Computationally Augmented Ethnography: Emotion Tracking and Learning in Museum Games

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Abstract. In this paper, we describe a way of using multi-modal learning analytics to augment qualitative data. We extract facial expressions that may indicate particular emotions from videos of dyads playing an interactive table-top game built for a museum. From this data, we explore the correlation between students' understanding of the biological and complex systems concepts showcased in the learning environment and their facial expressions. First, we show how information retrieval techniques can be used on facial expression features to investigate emotional variation during key moments of the interaction. Second, we connect these features to moments of learning identified by traditional qualitative methods. Finally, we present an initial pilot using these methods in concert to identify key moments in multiple modalities. We end with a discussion of our preliminary findings on interweaving machine and human analytical approaches.

Keywords: multimodal learning analytics · affect tracking · game-based learning · physical traces

1 Introduction

Informal learning environments can provide rich educational experiences without the need for an instructor or classroom [3]. While these sorts of learning environments have become more common, museum exhibits have long utilized these environments as the main way of engaging their visitors [6]. In order to assess the effectiveness of these exhibits, designers need to understand how participants' interactions with the environment inform their learning experience. However, it is often difficult to identify and track participants' learning through these open-ended interactions [16]. Traditionally, such work has been done through ethnographic practice, requiring researchers to be either *in situ* or sort through enormous amounts of video data manually. With the advent of multimodal sensing, many researchers have moved to a model of observation that focuses on instrumenting participants and the environment itself in order to capture many types of interaction streams. However, these automated multi-modal protocols lose the depth and detail that an experienced ethnographer can capture [15].

In this paper, we are working to augment ethnographic practice (e.g., observations and semi-structured interviews) with multimodal sensing. Instead of viewing the two skill sets as opposing models for data collection and analysis, we envision them working in concert. Multi-modal sensing could provide a lens through which to identify specific learning moments for more in-depth qualitative analysis. At the same time, qualitative analysis could reveal moments where social phenomena, such as side-by-side collaboration, might be better understood through a multi-modal lens. In the following sections, we show one possible use of computationally augmented ethnographic practice by analyzing a single dyad's learning trajectory as they interact with a table-top museum exhibit focused around the biology of ants. Specifically, we focus on how the relationship between affect and cognition can be utilized to better analyze learning in this environment.

2 Prior Work

This work is informed by prior research at the intersection of neurobiology, ethnography, and artificial intelligence. More broadly, the work builds on a growing body of research in multimodal learning analytics [16–18]. Research on neurobiological parts of memory shows that emotionally arousing stimuli consolidate and preserve more often over the long term [13].Both positive and negative emotions are associated with memorable moments controlled selectively within the basolateral amygdala. The brain region regulates the consolidation of memory for various experiences through projections from the amygdala to many other regions involved in storing newly acquired information [14].

More recent work has more explicitly explored the relationship between cognition and emotions. For example, D'Mello and Graesser [5] advance a model of affect dynamics that describes the complex interactions that exist among different emotional states, tracked through facial expressions, and how those afford learning. They are particularly concerned with how students transition in and out of moments of confusion. Central to their model are the roles of surprise and joy as indicators of a student transitioning into or out of a moment of confusion. While still discussed in terms of short term cognitive gains, the model implies that examining affective states can be instrumental for better understanding learning.

Worsley, Scherer, Morency, and Blikstein [26] similarly leverage the information embedded within affective states, or facial expressions, to segment multimodal data streams. Specifically, their paper uses changes in facial expression as a proxy for delineating meaningful changes in the learners cognitive or behavioral state. Put differently, they segment their data stream whenever the user has a change in their most probable facial expression. Underlying this proxy, is the assumption that affective information can be informative for examining complex learning experiences.

Different from prior work, however, we adopt strategies from data mining and qualitative ethnography in order to avoid analyses that are purely computational or purely human-annotated. Our motivation to do to this work is to provide an example of iteration between ethnographic practice and computational techniques to analyze a previously developed learning environment [11]. To this end, we focus on a single dyad interacting with an infromal learning environment in order to demonstrate our methodology in a particular informal learning activity. We also articulate future work to continue using these techniques with more participants and other modalities.

3 Data Collection

We collected data from 114 participants in 38 groups as they participated in a museum exhibit called *Ant Adaptation* [8]. Ant Adaptation is a game built from an agent-based model (ABM) implemented in NetLogo [23]. Two players interact with the game by controlling one of two ant colonies, using sliders to adjust ant behaviors and touchscreen gestures to set pheromone trails towards flowers for food. Ants can also "fight" over resources, which sets up a feedback loop that drives the action of the complex system. Through gameplay, players learn about (a) ant colony behavior and (b) entities' interactions in the complex system. More details of the game will be discussed in the following section.

To explore computationally augmented ethnography with Ant Adaptation, we collected two different types of data: (a) synchronous video, audio, and Kinect data streams using the Social Signal Interpretation framework [21] and (b) ethnographic data in the form of written field notes and a pre/post-gameplay semi-structured interview. This paper does not include analysis of the Kinect data.

In this paper, we present data collected on one dyad of the 38 groups. This pilot serves as a study on the potential of this approach before continuing to work with more participants and modalities. The dyad played the game side-by-side on a 52 horizontal touch screen in a research lab. A researcher interviewed the dyad before and after gameplay in order to probe their evolving under-standing of the ant life cycle. We placed the camera and Kinect approximately five feet away from the dyad in order to capture facial expressions and body motions for further analysis. Audio of interviews and gameplay conversation were transcribed verbatim.

4 Ant Adaptation

Agent-based modeling (ABM), and NetLogo ABM in particular, has been shown to be an effective and empowering platform for classroom learning with successful curricula spanning many disciplines, from chemistry [22], to physics [1], to biology [24]. Ant Adaptation builds off this rich history of ABM for learning, but positions itself as a rich tangible interaction form factor for walk-up-and-play use in an informal learning space. As shown in Figure 1, Ant Adaptation simulates two ant colonies side by side. Leveraging a large multi-touch display

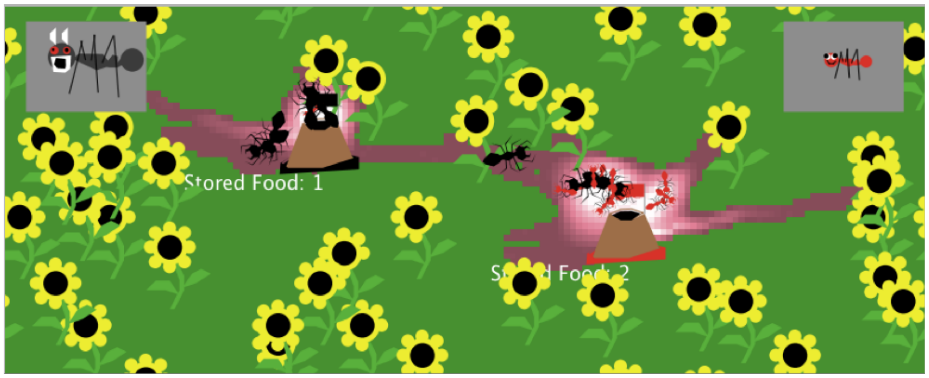

Fig. 1. A screenshot of the Ant Adaptation table-top game.

mounted horizontally as a table-top exhibit, the model tracks players' touches within the model. Through this interface, players can both interact directly with the gameplay area and with sets of widgets that directly control parameters of the core simulation.

4.1 Ant Adaptation as an ABM

It is important to note that Ant Adaptation is a fully functioning ABM. Even without user interaction, ant agents go out to collect food and return to the nest. As they return to the nest, ants lay down a pink pheromone that attracts others nearby. When ants find a flower, their food source, they return, lay down more pheromones, and thus reinforce the pink trail. This creates an emergent feedback loop that routes more and more ants to successful sites of forage. As the ants exhaust a food source, they must find new locations and thus repeat a cycle. When two or more ants of opposing colonies encounter each other, they fight or scare each other away also leaving chemicals that attract more ants. For the winner, this works to protect the food source from competing colonies. The ant queen reproduces when the ants in her colony collect enough food, in other words when collection surpasses the current Create Cost. Flowers periodically grow up around the map, adding food to the game.

The player interacts with this complex system by tweaking parameters and effecting the environment. Through interacting with the system, users form a functional understanding of the ants and their mechanisms of action (i.e. agents and their rules) in the model.

4.2 Ant Adaptation as a Digital Table-Top Game

To supplement the original NetLogo software [23], we have developed software designed for touch interaction with the model, NetLogo Touch [10]. The original NetLogo software only allows for a single interaction by a single user at any

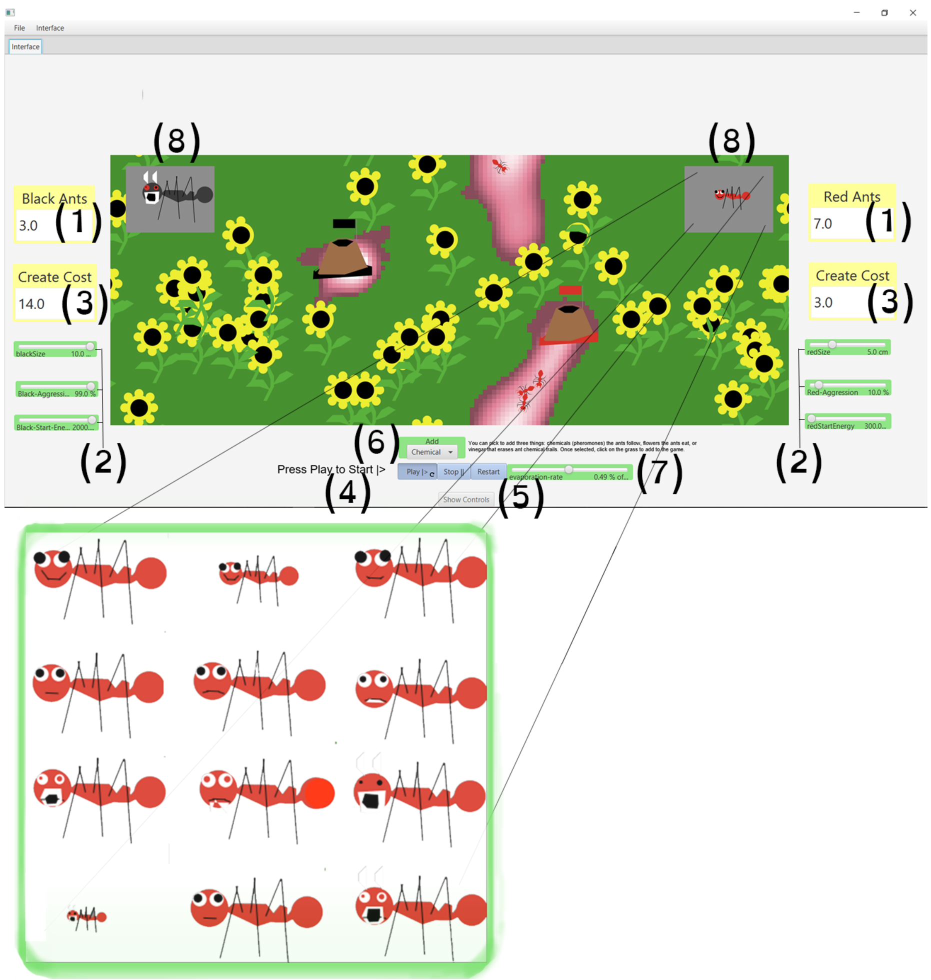

Fig. 2. A view of the Ant Adaptation table-top game interface.

given time. That model is simply not conducive to cooperative or simultaneous gameplay as in Ant Adaptation. As such, NetLogo Touch allows users to interact with the model simultaneously and via touch instead of via the more traditional mouse-based input.

Each team is given control of three simulation parameters via widgets in addition to two *monitors* that give summary information about a colony. From Figure 2, element (1) is a monitor of the ant populations labelled Black Ants on the left and Red Ants on the right which simply keeps track of population sizes. Element (2) shows the three widgets which are sliders players can use to adjust their ants' size, aggressiveness, and the maximum amount of energy. In this particular model, energy is essentially equivalent to how long ants can walk without eating. These sliders can be adjusted at any time during the game to experiment with different settings for each colony depending on the players' wishes. Element (3) is another monitor that shows the *Create Cost* of an ant or the amount of energy required from the colony to spawn a new ant.

Players decide how big and aggressive their ants are. As the size of ants increases, they become slightly stronger in a fight against other ants. At the highest levels they are 13 times stronger than ants of the smallest size. When players make their ants more aggressive, it increases the radius in which ants detect opposing ants and thus the probability that they will attack. Increasing either the size or the aggressiveness also increases how much energy is required to raise a new ant, so the largest ant requires 13 times as much food to feed to adulthood. Increases in either of these parameters reduces the expected population of the colony by increasing the Create Cost, though it increases their likelihood of fighting and winning through the emergent interactions of parameters (size and aggressiveness) and agent actions (collecting food, leaving trails, and fighting).

The colony produces a new ant when the stored food is greater than the Create Cost. This is an example of what Chi et al. [2] call an opaque summing mechanism that NetLogo designers employ, where the collective mechanism is computed by the NetLogo system itself, thus [left] opaque to the students (p. 21). The cost is calculated by the current value of three sliders, meaning players can change the create cost of their ant using these three dimensions. Because the outcome of the calculation is the current cost for the colony to birth one more ant, this summing mechanism becomes a key element of the gameplay for players to understand in order to strategize.

Lastly, there are two representations of the players' ants in the top right and left of the play space. These show the user how large and aggressive their ants are when born. As shown in element(8) of Figure 2 the display changes according to the mixture of aggressiveness and size the player chooses for their team. This provides the player immediate feedback for changing slider parameters, giving them a better sense of cause and effect in the model. This is important because adjusting the sliders only affects new ants born, instead of extant ants. So the effect of the interaction is longer than the 30 to 60 Hz, 16.6 to 33.3 millisecond periods, people associate with cause and effect within games [7].

In addition to the the colony controls, the players share five widgets in the bottom center of the screen. As shown in Figure 2, element (4) Play and Stop buttons, which control the model's time; element (5) a Restart button, which sets the model back to initial conditions; element (6) a drop-down chooser which allows players to select the main action of the game as a series of strategic choices (which will be discussed in more detail in a moment); and element (7) a slider to control the evaporation rate of pheromonesa chemical trail that ants leave behind them as they travel in the world.

Element (6) of Figure 2 is a main mechanism of the gameplay, allowing users to select the action that takes place when they touch within the game world seen in Figure 2. Players can choose to add *chemical*, *flowers*, or *vinegar*. Chemical is a pink pheromone that usually is only laid down by ants. Ants are attracted toward the highest concentration pheromone near their location, which is displayed by whitish-pink shades. Flowers are these ants' main food source. Ants collect and eat the flowers to feed themselves and bring food back to the colony for collective rearing of young. Vinegar erases ants' trails allowing the player to mask pheromones, disrupt communications, and clear the ground by applying vinegar to the chemical trails. In essence, this chooser allows players to decide whether to have their colony focus on collecting food, thereby increasing the population, go on the warpath, forcing colonies to fight for resources, or perhaps purposefully prevent their colony from finding the opposing colony. However, it is important to remember that in order to use these elements effectively, a player must understand how the ants react to each of these different action items. These three options are not directly affecting the ants, but rather the world that the ants live in. As such, players are forced to try to understand how, in this particular complex system, the environment and agents interact.

Each method of play could lead to high populations or the elimination of the opponent through better-controlled food resources. For example, after learning about the consequences of strategic choices through gameplay, players could strategize by increasing ants' size, aggressiveness, or both. This might lead them to win the game by annihilating the other group's ant colony. However, bigger and/or more aggressive ants consume more food to reproduce and potentially reduce the colony's population size. Thus, a player could strategize by adding more flowers and pheromone tracks around the colony to help the larger ants survive. This learning and strategy cycle interweaves the learning into the gameplay. The design scaffolds experimentation and encourages players to interact with emergent phenomenon like feedback loops, local optima, and more.

Ant Adaptation has four main affordances that support two central learning objectives. In Ant Adaptation, playing with parameters allows players to: (1) construct their colony in competition with an opponent; (2) share strategies through comparison; (3) discuss what is happening through observer scaffolding such as parents' intervention or interaction between players, including slapping hands; and (4) learn about the emergent impacts of colony behavior arising from individual ant behavior in a complex system game. This approach allows visitors to learn (1) the impacts of adaptation on ant colony life and (2) how attractants such as pheromones work in ants' organization to increase the population. As such, the game also offers the potential to scaffold learners in switching from a direct to an emergent schema of how the phenomenon we see in everyday life might occur [12]. Next, we analyze and discuss these learning opportunities by looking at participant data via a qualitative and computational lens.

5 Data Analysis

We began our analysis with traditional qualitative methods involving multiple coders following a constructivist dialogue mapping approach [9] a type of concept mapping [15] on transcripts of interviews and gameplay conversation. We extracted emotional evidence from gameplay video to identify segments when learning occurred. Finally, we describe how iterative explorations of emotion informed and augmented our analysis of dialogue, and vice versa.

5.1 Using Joy Values Based on Facial Recognition to Identify Potential Learning Moments

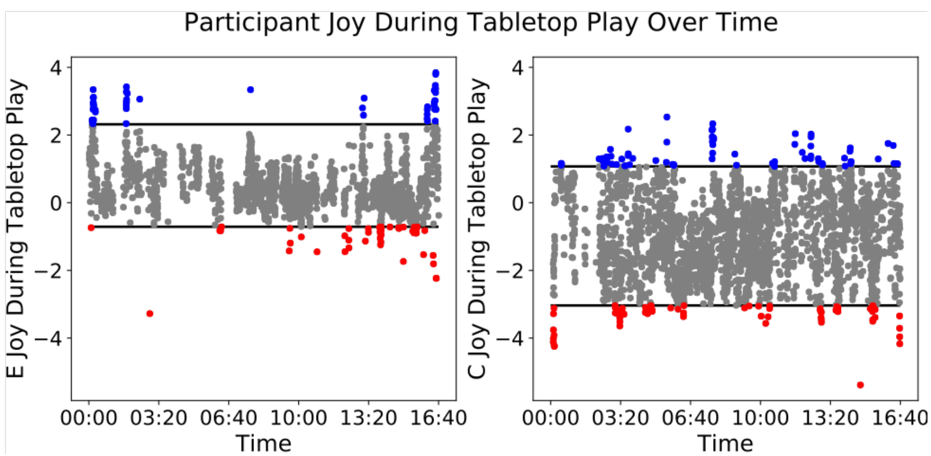

Fig. 3. A visualization of participant joy over time, as detected by FACET analyzing facial expressions extracted from videos. Emotional peaks and valleys outside of the middle 95% of the data are colored.

We used FACET [20] to extract the strength of detected emotions through the proxy of facial expressions. The basolateral amygdala is an essential component of the neuromodulatory system regulating behavioral states and is thought to consolidate experience-dependent plasticity [14]. As a result, both positive and negative emotions are behavioral states that may be involved in vital brain function modulating the neuronal representation associated with memorable moments. To identify reasonable emotional moments that might be associated with moments of learning [13, 14], we used a 2.5th and 97.5th percentile threshold to reveal peaks and valleys of joy values computed via FACET. The percentile thresholds are visualized as horizontal line boundaries in Figure 3. This search for peaks and valleys is informed by McGaugh's previous work, which argued high stimulus periods lead to higher memory encoding. We then extracted the dialogue from the transcript that occurred approximately ten seconds before each peak or valley to compare and further analyze whether learning occurred at these time segments. We call these segments *learning windows*. Note we do not directly compare FACET values between participants, but instead focus on FACET values for each participant individually.

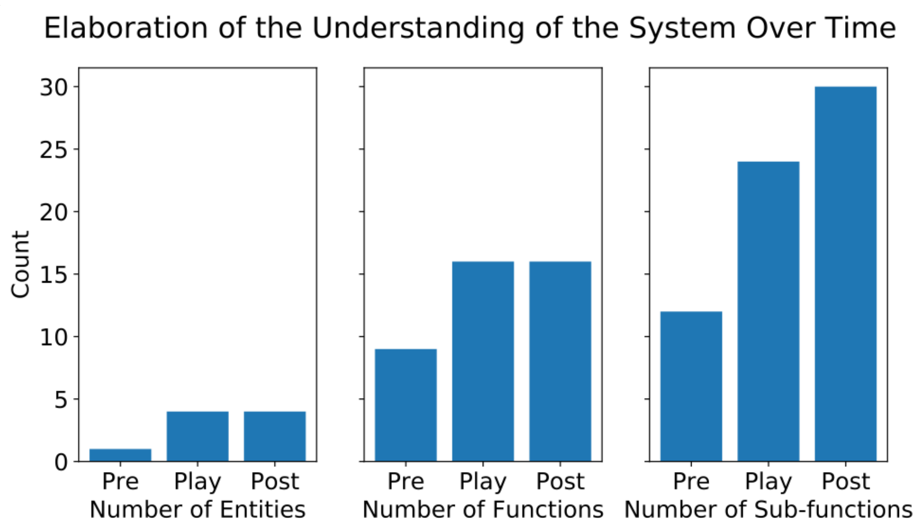

Fig. 4. A plot of how many entities, functions, and sub-functions the dyad verbalized during the pre-gameplay interview, gameplay, and post-gameplay interview.

Cognitive Mapping for Learning Concepts We define learning in this dataset as how the participants elaborate their understanding of the ant life cycle through informal play. For example, if initially they say "ants walk," but after play "ants walk to follow paths to reach food to feed the colony and themselves", we would interpret this as an elaboration of their understanding. This is based on how Ant Adaptation is designed to embed learning into gameplay as participants manipulate ant parameters (e.g., aggression, size, distance to food) [11].

With this in mind, each coder created a concept map for transcripts of the interview before gameplay, during gameplay conversation, and of the interview after gameplay.

Each map consisted of entities, functions, and sub-functions discussed by the dyad. Entities included different agents and resources in the game, such as ants and flowers. Functions are the processes that engage entities, such as leaving a trail. Sub-functions are the motivations or results for functions, such as collecting food or directing the paths of other ants. Two coders created cognitive maps, and had 96% inter-rater reliability on the functions and sub-functions they identified.

6 Results

In this section, we present results from our cognitive mapping analysis and three examples of learning windows identified at the timestamps of peaks and valleys in Figure 3. In addition to providing more insights on learning processes that we already manually coded with cognitive mapping analysis, emotion tracking unveils other learning processes that we did not notice previously. We see this interlacing of human coders and computational techniques having potential in iterative qualitative research processes. When we used facial expressions to locate moments we find three main benefits: (1) Through indexing moments of high joy, we find moments we would not otherwise notice; (2) Tracking facial expressions can provide addition insight into learning moments; (3) Using affective tracking we can see past epistemological bias to see moments of learning in a new way. This third benefit focuses on the main purpose of multimodal learning analytics in computational ethnography: to see the interactions with additional subjective lenses to gain a fuller understanding of learning in the space.

6.1 Cognitive Mapping

As shown in Figure 4, we found that during the pre-gameplay interview which focused on questions of ants, players described one entity (ants), with nine functions (e.g., placing paths to signal food) and twelve subfunctions. Participants elaborated both the entities and functions of those entities through playing the game. During gameplay, players mentioned three additional entities (flowers, queen ants, and a GUI element in the interface) as well as sixteen functions, such as "ants hiding in their colony" and "organizing society". They also discuss twenty-four sub functions (e.g., food collection through leaving attractant pheromones). By the end of the intervention, the participants expanded to thirty sub-functions. In other words, most of the "learning" (75% of the entities and 40% of the subfunctions) were elaborated on during play.

While cognitive mapping provides a structured set of codes about participant sense making, one key limitation is that it extracts insight solely from transcribed audio and not necessarily capture evidence of learning in other modalities. Next, we share three examples of how emotion tracking extended our analyses of participant knowledge evolving throughout the session.

6.2 Seeing past epistemological bias: Learning occurs during instruction before gameplay

This example shows how emotion tracking revealed potential moments of learning that we missed in our qualitative coding. In Figure 3, we noticed a peak joy value with Emma (pseudonym) and a valley joy value with Chris (pseudonym) at timestamp 00:04, showing that this is a high-stimulus moment for both participants. Revisiting the transcript, this moment corresponded with when the facilitator described how to play the game, "On your side of the board, you have three sliders. One of them changes the size of new ants formed, one of them changes the aggressiveness...".

This evidence of potential learning during instruction was overlooked because when coding interview transcripts, the analyst cannot confirm whether participants are learning when they are not verbalizing. Additionally, given our interest in informal learning that occurs in museums through games, we primarily focus on the spontaneous, emergent learning that occurs rather than learning that happens during instruction. As such, during the cognitive mapping analysis, we did not identify learning during the moments when the facilitator instructed participants about the game.

Ultimately, emotion tracking enabled us to detect a potential learning moment when participants were silently listening to instructions on how to play the game. We see the potential to augment qualitative coding beyond what can be detected with a single analytic frame and transcription techniques.

6.3 Learning while experimenting with gameplay

Both Chris and Emma had a peak joy value (3.5 and 2.1, respectively) near timestamp 13:30 on Figure 3. We did not initially code this as a learning moment because functions and sub-functions were not clearly articulated in the transcripts. Revisiting the video near this peak's timestamp, we noticed participants were comparing their different slider conditions to draw conclusions about ant behavior as Chris says "Wait, how aggressive are you?... Wait, are you are a lot...you're slightly bigger than I am." while noticing that Emma's population count had risen to 77. As they watch the action unfold on screen, they noticed how different settings led to the victory or loss of their ant colonies.

While the first example revealed learning while silently listening to the facilitator's instructions, this example reveals how participants elaborated their understanding as they experimented with the game interface's sliders but did not verbalize an updated understanding of ant behavior. Using Constructionist Dialogue mapping during these moments lets us more carefully chronicle learning during moments of higher memory encoding. This example is another instance of how emotion tracking revealed moments of learning that we glossed over in our initial cognitive mapping analysis. By triangulation we came to better understand our data.

6.4 Joy during previously identified learning moments

Looking at Figure 3 at timestamp 7:00, Emma and Chris have peak joy values of 3.8 and 1.8-2.2, respectively, and we revisited the video at this segment for further analysis. Chris and Emma verbalized that the flowers at close proximity to the ant hill increases their ants' population. Chris says, "Can I have more flowers?" Emma responds, "Yes. Ring of flowers." They place a ring of flowers around their ant hills and notice ants picking up the food. Both watch the tabletop intently to observe the resulting ant behavior and Chris says, "Ooh, now I've got lots of ants." The dyad discovered a powerful relationship they can use to manipulate the environment. In contrast to previous examples, this example shows how emotion tracking provided additional insight on a learning moment identified in the cognitive mapping analysis.

As the dyad continues tinkering with parameters, they laugh through their trial and error attempts, and cemented the concept that food close to the nest increased the population of ants. This moment was coded in the cognitive mappings as one of the flowers' primary functions and our emotion analysis adds an additional understanding to this moment. That is, this discovery led to a sense of joy or what might be interpreted as "satisfaction" which is important to cultivate in informal learning environments and gameplay. Though we selected many of the same moments using emotion logging as we did through manual cognitive mapping, emotion logging also drew our attention to moments we would not have analyzed otherwise. In other words, the approach both reinforced our prior units of analysis and added to our approach to analyzing the interaction. We aim to continue this back-and-forth between qualitative methods and computational techniques as we collect data on more dyads and extract insights from other modalities.

7 Future Work

Applying computational techniques to understand ethnographic datasets has a lot of potential [4, 19, 25]. Researchers are examining means for human and artificial intelligence to interact by both bootstrapping human analysis with artificial intelligence and using human inference in the computational data analysis pipeline. As we continue collecting and analyzing data from different dyads, we will renew our pipeline and iteratively update our findings. For example, we want to correlate emotions with body positions. If we could correlate emotions to taxonomies of gestures identified in prior work [18] , then body position could also be a proxy for emotion and reveal learning windows. We aim to develop tools to integrate exploratory analyses of data captured in different modalities to better understand learning and interaction.

8 Conclusion

This paper presented a preliminary approach to augment qualitative analysis of an informal learning environment. Using techniques from multimodal learning analytics, we were able to expand our analysis of learning while participants interacted with a multitouch environment. Our methodological approach required us to extract emotions from the low-level logs of facial action units using FACET and then revisit video corresponding to particular FACET values to identify moments of high emotional stimulation theoretically implicated in learning. Working towards a whole-body analysis, we are continuing to refine our pipeline to identify proxies of learning that are useful in museums and other informal learning environments. While our use of constructivist dialogue mapping showed that the users learned during their interaction with Ant Adaption, emotional logging identified alternative moments of learning outside of our analytic framework. These approaches augment each other by creating an iterative analysis approach where computational and traditional coding feed into each other, so the machine can learn from us, and we can learn from the machine. This work has the potential to allow ethnographers in informal learning environments to leverage computational techniques without losing the depth of information that ethnographic field work captures.

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