# GameStory Task at MediaEval 2018

Mathias Lux<sup>1</sup>, Michael Riegler<sup>2,3</sup>, Duc-Tien Dang-Nguyen<sup>4</sup>, Marcus Larson<sup>5</sup>, Martin Potthast<sup>6</sup>, and Pål Halvorsen<sup>2,3</sup>

<sup>1</sup>Alpen-Adria-Universität Klagenfurt, Austria; <sup>2</sup>SimulaMet, Norway; <sup>3</sup>University of Oslo, Norway;

<sup>4</sup>University of Bergen, Norway; <sup>5</sup>ZNIPE.TV; <sup>6</sup>Universität Leipzig, Germany

mlux@itec.aau.at,michael@simula.no,ductien.dangnguyen@uib.no,marcus@znipe.se,

martin.potthast@uni-leipzig.de,paalh@simula.no

#### ABSTRACT

That video games have reached the masses is well known. Moreover, game streaming and watching other people play video games is a phenomenon that has outgrown its small beginnings. Game video streams, be it live or recorded, are viewed by millions. E-sports is the result of organized leagues and tournaments in which players can compete in controlled environments and viewers can experience the matches, discuss and criticize, just like in physical sports. In the GameStory task, taking place the first time in 2018, we approach the game streaming and e-sports phenomena from a multimedia research side. We focus on the task of summarizing matches using a specific relevant game, *Counter-Strike: Global Offensive*, as a case study. With the help of ZNIPE.tv, we provide a data set of high quality data and meta data from competitive tournaments and aim to foster research in the area of e-sports and game streaming.

## **1** INTRODUCTION

E-sports is huge. Already in 2013, the number of concurrent users for a single event exceeded eight million for a League of Legends Championship.<sup>1</sup> In 2016, approximately 162 million viewers accessed e-sports streams frequently.<sup>2</sup> In August 2018, the most popular game streamer at that time, Tyler "Ninja" Blevins, was the first person to reach ten million subscribers with a single game streaming channel.<sup>3</sup>

Undeniably, in game streaming, a lot of content is created and consumed. The rich bouquet of data includes audio and video streams, commentaries, game data and statistics, interaction traces, viewer-to-viewer communication, and many more channels. The heterogeneity of all these different media allows for manifold and challenging multimedia research questions. However, the many research opportunities are yet unexplored. New fields like game analytics [2, 3] try to investigate the highly interactive nature and narrative nature of video games [1]. A lot of work has been done in video and multi-modal summarization [5–7, 11], but summarisation of video games are still sparsely investigated. For GameStory we have picked a specific game with a solid player and viewer base population called *Counter-Strike: Global Offensive* (CS:GO), serving more than 10,000 matches simultaneously with over 240,000



Figure 1: Overview of general CS:GO game play. Two teams, terrorists (T) and counter terrorists (CT), play *DE\_Map* (majority), *CS\_Map*, or *AS\_Map* being the game modes played.

players.<sup>4</sup> The task is to summarize matches and tournaments automatically. As e-sports is multi-modal, our data set contains a wide range of modalities including *video streams* from multiple perspectives on a given match, *audio streams* from players, commentators, and moderators, and *telemetry* obtained from game engines. Participants need to identify critical moments in the game, tipping points, actions with strategic importance and other important points in the timeline of a game's progress to then create a multi-modal summary that provides a captivating story of the games progress. The GameStory task is open ended in that sense that there is no ground truth, but participants can be creative and identify critical parts themselves.

# 2 DATA SET

CS:GO is a first person shooter (FPS) and, as an e-sports game, has very strict rules of play. Matches consists of several rounds, and players only re-spawn in between rounds. So, if a player's avatar gets eliminated, the player has to wait until the next round begins. In between rounds, players can outfit their avatars with weapons, ammo, tools, and armor. The resources available are determined by the success in previous round, e.g., players earn money if they plant or defuse the bomb, eliminate other avatars, etc. <sup>5</sup>

A typical CS:GO match is decided in a best of 30 fashion.After 15 rounds team switch sides, i.e., terrorists (T) become counter terrorists (CT) and vice versa. If two teams end up with a draw after 30 rounds, rules specific to the tournament or league (context of the match) apply. If draws are not allowed, teams play overtime to determine the winner. *Economy management* is a critical part of a teams strategy in competitive CS:GO matches and includes outfitting the avatars and planning for in-game money to be available

<sup>&</sup>lt;sup>1</sup>https://associate.vc/esports-millions-of-viewers-millions-of-dollars-e7b411b57ba6, accessed 2018-02-28

 $<sup>^2</sup>https://www.statista.com/statistics/490480/global-esports-audience-size-viewer-type, accessed 2018-02-28$ 

<sup>&</sup>lt;sup>3</sup>https://variety.com/2018/gaming/news/ninja-twitch-10-million-1202894566/, accessed 2018-08-06

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<sup>&</sup>lt;sup>4</sup>https://csgo-stats.com/, accessed 2018-03-08

<sup>&</sup>lt;sup>5</sup>http://www.tobyscs.com/csgo-economy-guide/, accessed 2018-03-09

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for that. Strategies typically span over multiple rounds and include full buys, where teams can afford to buy what they need, eco rounds, where teams save money for full buys, anti-eco rounds as a counter strategy to eco rounds, and so on. In general, a winning condition is to eliminate all opponents. However, there are also map-based winning conditions. For example, beside eliminating all opponents, in a DE\_Map round, the goal for the T team is to plant the bomb to some specific locations and protect it from being defused (until the end of the round), while the CT team has to defuse the bomb (if it is already planted) before detonation (typically in 40 seconds). Other map types and summary of the CS:GO game play is illustrated in Figure 1. A match in CS:GO develops over multiple rounds, and teams have to adapt to new situations in short time to be able to turn the game around to their favor. Common tipping points in CS:GO are rounds where both teams can afford to buy what they need. and teams can go for comebacks after consecutively losing rounds to the other team.

For the GameStory task, our partners from ZNIPE.tv provide training and test data from an ESL One tournament in Katowice in 2018. ESL is to date the largest e-sports organizer world wide. The ESL One tournament series focuses on premier offline tournaments of specific games including CS:GO and DOTA 2 and counts among the most prestigious events in e-sports for CS:GO, also supported by the publishers and developers of CS:GO, Valve Corporation. The data consists of twelve saved video streams along with meta data. Ten files give the view of the players with the in-game audio streams. One file gives the commentator stream, where a professional cutter selected the parts of the player views to be shown as well as videos from the audience and the teams and the commentator provides the spoken content mixed with recordings from the game and audience cheering. The last one shows the game world from above with icons indicating the position of players. A meta data file indicates start and end of games and content in the commentators stream. JSON files - one for each match in the data set - capture player activity and events in addition to the raw video. Events range from kills, death, round end and starts to what the players bought at the beginning of rounds and when a if a bomb was set or a grenade was thrown or went off.

#### **3 SUMMARIZATION & EVALUATION**

Compared to sports summaries [4, 8–10], video games are not focused on a small number of attention points like the ball and the goals on a soccer field. Video games provide multiple views and concurrent events within a clearly defined game world (map), which can change in between games, but stays the same in one single game. Compared to a soccer match, there are also clearly defined and well-formatted statistics on events relevant to the game's progress within these streams. It is not only a linear progression of the game with one event of importance leading to another, but often many things happen (nearly) at once, and all together, they lead to a specific outcome. Also, events may be connected across longer time frames, for example, one player setting a booby trap at the beginning of a match, whereas another player runs into it only at end, deciding the game Moreover, game statistics only carry active and obvious events, but miss those with semantics on a tactical level, like intentional misses, fake tactics, intentional acts risking a re-spawn or player's avatar death, etc.

In CS:GO, a good summary should be able to reflect the development of a match over all rounds by also showing the economy management and the effect of it on the rounds played. Tipping points of a match economy wise should result in turning around consecutive fails in consecutive wins. However, in contrast to the economy management, tactics employed within the round also impact the outcome in combination with the execution of the economy management. Lucky shots, badly synchronized plan execution, or even bad luck can change the game. While it is easy to create a short video from multiple streams and present it to viewers, the viewers ultimately decide if the summary was good. There are few formal requirements for run submission, for it only needs to be a single video file and it needs to be significantly shorter than the match to be summarized. Within the GameStory task, we ask a jury made up from experts from ZNIPE.tv, CS:GO players and game researchers to evaluate and reflect on the summaries. The jury outlines strong and weak points of the submissions and ranks them according to the summaries' ability to reflect the story of the match or tournament. Judges are asked to summarize and argue strong as well as weak points of submissions and to rate with a 5-point Likert scale (strongly agree to strongly disagree) on the following statements:

- (1) The submission gives a summary of the match at hand.
- (2) The submission is entertaining.
- (3) The submission provides the flow and peak of a good story.
- (4) The submission provided an innovative way to present a summary of an CS:GO match.
- (5) A summary like this submission can be applied to games different from CS:GO.

#### 4 DISCUSSION & OUTLOOK

The GameStory task is necessary in our opinion as the domain of video games and game streaming has not yet been fully recognized for its full potential in research. Video games and game streaming are areas where huge amounts of content and data are created by millions of players, viewers, and even creators and producers on a daily basis. The highly interactive nature makes the outcome of every game created and played unpredictable. Research in this area is still in its infancy but has the potential for a high social impact. Players and viewers are often young, and games and the context of the game culture tend shape young people and influence them for the rest of their lives. The novelty of the GameStory task gives it an exploratory nature. In the following years we aim to split the task in compulsory and freestyle task. For the compulsory part we aim for objective, quantitative evaluation, ie. finding kill streaks, synchronize streams, or identifying relations between consecutive wins and economy in the game streams, and the freestyle part will then be summary of GameStory 2018.

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