Delft University of Technology

When Game Becomes Life

The Creators and Spectators of Online Game Replays and Live Streaming

Jia, Adele Lu; Shen, Siqi; Epema, Dick H J; Iosup, A.

Important note
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

A

When game becomes life: The creators and the spectators of online game replays and live streaming

Adele Lu Jia§, Siqi Shen♯†‡, Dick H.J. Epema‡, and Alexandru Iosup‡,

§College of Information and Electrical Engineering, China Agricultural University, China.
♯Parallel and Distributed Processing Laboratory, National University of Defense Technology, China.
†School of Computer, National University of Defense Technology, China.
‡Software and Computer Technology Department, Delft University of Technology, the Netherlands.

Online gaming franchises such as World of Tanks, Defense of the Ancients, and StarCraft have attracted hundreds of millions of users who, apart from playing the game, also socialize with each other through gaming and viewing gamecasts. As a form of User Generated Content (UGC), gamecasts play an important role in user entertainment and gamer education. They deserve the attention of both industrial partners and the academic communities, corresponding to the large amount of revenue involved and the interesting research problems associated as UGC sites and social networks. Although previous work has put much effort in analyzing general UGC sites such as YouTube, relatively little is known about the gamecast sharing sites.

In this work, we provide the first comprehensive study of gamecast sharing sites, including commercial streaming-based sites such as Amazon's Twitch.tv and community-maintained replay-based sites such as WoTreplays. We collect and share a novel dataset on WoTreplays that includes more than 380 thousand game replays, shared by over 60 thousand creators with over 1.9 million gamers. Together with an earlier published dataset on Twitch.tv, we investigate basic characteristics of gamecast sharing sites, and we analyze the activities of their creators and spectators. Among our results, we find that (i) WoTreplays and Twitch.tv are both fast-consumed repositories, with millions of gamecasts being uploaded, viewed, and soon forgotten; (ii) both the gamecasts and the creators exhibit highly skewed popularities, with a significant *heavy tail* phenomenon; and (iii) the upload and the download preference of creators and spectators are different: while the creators emphasize their individual skills, the spectators appreciate team-wise tactics. Our findings provide important knowledge for infrastructure and service improvement, for example, in the design of proper resource allocation mechanisms that consider future gamecasting, and in the tuning of incentive policies that further help player retention.

CCS Concepts:•**Networks** → **Network measurement;**•**Social and professional topics** → *User characteristics;*

Additional Key Words and Phrases: Online game communities, gamecast sharing sites, repository characteristics, popularity dynamics., user behaviors

1. INTRODUCTION

Online games are today entertaining hundreds of million of users, and form a multi-billion-dollar global industry [McGonigal 2011]. Similar to professional sports such as football, the community involved in the activity includes not only amateur and professional players, but also a large group of spectators. Together, players and spectators watch and even study gamecasts (the equivalent of recorded or streamed broadcasts in sports) of talented teams or individual players, sometimes repeatedly, for entertainment or educational purpose. Numerous of online communities provide the opportunity for players to share their gamecasts. These communities often archives millions of

gamecasts that are watched and commented upon by millions of users. With the huge user base and the large revenue involved, gaming communities have attracted the attention from many industrial magnates. Among the leading communities, Amazon acquired Twitch.tv in 2014 and YouTube recently launched its own game streaming site.

In this work, we investigate two online gaming communities, WoTreplays [WoTreplays 2013] and Twitch.tv [Twitch 2011], which are leading representatives for the two most-popular classes of gamecast sharing sites. WoTreplays is community-maintained and *replay*-based. In just 2 years of operation, it has archived more than 380 thousand replays of games played by nearly 2 million players, and has attracted more than 5 million downloads. Twitch is a leading commercial community for game *live streaming*, wherein players broadcasts and commentates on their gamecasts in video streams to his spectators who, if they enjoy the gamecast, can follow the channel, give a heart, or further make his donation. This new form of communication introduces new relationships between Twitch players and their spectators. In February 2014, Twitch has become the fourth largest source of US peak Internet traffic [Fitzgerald and Wakabayashi 2014].

Our analysis of WoTreplays and Twitch mainly focuses on characterizing the repository and on analyzing the user activities. We do this for two reasons:

First, repository characteristics play an important role in infrastructure and service improvement, for example, designing proper resource allocation mechanisms based on the content popularity. Although much research has already focused on characterizing general content sharing sites [Cha et al. 2009], [Yu et al. 2006], [Pouwelse et al. 2005], [Abrahamsson and Nordmark 2012], little is known about the gamecast sharing sites' user behaviors. Given the rapid increase in the popularity and the market size of online games, we believe it is important and timely to characterize these sites.

Secondly, user activities provide important knowledge for maintaining the community prosperity, for example, through customizing incentive policies based on the user preference. Compared to general UGC sharing sites that often cover a wide range of topics and that lack explicit information of the contents, gamecast sharing sites have the advantages that they are exclusively for gaming contents and that many communities archive detailed game statistics such as the winning team and the in-game scores of each player. These game statistics provide fine-grained information for inferring user activities, including their upload and download preference.

In this work, we conduct an in-depth analysis of gamecast sharing sites starting from two real-world, large-scale datasets. Our analysis reveals the basic characteristics of the repositories and the user behaviors. We summarize our main contributions as follows:

(1) We collect, use, and offer public access[1] to the dataset that contains the full history of WoTreplays, with detailed statistics for 1,956,256 gamers (including their download and upload behaviors) and 382,760 games (including the team formation, the game result, and the reward each player obtained). We further include in our analysis an earlier published dataset on Twitch [Pires and Simon 2015], which archives more than 5 million game streaming sessions (Section 3).
(2) We investigate and compare the basic characteristics of WoTreplays and Twitch. Our analysis include (i) the repository scale including the gamecast injection rate and duration, and (ii) the statistical properties of the gamecast popularity including the *skewness*, the *heavy tail*, and the *long tail* phenomenon (Section 4).

---

[1]The complete dataset will be released in the Game Trace Archive [Guo and Iosup 2012].

(3) We provide a detailed analysis of user activities, including the activity level, the upload delay, the creator popularity, and the interactions between users and the repository. With the detailed in-game statistics archived by WoTreplays, we further investigate the upload and the download preference of its users (Sections 5 and 6).

2. RELATED WORK

In this section, we compare our work with the characterization research on: gamecast sharing site, game workload, general content sharing site, and content popularity.

Gamecast sharing site characterization Gamecast sharing is a relatively unexplored area. [Kaytoue et al. 2012] and [Pires and Simon 2015] provide preliminary characterizations on Twitch.tv. They analyze the dynamics of the game spectators and propose models for predicting the video popularity. Our previous work [Shen and Iosup 2011] analyze XFire, a social network of games and players. The analysis focuses on the global network, the gaming activity, and the social structure in XFire, with preliminary results on UGC. In this work, we discover over triple the amount of players and multiple orders of magnitude more replays than in [Shen and Iosup 2011], [Kaytoue et al. 2012]. Most importantly, we complement the above studies with a finer-grained dataset: the game statistics included in our WoTreplays dataset provide a better reference for understanding the user activities, including their upload and download preference.

Although not much quantitative analysis has been performed, gamecast sharing has been studied qualitatively. [Cheung and Huang 2011] provide a qualitative account of the experiences of StarCraft II spectators and they find nine personas in the data that demonstrate who the spectators are and why they spectate. [Downs et al. 2013] study the core aspects of audience experience in social video-gaming. [Hamilton et al. 2014] find that Twitch streams act as virtual third places, in which informal communities emerge, socialize, and participate.

Game workload characterization The popularity of the spectating activity of a game largely depends on the game's popularity. Understanding the workload of games and players can help better understanding the workload of gamecasts and developing better systems supporting gamecast sharing sites. There is a significant body of work which studies the workload of First Person Shooter (FPS) games and massively multiplayer online games (MMOGs) [Suznjevic and Matijasevic 2013]: [Henderson and Bhatti 2001] analyze the player population and network packets of FPS games. [Armitage et al. 2006] study the FPS games clients' round-trip time and hop-count distributions. [Chambers et al. 2010] characterize player and session distribution of FPS games and MMOGs. [Shen et al. 2014] study the mobility pattern of MMORPG avatars. Recently, cloud gaming systems such as OnLive, Gaikai, and StreamMyGame, have received much attention: [Claypool et al. 2014] analyze the workload of OnLive. [Chen et al. 2014] study the quality-of-service of OnLive and StreamMyGame. Different from the research focusing on game workloads, we focus on the workloads of gamecast sharing sites.

General content sharing site characterization General content sharing sites, wherein the shared contents cover a wide range of topics, have been extensively studied before. [Cheng et al. 2008] find YouTube videos have noticeably different statistics compared to traditional streaming videos. [Gill et al. 2007] analyze YouTube traffic generated by a collection of clients and provide a detailed view of the local UGC service usage. [Cha et al. 2007], [Cha et al. 2009] provide a complementary global view by crawling data of complete sets of video categories. [Qu et al. 2008] [Huang et al. 2008] provide a survey on Peer-to-Peer live streaming systems.

Content popularity characterization One major contribution of this work is a detailed statistical analysis of the gamecast popularity. Little related work has dealt

with this topic. [Kaytoue et al. 2012] provide a preliminary study and they identify skewed gamecast popularity in Twitch. [Pires and Simon 2015] further provide a Zipf fitting for the gamecast popularity based on Normalized Rooted-Mean-Square Deviation (NRMSD). Our work adopts a more sophisticated method for quantifying power-law behaviors as proposed in [Clauset et al. 2009]. Most importantly, we distinguish popular and non-popular gamecasts that often have different statistical properties, and we study the long tail and the heavy tail phenomena that have been observed in many general content sharing sites but have not been explored for gamecast sharing sites before.

For the content popularity in general content sharing sites, [Cha et al. 2009] analyze the content popularity in two popular UGC sites, which shows power-law-like characteristics. [Figueiredo et al. 2011] study the content popularity in YouTube and they find that copyright protected videos tend to get most of their views much earlier in their lifetimes. [Pinto et al. 2013] present two simple models for predicting the future popularity.

The skewed content popularity observed in many content sharing sites indicates that, instead of treating the contents indiscriminately, users have certain preference for sharing and consuming. However, because general content sharing sites often lack explicit and well-structured information for the contents (often with only the titles and the descriptions), little related work has provided a detailed analysis of the user preference. Our WoTreplays dataset contains detailed game statistics that provide important knowledge for analyzing the user preference for sharing and consuming. To the best of our knowledge, this is the first work that sheds light on this topic.

3. METHOD FOR CHARACTERIZING GAMECAST SHARING SITES

In this section, we present an empirical method for characterising gamecast sharing sites that consists of four main stages: (1) understanding the basic operations of these sites; (2) identifying interesting and important characteristics and metrics; (3) selecting and collecting datasets with representativeness and coverage; and (4) analyzing and presenting the results. We introduce them in turn in the following sections.

3.1. Basic operations of gamecast sharing sites

A gamecast sharing site keeps a *gamecast repository*, into which the creators inject the gamecast they generate, and from which the spectators watch the gamecasts they are interested in. During the viewing process, users (the spectators and the creators) may interact with each other via a number of methods like comment and chat. In the following sections, we give a more detailed introduction on the two examples we considered in this article, namely WoTreplays and Twitch.

3.1.1. WoTreplays. WoTreplays is a community-maintained replay-based gamecast sharing site for World of Tanks (WoT). WoT was developed and initially released in 2010 August by Wargaming, and has over 60 million registered players[2]. WoT is a typical MMOG in which teams of players, with a maximum of 15 players per team, confront each other in a battle. During a game, each player can gain some *credits*, with the actual amount depending on the player's actions such as how many tanks have been killed by the player. The credits of players reflect the levels of their gaming skills.

WoTreplays maintains a repository of replays shared by its users, which upon downloaded, can be viewed with the game engines. The replays capture all player actions including actions from the keyboard and they are useful for studying techniques of players. In WoTreplays, uploaded replays are displayed by its uploaded time, and the latest

---

[2]http://worldoftanks.com/en/news/19/world-tanks-hits-mark-60-million-registered-users/

ones are displayed first. To locate and download a replay, users can browse the website or search using various keywords (e.g., tank types). Besides downloading, users can interact with the other users through leaving comments and giving hearts to express their appreciation.

3.1.2. Twitch.tv. Twitch.tv is a leading commercial community for game live streaming. It has over 100 million monthly unique viewers.[3] Twitch.tv contains multiple game genres, such as League of Legends, FanDuel, WoT, and StarCraft II. Twitch players maintain channels, wherein players broadcast gamecasts, chats and explains game styles to spectators. Channels are grouped by games and sorted according to their number of concurrent views. Besides browsing channels, users can use some keywords to search channels. A Twitch user can watch the game stream, chat with the player and other spectators, and if the user enjoys the gamecast, the user can further follow the channel, give a heart, or make a donation. Further, Twitch adopts a partnership program that allows streamers to earn revenue by running advertisements, and a subscription program that enables a viewer to subscribe to their channel and pay monthly subscription fee [Kang 2014].

3.1.3. Terminology. **Gamecast (replays and streaming sessions):** *gamecast* refers to the record of a game being played. In WoTreplays, gamecasts are shared after the games are finished, and we name them *replays*. In Twitch, gamecasts are broadcasted via live streaming, and we name them game streaming *sessions*.

User classification: For WoTreplays, there are four types of users: *creators*, *gamers*, *uploaders*, and *players*. Their meanings are defined over the entirety of the WoTreplay dataset, and are listed as follows.

(1) Creators are users who have uploaded at least one replay.
(2) Gamers are users who have played at least one game.
(3) Uploaders are users who have uploaded at least one replay and have played at least one game.
(4) Players are users who have played at least one game but have not uploaded any replay.

For Twitch, we name players who create the channels and stream their gamecasts as *streamers*. Depending on the schedule of the streamers, the live streaming of a channel contains a series of *sessions*. The Twitch dataset does not contain detailed game information, so we analyzed indiscriminately the Twitch sessions. For WoTreplays, there are three major types of games: *Winning games*, *Losing games*, and *Survived games*, which are defined as follows.

(1) A winning/losing game is a game wherein its uploader's team has won/lost.
(2) A survived game is a game wherein its uploader's in-game representation (i.e., tank) stayed alive at the end.

3.2. Characteristics and metrics

To characterize gamecast sharing sites and users, we identify the following three important aspects that consists the basic operations of these sites:

Repository characteristics. We consider in this article (i) *gamecast injection* and *duration* that measure the scale of the repository, in terms of the number and the workload of its contents; and (ii) *gamecast popularity* that measures the preference of the spectators in the gamecast level, which is defined as the number of views collected by the gamecasts. We report the injection rate and the duration for gamecasts in the

---

[3]http://www.twitch.tv/year/2014

entire repository, analyze the statistical properties of the gamecast popularity, and study its correlation with other features including the age of the gamecasts.

Creator characteristics. We identify four aspects that cover most creator activities, including (i) *creator-level gamecast injection* and *duration* that measure the activity level of the creators; (ii) *creator popularity* that measures the preference of the spectators in the creator level, which is defined as the total number of views collected by gamecasts shared by a creator; and (iii) *upload delay* that measures the eagerness of the creators for sharing the gamecasts, which is defined as the time lag between the finish time of a game and the upload time of its replay; and (iv) *upload preference* that measures the preference of the creators for sharing gamecasts.

In this article, we report the injection rate and the duration of gamecasts shared by each creator, analyze the pattern of the creator popularity, and study its correlations with other features including the activity level of the creators. Further, we investigate four features that potentially influence the creators' upload preference, including (i) *game count*, i.e., the number of games a gamer has played, and similarly, *winning/losing/survived game count*, i.e., the number of games a gamer has won/lost/survived; (ii) *win ratio*, i.e., the fraction of games a gamer has won, (iii) *upload count*, i.e., the number of replays a creator has uploaded, and (iv) *upload ratio*, i.e., the upload count divided by the game count of an uploader.

Spectator characteristics. We identify two important aspects for the spectator activity specifically (i) *download preference* that measures the preference of the spectators for the gamecasts and (ii) *interactions with gamecasts* that demonstrates the explicit interactions between the spectators and the gamecasts, for example, through leaving comments and giving hearts to gamecasts they like.

3.3. Dataset

For each replay, WoTreplays achieves two types of metadata: (1) **gamecast statistics**, including the name of the creator, the upload time, the replay duration, the number of downloads/comments/hearts; and (2) **in-game statistics**, including, for the game represented in the replay, the start time, the team formation, the winning team, and for each player in the game, the damage and the number of kills he has made, the credits he has gained, and his status at the end of the game (survived or dead).

Twitch maintains basic **gamecast statistics**. For each streaming session in each channel, it contains the information of the start time, the name of the player, the number of views per 5 minutes, and the number of hearts. Unlike WoTreplays, Twitch does not maintain metadata on in-game statistics.

To collect the metadata in WoTreplays, we performed a number of separate crawls (fetching webpages through web links) and we have obtained the *full history* of WoTreplays since it was first launched in March, 2013 until March, 2014. In total, we obtained 382,760 replays including 1,956,256 gamers, uploaded by 63,308 creators. We counted the gamers and creators based on their unique in-game ids, it is possible that a user have multiple accounts, we just count those accounts are from different users. In total, these replays received 5,818,625 downloads, 16,641 comments, and 53,485 hearts from the spectators. For Twitch, we use an earlier published dataset [Pires and Simon 2015], which contains the detailed information of 1,068,001 streamers and 7,492,008 game streaming sessions.

In addition, we include two datasets (DotA and StarCraft II) from our previous work [Iosup et al. 2014]. Although gamecasts in these two datasets are recorded directly by game servers instead of shared individually, they help comparing game features in different game genres, such as the team size and the gamecast duration. Particularly, for the DotA dataset, we performed a second crawl at September 2012 to include more games. The basic statistics of the four datasets are summarized in Table I.

Table I: Overview of the datasets. (Y means that the dataset contains related information)

Dataset	# gamecasts	# creators	# players	upload time	gamecast info.	in-game info.
WoTreplays	382,760	63,308	1,896,353	Mar 2013 - Mar 2014	Y	Y
Twitch	7,492,008	1,068,001	N/A	Jan 2014 - Apr 2014	Y	
DotA	991,720	N/A	1,064,575	Apri 2010 - Sep 2012		Y
StarCraft II	85,532	N/A	83,119	Mar 2012 - Aug 2013		Y

(a) WoTreplays

(b) Twitch
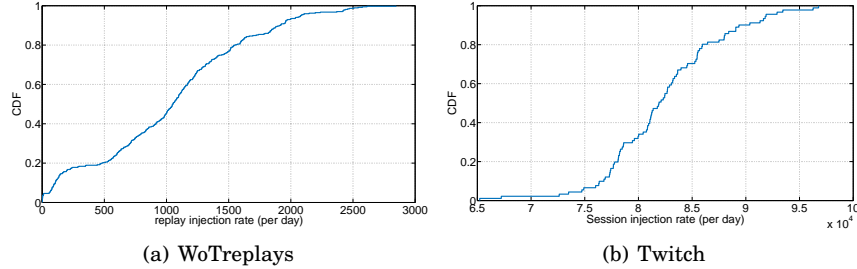
Fig. 1: CDF of the gamecast injection rate. Note the difference in the scale of the horizontal axis.
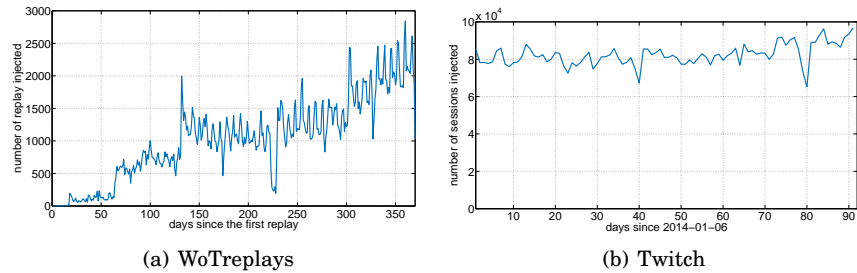

(a) WoTreplays

(b) Twitch

Fig. 2: Chronological gamecast injection rate.

4. REPOSITORY CHARACTERISTICS

In this section, we provide a basic characterization on the gamecast repository of WoTreplays and Twitch. We mainly focus on three aspects, namely the system-level gamecast injection, duration, and the gamecast popularity.

4.1. Gamecast injection

Fig. 1 shows the cumulative distribution function (CDF) of the gamecast injection rate, i.e., the number of new gamecasts per day. We find that, on average, 1,034 replays and 82,330 sessions are injected each day in WoTreplays and Twitch respectively. Moreover, we find that the gamecast injection rate in WoTreplays is highly skewed: during two periods that both represent 20% of its history, it achieves fewer than 500 and higher than 1500 daily injections, respectively. To identify this difference, we show in Fig. 2(a) the chronological game replay injection rate over the full history of WoTreplays. We see that *as WoTreplays evolves, it attracts more daily injections, indicating that this one-year-old game replay sharing site is gradually expanding*. Though Twitch was first introduced in June 2011, we were only able to obtain its history from January to April 2014, and we observe a relatively stable daily session injection rate, as shown in Fig. 2(b).

We also observe from Fig. 2, for both WoTreplays and Twitch, a clear *weekend pattern*, with higher daily injection rates in the weekends than in the workdays. Table II shows the statistics, including the mean and standard deviation, of the daily injection rate in different days of a week. The weekend pattern has been observed in other UGC sharing sites, such as YouTube-Live [Pires and Simon 2015], and Daum (a Koren UGC site) [Cha et al. 2009] and a DotA gaming site [van de Bovenkamp et al. 2013].

Table II: Daily injection rate (mean and standard deviation) in different days of a week.

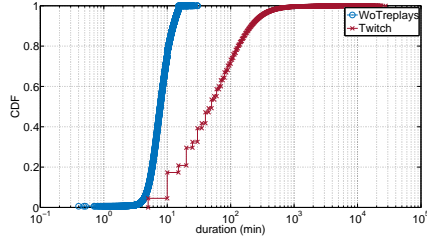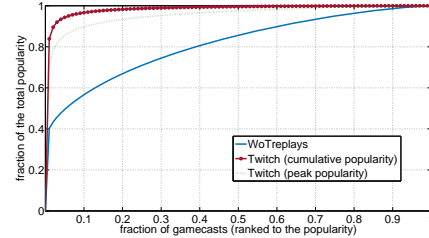| mean (std)	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
WoTreplays	1,026 (606.2)	984 (577.7)	948 (549.7)	929 (557.5)	956 (576.4)	1,160 (735.2)	**1,239** (767.7)
Twitch	80,745 (3,622.9)	78,668 (9,433.6)	82,671 (4,651.0)	80,669 (7,830.3)	83,481 (3,458.6)	**85,366** (5,009.1)	82,235 (6,380.0)

Fig. 3: CDF of the gamecast duration

Fig. 4: Skewness of gamecast popularity

4.2. Gamecast duration

Gamecast duration directly measures the scale of the repository in terms of the workload of its contents, especially for game live streaming sites like Twitch. As shown in Fig. 3, in general, sessions in Twitch have longer durations than replays in WoTreplays: while 80% of replays in WoTreplays are within 10 minutes, 80% of sessions in Twitch are longer than 20 minutes (see Sec. 5 for further discussion).

The above difference is possibly due to the fact that Twitch users can continue to stream commmentary and interviews after the games are finished, and that Twitch covers a wide range of game genres, including WoT, DotA, the StarCraft series, etc, while WoTreplays specializes in WoT. Consistently, our DotA and StarCraft II datasets (as introduced in Section 3.3) show that DotA and StarCraft II games are much longer than WoT, achieving an average duration of 36.4 minutes and 18.3 minutes, respectively.

More specifically, the average and the median gamecast duration for WoTreplays is 8.20 and 7.73 minutes, with a low standard deviation of 2.87 minutes. The average and the median session duration for Twitch is 96.37 and 50 minutes, with a high standard deviation of 234.09 minutes. Compared with previously published results [Cha et al. 2007], [Cha et al. 2009], we find that the median gamecast duration in WoTreplays and Twitch is longer than the median content duration in general UGC sites (e.g., 3 minutes for YouTube), but shorter than the median content duration of non-UGC sites (e.g., 94 minutes for LoveFilm, was one of the Europe's largest online DVD rental stores [Cha et al. 2009]).

4.3. Gamecast popularity

In any UGC sharing site, the content popularity provides important knowledge for the activity level of the users and the potential workload for maintaining the site. As a form of UGC, here we measure the popularity of a gamecast in terms of the number of downloads (views) it collected. Particularly, as Twitch provides a gamecast streaming service, we consider both the number of total views a gamecast collected, and the peak number of its concurrent views, denoted as *cumulative popularity* and *peak popularity*, respectively. In this section, we conduct a set of analyses that provide a holistic view of the gamecast popularity. We first study the skewness of user requests across gamecasts. Then, we analyze how user requests are distributed across popular and non-popular gamecasts by examining the heavy tail and long tail phenomena [Mahanti et al. 2013].

4.3.1. The skewness of gamecast popularity. To study skewness of popularity in gamecast sharing sites, we calculate the fraction of the total popularity aggregated by the rth most popular gamecasts in WoTreplays and Twitch, respectively. Results are shown in Fig. 4. The horizontal axis represents the fraction of gamecasts ranked from the most popular to the least popular. For Twitch, 10% of the gamecasts account for more than 90% of the total popularity in the repository, in terms of both the cumulative and the peak popularity. Compared to Twitch, the gamecast popularity in WoTreplays is less skewed, with 10% of gamecasts representing less than 60% of the total popularity.

In general UGC sites like YouTube, the skewness of popularity has been observed as well, with roughly 10% of contents representing 80% of the total popularity [Cha et al. 2007]. It is interesting to notice that, the skewness of the gamecast popularity in Twitch and WoTreplays, lies above and under the one for general UGC sites, respectively.

We conjecture that the difference in the popularity skewness is a consequence of the recommendation algorithms used in these sites. By default, Twitch sorts its gamecasts by the number of concurrent views in its browse list, while WoTreplays merely display gamecasts by date. It is likely that *the recommendation algorithm used in Twitch helps promote the dominance of popular gamecasts, and therefore, induces a highly skewed gamecast popularity.* The recommendation algorithm used in YouTube is more complicated, with considerations of both the content popularity and many other aspects [Davidson et al. 2010], resulting a content popularity that is less skewed than Twitch, wherein the default promotion is solely for popular gamecasts, and that is more skewed than WoTreplays, wherein the default promotion is irrelevant to the current gamecast popularity.

4.3.2. Statistical properties. In this section, we delve further into the statistical properties of the gamecast popularity and examine whether power-law characteristics apply. A distribution is considered to follow a power-law relationship if its probability density function takes the form $f(x) = Cx^{-\alpha}$. The constant α is called the scale, and once α is fixed, the constant C is determined by the requirement that the distribution $f(x)$ sum to 1. Taking logarithms on both sides produces $log(f(x)) = -\alpha log(x) + log(C)$. This expression exhibits a linear relationship with a slope of $-\alpha$ when plotted on a log-log scale.

Two frequently occurring (and confusing) terms associated with power-law distributions are *heavy tails* and *long tails*. A distribution is considered to have a heavy tail if its tail is not exponentially bounded. A power-law distributed tail is one example for a heavy tail. In the context of content sharing, a heavy tail represents a small number of popular contents accounting for a large fraction of the total popularity. The long tail, on the other hand, is a manifestation of power-law relationships. The term became popular when researchers showed that online purchasing sites like Amazon benefit from the long tail, i.e., a large number of items, each attracted to only a few customers, but altogether account for a significant part of the total sale [Anderson 2004].

In the context of gamecast sharing sites, the heavy and the long tail represent the popular and non-popular gamecasts respectively, which we will use for our analysis in this section. To study the heavy tail phenomenon, we consider a Complementary Cumulative Distribution Function (CCDF) graph that shows the fraction of gamecasts with popularity that is higher than a variety of values as shown in the horizontal axis. To study the long tail phenomenon, we use a plot of gamecasts ranked in the decreasing order of their popularity. The tails of the CCDF graph and the plot represent the popular and non-popular gamecasts, respectively.

Heavy tail: the popular gamecasts. Fig. 5 shows the CCDFs of the gamecast popularity in WoTreplays and Twitch, respectively. The dashed lines represent the
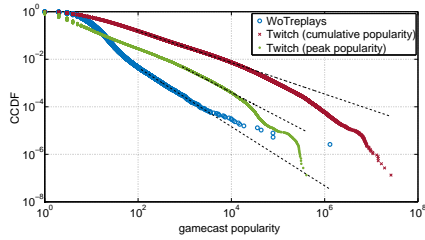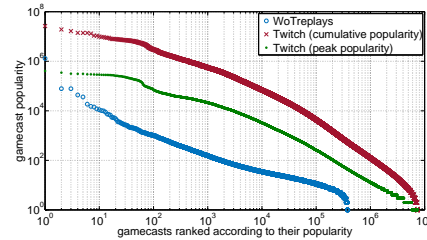
Fig. 5: CCDF of the gamecast popularity.

Fig. 6: Gamecast popularity, in log-log scale.

Table III: Power-law fitting results for the gamecast popularity (number of downloads/views).

	x_{min}	α	p-value	D	n_{tail}	n_{tail}/n	p_{tail}/p_{total}
WoTreplays	116	2.2437	0.513	0.0143	1424	0.37%	36.98%
Twitch (cumulative popularity)	92	1.6228	0.483	0.0069	1,218,805	16.29%	97.85%
Twitch (peak popularity)	880	2.0229	0.496	0.0187	36,134	0.48%	62.11%

fitted power-law distributions. When plotted on a log-log scale, all of them exhibit a straight line, especially on the tails, indicating a power-law distributed characteristic. To be more rigorous, we further perform power-law fittings to test whether the heavy tail phenomenon occurs.

We use the tool proposed in [Clauset et al. 2009] for discerning and quantifying power-law behaviors. The tool combines maximum-likelihood fitting methods with Goodness-of-Fit (GoF) tests. In practice, few empirical phenomena obey power laws for all values of the data. More often the power law applies only for values greater than some minimum value, denoted by x_{min}. Therefore, instead of fitting the whole data, this approach focuses only on $x \geq x_{min}$, i.e., the tail—this is exactly what we need for testing whether the heavy tail phenomenon occurs.

Besides the start of the fitting, x_{min}, the above method also returns the scale α and the p-value for the fitted distribution. The scale measures the heterogeneity of the data. In our analysis, a larger value of α indicates more skewed popularity. For the p-value, we use 0.05 as the significance level, below which the null hypothesis that the fitted distribution represents the empirical data is rejected. In addition, we also calculate the largest gap between the empirical Cumulative Distribution Function (CDF) and the fitted CDF, denoted by D, the number and the fraction of data contained in the tail (i.e., $x \geq x_{min}$), denoted by n_{tail} and n_{tail}/n, and the fraction of total popularity achieved by the tail, denoted by p_{tail}/p_{total}. The fitting results are shown in Table III.

We find that, for both WoTreplays and Twitch (and the two types of popularity we considered in Twitch), power-law distributed popularity holds for the very popular gamecasts (with p-values significantly larger than 0.05 for $x \geq x_{min}$), indicating that *the heavy tail phenomenon occurs in these two gamecast sharing sites*. Nevertheless, the size of the heavy tails and the fraction of total popularity achieved by them are different across WoTreplays and Twitch. The tail for the cumulative popularity in Twitch contains the most gamecasts, which is over 30 times more than the tail for the peak popularity in Twitch, and is over 850 times more than the tail for the popularity in WoTreplays. Further, we observe that the tails in these sites all account for a significant part of the total popularity, and again with the tail for the cumulative popularity achieves a higher fraction of its total popularity than the tail for the peak popularity in Twitch, which in turn is higher than the tail for popularity in WoTreplays. This is consistent with our previous result in Fig. 4 that shows the same pattern of difference in the level of the skewness observed in these two sites.
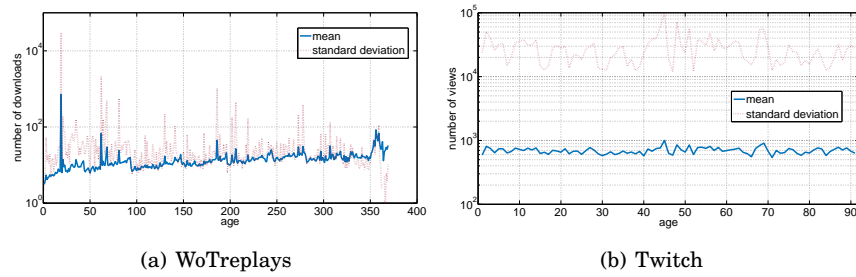
(a) WoTreplays   (b) Twitch

Fig. 7: Gamecast popularity versus the gamecast age, the vertical axis is in a logarithmic scale.

Long tail: the non-popular gamecasts. The long tail phenomenon is often analysed based on the *rank/frequency* plot [Newman 2006], which we show in Fig. 6. Here, the vertical axis shows the popularity for each gamecast and the horizontal axis shows the ranking of gamecasts based on the decreasing order of their popularity. For each dot on this plot, its pair of values, say (x, y), represents that there are x gamecasts with popularity higher than y. The *rank/frequency* plot in fact is another form of the CCDF plot.

For both WoTreplays and Twitch, we observe roughly straight lines for the tails in this log-log plot, representing a power-law characteristic for the non-popular gamecasts. This result indicates that, in both sites, there exists long tails that contain a large number of gamecasts with low popularity. Together with the results shown in Figs. 4 and 5, we find that 90% of the replays in WoTreplays and 60% of the sessions in Twitch have been watched in total for less than 20 times, accounting for 40% and 2% of the total popularity, respectively. We also find that 84% of the sessions in Twitch achieve fewer than 10 peak concurrent views, accounting for less than 10% of the total peak popularity. These results may indicate that, *in both WoTreplays and Twitch, the long tail phenomenon occurs, and the long tail in WoTreplays plays a more important part for the total popularity than that in Twitch.*

4.3.3. Popularity and age. In this section, we study the cumulative effect of time by analyzing the popularity of gamecasts. We count the age of a gamecast as the total number of days since the gamecast was published online. Fig. 7 shows the popularity (number of downloads/views) achieved by gamecasts in different age groups. For both WoTreplays and Twitch, we have two interesting observations. First, we did not find a strong correlation between the gamecast popularity and the age, which only achieves a Spearman Ranking Correlation Coefficient (SRCC) [4] of 0.0007 and 0.0004, respectively. Secondly, we observe very high deviations for gamecasts in the same age group: for WoTreplays, it is in the same level as the mean value, and for Twitch, it is two orders of magnitude higher than the mean value.

The above results indicate that, statistically, in both WoTreplays and Twitch, *gamecasts do not necessarily accumulate more downloads and views over time*. To further demonstrate this effect, we show in Fig. 8 the popularity of each gamecast in five different age groups, with the gamecasts ranked in the decreasing order of their popularity. For WoTreplays, we only observe a slight increase from one day old to 10 day old gamecasts in the same rank; while for Twitch, gamecasts in the same rank of different age groups achieve very similar popularity. In general UGC sites like YouTube, though contents often accumulate a large amount of views at their early ages, the cumulative

---

[4]In brief, SRCC assesses how well the relationship between two variables can be described using a monotonic function [Spearman 1904].
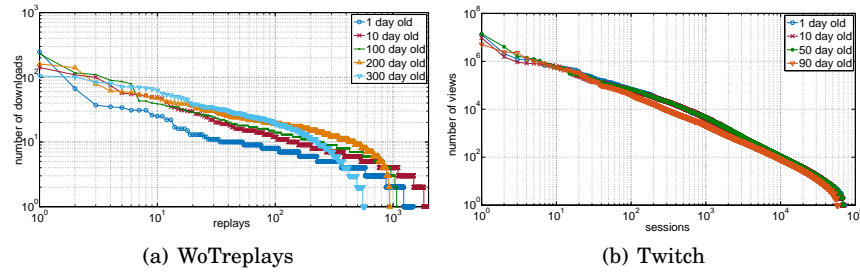
(a) WoTreplays   (b) Twitch

Fig. 8: Gamecast popularity in different age groups, in log-log scale.

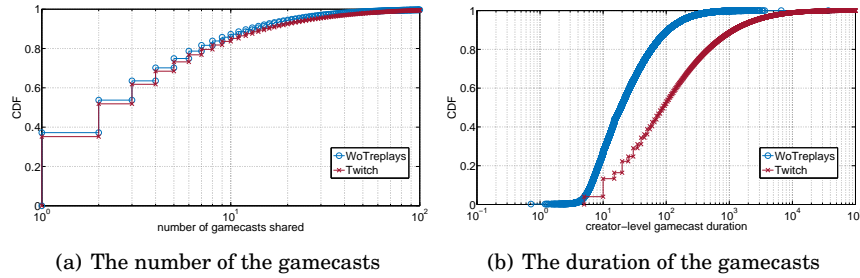(a) The number of the gamecasts   (b) The duration of the gamecasts

Fig. 9: CDF of the number and the duration of the gamecasts shared by creators.

effect of time is still observable—roughly the content popularity for videos of three month old is two orders of magnitude higher than videos of one day old in YouTube [Cha et al. 2009].

Together with the comparatively large gamecast injection rate, we believe that *WoTreplays and Twitch are repositories of items that have short-term values: a considerable amount of gamecasts are injected, viewed, and soon forgotten*. We conjecture that this is due to the nature of gaming: as game-playing techniques evolves quickly over time, stale gamecasts no longer provide enough information for education or entertainment.

5. CREATOR CHARACTERISTICS

We have shown that WoTreplays and Twitch are constantly expanding repositories, with a large number of new gamecasts being injected on a daily basis. In this section, we investigate the basic characteristics of the creators. We first show their activity level and upload delay. Then, we conduct an analysis of the creator popularity, with a focus on its statistical properties. Finally, with the detailed in-game statistics archived by WoTreplays, we analyze the upload preference of the creators.

5.1. Activity level of the creators

We use the number and the duration of gamecasts shared by the creators to measure their activity level. As shown in Fig. 9, for creators in WoTreplays and Twitch, their activity levels are highly skewed: while 70% of the creators have shared less than 5 gamecasts, 3% of the creators have shared more than 40 gamecasts. We observe similar skewness for the total duration of gamecasts shared by creators as well.

Meanwhile, though the number of gamecasts shared by creators in these two communities achieve similar statistical patterns, creators in Twitch in general accumulate one order of magnitude longer gamecast duration than creators in WoTreplays.

Table IV: Statistics on the creator activity level, including the mean, the median, the maximum, the minimum, and the standard deviation (std).

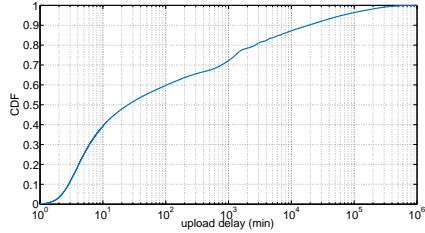|	number of gamecasts					duration (minute)				
	mean	median	max	min	std	mean	median	max	min	std
WoTreplays	6.04	2	4683	1	23.64	49.67	19.11	36,978	0.72	185.02
Twitch	7.01	2	5388	1	20.59	676.18	90	130,410	5	3320.6

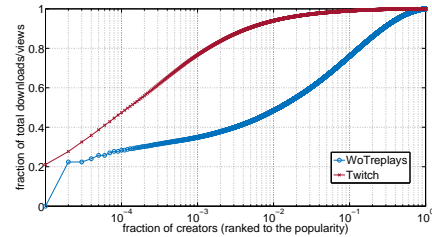Fig. 10: CDF of the upload delay in WoTreplays.

Fig. 11: Skewness of creator popularity

Together with the fact that our WoTreplays and Twitch datasets contain histories of one year and 3 month respectively, we conclude that creators in Twitch are more active than those in WoTreplays. The detailed statistics are shown in Table IV.

Interestingly, we identify a considerable amount of creators in Twitch who have streamed almost continuously. We find that 500 creators have streamed on average more than 12 hours a day, and 100 creators have streamed in total more than 80 days during the whole data collection period (90 days). As Twitch's partnership program allows streamers to earn revenue through streaming, it is possible that some of these creators are teams of professionals in online e-sports streaming, rather than just players.

In regular content sharing sites, the upload time often reflects the timeliness of the content. For example, contents related to breaking news are normally immediately uploaded when they are available. Here, we use the *upload delay* to measure how quickly creators upload their replays in WoTreplays, which is defined as the time difference between the finish time of a game and the upload time of its replay. Fig. 10 shows the CDF of the upload delay for each replay in WoTreplays. We see that 50% of the replays are uploaded within 20 minute after the games are finished, indicating that creators are often very eager to share their games. In Twitch, the gamecasts are broadcasted via live streaming, i.e., no upload delay. In the meantime, the broadcasters chat and explain their game styles to their spectators. This new form of communication helps the broadcasters to build relationships with their spectators, which partially sparks interest for users in online e-sports.

5.2. Creator popularity

In Section 4.3 we have conducted a detailed analysis of the gamecast popularity. In the context of UGC sites, content popularity has received great attention for scientific research because of the importance of understanding the user's preference. However, to the best of our knowledge, the popularity patterns for their creators are still unexplored. Nevertheless, it is equally (if not more) important to understand the popularity of the content sharers—those who directly generate the contents—and maintain high content popularity by keeping the activity level of the popular content sharers. In this section, we analyze the creator popularity in gamecast sharing sites.

We use two metrics to measure the popularity of the creators, namely the total number of views, and the average number of views for the gamecasts they share. Following
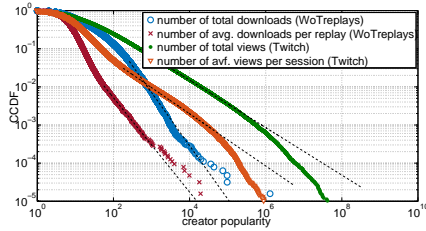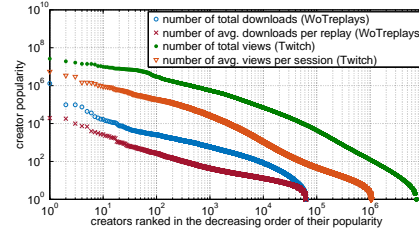
Fig. 12: CCDF of the creator popularity.

Fig. 13: The creator popularity, in log-log scale.

Table V: Results of the power-law fitting for the creator popularity.

	x_{min}	α	p-value	D	n_{tail}	n_{tail}/n	p_{tail}/p_{total}
WoTreplays (total downloads)	261	2.3961	0.494	0.0179	2954	4.67%	65.25%
WoTreplays (avg. downloads per replay)	56	2.2374	0.497	0.0224	670	1.06%	27.41%
Twitch (total views)	477	1.6230	0.502	0.0044	107,010	10.02%	99.01%
Twitch (avg. views per session)	181	1.6847	0.482	0.0155	32,894	3.08%	90.96%

the methods used in Section 4.3, our analysis focuses on examining the skewness of popularity and studying the statistical properties for the popular creators (i.e., the heavy tail) and the non-popular creators (i.e., the long tail).

5.2.1. Skewness. In Fig. 11 we show the fraction of the total popularity aggregated by the rth most popular creators in WoTreplays and in Twitch, respectively. In general, we observe a very skewed creator popularity in both communities: for WoTreplays, 10% of creators account for 75% of the total downloads, and for Twitch, 1% of the creators even have accumulated more than 90% of the total views. Together with the results of the skewness analysis for the gamecast popularity (as shown in Fig. 4), we find that, for the same community, the creator popularity is more skewed than the gamecast popularity. This result indicates that, *to attract more users, maintaining popular creators is potentially more effective than maintaining popular gamecasts*.

5.2.2. Heavy tail: the popular creators. In Fig. 12 we show the CCDF of the creator popularity in WoTreplays and Twitch, respectively. The dashed lines represent the fitted power-law distributions. We have used the same method for the power-law fitting as described in Section 4.3.2, and the fitting results are shown in Table V.

We find that, for both WoTreplays and Twitch, power-law distributed popularity holds for very popular creators (with p-values significantly larger than 0.05 for $x \geq x_{min}$), indicating that *the heavy tail phenomenon applies to the creator popularity in both of these two sites*. Nevertheless, the size and the fraction of total popularity achieved by their heavy tails are different. Possible reasons are that, as shown in Fig. 11, creator popularity in Twitch is more skewed than that in WoTreplays, and therefore, its heavy tail contains a larger fraction of creators and accounts for a higher fraction of the total popularity—in other words, *the tail of the creator popularity is heavier in Twitch than in WoTreplays*.

5.2.3. Long tail: the non-popular creators. To examine the long tail phenomenon, we show the *rank/frequency* plot of the creator popularity in Fig. 13. Here, the vertical axis shows the popularity for each creator and the horizontal axis shows the ranking of the creators based on the decreasing order of their popularity. As discussed in Section 4.3, the *rank/frequency* plot is another form of the CCDF plot.

For both WoTreplays and Twitch, we observe almost straight lines for tails in this log-log plot, representing a power-law characteristic for the non-popular creators. This result indicates that *both WoTreplays and Twitch contain a large number of creators*

Table VI: Correlations between the creator popularity, p_c, the number of gamecasts, n_g, and the average popularity of gamecasts shared by the creators, avg. p_g.

SRCC	p_c vs. n_g	p_c vs. avg. p_g	n_g vs. avg. p_g
WoTreplays	0.8446	0.7361	0.2906
Twitch	0.8323	0.8766	0.4906

with low popularity. Together with the results shown in Figs. 11 and 12, we find that 90% of the creators in WoTreplays have attracted in total less than 100 downloads for the replays they share, roughly accounting for 25% of the total downloads; In Twitch, more than 70% of the creators have collected less than 100 views for their streaming sessions, however, these non-popular creators only account for 0.025% of the total views.

5.2.4. Discussion. Combining the above results on the creator popularity with the results on the gamecast popularity (as shown in Section 4.3), we conclude that *both the gamecast and the creator popularity in WoTreplays and Twitch are skewed*, with the creator popularity more skewed than the gamecast popularity. We also confirm that *the heavy tail phenomenon occurs in these two sites*, indicating that a small number of popular gamecasts and creators account for a large amount of the total popularity. Nevertheless, we observe *different long tail phenomena in these two sites*. While they both contain a large number of gamecasts and creators with low popularities, in WoTreplays, these gamecasts and creators accumulate a considerable amount of the total popularity; but in Twitch, their share in the total popularity is neglectable.

One immediate application of the above findings is to maintain the user activity level in these sites. Understanding users' preferences for gamecasts and creators, the administrators of these and similar sites can identify the popular gamecasts and creators, customize incentive policies for them to share more, and hence, attract more users to the sites[5]. Further, for sites with significant long tail phenomenon (e.g., WoTreplays) wherein non-popular contents accumulate a considerable amount of the total popularity, better recommendation algorithms can be applied to promote the non-popular contents, so as to elaborate their potential of attracting more users.

5.3. Building up the creator popularity

We have shown that popularity distribution of creators in WoTreplays and Twitch are skewed. In this section, we explore possible reasons for this skewness. Table VI shows the SRCCs between the creator popularity, the number of gamecasts, and the average popularity of gamecasts shared by the creators. We observe clear correlations between either of latter two metrics and the creator popularity, but not between these two metrics. This result suggests that *a popular creator tends to have many popular gamecasts*. Nevertheless, we can still identify a small number of creators who have achieved extremely high popularity with only a few gamecasts. For example, in WoTreplays, 30 creators in the top-100 most popular creators have shared in total less than 20 gamecasts. And in Twitch, 37 creators in the top-100 list have shared no more than 50 gamecasts. We conjecture that their popularity is due to their gaming reputation, while in general the creator popularity is built up gradually through constant sharing.

A creator's gaming reputation may consist of various aspects, including the skill and the style of his gameplay. A more detailed analysis of the relationship between the reputation and the popularity of creators requires quantifying their gaming reputation, which potentially needs more data on the in-game performance and possibly a user survey. We leave this as our future work.

---

[5]Twitch's partnership program encourages popular creators to share more high-quality gamecasts. However, the details of the program are not specified to an extent that enables service-level analysis.
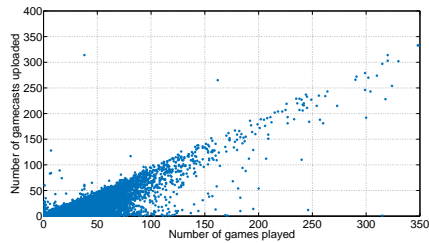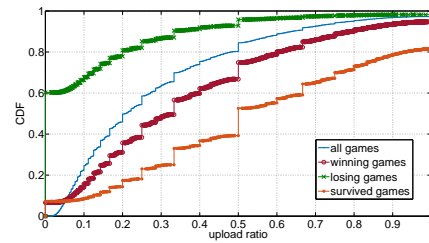
Fig. 14: Upload count versus game count

Fig. 15: CDF of the upload ratio

5.4. Upload preference

In this section, we analyze the upload preference of the creators, i.e., whether and how the creators are selective when choosing gamecasts to share. This analysis requires detailed game statistics, including the team formation, the winning and the losing team, the in-game skill of each player, and the reward the player gets at the end of the game. Since only the WoTreplays dataset contains such information, our analysis in this section focuses on the uploaders in WoTreplays, i.e, creators who have played at least one game. The behavioural metrics we considered are as introduced earlier in Section 3.2.

5.4.1. Upload everything? We first show in Fig. 14 the scatter plot of the upload count and game count for each uploader. We observe a modest correlation between these two metrics, achieving a SRCC of 0.5414. This result indicates that *uploaders do not necessarily upload more games when they have played more*.

To further illustrate this phenomenon, Fig. 15 shows the CDF of the upload ratio (defined as the upload count divided by the game count of an uploader). We find that it takes a wide range of values, and only 20% of the uploaders have uploaded more than half of all the games they have played. This result indicates that *the uploaders do not upload indiscriminately*. In the following sections, we investigate this selective upload behavior.

5.4.2. Upload the winning and the survived games? We conjecture that two possible reasons for an uploader to share a replay are the victory of his team and/or of himself. Following this intuition, we test whether an uploader is prone to upload the games he has won and the games he has survived in (See Sec. 3.1.3 for definitions).

Fig. 15 shows the CDF of the upload ratio for winning, losing, and survived games, respectively. We find that, in general, the upload ratio for winning games is much higher than that for losing games: while only 3% of the uploaders have uploaded at least half of their losing games, 30% of the uploaders have done so for their winning games. As it turns out, uploaders are even more prone to share survived games: 60% of the uploaders have shared at least half of their survived games, and 20% of the uploader even have shared all of them. We have also calculated the SRCCs between the upload count, and the winning, the survived, and the losing game count, which are 0.6217, 0.7201, and 0.3067, respectively. Clearly, *uploaders are more prone to share the winning and the survived games than the losing games*.

With the above upload preference, it is natural that uploaders achieve higher win ratio in the archived games than players who did not upload any replays. We find that more than 20% of players have not won any games, while more than 50% of uploaders have won at least half of their games. We also observe that around 20% of players and around 5% of uploaders have achieved a win ratio of 100%. We conjecture that the complete victory is due to the small game count of these players (on average, fewer than 2 and 4 games for players and uploaders, respectively).

Table VII: Statistics for the upload ratio and the fraction of different types of games in the played and the uploaded games of each uploader, with the mean and the standard deviation (std).

	upload ratio mean (std)	fraction in played games mean (std)	fraction in uploaded games mean (std)
winning games	0.3717 (0.2736)	0.6088 (0.1758)	**0.8379** (0.2817)
losing games	0.1120 (0.1989)	**0.3912** (0.1758)	0.1475 (0.2686)
survived games	0.5526 (0.3185)	0.3738 (0.2017)	**0.7802** (0.3139)
losing and survived games	**0.4982** (0.4760)	0.0177 (0.0486)	**0.0338** (0.1347)
losing but not survived games	**0.0852** (0.1672)	**0.3736** (0.1744)	0.1173 (0.2402)

5.4.3. Upload the losing but survived games? Though uploaders prefer to upload winning and survived games, from Fig 15 we still observe a considerable amount of losing games being uploaded and we can identify 40% of uploaders that have uploaded at least one of their losing games. In this section, we test what kind of losing games that uploaders are inclined to share. Following the results shown in the last section, we focus on the games an uploader has lost but survived in the end.

Table VII shows the statistics for the upload ratio of different types of games. Clearly, the upload ratio for the losing and survived games is much higher than that for the losing but not survived games. We conjecture that when an uploader decides to share a losing game, the uploader mainly does so to show the uploader's individual skills. To better illustrate this phenomenon, we further show in Table VII the statistics on the fraction of different types of games in the played and the uploaded games of each uploader. We see that the winning games, the survived games, the losing but survived games all take higher fractions in the uploaded games than in the played games, suggesting the uploader's preference for them. We conjecture that, *for uploading game replays, the uploaders in general focus more on their individual performance than the outcome of their teams.*

5.4.4. Show off skills? In this section we study the in-game skills of uploaders. The in-game skill of a WoT gamer can be measured via the number of tanks he has killed, the damage he has done, and the credit he has gained. In our analysis, we focus on the number of kills, since we can use the maximum team size (i.e., 15 players) as the baseline to infer a gamer's skill.

We find that, while in WoT each team has maximum 15 players, more than 40% of the uploaders have killed at least 5 tanks, i.e., one third of the opponents. More specifically, the average number of kills takes a mean value of 4.64, a median value of 4.5, and a maximum value of 15 respectively, with a standard deviation of 2.19. It is very likely that uploaders are showing off their skills through sharing the replays.

6. SPECTATOR CHARACTERISTICS

Spectator activity captures the most basic characteristics of gamecast sharing sites. In the previous sections, we have indirectly investigated their download activity through an extensive analysis of the gamecast and the creator popularity, which, as it turns out, are both highly skewed. In this section, we further explore the download preference of the spectators, and we conduct an analysis of the interactions between the spectators and the WoTreplays repository, in terms of the comments and the hearts they give.

6.1. Download preference

To understand the download preference of spectators, we first study the spectator's potential preference for replays of different game types, i.e., winning, losing, and survived games. Then, we analyze the possible influence of the gaming skills of the uploaders.
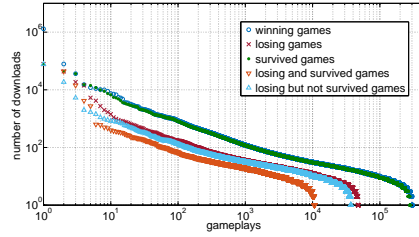
Fig. 16: Number of downloads for different types of games.

Table VIII: Statistics for the size and the number of downloads of replays of different game types.

	fraction of games	fraction of total downloads	mean	number of median	downloads max	std
winning games	79.65%	88.13%	15.74	7	1,299,174	2359.00
losing games	12.57%	11.87%	13.43	7	77,869	422.32
survived games	73.76%	61.09%	11.78	7	78,378	193.75
losing and survived games	2.8%	3.24%	16.38	7	43,546	444.39
losing but not survived games	9.8%	8.63%	12.58	7	77,869	415.75

6.1.1. Preference for game types. We first show in Fig. 16 the number of downloads for replays of different game types, where the replays of each game type are ranked in the decreasing order of the number of downloads they collected. In general, the spectators prefer to download winning and survived games over losing games, and within the losing games, they prefer survived over not survived losing games. The detailed statistics are shown in Table VIII. We have two interesting observations, as follows.

First, compared to the losing and the survived games, the winning games have the largest fraction (79.65%), account for the largest fraction of the total downloads (88.13%), and achieve the highest average number of downloads (15.74, the mean value). Secondly, the losing games achieve a higher mean value for the number of downloads than the survived games. The 5-time difference in the number of losing games and the number of survived games suggests that the survived games contain a longer tail than the losing games, and this long tail, meaning a large number of games with a small number of downloads, induce a relatively small mean value. If we compare the top-n survived and the top-n losing games ($n \leq 48,113$, which is the number of the losing games), as shown in Fig. 16, the survived games always achieve a larger number of downloads. The same argument applies to the losing and survived games that achieve a large mean value of the number of downloads as well.

The above results indicate that, when making download decisions, *the spectators appreciate the team performance more than the individual performance of the uploaders*. Note that earlier in Section 5.4 we have shown an opposite tendency for the upload preference of uploaders: *they focus more on the individual than the team performance*.

6.1.2. Preference for uploaders' skills. Uploaders' gaming skills are reflected by a number of metrics. Our WoTreplays dataset includes (i) for each game, the *number of kills*, the *experience* (number of stars), the *damage*, and the *credit* that the uploader has earned at the end of the game; and (ii) in the long run, his *win ratio* (the fraction of winning games in all the games he has played). We calculate the SRCCs between the number of downloads and the above five metrics, in both the replay and the uploader level. Taking the number of kills as the example, in the replay level, we calculate the SRCC between the number of downloads of each replay and the number of kills made by its uploader, and in the uploader level, we calculate the SRCC between the average number of downloads for replays uploaded by each uploader and the average number of kills he has made in those replays. The results are shown in Table IX.

Table IX: Correlation between the number of downloads (dls) and the uploader skills.

SRCC	kills	stars	damage	credit	win ratio
dls (per replay)	0.1361	0.2076	0.2315	0.1572	N/A
dls (per uploader)	0.1702	0.2702	0.3232	0.2234	0.1032

Table X: Statistics on the comments in the replay level.

#comments	mean	median	std	max	frac. of comments	mean	median	std	max
all	1.3195	1	1.2286	43					
from the uploaders	0.5951	1	0.5882	11	from the uploaders	**0.4994**	0.5	0.4733	1
from the gamers	0.1034	0	0.3307	5	from the gamers	0.0863	0	0.2723	1
from the spectators	0.6209	0	1.2184	41	from the spectators	**0.4143**	0	0.4676	1

In brief, we did not observe any strong correlations between the number of downloads and the number of kills the uploaders have made, nor for their experience, their damage, their credit, or their win ratio. Nevertheless, we do find that the SRCCs are in general larger when the metrics are considered in the uploader level than in the replay level.

6.2. Interactions with replays: comments and hearts

As in a general UGC sharing site, users in WoTreplays can comment and give hearts to the replays they are interested in. In total, 12,377 (42,964) replays have received at least one comment (one heart), with a maximum number of comments and hearts of 43 and 80, respectively. Among these replays, 80% of them have received only one comment (one heart). Meanwhile, we find that the number of comments correlates with the number of hearts received by each replay, achieving a SRCC of 0.5407.

6.2.1. Comments in the replay level. While WoTreplays only archives the number of hearts a replay has received, it archives more detailed information on the comments, including the time, the contents, and the names of the users who have left the comments. Table X shows the basic statistics on the comments in the replay level. We see that, for each replay, the comments it received are in general equally split among the uploaders and the spectators, achieving a mean value for the fraction of comments of 0.4994 and 0.4143, respectively. This result indicates that *the comment function maintained by WoTreplays provides the opportunity for the uploaders and the spectators to interact with each other, explicitly.*

6.2.2. Comments in the user level. We further conduct an analysis of the statistical properties of the comments in the user level. We find that in total 8,875 users ($< 0.5\%$ of total users) have left at least one comment, resulting a total number of 16,331 comments for the replays achieved by WoTreplays. Among these users, 5,319 users, 983 users, and 3,755 users have left at least one comment as an uploader, a gamer, and a spectator, respecitively. The detailed statistics are shown in Table XI.

In general, users are more likely to leave comments as uploaders and as spectators, achieving an average number of comments of 0.8300 and 0.8659, respectively. This is consistent with our previous results which show that, in the replay level, the comments are mainly left by the uploaders and the spectators. Particularly, we find the user with the most comments has left 205 comments in 181 replays, as an spectator. By manually checking the contents of these comments, we find that he is mostly asking for permission of sharing the replays on YouTube. Although these users have on average uploaded 12.8397 replays and played 14.6173 games, they have commented in less than 10% of them.

The above results indicate that *many users in WoTreplays are silent spectators*: they mostly download the replays without engaging in any explicit interactions. Nevertheless, through delicate modeling, rich (social) relationships can be detected in such com-

Table XI: Statistics on the comments in the user level.

#comments	mean	std	median	max
all	1.8401	3.7891	1	205
as uploaders	**0.8300**	1.3782	1	74
as gamers	0.1442	0.4796	0	8
as spectators	**0.8659**	3.4956	0	**205**
#uploaded replays	12.8397	28.7852	5	1000
#played games	14.6173	12.1819	12	180

Table XII: Correlation between the number of downloads (dls), and the number of comments (c), from the uploaders (c_u), from the gamers (c_g), and from the spectators (c_a).

SRCC	c	c_u	c_g	c_a
dls (per replay)	**0.3060**	0.0798	0.0515	**0.3716**
dls (per uploader)	0.1712	**0.3783**	0.0720	0.1845

munities and used to improve gaming services, such as match recommendation and game population retention, which are important for the user experience and the commercial value of the companies who run these communities. We refer the interested readers to our previous work [Jia et al. 2015] for the details.

6.2.3. Comments and the popularity. The number of comments received by a replay reflects its prosperity, and the number of comments left by a uploader reflects the uploader's activity level. Intuitively, replays and uploaders with many comments are potentially popular among the spectators, and therefore, they may collect a considerable amount of downloads. To study the influence of the number of comments on the replay and the uploader popularity, we calculate the SRCCs between these two metrics in both the replay and the uploader level. More specifically, for each replay, we consider its total number of comments, and its number of comments from the uploader, from the gamer, and from the spectators. For each uploader, we consider his total number of comments, and his number of comments as an uploader, as a gamer, and as an spectator. The results are shown in Table XII.

We do not observe any strong correlations between the number of comments and the replay and the uploader popularity. Nevertheless, we do find that, in the replay level, the SRCC between the replay popularity and the number of comments *from the spectators* is one order of magnitude higher than SRCCs between the replay popularity and the number of comments from the uploaders or from the gamers. And in the uploader level, the SRCC between the uploader popularity and their number of comments *as uploaders* is 2-5 times higher than SRCCs between the uploader popularity and their number of comments as gamers and as spectators. These results suggest that for the replays, comments from their spectators, and for the uploaders, their comments as uploaders, are more important for boosting their popularity.

7. DISCUSSION

In previous sections, we have investigated the workload and the user behaviors in WoTreplays and in Twitch. In this section, we discuss possible future work that is worth exploring.

Gamecast platform: With the workload fluctuation we observed in WoTreplays and in Twitch, smart resource scheduling policies can be developed to reduce the operational cost of these two sites while still satisfying the Quality of Service (QoS). For example, [Aparicio-Pardo et al. 2015; Pires and Simon 2015] propose a method based on Adaptive Bitrate Streaming. Nevertheless, their method only deals with fixed instead of dynamic number of computing resources. [Nae et al. 2011; Li et al. 2015]

further propose to use cloud resources in an on-demand manner. We believe that a combination of their methods could be a good direction to solve this problem.

Another way to reduce the operational cost is by taking into account the skewness of the gamecast popularity. For example, to balance the workload, gamecasts could be allocated to servers based on their popularity instead of the pure number. It should be noted that, as the gamecast popularity in Twitch is more skewed than that in WoTreplays, a platform optimized for Twitch may be sub-optimal for WoTreplays: a method dedicated to Twitch may place a number of most popular gamecasts on one server, but for WoTreplays, placing the same number of top-popular gamecasts on one server will make it underloaded. Further, as gamecasts often attract fewer downloads over-time, especially in Twitch-like platforms with streaming serives, gamecast platforms should take the evolution of the gamecast popularity into account and allocate the latest gamecasts to fast cache/storage and the old gamecasts to cheaper but slower one.

Gamecast recommendation: Although recommendation mechanisms of general UGC sites such as YouTube have been widely analysed [Davidson et al. 2010], gamecast recommendation is relatively less explored. [Kim and Kim 2014] propose a method based on the in-game features and the user rating. Nevertheless, their method requires users to rate the replays with non-neglectable efforts. Further, besides in-game statistics, we believe that the popularity and the co-watched counts of gamecasts[6] can also be leveraged to design better gamecast recommendation algorithms.

On the other hand, as we observed that a number of WoTreplays users have uploaded replays of games wherein they did not play, it would be interesting to understand the reason behind this behavior, e.g., whether it is because that these replays are well-played. An in-depth analysis of these games may provide insight into the design of gamecast recommendation algorithms.

Pre- and Post-game periods: In Twitch-like platforms, a gamecast records not only the game but possibly also what happened before and after the game, such as the creators chatting with the spectators. The pre- and the post- game periods provide good opportunities for the creators to socialize with their spectators and to increase their popularities. Because it is difficult to extract the pre- and the post- game periods from a gamecast, the analysis of these periods is still missing. In this work, we provide a preliminary analysis of this topic by examining the upload delay, i.e., the time between the end of a game and the upload time of the gamecast, which provides a hint for the post-game periods. However, a further analysis is needed to better understand the pre- and the post- game periods.

Methedology: Our study, albeit conducted in faith and with due care for scientific norms, suffers from the same limitations as the experimental, data-driven studies conducted by others. First, the experimental nature of this work means that inability to reproduce the data collection process is among the core threats to validity. We have tried to alleviate this problem by using rich, long-term, large-scale datasets in this study, which offset to some extent the biases of sparser, shorter, and smaller datasets. Future work should perhaps also focus on other games and game genres than this study. Second, much of the work in this study focuses on identifying meaningful correlations, but, due to methodological limitations such as an uncontrolled environment, it cannot establish causal influences between the studied variables. For example, although the number of gamecasts is highly correlated with the popularity of a gamecast creator, we cannot simply infer that building up a large number of gamecasts is guaranteed to cause high popularity for the creator. Future work could focus on new methodologies that allow to prove causality, for example by involving small-scale lab experiments in combination with large-scale uncontrolled data collection.

----

[6]the number of times a pair of gamecasts were watched in a same period.

8. CONCLUSION

The growth in popularity and market size of gamecast sharing sites, has not been matched by a comprehensive scientific analysis of their characteristics. To address this issue, in this article we have presented a large-scale measurement study on gamecast sharing sites exemplified by the leading and representative sites, WoTreplays and Twitch. We have presented the first publicly accessible dataset with both *gamecast statistics* and *in-game statistics*. Based on statistics for over 7 million gamecasts, over 1 million gamecast creators, and nearly 2 million players, we have investigated the repository, the creators and the spectators of gamecast sharing sites.

Among our results, we have found that both WoTreplays and Twitch are fast-consumed repositories, with a large number of gamecasts being shared, viewed, and soon forgotten. And in both types of communities we have studied, the gamecast and the creator popularity are highly skewed, with a significant *heavy tail* phenomenon that represents a small number of gamecasts and creators accounting for a large fraction of the total popularity. Further, we have observed a noticeable *long tail* phenomenon in WoTreplays, wherein a large number of gamecasts and creators with low popularities accumulate a considerable amount of the total popularity. Last, we have also found that the creators and the spectators have markedly different preference for sharing and consuming the replays: while the creators often emphasize their individual skills, the spectators appreciate team-wise tactics. Our findings provide important reference for gamecast sites to improve their services, for example, through designing better recommendation algorithms for the non-popular contents to elaborate their potential of attracting more users.

REFERENCES

H. Abrahamsson and M. Nordmark. 2012. Program popularity and viewer behaviour in a large TV-on-demand. In *Internet Measurement Conference (IMC'12)*.

C. Anderson. 2004. The long tail. *WIRED magazine* 12 (2004). Issue 10.

R. Aparicio-Pardo, K. Pires, A. Blanc, and G. Simon. 2015. Transcoding live adaptive video streams at a massive scale in the cloud. In *Multimedia Systems Conference (MMSys'15)*.

G. Armitage, C. Javier, and S. Zander. 2006. Post-game Estimation of Game Client RTT and Hop Count Distributions. In *Network and System Support for Games (NetGames'06)*.

M. Cha, H. Kwak, P. Rodriguez, Y. Ahn, and S. Moon. 2007. I Tube, You Tube, Everybody Tubes: Analyzing the World's Largest User Generated Content Video System. In *Internet measurement conference (IMC'07)*.

M. Cha, H. Kwak, P. Rodriguez, Y. Ahn, and S. Moon. 2009. Analyzing the Video Popularity Characteristics of Large-scale User Generated Content Systems. *Transactions on Networking* 17, 5 (2009), 1357–1370.

C. Chambers, W. Feng, S. Sahu, D. Saha, and D. Brandt. 2010. Characterizing Online Games. *Transactions on Networking* 18, 3 (2010), 899–910.

K.-T. Chen, Y.-C. Chang, H.-J. Hsu, D.-Y. Chen, C.-Y. Huang, and C.-H. Hsu. 2014. On the Quality of Service of Cloud Gaming Systems. *Transactions on Multimedia* 16, 2 (2014), 480–495.

X. Cheng, B.C. Burnaby, C. Dale, and J. Liu. 2008. Statistics and Social Network of YouTube Videos. In *Workshop on Quality of Service (WQoS'08)*.

G. Cheung and J. Huang. 2011. Starcraft from the stands: understanding the game spectator. In *Human Factors in Computing Systems (CHI'11)*.

A. Clauset, C.R. Shalizi, and M.E.J. Newman. 2009. Power-law distributions in empirical data. *SIAM Rev.* 51, 4 (2009), 661–703.

M. Claypool, D. Finkel, A. Grant, and M. Solano. 2014. On the performance of OnLive thin client games. *Multimedia Systems* 20, 5 (2014), 471–484.

J. Davidson, B. Liebald, J. Liu, P. Nandy, and T. van Vleet. 2010. The YouTube Video REcommendation System. In *Recommender systems (RecSys'10)*.

J. Downs, F. Vetere, S. Howard, and S. Loughnan. 2013. Measuring Audience Experience in Social Videogaming. In *Computer-Human Interaction Conference (OzCHI'13)*.

F. Figueiredo, F. Benevenuto, and J.M. Almeida. 2011. The tube over time: characterizing popularity growth of youtube videos. In *Web search and data mining (WSDM'11)*.

D. Fitzgerald and D. Wakabayashi. 2014. Apple Quietly Builds New Networks. *Wall Street Journal* (2014).

P. Gill, M. Arlitt, Z. Li, and A. Manhanti. 2007. YouTube Traffic Characterization: A View from the Edge. In *Internet Measurement Conference (IMC'07)*.

Y. Guo and A. Iosup. 2012. The Game Trace Archive. In *Network and System Support for Games (NetGames'12)*.

W.A. Hamilton, O. Garretson, and A. Kerne. 2014. Streaming on Twitch: fostering participatory communities of play within live mixed media. In *Human Factors in Computing Systems (CHI'14)*.

T. Henderson and S. Bhatti. 2001. Modelling user behaviour in networked games. In *Multimedia (MM'01)*.

Y. Huang, T.Z.J. Fu, D.M. Chiu, J.C.S. Lui, and C. Huang. 2008. Challenges, design and analysis of a large-scale P2P-VoD system. In *Special Interest Group on Data Communication (SIGCOMM'08)*.

A. Iosup, R. van de Bovenkamp, S. Shen, A.L. Jia, and F. Kuipers. 2014. An Analysis of Implicit Social Networks in Multiplayer Online Games. *Internet Computing* 18, 3 (2014), 36–44.

A.L. Jia, S. Shen, R. van de Bovenkamp, F. Kuipers, A. Iosup, and D.H.J. Epema. 2015. Socializing by Gaming: Revealing Social Relationships in Multiplayer Online Games. *Transactions on Knowledge Discovery from Data* 10, 2 (2015), 11:1–11:29.

C. Kang. 2014. He wants to make it playing video games on Twitch. But will people pay to watch? http://www.washingtonpost.com/. (2014).

M. Kaytoue, A. Silva, and C. Raissi. 2012. Watch me Playing, I am a Professional: a First Study on Video Game Live Streaming. In *World Wide Web Conference (WWW'12 Companion)*.

H. Kim and K. Kim. 2014. Learning to recommend game contents for real-time strategy gamers. In *Computational Intelligence and Games (CIG'14)*.

J. Li, D. Li, Y. Ye, and X. Lu. 2015. Efficient multi-tenant virtual machine allocation in cloud data centers. *Tsinghua Science and Technology* 20, 1 (2015), 81–89.

A. Mahanti, N. Carlsson, A. Mahanti, M. Arlitt, and C. Williamson. 2013. A Tale of the Tails: Power-laws in Internet Measurements. *IEEE Network* 27, 1 (2013), 59–64.

J. McGonigal. 2011. *Reality is Broken: Why Games Make us Better and How They Can Change the World*. Jonathan Cape. 1–400 pages.

V. Nae, A. Iosup, and R. Prodan. 2011. Dynamic Resource Provisioning in Massively Multiplayer Online Games. *Transactions on Parallel and Distributed Systems* 22, 3 (2011), 380–395.

M.E.J. Newman. 2006. Power laws, Pareto distributions and Zipf's law. *Contemporary Physics* 46 (2006), 323–351.

H. Pinto, J.M. Almeida, and M.A. Goncalves. 2013. Using early view patterns to predict the popularity of youtube videos. In *Web search and data mining (WSDM'13)*.

K. Pires and G. Simon. 2015. YouTube Live and Twitch: A Tour of User-Generated Live Streaming Systems. In *Multimedia Systems Conference (MMSys'15)*.

J.A. Pouwelse, P. Garbacki, D.H.J. Epema, and H.J. Sips. 2005. The BitTorrent P2P file-sharing system: Measurements and analysis. In *Peer-to-Peer Systems (IPTPS'05)*.

Y. Qu, G.Y. Keung, C. Lin, J. Liu, B. Li, S. Xie, and X. Zhang. 2008. Inside the New Coolstreaming: Principles, Measurements and Performance Implications. In *Computer Communications (INFOCOM'08)*.

S. Shen, N. Brouwers, A. Iosup, and D. Epema. 2014. Characterization of Human Mobility in Networked Virtual Environments. In *Network and Operating Systems Support for Digital Audio and Video (NOSSDAV'14)*.

S. Shen and A. Iosup. 2011. The XFire Online Meta-Gaming Network: Observation and High-Level Analysis. In *Massively Multiuser Virtual Environments (MMVE'11)*.

C. Spearman. 1904. The proof and measurement of association between two things. *American Journal of Psychology* 15 (1904), 72–101.

M. Suznjevic and M. Matijasevic. 2013. Player behavior and traffic characterization for MMORPGs: a survey. *Multimedia System* 19, 3 (2013), 199–220.

Twitch. 2011. (2011). http://www.twitch.tv/.

R. van de Bovenkamp, S. Shen, A. Iosup, and F.A. Kuipers. 2013. Understanding and Recommending Play Relationships in Online Social Gaming. In *COMmunication Systems and NETworkS (COMSNETS'13)*.

WoTreplays. 2013. (2013). http://www.wotreplays.com.

H. Yu, D. Zheng, B.Y. Zhao, and W. Zheng. 2006. Understanding User Behavior in Large-Scale Video-on-Demand Systems. In *European conference on Computer systems (EuroSys'06)*.