in a repository manager (available in layer 4), and persisted in an external database. They may be related to the user profile and/or related to a specific application domain in which the recommender system is applied.

2. Discovery Layer — in this layer, the user's feedbacks produced are delivered to the Discovery/Mining Component. This component (Fig. 1c) mines these data and the one sent by the Context Layer to compose the unified information to be submitted to the Recommendation Engine. The whole discovery process may be driven by rules that describe how the ontology instances of all models can be related to match a specific recommendation result.

3. Recommendation Layer — this layer receives as an input the mined data by its upper layer (Discovery Layer). The Recommendation Engine (Fig. 1d) is responsible for the following processes: a) calculation of the semantic similarity between defined concepts in the User Profile and Domain Specific Context, b) listing of items based on the calculated semantic similarity and c) display of items which meets the user's preferences.

4. Ontology Layer — the ontology repositories (Fig. 1e) have previously been developed for enterprise systems and the Semantic Web, for creating, browsing and editing ontologies. Ontology repositories are more specific that semantic web search engines and their navigation/search interfaces can vary greatly. They offer tools that may be specific to the type of applications the repository was designed for. In Fig. 1, the ontology repository is the component responsible for the task of storing artifacts representations instances from models used ontologies in architecture. These models can be a) domain-specific architecture b) related logs made by users and/or related rules that will be applied by the Recommender Engine to make a final recommendation.

The components of Context Layer populate and use the instances of their respective ontology models (one for the user logs and one for domain specifics definitions). These instances will be the basis for mining that is supposed to be done in the second layer by the discovery component. These mining results and the behavior rules stored in the repository the Recommendation Engine are able to identify a possible recommendation to the user inside the specific application domain.

VI. Conclusion

In this paper, a diversity of works in the field of ontology-based recommender systems has been described. Main features were presented with the aim to propose a generic hierarchical architecture for ontology-based recommender systems.

Most of papers in section IV did not report a complete use of the ontologies potentialities, e.g., the reuse process although this does not ensure that it has not been applied. However, it is essential to consider that an ontology-based application implements the reuse process because this is one of the main features which justify the ontology use. Furthermore, it has been noticed that there are different nomenclatures and classifications for the components that perform the same function within specific recommender systems architectures in literature.

This lack of consensus on a common architecture hinders the understanding of the basics of ontology-based recommender systems. This paper identified presented common functionalities of an ontology-based recommender system and its organization in layers. A generic hierarchical architecture has been presented to clarify the understanding of the components and its inter-relations of these systems.

Acknowledgment

The authors would like to thank the reviewers for their valuable comments and suggestions of improvements. This paper is supported by the Universidade Federal do Rio Grande do Norte (UFRN).

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