Esports athletes' group sensemaking of team gameplay data analytics

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Abstract: In this exploratory case study, we investigate how a collegiate esports team makes sense of gameplay data visualizations. Through our intervention we introduced the team to new data collection practices, provided data analysis and visualization support, and organized sensemaking sessions with the team to discuss implications of the analytics. Through an exploratory analysis of video footage, we identified three different sensemaking activities.

Introduction

Recently esports has catapulted into relevance largely due to a significant increase in online viewership of esports competitions via websites like *Twitch* (Takahashi, 2016). Universities have taken notice and supported creation of varsity esports teams, with some even providing scholarships for exceptional players. Esports games often involve a team of players competing against another team in a highly dynamic, fast-spaced digital environment. While there is a growing body of compelling sociologically-oriented research examining esports (e.g., Taylor, 2018), research on esports from a learning perspective is still emergent (e.g. Kou & Gui, 2018; Richard, et al., 2018). Our specific interest focuses on the learning that can take place among esports athletes when they engage with data. Following situated models of learning, we do not seek to examine learning as new output resulting from prescribed instructional intervention. Rather, we seek to understand how knowledge is implicated and used in situ and as situations change. As such, our examinations of learning will illustrate how what we might colloquially label as "knowing" or "comprehending" takes place. Those are, to our view, micro-moments and interactions in which the phenomenon of "learning" takes place.

In the project from which this study originates, we worked with a *League of Legends* (*LoL*) collegiate esports team to introduce team analytics of their gameplay data into their existing practices. In this paper, we describe some of the sensemaking that was observed when the team reviewed and interpreted prepared analytics of their data. We draw from the distributed resources model for sensemaking (Attfield et al., 2018) to inform our observations of how members of this esports team made sense of a small set of prepared team gameplay data visualizations.

Sensemaking

Klein et al. (2007) describe sensemaking via the data-frame model (DFM) as an iterative and bidirectional process of fitting data to a frame and adapting a frame to data. In this definition "data are the interpreted signals of events; frames are the explanatory structures that account for the data" (Klein et al., 2007, p. 120). For example, a frame could be one's understanding of gravity, and an apple falling would be data that fits into that frame. When perceived data does not fit into a frame, one engages in sensemaking. Sensemaking is then said to continue until congruence between the perceived data and framing is met. This may involve rejecting the data, readjusting the frame, or finding a new frame. It's important to note, that according to this model, data are not always exact representations of reality as they are often perceived and constructed via frames. For example, because tomatoes are often used for cooking, some people may use this cooking frame to identify them as vegetables rather than fruit. According to the DFM, experts and novices engage in sensemaking via same process, but experts engage in the process utilizing a larger repertoire of frames. This bidirectional view of applying frames to a data, or fitting data to frame also explains how different individuals abstract unique data from the same phenomenon. The frame that one applies to an event or situation will emphasize data that supports or contradicts the chosen frame. This touches on a final important feature of DFM which states that some data points can act as anchors for creating or selecting a frame to explain the phenomenon. Attfield et al. (2018) expand on the DFM by arguing that sensemaking does not simply involve the integration of data into one frame, but rather multiple frames that are interconnected. Further the authors argue that sensemaking is often distributed physically, socially, and overtime and involves considerations of the sense maker's values and goals. Verbert et al. provide a model for processing and making sense of learning analytics which is relevant to this study. Their model consists of four stages: awareness (data visualizations), reflection (questions about the data and frames), sensemaking (adjusting the frames or explaining away the data) and impact (action taken as a result of sensemaking). In this study we explore how an esports team engages in distributed sensemaking of data visualizations on their own gameplay. We apply Verbert's et al. (2013) model of analyzing sensemaking and operationalize sensemaking according to Attfield's et al. (2018) expanded conceptualization of sensemaking as a distributed cognitive act that accounts for values and goals.

Methods

This study is an exploratory case study that is interventionist in nature. It is interventionist in that with the agreement of the participants, we introduced and facilitated new activities into the existing activities of the participants. Our vision of esports team gameplay data analytics involves players producing data, that data being retained, computational and visualization techniques being used to manipulate and represent those data, and then subsequent sensemaking of those representations of data. This is represented in Figure 1.

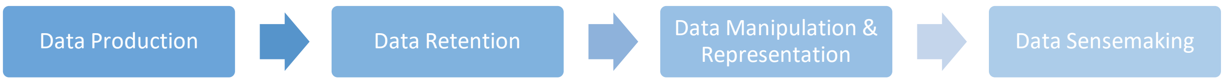

Figure 1: Esports team gameplay analytics processes

However, this was not the existing practice of the esports team that participated in this study. While they produced data at the end of each game, the team did not retain them. Because no data were retained, other steps, including sensemaking, did not take place as a team activity. Therefore, in order to understand how the participants made sense of team gameplay data and analytics, there needed to be new processes of data retention. Furthermore, the researchers were involved in manipulating and representing the data and organizing sessions so that the sensemaking could be observed. Given that most of these activities were new and exploratory, we opted to obtain video footage of sensemaking sessions and focused on characterizing observed sensemaking as the primary goal of our work. As video were our primary source of data, we followed recommendations from Derry et al. (2010) for the collection and review of video data including use of equipment and operation, video segmentation, and analysis and review processes.

Participants and Setting

Participants in this study were members of a newly established varsity collegiate esports team for the game *League of Legends*. *LoL* is a team-based arena battle game in which characters with different attributes and fighting capabilities are selected in order to reach an opposing team's 'Nexus' structure while simultaneously protecting their own structure. Along the way, game currency and points can be earned to increase character levels and to purchase items to assist. In-game challenges include defeating dragons or controlling specific resources can be targeted and pursued with various benefits.

At the start of the study, 7 participants (2 coaches and 5 players, all university students) completed a pre-survey with questions about their own histories and backgrounds with esports and looking at esports data. The average age of the participants was 20.43 and the average amount of experience playing *LoL* was 6.29 years. There was one player who identified as female and the others identified as male. For the post-interview, the team added two additional male players who had been reserves in the past but were moving into the starting rotation at the end of the study. No pre-survey data was collected for the two additional players who joined the team mid-semester.

Procedures

The team had reported and been observed making temporary use of data that were provided at the end of each game. The coaches would record data on a whiteboard from a single competition or practice and then immediately make intuitive summations about gameplay based on what kind of numbers they had seen in past games and what they observed, and then the written data was discarded. To support retention of data, a cloud-based storage for gameplay data was established and players and coaches agreed to enter data from each practice, skirmish, and competition. To support this, a research assistant observed and facilitated logging of these data.

After one month of data retention, the researchers processed and manipulated the data using *R* in order to produce data representations for the team to review in a full group sensemaking session. Decision trees were among the data manipulations and representations used. The researchers videorecorded the group sensemaking session where a researcher projected the representations (i.e., decision tree) and explained how to read the notation. Then the team agreed to collect and retain another two months of data and do a second video-recorded group sensemaking session. Individual post-interviews were done with players and coaches about their experience with these new data routines and what, if any, insights they gained.

Data Collection and Analysis

While information obtained from surveys and observations during game play are used to provide background, this paper draws primarily from video recordings of the two data group sensemaking sessions. The two sessions were approximately 30 and 60 minutes respectively. Visualizations were provided of game play analytics as computed in *R*, and a researcher provided guidance for reading the visualizations. Team members were then invited to provide their interpretations of the data. The videos were transcribed, those transcriptions were annotated, and excerpts discussed and ultimately coded through the induced scheme presented in the results. In the results section, we also provide illustrative examples of the observed sensemaking. Pseudonyms are used for all participants below.

Decision Trees

The *LoL* team's data were analyzed using a classification and regression tree (CART) analysis, also called a decision tree analysis. CART analysis uses an algorithm that chooses the variables that reduces the sum of a squares in a regression model. It's often used to help determine the most important variables in predicting an outcome variable (Hong, 2018). In the case of this study the outcome variable was a binary variable indicating whether the team won or lost.

Decision trees were used as the primary representation for the esports teams' data for a few reasons. First, the visual representation of decision trees makes them easier to interpret and understand. Given that many of the students had limited formal statistical knowledge it was important to present them with an analysis that they could read and make interpretations about. Secondly, CART analyses can handle both categorical and continuous variables. It can also accommodate variables that are not normally distributed.

The data collected from the team's gameplay was diverse. It included categorical variables (e.g. Did they get the Rift Herald?) and continuous variables (e.g. creep score per minute). The data set also included variables that were on different scales. For instance, time of a match measured in seconds reached 980 seconds compared to a variable measuring the number of dragons killed (1-4). Figure 2 below shows an example of a decision tree used to analyze the team's first month of gameplay.

In Figure 2, the topmost node shows "12 12" indicating that in 24 matches, the team won 12 and lost 12 matches. The first split is on the dragon variable. (Dragons are a team objective in *LoL* and when this objective is achieved the team gains additional strength.) The CART analysis shown in Figure 1 reveals that when the team had more than 2 dragons (on the right side), they won 11 games and lost only 1, however the opposite was true when they had less than 2 dragons. Continuing with the right side, and the remaining 12 games, if the team killed one Baron (another team objective) in addition to killing more than or equal to 2 dragons, they were undefeated with 11 wins. This same logic can be applied to both sides of the decision tree.

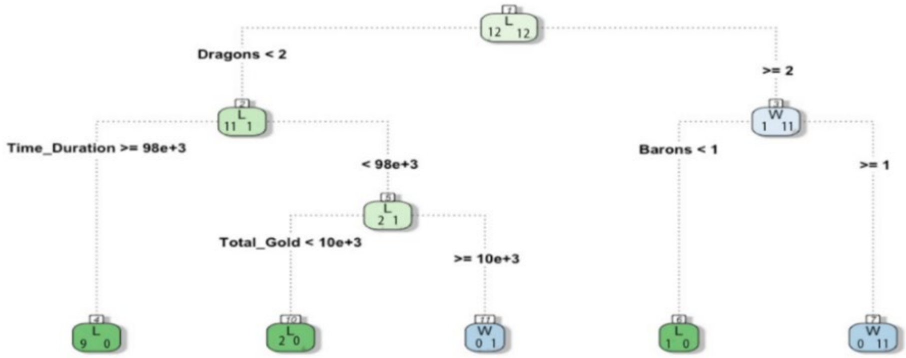

Figure 2: Sample Visualization used in data session

Results

There were three major observed types of sensemaking activities that appeared across sessions. These include *confirmations* where the data was interpreted as supporting a previously held belief (frame) about a player or gameplay; *contextualization* where prior knowledge or beliefs about players were used to interpret what the numbers in the data visualization meant; and *gaining insights* which occurred when team members discovered and accepted something unexpected about their collective gameplay from the data visualizations. Frequencies for these codes are displayed in Table 1.

Table 1

Frequency of Codes

	Confirmations	*Contextualization*	*Insights*	*Total*
Data Consultation 1	2	4	3	9
Data Consultation 2	3	4	3	10
Total	5	8	6	19

Confirming Strategies (Preserve Frame)

Confirmation was the discursive and interpretive activity of using the gameplay analytics to confirm previously held beliefs about gameplay. Both team members and coaches used the analysis to affirm the goodness of strategies that were already being implemented. According to the DFM, these are examples of new data being readily fitted into an existing frame. One of the team analytics results was that game duration, specifically long games, were predictors of losses. This led one player to suggest that they needed to finish before 35 minutes. Both coaches then agreed with this assessment and then the head coach reminded the team that this was part of the drafting (character selection) strategy that they had been advocating.

> *Mike: We've drafted a lot to like, our champions are better to team fight-esque orientation. So like right after lane phases where like they're really strong until like… 32-ish [minutes]yeah and then they'll start to taper…*

In the next example, a player uses the team's strategy as justification for the data. When looking at the data for the player who occupies the top lane (a region of the digital arena), the team members and coaches notice that "kill participation" was an important variable. Kill participation measures how involved a player is in all the kills. Normally, kill participation is higher for a player that occupies the middle lane because they can easily get to the top or bottom of the map and subsequently engage in more team battles. The top lane is typically a solo lane, meaning the player is left to fend for themselves. When trying to make sense of why the team had 11 wins and 0 losses when their top lane player had a higher kill participation score, a team member (Kyle) said the following:

Kyle: But normally kill participation would make sense that like the higher it is the better it is because. I mean we used to play through top before …and we won all our games
Mike: We're just going to switch to playing through top to finish up

Kyle pointed out that when this data was collected the team strategy was to play through the top lane. This means that the top lane character plays aggressively thus allowing for other players to come in and support, which would lead to higher kill participation scores. Kyle further points out that when kill participation is high for the top lane, or when they are 'playing through the top,' they were undefeated. This prompted the coach (Mike) to declare that the team would be returning to that strategy.

Contextualizing Player Tendencies (Expanding on Frames)

The second kind of sensemaking we observed in the analyzed transcripts was "contextualizing player tendencies" within the analysis. To make sense of findings in the analysis that were not always intuitive, some team members offered a variety of player tendencies or playstyles that could account for the findings. This was a form of post hoc justification. According to the DFM model, this would be example of using multiple frames to fit the data, rather than fit the data into an existing frame. For example, when interpreting a decision tree created for one of the better players on the team, it was noted that a high 'creep score' (a measure for minion kills that is associated with gold accrual, abbreviated as 'cs') and winning one's lane was not associated with the team's overall wins. The team discussed this phenomenon in the excerpt below:

Mike: I feel like… the kill participation plot at least makes sense for him because the way he plays lane like he's just so aggressive but he's naturally building a lead so like he's gonna accrue like X amount of gold lead by 20 minutes just by being in his lane so it makes sense that his kill participation is kind of like neutral at least like this
Thomas: Makes sense because if he's (middle lane player) not participating in the kills that means the lanes are just being pushed
Mike: Oh, that's. Oh, yeah, no no no. you're right, you're right. I read that backwards

In this example, the players were first trying to make sense of the data that shows when their best player performs well according to several metrics, they don't win as much. This was counterintuitive to their prior beliefs. Just prior to the above excerpt, Brent (another player) noted that the team often ends games before Thomas has the chance to reach 100 cs which is indicative of them winning early. The team also noted earlier in the sensemaking session that they are built to win early and that they become weaker as the game lasts longer. This point is a nod to the fact that if Thomas reaches 180 cs, it means that the game has gone longer than they would have liked, and that they have lost the advantage. This conversation then led the team to contextualize another finding that previously stumped them. In an earlier conversation, the team noted that Mike, who often plays the middle lane, does not need to participate in kills for the team to get wins. This is strange because the middle lane player is in the optimal position to help out on team battles given their location in the middle of the map. Based on the conversation around Thomas' play, he attempts to contextualize the findings around Mike's kill participation score by noting if each of the team members are winning their lanes (individual battles) then there is little need for team battles (or team participation). This further explains why only Mike's decision tree noted team participation as a key variable because his player is often most involved in team participation, so lack of team battles would show up on his decision tree.

In a second example, when interpreting the decision tree for the for a new player on the team who plays the jungler*,* a team member and a coach make sense of surprising findings by contextualizing the results in the player's tendencies. The jungler typically begins the game in the jungle battling minions rather than actual players. The decision trees for this particular jungler found that when this player averaged less than 356 gold per minute (which is high for a jungler), the team lost all of their matches. The assistant coach (Robert) then provided some insight:

Robert: So you get gold from like the CS and then also from kills. And jungle like pathing right now. Like how they play, there's a lot of time to like find skirmishes early on. And so when he's playing like early game damage champions or something like that, he always wants to take the fight. So if he gets the kill in those early skirmishes, it's like propelling him to win these like snowballing off it or something. But if he's not, then he has to like, go back to CS to try and make up for the lack of gold that he got… So just stop trying to kill people and just focus on cs, or even like consistency…

The coach uses this opportunity to bring up a tendency of the jungler to leave his post in the jungle and try to gank (assassinate) a member of the opposing team. The coach notes that when these attempts are successful the team does win, but most importantly when they are not successful (which is normally the case) the team loses. In this example, the data suggests that the jungler needs an exorbitantly high rate of gold per minute which seems to align with the current framing of the players. However, the coach readjusts the frame by illustrating how it is unlikely that the jungler will reach those numbers consistently, and thus uses the analytics to explain how the high-risk tactics of the jungler led to the low probability win conditions. Thus, the team expanded on their understanding (frame) of how the jungler contributes to win conditions.

Insight on Dragons (Creating New Frames)

Finally, insights were sensemaking activities that emerged when existing frames concerning win-conditions were challenged and then new frames were created. An example of this was the discovery of the importance of killing dragons for the team's success. Team members all reported knowing that getting dragons (a team objective within the game) was valuable because it gives a team "buff" (a temporary increase in character attributes), gold, and the effects of each subsequent dragon can stack, meaning they become progressively more beneficial. However, they were still surprised to learn based on a decision tree visualization (See figure 1 above) that they won 11 games and only lost one if they had killed more than two dragons. This meant that killing two or more dragons in a game seemed predictive of a win outcome.

Researcher: If you get more than two dragons, you're 11 and 1, if not 1 and 11.

Mike: I can say, I definitely didn't expect that…So our one loss was when we did not get two dragons… that's actually really cool.

Thomas: Wait so we lose more when we get Herald

Brent: Because I think we give up drags when we get Herald

This insight into the value of dragons on the team's performance led to an explanation on another surprising finding. Thomas questioned another finding, also from a decision tree, that the team loses more when they get the Rift Herald (another team objective). Brent pointed out that this was likely because they exchanged dragons for the Rift Herald. This provides an example of both adapting one's frame to the given data and distributed sense making. In a post interview, the Mike described in detail how the impact of the analysis affected not only the groups' perspective towards in-game team objectives (e.g. Dragons, Baron, Rift Herald), but also how statistical knowledge of the game filtered into other aspects of their team strategies.

Mike: I found it was more interesting how, like the switch to objectives came about, and how barons popped up in priority and like dragons were more prevalent…in everybody's individual data plots, we could see why… we would get more dragons and why we would get less like when …bot [bottom] lane has what's called forward pressure and towards what's known as forward percentage win, pushed up against the enemy team that gives you control over the wider majority of the map. And since dragons are on the bot [bottom] side, when we had that bot side control early, it let us know that like picking up those, the dragons were easy, because like we have that avenue, and also statistically led to more awareness, which I thought was really cool.

Together, these pairs of insights led to a team behavior change following the data consultation. This further provides evidence of how values and goals contribute to sensemaking. Without any urging from the researchers, the team took on slaying dragons as a new strategic priority in their scrimmages and games. They began to de-emphasize pursuit of the rift herald. This insight led to explicit change in thinking and behavior for the team.

Conclusion

Use of team analytics in collegiate esports is understudied and perhaps also underutilized among esports athletes. However, just as traditional field-based sports are increasingly relying on data collection and analytics, we could anticipate the same is coming for esports. Given esports as a gaming context and the potential of data to be important to influencing thinking and reasoning – what we view as the substance of what happens when we examine learning in situ – there are numerous questions we could ask about how data are interpreted and sense is made. Through an interventionist approach and analysis of video footage, we noted three different sensemaking activities from a team reviewing their own gameplay analytics. There were some occasions when the analytics were used to confirm what team members already believed. However, we also found that what players already knew about the game could also help to generate interpretations that gave them a better handle on what the various analytics could mean. Finally, there were some occasions when insight – new frames for understanding the team, game, and the team's gameplay – came about. This latter activity is likely one that we want to support and encourage. Can we engineer group data review experiences and environments that can enable insight to come about? How can we best utilize prior game and team knowledge to support interpretation and reduce inaccurate confirmation biases? These are a new form of "quantified self" experience where a notable form of digitally-mediated learning could take place (Kou & Gui, 2018; Lee, 2013). With the set of descriptors for team analytics sensemaking offered here, we hope that more work can be done so that it helps us to further our understanding of how learning is supported and situated within collegiate esports and other popular forms of digitally-mediated gameplay.

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