Towards Modeling the Interplay of Personality, Motivation, Emotion, and Mood in Social Agents

Extended Abstract

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ABSTRACT

Creating social agents that interact in believable ways is a challenging task. The agent's emotional state must be faithfully modeled and should influence its behavior. In this paper, we introduce a computational model of affect which incorporates an empirically-based interplay between its various affective components - personality, motivation, emotion, and mood. These affective components as well as the relations between them capture a number of important mechanisms that are observable in human beings (e.g., motivation driven planning, emotional reactions, or coping) and influence the agent's decision making. Further, these mechanisms, reflected in the agent's behavior, are integral to human-human interaction and are therefore likely to contribute to improved human-agent interaction. In a preliminary evaluation of our approach, we demonstrate the impact of the various components in the model and their interaction with one another on the agent's decision making and behavior, by showing that the agent displays disparate behavior with and without the inclusion of specific components in our model.

KEYWORDS

Emotion; Mood; Personality; Motivation; Social Agents

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1 INTRODUCTION

A long-standing goal for Artificial Intelligence research has been the creation of emotionally complex, believable, and engaging agents and as these agents are given increasingly sensitive and impactful roles in society, it is important to create social agents that benefit those they interact with by utilizing human emotion. Specifically, it is challenging to create a social agent which is able to meaningfully interact with a human user via a believable mechanism that maps the agent's affective state into behavioral and cognitive changes. To facilitate the creation of such agents, the underlying computational model of affect must incorporate an interplay between its various affective components, as well as handle emotions in a way that is not foreign to a human user.

Various computational models of affect have been proposed in the past, differing in the affective components they consist of and, crucially, the interaction between their various components (e.g., [1, 3, 5–7]). However, previous work has struggled to capture a number of important mechanisms which influence behavior, either due to the insufficient modeling of each individual component of affect, or the lack of coupling between the components. E.g., while some previous work has incorporated the influence personality has on an individual's emotion and mood [5], it does not incorporate a motivational profile for the agent, nor does it include an affect-consequent model which draws a correspondence between the type of emotion experienced by the agent, and its motivations.

Our Model

In this work, we propose a computational model of affect which includes an empirically-based, interplay between the various components driving the agent's behavior, namely personality, motivation, emotion, and mood. Our proposed framework consists of the following components: a personality model, based on the Five Factor Model (FFM) [9]; a motivational model, based on Reiss' theory of 16 basic desires [14]; an emotional model, based on appraisal theory and the PAD (Pleasure, Arousal and Dominance) theory [11], where emotion and mood are differentiated and represent different temporal resolutions of the agent's affect. Crucially, we model the interplay between the aforementioned components (see Figure 1). We model the influence of **personality on the emotional state** of the agent based on research that has shown that individuals with different personality traits experience emotions differently [9]. Additionally, the model accounts for an impact of an agent's **personality on its motivation** which reflects a correlation between an individual's personality traits and the importance they assign to each of Reiss' 16 basic desires [13]. Following empirical findings that mood affects the intensity of an experienced emotion [12], our model incorporates an interaction between **mood and emotions**. Further, the agent's active emotions change its mood such that it faithfully represents this empirically-based definition of mood: "an average of a person's emotional states across a representative variety of life situations" [10]. Lastly, we model the influence of **emotion on motivation** via an affect-consequent model which is grounded in therapeutic psychological literature [8] and which allows emotions to influence the agent's motivation (which, in turn, drive its decision making). Our proposed model addresses these interactions and thereby allows to model agents with rich and believable behavior. The conceptual framework described in this paper can be used as the basis to drive other application-specific agent

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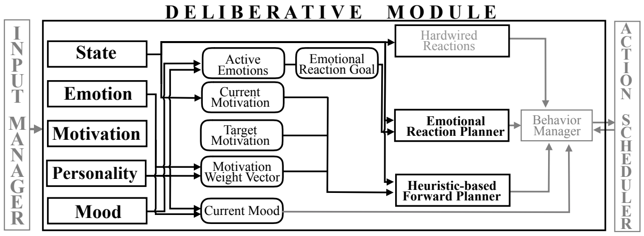

Figure 1: Overview of the model of affect, including its interactions and influence on the agents behavior generation.

architectures including story-driven agents [2] or emotion-aware embodied conversational agents [15].

Motivation-driven Planning. Human decision making, specifically our goal-oriented action selection, is affected by many different factors, with our intrinsic motivations and desires being perhaps prime among them [14]. To facilitate the idea that an agent strives to fulfill its basic desires and motivations we use a forward planner with an A* heuristic search algorithm to produce a plan π_{A^*}. The heuristic is a weighted Euclidean distance in the motivation space, where the weighting is influenced by the agent's personality and emotions, and the distance is computed based on a state-dependent current motivation and an agent specific target motivation.

Acting on Emotions. Emotions play the important function of prompting behavior in the form of reactive action urges [8]. For example, if the agent is sufficiently angry (defined by a threshold on the *intensity* of the emotion), it may be prompted to throw an object, or yell, at a nearby agent. Such behavior will be considered an action urge associated with the agent's experienced anger. To enable the agent to express its experienced emotions, we implement an emotionally reactive layer within the deliberative module which can trigger an appropriate emotional reaction, based on the emotion that requires expression and the state in which the agent is situated.

Emotion and Motivation. Following the work on DBT [8], we allow the agent's emotional state to influence its behavior by drawing a correspondence between what is implicitly communicated to the agent by its emotions, and the 16 basic desires which drive the agent's decision making and behavior. This influence is achieved by changing the weighting that is given to each motivation. Since this weighting is directly used in the heuristic of the A* planner, the resulting goal driven behavior may reflect the current emotion. Finally, this relation also allows an agent to address the negative emotion as the motivations corresponding to the emotion, importantly correspond to the underlying emotional need of the emotion.

2 MODEL ASSESSMENT

The objective of our preliminary evaluation is: (1) to showcase how different behavior can result from slightly different agent configurations, thus highlighting the benefits of our proposed model; and (2) to demonstrate the impact of the various components in the model and their interaction with one another on the agent's behavior.

To perform the evaluation, we introduce a scenario that is independently acted out by various agents. We selectively enable different interactions between the components in each of the agents' models, such that on one end there are no interactions at all, and on the other we include all interactions present in our model. The scenario is as follows: the agent is very hopeful about passing an exam it is about to take, however, it fails miserably which naturally leads to a strong feeling of disappointment. The agent then proceeds to work on a puzzle and is told that it can cheat and complete it in a fraction of the time it would normally take. We implemented this scenario in the Racket programming language [4]. The state of the agent's world, as well as its emotional state, are symbolically represented and are updated in every iteration of the system's loop. In total, the scenario's domain included roughly 100 actions, 60 state-motivation rules, and 10 objects and the planner was able to compute plans in less than 100ms of planning time.

From this preliminary evaluation, we can report on a number of interesting behavioral manifestations of our model. For instance, when simulating an agent high on the openness and agreeableness universal personality traits, the agent did not cheat when solving the puzzle, as it especially values the *honor* and *idealism* motivational dimensions. To contrast, an otherwise identical agent, except for its low openness and agreeableness, chooses to cheat since the motivational gain of succeeding may outweigh the negative impact of cheating. Next, we contrast an agent whose personality inhibits its experienced disappointment after failing the exam, thus preventing an emotional reaction, with an agent whose personality does not inhibit this reaction. Simply by assigning the latter agent a neurotic personality, it experiences negative emotions more intensely, leading to an increased number of emotional reactions on average. Finally, in an agent with the emotion-motivation relation enabled, the disappointment following the exam influences the agent's motivations and decision making. The agent is thus able to address the negative emotion as the *social-contact* motivational dimension is given additional weight. In our simulation, this leads to the agent reaching out to a fellow agent to share its disappointment.

3 CONCLUSION

We set out to create a computational model of affect, underlying an emotionally complex and believable agent. Our model incorporates a rich, empirically-based, interplay between the different components driving the agent's behavior, namely personality, motivation, mood, and emotion. The relations between the different components, specifically the way in which they influence one another, are grounded in psychological theory, with the hope of enabling a relatable and emotionally meaningful interaction with the human user. Our preliminary evaluation shows that different agents, which differ in their personality profile and in the degree of interaction between the affective components in their model, behave very differently. Rather than having the agent's behavior be driven solely by its motivations, the agent's emotional state influences its decision making via an affect-consequent model. In the future, we wish to conduct a study to evaluate the nature of interactions between our agent and a human.

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