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Effect of the initial configuration for user–object reputation systems

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HIGHLIGHTS

- We investigate the effects of the initial configuration on identifying online user reputation for the user–object bipartite networks.
- When the parameter q equals to 0.8 and 0.9, the accuracy value AUC would increase about 4.5% and 3.5% for the Netflix data set.
- Online users' reputations will increase as they rate more and more objects.

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ABSTRACT

Identifying the user reputation accurately is significant for the online social systems. For different fair rating parameter q, by changing the parameter values α and β of the beta probability distribution (RBPD) for ranking online user reputation, we investigate the effect of the initial configuration of the RBPD method for the online user ranking performance. Experimental results for the Netflix and MovieLens data sets show that when the parameter q equals to 0.8 and 0.9, the accuracy value *AUC* would increase about 4.5% and 3.5% for the Netflix data set, while the *AUC* value increases about 1.5% for the MovieLens data set when the parameter q is 0.9. Furthermore, we investigate the evolution characteristics of the *AUC* value for different α and β, and find that as the rating records increase, the *AUC* value increases about 0.2 and 0.16 for the Netflix and MovieLens data sets, indicating that online users' reputations will increase as they rate more and more objects.

1. Introduction

Reputation systems based on the Bayesian framework have been widely used to identify user reputation for user networks, which provides a flexible framework for integrating reputation services into e-commerce applications [1,2], where the user reputation is denoted by the beta distribution [3–5]. The basic idea based on the beta distribution is to define the user reputation as the expectation value of the beta probability density function(PDF) with $\alpha = 1$ and $\beta = 1$, which applies not only to user–user networks but also to user–object bipartite networks [6,7].

Mui et al. [8] proposed a probabilistic mechanism for inference among trust, reputation, and level of reciprocity, where the user reputation was defined as a quantity embedded in the social network for evaluating the agent and encounter historical behaviors. Jøsang et al. [9] used the beta PDF to combine feedback and derive reputation ratings based on the probability expectation value. To filter out unfair ratings, Whitby et al. [10] proposed a statistical filtering technique based on the beta

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distribution. In the recent years, the reputation systems based on Bayesian framework for user–object bipartite networks have been developed. Based on the beta distribution, Liu et al. [11] presented a parameter-free algorithm for ranking online user reputation via the beta probability distribution (RBPD), where the user reputation is calculated based on the expectation value of the probability that the user will give fair ratings. It could be not noticed that the initial fair and unfair rating distributions are set as uniform ones, denoted by the parameters $\alpha = 1$ and $\beta = 1$.

There were some Bayesian algorithms considering other forms of α and β. Jøsang et al. [12] transformed continuous ratings into discrete ratings by using the fuzzy set membership function where the parameters α and β are determined by the function and the ratings. Then Jøsang et al. [13] introduced the non-informative prior weight as a parameter to calculate user reputation scores. Although these models changed the initial configuration in the way of changing the parameters α and β, the effects of the initial configuration on reputation systems have been not discussed. Zhou et al. [14] pointed out that the configuration of initial resource distribution affects the accuracy of recommendation algorithms, even under the simplest case with binary resource. Inspired by this idea, we investigate the effects of the initial configuration on the reputation algorithm for user–object networks.

In this paper, we investigate the effect of the initial configuration for Bayesian reputation systems. The user reputation is based on the beta PDF with different parameters α and β. Firstly, we calculate user reputation scores and object quality values by the RBPD algorithm in user–object bipartite networks and take the ratio of all the opinions denoted by a fair rating parameter q into consideration at the same time. Empirical results show that comparing with the uniform initial configuration, the *AUC* value changes with the increase of the parameters α and β and the larger the parameter q is, the larger the *AUC* value is. More significantly, when the parameter q is 0.8 and 0.9, comparing with the case of $\alpha = 1$ and $\beta = 1$, the *AUC* value would increase about 4.5% and 3.5% for the Netflix data set, while the *AUC* value would increase about 1.5% for the MovieLens dat set when the parameter q equals to 0.9, meaning that the effects of the initial configuration for different data sets are different. Furthermore, we investigate the evolution characteristics of the *AUC* value for different α and β. The integrate timestamp is divided into 10 time intervals of the same length. We can find that the *AUC* value gradually increases as the rating records increase, indicating that users' rating accuracy will be enhanced as the time they stay in the system becomes longer.

2. Methods

The rating system represented by a bipartite network consists of the user set U and the object set O. We use Latin and Greek letters to distinguish users and objects, respectively. Consequently, $r_{i\gamma}$ denotes the rating given by user i to object γ and R_i denotes user i's reputation. U_γ denotes the set of users who rated a given object γ, while O_i denotes the set of objects rated by user i, and k_γ and k_i denotes the degree of object γ and user i, respectively.

2.1. Bayesian reputation systems

Bayesian reputation systems [15] take binary ratings as input: Fair rating or unfair rating. When a rating $r_{i\gamma}$ is consistent with the majority of opinions among users set U_γ, it is considered as a fair rating for bipartite networks [16], otherwise as an unfair rating. We use a fair rating parameter q to denote the ratio of all the opinions where $q \geq 0.5$. We adjust the ratio of all the opinions to find the changes of the algorithm. For example, when the parameter q is 0.5, a rating need to account for more than half of all opinions and then it will be considered as a fair rating. As the parameter q increases, the difficulty that a rating is considered as a fair rating increases. For the reputation systems based on the beta PDF, the posteriori reputation score is calculated by combining the priori reputation score with the new rating [1]. User reputation scores can be represented in the form of the probability expectation value of the beta PDF, where the parameters α and β represent the amount of fair and unfair ratings respectively.

The PDF of the beta distribution is a power function of the probability variable θ and its reflection $(1-\theta)$ as follows with the gamma function Γ:

$$Beta(\theta|\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\theta^{\alpha-1}(1-\theta)^{\beta-1}, \tag{1}$$

where $0 \leq \theta \leq 1$ and the parameters $\alpha > 0$, $\beta > 0$. The expectation value of the beta distribution is denoted by $E(\theta) = \alpha/(\alpha+\beta)$. Generally, the priori distribution is defined as the uniform beta PDF with $\alpha = 1$ and $\beta = 1$. After considering user i's rating records that there are s fair ratings and f unfair ratings, respectively, the posterior distribution is the beta PDF with $\alpha = s + 1$ and $\beta = f + 1$. However, the uniform initial configuration may affect the accuracy of the algorithm [14]. Therefore, we assume the priori distribution of the beta PDF is not uniform and user i's reputation is denoted by the probability expectation value of the beta distribution,

$$R_i = \frac{\alpha+s}{\alpha+\beta+s+f}, \tag{2}$$

where the parameters α and β denote the amount of fair and unfair ratings given by user i when there is no rating records in the initial stage of the system.

2.2. Transforming ratings to binary events

Considering that different users have different rating criteria, where some users tend to give high ratings and others tend to give low ratings, a normalized method is used to transfer the ratings to $[-1, 1]$. The normalized rating is denoted by $r'_{i\gamma}$ through the following way,

$$r'_{i\gamma} = \begin{cases} \dfrac{2(r_{i\gamma} - r_i^{min})}{r_i^{max} - r_i^{min}} - 1, & r_i^{max} \neq r_i^{min} \\ 0, & r_i^{max} = r_i^{min}, \end{cases} \tag{3}$$

where r_i^{max} and r_i^{min} denote the maximum and minimum ratings given by user i, respectively. And $r_{i\gamma}$ denotes the rating user i gives object γ. Now all the ratings of user i are transferred to $[-1, 1]$. If the normalized rating $r'_{i\gamma}$ is greater than or equal to 0, user i is considered to give object γ a positive evaluation, otherwise user i is considered to give object γ a negative evaluation. In the condition that the number of the positive evaluation object γ gains is more than q of all opinions and user i also gives object γ a positive evaluation, the rating $r'_{i\gamma}$ can be considered as a fair rating. The fair rating means it is consistent with the majority of opinions to the object. The numbers of fair and unfair ratings are denoted by s and f, respectively.

2.3. Evaluating the object quality

Users with higher reputations may give more fair ratings which reflect objects' inherent quality, therefore users' reputation and their ratings should be assigned more weight [17–20]. Considering that a user rates many objects and his reputation is still high, the user is more reliable [21]. Consequently, the object quality relies on not only the received weighted average rating, but also the maximum reputation of the users who rate it. The aggregate estimated quality of object γ is denoted by Q_γ, so Q_γ could be expressed as

$$Q_\gamma = \max_{i \in U_\gamma}\{R_i\} \frac{\sum_{i \in U_\gamma} R_i r_{i\gamma}}{\sum_{i \in U_\gamma} R_i}, \tag{4}$$

where $\max_{i \in U_\gamma}\{R_i\}$ is a penalty factor based on the hypothesis: An object will not gain a high quality if it is rated only by low reputation users even though it is given many high ratings.

3. Experimental results

3.1. Evaluation metrics

In this paper, the AUC value is used to test the ranking accuracy for different parameters α and β [22]. We select a group of benchmark objects which should be generally with high quality and the others as non-benchmark objects. Among n independent comparisons of one pair of benchmark and non-benchmark objects, there are n_1 times that the quality of the benchmark object is higher and n_2 times that they are the same. The AUC value is defined as

$$AUC = \frac{n_1 + 0.5 n_2}{n}. \tag{5}$$

Here we set $n = 10^9$ in the experiments for the empirical networks. $AUC = 0.5$ corresponds to a completely random ranked object list, while $AUC = 1$ means that all of the benchmark objects are ranked in front of the non-benchmark objects. The closer the AUC value is to 1, the more accurate the rank is. For empirical data sets, the movies nominated for the Oscars [23] are regarded as benchmark objects and the others as non-benchmark objects. There are 277 and 150 benchmark movies in MovieLens and Netflix data sets, respectively.

Generally, the initial configuration is considered as the uniform when $\alpha = 1, \beta = 1$. By change the values of α and β, we investigate the effect of the initial configuration for Bayesian reputation systems. The ΔAUC is used to denote the difference between the AUC value of α and β as other values and that of $\alpha = 1, \beta = 1$. The ΔAUC is expressed as

$$\Delta AUC(\alpha, \beta) = AUC(\alpha, \beta) - AUC(\alpha = 1, \beta = 1), \tag{6}$$

where $AUC(\alpha, \beta)$ denotes the AUC value for different parameters α and β and $AUC(\alpha = 1, \beta = 1)$ denotes the AUC value when $\alpha = 1, \beta = 1$. The higher the ΔAUC is, the greater the effects of the initial configuration is for the reputation systems.

3.2. Data sets

Two empirical data sets, Netflix and MovieLens, are introduced in this paper. The Netflix and MovieLens data sets contain time and rating records on movies [24], provided by the Netflix Prize [25] and the GroupLens [26], respectively.

Table 1
Basic statistics of the Netflix and MovieLens data sets where $|U|$ and $|O|$ denote the numbers of users and objects, respectively. $\langle k_U \rangle$ and $\langle k_O \rangle$ are the average degrees of users and objects, respectively. η is the network sparsity, which is the proportion of the number of links to the maximum possible number of links. What is more, t_b and t_e denote the beginning and ending time of the users' rating behaviors, respectively.

Data set	$\|U\|$	$\|O\|$	$\langle k_U \rangle$	$\langle k_O \rangle$	η	t_b	t_e
Netflix	261,527	6,798	77	2965	0.0113	2000	2004
MovieLens	45,457	10,673	182	774	0.017	1999	2009

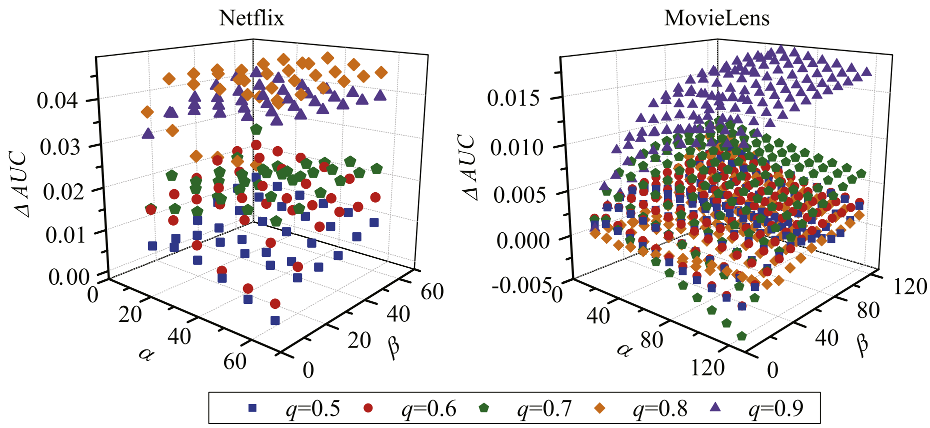

Fig. 1. (Color online) The ΔAUC of the RBPD algorithm with different α and β for the Netflix and MovieLens data sets. We use three-dimensional diagrams to show the change of ΔAUC for different q with the increases of α and β, where the parameters α and β are the two parameters of the initial configuration and the ΔAUC is the difference between the AUC value of α and β as other values and that of $\alpha = 1$, $\beta = 1$. In addition, the parameter q is the ratio of all opinions. One can find that the ΔAUC for the Netflix data set is larger than that for the MovieLens data sets.

The timestamp for two data sets is different, such as just 5 years (2000–2004) for the Netflix data set and nearly 10 years (1999–2009) for the MovieLens data set. The Netflix data set uses a 5-point rating scale where 1 is the worst and 5 is the best, while the MovieLens data set uses a 10-point rating scale which begins at 0.5 and increment by 0.5. We sampled and extracted two smaller data sets from the original data sets, respectively, by choosing users who have at least 20 ratings. Some basic statistical properties of two data sets are summarized in Table 1.

3.3. Result analysis

When investigating the effects of the initial configuration for Bayesian reputation systems with different α and β, we also take the ratio of all the opinions q into consideration. Here the parameter q lies in [0.5,0.9] and the interval is 0.1. In addition, we use ΔAUC to denote the differences between the AUC values of α and β as other values and that of $\alpha = 1$, $\beta = 1$. Fig. 1 shows the ΔAUC of the RBPD algorithm with different α and β for Netflix and MovieLens data sets. We can find that the ΔAUC fluctuates as the parameters α and β increase and the changes of the ΔAUC are increasingly obvious with the increase of the parameter q. For the Netflix data set, when $q = 0.8$, the ΔAUC changes between about 1.5% and 4.5%, and when $q = 0.9$, the ΔAUC changes between about 3% and 4%, obviously higher than that of q as other values. However, the results are relatively different in the MovieLens data set. We can find that the ΔAUC of $q = 0.9$ gradually increases from about 0.1% to 1.5% as the parameters α and β increase. When the parameter q retains fixed, the δAUC fluctuates as the parameters α and β increase. For different values of the parameter and different data sets, the range of the fluctuation is different. Comparing with the results for the two different data sets, the Netflix data set is more sensitive to the change of the parameters α and β than the MovieLens data set.

In real rating systems, there are some distorted ratings, which can affect the accuracy of ranking methods [27,28]. To test the performance of the algorithm of different parameters α, β and q, we manipulate the real data sets by adding artificial spammers who randomly give objects ratings. In the calculation process, we randomly select d users and turn them into spammers who randomly choose objects they have not rated with random ratings. The ratio of spammers is denoted by $p = d/m$, where m is the number of all ratings. We investigate the ΔAUC value of different α and β for different ratio of spammers p showed in Figs. 2 and 3. When $p = 0.1$ and $q = 0.9$, the results show that the ΔAUC can increase from 4% to 6.3% for the Netflix data set and from 0.1% to 3% for the Movielens data set, which indicates that the ΔAUC is affected by the increase of the parameters α and β and the effects of the initial configuration for different data sets are different. Fig. 2 shows the ΔAUC of different α and β for the Netflix data set, from which one can find that for random spamming attacks, the ΔAUC increases as the parameter q increases. The results for the MovieLens data set are shown in Fig. 3, from which one can find that for random spammers, when $q = 0.9$, the ΔAUC increase about 4% for different α and β, while the ΔAUC is very small when the parameter q is other values.

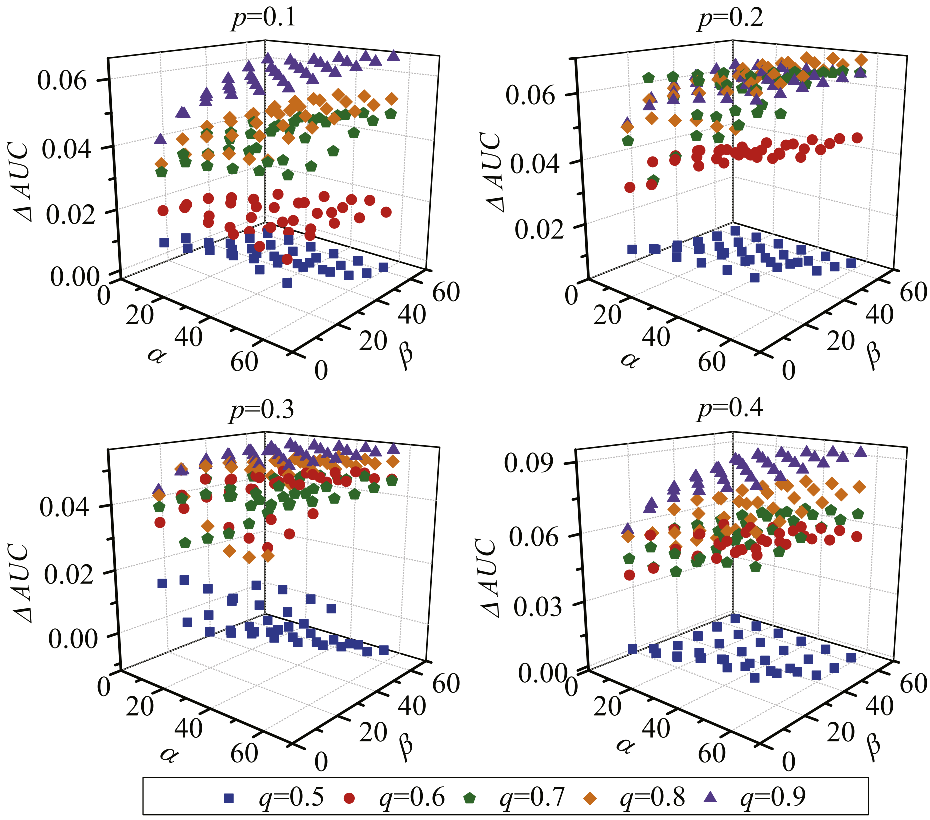

Fig. 2. (Color online) The ΔAUC of the RBPD algorithm with different α and β for the Netflix data set, where the parameters p and q are the ratio of spammers and the ratio of all opinions, respectively. One can find that the ΔAUC changes with the increase of the parameters α and β, and the larger the parameter q is, the larger the ΔAUC is.

As users rate more and more objects, their rating behavior will change [29–32]. At this point, we investigate the evolution characteristics of the *AUC* value for different α and β. Here, we set the parameter q as 0.5 according the initial parameter value of the RBPD method [11]. Firstly, according to the starting and ending time of the users' rating behaviors, we divide the integrate timestamp into 10 time intervals of the same length. We use $t_1, t_2, \ldots, t_{10}$ to denote 10 time intervals, respectively. The length of the time intervals is different for the two data sets, 6 months for Netflix and nearly 12 months for MovieLens, respectively. Secondly, we only take users who have rating behaviors for every time interval into consideration. For the Netflix and MovieLens data sets, there are 1623 and 161 users who satisfy the conditions, respectively. Then, we accumulate users' rating records for each time interval and calculate their reputation scores. In each time interval t, every user has a reputation that includes the effects of ratings for the front time intervals. Thirdly, we calculate the *AUC* value of each time interval t. Finally, we analyze the evolutions of the *AUC* value for the incremental data.

The *AUC* value of different α and β for the incremental data is shown in Fig. 4, from which we can find that the *AUC* values gradually increase as the time users stay in the rating system becomes longer. For the Netflix data set, the *AUC* values increase about 0.2 from 0.62 to 0.82 as the time duration is longer. In the MovieLens data set, the *AUC* values increase about 0.16 from 0.68 to 0.84 as the time duration becomes longer. The experimental results for both data sets suggest that users' ratings will be more accurate as they rate more and more objects. However, the *AUC* values hardly change as the increase of the parameters α and β, indicating that from the points of the time incremental data, the parameters α and β have little effect on users' rating accuracy.

4. Conclusion and discussions

In this paper, we investigate the effect of the initial configuration for Bayesian reputation systems. Firstly, based on the RBPD algorithm, we calculate user reputation scores and object quality values by changing the parameters α and β, and take the ratio of all the opinions denoted by a parameter q into consideration at the same time. Experimental results for the Netflix and MovieLens data sets show that the increment of the *AUC* value ΔAUC increases as the parameters α and β increase and the changes of the ΔAUC would increase as the parameter q increases. For the Netflix data set, when $q = 0.8$, the ΔAUC increases from 1.5% to 4.5% and the change of ΔAUC with different α and β is the largest. For the MovieLens

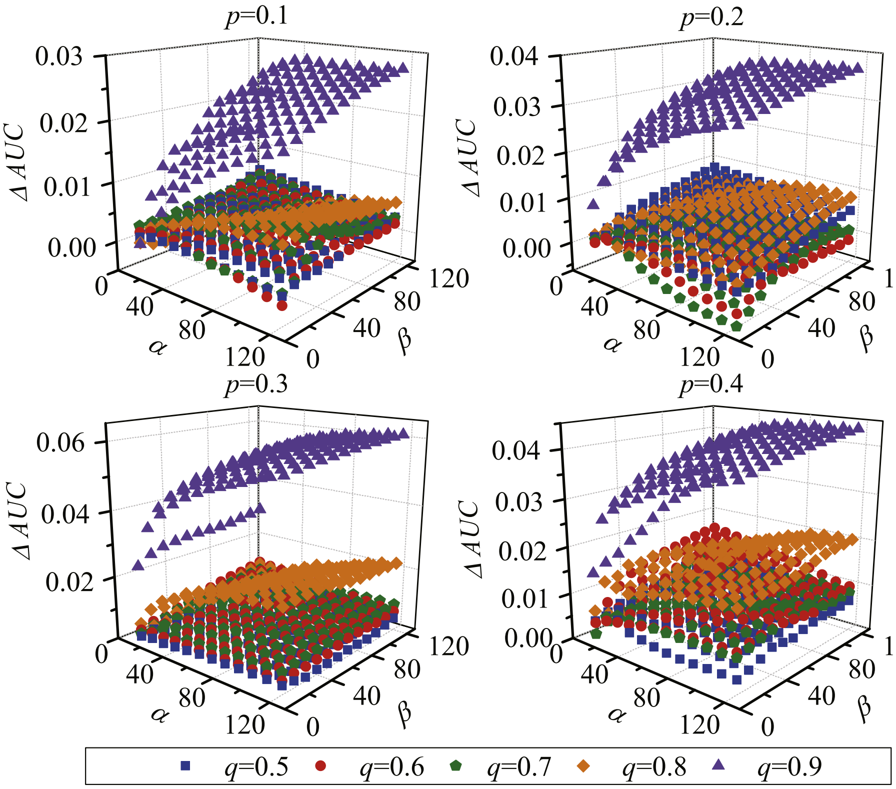

Fig. 3. (Color online) The ΔAUC of the RBPD algorithm with different α and β for the MovieLens data set, where the parameters p and q are the ratio of spammers and the ratio of all opinions, respectively. One can find that the ΔAUC changes with the increase of the parameters α and β, and the larger the parameter q is, the larger the ΔAUC is.

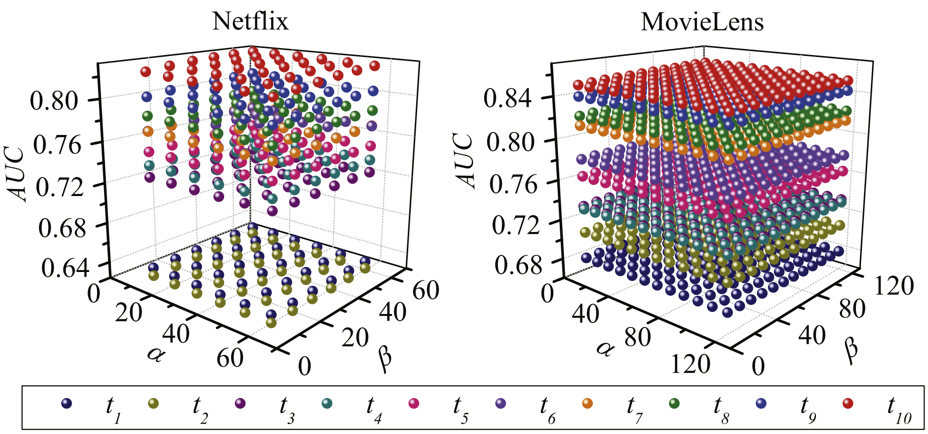

Fig. 4. (Color online) The evolution characteristics of the AUC value for the Netflix and MovieLens data sets. The integrate timestamp is divided into 10 time intervals of the same length, which are denoted by $t_1, t_2, \ldots, t_{10}$. For two different data sets, the time intervals are different. Each time interval for Netflix data set is 6 months, while the time interval for MovieLens data set is about 12 months.

data set, when $q = 0.9$, the ΔAUC increases from 0.1% to 1.5%. What is more, considering the spammers' attacks, we add artificial spammers of different ratios. Numerical results indicate that the increment of the AUC value ΔAUC of different q for the Netflix data set is larger than that for the MovieLens data sets, meaning that the Netflix data set is more sensitive to the change of the parameters α and β than the MovieLens data set. In addition, taking the time incremental data into consideration, we compared the evolutions of the AUC value for different α and β. The experimental results show that the AUC values increase about 0.2 from 0.62 to 0.82 for the Netflix data set and 0.16 from 0.68 to 0.84 for the MovieLens data set as the time duration is longer, meaning that users' ratings will be more accurate as they rate more and more objects.

The change of the parameters α and β is essentially the change of users' rating behaviors [33,34]. Consequently, we further focus on designing a self-adapting reputation method in terms of users' rating behaviors. Furthermore, according to users' different behavior patterns of different systems, how to accurately depict the effect of the initial parameters on the user reputation measurement is the priority in our future work. In addition, the results of the Netflix and MovieLens data sets are different, which may be related to the network structure and the different numbers of rating values. How to design a reputation system based on the community structures [35] is also our future work.

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References

[1] A. Jøsang, R. Ismail, C. Boyd, A survey of trust and reputation systems for online service provision, Decis. Support Syst. 43 (2) (2007) 618–644.
[2] T. Luo, S.S. Kanhere, J. Huang, S.K. Das, F. Wu, Sustainable incentives for mobile crowdsensing: Auctions, lotteries, and trust and reputation systems, IEEE Commun. Mag. 55 (3) (2017) 68–74.
[3] X.L. Liu, Q. Guo, L. Hou, C. Cheng, J.G. Liu, Ranking online quality and reputation via the user activity, Physica A 436 (2015) 629–636.
[4] X. Fan, L. Liu, M. Li, Z. Su, GroupTrust: Dependable trust management, IEEE Trans. Parallel Distrib. Syst. 28 (4) (2017) 1076–1090.
[5] L. Muchnik, S. Aral, S.J. Taylor, Social influence bias: A randomized experiment, Science 341 (6146) (2013) 647–651.
[6] M. Bouvard, R. Levy, Two-sided reputation in certification markets, Manage. Sci. (2017).
[7] S. Ruohomaa, L. Kutvonen, Trust management survey, Trust Manag. 40 (3) (2005) 77–92.
[8] L. Mui, M. Mohtashemi, A. Halberstadt, A computational model of trust and reputation, in: Proceedings of the 35th Annual Hawaii International Conference, 2002, pp. 2431–2439.
[9] A. Jøsang, R. Ismail, The beta reputation system, in: Proceedings of the 15th bled electronic commerce conference, Vol. 5, 2002, pp. 2502–2511.
[10] A. Whitby, A. Jøsang, J. Indulska, Filtering out unfair ratings in bayesian reputation systems, in: Proc. 7th Int. Workshop on Trust in Agent Societies, Vol. 6, 2004, pp. 106–117.
[11] X.L. Liu, J.G. Liu, K. Yang, Q. Guo, J.T. Han, Identifying online user reputation of userCobject bipartite networks, Physica A 467 (2017) 508–516.
[12] A. Jøsang, X. Luo, X. Chen, Continuous ratings in discrete bayesian reputation systems, in: IFIP International Conference on Trust Management, Vol. 263, Springer, US, 2008, pp. 151–166.
[13] A. Jøsang, W. Quattrociocchi, Advanced features in bayesian reputation systems, in: International Conference on Trust, Privacy and Security in Digital Business, Vol. 5695, Springer, Berlin Heidelberg, 2009, pp. 105–114.
[14] T. Zhou, L.L. Jiang, R.Q. Su, Y.C. Zhang, Effect of initial configuration on network-based recommendation, Europhys. Lett. 81 (5) (2008) 58004.
[15] J.O. Berger, Statistical Decision Theory and Bayesian Analysis, Springer Science and Business Media, 2013.
[16] J. Zhang, R. Cohen, A framework for trust modeling in multiagent electronic marketplaces with buying advisors to consider varying seller behavior and the limiting of seller bids, ACM Trans. Intell. Syst. Technol. 4 (2) (2013) 24.
[17] Y.B. Zhou, T. Lei, T. Zhou, A robust ranking algorithm to spamming, Europhys. Lett. 94 (4) (2011) 48002.
[18] J. Gao, T. Zhou, Evaluating user reputation in online rating systems via an iterative group-based ranking method, Physica A 473 (2017) 546–560.
[19] J. Gao, Y.W. Dong, M.S. Shang, S.M. Cai, T. Zhou, Group-based ranking method for online rating systems with spamming attacks, Europhys. Lett. EPL 110 (2) (2015).
[20] P. Laureti, L. Moret, Y.C. Zhang, Y.K. Yu, Information filtering via iterative refinement, Europhys. Lett. 75 (6) (2006) 1006.
[21] H. Liao, A. Zeng, R. Xiao, Z.M. Ren, D.B. Chen, Y.C. Zhang, Ranking reputation and quality in online rating systems, PLoS One 9 (5) (2014) e97146.
[22] J.A. Hanley, B.J. McNeil, The meaning and use of the area under a receiver operating characteristic (ROC) curve, Radiology 143 (1) (1982) 29–36.
[23] http://www.filmsite.org.
[24] Y.S. Zhao, B. Shen, Empirical study of user preferences based on rating data of movies, PLoS One 11 (1) (2016) e0146541.
[25] http://www.netflixprize.com.
[26] http://www.grouplens.org.
[27] A. Zeng, G. Cimini, Removing spurious interactions in complex networks, Phys. Rev. E 85 (3) (2012) 036101.
[28] D.D. Zhao, A. Zeng, M.S. Shang, G. Jian, Long-term effects of recommendation on the evolution of online systems, Chin. Phys. Lett. 30 (11) (2013) 118901.
[29] J.H. Wang, Q. Guo, K. Yang, Y.L. Zhang, J.T. Han, J.G. Liu, Popularity and user diversity of online objects, Physica A 461 (2016) 480–486.
[30] J.G. Liu, T. Zhou, Q. Guo, Information filtering via biased heat conduction, Phys. Rev. E 84 (3) (2011) 037101.
[31] L. Hou, X. Pan, Q. Guo, J.G. Liu, Memory effect of the online user preference, Sci. Rep. 4 (2014) 6560.
[32] Q. Guo, L. Ji, J.G. Liu, J.T. Han, Evolution properties of online user preference diversity, Physica A 468 (2017) 698–713.
[33] Q. Guo, Y. Li, J.G. Liu, Information filtering based on users' negative opinions, Internat. J. Modern Phys. C 24 (05) (2013) 1350032.
[34] L. Zhang, S. Jiang, J. Zhang, W.K. Ng, Robustness of trust models and combinations for handling unfair ratings, Trust Manag. VI (2012) 36–51.
[35] K. Yang, Q. Guo, S.N. Li, J.T. Han, J.G. Liu, Evolution properties of the community members for dynamic networks, Phys. Lett. A 381 (11) (2017) 970–975.