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Visually Exploring Team Communication and Gameplay Events in League of Legends

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Abstract

Popular team-based esport games such as League of Legends rely on effective verbal team communication. Analyzing and reflecting on the own communication behavior is hence a relevant optimization strategy for a team, but needs to be sufficiently contextualized through game events. In this work, we present an analysis approach to investigate both communication and game events in an integrated visual analytics system. Aside to providing overview statistics, this novel blend builds on timeline and word cloud representations to show the rich data from League of Legends game sessions, visually comparing the opposing teams. We demonstrate the approach through analyzing relevant communication patterns in an application example.

1. Introduction

Team-based esports games like *League of Legends* [Rio09] attract millions of players and spectators globally. Such multiplayer online battle arena (MOBA) games require players to devise strategies and execute coordinated gameplay. Hence, communication with teammates is crucial (cf. [LLN*24]), with players considering it highly relevant for decision-making [WVWBK21]. Through communication, a team builds shared awareness of the situation and team members act accordingly—they develop a joint *team cognition* [MZM*21]. To optimize a team's performance and reflect on team cognition, it becomes necessary to analyze and understand the team communication in the context of in-game actions, movements, and events. Moreover, the intricacies of these games involve a constant interplay between competing teams. Thus, an effective exploration of a team's communication and gameplay behavior should include a comparison with the opposing team as well. However, while different visual solutions for conveying statistics (e.g., [Gam24, OP.24]) and the spatio-temporal evolution (e.g., [ACGV19, WWD23]) of MOBA matches have been proposed, current approaches fall short in enabling such exploratory analysis of team communication. A recent study [WDW24] investigating the different features of 15 live companions for *League of Legends* and *Valorant* [Rio20] did not identify any communication related features in any of the tools.

To address this gap, we propose a visual analytics approach designed for exploration, comparison, and understanding of team communication in relation to gameplay behavior, using *League of Legends* and verbal communication therein as an example. The approach builds on transcripts of the players' communication processed with sentiment analysis; it enables comparative analysis of both teams' gameplay and communication behavior. The proposed interactive interface consists of multiple linked views, including a horizontal timeline to convey information about the game context (e.g., actions, events), an enriched word cloud to highlight the most frequently used words in communication while showing the differences between teams, and a scoreboard showing a summary statistics of all players. We demonstrate the approach in an application example to analyze and derive insights about the communication behavior of teams in *League of Legends*. The dataset as well as a video demonstration of the prototype can be found in the supplementary material. The interactive prototype is available at `https://vis-proj.netlify.app/`, and the source is published on *GitHub*: `https://github.com/HexisHakon/VIS-Proj-M`.

2. Background and Related Work

In *League of Legends* [Rio09], two teams (referred to as the *red* and *blue* team) of five players each aim to destroy the opposing team's base, known as the *Nexus*. Each player controls a single *champion* which can be selected from a diverse roster. The game is played on a square map divided into three main paths, or *lanes*, with areas between them referred to as the *jungle*. Each lane is guarded by three towers that must be destroyed sequentially before progressing towards the enemy's base. The *Nexus* itself is protected by two additional towers that need to be taken down before the *Nexus* can be attacked. The destruction of the enemy's *Nexus* ends the game and secures victory for the team. In addition, *minions* spawn periodically from a team's *Nexus* and automatically attack enemy units and structures. Furthermore, neutral monsters reside in the jungle; killing them provides additional benefits. The two most powerful are the *Baron Nashor* and the *Dragon*.

There exist several tools that help players in the retrospective analysis of the gameplay data and improve their performance in esports games. For *League of Legends*, *Mobalytics* [Gam24], for instance, helps to reflect on the gameplay performance of individual players by using key metrics; *OP.GG* [OP.24] uses visualizations to compare different players via general statistics; and *Lolcompbuilder* [Bas20] shows the collective strength of selected champions in different roles to help build a team. However, communication aspects of gameplay are not included in these tools.

Within the academic sphere, communication between players in *League of Legends* has been analyzed using different techniques. For instance, Tan et al. [TRN*22] analyzed the recorded voice communication to understand the cohesion and satisfaction of a team, finding, among other results, that communication sequences are more important than frequency. Lee et al. [LLN*24] developed an active communication skill index based on the number of smart pings used during a match and found that using smart pings more actively points to higher expertise. Şengün et al. [cSS*22] investigated the differences in communication behavior based on the character chosen by players, finding that *champion*'s characteristics do influence valence and toxicity. Especially, the latter has been the subject of various dedicated studies to understand how toxicity influences the communication behavior of players and experience (cf. [Kou20]). For instance, Poeller et al. [PDKM23] asked players to reflect on chat logs of *League of Legends*, finding that players tend to respond to negativity by muting the chat, thus missing other beneficial social interactions during play. These efforts are, however, scientific studies for understanding communication in games, but they are not aimed towards helping players to reflect on their communication skills, activities, and behavior themselves.

Visualizations are being increasingly used in the retrospective analysis of the gameplay data and have been found useful by players to reflect on their performance, for instance, with respect to efficiency, correctness, and suitability of the adopted strategies [KWP14, WK16]. However, the visualization of communication patterns in the context of video games has received far less attention. Chen [Che09] was among the first to use visualizations to analyze chat log data to identify frequency and patterns within *World of Warcraft* player groups. *TwitchViz* [PBN16] is a visualization tool aimed at supporting players (and game designers) to understand the relationship between chatting behaviors and gameplay. Mueller et al. [MSK*15] developed a visualization tool for *Minecraft*, which, among different other views, includes a graph showing connections among players who conversed with each other. Following similar lines, our approach particularly focuses on the exploratory visual analysis of communication among players over time.

Aside the communication aspect, our approach is also an event visualization technique [SP19, GGJ*22]. In the design space for event visual analytics approaches proposed by Guo et al. [GGJ*22], our work can be characterized as visualizing a *sequence* of events (all events from one match) using *timeline-based*, *chart-based*, and other visualizations (e.g., word clouds, which are not described in the event-focused design space). Few approaches integrate event sequence timelines with text visualization (e.g., to show financial trends with news text [WJS*16]), but do not focus on analyzing gameplay. Different timeline-based visualizations have been proposed for player data, for example, to provide an overview of the entire game (e.g., storyline visualizations for *League of Legends* [WWD23]) or to support an in-depth analysis of a match via multiple linked-views (e.g., [LXC*17]). Kleinman et al. [KAT*20] have discussed how time-series and sequence data can be useful for the contextualization and analysis of gameplay data in MOBA games. We thus connect a timeline-based event visualization with representing communication data in our approach.

3. Dataset

We collected a communication dataset between players in *League of Legend* along with the game context. We recruited 20 players who play *League of Legends* regularly and divided them into four teams, with each team consisting of five players. The data collection involved three matches between teams in a knockout tournament. We organized custom matches through the external service *Challengermode* [Cha24] and used the *Match-v5* endpoint in the *Riot API* [Rio21] to record the gameplay data. Players recorded their voice using a software of their choice, and, post-match, we removed any interfering noises and normalized length and volume. We selected the match with the best sound quality and transcribed the recordings using the *VOSK* speech recognition toolkit [Alp24]. Each JSON transcription file comprises recognized words in statements with confidence levels, as well as start and end timestamps. Since not everything was recognized correctly, the files were additionally cleaned manually. Players communicated in German. For presentation purposes, this was translated into English. To further enrich the dataset, we performed sentiment analysis. We used a modification of the word lists dataset provided by *Kanade* [Kan24], which classifies words as positive or negative, and assigned averaged sentiments scores per 10-second intervals.

4. Visual Analytics Approach

To facilitate exploratory and in-depth analysis of communication behavior among players in *League of Legends*, we propose a linked-view visual analytics approach that shows one match at a time. It consists of a scoreboard (Section 4.1), a timeline-based visualization providing a summary of the actions and events of the match for each player (Section 4.2), and an enriched word cloud to compare the communication behavior of each team (Section 4.3). Figure 1 gives an overview of the complete visualization interface and its components. Two colors (red and blue) are used consistently across all visualizations to discern between the two teams.

4.1. Scoreboard

The scoreboard (see Figure 1, A) provides a summary of a match using commonly used statistics for individual players. These statistics include the number of *kills* (number of enemies killed), *deaths*, *assists* (helping a teammate kill enemies), *creep score* (minions or non-player characters killed), *vision score* (overview of the map granted or denied), and *level* (character level attained). The scoreboard is interactive, allowing users to select or deselect individual players, which adjusts the other views of the tool to display information only for the selected players.

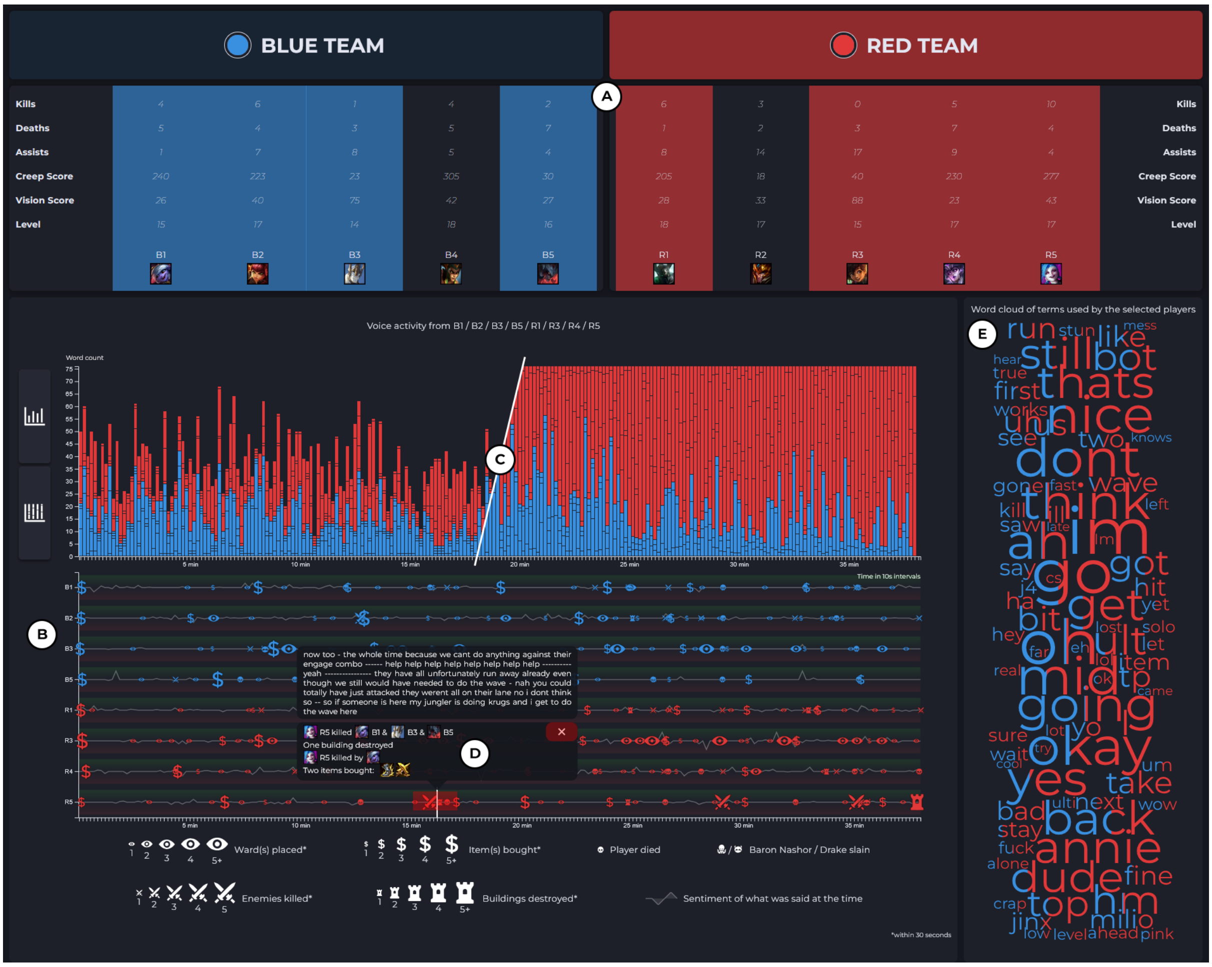

Figure 1: *Overview of the visualization interface with scoreboard (A), timeline visualization (B) showing events and voice activity (C), details on the verbal communication (D), and enriched word cloud (E).*

4.2. Timeline

For an overall picture of a selected match, we integrated a timeline visualization. As shown in Figure 1 (B), the x-axis represents the match's elapsed time in 10-second intervals, and the y-axis represents each player in a row. The rows are grouped and ordered based on their occurrence in the scoreboard. In each row, the player-specific events are encoded via symbols: *ward placed* (indicating visibility in the map), *item bought*, *enemy killed*, *building destroyed*, *player died*, and / *Baron Nashor/Dragon slain*. The size of a symbol on the timeline indicates occurrence frequency. To avoid clutter, events within 30-second intervals are grouped. The white line chart in each row shows the sentiment (positive or negative) of the verbal communication of each player. At the top of the timeline, a chart (see Figure 1, C) aggregates voice activity for the selected players, divided by team. The numbers of words within the 10-second intervals are summed and displayed in a colored stacked bar chart, visualizing the absolute distribution of communication. In a second mode, the relative proportion of communication within the respective interval can be displayed to compare the communication density. To focus on a specific section of the match for a player, as shown in Figure 1 (D), clicking inside the timeline highlights a 120-second window. A panel displays the corresponding statements from the verbal communication, with hyphens indicating silence. It also provides a chronological list of events that occurred in the selected period.

4.3. Enriched Word Cloud

Word clouds are an intuitive and widely used visualization technique for analyzing the main terms present in a text [HLLE14]. However, to effectively compare communication between two teams, we need a method that highlights differences. Juxtaposed word clouds for each team could be used, but this makes direct comparison challenging, especially when searching for the same word in both clouds, as word sizes and arrangements might differ. To address this, we designed an enriched word cloud that facilitates comparison between two teams. It can be considered a simplified variant of word clouds that contrast multiple sets of documents [JML*18, BLB*14, DES*15]. As shown in Figure 1 (E), the

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frequency of all the words spoken by the selected players from both teams is calculated and displayed in a single word cloud. The size of each word represents the combined frequency of its occurrence by players across both teams. Additionally, each word is partially colored blue and red, proportionate to the frequency it was spoken by players of each team. For instance, a word predominantly colored blue indicates being more frequently used by players of the blue team, while a predominantly red-colored word indicates higher frequency by the red team. This design allows for a direct comparison between the two teams within a single view.

5. Application Example

To illustrate how the approach can be used, we present an application example based on the dataset described in Section 3. We refer to players of the blue team as B*x* and to players of the red team as R*x*. In particular, we first use the timeline component to compare the communication of player B2 with other players from the same team during a fight. Then, a comparison to R4 is made, who had the same role as player B2 during the match in the opposing team. To see the positioning and its change over time of the respective players in the following situation, we consult additional video recordings of the match. Finally, we analyze the communication of the blue team in comparison to the red team using the word cloud.

After a match, communication should be analyzed for clarity of intent and relevance at crucial moments and compared within the team and to that of the opposing team. To achieve this, the relevant players are first selected via the scoreboard. In our example, we select player B2, together with B1 and B3, and analyze a situation in minute 14 of the game. At this time, B2 first scored a double kill on R3 and R5, but then is killed by R4. As can be seen in Figure 2, B2 announces the plan to go to the bottom lane and confirms it again shortly after. B3 briefly acknowledges by announcing that they will come back, and B1 also confirms, saying that they proceed onto the target. The sentiment analysis shows a positive swing for B2, suggesting that the player is already expecting a positive outcome of the situation. Subsequently, B2 is satisfied with the outcome, claiming they did very well, while B1 notices that an opponent will appear nearby soon by using a *tp*, short for teleport. B2 asks for help from a fellow player to attack the enemy, to which B3 replies that no help can be offered, but B1 promises to be present. Afterward, B2 announces that B2 is eliminated. In this example, the visualization helps to reconstruct the sequence of events, including the individual actions of the players, and shows that active communication with clear intent and relevance prevails; the plan was exchanged efficiently, in a few words only.

Looking at the opponent's side of this situation, shown in Figure 3, the sequence of events can also be reconstructed. R5 announces the plan to take plates from a tower and repeats it several times. R3 confirms briefly, but then remarks that there is no possibility to support left as they do not have *mana*. R4 notices that B2, playing the champion *Annie*, is missing and, shortly afterward, realizes that B2 is close to R3 and R5. R3 also recognizes this, but too late, which is why they immediately announce that R3 and R5 have both been killed by B2. The sentiment analysis shows a negative swing for both R3 and R5 before getting killed, suggesting that both realized the inevitability of their deaths. R4 acknowledges their deaths and subsequently kills B2. This sequence illustrates that R4's communication had clear intent and relevance, but was slightly delayed, such that B2 was able to kill R3 and R5.

Using the enriched word cloud, seen in Figure 1 (D), to look at the communication of both teams throughout the duration of the match, game-specific terms such as the names of the champions involved or locations on the map, quickly become apparent. However, this also indicates that some players sometimes addressed each other by their champion names. For example, the name *Milio*, a champion played by the red team, has a certain amount of red in the word cloud and therefore the red team also used the word. Furthermore, affirmative words such as *fine* or *nice* are used almost exclusively by the red team. These insights suggest that game-specific terms were used consistently, as no alternative terms can be seen. In addition, positive exclamations were used in the red team, which may be a sign of a more positive mood in the team.

6. Discussion

As illustrated, our tool helps to analyze team communication in relation to different game events. While this work has focused on presenting and demonstrating the tool, future work will need to look into evaluating the tool with players to confirm its value. Especially, long-term studies could be helpful to explore how player-oriented tools like ours can shape communication over time. There are also several avenues for extending the current prototype and the visualization approach.

Dataset Collection and Pre-processing. Currently, player recordings are processed partly manually with *VOSK*. Fully automating data collection with platforms such as *Discord* [Dis24] or *TeamSpeak* [Tea24] and using a recording bot would streamline the process, allowing synchronous recording and real-time speech-to-text conversion with *VOSK*. Additionally, enhancing sentiment analysis with more recent techniques (e.g., leveraging large language models [SBP*21]) could cover a broader spectrum of emotions, and specifically allow the recognition of advanced concepts such as irony or sarcasm.

Usage Scenarios. The insights provided by the prototype could also be valuable to other users too. For example, analysts or coaches could use it to evaluate and improve team performance. Additionally, event organizers could leverage the approach to enhance broadcasts of esports events, providing deeper insights into team dynamics by showcasing sentiment changes and key statements around crucial moments, thus explaining strategic decisions.

Analyzing Multiple Matches. While the current approach facilitates the analysis of a single match at a time, it could be extended to compare multiple matches. Such an extension would allow for the analysis of team communication behavior over successive matches. Aside to selecting specific matches, additional visualizations would be desirable to help find interesting matches. As multiple teams will be involved in such high-level summary visualizations, we need to find solutions beyond coloring teams in blue and red, as well as good summary visualizations of each match (e.g., visual glyphs summarizing events and communication [LAK*23]). Moreover,

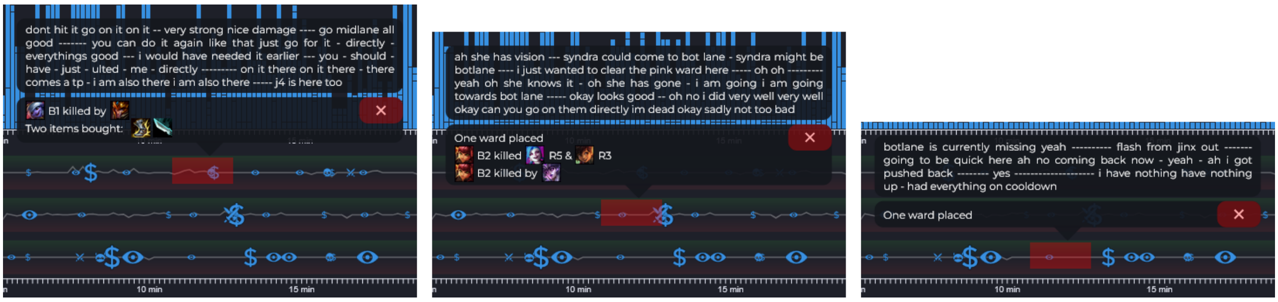

Figure 2: *Excerpts of the timeline showing the communication and events related to B1 (left), B2 (middle), and B3 (right) during a fight.*

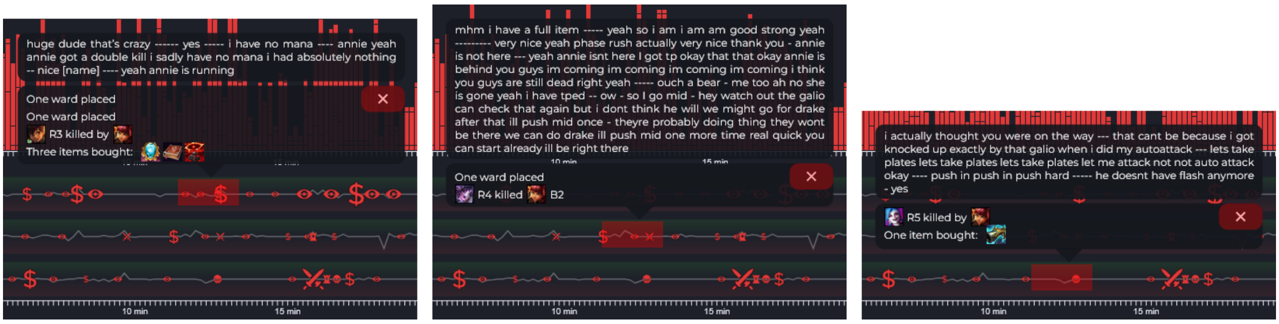

Figure 3: *Excerpts of the timeline showing the communication and events related to R3 (left), R4 (middle), and R5 (right) during a fight.*

the visualizations could be extended or complemented to display aggregated data from multiple matches, providing a more comprehensive understanding of team dynamics.

Spatial Analysis. Our approach focused on the matter of communication, which has gained little attention in visual game analytics so far. While we paired its analysis with player-specific events that showed to be helpful in revealing valuable insights, the visualizations do not show the spatial aspect of these events. However, in a game such as *League of Legends* player positions play an important role in understanding the strategies. Our approach can be extended in this respect, for example, by integrating it into a replay viewer similar to van Kempen et al. [vKvdSW22] or by combining it with already proposed map-based visualizations such as *VisuaLeague* [ACGV19] or a more abstract representation such as a storyline approach [WWD23].

7. Conclusion

We introduced a visualization approach to understand and compare team communication in *League of Legends*. We demonstrated the approach in an application example to reveal valuable insights about the team dynamics. The sketched ideas for future research outline a larger potential for integrated communication and game analysis. While we focused on one specific game, we see potential for the approach for similar team-based games where synchronous, verbal communication is an essential mode of information exchange such as similar MOBAs like *Dota 2* or tactical team-based shooters such as *Valorant* where communication is also essential for efficient teamwork. Hence, the main concepts and visualization methods used in our work should generalize with small adaptions to other team-based esports games. It might even be relevant for analyzing professional synchronous communication for time-critical collaborative tasks (e.g., handling a specific situation in a control room scenario or in a medical emergency). Here, the scenarios might not be adversarial and combat-like, but still, contrasting different teams on comparable tasks (e.g., in a controlled training) would provide insights into team traits and performance.

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