Building a Probabilistic Model of User Affect from Causes and Effects

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Research Goal

- A computational model of user emotions during interaction with a computer system

Key assumption

- Understanding user emotions (affect) helps the system interact more effectively with the user
Example: Educational Games

- Educational systems designed to teach via game-like activities

- Pros: generate high level of emotional engagement and motivation.

- Cons:
  - Often possible to play the game without understanding the underlying knowledge
  - Suitable only for certain types of learners
Possible Solution

Emotionally Intelligent Pedagogical Agents that

- Monitor how students learn from a game
- Generate tailored interventions to trigger constructive reasoning…
- …while maintaining a high level of emotional engagement

Crucial to model student affect in addition to learning
The Challenge of Modeling Affect

- High Level of Uncertainty
  - Mapping between emotions, their causes and their effects on bodily reactions can be highly ambiguous

- Especially true in the presence of
  - Multiple, possibly overlapping emotions
  - Changing rapidly

- This is often the scenario in educational games
Overview

- Our solution: a probabilistic model based on both *predictive* and *diagnostic* inference

- Our test-bed application: the Prime Climb educational game

- Design and evaluation on the predictive part of the model

- Adding physiological sensors as diagnostic components

- Conclusions/future work
Our Solution

- Explicitly deal with the uncertainty of modeling affect with a formal *probabilistic approach*
- Based on *Dynamic Bayesian Networks (DDN)*
- Integrate information on
  - *causes* of emotional reaction (*predictive* inference)
  - Their *effects* on bodily expressions (*diagnostic* inference)
Bayesian Networks - Definition

- Bayesian network: directed, acyclic graph
  - Nodes => set of random variables $X_1 X_2 .. X_n$
  - Links => probabilistic dependencies among variables
  - Conditional probabilities => quantify the dependencies

Bayesian Networks

- P(B) = 0.01
- P(J | A) = 0.70
- P(J | ¬A) = 0.05
- P(J | A) = 0.90
- P(J | ¬A) = 0.05
- P(A | B, E) = 0.95
- P(A | B, ¬E) = 0.94
- P(A | ¬B, E) = 0.29
- P(A | ¬B, ¬E) = 0.001
- P(E) = 0.02
- P(J | A) = 0.70
- P(J | ¬A) = 0.01
Bayesian Networks - Inference

**Diagnostic**
- Burglary
  - P(B) = 0.016
  - Alarm
    - P(A) = 1.0
    - JohnCalls
      - P(J) = 1.0

**Predictive**
- Burglary
  - P(B) = 1.0
  - Alarm
    - P(A) = 0.67
    - JohnCalls
      - P(J) = 0.67

**Mixed**
- Earthquake
  - P(¬E) = 1.0
  - Alarm
    - P(A) = 0.03
    - JohnCalls
      - P(M) = 1.0

Update algorithms exploit dependencies to reduce the complexity of probabilistic inference.
Dynamic Decision Networks (DDN)

- Extension of Bayesian networks to model variables with values that change over time (e.g., earthquake happening)

- Include nodes to represent decision points in addition to probabilistic events

\[ P(E_{t_i+1} | E_t) = 0.9 \]
\[ P(E_{t_i+1} | \neg E_t) = \ldots \]
DBN for Affective Model

Causes

Predictive Assessment

User goals, personality traits
world states

Emotional State

Bodily Expressions

Detectors

Diagnostic Assessment

Effects

User goals, personality traits
world states

Emotional State

Bodily Expressions

Detectors

$t_i$

$t_{i+1}$
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The Prime Climb Educational Game

Designed by EGEMS group at UBC to teach number factorization to students in 6th and 7th grade
The Prime Climb Pedagogical Agent

- Answers to students’ help requests
- Provides unsolicited hints to help students learn from the game
- Hints based on
  - A model of student learning (Manske and Conati 2005) - for now
  - AND a model of student affect – in the future
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DDN for Affective Model

Based on the OCC Theory of Emotions (Ortony Clore and Collins, 1998)

Predictive Assessment

Causes

User goals, personality traits, game states

Bodily Expressions

Emotional State

User goals, personality traits, game states

Diagnostic Assessment

Effects

$t_i$

$t_{i+1}$

Detectors
Based on the Ortony, Clore and Collins (OCC) Theory of Emotions

OCC Model: example

Admiration/Reproach

Joy/Distress

Goals

e.g., Have Fun
Learn Math
Avoid Falling
Succeed by Myself
Beat Partner

Pride/Shame

Joy/Distress

OUTCOME

action

action
DDN for the OCC Theory

Personality

Goals

Interaction Patterns

User Action Outcome

Goals Satisfied

Joy/Regret

Pride/Shame

Agent Action Outcome

Goals Satisfied

Joy/Regret

Admiration/Reproach

Personality

Goals

$t_i$

$t_{i+1}$
Model Assumptions

Two main assumptions in the model:

- Students’ goals are static
- No modeling of goal priority (goals are binary variables that are either TRUE or FALSE)
Nodes For Goal Assessment

Personality [Costa and McCrae, 1991]

Agreeableness

Extraversion

Conscientiousness

Neuroticism

Goals

Have Fun

Succeed by Myself

Learn Math

Avoid Falling

Beat Partner

Interaction Patterns

Use Mag. Glass Often

Move Quickly

Ask Advice Often

Follow Advice

Fall Often

Links and probabilities derived from data (Zhou and Conati 2003)
Sub-network for Emotion Appraisal

After student’s action

Student’s Goals
- Avoid Falling

Goals Satisfaction
- Avoid Falling Satisfied
- Succeed by Myself Satisfied
- Beat Partner Satisfied
- Have Satisfied
- Learn Math Satisfied

Emotions
- Joy/Distress
- Pride/Shame
- Admiration/Reproach

Have Fun
- Satisfied
DNN for the OCC Theory

- Personality
- User Action Outcome
- Goals Satisfied
- Joy/Regret
- Pride/Shame
- Interaction Patterns

Agent Action Outcome
- Personality
- Goals Satisfied
- Joy/Regret
- Admiration/Reproach

$t_i$ and $t_{i+1}$
Sub-network for Emotion Appraisal

(2)

After agent’s action

Agent’s actions

- Congratulate
- Hints to recover from fall
- Reflect on success

Student’s Goals

- Succeed by Myself
- Have Fun
- Learn Math

Goals Satisfaction

- Succeed By Myself Satisfied
- Have Satisfied
- Learn Math Satisfied

Emotions

- Joy/Distress
- Pride/Shame
- Admiration/Reproach

Satisfied

Learn Math
Refinement and Evaluation of the Predictive Model: User Study

◆ Primary goal – refine the appraisal part of the model

◆ 60 students from Vancouver schools:

◆ Take a personality test

◆ Each plays an individual game session for 10-15 minutes.
  – Interact with an experimenter as a partner (no Wizard of OZ)
  – Agent intervenes based on a model of student learning during game play (Manske and Conati 2005)
Refinement and Evaluation of the Predictive Model

- Initial predictive model runs during the interaction,
  - Not used to direct agent’s interventions.

- Students report their feelings towards the game and the agent during the session.
  - Model predictions at these times are logged

- Answer post-questionnaires on:
  - their goals
  - which student and agent actions influence HaveFun and LearnMath
Emotional Reports (Conati ADS ‘04)

- Self-report box pops up when either one of the following holds:
  - The affective model predicts a change in the student affect.
  - A given amount of time lapsed without a self-report.
Changes to the Model

After student’s action:

- Move Successful
- Ahead of Partner
- Beat Partner
- Big Number

Student’s Goals:
- Avoid Falling

Goals Satisfaction:
- Avoid Falling Satisfied
- Succeed By Myself Satisfied
- Beat Partner Satisfied
- Have Satisfied
- Learn Math Satisfied

Emotions:
- Joy/Distress
- Pride/Shame
- Admiration/Reproach
Changes to the Model (cont.)

After agent’s action

Agent’s actions

• No Action
• Congratulate
• Hints to recover from fall
• Reflect on success

Move Successful

Want Help
Succeed by Myself

Want Help Satisfied
Succeed By Myself Satisfied

Have Fun
Learn Math

Learn Math Satisfied

Have Satisfied

Joy/Distress
Pride/Shame
Admiration/Reproach

Satisfied

Want Help

Move Successful

Successful

?
Evaluation of the New Diagnostic Model

A Prime Climb simulator is run with:

- The diagnostic model with the refined appraisal network
- The log-files from the study
  - we can do it because the affective model is not used during the interaction
- New model predictions are recorded in correspondence to the previous students self-report
- Accuracy computed through 3-fold cross validation
  - 2/3 of the data is used to train the model CPTs (training set)
  - 1/3 is the test set: how often model agreed with self-reports
  - Repeated 3 times
We are doing pretty well, but for Reproach

- Priority of goal Want Help seems to change during the interaction
- Depends on individual traits that we are currently unable to detect
We do pretty well with diagnostic assessment only, but there are limitations, as to be expected

- Hard to accurately assess some of the goals, especially when they change during interaction
- We cannot classify any point with “neutral” self-reports, because the predictive model cannot detect lack of emotional arousal

Can we do better by adding diagnostic information on subjects emotional reactions?
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DDN for Affective Model

Causes

Predictive Assessment

Student goals, personality traits, game states

Predictive Assessment

Emotional State

Bodily Expressions

Detectors

$\text{Emotional State}$

$\text{Bodily Expressions}$

$\text{Detectors}$

$t_i$

$t_{i+1}$

Student goals, personality traits, game states
Long term goal: integrate multiple detectors: physiological sensors, face and intonation recognition…

Current focus: physiological sensors

- Electromyogram (EMG) to discriminate positive vs. negative affect
  » thus improve model accuracy overall, and for Reproach in particular

- Skin Conductance (SC): to assess arousal, currently not modelled in the causal part
Research Question

◆ What can we get from physiological sensors in recognition of
  – Multiple emotions
  – Expressed spontaneously

◆ Most previous work:
  – General arousal and valence, or one specific emotion
  – Multiple emotions expressed on demand
EMG Analysis: Previous Findings

- EMG on the forehead detects activity in the corrugator muscle
- Connections between this activity and affective valence (Cacioppo 1993)
  - greater activity is a reliable indicator of negative affect
  - reduced activity is an indicator of positive affect
User Study on Physiological Sensors

- Similar design as before, 41 subjects (from 6th and 7th grade)
- But this time subjects played Prime Climb while connected to EMG and SC sensors

- Log files included readings from these sensors
Mapping Signals to Affective Reports

Set of data points: <student report, signal prediction>

*student report* – Valence from student’s report of emotions towards game and agent.

*signal prediction* - created from 4 seconds recorded after most recent game event.
Translating Affect Reports to Valence

<table>
<thead>
<tr>
<th>Valence</th>
<th>Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clear Positive</td>
<td>2 positive answers, 1 strongly positive, 1 neutral</td>
</tr>
<tr>
<td>Clear Negative</td>
<td>2 negative answers, 1 strongly negative</td>
</tr>
<tr>
<td>Mild/Mixed</td>
<td>Everything</td>
</tr>
</tbody>
</table>

We did our analysis with Clear Positive to start with because it should produce clearer results.
Translating EMG signal to Valence

$T_{EMG} = \text{mean of entire EMG recording.}$

$\text{Mean (4 secs)} \leq T_{EMG} \quad \rightarrow \quad \text{positive valence}$

$\text{Mean (4 secs)} > T_{EMG} \quad \rightarrow \quad \text{negative valence}$
Adding EMG Evidence to the Model

Causes

User Traits

Goals

Interaction Patterns

User Action Outcome

Goals Satisfied

Emotional States

Overall Valence

Signal prediction

Effects

diagnostic assessment

predictive assessment

CPT for Signal Prediction|Valence is derived from frequencies in our datapoints

\( t_i \)

\( t_{i+1} \)

Overall Valence

Signal prediction

Effects
Adding EMG to the model

<table>
<thead>
<tr>
<th>EMG prediction</th>
<th>Affect report</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pos</td>
</tr>
<tr>
<td>Pos</td>
<td>33</td>
</tr>
<tr>
<td>Neg</td>
<td>41</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>EMG prediction</th>
<th>Overall Valence</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pos</td>
</tr>
<tr>
<td>Pos</td>
<td>0.48</td>
</tr>
<tr>
<td>Neg</td>
<td>0.52</td>
</tr>
</tbody>
</table>

Emotional State

Overall Valence

EMG prediction
Evaluation of the Combined Model: Clear-valence Data Points

- Run the simulator on the combined model with log files from the study
- 3-fold cross validation, using only datapoints with clear valence
  - 2/3 used to train the CPT for Signal Prediction|Valence
  - 1/3 used for testing the model prediction over specific emotions (joy/distress, admiration/reproach)
<table>
<thead>
<tr>
<th>Emotion</th>
<th>Accuracy (%)</th>
<th>Total number of Data Points</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Causal Model</td>
<td>Combined Model</td>
</tr>
<tr>
<td>Joy</td>
<td>75.87</td>
<td>77.82</td>
</tr>
<tr>
<td>Distress</td>
<td>25</td>
<td>75.00</td>
</tr>
<tr>
<td>J/D Combined</td>
<td>50.43</td>
<td>76.41</td>
</tr>
<tr>
<td>Admiration</td>
<td>77.17</td>
<td>82.66</td>
</tr>
<tr>
<td>Reproach</td>
<td>52.22</td>
<td>72.22</td>
</tr>
<tr>
<td>A/R Combined</td>
<td>64.70</td>
<td>77.44</td>
</tr>
</tbody>
</table>

- Encouraging evidence that EMG can help model assessment of individual emotions with clear overall valence
Evaluation of the Combined Model: Mixed/Mild Valence Data Points

- 3-fold cross validation using
  - Only clear valence data points in training set to learn the CPT for Signal Prediction|Valence
  - Only Mixed/mild valence data points in test set for computing accuracy
## Evaluation of the Combined Model: Mild/Mix Valence Data Points

<table>
<thead>
<tr>
<th>Emotion</th>
<th>Causal Model</th>
<th>Combined Model</th>
<th># Data Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joy</td>
<td>83.52</td>
<td>67.49</td>
<td>↓ 51</td>
</tr>
<tr>
<td>Distress</td>
<td>51.11</td>
<td>40.00</td>
<td>↓ 15</td>
</tr>
<tr>
<td>J/D Combined</td>
<td>67.31</td>
<td>53.75</td>
<td>↓</td>
</tr>
<tr>
<td>Admiration</td>
<td>67.35</td>
<td>72.12</td>
<td>↑ 28</td>
</tr>
<tr>
<td>Reproach</td>
<td>32.42</td>
<td>16.77</td>
<td>↓ 33</td>
</tr>
<tr>
<td>A/R Combined</td>
<td>49.89</td>
<td>44.44</td>
<td>↓</td>
</tr>
</tbody>
</table>

- One EMG on forehead is not so useful in helping with the assessment of mixed or mild emotions.
- May need to use more than 1 EMG on forehead, and/or integrate it with other sensors, i.e. vision for expression recognition.
Mixed Valence

Suggestion: Valence and EMG prediction nodes should include a ‘neutral’ value.

Positive/Negative Valence forces J/D and A/R to have the same valence.

Evidence from EMG signal forces Valence node to be positive or negative.
Analysing SC

◆ We also did a preliminary analysis of Skin Conductance (SC) to detect affective arousal

◆ Did not get good results:
  - SC analysis may be affected by the fact that our self-reports do not gauge arousal directly =>
  - hard to get sound training set.
Conclusions

- Probabilistic model of user affect
- Deals with task uncertainty by
  - using formal probabilistic approach
  - integrating causes and effects
- Built iteratively from design and evaluation
- Inclusion of diagnostic EMG evidence
- Achieves very good performance on Clear valence data points
Future Work

- Add second EMG sensor on forehead
- Investigate SC after getting reliable self-reports for arousal
- Integrate model of affect and model of learning
- Add animations and gestures to the agent
- Create decision theoretic agent that takes into account both student affect and learning to decide how to act