

Solving the Rating Scarcity Issue using an Enhanced Memory-based Collaborative Filtering Method



Arnab Paul, Sudipta Roy

Abstract: In Service Oriented Architecture (SOA), reputation-oriented web service discovery has gained popularity in finding the optimal service from a pool of services having similar functionality. Almost all reputation-oriented discovery mechanisms make use of the feedback ratings reported by the users in order to assess service reputations. However, there are certain factors which, if not addressed carefully, may affect the process of precise service reputation evaluation. One such factor is the issue regarding rating scarcity. When the percentage of users who rate the web services compared to the percentage of users who avail the web services is low, the issue of missing feedback rating arises which leads to incomplete rating matrix. Since all users, after availing services, may not report their satisfaction levels in the form of feedback ratings, it is obvious that the system will encounter incompleteness in rating information while evaluating service reputations. In this paper, an approach to solve the rating scarcity issue in reputation-oriented service discovery is proposed using an enhanced memory-based collaborative filtering method. Experiments are performed and the results are reported in this paper.

Index Terms: Web service, rating scarcity, missing feedback rating, collaborative filtering.

I. INTRODUCTION

Web service is gaining significant attention day by day. W3C defines web service as: “A Web service is a software system designed to support interoperable machine-to-machine interaction over a network. It has an interface described in a machine-processable format (specifically WSDL). Other systems interact with the Web service in a manner prescribed by its description using SOAP messages, typically conveyed using HTTP with an XML serialization in conjunction with other Web-related standards” [1].

Currently, there exist a number of web services having similar functionality. Therefore, selecting the optimal service from the pool of services has become an important task. Hence, trust and reputation systems are proposed to find the best service that can satisfy a user’s need. The factor trust can be

defined as “a subjective probability an agent has about another's future behavior” [2]. It is the degree of trustworthiness a user assigns to a service for its performance. “Reputation is what is generally said or believed about a person's or thing's character or standing” [3]. It is the collective opinion or evaluation of a service based on the feedback ratings reported by its users. The higher the reputation score, the better is the service.

Feedback rating is considered to be the prominent indicator of service reputation. Therefore, the system must ensure that sufficient amount of feedback ratings are available in order to evaluate service reputations accurately. Working with incomplete rating matrix may result in erroneous evaluation of service reputations. So, in reputation-oriented service discovery, the first and foremost factor that needs to be addressed is the issue regarding rating scarcity. When the percentage of users who rate the web services compared to the percentage of users who avail the web services is low, the issue of missing feedback rating arises which leads to incomplete rating matrix. Since all users may not submit the feedback ratings after availing the services, the service usage volume becomes higher than the number of feedback ratings actually received [4]. It happens because users show less interest in rating the services unless they are extremely satisfied or dissatisfied with the performance of the service. Even if they are dissatisfied, they may restrain themselves from giving negative feedbacks in fear of reprisal from the service providers and prefer to remain silent. Also, users sometimes restrict themselves from providing feedback ratings due to the lack of motivation to act as raters. Some users intentionally avoid the task of feedback rating submission, while some are inexperienced in using the rating rubrics. Due to these reasons, feedback ratings from various users are sometimes unobserved which lead to the issue of rating scarcity in the system. Therefore, predicting these missing feedback ratings is an important step in the process of service reputation measurement.

In the previous studies regarding reputation-oriented service discovery, the issue of rating scarcity is rarely addressed. It is found that rating aggregation systems are often subject to this weakness [5]. The accuracy of the service reputation measurement approach may be compromised due to the missing feedback ratings [6–8].

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* Correspondence Author

Arnab Paul*, Computer Science & Engineering, Assam University, Silchar, India.

Sudipta Roy, Computer Science & Engineering, Assam University, Silchar, India.

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In this paper, an approach to solve the rating scarcity issue in reputation-oriented service discovery is proposed using an enhanced memory-based collaborative filtering method. Discussion and evaluation of the performance of the proposed algorithm using synthesized data are presented.

The rest of this paper is organized as follows. Section 2 discusses the basics related to this domain. Section 3 reviews the related works. In Section 4, the proposed missing feedback rating prediction approach is presented. In Section 5, the experimental results based on simulated scenarios are discussed. Section 6 concludes the paper.

II. BACKGROUND

Due to the proliferation of services providing equivalent functionalities, it has become vital to introduce recommendation system that can recommend the correct item/service to a user based on its preferences. There are mainly two methods to design a recommendation system.

(i) Content-based filtering: This approach is utilized to recommend additional items having similar properties, to a user, based on some distinct pre-designated features [9]. The recommendation is done based on the relationship between the user and the content of similar items [10].

(ii) Collaborative filtering: Unlike content-based filtering, collaborative filtering does not use the features of an item; instead, the recommendation is done based on user-item interactions. This approach constructs a model based on a user's previous behaviors as well as the opinions of other users on similar items. This method assumes that the users who had similar selections in the past will have similar selections in the future [11]. Collaborative filtering can again be classified into two methods:

(a) Model-based method: In this method, a model is built based on the dataset of feedback ratings i.e. it collects some information from the available dataset which acts as a model to predict the feedback ratings without using the complete dataset at every step [12, 13].

(b) Memory-based method: Also known as neighborhood-based collaborative filtering which fundamentally uses the feedback ratings given by users towards items to assess the similarities between users and/or items and then applies these similarities as weights to predict a rating for a user and an item [14]. It consists of two methods: user-based CF and item-based CF. In user-based CF, similar users corresponding to an active user (the user for whom a prediction is to be done) are found based on their commonly rated items. Then, a prediction is done for an item which has not yet been rated by the active user based on the ratings from those similar users on that item and their similarity scores with the active user. Item-based CF is also similar to the user-based CF. The only difference is that item-based CF employs the similarity between items instead of users. The similarity scores between items are measured by observing all the users who have rated both the items. Then, a rating from a user towards an item is predicted based on the ratings from that user on these similar items and the similarity scores with the item [15].

In this paper, an enhanced memory-based collaborative filtering method is applied for the prediction of missing

feedback ratings. In the present literature, there are mainly three types of missing data mechanisms and these are missing completely at random (MCAR), missing at random (MAR) and missing not at random (MNAR). For a clear understanding of these mechanisms, an example is given in table I. The mechanisms are employed on 15 services ($S = s_1, s_2, \dots, s_{15}$) where services s_1 to s_5 are launched before the year 2016 and the rest of the services are launched from the year 2016 to till date.

Table I. Ratings for MCAR, MAR and MNAR mechanisms

Service	Feedback Ratings			
	Complete	MCAR	MAR	MNAR
s_1	5	-	-	5
s_2	8	8	-	8
s_3	7	-	-	7
s_4	3	3	-	-
s_5	6	6	-	6
s_6	4	4	4	-
s_7	9	9	9	9
s_8	1	-	1	-
s_9	2	2	2	-
s_{10}	3	3	3	-
s_{11}	4	4	4	-
s_{12}	7	-	7	7
s_{13}	8	8	8	8
s_{14}	10	10	10	10
s_{15}	9	9	9	9

Missing Completely at Random (MCAR): It is a mechanism where the possibility of a variable having missing value is not related to the variable itself or any other observed variables within a dataset [16]. In other words, the values are missing in a non-systematic way. The missing values are predicted based only on the observations which are available [17]. For example, from table I, it can be observed that the missing data does not depend on any of the services and the ratings are missing in a completely random fashion. The advantage of MCAR is that the analysis remains unbiased.

Missing at Random (MAR): It is a mechanism where the possibility of a variable having missing value is related to other observed variables in the dataset, but not to the variable itself [16]. For example, from table I, it can be observed that only services which were launched before the year 2016 have missing values. Unfortunately, the MAR assumption cannot be confirmed as it is impossible to test whether the possibility of a variable having missing value is entirely a function of other observed values.

Missing not at Random (MNAR): It is a mechanism where the possibility of a variable having missing value is related to the variable itself regardless of any changes to other variables in the dataset [16, 18]. For example, from table I, it can be observed that the services with feedback ratings less than 5 have missing values.

In such instances, it is quite difficult to make estimations of the missing values, since it is impossible to determine whether the values are MNAR without having any knowledge of the missing values [19].

The present work is based on the scenario where the feedback ratings are missing completely at random and these missing feedback ratings are predicted based on the available observations within the dataset.

III. RELATED WORK

In this section, some of the existing prediction approaches are discussed.

Zibin Zheng et al. [20] proposed WSRec, a Web service recommender system, for selecting and recommending Web services. WSRec includes a user-contribution method for gathering Quality of Service (QoS) information of Web services and a hybrid collaborative filtering algorithm for predicting QoS values of Web services. For active service users, the QoS functioning of web services are predicted using this hybrid CF method. They calculated the similarity scores between the users and also between the items using the Pearson Correlation Coefficient (PCC) in order to identify sets of similar neighbors for all users and all items. Then, missing QoS values are predicted using the user-based and item-based collaborative filtering methods. The predicted values from these two CF methods may have different prediction accuracy, so two confidence weights are employed to balance these two predicted values. These confidence weights regulate the use of the predicted values from the user-based CF and the item-based CF to achieve higher prediction accuracy.

Jebrin Al-Sharawneh et al. [21] proposed a Feedback Forecasting Model (FFM) based on the Expectation Disconfirmation Theory (EDT) to predict the user feedback about its satisfaction with the service. FFM depends on the amount of expected service quality and perceived service quality. The EDT theory links the expected quality, perceived quality and quality disconfirmation i.e. the variation between the expected and the perceived qualities from a service.

Wei Lo et al. [22] proposed an extended Matrix Factorization (EMF) model with relational regularization to predict the missing QoS values. Using Pearson Correlation Coefficient (PCC), the similarity relationships between the users and also between the services are captured to identify the sets of top- k neighbors of all users and services, respectively. Then, user relational regularization and service relational regularization are developed to capture the user relationships and service relationships in their corresponding neighborhoods. Finally, the user-side and service-side regularization terms are combined into a unified Matrix Factorization framework to make predictions about missing QoS values.

Miao Wang et al. [23] introduced a High-reliability Multi-faceted Reputation (HMRep) evaluation approach for online web services. They addressed and estimated the missing feedback ratings of various services based on rating behavior of the user and quality of the service. A positive value of rating behaviour indicates that a user tends to give above-average ratings whereas a negative value of rating

behaviour indicates that a user tends to give below-average ratings.

Jianlong Xu et al. [24] developed a prediction methodology of Quality of Service (QoS) of web service for predicting unknown QoS values. Their proposed approach (RMF) is based on user reputation enabled matrix factorization in predicting missing QoS values by dealing with QoS values obtained from unreliable users. Matrix factorization is a model-based method of collaborative filtering technique used in recommender systems. In matrix factorization method, the observed QoS values of different services contributed by different users are maintained as a user-item interaction matrix. In this RMF model, the objective function of basic matrix factorization method is equipped with user reputation to act as a weight to enhance prediction accuracy.

Other similar approaches [25–27] have also employed collaborative filtering method to make predictions about missing QoS values.

IV. PROPOSED APPROACH

In Service Oriented Architecture, there exists an interaction between two kinds of entities namely user and service. Service user submits its satisfaction level in the form of feedback rating after availing a service. Let $C = (c_1, c_2, \dots, c_m)$ denotes the set of m users and $S = (s_1, s_2, \dots, s_n)$ represents the set of n services. The feedback rating from user c_i to service s_j is denoted by $r_{i,j}$.

In solving the ratings scarcity issue, existing approaches, which employ collaborative filtering method, predict the missing feedback ratings at one go. The proposed approach also employs collaborative filtering method for missing feedback rating prediction, but in an iterative way. A prediction about the missing feedback rating is done in the first iteration and the prediction gets refined in successive iterations.

In previous approaches employing collaborative filtering method in missing data analysis, the similarity between users and/or services is computed in the first step and then the predictions about the missing values are done. The similarity score computation between two users depends on the number of commonly rated services by both the users. The large the set of commonly rated services, the more accurate will be the similarity score. Since the objective here is to predict the missing feedback ratings, it is obvious that obtaining a large set of commonly rated services for any two users may not be feasible always. Therefore, the similarity score computation between the users under different circumstances of missing feedback ratings and then the predictions about the missing ratings based on these user similarity scores may challenge the prediction accuracy. To overcome this issue, the proposed approach first makes initial predictions about all missing feedback ratings to obtain a complete rating matrix and then computes the similarity scores between the users. Now, based on these similarity scores, the top K nearest neighbors of a user is selected whose feedback ratings collectively influence the final prediction about the missing feedback rating in any iteration.

These steps are repeated until every missing value individually converges. Let, there is a total of p missing feedback ratings. After a number of iterations, predictions for q missing feedback ratings are obtained which have already converged. So, from the next iteration onwards, the predictions will be carried out only for the remaining $p - q$ missing feedback ratings.

Again, after a number of iterations, let l missing feedback ratings are predicted and are converged. So, in the next iteration, predictions about the missing feedback ratings will be done for the remaining $p - (q + l)$ values. Once all missing feedback ratings have individually converged, the iteration stops. The detailed algorithm is described in the following section.

Step I: For every missing feedback rating $r_{i,j}$ from user c_i towards service s_j , let $S_{i(j)}$ denotes the set of services obtained for user c_i in connection with the prediction of a feedback rating for service s_j by excluding the following service(s) from the set of all services S .

(i) the service s_j , for which a prediction of a feedback rating from user c_i is sought.

(ii) the set of services for which feedback ratings from user c_i are unobserved.

Now, for each service $s_k \in S_{i(j)}$, let O_k denotes the set of users from which feedback ratings are observed for service s_k . Then, calculate the average of all feedback ratings, $r_{x,k}$ ($c_x \in O_k$), for each service $s_k \in S_{i(j)}$, denoted by $avg(s_k)$.

$$avg(s_k) = \frac{1}{|O_k|} \sum_{c_x \in O_k} r_{x,k} \quad (1)$$

Here, $|O_k|$ represents the size of set O_k .

Step II: Calculate the overall rating deviation of user c_i based on its feedback rating submissions towards services $s_k \in S_{i(j)}$. The notation $dev_{i(j)}$ is used to represent the degree of rating deviation found for user c_i which would aid in predicting a feedback rating for service s_j . This is calculated by the use of Root Mean Square Deviation (RMSD) between the feedback rating $r_{i,k}$ of user c_i and the average of all observed feedback ratings of services $s_k \in S_{i(j)}$.

$$dev_{i(j)} = \sqrt{\frac{\sum_{s_k \in S_{i(j)}} (avg(s_k) - r_{i,k})^2}{|S_{i(j)}|}} \quad (2)$$

Step III: The initial prediction for every missing feedback rating $r_{i,j}$ from user c_i towards service s_j is done in this step, which is denoted by $r_{i,j}^{ip}$. The prediction is done based on the observed feedback ratings of service s_j and with the help of $dev_{i(j)}$ obtained from step II. The basic idea is that while reporting feedback ratings for services $s_k \in S_{i(j)}$, if user c_i deviates by an amount of $dev_{i(j)}$ from the average of all observed feedback ratings of services $s_k \in S_{i(j)}$, then a feedback rating for service s_j from user c_i will also deviate from the average of all observed feedback ratings of service s_j by the same amount. The equation for initial prediction of missing feedback rating, $r_{i,j}^{ip}$, is derived based on this concept and is given in equation (4).

Let $O_{j(i)}$ denotes the set of users obtained for service s_j in connection with the prediction of a feedback rating from user c_i by excluding the following user(s) from the set of all users C .

(i) the user c_i , from which a prediction of a feedback rating towards service s_j is sought.

(ii) the set of users from which feedback ratings towards service s_j are unobserved.

Then, calculate the sum of all feedback ratings, $r_{x,j}$ ($c_x \in O_{j(i)}$), for service s_j , denoted by $sum(s_j)_{(i)}$.

$$sum(s_j)_{(i)} = \sum_{c_x \in O_{j(i)}} r_{x,j} \quad (3)$$

The notation $sum(s_j)_{(i)}$ is used to represent the sum of feedback ratings of service s_j when predicting a feedback rating for it from user c_i .

Now, compute $r_{i,j}^{ip}$ as:

$$r_{i,j}^{ip} = \frac{sum(s_j)_{(i)} - \left((|O_{j(i)}| + 1) * dev_{i(j)} \right)}{|O_{j(i)}|} \quad (4)$$

Here, $|O_{j(i)}|$ represents the size of set $O_{j(i)}$.

Step IV: An initial complete rating matrix will be obtained after the execution of step III. Each feedback rating in this matrix will be either an observed feedback rating, $r_{i,j}^{ob}$, or an initial prediction of the feedback rating, $r_{i,j}^{ip}$. However, to simplify the rest of the description of this algorithm, any feedback rating in this complete rating matrix will be termed as $r_{i,j}$ from step IV onwards.

In this step, the similarity between the users is calculated using Pearson Correlation Coefficient (PCC). The notation $sim(c_i, c_x)$ is used to represent the similarity between two users c_i and c_x . Here, $r_{i,j}$ and $r_{x,j}$ denote the feedback ratings issued towards service s_j by users c_i and c_x , respectively. r'_i denotes the average of feedback ratings issued by user c_i towards all the services $s_j \in S$; similarly, r'_x denotes the average of feedback ratings issued by user c_x towards all the services $s_j \in S$. A value for $sim(c_i, c_x)$ lies in the range $[-1, 1]$. A higher similarity score implies a tight bonding between two users, c_i and c_x .

$$sim(c_i, c_x) = \frac{\sum_{s_j \in S} (r_{i,j} - r'_i)(r_{x,j} - r'_x)}{\sqrt{\sum_{s_j \in S} (r_{i,j} - r'_i)^2} \sqrt{\sum_{s_j \in S} (r_{x,j} - r'_x)^2}} \quad (5)$$

Step V: For precise prediction of every missing feedback rating from user c_i , the selection of nearest neighbors of user c_i is important. For the user c_i , its top K nearest neighbors are selected based on the similarity scores, obtained by using PCC, between the user c_i and other users $c_{x \neq i} \in C$.

Here, the set of nearest neighbors of user c_i is denoted by $nn(c_i)$, which contains those users whose similarity scores with the user c_i are found to be greater than 0.

$$nn(c_i) = \{c_x | sim(c_i, c_x) > 0\} \quad (6)$$

Step VI: The final prediction for every missing feedback rating $r_{i,j}$ from user c_i towards service s_j is done in this step, which is denoted by $r_{i,j}^{fp}$ and is given by equation (7). The prediction is done based on the followings:

- (i) the initial prediction of feedback rating, $r_{i,j}^{ip}$ (termed as $r_{i,j}$ in this step), from user c_i towards service s_j , as obtained from step III.
- (ii) the feedback ratings, $r_{x,j}^{ip}$ or $r_{x,j}^{ob}$ (both termed as $r_{x,j}$ in this step), from users $c_x \in nn(c_i)$ towards service s_j .
- (iii) the similarity scores, $sim(c_i, c_x)$, of users $c_x \in nn(c_i)$ with user c_i .

$$r_{i,j}^{fp} = \frac{r_{i,j} + \sum_{c_x \in nn(c_i)} r_{x,j} * sim(c_i, c_x)}{1 + \sum_{c_x \in nn(c_i)} sim(c_i, c_x)} \quad (7)$$

Step VII: Repeat steps I to VI until every missing feedback rating individually converges.

The algorithm runs for at least two iterations. Let, $(r_{i,j}^{fp})_{d-1}$ and $(r_{i,j}^{fp})_d$ denote the final predictions of feedback rating $r_{i,j}$ from user c_i towards service s_j , obtained from step VI, in the $(d-1)^{th}$ and d^{th} iterations, respectively. Also let, th_{con} denotes the threshold for feedback rating convergence, as maintained by the system. Now, after the d^{th} iteration, if it is found that $|(r_{i,j}^{fp})_{d-1} - (r_{i,j}^{fp})_d| \leq th_{con}$, then the feedback rating $r_{i,j}$ is said to have converged and no further prediction for this feedback rating will be carried out from $(d+1)^{th}$ iteration onwards.

V. RESULTS AND DISCUSSIONS

To evaluate the performance of the proposed model, experiments on simulated environment are performed which consists of 200 users and 100 services with different deserving ratings ($des_rat \in [1, 10]$). The service pool is divided into ten groups of ten members each and each group corresponds to a distinct deserving rating.

Users submit their feedback ratings about the services on a 10-point integer rating scale. Three types of users exist in the simulated environment:

UserType#1: The users of this category are honest in reporting their feedback ratings. They report the feedback ratings at par with the deserving ratings (des_rat) of the services.

UserType#2: There are users who are honest but report the feedback ratings about services based on their subjective preferences. In the simulated environment, the feedback ratings for this type of users are generated with a deviation of $\pm[1, 2]$ from the deserving ratings (des_rat) of the services. That is, the generated feedback ratings for this type of users lie in the range of $[max(1, des_rat - 2) : min(des_rat + 2, 10)]$ excluding des_rat .

UserType#3: These are dishonest or malicious users. They report their feedback ratings which never conform to the deserving ratings of the services. In the simulated environment, the feedback ratings for this type of users are generated in the range $[1, 10]$ excluding $[max(1, des_rat - 2) : min(des_rat + 2, 10)]$.

The experimental setup, to validate the effectiveness of the proposed approach in missing rating analysis, is designed to imitate every possibility that may occur in real-world applications. To start with, the following feedback rating matrix is considered:

des_rat_{mxn}: This matrix is generated assuming only *UserType#1* exists in the system. It is a complete rating matrix which contains only the deserving ratings of the services. And then, another version of feedback rating matrix is generated as stated below.

smd_rat_{mxn}: This matrix is also a complete rating matrix which contains both subjective and malicious ratings along with the deserving ratings of the services. This matrix is created based on *des_rat_{mxn}* in which a percentage of the randomly chosen deserving ratings are replaced with subjective and malicious ratings assuming the existence of both *UserType#2* and *UserType#3* along with *UserType#1*.

Five sets of experiments are conducted to evaluate the rating prediction accuracy of the proposed model. In each experiment, *smd_rat_{mxn}* is generated by introducing 10%, 20%, 30%, 40%, and 50% subjective and malicious ratings. Also, the densities of both subjective ratings and malicious ratings are equal in all these experiments.

In all experiments, the input to the proposed approach is an incomplete rating matrix which is created based on *smd_rat_{mxn}*. The incomplete rating matrix is generated employing MCAR. That is, to have rating matrix with missing ratings, a percentage of the ratings are randomly deleted from *smd_rat_{mxn}*.

The objective of this experiment is to analyze the behavior of the proposed approach under different circumstances of incomplete ratings. The amount of subjective and malicious ratings, and also the amount of missing ratings in all these experiments are taken as follows.

Experiment#1: This experiment is conducted with 10% subjective and malicious ratings. It is again divided into five sub-experiments based on the percentage of missing ratings. That is, each sub-experiment consists of 10%, 20%, 30%, 40%, and 50% missing ratings, respectively.

Similarly, *Experiment#2*, *Experiment#3*, *Experiment#4*, and *Experiment#5* are conducted by introducing 20%, 30%, 40%, and 50% subjective and malicious ratings, respectively. In each experiment, five sub-experiments are conducted with 10%, 20%, 30%, 40%, and 50% missing ratings, respectively.

To check the accuracy of the model in predicting the missing ratings, the Root Mean Square Errors (RMSEs) between the subjective and malicious ratings (*smd_rat*) and the predicted ratings (*pred_rat*) of the services, obtained by equation (8), are reported in this paper.

$$RMSE_{smd_rat} = \sqrt{\frac{\sum_{i=1}^{nmr} (pred_rat_i - smd_rat_i)^2}{nmr}} \quad (8)$$

where, *nmr* is the number of missing ratings. The smaller the RMSE value, the higher is the prediction quality.

The RMSEs recorded for *Experiment#1*, *Experiment#2*, *Experiment#3*, *Experiment#4*, and *Experiment#5* are presented in Tables II, III, IV, V, and VI respectively.

Table II. RMSEs for Experiment#1 (10% subjective and malicious ratings)

Missing	$RMSE_{smd_rat}$
10%	0.5500
20%	0.6877
30%	0.7565
40%	0.8134
50%	0.8419

Table III. RMSEs for Experiment#2 (20% subjective and malicious ratings)

Missing	$RMSE_{smd_rat}$
10%	0.8726
20%	0.9662
30%	1.0782
40%	1.1615
50%	1.3090

Table IV. RMSEs for Experiment#3 (30% subjective and malicious ratings)

Missing	$RMSE_{smd_rat}$
10%	0.9361
20%	1.1538
30%	1.2462
40%	1.3697
50%	1.5826

Table V. RMSEs for Experiment#4 (40% subjective and malicious ratings)

Missing	$RMSE_{smd_rat}$
10%	1.2670
20%	1.3411
30%	1.4679
40%	1.6746
50%	1.9135

Table VI. RMSEs for Experiment#5 (50% subjective and malicious ratings)

Missing	$RMSE_{smd_rat}$
10%	1.3305
20%	1.5037
30%	1.6222
40%	1.8545
50%	2.0396

Table II records the $RMSEs$ of *Experiment#1* which consist of 10% subjective and malicious ratings, and 90% deserving ratings. It should be noted that the incomplete rating matrix, which is the input matrix for the model, consists of subjective, malicious as well as deserving ratings of the services. Therefore, while predicting the missing ratings, the model makes use of the various kinds of available ratings of the services which directly influence the $RMSEs$. From this experiment, it can also be seen that with the increase in the percentage of missing ratings, the $RMSE_{smd_rat}$ increases. This

is due to the fact that as the number of missing ratings increases, the model has to work on limited number of available ratings to predict these missing ratings.

Table III records the $RMSEs$ of *Experiment#2* which consist of 20% subjective and malicious ratings, and 80% deserving ratings. The facts stated for $RMSEs$ recorded in table I also hold for $RMSEs$ recorded in table II. However, it can be seen that $RMSEs$ of all sub-experiments under *Experiment#2* are correspondingly slightly more than those under *Experiment#1*. This is due to the existence of more percentage of subjective and malicious ratings in *Experiment#2* than *Experiment#1*.

Similarly, it can be seen from table IV, V, and VI that the $RMSE$ increases as the percentage of subjective and malicious ratings increases along with the increase in percentage of missing ratings. However, the $RMSEs$ recorded in table II to VI are all within the acceptable range considering the current experimental setup formulated in this paper to report the validity of the proposed approach.

Figure (a) shows the summary of prediction accuracy of the proposed model under different circumstances as stated in *Experiment#1* to *Experiment#5*.

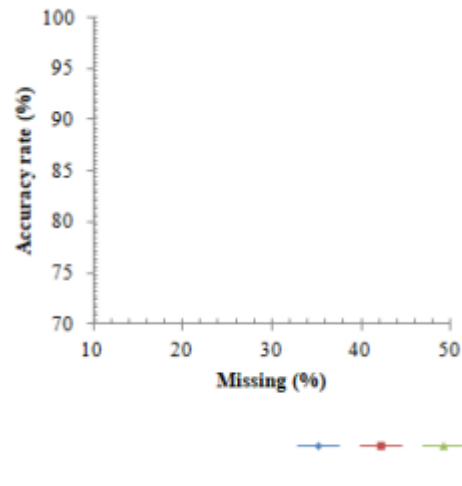


Figure (a): Summary of prediction accuracy of the proposed model

It can be seen from figure (a) that the prediction accuracy depends on the percentage of missing ratings and also on the percentage of subjective and malicious ratings. As already told, under the current experimental setup, the prediction accuracy of the proposed model is satisfactory. And thus, it can be concluded that the model can fairly predict the missing ratings under different situations of incomplete rating matrix and different kinds of available ratings.

VI. CONCLUSION AND FUTURE SCOPE

Feedback rating is considered to be the reflector of service reputation. However, because of a number of reasons, consumers sometimes refrain themselves from submitting feedback ratings after availing the services which leads to the issue of rating scarcity.

Under such situations, reputation systems may evaluate the service reputations erroneously which is not acceptable in the current competitive business market. Therefore, the rating scarcity issue must be addressed before evaluating the service reputations. This paper proposes an approach for solving the issue of rating scarcity using an enhanced memory-based collaborative filtering method. The strength of the proposed model is that it first makes initial predictions of the missing ratings and then successively refines these predictions to achieve better prediction accuracy. By considering the fact that both subjective and malicious ratings can also exist along with the deserving ratings of the services, the experimental setup is designed to mimic the real-world applications. Experiments are conducted by increasing the percentage of subjective and malicious ratings, and percentage of missing ratings. The experimental results depict that the prediction accuracy of the model is satisfactory under the current experimental setup formulated in this paper.

Since this paper reports the results of the experiments conducted on simulated environment, more experiments will be conducted in the future on real world dataset. Also the performance of the proposed model will be compared with that of another existing popular approach of same kind in the future.

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AUTHORS PROFILE



Arnab Paul is an Assistant Professor in the Department of Computer Science & Engineering, Assam University, Silchar, Assam, India. He received the M. Tech degree in Information Technology from Tezpur University, Assam, India in 2010. He is pursuing Ph. D. in Computer Science & Engineering from Assam University. His research interests include Service Computing and Trust & Reputation Systems.



Sudipta Roy, PhD, is a Professor in the Department of Computer Science & Engineering, Assam University, Silchar, Assam, India. He was associated with ACE Consultants, Kolkata as a Software Professional and Bengal Institute of Technology, Kolkata, India as a faculty. His research interests are Image Processing, Soft Computing techniques and its applications. He has published numerous papers in reputed journals and conference proceedings. He is a member of Fiete, Lmcsi, Smieeee, Mie, Minns, Lmiste.