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A survey of web service recommendation methods

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Abstract - Web Services (WS) are application components which help in integrating various Web based applications. WS are used by almost all web applications. With the help of WS, web applications can provide service on the internet without any restrictions to the operating system or programming language. Today the number of WS on the internet is rising and it is difficult for the user to select a well suited service among a large number of services which gives low performance to the user and it is a potential risk for a business process. In this paper, we first Introduce content based filtering approach and than CF tasks and their main challenges, such as data sparsity, gray sheep. And after that a hybrid approach is introduced. A survey is performed in this paper related to methods and algorithm which are used for Web service recommendation by different author.

Keyword - *Web service recommendation, content based filtering, collaborative filtering, hybrid filtering, data mining, text mining.*

I. INTRODUCTION

Web service recommendation is a process of proactively discovering and recommending suitable Web services to end users. In order to predict Web Services for a user, user preferences, user location and web service properties should be considered, like QoS which has been considered as a major factor in service selection. QoS includes response time, price, correctness, etc. Among these properties some values like response time, etc. must be measured at the client side in order to get accurate feedback from the end user's point of view, which results in obtaining accurate results. Some QoS factors like reliability needs to be calculated by observing for long period of time. For the recommendation system it becomes difficult to get QoS data for all the services due to huge number of web services. These problems are overcome by giving personalized predictions to the user based on past user experiences or the feedback data. And the users can select the service which gives them optimal performance.

II. SERVICE RECOMMENDATION METHODS

2.1Content-based Methods for Service Recommendation

CBF algorithms base recommendations on the features extracted from the items' content. The typical bag-of-word approach represents items as vectors of features stored into a feature-by-item matrix, which is referred to as item-content matrix (ICM) and denoted by **W**. Each column in the ICM represents an item, and each row represents a feature. Values indicate that an item have a certain feature with a certain weight. Items' content requires to be processed in order to identify terms (tokenizing), to remove useless words (stop words), to normalize words (stemming), and to weight each feature (weighting).
Content-based service recommendation approaches focused on exploring the description information of Web services and the user's own service usage history. Generally, the Web services which are highly relevant to the user's service usage history and own high QoS utility would be recommended to users. Kang et al. proposed an active Web service recommendation approach based on service usage history which incorporates both user interest and QoS preference into Web service recommendation. With the user interest and QoS preference, recommender systems can recommend top-k optimal services with user-desired functional and non-functional requirements. A user's potential QoS preference is acquired by the average QoS preference from service usage history [1]. This potential QoS preference is used for all the service candidates. However, the QoS preference may be not accurate because a user may have different QoS preferences to different ser-vices. Therefore, this approach should be further improved. Liu et al. proposed a semantic content-based recommendation approach that analyzes the context of intended service use to provide effective recommendations in conditions of scarce user feedback. Hu et al. proposed a personalized search approach for Web service recommendation, in which interests are extracted from users' records. While these two works do not consider QoS preferences and potential user interests of users, which will be ad-dressed in this work.

Newly-deployed web services can be recommended by this technique. Also, content-based techniques have the overspecialization problem, that is, they can only recommend items that score highly against a user's profile or his/her rating history [2].

2.2 Collaborative filtering Methods for Service Recommendation

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 is a technique used by the recommender systems to make predictions and recommend potential favorite items to a user by finding similar users to that user, CF is based on user-item matrix. The underlying assumption of the collaborative filtering approach is that if a person *A* has the same opinion as a person *B* on an issue, *A* is more likely to have *B*'s opinion on a different issue *x* than to have the opinion on *x* of a person chosen randomly. Breese et al. divide the CF algorithms into two broad classes [1]:

Memory based algorithms and model-based algorithms. Memory based collaborative filtering includes user-based approaches, item-based approaches and their fusion. User-based approaches predict the ratings of users based on the ratings of other similar users, and item-based approaches predict the ratings of users based on the similarity of the item. Memory-based algorithms are easy to implement, require little or no training cost, and can easily take ratings of new users into account but do not scale well to a large number of users and items due to the high computation complexity.

Model-based CF algorithms, on the other hand, learn a model from the rating data using statistical and machine learning techniques. Examples include clustering models, latent semantic models, latent factor models, and so on. These algorithms can quickly generate recommendations and achieve good online performance. However, these models must be rebuilt when new users or items are added to the system. The importance of collaborative filtering methods is: guessing the usefulness of a particular item for a particular user depending upon the previous history of other users.

2.2.1 Challenges of Collaborative Filtering

2.2.1.1 Data Sparsity

In practice, many commercial recommender systems are used to evaluate very large product sets. The user-item matrix used for collaborative filtering will thus be extremely sparse and the performances of the predictions or recommendations of the *CF* systems are challenged. The data sparsity challenge appears in several situations, specifically, the *cold start* problem occurs when a new user or item has just entered the system, it is difficult to find similar ones because there is not enough information (in some literature, the *cold start* problem is also called the *new user problem* or *new item problem).* New items cannot be recommended until some users rate it, and new users are unlikely given good recommendations because of the lack of their rating or purchase history. *Coverage* can be defined as the percentage of items that the algorithm could provide recommendations for. The *reduced coverage* problem occurs when the number of users' ratings may be very small compared with the large number of items in the system, and the recommender system may be unable to generate recommendations for them. *Neighbor transitivity* refers to a problem with sparse databases, in which users with similar tastes may not be identified as such if they have not both rated any of the same items. This could reduce the effectiveness of a recommendation system which relies on comparing users in pairs and therefore generating predictions. To alleviate the data sparsity problem, many approaches have been proposed. Dimensionality reduction techniques, such as *Singular Value Decomposition (SVD)*, remove unrepresentative or insignificant users or items to reduce the dimensionalities of the user-item matrix directly [3].

2.2.1.2Gray Sheep

Gray sheep refers to the users whose opinions do not consistently agree or disagree with any Group of people and thus do not benefit from collaborative filtering[9].

2.2 Hybrid Methods for Service Recommendation

Both content-based recommender systems and *CF* systems have limitations. Hybrid *CF* techniques, combine *CF* and content-based techniques, hoping to avoid the limitations of either approach and thereby improve recommendation performance [4].

III. LITERATURE SURVEY

Guosheng Kang presented a Web service recommendation approach with diversity to find desired Web services for users. He incorporate functional interest, QoS preference, and diversity feature for recommending top-k diversified Web services. A diversified Web service ranking algorithm is proposed to find the top-k diversified Web service ranked list based on their functional relevance including historical user interest relevance and potential user interest relevance, non-functional relevance such as QoS utility, and diversity feature [1].

Z. Erkin,propose technological mechanisms to protect the privacy of individuals in a recommender system. He founded on homomorphic encryption, which is used to obscure the private rating information of the customers from the service provider. While the user's privacy is respected by the service provider, by generating recommendations using *encrypted* customer ratings [2].

Lina Yao propose a three-way aspect model that considers both QoS ratings and the semantic content of web services. User preferences are modeled as a set of latent variables in the aspect model, which can be statistically estimated using the expectation maximization method. To avoid overfitting problems caused by data sparsity, further propose two strategies. The first one is to pre-process data matrix using a data smoothing technique and the second one is a modified aspect model that captures relationship between users and semantic content descriptors of web services [3].

Yan Hu propose an improved time-aware collaborative filtering approach for high-quality web service recommendation. He integrates time information into both similarity measurement and QoS prediction. Additionally, in order to alleviate the data sparsity problem, a hybrid personalized random walk algorithm is designed to infer indirect user similarities and service similarities [4].

Xi Chen propose a novel collaborative filtering-based Web service recommender system to help users select services with optimal Quality-of-Service (QoS) performance. recommender system employs the location information and QoS values to cluster users and services, and makes personalized service recommendation for users based on the clustering results [5].

Huifeng Sun present a new similarity measure for web service similarity computation and propose a novel collaborative filtering approach, called normal recovery collaborative filtering, for personalized web service recommendation [6].

Zibin Zheng propose an approach for predicting QoS values of Web services by systematically combining the user-based PCC approach and the item-based PCC approach [7].

Xi Chen and Xudong Liu,present RegionKNN, a novel hybrid collaborative filtering algorithm that is designed for large scale web service recommendation. Different from other approaches, this method employs the characteristics of QoS by building an efficient region model. Based on this model, web service recommendations will be generated quickly by using modified memory-based collaborative filtering algorithm [8].

By considering the third dynamic context information, a Temporal QoS-Aware Web Service Recommendation Framework is presented to predict missing QoS value under various temporal context. Further, Wancai Zhang formalize this problem as a generalized tensor factorization model and propose a Non-negative Tensor Factorization (NTF) algorithm which is able to deal with the triadic relations of *user-service-time* model [9].

Jianxun Liu propose a location-aware personalized CF method for Web service recommendation. The proposed method leverages both locations of users and Web services when selecting similar neighbors for the target user or service. The method also includes an enhanced similarity measurement for users and Web services, by taking into account the personalized influence of them [10].

Number	**Paper title**	**Year**	**publication**	**Reference number**	**Features**	**Methods**
1	Diversifying web service recommendation results via exploring service usage history	2015	IEEE transactions on services computing	1	Novel Web service recommendation approach incorporating a user's potential QoS preferences & diversity feature	Collaborative filtering
2	Location-aware and personalized collaborative filtering for web service recommendation	2015	IEEE transactions on services computing	10	Cluster user according to location	Location-aware collaborative filtering method

3	Time aware and data sparsity tolerant Web service recommendation based On improved collaborative filtering	2015	IEEE transactions on services computing	4	Integrates time information into both similarity Measurement and QOS prediction	Collaborative filtering
4	Unified collaborative and content-based web Service recommendation	2015	IEEE transactions on services computing	3	To avoid over fitting problems caused by data sparsity,data smoothing & modified aspect model used	Hybrid approach that combines Collaborative filtering and semantic content-based Methods
5	Temporal QOS-aware web service recommendation via Non-negative tensor factorization	2014	ACM	9	Non-negative tensor factorization (NTF) algorithm to deal with user-service-time model	Collaborative filtering
6	Web service recommandation via exploiting Location and Qos information	2014	IEEE transactions on parallel and distributed systems	5	Location information and QOS values to cluster users and services	Collaborative filtering
7	Personalized web service recommendation Via normal recovery collaborative filtering	2013	IEEE transactions on services computing	6	Normal recovery collaborative Filtering approach (named NRCF)	Collaborative filtering
8	Privacy-preserving content-based recommender system	2012	ACM	2	Recommendations using Encrypted customer ratings	Content-based recommender systems
9	QOS-aware web service recommendation By collaborative filtering	2011	IEEE transactions on services computing	7	QOS value Prediction approach by combining the User-based and item-based collaborative filtering Methods	Collaborative filtering
10	A scalable hybrid collaborative filtering	2010	IEEE international conference on web	8	New region model for clustering users & hybrid	Collaborative filtering

	algorithm for personalized web Service recommendation		services		model-based and memory-based CF algorithm	

IV. CONCLUSION

Different parameters and algorithms are considered by different author for recommendation. The basic idea is to predict Web service QoS values and recommend the best one for active users based on historical Web service QoS records. Here literature survey is performed of different parameters considered in web service recommendation.

V. FUTURE WORK

We will proposed the system that can produce the recommendation result by applying data mining on history data and text mining on comments.And for clustering and classification techniques will be used.

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