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A MULTIDIMENSIONAL PAGERANK ALGORITHM OF LITERATURES

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ABSTRACT

Literature is usually evaluated based on impact factor, cited information or the quality of literature database. Here, some more exact evaluation schemes and algorithms are investigated and a synthetically reputation model and its evaluation algorithm are proposed. The reputation model integrates much more information of academic interactions such as reviews and comments. The literature reputation can be modeled by complex relationships among literature, authors, publish sources and readers. The model is in some ways similar to the Google PageRank model. However, in the literature reputation model, the relationships belong to different classes and have different importance that is great different from PageRank which regard all links as the same class. We propose a centralized algorithm that can compute the reputation most exactly and a distributed version that can run in P2P systems. The simulations show that the reputation evaluation algorithm is convergent and efficient. The communication cost of the distributed algorithm is low if the convergence condition is relaxed.

Keywords: *Reputation Evaluating, Literature Evaluation, PangRank, Impact Factor*

1. INTRODUCTION

Nowadays, since science research activity becomes more and more complex, the communication and collaboration between different domains, different researchers and groups are more urgent and frequent. Development of computer and communication technologies facilitates knowledge acquisition in their studies, generally by BBS, Email, instant communication, WWW and so on, which has been necessities in daily activities. A main way to gain new knowledge in academic research is through reading scientific documents[1]. In this process, researchers often refine and store their thoughts into notes. This process information is usually important for others to enlighten them on their researches more effectively. In the discipline of education, it is called computer-supported collaborative learning (CSCL)[2] which can also been applied in science research.

However, the user groups and environment characteristics in research are very different to that in education. In researches, the user group is enormous and they are usually having not uniform benefits. Since everyone generally has the self-interested tendency and his academic thought is the valuable personal wealth, he is willing to share the information only when he can receive equivalent services. In game theory, it is a problem of reciprocity and incentive mechanism. On the other hand, the system is opened and any kind of information can spread in it, so how to find out the good from enormous jumble information is considerable challenging [3]. Because of the lack of systematic support, it is often hard to choice the peer in this interaction.

Academic forums are a common form to share the process information, the organization structure of forums is more fitful for the above objective. However, the existed systems by now cannot provide the enough incentive and still cannot attract the researchers participating widely. The effective incentive mechanism depends on two factors: the assessment accuracy of user reputation and the strength of the incentive measure. User reputation assessment is the level of user participation which accuracy is the base of incentive efficiency. The strength of the incentive is proportionate to the ratio of the user utility to his cost. General forums system provides services (ways to improve users of utility) is too monotone, more incentive methods, for example recommending suited collaborators in researches according to user reputation, need to be employed to increase the incentive power to participate.

Following this idea, we developed a cooperative research prototype system which structure is show in Figure 1. The system connects authors to learners by literature indexes and user comments. In the system, the information about a literature, such as authors, source, subject, keywords and references is

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offered. However, the file itself cannot be shared. User comments are offered in the form of forum. Reputation evaluation module implements the evaluation of literature quality, comment quality and user prestige (i.e. reputation). The user here may be a common user or the author of a literature. If he registers as an author, he can gain an initial reputation according to the quality of literature source. All users interact with each other in peer model and form a relationship network, which is achieved by client software. However, the client must send interaction information to the server platform in the same while, so the system can record the information into user network view database.

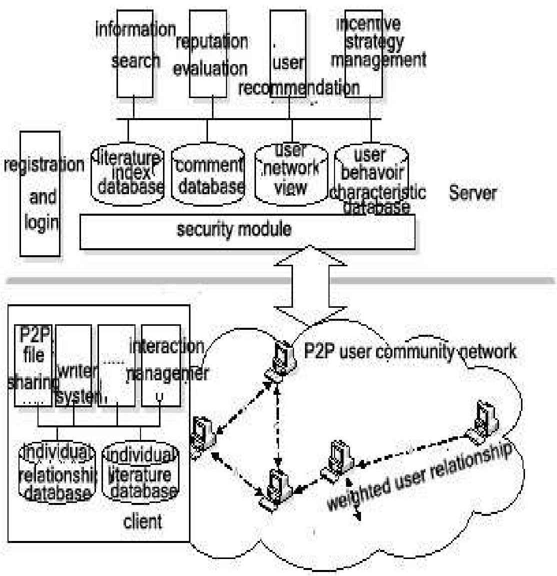

Figure 1: Cooperative Research System

Information search is a primary function that uses keyword search, importance sort based on information quality and information filter based on cooperative recommendation to improve the preciseness.

User recommendation can be used to search and locate the peers who have similar research interests or learning demands. Reciprocity and trustworthiness are also considered. The reputation is used to filter the users who cannot be trusted enough. The users with similar interests can be located based on their behaviors and the relationship network.

Incentive strategies management module implement all kinds of incentive mechanisms. Up to now, the mechanisms include information access control based on user right, reputation-based object choice for user recommendation, interference proof and the special setting to gain the right to read comments.

Obviously, reputations of various objects are key elements in searches, filters and incentive mechanisms. This paper proposes a centralized reputation model of elements in the forum system presented as Figure 1 to support cooperative learning and improve the learning efficiency of the researchers.

The forum can also be built in distributed mode that can be fit to the P2P structure of the client system. The software architecture is shown as Figure 2.

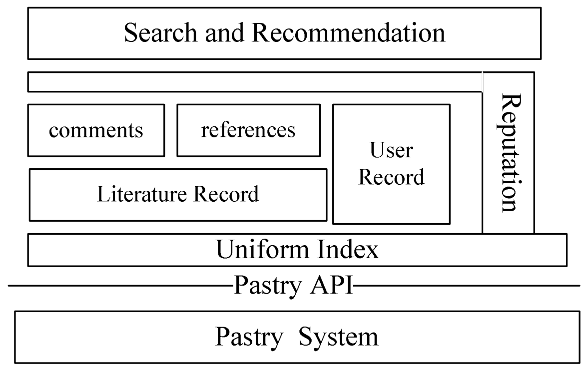

Figure 2: Client System Structure

The system applies Pastry to build the P2P storage system to implement the basic storing, locating, and searching. The data in the system, including papers, comments, citations and user records, are stored by a distributed way. Single-point failure can be avoided since there is no centralized server in the system. However, it brings new problems about information search and reputation calculation. They are key problems that will be considered in this paper.

2. BACKGROUND

Reputation is generally defined as the evaluation of a group of entities to the behavior of a special entity[4]. The evaluations include direct, indirect and recommendation reputation, focusing on the subjectivity and credibility of the reputation in the model of community networks. The direct one evaluates the entity by directly interacting history, and the recommendation reputation is based on the direct evaluation, indirect evaluation of the recommendation. Reputation model can deduce the globe reputation from the above factors.

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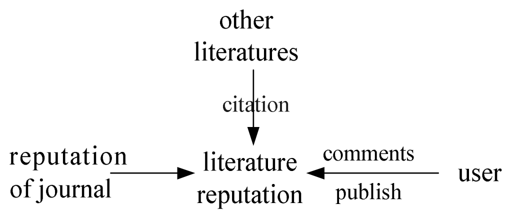

Figure 3: Reputation Model

In the field of academic research, the reputation of a literature is the quantitatively evaluation of the literature value which can be simply estimated by the times cited of the literature. Nowadays, the most representative type of reputation is based on citation analysis, among which SCI [5] is the most famous one. However, SCI can only make quantitative evaluation on the periodical, which can't reflect the differences between different literatures in the same journal [6]. The SCI can only be counted on the data from the limited journal list, so 80% of a journal's IF is determined by only the 20% of the papers published[7].

Usually, academic reputation are not only judged based on single quantitative variable but through synthesizing multiple subjective factors. This method has great difficulty to implement, especially in literature search and recommendation, and dramatically increases the learning cost of researchers. The Index Copernicus Scientists[8] provides scientists with global scientists networking and international research collaboration, presents a multi-parameter career assessment system, which analyses the researcher individual profile. This goal is accomplished by a uniform scoring system that evaluates the contribution of scientists in three areas of professional activity: research potential, teaching potential and administration experience. The ResearcherID[9] is a website where researchers can register for a unique researcher ID number to avoid the frequent difficulty of author misidentification. In this way the researcher build their publication list using Web of Science and citations counts will be automatically updated in order to generate citation metrics. The h-index[10] for ResearcherID participants is also calculated. Remarkably, it was discussed very recently the need for speed the personal IF assessment in which the subject of calculation is the scientist and not the journal. This measure would really provide a more accurate measure of an individual’s citation rate. Journal to Field Impact Score (JFIS) [11] developed an alternative system for the journal impact evaluation. Its source to compute index includes literatures, technical reports, notes and reviews.

PageRank algorithm [12], which is widely used in search engines, extends the reputation evaluation model and improves the validity of the information recommendation[13] through introducing weighted links in citation analysis. Google Scholar uses PageRank with a broad range of open data sources: peer reviewed literature from scholarly journals as also non-reviewed material like books, abstracts, technical and other reports etc. Popular journals are those that are cited frequently by journals could be with little prestige. These journals therefore could have a very high IF and a very low weighted PageRank. Bollen has proposed a measure that combines Google’s PageRank with Impact Factor[14]. The reputation model EngerTrust[15] employs the concept of explicit recommend and the computation method of the global reputation based on weighted recommending credibility reflects the thought of weighted citation analysis.

Our scheme is similar to PageRank and EngerTrust algorithm. However, different from all the schemes above, the data used to compute reputation includes users, literatures and comments, which come from data or activities in the academic forum as Figure 1 and can be easily obtained by systematic means. By combining various classes of data, the reputation model is steadier than single reputation. This paper will examine how to utilize the forum information to construct a complete reputation model and discuss the feasible reputation evaluation algorithm. The Evaluation algorithms in the model are proposed and analyzed below.

3. THE BASIC REPUTATION MODEL

This system is a platform for the researchers to communicate with the others and their literatures. The system is formed as a forum in which the basic unit is the literature. Other readers can discuss about a paper by feed his personal comments back. The explicit feedback can serve as reputation. Combined with impact factor and author's reputation, we can evaluate the literature more accurately.

The papers must be published formally. Literature authors and common users without any literature register with different identity and gain different initial reputations. Based on the impact factor of the literature, author reputation and its citations, the initial reputation of the literature can be computed. Other users can post reviews and scores the literature. The literature reputation and

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user reputation will change dynamically if the discussion takes place. There are complex interactions among user reputation, literature reputation and review reputation, as shown in Figure 3.

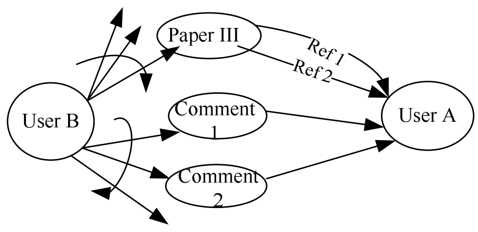

Figure 4: Recommendation Relation

In order to effectively calculation user reputation, the above reputation model needs some simplification. As links in PageRank or EngerTrust, is we can regard literature review or citation as recommendation which weight is decided by the presenter's reputation and the total amount of recommendations, as shown in Figure 4.

A. Literature reputation model

Literature reputation R_p shall consider at least three factors: authors, citations and comments. The formula (1) shows the reputation evaluation of literature i:

$$R_p(i) = \lambda_1 R_s(s(i)) + \lambda_2 R_a(a(i)) + \lambda_3 R_c(i) + (1-\lambda_1-\lambda_2-\lambda 3)R_r(i) \quad (1)$$

Here, R_s is the initial reputation of the journal or the proceeding the article published on. Usually it is in proportion to its impact factor. If it has not impact factor, its initial reputation is 0.

R_a is the reputation of the first author, defined in formula (3). $R_c(i)$ is the score from comments about it, as show in formula (4).

R_r denotes citation value of the article.

$$R_r(i) = \sum_{j \in ref(i)} \frac{R_p(j)}{|ref(j)|} \quad (2)$$

$|ref(j)|$ donates the number of the citations of literature j.

B. User reputation model

User reputation reflects the user's academic authority and the academic value of his articles and reviews. There are two kind of user reputation: reputation of author and common reader. Figure 4 shows that the relation between two users is built on comments or articles. Therefore, we can calculate the two kinds of reputation by formula (3):

$$R_a(u) = \lambda_4 \sum R_p(i) + (1-\lambda_4)\sum R_c(j) \quad (3)$$

Here, i is a paper issued by the author u, j is a comment about u.

C. Comment reputation model

Comment reputation of a comment k includes two parts: commentator reputation and the comments on this comment by other readers.

$$R_c(k) = \lambda_5 \frac{R_a(a(k))Val(p(k),a(k))}{|comments(a(k))|} + (1-\lambda_5)\sum_{i \in sub(k)} \frac{R_c(i)Val(k,i)}{5|comments(i)|} \quad (4)$$

$|comments(a(k))|$ denotes the total number the user $a(k)$ has posted, $Val(p(k),a(k))$ is the score $a(k)$ marks on $p(k)$ and $|comments(i)|$ is the total number of the comments posted by user i.

The comments form a tree structure that a father comment can be made up of a few child comments and each child may have a few children of him. The reputation formula is a recursive function: the end node in the comment tree is firstly evaluated by only R_a, his father then combines R_a and the reputations of child comments gained just now.

D. Rank leak

The formula above is based on a hypothesis: all the elements and their relationship form a strong connected graph. However, it should not be true in most instances. There are always many isolated elements, which hasn't any link to other elements. When a user hasn't any paper citing other papers and no comment, he is called dangling user. Simultaneously, the dangling paper is the paper without any citation. A comment always has an out link so it hasn't the dangling problem. Dangling entities can disturb the reputation evaluation of other entities because the "rank leak" problem. Rank leak will cause the reputations of all the elements go on decreasing until zero.

Two methods can solve the problem to ensure the reputation computation convergent: (1) add a virtual link from the entity to all other available entities, the user can link to literatures and comments, the literature can link to literatures; (2).introduce a new element, rank source, to recruit the reputation of each element. Therefore, reputation does not depend only on relationships among the elements. Moreover, the absolute difference of reputations cannot represent the

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importance of the literature, the user or the comment. However, the rank can. Rank is the order of the reputation in the literature set.

The modified formula is as below:

$$R_p(i) = \frac{d}{m} + (1-d)[\lambda_1 R_s(s(i)) + \lambda_2 R_a(a(i)) + \lambda_3 R_c(i) + (1-\lambda_1-\lambda_2-\lambda_3) R_r(i)]$$

$$R_a(u) = \frac{d}{m} + (1-d)[\lambda_4 \sum R_p(i) + (1-\lambda_4)\sum R_c(j)]$$

$$R_c(k) = \frac{d}{m} + (1-d)[\lambda_5 \frac{R_a(a(k))Val(p(k),a(k))}{|comments(a(k))|} + (1-\lambda_5)\sum_{i\in sub(k)} \frac{R_c(i)Val(k,i)}{5|comments(i)|}]$$

Here, d is a decay factor satisfying $0<d<1$ and is usually set to 0.85. m is the number of all the entities in the system.

E. Initial reputation

Formula (1) can be used to compute initial literature reputation, here $R_s(j)$ is the reputation of journal or proceeding j can be gained by literature databases. By now we choose most well-known databases include SCI journals, EI source, the list of Chinese core journals of PKU. The normalized computing is as (5):

$$R_s(j) = \begin{cases} 1-0.5^{factor(j)} & j \in \text{SCI} \\ 0.3 & j \in \text{EI} \\ 0.1 & j \in \text{core journal list of PUK} \end{cases} \qquad (5)$$

Then, with the initial literature reputation above, initial user reputation can be computed by (3).

A user who hasn't published any paper will receive a reputation of 0.1 firstly.

F. Reputation evaluation algorithm

Evidently, reputation variables in (1)~(4) is not independent, so reputation computing is an iterative process and must be convergent. The adopted algorithm refers to the idea of recommendation networks, for example PageRank, which can be expressed in a common form of matrix:

$$T_k = \sum_j (C_{ij} \times C_{jk})$$

It can be proved that globe reputation T_k is converged to principal left eigenvector of recommendation trust degree matrix C, the condition of convergence is irreducibility and non-periodicity of matrix C.

The evaluation algorithm is detailed in Figure 5.

10 Procedure Evaluation
20 Begin
30 For each user u and literature i, $R_a(u)$=1 and $R_p(i)$=1
40 calculate initial reputation $R_p(i)$ by formula (1), (2) and (5)
50 store reputations of all entities t in $R(t)$
60 recalculate user reputation $R_a(u)$ with formula (3)
70 recalculate literature reputation $R_p(i)$ with formula (1)
80 recalculate comment reputation $R_c(k)$ with formula (4)
90 store reputations of all entities t in R'(t)
100 if $\max_{\forall t} \|R(t) - R'(t)\| > \varepsilon$ goto 50
110 End

Figure 5: The Iterative Reputation Evaluation Algorithm

4. DISTRIBUTED IMPLEMENT OF REPUTATION MODEL

P2P system, such as Pastry, supports storing, searching and locating the literature information and its reputation. But as explained above, reputation algorithm is iterative, so it isn't suitable to be implemented in distributed mode, which will bring too high communication cost. On the other hand, the globe algorithm is static that it is unavailable in dynamic network. Furthermore, m cannot be gain in a P2P network because each peer has only a local view of the network.

We propose a scheme P2PEval that can overcome above defects. P2PEval refers to existed partitioning algorithms[16], These methods shorten the iterations for convergence at the expense of increased computation and space consumption. Data is located based on their main keywords. Most data are related to the authors except the reader who hasn't published any paper. The data about an author include the papers he publishes and the comments about his paper. All the data will located to a node whose node id is most close to H(author name), the hash value of the author name. The reputation is also stored and located by its keyword.

Firstly, each node calculates the reputation of local entities, regardless of inlinks that refer to the entities at the node. Then the node queries the inlinks at other nodes and melts the outer reputations. Modification affects only local entities,

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so the iterative algorithm will repeat for several times to gain stable globe reputation.

To decrease the communication overhead, P2PEval applies a dynamic partitioning strategy: Each node i is associated with a value called connection intension, which is decided by the amount of links from this node to an outer node j, denoted by $L(i,j)$. When the node finishes a round of iteration, it send the reputation update to the linked node j proportional to $L(i,j)$. Obviously, nodes with higher connection intension will update their reputation more frequently.

Dangle entity is another problem. Apply the globe algorithm in each node can solve the problem locally but cannot diminish all the outside dangle entities. The local reputation model is shown as:

$$R_p(i) = d + (1-d)[\lambda_1 R_s(s(i)) + \lambda_2 R_a(a(i)) + \lambda_3 R_c(i) + (1-\lambda_1-\lambda_2-\lambda_3)R_r(i)] \quad (6)$$

$$R_a(u) = d + (1-d)[\lambda_4 \sum R_p(i) + (1-\lambda_4)\sum R_c(j)] \quad (7)$$

$$R_c(k) = d + (1-d)[\lambda_5 \frac{R_a(a(k))Val(p(k),a(k))}{|comments(a(k))|} + (1-\lambda_5)\sum_{i\in sub(k)} \frac{R_c(i)Val(k,i)}{5|comments(i)|}] \quad (8)$$

Here, the decay factor is d that will not break the order computed by d/m.

Assuming x is an entity at node i, y *is* an entity at node j, and exists a relationship (x, y) from x to y. When i transport reputation data to j, the reputation will be amended as below:

$$R(y) = R(x) - d(1 - \frac{1}{L(i,j)}) \quad (9)$$

Here, we regard all the entities at a node as whole and each outlink can only gain mean reputation compensation that total is d. Therefore, the sum of reputations of all the entities in the system can keep invariable.

The P2PEval algorithm is detailed in Figure 6.

10 Procedure P2PEval (i) , i is node id
20 Begin
30 For each user u and literature x, $R_a(u)$=1 and $R_p(x)$=1
40 calculate initial reputation $R_p(x)$ by formula (6), (7) and (5)
50 count $L(i, j)$ for each peer j who has a link from i
60 while ($\max_{\forall t}\|R(t)-R'(t)\| > \varepsilon$ **)** t is any entity at i
70 send reputation info to j with the probability of $L(i, j)/\sum L(i, x)$, x denotes any peer who has a link from i.
80 receive reputation info from other peers
90 compute local reputation by globe iterative algorithm
100 end while
110 End

Figure 6: P2PEval algorithm

5. SIMULATIONS AND PERFORMANCE ANALYSIS

Simulations abstract literature indexes randomly from SCI and EI database to construct the test base database, which is selected from 1995 to now, mainly from the field of computer science. The first authors of the papers in the base dataset are added into test user set. The dataset contains approximately 33, 500 articles, with 510, 000 citations. There are about 15, 000 authors. Two authors are considered identical if their full names match. A few citations to an article published outside the paper set were removed.

In the same while, the test produces a number of users who are not the authors, and only issue comments but not publish new literatures. The proportion of the users who are not authors to authors is 2. There are some comments randomly issued for each literature, includes direct comments upon the literature and indirect comments that are comments to other comments. The numbers of direct and indirect comments follow the Poisson distribution of $P(1)$. Commentators are chosen randomly from all users. Here, λ_1=0.2, λ_2=0.3, λ_3=0.2, λ_4=0.8, λ_5=0.5. Comment mark level is an integer selected from 0 to 5.

We firstly experiment to check the convergence of globe iterative algorithm. The experimental papers are selected randomly from base dataset. The number of documents in base dataset is called dataset scale.

At first, we specify a series of dataset scales from 400 to 33, 500 and apply the globe algorithm to calculate the reputation. The end condition is ε<0.001. The experiment with each dataset runs for 5 times, counts the entities not satisfied with end condition and records the calculation time. That can be used to evaluate the algorithm complexity. The result is shown in Figure 7 and table 1.

This simulation proves that the globe algorithm can converge to a determinate value within different base datasets in limited iterations, which proves the availability of the algorithm. On the

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other hand, if the data scale increases, the calculation complexity increases dramatically.

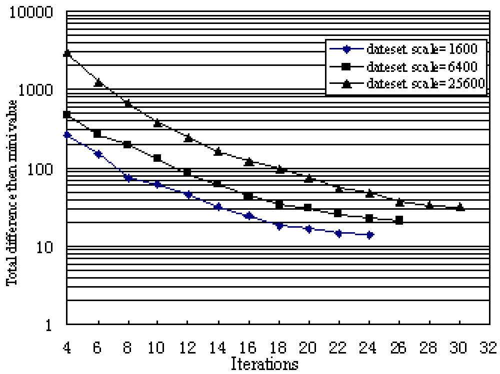

Figure 7: The Availability Of Centralized Algorithm

Dataset scale	Iteration rounds	time cost(s)
400	17.8	3.5
800	20.4	25.1
1600	22.8	64.2
3200	23.2	388
6400	25.6	1903
12800	27.2	7350
25600	28.8	34723

Table 1: Algorithm Complexity Of Iterative Algorithm For Reputation Evaluation

Then the efficiency of the P2P algorithm is assessed. The main index is the difference to the centralized algorithm. Here an index from the literature[17] is applied that denotes the difference of the order of *k* entities which reputations precede others.

$$K(G,D)=\sum\frac{K_{(i,j)}(G,D)}{k(k-1)} \qquad (10)$$

K(*G*,*D*) denotes the difference of two sequences *G* and *D*, *i* and *j* is two entities in G. if i or j doesn't exist in D,

$$K_{(i,j)}(G,D)=\begin{cases}0 \text{ if } i\notin D \text{ or } j\notin D\\ 0 \text{ if the order in } G \text{ is not the same in } D\\ 1 \text{ if the order in } G \text{ is the same in } D\end{cases} \qquad (11)$$

The simulation introduced 2000 peers that stored a few of literatures. The assignment is random and the comments about the literature are stored at the same node. Because the keywords of all the entities are the author, the reputation is also stored at the node. We specify a series of dataset scales from 4000 to 33, 500 and compare the P2PEval to the globe one by *K*(*i*,*j*)(*G*,*D*). *G* is first 300 entities of centralized algorithm.

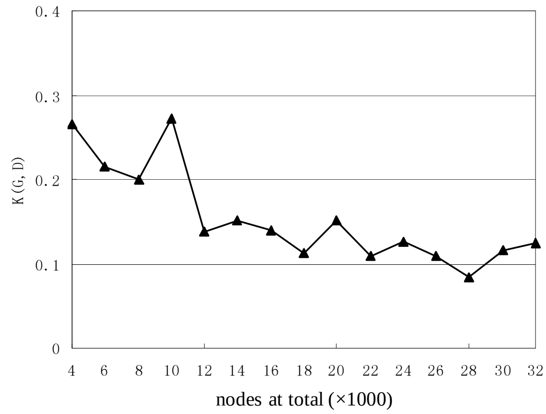

Figure 8: The Availability Of P2peval

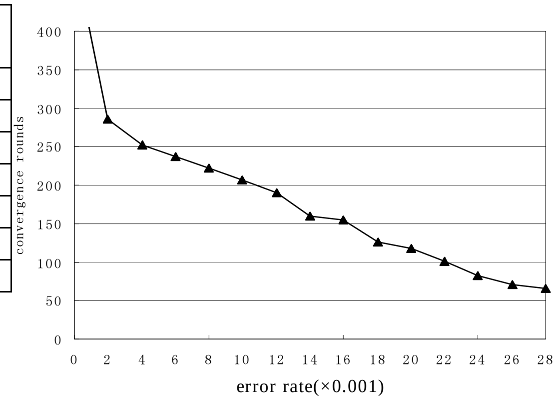

Figure 9: Convergence Times Of P2peval

The simulation shows in Figure 8 that P2PEval can gain acceptable exactness when the literatures increase over 14000. When the literature set is too small, the result is unstable and the error is higher. It is mainly due to the low centrality when a node can only be assigned a few entities. At that condition, the inaccuracy brought by dangle entities effect the computation more remarkably and the exactness of globe computation drops.

We also measure the convergence times at different ε that satisfy $\max_{\forall t}\|R(t)-R'(t)\|>\varepsilon$. The dataset size is 6400. The result is shown in Figure 9. It is obvious that if the convergence condition is relaxed, the communication cost will decrease dramatically. If ε=0.028, the P2P system will converge in 70 rounds.

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6. CONCLUSION

We present a new reputation evaluation mechanism that can be used to evaluate reputation of literatures and researchers. The basic idea is that there are some relationships among literatures, its author, periodicals and readers. The relationship can be regard as recommendation for each other that is in some ways similar to hyperlink in Google. Therefore, we build a similar reputation model here and propose a PageRank-like algorithm. By simulations, we prove that the mechanism is feasible and convergent. We also discuss the strategies to apply the algorithm to gain better performance. A tradeoff scheme is proposed to replace the globe reputation by a local one. The outstanding advantage of local scheme is its simplicity and decentralization. Therefore, it is easy to deploy in huge distributed forum systems.

There are some issues remained unsolved. One is that if the reputation model and the evaluation method can exactly indicate the academic values of literatures or researchers. What is the standard? In despite of impact factor is widely accepted, but whether it is the most scientific one is in doubt. Another problem is how to decide the values of the parameters, such as λ_1~λ_5. Here the values are specified subjectively. Lastly, because the comment is a key factor of reputation model, how to promote users to issue their reviews is the next work in the future.

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