CSCF: A Mashup Service Recommendation Approach based on Content Similarity and Collaborative Filtering

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Abstract

*Lightweight Mashup service become very prevalent now since there are lots of advantages for them, such as easy use, short development time, and strong scalability. It is a challenge problem how to recommend user-interested, high-quality Mashup services to user with the rapid development of more and more Mashup service. In this paper, we propose CSCF (a Mashup service recommendation approach based on **C**ontent **S**imilarity and **C**ollaborative **F**iltering). CSCF firstly computes the content similarity between user history records and Mashup services and gets user interest value. Secondly, according to Mashup QoS(Quality of Service) invocation records of user, user similarity model and service similarity model are designed, and then get the QoS prediction value of active user to target service by using collaborative filtering. Finally, combining user interest value and QoS predictive value of Mashup service, CSCF ranks and recommends Mashup services to user. The experiments are performed with real Mashup services dataset, and the results of experiments show that CSCF can effectively recommends Mashup services to user with well-interesting, high-quality, better prediction precision.*

Keywords: *Mashup; content similarity; collaborative filtering; service recommendation*

1. Introduction

Mashup service is a new web application model that use existing web services to create composite service [1]. Due to easy use, short development time, and strong scalability of them, lightweight Mashup service becomes very prevalent nowadays, and many Mashup service platform emerge, such as Microsoft Popfly, Google Mashup Editor, IBM Mashup Center, which can well support the development and application of Mashup service[2-4]. With the rapid development of Mashup technology, there have more and more Mashup services application. For example, to December 25 2013, the famous site ProgrammableWeb[5] possesses 7281 Mashup and 10648 Web API, and the numbers of them are increasing. It is a challenge problem how to recommend user-interested, high-quality Mashup services to user facing so much Mashup services.

This paper proposes a Mashup service recommendation approach based on Content Similarity and Collaborative Filtering, named as CSCF. According to users' invocation records of Mashup services, CSCF firstly computes the content similarity between user history invocation records and Mashup services and gets user interest value. Secondly, user similarity model and service similarity model are designed by using the QoS invocation records of user to Mashup service, and then get the QoS prediction value of active user to target service by using collaborative filtering. Finally, CSCF ranks and recommends Mashup

service to user by integrating user interest value and QoS prediction value, and the experiments are performed to validate the feasibility and effectiveness of CSCF.

The rest of this paper is organized as follows: Section II introduces related works. Section III presents our approach of Mashup service recommendation. Section IV discusses the experimental results. Finally, we draw conclusions and discuss our future work in Section V.

2. Related Work

Although the research work related to mashup service recommendation methods is recently booming and obtaining some valuable research results, they are still less and forefront. We preliminary summarize them into the following three aspects.

Web Services Recommendation Approach based on Collaborative Filtering. Web service recommendation systems are attracting more and more attention, which can recommend the best service with high QoS (Quality of Service) to user [6]. Most Web service recommendation approaches are base on collaborative filtering (CF) [7-10]. CF is a popular recommendation algorithm, which make automatic prediction (filter) about the interests of a user by collecting preferences or taste information from many users (collaborating). These approaches compute similarity of users or services, predict missing QoS values for users based on the QoS records of similar users or services, and recommend the best service to users. However, they consider little about users' history to use Web service. Furthermore, compared with mashup technology, web service SOAP-based is complex, the application of it is limited.

Mashup Service Recommendation based on Complex Network or Social Network. Some researchers have performed to recommend mashup service to users from the perspective of complex network or social network. Among this, according to the users' interactions and a social network implicitly built from the interactions between users and services, A Maaradji provides dynamic recommendations for services discovery and selection [11, 12]. K Huang et al proposes an empirical study of Service-Mashup System for ProgrammableWeb, and perform a comprehensive network analysis to quantitatively characterize the static structure and dynamic evolution of the ecosystem [13]. These approaches focus on the relationship of Mashup service, which can mine the potential service composition relationship and perform service recommendation. However, users' invocation history of Mashup service are not involved, resulting in the recommendation results are not well-interesting to users.

Mashup Service Recommendation based on QoS. Muhammad R [14] built the QoS model of Mashup service, define some QoS attribute, and propose QoS computation method. Cinzia C [15, 16] discussed the information quality in Mashups, and analyzed the quality properties of Mashup components (APIs), and defined a quality model. Picozzi M [17] proposed a Quality-based recommendation for Mashup composition to recommend Mashup service. These approaches locate quality of Mashup service to realize high-quality service recommendation.

To sum up, recommendation technology are applied to web service field, but they may cannot be used to recommend Mashup-oriented services which are typically not described by WSDL. Mashup service recommendation based on QoS and complex network or social network are not consider users' history records, which will lead to recommendation results are not well-interesting to users. In previous work [18, 19], we perform Mashup service recommendation based on usage history and service network, but are not involved in the collaborative filtering to QoS invocation records of user. By

combining content similarity and collaborative filtering, we propose **CSCF** (**M**ashup **S**ervice **R**ecommendation Based on **C**ontent **S**imilarity and **C**ollaborative **F**iltering) to recommend Mashup services with well-interesting and high-quality for user.

3. A Mashup Service Recommendation Approach based on Content Similarity and Collaborative Filtering

3.1. User Interest Value

According to the history records of users to Mashup services, the content similarity can be computed and the user interest value can be gained by employing TF/IDF (Term Frequency/Inverse Document Frequency) technology [20].

Firstly, Mashup service data include their name, description, the invoking Web APIs, the marking tags, and developer information will be crawled from ProgrammableWeb site and form Mashup service document. Preprocess operation will be performed to remove some meaningless words or symbols, such as +, -, a, an, the, and so on. Based on the history records of user to Mashup service, a big Mashup service document can be built by combining these users' usage history document of Mashup services and form user interest vector by employing TF/IDF algorithm, the corresponding computation formulas are as follows:

$$TF(t_{ij}, MSDoc_i) = \frac{frequency(t_{ij}, MSDoc_i)}{|MSDoc_i|} \tag{1}$$

$$IDF(t_{ij}, MSDoc) = \log \frac{|MSDoc|}{1 + |\{MSDoc_i : t_{ij} \in MSDoc_i |\}} \tag{2}$$

$$W_{ij} = TF(t_{ij}, MSDoc_i) \times IDF(t_{ij}, MSDoc) \tag{3}$$

$$UI\_Vector = \{(t_1, W_{UI,1}), (t_2, W_{UI,2}), ..., (t_m, W_{UI,m})\} \tag{4}$$

Where, in the formula (1), t_{ij} is the jth word of the ith Mashup service document $MSDoc_i$. $|MSDoc_i|$ is the number of words in the $MSDoc_i$. $frequency(t_j, MSDoc)$ is the frequency or appearance number of t_{ij} in the $MSDoc_i$. In the formula (2), $|MSDoc|$ is the number of Mashup service documents, $|\{MSDoc_i : t_{ij} \in MSDoc_i|$ represent the number of t_{ij} in the $MSDoc_i$. In the formula (3), $IDF(t_{ij}, MSDoc)$ represent the importance measurement of t_{ij}, W_{ij} is the product of $TF(t_{ij}, MSDoc_i)$ and $IDF(t_{ij}, MSDoc)$. In the formula (4), $t_i(i = 1 \sim m)$ is the ith word of users' usage Mashup service document, $W_{u,i}(i = 1 \sim m)$ is the weight of TF/IDF, UI_Vector is the built user interest vector.

Secondly, each Mashup service document can be converted to the corresponding Mashup service vector by employing the formula (1)-(4), which can be described as follows:

$$i\_Vector = \{(t_1, W_{i,1}), (t_2, W_{i,2}), ..., (t_m, W_{i,m})\} \tag{5}$$

Finally, according to user interest vector and Mashup service vector, the content similarity can be measured by the cosine angle of the two vectors and can be denoted as user interest value $UIV(i)$, which can be computed as follows:

$$UIV(i) = \frac{\sum_{k=1}^{m}(W_{UI,k} \times W_{i,k})}{\sqrt{\sum_{k=1}^{m}(W_{UI,k}^2) \times \sum_{k=1}^{m}(W_{i,k}^2)}} \tag{6}$$

3.2. QoS Prediction Value

This section will construct user similarity model and service similarity model by using the invoking records of users to Mashup service, and select apposite similar neighbors and predict QoS missing values for active user.

(1) User Similarity Model

Based on the QoS (*e.g.*, ratings) value of the same Mashup service given by different users, user similarity model will be designed by Pearson Correlation Coefficient, which can be described as follows:

$$Sim(u1,u2) = \frac{\sum_{i \in I}(q_{u1,i} - \overline{q}_{u1})(q_{u2,i} - \overline{q}_{u2})}{\sqrt{\sum_{i \in I}(q_{u1,i} - \overline{q}_{u1})^2} \sqrt{\sum_{i \in I}(q_{u2,i} - \overline{q}_{u2})^2}} \tag{7}$$

Where, $Sim(u1,u2)$ present the similarity between user u1 and u2, $I = I_{u1} \cap I_{u2}$ is a common mashup service set invoked by u1 and u2. $q_{u1,i}$, $q_{u2,i}$ represent the QoS value given by u1 and u2 respectively. $\overline{q}_{u1}$, $\overline{q}_{u2}$ represent the mean value of all QoS given by u1 and u2 respectively.

(2) Service Similarity Model

The same to user similarity model, according to the same invoking user of different Mashup services, service similarity model will be designed by Pearson Correlation Coefficient, which can be described as follows:

$$Sim(i,j) = \frac{\sum_{u \in U}(q_{u,i} - \overline{q}_i)(q_{u,j} - \overline{q}_j)}{\sqrt{\sum_{u \in U}(q_{u,i} - \overline{q}_i)^2} \sqrt{\sum_{u \in U}(q_{u,j} - \overline{q}_j)^2}} \tag{8}$$

Where, $Sim(i,j)$ present the similarity between Mashup service i and j, $U = U_i \cap U_j$ is a common user set which invoke i and j. $q_{u,i}$, $q_{u,j}$ represent the QoS value given by user u to i and j respectively. $\overline{q}_i$, $\overline{q}_j$ represent the mean value of all QoS given by different users to i and j respectively.

(3) Similar Neighbor Selection and QoS Missing Value Prediction

After finish user similarity and service similarity computation, the user similar matrix and service similar matrix can be gotten to predict QoS missing value.

Firstly, two similar neighbors set Set (u) and Set (i) will be generated by the user similar matrix and service similar matrix.

Secondly, predict QoS missing value of target user by using user similarity computation for Set (u).

$$PRE_u\left(q_{u,i}\right) = \overline{u} + \frac{\sum\limits_{u_a \in Set(u)} Sim\left(u_a, u\right)\left(q_{u_a,i} - \overline{u}_a\right)}{\sum\limits_{u_a \in Set(u)} Sim\left(u_a, u\right)} \tag{9}$$

Where, $PRE_u\left(q_{u,i}\right)$ is predicted QoS missing value, $\overline{u}$ is the mean QoS value of target user, $\overline{u}_a$ is the mean QoS value of user a, $q_{u_a,i}$ is the QoS value invoked by user a to service i.

Similarly, predict QoS missing value of target user by using service similarity computation for Set (i).

$$PRE_i\left(q_{u,i}\right) = \overline{i} + \frac{\sum\limits_{i_k \in Set(i)} Sim\left(i_k, i\right)\left(q_{u,i_k} - \overline{i}_k\right)}{\sum\limits_{i_k \in Set(i)} Sim\left(i_k, i\right)} \tag{10}$$

Where, $PRE_i\left(q_{u,i}\right)$ is predicted QoS missing value, $\overline{i}$ is the mean QoS value of service i, $\overline{i}_k$ is the mean QoS value of service i_k, q_{u,i_k} is the QoS value invoked by target user to service i_k.

Finally, combine the predicted QoS missing value of target user by using user similarity computation and service similarity computation, and perform comprehensive prediction according to the following formula.

$$PRE(q_{u,i}) = \alpha PRE_u\left(q_{u,i}\right) + (1-\alpha)PRE_i\left(q_{u,i}\right) \tag{11}$$

3.3. The Total Recommendation Value of Mashup Service

Based on the user interest value of formula (6) and the QoS prediction value of formula (11), the total recommendation value of all Mashup service can be computed and denoted by formula (12).

$$TRV(i) = \lambda UIV(i) + (1-\lambda)PRE(i) \tag{12}$$

Where, λ is users' preference value. The larger $TRV(i)$ indicate that the recommended Mashup service i not only well-interesting to user, but also high-quaility to user.

In short, CSCF can rank and recommend Top-k Mashup services with well-interesting and high-quality to user by decreasing $TRV(i)$.

4. Experiments

4.1. Experiments Settings and Evaluation Standard

Based on the users' QoS (*e.g.*, ratings) values (1~5) of 100 Mashup services crawled from Programmableweb site, we randomly generate the ratings values of 50 users to 100 Mashup services, and build 50*100 user-service matrix. Furthermore, assuming user have used 10 Mashup services of the crawled Mashup services set, which will form user interesting value of Mashup services.

4.2. Experiment Comparison and Analysis

There have other four recommendation approaches for experiment comparison and analysis, respectively are Mashup service recommendation approache only based on

collaborative filtering (denoted by CF-Based) when λ=0 in the formula (12), only based on content similarity (denoted by CS-Based) when λ=1 in the formula (12), based on collaborative filtering of users (denoted by UPCC [21]), based on collaborative filtering of services (denoted by IPCC [22]).

(1) User Interest Relevance

The purpose of user interest relevance experiment is to evaluate the user interest relevance of Top-K Mashup service. Aiming to CSCF, CF-Based and CS-Based, the DCG defined by formula (13) is used to evaluate the relevance degree between user interest and Top-K Mashup service recommendation list.

$$DCG_K = \sum_{p=1}^{K} \frac{(2^{UIV(i)} - 1)}{\log_2(1+p)} \tag{13}$$

Where, p is the rank position of Mashup service i in the Top-K Mashup service recommendation list, $UIV(i)$ is the user interest value of i, DCG_k is the DCG value of user interest value for Top-K Mashup service. The larger DCG_k mean the the higher user interest degree of Top-K Mashup service.

(a) λ=0.7   (b) λ=0.3
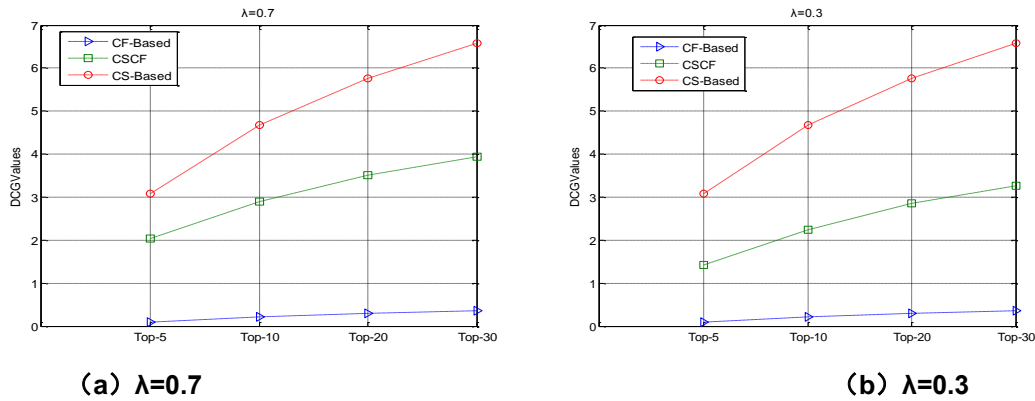
Figure 3. The DCG Value of User Interest Degree of Top-K Mashup Service

From the above Figure 3 we can see that the DCG value of user interest value for Top-K（k=5/10/20/30） Mashup service produced by CSCF is much higher than CF-Based, and slightly lower than CS-Based. For example, in the Figure (3a), the DCG values of CSCF is 3.52, CS-Based is 5.76, and CF-Based is 0.29 when k is 20 andλ is 0.7. This illustrate that the recommended Mashup service by CSCF have the higher user interest degree. Moreover, the DCG value of CSCF is reducing with the decreasing of λ . For example, in the Figure (3b), the DCG value of CSCF is 2.86 when k is 20 andλ is 0.3. This illustrate that the user interest degree of the recommended Mashup service is reducing with the decreasing of user interest preference.
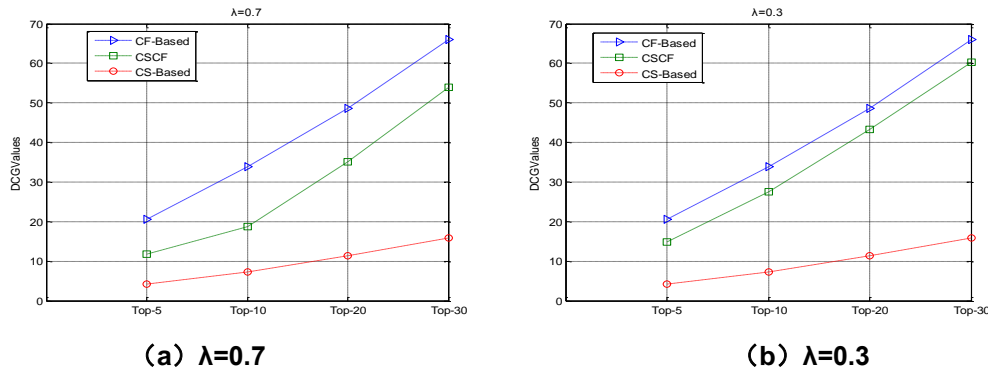
(2) Mashup Service Rating Relevance

Similarly, the purpose of Mashup service rating relevance experiment is to evaluate the service rating relevance of Top-K Mashup service. Aiming to CSCF, CF-Based and

CS-Based, the DCG defined by formula(14) is used to evaluate the relevance degree between service rating and Top-K Mashup service recommendation list.

$$DCG_K = \sum_{p=1}^{K} \frac{(2^{PRE(i)} - 1)}{\log_2(1+p)} \qquad (14)$$

Where, p is the rank position of Mashup service i in the Top-K Mashup service recommendation list, $PRE(i)$ is the rating prediction value of i, DCG_k is the DCG value of service rating value for Top-K Mashup service. The larger DCG_k mean the higher service rating degree of Top-K Mashup service.

（a）λ=0.7　　　　　　　　　　（b）λ=0.3

Figure 4. The DCG Value of Service Rating Degree of Top-K Mashup Service

As can be seen from the above Figure 4, we know that the DCG value of service rating value for Top-K（k=5/10/20/30）Mashup service produced by CSCF is much higher than CS-Based, and slightly lower than CF-Based. For example, in the Figure (4a), the DCG values of CSCF is 35.1948, CS-Based is 11.3192, and CF-Based is 48.6016 when k is 20 and λ is 0.7. This indicate that the recommended Mashup service by CSCF have the higher service rating degree. In addition, the DCG value of CSCF is raising with the decreasing of λ. For example, in the Figure (4b), the DCG value of CSCF is 43.2085 when k is 20 and λ is 0.3. The results show that the service rating degree of the recommended Mashup service is improving with the increasing of service rating preference.

Thus, by the experiments of user interest relevance and Mashup service rating relevance, it can be known that the recommended Top-k Mashup service not only well-interesting but also high-quality high-quality to user.

(3) Recommendation Performance Comparison

Aiming to CSCF, UPCC and IPCC, the NMAE defined by formula (15) is used to evaluate the recommendation performance.

$$NMAE = \frac{MAE}{\sum_{i,j} r_{i,j} / N} \qquad （15）$$

$$MAE = \frac{\sum_{i,j} \left| r_{i,j} - \hat{r}_{i,j} \right|}{N} \qquad （16）$$

Where, $r_{i,j}$ is the expected QoS (*e.g.*, rating) value of user i to service j, $\hat{r}_{ij}$ is the predicted rating value, N is the number of the predicted value. MAE is the mean absolute error, which have be widely used to measure the prediction quality of collaborative filtering. Because there are many QoS attributes for different values and their range, we employ the normalized mean absolute error $NMAE$ to measure the prediction precision. The smaller $NMAE$ display the higher prediction precision.

In this experiment, 50 users are divided into two parts, one is training users, and the other is active users. For active users, the number of given rating values is set to 10, 20 and 30 respectively by randomly removing rating values in user-service matrix. The number of training users is set to 20 and 40 respectively. The prediction precision will be measured by randomly removing a part of rating value of active users and comparing the expected, removed rating values with the predicted rating value. The experiments are firstly performed by removing 10%, 20% and 30% rating values (*i.e.*, training matrix density) in the user-service matrix respectively, and then predict rating missing values and compute the $NMAE$ for UPCC, IPCC and CSCF (λ is set to 0.5 in the formula (12)), which repeatedly run 30 times and take the mean $NMAE$ as experimental results shown in Table 2, 3 and 4.

From Table 2, 3 and 4, we can be known that, one is CSCF has the smallest NMAE and the best prediction precision comparing to UPCC and IPCC. The other is, with the increasing of the given rating values from 10 to 30, the values of NMAE are decreasing, which indicate more rating values improve prediction precision. Besides, the growing number of train users from 20 to 40 and training matrix density from 10% to 30% also improve prediction precision.

Table 2. NMAE of 10% Training Matrix Density

QoS	Training Users = 20			Training Users = 40		
	Rating			Rating		
Given	10	20	30	10	20	30
UPCC	0.917	0.872	0.884	0.897	0.843	0.812
IPCC	0.905	0.862	0.791	0.847	0.717	0.602
CSCF	0.739	0.680	0.541	0.697	0.509	0.418

Table 3. NMAE of 20% Training Matrix Density

QoS	Training Users = 20			Training Users = 40		
	Rating			Rating		
Given	10	20	30	10	20	30
UPCC	0.890	0.806	0.736	0.825	0.753	0.698
IPCC	0.851	0.817	0.749	0.783	0.672	0.570
CSCF	0.694	0.603	0.496	0.646	0.428	0.379

Table 4. NMAE of 30% Training Matrix Density

| QoS | Training Users = 20 | | | Training Users = 40 | | |
| | Rating | | | Rating | | |
Given	10	20	30	10	20	30
UPCC	0.849	0.783	0.674	0.790	0.708	0.617
IPCC	0.819	0.769	0.705	0.758	0.636	0.548
CSCF	0.583	0.492	0.385	0.529	0.408	0.327

5. Conclusions and Future Work

This paper present a Mashup service recommendation approach based on content similarity and collaborative filtering to rank and recommend Top-k Mashup service by combining the user interest value and the rating prediction value. The experiments for user interest relevance, Mashup service rating relevance and recommendation performance are conducted to verify the total performance of CSCF, and the results of experiments show that CSCF can effectively recommends Mashup services to user with well-interesting, high-quality and better prediction precision. In future work, we will introduce the provider information of Mahsup service and study Mashup service recommendation from social network and trust aspect.

Acknowledgements

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