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A Semantic-Based Friend Reference System for Social Networks

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Abstract:

Remarkable accomplishment of rising Web 2.0, and different casual group (interpersonal organization) Sites, for instance, Amazon and movie lens, recommender systems are making striking opportunities to help people checking the web when hunting down apropos information, and settling on choices. Overall, these recommender systems are orchestrated in three characterizations: substance based, shared differentiating, and cross breed based proposal structures. Generally speaking, these systems use standard recommendation schedules, for instance, fake neural systems, closest neighbor, or Bayesian frameworks. In any case, these philosophies are obliged diverged from frameworks concentrated around web applications, for instance, casual groups or semantic web. In this paper, we propose a novel philosophy for recommendation systems called semantic social proposition structures that enhance the evaluation of casual groups (informal organization) mishandling the power of semantic interpersonal association examination. Explores genuine data from Amazon take a gander at the way of our proposal framework and furthermore the execution of our proposal computation.

Keywords: Semantic System; Social Networks; Reference systems

1. INTRODUCTION

Fifteen years ago, people typically made friends with others who live or work close to themselves, such as neighbors or colleagues. We call friends made through this traditional fashion as G-friends, which stands for geographical location-based friends because they are influenced by the geographical distances between each other. With the rapid advances in social networks, services such as Facebook, Twitter and Google+ have provided us revolutionary ways of making friends. According to Facebook statistics, a user has an average of 130 friends, perhaps larger than any other time in history [2].One challenge with existing social networking services is how to recommend a good friend to a user. Most of them rely on pre-existing user relationships to pick friend candidates. For example, Facebook relies on a social link analysis among those who already share common friends and recommends symmetrical users as potential friends. Unfortunately, this approach may not be the most appropriate based on recent sociology findings [16], According to these studies

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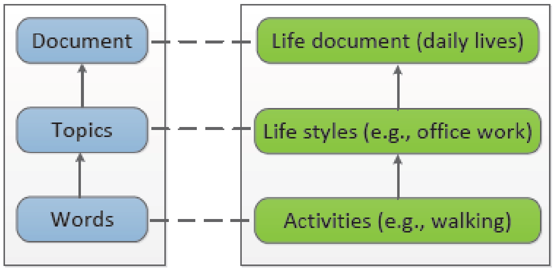

Fig 1.An analogy between word documents and people's daily lives.

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.Recommender systems has three main categories [2]: (1) content-based [5] where the users are recommended with items that are similar to those that they liked in the past,(2) collaborative-filtering (CF) or social recommendation [19] where the recommendation depends on the user's neighbors' opinions and not on the item itself, and (3) hybrid recommendation that combines the content-based and social based recommendation methods [11].

II.RELATED WORK

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.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]. 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] Collaborative filtering recommender systems have three types: item-based, user-based, and item-user-based [31]. In user-based collaborative filtering, 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).

III 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. Early generation of collaborative filtering systems, such as GroupLens [28], propose Newsnet; a recommender system for newsletters. Newsnet is a user-based, and uses Pearson r correlation coefficient to compute the similarity or weight among users and make predictions or recommendations according to those calculated similarity values. Later, Grouplens implemented this algorithm on Usenet news [17].In [30] authors introduced a personalized recommender system called Ringo, which recommends music and artists to users. For this system the authors implemented and compared four CF algorithms. These algorithms are:

(1) The mean squared differences algorithm; which measures dissimilarity between users,
(2) The Pearson r algorithm,
(3) The constrained Pearson r algorithm and
(4) The item based CF algorithm.

Their results showed that the constrained Pearson algorithm gives the best results.In [18] Spearman ranking correlation coefficient as another recommendation measure is proposed. Spearman correlation is the same as Pearson correlation, but instead of handling the ratings, the algorithm handles the ranking of the ratings. These results proved that Spearman ranking correlation performs as well as Pearson correlation.In [3] authors proposed an intelligent recommendation algorithm called IRA. This algorithm is a graph based collaborative filtering recommendation algorithm, where users are connected via directed graph. The nodes of this graph represent users while the directed edges of this graph represent the horting and predictability relation between these users; horting and predictability relation is mathematically defined in [3]. The algorithm recommends item j to user i by computing the shortest path in it’s entirely between the user i and group of users. Each user in this group should have common rated items with the user I and should have already rated the item j. In this algorithm the author proposed the breadth first search algorithm to compute the shortest paths between users. In [22] the authors proposed Movie recommender system.
In this system three graphs have been defined, the first graph is the bipartite graph. Its nodes are divided into two sets; the people set P, and the movie set M. The edges E are created between P and M and represent the ratings and viewing preferences between P and M. The second graph is the collaboration network graph which is a

one-mode projection graph between the users; two users will have collaboration connection between them, if they have at least one movie in common. The third graph is the recommender graph which is a sum of the social collaboration graph and the bipartite graph. In order to give the recommendation, shortest path algorithm is applied on the recommender graph.

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.

IV 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 between's centrality focuses on the capacity of a node to be an intermediary between any two other nodes.

4.1 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. 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, between's centrality, and graph annotations are computed using SPARQL1. 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.

4.4.1 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 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,

4.4.2 Social Networking Ontology's

The two most important achievements in build ontologies to classify social networking activities so far: the Friend of a Friend project (FOAF 4), and the Semantically Interlinked Online Communities (SIOC5).FOAF FOAF4 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 SIOC5 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).

V. SEMANTIC SOCIAL REFERENCE SYSTEMS

The recent emergence of semantic social networks (SSNs) gives us an opportunity to investigate the role of semantic social influence in recommender systems [32]. 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, between's centrality, influence).In this work, we propose to combine the content based recommendation and the social information in the social network to make a recommendation system in a semantic social network.

5.1 Semantic Social Recommendation Algorithm

We suppose, a semantic social network of connected customers, also we suppose, a new product. This product should be recommended to the most relevant customers from the semantic social network.The semantic social recommendation algorithm depends on two types of data: semantical data, and social data. In semantical data we integrate the semantic profile aspects to represent customers and products. In social data we create collaborative social network where nodes represent customers, and edges have weights and represent the similarity between these customers. The recommendation algorithm is shown in table 1; algorithm input are products, and algorithm output are group of. These customers are supposed to like the input product and to buy it. We introduce the social influence which plays an important role in product marketing. However, it has rarely been considered in traditional recommender systems.

6. CONCLUSION

Semantic interpersonal organizations give an imperative wellspring of data in regards to clients and their relations enhanced by learning base normally characterized as philosophy. This is particularly important to reference frameworks. In this paper we proposed a semantic social suggestion computation which makes suggestions by considering an item proposal to clients, which are joined through semantic informal organization, and we utilizes the informal community investigation measures in the proposal procedure, to profit from the social relations between interpersonal organization clients.

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