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A Review Paper: Personalized QOS Web Service Recommendation and Visualization

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Abstract— Recommender systems have become extremely common in recent years, and are applied in a variety of applications. The most popular ones are probably movies, music, news, books, research articles, search queries, social tags, and products in general. However, there are also recommender systems for experts, jokes, restaurants, financial services, life insurance, persons (online dating), and Twitter followers. In this paper, we present review of collaboration filtering for accurate web recommendation service using characteristics of QoS and user location and we use recommendation visualization map.

Keywords— service recommendation, collaboration filtering, visualization, QoS

I. INTRODUCTION

Web services are open standard (XML, SOAP, HTTP etc.) based Web applications that interact with other web applications for the purpose of exchanging data Web Services can convert your existing applications into Web-applications.In recent, web service have attracted wide attention from both industry and academia, and the number of public web services is steadily increasing.

From the several different services the best one must be chosen to attain the high services efficiency. In last few years many methods have be introduce to get the better services. Thus collaborating filtering has been used in providing best service.

The growth of the Internet has made it much more difficult to effectively extract useful information from all the available online information. The overwhelming amount of data necessitates mechanisms for efficient information filtering. One of the techniques used for dealing with this problem is called collaborative filtering.

The motivation for collaborative filtering comes from the idea that people often get the best recommendations from someone with similar tastes to themselves. Collaborative filtering explores techniques for matching people with similar interests and making recommendations on this basis.

II. EXISTING WORK

Several previous works has applied collaborative filtering (CF) to web service recommendation[3][6]. These CF-based web service recommender systems works by collecting user observed QoS records of different web services and matching together users who share the same information needs or same tastes. Users of a CF system share their judgments and opinions on web services, and in return, the system provides useful personalized recommendations.

There is some drawback of existing system,

I] it is fail to recognize the QoS variation with users physical location.

II] Online time complexity of memory based CF recommendation for tens of thousands user in real time.

III] Current recommender system are all black boxes, providing list of ranked web services with no transparency into the reasoning behind the recommendation system.

III. PROPOSED SYSTEM

In this proposed system we propose an review of innovative CF algorithm for QoS-based web service recommendation.
To address the third problem that is Current recommender system are all black boxes, providing list of ranked web services with no transparency into the reasoning behind the recommendation system and enable an improved understanding of the web service recommendation , In [1] provide a personalized map for browsing the recommendation results. The map explicitly shows the QoS relationships of the recommended web services as well as the underlying structure of the QoS space by using map metaphor such as dots, areas, and spatial arrangement. Visualization map allow the user to zoom in zoom out so that one can know which company will provide the better

services .Interactive visualization maps will also provide longitude and latitude so that it make the user know the exact services also give, interactive visualization map is done by the techniques called subsurface geology techniques.

IV. RECOMMENDATION APPROACH

Collaborative filtering algorithms often require (1) users' active participation, (2) an easy way to represent users' interests to the system, and (3) algorithms that are able to match people with similar interests.

Typically, the workflow of a collaborative filtering system is:

1. A user expresses his or her preferences by rating items (e.g. books, movies or CDs) of the system. These ratings can be viewed as an approximate representation of the user's interest in the corresponding domain.
2. The system matches this user's ratings against other users' and finds the people with most "similar" tastes.
3. With similar users, the system recommends items that the similar users have rated highly but not yet being rated by this user (presumably the absence of rating is often considered as the unfamiliarity of an item)

A key problem of collaborative filtering is how to combine and weight the preferences of user neighbors. Sometimes, users can immediately rate the recommended items. As a result, the system gains an increasingly accurate representation of user preferences over time.

1. Memory-based

This mechanism uses user rating data to compute similarity between users or items. This is used for making recommendations. This was the earlier mechanism and is used in many commercial systems. It is easy to implement and is effective. Typical examples of this mechanism are neighbourhood based CF and item-based/user-based top-N recommendations.[3] For example, in user based approaches, the value of ratings user 'u' gives to item 'i' is calculated as an aggregation of some similar users rating to the item:

$$r_{u,i} = aggr_{\,u' \epsilon U} r_{u',i}$$

where 'U' denotes the set of top 'N' users that are most similar to user 'u' who rated item 'i'. Some examples of the aggregation function includes:

$$r_{u,i} = \frac{1}{N} \sum_{u' \in U} r_{u',i}$$

location where the services are provide. Through the interactive visualization map more information about the

$$r_{u,i} = k \sum_{u' \in U} simil(u,u') r_{u',i}$$

$$r_{u,i=\bar{r}_u} + k \sum_{u' \in U} simil(u,u')(r_{u',i} - \bar{r}_{u'})$$

where k is a normalizing factor defined as

$$k = \frac{1}{\sum_{u' \in U} |simil(u,u')|}.$$

and $\bar{r}_u$is the average rating of user u for all the items rated by that user.

The neighborhood-based algorithm calculates the similarity between two users or items, produces a prediction for the user taking the weighted average of all the ratings. Similarity computation between items or users is an important part of this approach. Multiple mechanisms such as Pearson correlation and vector cosine based similarity are used for this.

The Pearson correlation similarity of two users x, y is defined as

$$sim(x,y) = \frac{\sum_{i \epsilon I_{xy}} (r_{x,i} - \bar{r}_x) . (r_{y,i} - \bar{r}_y)}{\sqrt{\sum_{i \epsilon I_{xy}} (r_{x,i} - \bar{r}_x)^2} . \sqrt{\sum_{i \epsilon I_{xy}} (r_{y,i} - \bar{r}_y)^2}}$$

where $I_{x,y}$ is the set of items rated by both user x and user y.

The cosine-based approach defines the cosine-similarity between two users x and y as

$$sim(x,y) = \cos(\vec{x}, \vec{y}) = \frac{\vec{x} . \vec{y}}{||\vec{x}|| \times ||\vec{y}||} = \frac{\sum_{i \in I_{xy}} r_{x,i} \, r_{y,i}}{\sqrt{\sum_{i \in I_x} r^2_{x,i}} \sqrt{\sum_{i \in I_y} r^2_{y,i}}}$$

The user based top-N recommendation algorithm identifies the k most similar users to an active user using similarity based vector model. After the k most similar users are found, their corresponding user-item matrices are aggregated to identify the set of items to be recommended. A popular method to find the similar users is the Locality-sensitive hashing, which implements the nearest neighbor mechanism in linear time.

The advantages with this approach include: the explainability of the results, which is an important aspect of recommendation systems; it is easy to create and use; new data can be added easily and incrementally; it need not consider the content of the items being recommended; and the mechanism scales well with co-rated items.

There are several disadvantages with this approach. First, it depends on human ratings. Second, its performance decreases when data gets sparse, which is frequent with web related items. This prevents the scalability of this approach and has problems with large datasets. Although it can efficiently handle new users because it relies on a data structure, adding new items becomes more complicated since that representation usually relies on a specific vector space. That would require to include the new item and re-insert all the elements in the structure.

2. *Model-based*

Models are developed using data mining, machine learning algorithms to find patterns based on training data. These are used to make predictions for real data. There are many model-based CF algorithms. These include Bayesian networks, clustering models, latent semantic models such as singular value decomposition, probabilistic latent semantic analysis, Multiple Multiplicative Factor, Latent Dirichlet allocation and markov decision process based models.

This approach has a more holistic goal to uncover latent factors that explain observed ratings. Most of the models are based on creating a classification or clustering technique to identify the user based on the test set. The number of the parameters can be reduced based on types of principal component analysis.

There are several advantages with this paradigm. It handles the sparsity better than memory based ones. This helps with scalability with large data sets. It improves the prediction performance. It gives an intuitive rationale for the recommendations.

The disadvantages with this approach are in the expensive model building. One needs to have a tradeoff between prediction performance and scalability. One can lose useful information due to reduction models. A number of models have difficulty explaining the predictions.

3. *Hybrid approach*

A number of applications combines the memory-based and the model-based CF algorithms. These overcome the limitations of native CF approaches. It improves the prediction performance. Importantly, it overcomes the CF problems such as sparsity and loss of information. However, they have increased complexity and are expensive to implement. Usually most of the commercial recommender systems are hybrid, for example, Google news recommender system.

CONCLUSION

In this paper, we have review innovative approach to web service recommendation and visualization but in this we combine factor of prediction accuracy and time complexity. In this review, recommendation approach considered the correlation between QoS records and users' physical locations by using IP addresses, which has achieved good prediction performance. In some cases, however, users in the same physical locations may observe different QoS performance of the same web service. Besides the user physical location, we will investigate more contextual information that influences the client-side QoS performance, such as the workload of the servers, network conditions, and the activities that users carry out with we services (e.g., web services are used alone or in composition).

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