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Towards Transferrable Affective Models for Educational Play

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Abstract

Modern computational agents in adaptive educational systems primarily rely on cognitive (i.e. curricular performance) data, while ignoring important multimodal affect cues which human tutors use to personalize their interactions with students. Students' affective responses are highly idiosyncratic, noisy, and dependent on interactive context, challenges which defy many standard assumptions of computational player modeling. As a result, recent research efforts to model student affective response have focused on specific, single-task interactions, limiting the amount and variety of affective input from an individual player.

For my thesis research, I plan to address these limitations in two ways. First, by developing a new paradigm for modeling student affective data, not as a scalar reward signal, but as a *policy label*, i.e., feedback on an agent's recent behavior, and additionally by developing transfer learning methods to apply this policy feedback data across multiple game tasks. Together, these two advances may lead to more data-efficient learning and more flexible and generalizable affective models of players.

1 Motivation and Introduction

In Neil Stephenson's sci-fi epic "The Diamond Age," a young girl named Nell is gifted an interactive device that changes her life: an 'electronic book' called 'The Young Lady's Illustrated Primer' that teaches, inspires, and coaches her through life. The book adapts its content and interacts with Nell based on her age, mood, and environment, providing her with the right content, presented in the right way, at the right time, thereby setting her on a journey towards a lifetime of learning and adventure. Not all of the futuristic technology from The Diamond Age has moved from fiction to feasible, but research on personalized, adaptive tutoring AI has progressed rapidly in recent years.

My research focuses on developing social robot tutors that can model and interact with individual students in ways similar to expert human tutors. I have primarily conducted this research in the context of a suite of educational games designed to help students practice early language and literacy skills through educational play. In recent years, our understanding of children's language development has underscored the the cognitive, affective, and social nature of language learning, suggesting that interactive agents, particularly social robots, can be an effective tool for helping children learn these skills through play-based activities.

Prior research has demonstrated that these systems can increase engagement and improve learning over long-term interactions by leveraging computational models of student's knowledge and personalizing curricular content to each student's level (Vogt et al. 2019). However, these systems typically do not incorporate the rich social channels of student affect and are designed around just a single game activity, repeated over many sessions, leading to decreased engagement over time. A major roadblock to breaking out of this single-task paradigm is the inability of current models to generalize across different learning environments and tasks. In my thesis research, I am developing an agent-based algorithmic framework that uses multimodal social signals and gameplay data to: **(1)** interactively learn affect-based agent models to promote learning and engagement; and **(2)** apply transfer learning methods to enable data and models to be shared across different tasks for more efficient and proficient learning.

1.1 Adaptive, Affective Social Robots for Education

Social robot learning companions have great potential to help promote childhood education by engaging children socially and emotionally in learning interactions. Prior research from the field of human-robot interaction (HRI) has demonstrated the efficacy of *personalization* in interactive educational play (Baxter et al. 2017), (Leyzberg, Spaulding, and Scassellati 2014). One particularly intriguing research frontier is the use of real-time multimodal data (e.g., facial expression, body posture) to detect relevant student affective states such as engagement, boredom, or frustration and guide a tutoring agent's interactive behavior (Spaulding, Gordon, and Breazeal 2016).

In educational games and other "intelligent tutoring systems" (ITS), it is primarily 'cognitive' models (i.e. models of student knowledge) that guide interaction, such as the introduction and pacing of specific curricular content. Through my research, I seek to develop more fluent and emotionally resonant interactive experiences by designing *affective* player models that are used to shape the agent's behavior during these games, for example, learning when to offer hints, encourage a student, or switch learning strategies.

An 'affective model' is simply a model of how a player responds 'affectively' or emotionally, encapsulating aspects of player mood, valence, and energy in response to particular in-game events or agent behaviors. Though affective models in adaptive games (e.g. (Lobel et al. 2016)) are still in an early stage (Yannakakis and Paiva 2014), early uses have demonstrated their potential for creating more engaging and 'resonant' learning experiences (Klopfer et al. 2018).

1.2 Prior Research

Long-term interactions are recognized by the HRI community as a necessary challenge to confront, for better science and for real-world impact (Irfan et al. 2019). Two prior studies [(Gordon et al. 2016) and (Park et al. 2019)] have demonstrated that incorporating sensed affect as a scalar input to an RL reward function used to train an agent's educational behavior can boost engagement and learning over a long-term interaction. However, these past projects also highlight the challenges of affect modeling in long-term interactions. For instance, while the model-free RL approaches in these projects have advantages in domain flexibility, treating affective data as a form of human-generated reward is generally not very sample-efficient. This in turn leads to an emphasis on modeling within a single educational task, repeated several times over the course of a long-term interaction. Affect personalization helps maintain engagement longer than non-personalized interactions, but after a few sessions we still see engagement decline, a phenomenon well-known among HRI researchers as the "novelty effect".

2 Transferrable Affective Models

2.1 Affective Policy Shaping

Instead of modeling player affect response as a scalar reward, I propose to model affect as behavior feedback label, under the framework of 'policy shaping'. Policy shaping (Cederborg et al. 2015) is a (relatively) efficient form of interactive agent behavior learning in which humans label behaviors as correct or incorrect as agents perform a task, and has been shown to help agents improve complex task learning under more realistic conditions (e.g., even when humans are inattentive or distracted (Kessler Faulkner et al. 2019)).

Human affective response, however, unlike expert policy labels, is typically ambiguous, automatic, and unconscious. It unfolds over interactive turns of several seconds — thousands of data points, sensed at a typical 30fps frequency. For an agent to use this data as a policy label, affective data must be *interpreted* after detection. As part of my thesis research, I developed a pipeline for analyzing, interpreting, and using affective facial expressions in interactive context, detailing the challenges of affect interpretation and emphasizing its distinct role in a framework for affect-aware agents. I showed that simple methods of personalization in affect interpretation substantially improve the quality of the inferred labels (Spaulding and Breazeal 2019), laying the foundation for continued research of policy shaping as an approach for modeling human affect and learning personalized affect-based behavior policies.

2.2 Affective Model Transfer

Alongside research on affective policy shaping for single-task behavior models, I propose to apply transfer learning methods to affective policy labels, aimed at using data from one interactive game task to more quickly train behavior policies in a separate game interaction. Player affect data, particularly in educational games, is highly idiosyncratic and heavily dependent on interactive context (Chen et al. 2020). As a result, many traditional approaches to personalized modeling (e.g. training on group data and fine-tuning on personalized data) are infeasible for affect-based learning applications. Instead, I propose a more direct transfer learning approach, adapting personalized affective data from one learning task to another, leveraging known structural similarities between task contexts. Specifically, I am developing an instance-weighting algorithm, transferring affective policy label data from a source task to a novel target task, with the transfer weight determined by task similarity metrics.

Due to the unique design requirements of each game interaction, the agent may have non-overlapping action sets available in each tasks. Some actions (e.g. highlighting an object or displaying content) will be unique to each game, whereas others (e.g., offer a hint, give verbal encouragement) are common to all. Transferred policy labels could help the agent start off with more accurate model of the common actions, allowing the agent to explore the impact of novel actions in familiar state spaces or familiar actions in novel state spaces while maintaining an acceptable level of interaction performance.

2.3 Planned Evaluation

I have been developing a pair of educational games designed to help students practice either rhyming and spelling. Each game features unique mechanics to elicit different behavioral data (e.g., matching or sorting) and have already been playtested or evaluated in pilot studies with students. During the final years of my PhD, I plan to finalize the system infrastructure and evaluate the policy shaping approach for affect modeling in each game individually, then evaluate the transfer learning methods and the unified system in a final study in partnership with a local elementary school in which children engage in each game activity sequentially over the course of a multi-session interaction.

My initial research questions primarily concern the effect of policy shaping and model transfer on model inference and student engagement. How does a policy shaping personalization approach affect sample-efficiency of learning, compared to more standard RL methods? How does a final model for the target game task, seeded with data from the source game task, compare to a model personalized only via the target task? By answering these algorithmic questions, grounded in educational game scenarios, I hope to advance research towards more flexible, adaptable, and efficient computational tutors.

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