What Moves Players? Visual Data Exploration of Twitter and Gameplay Data

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ABSTRACT

In recent years, microblogging platforms have not only become an important communication channel for the game industry to generate and uphold audience interest but also a rich resource for gauging player opinion. In this paper we use data gathered from *Twitter* to examine which topics matter to players and to identify influential members of a game's community. By triangulating in-game data with *Twitter* activity we explore how tweets can provide contextual information for understanding fluctuations in in-game activity. To facilitate analysis of the data we introduce a visual data exploration tool and use it to analyze tweets related to the game *Destiny*. In total, we collected over one million tweets from about 250,000 users over a 14-month period and gameplay data from roughly 3,500 players over a six-month period.

ACM Classification Keywords

K.8.0 General: Games; H.5.m Information Interfaces and Presentation (e.g., HCI): Miscellaneous

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Twitter; Gameplay Data; Online Community; Destiny

INTRODUCTION

Every day, millions of active users (cf. [37]) share news, thoughts, and opinions on any imaginable topic through various social media platforms. This has made social media an important and useful information source for business and research alike as it can offer insights about the interests and opinions of a target audience, can help to identify trends or events, or can reveal problems and weaknesses of a product or service. For example, detecting points-of-interest of users

shared on microblogging platforms such as *Twitter* can be a powerful marketing instrument for all kinds of location-based businesses and services (cf. [36]). City and traffic planners can gain valuable insights about the dynamics of cities [19] or can develop a better understanding of the travel characteristics of short term visitors or residents [1] by studying the opinions and activities that people share on social media. Governmental as well as non-governmental organizations and citizens themselves – to name a further example – can benefit greatly from applications that harness substantial information and metadata from microblogging services in order to detect and prepare for emergencies, enhance information flow, or to provide support and relief during and after disasters [42]. Others (e.g., [25, 52, 57]), in turn, investigated social media data, such as real-time tweets to analyze activities (e.g., emotional responses and fan engagement) with respect to sporting events.

It is thus not surprising that social media has also become a useful communication channel for the game industry. Feedback shared by players on social media platforms is immediate. This gives developers an important tool to quickly react to issues or concerns, to better understand their audience (e.g., what matters to the players), to develop strategies for improving player retention, and to market their games. Moreover, several studies have confirmed an effect of electronic word-of-mouth on purchase decisions (see Rosario et al. [43] for an in-depth discussion) or early product adaption, for example, movies [23]. This effect can also be observed for games. A recent study prepared by *Deloitte LLP* [14] for *Twitter UK* showed that the sentiment of people's conversation about games can influence the sales performance of video games. The wealth of data that can be derived from online social networks has also made such platforms an increasingly attractive option for research focusing on player communities. For example, Albrechtslund [2] and Jordan et al. [29] analyzed online forums of games using methods such as virtual ethnography and participatory observation in order to understand how players build a community identity and to assess the impact of a gamer community on game design. Others have relied on *Twitter* data to examine gaming related topics, such as reactions to the *Global Game Jam* [40] or the *Gamergate* controversy [12].

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The work presented in this paper can be viewed as a continuation of these efforts. Compared to prior work in games user research we employ a visual data analysis approach to explore large-scale microblogging data corresponding to a specific game and relate it to actual in-game data in order to obtain a more holistic view of microblogging and in-game behavior. For example, players' social media activities can provide context for increased or decreased play activities. For that reason, we introduce an interactive web-based tool to facilitate the analysis of *Twitter* and in-game data in order to (i) identify topics which are of interest for players, to (ii) understand fluctuations in in-game activity, and to (iii) identify members who take on an important role in a player community. Different types of visualizations are supported and combined with analysis methods such as sentiment analysis to uncover relationships as well as patterns in the multivariate data. Given the complex nature of the problem we believe such a visual analytics approach is well suited for this kind of task as it combines the reasoning capabilities of humans with data analysis methods (cf. [31]).

In the second and main part of the paper we use our tool for the analysis of tweets and in-game activity related to the game *Destiny* [8] – an online-only multiplayer first-person shooter. We have chosen *Destiny* as our object of study because it has a large player community which ensures that there is a reasonable amount of tweets about the game, it is constantly updated with new content, giving us the opportunity to analyze the reaction of the players to this content, and – importantly – it offers access to in-game data through a public Application Programming Interface (API) [9]. Specifically, we used the API to gather gameplay data from players who shared their *Xbox Live* gamertag or *PlayStation Network* ID (PSN ID) on their *Twitter* profile. In total, we collected 1,062,390 tweets from 246,881 users over a period of about 14 months and gameplay data from 3,548 players over a six-month period.

To summarize, our primary contribution in this paper is an analysis of tweets and in-game activity of the *Destiny* player community using a visual data exploration approach. Our case study on *Destiny* sheds light on what topics matter to players, influential members of the community, and how microblogging data can provide explanations for variations in in-game activity. Our results contribute to the understanding of player communities and thus can help in building strong communities and, in turn, sustaining interest in a game or game franchise.

Lastly, it is also important to note that while our focus is on player communities, understanding how consumers feel about a certain product or service and how this affects use of it is not restricted to games. As such we believe that tools and studies such as the one presented here are of interest for other areas of user research as well.

RELATED WORK

A considerable amount of work has focused on communities formed within a game itself, in particular social structures in multiplayer online role-playing games (MMORPGs). For example, work of Ducheneaut et al. [17, 18] looked into the social dynamics of guilds, i.e., long-lived groups of players, in the MMORPG *World of Warcraft*. Similarly, Chung et al. [13]

analyzed the structural patterns of social interactions in groups of players in the game *Aion*, another popular MMORPG. Kou et al. [33], in turn, explored how the introduction of a new system for reporting players exhibiting toxic behavior in *League of Legends* affected prosocial behavior.

Common to all these studies is their focus on in-game communities whereas our concern is on out-of-game communication of players. One of the first studies in this respect was carried out by Seay et al. [46]. Looking into both, social experiences of guilds inside and outside the gaming environment, Seay et al. found that web pages of the guilds themselves as well as game forums were the most popular means for player communication outside the game. Indeed, several works since then have focused on analyzing the exchange between players on web forums, typically from a qualitative point of view. To give two examples, Albrechtslund [2], through participatory observation of the web forums of a *World of Warcraft* guild, explored how and why online communities construct narratives and how this contributes to identity formation and community building. In the same vein, Jordan et al. [29] studied the impact of the player community on the overall game design of *KingsRoad* – a browser-based MMORPG – by passive participatory observation of the official game forum and through virtual ethnography inside the game. This study is testament to the influence a player community can exert, highlighting two cases where the community could successfully persuade the developer to reverse certain changes in the game design.

Beside forums, social media channels – including microblogging platforms we are concerned with – have increased in popularity among players with *Twitter* reporting that gamers are quickly becoming one of the most active and engaged groups on the platform (cf. [3]). Consequently, *Twitter* has also moved into the focus of attention in games-related research. For example, Hicks et al. [24] explored challenges and opportunities in utilizing *Twitter* as a gaming platform. Of particular interest in the context of this paper are, however, studies which use *Twitter* to understand player communities. Work in this area is limited though and is usually confined to understanding public debates revolving around game-related topics. For instance, Chatzakou et al. [12] used data from *Twitter* to study the infamous *Gamergate* controversy. McDonald and Moffat [40], on the other hand, explored how people reacted to the themes of the *Global Game Jam* over a period of seven years. Kalaitzis et al. [30] proposed a system for predicting various game-related traits from the tweets of a player. Common to these studies is their focus on quantitative analysis methods. Our work is different from these efforts in that we focus on analyzing the public discourse surrounding a specific game and on identifying influential members of the community using a visual data analysis approach. Furthermore, we extend previous research by connecting *Twitter* data with in-game data.

Shifting the focus away from games, public communication on *Twitter* has also been studied for urban and traffic planning (e.g., [1, 19, 34]), for analyzing political discourse (e.g., [47]), or for enhancing situational awareness in crisis situations (e.g., [38, 53]) but also in entertainment domains more closely

related to video games such as television and sports. As Han et al. [22] note, there is a growing body of research aimed at understanding what types of messages people share on social media and how it is related to the television program they are watching. For example, studies conducted by Buschow et al. [10] and Wohn and Na [55] provide evidence that different types of programs evoke different types of messages. These works are similar to ours in that we are interested in triangulating postings made on *Twitter* with in-game activity. Also worth noting in this context is the work of Scharl et al. [45] who proposed a web-based application specifically targeted towards analyzing the public debate surrounding the television show *Game of Thrones*.

Similar efforts have also been made in sports related research. Several works have explored the potential of using *Twitter* data for identifying significant moments during a sports event (e.g., [35, 52]). Others have explored fan communication on *Twitter* during large sports events such as the *Super Bowl* [22], the *FIFA World Cup* [57], or the *Tour de France* [25]. These works are, however, mainly concerned with events of limited duration while we are adopting a longitudinal perspective. Nevertheless, in many of the above examples [25, 34, 38, 45], visual analytics approaches have been proven to be a successful means for making sense of conversations on *Twitter*.

OUR APPROACH

In order to facilitate the analysis of game-related *Twitter* activity and its possible relation with in-game activity we developed an interactive web-based tool based on *JavaScript* and *Node.js*. Specifically, the goal of our tool is to assist in answering the following questions:

1. What are players tweeting about? How is the players' sentiment towards these topics?
2. Can *Twitter* messages provide valuable contextual information for understanding fluctuations in in-game activity? For example, reasons for increased or decreased play activity.
3. Which members take on an important role in an online player community? For example, does only a minority of users drive discussion or does the community contribute equally?

At this point we should note that we focus on *Twitter* because of its popularity and ease of data access but other microblogging platforms could be used as data source as well. In brief, *Twitter* allows user to publish short messages of up to 140 characters, so-called *tweets*. Users can follow other users to receive updates of the followed users in their news feed and tweets can be *retweeted* to share them with one's own followers. While the number of followers can be considered a popularity indicator, retweeting is a form of information diffusion on *Twitter* (cf. [50]). Users can also like tweets (formerly called favorites) to bookmark them. We will use retweet count and likes as proxies of attention a tweet receives. In addition, following Yan et al. [56] we calculate a popularity score p for each tweet which is derived from the number of retweets n_r and likes n_l and is given by $p = (1 - \mu)n_r + \mu n_l$ where μ is a weighting factor. By default we use a value of $\mu = 0.5$ in order to treat retweets and likes as equally important.

From an implementation point-of-view the tool consists of five components: First, a crawler gathers tweets which match a user-specifiable query. Second, a MySQL database stores information about the collected tweets such as the text of the tweet, retweet count, likes (i.e., favorites), popularity score, and profile information. In addition, the database stores, if available, gameplay data. Third, a sentiment component determines the sentiment of the tweets using *Sentiment140* [20], a sentiment classifier specifically developed for *Twitter* data. Tweets are sent in batches to the *Sentiment140* service which then classifies tweets into negative, neutral, or positive. The returned sentiment values are stored together with the tweet in the database. Fourth, an importer reads, converts, and finally stores gameplay data – specifically gameplay metrics which can be gathered on a daily basis such as the number of matches played, experience points earned, or time spent playing – in the above mentioned database. Lastly, the front-end visualizes the data by means of different views (described in detail in the next section). The front-end was designed in such a way that it resembles a report which can directly be used by the researcher or data analyst to communicate the results and insights to different stakeholders (e.g., game designer). The design of the front-end followed the overview-first, details-on-demand paradigm advocated by Shneiderman [48]. For that purpose the tool integrates different visualizations (i.e., views) with different levels of abstraction. These views can be added and removed dynamically to adjust the visual dashboard to the needs of the analysis task. The time span of the data to be included can be defined separately for each view to allow the analyst to focus on different levels of granularity. In addition, all views are interactive, for example, it is possible to zoom into regions of interest to reveal more details, to view tooltips when hovering over data points, or to sort tables by a specific column in ascending or descending order. As an example, Figure 1 shows how the result of an analysis may look like.

Views

Timeline Views: The tool offers two timeline displays. The first timeline visualization shows the daily amounts of tweets¹ over a user-specifiable time span (see, e.g., Figure 1 or 2). In most cases this chart will serve as the starting point for the analysis as it allows the analyst to identify interesting days (e.g., days with large amounts of tweets) on which to build the further analysis. Being able to find such days constitutes an important element when studying social media data (cf. [41]). Tweets can also be filtered in order to only include tweets about a certain topic. The second timeline visualization compares daily tweet activity with an in-game metric such as, for example, number of matches played or play duration (see Figure 3). It can be used to reveal interesting time intervals in terms of gameplay, for example, periods where in-game activity was low or very high. Tweets posted during such a time span may provide indications for why a drop in in-game activity occurred or why interest grew. The in-game metric to be displayed can be chosen from a drop-down list and compared with the daily tweets of either the full sample or just against tweets from users for whom gameplay metrics are available.

¹Retweets are counted as tweets.

Figure 1. Excerpt from an analysis performed with our tool with time-line view (top), daily top tweets (middle, left), sentiment chart (middle, right), and tweets list view (bottom).

Daily Top Tweets: A bubble chart shows the 20 most often retweeted tweets on a given day (cf. Figure 1). The location on the y-axis and the size of the bubbles represents the number of retweets. In addition, bubbles are colored according to the sentiment of the tweet. Throughout the system, gray, green, and red are used to indicate tweets with neutral, positive, and negative sentiment. Hovering over a bubble will show the content and the author of the tweet as well as the number of retweets and likes.

Sentiment: This view offers a stacked bar chart showing the daily percentage of positive, negative, and neutral tweets (cf. Figure 1). Understanding the overall sentiment of tweets has emerged as an important facet in social media analytics as it offers a way to gauge the public's overall attitude towards a certain event, brand, or product (e.g., [15, 16, 27, 39]). In addition, Brooks et al. [7] note that the visualization of sentiment helped them to identify certain events more easily. As such we also deem it important for analyzing game-related social media data as it can give insights into how the player community reacts to, for instance, new in-game content.

Topics: A tag cloud shows the relative frequency of popular keywords mentioned in tweets during a particular time-period (see Figure 5 for an example). Tag clouds can be based on the sentiment of the tweets, for example, it is possible to view a tag cloud for positive tweets only. By clicking on a tag the term is automatically copied into a search box which can then be used to find tweets containing the keyword if desired. Clicking on an URL in the tag cloud will open the respective link in a new browser window.

List Views: Three different list views are provided. One shows information about the *Twitter* accounts responsible for the tweets in a given time period. Another list view provides information about accounts for which a valid gamertag or PSN ID could be extracted. Both tables provide data about the number of followers, the overall number of tweets posted and the number of tweets during the given time period, gamertag and/or PSN ID if successfully extracted from the user profile, as well as the average number of retweets, the average number of likes, and the average popularity score of the tweets from the user. These two views are useful for identifying accounts of key influencers. Following recent work in this area (e.g., [11, 26]) we also offer a means to only include *active users* in the lists, that is, users with a certain minimum number of tweets. This way accounts who are inactive or only post once in a while about a game can be excluded from the analysis. The third list view provides detailed information about the tweets themselves, including the full text of the tweet, the sentiment of it, the number of retweets and likes, and the author of the tweet (see Figure 1). The table can be adjusted to only show tweets matching a given search query. All three tables can be sorted by any column in either ascending or descending order.

Tweet Popularity: This view shows the number of retweets and likes for each tweet by means of a scatter plot. It offers a visual means to assess the popularity of a tweet. Data points can either be colored according to their sentiment or tweets of certain authors can be highlighted (cf. Figure 6). This can be helpful for determining which users are responsible for the most or least influential tweets. Tooltips show the text of the tweet, the number of retweets and likes, and the author of the tweet. Together with the list views it offers a useful means to determine influencer in the social space under investigation.

Player Activity: The player activity view uses a scatter plot to compare the *Twitter* activity (in terms of number of tweets) of individual players with a selected gameplay metric. This view is intended for establishing relations between the players' in-game behavior and their amount of tweets. For example, highly active players may also tweet more about the game.

CASE STUDY: DESTINY

Destiny [8] is an online multiplayer first-person shooter video game developed by *Bungie* and released for *Xbox* and *PlayStation* platforms in September 2014. The game takes place in a science fantasy setting where players take on the role of *Guardians* whose mission is to defend mankind against different hostile alien species. Players can partake in a variety of activities spanning Player vs Environment (PvE) game modes such as cooperative three-player *strikes* and six-player *raids* and different Player vs Player (PvP) modes. *Destiny* features different species and classes from which players can choose and offers extensive customization options for appearance and equipment such as weapons and armor.

We have selected *Destiny* as our object of study for three main reasons: First, we needed a game which has a large player community to ensure that there is a reasonable amount of tweets concerning the game. As of the first quarter of 2016, *Activision* – the publisher of *Destiny* – reported 30 million registered players (see [6]). Secondly, *Destiny* is constantly

Figure 2. Volume of tweets per day in our sample between June 9th, 2016 and July 17th, 2017.

updated with free and paid content and hosts a multitude of smaller and larger temporary events which feature new challenges and rewards. This gives us the opportunity to explore how players react to the new content and events. Thirdly, we required a game which permits access to in-game data in order to be able to relate in-game activity with *Twitter* activity. In case of *Destiny* this is possible through the public Application Programming Interface (API) [9] provided by *Bungie*. The API offers access to a wealth of in-game data for a given player, such as the number of PvP activities on a certain day.

Data Collection

We collected two data sets: i) a dataset containing tweets related to *Destiny* during a period of about 14 months and ii) a dataset containing *Destiny* gameplay data of *Twitter* users from which we were able to extract their *Xbox Live* or *PlayStation* Network username for a six-month period.²

Tweets were collected using the *Twitter Search API* [51]. As the term *Destiny* also appears in many other contexts we combined the term *Destiny* with other game-related keywords such as *Bungie* or *Guardians* and included *Destiny* related hashtags such as *DestinyTheGame* in order to reduce the chance of mining tweets where the term *Destiny* is used in non-game related contexts. In the end, the following query was used:

```
(destiny AND (E3 OR activision OR bungie OR
crucible OR crota OR guardians OR ironbanner OR psn
OR xbl OR gamertag OR gameplay)) OR RiseOfIron OR
destinygame OR destinythegame OR Gjallarhorn
```

Please note, that since the API only searches against a sample of tweets the returned tweets do not constitute an exhaustive list of tweets which match the query (cf. [51]). The search was repeated on a regular basis as the API only returns tweets published within the past 7 days. In total, 1,062,390 tweets from 246,881 users were collected during a period of about 14 months, specifically from June 9th, 2016 to July 17th, 2017.

Twitter profiles of users were searched for gamertags or PSN IDs which were later used for gathering in-game data of these users. However, as user profiles can – as the tweets themselves – be unstructured, player IDs are not always readily extractable. We thus searched user profiles using various regular

²This shorter six-month period mainly arose from practical considerations as collecting the in-game data proved to be more time-consuming than retrieving the *Twitter* data. Thus, instead of limiting the *Twitter* dataset to this shorter period we continued tracking tweets while collecting in-game data, resulting in the 14-month dataset.

expressions including tags such as gamertag, GT, PSN, or XBL to extract gamertags and PSN IDs. Extracted player IDs were checked against the *Bungie* API for existence and non-existing IDs were removed. Valid gamertags and PSN IDs were then used to gather gameplay data for these players through the *Bungie* API [9] for the first six months, that is, from June 10th, 2016 to December 1st, 2016. Players for which no daily data was available during that period were excluded as well. This process resulted in gameplay data for 3,548 players. Please note that in the following analysis we will always use the complete *Twitter* dataset as visual inspection of the plots of tweet activity of the subsample with available gameplay data showed that it followed the same trends, i.e. proportional increase and decrease in activity, as the whole sample.

The extracted game data includes aggregated daily activity metrics, including the amount of activities entered and the time spent playing of which we will make use in the following. Since the current API does not allow for retrieving daily statistics about the whole player population, we relied on statistics of individually extracted players.

Results and Discussion

Below we report insights gained from analyzing the gathered datasets with the above described tool. Throughout the discussion we will use a preceding @ to indicate *Twitter* accounts.

Events leading to increased activity

Using the daily tweet activity timeline view we looked for time periods with spikes in activity and then analyzed these days using the top tweets, topics, and list views to infer potential reasons for the increased activity. Figure 2 shows the number of tweets per day (for the sake of discussion notable peaks in activity are labeled from *a* to *m*). The release of the major *Rise of Iron* extension (September 20th, 2016; labeled *a* in Figure 2) and the announcement of the game's successor *Destiny 2* triggered the largest activity. In case of the latter, an in-game character teased the reveal trailer on March 28th, 2017 (*b*) and the actual trailer was then released two days later (*c*). The reveal of a gameplay trailer on May 18th, 2017 (*d*) led to even more activity while the announcement of the *Destiny 2* beta (*e*) did not evoke as much interest. The two peaks preceding the *Rise of Iron* launch (*f* and *g*) correspond to announcements in connection with it. Of equal, or perhaps even greater, interest are days which exhibit local peaks in activity as for example the announcement of the Halloween inspired *Festival of the Lost* or the Christmas holiday event *The Dawning*. It is notable

Figure 3. Number of in-game activities entered and the amount of tweets per day during June and July 2016.

here that in both cases the announcement (*h* and *j*) seems to garner more attention than the event going live (*i* and *k*). However, other factors may be at play here, including concurrent events. In case of the *Festival of the Lost*, the announcement coincided with two people proclaiming their engagement (see below). Other notable days are August 16th, 2016 (*l*) when it was made public that *Destiny* is coming to *GameBattles*³ and July 13th, 2017 (*m*) where inspection of the daily top tweets indicated the start of pre-loading of the *Destiny 2* beta.

Topics evoking positive or negative sentiment

While the overall ratio of positive, negative, and neutral tweets is approximately constant over time (with, on average, $5.1\% \pm 2.8\%$ tweets classified as negative, $24.2\% \pm 6.6\%$ as positive, and $70.7\% \pm 7.2\%$ as neutral), interesting events could be uncovered by examining days with a larger-than-usual amount of positive or negative tweets. This was done by first identifying such days using the sentiment view and then inspecting these days more closely using the topics and daily top tweets views. For example, on August 25th, 2016 and the following day there was a large share of positive tweets (33.6% and 49.5%) when @Twitch announced that *Destiny* players collected a large sum for charity:

\$500,000! Huge props to the @DestinyTheGame Community Con for raising half a million dollars, all for charity!

Other days with large volumes of positive tweets were *Bungie*'s birthday with many players congratulating or two instances where people proposed to each other (see below) with one coinciding with New Year's Eve. The release of *Destiny* related fashion by *Insert Coin* on November 30th, 2016 (35.2%) and the announcement of the *Gjallarhorn Day 2016* (39.2%) were also positively received. The latter is a holiday declared by the *Destiny* subreddit⁴ on which moderators do not fulfill their obligations and silly posts, reposts, memes, or the like are instead encouraged.

Days with an increased number of negative tweets mainly coincided with players facing server issues. On such days players are complaining that they are not able to login, sometimes

making use of the mention feature of *Twitter* and including the @BungieHelp account in their tweets. For example:

@BungieHelp @Bungie are you aware of the issues that players are having when trying to sign in to destiny?

On September 20th, 2016 – the day of the *Rise of Iron* launch – the overall percentage of negative tweets was relatively low (8.5%). It seems overall excitement concerning the extension prevailed but negatively classified tweets point to server issues as well, probably due to the large playing activity as some users reported connection issues, such as a relatively often shared tweet of a streamer who noted:

I wish my friends tried to contact me as much as I'm trying to contact Destiny servers right now #RiseofIron

On other occasions players complained about long download times of updates such as on December 13th, 2016 (7.1% negative tweets). Soon after the *Electronic Entertainment Expo 2017* on June 7th, 2017 critical voices expressed their disappointment that there will be no 4k support on *Xbox One X* despite being supported on *PS4 Pro*, with 22.63% of tweets being considered negative on that day.

To sum up, there appears to be a tendency that topics causing negative reactions are directly linked with the game itself (e.g., server issues, long download times, different treatment of *Xbox* and *PlayStation* version) while positively received matters concern the community and game-related topics (e.g., charity, game-inspired fashion).

Twitter as a means to understand variations in in-game activity

Figure 3 compares the number of in-game activities entered on a given day with the amount of daily tweets during June and July 2016. In the following we will focus on two specific time points. Immediately noticeable is a large peak in in-game activity on July 1st, 2016 making the impression that, for instance, some special event was happening. This was actually the case as the *Iron Banner*⁵ was held starting with June 26th, 2016 but this seems to explain the large increase in activity on that day only to a certain extent. As the word cloud in Figure 5 shows *Bungie* was seemingly facing temporary server issues on that day as well. One player, for example, posted:

³GameBattles is a competitive gaming website hosting tournaments for various games, see gamebattles.majorleaguegaming.com (accessed August, 2017).

⁴https://www.reddit.com/r/DestinyTheGame/comments/4xcosa/welcome_to_gjallarhorn_day_2016/ (accessed August, 2017)

⁵The *Iron Banner* is a PvP event that takes place once per month and lasts for about a week.

Figure 4. Time spent playing per day and daily amount of tweets from September 4th, 2016 to October 23rd, 2016.

ok WTF is up with #Destiny Servers ? keep getting kicked, can't even play PVE @Bungie #destinythegame

Players repeatedly trying but not being able to finish activities may thus have contributed to an increase in activity. Also worth mentioning are the 14th and 15th of June 2016 when gameplay activity is among the lowest but *Twitter* activity reaches its peak during the two months. During that period the *Electronic Entertainment Expo 2016* was held with *Bungie* sharing news on the *Rise of Iron* extension on the 14th. As such many *Destiny* fans may have opted to follow the live stream. Together with a scheduled server maintenance held on the same day (announced through *Twitter*) this may have contributed to the overall low in-game activity on that day.

Turning our attention to Figure 4 we observe that the time spent playing during the depicted period was lowest on September 8th, 2016. This is an interesting case, as neither the volume of tweets nor the sentiment of tweets on that particular day indicate any irregularity. Closer examination of the tweets revealed that players complained about server maintenance and large updates despite only 5.9% of the tweets being classified as negative. As one user put it:

just waited 3 hours for a 13GB update to download,
and now the @DestinyTheGame servers are down..
#FML

The increase in gameplay on September 20th, 2016 and the following days coincidences with the release of the *Rise of Iron* expansion. On October 1st, 2016 *TwitchCon*⁶ might have contributed to a surge in in-game activity as players were tweeting about being live streaming, for example:

Still sad I'm not in San Diego, but I'll be streaming some #riseofiron later to make up for it.
#stealthplayers #stream #twitch #Destiny

It is interesting to see that the time spent playing on that day even exceeds the amount of time spent within *Destiny* on the day *Rise of Iron* was released. Afterwards, the time spent playing decreases gradually until it culminates in a local peak on October 19th, 2016. A day earlier, the *Wrath of the Machine Heroic Mode* was released which increased the maximum light level (a character attribute) to 400. On that day several tweets, some among the daily top tweets, were related to the light

⁶*TwitchCon* is a convention organized by the live video game streaming platform *Twitch.tv*. In 2016 it was held in San Diego.

level with players boasting to have already reached light level 400 but also providing guides to assist others in reaching the new level cap, for instance:

Want to hit LL 400? Here's a chart to help. Team up @<https://t.co/MaM2gcKDHL> #Destiny #RiseofIron...
<https://t.co/gweapysufg>

While we have focused only on a few instances above, we have chosen these cases to exemplify the usefulness of *Twitter* as a source for contextual information for understanding gameplay activity and to illustrate that certain events may be easier identified by using in-game data instead of sentiment or volume of tweets. However, one should be careful to not imply a causal relationship solely on gameplay activity and what types of messages people are posting as many other explanatory factors may be at play. Still it can reveal possible influencing factors and thus serve as a basis for further investigation. On a side note, we would also like to point out that we found it advantageous to take multiple game metrics into account. For example, the local peak on October 19th, 2016 was not evident when only looking at the number of activities entered.

Recurring themes

By exploring days with increased activity or overly positive sentiment more closely using the detail views offered by our tool (daily top tweets, topics, tweet popularity, and list views) we could observe several recurring themes.

Social conversation not related to the game: We witnessed a surge of interest in matters which go beyond the game itself and sometimes even extend into the private life of community members. Indeed, the most retweeted and most often liked tweet (labeled w in Figure 6) not written by any official *Destiny*

Figure 5. Word cloud of terms (excluding *Destiny*) appearing in tweets on July 1st, 2016.

related account was by @tha_rami announcing that he got a proposal for marriage:

Wait let me redo all this in one tweet. Ok so @MsMinotaur proposed to me in @DestinyTheGame so yeah I said yes <3

In return, other users tweeted congratulations, including video game magazine *Game Informer* which picked up the story and also published an article⁷ on how *Bungie* created customized in-game content in order to make the proposal happening:

A big congrats to @MsMinotaur and @tha_rami on their engagement in Destiny, thanks to some help from @Bungie. http://bit.ly/2eoKfSF

Although not attracting as much attention but still causing particular interest was when @loriipops – a popular streamer (see Table 1) – proclaimed her upcoming wedding on December 31st, 2016.

Looking for others to play with: In 2004, before microblogging services became popular, Seay et al. [46] conducted a survey on social experiences of players of massively multiplayer online games and found that approximately 57% of the respondents use out-of-game communication – which at that time primarily took place via game-related message boards (cf. [46]) – to coordinate and schedule activities. We could observe a similar behavior in our data set, with players using *Twitter* to look for teammates. However, given the fast-paced nature of *Twitter* this takes place in an ad-hoc fashion rather than for coordinating in advance. We especially noticed this on days when the *Iron Banner* event was held. Examples of such kinds of tweets include:

Anyone on Destiny ps4 willing to do crucible? Got a quest I need to do fireteam matches with

Jumping in the PS4 Iron Banner, need a fireteam? I gotch you #destiny #ironbanner

Sharing of fan art: Players of *Destiny* also use *Twitter* to post about fan art they have created. For instance, around *Bungie*'s birthday on July 7th, 2016 tweets indicate the release of *Project Tiger*⁸, a fan-made 2D *Destiny* inspired side-scroller. Others, in turn, have posted about fan-made trailers and covers of *Destiny* music. During the *Festival of the Lost* a military charity used fan art for their cause by promoting the sale of a *Destiny* inspired T-shirt designed by a community member:

The @captaintwaz @DestinyTheGame community t-shirt is for sale, with proceeds supporting troops through Stack-Up!

Albrechtslund [2], citing Jenkins [28], notes that the creation of fiction and art has always been a defining practice of fan communities. Kollock [32] points out several motivations for voluntary contributions on *Usenet* newsgroups, among them, increasing one's own reputation and having an effect on the community. Salovaara et al. [44] identified similar motivational factors in people who voluntarily arrange resources to facilitate gameplay (e.g., game masters). In that sense, *Twitter*

seems to be a convenient way of making others aware of one's creations although we observed in several instances that it can be difficult to attract attention from the community. However, from time-to-time *Bungie* itself is posting links to fan art through their official account. By way of illustration, a tweet by @DestinyTheGame on August 1st, 2016 reading

A hero to the City and a legend in his own right ... https://t.co/jAWJznruQU

and pointing to fan art was the most retweeted one on that day in our collected subset. Another example would be July 1st, 2016 when a similar tweet by @DestinyTheGame promoting fan art also received the most retweets.

Posting of guides and walkthroughs: When we explored what players are tweeting about in periods of high in-game activity, usually after the release of new content, we noticed that players engage in preparing guides and walkthroughs and then use *Twitter* to share them with other members of the community in a timely manner. One example was already noted above when we discussed the exploitation of *Twitter* for providing context for game activity. Another instance where this behavior was apparent was after the release of *Rise of Iron* on September 20th, 2016 when one day later a user already posted a guide for finding all new *Dead Ghosts* (in-game collectibles):

[Spoiler] Rise of Iron - Every New Dead Ghost Added Location (Including 2.4.0 Ghosts) - Text & Video Guides https://t.co/BNIP1KxfYB

However, tweets pointing to guides are also posted independently of events, for example, guides that describe how to obtain exotic weapons or which take new players through difficult raids (a type of cooperative mission).

Influential community members

In order to identify influential users we used the account list view and the tweet popularity view of our tool and inspected the *Twitter* user profiles. Focusing on the top 20 accounts, the most influential users in terms of average popularity score and with more than ten tweets during the 14 month period (see Table 1 for a summary of these accounts) are i) accounts affiliated with the developer and publisher of *Destiny* (e.g., @Bungie, @Activision), of which the official *Twitter* account of the game – @DestinyTheGame – by far has the biggest popularity, ii) gaming websites such as @IGN or @Kotaku, iii) *Twitch* and *YouTube* streamers such as @MoreConsole, @loriipops, or @Lirik, and iv) e-sports related accounts such as the *Major League Gaming* (@MLG). Figure 6 shows a scatterplot of the 10,000 most retweeted posts. Tweets made by the official accounts @DestinyTheGame and @Bungie are highlighted in color. As can be seen from the figure, the large majority of the most retweeted and liked tweets can be attributed to these two accounts.

The role of streamers

Beside accounts run by the game developer or publisher and accounts of news outlets, streamers maintain some of the most influential accounts (in terms of the average number of retweets and likes, see Table 1) as stated above. Blight [5] conducted a survey among users of streaming platforms and reported that streamers make use of social media to connect

⁷<http://www.gameinformer.com/b/news/archive/2016/10/21/bungie-helps-two-game-developers-get-engaged-in-destiny.aspx> (accessed August, 2017)

⁸<https://helix333.itch.io/project-tiger> (accessed July, 2017)

Account	Followers	Tweets [†]	$\bar{r}t$	$\bar{l}$	$\bar{p}$	Description
@DestinyTheGame	1,810,558	391	724.55	2177.02	1450.78	the official <i>Destiny</i> Twitter account
@PlayStation	13,977,765	27	441.85	1377.48	909.67	the official <i>PlayStation</i> Twitter account
@Bungie	1,994,114	142	379.37	1206.52	792.95	the developer of <i>Destiny</i>
@Twitch	4,243,800	19	421.89	1049.26	735.58	the official account of <i>Twitch</i>
@cgbarrett	25,249	14	188.14	656.36	422.25	game director at <i>Bungie</i>
@MoreConsole	233,621	94	90.21	598.41	344.31	a streamer
@IGN	5,861,913	38	184.50	486.55	335.53	a gaming website
@Lirik	39,4486	20	54.20	594.40	324.30	a streamer
@BungieHelp	381,001	136	140.42	368.10	254.26	official <i>Twitter</i> support for <i>Destiny</i>
@loriipops	20,479	15	170.33	303.87	237.10	a streamer
@MLG	2,062,758	36	122.56	316.14	219.35	account of <i>Major League Gaming</i>
@DeeJ_BNG	315,458	47	37.32	337.38	187.35	the community manager for <i>Destiny</i>
@BlueWestlo	56,132	16	28.25	341.13	184.69	a streamer
@GFuelEnergy	1,086,958	21	53.29	309.57	181.43	an e-sports energy drink
@Kotaku	1,751,504	17	120.12	241.35	180.74	a gaming website
@DattosDestiny	169,672	15	65.80	294.53	180.17	a streamer
@Activision	668,047	36	63.78	291.17	177.47	the publisher of <i>Destiny</i>
@IsakKnyght	671	12	137.92	212.92	175.42	a streamer
@DestinyNews_net	230,482	31	85.00	228.71	156.85	a <i>Destiny</i> fan website
@Gothalion	278,852	42	30.79	275.00	152.89	a streamer

[†] not including retweets

Table 1. Influential *Twitter* users related to *Destiny* based on the average popularity score $\bar{p}$ of tweets together with the number of followers and tweets as well as the average number of retweets $\bar{r}t$ and likes $\bar{l}$.

Figure 6. Relationship between the number of retweets and likes of the 10,000 most retweeted messages. Tweets posted by the official game and developer account @DestinyTheGame and @Bungie are colored in blue and pink.

with their viewers and to share their streams. This is evident in our dataset as well. Streamers such as @MoreConsole announce new videos with tweets like:

[NEW VIDEO] *Destiny* - NEW GUNS! NEW GEAR! NEW GAMEPLAY! <https://t.co/3pLfrm2MtR>

However, we also noticed that streamers use *Twitter* to announce that they are currently live streaming. A tweet by @001Kn0w on September 29th, 2016 is a good example for this kind of usage:

Live on #Twitch!! Come join me in #Destiny for some #ironbanner !! <https://t.co/UE3lqZkqbv>
#SupportSmallStreamers #Supportsmallstreams

Not so well-known streamers often include the *SupportSmallStreamers* hashtag to gather attention (in our sample 4892 tweets make use of it). Research on streaming communities [21, 49] found that feeling a sense of community is an important social aspect for consumers of streams, resulting in people closely following streamers and regularly showing up at their streams. The high average number of retweets and likes of tweets of popular streamers in our sample echoes these

findings to some degree as it seems to suggest that streamers are also attracting a loyal following on *Twitter*. However, further research will be necessary to confirm this hypothesis.

CHALLENGES, LIMITATIONS, AND FUTURE WORK

Our study was exploratory and qualitative in nature, employing a visual analysis approach to explore a large-scale sample of tweets and gameplay data in order to develop a better understanding of player communities on *Twitter*. Thus, further research will be necessary to quantify our qualitative observations. Additionally, our study focused on the community of a single game, specifically a massively multiplayer first-person shooter. Although we would argue that some findings transfer to other types of games as well (e.g., sharing of fan art or guides), some may only apply to a specific (type of) game. For example, looking for other players to play with is unlikely to apply to single-player games. It would thus be useful to study other types of games in the future to see if and how different games and genres elicit different microblogging behaviors. We should also mention two possible sources of sampling bias which may influence our results. First, besides

bias introduced by the *Twitter Search API* [51] itself, we sampled tweets corresponding to a specific query which combines the term *Destiny* with certain game-related keywords. We did this to avoid gathering a large number of tweets not related to the game but on the other hand this is likely to bias the result in favor of these keywords. However, we were careful not to make inferences with respect to these particular keywords. Secondly, the *Bungie API* [9] does currently not expose aggregated daily behavioral data for the whole player population. Consequently, we needed to rely on the gameplay activity of a subset of players to get an estimate of the relative in-game activity over time. At this point it is also worth highlighting that we did not discover any noteworthy insights concerning the relation between the players' in-game and *Twitter* activity using the *Player Activity View*. Further statistical analysis may shed more light on this issue. Related to this, we would like to mention that we focused on two gameplay metrics that reflect overall playing activity on a given day. However, other, more specific metrics could be worthwhile to consider in the future.

Lastly, we would like to echo Bertone and Burghardt [4] who emphasized that the comprehension of tweets is not straightforward due to containing, among others, a lot of abbreviations and slang language. Aggravating this situation, the meaning of words as used in a games context can be different, as opposed to being used in the general case. Although we used a sentiment analysis approach specifically designed for short length *Twitter* messages this has resulted in some tweets being incorrectly classified. The need for inclusion of domain-specific knowledge is, however, not specific to our application area. For example, research in sports [25, 57] has reported similar issues when attempting to automatically classify sports-related tweets. In any case, this should not have substantially affected our results as we were interested in the overall sentiment. In this context it should also be noted that in some cases the text of the tweet itself did not allow to make conclusions about what the tweet is about (e.g., fan art) without, for example, inspecting included links. The following tweet by @DestinyTheGame about fan art on July 1st, 2016 is an example of such a situation.

But Ghosts are not immortal. As far as Guardians know, every loss is irreplaceable.
<https://t.co/A9X3z8S9qE>

While the above caveats are to keep in mind they also support our decision to adapt a visual data analysis approach. With respect to the tool, future work will focus on the integration of additional visualizations, for example, word-trees (see [54]) to allow users to view the context in which keywords appear.

RECOMMENDATIONS

- There appears to be a tendency that topics causing negative sentiment are confined to the game itself while topics evoking positive reactions also go beyond the game and extend to community matters. Indeed, social discourse not related to the game itself constituted an important element in our data. Given that a recent study [14] provided indication that positive tweets have a higher impact on video game sales it may hence be desirable to support community efforts such as charities or special occasions (e.g., by providing customized in-game

content). Actively supporting such activities may contribute positively to community building and, in turn, possibly result in better out-of-game experiences and positive word-of-mouth.

- Tweets showed to be able to offer valuable contextual information for understanding fluctuations in in-game activity in certain instances. On the other hand, in-game data may be used as a useful identifier for events of interest in addition to sentiment and tweet activity. However, we also need to mention that integrating in-game and *Twitter* data was not insightful in every case.
- Players use *Twitter* to find people to play with in the short term. Developers may thus want to consider to offer facilities which makes it easier for players to find teammates on *Twitter* in the short-run, for example, by providing an official hashtag.
- Sharing of fan art and of guides and walkthroughs both showed to be another important use of *Twitter*. Posting fan art or guides through the official account potentially increases reach and is likely to please the creator as it helps to gain reputation within the community and shows that the developer cares about what fans are creating.
- Beside the official game-related accounts, mostly gaming websites and *Twitch* and *Youtube* streamers are among the most influential members in terms of triggering retweets and likes. Streamers make use of *Twitter* to connect with their viewers, to promote videos, and to announce that they are live streaming. Due to high average number of retweets and likes, game community managers may thus wish to actively support streamers to increase conversation about and, in turn, promote interest in the game.

CONCLUSIONS

In this paper, by adopting a qualitative approach and by using the online-only multiplayer shooter *Destiny* as a case study, we explored for which communication purposes players use *Twitter*, which users constitute important members, and if *Twitter* can help in explaining in-game activity. Our study shows that while the volume of tweets and changes in sentiment are useful indicators for identifying potential events of interest, gameplay data can provide an additional means to assist in this regard. At the same time, our results suggest that *Twitter* can act as a valuable source for contextual clues to help understand variations in in-game activity. Our results also provide evidence that players use *Twitter* for a variety of communication purposes, including the sharing of fan art and game guides, searching for other people to play with, for discussing game-related issues and, in certain instances, even private matters of community members, as well as – in case of streamers – for announcing on-going live sessions. In terms of influential community members, streamers maintain some of the most popular accounts besides the official game and developer affiliated accounts.

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