An Analysis of Social Gaming Networks in Online and Face to Face Bridge Communities

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ABSTRACT

Online social games are Internet-based games that use the social networks formed by players to extend in-game functionality. For example, gamers participating in the BBO Fans community combine online bridge play with social networking. Despite an increase in the popularity of online social gaming—currently, there exist over one million online bridge players—, and of decades of research on social networks, the activity characteristics and the community structure of online social gaming remain relatively unknown. In this work we investigate and contrast these aspects for two bridge communities, BBO Fans (online) and Locomotiva (face to face). We propose the use of playing relationships instead of traditional social relationships such as friends and friends-of-friends. Using long-term, large-scale data we have collected from both the online and face to face bridge communities, we analyze user behavior, social network structure, and playing style in bridge communities. We find many similar characteristics in the two studied communities, but we also find more variation in the activity levels and fewer stable partnerships for the face to face bridge community.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Database applications—*Data mining*;
C.4 [**Performance of Systems**]: Measurement techniques;
K.8.0 [**Personal Computing**]: General—*Games*;
C.2.4 [**Computer-Communication Networks**]: Distributed Systems—*Client/Server*;
K.6.2 [**Management of Computing and Information Systems**]: Installation Management—*Performance and usage measurement.*

General Terms

Measurement, Experimentation, Performance, Human Factors.

Keywords

Social networks, Community structure, Gaming, Online social networks, Face to face social networks, Bridge, User behavior, Playing style.

1. INTRODUCTION

Traditional games have recently started to become online social games. Once accessible only through face to face encounters or slow mail exchanges, games such as bridge, chess, and go are now played online by millions of gamers. Other online social games, such as FarmVille and Cafe World, already exploit the characteristics of the social network formed by gamers to improve and grow the online communities. For example, FarmVille routinely gives high-level (expert) players new items and broadcasts gameplay achievements through the social links. User behavior, social network, and play style analysis are not new research topics [3, 6–8], but the study of online social gaming communities provides a new domain of application with the potential to influence millions of lives. Moreover, a good understanding of online social networks, which are large-scale Internet-based applications, may shape the way we engineer large-scale socio-technical systems. In this work we analyze and compare two communities of bridge players, Locomotiva and BBO Fans.

In contrast to many other social networks, which are based on cooperation and friendship among participants, gaming social networks may also grow due to an adversarial context. Due to this context, players may be motivated to be active longer than they would in a traditional social network. As shown recently [14, Ch.5], the adversarial context present in games also leads to two additional prosocial emotions[1], happy social embarrassment (being happy for getting embarrassed in front of friends) and vicarious pride (being happy for the success of your students), which complement the prosocial emotions found in traditional social networks,

[1]Prosocial emotions are "emotions that are directed toward others." [14, p.82]

such as compassion, admiration, and devotion. Thus, studying online social gaming may lead to complementary results to many of the classic social network studies [8, 21]. Additionally, online social gaming studies may complement earlier studies on player activity and behavior [3, 6] and more recent social network studies [11–13].

Although several recent studies have focused on online social gaming, analyzing the community behavior emerging in the Massively Multiplayer Role-Playing Game World of Warcraft [5] or the friendship relations for the casual online social game Fighters Club [16]. the previous online social network and social gaming studies rely on networks in which links are precisely specified before the networks are observed, for example as "guild members" or "FaceBook friends" relationships, respectively. In contrast, in this work we set to investigate a community of online players where social relationships between the players are not directly specified, but may be established and strengthened by every game session.

In this work we conduct the first study that compares the characteristics of online and face to face bridge communities; our comparative study has a twofold motivation. First, the online social games that extend traditional games may add new dimensions to existing studies of user behavior, social networking, and play style: the presence of a "ground truth", the presence of a teacher-student relation, etc. The "ground truth" can be obtained from the smaller, face to face game communities, which can be analyzed in detail [17, 18] and for which expert confirmation of the findings is usually available. Many traditional games have developed conventional plays, such as openings and endings in chess, and conventions in bridge; for these games, a few of the more experienced players may have the additional community role of attracting and teaching new players. Second, the combined study of online and face to face social networks of the same (traditional) game may allow scientists to validate their theories and findings when knowledge about either the online or the face to face environments already exists.

Our main research question is *What are the unique characteristics of an online bridge community?* To answer this question, we investigate the characteristics of two bridge communities, one face to face (Locomotiva) and one online (BBO Fans), with four main contributions:

1. We collect two long-term bridge community datasets (Section 3). This extends our previous work [19] with another long-term dataset, which can also be used as "ground truth" for our algorithmic findings.
2. We propose a method for analyzing user behavior, social networking, and playing style in online and face to face bridge communities (Section 4). We extend our previous work [1, 19] primarily with a formalism for social connectivity based on playing relationships. Our method allows us to validate algorithmic findings through human expert advice, and to automatically tune the parameters of the automatic analysis of the online community using values found from the face to face community analysis.
3. We demonstrate the use of the proposed method by analyzing two popular and active bridge communities, the BBO Fans online bridge community and the Locomotiva face to face bridge community (Section 5).
4. We discuss potential applications for our findings (Section 6).

Our work is carried within the context of the ongoing project BridgeHelper (`http://www.bridgehelper.org`), which aims to improve the game of bridge for every (online) player. Within this project, we aim to show that social network analysis and computer system design can become catalysts for a variety of functions associated with the social game of bridge, from rating of players to to pairing players, and from tutoring players to providing incentives to join and participate in the game.

2. BACKGROUND ON BRIDGE

Bridge is a popular game for groups of four people playing in pairs. Bridge was the only team game at the last World Mind Sports Games (Beijing, 2008), which motivates making bridge our focus. Specifically, we are interested in duplicate bridge, where the same distribution of cards is played at several tables and the winner is decided by comparing the results at each table. Competing only against players with identical cards is meant to reduce the luck factor and enhance the skill factor in winning.

A single game in bridge is called a *hand*. A bridge hand lasts for 6-8 minutes, enough time for the players to bid, play, and comment on the hand. In the bidding phase. players take turns in specifying a number of tricks and a trump suit (i.e., "1 club" bids the taking of 7 out of 13 tricks, where club is the trump suit). The bidding mechanism allows any bid to be overridden with a higher bid by any of the players next in turn. This makes it possible for partners to assign arbitrary, conventional meanings to bids. The bidding is followed by the play of the hand, where the side who bid highest tries to win as many tricks as possible with the specified suit as trump. In the play, the partners may exchange information through the cards they choose to play, which have a pre-established, conventional significance. The rules of the game encourage even the weakest pairs to have many conventional agreements subject to continuous refinement often acquired over a long-term, social relationship.

There are two types of bridge games, the pairs game and the team game. In a pairs game, each hand is played at a number of tables; after the play all the recorded scores are compared. A pairs game can be run as a tournament or as casual club play. In tournaments, all pairs play a fixed number of hands, which makes it possible to determine a winner fairly. In casual club play, gamers can play for as long as they want, but the result of each player will be obtained by comparing only on the hands of that player with the restricted set of players who happened to play the same hand. In casual club play, only individual scores are assigned and no ranking is determined. A team game takes place at exactly two tables. Each team is represented by two pairs, one seated at each table. In team games, each hand's result is only compared to the result at the other table; the winner is determined by adding up the results of all comparisons.

Bridge player communities are often organized in (local) clubs where players meet and play face to face in a relaxed and friendly environment. Such clubs have fixed schedules and are not easily reachable by everybody; as a result, club activity rarely amounts to over 15 hours/week. Many bridge players have (also) joined online bridge communities such as Bridge Base Online and Yahoo Bridge (free play sites), and OKBridge, Swan Games, and Bridge Club Live (subscription sites).

What makes bridge special for our purposes is its reliance

Table 1: The bridge community datasets.

Characteristic	Locomotiva	BBO	BBO Fans
Period	January 1–December 31, 2009	September 5–October 15, 2009	
Tournaments/Week	4	n/a	21
Players	275	142,401	8,609
Hands	28,756	3,115,536	565,799

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 [20]. The play experience is often gathered over a long period of time and may be paralleled by a long-term, social relationship.

3. BRIDGE COMMUNITY DATASETS

We have collected two datasets, each corresponding to the long-term operation of a large bridge community. Specifically, we have collected information about one face to face bridge community, Locomotiva, and one online community, BBO Fans. The BBO Fans community uses the services of a general online bridge platform, BBO, through which they may play bridge with non-BBO Fans members. We explain in the remainder of this section, in turn, the characteristics of each community; Table 1 summarizes the properties of the collected datasets.

3.1 Locomotiva: A Face to Face Bridge Club

The Locomotiva Bridge Club (Locomotiva) is a traditional bridge club located in the center of Bucharest, Romania. The club's activity involves 4 tournaments per week and around 15 bigger events per year. A regular club tournament gathers 20-60 people and takes about 4 hours. The club attracts several of the best players in Romania, including players who have been or are the national champions. The total number of active players, which for the data studied in this work is 275, is large for a face to face club; although larger clubs exist, many other clubs operate with less than 100 active players.

Our expert knowledge about the organization and personal relationships in this community make it an ideal study item, and a good "ground truth" for the analysis method we introduce in Section 4. Moreover, with the exception of its large size, Locomotiva is a typical face to face community; most of the clubs in Romania[2], France[3], the Netherlands[4], the UK[5], and the US[6] have a similar organization and operation.

We have collected from Locomotiva one full year of tournament records, between January 1 and December 31, 2009. The original data contain both elements that are manually entered and automatically collected data. Tournaments are set-up by manually entering into the tournament management software (Magic Contest) the names of the tournaments participants. The club is equipped with a wireless scoring system, which provides real-time results to the tournament management software. We have collected the data recorded by Magic Contest, which includes for Locomotiva all the games played between regular club members in regular and special tournaments. Because the same player may be recorded by the various human operators under different names in the system (for example, John Smith and Smith, J.), the manually entered data must be cleaned. We have used our expert knowledge about the community to create an automated tool that eliminates the naming errors for the almost 30,000 hands played in 2009; our automated data cleaning tool has supported Locomotiva's player ranking system throughout 2010 and is currently in use at the club.

3.2 BBO Fans: An Online Bridge Club

We also focus in this work on Bridge Base Online (BBO), which is one the most popular free platforms for online bridge. BBO attracts many professional and world-class players, and a large and active community of over 200,000 players. BBO users can play casually, in pairs tournaments, or in team matches. They can also watch live broadcasts of important events or regular games between other users.

Similarly to Locomotiva for face to face bridge, BBO is a typical, albeit much larger than the average, online venue for bridge. Other online bridge platforms, such as Yahoo (the Bridge tables), Pogo, OKBridge, Swan Games, and Bridge Club Live are similarly organized and operated. The subscription-based sites OKBridge, Swan Games, and Bridge Club Live are much smaller than BBO. Our in-depth knowledge of the BBO platform derives from active use.

BBO has some built-in support for connecting its members: players can organize in public or private clubs, manage lists of friends and adversaries, and search for other players by features such as nationality and skill. However, the links created 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 and use the BBO platform only to play.

We focus in this work on the BBO players that are also

[2]For example, Bridge Club Brasov [Online] Available: `http://bridgeclubbrasov.blogspot.com` and Inter-Macedonia Bridge Club [Online] Available: `http://intermacedonia-bridgeclub.blogspot.com`.

[3]List of all clubs affiliated with the French Bridge Federation, by region. [Online] Available: `http://www.ffbridge.asso.fr/decouvrir/clubs.php?m=1,21`.

[4]For example, Delft Bridge Club [Online] Available: `http://www.delftsebridgeclub.nl`.

[5]For example, Manchester Bridge Club [Online] Available: `http://www.manchesterbridge.co.uk/`.

[6]List of clubs in the New York area [Online] Available: `http://web2.acbl.org/As400/clubs/allClubs/uclub-NY.htm`.

members of the BBO Fans community[7], which is a large online bridge community (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 skill level. BBO Fans exploits many of the features that BBO is offering for community building. The mechanism of individual tournaments requires each player to play 1-2 hands with each of 4-8 different random 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 register as partners in pairs tournaments. Membership is free, which may attract gamers that play for 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 have collected data for the BBO Fans community and their games played through the BBO platform for 40 full days, from September 5 to October 14, 2009. Our data collection comprises two steps; for details we refer to our previous work [19]. First, we collect a complete list of players from the official community website. The list includes the BBO user name, which holds for many other BBO-based communities and 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 Web 2.0 API for direct access to player records. Since BBO was not built for massive data retrieval, the size of the collected dataset was large and some of our more aggressive crawlers got banned for a period of over three months. As a result, we have stopped our data collection process after achieving our goal of collecting over one month of data; although we are currently collecting new data, we do not have in this work a longer overlapping period between the BBO and Locomotiva datasets.

4. METHOD OF ANALYSIS

In this section we present our method for analyzing bridge communities. The main challenge is building the social graph of the BBO Fans community, for which we do not have social relationship or "ground truth" information.

4.1 User Behavior

We investigate two aspects of user behavior, temporal and quantitative. The temporal aspect refers to the presence of players in the online social game. We analyze the *number of daily active users*, as an indicator of social network persistence, and the *number of weekly player joins*, as an indicator of social network growth. The number of daily active users can be used to compare face to face and online (bridge) communities, and is commonly used in system design and resource provisioning for massive online systems [16]. We define the join of a player as the first moment when the player is observed in the collected data. We account the joins over weekly intervals because face to face bridge communities often schedule different types of tournaments over the course of each week; new players may participate first in the tournaments that suit their interests.

The quantitative aspect refers to the contribution to the game of and the resource consumption incurred by players, while being present in the system. We analyze in this work the *number of hands played* over daily and weekly periods, as an indicator of contribution, and the *network traffic*, as an indicator of consumption. We characterize the network traffic of the game client through an aggregate of the inbound and outbound bandwidth and packets. While the network traffic may be analyzed in greater detail [3,6,9], and both for the client and the server [6], our characterization can give a first-order estimate of the resource-related challenges raised by online bridge.

4.2 Social Gaming

Play Relationship: Friendship-based social networks have been modeled often as undirected graphs [8, 21]. Similarly, we model online bridge communities as general undirected graphs $G = (V, E)$, where V is the set of nodes (bridge players) and E is the set of edges. But *what is an edge in this graph?* The edges should represent social relations, together forming a symmetric and transitive relationship. Thus, the question becomes *what is a social relation in a bridge community?* We can consider that two bridge players have a social relation if they relate strongly through play: they have met online, have played as partners and/or opponents a number of hands (aspect P in our formalism), or have played in a number of sessions together as partners and/or opponents (S). We have previously [19] investigated this play-related relationship concept, but using only the "number of hands played together" as an indicator of social relationship. One of the main contributions of this work is extending this investigation with (many) other types of playing relationships. We also consider in this work that playing relationships are cooperative (P_+, S_+) or adversarial (P_-, S_-), and consider not only single-aspect but also multi-aspect criteria (such as "$(P_+ \geq 24)\ AND\ (S_+ \geq 3))\ OR\ ((P_- \geq 48)\ AND\ (S_- \geq 5)$").

Social Gaming Network: Our method generates, for each play relationship criterion specified by the analyst, the graph $G' = (V, E')$, where V is the original set of bridge players, but E' is the set of edges $e = (u, v)$ for which the criterion is satisfied for the players u and v. For the multi-aspect criterion example presented earlier in this section, E' would contain edges between each pair of players that have played together at least 24 hands in at least 3 sessions, or have played as opponents at least 48 hands in at least 5 sessions.

Modularity: We extracts the distinct communities from each generated graph G' using a greedy algorithm [4] that maximizes the modularity of the graph, where modularity quantifies the quality of a division of a social network in communities. The *modularity* of a division of a graph's nodes into groups is the fraction of the graph's edges occurring only within the groups, from which the expected fraction if edges were distributed uniformly random is subtracted.

This method can be applied to any bridge graph, which allows us to compare the characteristics of Locomotiva and BBO Fans. Additionally, we can use expert knowledge regarding Locomotiva to validate algorithmic findings; we do not have such information for BBO Fans. Thus, we analyze our community data in two steps. We first analyze the

[7]The BBO Fans community. [Online] Available: `www.bbofans.com/`.

data taken from Locomotiva for different play relationship criteria (combinations of values and parameters P and S). Then, we use the combination of parameters validated by the Locomotiva experts to analyze the BBO Fans bridge club. Besides using a “ground truth”, this approach allows us to avoid the time- and resource-wise costly social networking analysis on the large-scale BBO Fans/BBO community.

4.3 Playing Style

In our method, the playing style investigation analyzes how players relate to their partners and with the other members in the club. Thus, we investigate the roles and functions of players as members of bridge-playing communities. As a refinement of the taxonomy introduced in our previous work [19], we define four types of bridge players based on the amount and intensity of playing relationships: the community builder, the community member, the random player, and the faithful player.

The *community builders* are very active, playing a large number of hands with a large number of players. Community builders are a small but valuable category, as they help maintaining and growing the community. This type can be identified as having a large connectivity degree, even for large values of P (see Section 4.2).

The *community members* have each a moderate number of relations in the community. They usually play with 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).

Last, the *random players* enjoy to play bridge but do not have a stable partner and are not part of a community. The *faithful players* have each at most two stable partners. Although not active in the community, faithful players are the most active players.

5. ANALYSIS RESULTS

In this section we present an analysis of the Locomotiva and BBO Fans datasets (see Section 3).

5.1 User Behavior

We use the method introduced in Section 4.1 to analyze the user behavior (activity levels) of Locomotiva and BBO Fans.

Daily activity. We have analyzed the number of players and hands over time for BBO and BBO Fans in our previous work [19]. Our main finding was the presence of a steady daily activity in the BBO Fans community, and similar levels of activity with similarly-sized games on Facebook. We have repeated the process with the Locomotiva dataset, and depicted the results in Figure 1. We find a relatively stable number of played hands, with few specific tournament sizes, see Figure 1(top). As depicted in Figure 1(bottom), we also find a much less stable number of players, which is mainly explained by the different tournament formats, by the overlap between club and national or international tournaments (especially on Fridays), and by holiday and vacation periods.

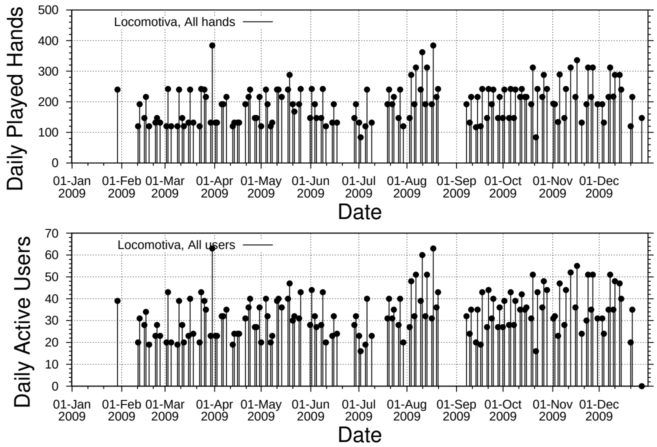

Figure 1: Daily number of (top) played hands; and (bottom) players for Locomotiva. For the top graph, bars of equal height, e.g., vertical axis value of 120, correspond to specific tournament sizes.

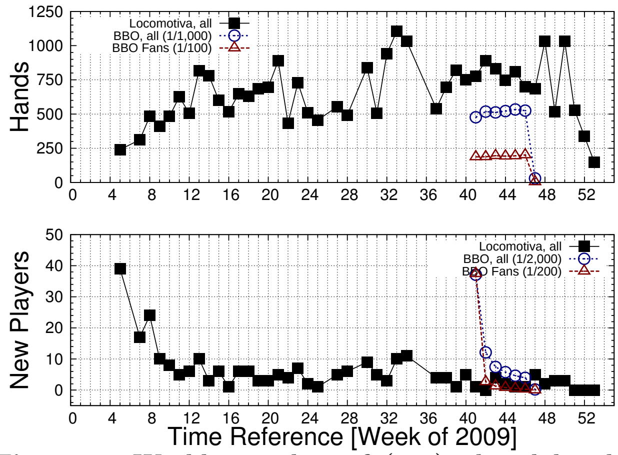

Figure 2: Weekly number of (top) played hands; and (bottom) new player joins. Data for Locomotiva (filled squares), BBO (circles), and BBO Fans (triangles). Values for BBO (BBO Fans) scaled down by a factor of 2,000 (200).

The face to face community exhibits much more variation in number of played hands than the online community. We next look at the weekly number of played hands. Figure 2(top) depicts the weekly number of played hands for Locomotiva, for BBO, and for BBO Fans. The BBO and BBO Fans measurements lead to incomplete data; the last point on their respective curves can be discarded. The horizontal axis in the figure does not include several weeks at the beginning of the year, when Locomotiva is closed. The number of weekly hands fluctuates strongly for Locomotiva, but is relatively stable for BBO and BBO Fans. For Locomotiva, the smallest number of hands played in any one week (observed for week 53 of 2009) is an order of magnitude smaller than the peak (week 33).

The face to face bridge community exhibits many player joins over the course of the year; the online community is relatively closed. The joining of new players is another time-varying community characteristic. We expect to find a “first-sample” effect, where all the players

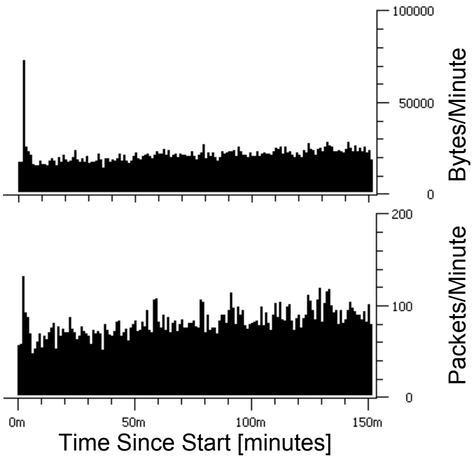

Figure 3: Session network traffic. (top) Bytes per minute; (bottom) Packets per minute.

observed in the first dataset sample are identified as new. Beyond the first sample, we expect the number of new players to fluctuate over time for an open, changing community, and to converge quickly to zero for a closed community. Figure 2(bottom) depicts the weekly number of new players observed for Locomotiva, for BBO, and for BBO Fans. We see that Locomotiva is not a closed community; over 80% (65%) of its players join after the initial week (three weeks), with a fluctuating pattern over the course of the year. While we do not have complete data for BBO and BBO Fans, the data we have indicate a closed community trend; for BBO Fans, less than 15% of its players join after the initial week.

The network traffic per client is low, with small and infrequent packets. We investigate the network traffic per client by carrying out play sessions on BBO using the standard game client provided by the platform; we use Wireshark to record the traffic on an otherwise quiet network. Figure 3 depicts the combined inbound and outbound traffic observed during a typical play session of $2\frac{1}{2}$ hours. Except for a peak at the very start of the session, when the client is updating, the traffic characteristics are relatively stable when aggregated over 1-minute intervals. The bandwidth for this session, depicted in Figure 3(top), is about 20,000 bytes/minute, or 2.4 kilobits per second (kbps). The number of packets, depicted in Figure 3(bottom), increases slightly over the course of the session, from 60 to 100 packets per minute; the average is 1.2 packets per second (pps). In comparison, the average client traffic is 5-8 kbps and 5 pps for a popular MMO Role Playing Game [3], 40 kbps and 20-50 pps for several popular First-Person Shooters [6], and 775 kbps and up to 40 packets per second for a popular virtual world [9]. The small traffic requirements indicate that bridge platforms do not raise significant quality of service challenges in comparison to these online applications.

5.2 Social Gaming

Following the method introduced in Section 4.2, we have first extracted the communities present in Locomotiva using a greedy algorithm [4]. We have only used combinations of cooperative play aspects (P_+ and S_+, see Section 4.2), as adversaries are randomly assigned in most Locomotiva competitions. Table 2 summarizes the main community characteristics observed for Locomotiva for various play relationships. When the multi-aspect criterion includes $P_+ \geq x$, the results obtained with the multi-aspect criterion are very similar or even identical with the results obtained when using the single criterion $P_+ \geq x$. We explain this by the regular structure of the tournaments (sessions) played at Locomotiva (see also Section 4.1); since players rarely leave a tournament, and the number of hands played by each player during each tournament is intended to be stable (20–25 hands), S and P are correlated for Locomotiva.

Table 2: Community structure characteristics for Locomotiva. N is the number of non-isolated nodes; NC is the number of communities; CS is the mean Community Size; Q is the maximum Modularity.

Single-aspect	N	NC	CS	Q
$P_+ \geq 20$	249	35	7.11	0.22
$P_+ \geq 40$	170	35	4.85	0.29
$P_+ \geq 60$	138	29	4.75	0.30
$P_+ \geq 80$	119	27	4.40	0.34
$P_+ \geq 100$	109	28	3.89	0.36
$P_+ \geq 120$	104	30	3.46	0.40
$P_+ \geq 140$	100	30	3.33	0.41
$P_+ \geq 160$	94	28	3.35	0.41
$P_+ \geq 180$	88	29	3.03	0.41
$P_+ \geq 200$	87	30	3.90	0.43
$S_+ \geq 3$	138	29	4.75	0.30
$S_+ \geq 7$	100	30	3.33	0.41
$S_+ \geq 10$	83	30	2.76	0.43
Multi-aspect	N	NC	CS	Q
$(P_+ \geq 80)$ OR $(S_+ \geq 4)$	119	27	4.40	0.34
$(P_+ \geq 160)$ OR $(S_+ \geq 8)$	94	28	3.35	0.41
$(P_+ \geq 200)$ OR $(S_+ \geq 10)$	87	30	2.90	0.43

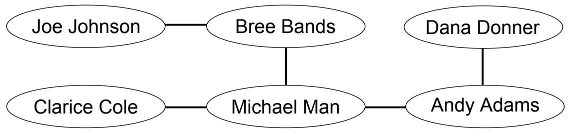

Figure 4: Partial Locomotiva graph showing one identified community (anonymized).

The communities obtained were manually examined by two independent experts: one of the organizers of the Locomotiva tournaments and a regular member of the club. To help the experts better identify the communities produced by the algorithm, we provided a visualization of each community, an example of which is shown in Figure 4. For each combination of values of the play relationship criterion's parameters the resulting communities were examined by the experts, who used the following criteria: (i) are there regular partners in the same community? (ii) are there persons who play frequently together in the same community? (iii) are there persons who are known to be friends or in a close relationship in the same community? (iv) are there persons who dislike each other in the same community? Each community for which the answer was "*yes*" for criteria (i)–(iii) scored 1 point; each community for which the answer was "*yes*" for criterion (iv) scored -1 point. We have tallied the results and concluded that the best criterion for extracting communities from the Locomotiva dataset is $(P_+ \geq 200)$ OR $(S_+ \geq 8)$. For these values of the S and P parameters, the modularity obtained is 0.43 (the value for $P_+ \geq 1$ is only 0.2), which also indicates a good community structure for the chosen parameters. The results corroborated with the low average community size show that the communities in face to face bridge are small, with most players having only one regular partner.

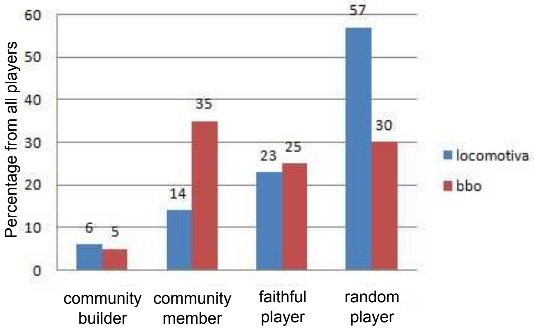

Figure 5: Percentage of players by player type for Locomotiva (left bars) and BBO Fans (right bars).

After obtaining a suitable play relationship criterion from the Locomotiva dataset, the following step was to normalize the values of the parameters S and P according to the time interval during which the data was gathered. The main reason is that both P and S are cumulative aspects. For Locomotiva, the data was gathered during a interval of $T^L = 50$ *weeks*; for BBO Fans, $T^B = 5$ *weeks* (10 times shorter period). We have computed the BBO Fans communities using, i.e., $P_+^B = P_+^L \times \frac{T^B}{T^L} = 20$ *hands*, obtaining 4,373 communities and a modularity is 0.43, which is the same maximum modularity obtained for Locomotiva. Over 90% of these communities have at most 4 players.

5.3 Playing Styles

We analyze in this section the gamer playing styles for the face to face and for the online community, using the play styles introduced in Section 4.3.

The players from the Locomotiva community were classified by our two experts, together. The BBO Fans players were classified automatically, starting from the social graph computed and used in Section 5.2. The results for the two communities are summarized in Figure 5. The community builders and the faithful players represent the same percentage of the player base in both communities, about 5% and 25%, respectively. The percentage of random players in the community is high for both communities. We attribute this situation to many players finding it difficult to adjust to the rigors of a fixed tournament schedule. Perhaps surprisingly, there are significantly more random players in the face to face bridge club than in the online club (57% and 30%, respectively). We attribute this discrepancy to the additional requirement of physical presence raised by Locomotiva, and to the relative ease of becoming a community member through the means of a round-the-clock, online platform such as BBO.

6. FUTURE APPLICATIONS

The study of online social gaming networks, in general, can lead to advances in a number of seemingly disjoint research areas. In this section we discuss several such applications for our work.

Building an Online Bridge Platform The findings in our study (see Section 5) can readily be used to analyze the system requirements for supporting a large online bridge community. Beyond large-scale system provisioning and operation, which are traditional performance-related issues, we propose to investigate two functionality-related issues. First, *building incentives for continued player activity* is a critical issue for online communities—player departure is a major cause of concern for the online gaming industry [14, p.43], because losing players quit early and successful players may become addicted to the game, which leads to increased playtime, then to burn-out and long-term game departure. We conjecture that continuous analysis of the social network's modularity (as introduced in Sections 5.1 and 5.2) can help in the automated detection of declining community activity. We further conjecture that social play style (as analyzed in Section 5.3) may provide the game operators with the information needed to efficiently target their incentives. Second, finding the appropriate partner in bridge is a difficult yet rewarding problem; *building a teaming (pairing) system* is a desirable function for many online gaming platforms. We conjecture that good recommendations for bridge pairing can rely on the method of analysis presented in Section 5, if the results are detailed per player and correlated between players. We are currently pursuing both of these issues within the BridgeHelper project.

Helping the Elderly with Bridge Communities Playing bridge may be an activity that the elderly can use to maintain their brain fitness; the "90+ Study" studies the relationship between avoiding dementia by the elderly (65 years or older) and the oldest-old (90-years or older), and mental challenges and social interaction through activities such as bridge [2]. Studying (online) bridge communities may ultimately help in improving the quality of life for the elderly (although this direction of research is outside the scope of this article.)

Beyond Bridge Communities Although the number of online bridge players is already large, our method of analysis, and in particular our use of play relationships as a substitute for social relationships, can be used for studying more (traditional) gaming networks. In contrast to chess, go, and poker, the game of bridge involves teams (pairs) of players involved in the same game instance (hand).

Beyond Friends and Friends-of-Friends As discussed in Section 1, due to their adversarial context games foster new prosocial emotions, such as happy social embarrassment and vicarious pride. Thus, the study of online social networks, starting from the relationships identified using the method proposed in this work, may provide new insights into the formation and operation of social networks. In particular, defining and analyzing social relationships that are not only based on friendship and extensions thereof, but also on the adversarial context, is a goal of the BridgeHelper project.

Beyond Online OR Face to Face Communities Our study is the first to focus on *both* online and face to face communities. We advocate the use of this method, with the hope that leveraging previous results from social network analysis in both online and face to face settings will be in this way greatly facilitated.

7. RELATED WORK

The analysis of (large-scale) social networks has spurred numerous studies over the past three decades [7, 8, 10, 11, 13, 16, 17, 21]. In contrast with these studies, our work focuses on bridge, which is a complex online social game with a large player base. Our work also investigates a novel way to extract social relationships from game sessions, and compares an online with a face to face community.

In comparison with our own related work [19], in this work we extend the formalism for social connectivity based on play relationships, we define four player types based on their playing relationships, we collect a new dataset (the "ground truth"), and we test our new methods on previous and new datasets. This work is also a much extended version of our previous study [1]; we add here, in particular, a description of the analysis method and more results.

The analysis of large-scale online social networks is close to our previous work. Our study investigates a *complex* online social game, which distinguishes it from the body of research investigating the social networks such as Facebook , Orkut, LiveJournal, Youtube, and Flickr [13, 15], the instant messaging network Microsoft Messenger [11], the online game World of Warcraft [5], and the online casual game Fighters Club [16].

8. CONCLUSION AND ONGOING WORK

Online social gaming, a new Internet application with millions of active users, poses new challenges in understanding online communities. In this work we have investigated the user behavior, social networking, and playing style characteristics of online bridge communities, with three main contributions. First, we have collected data from two large bridge communities, the face to face community Locomotiva and the online community BBO Fans. Second, we have presented a method for analyzing online social gaming communities. Notably, we have introduced a formalism for social connectivity to support our method's novel approach of detecting social relationships when only bridge play relationships are known. Third, we have demonstrated the use of our proposed method in practice using the two collected datasets.

Methodologically, we have used a new approach that combined human expertise with automated (and comparative) data analysis. Using this approach, we were able to validate the algorithmic findings from the face to face community data using the advice of experts from the same community. This approach also allowed us to select appropriate threshold values for the automated analysis of the online community, based on the relative scale of the online and face to face communities. We were also able to effectively compare the characteristics of the online and face to face communities, with surprising results. For example, although our comparative analysis revealed similar patterns in the two observed communities, we have also found more variation and a significantly higher fraction of players that are not attached in the community (random players) for the face to face community Locomotiva.

We are currently investigating ways to improve the BBO gameplay experience and to compare online bridge communities to communities organized around other social games.

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