Building reputation systems for better ranking

Luo-Luo Jiang\(^1,2\), Matúš Medo\(^1\), Joseph R. Wakeling\(^1\), Yi-Cheng Zhang\(^1\), and Tao Zhou\(^{1,2,∗}\)

\(^1\) Department of Physics, University of Fribourg, Chemin du Muse, CH-1700 Fribourg, Switzerland
\(^2\) Department of Modern Physics, University of Science and Technology of China, Hefei 230026, PR China
\(^3\) Web Sciences Center, University of Electronic Science and Technology of China, 610054 Chengdu, PR China

(Dated: January 13, 2010)

How to rank web pages, scientists and online resources has recently attracted increasing attention from both physicists and computer scientists. In this paper, we study the ranking problem of rating systems where users vote objects by discrete ratings. We propose an algorithm that can simultaneously evaluate the user reputation and object quality in an iterative refinement way. According to both the artificially generated data and the real data from MovieLens and Amazon, our algorithm can considerably enhance the ranking accuracy. This work highlights the significance of reputation systems in the Internet era and points out a way to evaluate and compare the performances of different reputation systems.

PACS numbers: 89.20.Hh, 89.65.Gh, 89.70.+c, 89.75.-k

I. INTRODUCTION

Ranking may not be the best way to describe a system, but definitely provides valuable and impressive information, especially for the people who do not comprehensively understand the internal interactions and organization of this system. Nowadays, ranking techniques are becoming increasingly important in many online services, and we are always curious for rankings of web pages, books, scientists, movies, movie stars, and so on. For a simple undirected graph, the centralities are usually used to rank the importance of nodes \(^1\), while for directed graph, PageRank is the most widely applied algorithm who mimics the random walk process with restart \(^2\). Considering a possibly underlying mixing role of each node, the HITS algorithm \(^3\) may provide better ranking. Recently, some scientists proposed a number of iterative refinement algorithms to rank the scientists and scientific publications based on the citation and co-authorship data \(^4\).

In this paper, we consider the ranking problem in a different kind of systems called the rating systems, where each user vote some objects with ratings (usually discrete ratings from 1 to 5, like in Netflix.com and Amazon.com). A straightforward method is to rank objects according to their average ratings. However, a drawback is that some users are not serious to their votes at all, therefore the evaluation by simply averaging all ratings may be less accurate. A promising way to overcome this problem is to estimate the reputation or trust of each user and to assign more weight to the user with higher reputation. In fact, to build reputation systems or reputation societies is a vital task in the Internet era \(^5\), which could find its applications in personalized recommendations \(^8\)\(^9\), management of peer to peer systems \(^10\)\(^11\), online sales in e-commerce systems \(^13\)\(^14\), design of mobile ad-hoc networks \(^15\), and so on. However, to estimate the reputation of a user is not a trivial task. Yu et al. \(^16\)\(^17\) proposed an iterative refinement algorithm, where the quality of an object is quantified by its weighted average rating and a user whose ratings are closer to the weighted average ratings is considered to be of higher reputation. A user having higher reputation will be assigned more weight. At each time step, every user’s reputation and every object’s weighted average rating are recalculated, until the system converges to steady distributions of reputations and weighted average ratings. To achieve better estimation of user reputation and object quality, the basic iterative refinement model can be further extended by accounting for the truncation of the rating and by assuming a prior distribution on the parameters according to a Bayesian model \(^18\). Similar problems based on partial information \(^19\) and changing data \(^20\) have also been considered.

Most of the previous works used artificially generated data to evaluate the algorithmic performance. In this paper, beyond the artificial data, we use real data to test a modified iterative algorithm. The winners of the Best Picture of Oscar Awards among the movies in MovieLens data and the winners of the National Book Awards among the books in Amazon.com are treated as benchmark objects. Experimental analysis shows that our modified algorithm gives considerably higher ranks of the benchmark objects than the average ratings.

II. METHOD

A rating system consists of \(N\) users and \(M\) objects, where each user rates some objects. Denoting by \(ρ\) (\(0 ≤ ρ ≤ 1\)) the density of ratings (each user has voted \(ρM\) objects on average), \(x_{ik}\) the rating of object \(k\) by user \(i\), and \(Q_k\) the intrinsic quality of object \(k\) which is usually not observable. If \(Q_k\) is known, the mean square deviation of user \(i\)’s votes from the objects’ intrinsic qualities...
We set the initial condition as \( \xi_i = 1 \), and at each time step we first estimate \( q_k \) by Eq. (2) and then update \( \xi_i \) by Eq. (3). The maximal difference for \( q \) and \( \xi \) at the \( n \)th time step is defined as:

\[
\Delta q(n) = \max_k |q_k(n) - q_k(n-1)|, \tag{4}
\]
\[
\Delta \xi(n) = \max_i |\xi_i(n) - \xi_i(n-1)|. \tag{5}
\]

The iterative process stops when both \( \Delta q \) and \( \Delta \xi \) are smaller than the threshold \( \Delta_q = 10^{-5} \), and the resulted \( \tilde{q} \) and \( \tilde{\xi} \) are used to rank the object quality and user reputation, respectively.

## III. RESULTS OF ARTIFICIAL DATA

In this section, we test our algorithm by artificial system where the numbers of users and objects are fixed as \( N = 2000 \) and \( M = 1000 \). We first generate the intrinsic qualities of objects \( \bar{Q} \) and the noise levels of users’ judgements \( \bar{\xi} \) according to some given distributions (see later). Here the known (exact) qualities and mean square derivations are denoted by \( \bar{Q} \) and \( \bar{\sigma} \) (later we will see that in the statistical level \( \sigma \sim \bar{\xi}_k^2 \)), while the estimated values are \( \tilde{q} \) and \( \tilde{\xi} \). Then for each user-object \( (i-k) \) pair, with probability \( \rho \), we generate the artificial rating \( x_{ik} \) as

\[
x_{ik} = Q_k + \psi \xi_i,
\]

where \( \psi \in [-1, 1] \) is a random variable. The lower and upper boundaries of the rating system are set as 0 and

![FIG. 1: \( \delta \) and \( \tau \) as functions of \( \alpha \), where \( Q \) and \( \zeta \) obey the uniform distribution. The rating density is fixed as \( \rho = 0.05 \). All data points are obtained by averaging 100 independent realizations.](image1)

![FIG. 2: \( \delta \) and \( \tau \) as functions of \( \alpha \), where \( Q \) obeys the power-law distribution \( p(Q) \sim Q^{-1.5} \) and \( \zeta \) obeys the uniform distribution. The rating density is fixed as \( \rho = 0.05 \). All data points are obtained by averaging 100 independent realizations.](image2)
the convergent algorithm described in Eqs. (2) and (3). After we obtain intrinsic qualities of objects:

\[ q_i = \text{sgn}(\alpha - \tau), \]

we simply assume that \( q_i \) obeys a uniform distribution in the range \([0, 5]\). For the qualities of objects, we test on two kinds of distributions: the uniform distribution and the power-law distribution \( p(Q) \sim Q^{-1.5} \). We adopt the latter distribution because for many user-object bipartite systems the degrees of objects are very heterogeneous \cite{22}, indicating that the qualities of objects may be also heterogeneous. The value of \( Q \) is also restricted in the range \([0, 5]\).

Figure 1 and Figure 2 respectively report the algorithmic performance with different distributions of object qualities. Although the shapes of \( \delta - \alpha \) curves and \( \tau - \alpha \) curves in Fig. 1 and Fig. 2 are different in some details, both figures clearly show the advantage of our algorithm. Compared with the simple average (i.e., the case of \( \alpha = 0 \)), our algorithm can provide considerably better evaluations on user reputation and object quality. We next study the effects of rating density on algorithmic performance. As shown in Fig. 3, the algorithm performs better for denser data but the qualitative features do not change for different \( \rho \).

IV. EXPERIMENTAL RESULTS

In this section, we test our algorithm on two real data sets: MovieLens (http://www.grouplens.org/) and Amazon (http://www.amazon.com/). The former consists of 6040 users and 3900 movies, and the latter consists of 16311 users and 10000 books (the Amazon data was collected from July 2005 to September 2005). All the ratings on movies and books are discrete integers from 1 to 5. Since in the real world, the users’ reputations and objects’ qualities could never be exactly observed or quantified, we are not able to test the algorithmic performance in a direct way. Instead, we first select a subset of objects as benchmark ones that are known to be of high quality, and then see whether our algorithm assigns in average higher ranks to these benchmark objects than the simple average of ratings. We apply the AUC statistics \cite{23} to evaluate our algorithm, which is the probability a randomly selected benchmark object is assigned topper rank than a randomly selected non-benchmark one, as

\[ AUC = \frac{1}{S} \sum_{i} \frac{M - R_i}{M - S}, \]

where \( S \) denotes the number of benchmark objects, \( i \) runs over all benchmark objects and \( 1 \leq R_i \leq M \) is the rank of object \( i \). A completely random order of objects corresponds to \( AUC = 0.5 \), therefore, the degree to which \( AUC \) exceeds 0.5 indicates how much better the algorithm performs than pure chance. 74 movies winning the
FIG. 4: AUC value as a function of $\alpha$ for Amazon (a) and MovieLens (b). Results are obtained by averaging over 100 independent realizations since the objects with the same $q$ value may be assigned different orders in different realizations.

Best Picture of Oscar Awards and 189 books winning the National Book Awards are selected to be the benchmark objects for MovieLens and Amazon, respectively. The basic statistics of real data sets are shown in Table 1.

Figure 4 reports the experimental results. Although the shapes of AUC$-\alpha$ curves are different for MovieLens and Amazon (they are also different from the artificial systems), our algorithm outperforms the simple average in both two data sets. In accordance with the results of artificial data, the sparser the ratings are, the smaller the AUC is.

V. CONCLUSION AND DISCUSSION

As stated by Masum and Zhang [7], how to quantify people’s reputation is an urgent challenge in the Internet era. For example, spammers intentionally produce noisy and evil information that misleads our judgement, and the well-designed reputation systems can dig out these nasty users or reduce their impacts. In this paper, we focus on the bipartite rating systems, and design an iterative refinement method to evaluate the users’ reputations and objects’ qualities. According to both the artificially generated data and the real data, our algorithm could considerably improve the evaluation accuracy. In addition, the method adopted to test the algorithm for real data (a similar method is reported very recently in Ref. [14]) suggests a good platform for the quantitative competition of different ranking algorithms. To our knowledge, although some reputation-based ranking algorithms have been proposed previously [16–18, 20], no empirical comparison between them has been reported yet, and it is not easy to say one algorithm could beat another without a reasonable metric on algorithmic performance for real data. Thanks to the increasing number of available data sets and the metric suggested in this paper, extensive comparison between various algorithms become feasible [24], from which we hope the effectiveness and efficiency of related algorithms can be largely improved in the near future.

Acknowledgments

We acknowledge the GroupLens Research Group for MovieLens data and František Slanina for collecting the Amazon data. This work was partially supported by the Future and Emerging Technologies programme FP7-COSI-ICT of the European Commission through project QLectives (Grant No. 231200) and the Swiss National Science Foundation (Grant No. 200020-121848). TZ acknowledges the National Natural Science Foundation of China under Grant Nos. 10635040, 60744003 and 60973069.

[1] L. C. Freeman, The Development of Social Network Analysis: A Study in the Sociology of Science (Empirical Press, Vancouver, Canada, 2004).
[2] S. Brin and L. Page, Comput. Netw. ISDN Syst. 30, 107 (1998).
[3] J. Kleinberg, J. ACM 46, 604 (1999).
[4] D. Walker, H. Xie, K.-K. Yan, and S. Maslov, J. Stat. Mech. P06010 (2007).
[5] Y. Ding, E. Yan, A. Frazho, and J. Caverlee, J. Am. Soc. Inf. Sci. Technol. 60, 2229 (2009).
[6] F. Radicchi, S. Fortunato, B. Markines, and A. Vespignani, Phys. Rev. E 80, 056103 (2009).
[7] H. Masum and Y.-C. Zhang, Manifesto for the reputation society, First Monday (5, July, 2004).
[8] P. Massa and B. Bhattacharjee, Lect. Notes Comput. Sci. 2995, 221 (2004).
[9] C.-N. Ziegler and G. Lausen, Lect. Notes Comput. Sci. 3291, 840 (2004).
[10] M. Gupta, P. Judge, and M. Ammar, A reputation system for peer-to-peer networks, in Proceedings of the 13th international workshop on Network and operating systems support for digital audio and video (ACM Press, 2003, p. 144-152).
[11] D. Wei, S.-B. Yang, and L.-T. Gao, Object Reputation Based Anti-Pollution P2P File Sharing System, in Proceedings of the 1st IEEE International Conference on Digital Information Management (IEEE Press, 2006, p. 538-543).
[12] K. Walsh and E. G. Sirer, Experience with an Object Reputation System for Peer-to-Peer Filesharing, in Proceedings of the 3rd Symposium on Networked Systems Design and Implementation, 2006.
[13] P. Resnick and R. Zeckhauser, Adv. Appl. Microeconomics 11, 127 (2002).
[14] A. Jøsang, R. Ismail, and C. Boyd, Decision Support Syst. 43, 618 (2007).
[15] S. Buchegger and J.-Y. Le Boudec, EPFL IC Technical Report IC/2003/50.
[16] Y.-K. Yu, Y.-C. Zhang, P. Laureti, and L. Moret, Physica A, 371, 732 (2006).
[17] P. Laureti, L. Moret, Y.-C. Zhang, and Y.-K. Yu, Europhys. Lett. 75, 1006 (2006).
[18] F. Fouss, A. Achbany, and M. Saerens, A Probabilistic Reputation Model (unpublished).
[19] P. Laureti, L. Moret, and Y.-C. Zhang, Physica A 345, 705 (2005).
[20] C. de Kerchove and P. van Dooren, arXiv: 0711.3964.
[21] M. Kendall, Biometrika 30, 81 (1938).
[22] M.-S. Shang, L. Lü, Y.-C. Zhang, and T. Zhou, arXiv: 0909.4938.
[23] J. A. Hanely and B. J. McNeil, Radiology 143, 29 (1982).
[24] M. Medo, J. R. Wakeling, T. Zhou, L.-L. Jiang, C.-H. Jin, and Y.-C. Zhang, Comparative study of reputation-based ranking methods (unpublished).