Using Semantic Recommenders for Personalized Recommendations

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Abstract— With the ever increasing information overload on the internet, recommender systems have long become a necessity. The popularity of e-commerce sites is increasing by the day and an abundance of shopping sites are presenting users with an increasing number of choices. It has become a challenging task to meet expectations of customers to better understand their needs and provide them with information and suggestions of their interest. With the e-commerce field being fiercely competitive, businesses have started to feel the need of personalization which helps them in building customer loyalty [17]. Personalized recommendations can prove to be the most important aspect of the evolution of the recommender systems. Personalized recommendation services provide opportunities to promote new products, increase sales, click-through and conversion rates [18].

The use of semantic web technologies in recommender systems can effectively enhance the quality of recommendation. Semantic web has provided structured knowledge representation tools such as taxonomies, ontologies, powerful languages such as Resource Description Framework (RDF), Web Ontology Language (OWL), etc. which can be used to represent rich, complex knowledge about things and their relationships and query languages such as SPARQL, reasoning engines that can infer logical consequences from a set of assertions. Semantics enable machines to process natural languages in a manner close to human cognition and mimic human reasoning to a certain extent [12]. This can greatly help to generate personalized predictions in the recommender framework [6].

Keywords- *Knowledge Representation; Personalization; Semantic Recommender; Semantic Relatedness; Semantic Tools; Similarity Calculation*

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I. INTRODUCTION

Recommender systems are software applications that give suggestions about the items or products that might interest a user. They can be viewed as a subclass of information filtering systems that try to predict users' response or preference over a set of choices. The main goal of the recommender system is to assist a user to deal with information overload problem by filtering through a large amount of information and option-space and to narrow down the set of choices. It has been observed that suggestions or recommendations about a particular item from peers or experts greatly influence the decision-making processes of humans. Computer-based recommender systems can expand the set of people from whom one can obtain recommendations [3].

Formally, a recommender system can be expressed as containing a set of users U - $\{u_1, u_2, u_3, \ldots u_n\}$ and a set of items I – $\{i_1, i_2, i_3, \ldots, i_m\}$, and computing for every pair $\{u_i, i_j\}$ a score $r_{i,j}$ that will measure predicted interest of user i in item j. Numerous e-commerce websites are taking advantage of the tendency of humans of being influenced by recommendation, by providing recommendations about their products. Recommender systems are being used increasingly in e-commerce websites for recommending books, music, video, TV shows, and other consumer products. Personalized recommendation services provided by these websites provide them opportunities to promote new products, increase sales, click-through and conversion rates [18]. With the e-commerce field being highly competitive, businesses have started to feel the need of personalization which helps them in building customer loyalty [17].

A. *Types of Recommender Systems*

The purpose of recommender systems is to estimate the ratings for items that are not yet seen by the user. These estimates are provided by various algorithms based on the study of the available transactional data to find out user preferences based on the items that the user may already have purchased or liked and other user characteristics [1]. Recommender systems estimate ratings of items based on various methods ranging from machine learning, approximation theory, to heuristics. Typically recommender systems are commonly classified into three broad categories depending on the method they use for estimating the ratings;

Content-based recommenders: In this type, recommendations are made based on items that have already selected by the user. These systems store item descriptions and user's profile including a model of user's preferences which capture user's interest in a particular item, as well as the history of user activities such as the items purchased or viewed by a user. This information can be used to as training data to algorithms that calculate or predict the utility score that a user might give to items not yet seen by her [2].

Collaborative recommenders: In this class of recommenders, the items are recommended based on what preferences other users have expressed for the same item. These systems are based on the assumption that other users' opinions and preferences for a particular item can be summarized in a way to predict ratings for the current user profile [3].

Hybrid recommenders: As the name suggests, hybrid recommender systems combine two or more recommendation techniques. A hybrid approach, often called as collaboration via content-based, tries to use information used by collaborative as well as content-based approaches to produce recommendations. This class of systems tries to overcome problems such as cold start, stability vs. plasticity, etc [4].

There cannot be a unique recommender system that will solve all problems. Rather the system needs to be designed or altered depending on the specific task at hand, information need, and item domain [3]. Recommender systems constantly need improvements in terms of better methods in representing user behavior, representation of information about the items that are to be recommended, and advanced recommendation modeling [1].

II. SEMANTIC RECOMMENDER SYSTEMS

With the ever increasing information overload on the internet, recommender systems have long become a necessity. The popularity of e-commerce sites is increasing by the day and an abundance of shopping sites are presenting users with an increasing number of choices. It has become a challenging task to meet expectations of customers to better understand their needs and provide them with information and suggestions of their interest. Personalizing recommendations can prove to be the most important aspect of the evolution of the recommender systems. In personalized recommendation scheme, instead of just getting a list of top selling items, each user will see a different list suiting to his or her taste [19]. It has been proven that personalized recommender systems can lead to generating better cognitive and emotional trust of users in the system which can greatly improve its adaptability [8]. Personalization also improves customer loyalty and enables cross-selling [9][10] [17].

Personalizing the recommender systems means making recommendations by taking into consideration users' interests as well as other contextual information such as users' location, schedule, and habits which might affect users' decision-making process while selecting an item. Representation of such information can be greatly simplified with the use of structured knowledge representation tools [7]. As the world is rapidly moving towards semantic web, one should think of merging these two domains. The use of semantic web technologies in recommender systems can effectively enhance the quality of recommendation. The advent of semantic technologies has led to more structured ways of knowledge representation in the form of taxonomies, ontologies. Extensive research in this field has led to powerful knowledge representation languages such as Resource Description Framework (RDF), Web Ontology Language (OWL), etc. which can be used to represent rich, complex knowledge about things and their relationships and query languages such as SPARQL Protocol and RDF Query Language (SPARQL). A number of reasoning engines have been developed that can infer logical consequences from a set of assertions. Semantics enable machines to process natural languages in a manner close to human cognition and mimic human reasoning to a certain extent [12]. This can greatly help to generate personalized predictions in the recommender framework [6].

III. LITERATURE REVIEW

Joan Borràs Nogués [6] has developed a semantic recommender system to provide personalized information of tourist activities in a particular region. The author notes that by using structured knowledge representation tools, the needed information such as description of items to be recommended, users' profile and preferences can be represented precisely and better matching performance can be obtained by employing semantic similarity measures and reasoning tools. The system SigTur/E-Destination makes use of domain ontology based on which user profile and characteristics of tourist activities are annotated. Based on the explicit and implicit information gathered from the user, the system then calculates preference score and confidence values which are then summarized to generate the recommendations [6].

Salam Fraihat and Qusai Shambour [11] have proposed a semantic recommender system to personalize e-learning. It will assist learners to find learning objects matching their interests in an e-learning environment. The framework utilizes intra and extra semantic relationships between the exact needs of a learner and the properties of learning objects. The algorithm tries to find semantic relatedness between expanded query terms with the help of semantic reasoning on a domain ontology. Authors Montuschi, Lamberti, Gatteschi, and Demartini [12] have developed a semantic-based recommendation system that matches job seekers' background information and job profiles with an online course catalog to propose relevant courses to job seekers to remain competent and to adapt their learning initiatives to the requirements of the job market. Authors created ontologies for the domain of interest. With the help of these ontologies, they generated semantic annotations for job seekers' profile or résumé, job advertisements, and course details and learning outcomes in a semi-automatic fashion. Competency gap is then identified by matching job seeker's profile and job posting details. An algorithm calculating semantic distance is then applied on a semantically annotated listing of learning resources to identify the courses that can bridge the competency gap.

In their paper, Massimiliano Albanese et. al. [13] have proposed a semantic recommender system for intelligently browsing the multimedia collection to find objects that are most likely to satisfy users' interest. They have used importance ranking method for ranking the choices. The proposed system computes customized recommendation score by combining several features of multimedia objects, past behavior of a user, and overall behavior of the entire community. The system uses a model of the browsing system in the form of a directed graph of objects where links between nodes denote patterns and similarity between objects. Different weights are assigned to edges depending on semantic relatedness which is calculated based on the distance between terms in the domain ontology. Angel L. Garrido and Sergio Ilarri [14] have developed a context independent tool for recommendation based on item's description and reviews. They have used diagrammatic representation called *topic maps* to show relationships between concepts within a particular context. Using NLP tools, item descriptions and user profile descriptions are processed to generate abstractions of themes, subject areas from items and users profile including likes and dislikes of the user. These topic maps are compared to find the degree of similarity between them to generate recommendations.

Wang and Kong [16] have designed a semantic-enhanced personalized recommender system that makes use of item category ontology. Semantic features of item's category, as well as user demographic information along with usage data, is used to form user-item rating matrix. This matrix is then used to produce recommendations. Three kinds of similarity measures are considers while doing this; similarity of users' evaluation history, the similarity between user's demographic data, and similarity between users' interests. This method is claimed to perform more effectively as compared to traditional collaborative methods in terms of recommendation precision and scalability.

IV. Conclusion

For generating personalized recommendations capturing accurate user profile is of utmost importance. The users' profile should reflect long-term information needs and interests of the particular user. An inadequate profile may lead to low quality and inadequate recommendations [15]. Semantic technologies provide a structured way of representing such information or knowledge. They also have proven techniques in the form of reasoners to infer information from a set of assertions. These techniques can be effectively employed to represent information about items to be recommended and users' profiles, likes, and preferences. Various methods of semantic similarity calculation can then be used to find utility score or relatedness score between each pair of item and user. These scores can be used to generate relevant recommendations which will be of personalized nature. The semantic reasoners can also help minimize the cold-start problem by completing the incomplete information through inference [5]. Thus, the use of semantic web technologies in recommender systems can effectively enhance the quality of recommendation.

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