First Annual Conference on Advances in Cognitive Systems Poster Collection (2012) 119-129

Memory Framework for Complex Emotion Integration with Cognition

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Abstract

To allow better models of emotions integrated into cognitive architecture, we propose a memory framework which supports both traditional cognitive processes as well as appraisal theories of emotion. This is a new approach in emotion representation that we argue allows for deeper integration of emotion and cognition as well as greater emotional expressivity.

1. Introduction

Within the last two decades, there has been much interest in computational models of emotions. This is largely due to work by Bechara and Damasio that reinvigorated the idea that emotions are necessary for general intelligence (Bechara, Damasio, & Damasio, 2000).

Since then, much work has been done to further our understanding of emotions and intelligence, to yield systems with more human-like behavior, and to build systems with greater general intelligence.

Computational models of note include EMA (Marsella & Gratch, 2009), Soar-Emote (Marinier, Laird, & Lewis, 2009), and WASABI (Becker-Asano & Wachsmuth, 2009). These systems represent the state of the art given that emotions are implemented on top of a cognitive architecture (e.g. Soar, ACT-R) or built without the consideration of the context of cognitive architecture.

Some of these models contribute to our understanding of the interplay between emotion and cognition by demonstrating a confined relationship such as that between emotion, plans, and coping in EMA, emotion and executive control in Soar-Emote, emotion and reinforcement learning (Marinier & Laird, 2008), and emotion and memory recall (Stocco, Fum, & Zalla, 2005). No existing model has been capable of unifying all these results, but we suggest that it should be possible with our proposed approach.

However, the emotional overlay approach has a structural flaw as there is much evidence that higher levels of cognition were built on an emotional foundation (Davidson, 2000; Cohen, 2005). This, combined with the plethora of evidence that suggests emotion and cognition are intimately intertwined (e.g. (Lerner, Small, & Loewenstein, 2004; Lazarus & Smith, 1988; Damasio, 2000; Blanchette & Richards, 2010)) suggests the need for a cognitive architecture built from the ground up, with emotion in the basic structure as a first class element.

There are nearly no models that take this theoretical approach. For the few that do, such as H-CogAff (Sloman, 2001), there are many open questions regarding details and certain theoretical aspects. For example, with H-CogAff, Sloman addresses how emotions may be used as an alarm signal throughout, but does not implement the model, nor provide any detail of the processes and data or an emotional theory, leaving the model lacking in emotional nuance.

To address such problems, the first step should be to design and implement a foundation which can be used to support both cognition and emotion on equal terms, with the integration of the two supported and facilitated.

We propose a memory framework (working memory and long term memory) based on previous work on associative memory, semantic networks, and appraisal theory. For emotion, we fundamentally leverage the OCC appraisal theory (Ortony, Clore, & Collins, 1988), which is the most basic of appraisal theories, positing that emotions can be expressed as evaluations of desirability (of an event), praiseworthiness (of an action), and like/dislike (of an entity). These are generalized into the concepts of valence (like/dislike) and arousal which are found throughout nearly all theories of emotion. With the added concept of semantic links, we have extended the memory framework to support the emotional complexity argued for by theories such as Scherer's (2001). Scherer's theory argues that many more appraisals (most dimensions of any appraisal theory) cause emotion related behavior.

We raise the following hypotheses:

1 Semantic associative networks can represent appraisal information from any appraisal theory and allow for far more expressiveness for complex emotions
2 Facilitation of cognition's role in appraisal becomes trivial when integrating via semantic associative network
3 Previous work in demonstrating emotional effects on cognition can be easily reproduced in this framework

We will provide some discussion which suggests all these hypotheses are likely true and thus making semantic associative networks the most promising emotion representation as well as approach to integration of cognition and emotion.

2. Related Work

The use of working memory and long term memory in a cognitive architecture has been a long lasting robust approach for modeling memory in intelligent systems. There is a long tradition of work in this area, but none that integrates emotion as first class data. The most notable is that of ACT-R (Anderson et al., 2004) which used an associative network model of working memory and long term memory. It most famously shows recall of concepts through activation (base activation–recency of last access, and number of past accesses–and relevance), but has also demonstrated other forms of cognitive activity over the network as well.

A pre-cursor to the ACT-R work in memory was actually centered around emotions and cognition in memory by Bower, called the Associative Network Theory of Emotions (Bower, 1981). This was used to explain the relationship between mood and memory. There was only a singular notion of emotion (moods) and they were represented as discrete emotion.

Many other cognitive architectures have also displayed different approaches to working memory and long term memory such as memory in Soar (Laird, 2008) and hypergraphs in OpenCog (Goertzel et al., 2010). There has also been a factor graph representation to generalize implementation of various types of memory which has been demonstrated to support basic cognitive activity such as inference and production matching (Rosenbloom, 2011).

Also included in many of these systems is the notion of a semantic network. This is generally achieved by adding a specific class of links between nodes (nodes) that represent their relationship. Bower (1981) was also one of the earliest to demonstrate this idea and how it can be useful.

On the side of emotion representation, the state of the art revolves around the use of appraisal frames, for instance as associated with plan steps in EMA (Marsella & Gratch, 2009). An appraisal frame is a vector of all the appraisal variables and their values. This has proven difficult to use, however, because most demonstrated effects of emotion are based on much simpler values (as a heuristic or bias) and thus systems which use appraisal frames use a method to convert the values into a much simpler value (e.g. single categorical emotion or value in dimensional space).

Other approaches to emotion representation do not include appraisal as a fundamental theory and have been shown to be far less expressive but are worthy of mention. Such approaches include discrete emotion representations and dimensional representations. In discrete emotion representations, a pre-determined repertoire of emotions is constructed (e.g. happy, sad, angry) and various models transition between these emotions as states or maintain varied levels of each emotion. In dimensional theories, emotion is represented as a single point in a multi-dimensional space, typically along the dimensions of pleasure, arousal, and dominance. There are also hybrid approaches, which use dimensions to capture ranges of appraisal variables, which are then translated into emotional values or emotional effects.

3. Proposed Approach

We propose a memory framework with emotional data and cognitive schemata uniformly and broadly integrated in a way which OCC appraisal (Ortony, Clore, & Collins, 1988) and data from empirical psychology suggests. This being, at the core of emotion, we attribute valence and arousal to specific items, which enables biases or heuristics in various cognitive tasks such as action selection and recall.

This memory framework takes the form of a semantic associative network which is an associative network with additional directed links between nodes to represent semantic relationships. This is not unlike other forms of memory in systems such as ACT-R (Anderson et al., 2004), Soar (Laird, 2008), and OpenCog (Goertzel et al., 2010) which all also use a network of nodes connected by associative and (in certain instances) semantic links. There are two atomic components to the semantic associative network:

Node Representation of an object, idea, concept, or proposition.

Link Relational link between two nodes. Links can be directed or undirected, carry an associative weight and/or semantic labels.

The OCC appraisal theory can be seen as the most fundamental appraisal theory, proposing we attribute valence and arousal to singular concepts (event, action, entity). Thus we suggest a single node represent an atomic cognitive concept, containing information for valence and arousal attributed to that concept. All simple emotions regarding specific concepts can be addressed with just these values added to individual nodes. The remaining, more complex, appraisal heavy emotions should be implicit in the relationships between nodes, through semantic links.

Associative links are undirected edges between two nodes, carrying a value denoting the association strength between the two nodes. The specifics for why there is an association can be captured through semantic labels.

Semantic links are generally directed edges between two nodes that carry a semantic label and possibly a value. We will argue in section 4.1 that the following class of semantics will be sufficient to represent all of Scherer's appraisal dimensions, including the flexibility to incorporate a full plan-space (see discussion section of theoretical flexibility):

Table 1. Class of semantic links sufficient for representing all appraisal dimensions in Scherer's theory

Semantic Link	Indication	Parameter
Cause	The cause of an event or state by an event, agent, or intention	None
Deadline	Real time deadline perceived for a cognitive unit	None
Outcome	A possible outcome from an action or event in plan space	Percentage likelihood
Step	An event or action possible (or already taken if in past) from a given state in place space	None

3.1 Supporting Emotional Process: Grounding and Diffusion

One major new process is required within this model to support more complex emotional phenomena. This is the assignment and maintenance of valence and arousal over all nodes. This process can be broken into two subtasks: the initial assignment of valence and arousal and then the updating of valence and arousal over time.

We posit the proposition that valence and arousal over a single node (emotion regarding a single concept) gets its initial value (no stored value in working or long term memory) either through a chain of influence from related nodes or from physiological signals (where chains are grounded). For an example, we may have a negative opinion of someone who was involved in a negative event, even if we know nothing about them or have incomplete information about the event. We may also like a novel idea because it contains a concept we previously liked.

There is a portion of cognitive units which gain valence and arousal through bodily feedback, and all units (including those which may be grounded) are subject to adjustment through diffusion from related nodes. We propose an algorithm similar to influence diffusion in social networks (Kempe, Kleinberg, & Tardos, 2005).

Table 2. Algorithmic procedure to assign and maintain valence and arousal over a node which did not previously exist in working memory

Require: Stimulus s and $s \notin$ WM
Ensure: s given valence and arousal
  Create node for s
  $s.arousal \leftarrow 0$
  $s.valence \leftarrow 0$
  Search LTM for equivalent node
  if found **then**
    Copy remembered associations and valence and arousal
  end if
  Create associations for current context
  if body provided pain/pleasure and intensity **then**
    SET$s.arousal$ and $s.valence$ to physiological values
    Diffuse outward to existing WM nodes
  end if
  Enter cognitive elaboration
  if Elaboration creates new links **then**
    Diffuse valence and arousal between newly linked nodes
  end if

The algorithm presented in Table 2 describes a procedure for assigning and maintaining valence and arousal following a stimulus until the end of the cognitive elaboration based on the principals above.

Having this mechanism simply allows models to explain attribution and judgment of unknowns (e.g. halo effect (Cooper, 1981)). A similar mechanism was also employed in Soar-Emote, using various appraisal variables to calculate a resulting emotional arousal. This also allows us to use emotional data easily and quickly as suggested by the literature.

4. Discussion

In this section, we seek to lay the groundwork for supporting the hypotheses that we originally laid out. We argue for the memory framework's ability to support more expressive emotional representation, its theoretical flexibility, and ability to facilitate integration of cognition and emotion. Finally, we raise what overall contributions are made towards solving the original problems we declared.

4.1 Hypothesis: Appraisal Theory Flexibility

There is the question of why it may be an important task of supporting multiple appraisal theories in the first place. Many appraisal theories differ in providing a profile of what kind of appraisals may result in certain emotional behavior. Though they argue for different sets of dimensions and are capable of explaining various sets of phenomena well, the various major theories do a rather good job in arguing why their chosen dimensions impact emotions. In previous models of emotion that are based on appraisal theory, they require a certain level of commitment to a single theory and thus are

Table 3. Identification of the implicit presence of all of Scherer's appraisal dimensions using the semantic associative network with simple set of semantics defined in table 1. Also points out which classical cognitive processes may participate in the appraisal.

Scherer dimension	Identification within semantic associative network	Cognitive process(es) involved
Novelty	Novelty depends on if a concept already exists in long term memory, last time it was within working memory, and frequency of past usage within working memory	Long term memory recall
Goal relevance	Strength of association, either direct or indirect, to the node representing a desired or undesired state	Association management, planning
Intrinsic pleasantness	Grounded valence and arousal of nodes within the cognitive schema representing object; provided through the body or through emotional memory	Assignment of initial valence and arousal, recall
Outcome probability	In the plan space, semantic links denoting possible outcomes and their probability	Planning
Discrepancy from expectation	The distance from the generated expected outcomes in the plan space, if matching completely a low probability but expected case, the probability is the sole influence on discrepancy calculation	Perception, planning, and state matching
Conduciveness	Classical planning check to see if a stimulus blocks, enables, or is insignificant to the critical path within a plan space from current state to a goal	Planning
Urgency	Perceived deadline associated with a goal, action, or event	Time keeping
Agent and intention	Semantically link an agent in working memory to the event as the cause and the intention to the agent and event	Causal reasoning
Control	In the plan space, the amount of actions available dependent on the sole agent	Planning
Power	In the plan space, the amount of actions available that can change or avoid undesirable outcomes, or achieve desirable ones	Planning
Adjustment	In the plan space, the amount of actions available for internal restructuring after reaching a final outcome	Planning
Compatibility with internal and external standards	Relationship with valence and arousal over concepts and actions already in long term memory (standards) and their influence	Long term memory, network diffusion

left with the explanatory power of that theory. If the framework was capable of supporting multiple appraisal theories simultaneously, this would lay groundwork for a unifying model of appraisal.

As mentioned in Section 3, we have built the foundation of the framework on the OCC appraisal theory. In Table 3 we try to illustrate how all of Scherer's appraisal dimensions can be quite simply extracted from the structure of the semantic associative network. All the values are implicit through the structure, this results in three significant capabilities:

- Allowance of similar concepts from different appraisal theories to co-exist (e.g. Scherer's goal significance and Smith's importance and certainty)
- Binding of appraisal to cognitive context, truly allowing for subjective evaluation (aiding in our suggestion of truth for hypothesis in section 4.2)
- Allowance of cognitive processes to be agnostic to appraisal theory and can operate on emotional information in a fast and easy fashion (aiding in our suggestion of truth for hypothesis in section 4.3)

Scherer's appraisal theory is widely regarded as the most complex in terms of proposed dimensions as well as processes. Most other theories only have a subset of Scherer's dimensions. We have illustrated the flexibility of our approach to support both the simplest appraisal theory and the most complex together in a seamless manner, and it should be quite intuitive for how to add or find dimensions from other theories.

4.2 Hypothesis: Deeper Integration of Cognition in Appraisal

Also illustrated in Table 3 are the cognitive processes and structures within the semantic associative network where appraisal information can be found. It becomes clear that traditional cognitive processes do not need to deal with any new structures (e.g. appraisal frames) and can operate as they always have but still provide the required information for appraisal.

A separate process of diffusion also manages the evolution of emotions based purely on valence, arousal, and links placed by cognition. There is no need for cognitive processes to develop any specialized interaction with emotional processes.

EMA is thus far the most successful demonstration of appraisal frames. The appraisal frames are created for each plan step in a plan space and various appraisal variables may be filled in by explicitly invoking cognitive processes. It becomes rather unclear under what context the system should invoke inference to fill in certain variables and when to leave it null or how other processes (such as actively planning) contribute to population of the appraisal frame (some proposed dimensions are left uncomputed or manually filled in).

In the semantic associative network, we are leaving all traditional constructs of working memory available for cognition but extending it in a way that binds emotion directly to the cognitive context. As all cognitive processes have a rich history of operating over this very type of memory, this ostensibly integrates the cognition in appraisal generation in a far deeper way than before.

4.3 Hypothesis: Broader Integration of Emotional Effects

One powerful advantage of using a semantic associative network (with its attendant functions of association maintenance and diffusion) as a substrate for emotional cognitive representation is that many direct emotional effects on cognition can be modeled without need to resort to specific mechanisms to trigger or encode each effect. These effects can be loosely defined as biases or heuristics. Table 4 presents a few examples of how emotional effects on cognition can be easily modeled within a semantic associative network.

The idea of emotions as an important signal for what cognitive attention should focus on was most influentially raised by Simon (1967). As each concept has a valence and arousal maintained

Table 4. Example emotional effects on cognition as enabled by the semantic associative network

Emotional Effect on Cognition	Affective Information Used	Cognitive Response
Cognitive refocus (attention shift)	High-arousal on a new node	Attentional process selects new node in SAN for focus due to high arousal levels; associated nodes gain activation
Mood-congruent cognition (action selection, recall)	Aggregate valence arousal values of nodes in working memory	Long term memory nodes with valence congruent to mood recieve more preference or activation
Affective priming	Valence of nodes within schema representing priming concept	Concepts more congruent with the valence of the priming schema receive more preference

over it, an attention process may select a single node as a center of attention (similarly done in OpenCog) for cognitive elaboration.

Various forms of mood congruent cognition were empirically shown by Bower (1983). A notion of mood was taken as an aggregate of all valence and arousal within working memory and that value was used to compare with remembered valence values on nodes in long term memory to calculate congruence as a parameter for activation. This mechanism was used by Fum within ACT-R to explain the famous Iowa Gambling Task results (Fum & Stocco, 2004).

Affective priming is a phenomena most notably explored by Moors in which inducing certain affective states (negative/positive) caused congruent responses to occur much faster and incongruent responses to occur slower. This may be very closely related to the mood congruent recall mechanism in that incongruent recall may require more cycles before the appropriate answer could be brought to working memory.

For each of these, the semantic associative network (and its processes, particularly association maintenance and activation diffusion) contributes to both cause and effect. Of primary importance to these effects are the semantic associative network node values (pleasure, arousal, and general activation strength) and link association strength. The semantic links between nodes play a background role in determining new ratings (appraisal values) for associated nodes, but do not directly contribute to the effects outlined above.

Most notably, however, is the fact that cognitive processes do not need to know anything about appraisals. In models where appraisals are explicitly represented (e.g. appraisal frames), special mechanisms and processes for each cognitive process must be developed. In most cases, most systems simply convert an appraisal frame into a singular value so it may be used in the intuitive way the literature suggests emotions are used. Here we keep the broad range of various valence and arousal values without losing any context of the appraisals or cognitive information, which influence the evolution of all values as time passes.

This allows us to directly unify results from various disjoint works under one model. For an example, the mechanism for emotion congruent recall used to explain the Iowa Gambling Task, Marinier's proposal for emotion as a reinforcement signal in learning (Marinier & Laird, 2008), emotion for action selection in planning (Franklin & McCauley, 2004), and more would have incompatibilities if they were to try to combine with other models. All these results can be directly brought together into the semantic associative network framework without the need to address additional problems.

5. Conclusion

Since emotions are different than traditional high level cognitive processes, in that they were developed far earlier within the reptilian brain and are intertwined with all aspects of the mind, it is absolutely paramount to continue making models which study emotion within the context of an intelligent system. For most, this means emotion must be broadly and deeply integrated into a cognitive architecture, which we believe has not been fully addressed before.

This paper has proposed a novel approach for representing emotions which also serves as an approach for integrating emotions into a cognitive architecture. Traditional working memory and long term memory structures of associative memory and semantic memory are minimally extended with valence and arousal over individual nodes, along with a process to maintain these values, to yield what we have called a semantic associative network.

It was hypothesized that this memory framework allows greater expressivity in representation and facilitation between emotion and cognition than any other approach. Arguments for this were presented which suggest that the hypotheses may be true, and that this approach to representing emotions in memory is a promising one.

6. Future Work

This introductory paper presents an idea and lays the appropriate groundwork for strong hypothesis. The next step in our research would be to flesh out all the abstractions in regards to the semantic associative network. Particularly, topics such as the granularity of cognitive schema which nodes should represent, the appropriate class of semantics, and the precise algorithm for diffusion will likely need to be addressed.

There is also a need to provide more empirical evidence for the claims we believe are likely true here. To do this, an implementation is planned, but it may require a tremendous effort as building an entire cognitive architecture typically does. There are plans to scope the implementation in ways such that results can still be found in incremental fashion. This experimental design will be to implement simple, transparent cognitive models of the various processes affected by emotional cues.

Another point of future work will be to complete the cognitive-emotional “loop” which begins/ends with appraisal/reappraisal and courses through effects on cognitive processes and updates of the semantic associative network. For instance, emotion-enabled case-based planning: success or failure of a plan step may alter emotional state, and that emotional state, combined with the previous result itself, may in turn affect the formation of future plans.

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