Analyzing Player Networks in Destiny

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***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 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.**

I. 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 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 performance. Similar networks can be established in MOBAs [6], [8] and instanced battlegrounds in some MMOGs [16]. 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*.

Destiny is a hybrid game title merging 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*. 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.

II. 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*. 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. It is to the best knowledge of the authors the first time such competitive networks have been constructed in a hybrid online shooter game. The use of competitive player networks for behavioral analysis is described. 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 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 a) win/loss ratios; b) kill/death ratios and c) the impact of player-run guilds/clans.

III. Related work

The use of behavioral 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], [9], [10], using methods ranging from simple descriptive statistics to machine learning [2].

However, the players' behaviour and their motivations to play are different in multi-player online games and lets multi-player game designer face new challenges [11], [12], [13]. Prior work has shown the influence of direct and indirect interactions and collaboration with other players on the in-game behaviour and the effect on enjoyment and the learning of the game [14], [13]. 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 [15]. However, the form, extend, and nature of the social interactions can clearly differ. A form to represent such rich social connections and interactions are social network graphs.

Social player networks - a tool to illustrate player interactions - are important to analyze player behaviour and the interaction dynamics in a social context. In recent years, social network analysis (SNA) of social connections and structures has become more and more popular. In particular work on large-scale user platforms such *Facebook* or *Twitter* and its potential for recommendation and prediction of user behaviour drew the attention to the power of SNA-techniques [17], [18]. More recently several authors have also described different network analysis approaches of multi-player-games and social digital game environments. One main challenge is the identification of meaningful connections between players to generate the network.

Ducheneaut et al. have 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 seems to be essential and engaging for the players' social online experience [11].

Stafford et al. [21] 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 guilds [5]. Ducheneaut et al. describe 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 investigates the guilds by building social networks based on online-time or on location-based information[11].

Most studies mostly use social interactions based on direct connections such as friendship information and guild information or indirect connections such as map data.

To our knowledge there have been only a few studies examining social networks in games based on match-based data. Exceptions include Iosup et al. [6], who examined networks in the multi-player games *Defense of the Ancients* (Dota) and *StarCraft* with the focus on modeling the social structure, socially-aware matchmaking, and network robustness against player departure.

Jia et al. [20] compare social relationships in different multi-player games across different genres but also with online social networks such as Facebook. They introduce a model to analyze such relationships. The authors describe five type of interactions, which can be used to generate graphs. 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 describe a number of experiments with network measures, whereas the focus here is on relating network information with behavioral performance metrics.

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, in this paper we are able to connect specific network metrics to the players' in-game performance. In contrast to prior work, in this paper we are able to analyze social influence of different interactions groups on performance in a new game genre.

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

TABLE I
STATISTICS OF THE DESTINY DATASET

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

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.

V. Dataset and Pre-processing

A. Dataset

The dataset used in this study consists of player activities of a random sample of 10,000 *Destiny* players that played the game at least two hours. This limit was set to avoid people who installed the game but never played beyond the first few steps of the tutorial. In-game activities are based on either player versus player (PvP) or player versus environment (PvE). The PvP mode, accessed via the *Crucible*, covers a variety of different match-based activities played across three-versus-three to six-versus-six matches. The current analysis is based on networks derived from 930,720 Crucible match records that took place between September 2014 and January 2016. Each 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. Also included 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. The basic statistics about the used dataset are shown in Table. I.

TABLE II
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)

B. 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. 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, as the resulting graphs are mostly team-based. The resulting property lists where then divided into classes, to extract information on a per class-basis.

Fig. 1 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 II, 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).

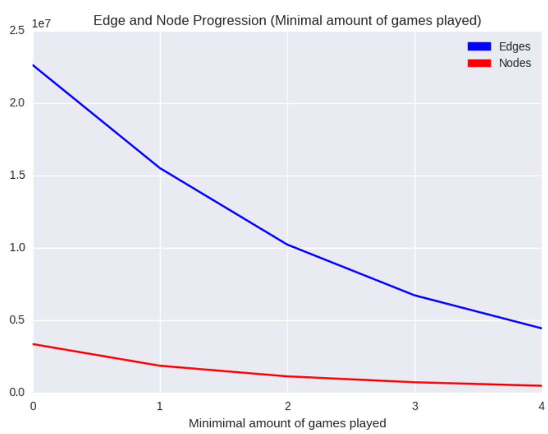


Fig. 1. Deletion of nodes - After removing players who have not played together at least four times many connections are removed

C. 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. 2 shows the varying preferences of the classes of the users. Fig. 2 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.

Fig. 2. Class distribution of players' "first choice" character

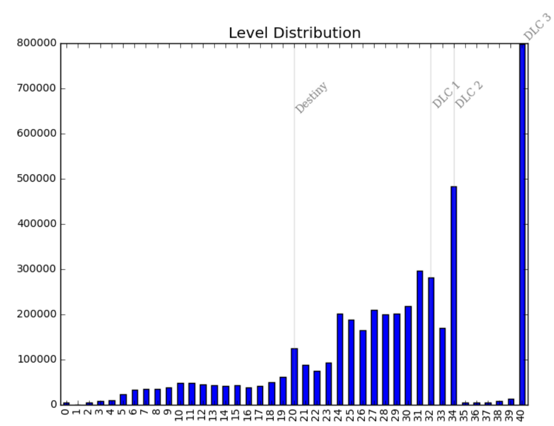


Fig. 3. Level distribution

VI. 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.

A. 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

TABLE III
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)

TABLE IV
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 V
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

different ways. Based on the match data we were able to create three networks on how players interact with each other. For such 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 III 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 IV 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 V illustrates how many matches 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.

VII. 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.

A. 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 VI 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.

a) Degree distribution: The *degree* (k) of a player in the graph refers to the number of links to other players. Table VII 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.

b) Average degree (k_avg): The *average degree* (k_avg) describes the average of all players' degrees in the graph. As shown in Table VI the average degree is much lower in "same team" graph T compared to the other graphs. That shows, that players playing tend to play more with the same players in a team than against them.

c) 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.

d) 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.

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

e) 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. 4 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.

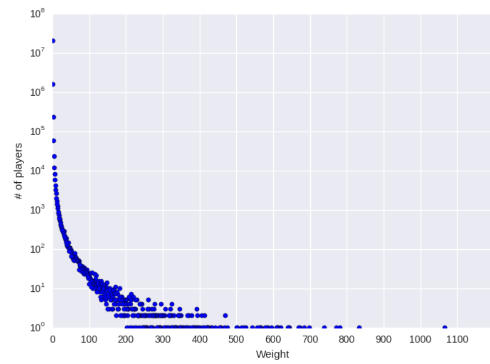
f) Largest Connected Component (LCC): The largest connected component (LCC) is the largest self-contained subgraph of the main network. As shown in Table VI, the number of nodes and links of the LCC only slightly differs from the main graphs. This means, that the players are very well connected through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

TABLE VI
METHODOLOGICAL COMPARISON OF THE THREE NETWORKS (THRESHOLD MINIMUM GAMES PLAYED - 3)

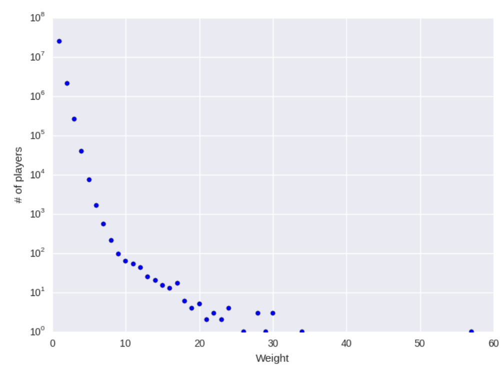
	Same Team (T)	Opposite Team (O)	Same Match (M)
Nodes	725,704	725,704	725,704
Nodes in LCC	725,599	725,693	725,703
Avg. Degree (k_avg)	18.55	23.93	38.72
Links	6,729,257	8,682,726	14,048,455
Links in LCC	6,729,190	8,682,726	14,048,455
Diameter (D)	13	11	9
Avg. Clustering Coefficient (C_avg)	0.024	0.0082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

TABLE VII
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



(a) Playing on the same team



(b) Playing against other players

Fig. 4. Edge weight distribution

VIII. EXPERIMENTS

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

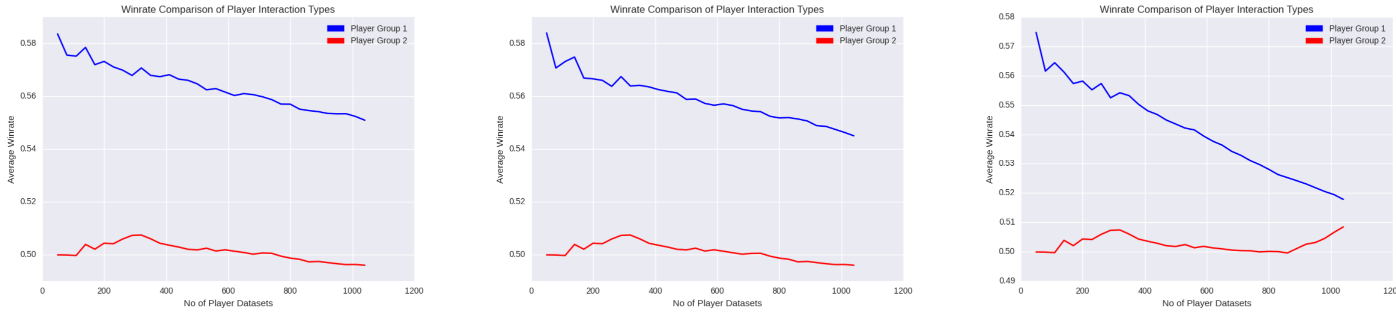
1) *Do player relationships/interactions relate to the win/loss ratio in multi-player PvP matches?*
2) *Do player relationships/interactions relate to combat performance (measured with kill/death ratio)?*
3) *Does clan membership impact the performance of* Destiny *players?*

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.

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

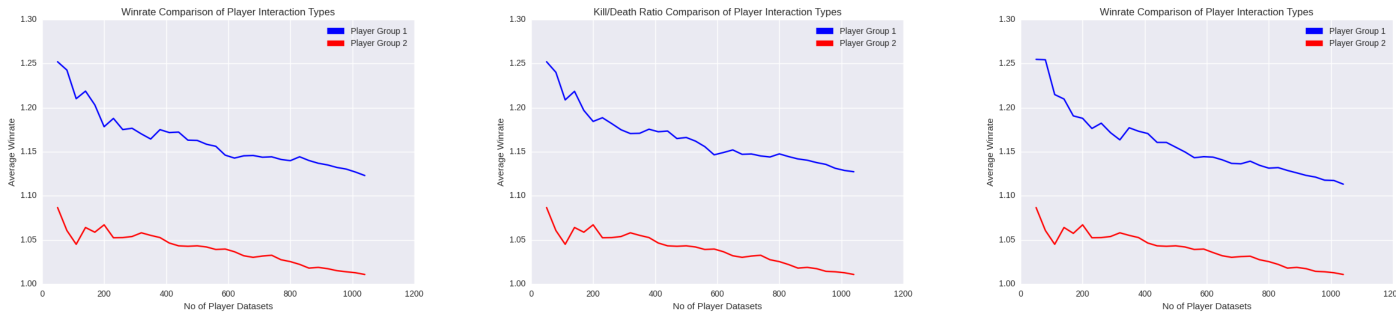
1) Do player relationships/interactions relate to the win/loss ratio in multi-player PvP matches?: Fig. 5 compares the winrate of the two different player groups in crucible matches. The three sub-figures refer to the number of matches players have to have played in order to be included for the analysis. 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.

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



(a) 10 (b) 100 (c) 250

Fig. 5. The winrate comparison of player groups playing crucible matches.



(a) 10 (b) 100 (c) 250

Fig. 6. Kill Death ratio comparison of player groups in crucible matches.

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. 6 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.

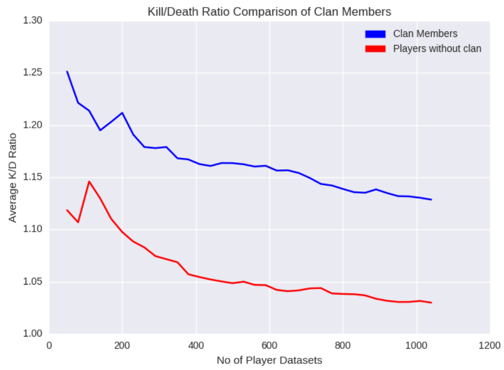
3) Does clan membership impact the players' performance?: To answer this question, we construct two similar experiments as in the first two research questions. Both of the experiments take a look at measures that determine a players success. The list of players is now split into two lists, one for players 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. 7 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.

IX. Conclusion and Discussion

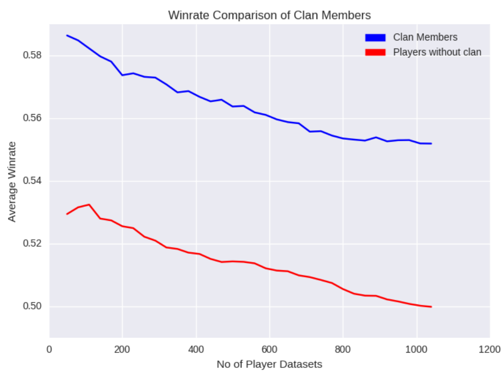
As multi-player online games become more and more popular, but also more complex it is crucial to find news ways to analyze the player behaviour [2], [1], [10]. With this paper we present some common techniques from social network analysis [17] and discuss and present the relevance for player networks based on match-based data to analyze aspects such as player performance.

In the above competitive networks have been developed based on almost 3.5 million players of 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.

Although social networks in online games have been explored in the past, e.g. [6], [19], [20], player networks in *Destiny* have not been developed prior to the work presented here, and the focus in this paper has therefore been on exploring the developed networks of the players along three different 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



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



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

Fig. 7. Clan membership

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.

Moving forward, we will advance this player network analysis to different directions: Firstly, future work will expand on the experiments presented here to include additional features from the over 1400 available in the telemetry data from *Destiny*. The three experiments presented here are examples of some of the most basic analyses that can be performed when behavioral metrics are combined with player networks, and there are a wealth of performance measures that can be integrated, for example performance with specific weapon classes, or across specific PvP game modes. Secondly, given the high dimensionality in the data, implementing behavioral profiling [9], [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. Thirdly, 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], [10].

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 and A. Canossa. *Game Analytics - Maximizing the Value of Player Data*. Springer publishers, 2013.

[2] A. Drachen, C. Thurau, J. Togelius, G Yannakakis and C. Bauckhage. *Game Data Mining*. In (M. S. El-Nasr, A. Drachen and A. Canossa, Eds.) Game Analytics: Maximizing the Value of Player Data, Springer Publishers, 2013.

[3] M. Szella, R. Lambiotteb and S. Thurnera. *Multirelational organization of large-scale social networks in an online world*. Proceedings of the National Academy of Sciences of the United States of America, 107(31), 13636-13641, 2008.

[4] J. Srivastava. *Data mining for social network analysis*. Proceedings of Intelligence and Security Informatics, 2008.

[5] C. Thurau and C. Bauckhage, *Analyzing the evolution of social groups in World of Warcraft*. In Computational Intelligence and Games (CIG), 2010 IEEE Symposium on (pp. 170-177). IEEE, 2010.

[6] A. Iosup, R. Van De Bovenkamp, S. Shen, A. L. Jia and F. Kuipers, *Analyzing implicit social networks in multiplayer online games*, Internet Computing, IEEE, 18(3), 36-44, 2014.

[7] J. Kawale, P. Aditya and J. Srivastava. *Churn Prediction in MMORPGs: A Social Influence Based Approach*. Proceedings of CSE, 2009.

[8] A. Drachen, M. Yancey, J. Maquire, D. Chu, Y. I. Wang, T. Mahlman, M. Schubert and D. Klabjan. *Skill-Based Differences in Spatio-Temporal Team Behaviour in Defence of The Ancients 2 (DotA 2)*. In Proceedings of the IEEE Consumer Electronics Society Games, Entertainment, Media Conference, 2014.

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

[10] R. Sifa, F. Hadiji, J. Runge, A. Drachen, K. Kersting and C. Bauckhage. *P*redicting Purchase Decisions in Mobile Free-to-Play Games. Proceedings of AAAI Artificial Intelligence and AI in Digital Entertainment, 2015.

[11] N. Ducheneaut, N. Yee, E. Nickell, and 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, pp. 407-416. ACM, 2006.

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

[13] B. Nardi, and J. Harris, *Strangers and friends: Collaborative play in World of Warcraft*, In Proceedings of the 2006 20th anniversary conference on Computer supported cooperative work (pp. 149-158). ACM, 2006

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

[15] N. Yee, *Motivations for play in online games*, CyberPsychology and behavior, 9(6), 772-775, 2006.

[16] J. L. Miller and J. Crowcroft. *Group Movement in World of Warcraft Battlegrounds*. International Journal of Advanced Media and Communication, 4(4), 387-404, 2010.

[17] J. Scott, *Social network analysis*. Sage, 2012.

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

[19] R. van de Bovenkamp, S. Shen, A. Iosup and F. Kuipers, "Understanding and recommending play relationships in online social gaming," 2013 Fifth International Conference on Communication Systems and Networks (COMSNETS), Bangalore, 2013, pp. 1-10, 2013.

[20] A. L. Jia, S. Shen, R. V. D. Bovenkamp, A. Iosup, F. Kuipers and D. H. Epema, *Socializing by Gaming: Revealing Social Relationships in Multiplayer Online Games*. ACM Transactions on Knowledge Discovery from Data (TKDD), 10(2), 11, 2015.

[21] G. Stafford, H. Luong, J. Gauch, S. Gauch, and J. Eno, J. *Social network analysis of virtual worlds*, Active Media Technology (pp. 411-422). Springer Berlin Heidelberg, 2012.