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Beyond the individual: Understanding social structures of an online player matchmaking website

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ABSTRACT

Engagement and player experience in multi-player games is influenced by the people you play with. For that reason, grouping features and matchmaking facilities in games, as well as third-party services, have gained in popularity in the industry and player community as they assist in building and maintaining social relationships with like-minded players. Understanding how social connections are formed and how these relations can foster in-game activity offers insights for building and maintaining a player base and can, in turn, improve retention and engagement. This paper examines the social network formed by users of the `the100.io` – a social matchmaking website for the game *Destiny*. The service provides an opportunity to examine an online social network formed around a game combined with demographic and preference data. The paper explores the correlation of structural network properties with preference and game-related performance data, provides metrics useful for analyzing and understanding the structure of these kinds of player networks and showcases how community analysis and behavioral profiling can be applied to inform game developers about behavioral groupings in social player networks.

1. Introduction

Engagement and user experience in online multi-player games are to a substantial extent influenced by the presence of and connections with other players. Social interaction and relationships in games are key drivers of engagement, retention, and monetization in multi-player games, and the facilitation and shepherding of social connections and player communities forms an important component in maintaining a player base [1]. They have been shown to be an invaluable tool to enhance user engagement and in-game performance [2,3]. Despite these potentials, this remains an under-explored topic in games user research. The impact of social connections in games means that online multi-player or massively multi-player games provide dedicated matchmaking or group-generation facilities in order to group players with similarly skilled teammates, clanmates, guildmates, or opponents. Other games, however, lack such features or the grouping takes place in an ad-hoc only fashion to find people for an upcoming match. In parallel, online player-grouping services and matchmaking services have gained in popularity because they assist in finding like-minded people to play with and thus in building and maintaining long-term social relationships in and around games. For many players, such services have become an important aspect of their game playing activity. Understanding social structures and how they are formed on such platforms – whether provided as part of the game or grown around a game or set of games – and how these relate to in-game activity can offer actionable insights for building and maintaining a player base and can thus, in turn, improve retention and engagement [4]. Both of these factors are vital for building a financially viable game, notably in online multi-player games that rely on a semi-persistent or persistent structure [3,5,6].

Social networks established via grouping or matchmaking features or services with the same aim can be analyzed and visualized using techniques from Social Network Analysis (SNA, e.g., [3,6–10]) to illustrate cooperative and competitive in-game interactions. SNA can hence be used as a basis for investigating player interactions and relationships. For example, Pirker et al. [4] explored social connections

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formed in direct competitive play in the hybrid shooter *Destiny* [11] and investigated the impact of indirect social connections (connections formed through playing matches together) and direct social connections such as clan memberships on in-game behavior and combat performance.

For data analysis, however, a central challenge remains in previous and current work on social networks in and around digital games, in the lack of relation between the networks themselves and the individual user, including, for example, preference, motivational, and demographic data. This means that current knowledge is limited about how network behavior in games correlates with real-world preferences. Furthermore, without taking such individual information in network analysis into account, results can be difficult to act on by game companies. Telemetry-based information about the social connections between players generally provides information concerning in-game interactions and does not link these to any self-report information, demographic data or personal preferences. If such information is present, it will typically be only basic demographics gathered through third-party providers, or data on a small scale, for example, via associated lab-based user research.

1.1. Contribution

Analysis of player social networks has so far largely focused on networks based on implicit relationships formed through interactions of the players with each other inside the game environment. Quantitative structural analysis of online player communities, on the other hand, is considerably scarcer, with Jia et al.'s [9] work on multiplayer online games communities forming a notable exception. The `the100.io` player grouping service we are investigating in this paper provides a rich view on the preferences of thousands of users of the service, offering a unique opportunity to examine a social network formed around a major commercial title, i.e., *Destiny* – a hybrid online first-person shooter and multi-player/massively multi-player game. In previous work, Schiller et al. [12] investigated the groups in which players are grouped into by the `the100.io` based on provided preference data and how group characteristics such as the composition of groups and the social connections within a group translate to game-related activity. In contrast, the study presented here focuses on the entire social network formed by the users of the platform and, for example, how social activities or network metrics of individual players relate to their game-related behavioral metrics. Specifically, SNA is combined with personal preference data and graph visualization in this paper with the dual intention of:

(A) Investigating the structure of the `the100.io` network formed by players of the hybrid online massively multi-player game *Destiny*, including general network properties and its community structure. Several sets of observations of the behavior of the `the100.io` network and its constituent players are presented, including metrics related to network properties such as centrality. We explore the distribution and relationship between social activities such as taking on the role of moderator or sherpa, personal preferences such as profanity tolerance and favored play style, and game-related behavioral metrics such as character and light level.

(B) Based on social network metrics, player behavior in the network as expressed via `the100.io` features, as well as game-related metrics such as character and light level, archetypes of groups in the network, are developed using archetypal analysis [13,14].

Investigating player networks using properties such as centrality measures and behavioral profiling offer new ways for game development companies to monitor and analyze live player communities. For example, clustering player social behavior, and exploring the underlying community structure using community detection techniques provide tools for understanding patterns in the social behavior of players.

2. Related work

The analysis of social connections and structures has become commonplace – originally for physical environments but with the introduction of online social networks also increasingly in such contexts since these networks facilitate the analysis of very large samples. In particular work on large-scale user platforms such as *Twitter*, *Facebook*, *Snapchat* and the like have drawn attention to the uses of SNA to describe networks and cater to the needs and interests of the individual users (e.g., [10]). Due to the large body of work in this space and in order to keep the discussion relevant to our work, we limit our discussion to work in the context of digital games.

SNA in games has attracted relatively limited previous interest from the research community. This is not because game-related social networks are less complex or evolved than online social networks in other contexts but rather because data access is not as ubiquitous as for other online social networks [15]. However, results so far indicate that the interactions between players influence in-game behavior and, ultimately, the user experience. Furthermore, social connections and interactions in games appear to be important motivational drivers for the game playing activity itself [2,5,16,17]. This has sparked interest among game companies, which are interested in social networks primarily from the perspective of the impact social connections between players have on the playing experience, notably towards driving engagement, retention, and monetization [2,6]. SNA employed to investigate the social interaction among users gained popularity in the context of digital games with the introduction of social network games, i.e., games that are embedded in and played via an existing online social network. For example, Kirman et al. [18] analyzed the structure of two social games on *Facebook*. With the proliferation of persistent online games and social mobile games, SNA has also migrated to these game formats. Until recently, social networks forming in or around the game playing activity have been mainly analyzed using qualitative research methods such as participatory observation or virtual ethnography (e.g., [7,19–21]). Williams et al. [22] used quantitative sampling and centrality measures to obtain a dataset of guilds in *World of Warcraft* [23] which served as a pool for a stratified sampling method to select an equal number of players from different categories (e.g., low and high centrality) for conducting ethnographic interviews.

Less attention has been given to quantitative SNA. A core challenge across these studies has been to try to identify meaningful connections between players to use as a basis for network generation and description [9,10,17]. Moreover, the work that currently exists in academia is focused on massively multi-player online games and shared online virtual environments. This means that there continues to be a gap in the state-of-the-art when it comes to the broader exploration of how social networks operate in games and their influence on player experience, retention, or monetization [2,3]. Exceptions to this include Iosup et al. [8] who examined social networks in *Defense of the Ancients* [24] and *StarCraft II* [25], focusing on socially-aware matchmaking strategies and exploring how robust networks can work against player departure. Rattinger et al. [3] developed unique strategies for developing social networks in *Destiny* [11], a game that does not include mechanics for explicit friendships in the game itself. At the same time they showcased how the most heavily engaged and retained players in the game were characterized by having large social networks in *Destiny*. Both, Ducheneaut et al. [5] and Shen [26] examined social interactions in MMOGs, with the former focusing on *World of Warcraft* [23] and the latter on *EverQuest II* [27]. Both led to a similar conclusion: sociability among players in MMOGs is not as prevalent as one would expect. Keegan et al. [28] analyzed the trade networks of *gold farmers* – gamers playing a game to acquire in-game currency which is later sold for real-world money – arguing that understanding the structure of such networks can be used to detect deviant activity. Kokkinakisa et al. [29] investigated whether the valence of in-game interactions in *League of Legends* [30] is reflected in a player's tendency towards choosing anti-social user names. Szell and Thurner [31], studied the structure of friend, enemy, and communication networks in the MMOG *Pardus* [32] and found, amongst other issues, that friend and enemy networks exhibit strong topological differences. Others have derived information about the social connections of players by relying on survey data. Shen and Chen [33] used an online survey to study how the networks of players differ by sociodemographic, socioeconomic, and gameplay patterns. Mason and Clauset [34] asked players about their online and offline friendships and triangulated the data with behavioral in-game data.

Another line of research has looked into the composition of in-game groups formed by players. For instance, Thurau and Bauckhage [35] analyzed the evolution of guilds in *World of Warcraft* [23] based on descriptive statistics of the guild such as size, experience levels of the members, and joining and leaving players. Ducheneaut et al. [36] used SNA metrics such as density and centrality to explore the structural properties of guilds in *World of Warcraft* [23] and Poor [37] studied the social networks of guilds in *PlanetSide 2* [38]. Chen et al. [39], in turn, derived categories of guilds based on various guild characteristics.

It is important to emphasize that all of the above works focus on social relationships formed within a game whereas our focus lies on understanding the social connections formed on community websites, specifically player-grouping services and here in particular the `the100.io`. `the100.io` provides a valuable data source in this respect as compared to similar websites as it is targeted towards establishing long-term relationships between players. As mentioned earlier, Schiller et al. [12] investigated the structure of the player groups formed by the `the100.io` (similar to what some of the above works did for in-game groups) but did not analyze the overall social network of the community. Having said this, the work most closely related to ours is perhaps that of Jia et al. [9] who investigated social networks of four online player communities which all offered match-making features. The collected networks were compared against each other and with online social networks from, for instance, *Facebook*.

In summary, SNA has in the context of game development and research been hitherto focused on the interaction between players and the associations that form between them during and around the playing activity [3,5,9,40]. However, previous work focuses predominantly on data derived from in-game social networks only, whereas the work presented here is based on a social network formed by users of an online player-grouping website. The work presented here thus forms a direct extension of previous efforts by correlating a social network formed by a player community with self-reported preference information about these players.

3. Destiny

Destiny [11] is a science-fiction themed game where players need to defend the Earth from alien aggressors, with humanity being on the brink of destruction. Players take on the role of so-called *Guardians*, the last and best hope of a race reduced to one last city. At the same time, the *Guardians* work towards reviving a planetoid-sized sphere called the *Traveler*, which protected human civilization in the past but currently lies dormant. Players journey to different planets in the solar system, complete missions, events, raids, engage in combat and other activities in order to build up their characters to fend off the alien invasion. *Destiny* blends features from a number of traditional game genres with strong shooter elements and mechanics. The core of the gameplay is focused on individual and small-team operations and tactics.

Destiny features three different player classes and players can level up their characters up to level 40. Along with unlocking new abilities and obtaining new weapons and other equipment through gameplay players become gradually more powerful. The game has multiple different Player vs Player (PvP) and Player vs Environment (PvE) modes, the former accessible via the *Crucible*, the central hub for PvP content in the game. Multi-player is often performed by organizing players into fireteams, made up of three players per team. In both PvE and PvP game modes, players are rewarded with new weapons and items through random drops or by completing specific tasks. Players have access to a wide variety of weapons, armor, enhancements, emotes, ships and other equipment with most of these being modifiable in various ways.

4. Dataset

We have chosen the popular player grouping website `the100.io` for the present study, for three main reasons. First, compared to many other looking-for-group websites which focus on establishing ad-hoc connections, the `the100.io` aims at establishing a permanent group of players sharing the same preferences, which makes connections much less volatile. Secondly, the `the100.io` collects basic information about its users which allows us to relate social network measures to self-reported data. Lastly, we required a website from which we could obtain data about players' friends and group memberships. In the following we provide a short summary of how the `the100.io` works.

The website allows players to add friends, join groups, and most importantly schedule and sign up for *Destiny*-related activities. For example, a player can schedule a raid for 6 p.m. PST and allow other members to sign up for this activity. Many activities in *Destiny* require teams of players, and scheduling games on `the100.io` provides a way for small groups of friends or individuals to find the help they need. This is extremely useful for some players as a number of activities in *Destiny*, such as raids, do not have matchmaking. Another benefit of `the100.io` is that because the game creator can set a specific time and see beforehand whether enough players have signed up, the uncertainty involved is greatly reduced compared to other options such as online Looking for Group (LFG) websites.

Each user of `the100.io` must create a profile which requires the user to enter various self-report data such as maximum character level, light level, age, or gender. Some of these questions are asking about preferences, for instance, preferred platform and playtime which we will refer to as preference data. Groups also have distinct characteristics such as the preferred platform, play style, typical time of day, and size. Each group can have moderators and sherpas (i.e. self-described experts willing to help teach other players how to improve their skills or complete activities). Lastly, `the100.io` also stores information on each activity that has been created, such as the activity type, scheduled date and time, and players who signed up to participate.

4.1. Data collection and processing

All three areas of information (users, groups, and games) are listed within pages in `the100.io` using sequential integer values. Using a Python script, data for all existing users, groups, and games on the `the100.io` was collected as of December, 16, 2016. All told, we were able to obtain data on over 200,000 users, about 2500 groups, and over 2,000,000 games which have been played since the launch of `the100.io`. Together, this creates a rich dataset on players' self-reported social connections without relying solely on approximations based on in-game API data. It is important to emphasize that in this paper we will focus the discussion on the user level and on the social connections between the users. The structural properties of the groups themselves are beyond the scope of this work. The main variables of interest for each user are:

- **Age** – the self-reported age of the player.
- **Gender** – the self-reported gender of the player.
- **Time zone** – the self-reported time zone of the player.
- **Preferred platform** – either Xbox 360, Xbox One, PlayStation 3 (PS3), PlayStation 4 (PS4), or PC.
- **Play Style** - Either *casual/having fun is the priority* or *serious/getting it*

done is priority. This measure has been derived from a player's group memberships. If a player belongs to at least one *serious* group, s/he was treated as *serious* player.
- **Profanity** – indicates whether a user is fine with profanity or not.
- **Preferred playtime** – this refers to the preferred schedule for play, with four options being: weekday mornings and weekends, weekday afternoons and weekends, weekday evenings and weekends, and weekday late-nights and weekends.
- **Level** – the maximum character level across all the player's characters (a player can have multiple characters in *Destiny*).
- **Light level** – light level is a character attribute in *Destiny* which depends on the overall quality of the gear of the player. Light level impacts the damage dealt and reduces the damage taken.
- **Sherpa score** – A sherpa in *Destiny* terminology is someone who is willing to guide other players. This score is calculated by `the100.io` based on the number of activities a user participated in and which involved helping players.
- **Friends** – Users can also add friends by sending friend requests to other users. Once the other party accepts the friendship request it constitutes a confirmed connection and information is exchanged. Although certain information is already shared when the request is unconfirmed we are ignoring these connections to avoid noise, for example, caused by users sending out lots of requests which have never been answered. This way, only friendships which have been actively agreed upon are considered.
- **Number of groups** – number of groups a user is part of.
- **Activity score** – measures how many sessions a user has joined or created. Users can also increase their score by inviting others to join the `the100.io`.[2]
- **Active game count** – sum of recent and upcoming games as listed on a user's profile page. Compared to the activity score, which is an all-time score, the active game count is an indicator of the current activity level.
- **Karma** – `the100.io` calculates a *karma* score for each player to value players which have a positive impact. Players can give karma to other players (but only once per player), usually after playing with them if they had a good experience with them, considered them especially friendly or helpful, etc.

Information listed on user profiles was collected for 218,213 users. However, many of the users in the obtained dataset had no friendships at all. As we are mainly interested in the social connections and their influence we exclude these users, which resulted in a sample of 53,017 users. Based on these users and their friendship information we derived a social network consisting of 3229 connected components of which we isolated the largest connected component (LCC) consisting of 45,221 nodes and 135,747 edges. The LCC accounts for 85.3% of all users and has an average clustering coefficient of $\overline{C} = 0.1812$ which is in line with clustering coefficients found for other online social networks such as *YouTube* or *Orkut* [41].

The following analysis is based on this component (all other components have less or equal than 18 nodes). For each user (node) in the LCC we calculated the following centrality measures (using Stanford's Network Analysis Platform [42]) which are considered to be perhaps the most frequently used (cf. [43]) in social network analysis (specifics can be found in, for example, [44]):

- **Degree centrality**: A first order centrality measure indicating the level of connectedness of a given player in terms of number of links they have. This measure is directly proportional to the number of friends.
- **Betweenness centrality**: A common measure of information flow that is related to the number of shortest paths passing through a player.
- **Eigenvector centrality**: A common measure to model the influence of a player in the network by checking the connectivity to highly influential players.
- **Closeness centrality**: The *closer* an actor is to others the more central the actor is in the network. It is calculated as the average length of the shortest paths between the actor and all other nodes.

The several centrality models are used here for robustness and validation. It is important to note, however, that each of the above listed measures has different strengths and concentrates on different aspects of the notion of centrality of an actor.

5. Results

5.1. Basic data description

Of the 45,221 users in the LCC 53.05% prefer PlayStation platforms and 46.16% prefer Xbox platforms. By far the largest group is comprised of players using the current generation editions of these consoles with 49.77% playing on PS4 and 43.26% on Xbox One. PS3 and Xbox 360 only play a marginal role with 3.29% and 2.93% respectively. The remaining 0.76% stated a preference for playing on a PC (although it should be noted here that *Destiny* has not been released for PC). Users are on average 30.82 years old (SD = 9.54) with about 0.4% claiming to be older than 70 years. 50.76% of the users stated to be male, a minority of 2.15% to be female, and 0.43% indicated *other*. The remaining 46.66% preferred to keep their gender private. A vast majority of 75.45% stated that they lived in US and Canada related time zones (Eastern, Central, Pacific, or Mountain). Most of the players indicated a preference for playing late-night on weekdays or on weekends (52.52%) followed by weekday evenings or weekends (21.35%), weekday mornings or weekends (17.94%), and lastly weekday afternoons or weekends (8.18%). The large majority of players (29,177) is OK with profanity while only 783 players indicated not being OK with profanity. Only one player in our sample chose *some profanity*. We will thus not consider this option in the further analysis. Concerning play style, there are approximately three times as many *casual* players (12,322) as *serious* players (4220).

In terms of *Destiny* performance, players in the dataset at hand can mostly be considered as relatively experienced *Destiny* players, with most of them indicating a level of 40 followed by a level at or slightly below 34 (see Fig. 1a). These peaks correspond to the level cap before and after the release of *The Taken King* expansion. In general, the `the100.io` is seemingly used more by high-level players with only 1,410 players having a character level of $\leqslant 20$ while 73,661 users have a level of $\geqslant 34$. Most players also indicated a light level greater than 280 as shown in Fig. 1b. The two peaks coincide with the light level cap before and after the release of the fourth and to date latest extension *Rise of Iron* which raised the cap from the previous 335–400. Please note, that these values (level and light level) need to be entered manually by the user and that entering the light level is optional. However, as the `the100.io` is a matchmaking service we assume that users are by and large keen to provide honest responses since this will influence with which other users they will be grouped with.

Fig. 1c–f show the distribution of the `the100.io` related variables number of friends, sherpa score, karma, and activity score. As evident from the figures, all four metrics decrease exponentially. At this point it should also be noted that the vast majority of users (95.6%) has not obtained a sherpa score yet (these are not included in Fig. 1d). Table 1 shows the descriptive statistics of all variables used in our study along with the number of missing entries.

Table 2 shows the results of Mann-Whitney U tests (performed due to the non-normality of the data) assessing the impact of a player's play style and preference for profanity on game-related metrics, `the100.io`

[2] https://the100io.zendesk.com/hc/en-us/articles/208292158-Activity-score-and-how-to-increase-it.

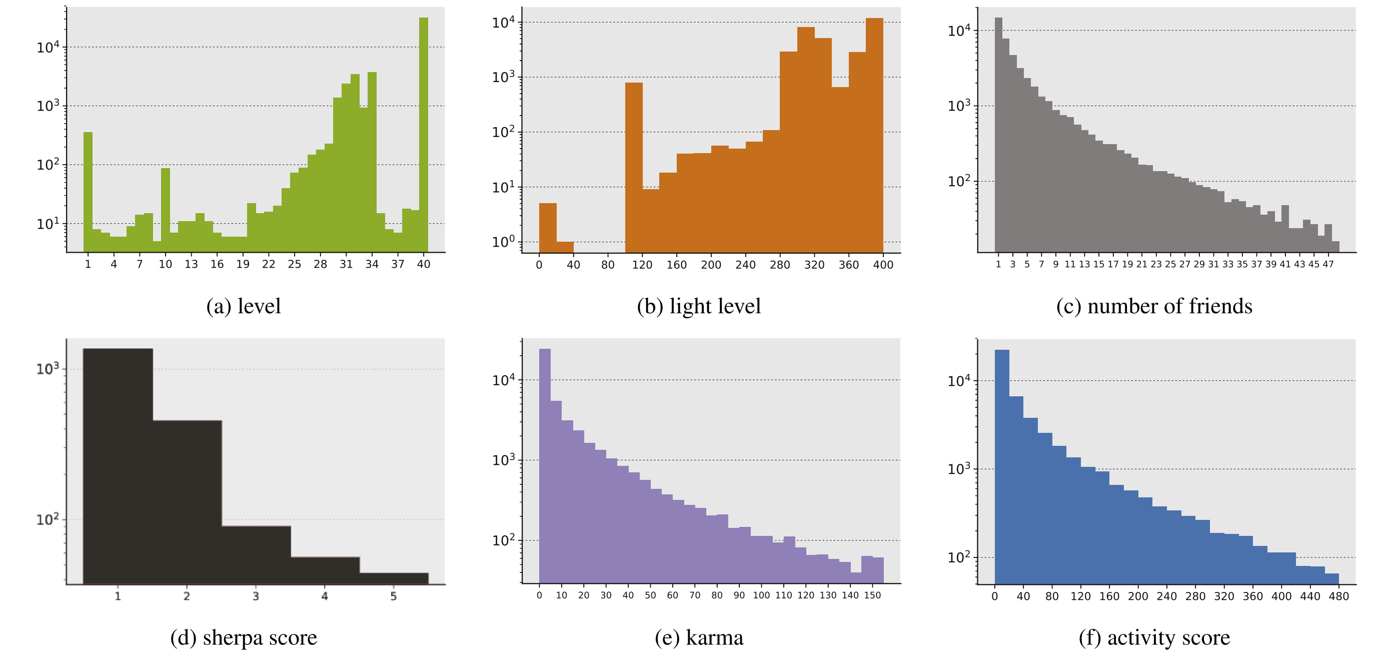

Fig. 1. Distribution of *Destiny* (a and b) and the `the100.io` (c–f) related measures (*y*-axes indicate the number of players and are log-scaled).

Table 1
Descriptive statistics of variables together with the number of missing entries.

	Value range	mean	std. dev	Missing entries
Age	[13–99]	30.82	9.54	5078
Gender	Male, female, other, private	–	–	0
Time zone	e.g., Pacific Time, Central, Time, ...	–	–	1
Preferred platform	Xbox 360, Xbox One, PS3, PS4, PC	–	–	0
Level	[1–40]	37.24	5.37	35
Light level	[10–400]	341.26	56.53	12,533
Sherpa score	[0–5]	0.066	0.357	0
Friends	[0–631]	5.83	11.68	0
Number of groups	[0–8]	0.49	0.77	0
Activity score	[0–7419]	59.04	108.66	129
Active game count	[0–23]	0.47	1.56	0
Karma	[0–572]	15.50	31.78	0
Preferred playtime	e.g., Weekdays Late-night and Weekends	–	–	1
Play style	Casual, serious	–	–	22,323
Profanity	Profanity OK, no profanity, some profanity	–	–	15,248

variables, and social network measures. It shows significant differences between players adapting a casual or serious play style. The latter not only score higher in game-related measures such as level or light level but also have significantly higher sherpa scores (which seems reasonable since serving as a good sherpa requires a certain level of experience in the game), higher karma, and higher centrality. There are less significant differences concerning profanity. Players who prefer no profanity exhibit higher karma scores which may suggest that other players approve of players who refrain from profanity and reward them with karma points. In turn, players who are OK with profanity have higher activity scores and higher centrality measures. Table 3 shows the results of Kruskal-Wallis tests to assess the impact of the preferred playtime on the various measures. Significant results were followed up by pair-wise Mann-Whitney U post hoc tests. Except for light level, all other measures are affected by playtime. Most of the significant differences are between players preferring to play late-night or on weekends (the preferred time for playing for about 50% of the users) and other time periods.

5.2. Communities

We applied a community detection algorithm, specifically the Clauset-Newman-Moore community detection method for large networks [45], to detect densely connected groups of users, which at the same time are only loosely connected with other groups, i.e., communities can be considered to be fairly independent clusters of a graph. In this respect, it is important to stress that these communities, do not in general have any direct relation with the groups formed by `the100.io` service, as the detected communities are based solely on user-to-user relationships (i.e., players get assigned to groups while communities are detected based on player established friendships). In the following we will thus use the term *group* only if we refer to `the100.io` created groups and use the term *community* when referring to structures generated by SNA.

Fig. 2 presents a node-link visualization of the community structure of the largest connected component with communities of more than 50 members (36 communities in total) enclosed by a black border. As the visualization shows, communities are primarily evolving around the two major platforms Xbox and PlayStation, resulting in a quite noticeable split between these two. This is to a certain extent not surprising, however, as *Destiny* does not support cross-platform play. For both platforms players mainly congregate in one large community composed of 12,984 (community #0, PlayStation) and 10,993 players (community #1, Xbox), henceforth referred to as the principal communities. All smaller communities are directly connected to either of the two whereas direct connections between smaller communities are scarce. Also worth noting is that users playing on the previous generation (PS3 or Xbox 360) mainly conglomerate in one single community (community #2 and #3, the second largest for both platforms). This might be due to the fact that there are less than 1/10 PS3 and Xbox 360 users compared to PS4 and Xbox One owners and as such the likelihood of connecting with the same cluster is higher, especially when specifically looking for others still playing on the older generation platform. Fig. 2 also shows a large number of players who do not belong to any community and only have few connections, preliminarily to members of the two principal communities. These may be users who are new to `the100.io` or signed up and lost interest in using the service further. Users who stated that their preferred platform is the PC are relatively isolated in the network, forming two small communities

Table 2
Results of Mann-Whitney U tests to determine differences based on indicated preferences for play style and profanity.

	Play style			Profanity		
	Casual	Serious	U-value	No profanity	Profanity OK	U-value
Level	38.73 ± 5.17	39.03 ± 4.75	25107646.0*	37.71 ± 4.86	37.98 ± 4.53	11147076.0
Light level	355.54 ± 55.86	370.61 ± 51.86	17033333.5*	340.37 ± 56.88	343.94 ± 55.37	6923602.0
Activity score	80.73 ± 119.12	151.38 ± 206.09	17955417.0*	61.15 ± 103.28	69.81 ± 119.97	10513453.5*
Active game count	0.81 ± 1.88	1.88 ± 2.95	19803365.5*	0.47 ± 1.55	0.56 ± 1.71	11192000.0
Group count	1.00 ± 0.02	2.37 ± 0.70	4528.5*	0.56 ± 0.82	0.56 ± 0.82	11399725.0
Sherpa score	0.09 ± 0.41	0.24 ± 0.72	24052980.0*	0.10 ± 0.47	0.08 ± 0.39	11280570.5
Karma	22.10 ± 36.11	39.80 ± 50.84	18121687.5*	18.51 ± 39.62	18.38 ± 34.01	10518824.0*
Age	32.94 ± 9.89	34.96 ± 10.61	16048118.0*	30.96 ± 11.72	31.18 ± 9.31	8115576.0
Degree centrality	0.00017 ± 0.00029	0.00035 ± 0.00058	17792896.5*	0.00015 ± 0.00030	0.00016 ± 0.00030	10533640.0*
Betweenness centrality	0.00013 ± 0.00065	0.00041 ± 0.00183	18064065.0*	0.00016 ± 0.00084	0.00013 ± 0.000788	10912867.5
Closeness centrality	0.18 ± 0.02	0.20 ± 0.025	19090195.0*	0.18 ± 0.03	0.18 ± 0.024	10596000.5*
Eigenvector centrality	0.0014 ± 0.0055	0.0035 ± 0.0104	20364882.5*	0.0011 ± 0.0046	0.0012 ± 0.0053	10974970.0

* significant at $p < .0042$, Bonferroni corrected.

Table 3
Results of Kruskal Wallis (K-W) and Mann-Whitney U post hoc tests to determine differences based on preferred playing time (l = weekday late-night and weekends, e = weekday evenings and weekends, a = weekday afternoons and weekends, m = weekday mornings and weekends, K-W = Kruskal-Wallis).

						Mann-Whitney U tests					
	l	e	a	m	K-W H	l-e	l-m	l-a	e-m	e-a	m-a
Level	37.31 ± 5.34	37.15 ± 5.42	37.25 ± 5.31	37.04 ± 5.47	22.06*	**	ns	**	ns	ns	ns
Light level	341.29 ± 56.59	341.30 ± 56.57	340.87 ± 56.66	341.88 ± 55.75	0.88	–	–	–	–	–	–
Activity score	61.28 ± 115.20	54.09 ± 91.07	57.56 ± 108.85	60.82 ± 106.75	37.50*	**	**	ns	ns	ns	ns
Active game count	0.49 ± 1.57	0.43 ± 1.49	0.46 ± 1.56	0.46 ± 1.63	19.17*	**	**	**	ns	ns	ns
Group count	0.50 ± 0.78	0.47 ± 0.77	0.50 ± 0.76	0.47 ± 0.79	33.15*	**	ns	**	**	ns	**
Sherpa score	0.06 ± 0.35	0.07 ± 0.36	0.07 ± 0.35	0.09 ± 0.42	14.94*	ns	ns	**	ns	**	**
Karma	15.77 ± 32.05	14.91 ± 30.61	14.52 ± 30.44	17.39 ± 35.61	23.79*	**	**	ns	ns	ns	ns
Age	31.15 ± 9.17	29.87 ± 10.06	31.05 ± 9.52	30.58 ± 10.35	185.41*	**	ns	**	**	**	**
Degree centrality	0.00013 ± 0.00024	0.00012 ± 0.00022	0.00013 ± 0.00029	0.00015 ± 0.00042	50.15*	**	**	**	ns	ns	ns
Betweenness centrality	0.00010 ± 0.00057	0.00009 ± 0.00045	0.00011 ± 0.00073	0.00016 ± 0.00137	32.53*	**	**	ns	ns	ns	ns
Closeness centrality	0.18 ± 0.02	0.18 ± 0.024	0.18 ± 0.02	0.18 ± 0.02	50.15*	ns	ns	**	ns	**	**
Eigenvector centrality	0.00092 ± 0.00378	0.00080 ± 0.00311	0.00133 ± 0.00641	0.00135 ± 0.00711	34.75*	**	**	ns	ns	**	**

* significant at $p < .0042$, Bonferroni corrected; ** significant at $p < .008$, Bonferroni corrected; ns = not significant.

(community #22 and #26) composed of PC players only. As *Destiny* has only been released on Xbox and PlayStation these players may have a hard time making friends as other players do not know on which platform they are actually playing the game.

Table 4 lists detailed statistics for all communities with more than 50 members. In terms of density (number of connections within a community divided by the number of possible connections), smaller communities are more densely connected than larger ones. However, in absolute terms users in larger communities maintain more friendships as reflected by the average degree (the number of incident edges, i.e., friends). In terms of average character level the communities do not differ much. Likewise, communities display similar patterns when it comes to the preferred playing time of its members, with late-night and evenings being the preferred time for most of them. However, in terms of activity score there is quite some variation among the different communities. The two principal communities evoke the highest activity among its members, most likely because more friends mean more opportunities for taking part in matches. However, some of the smaller communities also have large average activity scores such as community #15, #25, or #28. By contrast, however, there are also communities with a very low average activity score, for example, community #31 and, especially, #12. The two PC communities (#22 and #26) also have less active members which may relate back to the point made above. Almost all communities are also mainly composed of users from US and Canada related time zones (not shown in the table) which is to be expected given that ~75.5% of all users live in these time zones (see Section 5.1).

5.3. Correlations

Table 5 provides a summary of the Spearman's rank correlation coefficients between age (we excluded gender due to the gender ratio being heavily skewed towards male and almost half of the users not reporting their gender at all), `the100.io` related metrics (activity score, active game count, group count, sherpa score, karma), *Destiny* specific traits (level and light level), and the four centrality measures. All correlations were shown to be significant with $p < .00083$. In the following, however, we will focus the discussion on correlations with at least moderate coefficients ($\rho > .3$, following Cohen's [46] convention).

First, it can be observed that *Destiny* related experience measures (level and light level) are moderately correlated with the various centrality measures; that is, players who are more socially connected are also more advanced in the game itself. Higher-level players also belong to more groups and have more recent and upcoming games (active game count). However, we cannot say for certain if they are better connected because of being higher-level players or if the higher levels are a result of having more friends and thus more opportunity to play. Similarly, `the100.io`'s calculated activity score also has large correlations with all the centrality measures; that is, players with a prominent position in the network also exhibit higher activity. This is further underlined by the fact that users with higher activity scores also have more active games.

Interestingly, group count is only weakly to moderately correlated with the different centrality measures. Being a member of more groups does not result in considerably more friends or vice versa. A potential

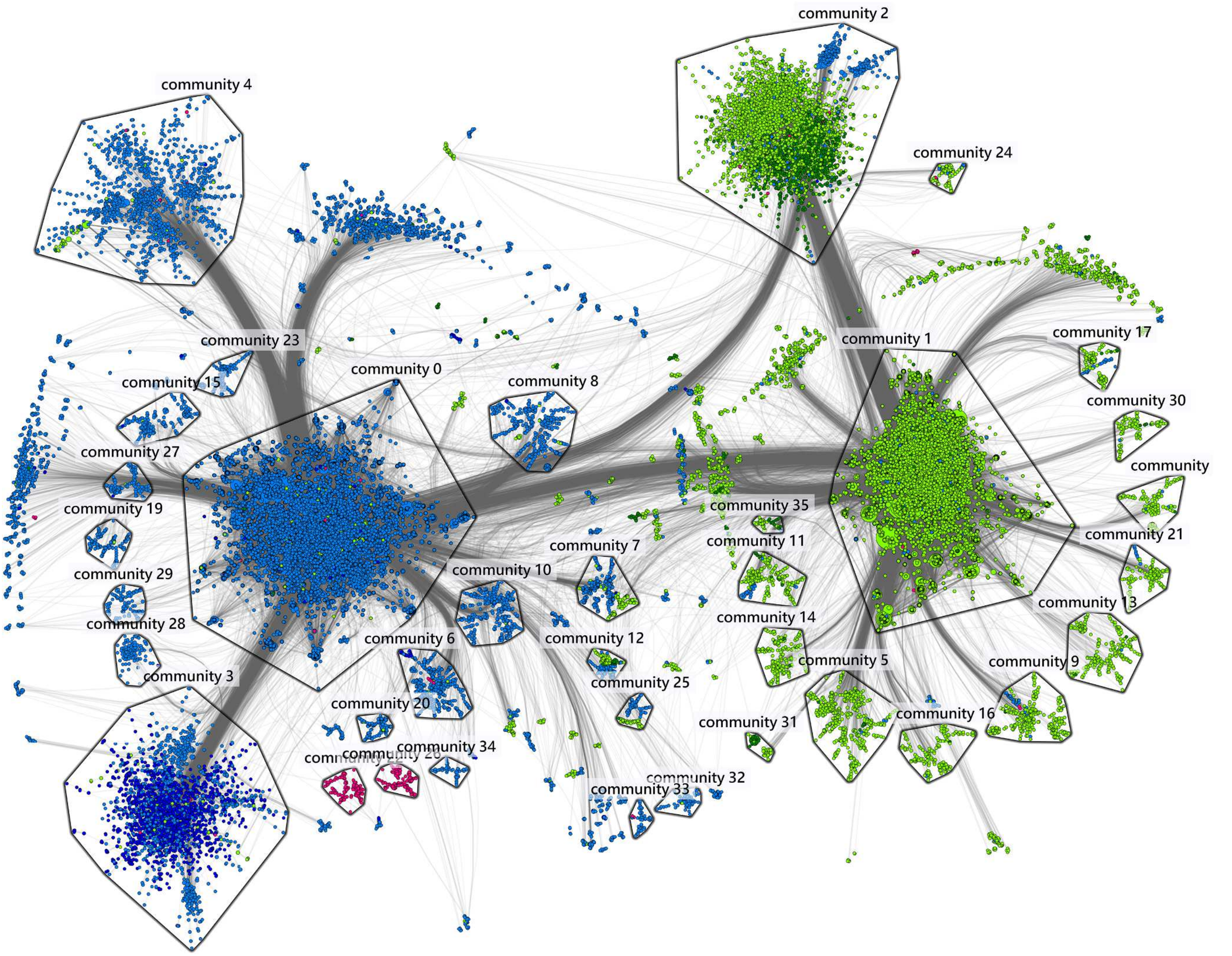

Fig. 2. Visualization of the community structure of the largest connected component ($|N| = 45,221$, $|E| = 135,747$) of the `the100.io` website. Communities with more than 50 members are enclosed by borders. The coloring of the nodes reflects the platform the individual users prefer to play on (■ = Xbox 360, ■ = Xbox One, ■ = PS3, ■ = PS4, ■ = PC). The size of a node is proportional to the number of friends. Edge bundling with alpha blending was used to accentuate the flows between communities.

explanation could be that users mainly seek friends within a single group such as, for example, the group which they consider to be their primary group.

Karma is highly correlated with all the centrality measures, mostly with closeness centrality; that is, players having a more central position in the network have higher karma values. More friends increase the likelihood of receiving more karma points, especially since karma can only be given once to another player. Karma also correlates highly with the activity score and the active game count since here again, participating in more game sessions increases the chances of receiving karma. However, from the existing dataset we are currently unable to infer if karma also acts as an incentive to actively seek out new friends or to partake in more sessions. An interesting point at first sight is that players with higher level and light level also have higher karma. Considering that high level players are also more active (members of more groups, higher number of active games) on the platform and are more central members of the social network mitigates this observation to some degree.

Sherpa score is only moderately correlated with karma. Also, sherpas would appear to occupy only marginally more central positions in the social network than users with no sherpa activity. This is to some extent surprising as sherpas might well appear to be attractive friends for players who need guidance or help in difficult scenarios. One aspect, however, which may come into play here is that `the100.io` is used to a great extent by relatively experienced players (see Section 5.1). Another factor contributing to this could be that sherpas are possibly not very easy to find on the platform, making it harder to purposefully befriend sherpas.

5.4. Archetypal analysis

Archetypal analysis [13] is a soft-clustering method (i.e., a data point can belong to multiple clusters) which represents the data points as a convex combination of extreme data points – the so-called archetypes. The archetypes lie within the convex hull of the data and provide an interpretable way of analyzing complex behavioral datasets with respect to extremal entities. More specifically, it represents a collection of the behavioral features of each player as an $m \in \mathbb{N}$ dimensional data point and by grouping all the $n \in \mathbb{N}$ data points in a column data matrix $X \in \mathbb{R}^{m \times n}$, Archetypal analysis aims to find a matrix $Z \in \mathbb{R}^{m \times k}$ containing $k \in \mathbb{N}$ archetypes and the column stochastic coefficient matrix $A \in \mathbb{R}^{k \times n}$, that contains the soft-clustering belongingness coefficients, by minimizing the matrix norm $\|X - ZA\|^2$. Archetypes in Z can then be defined as convex combinations of data points in X (cf. [13]) or particular extremal prototypes (see [47]). Archetypal analysis has been successfully used previously in the context of player profiling, recommender systems, and for investigating social phenomena in video

Table 4
Descriptive characteristics of communities with more than 50 members. Degree, activity score, and level are expressed as mean ± standard deviation. (= Xbox 360, = Xbox One, = PS3, = PS4, = PC, = mornings & weekends, = afternoons & weekends, = evenings & weekends, = late-night & weekends).

community	size	density	degree	pref. platform	act. score	level	pref. time
#0	12984	0.000506	6.57±0.11		78.53±118.14	38.05±5.02	
#1	10993	0.000744	8.18±0.15		77.62±120.61	38.56±4.11	
#2	4715	0.000928	4.37±0.09		61.01±153.99	36.30±5.25	
#3	2533	0.001563	3.96±0.11		40.85±75.37	36.49±4.99	
#4	1399	0.002424	3.39±0.12		47.28±88.51	35.58±5.17	
#5	516	0.004990	2.57±0.12		33.12±49.65	35.88±4.18	
#6	497	0.005452	2.70±0.12		34.67±60.81	35.26±5.74	
#7	446	0.008787	3.91±0.23		28.61±55.46	38.13±4.64	
#8	422	0.006878	2.90±0.18		25.94±38.42	35.99±4.52	
#9	392	0.007190	2.81±0.22		22.48±41.78	30.57±13.04	
#10	367	0.009038	3.31±0.19		42.52±60.08	36.70±5.14	
#11	247	0.010434	2.57±0.16		41.47±58.79	36.94±4.59	
#12	242	0.012585	3.03±0.30		1.34±8.21	24.93±11.41	
#13	242	0.010356	2.50±0.19		26.59±54.52	34.93±5.10	
#14	223	0.011393	2.53±0.18		34.63±60.14	35.51±5.12	
#15	207	0.017541	3.61±0.37		82.70±167.83	35.43±5.04	
#16	188	0.014621	2.73±0.19		26.40±37.58	38.22±3.37	
#17	163	0.023101	3.74±0.53		22.13±33.80	38.13±4.50	
#18	159	0.020221	3.19±0.33		33.73±53.59	36.58±5.37	
#19	155	0.016590	2.55±0.16		37.22±62.90	37.03±3.97	
#20	151	0.018190	2.73±0.30		23.26±31.61	36.03±6.18	
#21	134	0.025025	3.33±0.31		58.96±78.31	36.76±4.92	
#22	134	0.018292	2.43±0.19		10.58±21.91	20.33±13.31	
#23	131	0.027011	3.51±0.47		22.60±33.26	39.36±2.26	
#24	124	0.022292	2.74±0.27		35.87±58.00	35.39±4.37	
#25	123	0.027856	3.40±0.29		74.42±108.57	37.13±4.11	
#26	120	0.018908	2.25±0.26		13.96±28.15	38.65±5.87	
#27	119	0.027631	3.26±0.38		30.47±42.65	37.41±4.53	
#28	109	0.041454	4.48±0.63		75.42±88.41	38.40±4.59	
#29	108	0.023018	2.46±0.17		28.25±36.63	35.43±4.09	
#30	106	0.024618	2.58±0.22		32.31±42.65	37.16±5.12	
#31	67	0.064677	4.27±0.68		12.10±25.58	34.76±5.25	
#32	60	0.050847	3.00±0.44		56.57±72.03	39.98±5.24	
#33	56	0.043506	2.39±0.35		15.61±19.76	34.77±11.36	
#34	52	0.041478	2.12±0.25		22.17±35.62	32.42±8.01	
#35	52	0.042986	2.19±0.49		20.63±28.42	37.29±5.01	

Table 5
Spearman rank correlation between various user-related variables and centrality measures. Moderate or larger correlations ($\rho > .3$) are written in boldface.

	Level	Light level	Activity score	Active game count	Group count	Sherpa score	Karma	Age
Level	1							
Light level	.249*	1						
Activity score	**.429***	**.451***	1					
Active game count	.235*	**.484***	**.405***	1				
Group count	**.329***	**.421***	**.340***	**.414***	1			
Sherpa score	.113*	.246*	.272*	.281*	.158*	1		
Karma	**.595***	**.615***	**.759***	**.451***	**.428***	**.312***	1	
Age	.156*	.193*	.170*	.182*	.223*	.072*	.247*	1
Degree centrality	.285*	**.357***	**.666***	**.327***	**.312***	.214*	**.591***	.259*
Betweenness centrality	.240*	**.315***	**.630***	.284*	.253*	.217*	**.515***	.198*
Closeness centrality	**.383***	**.402***	**.617***	**.331***	.277*	.236*	**.679***	.248*
eigenvector centrality	**.327***	**.304***	**.480***	.284*	.240*	.181*	**.537***	.208*

cases with missing values were excluded, $^*p < .00083$, Bonferroni corrected

games (e.g., [48–51]) and has been adapted here as we are interested in finding prototypical users of the `the100.io`.

As features we included sherpa score, activity score, karma, friend count, group count, and the level of the players. We tried to have a mixture of `the100.io` and *Destiny* related features while at the same time keeping the number of features at a reasonable level to maintain interpretability. Also, we excluded features which had too many missing values. For example, light level was not considered since more

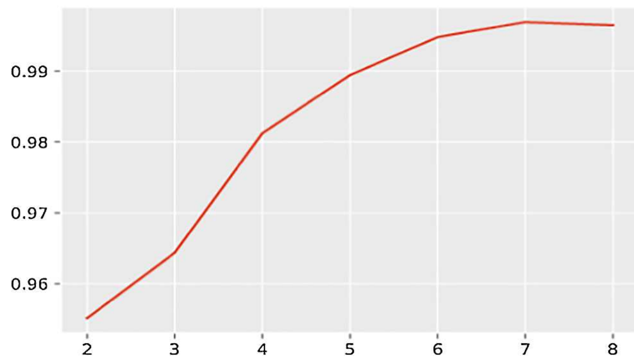

Fig. 3. Scree plot showing variance explained by principal convex hull analysis for two to eight clusters.

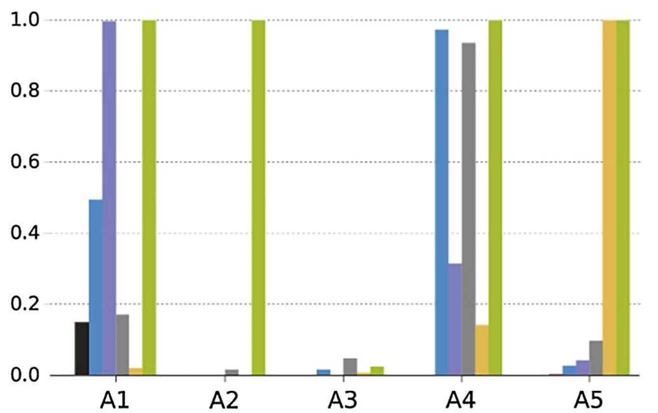

Fig. 4. Archetype profiles across six `the100.io` and *Destiny* related features (■ = sherpa score, ■ = activity score, ■ = karma, ■ = friend count, ■ = group count, ■ = level).

Table 6
Distribution of players when assigned to their main archetype.

archetype	number of players
A1	1,749
A2	39,588
A3	616
A4	1,289
A5	409

than 10,000 players provided no information about their light level which would have reduced the total number of players on which the archetypal analysis could be run by almost 25%. Friend count, karma, and activity score values above the 99th percentile of the data were excluded in order to remove outliers. In addition, all players without data for any of the selected features were excluded. The features for the approximately 43,000 remaining players were then normalized to the [0...1] range by dividing the values with the maximum value of the respective feature. The archetypal analysis was then run for three to ten archetypes using `py_pcha` [52], a Python implementation of the algorithm proposed by Mørup and Hansen [53] and which is suitable for processing large scale datasets like the one at hand. Visual inspection of the scree plot of the percentage of variance (cf. Fig. 3) indicated either a four or five-cluster solution using the elbow criteria. After inspecting the resulting clusters for interpretability we decided on the five cluster solution (in case of the four-cluster solution `A4` and `A5` are merged into a single one).

Fig. 4 shows the archetype profiles (`A1` – `A5`) of the five extracted archetypes. To give an impression of the prevalence of the different

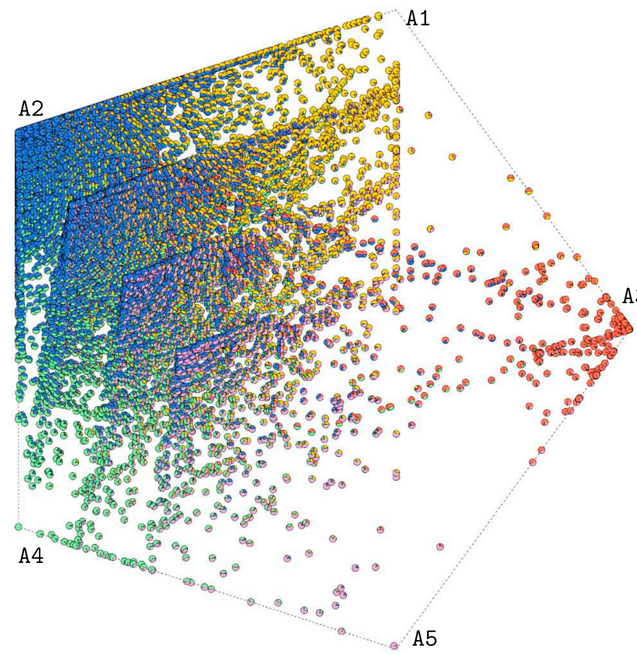

Fig. 5. Players degree of membership to each of the five archetypes (■ = `A1`, ■ = `A2`, ■ = `A3`, ■ = `A4`, ■ = `A5`). Each corner of the pentagon represents one archetype. Each pie-chart represents one player, placed by weighting the positions of the corners based on the player's belongingness coefficients.

archetypes Table 6 shows the distribution of the players when assigned to their principal archetype (i.e., the one with the largest belongingness coefficient). Fig. 5 visualizes the players belongingness to the different archetypes.

- `A1`: This archetype mainly distinguishes itself from the others by the high sherpa scores. Players in this archetype also have high character levels. This is to a certain extent expected since in order to be able to provide reasonable help for unskilled players a certain level of mastery is required. At the same time, however, players belonging to this archetype have fewer friends than those belonging to `A4` and are only members of a small number of groups. This tendency is also reflected in the correlations results (see Table 5) which only show weak correlations between sherpa score and group count as well as degree centrality (that is, number of friends). One possible explanation might be that players acting as sherpas mainly focus on guiding players of a specific group, or to put it otherwise, they can be considered loyal to *their* group(s). Sherpas may thus mainly be interested in friendships with members of the groups they belong to. This archetype is also characterized by the largest karma values across all archetypes. As discussed previously, karma is intended to act as a reward for friendly and helpful players (see also Table 5). It would appear that users are really making use of this feature to express their gratitude.
- `A2` & `A3`: These two archetypes correspond to users who did not use, or at least were not yet using the platform very actively (as reflected by the low number of friends and groups, as well as activity score). These may be users who are new to the platform and are just starting to use it or users who have registered but did not have an interest in using it further. The main distinction between these two archetypes is how experienced the users are in *Destiny* with `A2` encompassing high-level players and `A3` players who are quite new to the game (low level). However, compared to `A2` only a very small

fraction of the users belongs primarily to A3 (cf. Table 6) which corresponds to the fact that inexperienced players only constitute a small portion of the user base as discussed in Section 5.1. At this point it should be emphasized that all other archetypes relating to active users (A2, A4, and A5) show high character levels suggesting that players who use the platform frequently increase their *Destiny* skills or that high level players are more likely to keep on using the service.

A4: Users belonging to this archetype are characterized by being very active on the platform (high activity score), high character levels (which is most likely a result of partaking in many sessions), and having many friends. As degree centrality is correlated strongly with karma, it is not surprising that these players also received a good share of karma points.

A5: This last archetype comprises users who change their group frequently and only have a few friends. They also do not partake in many sessions as reflected by the low activity score. These may be users who are not happy with the groups they are currently in and are thus, for example, looking for other groups but have a hard time finding a suitable one.

6. Discussion

One challenge of SNA in games is the derivation of the social network itself since it is typically not directly exposed by a game's API. Also many games either do not offer or only offer limited social networking features (cf. [8]) which makes it difficult to explicitly express relationships. Consequently, the social networks need to be approximated based on the accessible data. For example, Ducheneaut et al. [36] created ties between guild members if they were in the same zone in the game world – assuming that in such case they are likely to play together. Iosup et al. [9] linked players, for instance, if they were present in the same match. Online communities forming around these games attempt to overcome the shortcomings of in-game social features, giving players opportunities for self-organization. The the100.io we are concerned with offers a group-finding service targeted towards establishing long-term play groups and making explicit friendships. As such the work presented here offers insight into the social structures of an online grouping service rather than into in-game social structures. The network we derived is based on the friendship information explicitly expressed by the users of the service. This also has the drawback, however, that we do not have a means to ascertain how strong the relations really are. Although we excluded unconfirmed friendships, people may randomly add friends on social networks which may only constitute weak connections. When interpreting the results one should thus keep in mind that the network may be denser, as when only including connections which interact on a regular basis. Please note, that we are concerned with users of this service and as such we do not intend to draw conclusions about *Destiny* players in general. Because of this and because we crawled the complete website we also do not expect any sample bias to be present. However, we should stress that the data contains self-reported measures by the players. Given that the responses to the questions influence to which groups players are assigned, we assume that users by and large report and update the values truthfully.

Before discussing our results it should also be noted that works focusing on in-game networks in many cases collect information about in-game characters and not about the players themselves. While players often create several alternative characters for a game (see, e.g., [5,22]) it seems counterintuitive that people create several accounts on the the100.io as the goal of the service is to find people who share your interests in the game. As such we do not expect that multiple accounts affect the validity of the analysis.

6.1. General network properties

The first observation which deserves consideration is that around 75% of the over 215,000 users maintained no friendships whatsoever. Some of these users might only have recently joined the the100.io or had not used the service further after trying it, but nevertheless this still represents a very considerable number. Even if we look at the number of friendships of people in the LLC (Fig. 1c) we can observe that the large majority only maintains a small number of friendships. While the the100.io can be used without establishing friendships, making friends has certain benefits such as notifications when those people are online and information about their upcoming games. Using the built-in friend function, users can keep track of people with whom they played together well. As such we would have expected that people are more eager to make friends if they sign up for such a service. This seems reminiscent of the 'alone-together' phenomenon described by Ducheneaut et al. [5] – people are playing a game together with others but are not necessarily actively interacting with them. Shen [26] made a similar observation in her study of *Everquest II* [27] players. Many users of the the100.io thus seem to mainly be interested in finding ad-hoc playmates rather than longer lasting relationships.

Multi-player games such as *Destiny* depend to a great extend on players being able to find proper friends with whom they can play. In the present case we can observe that players who are better connected also exhibit considerably higher activity. This is in line with Jia et al. [9] who also found a positive correlation between the number of friends of users of *Dota-League* – a former community website for *Defense of the Ancients* [24] players – and their interaction in matches. More friends also means higher-level in-game characters. Shen [26] found a similar connection, noting that higher-level in-game characters also maintain larger chat and trade networks in *Everquest II* [27]. Given our current dataset we cannot say for sure, however, if those players are more active because they are more advanced or the other way round, although the latter would appear to be plausible – at least to a certain extent – as characters are leveled-up by playing the game. As hypothesized by Shen [26] players with high-level characters spend more time in the game and thus accumulate more contacts over time. This also sounds reasonable in the case of social matchmaking services. Individuals having more (real-life or on-line) friends have more opportunities to play and playing more frequently, in turn, again increases the character (and light) level. By contrast, however, this also means that players not having many friends are also less active, perhaps precisely for this reason. Thus, identifying players who are not socially active or in danger of leaving can be of great value in order to counteract this development, for instance, by offering incentives to these players or providing them with the kind of help they might need (e.g., by suggesting friends or groups or by connecting them with sherpas).

Another useful feature of the the100.io seems to be the karma value. Karma is highly correlated with all centrality measures, with activity (i.e., activity score and active game count), and game-related attributes (level and light level). While sherpas also receive moderately more karma than non-sherpas we would have expected to find a higher correlation. Here, the number of friends seems to be the decisive factor and sherpas do not have many more friends than others. In that sense, there might be a point in providing opportunities for sherpas which allow them to better promote their service. Moreover, karma seems to be really used by the players to reward other players and hence seems to be a good tool for community building. In this connection it is worth emphasizing that karma is a community-driven measure, essentially a voting mechanism of sorts, which allows the community to self-identify friendly and helpful players, while sherpa score is a site-designed measure which provides an indication of helpfulness. This distinction raises important questions along the lines of if community voting mechanisms work better than site-designed mechanics. Our results seem to provide at least some evidence that the karma system is more reliable than the sherpa score.

Concerning gender representation we should highlight that users are predominantly male with females only accounting for approximately two percent. Given the large number of people not reporting there gender we cannot, however, be sure if the number of females is really so low. Due to this we do not attempt to make any gender comparisons here although previous research on MMOGs suggests male and female players have different social interactions in MMOGs (cf. [26]). With respect to age we found small to moderate correlations between age and the various centrality measures, showing that with increasing age the centrality in the network also increases. This is in contrast with observations made by Shen [26], who found that younger players are more socially connected although the observed effect was very small.

6.2. Structure and communities

In terms of social network structure roughly 85% of all users belong to one giant connected component (see Fig. 2) – a common property typically exhibited by social or economic networks (cf. [54,55]). Kirman et al. [18] found similar structures in their analysis of player networks in social network games, observing that ~75% of the player-base belongs to one single component and with the other components being many times smaller. Another common attribute of such networks is the existence of a community structure (i.e., groups of densely interconnected nodes) which may reflect real social groupings arising to due common interests or cultural background (see, e.g., [56,57]). They may reflect formal structures imposed by an organization or may arise informally due to the self-organization of individuals. For that reason, and because information flow is mostly confined within these communities, they are an important topological property of social networks. In our case, these communities first and foremost evolve around the PlayStation and Xbox platforms. As stated earlier, this is not surprising given that *Destiny* does not support cross-platform play and is also reasonable in this specific scenario.

Activity score is also a measure which fluctuates across communities. While some of the smaller communities show high activity among members, we suggest that precautions should be taken to avoid the formation of isolated communities as these seem to be prone to reduced activity. This could be done, for example, by proposing random friends, users with similar preferences, or friends chosen based on specific likeness and/or neighborhood criteria in order to help users escape their immediate neighborhood. On the other hand, neither preferred play-time nor time zone appear to have any huge influence on the emergence of communities. Although the latter is most likely caused by the fact that users are largely based in the US or Canada (about 75%). On the other hand, this also means that it would appear to be feasible for European users (~15.8%) to adjust to the majority of US/Canada based players to establish friendships despite a time difference of at least 5 h for playing together. However, there is one notable exception, namely community #28 which can be considered as the *Australian community* since virtually all its members live in Australian time zones. This can, for example, be a result of time zone isolation, and it would be valuable to explore if similar patterns also develop in other games along with strategies for overcoming such isolation patterns. For example, by offering facilities which will help users to connect with people in their geographic area or time zone. This would increase the chances of finding people who play at the same time and in turn, may lead to increased activity. Most communities exhibit high average character levels which is somewhat expected given that the user base of `the100.io` is skewed towards high-level players. However, given the small number of players with low character levels it is perhaps worthwhile to note that we can witness the existence of communities which are mainly composed of such players, specifically community #12 and #22 (cf. Table 4). These communities are also characterized by the lowest average activity scores. In this regard, it should also be mentioned that many communities only have small variations in character level, indicating that these are fairly homogeneous in terms of player skill.

To recapitulate we can state that we can observe the formation of some communities which have distinct characteristics but also a number of communities with similar attributes. This might be a specific property of the network in hand but may also be due to the variables used in the analysis not sufficiently capturing the individual characteristics of the communities. It could also be a direct consequence of the fact that the user base of `the100.io` is itself relatively homogeneous (majority of high-level players from the US and Canada). While we used variables which are publicly displayed on the profile page of users and may thus be used by players to build friendships, other factors (such as in-game experiences) could also play a role here. Future work may thus focus on exploring which variables are useful descriptors of communities on matchmaking websites. It would also be interesting to examine possibilities for facilitating the formation of more specialized communities, for example, to accommodate for players with specific preferences or special needs.

6.3. Archetypes

Shifting the focus to the archetypal analysis, we could identify five prototypical users of the `the100.io`: `A3`) new and inexperienced subscribers, `A2`) new but experienced users, `A1`) players willing to assist others, i.e., sherpas, `A4`) highly active players, and `A5`) users belonging to many groups but who only exhibit low activity. Once players fall within the latter three archetypes they are also characterized by high-level characters. Comparing `A3` with the other archetypes shows us that the `the100.io` predominantly attracts skilled players while inexperienced *Destiny* players are in their minority (see also Fig. 1a). The large fraction of high-level players may provide a certain indication that the website facilitates play, which in turn increases character attributes. However, this could also be due to the website attracting more skilled players in the first place. The cluster imbalance towards `A2` when players are assigned to their predominant archetype might be surprising at first but given the exponential decrease in the number of friends (cf. Fig. 1c) this is to be expected to a certain degree. When interpreting these results, one should also keep in mind that users can belong to different archetypes with varying degrees, meaning they might represent a mixture of these prototypical users. Moreover, archetype membership can change over time. For example, a user who initially belonged primarily to `A1` or `A3` may transition to, for instance, `A4` over time.

6.4. Industry applications

The work presented here is foundational in nature, aiming to conduct exploratory research into a large community of players surrounding a major commercial game title.

Social network analysis has been applied in games from different perspectives in academia, however, such work is limited by a lack of access to data, as compared to online social media platforms such as *Facebook*, *Snapchat*, and *Twitter*. In the games industry, there is not a strong tradition for collecting data on social behavior, with the notable exception of esports where toxicity remains a problem [58], but even in situations where companies collect social data, the results of any analysis is not shared publicly. This means that there is no solid body of literature available for designers to turn to that is specifically related to social behavior or social structures in game design, even given foundational work such as Ducheneaut et al. [7,59], Szell et al. [60], and Yee et al. [61] on massively multi-player online games.

In industrial game analytics, questions about the impact of social features and optimal design of such features are of perennial importance [2]. However, these are also questions that are among the least well understood in game analytics, and it can be challenging for analytics teams to address such questions, due to the lack of a solid and broad foundation of research focused on social behavior in games.

Added to this is the challenge many game studios face in terms of their ability to track friendships or other social connections in games. There can be several reasons for this challenge, including lack of prioritization in data collection of social features as compared to feature improvements [6]. It is notably a challenge for console-based games, as the "first party" networks contain the friendship information. That is, the players using the consoles or platforms already have friendships through these, and may not create friendship-like links within the game that data could be captured. The only solution for game studios is often to approximate friendship based on shared playtime with other players. But without any starting point which would filter potential friends, and the vast amount of interactions occurring on a minute-by-minute basis [62], this type of work is usually deemed infeasible or too costly in terms of an analyst's time.

This is where work such as the one presented here and, for example, Rattinger et al. [3] who used match-based information to build competition networks or Jia et al. [9] who used opponent networks, are valuable to the industry in suggesting ways of constructing networks that do not rely on platform data. Identifying the structure of the network is the first step in understanding a player base. Here an example of such an analysis of a player community is presented, along with the suggestion of tools such as archetypal analysis [13] to identify player groups of specific properties.

Even in situations where high quality data on social connections can be captured such data would rarely be shared publicly. This is exemplified by the lack of talks about this topic at major industry events. Game studios are extremely protective of their data [6], even between studios and their parent publishing house. The public sharing of data in game analytics remains rare, and only few academics are directly working with the industry in the space. New legal protection acts such as the GDPR means that this type of information sharing may be even less likely in the future.

Overall, studio-produced research on social activity in games remains limited and there remains a widespread issue of doubt in the industry about the external validity of academic research studies due to such research mainly working on specific MMOGs and MOBAs where data is more easily accessible – hence targeting a narrow range of games and virtual environments. Designers thus correctly question whether such results are useful for their titles. External research based on data coming from their specific game is very valuable in overcoming this roadblock, and the work presented here represents such a situation where the data pertains to a specific title – *Destiny* – but is produced outside the core game itself. This type of research, based on third-party websites or public APIs, is valuable to game designers who consider social activity in their game. Similarly, analytics teams can utilize this type of research as it gives them access to evidence and examples to make more confident recommendations.

We are not claiming to cover all tools and metrics useful to the game industry here, but there is a clear need for foundational research focused on social behavior in and around games. The work presented here represents a step in that direction, uncovering structural properties of the `the100.io` player network. Concrete findings such as the importance of moderators for group activity and the reduced activity of isolated communities are of direct interest to community managers in game companies. For example, the importance of moderators means that community managers should attempt to support them and assist isolated communities with making connections with neighboring groups towards increasing their activity.

6.5. Future work

There are several venues for further research. To begin with, this study relied solely on data gathered from the `the100.io`. While this gave us the benefit of a rich dataset on the self-reported social connections of the players without the need to rely on approximations based on data gathered through the *Bungie Destiny* API [63], the current results could be extended by correlating the self-reported preferences and the `the100.io` related measures such as activity score or karma with actual in-game behavior. This will allow further insights into the impact of social connections on, for example, play style or in-game performance. It will also allow us to compare behavioral metrics before and after people have joined the `the100.io` and thus to examine in greater depth the effect of such services on in-game behavior. Related to this, as we only looked at one matchmaking website in the current analysis our results may not generalize across all different matchmaking services. However, different platforms or social communities have different features and elements, which often makes it hard to compare them without an initial deeper understanding of the specific platform as offered by our study in this paper. Such in-depth single-platform studies as ours are thus also not uncommon in SNA in general (e.g., [64,65]) and when analyzing games. Nardi and Harris [16], Thurau and Bauckhage [66], or Ducheneaut et al. [36], for instance, focus on analyzing the social aspects of *World of Warcraft* while Mora-Cantallops and Sicilia [67] look into the personal player networks formed in the game *League of Legends*. Especially when, for example, building recommender systems it is also important to focus on the specific social and behavioral elements of the specific platform or game in question. Moreover, our study puts forward interesting insights into the optimal design of social features which can be of interest for matchmaking sites in general. That said, a comparison between the social networks formed on different matchmaking services may provide further valuable insights and would be an interesting next step for future work.

Secondly, as `the100.io` has recently also launched for the open world third-person shooter *The Division* [68] it would be worthwhile to investigate how different games shape – if at all – the structure of player communities. Lastly, building upon the ideas and techniques put forward in this paper there is the opportunity to investigate the temporal dynamics of the network structures on the `the100.io`. Such a dynamic analysis can help uncover how successful groups form and how engagement changes over time and thus may directly lead to valuable insights for improving retention. Better understanding of how to establish a thriving community, which is well-aligned with the particular needs of a particular game can be a valuable asset for ensuring long-time engagement and, in turn, retention.

7. Conclusions

In this paper the social network formed by users of the `the100.io` – a player-grouping service for the online multi-player shooter *Destiny* – was investigated. Our results contribute to the understanding of online player communities, more specifically player-grouping services. Better understanding of social structures and how these can potentially be leveraged to enhance player-grouping, matchmaking, in-game activity, or engagement can directly contribute to a more sophisticated player experience in multi-player games. At the same time, our results – while promising – only address one part of a broader problem, thus providing a strong motivation to further investigate the social connections in and around games. Toward this end, some suggestions for further research were discussed.

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