Cooperation and Competition Dynamics in an Online Game Community

Ruixi Yuan, Li Zhao, and Wenyu Wang

Center for Intelligent and Networked Systems, Department of Automation, Tsinghua University, Beijing, China
ryuan@tsinghua.edu.cn, zhaoli04@mails.tsinghua.edu.cn

Abstract. Cooperation and competition are important subjects in social and economical studies. Similar dynamics exists in large-scale online communities. In this paper, we present a quantitative study on the cooperation and competition dynamics of an online gaming community. During a period of four months, we collected a total of over one million data points in an open game room with an online gaming site (www.ourgame.com.cn) for a popular card game "upgrade". The "upgrade" game room provided us an excellent environment to observe how cooperative and competitive relationships are formed in an online community. Through the statistical analysis, we obtain the probability for players with different score tags forming cooperative and competitive relationships with each other. Our analysis shows that all players exhibit preferential bias in their partner selection process, but shows little bias in their selection of competitors. Further, the cooperation bias is the strongest in both the low score and high score ends of the player population. We also discuss the effect of such preferential bias on the population distributions in the game community. To our knowledge, this is the first large-scale quantitative study on the cooperation dynamics in online gaming community. The online game community environment offers us a great proxy to study the same dynamics that is difficult to investigate in the real world social environment. The large, statistically significant amount of data enables us to develop and test many hypotheses.

Keywords: communities, game, cooperation, competition, and preferential bias.

1 Introduction

1.1 Background

Competition and cooperation dynamics has long been the subject of game theory and economic studies, [e.g. 1, 2]. In the past two decades, how cooperation might arise and evolve in a competitive environment has attracted increasing attentions. For example, the iterated prisoner's dilemma (IPD) game has been the subject of numerous theoretical and experimental studies [3]. Most notably the work of Robert Axelrod [2,4,5] has shown that cooperation can emerge as a norm in an environment comprising individually selfish entities. Additionally, the introduction of an arbitrary tag and

D. Schuler (Ed.): Online Communities and Social Comput., HCII 2007, LNCS 4564, pp. 475–484, 2007.

its effect of the evolution of cooperation have been extensively studied using computer simulation [6,7]. It is shown that tag induced partner selection bias can greatly facilitate the emergence of cooperation even without direct or indirect reciprocity [7]. However, how an arbitrary tag affects the partner and opponent selection process in a real world environment with both cooperation and competition is still unclear.

Large-scale online communities offer us great environments to study the social and economical behavior of large population. First, it is relatively easy to find large virtual communities that evolve rapidly through cooperation and competition. Second, online data acquisition can be automated and large amount of data obtainable in a relatively short amount of time. Third, the pseudo-anonymous nature of online environment encourages users to display their true behaviors, not revealing their identities in the real world. Hence, the study of online community offers great opportunity to understand a wide range of social, economical and network systems.

1.2 Related Works

While the online virtual community represents a great opportunity for the research on social interaction and behavior, much of the research has focused on improving human-computer interaction [e.g. 8, 9], or the how the electronic media is changing the human-human interaction [e.g. 10, 11]. Fewer research have focused on using the online communities as observation environments for the study of human interactions and behaviors.

Closer to our work, there are several recent researches in human computer interaction that have paid attention on virtual communities including online dating [12,13], online game [14], and online social environment [15]. Andrew T. Fiore and Judith S. Donath [12, 13] have discussed how people choose their romantic relationship with others in online dating system and propose the intrinsic factors for successful attraction. The factors involve physical features, odors, economic status, hobbies, and so on. they serve as tags in preferential partner selection for each individual. However, these tags are static and remain unchanged throughout the process of the courtship. Furthermore, the distinct values (e.g. gender, race) does not offer continuous ranges for more detailed analysis. Authors in [14, 15] studied online game environment; explored both the promises and inadequacies of online gaming environment in studying the social interactions. Barry Brown and Marek Bell studied an online environment in [16] and made a case for improving the social interaction by better integrating multiple sensory methods.

1.3 Our Study and Main Contributions

In this paper, we present the study of large online game rooms at a highly popular gaming website in China (www.ourgame.com.cn). Over one million of cooperation and competition pairing data points are collected from the game rooms where thousands of players congregate. Through the statistical analysis of the collected paring, we obtain the probability for players with score “S1” in cooperative relationships with other players with score “S2” (the players’ score is described in detail in section 2). This probability is then compared with the “expected” probability for purely random relationship forming. Our analysis showed that all players exhibit preferential bias in their partner selection process. That is, players tend to form cooperation relationship with others with similar scores. Further, the preferential bias is the strongest in both the low score and high score ends of the game room, and the bias is the weakest in the middle of the score range. In the meantime, players are much less selective in the choice of opponents.

To our knowledge, our paper is the first study on cooperation and competition dynamics from large-scale online communities. For the first time, the quantitative values of preferential bias with respect to the degree of similarity are obtained. Analysis also showed that the value and trend of the bias plays a critical role in the population evolution of the game system. As online communities a proxy for real-world environments, such study should also be applicable in real social and economical environments.

2 The “Upgrade” Game Community

The “upgrade” game is a popular card game played throughout China. It involves four players; two players form a partnership and play against the partnership of the other two players. The winning depends on both the cards being dealt and the quality of cooperation between the partners.

The “Ourgame” site (www.ourgame.com.cn) is one of the most popular online game sites in China. It enables players all across the country to form partnerships and play against each other online. The computer is responsible for dealing the cards and calculates score after the completion of each game as well as supplying information of each player in the communities. Each player online is identified by a unique ID (an ASCII string) and has the following attributes.

Score: An integer used to record player’s historical wins and loses . Players gain positive score when they win the game and gain negative score when they lose. Winning a game usually causes the score increase by one and losing a game resulted the score decrease by one.

Historical rounds: The number of rounds this player has played.

Upon logon, a player is presented with multiple game rooms, each with a limit of 300 participants. The player enters the game room by clicking the room’s link. Each room contains 100 game tables which are adequate to hold all the players in the room playing games. Each game table has four seats (East, West, North and South). Seating at the opposite end of the table means the willingness to form a cooperative relationship. When a table has seated four players, and all agrees to proceed to playing (by raising the virtual hand), the game begins. There are two types of game rooms: open game rooms and advanced game rooms. The open games are open to everyone regardless of their score and historical rounds. The advanced game rooms are only open to players with scores greater then 30 and historical rounds greater than 50. Figure 1 shows a section of the open game room with eight tables.

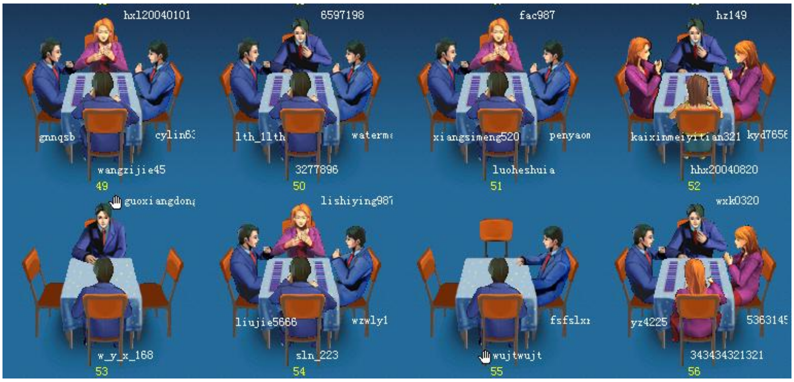

Fig. 1. A section of the game room where 8 tables are displayed, tables 49, 50, 51, 52, 54 and 56 have four players seated and have already begun to play. Table 53 has two players sitting opposite, signaling their willingness to form a cooperative relationship. Table 55 has two players sitting adjacent to each other, signaling their willingness to form a competitive relationship.

As shown in figure 1, six game tables are already occupied with ongoing games. Two table have only two players, and waiting for others to join. One table (table 53) has two players sitting at the opposite sides, meaning that they are willing to cooperate and waiting another pair to join. Another table (table 55) has two players sitting at the adjacent sides, signaling their willingness to form a competitive relationship. A player may choose to join a partially filled table or simply sit at an empty table and waiting for others to join. When a new player joins a table, the existing players may choose to leave if he/she is not satisfied with the resulting cooperative and competitive relationships.

Clearly, a round of game requires two successful cooperative relationships (E-W, N-S) and four successful competitive relationships (E-N, E-S, W-N, and W-S). A player is entitled to leave the table if the player is not satisfied with any of the relationships. A player can make his/her decision based on many factors. Usually, the accumulative score is the most important factor.

In order to automate the data collection, we wrote our own data collection robot. The robot periodically logs onto the game site and enters the game room. Each time it enters the game room; it records all the players in the game room, including those already in play, and those still waiting to form relationships. To avoid duplicate sampling, we choose the periodic interval of 6 minutes, which is a sufficient duration to complete a round of game and allow old relationship to dissolve and new relationship to form. During the period between March 2005 and July 2005, we successfully collected data from a total of 5890 open game rooms. The aggregated total data points is 1,007,248 player×round data points. Table 1 shows some statistics of the collected data points.

The population distribution across the score range is for the players with historical rounds > 50, and is shown in Fig. 2. It has a peak at score 0, because 0 is the default assigned score for all the new players. There is a sharp drop of players at the score of 30. When a player's score reaches 30, he/she is eligible to enter advanced game rooms and probable leaves the open game room.

Table 1. The statistics for the 1 million collected data points

Number of distinct player×round	Total number of distinct players	Number of players with historical rounds > 50	Number of players with observed rounds> 50
1007248	192315	129121	2800

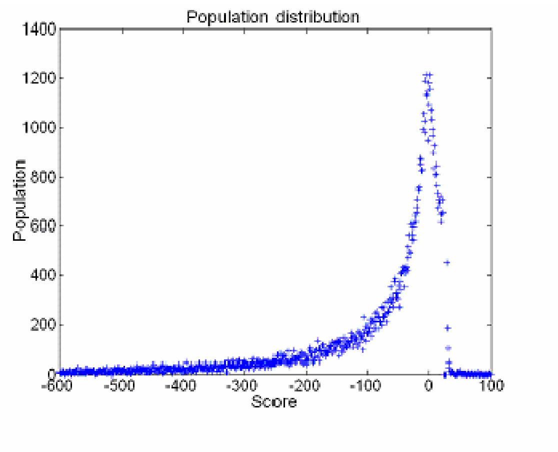

Fig. 2. The population distribution across the score range for players with more than 50 historical rounds in the open game room. The default score value 0 for all players produced the peak at 0. The sharp drop at 30 is caused by players leaving the open game room for advanced game room when they become eligible with score 30.

3 Cooperation and Competition Bias

We are interested in the dynamics of how players interact with each other. Most notably, how does one player decide to form cooperative or competitive relationship with each other? The collected raw data from the game room showed the players in cooperative and competitive relationships, as well as those in the game room waiting. However, it does not directly tell the likelihood of forming relationship when one player meets another player. Therefore, we must infer the likelihood from the existing relationships and their distributions. Our analytical approach is describes below.

3.1 Analytical Approach

We first divide the players in the game room into fixed score range classes. For each class of players, we compare the actual numbers of successful relationships with the expected numbers with random selections.

Suppose player class i of has n_i players and player class j of has n_j players. If the players chose partners at random, then the total number of cooperative relationships formed between class i and class j should be proportional to $n_i \times n_j$. From the game room data, we can obtain the actual numbers of cooperative relationships between class i and class j as C_{ij}. (obviously, C_{ij} equals C_{ji}) Next, we compute the value $R_{ij} = C_{ij} \div (n_i \times n_i)$, and R_{ij} is then averaged across all the game room data. We denote the ensemble average $<R_{ij}>$ as the preferential bias strength between class i and j. For special cases with relationship formation within the same class, the normalization factor is $n_i \times (n_i\text{-}1)/2$ instead of n_i^2. The reason is that when 2 players both in the same class form cooperative relationship, 2 choices by different players actually happened, but only 1 cooperation relationship is established so we increased C_{ii} by 1, which is likely only 1 player's takes effect. Comparatively, when 2 players in different classes become partners, the two players' choices will make both C_{ij} and C_{ji} increase, thus each player's choice takes effect.

As an example, suppose there are 3 classes of players i, j and k, and each class has 100 players. If the number of actual cooperative relationships are observed as $C_{ii} = 30$, $C_{ij} = 60$ and $C_{ik} = 30$. Then, $R_{ii} \approx 0.0061$, $R_{ij} = 0.006$. $R_{ik} = 0.003$. Obviously, it is twice more likely for players in class i to form cooperative relationships with players in class j than in class k. R_{ii} is slightly higher than R_{ij} since a player has a relatively smaller selection range in his/her own class. Hence, the preferential bias strength is directly proportional to the likelihood of players forming relationships with each other.

For the collected data from the gaming community, we divide the entire score spectrum into fixed ranges. Players with score fall into each range are then in the same class. It is worth noting that the value of the score range may affect the calculation. Obviously, if the score range is too wide (the extreme being the entire score range as a single class), it cannot capture the fine granularity of the preferential strength. On the other hand, if the score range is too narrow (the extreme being a single exact value), the number of players in the range is not sufficient to have statistical significance. We have experimented with a wide range of values for the score range, and found that the results are stable as long as there is sufficient number of players within each class. The results in the next subsection are obtained with a score range of 50.

3.2 Preferential Bias Strengths for Cooperation

Using the collected data from the game community, we computed the preferential bias strength for cooperative relationship formation. Fig. 3 shows the contour plot for the cooperative preferential bias strength for the game community. The preferential bias is the strongest along the diagonal. This is easy to understand as players tends to form cooperative relationship with other at the same score level. What is surprising in our finding is that the bias is stronger in both the high and low end of the score ranges, but weaker in the middle. Note the two big peaks at (50, 50) and (-150, -150), and relative flatness between in between. Hence the players in the middle range are less discriminatory against players in both high and low end of the spectrum. A cross section at for the contour plot at value 50 is shown in Fig. 4. The trend of the preferential bias exhibits non-linear descends from the peak. The exact form for the preferential bias as a function of the score differential is also important and will be the subject of a separate research.

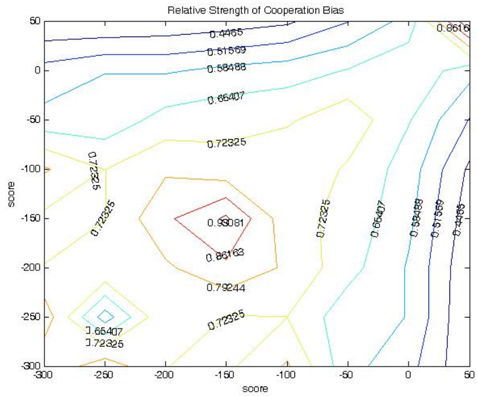

Fig. 3. The contour plot for preferential bias strength in cooperative relationship formation. The strength is normalized so that the large value is normalized to 1. Two large peaks are obtained at (50,50) and (-150, -150).

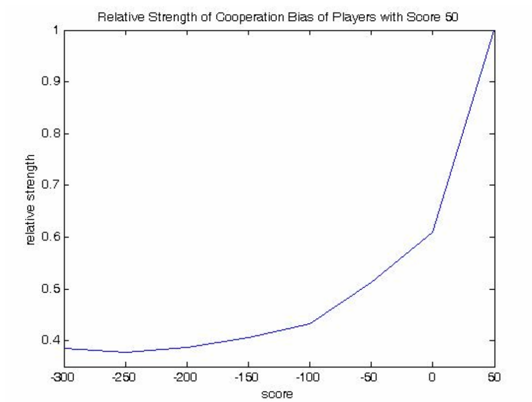

Fig. 4. The preferential bias strength in cooperation for players in score range (0,50]

3.3 Preferential Bias Strengths for Competition

The same computation can be carried out for the competitive relationship formation. Fig. 5 shows the contour plot for the competitive preferential bias strength for the same game community. Unlike the cooperative bias, we find that the bias is much weaker in the forming of competitive relationships for all players regardless of their score range. This is also surprising as one might expect players will also be careful in choosing their opponents. Obviously, the players are much more selective in choosing their partners than their opponents. A cross section at for the contour plot at value 50 is shown in Fig. 6. One can observe that the smaller variations (from 0.84 to 1.00) of the preferential bias, and the exhibits a somewhat linear trend when the score differentials are large.

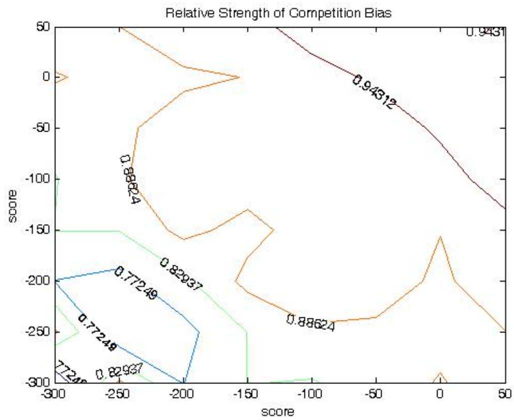

Fig. 5. The contour plot for preferential bias strength in competitive relationship formation. The strength is normalized so that the large value is normalized to 1. There are no obvious peaks in the figure.

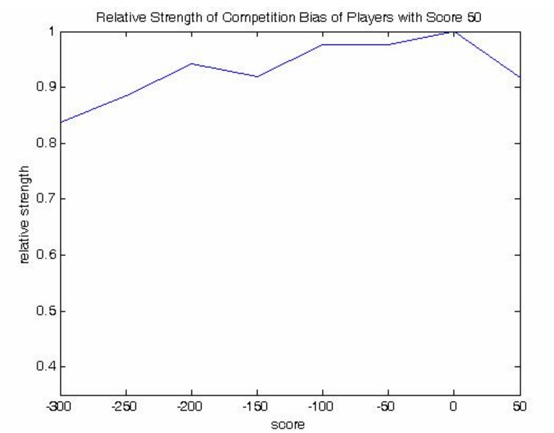

Fig. 6. The preferential bias strength in competition for players in score range (0,50]

4 Discussion and Summary

Two surprising, yet understandable conclusions were found from the analysis of game room data. First, there exists strong preferential bias in forming cooperative relations among players. However, the preferential bias strength is not uniform across the score spectrum. Rather, the bias is the strongest in both the high and low end of the player population, while players in the middle exhibit weak preferential bias. Second, there is little preferential bias in forming competitive relationships for players regardless of their score ranges. Players are much more tolerant towards their opponents' score differences.

It is very important that the preferential bias in the middle score range is weak, as the middle population serves to bridge the players in the high and low end scores. This contributed the prosperity of the game room community. Theoretically, if the preferential bias is strong throughout the entire score range for cooperative and competitive relationships, the game community will be fragmented into different sub-communities, each only contain a small number of players with narrow score ranges. This will lead to the collapse of entire community.

During our study of the game room, we observed that finding the right partner could be a relatively long process. This is directly caused by the selection bias, which narrows down the potential partner set, especially for players in the two extreme ends. However, such long waiting time could also contribute to the reduction of preferential bias, as the discriminatory behavior reduces the chance of game participation. When the perceived cost of lost opportunity outweighs the risk of losing a game, a player may choose to form a cooperative relationship that is imperfect.

We believe that the preferential bias in selecting cooperative partners is one of the most fundamental aspects for interactions in virtual communities. Such preferential bias is also prevalent in real world social and economical environments. Many previous cooperation dynamics study (e.g. iterated prisoners' games) has assumed uniform preferential bias. Our Quantitative study showed that such assumptions are not accurate. Detailed understanding of the preferential bias will also enable us to better design and implement policies that foster the prosperity of both virtual and real communities.

The gaming dynamics of online communities offer us a great proxy to study the same dynamics that is difficult to investigate in the real world social environment. The large, statistically significant amount of data enables us to develop and test many hypotheses. In particular, the cooperation dynamics and its effect on population distribution evolution warrant further study. Other topics, such the quantitative range of human perception on score differential are also meaningful and can find its way into social and economical area.

References

1. Camerer, C.F., Loewenstein, G., Rabin, M.: Behavioral Economics: Past, Present, Future. In: Advances in Behavioral Economics, Princeton University Press, Princeton, NJ (2003)
2. Axelrod, R.: The Evolution of Cooperation. Basic Books, New York (1984)
3. O'Riordan, C.: Iterated Prisoner's Dilemma: A Review. Technical Report No. NUIG-IT-260601, National University of Ireland, (2001)
4. Axelrod, R., Dion, D.: The Further Evolution of Cooperation. Science 242, 1385–1390 (1988)
5. Riolo, Cohen, M.D., Axelrod, R.: Evolution of Cooperation without Reciprocity. Nature 414, 441–443 (2001)
6. Holland, J.: The Effect of Lables (Tags) on Social Interactions. Santa Fe Institute Working Paper 93-10-064, Sante Fe, New Mexico (1994)
7. Riolo, R.L.: The Effect of Tag Mediated Selection of Partners in Evolving Populations Playing the Prisoner's Dilemma. Sante Fe Institute Working Paper 97-02-016, Sante Fe, New Mexico (1997)

8. Grossman, T., Balakrishnan, R.: The Bubble Cursor: Enhancing Target Acquisition by Dynamic Resizing of the Cursor's Activation Area. CHI 2005 (2005)
9. Aoki, P.: Making Space for Stories: Ambiguity in the Design of Personal Communication Systems. CHI 2005 (2005)
10. Mantovani, F.: Cyber-attraction "The emergence of computer-mediated communication in the development of interpersonal relationships". In: Anolli, L., Ciceri, R., Riva, G. (eds.) Say not to say: New perspectives on miscommunication, IOS Press, Amsterdam (2001)
11. Rashid, A.M., Ling, K., Tassone, R.D., Resnick, P., Kraut, R., Riedl, J.: Motivating Participation by Displaying the Value of Contribution. CHI 2006 (2006)
12. Fiore, A.T., Donath, J.S.: Online Personals: An Overview. CHI 2004 (2004)
13. Fiore, A.T., Donath, J.S.: Homophily in Online Dating: When Do You Like Someone Like Yourself?' CHI 2005 (2005)
14. Papargyris, A., Poulymenakou, A.: Learning to fly in persistent digital worlds: The case of massively multiplayer online role playing games. ACM SIGGROUP Bulletin 25(1), 41–49 (2005)
15. Golder, S.A., Donath, J.S.: Hiding and Revealing in Online Poker Games. CHI 2004 (2004)
16. Brown, B., Bell, M.: Social Interaction in "There". CHI 2004 (2004)