Agent-based Modeling for Differentiated Admission in P2P systems Using Evolutionary Game Theory Focused on Ownership Reputation

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Abstract

P2P systems, which are composed of unknown agents, have many problems in data sharing and creating. The main problem is concerned with the absence of the proper incentive mechanism for cooperating and feeding the systems. If the participants of P2P systems are not supported by proper incentives for data sharing and creating, the systems will starve from resources through extinction of sharers and creators[6]. This paper analyzes the Eigenvector-based reputation system with differentiated admission, which can provide proper incentives to contributors through access priority between agents in P2P systems[1]. Based on the results from multi-agent transaction modeling using evolutionary game, we present the potential risk of ownership reputation in differentiated admission system. In our model, reputation condensation, caused from ownership reputation Eigenvalue, can be critical hindrance of vitalizing P2P systems. In conclusion, the importance of balance between incentive provisioning and transaction proliferation for reputation mechanism design is suggested.

1. Introduction

There have been various approaches of computational experiments for modeling users' behavior in P2P systems[4][5], but these former researches have not considered several specific characteristics of P2P systems suitably. In this paper, we supplement these missing factors, which includes recent findings of measurement study about P2P networks like followings[2].

- Users in P2P systems rarely re-download the same object. - In Kazaa network, 94% of the time, a user fetches an object at-most-once.

- Newly popular objects tend to be recently born. – In case of audio objects, 79% were born a month before becoming popular.

We also consider the possibility of ownership falsification when the rewarding mechanism for users, who supply objects to the system, operates. In addition to this, we enable the adaptation of users' behavioral strategies for sharing, creating, and counterfeiting in the simulated model. For modeling adaptation of agents, we used the replicator equation of evolutionary game theory[3], and this can be thought as adaptive strategy decision caused by agent's learning. The relationship between learning and replicator dynamics in P2P systems can be explained by the procedure of searching and imitating activities of individual agents to be successful nodes, and evolutionary approach already has been used for learning theory in other research areas frequently[11]. The heterogeneous propensity in changing one's strategy is also reflected in the model as personal characteristics of users.

For applying above various aspects, we selected differentiated admission mechanism among already introduced systems, which provide the incentives of contribution, because it can induce cooperation with relatively small opposition of the users who reject any payment[7]. In addition to this, reputation management systems based on differentiated admission need not subsidiary training of users for data transferring after adoption. For this reason, it can be more easily adopted without forcible adjustment of users' operating habits. In this paper, the creation of resources can be any kind of exogenous inflow to the P2P system, and we assumed that the agent who introduced an object to the system in the first place has ownership about it. The term, 'agent', will be used for a user (node) in simulated P2P system.

2. Basic Payoff of Agents

Agents' payoff is determined by the summation of cost and benefit elements. In our model, the cost is the function of used bandwidth for transferring objects, and the marginal cost of bandwidth increases as the quantity of used bandwidth raises. The reason of increasing marginal cost of bandwidth is why the employed bandwidth for the P2P system reduces agents' bandwidth availability for other tasks, and the cost of renunciation for other tasks increases because users decide the order of abandonment based on the values of tasks. Accordingly, even if the bandwidth usage is charged by flat pricing, the cost of bandwidth shows increasing return to scale in the view point of opportunity cost. In addition to this, the usage capacity of each agent's bandwidth is limited at the same amount. The agent's benefit comes from downloaded objects, and the benefit per an object is assumed to have different values according to the sequence of requests as follows.

$$Benefit_i = \sum_j f(request\ order(j,i)) \quad (1)$$

i = identity of an agent
j = identity of an downloaded object

In the above formula, f is designed to be a decreasing function to the increasing request order because preferred objects take precedence among searched objects in agents' downloading behavior. In this paper, the request for an object is generated based on the popularity of objects, and the popularity of objects are assumed to follows the Zipf distribution, which is reported as the probability distribution function of requesting frequency for websites and P2P contents[2]. In addition to this, all of the objects in the P2P system are restricted to be fetched at-most-once by one agent, and the order of requesting opportunity of agents is assumed to be randomly distributed.

3. Behavioral Strategy of Agents

All the agents in the system are designed to follow their own behavioral strategies. Each agent's behavioral strategy is designed to maximize temporal payoffs within the given system rules. Basically, all the agents in our model obey the following 5 steps, when one's requesting turn comes round and available bandwidth exists.

① Decide the object, which will be requested on the basis of popularity distribution, except preoccupied objects (In repeated operation, preempt formerly requested objects which is determined as unavailable)

② Calculate additive payoff($\triangle p$) of downloading

ⓐ If $\triangle p$ <0, break

③ Make the list(L) of connected agents who have the requesting object in searched area

ⓑ If L is null, go to ①

④ Confirm the objective agent in L if the constraints for access priority and bandwidth capacity is satisfied

ⓒ If ④ is not fulfilled, go to ①

⑤ Complete requesting opportunity after transferring is activated

The quantity of requesting opportunity for each agent is assumed to be uniformly distributed, and one unit of requesting opportunity of subjective agent is consumed after one iteration of above process. The searched nodes are decided randomly, and 'searched area' means pre-fixed total number of searched agents in the process of making 'L'. One operation of this 5-step procedure finishes by the conditional statement in ⓐ or completion statement in ⑤.

4. Reputation Management by Differentiated Admission

In our model, contributing agents for the P2P system are promoted by differentiated admission based on the reputation Eigenvalue. All the agents have their own rankings, which are calculated by service and usage reputation. Service reputation Eigenvalue of *agent i* is decided by historical uploading quantity and the total downloading quantity of other agents for the objects which are created by *agent i*. Usage reputation Eigenvalue of *agent i* is determined by the quantity of downloads of *agent i*. In this paper, we fixed Eigenvalue for one uploading event as 1, and for one downloading event as -0.5. In a fully decentralized system, the reputation Eigenvalue cannot reflect whole data transferring events, but we assumed that whole object transfer is recorded and posted to all nodes. This assumption is surely too strong in the view point of deploying a real decentralized system. However, if the sufficient transaction amount is guaranteed in comparing to system size, the results of our model will not show significant difference from practical decentralized systems which have proper referring mechanisms for reputation score. In our model, fixed 500 identities are simulated during 2 years. Therefore, the problems come from the lack of information befall with relatively small probability. Unless enough information can be provided, the fitness of each strategy will be differentiated from our simulation results, and the policy for strange nodes will take more important roles than in our model. In that case, information asymmetry between nodes and uncertainty of information will become essential problems which should be concerned.

After applying the Eigenvector-based reputation system, all the agents own their individual reputation Eigenvalues through historical transacting events. We assumed that all the participated agents are designed to have obligations of complying with the request of other agents, having higher reputation values, in the limit of bandwidth capacity. If all the users in P2P systems want to report their benefits from downloaded objects truthfully, the contribution of each user will be measured more properly by gathering each one's personal benefit report, but it is hard to implement the mechanism which can check authenticity of users' report. On this reason, we calculate reputation values just based on occurred events.

5. Evolutionary Agents' Strategy Change

Our simulation considered the adaptation of each agent's strategy about advertising amount and also choosing one's species which determine the behavior of creating or counterfeiting. First, for implementing adaptation we split whole population in 4 species on the basis of creating and counterfeiting strategy as ‘Creators’, ‘Fair sharers’, ‘Passive hackers’, and ‘Active hackers’ like following table 1.

Table 1. Four species of agents in the modeled system

	Creators	Fair sharers	Passive hackers	Active hackers
Creating	O	X	X	X
Ownership counterfeiting	X	X	O	O
Strategic gathering	X	X	X	O
Sharing	O	O	O	O

‘Creators’ introduce new objects to the system with pre-fixed creating cost in every regular time interval (In this paper they introduce new objects every 5 days, and the popularity ranking of a newly born object is decided randomly in the range of 30% of total objects). ‘Fair sharers’ neither create nor counterfeit objects. ‘Passive hackers’ counterfeit ownership information of downloaded objects with pre-fixed hacking cost, and ‘Active hackers’ add strategic gathering action to Passive hackers’ falsification. Strategic gathering means that the action of downloading objects which have no benefit to the downloading agent, for the purpose of increasing reputation value when the idle bandwidth is generated. In the model, when the bandwidth has not been used at the end of the day, one unit of bandwidth is considered as idle. We also implemented the adaptation process for deciding the strategy for advertising object quantity. Every agent, irrespective of included species, changes the amount of advertising objects depending on the payoffs of the previous period. The strategy set related to advertisement is classified as the following three : increasing one unit, decreasing one unit and holding present quantity.

For implementing above adaptation of agents’ strategy, we use the replicator dynamics, which is the popular methodology in evolutionary game theory[3][10]. Following equation is the general matrix form of replicator equation.

$$\vartriangle x_i = x_i((Ax)_i - x^T Ax) \qquad (2)$$

x_i is the proportion of agents who have the characteristic i, and A is the matrix which contains the information about the payoffs of the groups with each characteristic. By replicator dynamics, the number of agents, who change their species and advertising amounts, is adjusted based on the payoffs which are accumulated during former time interval (In our simulation, this time interval is fixed as 5days).

In the model, we considered the random perturbation in agents’ strategy choices and heterogeneous propensity about strategy change as well. When evolution of agents’ behavioral strategy proceeds, 5 percentages of agents choose their strategy about creating, counterfeiting and advertising randomly. Adding to this, the specific agent who adjusts strategy is chosen based on the personal likelihood about change during replacement process. This likelihood of strategy adjustment reflects heterogeneous sensitivity of each agent about relative payoff amount.

6. Creating Cost vs. Hacking Cost

In our simulation, we assumed equal size of objects, and uniform distribution for the number of initially stored objects. Reputation Eigenvalue of each agent and population of each species in the initial state are also assumed to be homogeneous. Following matrix represent specific values of benefit from an object download depending on the request order, and marginal cost of bandwidth usage according to the decrement of available bandwidth. Hence, the numbers in the cost and benefit matrix is used in calculating additive payoffs.

Benefit from an object = [2.0, 1.5, 1.0, 0.5]
Cost of bandwidth = [-0.4, -0.6, -1.0, -1.6]

Upper limit of bandwidth usage per day is limited to four objects transferring, and initial total number of agents and objects are 500 and 1500.

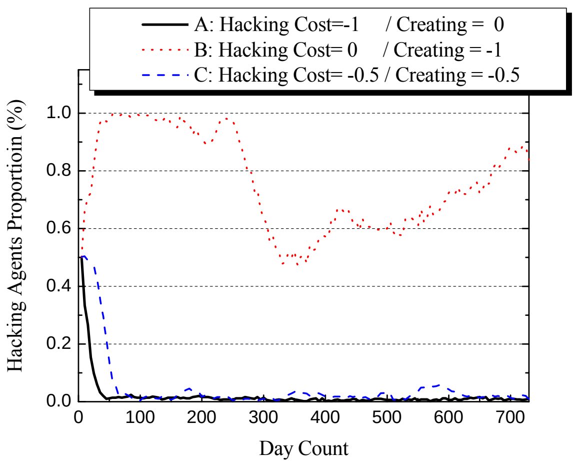

Figure 1. Transition of hacking species proportion with different creating and hacking cost

Figure 1 shows that the population of hacking species can be reduced by increment of hacking cost. This means that proper cost burden can proliferate the fair users of P2P systems. Total object quantity of A, B and C cases in Figure 1 is 44935, 1900 and 6956 at the end of simulation period(2 years). This result, connected with the quantity of creation, represents that lower creating cost can promote the creating strategy. At the end of the simulating period, ‘Creators’ dominate other species in B case, and ‘Fair sharers’ dominate in C case.

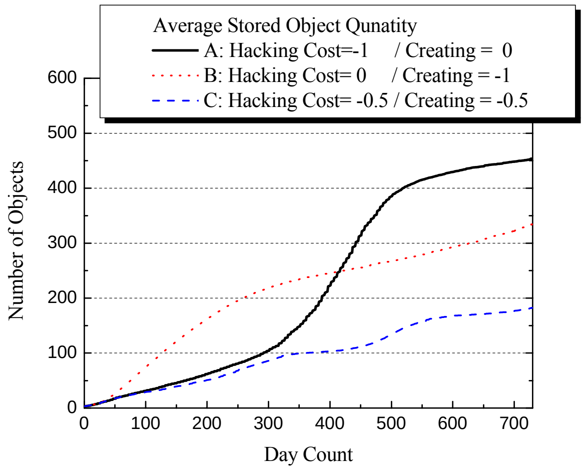

Figure 2. Transition of average possessed object quantity in A, B and C cases

In contrast to drastic change of total amount of objects in A, B and C cases, average stored object quantity shows relatively small difference in each case as shown in Figure 2. This is caused from the difference in transaction amount of each case. Total accumulated transaction amount in A and B cases are 91426 and 155190, which shows the opposite trend to the amount of total object numbers. Because of extinction of newly introduced objects, accumulated payoff of total population is still larger in Case A. However, the smaller total transaction amount in Case B notices that the factors, which cause hindrance in transaction, can be generated by applying ownership Eigenvalue for a reputation management system.

6. Effects of Ownership Reputation Eigenvalue

In Figure 3, curved arrows represent objects transferring, and a dotted arrow shows the addition of reputation Eigenvalue from k times transaction of other agents for the object created by *agent j*. If we assume that sequentially alternating requests from one agent to the opposite with the same initial reputation Eigenvalues, all the sequential requests will be fulfilled in case (a). However, in case (b) the requests of *agent i* will not be satisfied until the reputation difference from ownership($k \times c$) is diminished by asymmetric transfer (*agent i*’s uploads and *agent j*’s downloads). This is the main reason why transaction amount decreases in case A of former section.

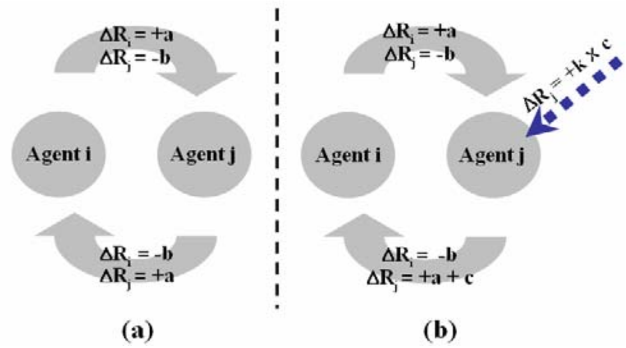

Figure 3. Reputation Eigenvalue adjustment from objects transferring (a) Without ownership (b) With ownership of *agent j* (ΔR = reputation Eigenvalue change, a = uploading Eigenvalue, -b = downloading Eigenvalue, c = Ownership Eigenvalue)

Based on this analysis, we tested following two possible solutions, which can decrease the negative effects of ownership reputation Eigenvalue.

- Reduction of proportion for ownership in total reputation Eigenvalue
- Restriction on accumulating period for reputation Eigenvalue

6.1 Effects of Ownership Eigenvalue Magnitude

Ownership reputation cannot provide proper incentive to ‘Creators’ when the falsification of property information can be easily accomplished. In that case, ‘Hackers’ can steal reputation of ‘Creators’ by counterfeiting the ownership information of objects. By the reason of this, ownership reputation can be harmful to fair users without blocking falsification. Accordingly, the ownership reputation should be applied when enough hacking cost is guaranteed through subsidiary mechanisms like monitoring & imposing penalty or technological protection like DRM(Digital Right Management). For measuring the effect of relative magnitude of ownership Eigenvalue in ideal situation, we fixed hacking cost and creating cost to –1 and 0, respectively. Because of low cost for creating, dominant species in the modeled system are ‘Creators’ in the equilibrium. Owing to the duration of maintaining equilibrium is much longer than the elapsing time for convergence, the created amount of objects doesn’t show significant difference by the change of ownership Eigenvalue. However, the accumulated payoff and object quantity per an agent decreases definitely as ownership Eigenvalue increases as shown in Figure 4. This result is caused by the transaction hindrance effect from ownership reputation Eigenvalue, as illustrated in Figure 3.

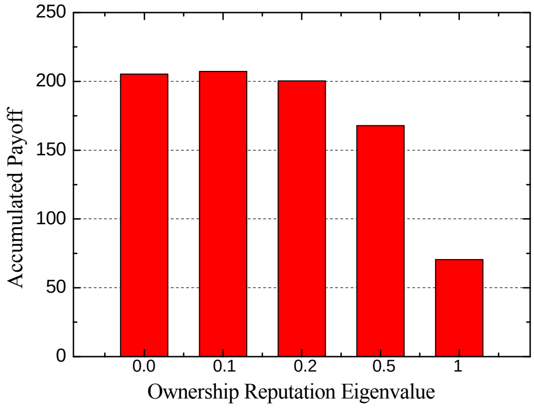

Figure 4. Total accumulated payoffs of whole population in 2 years with different Ownership reputation Eigenvalues

This hindrance effect can be removed by choosing relatively small Ownership Eigenvalue in ideal situation as shown in Figure 4. However, if the reputation mechanism designer wants to provide incentives to 'Creators' through ownership reputation in the situation when some creating cost exists, the trade-off in selecting ownership Eigenvalue should be considered carefully. Ownership reputation supplies the indirect incentives to 'Creators' through access priorities, but it reduces the possibility of accomplishment for requests as well by widening the gap of the reputation wealth.

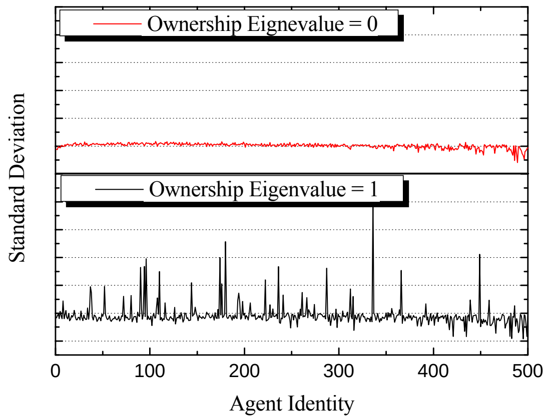

Figure 5. Standard deviations of time series about each agent's additive reputation value per a day during 2 years with different ownership Eigenvalues.

The transaction hindrance effect of ownership reputation originates from the abrupt transition of individual reputation values as time goes. This individual abrupt change in reputation of larger ownership value is shown in Figure 5. The changes of additive reputation values with heterogeneous speeds and directions generate condensation of reputation. When accumulated reputation values show relatively large differences among agents because of this condensation, the access approval frequency decreases if requesting opportunity and bandwidth capacity are uniformly distributed like in the simulated system. The standard deviation values about whole agents' individual standard deviations of reputation time series are 0.0890, 0.1408, 0.1914, 0.2550 and 0.4125 when ownership values are 0, 0.1, 0.2, 0.5 and 1 respectively. These values support the analysis about reputation condensation, and they also show strong consistency with the results in Figure 4. In conclusion, reputation condensation gives hard access to the agents who have rich reputation when relatively poor majority wants to access, and planless implementation of ownership reputation has the risk of inducing reputation condensation in P2P systems.

6.2 Effects of Period Length Limitation for Reputation Accumulation

In all the former simulation results, the accumulating period for reputation was fixed to 10 days. This means that accumulation of reputation value, which is generated from 10 days ago to the present day, decides the access priority. For the experiment measuring the effect of reputation memory window(time interval for accumulating reputation), the size of memory window is adjusted to 5 days with holding all other conditions. As the result, total accumulated payoff of whole population increases more than twice, and the amplitude of additive reputation transition is more stable in smaller size of memory window as shown in Figure 6.

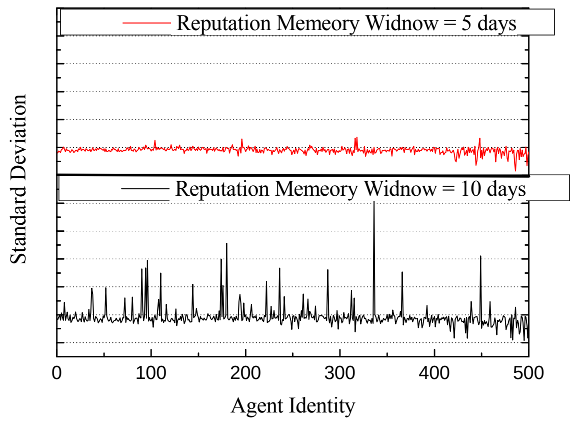

Figure 6. Standard deviations of time series about each agent's additive reputation value per a day during 2 years with different reputation accumulating periods.

Because the additive reputation time series show similar characteristics between Figure 5 and Figure 6, the reduction of memory window can infer the diminution of reputation gap among agents. In other words, the reduction of memory window causes increment of total accumulated payoff because of the decrement of failures in agents' requirements by easing transaction. The reason for diminution of reputation condensation with the decrement of window size is related with the duration of the effect from condensation event. If we reduce the memory window size, the period, during which the temporal condensation events influence access priority, will also decrease. By this reason, the reduction of memory window size discounts the time share that condensation matters worse.

7. Summary and Concluding Remarks

If creating cost increases and hacking cost deceases, the results related with payoff and transaction amount in former section will be changed because of extinction of newly born objects. However, the importance of special consideration on specific magnitude of reputation Eigenvalue and size of memory window is consistently testified. A reputation management system, which utilizes reputation Eigenvalue as an indispensable factor for object transaction, is expected to have similar reputation condensation problem such as in the modeled system in this paper. Accordingly, the realization of reputation management systems with perfect information about ownership may not guarantee the improvement of social welfare even if the productivity about created object quantity expands. The main difference between wealth condensation and reputation condensation is the availability of investment for earned property. Without the function of investment and saving, the condensed property can contribute to neither economic growth nor social welfare. In this point view, condensed reputation is similar to the money which is kept in one's basement. If all the condensed property is managed like that way in real economy, the huge business contraction will occur, and the social welfare will get worse steeply like the case of reputation condensation. To make matters worse in reputation case, the consumption of reputation is constrained to the capacity of bandwidth. Because of this, much time should elapse before resolving the reputation condensation.

The methods suggested in this paper can promote the transaction by smoothing each user's reputation value, but these adjustments will decrease the incentives for gaining reputation, and weaken the penalty for free riding. Accordingly, the careful consideration about this trade-off should be conducted before implementing reputation management systems. This implication also emphasizes the importance of relative magnitudes between different kinds of rewards, which should be implemented in practical systems. If the transaction of reputation score is allowed among agents, the solution for condensation problem will vary greatly from method of this paper. In addition to this, if the P2P systems cannot guarantee enough cost for counterfeiting intellectual properties, the incentives for creation would rather nourish hackers than promote creators.

In our study, we improved existing agent-based modeling through the consideration about users' realistic behaviors, and simulated agents have more freedom in choosing their behavioral strategies, which is the way of utilizing P2P systems. However, there still exists insufficiency caused from the complexity of human behaviors and environments. For overcoming this vulnerability of simulation, we need more sophisticated supplements, which can describe human behaviors more realistic. Therefore, the methodology, which can reflect the human ability for adaptation and expectation, needs to be developed consistently on the foundation of existing researches. In addition to this effort for representing human complexity, we plan to advance our model by applying real network topology and practical decentralized mechanism in ongoing study.

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