Inferring Cognitive Behaviors from Low-level User Interactions in Games

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ABSTRACT
The study of low-level user interactions from input devices such as mice is interesting in that interactions are ultimately a reflection of cognitive processes that occur far ahead of the actual motor actions. However, the extent to which cognitive behaviors are identifiable when these interactions are observed through computer-mediated game interfaces remains an open question which I plan to answer in my dissertation. In my research, I seek to determine initial characteristics on the range and depth of behaviors that can be predicted through this indirect proxy measure. Because of their cognitive affordances, I use games as a scientific vehicle for inducing cognitive behaviors in human players. I propose the use of machine learning approaches to identify features that provide discriminatory capabilities for players under different task constraints. I then develop cognitive models to provide psychologically rooted explanations for the observed interactions. The results of my work can be used to inform games so that they are able to provide more engaging, usable, and affective experiences for their players.

Categories and Subject Descriptors
H.1.2 [**Information Systems**]: User/Machine Systems—*Software psychology*; I.2.0 [**Artificial Intelligence**]: General—*Cognitive simulation*; K.8.0 [**Personal Computing**]: General—*Games*

General Terms
Design, Human Factors

Keywords
casual games, behavior detection, input dynamics

1. OBJECTIVES AND SIGNIFICANCE

> I hypothesize that elements of cognitive behaviors in players are reflected through their interactions with input devices, and that these behaviors can be identified computationally through statistical machine learning techniques and subsequently explained psychologically using cognitive architectures.

Research in motor cognition [6, 12] indicates that actions can reveal intentions, desires, and goals, but the mechanisms to identify and explain these behaviors through actions within computer-mediated game interfaces remains an open question which I plan to answer in my dissertation. A contribution of my research is that it offers following guarantees: data collection uses conventional input devices, the data is always passively collected, the methodology is to difficult to manipulate by players, and the techniques provide *both* discriminatory as well as explanatory insight into player behaviors. Existing approaches to studying player behavior provide only a limited subset of these guarantees.

The impact of my research is that it will offer game designers and researchers an avenue for inferring cognitive behaviors through real-world game play, without the need for specialized equipment and using conventional input devices. I focus on casual games as the vehicle for obtaining my research results, as they have become popular in recent years due to social networks [15]. Such games are a platform well-suited to the study of cognitive behaviors because they provide affordances not available in general applications [14].

Using machine learning approaches, my research will identify low-level input features (e.g., mouse click position or velocity) that are sufficient for classifying players under different task constraints. Unlike surveys, low-level features are a fully passive approach to data collection. And unlike high-level metrics, such as "achievements unlocked" or "locations visited" [13], low-level motor actions are executed unconsciously [6]. My research will demonstrate that these unconscious features are difficult for players to manipulate, either accidentally or intentionally, making them a powerful tool for accurately discriminating player behavior in games.

While machine learning allows for discrimination, it is not explanatory and therefore provides little insight into why observed actions are being produced in the first place. The final component of my dissertation will augment machine learning with cognitive modeling to provide psychologically rooted explanations for observed actions. If the results of the cognitive models are inconsistent with the game designers' desired intention, these models can offer insight as to how to modify specific game elements to reconcile the differences.

To address these research challenges, I propose several user studies. I have completed the first online study, which confirms that a game environment can influence cognitive behavior to the extent that these influences are reflected in input traces. I will design a second online study to determine whether a player can be classified solely from their input traces when the player is given explicit task constraints. I will then design a third in-person study that seeks to address whether unconscious motor actions can be easily manipulated by asking players to play deceptively. Finally, I will perform a validation in which a cognitive architecture is used to develop models whose simulations are consistent with the collected input traces. The validation will offer plausible explanations for the observed actions.

2. RELATED WORK

A large body of psychophysiology research exists on studying game effects [8]. These approaches use specialized instruments to measure physiological responses to stimuli, such as pupil size and heart rate. One advantage of psychophysiology research is that they use involuntary measures, and therefore are not contaminated by answering style or observer bias [8]. The disadvantage is that these measures are not readily available for actual players once games are deployed outside of player testing.

As interactive behavior is constrained by the affordances of the input devices, a limited number of atomic operations are available for analysis. Combinations of these atomic operations, however, form *microstrategies* when input interactions are measured at millisecond resolutions [3]. Interfaces influence these microstrategies and change the way users perform tasks. Similar techniques may be used to infer behaviors.

Low-level mouse features have been used to detect user expertise, but only for GUI menu elements [5]. My approach uses mouse features without any dependencies on the underlying interface. The TRUE system combines instrumented behaviors with attitudinal, demographic, and contextual data in the game Halo 2 to assess a user's perception of difficulty [7]. I remove the dependency on survey data and rely solely on passively collected data. The use of interactions have shown initial promise in video games when applied to game pads through the examination of button pressure when correlated with arousal [16], immersion [4], and frustration [2] in players, and suggests that this work can be applied to other input modalities.

Machine learning approaches have been used to identify influential game play elements [17], but do not provide explanations for why they are important to players. Cognitive architectures have been used to create models that simulate human-level performance using controls similar to what is available to human players [9, 10]. Space Fortress, for example, was developed as a research tool for psychology in order to study complex skills and their acquisition [11]. These experiments assume that the player has no ulterior intentions. This assumption is reasonable in controlled environments, but generally unenforceable when experiments are conducted in real-world settings.

3. PROJECT PLAN

Figure 1: An online implementation of *Scrabble*. I record mouse interactions in order to discriminate between bots and humans.

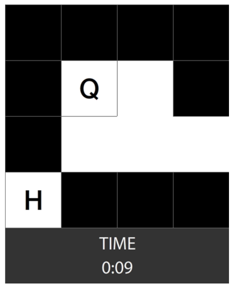

Figure 2: Concentration game with the constraint (suggested intention) of minimizing time. The player has cleared two of the tiles on the board, and has revealed the mismatched tiles Q and H.

I outline the research I have completed thus far and the direction I plan to pursue in my research in this and the next academic year.

3.1 Scrabblesque Experiments

I have developed an online version of *Scrabble*, a word game where players receive tile letters which they use to create words on a board. For the layout of the game, see Figure 1. For this experiment, I recorded mouse clicks and their associated time and position, and mouse movement position information at 20 ms sampling intervals. The results confirm that players have game-specific interactions that are unique to the particular game environment, which I call *game signatures*. Results from model fitting suggest that these user interactions are cognitively influenced and are not simply responses to external events. The work has been successfully applied to bot detection, where bots emulate actions without cognitive knowledge [1].

3.2 Concentration Experiments

Concentration is a card game in which all of the cards are laid face down and during each turn, the player turns two cards face up. The object of the game is to turn over pairs of matching cards at each turn until all of the cards are exhausted. I have conducted an online study in which players are asked to play this game under two constraints. In the first constraint, players are asked to play the game such that they minimize the time needed to clear the game board, as shown in Figure 2. In the other, players are asked to minimize mismatches without regard to timing.

A final user study will identify when deceptive play can be detected. In this variation, players are split into two groups. The first group plays the game under either the time or accuracy game constraints. The second group is also asked to play the game under these constraints, but is given the opportunity to memorize board arrangements and then play the game *as if* they had not received this information. I hypothesize that deception activates subtly different cognitive pathways that are detectable through input traces.

From the user study data, I will extract low-level mouse features as input to machine learning algorithms to classify players. I will compare the performance of these low-level features against a baseline classifier which uses the high-level features such as the number of mismatches and the time taken to complete a round. Both the feature selection and the choice of machine learning algorithms will play an important role in the effectiveness of classification. I will also investigate motif discovery or other pattern recognition techniques to identify appropriate microstrategies [3] for potential selection by cognitive models.

For validation, cognitive architectures will be used to develop cognitive models whose output can be quantitatively compared against the low-level data obtained from human players. Though actions are overt, the cognitive behaviors that elicit these actions are unobservable. However, if a cognitive model can simulate behaviors to generate actions that are consistent with the observed actions of the player, then I can infer that the behaviors selected in the model are a plausible explanation for the observed player actions, and that these observed actions are unlikely to have occurred from other cognitive processes.

4. CONCLUSION

By the end of my Doctoral research, I will have provided the following deliverables: 1. Initial characteristics for the range and depth of cognitive behaviors that can be elicited from observing low-level input interactions, 2. Computational techniques for classifying players' behaviors based on these low-level input observations, and 3. Cognitive simulations that offer plausible explanations for these behaviors.

5. ACKNOWLEDGEMENTS

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