An Analysis of the BBO Fans Online Social Gaming Community

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***Abstract*— Online social gaming is an emerging Internet application that combines online gaming and online social networking functionality for the benefit of millions of daily users. While researchers have investigated the structure of (social) networks for decades, the activity characteristics and the community structure of online social gaming remain relatively unknown. To address this situation, in this work we investigate the BBO Fans club for online bridge. First, we introduce a method to collect and analyze data from BBO Fans and its underlying gaming platform. Our method is novel in that it addresses the lack of a strict definition of social relationship between BBO Fans players, and it defines several player types with implications on community formation and operation. Second, we use the proposed method to collect and analyze a 40-day BBO Fans dataset comprising over 140,000 unique players and over 3,000,000 unique play sessions. Third, we compare the characteristics of BBO Fans with other large social networking and online gaming applications. We find in particular that BBO Fans generates similar levels of activity as but has different community characteristics than similarly-sized games on FaceBook, the largest social network in the world.**

I. Introduction

Online social gaming applications such as FarmVille and Fighters Club [1] already entertain hundreds of millions of Internet users. The online social gaming operators actively encourage the growth of social relationships between players, and analyze the social network formed by the players and their relationships to improve the playing experience and thus to retain and grow the player base. While much research has been put into developing and applying methods of (social) network analysis [2], [3], [4], [5], the study of online social gaming communities remains largely uncharted [1]. To address this situation, in this work we propose and apply a novel method for analyzing online gaming communities.

The player base of online social gaming is growing quickly. As exemplified by early online social games such as FarmVille, such games have the potential to gather quickly user bases of tens of millions of players each; FarmVille exceeded 1 million players during the first month of operation and currently has over 70 million daily players. This growth has been triggered in part by the opening of popular social networking platforms such as FaceBook and MySpace to third-party developers; the independent assessor developerAnalytics certifies that there exist over 35,000 FaceBook applications as of July 2008, with the top applications counting daily over one million players each [1]. Online social gaming is also growing due to the evolution of traditional online gaming: to retain players and to increase their user base, many online games have started to facilitate and encourage social relations between players. Thus, online social gaming has started to transform from simple, casual games such as FarmVille and Fighters Club into complex, deeply-engaging games such as World of Warcraft and even bridge and chess.

The growth of online social gaming networks motivates the study of social gaming communities, where communities are defined as subgraphs of the social network graph whose density of edges (social relations) is higher than the density of the rest of the graph. Recent social network studies [5], [6], [7] have shown that social networks and applications can lead to much larger communities, where each individual may be linked to 100-150 others. In contrast, decades of research show that game communities are much smaller and share only some of the characteristics of social networks. Zachary studied as early as 1977 the social relations in a real-world karate club [4], while Ducheneaut et al. [8] analyzed the community behavior emerging in World of Warcraft; these and similar studies established that gaming communities cannot grow past a few tens of players. Granovetter [2] showed that weak ties, that is, connections between people who are not closely related, are important in the formation of communities. So far, a single study [1] other than ours has started to investigate how these previous findings apply for online social games; however, this earlier study focuses on Fighters Club, which is one of the simple, casual games. Moreover, the previous online social network and social gaming studies rely on networks in which links are specified at data acquisition. In contrast, in this work we set to investigate a community of online bridge players. Bridge is a complex game played with cards by teams of players; a social relationship between the players is established and strengthened by every game session. Our main research question is *What are the unique characteristics of an online bridge community?* Our main contribution in answering this question is threefold:

1) We design a method for collecting and analyzing data for online bridge communities (Section III). Our method introduces a way for extracting automatically social relationships from game sessions and a taxonomy of playing behavior that affects community building;

2) We demonstrate the use of the proposed method by collecting and analyzing a large dataset from the BBO Fans online bridge community (Section IV);
3) We analyze the activity levels and community structure of BBO Fans, and compare them with other social (gaming) applications (Section IV).

II. Background on Online Gaming Communities

There exist numerous online gaming communities; of these, many are built around playing traditional games such as go, chess, and bridge. Motivated by the inclusion of bridge as the only team game within the World Mind Sports Games[1], in this work we focus solely on bridge gaming communities. In this section we present a background on the game of bridge, on online bridge communities, and on the community we investigate in this work.

A. Club Bridge

Bridge is a game for groups of four people playing in pairs. Our interest concentrates on duplicate bridge, where the same distribution of cards is played at many (10+) tables and the winning pair is decided by comparing the results at each table. There are various scoring methods to support duplicate bridge and, over the long term, they practically eliminate the luck factor and turn bridge into a fair competition.

A typical bridge game (*hand*) lasts for 7-8 minutes, enough time for the players to bid, play, and comment on the hand. The bidding phase consists of each player specifying the number of tricks his pair (side) should win (i.e., 1 club for 7 tricks where club is the trump suit), in an effort to find the maximum number of tricks the pair can obtain. The bidding is followed by the play of the hand, where each side tries to win as many tricks as possible. What makes bridge special for our purposes is its reliance on the social relationship of the players who play as a pair. Both in the bidding and in the play, the partners exchange information through the calls they make or the cards they choose to play, which have a pre-established, systemic significance. The strongest pairs tend to have many such agreements and much experience playing with each other; such experience is often gathered over a long-term, social relationship.

The bridge player communities are organized in (local) clubs where players can meet and play in a relaxed and friendly environment. Such clubs have inflexible schedules and are not easily reachable by everybody, and do not have enough players during regular work hours; as a result, club activity is often reduced to less than 15 hours/week. Instead, many bridge players have joined online bridge communities such as Bridge Base Online and Yahoo Bridge (free playing sites), and OKBridge, Swan Games, and Bridge Club Live (subscription sites).

[1]The last World Mind Sports Games were held in Beijing, in 2008.

B. Bridge Base Online: Online Bridge at Massive Scale

Our focus in this paper is the Bridge Base Online (BBO) community, the most popular free bridge site available. BBO attracts many professional and even world-class players, and a large and active community of over 200,000 players. Among the reasons for the popularity of BBO are that users can play casually or in tournaments, and the presence of game-improving facilities such as live broadcasting of important events and kibitzing of regular BBO games.

BBO has some built-in support for developing connections between members: it offers its players the possibility to organize public or private clubs, a mechanism for creating and using lists of friends and enemies, and various player filtering options such as by nationality and by skill. However, the links created between players through these lists are not publicly available, so players do not benefit from the formation of social networks, for example through friends-of-friends exchanges. In lack of social incentives, quitters and cheaters (players can use instant messaging to pass unauthorized information to each other) can still ruin the gameplay experience of BBO players. To cope with this situation, groups of players have started to organize into online bridge clubs that function as social networks above the BBO platform.

C. BBO Fans: A BBO-Based, Online Bridge Club

In this work we focus on BBO Fans, a large online bridge club based on the BBO platform. This club offers to its over 8,000 registered members 6 daily tournaments (3 individual and 3 for pairs of members), directed by volunteers who are members of the club. Unlike other player-created clubs, BBO Fans accepts members of all nationalities and of various skill. BBO Fans exploits many of the features that BBO is offering for community building. The default structure of individual tournaments requires each player to pair random partners, usually for 1-2 hands played with each of 4-8 different partners; having 3 such tournaments daily should facilitate the development of a community inside the bridge club. The players get acquainted during individual tournaments and may consequently take part in pairs tournaments, where all hands are played with the same partner. Membership registration is free, which may attract many members that play as a relaxation after work hours; such players may not be interested in participating regularly in club tournaments, and may not be willing to form long-term partnerships. We conclude that BBO Fans is a good target for our online social gaming analysis.

III. Our Method for Social Gaming Analysis

In this section we present our method for creating and analyzing the social graph of the BBO Fans community. We model any online bridge community as a general undirected graph $G = (V, E)$, where V is the set of nodes (bridge players) and E is the set of edges (pair play relationships). An undirected graph is a good model because the edges are based on the pair play relationships, which are symmetric. For this work we are only interested in the BBO Fans graph, that is, in the subgraph of the BBO graph that includes all the bridge players from the BBO Fans community, all the bridge players with or against whom BBO Fans players have played, and the pair play relationships between them. We describe in the following our method for creating and analyzing the BBO Fans graph.

A. Data Collection

In our method, any web site presenting BBO and BBO Fans data can be a data source, as opposed to actual system logs. Thus, our method does not require administrative-level access to data, which is often unavailable to other researchers for business and even legal reasons. However, the data collection technique must be carefully selected, so as not to bias the results.

We identify two methods for collecting the data necessary to build the graph, complete coverage and sampling. Complete coverage techniques collect information about all the nodes and edges in the real graph. In contrast, sampling techniques collect information about a subset of the nodes and edges in the real graph, and then infer the properties of the complete graph. For our data source (web sites), complete coverage techniques may require orders of magnitude more computational and storage resources than sampling, but do not bias the data and guarantee the presence of a ground truth. Countering data bias and the lack of a ground truth are major challenges in large-scale graph sampling, with various solutions for the Web [9] and P2P [10], [11] domains, and early proposals for social graphs [12], [13]. We therefore opt for complete coverage.

The BBO website provides complete hand records for any player in the last six weeks, but no index of its players. To address this problem, our implementation of complete coverage is based on a two-step, exhaustive web site crawl. First, we collect a complete list of players from the official community website. The implicit assumption that the collected player data also includes the BBO user name, which holds for BBO Fans, is motivated by the strong incentive of community administrators to facilitate member discovery and inter-member contacts. Second, we collect the hand records for each BBO Fans player using the BBO website.

B. Data Analysis

Like many other social (gaming) networks, BBO Fans does not define the social links among its users. Thus, we begin our analysis with the automatic extraction of social relationships. In light of the special relationship that is built among bridge pairs, (see Section II) we consider two players to be socially connected if they have played a number of hands as partners. Let parameter *p* of our automatic extraction algorithm be the minimal (threshold) number of hands played by two socially-connected players; given a value for *p*, our algorithm traverses the dataset and counts pairing events, then builds the graph corresponding to the identified social connections. We analyze using traditional social network analysis techniques [14] each extracted graph: we detect the connected components (*communities*), we choose the largest connected component, and we measure the clustering coefficient. The clustering coefficient shows the degree to which the nodes tend to cluster together. The formula for the clustering coefficient in an undirected graph is:

$$\bar{C} = \frac{1}{n} \sum_{i=1}^{n} C_i$$

where n is the number of nodes in the graph and C_i is the local clustering coefficient. The local clustering coefficient is defined for undirected graphs as:

$$C_i = \frac{2|e_{jk}|}{k_i * k_{i-1}}$$

where e_{jk} are edges in the graph and v_j, v_k are adjacent to v_i. A large clustering coefficient shows that the graph represents a small world network [14].

We also identify in the extracted graphs four types of bridge players, the community builder, the community member, the random player, and the faithful player, which we define as follows.

The *community builder* is very active, playing a large number of hands with a large number of players. Community builders represent a small but relevant part of the community: they spend much time online and help maintaining the community; thus, they are valuable members for the owners of the website. This type can be identified as having a large connectivity degree, even for large values of *p*.

The *community member* is the player who knows other people in the community and enjoys playing with them. He usually plays with his friends and/or with players of comparable skill. To retain such players, the community needs to be structured according to their preferences; this explains why many online bridge clubs are skill-based or region-based, or even friends-only. Skill-based communities bring together players with similar skill, but sometimes adopt weaker players and help them evolve, or are visited by stronger players. Similarly, region-based communities gather people who can speak the same language (often not English). BBO Fans does not build exclusive skill-based or region-based relationships, but allows players to specify their skill and nationality, and ranks the players according to their club tournament results. The community member has intermediate values of the degree for larger values of *p* - meaning he plays a relevant number of hands with an intermediate number of partners.

The *random player* enjoys to play bridge but he does not have a stable partner and is not part of a community. This player type joins randomly an open online table, or (rarely) plays in individual tournaments. These players have a relatively large degree for *p*=1 or 2, but the degree decreases rapidly as *p* increases.

The *faithful player* has one or two stable partners. This player type pairs rarely with another player. Although not active in the community, faithful players are probably the most active players. They have a degree larger than 0 for large values of *p* and the degree does not increase much as *p* decreases.

The analysis is performed on two sets of graphs. The first set of graphs is created using the automatic extraction

TABLE I

SUMMARY OF THE BBO FANS TRACE CHARACTERISTICS.

Metric	Value
Users, All (incl. BBOFans)	142,401
Users, BBOFans	8,609
Hands, All (incl. BBOFans)	3,115,536
Hands, 1+ BBOFans pair	565,799
Hands, only BBOFans	116,237

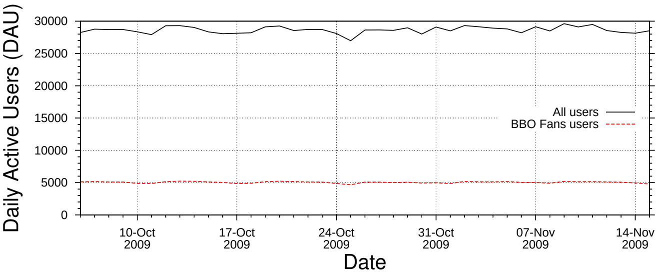

Fig. 1. Number of daily active players.

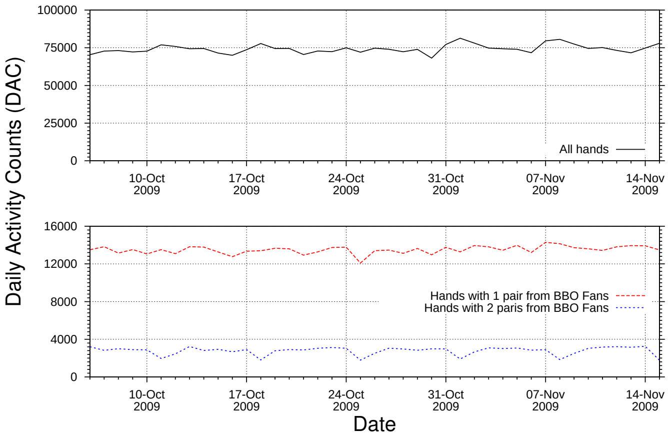

Fig. 2. Daily Activity Count: number of hands over time: (top) all hands; (bottom) only hands with at least one pair from BBO Friends and only hands with both pairs from BBO Friends.

of social connections when considering from the complete dataset the players with at least 20 played hands. The reason for filtering out players with very few played hands is that the information about them is either incomplete (we collect complete information for BBO Fans players, but only some information about non-BBO Fans players that play on BBO with BBO Fans players), or these players are inactive from a community point of view. The second set of graphs is created similarly, but when considering only the hands for which all players are BBO Fans members.

IV. ANALYSIS RESULTS

In this section we present an analysis of the activity levels and community structure exhibited by the BBO Fans data.

A. BBO Fans Data

We have collected using the method described in Section III-A data for 40 full days, from September 5 to October 14, 2009; Table I summarizes the characteristics of this dataset. Out of a total of 9,615 BBO Fans players, 8,609 have played at least one hand during the observed period. Each observed day registers over 75,000 played hands, or above 9 hands/player. The observed hands do not involve only BBO Fans players; it turns out that BBO Fans players often choose partners and opponents outside their community–BBO Fans players represent only 6% of the players we have observed. Moreover, only 18% of the observed hands include a complete pair of BBO Fans players, and under 4% of the hands are played only between BBO Fans players.

B. Activity Levels

1) Number of Players and Hands: The number of daily active users is a good indicator of the activity of an online service. Similar to previous work [15], [1], we define the number of daily active users (DAU) for a day as the number of unique users that use the service (play bridge hands) at least once during that day. Figure 1 depicts the evolution of the DAU over time, when considering all the players observed in our traces and only the players in BBO Fans. The DAU when considering all players is about 28,500, which places the impact of the BBO Fans community on par with the third quartile of the top 200 FaceBook applications in 2008 [1] and around the top 500 FaceBook application in 2010[2]. The DAU when considering only BBO Fans players is about 5,000, around the top 1000 FaceBook application in 2010, but two orders of magnitude lower than the peaks of popular massively multiplayer online games [16]. We conclude that BBO Fans is a large, active community.

We also define the number of daily activity count (DAC) for a day as the number of unique service invocations (number of played hands) during that day. The DAC characterizes the stress put on the service provider by the users, and can be used to quantify future system resource requirements or to explain past service failures. Figure 2 depicts the number of hands in our traces when considering all the observed hands (overall DAC), and when one or both pairs are formed with BBO Fans players. The overall DAC is around 75,000; since each hand involves bidding then playing 52 cards, the overall DAC of BBO Fans is on par with that of similarly-sized social gaming applications such as FaceBook's Fighters Club [1]. However, the hands where BBO Fans players cooperate exhibit much lower DACs: around 13,000 for at least one pair and below 4,000 for both pairs. We conclude that the BBO Fans community generates service requests similarly to FaceBook social gaming applications, but not due to BBO Fans players playing among themselves.

2) Time Patterns: System design and resource provisioning processes often rely on understanding the presence of time and especially daily patterns in service requests. Figure 3 depicts the hourly number of hands for the hands in our dataset. There is a strong hourly pattern, with late evening and early night hours (hours 20pm–3am) being the peak of the playing time; we call this the overall daily pattern. We also observe an

[2]DAU of FaceBook applications data from `http://www.developeranalytics.com/`, collected April 2010.

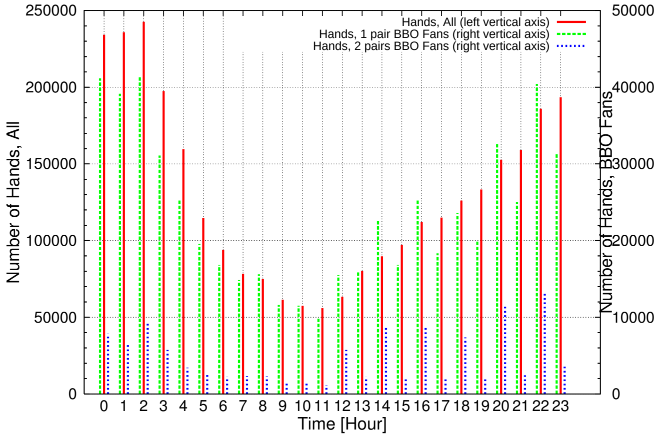

Fig. 3. Hourly patterns in the number of hands.

TABLE II
COMMUNITY STRUCTURE CHARACTERISTICS FOR THE BBO FANS CLUB. NC IS THE NUMBER OF COMMUNITIES; CS IS THE MEAN COMMUNITY SIZE; NLCC IS THE NUMBER OF NODES IN THE LARGEST CONNECTED COMPONENT; CC IS THE MEAN CLUSTERING COEFFICIENT.

p	# of edges	NC	NLCC	CS	Avg. Degree	CC
1	1,100,647	351	71,771	206.42	15.19	0.06
2	652,570	470	71,559	154.16	9.00	0.05
5	307,069	3,382	68,094	21.42	4.23	0.05
10	98,654	24,175	44,705	2.99	1.36	0.07
20	30,249	48,670	17,856	1.49	0.41	0.09
50	9,385	63,311	2,927	1.14	0.13	0.05
100	3,824	68,655	33	1.05	0.05	0.00
200	1,339	71,116	7	1.02	0.02	0.00
500	210	72,245	3	1.01	0,00	0.00
1000	24	72,431	2	1.00	0,00	0.00

increase in the number of hands played only among BBO Fans players for even hours, starting from 12pm and ending with 2am; this pattern coexists with the overall daily pattern for the hands played with at least one pair from BBO Fans. We conclude that there exists a strong overall daily pattern, which is coupled exclusively among the BBO Fans players with a weaker daily play pattern.

C. Community Structure

The *p* parameter together with the degree parameter provide the classification into four types of players that we have described in the previous section. We can also observe the distribution of each player type in the community.

The community builders are the 5% who have played 10 hands with at least 15 partners and they are best represented by the almost one percent who have played at least 20 hands with at least 10 partners. They are probably the most influential people in the community, having a large number of solid connections. Our future research will examin this influence and the distribution of community builders' regular partners (community members and/or random players).

The community members have the degree between 3 and 10 with $p \in [5, 20]$. They represent 30-40% of the entire player base. This is the most consistent group, having a large number of relevant connections.

The random players are the 30% who have the degree larger than 25 for $p = 1$ and equal with 0 for $p = 10$. They are not influential inside the community as their relations are unsubstantial - they spend very little time with their partners.

The faithful players are the 20-30% who have the degree at least 1 for *p*=20 and between 1 and 3 for $p = 50$. Considering $p = [20, 50]$ and that a hand played online averages 6 minutes, it means that these players have spent between 2 and 5 hours per month playing together, sometimes even more.

We next look at the clustering coefficient as showed in table II. Its values for different values of *p* show that a good value for $p = 20$—the maximum value of the clustering coefficient for our set. The clustering coefficient for our network for $p = 20$ is much less than the value for Nazir's Facebook applications [1] but close to the one generally accepted for the Web (0.31-0.81). Its value is also less than the ones measured in [17] for Orkut, Youtube, Flickr and LiveJournal (0.136-0.313). We attribute this to the relations developed on BBO being much more consistent than the more shallow relations in other social networks. These BBO relations do not imply acknowledging a connection to someone, but they imply spending an actual hour once a month playing with the other person. Players in stable partnerships prefer to play with their partner whenever he is available, otherwise they might pair some acquaintance or some random player. When the partner logs in, there is a slight chance to keep playing with the same players, therefore the small clustering coefficient. Another reason why the clustering coefficient is so small is that we didn't consider frequent games between same pairs as social relations. When expanding this analysis we should add these relations, since repeatedly choosing the same opponents implies you enjoy playing against them.

When analyzing the BBO Fans bridge club we discover that for p=1 we have 1206 unconnected nodes - players who played none of the BBO Fans tournaments and with no other member of BBO Fans in the observed period. They are not inactive, as this number doesn't appear in the general analysis. Only 40% of the player base have played together more than 10 hands in a month (a tournament typically has 8 hands) and the clustering coefficient has very small values for $p > 1$. Finally, the degree is quite high for $p = 1$—40% of the players in BBO Fans have played at least a hand with other members of the club. However, this is due mainly to the frequent individual tournaments. The degree decreases very fast for larger values of p. Only 5% of the members have played at least 5 hands with more than 10 partners and less than 1% played more than 10 hands with more than 10 partners from the club. The results confirm that BBO Fans is not a small world network, but we can consider it a weakly tied community.

V. RELATED WORK

Much work has been put recently into the analysis of (large-scale) social networks, including [2], [14], [6], [7], [18], [4], [3], [1]. In contrast with these studies, our work focuses on

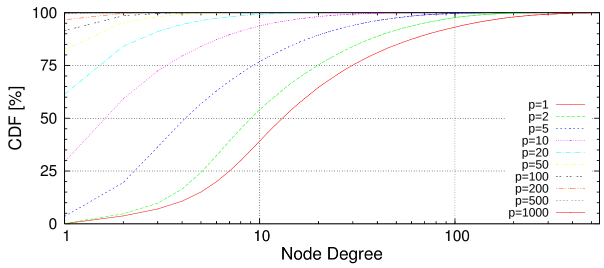

Fig. 4. Node degree vs parameter p for all players.

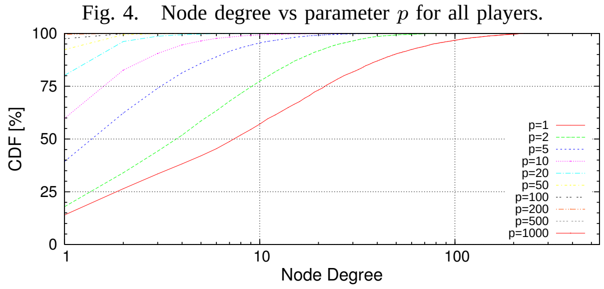

Fig. 5. Node degree vs parameter p for BBO Fans players.

bridge, which is a complex onine social game with a large player base. Our work also proposes a novel way to extract social relationships from game sessions, and a new taxonomy of player behaviors.

From the studies before 1990s, Milton's analysis of an email chain [18] and Zachary's early evaluation of a real-world karate club [4], [19], have set the basis of empirical evaluation of the characteristics of social networks. Extensive analysis on these networks has revealed that social networks are often exhibiting 6 degrees of separation [14], have tightly-coupled components [6], [7], [18], [4], [3], and that smaller networks combine over time into larger communities until an upper threshold is reached [5], [7].

Closest to our work is the analysis of large-scale online networks. Different researchers have studied the social networks FaceBook, Orkut, LiveJournal, Youtube, and Flickr [6], [17], the instant messaging network Microsoft Messenger [7], the online game World of Warcraft [8], and the online social game Fighters Club [1]. In contrast with this body of research, ours is the first study of a complex online social game; our findings show that this game exhibits new characteristics, which distinguish it from previously studied social and gaming applications.

VI. Conclusion and Ongoing Work

Motivated by the lack of knowledge about online social gaming, which is an Internet application with hundreds of millions of users, in this work we have introduced and used a new method for analysing online social gaming communities. Our method stands out in comparison with previous work through its focus, ability of identifying community relationships from gaming sessions, and a new player type taxonomy with implications on community building and operation. We have demonstrated the use of the proposed method in practice by collecting a large-scale dataset from BBO Fans, a large online bridge club, and by analyzing the collected dataset. Our analysis has characterized both the activity levels and the community structure of BBO Fans, revealing it as an active community with daily activity patterns, despite its community structure *not* being a small-world [14].

We are currently investigating new ways to detect communities for networks lacking such information, and performing a more in-depth analysis of the BBO Fans club and its underlying gaming platform. For the future, we would like to validate our user type models in other social gaming networks.

References

[1] A. Nazir, S. Raza, and C.-N. Chuah, "Unveiling FaceBook: a measurement study of social network based applications," in *IMC*, 2008, pp. 43–56.

[2] M. Granovetter, "The Strength of Weak Ties: A Network Theory Revisited," *Sociological Theory*, vol. 1, p. 201, 1983.

[3] M. Girvan and M. E. J. Newman, "Community structure in social and biological networks," *Proc Natl Acad Sci USA*, vol. 99, no. 12, pp. 7821–6, June 2002.

[4] M. E. J. Newman, "Detecting community structure in networks," *The European Physical Journal B*, vol. 38, 2004.

[5] J. Leskovec, J. M. Kleinberg, and C. Faloutsos, "Graphs over time: densification laws, shrinking diameters and possible explanations," in *KDD*, 2005, pp. 177–187.

[6] J. Leskovec, K. J. Lang, A. Dasgupta, and M. W. Mahoney, "Statistical properties of community structure in large social and information networks," in *WWW*, 2008, pp. 695–704.

[7] J. Leskovec and E. Horvitz, "Planetary-scale views on a large instant-messaging network," in *WWW*, 2008, pp. 915–924.

[8] N. Ducheneaut, N. Yee, E. Nickell, and R. J. Moore, "The life and death of online gaming communities," in *CHI*, 2007, p. 839.

[9] M. R. Henzinger, A. Heydon, M. Mitzenmacher, and M. Najork, "On near-uniform URL sampling," *Com.Net.*, vol. 33, no. 1-6, pp. 295–308, 2000.

[10] D. Stutzbach, R. Rejaie, N. G. Duffield, S. Sen, and W. Willinger, "On unbiased sampling for unstructured peer-to-peer networks," *IEEE/ACM Trans. Netw.*, vol. 17, no. 2, pp. 377–390, 2009.

[11] A. Iosup, P. Garbacki, J. A. Pouwelse, and D. H. J. Epema, "Correlating topology and path characteristics of overlay networks and the internet," in *CCGRID*, 2006, p. 10.

[12] B. Krishnamurthy, P. Gill, and M. Arlitt, "A few chirps about Twitter," in *WOSP '08: Proceedings of the first workshop on Online social networks*. New York, NY, USA: ACM, 2008, pp. 19–24.

[13] M. Gjoka, M. Kurant, C. T. Butts, and A. Markopoulou, "A walk in facebook: Uniform sampling of users in online social networks," *CoRR*, vol. abs/0906.0060, 2009.

[14] D. J. Watts and S. H. Strogatz, "Collective dynamics of small-world networks," *Nature*, vol. 393, no. 6684, pp. 440–442, June 1998.

[15] M. Cha, H. Kwak, P. Rodriguez, Y.-Y. Ahn, and S. B. Moon, "I tube, you tube, everybody tubes: analyzing the world's largest user generated content video system," in *IMC*, 2007, pp. 1–14.

[16] V. Nae, A. Iosup, S. Podlipnig, R. Prodan, D. H. J. Epema, and T. Fahringer, "Efficient management of data center resources for massively multiplayer online games," in *SC*, 2008.

[17] A. Mislove, M. Marcon, K. P. Gummadi, P. Druschel, and B. Bhattacharjee, "Measurement and analysis of online social networks," in *IMC*, 2007, p. 29.

[18] J. M. Kleinberg, "The convergence of social and technological networks," *Commun. ACM*, vol. 51, no. 11, pp. 66–72, 2008.

[19] M. Newman, "Modularity and community structure in networks," *Proc. Nat. Acad. Sci., USA*, vol. 103, no. 23, pp. 8577–8582, 2006.