SERVICE RECOMMENDED SYSTEM FOR BIG DATA APPLICATION USING KEYWORD

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Abstract

Service recommender systems are valuable tools for providing appropriate recommendations to users. In the last decade the rapid growth of the number of customers, services and other online information yields service recommender systems in Big Data environment. In keyword aware service recommendation system, keywords are used to indicate both of user’s preferences and quality of candidate services. A user based collaborative filtering algorithm is adopted to generate appropriate recommendations. In CF based systems, users receive recommendations based on people who have similar tastes and preferences. The preference of previous users are extracted from their reviews and formalized into a keyword set. An active user can give his/her preferences about candidate services by selecting keywords from a keyword candidate list, which reflect the quality criteria of the services he/she is concerned about. The previous users who have similar tastes to an active user are found based on similarity of their preferences and recommendations are provided to the active user. But the system only depends on explicit user feedback, and thus is intrusive. It only considers user reviews and does not consider the temporal information about locations of the services. The limitations of the current recommendation system are reduced by possible extensions that provide better recommendation capabilities and usability of the system. These extensions include incorporation of temporal analysis into the recommendation process. This improves the accuracy of the predictions of recommendations.

Introduction

Recommender systems are software applications that attempt to reduce information overload by recommending items of interest to end users based on their preferences. It can be defined as a system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful services in a large space of possible options. The first recommender system, Tapestry, was designed to recommend documents from newsgroups[11]. Nowadays, the trend “everything as a service” has been creating a Big Services. The big data comprises high volume, high velocity, and high variety information assets, which are difficult to gather, store, and process by using the available technologies. A keyword-aware service recommendation method, named KASR, uses a user-based Collaborative Filtering algorithm. In KASR, keywords extracted from reviews of previous users are used to indicate their preferences and to generate new recommendations.
In Existing System,

This further improves the usability of the system. Implementation on a Big data platform like MongoDB significantly improves the accuracy and scalability of service recommender systems over existing approaches and performs better with larger datasets. It can be compared with the existing keyword aware service recommender system. The metric used to evaluate the accuracy is MAE, Mean Absolute Error. MAE is a statistical accuracy metric often used in CF methods to measure the prediction quality. It is defined as the average absolute deviation between a predicted rating and the real rating.

The existing system only recommends services to users and does not take into consideration about the preference of location of the particular service. Users of these online social services not only encounter the problem of information overload, but also have mutable interests which change fast along with the social information streams.

In Proposed System,

These features pose great challenges to recommender systems, since the purpose of such systems is to provide suitable recommendations that match users real-time interests, which is quite difficult among massive candidates and fast changing user preferences. To improve the system we can include temporal data. Various limitations of the current recommendation methods discussed in the can be reduced by possible extensions that can provide better recommendation capabilities. These extensions include, the improved modeling of users and service providers by the incorporation of temporal analysis into the recommendation process.

The user can also be provided with the choice of selecting a new location if the temporal analysis of the location is not satisfactory or else user can proceed with the same. Experiments are conducted to evaluate the accuracy of the system. The figure shows the comparison of MAE measure. The figure shows the analysis of the proposed system in terms of number of similar members generated for the number of keywords selected. Analysis of proposed system is done with the help of WEKA tool. Three locations were selected for the analysis.

System Architecture

![System Architecture Diagram]

Modules

• Admin Module
• Dynamic feature extraction
• Adaptive weighting algorithm

Admin Module

For the sparsely of recommendation data, the main difficulty of capturing users dynamic preferences is the lack of useful information, which may come from three sources user profiles, item profiles and historical rating records. Traditional algorithms heavily rely on the co-rate relation. Which is rare when the data is sparse.

Intuitional and physically significant when we go one or two steps along, but it strongly limits the amount of data used in each prediction.
**Dynamic feature extraction**

Users preferences or items reputations are drifting, thus we have to deal with the dynamic nature of data to enhance the precision of recommendation algorithms, and recent ratings and remote ratings should have different weights in the prediction.

Three kinds of methods were proposed in concept drift to deal with the drifting problem as instance selection, time-window (usually time decay function) and ensemble learning.

**Adaptive weighting algorithm**

Item’s reputations are commonly affected by only a few principle factors, indicating that using more features might also bring noise into the recommendation so we changed the destination of the optimization and limited the quantity of the features by regularization.

**A. Content-based filtering**

Content-based recommender systems work with profiles of users that are created at the beginning. A profile has information about a user and his taste. Taste is based on how the user rated items. Generally, when creating a profile, recommender systems make a survey, to get initial information about a user in order to avoid the new-user problem.

The content-based approach to recommendation has its roots in information retrieval and information filtering systems. Because of the significant and early advancements made by the information retrieval and filtering communities and because of the importance of several text-based applications, many current content-based systems focus on recommending items or services containing textual information, such as documents, Web sites (URLs), and Usenet news messages. The profiling information can be elicited from users explicitly, e.g., through questionnaires, or implicitly—learned from their transactional behavior over time[2].

**B. Collaborative filtering**

Collaborative filtering became one of the most researched techniques of recommender The idea of collaborative filtering is finding users in a community that share appreciations . If two users have same or almost same rated items in common, then they have similar tastes. Such users build a group or a so called neighborhood. A user gets recommendations to those items that he/she hasn’t rated before, but that were already positively rated by users in his/her neighborhood. The taste is considered to be constant or at least change slowly In CF based systems, users receive recommendations based on people who have similar tastes and preferences, which can be further classified into item-based CF and user-based CF.In the user-based approach the items that were already rated by the user before, play an important role in searching a group that shares appreciations with him.In item-based systems, the predicted rating depends on the ratings of other similar items by the same user.

**C. Hybrid recommendation approaches**

For better results some recommender systems combine different techniques of collaborative approaches and content based approaches. Using hybrid approaches we can avoid some limitations and problems of pure recommender systems, like the cold-start problem. The recommendation methods described above have performed well in several applications. However, they have certain limitations, described in the TABLE 1. Moreover, in order to provide better
recommendations and to be able to use recommender systems in more complex types of applications most of the methods would need significant extensions.

D. Modern Recommendation Approaches

Context is the information about the environment of a user and the details of situation he/she is in. Such details may play much more significant role in recommendations than ratings of items, as the ratings alone don’t have detailed information about under which circumstances they were given by users. Some recommendations can be more suitable to a user in evening and doesn’t match his preferences in the morning at all and he/she would like to do one thing when its cold and completely another when its hot outside. The recommender systems that pay attention and utilize such information in giving recommendations are called context-aware recommender systems. As opposed to content information that is saved in profiles, context changes dynamically and often saved just permanently, as it is more likely to lose its currency after a certain period of time. That is why it is very important to periodically refresh the information. Context-aware recommender systems became much attention, as they noticeably increased the quality of recommendations and the approaches became more specific to use in certain areas.

Semantic based approaches

Most of the descriptions of items, users in recommender systems and the rest of the web are presented in the web in a textual form. Using tags and keywords without any semantic meanings doesn’t improve the accuracy of recommendations in all cases, as some keywords may be homonyms. That is why understanding and structuring of text is a very significant part recommendation. Traditional text mining approaches that is based on lexical and syntactical analysis show descriptions that can be understood by a user but not a computer or a recommender system. That was a reason of creating new text mining techniques that were based on semantic analysis[8].

Cross-domain based approaches

Finding similar users and building an accurate neighborhood is an important part of recommending process of collaborative recommender systems. Similarities of two users are discovered based on their appreciations of items. But similar appreciations in one domain don’t surely mean that in another domain valuations are similar as well. Standard recommender systems based on collaborative filtering compare users without splitting items in different domains. In cross-domain systems similarities of users computed domain-dependent. An engine creates local neighborhoods for each user according to domains. Then, computed similarity values and finite set of nearest-neighbors are sent for overall similarities computation. Recommender system determines the overall similarity, creates overall neighborhoods and makes predictions and recommendations.

Peer-to-Peer approaches

The recommender systems with P2P approaches are decentralized. Each peer can relate itself to a group of other peers with same interest and get recommendations from the users of that group. Recommendations can also be given based
on the history of a peer. Decentralization of recommender system can solve the scalability problem.

**Cross-lingual approaches**

The recommender system based on cross-lingual approach lets the users receive recommendations to the items that have descriptions in languages they don’t speak and understand. The main idea of cross-lingual based approach is to map both text and keywords in different languages into a single feature space, that is to say a probability distribution over latent topics. From the descriptions of items the system parses keywords than translates them in one defined language using dictionaries. After that, using collaborative or other filtering, the system gives recommendations to users. Cross-lingual recommender systems break the language barrier and gives opportunities to look for items, information, papers or books in other languages.

**CONCLUSION**

An improved Keyword Aware Service Recommendation System has been proposed in which apart from getting personalized recommendation about services, the user also gets an analysis of the location during a particular time of the year. The proposed method eliminate the intrusiveness of Keyword Aware Recommendation System by incorporating temporal constraints. Finally, the experimental results demonstrate that the proposed system significantly improves the accuracy and usability of service recommender systems over existing approaches.

**REFERENCES**