Between an Arena and a Sports Bar: Online Chats of Esports Spectators

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ABSTRACT

Hundreds of thousands of spectators use Twitch.tv to watch The International, a Dota 2 eSports tournament, and communicate in massive chats. In this paper, we analyse these chats and disentangle contextual meanings of emojis and short messages. We apply structural topic modelling and cross-correlation analysis to investigate topical and temporal patterns of chat messages and their relation to in-game events. We show that in-game events drive the communication in the massive chat and define its emergent topical structure to a various extent, connected with the number of chat participants. Based on the findings we propose ways of using chat data to support viewers and chat participants experience.

CCS CONCEPTS

• Human-centered computing → Empirical studies in collaborative and social computing; • Information systems → Chat;

KEYWORDS

Streaming, eSports, chat communication, Twitch.tv

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1 INTRODUCTION

Millions of people watch sports events in stadiums, arenas, sports bars, and at home. In the esports world, in which the sport is happening in a virtual space, public viewing places are replaced with streaming platforms. In these platforms, thousands and even millions of viewers watch an event and share their opinions and experiences via text chat.

In this work, we study communication between viewers of The International (TI), one of the most significant esports events in the world, and the biggest annual tournament in Dota 2, a team-based multiplayer online battle arena.

We used chat data from the main broadcast channel on Twitch.tv during TI7 (2017) to study what is called “crowdspeak” [5] – a meaningful and coherent communication of thousands of viewers in the chat.

First, we investigate the thematic structure of viewers communications and disentangle contextual meanings of emotes and text shortcuts using Structural Topic Modelling (STM) [9].

Second, we explore the connection between game events and topics occurring in the chat using cross-correlation analysis. In-game events to some extent define the topical structure of the chat – they provoke emotional response or discussion of players and teams, while the lack of action on screen leads to viewers frustration which is expressed with boredom-related memes and emotes.

Last, we unveil the nature of the inequality between topics in the chat. In larger chats, participants tend to focus on fewer topics while in smaller chats a variety of discussion points can be found. As the tournament progresses, viewers become more emotionally engaged and focused on cheering, omitting other topics.

Based on our findings, we propose design ideas aimed to enhance viewers’ experience.

2 RELATED WORKS

Groups of “like-minded fans” watch together sports events in public spaces, such as a pub or a bar, and cheer for their favourite teams and athletes ritually [16]. As fans share their experience with each other in various forms, spectatorship becomes an inherently social activity [11].

Viewers provide each other with information cues on how to behave oneself in a chat forming a “normative behaviour” [3, 14] which is quite different from the one in small chats [5]. Messages flow rapidly, forming a “waterfall of text” [6], which makes it almost impossible to read messages one-by-one and have a meaningful conversation.

When an interesting event happens in a game (e.g., a death of a hero in our case), viewers react “loudly”: they post a burst of messages, creating a “local meaning of the [in-game] event” [8]. Viewers copy and paste, or type emotes, abbreviations, and memes, launching cascades of messages which disrupt the usual flow of communication [12] causing a “communication breakdown” [8].

Communication in massive chats is far from meaningless. Users engage in various practices which ensure chat coherence. They post
and re-post abbreviations, acronyms, and emotes in chat, creating a “crowdspeak” in which messages from many viewers unite into “voices” [5, 13] – particular positions or discussion threads adopted and expressed by many participants. The most straightforward approach in the operationalisation of voice is to consider a repetition of a word or a phrase to be a voice and the number of repetition to be its strength[13]. Fort et al. [5] hypothesised that massive chats would have fewer unique voices in comparison to smaller chats; however, this hypothesis was not confirmed nor rejected.

3 BACKGROUND

Dota 2 is an online multiplayer game in which two teams of five players compete for domination over the game field (map). Confrontation involves elimination of opponent team’s characters (heroes) which later respawn to continue the fight. A typical game lasts for approximately 15 to 45 minutes. During esports events, teams confront each other in matches, which consist of 1 to 5 games each.

TI7, like most sports tournaments, has several stages: groups, playoff, and finals (see Table 1 for details). During group stages, the initial position of the team for the playoff is decided. In the playoff, losing teams are eliminated from the tournament. In the end, two teams compete in the finals.

4 DATA AND METHODS

We employed the Chatty application to record chat message of the dota2ti channel on Twitch.tv which broadcasted most of the matches of TI7. In total, we collected more than 3 million chat messages from approximately 180 thousand unique viewers. We complemented these data with information on in-game events, which we obtained by employing Open Dota 2 API and the Dotabuff.com database.

Table 1: TI7 stages

| Stage       | Groups | Playoff | Finals |
|-------------|--------|---------|--------|
| Days        | 4      | 5       | 1      |
| Games       | 100    | 43      | 7      |
| Messages    | 819857 | 1831529 | 381690 |
| Mean msg. length (SD) | 30 (47) | 26 (44) | 32 (47) |
| Documents   | 29378  | 36165   | 5672   |
| Mean doc. length (SD) | 867 (726) | 1405 (962) | 2274 (1387) |
| Viewers     | 78106  | 128278  | 59070  |
| Mean per viewer | 10 (38) | 14 (56) | 6 (16) |
| Share of emotes | 32%    | 36%     | 28%    |
| Share of mentions | ~1%   | ~1%     | <1%    |
| Mean viewers per game (SD) | 2573 (3444) | 8084 (15225) | 14490 (14199) |
| Mean msgs. per game | 8199   | 42594   | 54527  |

4.1 Structural Topic Modelling

We applied Structural Topic Modelling (STM) [9, 10] to analyze the contents of the chat. STM shares the same basic approach with other probabilistic topic models (e.g. Latent Dirichlet Allocation [1]): it takes a corpus of text documents as an input and produces a given number of topics – groups of words which occur in text often together.

STM, however, can take into account connection of topics probability with document-level metadata, which in our case was the stage of the tournament the game belongs to: Groups, Playoff, and Finals.

Chat messages on Twitch.tv are very short, often consisting of one or several words, emotes or shortcuts, which is not suitable for probabilistic topic modelling. We concatenated messages into documents, each covering a 7 second time window (mean = 7.99 messages per second, SD = 7, max = 115).

4.2 Analysis of Event-driven Nature of Communication

We applied cross-correlation analysis [2] to investigate the connection between in-game events and topics prevailing in the chat. In this work, for a given time window, we consider a topic to prevail in case it is the most frequently occurring according to the STM results. For each time window, we also calculated the number of happened in-game events: usually, 1 or 0. We tested the resulting time-series with the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to ensure they are stationary [7].

Cross-correlation analysis tests if there is a correlation between two time series with a lag in some range. It produces a vector of correlation coefficients, showing whether there is a tendency for events in one time series to precede, follow, or occur concurrently with the events in another.

As a result, for each of 100 topics, we computed a vector of correlation coefficients between two time series - in-game events and topic-prevalence - with lags in seven-seconds time frames. These temporal patterns show us if topics in the chat are preceded, followed, or prevail in the chat during the in-game event.

Having 100 vectors of correlation coefficients, we united them into groups of similar patterns. We used Spearman’s correlation as a measure of similarity between vectors and applied hierarchical clustering to produce the groups.

4.3 Analysis of Voices and Topical Inequality

To analyse the connection between the context (tournament stage), the number of participants and unique voices[13] in chats, we propose an alternative to Ford et al. operationalisation [5], treating STM topics as proxies to unique voices and looking at the topical inequality, measured by Gini coefficient[17].

For every game, we calculated Gini coefficient in the chat during the game. Gini coefficient ranges from 0 to 1, where 0 means absolute equality among topics (all topics are represented equally in the chat) and 1 means that only one topic is present while others are missing. We treat Gini coefficient as an estimate of the extent to which some voices prevail (are “stronger”[13]) in the chat over others.

Our analysis of this inequality is two-fold: (1) expanding Ford et al. approach to the whole text corpora, we look at Gini coefficient distribution in connection with the number of the particular game spectators, (2) we test for significant changes in median Gini index between different tournament stages.
Ford et al. suggested that massive chats would contain fewer unique voices and be less polyphonic. In our case, the number of voices (i.e., the number of topics) is predefined and constant. However, we can estimate and test the relation between the number of viewers in chat and topical inequality.

We applied Spearman’s correlation test to test the hypothesis that topics in larger chats would be less equally distributed. We also assessed differences in Gini coefficient between stages using Kruskal-Wallis test and Pairwise Mann-Whitney U-test to investigate if the topical inequality depends on the context of the chat.

5 ANALYSIS AND RESULTS

5.1 Event-driven Nature of Communication

After clustering topics according to their temporal patterns, we resulted in four groups of topics which we labeled based on their contents: Copypastas and Complains, Emotional Response, Game and Stream Content, and Professional Scene.

Association between these clusters and the topic model captures the differences in a context for similar topics and particular tokens (words, emotes), which is an especially fortunate feature for an emote-based contextually rich communication of streaming chats.

Boredom and Frustration. When nothing happens in the game, viewers are bored and convey this boredom and frustration in various ways. They send specific emotes (e.g. ResidentSleeper) or even start “copypasta” cascades by copy-pasting certain emotes and messages.

When no in-game events are happening, topics of this cluster are in the chat. When the tension starts building and viewers anticipate interesting events to happen, viewers stop sending boredom-related messages. During and after the event, the level of these topics in the chat remains low.

Emotional Response. This cluster of topics represents spectators’ response to in-game events: the death of a character, destruction of a building, or a cameraman missing an in-game event, for example. Messages often contain only one word or emote. Viewers write “gg” (abbreviation of “good game”), “ez” (short handing for “easy”) at the end of a match, “322” (a Dota 2 meme) to mock a player or team due to their poor performance, emotes “pogchamp” (glory) and “kreygazm” (excitement) to convey their feelings to what is happening on in the game.

Game and Stream Content. Topics in this cluster reflect viewers’ reaction to whatever is happening on screen at the moment. They discuss and cheer teams and players. Even though players can not perceive the audience, viewers still address their messages to them: “BudStar BudStar BudStar LETS GO LIQUID BudStar BudStar BudStar”.

Professional Scene. Topics of this cluster do not significantly relate to in-game events. Viewers cheer professional players and teams, discuss their in-game behaviour and even past incidents involving players almost all the time, and we did not notice any temporal pattern associated with these topics.

Besides listed, there are, of course, other topics in the chat which are less loud. They are included in the aforementioned four groups. Thus, our interpretation of each group is based on the prevailing content of its topics and does not necessarily take into account all of the variety of themes and discussion objects that can be found in the chat.

5.2 Voices and Topical Inequality

The finals of any sports tournament attract lots of people who come to cheer their favourite team, and TI7 was not an exception. Kruskal-Wallis test showed that there is a significant difference ($H = 32.2, p < 0.001$) in Gini coefficient among stages. Using Pairwise Mann-Whitney U-test, we found that the stages differ significantly (See Table 2) and Gini coefficient increases with the tournament’s progress (See Fig. 2).

Further exploration showed that 58% of messages during Finals belong to the single topic (topic 53) which is dedicated to cheering for one of the finals participants (See Fig. 3). Closer to the final game of the tournament cheering increases, displacing all other voices and discussion threads.

When we removed topic 53 from calculations, we could no longer claim significant differences between median Gini coefficients for Finals and other stages, while the difference between Groups and Playoff remains significant (see Fig. 2).
Table 2: Pairwise comparison of Gini coefficient of games on different stages (Mann-Whitney U-test)

|                         | (a) Topic 53 Included | (b) Topic 53 Excluded |
|-------------------------|-----------------------|-----------------------|
| Groups - Playoff        | $p < 0.001$           | $p < 0.001$           |
| Groups - Finals         | $p < 0.001$           | $p = 0.35$            |
| Playoff - Finals        | $p < 0.001$           | $p = 0.16$            |

Thus, during the Finals, a single topic was dominating the chat, reducing unique voices to variations of chanting for the favourite team.

While a limited number of cases in the later stages of TI7 does not allow us to explore the relationship between topic inequality and chat size, we explored this relationship on the case of the Group stage, performing Spearman’s correlation test for number of unique participants in each game and Gini coefficient for topics in that game. The test showed significant positive ($\rho = 0.47, p < 0.001$) correlation between the size of the chat and the Gini coefficient (see Fig. 4). Thus, in smaller chats topics are distributed more equally than in larger chats.

5.3 Prevalent Topics Over Stages

To compare stages of TI7 with each other, we compiled a list of prevalent topics which are associated (based on STM model) with the given stage.

Group stage has the set of 34 prevalent topics (see Fig. 5). Viewers mostly discuss broadcast-related issues (yellow) and famous players (green). They copy-paste texts unrelated to the stream content (e.g.

Figure 3: Cheering for Team Liquid during Finals

No job 4Head No girlfriend 4Head No friends 4Head No talents 4Head Wasting time on Twitch 4Head Must be me ) (cyan). The expression of emotions is present (brown) but does not stand out from other topics.

During Playoff (31 prevalent topics), in which teams are getting eliminated, chat communication becomes more focused on the game. Viewers discuss game elements: balance or position of the camera (violet), and actively express emotions (brown).

In the Finals (19 prevalent topics), more than a half of all messages were expressing support to Team Liquid – a western team which was opposing team Newbie from China. The emotional response to events is also present (brown) while forms of copypasta other than chanting almost disappear.

6 DISCUSSION

In-game events, the context of the game, and the number of participants in the chat – all of these factors contribute to the topical structure and contents of the chat during the stream.

Using Topic Modelling and statistical analysis methods we reveal some important factors behind the viewers’ behaviour in the chat. We show that the chat is overall event-driven: in-game events or the lack of those define the contents of strong voices heard in the chat. The context of the game affects the strength of heard voices: the closer to Finals, the stronger gets the cheering while other voices...
fad. The size of the chat contributes to the inequality between voices: larger chats have fewer strong voices while smaller chats are more polyphonic. The crowd adapts participation practices to characteristics of communication flow and context, which is driven by game events. E.g. copypaste on the earlier tournament stages can convey boredom and frustration, but when the tournament tension goes up, it is used mostly to cheer the favourite team. Thus, the chat becomes a tribune, an arena, or a sports bar, in which visitors watch the game and engage in discussions or cheer for their favourite team loudly.

We suggest that the experience of spectators is mediated by the same intra-audience effect [4] that emerges during live spectating and is consistent with a sports arena metaphor [5, 6]. However, we observe that a metaphor of a sports bar is more accurate since players do not receive any feedback from chat participants during the game. While shouts and chants do not reach the addressee, spectators still find these responses important [5], and thus the metaphor can lead to new design ideas.

7 DESIGN IMPLICATIONS

The event-driven and sentiment sharing nature of massive tournaments’ chats suggests rethinking its design goals. During analysis, we found that chat communication is driven by events represented on the stream. Moreover, there is a relationship between stage (and the number of participants) and voice taking practices which implies that in larger chats audience becomes more focused on particular topics rather than speaking of everything. Based on our results, we would like to propose two design implications to enhance the chat participants experience.

7.1 Highlights

Due to its event-driven nature, the chat can be a valuable and reliable source of information regarding in-game events: which are most notable, intense, or funny. A record of the game can be automatically cut (see [15] for examples) into a short, meaningful clip which would convey all vital information about the game for those viewers who want to re-experience it. By annotating the record with chat topic and event patterns metadata, we can ensure the preservation of the critical moments of the game which evoke the most vivid reaction in the audience.

7.2 Visualization of Prevailing Voice

As tension grows during the tournament and the topical inequality rises in the chat, certain topics become dominant and occupy significant screen space, leaving almost no place for other topics/voices. During the Finals of TI7, this topic was dedicated to cheering for the Team Liquid (see Fig. 3).

We suggest providing additional instruments of sentiment-sharing in the form of graphical elements or counters which would indicate the current sentiment of the chat. These indicators will inform users of the loudest voices in the chat, provoking to join one of them and participate in the coherent practice.

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