AWESOME Analyzing Player Network

Elsevier[1]

Radarweg 29, Amsterdam

Elsevier Inc[a,b], Global Customer Service[b,]*

[a]1600 John F Kennedy Boulevard, Philadelphia
[b]360 Park Avenue South, New York

Abstract

Destiny is a hybrid online shooter game which shares features with Massively Multi-Player Online Games and First-Person Shooters, and is the to date the most expensive digital game produced. It has attracted millions of players to compete or collaborate within a persistent online virtual environment. In multi-player online games, the interaction between the players and the social community that forms in persistent games, forms a crucial element in retaining and entertaining players. Social networks in games have thus formed the focus of research, but the relationship between player behavior, performance, engagement and the networks forming as a result of interactions, are not well understood. In this paper the first large-scale study of social networks in hybrid online games/shooters is presented. Working with a network of over 3 million players in Destiny, the social connections formed via direct competitive play are explored in three experiments focusing on the patterns of players who play with the same people and those who play with random groups, and how the differences in this behavior influences win/loss ratios in multi-player PvP matches, combat performance via kill/death ratios and the impact of clan membership on performance. The results show that players with stronger social relationships

[☆]Fully documented templates are available in the elsarticle package on CTAN.

[*]Corresponding author
Email address: `support@elsevier.com` (Global Customer Service)
URL: `www.elsevier.com` (Elsevier Inc)

[1]Since 1880.

in *Destiny*, i.e. with a tendency to play with the same people, have a higher performance based on win/loss ratio and kill/death ratio, as well as a tendency to play more PvP matches than those with weaker social relationships.

Keywords: `elsarticle.cls`, LaTeX, Elsevier, template

2010 MSC: 00-01, 99-00

---

1. Introduction

The social networks in persistent online games play a fundamental role in the user experience and retention of players, and building and maintaining communities in games form an important aspect of the design and maintenance of persistent games.

The networks forming between players in online games can be difficult to investigate without the right tracking of player interactions and -behavior, and furthermore typically are relatively volatile in terms of constantly changing as the community in a game evolves. This means that insights gained from investigating these networks are usually short-lived in the commercial sense. However, in recent years it has become possible to explore the networks forming between players in online games, thanks to new tracking technologies and business models that have enabled the collection of big data-scale telemetry datasets about player behavior in games. This further augments the investigation of player networks by providing contextual data about for example the in-game behavior of the players in the networks. In parallel with this development, the domain of game analytics has grown up to target the problem of dealing with behavioral, performance and process data from game development and game research, seeking to inform both game development and behavioral research [1, 2]. The interest in using large-scale behavioral telemetry data to investigate player behavior is increasingly used to target design, business, and research issues in digital games, and today game analytics form a core element in the toolbox of game developers.

From a research perspective, social networks in online games form the basis for investigating the nature of human interaction and a basis for behavioral experimentation. The networks between players in multi-player or massively multi-player games thus play a fundamental role, and several researchers have investigated such networks in a variety of different games from Real-Time Strategy (RTS) games to Massively Multi-player Online Games (MMOGs) [3, 4], for example to analyze group formation processes [5] or to investigate the robustness of multi-player games against player departure [6], as well as for outright churn prediction [7].

In this paper the focus is on a previously largely unexplored type of player network in online games: *Competitive Networks*; which forms via competitive team-based play. Specifically, the networks that form with players in team-based play, across either the friendly or competitive team. Combined with behavioral telemetry about player activity, such networks permit the investigation of correlations between network behavior and player behavior and performance. Similar networks can be established in MOBAs [6, 8] and instanced battlegrounds in some MMOGs [9]. In this paper, different forms of competitive networks are described and their potential for player network analysis in the context of multi-player, persistent online games discussed. The basis for the investigation is the hybrid online shooter game *Destiny*, however, the behavioral features utilized are generic to team-based online shooter games such as *CounterStrike* and *Call of Duty* and thus potentially relevant to a number of major esports titles [10, 11, 12].

Destiny is a hybrid game title because it merges design elements from a number of genres, including First-Person Shooters (FPS), MMOGs, MOBAs, and Role-Playing Games (RPGs). While traditional multi-player online games are based on RPG or RTS elements, *Bungie*, the developer of *Destiny*, introduced a different kind of shared, persistent world game that incorporates RPG, MMOG, and MOBA elements into a FPS genre, and thus enables a wide variety of gameplay options, which is evident in the many game modes across Player-versus-Environment (PvE) and Player-versus-Player (PvP) in *Destiny*, the latter gameplay mode which is the focus of the current paper. Of direct relevance to player network analysis is the restricted communication options in the game, which unlike mainline MOBAs, MMOGs and FPS do not permit open communication between players. Notably, friends lists and text-based chat channels are lacking, and voice communication between members of a group is only possible for specific fireteams (consisting of 3 players) and is opt-in, and only recently enabled for random groups.

2. Contribution

In this paper, social player networks are constructed based on data from almost 3.5 million players of the online hybrid shooter game *Destiny*, and the relationship between the social tendencies of players correlated with their performance in the game. The networks are based on records from the Player-vs-Player component of *Destiny*, the *Crucible*, which acts as the hub for all competitive aspects in the game. In the Crucible, players compete across a variety of game modes in team-based competitive play. Players can choose to play with random groups or with friends. The networks utilized here are built directly from records of who players choose to play with and against.

The networks are combined with performance telemetry data from *Destiny*, which enables the use of the player networks to explore the impact of playing with random people or repeatedly with the same groups, on the performance and engagement of the players. Three experiments are run exploring the relationship between the tendencies of the players to play with the same vs. random people and selected Performance metrics: a) win/loss ratios; b) kill/death ratios and c) the impact of player-run guilds/clans.

The results show that players with stronger social relationships in *Destiny*, i.e. with a tendency to play with the same people, and being a clan member, have a higher performance based on win/loss ratio and kill/death ratio, irrespective of the number of PvP matches played. Additionally, players with strong social relationships has a tendency to play more PvP matches than those with weaker social relationships.

While *Destiny* is a hybrid online shooter game, the emphasis is here on the PvP aspects of the game as these are the most directly comparable to non-hybrid (non-MMO) online team-based shooters such as the major commercial titles *CounterStrike*, *Medal of Honor* and *Battlefield*. This facilitates the potential transferability of the presented methodology, and possibly also results. It is to the best knowledge of the authors the first time such competitive networks have been constructed in a hybrid online shooter games or regular online shooter games.

3. Social Network Analysis: Introduction

4. Related work

The work presented here rests in two separate but related domains under the umbrella of game research: Behavioral Analytics (BA) and Social Network Analysis (SNA) in games. Behavioral Analytics is a specific application of Game Analytics [1, 13, 14], and is focused on the analysis of player behavior, usually in real-life situations outside the lab environment, generally using behavioral telemetry as the source of detailed behavioral data about the users. SNA is - in the context of games research - focused on the interaction between players and the associations that form between them during and around the playing activity [15, 6, 16, 17].

With respect to BA, the use of telemetry to analyze various aspects of player behavior has been the subject of increasing attention in recent years, covering a variety of topics across design, development, monetization, prediction, behavioral research, psychology and user experience optimization [1, 13, 18], using methods ranging from simple descriptive statistics to machine learning [2]. The central focus of the work in the domain is to describe, analyze and explain player behavior. Given that the success of games is directly dependant on the players and the experience they receive from playing the game in question, the majority of the work in Game Analytics to focus on the users [1, 13].

In parallel with the development in behavioral analytics, analysis of social connections and -structures has become commonplace with the introduction of various kinds of social media. In particular work on large-scale user platforms such *Facebook* or *Twitter* and its potential for recommendation and prediction of user behaviour has drawn the attention to the power of SNA-techniques [19, 20, 21] [CITE SIMOIN 2015].

SNA employed to investigate the social interactions and connections among people has found interest in many different domains, including digital games. Initially, such work focused on Social Network Games (SNGs) i.e. games played via an existing social network [22, 23, 24, 25]. In recent years, research has also described and analyzed networks in online/networked games with multiple players, as well as other forms of social game environments. A primary challenge here has been the identification of meaningful connections between players to generate networks [17, 5, 16].

In online/networked digital games in general (i.e. not embedded in social network platforms), social networks are employed to analyze player interaction dynamics in a social context. Social networks are of interest because research has indicated the influence of direct and indirect interactions and collaboration with other players on their in-game behaviour and the effect on the user experience, and learning, in these games [26, 15, 27, 28, 29]. Furthermore, social connections and -interactions in games appear to be important motivational drivers for the gameplaying activity itself [30, 31, 22, 23].

The motivation to play in online games incorporate many other components, such as socializing, building relationships, or playing as a team, but also many competitive components such as competitive achievements, or even the demonstration of power or status [31, 24]. However, the form, extent, and nature of the social interactions can clearly differ. As a tool for representing and analyzing rich social connections and -interactions, social network graphs have been employed, e.g. [17, 5, 16].

Social networks forming through or around games have been mentioned in numerous studies across Etnography and Social Science, and in some situations also described using qualitative data. However, substantially less attention has been given to quantitative analysis of social networks in games, notably at large scales. Furthermore, such large-scale work has been focused on Massively Multi-Player Online Games (MMOGs) and shared online virtual environments such as *SecondLife*. This means that there is a gap in the current state-of-the-art in terms of how social networks operate in games in general, and notably in games outside the MMOG and virtual world genres, including: esports games, major commercial titles such as *Destiny*, casual game titles and mobile games. The rapid evolution of game forms and formats is possibly an important factor in explaining these gaps in the current knowledge, meaning that it can be hard for academic research to keep up with development in the industry.

Most SNA research in general is based on explicit relationships such as "friendship" connections in social media [32, 33], and in games the majority of current social network research similarly use social interactions based on direct connections such as friendship information and guild information or indirect connections such as map data. Recent work in quantitative SNA includes Ducheneaut et al. [15] who investigated social structures and connections in *World of Warcraft* based on longitudinal data and found that even though players are often in the same area with other players, joint activities are not prevalent and direct interactions are less important even though the social presence of the others appears to be essential and engaging for the players' social online experience. Stafford et al. [17] analyzed networks in *Second Life* based on shared group information and explored the relation to different social networking websites. The authors used link definition of groups between avatars to generate the network.

Another way to investigate social interactions and the significance of the presence and interactions is the analysis of guilds and the player tendencies towards player-run guilds [5]. Ducheneaut et al. [15] described the impact of guilds on the player pattern as significant. Players are engaged to play more often and longer and support the informal playing group process The authors investigated the guilds by building social networks based on online-time or on location-based information.

There have been very few studies examining social networks in games outside MMOGs/virtual worlds. Exceptions include Iosup et al. [6], who examined networks in the Multi-Player Online Battle Arena (MOBA) games *DOTA 2* and the Real-Time Strategy (RTS) game *StarCraft* with the focus on modeling the social structure, socially-aware matchmaking, and network robustness against player departure.

Additionally, Jia et al. [16] compare social relationships in four multi-player online games and discusses how these compare to online social networks found on e.g. Facebook.

The authors introduce a model to analyze such relationships, describing five type of interactions, which can be used to generate graphs for online multi-player match-based games: Players (a) in the same match, (b) on the same side of the match, (c) on the opposite side of the match, (d) who won together in a match, and (e) who lost together in a match. The authors focus on evaluating network measures, whereas the focus here is on relating network information with behavioral performance metrics. The connections formed between players in multi-player matches can be both explicit and implicit. They are explicit when players form the relationships on their own initiative, e.g. joining a clan or playing in a group with real-life friends, and implicit when formed passively, e.g. via skill-matching in *Destiny* skill-ranking and subsequent skill-matching.

In summary, prior work on SNAs in digital games has covered a variety of genres, including MMOGs such as *World of Warcraft*, MOBAs such as *DOTA 2* and Real-Time Strategy (RTS) games such as *StarCraft*. In contrast, *Destiny* does not fit the previously described genres. It is described as a first "shared world shooter", a massively multi-player online game, which focuses on first-person shooter elements and lacks of many traditional role-playing features. Destiny's highly competitive character and its unique game mechanics make the game to an unique platform to analyze player interactions and networks in a new form.

While most previous studies on analyzing social structures in online game communities focus on identifying the network and the interactions, here the focus is on connecting network analysis and -metrics with the performance of the players in *Destiny*. Furthermore, in contrast to prior work, in this paper we are able to analyze social influence of different interactions groups on performance in a hybrid game genre.

5. Destiny - Gameplay

Destiny is a hybrid online game that combines elements from a number of game formats, notably those of FPS, RPGs, MMOGs and MOBAs. *Destiny* forms a unique case in that it shares design elements across these different kinds of games, without being completely similar to any previous title. For example, similar to MMOGs, the game has a persistent world, in-game currencies, public events, etc. Similar to RPGs, character development is a primary underlying mechanic, and the game features crafting and collection of items (weapons, armor, clothing, insignia, vehicles). Similar to FPSs, the vast majority of the gameplay deals with the elminiating of enemies, whether computer-controlled agent entities or other players. Finally, similar to MOBAs, team-based multi-player combat within restricted environments are a substantial part of the games offering on the PvP side, accessible via the Crucible, a hub for PvP-type content. All content under the Crucible takes place in instances.

The game was developed by Bungie, and published by Activision in September 2014. The game is only available on major gaming consoles and requires always-online access. Three major expansion packs has been released since launch: *The Dark Below*, *House of Wolves* and *The Taken King*, the latter which made considerable changes to the core gameplay. Following, Bungie introduced new limited-time events.

In the game, single- and multi-player activities feature in a distribution similar to MMOGs, although the core mechanics are more comparable to a FPS such as the series of *Counter-Strike* and *Medal of Honor*. However, the persistent world sets *Destiny* apart from these titles, and both player-versus-

Figure 1: *Destiny* gameplay example. (c) Bungie, Inc, Destiny, the Destiny logo, Bungie and the Bungie logo are registeret trademarks of Bungie, Inc. All rights reserved. Image used with permission by Bungie Inc.

environment (PvE) and player-versus-player (PvP) gameplay in included. Similar to MMOGs, *Destiny* provides incentive to players to explore the different zones of the virtual environment via quests and missions provided by Non-Player Characters, generally from an area referred to as Tower which includes also vendors where in-game items can be bought and sold. The combat system and damage system in *Destiny* is highly complex and includes a variety of damage types, weapon types, resistances, upgrade possibilities, customization etc. Every player character belongs to a class (Titan, Warlock, Hunter) which provides different core abilities. Each class has three subclasses. Players increase in character level (current level cap is 40) through earning experience points, earned via completing missions, killing enemies, etc. The current level cap is 40, and has been increased since initial release through expansions. Social or group activities in *Destiny* are based around teams of three players completing missions. Team-based PvP matches in the Crucible involves up to two fireteams per side. There are a number of PvP modes, from traditional deathmatches to take-and-hold scenarios. Co-operative PvE content exists in the form of Strikes

Figure 2: Character Inventory Screen in *Destiny*. (c) Bungie, Inc, Destiny, the Destiny logo, Bungie and the Bungie logo are registeret trademarks of Bungie, Inc. All rights reserved. Image used with permission by Bungie Inc.

and Raids, which similar to PvP content is instanced, and involves one or two fireteams. Raids include more content than Strikes.

Destiny does not feature the same kind of social and communicative options as MMOGs, as communication between players is restricted. This is particularly the case for the lack of text-based chat channels in the game, which means that a core component of the typical MMOG experience is missing from *Destiny*. The lack of text-based chat may relate to the game being focused on consoles. Voice communication was initially only possible between members of pre-formed "fireteams", i.e. between players who specifically accept being a member of these teams and thus this typically relates to people who know each other outside the game, including clan members. It was only recently that the option to enable voice communication between players who are randomly assigned to teams via automated matchmaking, but the voice-chat feature remains optional and players have to consent to participate in communication. These differences mean that social networks examined in MMOGs (e.g. Kawale and Srivastava [7]) such as via friends lists do not apply directly to *Destiny*, and that other approaches have to be adopted to define social networks in the game.

6. Dataset and Pre-processing

6.1. Dataset

The dataset used in this study consists of player activities from almost 3.5 million players. The data were generated as follows from the Destiny back-end collection servers:

To begin with, a random sample of 10,000 *Destiny* players that played the game at least two hours was developed. The 2 hour limit was set to avoid people who installed the game but never played beyond the first few steps of the tutorial.

In-game activities in *Destiny* are based on either player versus player (PvP) or player versus environment (PvE) gameplay. The PvP mode, accessed via the *Crucible*, covers a variety of different match-based activities played across three-versus-three to six-versus-six team-based matches.

The initial 10,000 player sample participated in 930,720 Crucible matches, covering their entire play histories from September 2014 to January 2016. This dataset forms the basis for the current analysis. Each match record covers information about the teams, the players, their classes, their weapon loadouts, and information about different scoring mechanisms as well as performance data such as Kill/Death (K/D) ratios and distances associated with kills for each player on both sides of a match. Also included in the dataset is 318,007 clan names (clans are player-formed communities). In order to build the players' networks, matches were processed, which in total includes 3,450,622 *unique* player identifiers. From this sample of players we have the complete history of the matches played.

The basic statistics about the used dataset are shown in Table. 1.

6.2. Pre-processing and Feature Definition

The first step in processing the data was identifying the important values in every single PvP game. Each entry contains match details such as the game mode, participating teams, and more detailed information about each player including different scoring mechanics and weapon usage.

Table 1: Statistics of the Destiny dataset

Players	3,450,622
Matches	930,720
Clans	318,007
Classes	3

There are three general categories of behavioral features (or metrics) in the *Destiny* data: Performance, Engagement and Social features.

Performance metrics provide data on the skill and playstyle of the players. Features include for example details about which weapons the player used, when, where and with how much success. Key performance features in shooter-type games include Kill-Death ratios, which given the skill-matching in *Destiny* (at the time of writing based on Microsofts TrueSkill system) is a proxy measure of how well the player in question performs in combat with peers. There are roughly 30 performance metrics tracked for each player in each PvP match, plus information such as whether a match was won or lost, total points scored etc.

Engagement features focus on the amount of time the player has played *Destiny*, the duration of play sessions and the amount of time spent playing in the different modes of the game (e.g. PvP and PvE).

Social features provide information about the interactions and between players. In the current case, the most important social feature is the gamertags of the people on the same team or the opposing team of the player in PvP matches.

We then generated a list of game modes encoded by unidentified ID's, and matched them to the actual crucible game-modes. The next step was to eliminate free-for-all games and and other special modes, that do not necessarily fit into a team-based model. While free-for-all game modes can also serve as the basis for social network definition, this game mode is not common in comparable games titles and was therefore not included here in order to faciliate the

Table 2: Overview of the threshold behaviour

Min Games	Nodes remaining % (Rel)	Edges remaining % (Rel)
1	55.46 (55.46)	68.53 (68.53)
2	33.68 (60.72)	45.21 (65.97)
3	21.58 (64.09)	29.73 (65.74)
4	14.35 (66.47)	19.64 (66.08)

potential applicability of the method and results to other online shooter games such as *Counter-Strike*. The resulting property lists where then divided into classes, to extract information on a per class-basis.

Fig. 3 shows how the network size changes by applying a threshold. The chosen threshold is defined by the minimal number of games a player has to play to be relevant in further data processing. This is further shown in Table 2, which displays the remaining player network data, when the thresholds are applied. The table describes how many nodes are remaining in the dataset after deleting this threshold (minimum number of shared games).

6.3. Player preferences

Our of a total of 3,450,622 players in the dataset, 38.64% are playing with the class Hunter, 29.20% Titans, and 32.15% Warlocks. Fig. 4 shows the varying preferences of the classes of the users. Fig. 4 shows the level distribution of the players including the reference to the different Down-Loadable Content packs (DLCs) (expansion packs). The split in the level distribution between DLC2 and DLC3 is caused by a leveling system overhaul which allowed to jump from level 34 to level 40 in less than a day, as well by restricting the access to many new activities to level 40 characters only.

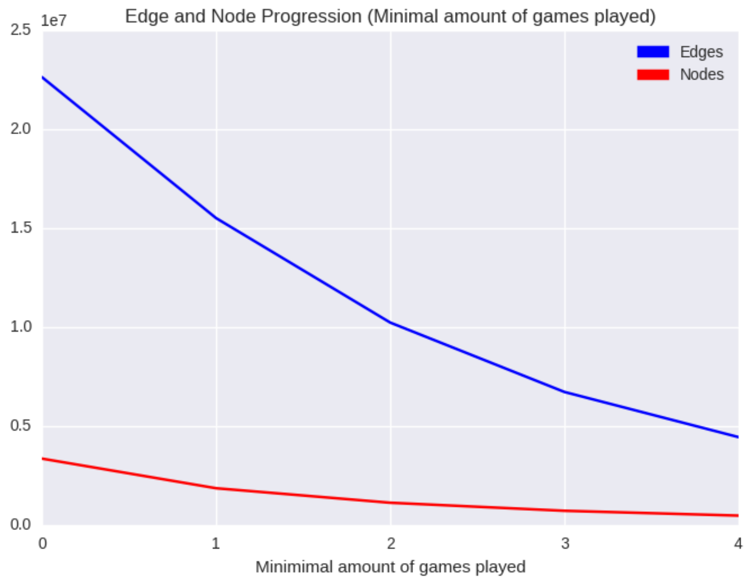


Figure 3: Deletion of nodes - After removing players who have not played together at least four times many connections are removed

7. Player Networks

The central question addressed here is whether match data from *Destiny* can be used to inform about how players are connected, and if the variations in these connections impact on the performance of the players. Based on the described match data we study different player networks. We represent the player relationships based on undirected graphs: nodes (v) represent players, edges (e) represent the link between two players who have interacted in a match. Based on different interactions types we generate three different networks.

7.1. Network Relationships

For the network generation we can build different networks (player interaction networks) based on match interaction information. Players might be connected with other players in different ways. Based on the match data we were able to create three networks on how players interact with each other. For such

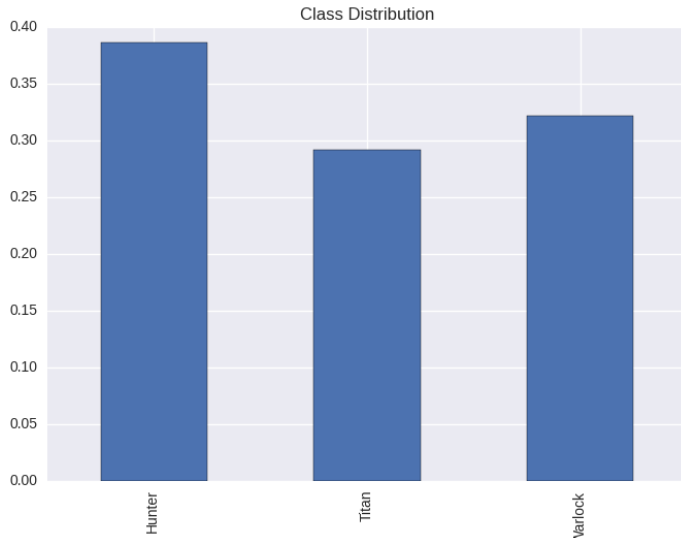


Figure 4: Class distribution of players' "first choice" character

Table 3: Network relationships

M	Players in the same match (Matchmates: M)
T	Players playing together in the same team (Teammates: T)
O	Players playing against each other as opponents (Opponents: O)

interactions we differ between players which are connected with each other by playing in the same team (T) or because they were playing as opponents (O) in a match. The last interaction network are Matchmates (M), players which were playing in the same match (on either side). Based on this match information, we built three interaction graphs, which demonstrate the different relationships. Table 3 summarizes the networks and the relationship information.

These networks can be created as weighted graphs with different metrics for weights, such as the number of times the players interacted with each other, won/lost matches, or similar interaction numbers. Table 4 shows how many matches were played by players in the dataset. 97.93% of the players in the dataset have played less that 11 games. Table 5 illustrates how many matches

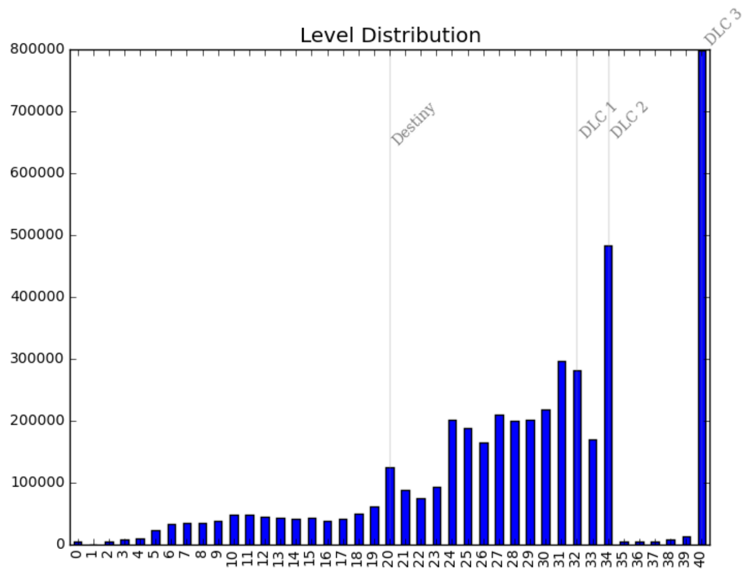


Figure 5: Level distribution

are played between different players, and shows that players play far less often against each other than they play with each other. 99.9% of all players (T) play less then 11 matches together. This statistics already reveals that players are more likely to play again with the same players in a team than as opponents.

8. Network Structure

In this section we want to examine the relation between the social network structure and the players' behaviour and gameplay or playing success. For example, can the network density relate to the players success in matches? Are players with strong "friendships" more successful in the game than an average player? To answer these question, we study the social network structure of different player groups, focusing on network size, density, and interconnectivity.

Table 4: Number of matches played by players

Games	Players
1-10	3,293,187
11-20	54,836
21-50	8,758
51-100	2,660
101-200	1,674
201-300	610
301-500	469
501-1000	333
1000+	109

Table 5: Number of matches played together between different players

Games	Same Team	Opposite Team	Complement
1-5	22,582,015	27,491,957	47,382,583
6-10	32,816	2,561	46,308
11-20	12,851	201	13,386
21-50	7,025	20	7,168
51-100	2,140	1	2,179
101-200	873	0	900
201-300	207	0	214
301+	135	0	140

Table 6: Methodological comparison of the three networks (Threshold minimum games played - 3)

	Same Team (T)	Opposite Team (O)	Same Match (M)
Nodes	725,704	725,704	725,704
Nodes in LCC	725,599	725,693	725,703
Avg. Degree (k_avg)	18.55	23.93	38.72
Links	6,729,257	8,682,726	14,048,455
Links in LCC	6,729,190	8,682,726	14,048,455
Diameter (D)	13	11	9
Avg. Clustering Coefficient (C_avg)	0.024	0.0082	0.026

8.1. Network Measures

Analyzing the network characteristics of the three created player networks sheds light on different aspects of player interactions. In this section we present and discuss the common social network measures. Table 6 gives an overview of the different social network measures for the three different graphs. For the following analysis a threshold of 3 (a minimum of three games played together) was applied. In the following sections we will describe and discuss the various measures.

Degree distribution. The *degree* (k) of a player in the graph refers to the number of links to other players. Table 7 shows that 79.19% of players in teams have a degree between six and twenty. Less than twenty percent played games with more different teammates than that.

Average degree (k_avg). The *average degree* (k_avg) describes the average of all players' degrees in the graph. As shown in Table 6 the average degree is much lower in "same team" graph T compared to the other graphs. That shows, that

Table 7: Comparison of Network Node Degrees -

Degree	Same Team (T)	Opposite Team (O)	Same Match (M)
0 - 2	1,477	1,990	12
3 - 5	54,812	128,146	1,747
6 - 10	1,627,084	1,502,516	145,872
11 - 20	1,004,600	991,962	1,703,801
21 - 30	322,135	377,496	617,112
31 - 40	129,651	170,993	318,234
41 - 50	56,783	82,109	193,247
51 - 60	26,379	41,892	123,064
61 - 70	12,987	22,646	80,429
71 - 80	6,766	12,535	52,356
81 - 90	3,726	7,152	35,120
91 - 100	2,160	4,479	23,848

players playing tend to play more with the same players in a team than against them.

Diameter (D). Looking at all shortest paths between two nodes, the *diameter (D)* of a network is the longest of this list to describe a linear size of the network.

Clustering Coefficient (C). The cluster coefficient (C) of a player describes the connectivity of its neighbor. The clustering coefficient (the network average clustering coefficient, C_avg) for an entire network is the average C over all players.

$$C(v) = \frac{E(v)}{k_v(k_v - 1)}$$

Edge Weight Distribution. Based on the number of interactions (matches played together) a weight can be applied to the single links. The edge weight distribution relates to the number of how many times players have interacted with the same players. Fig. 6 illustrates the comparison of edge weight distributions between players playing on the same team and players as opponents in matches. Players who play in same teams are playing more often with the same players compared to players on opposing sides.

Largest Connected Component (LCC). The largest connected component (LCC) is the largest self-contained sub-graph of the main network. As shown in Table 6, the number of nodes and links of the LCC only slightly differs from the main graphs. This means, that the players are very well connected through the matches.

9. Experiments

In this paper three experiments are performed, focusing on the following questions:

1. *Do player relationships/interactions relate to the win/loss ratio in multiplayer PvP matches?*
2. *Do player relationships/interactions relate to combat performance (measured with kill/death ratio)?*
3. *Does clan membership impact the performance of* Destiny *players?*

To answer these questions we first have to distinguish between players which are playing regularly with the same players (*Player Group 1: Focused Players*), and players who are playing more with different/random players (*Player Group 2: Open Players*). We created a metric to rank the players based on their interaction with each other. If a player interacts with the same group of other players many times, the player will receive a higher score than a player who always plays with different team members. For this metric we looked at a non-thresholded version of the team network (T) graph, to ensure unbiased results to the ranking. The second part of the equation serves to eliminate a score penalty that very active players would have received otherwise.

$$FocusedPlayer = \frac{Sum\,of\ weights}{degree} \cdot \frac{\#matches\,played}{\#matches}$$

9.0.1. Do player relationships/interactions relate to the win/loss ratio in multiplayer PvP matches?

Fig. 7 compares the winrate of the two different player groups in crucible matches. The three sub-figures refer to the number of matches players have to have played in order to be included for the analysis. The x-axis relates to the number of players from the focus-ranking (see above). The results indicate that players, which play more with same players have a higher winrate compared to players, which play more often with random players.

9.0.2. Do player relationships/interactions relate to combat performance (measured with kill/death ratio)?

To measure the combat performance we use a ratio between the kills and deaths of the players. A kill/death ratio greater than 1 relates to more active kills in a match. Higher numbers can be related to a better player performance. As fig. 8 illustrates, players with a higher rate of playing regularly with the same players demonstrate again a slightly higher performance based on kill/death ratio compared to the players who prefer to play with random players.

9.0.3. Does clan membership impact the players' performance?

To answer this question, we construct two similar experiments as in the first two research questions. Both of the experiments take a look at measures that determine a players success. The list of players is now split into two lists, one for players who are identified as clan members, and one for clan-less players. Players are identified as clan members if they played at least 90% of their games as part of a clan. If they played 90 % of their games without a clan they are identified as clan-less players. After applying a threshold of a minimum of a 100 games played, only 76 players out of 6222 are not fitting into this metric.

Fig. 9 illustrates that the performance of clan members exceeds that of players without a clan. The group of focused players (Player Group 1) is also 24.42% more likely to belong to a clan than the average player, and the open player group (Player Group 2) is 14.94% less likely to be members of a clan.

10. Conclusion and Discussion

As multi-player online games become more and more popular, but also more complex, it is crucial to find news ways to analyze the player behaviour in these games, which are capable of taking into account multiple viewpoints on the activity of the player base [2, 1, 18]. In this paper this problem has been targeted from the direction of combining game-based social networks and behavioral analytics: In this paper we have developed and presented a social network from the major commercial title *Destiny* and combined the network with behavioral features of the players, permitting analysis across social behavior and gameplay performance. It is to the best knowledge of the authors the first time the network aspect and performance aspect in digital games, including esports, has been combined. It is also one of the to day largest social network analyses performed in digital games, covering almost 3.5 million players.

We present techniques from Social Network Analysis [19], and discuss and present the relevance for player networks based on match-based data - competitive networks - to analyze aspects such as player performance. In the above, competitive networks were developed based on data from the hybrid online shooter game *Destiny*. The networks provide information about the tendency of players using the PvP game modes in the game, to play with the same people or random groups. In addition, behavioral telemetry about the individual behavior of the players were tied in enabling the evaluation of player performance in connection with the network.

The focus in this paper has been on exploring the developed networks of the players along three different performance and social vectors: a) Match wins via win/loss ratios, b) Performance, via k/d ratios, and c) Clan influence, i.e.

whether being a member of a clan impacts on the tendency of a player to play with the same people, as well as performance. Results indicate that players with stronger social interactions, i.e. with a tendency to play with the same people, have a higher performance based on win/loss ratio and kill/death ratio. Also, players who are part of a clan seem to perform slightly better across all the PvP modes of *Destiny* than those who are not part of a clan.

The results presented here are based on network features and behavioral features (e.g. K/D ratios) that can be found in other team-based online shooters such as major esports and -commercial titles like *Counter-Strike* and *Battlefield*. This facilitates the application of the presented techniques to other games than *Destiny*, and possibly the behavioral results. This needs to be verified by analysis of social networks of these games, but previous qualitative work such as [30] indicates that similar patterns exist for social behavior and performance in these games, as well in other multi-player online genres [6, 29, 16].

The work presented here indicate several venues for future work: A wealth of performance measures exist in *Destiny*s PvP modes (over 1400 metrics are recorded by Bungie, the developer of the game) and similar competitive multiplayer FPS games such as *Team Fortress 2* and *Counter-Strike*, and these can be combined with player networks, for example performance with specific weapon classes, or across specific PvP game modes. Furthermore, given the high dimensionality in the data, implementing behavioral profiling [13, 8] as a prior step to network analysis would be useful to reduce dimensionality and define playstyles which can then be correlated with social behavior. Additionally, temporal information can be employed to explore the evolution of networks in *Destiny* as a function of time, and player performance data tied in to permit time-series analysis about players and network, which can furthermore serve as the basis for behavioral prediction modeling, which is of direct interest in game development due to the trend towards more persistent games on the market [7, 2, 18].

Acknowledgment

The authors would like to extend their sincere gratitude to Bungie for making detailed behavioral telemetry from Destiny available.

References

[1] M. S. El-Nasr, A. Drachen, A. Canossa, Game analytics: Maximizing the value of player data, Springer Science & Business Media, 2013.

[2] A. Drachen, C. Thurau, J. Togelius, G. N. Yannakakis, C. Bauckhage, Game data mining, in: Game Analytics, Springer, 2013, pp. 205–253.

[3] M. Szell, R. Lambiotte, S. Thurner, Multirelational organization of large-scale social networks in an online world, Proceedings of the National Academy of Sciences 107 (31) (2010) 13636–13641.

[4] J. Srivastava, Data mining for social network analysis, in: Intelligence and Security Informatics, 2008. ISI 2008. IEEE International Conference on, IEEE, 2008, pp. xxxiii–xxxiv.

[5] C. Thurau, C. Bauckhage, Analyzing the evolution of social groups in world of warcraft®, in: Proceedings of the 2010 IEEE Conference on Computational Intelligence and Games, IEEE, 2010, pp. 170–177.

[6] R. van de Bovenkamp, S. Shen, A. L. Jia, F. Kuipers, et al., Analyzing implicit social networks in multiplayer online games, IEEE Internet Computing 18 (3) (2014) 36–44.

[7] J. Kawale, A. Pal, J. Srivastava, Churn prediction in mmorpgs: A social influence based approach, in: Computational Science and Engineering, 2009. CSE'09. International Conference on, Vol. 4, IEEE, 2009, pp. 423–428.

[8] A. Drachen, M. Yancey, J. Maguire, D. Chu, I. Y. Wang, T. Mahlmann, M. Schubert, D. Klabajan, Skill-based differences in spatio-temporal team

behaviour in defence of the ancients 2 (dota 2), in: Games media entertainment (GEM), 2014 IEEE, IEEE, 2014, pp. 1–8.

[9] J. L. Miller, J. Crowcroft, Group movement in world of warcraft battlegrounds, International Journal of Advanced Media and Communication 4 (4) (2010) 387–404.

[10] R. Rioult, M. J.-P., B. Helleu, N. Scelles, C. e. a. Durand, Mining tracks of competitive video games, in: Proc. of AASRI Conference on Sports Engineering and Computer Science, 2014.

[11] M. Schubert, A. Drachen, M. T., Esports Analytics Through Encounter Detection, in: Proc. of the 10th MIT Sloan Sports Analytics Conference, 2016.

[12] A. Drachen, Y. M., M. J., C. D., W. Y. I., M. T., S. M., K. D., Skill-Based Differences in Spatio-Temporal Team Behaviour in Defence of The Ancients 2 (DotA 2), in: Proc. IEEE Games and Entertainment Media Conference, 2014.

[13] A. Drachen, R. Sifa, C. Bauckhage, C. Thurau, Guns, swords and data: Clustering of player behavior in computer games in the wild, in: 2012 IEEE conference on Computational Intelligence and Games (CIG), IEEE, 2012, pp. 163–170.

[14] B. C., D. A., S. R., Clustering game behavior data.

[15] N. Ducheneaut, N. Yee, E. Nickell, R. J. Moore, Alone together?: exploring the social dynamics of massively multiplayer online games, in: Proceedings of the SIGCHI conference on Human Factors in computing systems, ACM, 2006, pp. 407–416.

[16] A. L. Jia, S. Shen, R. V. D. Bovenkamp, A. Iosup, F. Kuipers, D. H. Epema, Socializing by gaming: Revealing social relationships in multiplayer online games, ACM Transactions on Knowledge Discovery from Data (TKDD) 10 (2) (2015) 11.

[17] G. Stafford, H. Luong, J. Gauch, S. Gauch, J. Eno, Social network analysis of virtual worlds, in: International Conference on Active Media Technology, Springer, 2012, pp. 411–422.

[18] R. Sifa, F. Hadiji, J. Runge, A. Drachen, K. Kersting, C. Bauckhage, Predicting purchase decisions in mobile free-to-play games, in: Eleventh Artificial Intelligence and Interactive Digital Entertainment Conference, 2015.

[19] J. Scott, Social network analysis, Sage, 2012.

[20] N. Lin, Social capital: A theory of social structure and action, Vol. 19, Cambridge university press, 2002.

[21] J. Brown, B. A. J., L. N., Word of mouth communication within online communities: Conceptualizing the online social network, Journal of interactive marketing 21 (3) (2007) 2–20.

[22] D.-H. S., Y.-J. S., Why do people play social network games?, Computers in Human Behavior 27 (2) (2011) 852–861.

[23] D. Y. Wohn, Y.-H. Lee, S. J., T. Bjornrud, Building common ground and reciprocity through social network games, in: Proc. CHI Extended ABstract on Human Factors in Computing Systems, 2010, pp. 4423–4428.

[24] S. D. H., S. Y. J., Why do people play social network games, Computers in Human Behavior 27 (2) (2011) 852–861.

[25] S. Sunil, K. R. A., Social network games, Journal of Logic and COmputation 25 (1) (2011) 207–242.

[26] N. Yee, The demographics, motivations, and derived experiences of users of massively multi-user online graphical environments, Presence: Teleoperators and virtual environments 15 (3) (2006) 309–329.

[27] D. Williams, N. Ducheneaut, L. Xiong, Y. Zhang, N. Yee, E. Nickell, From tree house to barracks the social life of guilds in world of warcraft, Games and culture 1 (4) (2006) 338–361.

[28] B. Nardi, J. Harris, Strangers and friends: Collaborative play in world of warcraft, in: Proceedings of the 2006 20th anniversary conference on Computer supported cooperative work, ACM, 2006, pp. 149–158.

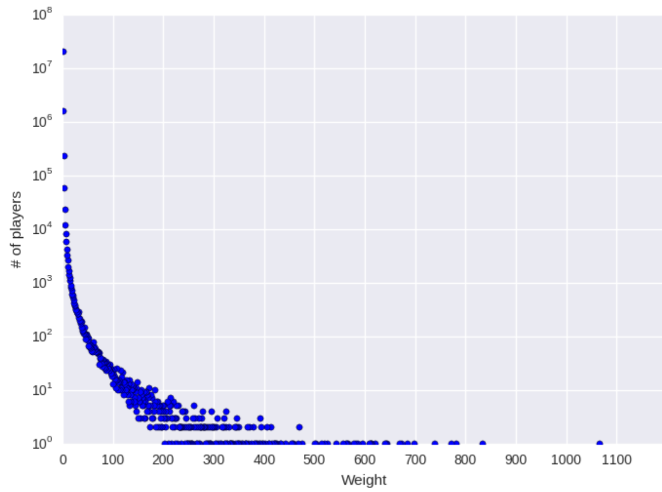
[29] R. Van De Bovenkamp, S. Shen, A. Iosup, F. Kuipers, Understanding and recommending play relationships in online social gaming, in: 2013 Fifth International Conference on Communication Systems and Networks (COMSNETS), IEEE, 2013, pp. 1–10.

[30] J. J., T. M., Appeal of playing online first person shooter games, Cyberpsychology

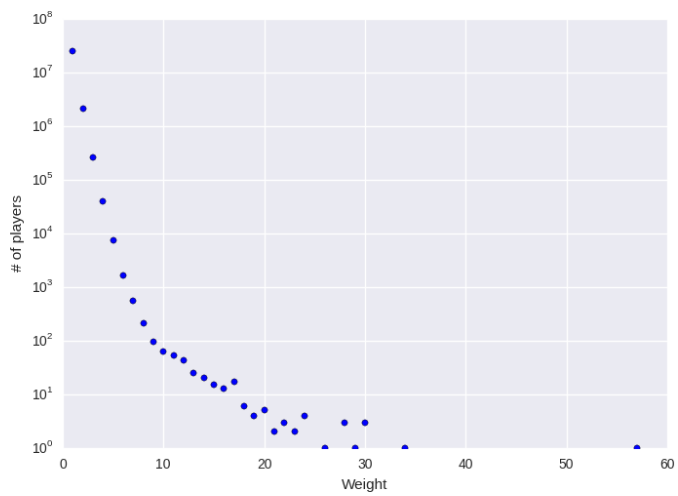
[31] N. Yee, Motivations for play in online games, CyberPsychology & behavior 9 (6) (2006) 772–775.

[32] D. S.R. Kairam, J. Leskovex, The life and death of online groups: predicting group growth and longevity, in: Proc. of the 5th ACM international conference on Web search and data mining, 2012.

[33] N. C. S. Garg, T. Gupta, A. Mahanti, Evolution of an online social aggregation network: an empirical study, in: Proc. of the 9th ACM SIGCOMM conference on Internet measurement conference, 2009.

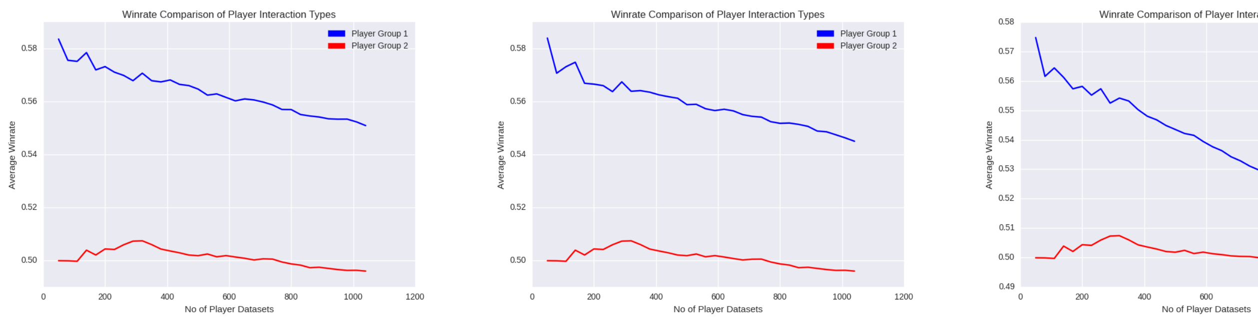


(a) Playing on the same team



(b) Playing against other players

Figure 6: Edge weight distribution

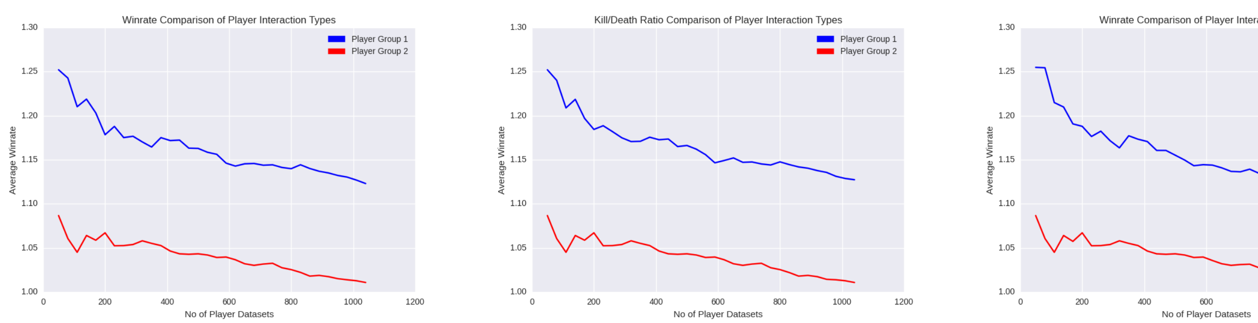


(a) 10

(b) 100

(c) 250

Figure 7: The winrate comparison of player groups playing crucible matches.

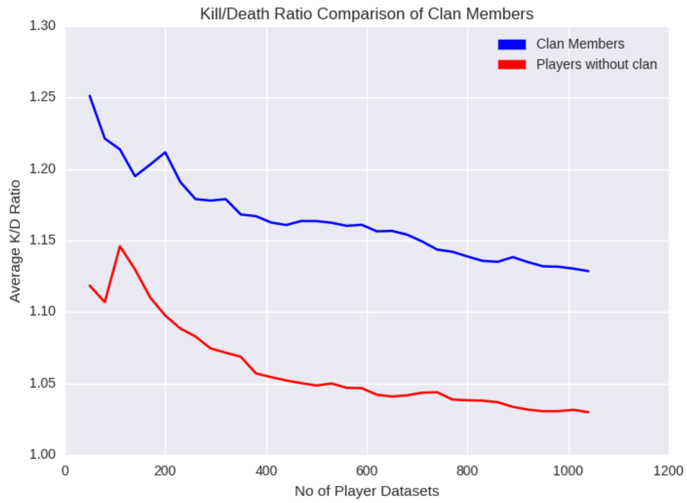


(a) 10

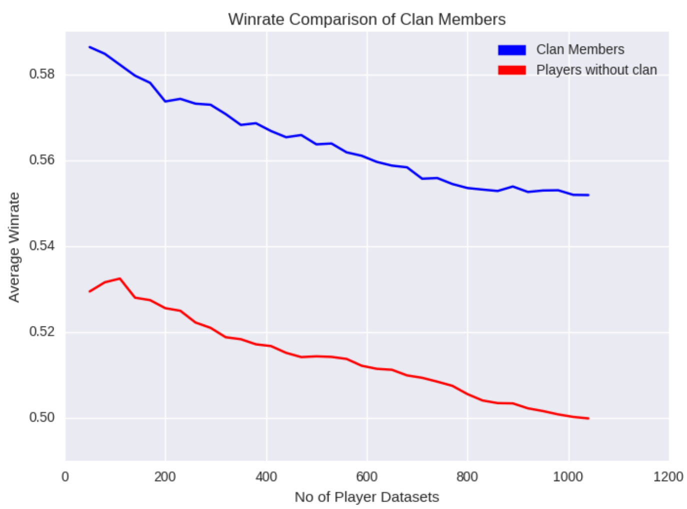
(b) 100

(c) 250

Figure 8: Kill Death ratio comparison of player groups in crucible matches.



(a) Kill & Death ratio comparison when players are part of a clan



(b) Winrate comparison when players are part of a clan

Figure 9: Clan membership