

Modeling Emotion within Symbolic Cognitive Architectures

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Abstract

We describe a generic approach for modeling the impact of emotion on cognition, perception, and behavior. The approach can model the effects of transient emotional states, longer moods, and stable personality and temperamental factors. The underlying assumption is that one of the primary ways in which emotions influence cognition and perception is by modulating a variety of processing parameters. We illustrate the approach in the context of both a generic integrated architecture of cognition, and a specific architecture, currently under development, designed to model decision making behavior. In this context, we illustrate how the approach would be instantiated within several representational formalisms (e.g., rules, belief nets). We focus on modeling the impact on tactical decision-making of three specific emotional states that have been studied extensively in experimental psychology: anxiety, negative affect (e.g., depression), and obsessiveness. The proposed approach can then be used both for investigating the interaction between cognition and emotion, and the resulting behavior, and for modeling specific types of personalities in interactive environments.

Introduction

Although central to human development and functioning, emotions have, until recently, had a somewhat marginal status in both cognitive science and neuroscience. The study of emotions was generally equated with such ineffable phenomena as qualia and consciousness, and it was not clear how these problems could be addressed or in what way the study of emotions could help elucidate the nature of human behavior and information processing.

Over the past 10 years, however, important discoveries in neuroscience and experimental psychology have contributed to an interest in the scientific study of emotion. A growing body of evidence from neuroscience research points to the existence of circuitry processing emotionally-relevant stimuli (i.e., stimuli that threaten or benefit the survival of the organism or its species) (LeDoux 1987). Cognitive psychologists have described a variety of appraisal processes involved in inducing a particular emotional state in response to a situation (Lazarus 1991) and several models have been proposed

(Ortony et al. 1988), some of which have been implemented in computational models (Reilly 1996; Scherer 1993; Bates et al. 1992). Cognitive and clinical psychologists have observed the differential impact of various emotional states on cognition; for example, increased attention to threatening stimuli in states of anxiety, increased elaboration of material in positive affective states, and the general phenomenon of mood-congruent recall (Williams et al. 1988; Mineka and Sutton 1992; Bower 1981; Blaney 1986; Isen 1993). This research provides evidence for the impact of emotion on cognitive processing and the central role of emotion in the control of behavior. The emerging findings also begin to blur the distinction between what has traditionally been thought of as the separate realms of cognition and emotion.

Recent research in emotion in both psychology and neuroscience has thus established that emotion is intricately linked with what has been traditionally thought of as purely cognitive functions; that is, attention, perception, memory, planning, learning, etc. It is now increasingly recognized that in order to fully understand cognitive processing and behavior, we must understand the nature and mechanisms of emotion.

Computational modeling represents a good approach for studying the mechanisms of emotion in general, and the interaction of emotion and cognition in particular, by providing the means of testing hypotheses generated from neuroscience and experimental psychology in terms of concrete, testable, computational implementations. The modeling approaches also provide a means of operationalizing high-level constructs generated by more theoretically-oriented psychological research. By building models which can define and test hypothesized mechanisms underlying emotion, cognitive modeling can play a unique and valuable role in furthering emotion research, and in contributing towards understanding of human information processing and behavior, both adaptive and maladaptive.

In this paper we describe a generic approach for modeling the impact of emotion on cognition, perception, and behavior. The approach can model the effects of transient emotional states, longer moods, and stable personality and temperamental factors. The underlying assumption is that one of the primary ways in which

emotions influence cognition and perception is by modulating a variety of processing parameters. We illustrate the approach in the context of both a generic integrated architecture of cognition, and a specific architecture, currently under development, designed to model decision making behavior. In this context, we illustrate how the approach would be instantiated within several representational formalisms (e.g., rules, belief nets). We focus on modeling the impact on tactical decision-making of three specific emotional states that have been studied extensively in experimental psychology: anxiety, negative affect (e.g., depression), and obsessiveness. The proposed approach can then be used both for investigating the interaction between cognition and emotion, and the resulting behavior, and for modeling specific types of personalities in interactive environments.

Impact of Emotional States on Cognitive Processing and Behavior

In this section we first provide a brief review of recent research in the impact of emotion on cognitive processing and behavior, and outline a set of parameters which could serve as candidates for modeling emotional states. We then provide examples showing the impact of these states on specific real-time planning and tactical decision-making.

Empirical Evidence

A number of studies in cognitive and experimental psychology have documented the differential impact of various emotional states on cognition. Three affective states and traits have been studied extensively: anxiety, obsessiveness, and depression, and the findings of these studies are briefly summarized below and in table 1.

Anxiety and Attention

- Narrowing of attentional focus
- Predisposing towards detection of threats

Mood and Memory

- Mood-congruent recall-an affective state induces recall of similarly valenced material

Obsessiveness and Performance

- Delayed decision-making
- Reduced ability to recall recent activities
- Narrow conceptual categories

Affect and Judgment & Perception

- Depression lowers estimates of degree of control
- Anxiety predisposes towards interpretation of ambiguous stimuli as threatening

Table 1: Impact of Emotion on Cognition

Anxiety The primary impact of anxiety is on attention. Specifically, anxiety narrows the focus of attention, predisposes towards the detection of threatening stimuli, and predisposes towards the interpretation of ambiguous stimuli as dangerous (Williams et al. 1997; Mineka and Sutton 1992).

Obsessiveness A number of studies have documented the impact of high-obsessiveness, characterized by "checking" behavior, on cognitive processing. Among the primary effects identified are the following: lack of confidence in own attention apparatus to capture salient features in the environment (Broadbent et al. 1986); narrow conceptual categories (Reed 1969; Persons and Foa 1984); poor memory for previous actions and a general lack of certainty about own ability to distinguish between events that occurred vs. those that were planned or imagined (Sher et al. 1989), and slower decision-making speed related to obsessive gathering of confirming information (Sher et al. 1989).

Depression The primary impact of depression is on memory, with the best documented phenomenon being mood-congruent recall (Bower 1981; Blaney 1986); that is, the observation that a particular affective mood induces recall of similarly valenced memories (e.g., depressed mood enhances recall of negative experiences and events in the past, including negative self-appraisals). Depression has also been studied in the context of particular inferencing tasks, such as judgment and decision-making. In these tasks depression appears to lower estimates of the degree of control (Isen 1993).

The research summarized above provides evidence for the ubiquitous impact of emotion on cognitive processing, and the central role of emotion in the control of behavior. The emerging findings also begin to blur the distinction between what has traditionally been thought of as the separate realms of cognition and emotion.

Impact of Emotions on Tactical Decision-Making

To illustrate the approach in a concrete context, we now briefly outline the impact of selected affective states on tactical decision-making; specifically, we focus on the different phases and aspects of decision-making of a Army platoon leader during mission planning. The scenario for this mission is described elsewhere (Pew & Mavor 1998). Table 2 summarizes examples of specific impacts of the selected emotional states on the platoon leader's decision making.

Overall Situation Analysis

- Depressed state induced by general combat stress level can induce recall of previous failures and bias against the considerations of otherwise suitable course of action alternatives

Situation Estimate and Course of Action Development

- Depressed leader may overestimate likelihood of losing critical equipment (e.g., helicopters), and may either not employ appropriate units, or may construct an overly-cautious plan
- Obsessive leader may micro manage his staff, thus creating bottlenecks during the planning process.
- Anxious leader may overestimate danger potential and choose an overly conservative course of action
- Obsessive leader may rehearse more thoroughly, thereby increasing chances of mission success

Plan Monitoring and Execution

- Anxious leader may interpret a ambiguous signals as the approaching enemy and fire too early, thus betraying platoon's position or risking fratricide
- Low-anxiety leader may fail to react to warnings due to high risk tolerance, putting personnel at greater risk
- Obsessive leader may not trust incoming data about approaching enemy and wait too long before initiating action

Table 2: Examples of Specific Emotions and their Impact on the Mission Planning Process

Generic Methodology for Modeling Emotions in Symbolic Cognitive Architectures

Early analytical, parametric, output-oriented models of cognition and performance allowed only stochastic perturbations of output behavior variables, such as speed or accuracy. These models generally did not provide adequate scope or parameter resolution within which to represent the individual differences behavior moderators discussed above. In other words, the human behavior representation within these models did not provide sufficient breadth to allow for an effective representation of individual variations in intelligence, skill level, and personality.

In contrast to the early modeling methods, recent modeling approaches allow more finely-tuned alterations of information processing via a number of parameters influencing specific cognitive modules or processes; e.g., perception, attention, memory, inferencing, and learning. This is particularly the case for integrated symbolic architectures such as Soar (Newell 1990) and ACT (Anderson 1983), but also for earlier parameterized models such as Model Human Processor (MHP) (Card et al. 1986). A number of more recent modeling efforts also

fall within this category (Hudlicka 1994; Hudlicka et al. 1992; Zacharias et al. 1996). These models typically consist of a number of modules and processes that either already are parameterized, or lend themselves to be parameter-controlled (e.g., in MHP, parameters control both the capacity and speed of access and decay of various memory stores; in ACT, parameters control the individual node thresholds in semantic memory and the speed of spreading activation).

In addition to parameter-controlled processing, symbolic cognitive architecture models also lend themselves to modeling emotional states, moods, and temperamental and personality factors in terms of the model structures (e.g., memory organization and content), represented in the knowledge-bases of the architecture components. For example, the type and number of rules in Soar, and the type and number of semantic network nodes in ACT, can be tailored to encode specific types of domain knowledge and individual history, with associated affective valence, and thereby generate different types of model behavior.

Table 3 lists examples of modeling parameters and model features that can be used to represent emotion-induced variations in these types of cognitive architectures. The space of possible behaviors defined by these parameters can accommodate the wide variability of behaviors due to specific emotional states, and the interaction of these states with a particular situation. As such, these modeling parameters provide an effective means of representing the impact of a variety of emotions and emotional states on behavior, including transient states, longer lasting moods, and more or less permanent temperamental and personality factors. This capability can then be used both for investigating the interaction between cognition and emotion, and the resulting behavior, and for modeling specific types of personalities in interactive environments.

To summarize, the behaviors described in table 2, and additional emotion-induced behaviors, can be modeled within a cognitive architecture in two primary ways:

- By manipulating the architecture structures, to reflect the desired characteristics; e.g., by constructing the memory modules in such a way that the desired behaviors can be generated.
- By manipulating the architecture processing parameters, to reflect a particular emotional orientation or emotional state, thereby biasing the architecture behavior in a particular direction.

This general approach is illustrated in figure 1.

Attention
Scan speed; Ease of engagement / disengagement
Scan intensity; Selectivity
Memory
<i>Content</i>
Degree of conceptual complexity and differentiation
Type and size of memory units
<i>Retrieval</i>
Speed and accuracy of retrieval
Divergent vs. convergent search
<i>Organization</i>
Type of internal structure (e.g., hierarchy, causal model)
Level of interconnectivity among knowledge units
Perception
Specificity of matching
Speed of detection and matching processes
Inferencing
<i>Generic</i>
Speed of inferencing; Decay of activated units
<i>Specific</i>
Meta-cognitive inferencing; What-if simulation
Causal analysis; Data-driven vs. goal-driven processing
Recall vs. derivation of required data

Table 3: Cognitive Architecture Parameters and Features Capable of Modeling Impact of Emotions on Cognition

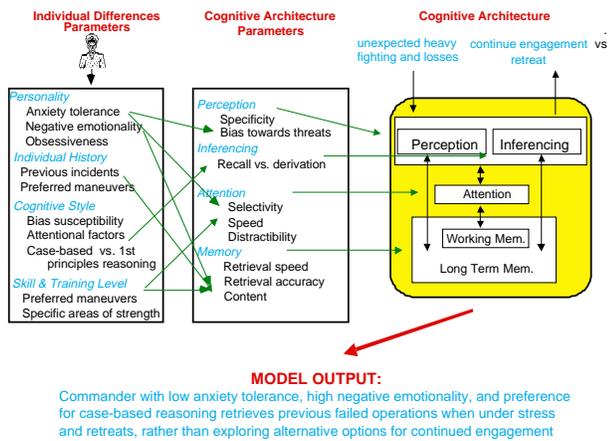


Figure 1: Summary of Proposed Approach for Representing Emotions within a Generic Cognitive Architecture

Modeling Emotions within Specific Representational Formalisms

We first illustrate the approach in the context of two well known cognitive architectures: Soar and ACT. We then illustrate the approach within a cognitive architecture for modeling decision-making currently under development: the SAMPLE architecture (Zacharias et al. 1996). SAMPLE consists of several modules using a variety of

representational formalisms (e.g., Bayesian belief nets, rules, scripts), which will allow us to demonstrate the applicability of the proposed methodology across a variety of representational and reasoning formalisms.

Modeling Emotions within Soar and ACT

Both Soar and ACT are well-suited for modeling the impact of emotion, both in terms of structure and processing. Modeling emotions in terms of structure (i.e., domain knowledge) can be accomplished by varying the type and number of operators (i.e., rules) or nodes with a particular affective content (e.g., likely to trigger anxiety, likely to interpret a signal as threatening, etc.). Modeling emotions in processing can be accomplished by varying the following components of these two architectures:

- Capacity of working memory (i.e., maximum number of rules in working memory).
- Degree and nature of rule or node interconnectedness within Soar and ACT long-term memory, which impacts mood-congruent recall.
- Accuracy, speed, and bias of rule matching process, which influence processing at any point in the computational cycle by influencing: 1) problem space/rule selection; 2) state selection; and 3) operator selection.
- Relative proportion of automatic and controlled processing determined by defining the proportion between elaboration and decision phases in rule selection.
- Speed of spreading activation through semantic memory as determined by node thresholds and link strength.
- Accuracy and speed of matching between nodes in declarative memory and rules in procedural memory by varying the parameters controlling: 1) degree of match; 2) production strength; 3) data refractory period; 4) specificity; and 5) goal dominance.
- Degree of goal-directed processing by varying the ability of goals to provide/maintain node activation.

Modeling Emotion within the SAMPLE Architecture

We now illustrate the proposed approach in the context of a cognitive architecture currently under development: the SAMPLE architecture (Zacharias et al. 1996).

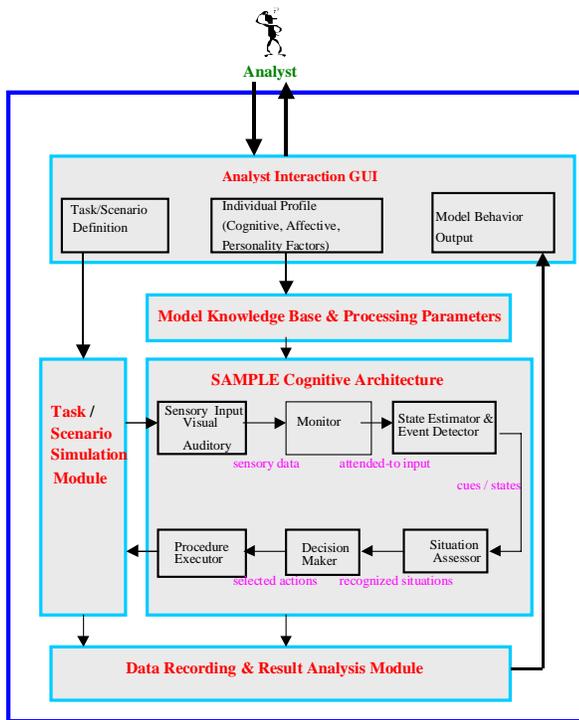


Figure 2: SAMPLE Cognitive Architecture Modeling Decision-Making Integrated within a Testbed Simulation Environment

This architecture, illustrated in figure 2, is designed to model tactical decision-making and consists of the following modules: monitor, state estimator and event detector, situation assessor, decision-maker, and procedure executor. The architecture includes several representational formalisms and as such represents a good testbed for demonstrating how the proposed approach can be instantiated within a number of specific representational systems. We now describe two of these modules in detail and illustrate how they model the impact of specific emotional states.

Monitor The monitor module selects a specific sensory input for processing and functions as an attention process. This module is implemented as a collection of procedures whose primary function is to make specific information from environment available to the state estimator and event detector module. Parameters controlling the monitor behavior include the following:

- Structure parameters: Orientation towards particular content (e.g., threatening stimuli);
- Process parameters: Scan speed, time required for engagement / disengagement, strength of stimulus required for attentional shifts (distractibility), selectivity, size of focal area.

These parameters represent primarily the impact of anxiety, which includes focus on threatening stimuli,

narrowing of attentional focus, and can either cause greater degree of distractibility or can cause delay in attentional shifts (Williams 1997; Mineka 1992; Eysenck 1997). Obsessive "checking behaviors" can be modeled by requiring multiple scans of input data before sufficient confidence is generated (Broadbent et al. 1986).

Situation Assessor The situation assessor module combines low-level variables and events (e.g., 3 vehicles approaching from the N at 10 km/hour) into high-level descriptions of specific situations (e.g., approaching enemy unit of size X), and mapping them onto situation types that suggest a particular response (e.g., withdraw patrols). The situation assessor is implemented as a set of belief nets (Pearl 1986), representing knowledge in terms nodes and links. Nodes represent particular features and events (e.g., vehicle moving from location x,y and approaching), intermediate results (e.g., vehicle entering friendly zone), and final overall situation types (e.g., initiation of engagement). Links represent causal and correlational relations between events and situations represented by the nodes, and are associated with weights representing probabilities of each transition. Parameters controlling the situation assessor include the following:

- Structure parameters: Content of BN nodes, number of nodes, network topology, BN probability matrix.
- Process parameters: Speed of propagation of probability weights along BN links, affective valence associated with particular nodes (e.g., a value associated with a particular situation or feature indicating whether it is desirable or undesirable).

Personality and affective factors are represented in this module by associating a specific affective value (positive or negative) with existing situations represented by the individual BN nodes. Negative or positive emotionality is then modeled by matching the decision-maker's affective state or predominant temperamental factors with similarly valenced situations in the belief net memory, thus causing certain situations to be recalled preferentially, due to mood-congruent recall, increasing the likelihood of their recognition, while failing to recall others, decreasing the likelihood that they will be selected during situation assessment. Obsessiveness can be modeled by reducing the overall processing speed of the situation assessment process, by reducing the confidence in the derived situations, thereby requiring additional data or additional passes over existing data to reach the desired level of confidence.

Conclusions

We have described a methodology for modeling the impact of emotion on cognition and perception, within the general context of symbolic cognitive architectures. We have illustrated this approach in the context of a

specific symbolic architecture, designed to model tactical decision-making, in terms of a variety of representational formalisms (e.g., rules, belief nets). We focused on modeling the impact of three well-studied emotional states: anxiety, negative affect, and obsessiveness.

The proposed methodology is suitable not only for modeling the influence of emotional states, moods, and stable personality factors on cognition and behavior, but also for modeling a larger spectrum of individual differences. These include cognitive and decision-making styles, susceptibility to particular cognitive and perceptual biases, training and skill level, and individual history.

The resulting models can then be used both for investigating the mechanisms of emotion and the interaction between cognition and emotion, and for modeling specific types of personalities and individual styles in interactive simulation and training environments.

We are currently developing the parameterized SAMPLE architecture and its associated testbed environment, designed to facilitate the investigation of the above phenomena.

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