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A rank based multi trust incentive mechanism for resource sharing in network transportation peer systems

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Abstract- Depending upon the level of co-operation among the participant nodes the performance of peer to peer resource sharing networks will change. Today, the cash based systems have become too complex, whereas the credit mechanism which carries lesser-weightage has not provided stronger incentives. In this paper, we propose a novel rank based incentive mechanism for resource sharing in network transportation peer systems. An indirect mapping is provided in this approach between the contribution level and the resultant benefit. The contribution level is represented by a rank, through which the users are prioritized in the system. Depending on the order of rank of the requester and the suppliers the peers' are selected. For example, equal or lower rank peers are allowed to become parent of a peer, as a result flexibility of choosing desired suppliers are offered to high rank peers, whereas the low rank peers have only limited options in selecting their parent hence the quality of streaming will be low. Let us discuss our proposal as a hybrid one between tit-for-tat and eigentrust.

Keywords: BitTorrent, multitrust, Maxflow, PageRank.

1. INTRODUCTION

The future generation networks are heterogeneous in nature with different component networks like wired or wireless, each vary in terms of interference tolerance, transmission speeds, errors and so on. Both Internet surfers and computer networking professionals worldwide got tremendous interest in this Peer to Peer networking. Some Peer to Peer software systems like Kazaa and Napster was ranked among the most popular software applications. Moreover Peer to Peer networking got good feedback and was also promoted by various websites and numerous businesses as "the future of Internet Networking". Though the other technologies have actually existed for more number of years, Peer to Peer technologies have some promising specifications to change the future of networking radically. Especially the resource sharing software of Peer to Peer has also created controversy over legality and "fair use". In general, experts disagree on various details of P2P and precisely how it will evolve in the future.

1.1 Incentive Mechanisms for Peer-to-Peer Systems

The Internet has become very successful as an open platform for all innovations in communication services. It is quick and flexible to use as a set of core communication services like network layer routing and its intelligence is delegate to the user controlled endpoints and can be implemented to all kinds of services in application layer. However, some important protocol software of the Internet lies outside the network because of its openness, the same way as some of the TCP implementations on various operating systems present in Internet attached hosts. Therefore, most of the behavior of the Internet is under the control of the end users. This is same and particularly true with respect to peer-to-peer technologies, but they are limited in their expressive capacity that the Internet provides to the services, still it gives great freedom to interact with each other in other arbitrary ways.

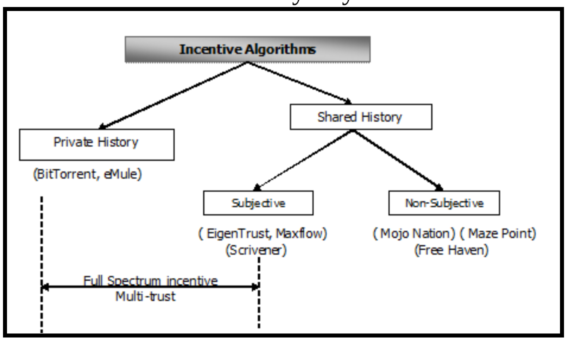

Fig. 1. Categories of Incentive Algorithms

1.2 Incentive Mechanism Design

Mechanism design must deal with all the configuration systems of the agents' utility functions. For tractability, for our convenience let us assume that all the possible utility functions are known, and based on the function it is currently using each agent will be assigned a type. The decision process can be improved by knowing the type of the other agents this in turn provides more possibilities for one to choose a better choice. But revealing their own type will not be beneficial always, it won't have worst effects too. An agent can be in better off if it lies about its type. An incentive mechanism design is considered to be incentive compatible if the agents get incentives to reveal their type. The best strategy for any agents is to reveal their true identity and to follow the protocol in an incentive compatible system.

Designing an incentive compatible peer-to-peer system is challenging and have got various attempts [1], [2], [3]. Among them, the BitTorrent [4] is a popular incentive compatible peer-to-peer based file distribution systems. It uses a “tit for tat” mechanism and the beautiful part of it is, it rewards the peer that contributes its capacity in larger amount by assisting the distribution process. But the disadvantages of these protocols include high cost of reputation management, course granularity in classifying their type of clients. In [5] and [6] an incentive compatible mechanism is proposed for selecting neighbors where the maintenance of reputation is not required. It also follows a “seeing-is-believing” resource sharing mechanism which tends the clients to comply with the protocol and contributes as much as they can and proved as the best strategy.

1.3 Incentives and Resource Sharing

In massively distributed systems, the use of markets to solve resource allocation problem is not a new idea [7], and it is discussed in wider way in the literature. But while comparing it to other algorithm design methodologies it just failed to spawn a large body of computer science research or to active wide spread distribution in end user applications.

Many Internet connected computer systems are experiencing a surplus amount of bandwidth and processing resources as the bandwidth and computing power become cheaper. Finally, a peer to peer system can harness a very large aggregated capacity. But it will incur very large overheads. Therefore in order to overcome this issue market economy [7] has been proposed based on the following recent changes in the Internet landscape.

Flashcrowds: In order to maintain adequate quality of service (QoS) levels, episodes of enormous and increased demand have been shown to require large over provisioning even though there is an increasing amount of idle resources in end-hosts. A compound fact is illustrated in many situations that flashcrowds are indistinguishable from distributed denial of service attacks [8]. Because the server of peer to peer system directly scales client power and similarly peer to peer system also scale well with sudden increase in demand, this allows consistent QoS level to be presented at the application layer.

Computational power: The computing power of the end hosts have increased enough such that it will be able to solve the combinatorial problems endogenous to best response function estimation and to pricing.

The responsibility of procuring one’s own resources is assigned in an optimum way by the market based solutions approach. Therefore the resource allocation problem can be easily managed by them. Each peer will have measure on how good it is for each peer and each peer has to adjust its own action thereby the responsibility of maximizing the utility lies within themselves depending on the actions of the other peers. If the environment has good resources with no scarcity, each peer will be able to access all the resources shared among them such that the quantity and quality and the utility based upon them is maximal. If the situation is worse and resources are scarce, resource allocation can be achieved having competition as a tool.

2. Related Work

The incentives are classified into two categories by Nielson et al. [10]. The first type is genuine incentives which are exemplified by incremental block exchanges as in BitTorrent[11]. This works well for files where there are many concurrent users in a session. From the experience with Maze system it is found that the distribution is a longtailed one, it is also found that for at most one downloader the percentage of downloading will be 80% per day. Thus we can conjecture that this is common for all other file sharing networks. This incentive system is required to record the current behavior of all such longtailed behaviors. Such type of incentive is termed as artificial incentives as it is based on observed history. Basically history is classified into different ways; Feldman et al. [12] classified history in to private history, shared history and subjective shared history. If the peer rewards other peers with which it has got good experience then it is known as private history. If the overall contribution of the peers is considered by sharing the private history it is termed as the shared history. In subjective shared history, a value is assigned by other peer which gives a reputation for a peer. Based on the weight of the reputation that is assigned to peers, new assignment will be done.

Though the systems are already been deployed in successful systems such as BitTorrent [11] and eMule [13] systems based on private history do not scale. Whereas in larger networks, each peer will interact only with a small percentage of peers [14]. Hence a transitive trading technique is proposed by Scrivener [15] to scale this relationship, but finding a valid path is complex, and becomes increasingly difficult when the systems scales up. Another related problem is that the performance of these systems in general will be degraded by these rigorous schemes. Thus many systems are proposed to let the peers to share their experiences in order to rank the other peers [4] [12] [16] [18] [19].

However, the other problem is a collusion which is introduced because of the shared history. The shared history to increase each other’s rankings or points is forged by the colluding peers. This active collusion is present in Maze [21] systems which motivated this work. A sound solution to this problem is to use a subjective shared history as proposed by Maxflow [12] and EigenTrust [20]. Maxflow’s proposals rank the other peers in its own perspective, whereas the all systems and peers are globally ranked in EigenTrust. Maxflow’s subject is ideal but comparatively expensive for real time systems. After experimental verification, even subjective shared history also has its own problem of false positives and false negatives.

3 Eigentrust

The PageRank [2] algorithm which is used by Google and EigenTrust works similar. In EigenTrust, the page link in the page rank algorithm becomes high in traffic flow. It comes under the subjective shared history category and assigns a global EigenRank value to each peer by computing an eigen vector of the trust matrix transit MT.

Mi;j is the rank of j from is perspective. The calculations we have done offline states that the EigenTrust helps in punishing the colluders in Maze, but suffers from both false positives and false negatives.

False negatives: According to the observations we have made the distribution of points across the users are highly skewed. Large number of uploads are provided by super peers to many users which will be downloaded infrequently. Though they have random downloads due their high reputation values their reputation is immediately boosted from a colluder.

False positives: The peers that are present as college networks which are inside the satellite networks are unfairly punished by the EigenTrust. They will just ignore the internal transactions and provides rank similarly to all peers with no variations. Thus, the local distributors will be unfairly punished. These local distributors are those that contribute heavily within the cluster. This result destroys the attempts to leverage network locality for efficient bandwidth utilization, in addition to the above problems. The bandwidth limited wide area links are traversed by the transfers rather than the internal links which has high throughput.

4. Multitrust Incentive Design

By collaborating with more peers which are reputed it is possible to improve a peer's reputation and return the same service that it gets. Thus the Tit-for-Tat [22][23] links incentive mechanisms with reputation. The purely private history like coverage and resolving it requires leveraging the other reputable peer's history is the main problem. But the direction can be pushed to its extreme. However, our multitrust solution at the Eigen Trust mechanism attempts to achieve the balance in between. We will now discuss the core algorithm and its implementation.

4.1 A Mathematical Discussion Of Multitrust Incentive

Let M be a N × N matrix which defines the one step rank among peers, i.e., Mi,j is peer j's rank from i's perspective. Practically, this can be measured as the normalized download volumes that is received by i from j during a period of T. e.g. k has uploaded ten times more than j does to i, then M i,k = 10Mi;j , and ∑j Mi;j = 1. Actually, this is Tit-for-Tat, and the matrix is sparse since it only covers a peer's immediate friends as nonzero entries.

Similarly, the two step rank matrix (one level indirect trust) is expressed as M2. The entry (M2)i;j aggregates other peers one step rank to yield the rank of j from i's perspective. For instance, if Mi;j is 0.5, and Mj,k = 0:1, then (M2)i;,k is added by the value of 0.05, and this is to be performed for all such j. Two effects are produced by this. First, the coverage of the rank matrix gets larger as it becomes exponentially less sparse. Second, the rank starts to mix in more and more peers opinions.

Continuing the above steps we can obtain the n-step rank matrix. The coverage increases continuously and the rank becomes more and more global while moving towards shared history based algorithm. M∞ is the EigenTrust matrix, and the entries in each column are the same and the matrix can be collapsed into the EigenTrust vector: every peer has the same rank on any other peer, and the vector offers a complete coverage.

The above discussion reveals that a full trust spectrum is given by the series of rank with Tit-for-Tat and EigenTrust as two extreme ends. The insight is that, we need to consider – ideally – all these matrices instead of one when deriving incentive metric for service differentiation. The immediate friends form the first tier; friends' friends form the next, and so on. Precisely each matrix represents the trust a peer imposes on others at a different level, and as the levels go deeper, the ranking become more global and less private. We cannot use M and M1 since the coverage is too small and also insufficient. Therefore we have discussed, EigenTrust is vulnerable to a number of issues.

Our multitier incentive scheme essentially imposes service differentiation by looking at which tier j falls into when its downloading request arrives at i. The smaller level it belongs to, the higher priority it is given. Within the same tier, two peers will be ranked according to their values in the matrix of that tier. Obviously, i only need the ith row of the matrix series, and for all practical purposes we only need small number of levels.

4.2 Rank Computation

Based on the score the user's ability to select the peers as the suppliers are determined. For example, if a user with Si as score requests for a particular file, the nodes which have less score or equal to Si will only respond to the request. The peer with higher score than Si will still respond and can be a supplier if it is selected; however they are not bound to do it. The knowledge about the score of one alone will not be sufficient to predict the expected quality received by the user. The score has to be marked into a percentile rank based upon the global distribution of scores. With this a user can determine whether the current score itself is sufficient enough for the user to obtain a streaming service of an acceptance quality level.

In order to compute this percentile rank, we calculate the cumulative distribution function (cdf) of the total scores. If the score is a discrete variable, the probability density function (pdf) is defined as the values where the score has a meaning value. Thus the cdf is defined as:

$$F(S) = \sum_{i=Slow}^{Shigh} f(i) \qquad (1)$$

where f is the pdf of the scores. The cdf provides a relationship between the percentile rank and the score. The percentile is obtained by dividing the cdf with the total number of peers.

5. Conclusion

The robust incentive algorithm for P2P system is a challenging research issue. We believe that the existing solutions such as private history based TitforTat and the EigenTrust algorithm each have their own pitfalls. We propose the multitrust algorithm (i.e multitrust incentive and percentile rank computation) as a hybrid that achieves the best balance.

References

[1] A. Blanc, Y. Liu, A. Vahdat. “Designing Incentives for Peer-to-Peer Routing.” Technical report, available at http://www.cs.ucsd.edu/ vahdat/papers/routing-game-tr.pdf.
[2] Kuhn, Steven, ”Prisoner’s Dilemma”, The Stanford Encyclopedia of Philosophy (Fall 2003 Edition), Edward N. Zalta (ed.), URL = http://plato.stanford.edu/archives/fall2003/entries/prisoner-dilemma/.
[3] I. Stoica, R. Morris, D. Karger, F. Kaashoek, H. Balakrishnan. “Chord: A Scalable Peer-To- Peer Lookup Service for Internet Applications.” Proc. ACM Sigcomm, August 2001.
[4] J.R. Douceur. “The Sybil Attack.” IPTPS 2002.
[5] Z. Abrams, R. McGrew, S. Plotkin. “Keeping Peers Honest in EigenTrust.” P2PEcon 2004.
[6] A. Blanc, Y. Liu, A. Vahdat. “Designing Incentives for Peer-to- Peer Routing.” P2PEcon 2004.
[7] J. Shneidman, C. Ng, D. C. Parkes, A. AuYoung, A. C. Snoeren, A. Vahdat, , and B. Chun. Why markets could (but don’t currently) solve resource allocation problems in systems. In Proceedings of Tenth Workshop on Hot Topics in Operating Systems, Santa Fe, NM, USA, June 2005. USENIX - (TCOS).
[8] W. Conner and K. Nahrstedt. Securing peer-to-peer media streaming systems from selfish And malicious behavior. In MDS ’07: Proceedings of the 4th on Middleware doctoral symposium, pages 1–6, New York, NY, USA, 2007. ACM.
[9] A. Habib and J. Chuang. Incentive Mechanism for Peer-to-Peer Media Streaming. Proc. of International Workshop on Quality of Service (IWQoS) 2004.
[10] S. J. Nielson, S. A. Crosby, and D. S. Wallach, "A Taxonomy of Rational Attacks" In Proc. of IPTPS, Ithaca, NY. February 2005.
[11] B. Cohen, "Incentives Build Robustness in BitTorrent,"In Proc. of P2P-Econ, June 2003.
[12] M. Feldman, K. Lai, I. Stoica, and J. Chuang, "Robust Incentive Techniques for Peer-to- Peer Networks," In Proc. of EC, May 2004.
[13] Y. Kulbak, and D. Bickson, "The eMule Protocol Specification", eMule project, http://sourceforge.net.
[14] R. Dingledine, M. J. Freedman, and D. Molnar. "The free haven project: Distributed anonymous storage service." LNCS 2009, 2001.
[15] A. Nandi, T-W. Ngan, A. Singh, P. Druschel, and D. S. Wallach, "Scrivener: Providing incentive in Cooperative Content Distribution Systems", In Proc. Of Middleware, Grenoble, France. Nov.-Dec. 2005.
[16] B. Wilcox-O'Hearn. "Experiences deploying a large-scale emergent network." In Proc. of IPTPS, Cambridge, MA, 2002.
[17] B. Wu, Brian D. Davison, "Identifying link farm spam pages," In Proc. of WWW, Chiba, Japan, May 2005.
[18] M. Yang, H. Chen, B. Y. Zhao, Y. Dai, and Z. Zhang, "Deployment of a Large-scale Peer-to-Peer Social Network," In Proc. of WORLDS, San Francisco, CA, Dec. 2004.
[19] M. Yang, Z. Zhang, X. Li, Y. Dai, "An Empirical Study of Free-Riding Behavior in the Maze P2P File-Sharing System," In Proc. of IPTPS, Ithaca, NY. February 2005.
[20] S. D. Kamvar, M. T. Schlosser and H. Garcia-Molina, "The EigenTrust Algorithm for reputation Management in P2P Networks" In Proc. of WWW, May 2003
[21] Q. Lian, Z. Zhang, M. Yang, B. Y. Zhao, Y. Dai, and X. Li, "An Empirical Study of Collusion Behavior in the Maze P2P File-Sharing System," Microsoft Research Technical Report, MSR-TR-2006-14, 2006.
[22] R. Axelrod, "The Evolution of Cooperation", New York: Basic Books, 1984.
[23] B. Cohen, "Incentives Build Robustness in BitTorrent," In Proc. of P2P-Econ, June 2003.