Inducing User Affect Recognition Models for Task-Oriented Environments

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Abstract. Accurately recognizing users' affective states could contribute to more productive and enjoyable interactions, particularly for task-oriented learning environments. In addition to using physiological data, affect recognition models can leverage knowledge of task structure and user goals to effectively reason about users' affective states. In this paper we present an inductive approach to recognizing users' affective states based on appraisal theory, a motivational-affect account of cognition in which individuals' emotions are generated in response to their assessment of how their actions and events in the environment relate to their goals. Rather than manually creating the models, the models are learned from training sessions in which (1) physiological data, (2) information about users' goals and actions, and (3) environmental information are recorded from traces produced by users performing a range of tasks in a virtual environment. An empirical evaluation with a task-oriented learning environment testbed suggests that an inductive approach can learn accurate models and that appraisal-based models exploiting knowledge of task structure and user goals can outperform purely physiologically-based models.

1 Introduction

Affect recognition is the task of identifying the emotional state of an individual from a variety of physical cues, which are produced in response to affective changes in the individual. These include visually observable cues such as body and head posture, facial expressions, and posture, and changes in physiological signals such as heart rate, skin conductivity, temperature, and respiration. Affect recognition work has explored emotion classification from self reports [1], post-hoc reports [9], physiological signals [3], [7], [8], combinations of visual cues and physiological signals [2], and from world state feature representations of temporal, locational and intentional information [6]. This body of research serves as the springboard for the work described in this paper, which reports on techniques for recognizing users' affective states from both physiological and task structure information. Because affect is fundamentally a cognitive process in which the user appraises the relationship between herself and her environment [4], affect

recognition models should take into account both physiological and environmental information. For task-oriented environments, affect recognition models can leverage knowledge of task structure and user goals to effectively reason about users' affective states. In particular, for task-oriented environments, affect recognition models can use appraisal theory [5] to recognize users' emotions generated in response to their assessment of how their actions and events in the environment relate to their goals.

In this paper, we present an inductive approach to recognizing users' affective states in task-oriented virtual environments by learning affect recognition models. The models, which exploit task structure as well as physiological and environmental information, are induced from training data acquired from traces of users performing tasks in rich virtual environments. Experimental results suggest that induced models can accurately predict users' affect states, and they are sufficiently efficient to meet the real-time performance requirements of interactive task-oriented environments.

2   Affect Recognition Models

The prospect of creating affect recognition model learners that can induce empirically grounded models of affect to recognize users' emotional states from a combination of physiological data and a representation of environmental information holds much appeal. To this end, this paper proposes an inductive approach to generating affect recognition models trained to recognize user affect in runtime task-oriented environments.

2.1   The Crystal Island Testbed

To serve as an effective "laboratory" for studying user affect recognition in an interactive task-oriented environment, a testbed should pose the same kinds of challenges that affect recognition modelers are likely to encounter in future runtime environments. It should offer users a broad range of actions to perform and provide a rich set of tasks and goals in a nontrivial task-oriented virtual environment. The goals should exhibit some complexity, and the environment should be populated by manipulable artifacts and be inhabited by multiple characters. To this end, we have devised Crystal Island, a task-oriented learning environment testbed featuring a science mystery. The mystery is set on a recently discovered volcanic island where a research station has been established to study the unique flora and fauna. In the current testbed, there are twenty goals that users can achieve, three hundred unique actions that users can carry out, and over fifty unique locations in which the actions can be performed.

2.2   Model Induction

In a formal evaluation, data was gathered from thirty-six subjects.   There were 5 female and 31 male participants varying in age, ethnic group, and marriage status.[1]   After filling out a consent form and demographic survey, participants began training sessions.   The training testbed provided them with specific goals and guided them through the solution to the mystery.   Periodically a "self-report emotion dialog" box would appear requesting input from them about their affective state.   Participants were asked to select one emotion from a set of six emotions (*excitement*, *fear*, *frustration*, *happiness*, *relaxation*, and *sadness*) that was most closely related to their feelings at that particular juncture. After solving the science mystery, participants completed a post-experiment survey before exiting the training session.   During the user interaction, the following observable attributes were logged:

- *User Actions*:   Affect recognition models can observe users' actions in the world and their relationship to achieving particular goals; affect recognition models also have access to auxiliary information about the interactions, e.g., any artifacts manipulated such as which objects have been picked up or which doors have been opened, as well as the characters with whom users have interacted.
- *User Locations*:   Affect recognition models have access to a variety of information about the user's precise location in the environment and the location's relationship to achieving particular goals.
- *Temporal Information*:   Affect recognition models can observe the time user's spend on a task, the time spent in particular abstract locations (e.g., particular rooms of the environment), and the time carrying out particular actions.
- *Task Structure*:   Affect recognition models can observe the user's task progression, i.e., whether the user is completing actions that will or will not help achieve certain goals.   The affect recognition model also has access to knowledge of the explicitly stated goal in the training environment.
- *Physiological Response*:   Affect recognition models can observe users' physiological changes (blood volume pulse and galvanic skin response) in response to events in the environment, such as carrying out an action, goal achievement, or interacting with a particular agent in the environment.
- *Self-report Affective States:*   A set of six self-report emotions (excitement, fear, frustration, happiness, relaxation, and sadness) were used as class labels during training the affect recognition models.

Each training log was first translated into a full observational attribute vector. Attributes observed directly from the environment were combined with physiological response attributes and self-reported affective states.   Once the dataset was prepared, it was passed to the learning systems.   The affect data were loaded into the WEKA machine learning tool [10], a naïve Bayes classifier and decision tree were learned, and tenfold

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[1] Approximately 44% of the participants were Asian, 50% were Caucasian, and 6% were of other ethnicities.   Participants' average age was 26.0 (SD=5.4).

cross-validation analyses were run on the resulting models. The entire dataset was used to generate several types of affect recognition models. These included models that considered different sets of observed attributes, e.g., datasets with and without goal knowledge.

2.3 Results

Table 1 below reports the overall results of naïve Bayes and decision tree affect recognition models. The percentages refer to correctly classified instances. The highest performing model is a decision tree affect recognition model induced from representations of user actions, locations, task structure, and temporal information. Because participants choose from a selection of six affective states, chance is 16.7%. An additional baseline to consider is selecting the most common affective state, frustration, which appeared in 34.4% of self-reported affective states.

Table 1. Classification results for decision tree and naive Bayes models with specified datasets.

Classifier	Physiological Data Only	Goals, Actions, Locations
Naïve Bayes	56.72%	62.94%
Decision Tree	71.34%	95.23%

The results suggest that an approach to affect recognition based on appraisal theory can be effective in task-oriented environments, and that representations of user action, location, task structure and temporal information can be used to realize it in a computational model. The affect recognition models reported on here appear to capture the relationship between user actions and goals that are assessed during users' appraisal periods.

3 Conclusion

Recent advances in affective reasoning have demonstrated that emotion plays a central role in human cognition and should therefore play an equally important role in human-computer interaction. This paper has introduced an inductive approach to generating affect recognition models. In this approach, affect recognition model-learners observe training users in a task-oriented environment in which user actions, locations, goals, and temporal information are monitored. After problem-solving traces have been recorded, affect recognition models are induced that are both accurate and efficient.

In the future, it will be important to investigate affect recognition models that will enable affect-informed systems to make "early" predictions of user affect, perhaps

informing runtime components of possible undesired user emotions. Early detection would allow systems adequate time to prepare for particular affective states or to take action in an effort to ward off states such as high levels of frustration.

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