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From Social Network to Semantic Social Network in Recommender System

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Abstract

Due the success of emerging Web 2.0, and different social network Web sites such as Amazon and movie lens, recommender systems are creating unprecedented opportunities to help people browsing the web when looking for relevant information, and making choices. Generally, these recommender systems are classified in three categories: content based, collaborative filtering, and hybrid based recommendation systems. Usually, these systems employ standard recommendation methods such as artificial neural networks, nearest neighbor, or Bayesian networks. However, these approaches are limited compared to methods based on web applications, such as social networks or semantic web. In this paper, we propose a novel approach for recommendation systems called semantic social recommendation systems that enhance the analysis of social networks exploiting the power of semantic social network analysis. Experiments on real-world data from Amazon examine the quality of our recommendation method as well as the performance of our recommendation algorithms.

Keywords: *Recommender system, social network, semantic web, user profile.*

1. Introduction

The prevalent use of computers and Internet has enhanced the quality of life for many people, tasks that were once done mostly through physical/human interactions, such as banking, shopping, or communication can now be done online; a seemingly simpler and better alternative. Also, with rapidly growing amount of information in the web, it is difficult to find needed information quickly and efficiently. That is where the recommender systems come in as a special type of information filtering. Nowadays many applications have used recommender systems; especially in the e-commerce domains such as http://www.amazon.com (see an example in Figure 1)

where a failure recommendation could cause great losses of time, effort, and money. Our objective is to review a solution to surpass the defects of failure recommendation, by presenting semantic social recommendation approaches. The idea here is to combine two important aspects; the social aspect by using social network analysis measures, and the semantic aspect by using the semantic similarity measures.

Fig 1: Amazon recommends products to customers by customizing collaborative-filtering systems

The paper is organized as follows: section 2 presents related work, section 3 details the new recommendation model proposed, section 4 explains our obtained results, and section 5 concludes and discusses future work.

2. Background knowledge and related works

The approach described in this paper relies on a combination of social network analysis and semantic web for semantic social recommendation. In this section, we

explore related works in recommendation systems using these techniques. We also highlight the originality of the approach we propose with respect to the state of the art.

2.1 Classification criteria for recommender systems

The recommendation problem is defined as follows [2]: let C be the set of all users and let S be the set of all possible items that can be recommended. Let u be an utility function that measures the usefulness of item s to user c. u : $C \times S \rightarrow R$, where R is a totally ordered set (non-negative integer or real numbers within a certain range). Then for each user $c \in C$, we want to choose such item $s' \in S$ that maximizes the user's utility. $\forall \quad c \quad \in \quad C$, $s'_c = argmax_{s \in S} u(c,s)$.

In the recommendation systems, the utility u refers to the rating. Each elements c of the user space C could be defined with a profile that contains the users' characteristics (id, name, age . . .). Each element s of the items space S is also defined with a set of characteristics. Traditionally, filtering and recommender systems were classified into three main categories relative to the filtering technique used [2]: content-based recommender systems [5], collaborative-filtering or social based recommendation [19], and hybrid recommendation systems [11].

In content-based recommender systems, users are recommended with items that are similar to those that they liked in the past [5]. The utility $u(c, s)$ of item s for user c is estimated based on the utilities $u(c, s_i)$ assigned by user c to items $s_i \in S$ where s_i are similar to item s [2]. Generally, content based recommender systems depend on three main processes: content analyzer, profile learner and filtering components [26]. The content analyzer is used for extracting information (keywords, concepts, etc) that represent items, and for extracting user's reactions towards these items. The profile learner is used to learn users' preferences, from their past reactions towards items, in order to construct and update user profile. Filtering components matches user profile with items characteristics to accomplish the recommendation.

In collaborative filtering recommender systems, recommendation is based on the user's neighbors' opinions not on the item itself [28]. The utility $u(c, s)$ of item s for user c is estimated based on the utilities $u(c_j , s)$ assigned to item s by those users $u(c_j , s)$ who are similar to user c [19].

Collaborative filtering recommender systems have three types: item-based, user-based, and item-user-based [31]. In user-based collaborative filtering, a user c who is interested in item x will be interested in item y, if there are other users. These users are similar to the user c and they are interested in the items x and y [28]. In item-based collaborative recommender system, if a user c likes item x, and the item x is similar to the item y according to the opinion to other users. Then item y should be recommended to the user c [29].

Hybrid recommender systems combine the characteristics of content-based and collaborative filtering methods for avoiding some limitations and problems of pure recommender systems, like the cold-start problem. The combination of approaches can proceed in the following different ways [2]:

1) Separate implementation of algorithms and joining the results.
2) Utilize some rules of content-based filtering in collaborative approach.
3) Utilize some rules of collaborative filtering in content based approach.
4) Create a unified recommender system that brings together both approaches.

However, another classification criterion of RS may be considered. For example, Depending on the information filtering method, there are (1) passive filtering systems [27] when a single recommender is generated for all system users, and (2) active filtering systems [8] where the recommendation is generated from the user's recommendation history to generate new customized recommendations.

There are also distinctions to be made between centralized systems (when the product descriptions and user profiles are stored in a centralized Server) and non-centralized Systems (generally developed on P2P networks).

We can also classify RS by considering the way user preferences are obtained and distinguish between explicit data collection systems (when the user is asked to voluntarily provide their valuations) and implicit data collection systems (where the system user is monitored).

The list below gives us an idea of the range of kind of classification criteria we can find in the literature. This list is not exhaustive, however, we are interested here on analyzing the state of this subject for a specific category of recommendation system that consist of the most future line of research in recent years: semantic social recommender systems.

2.2 Recommendation systems

The main idea of collaborative filtering recommender systems is to capture the user's tastes, compute the similarity between users, and predict the recommendations. Generally all the collaborative filtering algorithms have the main principals, but they differ in the way of computing the similarity between users.

Proposed in 1994 by Grouplens [28], Newsnet is one of the earliest collaborative filtering recommender systems. Newsnet is a user-based collaborative filtering, based on the Pearson r correlation coefficient. Ringo [30] is another

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collaborative filtering recommender system, which uses personalization to recommend music and artists. In 1999, IRA (Intelligent Recommendation Algorithm, [3]) was proposed as a graph based collaborative filtering recommender system, in which a breadth-first search algorithm is used to compute the shortest paths between graph vertices (users). Moreover, user-item bipartite graph and one-mode projection are used in a movie recommender system proposed in [22]. In this system a recommendation graph is defined as the sum of the bipartite graph and the one-mode projection graph, then a shortest path algorithm is applied on the recommender graph in order to compute the recommendation.

The limitation of the aforementioned works is the tight coupling with the collaborative filtering recommendation. Even if there are several graph based recommender systems, these recommender systems never employ the social network analysis measures in recommendation algorithms. For that reason, we propose to involve social network analysis measures in recommendation algorithms. Furthermore, we also propose to involve the user's semantic preferences in this recommendation algorithm, in order to have a semantic social recommendation algorithm.

2.3 Social network

Social Networks are networks in which vertices represent users, and edges represent links (social relations such as friendship and co authorship) among these users [24]. Social network analysis is the study of social networks by understanding their social entities, the people and their relationships. Examples considered indirectly as forms of social networks are: telecommunications, electronic mail, and electronic chat messengers (such as Skype, Google Talk or MSN Messenger). Actually, social network analysis measures are used to study the following structural properties of the social network [24, 14]. The **density** indicates the cohesion of the network. The **centrality** highlights the most important actors of the network and three definitions have been proposed. The **degree centrality** is based on the average length of the paths (number of adjacent edges). The **closeness centrality** is based on the average length of the paths (number of edges) linking a node to others and reveals the capacity of a node to be reached. The **betweenness centrality** focuses on the capacity of a node to be an intermediary between any two other nodes.

Furthermore, due to the recent evolution of social networks, social recommender systems are becoming more common, such as: (a) Finding the user's best co-workers in a social network [25], (b) Recommending friends, using graph based algorithms such as random walk [21], (c) Proposing music in a social network of connected artists [10], and (d) Tagging based recommender system for recommending photos [1]. Bookmarking uses a personalized tag recommendation system for users of

bookmarking sites using text mining similarity measures [9]. [4] Presenting a Facebook group recommender system, by using hierarchical clustering and decision tree techniques. Also, Facebook application has been proposed in [6] to find colleagues who can work in similar projects.

2.4 Semantic Social network

As we have seen, the use of software instead of users in the information filtering has some weaknesses: i) how to represent information complicates communication among agents and between agents and users, ii) reuse of information represented heterogeneously becomes too complicated.

With the arrival of the Semantic Web [7], these deficiencies are mitigated by the improvement and enrichment of the representation of information through the application of these technologies. Semantic Social Network is the composition of two types of technologies: semantic web technology [7] and social networks technology [14]. The first research question about the possibility of having a semantic social network was presented in 2002 [16]. Later in 2004 Stephen Downes [13] has proposed new type of Internet as a network within a network to reshape the Internet that we know. This type of Internet is based on merging semantic web technology and social network [14].

In [14], authors have proposed semantic social network analysis model semSNA, where social data are presented in RDF [1]. Then social network analysis features e.g. closeness centrality, betweenness centrality, and graph annotations are computed using SPARQL[1]. In [20], authors have used the social network analysis (SNA) for analyzing ontology and semantic web; they have applied some of social network analysis techniques on two different ontology's SUMO [2] ontology, and SWRC [3] ontology. In recent years several researches focused on the analysis of the semantic social networks and that propose various solutions in different fields, basically, they can be classified by way of representing the semantic aspect as: Semantic user profile in the social network, and Social Networking Ontologies.

1) Semantic user profile in the social network

Semantic user profiles have become a key part of adequate social network. In [23], authors have presented a semantic social network, applied to the PUII (Program for the University Industry Interface). Its objective was to identify the employees' skills in a company and to deal with knowledge in online communities. In this project the semantic social network is based on: (1) meta data representation of users and resources, (2) information

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[1] Semantic Web, W3C, http://www.w3.org/2001/sw/

[2] http://www.ontologyportal.org/

[3] http://ontobroker.semanticweb.org/ontologies/swrc-onto-2001-12-11.oxml

tailoring of user profile, using social network and ontology's, and (3) the semantic interoperability (Profile).
In [12], authors have used a multi-layered model to present the semantic social network; ontology has been presented as a semantic network of interrelated domain concepts, while user profiles have been described as weighted list of those concepts. User profiles have been clustered due to user's interests, and the similarity has been considered as a similarity measure between users and clusters,

2) **Social Networking Ontologies**
The two most important achievements in build ontologies to classify social networking activities so far: the Friend of a Friend project (FOAF [1]), and the Semantically-Interlinked Online Communities (SIOC[2]).

FOAF

FOAF[4] project, one of the largest projects in the semantic web, is a descriptive vocabulary built based on RDF and OWL, for creating a Web of machine-readable pages for describing people, the links between them and the things they create and do. It is accepted as standard vocabulary for representing social networks, and many large social networking websites use it to produce Semantic Web profiles for their users [15].

FOAF has the potential to become an important tool in managing communities, and can be very useful to provide assistance to new entrants in a community, to find people with similar interests or to gather in a single place, people's information from several different resources, decentralizing the use of a single social network service for example [15].

SIOC

The SIOC[5] project (Semantically-Interlinked Online Communities), is an ontology for representing rich metadata from the Social Web in RDF/OWL, accepted by The World Wide Web Consortium (W3C). It aims to enable the integration of online community information (wikis, message boards, weblogs, etc).

3. Our Method

The recent emergence of semantic social networks (SSNs) gives us an opportunity to investigate the role of semantic social influence in recommender systems. The performance of semantic social recommender systems are based in one hand on knowledge base usually defined as a concept diagram (like taxonomy) or ontology and in another hand on social network analysis measures (like degree centrality, betweenness centrality, influence).

3.1 Our Hybrid Item-Based Similarity Matching Method

In this work, we have extended existing methods to develop a hybrid item-based similarity matching method.

Item-Based Collaborative Filtering Multi-Attribute Similarity:
We developed a multi-attribute rating scheme that allows users to rate an item along five attributes. The algorithm is described below:
Step 1- *Specify user preferences.* The user assigns the weight values (W_A) to each attribute along which similarities between information items are to be computed.
Step 2- *Compute the similarity between items with respect to every attribute (subject, performance, overall likability).* For every attribute *A*, the similarity between information items *I* and *J* as given by [29]:

$$Sim_A(I,J) = \frac{\sum_{U \in Users}(R_A(U,I) - \check{R}_A(U))(R_A(U,J) - \check{R}_A(U))}{\sqrt{\sum_{U \in Users}(R_A(U,I) - \check{R}_A(U))^2}\sqrt{\sum_{U \in Users}(R_A(U,J) - \check{R}_A(U)}} \quad .(1)$$

Where $R_A(U,I)$ denotes the rating of user *U* on item *I* with respect to attribute *A*; $\check{R}_A(U)$ is the average rating of user *U* as per attribute *A*.
Step 3- Compute the CF multi-attribute similarity between
items. $$\textbf{MultSim}(I,J) = \frac{\sum_{A=1}^{3} W_A * Sim_A(I,J)}{\sum_{A=1}^{3} W_A} \quad (2)$$

Item-Based Semantic Similarity: In this method, we calculate the similarities between two items based on their semantic descriptions given in an ontology. The similarity between items *I* and *J* is based on the ratio of the common/shared RDF descriptions between *I* and *J* (*count_common_desc(I,J)*) to their total descriptions (*count_total_desc(I,J)*) as proposed by [32] and is given by: $$\textbf{SemSim}(I,J) = \frac{count\_common\_desc(I,J)}{coun\_total\_desc(I,J)} \quad (3)$$

Hybrid Item-Based Semantic-CF Similarity: Using (Eq.**2** and Eq.**3**) we calculate the hybrid Semantic-CF similarity using a linear weighted approach as:
$$sim(I,J) = W_M * MultSim(I,J) + W_S * SemSim(I,J) \quad (4)$$
Where W_M and W_S are the weights assigned to CF multi-attribute and semantic similarities respectively.

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[1] http://www.foaf-project.org/

[2] http://www.sioc-project.org/

3.2 Semantic-Social Recommendation Algorithm

The recommendation algorithm is shown in Table 1, we can define the algorithm input: as a product, and the algorithm output: as a group of customers (see table 1). These customers are supposed to like the input product and to buy it.

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1. Start the search from the semantic social network.
2. Look for the customers with the highest Degree Centrality.
    (a) Compare the semantic profile of the customer with the semantic profile of the product (Similarity)
    (b) Compare the similarity degree between customer and product with a threshold.
    (c) If the recommendation degree is not enough
        i. start the search again from another customer.
        Go to (2).
    (d) Else if
        i. add the customer to the output group.
        ii. Move to the next customer (This customers should be connected to the latter customer, with the highest similarity connection in the semantic social network)
        iii. Go to (a).
3. End

Table 1: steps of the recommendation algorithm

In this section, we introduce the dataset that we use for this research, and present some interesting characteristics of this dataset. Our dataset is obtained from a real online social network Amazon.com[1]. Our proposed algorithm depends on this dataset to build the semantic social network. For that, we have to build the semantic social network, then to apply the semantic social recommendation algorithm.

3.3 Performances of the semantic social network

To provide the recommendation algorithm, we built a semantic social network, from Amazon dataset, by two process: (a) Building the collaboration social network, each node of the social network represents a customer, and the edges represents the similarity between these customers (the similarity can be found, when two customers prefer same products with same ratings), (b) Building the semantic user profile, Amazon dataset has a conceptual presentation of products and users preferred products. A preliminary study on this collaboration social network yields the following results. The customers' number is 1974, the edges number is 125448, and the network density is 0,0664.

3.4 Performances of the recommendation algorithm

Give ten recommendation queries concerning a product that should be recommended to the most relevant

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[1] The complete dataset can be found in the link http://snap.stanford.edu/data/amazon-meta.html.

customers in the semantic social network. The experimental results are listed in Table 3 and table 4. From these tables, we present for each query, the number of relevant customers, the computation time and the number of discovered nodes in table 2, the mean absolute error, the precision and the recall in the table 3.

Items	Customers number	Computation time	Graph coverage
Item1	2	3m32s	361
Item2	2	3m33s	361
Item3	23	3m10s	361
Item4	2	3m50s	361
Item5	15	3m30s	361
Item6	3	3m40s	361
Item7	2	3m14s	361
Item8	17	3m38s	361
Item9	4	3m42s	406
Item10	4	3m21s	1123

Table 2: For each item we apply recommendation query, this tables show the number of recommended customers, the recommendation time and the number of discovered nodes

Items	Precision	Recall
Item1	0,83	0,91
Item2	0,53	0,91
Item3	0,74	0,85
Item4	0,61	0,74
Item5	0,56	0,67
Item6	0,55	0,56
Item7	0,45	0,45
Item8	0,55	0,69
Item9	0,76	0,87
Item10	0,65	0,69

Table 3: For each item we apply recommendation query, this tables show the precision and the recall measures.

1) Comparison Methods

As a comparison, we implemented the standard collaborative filtering algorithm described in Section 2. Then we notice that our recommendation algorithm provides a better precision // recall than the collaborative filtering algorithm, the computation time is better in the semantic social recommendation algorithm (if the time of building or uploading the social network is not considered).

As a heuristic nature the proposed approach algorithm explores between 70% and 80% explored users.

4. Conclusion and future work

Semantic social networks provide an important source of information regarding users and their relations enriched by knowledge base usually defined as an ontology. This is especially valuable to recommender systems. In this paper we proposed a semantic social recommendation algorithm which makes recommendations by considering a product recommendation to customers, which are connected via semantic social network, and we employs the social network analysis measures in the recommendation process, to benefit from the social relations between social network users. Our preliminary results by using Amazon dataset show a good computation time, good precision, and recall error values.

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