Processing of queries through Semantic Recommendation System

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Abstract

The rapid intensification of the Internet, facilitate the required users to search an enormous diversity of contents in a books, journals, newspaper articles, web pages or movies, although lacking the necessitate of a former specific information of the contents to the user. The bundle of knowledge arise confusion to the user against his findings. Semantic Recommendation System make an effort to assist the user, detailing the required those things he could be concerned in, also it mainly relates on his identified either preferences or with similar characteristics. This paper describe the processing of queries given by various users, relates on the basis of their finding behavior through Semantic Recommendation System.

Keywords: *Semantic Recommendation System, Semantic Interaction*

1. Introduction

The fast development of the semantic web, enable users find an excellent sort of books, newspaper articles, pages or movies, without the necessity of a previous precise knowledge of the contents of every one of them. Then there's got to search for guidance from their teachers or other companions that a lot of Internet users experience when endeavoring to settle on their readings, exercises o practices is a very common reality [1]. Let s suppose that, in a teaching environment, a student has a great number of electronic content, such as papers, lectures, practices and exercises. The student can access many more objects than he is able to use, and has no idea of where he should begin, so bearing in mind the electronic contents are classified by levels, he decides to begin with the basic level. The student browses through all these contents for their topics and remembers a friend told him how much he enjoys those exercises related with specific content. The student decides to start with those contents, and once he has finished with them he calls his friend so he can recommend him more since the ones he has already gone through did match what he was looking for [2].

Our investigation tries to prove the feasibility of using Semantic Recommendation Systems applications in electronic book environments. These electronic books can be used in a learning environment or in a more general way. This article introduces the work that is being done to provide the educational environment with a semantic Recommendation System.

In order to grant for this need many various information and recommendation strategies are developed. Semantic Recommendation Systems is one of these [3]. Users find themselves overwhelmed by the overload of data and seek help to spot the objects which can be more interesting for them. A Semantic Recommendation System is an application capable of presenting a user a suggestion for an object, obtained on the idea of his previous preferences and therefore the preferences of a community which has likings and opinions almost like his. Semantic Recommendation Systems help us reduce the overload of information we suffer nowadays, providing, at the same time, customized access to information for a specific domain [6]. Semantic Recommendation Systems are utilized in areas like e-commerce, leisure or digital libraries so as to unravel the knowledge overload they produce. However, there are many other fields that present an identical problem, like those domains associated with education and learning object. This paper presents a recommendation-based solution, for the case of intelligent electronic books using data gathered from the user interaction.

2. Literature Review

Recommender system was defined as a way of assisting and augmenting the human process of using recommendations of others to form choices when there's no sufficient personal knowledge or experience of the alternatives [4]. Recommender systems handle the matter of data overload that users normally encounter by providing them with personalized, exclusive content and repair recommendations. Recently, various approaches for building Semantic Recommendation Systems are developed, which may utilize collaborative filtering, content-based filtering or hybrid filtering [5]. Collaborative filtering technique is that the most mature and therefore the most ordinarily implemented in several application areas. GroupLens may be a news-based architecture which employed collaborative methods in assisting users to locate articles from massive news database [6]. Ringo is a web social information filtering system that uses collaborative filtering to create users profile supported their ratings on music albums [7]. Amazon uses topic diversification algorithms to enhance its recommendation [8]. The system uses collaborative filtering method to beat scalability issue by generating a table of comparable items offline through the utilization of item-to-item matrix [9]. The system makes use of a interface that assists users in browsing the Internet; it's ready to track the browsing pattern of a user to predict the pages that they'll have an interest in. Pazzani et al. [10] designed an intelligent agent that attempts to predict which sites will interest a user by using naive Bayesian classifier. The agent allows a user to supply training instances by rating different pages as either hot or cold. A number of the issues related to content-based filtering techniques are limited content analysis, overspecialization and sparsity of knowledge [11]. Also, collaborative approaches exhibit cold-start, sparsity and scalability problems. These problems usually reduce the standard of recommendations [12]. so as to mitigate a number of the issues identified, Hybrid filtering, which mixes two or more filtering techniques in several ways so as to extend the accuracy and performance of recommender systems has been proposed [13], [14].

3. Benefits of Semantic Recommendation System

The principal advantage of distance learning and the use of learning objects are:

(1) Open-mindedness: an excellent amount of individuals can access the formation, making temporal and geographic barriers disappear. Time problems disappear because the Internet is out there at any time. The movement problems disappear also as an individual are often formed without the necessity of travelling several kilometers or to a different city.

(2) Economical: more people are often formed with fewer resources.

(3) Tailored pattern: most of the courses are interactive allowing the user to settle on the way of his formation according to his needs or personal interests.

(4) Likelihood of being in touch with other students: allowing a greater collaboration and knowledge interchange.

4. Semantic Recommendation Systems

a. Content Based: the system recommends similar objects to those the user has liked within the past.

b. Collaborative: the system recommends the user objects that are liked by users with similar likings.

c. Hybrid Approach: Lately, the exploration has exhibited the joined methodology of collaborative filtering and content-based filtering might be progressively powerful sometimes [15]. A hybrid methodology is often realized during a few various ways: by making content-based and collaborative-based.

The Semantic Recommendation System must provide a mechanism to compile the biggest amount possible of information from the users in order to make better recommendations. This process is called ‘‘feedback”. This is one of the weak points, as we could see in our research users do not like to measure the contents, so in many cases there is no feedback.

5. Semantic Similarity generation

Content-based filtering uses similarity between items to recommend items almost like what the user likes. For example If user A watches two recipes of cakes videos, then the system can recommend videos of recipes there to user. Collaborative filtering Uses similarities between queries and items simultaneously to supply recommendations. If user A is analogous to user B, and user B likes video 1, then the system can recommend video 1 to user A (even if user A hasn’t seen any videos almost like video 1).

A similarity measure may be a function $s:E\times E\rightarrow R$ that takes a pair of embeddings and returns a scalar measuring their similarity. The embeddings are often used for candidate generation as follows: given a question embedding $q\in E$, the system looks for item embeddings $x\in E$ that embeddings with high similarity $s(q,x)$. To determine the degree of similarity, most Semantic Recommendation Systems using Cosine formulae.

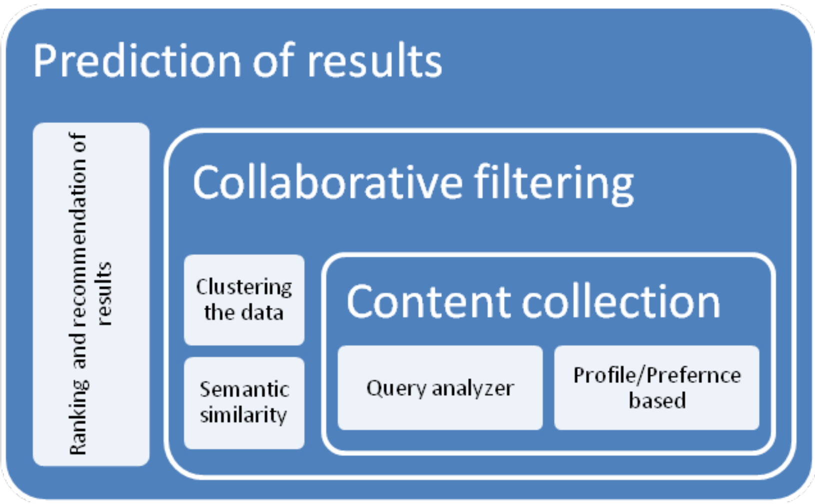

Figure 1: Phases of recommendation

The algorithm can be processed through following steps such as

Step 1: Content collection

a. Overview the profile of the user.

b. It analyses the query.

Step 2: Collaborative filtering

a. Cluster the query words.

b. Find the semantic similarity.

Step 3: Prediction of results

a. Ranking of the recommended results.

5. Results and discussion

When the user passes the second query to the web then it Semantic Recommendation System (SRS) is proposed interactive system to discover information from the web. SRS is a technique that predicts online behavior of the user while extracting intelligent information from the web. The design of semantic recommendation framework for the user profile is structured as

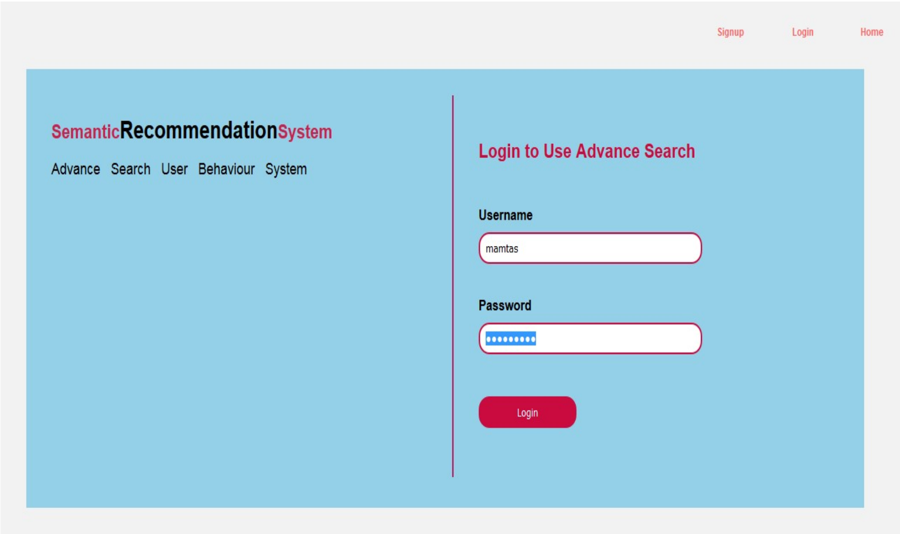

Figure 2: user profile

The framework for the recommendations can be obtained as below:

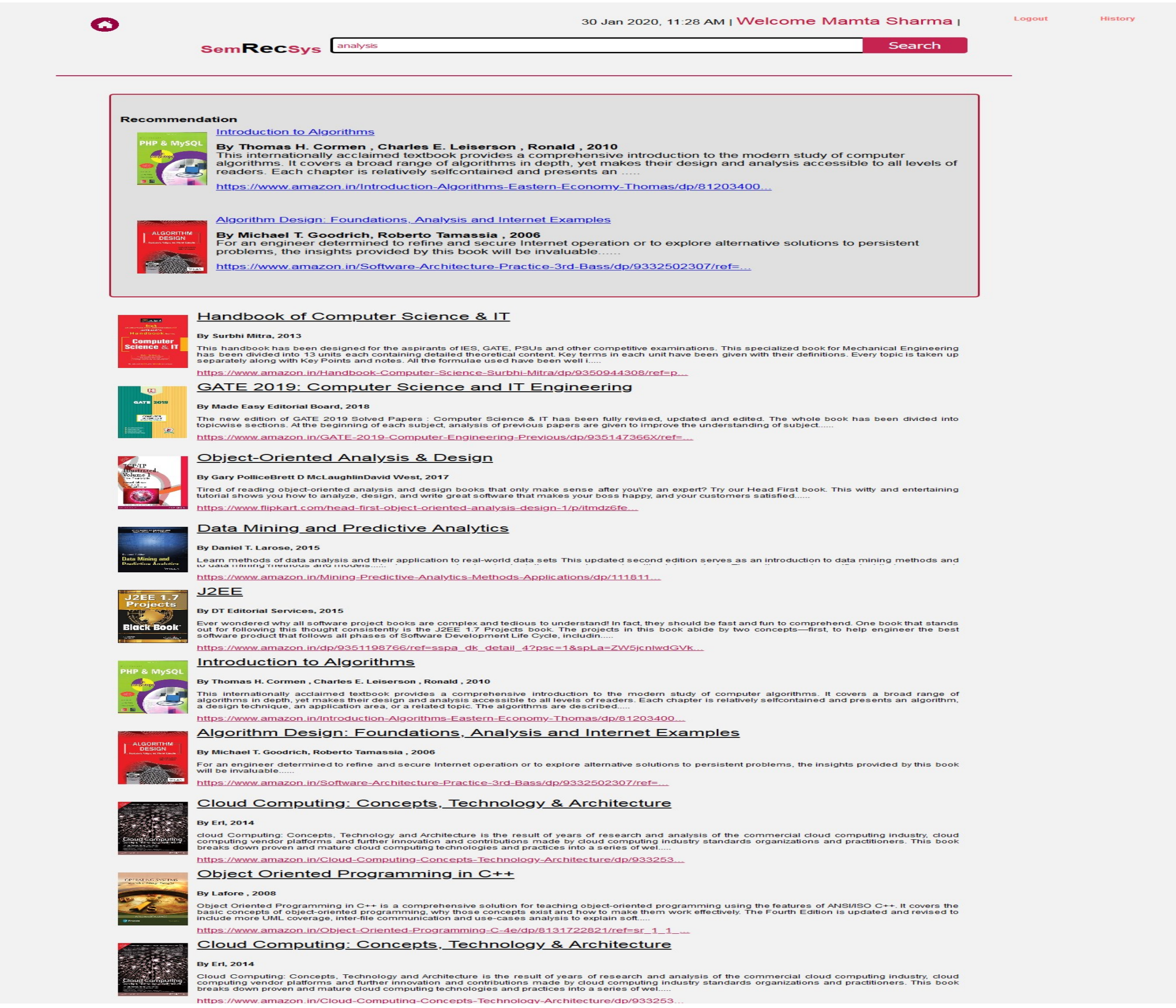

Figure 3: Recommendations after the evaluation

6. Conclusion:

The model doesn't need any data about other users, since the recommendations are specific to this user. This makes it easier to scale to a large number of users. The model can capture the specific interests of a user, and can recommend niche items that very few other users are interested in. Since the feature representation of the items is hand-engineered to some extent, this technique requires a lot of domain knowledge. Therefore, the model can only be as good as the hand-engineered features. The model can only make recommendations based on existing interests of the user. In other words, the model has limited ability to expand on the users' existing interests.

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