

Watch me Playing, I am a Professional: a First Study on Video Game Live Streaming

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ABSTRACT

“Electronic-sport” (E-Sport) is now established as a new entertainment genre. More and more players enjoy streaming their games, which attract even more viewers. In fact, in a recent social study, casual players were found to prefer watching professional gamers rather than playing the game themselves. Within this context, advertising provides a significant source of revenue to the professional players, the casters (displaying other people’s games) and the game streaming platforms. For this paper, we crawled, during more than 100 days, the most popular among such specialized platforms: TWITCH.TV. Thanks to these gigabytes of data, we propose a first characterization of a new Web community, and we show, among other results, that the number of viewers of a streaming session evolves in a predictable way, that audience peaks of a game are explainable and that a Condorcet method can be used to sensibly rank the streamers by popularity. Last but not least, we hope that this paper will bring to light the study of E-Sport and its growing community. They indeed deserve the attention of industrial partners (for the large amount of money involved) and researchers (for interesting problems in social network dynamics, personalized recommendation, sentiment analysis, etc.).

Categories and Subject Descriptors

J.4 [Computer Applications]: Social and behavioral sciences

Keywords

E-sport, Twitch.tv, Video game, StarCraft II, Social community, Popularity prediction, Ranking

1. INTRODUCTION

George Bernard Shaw once wrote that “*We don’t stop playing because we grow old, we grow old because we stop playing...*”. Enjoying video games at a professional level is not a young boy dream anymore and the best evidence is the amazing evolution of electronic sports over the last decade. Similarly to traditional sports, electronic sports attract a vast community of professional players (pro-gamers), teams, commentators, sponsors, and most importantly, spectators

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and fans. Indeed, a recent social study has shown that video game players prefer watching pro-gamers playing, rather than playing themselves [4].

The main difference with respect to traditional sports lies in the fact that the vast majority of the events are only online and an important remark is that members of the community are acquainted with social networks such as FACEBOOK or TWITTER and web platforms like YOUTUBE¹. As a consequence, a new type of social community is emerging, very active on several web social platforms and of a particular interest for the social network research community.

In this paper, we focus on the media that is gaining a lot of interest since last year in E-Sports: “*Online live video streaming*”, also known as *social TV* [1] which attracts tens of thousands of spectators on a daily basis. This success is mainly visible on TWITCH.TV, a live video streaming platform. Typically, major tournaments are broadcast, but generally a single player broadcast his games, chats, explains his game style and gives advices, which finally induces new kinds of relationships between him and his spectators.

Our goal is to give a first characterization of this new community by analyzing TWITCH audiences. We crawled the list of active live video streams along with their respective number of viewers every five minutes from September 29th, 2011 to January 09th, 2012. One of the authors of this paper is an active member of this community and also plays the expert role. Our data analysis enables (i) to characterize video streams qualitatively (identifying the games and the player location) and quantitatively through their viewer counts, durations, and audience, (ii) to early predict the audience of a stream, and finally (iii) to rank the most popular players. We believe that these results are of major interest for all actors of this community. For example, popularity is key in a pro-gamer career, strongly influencing his revenues (sponsors, invitations to tournament with prizes² and advertisement revenues while streaming³).

We argue along the paper that watching video game live streams tends more and more towards becoming a new kind of entertainment on its own. This new media democratizes the discovery of new video games or professional gaming scene. TWITCH is a witness of the growing interest in E-

¹The channel “HuskyStarcraft” which covers a real-time strategy game has more than 271 millions of views over the period from June 2009 to February 2012.

²e.g. <http://www.sc2charts.net/en/edb/ranking/prizes>

³ Enabling some pro-gamers to fully support themselves financially according to <http://wiki.teamliquid.net>

Sport that should get attention of researchers as well as industrials and business makers.

The rest of the paper is organized as follow. Firstly, we present our data and its main characteristics in Section 2. Then, Section 3 shows that linear regression can help predicting the audience of streamers. We then focus our attention over the most popular games and Section 4 shows how audience for each specific game is related with real-world events. Section 5 presents how TWITCH data allow to determine and rank popular progamers. The paper ends with related work in Section 6 and perspectives of further research, especially in social networks dynamics.

2. A FIRST INSIGHT INTO THE DATA

Our goal is to analyse the interest in E-Sport and the popularity of their main actors based on the web media TWITCH. A TWITCH user can be either a casual game player, a professional player, an E-Sport commentator or an organization. In all cases, the user streams video contents about a game that is watched by spectators over internet. TWITCH is provided with an Application Programming Interface (API) which allows to get a list of the active video streams at a given time, their description, and the number of spectators watching each stream. In this section, we present our dataset and its main characteristics that provide us a first characterization of video gaming community as web spectators.

Dataset. We crawled the list of active streams every five minutes on a period spanning from September 29th, 2011 to January 09th, 2012. The data collection is performed with a single HTTP request⁴ every five minutes. As a result, we obtain a list of more than 24 millions tuples of the form *(date, login, game, description, count, ...)* as explained in Table 1. Due to network issues, the crawling operation missed 832 timestamps on a total of 29,124 expected (i.e. less than 3% invalid data). We also filtered out illegal streams that were closed by TWITCH administrators due to terms of service violations after the request of the copyright holder of the streamed content. Table 2 gives a summary of our dataset⁵.

Table 1: Data tuples description (primary key).

field	description
date	The date of crawling of the tuple
login	Unique identifier of a user/streamer
game	The game or topic of the stream
description	A text description of the stream
count	The number of viewers/spectators watching the stream at a given time

Table 2: Summary of the dataset

Period of analysis	Sept 29, 11 - Jan 9, 12
#timestamps	28,292 (832 missing)
#logins	129,332
#games	17,749
#tuples	24,018,644
#illegal tuples	369,470 (1.54%)
#sessions	1,175,589
#views	27,120,337
Length streamed	215.3 years
Length watched	9,622.4 years

⁴api.justin.tv/api/stream/list.xml?category=gaming

⁵Available at <http://dcc.ufmg.br/%7Ekaytoue/?p=msnd12>

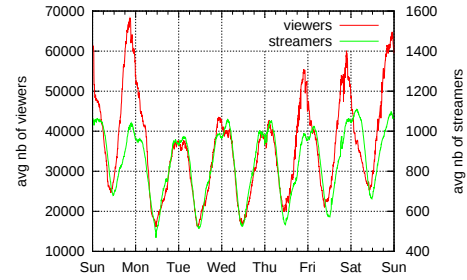


Figure 1: Average viewer count by weeks.

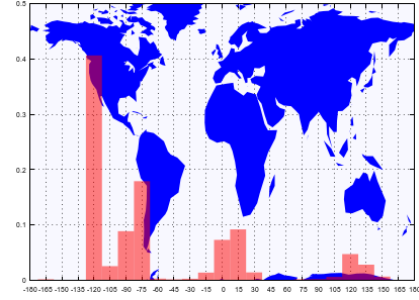


Figure 2: Longitudinal distribution of streams.

General audience characteristics. Figure 1 gives the average number of active streams and spectators for each day of the week. It clearly appears that streams are more followed at the end of the week, which highlights the entertaining nature of these videos (another important remark is that the vast majority of events like tournaments take place only on week-ends). One can also observe the following facts: *(i)* the ratio between the average number of viewers and streamers clearly grows from Thursday to Sunday due to tournaments, *(ii)* the average number of viewers and that of streamers appears to be synchronized during the working weekdays, this synchronization, however, is lost over the week-ends. Lastly, the curve representing the number of active streams shows for each day two consecutive peaks, which may correspond to European (first one) and

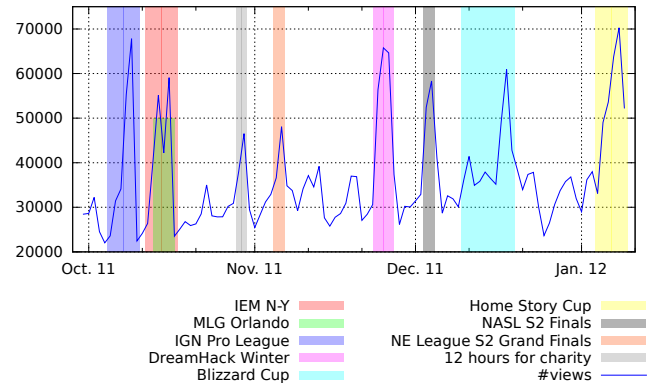


Figure 3: Average viewer count each day related with major E-Sport events.

American (second one) users, as was found for other live streaming workload [10].

Geographic distribution of streams. The geographic distribution of streams on TWITCH is illustrated through Figure 2, which is a per-longitude histogram. It is based on user-defined timezones provided by the TWITCH API, thus being prone to errors. Nevertheless, the results are consistent with our expectations, showing that most of the streams originate from North America, Europe, and East Asia. Based on our dataset, we infer that United States is the country with the highest activity on TWITCH, especially along the west coast, midwest, and east coast (with 41%, 9% and 18% of the dataset, respectively). These results are in accordance with our hypothesis regarding the consecutive peaks in audience along the week and are also explained with the geographical distribution of “Counter-Strike” game servers and players across the world [3].

Major events. Our dataset allows us to relate major E-Sport events or tournaments with audience as depicted in Figure 3. Each line point represents the average audience for a single day, i.e. the sum of all view counts divided by the number of crawled timestamps of the day. Bars in colors represents some of the major E-Sport events streamed on TWITCH that attracts many spectators.

Stream and Streamer characteristics. We define as a stream a continuous transfer associated to a unique login⁶. Our dataset contains 1,175,589 streams associated to 129,332 distinct streamers (see Table 2). Figure 4 shows the cumulative distribution function of the stream duration and of the aggregate duration of the content streamed by users. The average stream duration is 96 minutes with a high standard deviation (200 minutes). The longest stream was available for 20 hours and the median length is 45 minutes. The median duration of game streams is longer than the median duration of YOUTUBE videos [2], but shorter than the median duration of general-purpose live streams [10]. Aggregate streamer time presents even higher variation. During the period of analysis, users streamed during 14 hours on average - with a standard deviation of 54 hours. The median streamer time is 95 minutes, which represents the duration of about two streaming sessions. Surprisingly, there is a user that streamed for 97 days in aggregate (95% of the collection period). We found that this user represents a team of players that raises money for charity through game streaming⁷.

We also study the popularity (or number of views) of streams and streamers. Since the number of viewers of a stream varies along its session, we consider the stream popularity to be represented by its peak number of concurrent viewers. Streamer popularity is the sum of the popularity of his/her streams. The median and average popularity of streaming sessions is 2 and 23, respectively. Nevertheless, while most of the streams attract a very small audience, top popular streams attract many viewers. In order to evaluate the skewness of the stream popularity distribution, we check whether the Pareto Principle (also known as the 80-20 rule) holds for stream popularity. Figure 5(a) shows the aggregate popularity of the least r^{th} popular streams. Stream ranks are normalized between 0 and 100. The top 10% of streams account for nearly 88% of the views. Similar anal-

ysis for YOUTUBE videos [2], has found that the top 10% popular videos aggregate 80% of the views, which shows that content popularity on TWITCH is more skewed than on YOUTUBE. As shown in Figure 5(b), streamer popularity is even more skewed than stream popularity. The top 10% streamers concentrate 95% of all views, showing that the audience attention is grabbed by a very small set of streamers. Possible explanations for this results are: (i) scarcity of good streams/streamers and (ii) low quality of stream recommendation. In the next section, we present a technique for predicting stream popularity that may be applied for users stream recommendations.

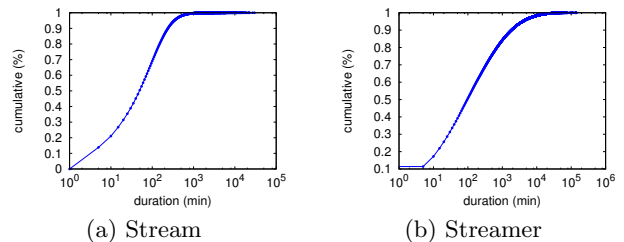


Figure 4: Duration of streams and aggregate duration of streamers

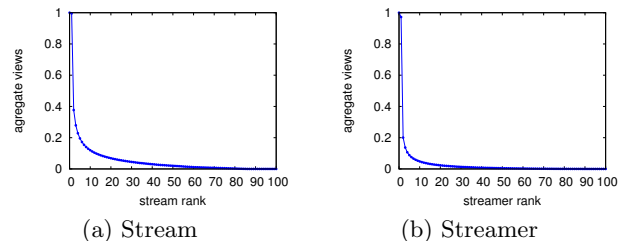


Figure 5: Stream and streamer audience

3. PREDICTING STREAMS POPULARITY

In this section, we study the problem of predicting the popularity of streams on TWITCH. Our objective is to show how a very simple technique may be useful in the early identification of streams that are likely to become popular. This is the first step towards providing better stream recommendation. As discussed in Section 2, a very small group of streamers hold most of the the audience on TWITCH. An explanation to this phenomenon is that TWITCH lists on its main page the streams with the highest number of viewers categorized by game. These lists may work as an information filter, making it difficult for a user to find streams that have not reached high popularity. As a consequence, good streams may take too long to (or even never) become visible to the community. Given the nature of live streaming content, timely recommendation becomes an important requirement for TWITCH and other analogous systems.

Similar to other online content [2, 11], the early popularity of live streams is expected to be highly correlated with their future popularity. In other words, streams that get many views overall are likely to attract viewers early on their sessions. While initial popularity usually does not lead these

⁶We set a timeout threshold of 10 minutes in order to reduce the effect of short network issues in the analysis.

⁷<http://zeldathon.net/>

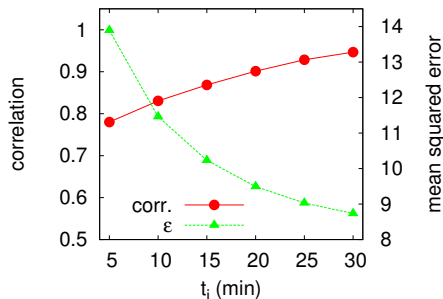


Figure 6: Correlation between stream popularity after t_i minutes and after one hour (corr.) and mean squared error of the predictions varying t_i .

streams to the top list, it may be useful for popularity forecasting. In order to investigate this hypothesis, we compute the Pearson Correlation between the popularity of a stream after the first t_i minutes and after one hour for t_i varying from 5 to 30 minutes. Figure 6 shows that early and future popularity are strongly correlated, even when information about only the first 5 minutes of the streaming session is available. As expected, this correlation increases as the reference time t_i gets close to the time for which the prediction is made, reaching 0.95 when t_i is set to 30 minutes. Figures 7(a) and 7(b) show in more detail how initial and future popularity are correlated when t_i is set to 5 and 30 minutes, respectively. The points are a random sample and represent only 5% of the streams considered. The axes are in log scale and a line indicates the linear fit of the points. A natural strategy to predict stream popularity at time t_f ($p(t_f)$) based on its popularity at t_i ($p(t_i)$), such that $t_i < t_f$, is the use of a linear regression model, as follows:

$$\log(p(t_f)) = \beta_0 + \beta_1 \log(p(t_i)) + \epsilon \quad (1)$$

The logarithm transformation is applied due to the high skewness of the popularity distribution. It is known that the distribution of the variations (ϵ) of log-transformed popularities of YOUTUBE videos and DIGG stories around their expected averages are distributed approximately normally with additive noise [11]. We assume that stream popularity on TWITCH may be described by a similar formulation, which justifies a logarithmic transformation. In order to evaluate the predictive power of the proposed model, we run a ten-fold cross validation using our dataset. In Figure 6, we show the mean squared error (MSE) of the predictions for t_i varying from 5 to 30 minutes. The linear regression model provides accurate estimates, achieving a MSE of 13.9 and 8.8 when using the popularity after 5 and 30 minutes of the streaming session, respectively. Figures 7(c) and 7(d) depict the correlation between predicted and actual popularities for $t_i = 5$ minutes and $t_i = 30$ minutes, respectively. Only 5% of the points, selected at random, are shown and the axes are in log scale. The model achieves good performance, specially for the most popular streams, and this can be trivially noticed by the proximity of the points to the function $y = x$.

4. GAMES ATTENTION

We are now interested in characterizing video games attention and studying how it evolves across the period of study. We identified the mostly watched games on TWITCH over times and correlated their peaks of attention with real-world events and best video games sells. As such, TWITCH reveals itself to be a perfect witness of events happening over the video game industry and community, as depicted by Figure 3.

Stream topic discovery. 27% of the data tuples miss a *game* field. This is problematic for the study of the per-game audiences. Furthermore, when given, this field may contain several synonyms (e.g. STARCRAFT II and SC2) and too general names (e.g. “Everything” and “Some games”). Fortunately, we can use the *description* field to infer what game(s) is (are) the topic of a tuple as follows. We listed all possible unique values of the field *game* resulting in 17,749 different topics. We kept only logins that at least at one time had more than 200 spectators resulting in only 1,370 different games. This list has been manually cleaned and the different synonyms were grouped together reducing the list to 375 different games. We used this list to infer the topic of each tuple by examining the *description* field. Finally, 78% of all original tuples are provided with one or several topics.

Global game attention. From this dataset, we studied the global interest in each video game. Table 3 gives the top 20 games with best audience: each percentage represents for one game the ratio between the sum of all its viewer counts across the period of study w.r.t. the total count. A first remark is that this list allows to highlight video games played at a professional level (in bold) and present in major tournaments of the E-Sport community. Secondly, six of the top 20 games are among the top 10 video games sales of 2011 (based on AMAZON sells). Other games either were released before 2011 and still benefit of a support and large community (e.g. “*World of Warcraft*”), or were released at the end of 2011 but already met a great success, e.g. “*The Legend of Zelda: Skyward Sword*” and “*Star Wars: the Old Republic*” both given with a “Game of the year” award from different criticisms, according to WIKIPEDIA sources. Without going into more details, one can relate each of the games of the list with major events of the year and best video games selling. Further such explanations are given in the next paragraph, where we analyse daily attention instead of global one.

Game attention dynamics. We study now game attention on a daily basis. For each of the 20 best games, we compute the proportion of viewers attracted towards it on a daily basis. Figure 8 gives the resulting plot. Bars on the X-axis represent ordered days across the period of study. One single bar gives the proportion of audience of each game along the day. Several interpretations of this graph can be made, many of them relating peaks of audience to major real-world event and large constant audience to most popular games. One can identify the game “*StarCraft II*” as the most constantly followed game, widely played at professional level with tournaments with important prize pools for the winners. Several games show also peaks of interest during particular events: “*Leagues of Legends*” from October 13th to 16th during a tournament “*Intel Extreme Master*”; “*Super Street Fighter 4*” from 5th to 7th November, during the “*Canada Cup*”. Finally, official release of several games coincides with an important audience that decrease over time, the case of “*The Elder Scrolls V: Skyrim*” at November 11th.

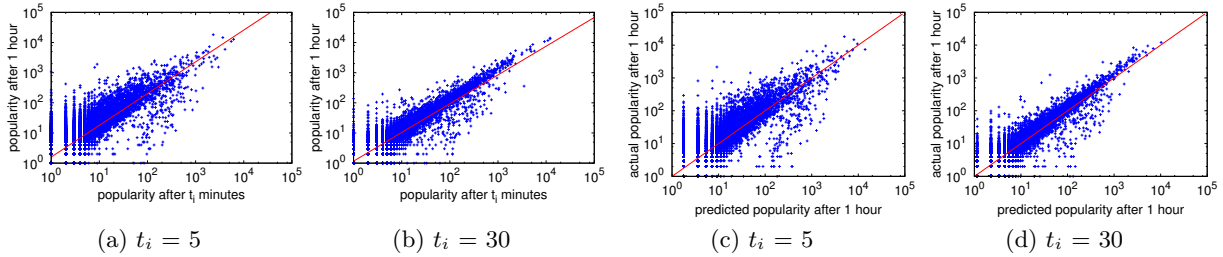


Figure 7: Correlations between stream popularity after t_i minutes and after 1 hour [7(a) and 7(b)] and between the popularity predicted by the regression model (Equation 1) and the actual popularity after 1 hour [7(c) and 7(d)] when t_i is set to 5 and 30 minutes. Lines represent linear fits in Figures 7(a) and 7(b) and the function $y=x$ in Figures 7(c) and 7(d).

One explanation is that for a potential customer, watching the game played is a good witness to take a final decision. A second explanation is that this game may not be really entertaining to watch. Such observations are important for video games producers, giving yet another information on the success or not of their products.

Table 3: Top 20 games with highest audience.

Game	Audience	Release
StarCraft II	35.05%	July 2010
Heroes of Newerth	8.89%	May 2010
League of Legends	8.19%	Oct. 2009
World of Warcraft	6.24%	Nov. 2004
Call of Duty: BO	3.88%	Nov. 2010
Street fighter 4	3.26%	Apr. 2010
Star Wars (TOR)	2.98%	Dec 2011
The Elder Scrolls	2.36%	Nov. 2011
MineCraft	2.03%	Nov. 2011
Rage	1.98%	Oct. 2011
Marvel vs. Capcom 3	1.67%	Feb. 2011
Dota 2 (beta)	1.55%	Sep. 2011
Battlefield 3	1.39%	Oct. 2011
Warcraft III	1.22%	July 2002
Halo: Reach	1.20%	Sept. 2010
Mario Kart 7	1.18%	Dec. 2011
Dark Souls	1.10%	Oct. 2011
Zelda SS	1.05%	Nov 2011
Gears of War 3	0.93%	Sept. 2011
Counter-Strike S	0.89 %	Nov. 2004
Others	12.95%	

5. RANKING STREAMERS

For a professional player, popularity is arguably more important than game performances (although they obviously are correlated). Indeed, most of their stable revenues come from advertisements displayed in the streams, sponsoring, special invitations in tournaments, etc. This section first discusses a simple, yet sensible, way to rank the streamers by popularity. A more sophisticated solution based on a Condorcet method is then presented. The resulting rankings are compared to a STARCRRAFT II fans vote on the web.

5.1 A simple ranking method

To rank the streamers by popularity, precautions must be taken. It was observed in Figure 1 that, along the week, there are strong variations of the number of viewers and sessions. To remain objective in our analysis, the streamers broadcasting games at unusual times and the number of viewers cannot be directly taken as a popularity measure.

That is why, in a pre-processing step, every number of viewers, $v \in \mathbb{N}$, is replaced with a value indicating by how much this number is above the expected value if all active streams were equal in popularity. At a given crawling time, this expected value is the total number of visualizations $v_{\text{tot}} \in \mathbb{N}$ (at this time) divided by the total number of active streams $s_{\text{tot}} \in \mathbb{N}$. The rough number of viewers v is therefore turned into $\frac{v \times s_{\text{tot}}}{v_{\text{tot}}}$. Such transformed numbers are called *uncorrected popularity scores* in the remaining of this section.

A simple way to rank the streamers is to compute, for each of them, the maximal uncorrected popularity they have ever received and order them according to this value. That only takes into account the crawl time that is the most advantageous for a streamer and actually makes more sense than aggregating scores obtained at every crawl time or at every session. Most of the sessions end while they are gaining audience and a ranking by popularity should not disadvantage streamers that broadcast during shorter periods of time (hence not reaching the audience they could have had if the session would last longer). To observe that, Figure 9 plots, along the session time, the percentage of the maximal uncorrected popularity that a streamer has in average. The curve itself is an average over the 100 top streamers (according to their maximal uncorrected popularity scores). For instance, the point at the extreme left tells that these streamers have, in average, 5% of their maximal uncorrected popularity when they start broadcasting (because the data are crawled every 5 minutes, the session started between 0 and 5 minutes earlier). In this same figure, the vertical lines separate the four quartiles of the session length distribution. The last one being before the maximal point of the curve, it can be written that more than 75% of the sessions end while they are still gaining audience. After the maximum (obtained at 6 hours and 45 minutes of streaming), the audience seems to get bored.

5.2 A Condorcet method

A more refined way to rank the streamers by popularity is to take them by pairs and see which one the viewers prefer to watch when both are broadcasting at the same time. The uncorrected popularity scores allow to ignore the daily and weekly variations of the audience but do not take care of ignoring these variations along the sessions (observed in Figure 9). That is why they cannot be directly used to state that, at a given crawl time where two streamers are broadcasting, one of them is preferred. Doing so would advantage a streamer that has been broadcasting games for

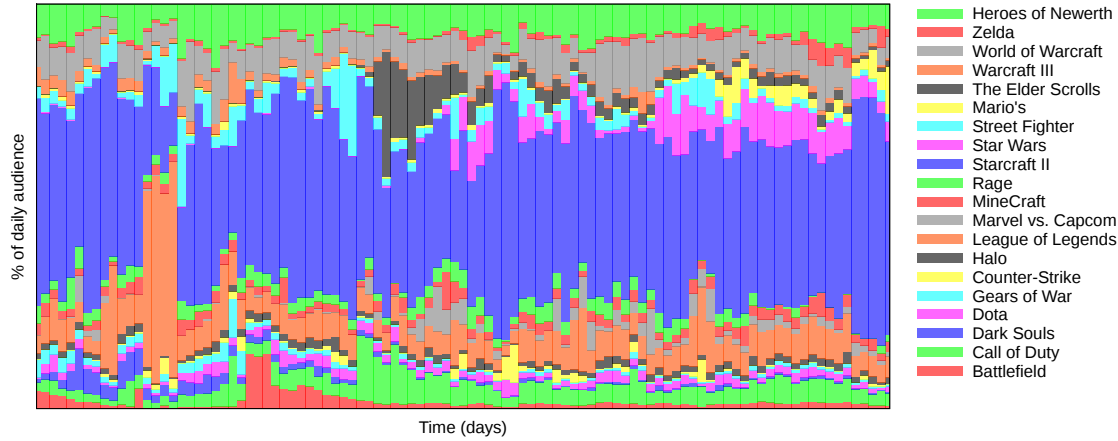


Figure 8: Proportion of attention of each top 20 games every days.

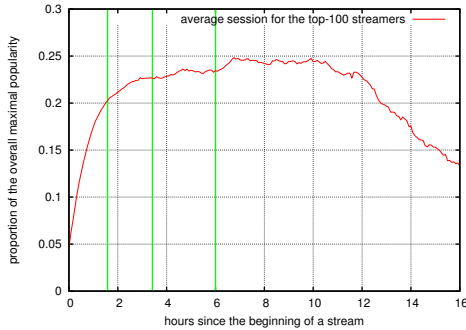


Figure 9: Along session time, reached proportion of the overall maximal uncorrected popularity.

quite some time over another one that has just initiated her stream. Therefore, a second pre-processing step is needed. To “correct” the uncorrected popularity scores, they are multiplied by a coefficient that depends on the time since the current session started. These coefficients are computed per-streamer (streamers can have different average growths of their audience) and transform her average uncorrected popularity score at a given session time into her maximal uncorrected popularity score. Table 4 exemplifies this second pre-processing step. The first part of the table gives uncorrected popularity scores of a given streamer and their averages. The second part of the table lists the multiplicative coefficients that transform these averages into maximal uncorrected popularity scores (4.5). The last part gives the popularity scores resulting from the correction. Their averages always are 4.5: the growth of the audience with respect to the session time is “ironed out”.

Thanks to this correction, it becomes possible to state which of two streamers is preferred when both are broadcasting at the same time: the one having the higher (corrected) popularity score. To obtain a ranking, this information must be aggregated and a Condorcet voting method is used, where the candidates are the streamers and the voters are the crawl times. We chose to use *Maximum Majority Voting* [9], which is a variation of the *Ranked Pairs* method [12] where the majority (i.e., X in the sentence “ $X\%$ of the

session time	0'	5'	10'	15'	20'
session 1	0.5	1.5	2	3	
session 2	0.5	3	4		
session 3	1	2.5	3.5	4.5	4
averages	0.67	2.33	3.17	3.75	4
coefficients	6.75	1.93	1.42	1.2	1.13
session 1	3.38	2.89	2.84	3.6	
session 2	3.38	5.79	5.68		
session 3	6.75	4.82	4.97	5.4	4.5
averages	4.5	4.5	4.5	4.5	4.5

Table 4: Correcting popularity scores.

voters *strictly* prefer candidate A to candidate B ”), instead of the margin (i.e., the difference between the majorities of the two candidates), is the primary criterion rank the preferences. This sub-family of Condorcet methods adds first the pairs of candidates with the clearest preferences (between the two candidates) and ignores pairs that contradict the previous information. When the goal is to rank candidates (and not to select *one* winner), it is commonly preferred to the other popular sub-family of Condorcet methods (the *Schulze method* being its most famous representative) that considers all pairs and then removes the weakest preferences until no contradicting information remains.

Although we claim to use *Maximum Majority Voting*, some differences need to be brought to account for our rather unusual context. First of all, in classical ballots, *all* candidates are present for *all* voters. Condorcet methods usually consider that a voter prefers the candidates she ranks to those she left unranked. In our context, this is not true: all streamers are not constantly broadcasting and, by being present, they could receive higher popularity scores than some streamers on air. As a consequence, the preference of a streamer over an another one is only computed from the crawl points where both are broadcasting. The number of such crawl points quantifies the certainty of the preference. That is why — and this is the second difference w.r.t. the standard *Maximum Majority Voting* — this valuable information is ultimately used to rank the tied pairs of streamers. All in all, two pairs, (A, B) and (C, D) , of streamers are ranked $(A, B) \prec (C, D)$ (meaning the preference of A over B is stronger than the preference of C over D) iff:

1. the majority of A over B (i.e., X in the sentence “ $X\%$

Table 5: Rankings of eight StarCraft II players.

Web poll (# votes)	Overall max (pos.)	Condorcet
WhiteRa (11,112)	EG.IdrA (20)	EG.IdrA
Mill.Stephano (9,192)	WhiteRa (21)	Mill.Stephano
EG.IdrA (6,746)	Liquid'Ret (31)	EG.HuK
EG.HuK (5,050)	EG.HuK (32)	WhiteRa
Liquid'HerO (2,160)	Mill.Stephano (33)	Liquid'HerO
Liquid'Sheth (846)	Liquid'HerO (53)	QxG.SaSe
QxG.SaSe (833)	Liquid'Sheth (72)	Liquid'Sheth
Liquid'Ret (684)	QxG.SaSe (91)	Liquid'Ret

of the time A and B stream together, A has a popularity *strictly* above that of B) is *strictly* greater than the majority of C over D ;

- both majorities are the same but the margin of A over B (the difference between the majorities of the two streamers) is *strictly* greater than the margin of C over D ;
- both majorities and both margins are the same but A and B were broadcasting together more often than C and D .

Once the pairs of streamers ranked, the ranking of the streamers themselves is obtained by reading the pairs in this order of preference and:

- Adding all tied pairs as edges of a directed graph;
- Deciding the existence of a path from the head of an edge, which has just been added, to its tail (i.e., searching for the existence of a cycle involving a newly added edge);
- Removing all edges that have just been added and that are involved in a cycle;
- Unless all ranked pairs have been processed, reading the next batch of tied pairs and going to 1.

After a transitivity reduction, the graph that is obtained usually is close to a list, i.e., a ranking of the streamers.

5.3 Ranking results and discussion

TWITCH’s logs were considered until January 9th. At this date, the result of an online poll was published [8] and we used it as a ground base for ranking. Stream viewers were indeed invited to vote for their two favorite STARCRAFT II pro-gamers from 16 players who were previously chosen by the IGN Pro League, a recognized E-Sport actor [7]. Among these 16 players, 10 have an account on TWITCH but two of them do not stream much (less than 31 hours during our 102 days of logs). The simple method, presented in Section 5.1, does not rank these two least active players among the top 100 streamers. Those same 100 streamers were selected to be ranked with the Condorcet method (see Section 5.2). Table 5 gives the rankings of the eight remaining STARCRAFT II players according to the Web poll (first column), the overall maximal uncorrected popularity (second column) and *Maximum Majority Voting* (third column).

Taking the Web poll as a ground truth, it can be observed that ranking the players by their overall maximal uncorrected popularity sometimes leads to glaring errors (although this ranking obviously is closer to the Web poll results than a random one). For instance, it ranks Liquid'Ret third, whereas he is the least popular player according to the Web poll. The Condorcet method “correctly” ranks Liquid'Ret last and, overall, is very close to the results of the Web poll. The largest difference relates to WhiteRa, the

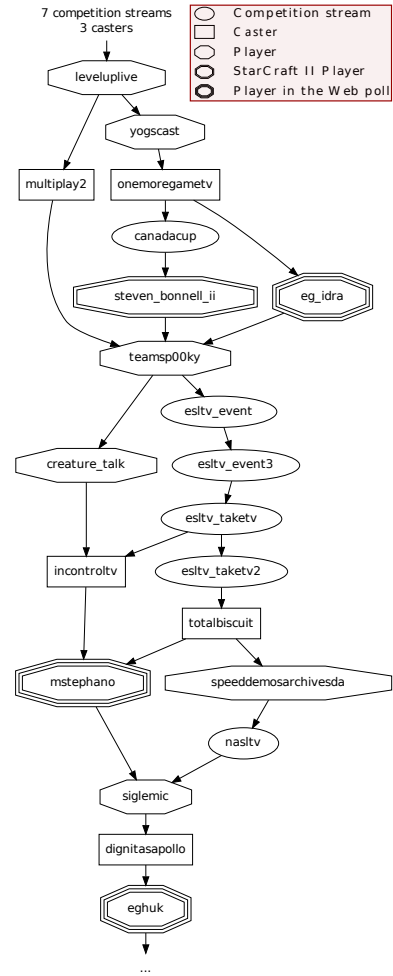


Figure 10: Top streams with the voting method.

player who is the most popular according the Web poll but “only” ranked fourth by the Condorcet method. There actually is an explanation: among the eight players, WhiteRa is, by far, the most active streamer (more than 262 hours in the considered logs, i.e., 6.3 times as much as EG.IdrA, 4.6 times as much as Mill.Stephano, etc.). As a consequence, finding WhiteRa broadcasting is not much of an event and the viewers may prefer to watch the other famous players even if WhiteRa’s stream is on air.

Figure 10 shows the top of the (transitively reduced) graph produced by *Maximum Majority Voting*. An interesting point is the excellent popularity of a STARCRAFT II player who was not chosen by the IGN Pro League to be among the options in the Web poll: Steven Bonnell II. He actually is incomparable with EG.IdrA (i.e., they have never streamed at the same time nor have been ranked differently w.r.t. a third streamer they would have streamed together with). The expert confirms the huge popularity of Steven Bonnell II. He considers that his popularity is more due to him “making the show” than to his gamer qualities, hence his absence among the options in the Web poll.

6. RELATED WORK

Live streaming workload characterization. The first extensive characterization of a live streaming workload was presented in [13]. A more recent study of a live streaming workload from a large content distribution network is examined in [10]. Although our work is not focused on the analysis or the generation of realistic server workloads, several of the results described in this paper, such as the skewness of the stream popularity distribution and the occurrence of weekly and daily temporal patterns in the access of content, are consistent with their findings. Nevertheless, game live streaming differs from general-purpose live streaming media in many aspects, including the fact that most of the content is generated by users and the strong effect of major events and game releases over audience attention across the time.

Characterization of online games. In the recent years, online gaming has attracted great interest from both industry and research communities. Several previous studies have focused on the analysis of game workloads in order to provide better resource provisioning and quality of service for online gamers [3, 5, 6]. Feng et al. [5] analyse the traffic of a “Counter-Strike” server and shows how it differs from other types of network traffic. The geographic location of game servers and players is studied in [5]. It is interesting to notice that we found similar geographic distribution of streamers on Twitch. In [3], the authors combine data from several sources as means to provide a comprehensive analysis of online gaming. They found that game popularity is highly skewed as we found for stream and streamer popularity (see Section 2). Moreover, while gamer activity follows very clear weekly and daily patterns, game popularity is subject to diverse variations that are difficult to predict. These properties also appear in the streaming and watching behaviours we identified in this paper. In particular, we have shown that various significant variations in game popularity on TWITCH are related to game releases and major events.

Predicting the popularity of online content. In face of the large volume and high dynamicity of the content produced and consumed online, predicting the popularity (or audience) of web content has become a major topic of interest. Cha et al. [2] has shown that early views records provide an accurate estimation of the future popularity of YOUTUBE videos. Szabo and Huberman [11] have provided a deeper statistical understanding of the general problem of predicting future audience of online content based on its popularity at an early time. In Section 3, we have shown that a linear regression model achieves good performance for predicting live game streams popularity on TWITCH.

7. CONCLUSION & PERSPECTIVES

A new Web community is emerging: e-sport fans watching live streams of video games. TWITCH is their favorite platform. We have analyzed the number of viewers of every TWITCH stream over a 102-day period. From this sole information, this paper has shown, among other results, that 1) tournaments and releases translate into clear growths of the game audience, 2) the future audience of a stream session can be accurately predicted from its beginning, and 3) a Condorcet method can be used to sensibly rank the streamers by popularity. Those results are of major interest for the actors of this community: the spectators, the pro-gamers, their sponsors, the game publishers, etc.

We are currently crawling complementary data such as announcements of streaming sessions on FACEBOOK and TWITTER, and the IRC chats associated with every TWITCH stream. By taking this information into account, more complicated questions will hopefully be answered: does announcing a streaming session have a measurable effect on its audience?, are the raising/dying E-Sport stars detectable?, are the stream viewers structured into sub-communities?, if yes, do they evolve?, do the individual viewers leaving a stream for another constitutes a better information for a popularity ranking?, how to achieve personal recommendation of streams?, do the strengths of the sentiments expressed by chatters correlate with the popularity of the streamers?, etc.

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