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Modeling What Happens Between Emotional Antecedents and Emotional Consequents

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19 April 2006

Introduction

- This is, unfortunately, NOT a inspiring, visionary closing talk
- This is a down-and-dirty, nuts-and-bolts, lessons-learned talk
  - With some bad math thrown in to boot (but no Pac-Man)
- I am as much looking for advice as I am offering it as I cannot keep up on the psychology literature as much as I would like and would love pointers to good resources
- As I will discuss, I am primarily interested in external realism
  - I use psychology as a source of useful ideas
  - But I fill in solutions as needed
    - Nobody really explains how to build multiple, social, resource-constrained agents with large numbers of semi-incompatible goals that live in complex, temporally extended, realtime environments with other interacting agents
  - Maybe these are interesting starting points for psychology?

A Bit of History

- Oz Project, Carnegie Mellon University, 1989-1996
  - Believable agents (interactive characters) for interactive art and entertainment
  - Designed and built original Em emotion modeling architecture for real-time, reactive, autonomous agents
- Zoesis Studios, 1996-2005
  - Believable agents for web-based entertainment and advertising
  - Believable agents for location-based entertainment
  - Believable agents for social and emotional learning products
    - Computer games that teach social skills and emotional intelligence to children
  - Rebuilt Em for greater efficiency and additional functionality
- Charles River Analytics, 2005-present
  - Lifelike agents (externally realistic) for training, procedure acquisition, mission rehearsal (mostly military)
  - Incorporating Em ideas into existing SAMPLE agent human-behavior-modeling architecture

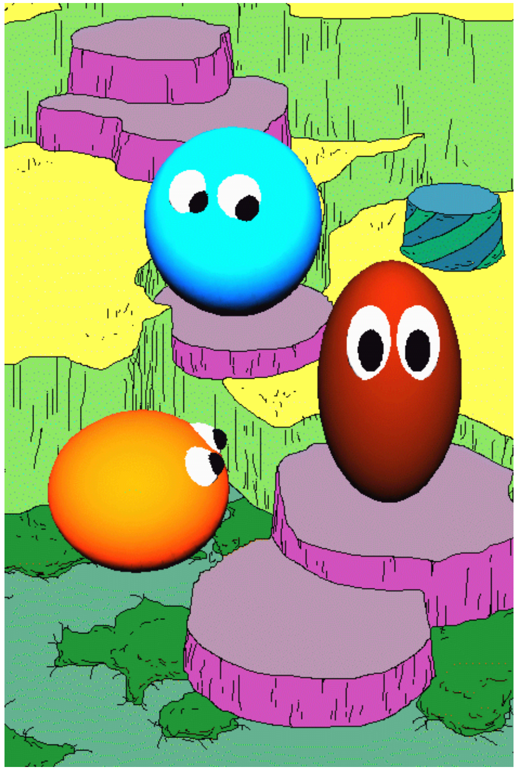
The Em Approach to Emotion Modeling

- Cognitive accuracy is a great and noble goal, but largely unachievable at this point. And there are interesting things to be done while we are waiting!
- I am going (as much as possible) for behavioral fidelity
  - I have found modeling plausible cognitive underpinnings of behavior a useful approach to doing so
  - I use a variant of the Ortony, Clore and Collins cognitive appraisal model as the default model
  - We can often get away with high-level cognitive plausibility where cognitive accuracy (esp. low-level accuracy) is unachievable
- Also interested in authorability
  - Need to be able to build emotional agents at reasonable cost
  - Sometimes need to trade off complexity and fidelity for usability
    - E.g., Em uses an explicit representation of emotions even though there is a good chance it is more accurate to model emotions as emergent properties of complex systems (Sloman)

Believable Agent Demos

- Mr. Bubb [MOVIE] (Can demo after talk)
- The Demon and the Princess [MOVIE]
  - Mr. Bubb and the Demon have hundreds of simultaneous goals and roughly a dozen simultaneous emotions in some cases






Lifelike Agent Examples

- MINDS (Modeling INdividual Differences and Stressors) Project
  - Modeling affect and other behavior moderators
  - Tactic and training development and testing for U.S. Army
  - Integrated within Charles River Analytics' SAMPLE (Situation Awareness Model for Person-in-the-Loop) Agent architecture within the U.S. Army's Infantry Warrior Simulation (IWARS)

Talk Motivation

- There has been significant work understanding…
  - How emotions arise (antecedents)
  - What effects emotions have (consequents)
- There has been less work focused on understanding what happens in between the recognition of an emotional situation and processing the effects of the emotion
  - E.g., combining multiple emotions, emotional decay, etc.
  - This is especially true in the computational modeling literature
    - Hypothesis 1: More important problems to be addressed first
    - Hypothesis 2: Simple agents in simple situations have allowed simple solutions
    - In any case, as agent models and environments become more complex we need to address these issues more directly
- Talk will present a few such emotion-modeling challenges, potential pitfalls, and a first-pass at solutions
  - Recall focus: authorability, usefulness in creating behavioral fidelity

1. Representational Structures

- How do we represent emotions? What data structures do we use?
- I have found a useful set to be:
  - *Type*, *Intensity*, Direction, External Cause, Internal Cause
  - E.g., "Very angry at Bob because he grabbed the last apple and I wanted it."
- Probably need a number more
  - Expectedness? Other appraisal variables?
  - They are there for a reason. You are going to need them, especially as we move towards language generation. Save them.

Emotion Effects Based on Elements of Emotion Structures

- Enables specificity in the expression based on each
  - Type: cry when sad, smile when happy
  - Intensity: cry when a little sad, bawl when more sad, withdrawn when most sad
  - Direction: angry at Bob then glare at Bob, not Sue (BF plug)
  - Internal Cause: Test leads to fear of failing in studious student and fear of missing football game in less studious student (same external cause, different internal causes)
  - External Cause: Fear of mugger leads to handing over wallet and fear of bear leads to playing dead (same internal cause [self-preservation threat], different external causes)

2. Computing Joy and Distress Intensity

- How intense is joy (and, thereby, joy expression)?
- Appraisal model: joy = desirable event occurs
  - Some intensity factors to consider (common in computational modeling)
    - Expectation of event occurring
    - How desirable/undesirable the event is based on comparison against desires/goals
- Some desirable traits in an intensity model for joy/distress (common pitfalls):
  - Unexpected events are more intense emotionally
    - Receive unexpected bonus vs. anticipated bonus
  - Incremental joy/distress as event becomes more likely
    - Learn that you are leading candidate for position leads to joy even though the actual hiring event has not yet happened
  - Asymmetry in success and failure
    - Loss aversion (Kahneman & Tversky)

Proposed Em Intensity Model

- Joy_intensity = desirability * Δlikelihood_of_success
- Distress_intensity = undesirability * Δlikelihood_of_failure

- These provide:
  - Unexpectedness leads to higher intensity
    - Greater delta leads to greater intensity
  - Incremental joy and distress
    - Based on delta in likelihood, not success/failure
  - Ability to create asymmetry in joy and distress
    - Desirability and undesirability are separate variables

- These are not right, but they have proven to be useful in behavior-level modeling (and maybe make a good starting theory)

3. Combining Intensities

- There are many cases where we want to compute the overall emotional intensity resulting from a number of distinct emotions
  - Group by type: *how angry am I?*
  - Group by direction: *how angry am I at Bob?*
  - Group by internal cause: *how scared am I that I will be hurt?*
  - Semi-arbitrary groupings:
    - *How good a mood am I in?* (group all joy/hope/etc. emotions)
    - *How emotionally aroused am I?* (group fear/anger/joy/etc. emotions)
- But, how can the intensities of such emotions be combined to answer such questions?
  - If I am angry because Bob hit me (intensity=0.6) and angry because I lost my homework (intensity=0.4), how angry am I?

Features of Intensity Combination

- Some desirable features of a combination function (common pitfalls):
  - Not strictly additive
    - 0.3 + 0.3 + 0.4 does NOT equal 1.0
    - I.e., do not use ADD
  - Multiple emotions should each play some role
    - 0.5 + 0.5 does NOT equal 0.5
    - I.e., do not use MAX
  - Results should be at least as intense as most powerful emotion
    - 0.5 + 0.3 does not equal 0.4
    - I.e., do not use AVG

Two Proposals

- Logarithmic combination (Em uses base 2)
  - 2+2=3 (0.5+0.5=0.6)

$$0.1 \times \log_2 \left(\sum_{em} 2^{10 \times \text{intensity}(em)} \right)$$

  - Linear near 0, less so as approaching 1.0
- Sigmoidal combination (Picard)
  - Flat near 0 and 1.0, linear near 0.5

- Both meet all requirements from previous slide
- Neither has experimental support (as far as I know)
- First has been field tested (not sure about second)

Results

- User studies
  - CMU, Zoesis: NFO, Ad research, Focus groups
    - NFO (Honey Nut Cheerios; n=141; ages 5-12; 5-day delay)
      - brand appeal: 29%→42%; 45% increase vs. -1%
      - purchase intent: 3%→10%; 233% increase vs. 0%
    - McDonalds, Krispy Kreme, Popsicle, Heinz
      - McDonalds: +45% brand appeal; +38% purchase intent (n=555)
      - Krispy Kreme (14+): +29% BA; +70% PI (n=301)
- Anecdotal
  - Rachael, Navy cadets, Web surveys, Museum
- Expert testimony (Disney, Pixar)
- Money (Fujitsu, ATP, Heinz, Disney)
- Awards: MIMC Best Technology 2001