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An Enactive Approach to Facilitate Interactive Machine Learning for Co-Creative Agents

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ABSTRACT

This paper introduces a novel approach to developing cocreative agents that collaborate in real time creative contexts, such as art and pretend play. Our approach builds upon recent work in computational creativity called interactive machine learning (IML). In IML, agents learn through demonstration, interaction, and real time feedback from a human user (as opposed to offline training). To apply IML to open-ended creative collaboration, we developed an enactive model of creativity (EMC) based upon the cognitive science theories of enaction. This paper introduces our enactive approach to building co-creative agents within the broader field of interactive machine learning by describing the theory, design, and initial prototypes of two co-creative agents.

Author Keywords

Computational Creativity, Creativity Support Tools, Collaboration, Cognitive Science, Human Computation

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION

The field of computational creativity can broadly be categorized into three domains: (1) *Creativity support tools* (CSTs) that enhance the creative product, such as Photoshop; (2) *Generative computational creativity* systems that autonomously produce creative artifacts, such as The Painting Fool [1]; and (3) *Computer colleagues* that collaborate with human users as a partner in the creative process [5]. Computer colleagues blend the first and second methods of computational creativity identified above to support the creative process through direct collaboration.

Collaborative creativity research points to significant benefits of collaboration for the creative process, such as inspiration, increased motivation, and synthesis of ideas [6]. Real time improvisation presents a unique collaboration context due to the continuous and varied feedback offered

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for thirdparty components of this work must be honored. For all other uses, contact the Owner/Author.

Copyright is held by the owner/author(s). *C&C '15*, June 22-25, 2015, Glasgow, United Kingdom ACM 978-1-4503-3598-0/15/06. http://dx.doi.org/10.1145/2757226.2764773 by different styles of turn taking and shared contribution. However, developing an agent that can interact effectively in open-ended creative applications is difficult due to the computational complexity of knowledge engineering and real-time adaptation.

While there are many approaches of developing co-creative agents, we selected the cognitive science paradigm of enaction that emphasizes how meaning gradually emerges through dynamic interactions and negotiations in a process referred to as sense-making. To formalize the theory, we developed the enactive model of creativity (EMC) that begins to apply this framework to model how agents dynamically co-construct meaning by using feedback to coordinate real time interactions [2]. Before we introduce our co-creative prototypes, Drawing Apprentice and PlayPartner, we will briefly introduce the field of interactive machine learning and delineate the proposed contribution of our enactive approach.

CREATIVE ARTIFICIAL INTELLIGENCE

The field of artificial intelligence and robotics still face a large unsolved problem: AI does not perform well in openended situations that required flexible adaptation [3]. The knowledge engineering requirements are too large. This problem is particularly relevant for computational creativity because collaborative creativity is perhaps the most openended domain possible.

The field of interactive machine learning attempts to mitigate this knowledge engineering bottleneck by creating agents that interact with human users and learn through demonstration, imitation, and feedback [4]. The approach advocated here extends the work being done on interactive machine learning by introducing EMC to enhance the design of interaction dynamics and feedback. Once we have a reliable method to model these features of interaction, we can potentially increase the efficiency of the interactive machine learning algorithms and increase the flexibility and robustness of co-creative agents interacting in unpredictable and open-ended creative contexts.

CO-CREATIVE ENACTIVE AGENTS

The goal of an enactive agent is to facilitate successful and compelling interaction in a real time context. This evaluation metric distinguishes our enactive approach from other IML approaches that employ interactions primarily as a method to increase the computational efficiency of the learning algorithms. The evaluation metrics for a successful co-creative agent are defined by a subjective evaluation from the user. Ideally, the human should perceive the agents as having a certain degree of competency and understanding of the creative collaboration. However, an enactive agent is not necessarily expected to 'understand' the meaning of its actions from a human perspective, i.e. the user's knowledge and the agent's knowledge are grounded in different experiences.

For the enactive agent, its knowledge of the world comes from its own set of experiences, which are strictly constrained to the input of the user, including demonstrations, interactions, and feedback. Thus, when the agent performs the appropriate action and appears to be 'creative' or 'intelligent' from the perspective of the user, the agent does not have the same type of knowledge representation as the user. Since enactive agents learn exclusively through experience, the approach advocated here includes pairing a human user with an enactive agent in a collaborative game to increase user engagement, acquire more users, and ultimately increase the creativity of the agent through human computation. Next, we describe two prototype systems employing an enactive approach to interactive machine learning.

SYSTEM DESCRIPTIONS

Drawing Apprentice is a co-creative drawing agent that collaborates with human users in real time abstract art collaboration. It learns through decomposing the user's lines, analyzing their styles, and learning the user's preferences based on the real-time interaction data. User feedback on successive interactions, such as 'liking' or 'disliking' the agent's reactions, help the agent hone its model to a level of detail and granularity appropriate for the current interaction. Since creative intentions dynamically grow and transform throughout the course of an artwork, the system's model of the user evolves dynamically throughout the course of collaboration. The Drawing Apprentice system is implemented on a web-based application shown in Figure 1.

PlayPartner is a co-creative pretend play agent that is able to dynamically define, modify, and generate actions based upon a co-constructed core activity. The system is meant to inspire, enhance and teach playful behavior to children. Similar to Drawing Apprentice, the PlayPartner employs the EMC to engage users in a process of participatory sense-making. The interactive machine learning algorithms in this system rely solely on perceptual information from the users performed actions in continuous real time interaction. The system is implemented in a virtual environment where players demonstrate play activities and interact with the system to refine and validate its knowledge.

CONCLUSIONS

This paper introduced an enactive approach to interactive machine learning. We describe two co-creative agents developed with our enactive model of creativity. This model formalizes the ideas of participatory sense-making



Figure 1: Top: Drawing Apprentice web application. Bottom: PlayPartner user interface.

in the recent cognitive science theory of enaction. Leveraging human users as a teacher and the system as a learner in these creative contexts reduces the overhead of authoring content for co-creative agent significantly. After explaining our novel approach to IML in the broader context of the field, we describe two co-creative prototype systems in the domain of collaborative drawing and pretend play.

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