Grid Service Recommendation System – A Survey

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Abstract— Grid Service Recommendation System provides service recommendations to users based on the Quality of Service parameters they require to run their project on the grid. The recommendation algorithm is based on collaborative filtering.

Keywords –recommendation, collaborative filtering, grid services

I. INTRODUCTION

A. Grid Computing

Grid Computing is now an upcoming technology which uses resource sharing between a set of systems of a domain, to solve a problem. The systems are distributed geographically, sometimes residing in different continents and more heterogeneous and loosely coupled. They work together to reach a common goal. It offers a transparent access for the user, through the use of consistent access protocols. The system resources are shared, but not the workload. The workload remains in the originating system itself. The resources are gotten from different systems in the domain. The computational grids are constructed using grid middleware software like Globus Toolkit, etc.

Some advantages of Grid Computing are

- can solve larger, more complex problems in a shorter time
- easier to collaborate with other organizations
- make better use of existing hardware
- high performance and scalability

B. Grid Service

Grid Service is the service provided by the computational grid to a system in its domain, so that it is able to use it to solve a complex problem. The grid services may be persistent or transient. The grid service can be used by several organizations to speed up and solve complex engineering problems, astronomical problems, medical research, scientific research, etc. Grids are extensively used for web hosting services. It makes easier for startup programmers to put their system online and check their working and success. If the need arises for more resources, then it can be bought from the grid service provider. The commercial grid service providers allows users to subscribe to services and buy resources incrementally as needed.

C. Recommendation System

Recommendation system is used to provide recommendations to users. It constitutes a problem rich research area and because of the abundance of practical applications that help users to deal with information overload and provide personalized recommendations, content and services to them. It may depend upon various factors like user's location, user browsing history, similar users browsing pattern, user profile, etc. The recommendation system is driven by complex algorithms that take into account user's browsing, searching and preferences. The algorithms may be,

- Content-based
- Collaborative
- Hybrid

In content-based method, the user will be recommended items similar to the ones the user preferred in the past. In collaborative method, the recommendation is based on the collective information gathered from similar users across the network. The hybrid method uses both content-based and collaborative methods to generate recommendations.

II. THE RECOMMENDATION SYSTEM

The recommendation system must generate recommendations of grid services that are appropriate and having high probability of user selection. The architecture consists of an user and the recommendation system. The user accesses the recommendation system server through a browser on a client system. The recommendations system is a web application that contains a 'recommendation engine' which produces recommendations to the user. The recommendation system uses a database to store and query information pertaining to users and services. The external system is as shown below,

Figure 1: External System Architecture

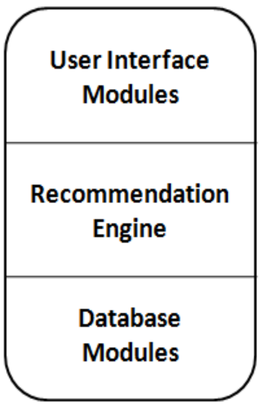

Figure 2: Recommendation System Architecture

The recommendation system consists of the following modules as shown above,

- *User Interface Modules*: These modules deal with the procedures that pertain to user interaction with the system. For example login procedures, signup procedures, rating & feedback procedures, etc.,
- *Recommendation Engine*: This contains the main complex algorithm that generates recommendations to the users. The algorithm takes into account many different kinds of parameters to produce recommendation.
- *Database Modules*: These modules deal with the connection establishment, query, formatting of output, etc., of the database.

III. ANALYSIS OF THE RECOMMENDATION SYSTEM

Recommendation systems help to handle the information overload of the internet and present individual suggestions based on the personal preferences of a user [3]. Recommendations are defined as "suggestions about a person, item or subject from another point of view" [3]. Advances in networking technology and computational infrastructure make it possible to construct large-scale and high-performance distributed computing environments. In order to meet the increasing requirement on computational power, grid is put forward to integrate those heterogeneous and distributed computing resources [2].
[3] defines the main principles for recommendation systems :

- classification based on single user information
- mapping newer users to known users, and derive from known preferences
- mapping users to prototypes and elaborating on the prototypes

The recommendations depend on mainly two properties of the grid service.

i. *Functionality*
ii. *Quality*

The functionality may differ like medical, astronomical or molecular biology, etc., The quality needed is specified by the user for his application. If he is not sure of the quality needed for his application to run on the grid, we must provide recommendations depending on the functionality of his application.

A. Service Matching

[1] proposes a scheme where service user provides his requirements using a semantic document. It also suggests that the service providers be registered with their QoS information and their service profile. The proposed scheme doesn't work because errors in the semantic document may yield unwanted recommendations. So the semantic parameters needed are put in a web form so that the user requirements can be validated and sent correctly.
A grid service matching scheme is proposed in [2] which translates grid resource characteristic to characteristic of item in recommendation system and setting up a satisfaction grade system considering history records with characteristic described in resources. In [1] a semantic matcher algorithm is used to match all available services to the user requirements. This is given to the 'Recommendation Engine' which orders and filters the recommendations on CF algorithms and user ratings. The tree parsing methodologies can be used to get the matching services. Services can also be selected based on the tags that are associated with it. By matching the tags and the input of the user, we can select the services [14]. The quality of tags can directly affect the recommendation process.

B. Recommendation Algorithm

In [2,4] it is suggested that we use Collaborative Filtering(CF) algorithms in the recommendation systems.

An improved item-based CF algorithm is proposed in [2] which could optimize grid resource matching process by

- Introducing user's experience in resource matching process to filter and classify complex and mixed resource description
- It could recommend new resources and find relationship between resources
- It could match and discover grid resources rapidly by learning feedback information from user's behaviors.

However, collaborative filtering has these problems or limitations [7],

- "cold start", which indicates dependency on a collaborative filtering technique that relies on inadequate user information
- they need a community of people who have similar preferences

Content based algorithm is not favorable here because the user may provide different characteristics every time he inputs data. The recommendations provided to him must be relevant to the current input.

In [8], two types of CF algorithms are given namely Weighted Slope One (WSO) [9] and Artificial Immune System (AIS). Matrix factorization techniques are proposed in [13] to improve effectiveness and recommendation accuracy.

C. User Similarity Prediction

In order to generate recommendation we should first determine the group of users with similar preferences. By measuring similarity, a group of users, that is neighbors, who have similar tastes with the active user can be found [6]. Some of the methods given in [8] are Kappa and Kendall tau, Pearson's coefficient [15] or cosine similarity measure. This may suffer from scalability problem if the customers and the items are in large numbers. We have to consider the computational power of both client side and server side machines in real time [11]. It should also consider user privacy issues and how the information is processed with a client-side model [11]. A linear regression model in an item-based CF algorithm is proposed in [6] where a group of similar users could be selected from the database and creating an expert based on the co-efficient of the polynomial model which are accurate and faster than the normal CF algorithm. In [2] user-item matrix is proposed to identify relationships between different items. An PAF(Popularity among Friends) algorithm is given in [3,9] which is CF algorithm which evaluates missing ratings in the user-item matrix. For finding various types of similarity matching, we need adequate characteristics of the user. Sometimes grouping can also be done based on the input given by the user.

A further 3 methods are suggested in [12]. They are

- *Cosine-based Similarity (cosine):* Users rating are thought of as vectors. The similarity between two users can be measured by computing the cosine of the angle between the two vectors.
- *Correlation-based Similarity:* Set of items rated by both users i and j, the correlation similarity between users i and j is computed.
- *Adjusted Cosine Similarity:* This similarity among items takes the difference in rating scale between different users into account.

These methods can also be used to detect similarity between items.

D. User Feedback

After selecting a service, there is a need of rating the service by the user [1,9]. One of the ways is defined in [2] by the use of 'user satisfaction grade matrix' as shown below.

	r_1	...	r_k	...	r_n
u_1	g_{11}	...	g_{1k}	...	g_{1n}
...	...	...	...	...	...
u_j	g_{j1}	...	g_{jk}	...	g_{jn}
...	...	...	...	...	...
u_m	g_{m1}	...	g_{mk}	...	g_{mn}

Where U={u1, u2, u3,...,u_m} are a set of users, R={r1, r2, r3,...,r_m} are resource characteristics and G={g1, g2, g3,...,g_{mn}} are grade matrix. This can be generated by the user feedback and can be used in future collaborative recommendations. A utility function S can be used to measure the usefulness of a resource r to a user u i.e., S= UxR [10]. The user characteristic can be represented by the Personal ID of the user [10]. The more the user ratings are done, more the useful information that can be used by CF algorithm [1]. It also proposes the similarity computation which computes the similarity between services based upon their grading, and prediction generation which predicts how a user will rate an service.

E. Estimation of non-rated items

Sometimes we cannot find ratings to a service because it has not yet been rated by any user. So, we have to estimate the rating to the service so that it can be used in our recommendation algorithm. The estimations can be done in many different ways using methods from machine learning, approximation theory, and various heuristics [10].

Some methods proposed in [12] are

- *Don't Take Into Account (DTIA):* In this case, we don't take the no-rated items into account.
- *Set As 0(SA0):* In this case, we set the no-rated items' value as 0.
- *Set as the Average of Item (SAAI):* In this case, we set the no-rated items' value as the average of rating score of the target item.
- *Set as the Average of User (SAAU):* In this case, we set the no-rated items' value as the average of rating score of the target user.

Other method used to predict missing ratings is by using Confidence Weights from both similar users and similar items con_u and con_i [15].

IV. CONCLUSION

From the above survey we can conclude that we can build a Web based recommendation system for Grid Services. The advantages and drawbacks of the different types of recommendation techniques were discussed. It is clear that Collaborative Filtering is the desired type, and similarity predictions in services can be achieved by various means. User grouping is one of the most important aspect of the recommendation system, and the different techniques that can be used for it are given. The prediction of the rating for non-rated items is as important, and the different methods used to do this have been looked into. The user feedback is also an aspect of the recommendation system that helps in future recommendations. System security is also important and dealing with the private information of the user on the client side is of the maximum priority. Further improvements can be done by proposing an able and user friendly client-based model for information rendering. The efficiency of the algorithm can be improved so that it will be able to cope with expanding customer base.

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