Yan Chen and K.J. Ray Liu

Understanding Microeconomic Behaviors in Social Networking

An engineering view

Content sharing and distribution over social networks is more popular now than ever before—we download music from Napster [1], share our images on Flickr [2], view user-created video on YouTube [3], and watch peer-to-peer (P2P) television using Coolstreaming [4], PPLive [5] and PPStream [6]. Within these social networks, users share, exchange, and compete for scarce resources, and thus influence each other's decision and performance. Therefore, to provide fundamental guidelines for better system design, it is important to analyze the users' behaviors and interactions in a social network, i.e., how users interact with and respond to each other.

In a social network, users are intelligent and have the ability to observe, learn, and make intelligent decisions. Since users usually belong to different authorities and pursue different goals, they will choose the strategies that can maximize their own payoffs. In such a case, traditional centralized optimization-based approaches are no longer suited since they only consider the efficiency of the whole system while they totally ignore the notion of fairness among users, which is an even more important issue in a social network. To better design the system, not only the efficiency issue from the perspective of a system designer but also the fairness issue from the perspective of a user should be taken into account. Moreover, since users in a social network are rational and thus naturally selfish [7], they tend to overclaim what they may need and will not truly report their private information if cheating can improve their payoffs. Therefore, enforcing truth-telling is crucial in a social network.

From the above discussions, we can see that the behavior dynamics among users in a social network are very complex. To understand the users' complex behavior dynamics and thus lead to a better system design, game theory is a powerful mathematical tool that analyzes the strategic interactions among multiple decision makers [8]–[12]. It has been developed for understanding cooperation and conflict between individuals in many fields such as economics, politics, business, social sciences, and

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biology. Thus, game theory is ideal and essential for studying, analyzing, and modeling the users' behaviors and interactions in social networking. Recently, it has drawn great attention in cognitive networking [13]–[16] and multimedia signal processing [17]. In this article, we will illustrate how game theory can be used to model users' behaviors in various social networks and analyze the corresponding equilibria.

RELATED WORKS ON SOCIAL NETWORKS

A social network is a social structure made of individuals and/or organizations called "nodes," which are connected with each other by certain types of interdependency, such as friendship, kinship, financial exchange, conflict, and trade. Many methodologies have been studied to formulate the relationships among members at all scales, from interpersonal to international, and social network analysis becomes a popular topic in sociology, economics, information science, and many other disciplines.

Most of the existing works on social networks fall into the following three categories [18]: 1) social network properties, 2) social network models, and 3) social network dynamics and evolution. In [19] and [20], the authors showed that the vertex connectivities in many large networks follow a scale-free power-law distribution. Such a property is found to be a consequence of two generic mechanisms: 1) networks expand continuously by the addition of new vertices and 2) new vertices attach preferentially to sites that are already well connected. Another important property of social networks is the "small-world" phenomenon. As pointed out in [21] and [22], most real-world networks exhibit relatively small diameter, i.e., the networks are highly clustered.

Besides the study of the social network properties, there are quite a lot of work on building models for social networks. The simplest model is the random graph model introduced in [23], where given a number of nodes, each pair of nodes has an identical and independent probability of being joined by an edge. However, since it fails to match the real-world social network properties, e.g., it does not produce power law degree distributions for the vertex connectivities, this model is not realistic. A better model that can produce power law degree distributions is the preferential attachment [24]–[26], where when a new node u arrives to the network, the probability of connecting to a node v is proportional to the degree of v. Another model that can also produce power law degree distributions is the copying model [27], where a new node joins the networks by uniformly creating random edges or first random choosing a node u and then linking to u's neighbors.

Another important research topic in the field of social network is the study of social network dynamics and evolution, where the researchers study how the social network evolve and how information spread over the networks. Many studies have investigated the dynamics and evolution of different networks, e.g., trendsetters selecting in viral marketing [28], inoculation targets identification in epidemiology [29], and studying trends in blogosphere [30].

All aforementioned works study and analyze the social networks at the macroeconomic level, i.e., from a system designer's perspective. However, since users may only care about their own objectives and their decisions greatly affect the evolution and performance of the social networks, social network analysis at the microeconomic level, i.e., from the users' perspective, is also very important and has drawn great attention recently. In [31], Braun and Gautschi proposed to use the generalized Nash bargaining solution (NBS) to analyze how users in the exchange networks split some fixed amount of money, and their resulting predictions for profit splits match closely with the experimental results obtained by Cook and Yamagishi [32]. Later in [33], Kleinberg and Tardos extended the NBS to the general graph and proposed an efficient way to find the equilibrium. To verify these theoretical predictions, a large-scale behavioral experiment is conducted by Chakraborty et al. in [34]. To discover the most influential nodes in a social network, Narayanam and Narahari proposed to use the Shapley value of the underlying cooperative game [35].

In this article, we will study and analyze the social networks from the users' perspective by modeling users' behaviors and interactions using game theory. Since users in different social networks may have different types of interdependency, to effectively model the users' behaviors and interactions, different game models for different social networks should be employed. The two most common types of users' interdependency in social networks are competition and cooperation, which leads to noncooperative social networks and cooperative social networks, respectively. In cooperative social networks, since users are rational thus naturally selfish, they will not cooperate with others unless cooperation can improve their own performance. Therefore, one important issue in cooperative social networks is cooperation stimulation. Without loss of generality, in this article, we will illustrate how to use game theory to analyze and model users' behaviors in social networks by discussing the following three general scenarios:

- In the first scenario, we consider a noncooperative social network where users in the social network compete for the same resource. We use multiuser rate allocation game [36] as an example for this scenario; details will be described in the section "A Noncooperative Social Network: Multiuser Rate Allocation."
- In the second scenario, we consider a cooperative social network where users in the social network cooperate with each other to achieve better performance. As discussed in the section "A Cooperative Social Network: Peer-To-Peer Streaming," we will use cooperative P2P streaming game [37] as an example.
- In the third scenario, we consider how to use the indirect reciprocity game to stimulate cooperation among users. In the section "Cooperation Stimulation: Indirect Reciprocity Games," we will use the packet forwarding game [38] to illustrate this scenario.

A NONCOOPERATIVE SOCIAL NETWORK: MULTIUSER RATE ALLOCATION

In a noncooperative social network, users compete with each other for the same resource. Due to selfish nature, users tend to claim as much resource as possible to maximize their own objective. Therefore, one important issue in a noncooperative social network is how to allocate the resource among different users. In this section, we use the multiuser rate allocation game as an example and discuss how to use game theory to model a noncooperative social network. As shown in Figure 1, in the multiuser rate allocation problem, there is a controller, N transmitters, u_1, $u_2, \ldots, u_N$, and N receivers, $r_1, r_2, \ldots, r_N$. Transmitter u_i transmits the video sequence v_i to the corresponding receiver r_i through a channel/link that is shared by other transmitters $u_1, \ldots, u_{i-1}, u_{i+1}, \ldots, u_N$. Since the channel has a limited bandwidth, it may not be able to satisfy the bandwidth requirements for all transmitters. The role of the controller is to allocate the channel bandwidth to $u_1, u_2, \ldots, u_N$. So, the question of how the controller allocates the bandwidth to the transmitters in an efficient and fair way is asked. In essence, the transmitters form a noncooperative social network since they compete intelligently for the same channel bandwidth.

The simplest multiuser rate allocation is the constant bit-rate allocation (CBR), where the available network bandwidth is equally assigned to each user. A major problem of CBR is that it does not consider the variable bit-rate characteristics of the video sequences. One way to overcome this disadvantage is to optimize a global objective function that involves the characteristics of all the video sequences using conventional optimization methods [39], e.g., to maximize the weighted sum of the peak signal-to-noise ratios (PSNRs) of the transmitters. However, the solution to the optimization-based methods is highly related to the selection of the weights. In the literature, the weights are usually heuristically determined, e.g., the weights are set to be uniform [40]. Moreover, such a formulation can only address the efficiency issue, e.g., how to maximize the weighted sum of the PSNRs. As such, the fairness issue, which is an important problem for multiuser rate allocation, has been generally ignored.

To efficiently and fairly allocate the bandwidth, we can resort to game theory to analyze this multiuser rate allocation social network. In this game, players/users are the transmitters who compete with each other for the available network bandwidth. By successfully transmitting the video sequences, users can receive a certain gain that is determined by the quality of the transmitted video. According to the human visual system (HVS) model, the quality difference in the low PSNR region is easier to be distinguished than that in the high PSNR region. With such an intuition, the gain function can be defined as the logarithm function of PSNR. Note that the reason of using ln(.) function is that ln(.) is a monotonically increasing function in its argument and its second order derivative is negative, due to which a certain increase in the low PSNR region will lead to a more significant gain than that in the high PSNR region. Other functions that have similar properties can also be used. While receiving a gain for transmitting video sequence, users, on the other hand, need to pay a certain cost for using the bandwidth for transmission. In the literature, due to the simplicity and efficiency, linear pricing is widely used [41]–[43]. Moreover, since the transmitter does not differentiate among all the bandwidth, it is reasonable to assume that the price of the bandwidth is constant, i.e., the cost function is linear. In such a case, the utility function of user u_i can be written as

$$U_i(R_i) = \ln(\mathrm{PSNR}_i) - aR_i = \ln(\gamma_i + \beta_i R_i) - aR_i, \qquad (1)$$

where R_i is the bit rate of the video sequence transmitted by user u_i, a is a parameter controlling the balance between the gain and cost, which can be treated as the unit price of the bandwidth, and γ_i and β_i are two parameters of the distortion-rate model $\mathrm{PSNR}_i = \gamma_i + \beta_i R_i$.

Since users are rational thus naturally selfish [7], they try to maximize their utilities subject to the individual constraint that the rate should be bounded and the global constraint that the sum of the users' bit rate does not exceed the available bandwidth. Therefore, the game can be formulated as

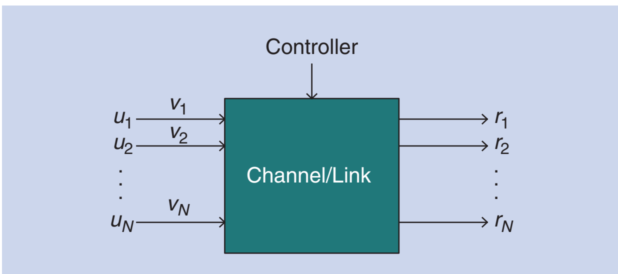
$$\begin{aligned} &\max_{R_i} \; U_i(R_i) = \ln(\gamma_i + \beta_i R_i) - aR_i, \\ &s.t. \quad R_i^{\min} \le R_i \le R_i^{\max}, \;\; \forall i = 1, 2, \ldots, N, \; \sum_{i=1}^{N} R_i \le R, \end{aligned} \qquad (2)$$

where $R_i^{\min}$ and $R_i^{\max}$ are the minimal and maximal rate constraints respectively, and R is the total available network bandwidth.

Through some analysis [36], one can find that the rate allocation game in (2) has a unique efficient Nash equilibrium (NE) when the unit price a is carefully chosen such that the total optimal rate from all users meets the available bandwidth constraint. Moreover, such an efficient NE is proved to be proportionally fair in terms of both utility and PSNR [36].

RELATION TO THE TRADITIONAL INFORMATION-THEORY-BASED APPROACH

While the task of rate allocation for a single user is to find the best tradeoff point on the rate-distortion curve, the traditional information-theory (IT)-based multiuser rate allocation approach can be seen as first constructing an overall rate-distortion curve by combining rate-distortion curves of all users, and then finding the best tradeoff point on the joint rate-distortion curve. However, it is difficult to construct the overall rate-distortion curve from all users' rate-distortion curve. The approach to maximize the weighted sum of PSNRs is one possible way, but there is no notion of fairness. Furthermore, the weights are hard to determine and are usually defined heuristically.



[FIG1] System model for multiuser rate allocation.

Instead of focusing on finding a good way of constructing the overall rate-distortion curve, the discussed game-theoretic framework considers each user's rate-distortion tradeoff in the utility function. Then, the notion of proportional fairness is introduced to balance the rate allocation among different users and to make sure that the total rate constraint is satisfied. Moreover, it can be theoretically proved that the traditional approach that maximizes the weighted sum of PSNRs is actually a special case of the game-theoretic framework by choosing the utility function as an exponential function of PSNR [36]

$$U_i(R_i) = e^{w_i \, \mathrm{PSNR}_i}. \tag{3}$$

Note that there are mainly three drawbacks of this kind of utility function. First, the parameters w_i are usually heuristically determined, i.e., the IT-based approach is inherently heuristic from the beginning of the problem formulation. Second, since no cost in video transmission is considered, selfish users may become too greedy and want to claim as much bit rate as possible, which is not good to the system [44]. Third, since the gain is defined as an exponential function of the PSNR, a certain increase of the bit rate in the low PSNR region will lead to a less significant gain than that in the high PSNR region. This contradicts with the HVS model since the quality difference in the low PSNR region is easier to be distinguished than that in the high PSNR region. All these drawbacks are not obvious from the information theory point of view, if not considered from a social networking perspective.

DISTRIBUTED CHEAT-PROOF OPTIMAL RATE ALLOCATION USING CLOCK AUCTION

To obtain the NE of the game in (2), there are two possible approaches: the centralized approach and the distributed approach. For the centralized approach, the controller knows exactly all of the private information of each user, i.e., γ_i, β_i, $R_i^{\min}$, and $R_i^{\max}$. Then, the controller can find the NE in a collective way. However, in general, the users can be geographically distributed in many places, it is therefore not feasible for the controller to collect all of the private information of each user. Moreover, since the users are selfish, they tend to overclaim what they may need, which means that they will not truly report their private information if cheating can improve their utilities [45]. To overcome this problem, we can develop a distributed cheat-proof rate allocation scheme using alternative ascending clock auction [46]. In the following, we briefly describe the scheme, while interested readers can find the detailed proof of the cheat-proof property shown in [36].

The rate allocation scheme is described as follows. Before the auction, the controller sets up a step size $\delta > 0$, clock index $t = 0$, and initializes a with a small value a^0. At the beginning of clock t, the controller first announces a^t to all the users. Then, each user submits his/her optimal demand to the controller. After collecting all the demands, the controller compares the total demand R_{total} with the available bandwidth R. If $R_{\text{total}} > R$, i.e., the total demand exceeds the supply, the auction is not concluded. The controller continues the auction and goes to next clock $t+1$ with an increased a computed by $a^{t+1} = a^t + \delta$. Moreover, the controller computes the cumulative clinch, which is the amount of bit rate that a user is guaranteed to win at current clock given by $C_i^t = \max(0, R - \sum_{j \neq i} R_j^t)$.

On the other hand, if $R_{\text{total}} \le R$, then the supply can meet all users' demands and the auction is concluded. Let the final clock index be L. As a increases discretely, we may have $R_{\text{total}} < R$ and do not fully utilize the bandwidth. To make sure that $R_{\text{total}} = R$, we introduce the proportional rationing [46], and the final cumulative clinch of u_i is given by $C_i^L = R_i^L + (R_i^{L-1} - R_i^L)/(\sum_i R_i^{L-1} - \sum_i R_i^L)[R - \sum_i R_i^L]$.

Finally, the rate allocated to u_i is $R_i^\star = C_i^L$. The utility of u_i is obtained as

$$U_i^\star = \ln(\gamma_{\mathrm{i}} + \beta_i R_i^\star) - P_i^\star, \tag{4}$$

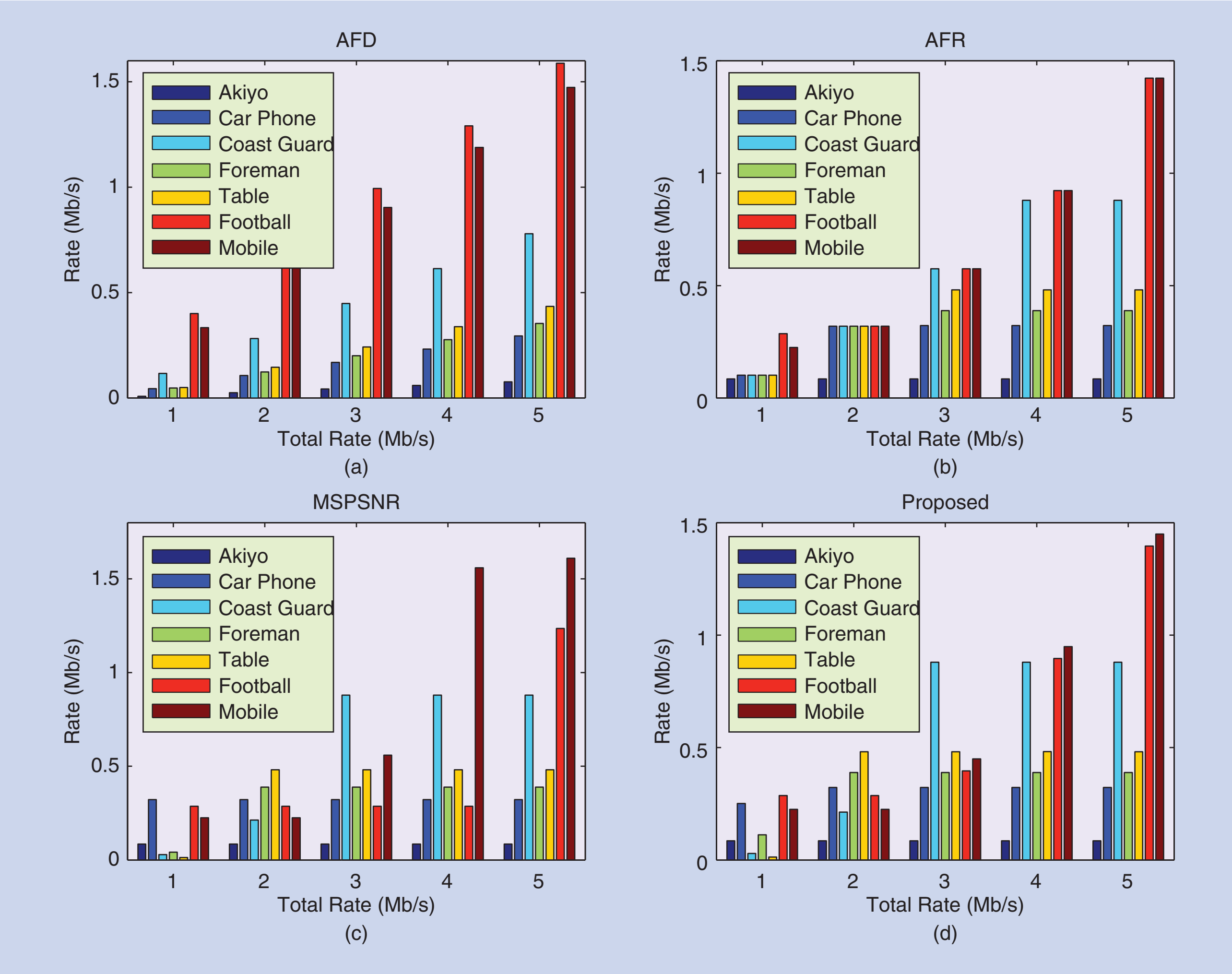
where $P_i^\star = C_i^0 a^0 + \sum_{t=1}^{L} a^t (C_i^t - C_i^{t-1})$ is the payment from user u_i.

From the above discussion, we can see that the amount of bit rate allocated to a user is determined by what other users report rather than what the user reports. Therefore, users has no incentive to cheat, i.e., the rate allocation scheme discussed above is cheat proof.

EXPERIMENTAL RESULTS

To evaluate the proposed multiuser rate allocation game, we conduct experiments on real video data. We compare the proposed method with three approaches: the absolute fairness in rate (AFR), which equally divides the available bandwidth to all the users, the absolute fairness in distortion (AFD), which minimizes the maximal distortion of all the users, and the approach maximizing the sum of the PSNRs (MSPSNR), i.e., the traditional optimization-based approach with uniform weights. Notice that for AFR, AFD, and MSPSNR, the allocated rate should be within $[R_i^{\min}, R_i^{\max}]$. Otherwise, we set it to be $R_i^{\min}$ or $R_i^{\max}$ and reallocate the rest of the rate for other users.

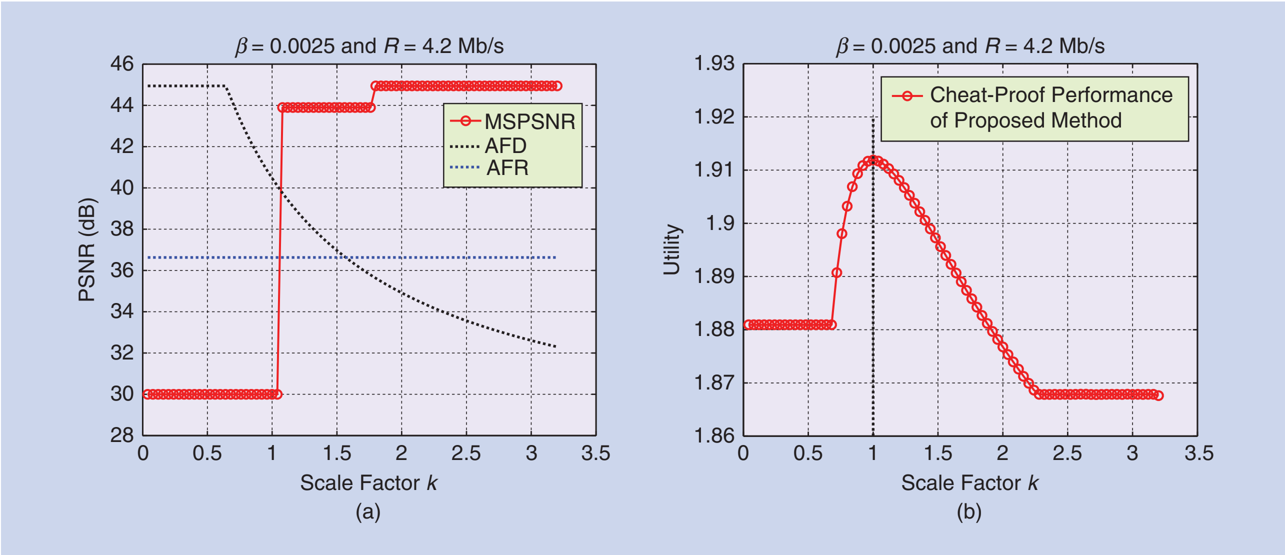
The allocated bit rate for each video sequence using different methods are shown in Figure 2. From this figure, we can see that AFR equally allocates the bandwidth to each users if the allocated bit rate is within $[R_i^{\min}, \mathrm{R}_i^{\max}]$. AFD tries to allocate more bit rate to the video sequence that has more complex motion and/or scene (a smaller $\beta^\star$) to preserve constant quality among different users. On the contrary, MSPSNR favors the video sequence that has a larger $\beta^\star$ since allocating more bit rate to the sequence with a larger $\beta^\star$ leads to a greater increase in the sum of the PSNRs. However, with MSPSNR, the sequence with $\beta_i^\star$ will not be allocated more bit rate than $R_i^{\min}$ if there is a sequence with $\beta_j^\star > \beta_i^\star$ who has not been allocated its maximal rate requirement $R_j^{\max}$ yet. Specifically, the rate controller will first allocate each user with $R_i^{\min}$. Then, the remaining rates will be first allocated to Akiyo until the bit rate of Akiyo achieves its maximal requirement. If there are still some unused rates, then car phone will be satisfied first. The bit rate of football with the smallest $\beta^\star$ stays at its minimal requirement until all other sequences with higher $\beta^\star$ have achieved their maximal rate requirements.



[FIG2] Allocated rates for Akiyo, car phone, Coast Guard, foreman, table, football, and mobile using different methods.

Obviously, this is not fair to the users who transmit the sequences with smaller $\beta^\star$. By taking the proportional fairness into account, the proposed method can avoid this disadvantage and balance the rate allocation between the sequences with a larger $\beta^\star$ and a smaller $\beta^\star$. For example, as shown in Figure 2, when the total available network bandwidth R increases from 3,000 kb/s to 4,000 kb/s, both the bit rate of mobile and football increase. This is because the proposed method with the proportional fairness criterion aims at maximizing the product of the utility function U_i, and keeping a certain balance between the sequences with a larger $\beta^\star$ and a smaller $\beta^\star$ leads to an increase in the product.

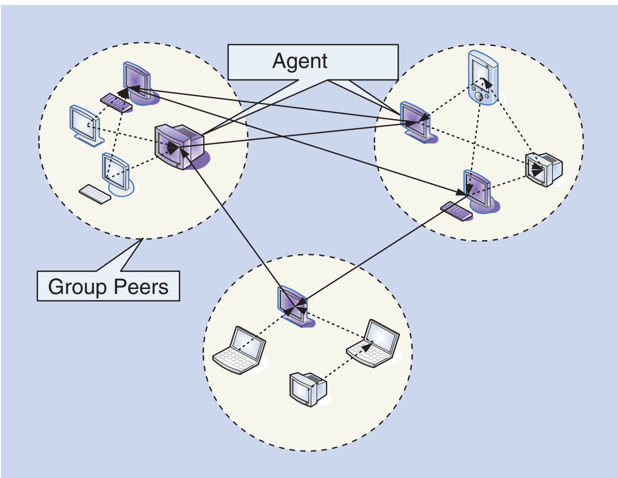
Then, we evaluate the cheat-proof property of different methods. We assume that u_6 who transmits mobile sequence will cheat while other users are honest. In AFD, AFR, and MSPSNR, u_6 reports a false $\widetilde{\beta}$ to the controller by scaling the original β with a factor k, i.e., $\widetilde{\beta} = k\beta$. In the proposed method, at each clock t of the auction, u_6 uses $\widetilde{\beta}$ to generate the "optimal" demand $\widetilde{R}_6^t$ and reports $\widetilde{R}_6^t$ to the controller. As shown in Figure 3(a), the PSNR performance of AFR is independent of the scale factor k. This is because AFR does not care about β and just equally allocates the bandwidth to each user if the allocated bit rate is within $[R_i^{\min}, R_i^{\max}]$. The PSNR performance of AFD decreases as k increases. This is because AFD tries to allocate more bit rate to the video sequence with a smaller β to preserve constant quality among different users. Therefore, with AFD, all users tend to report a smaller β to the controller to obtain a better PSNR performance. On the contrary, the PSNR performance of MSPSNR is an increasing piecewise constant function in terms of k. This is because, with MSPSNR, the sequence with β_i will not be allocated more bit rate than $R_i^{\min}$ if there is a sequence with $\beta_j > \beta_i$ who has not been allocated its maximal rate requirement $R_j^{\max}$ yet. To be allocated more rate and obtain a higher PSNR, u_6 should increase k until at least $k\beta_6 > \beta_j$, where $\beta_j = \min_l(\beta_l > \beta_6)$. Therefore, with MSPSNR, all users tend to report a larger β to the controller to obtain a better PSNR performance. However, with the proposed method, as shown in Figure 3(b), reporting the optimal demand generated by the true β ($k = 1$) will lead to the best utility. Any deviation will lead to a loss in terms of utility, which means that the proposed method is cheat proof. Therefore, the proposed method ensures all users will be honest about their private information.



[FIG3] Cheat-proof performance: (a) AFD, AFR, and MSPSNR and (b) proposed method.

A COOPERATIVE SOCIAL NETWORK: PEER-TO-PEER STREAMING

In a cooperative social network, users cooperate with each other to achieve better performance through contributing their own resource. However, due to the selfish nature, users tend to be free-riders and enjoy other users' resource. Therefore, one key issue in a cooperative social network is how to cooperate, i.e., who should contribute the resource and how much should they contribute? In this section, we use the cooperative P2P streaming game as an example and discuss how to use game theory to model a cooperative social network. As shown in Figure 4, in the cooperative P2P streaming problem, there is a set of group peers (three in this example) who want to view a real-time video streaming simultaneously. Within a group, every peer can choose either to be an agent or a normal peer. If the peer serves as an agent, he/she not only needs to act as a client to download video data from the agents in other groups, but also has to act as a server to upload video streams for both the agents in other groups and the peers in the same group. However, if the peer chooses not to be an agent, he/she only needs to download/upload data from/to the peers in the same group. Without loss of generality, we assume that the upload and download bandwidth within the group is larger than those cross groups. In such a case, peers tend to be a normal peer due to the selfish nature. Nevertheless, the normal peers, on the other hand, take a risk of receiving degraded streaming performance since there may not be sufficient agents to download data from other groups. To achieve good streaming performance, a question need to be addressed: Given a group of peers, which peers should serve as agents? Obviously, group peers form a cooperative social network since they cooperate with each other to achieve better streaming performance.



[FIG4] A cooperative streaming example.

Since peers' behaviors are highly dynamic, they may join in or leave the P2P network at any time. In such a case, a centralized approach may not be practical to determine the agents. Moreover, since all peers are selfish, they will cheat if cheating can improve their payoffs, which means that all peers are uncertain of other peers' actions and utilities. In such a case, to improve their utilities, peers will try different strategies in every play and learn from the strategic interactions using the methodology of understanding-by-building, which leads to the concept of "evolutionary game" [37], [47]. During the process, the percentage of peers using a certain pure strategy may change. Such a population evolution can be modeled by replicator dynamics [47]. Specifically, let x_{i,a_i} stand for the probability of peer u_i using pure strategy $a_i \in \mathcal{A}$, where $\mathcal{A} = \{A, N\}$ is the set of pure strategies including being an agent (A) and not being an agent (N). By replicator dynamics, the evolution dynamics of x_{i,a_i} are given by the following differential equation

$$\dot{x}_{i,a_i} = \eta[\bar{U}_i(a_i, x_{-i}) - \bar{U}_i(x_{i,a_i})]x_{i,a_i}, \quad (5)$$

where $\overline{U}_i(a_i, x_{-i})$ is the average payoff of peer u_i using pure strategy a_i, $\overline{U}_i(x_{i,a_i})$ is the average payoff of peer u_i using mixed strategy x_{i,a_i}, and η is a positive scale factor.

From (5), we can see that if adopting pure strategy a_i can lead to a higher payoff than the average level, the probability of a peer using strategy a_i will grow and the growth rate $\dot{x}_{i,a_i}/x_{i,a_i}$ is proportional to the difference between the average payoff of using pure strategy a_i and the average payoff of using mixed strategy x_{i,a_i}. The stable solution to the replicator dynamics equation is the evolutionarily stable strategy (ESS), which is "a strategy such that, if all members of the population adopt it, then no mutant strategy could invade the population under the influence of natural selection" [47].

ANALYSIS OF THE GAME FOR A HOMOGENEOUS GROUP

In a homogeneous group, let the cost of a peer serving as an agent be C. If the total download rate y_k (k is the number of agents) is not smaller than the source rate r, then the group peers can have a real-time streaming, and all the group peers can obtain a certain gain G. Otherwise, there will be some delay, where we assume the gain is zero. Therefore, the average payoff of a peer if he/she chooses to be an agent can be computed by

$$\overline{U}(A, x) = \sum_{i=0}^{N-1} \binom{N-1}{i} x^i (1-x)^{N-1-i} [Pr(y_{i+1} \geq r)G - C], \tag{6}$$

where x is the probability of a peer being an agent, and $\binom{N-1}{i} x^i (1-x)^{N-1-i}$ is the probability that there are i agents out of $N-1$ other peers.

If a peer chooses not to be an agent, then there is no cost. Therefore, the average payoff of a normal peer can be computed by

$$\overline{U}(N, x) = \sum_{i=1}^{N-1} \binom{N-1}{i} x^i (1-x)^{N-1-i} Pr(y_i \geq r)G. \tag{7}$$

At equilibrium $x^\star$, no player will deviate from the optimal strategy. According to (5)–(7), there are three possible equilibria $x^\star = 0$, 1, or the solutions to $\overline{U}_A(x) = \overline{U}_N(x)$. By examining the sufficient condition for each ESS candidate, we reach the following three conclusions with the detailed proofs given in [37]. First, when $Pr(y_1 \geq r)G \leq C$, that is, when the cost to serve as an agent is larger than the gain of one agent system, the equilibrium is $x^\star = 0$ and no one will volunteer to be an agent. Second, when $Pr(y_N \geq r)G - Pr(y_{N-1} \geq r)G \geq C$, that is, when the cost to serve as an agent is smaller than the additional gain receiving from the $(N-1)$-agent system to the N-agent system, then $x^\star = 1$ and all users become agents to ensure they can receive the realtime video streaming. Third, if $x^\star$ satisfies $\overline{U}(A, x) = \overline{U}(N, x)$, that is, with $x^\star$, the average payoff keeps the same no matter peers choose to be an agent or a normal peer, then $x^\star$ is an ESS.

[TABLE 1] UTILITY TABLE OF A TWO-PLAYER GAME.

	"A"	"N"
"A"	$(B_2 - C_1, B_2 - C_2)$	$(B_1 - C_1, B_1)$
"N"	$(B_1, B_1 - C_2)$	$(0, 0)$

ANALYSIS OF THE GAME FOR A HETEROGENEOUS GROUP

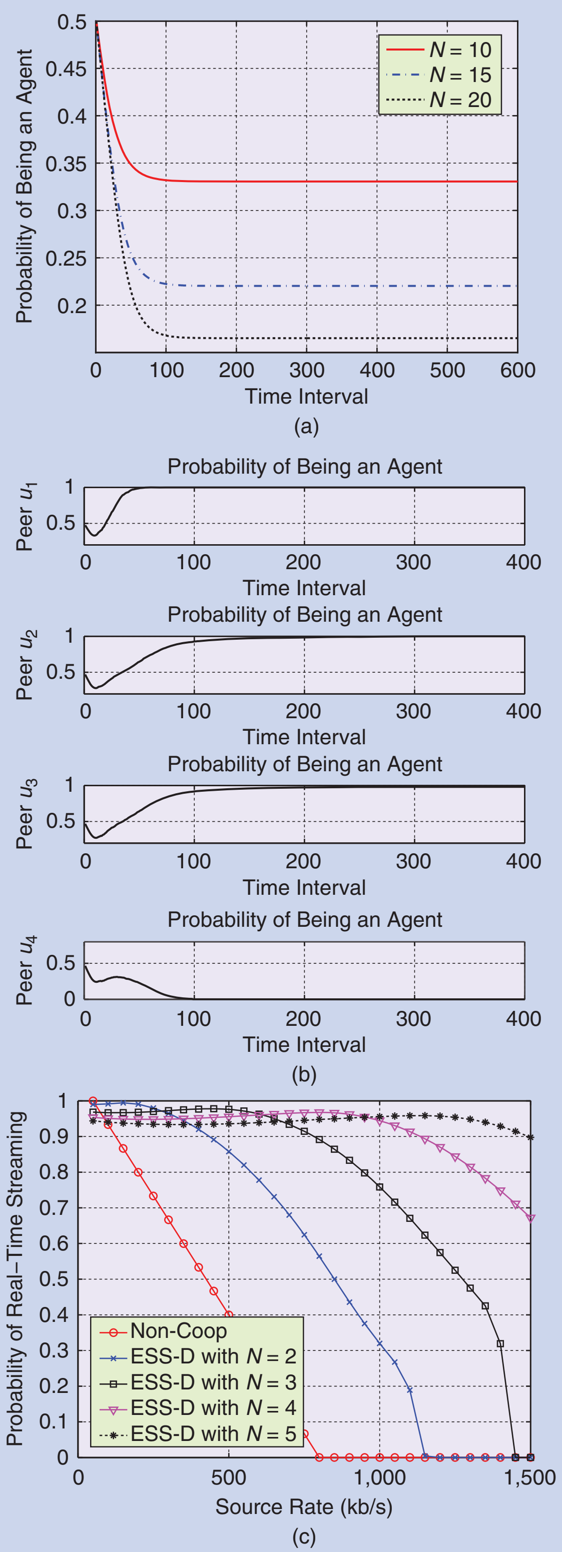
In a heterogeneous group, the costs of the peers acting as agents are different, which lead to different utility functions for different peers. In such a case, it is generally very difficult to represent average payoff in a compact form. Therefore, in the following, we first analyze a two-player game to gain some insight, and then generalize the observations to the multiplayer game.

Let x_1 and x_2 be the probability of users u_1 and u_2 being an agent, respectively. Let $B_1 = Pr(y_1 \geq r)G$ be the gain of one agent system and $B_2 = Pr(y_2 \geq r)G$ be the gain of two agents system. Then, the payoff matrix of u_1 and u_2 can be written as in Table 1. Following the same analysis as in the homogeneous case, this game has five possible equlibria, which are $(0, 0)$, $(0, 1)$, $(1, 0)$, $(1, 1)$, and the mixed strategy equilibrium $((B_1 - C_2/2B_1 - B_2), (B_1 - C_1/2B_1 - B_2))$. Then, by examining the sufficient condition for each ESS candidate, we reach the following four conclusions with the detailed proofs shown in [37]. First, if $B_2 - B_1 > C_1$ and $B_2 - B_1 > C_2$, i.e., the additional gain from a one-agent system to a two-agent system is larger than both users' cost of serving as an agent, then there is a unique ESS $(1, 1)$, where both u_1 and u_2 converge to be agents. Second, if $B_2 - B_1 > C_1$ and $B_2 - B_1 < C_2$, i.e, the additional gain from a one-agent system to a two-agent system is larger than u_1's cost but smaller than u_2's cost, then there is a unique ESS $(1, 0)$, where u_1 converges to be an agent and u_2 converges to be a free-rider. Third, if $B_2 - B_1 < C_1$ and $B_2 - B_1 > C_2$, i.e, the additional gain from one agent system to two-agent system is smaller than u_1's cost but larger than u_2's cost, then there is a unique ESS $(0, 1)$, where u_2 converges to be an agent and u_1 converges to be a free-rider. Finally, if $B_2 - B_1 < C_1$ and $B_2 - B_1 < C_2$, i.e., the additional gain from a one-agent system to a two-agent system is smaller than both users' costs, then there are two possible ESSs $(0, 1)$ and $(1, 0)$, where the converged strategy profiles depends on the initial strategy profiles.

From the above analysis, we can see that the user with a lower cost tends to be an agent while the user with a higher cost tends to be a free-rider, which means that the user with a higher cost tends to take advantage of the user with a lower cost. Such an observation can be extended to a multiplayer game. If there are more than two users in the game, the strategy of the users with higher costs will converge to normal peers with a greater probability. The users with lower costs tend to be agents since they suffer relatively heavier losses if no one serves as an agent.

SIMULATION RESULTS

We compare the discussed the ESS-based approach, denoted as ESS-D, with the traditional P2P noncooperation method,



[FIG5] (a) Behavior dynamic of a homogeneous group of peers; (b) behavior dynamic of a heterogeneous group of peers; and (c) the probability of real-time streaming comparison between Non-Coop and ESS-D.

denoted as Non-Coop, where each peer acts as an individual and randomly selects some peers for downloading video streams. We first evaluate the convergence property of the ESS-D. In Figure 5(a), we show the replicator dynamic of the cooperative streaming game with homogeneous peers, where $C = 0.1$ and $r = 500$. We can see that starting from a high initial value, all peers gradually reduce their probabilities of being an agent since being a free-rider more often can bring a higher payoff. However, since too low a probability of being an agent increases the chance of having no peer be an agent, the probability of being an agent will finally converge to a certain value that is determined by the number of peers.

In Figure 5(b), we show the replicator dynamic of the cooperative streaming game with 20 heterogeneous peers, where $r = 500$ and the cost C_i is randomly chosen from $[0.1, 0.3]$. We further assume that C_i is monotonically increasing in i, that is, u_1 has the lowest cost and u_{20} has the highest cost. From Figure 5(b), we can see that the peers with lower costs (u_1, u_2, and u_3 in this simulation) converge to be agents while the peers with higher costs ($u_4 - u_{20}$ in this simulation) converge to be free-riders. This observation coincides with our analysis, which is "the peers with lower costs tend to be agents since they suffer relatively higher losses if no one serves as an agent."

Then, we compare the performance of Non-Coop and ESS-D in terms of the probability of real-time streaming, which is defined as the probability that the total download rate is greater than the source rate. The simulation results are shown in Figure 5(c). We can see that with cooperation, the probability of real-time streaming can be significantly improved especially at the high source rate region. We also find that at the high source rate region, the probability of real-time streaming increases as N increases.

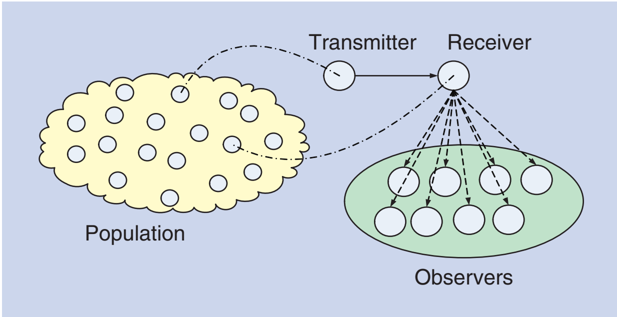
COOPERATION STIMULATION: INDIRECT RECIPROCITY GAMES

In the previous section, we have discussed how users in a cooperative social network should cooperate with each other to achieve better performance. Another important issue in a cooperative social network is cooperation stimulation, since users will not cooperate with others unless cooperation can improve their own performance. In this section, we will discuss how to use indirect reciprocity games to stimulate cooperation in a cooperative social network. As shown in Figure 6, let us consider a cognitive network with a sufficiently large population of nodes. Due to mobility and/or changes of environment, short interactions rather than long-lasting associations between anonymous partners are dominant. At each time slot, a fraction of players is chosen from the population to form pairs to forward packets. Within each pair, one player acts as a transmitter and the other player as a receiver. The receiver can obtain a gain g at a cost c to the transmitter. If both players cooperate with each other and forward one packet to the other player, both players receive $g - c$, which is better than what they would obtain by both defecting, particularly 0. However, a unilateral defector would earn g, which is the highest payoff, and the exploited cooperator would pay the cost c without receiving any benefit. The payoff structure yields an instance of the well-known prisoner's dilemma game and the unique Nash equilibrium (NE) is defecting, i.e., both players will not forward packet to the other player. Moreover, with backward deduction [48], the NE remains the same even the game is played a finite number of times. Thus, the question now is how to stimulate cooperation under such a scenario.

The noncooperative optimal strategy in such a scenario is mainly due to the use of direct reciprocity, where the action of a transmitter taking toward a receiver is purely determined by the history of how the receiver treats him/her. Obviously, under such a scenario, all transmitters have no incentive to forward packets since their behaviors will not be evaluated by other players except their corresponding receivers. To stimulate the cooperation under such a scenario, we use the indirect reciprocity game modeling, where the essential concept is "I help you not because you have helped me, but because you have helped others." The origin of the concept of indirect reciprocity is Alexander's book in 1987 [49]. Recently, the concept of indirect reciprocity has drawn a lot of attention in the area of social science and evolutionary biology [50], [51]. Here, we discuss how to use indirect reciprocity games to stimulate cooperation in a cooperative social network. A key concept in indirect reciprocity game is the establishment of the notion of reputation, which is the evaluation of the history of the players' action. Here, to simplify the analysis, we assume that the reputation is quantized to $L+1$ levels with "0" being the worst reputation and "L" being the best reputation, i.e., the reputation set can be represented as $\mathbf{T} = \{0, 1, \ldots, L\}$. During each interaction, the transmitter determines his action, i.e., how many packets to forward to the receiver, based on the receiver's and his/her own reputations. After each interaction, the reputation of the receiver remains the same, while the reputation of the transmitter is first updated by the receiver and the observers according to the social norm, and then propagated to the whole population through a noisy gossip channel.

An action rule, $\mathbf{a}$, is an action table of the transmitter, where the ith row and jth column element $a_{i,j}$ stands for the number of packets the transmitter will forward based on his/her own reputation i and the corresponding receiver's reputation j. The optimal action rule, $\mathbf{a}^{\star}$, should be the one that maximizes the payoff function as discussed later.

A social norm, $\mathbf{Q}$, is a matrix used for updating the immediate reputation of players, where the immediate reputation is the reputation that a transmitter can immediately obtain by taking an action. Each element $Q_{i,j}$ in the social norm stands for the immediate reputation assigned to a transmitter who has taken the action i toward a receiver whose reputation is j. Without loss of generality, we assume that all players in the population share the same norm. Although the immediate reputation is only determined by the action of the transmitter and the reputation of the receiver, we can see from the later discussion, the final reputation updating rule also involves the



[FIG6] System model for cooperation stimulation.

reputation of the transmitter. Based on the intuition that forwarding packets to the receiver with good reputation or denying forwarding packets to the receiver with bad reputation should receive good reputation, the immediate reputation $Q_{i,j}$ is defined as $Q_{i,j} = L - |i-j|$.

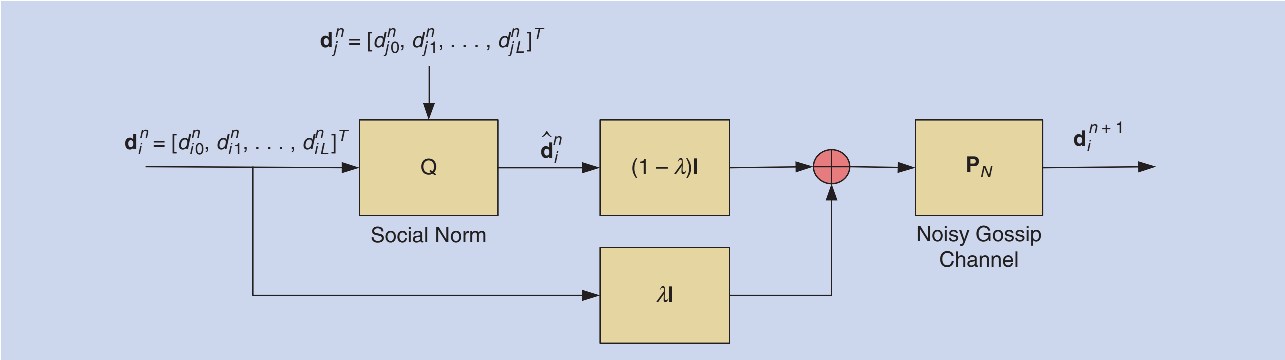
REPUTATION UPDATING POLICY

Since players monitor the social interactions within their group and help others establish the reputation of being a helpful player, one important step in indirect reciprocity game modeling is how to update reputation based on players' actions. In this subsection, we present a reputation updating policy based on the action of the transmitter, the reputation of the transmitter and the reputation of the receiver. To capture not only the mean behavior of the transmitter's reputation but also all likelihoods of the transmitter's reputation that may be, we assign a reputation distribution for each player. Let $\mathbf{d} = [d_0, d_1, \ldots, d_L]^T$ be a reputation distribution for a specific player. Then d_i stands for the likelihood of the player being assigned with reputation i.

The reputation updating policy is shown in Figure 7. Suppose, at time index n, a transmitter with a reputation distribution $\mathbf{d}_i^n$ is matched with a receiver with a reputation distribution $\mathbf{d}_j^n$. By taking a certain action, the transmitter is assigned with an immediate reputation $\hat{\mathbf{d}}_i^n$ based on the social norm. Then, the receiver and the observers will update the transmitter's reputation distribution using a linear combination of the transmitter's original and immediate reputations, where the weight λ can be treated as a discounting factor of the past reputation. Finally, the transmitter's reputation is propagated among the population by the receiver and observers through a noisy gossip channel.

In a simple example, we assume that the transmitter's reputation distribution is $\mathbf{d}_i^n = \mathbf{e}_i$ and the receiver's reputation distribution is $\mathbf{d}_j^n = \mathbf{e}_j$, where $\mathbf{e}_i$ and $\mathbf{e}_j$ are the standard basis vectors. Let $a_{i,j}$ be the action the transmitter takes toward the receiver. Then, the immediate reputation of the transmitter is $\mathbf{e}_{Q_{a_{i,j},j}}$. According to the reputation updating policy in Figure 7, after the transmission, the transmitter's reputation distribution becomes

$$\tilde{\mathbf{d}}_{i\to j} = \mathbf{P}_N\left(\lambda \mathbf{e}_i + (1-\lambda)\mathbf{e}_{Q_{a_{i,j},j}}\right). \tag{8}$$



[FIG7] Reputation updating policy.

STATIONARY REPUTATION DISTRIBUTION

Let $\mathbf{x} = [x_0, x_1, \ldots, x_L]^T$ stand for the reputation distribution of the entire population, where x_i is the portion of the population that have the reputation i. Since every pair of transmitter and receiver is chosen from the population, given the transmitter with reputation i, the probability of matching with the receiver with reputation k is x_k. After the transmission, the reputation of the transmitter is updated using the policy shown in Figure 7, which leads to a new reputation distribution of the entire population. At the stationary state, the reputation distribution of the entire population remains constant during the updating process, which means that the stationary reputation distribution $\mathbf{x}^\star$ is the solution to the following equation

$$\mathbf{P}_N(\lambda\mathbf{I} + (1-\lambda)\mathbf{P}_T)\mathbf{x}^\star = \mathbf{x}^\star, \tag{9}$$

with the ith row and jth column element of the matrix $\mathbf{P}_T$ being defined as $\mathbf{P}_T(j, i) = \sum_{k:Q_{a^\star_{i,k},k}=j} x_k$.

PAYOFF FUNCTION

Suppose that the cost of forwarding a packet is a constant, c, the total cost of the transmitter with reputation i taking action $a_{i,j}$ toward a receiver with reputation j is given by $a_{i,j}c$. Similarly, if the gain of receiving a packet is a constant, g, the total gain of the receiver with reputation i can be computed by $a_{j,i}g$.

Let $W_{i,j}$ denote the maximum payoff that a player, currently having reputation i and being matched with a player with reputation j, can gain from this interaction to future. Obviously, if the player with reputation i serves as a transmitter, by taking action $a_{i,j}$, he will incur an immediate cost $a_{i,j}c$ and his reputation distribution will change from $\mathbf{e}_i$ to $\widetilde{\mathbf{d}}_{i\to j}$ according to (8). Since his opponent in the next round is randomly sampled from the population with a stationary reputation distribution $\mathbf{x}^\star$, with probability $\widetilde{\mathbf{d}}_{i\to j}(k)\mathbf{x}^\star(l)$, the transmitter's reputation becomes k and his opponent's reputation is l. In such a case, the benefit the play can gain in the future with a discounting factor δ is $\delta\sum_k\sum_l \widetilde{\mathbf{d}}_{i\to j}(k)\mathbf{x}^\star(l)W_{k,l}$.

On the other hand, if the player with reputation i serves as a receiver, he can obtain an immediate gain $a^\star_{j,i}g$ when the corresponding transmitter takes the optimal action $a^\star_{j,i}$. As a receiver, the reputation will not change after the transmission. Since his opponent in the next round is randomly sampled from the population with a stationary reputation distribution $\mathbf{x}^\star$, with probability $\mathbf{x}^\star(l)$, the receiver's reputation is i and his opponent's reputation is l. In such a case, the benefit the play can gain in the future with a discounting factor δ is $\delta\sum_l x^\star_l W_{i,l}$.

Since the play acts either as a transmitter or as a receiver with equal probability 1/2 with each interaction, the Bellman equation which characterizes the optimality condition of $W_{i,j}$ can be written as

$$W_{i,j} = \max_{a_{i,j}}\left[\frac{1}{2}\left(-a_{i,j}c + \delta\sum_k\sum_l \widetilde{\mathbf{d}}_{i\to j}(k)\mathbf{x}^\star(l)W_{k,l}\right) + \frac{1}{2}\left(a^\star_{j,i}g + \delta\sum_l \mathbf{x}^\star(l)W_{i,l}\right)\right], \tag{10}$$

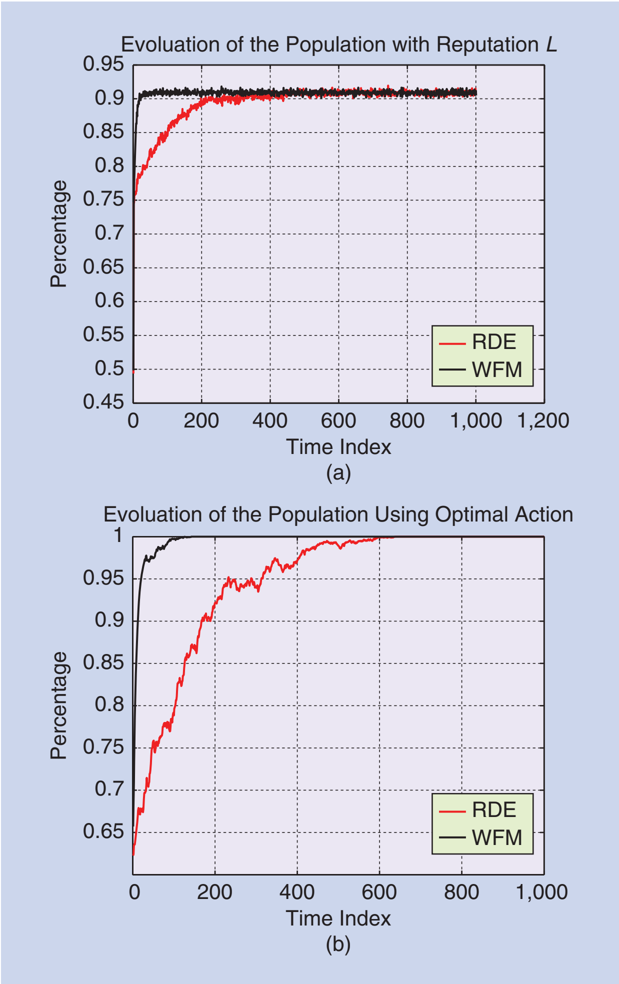
and the optimal action $a^\star_{i,j}$ is the one that maximizes $W_{i,j}$

$$a^\star_{i,j} = \arg\max_{a_{i,j}} W_{i,j} = \arg\max_{a_{i,j}}\left[\frac{1}{2}\left(-a_{i,j}c + \delta\sum_k\sum_l \widetilde{\mathbf{d}}_{i\to j}(k)\mathbf{x}^\star(l)\mathrm{W}_{k,l}\right)\right]. \tag{11}$$

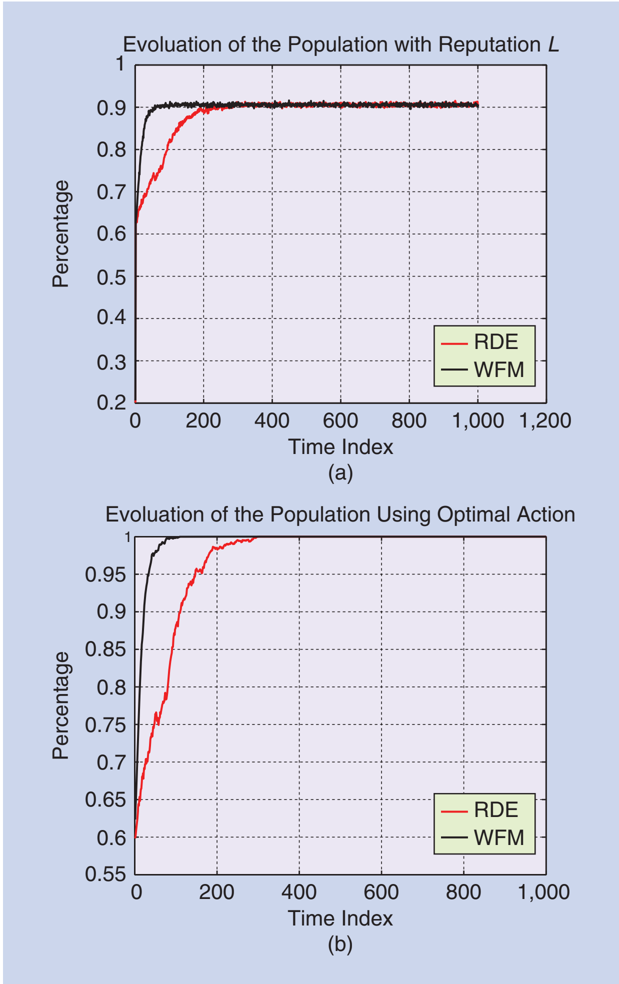
From (10) and (11), we can see that the problem of finding the optimal action rule is a Markov decision process (MDP), where the state is the reputation pair (i, j), the action is $a_{i,j}$, the transition probability is determined by $\widetilde{\mathbf{d}}_{i\to j}$ and $\mathbf{x}^\star$, and the reward is determined by c and g. Therefore, given the stationary reputation distribution, the optimal action can be found by solving (11) using dynamic programming.

SIMULATION RESULTS

To verify the proposed algorithm, we simulate the packet forwarding game. We study a fixed-size population, $N = 1{,}000$. Each new player receives a uniform initial reputation. Before any one elementary step of action updating, each individual has exactly 20 interactions with other randomly chosen individuals. Individuals act as transmitter and receiver on average ten times each. After each interaction, the reputation of the transmitter is updated according to the reputation updating policy shown in Figure 7. Then, the players choose their new action rules according to previous payoff history of the whole population. There are two possible action updating algorithms: one is the Wright Fisher model [52], which is



[FIG8] The population evolution when $L = 1$, $g = 1$, and $c = 0.1$: (a) the percentage of the population with reputation $L = 1$ and (b) the percentage of the population using optimal action.



[FIG9] The population evolution when $L = 4$, $g = 1$, and $c = 0.5$: (a) the percentage of the population with reputation $L = 4$ and (b) the percentage of the population using optimal action.

denoted as "WFM," and the other one is the replicator dynamic equation [47], which is denoted as "RDE." After updating the action rule, the payoffs of all players are reset to zero. The parameters λ, δ, and μ are set to be 0.5, 0.9, and 0.95 respectively. The parameter η that controls the speed of the evolution in RDE is set to be 0.1.

By solving (11), we find that one possible optimal action rule $\mathbf{a}^\star$ is to forward i packets to the receiver with reputation i. We then evaluate the evolutionary stability of $\mathbf{a}^\star$. In the simulation, the initial frequency of the optimal action rule $\mathbf{a}^\star$ is set to be 0.6. The initial frequencies of the other action rules are uniformly distributed. The results for the binary case $L = 1$ and multilevel case $L = 4$ are shown in Figures 8 and 9, respectively. We can see that for both WFM and RDE, the reputation distribution converges to the stationary reputation distribution. Compared with WFM, the convergence speed of RDE is a bit slower since a small speed controlling parameter $\eta = 0.1$ is used in RDE. We can also see that the optimal action rule will spread over the whole population, and once the whole population adopt it, no one will deviate. Therefore, the optimal action rule that forwards i packets to the receiver with reputation i is an ESS [47].

CONCLUSIONS

Social networks have pervaded our daily life. Understanding the human behaviors and dynamics in a social network is essential for its continued progress. In this article, we use game theory to analyze and model human behaviors in a social network to achieve better system design. Such analysis and modeling is very general and can be applied to many social networks. From the discussion in this article, we can see that different game models should be used for different social networks with different types of interdependency. When designing a system, not only the system efficiency but also the fairness among users should be taken into account. Moreover, since users are rational and thus naturally selfish, they tend to overclaim what they may need and will not truly report their private information if cheating can improve their payoffs. Therefore, one should consider users' selfish nature and develop cheat-proof strategies to guarantee satisfactory system performance.

AUTHORS

Yan Chen (yan@umd.edu) received the bachelor's degree from the University of Science and Technology of China in 2004, the M.Phil degree from Hong Kong University of Science and Technology in 2007, and the Ph.D. degree from the University of Maryland College Park in 2011. Now he is a research associate in the Department of Electrical and Computer Engineering at the University of Maryland, College Park. His current research interests are in social learning and networking, smart grid, network economic, game theory, and multimedia signal processing. He received the University of Maryland Future Faculty Fellowship in 2010.

K.J. Ray Liu (kjrliu@umd.edu) was named a Distinguished Scholar-Teacher of the University of Maryland, where he is the Christine Kim Eminent Professor of Information Technology. He received the 2009 IEEE Signal Processing Society Technical Achievement Award and various teaching and research recognitions from the University of Maryland. He is the president of the IEEE Signal Processing Society and was an editor-in-chief of *IEEE Signal Processing Magazine* and the founding editor-in-chief of *EURASIP Journal on Advances in Signal Processing*.

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