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Modeling Emotion: Arousal's Impact on Memory

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Abstract

It is generally accepted that an integrated cognitive architecture is required to fully explain complex functions of the brain such as learning and behavior. However, typical architectures do not include a theory of emotion. This article proposes a framework of emotion suitable for inclusion in an integrated architecture and examines the impact of arousal on memory and how a particular architecture that does not account for emotion fails to accurately model a classic psychological experiment. Simulations and memory models are also presented that account for arousal's impact on memory.

Introduction

The breadth and complexity of our emotions are critical to our human experience. In many ways, the sensation or feeling of these emotions is what makes life worth living. These emotions also provide adaptive advantages important for our well being and survival. They facilitate a compacting of our experience that can result in a fast and desirable decision without requiring a substantial amount of time for deliberation. This effect can be critical when a quick decision is necessary but all the relevant information is either not available or the time required to process would be too great.

It is our belief that emotion should be included as an integral component of any integrated cognitive architecture that strives to provide a rich and accurate explanation and framework for the emulation of human cognition. Such a model would have many applications in either an analysis or synthesis mode, including behavioral finance, interactive entertainment, automotive telematics, and computer assisted education.

Therefore, development is underway of a comprehensive computational model of emotion that is targeted at integration with cognition. This model is being formulated in terms of general mechanisms of the emotional system that interact with cognition and provide a mapping to typical emotional states, such as anger and happiness. An early step in this development is an analysis and simulation

of the interaction of arousal and memory, and this work is described in the sections that follow.

Modeling Emotion

Emotions are often tied to appraisals. Fear, for example, can be seen as a reaction to a prediction of danger. The emotional model we are pursuing is in line with this point of view except that the “appraisals” are not cognitive, but are instead mechanistic. Pain, for example, is a simple “appraisal” mechanism that is crucial to emotions. This model, put forth by Chown and others (Chown, 2006; Kaplan, 1991), posits that emotions are a fast, automatic assessment system consisting of three core parts or mechanisms: \mathbf{m}_1 : an arousal system that provides a measure of importance, \mathbf{m}_2 : a pleasure/pain system that assesses valence, and \mathbf{m}_3 : a clarity/confusion system that provides a measure of competence. All of these components are automatic (one does not decide to be confused for example), but can be affected by cognition. These mechanisms are chosen due to their ability to model a broad range of the emotional spectrum and can be used as a foundation for looking at how cognition and emotion interact. Typical emotional tags (angry, sad, happy) can be generated through a mapping of these mechanisms: $(f: \mathbf{m}_1 \times \mathbf{m}_2 \times \mathbf{m}_3 \rightarrow \text{tag})$.

The figure below illustrates how these mechanisms can be viewed in a 3-state space and how the model may drive these states over time in response to various stimuli.

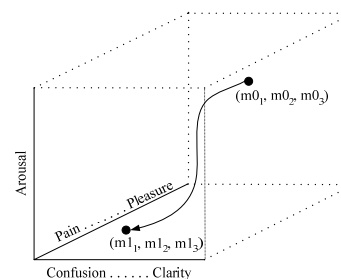


Figure 1: Representation of Emotion

The inter-relationship of these mechanisms are shown in the figure below. The pleasure/pain and clarity/confusion mechanisms are separated in the figure to depict their inhibitory relationships (e.g., a highly pleasurable stimulus may effectively negate minor pain stimuli). Each mechanism processes its own set of stimuli, which may include the state of another mechanism. For example, the clarity/confusion mechanism provides input to the pleasure/pain mechanism. Stimuli can be physically external (e.g., hearing a gun shot), internal (e.g., pain in stomach), and as a result of cognitive appraisal.

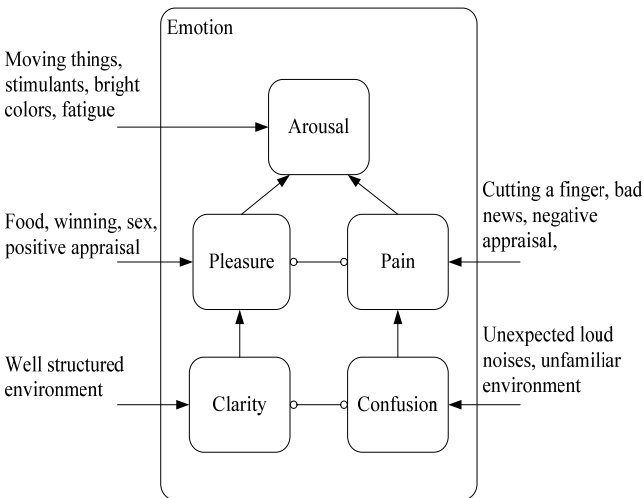


Figure 2: Emotional Mechanisms

Another way to view these mechanisms is in terms of their evolutionary development. Borrowing from Damasio’s tree metaphor (2003), the figure below depicts the evolutionary levels of our model with the trunk (arousal) being the most basic level. In contrast to Damasio’s view, we do not include basic bodily functions, such as metabolic regulation and immune responses, in our model.

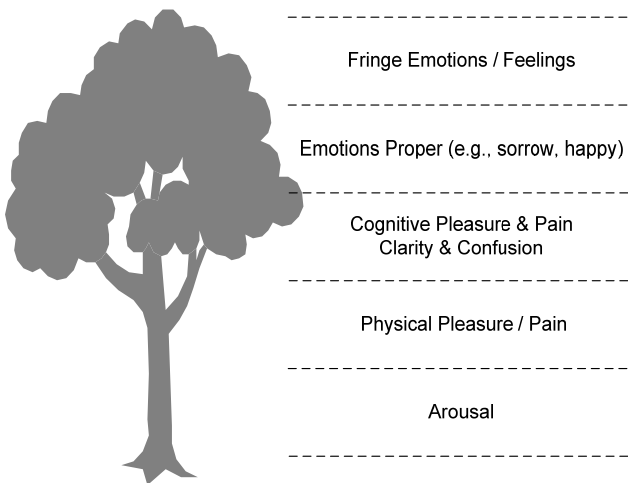


Figure 3: Evolutionary Levels of Emotion

Regardless of their role in the overall emotional architecture, all of these mechanisms are crucial in driving human behavior. This article focuses specifically on arousal, which forms the basis of the emotional model and, from our point of view, is most significant in its effects to changes in human behavior and performance. Future articles will expand this work and explore the other mechanisms in pursuit of a comprehensive computational model.

Arousal and Memory

A recent study on the brain and behavior (Garey, Goodwillie, J. Frohlich, et al, 2003) defined arousal as being more “responsive to a wide variety of external stimuli spanning sensory modalities” and being more “motorically active”. Conforming with this definition, arousal can also be viewed as a call to action with the other emotional mechanisms providing direction. For example, pain, whether physical or cognitive, facilitates an increase in arousal and impacts behavior and goal setting in such a way to bring about a change in behavior to alleviate the pain. A familiar effect of arousal is the inverted ‘U’ performance curve, which was first documented by Yerkes and Dodson (1908). As the following figure shows, there is an optimal level of arousal related to performance. This optimal level is a mid range of arousal in contrast to too little arousal, which facilitates a lethargic condition that can inhibit motivation, and too much arousal, which facilitates a hyperactive condition that can inhibit concentration. Performance in this sense is applicable to both memory and learning (Sherwood, 1965) as well as task execution. When arousal is high, tasks that require a relatively high cognitive workload (complexity) or are less well-learned are less likely to be pursued. However, high levels of arousal can increase the likelihood that physically demanding tasks (e.g. running) will be pursued.

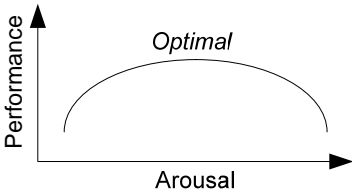


Figure 4: Inverted U Curve

Regarding memory, high arousal during encoding can facilitate long term retention, but it is also associated with an inability to retrieve information for a short period of time (up to about 30 minutes) following the original encoding. A classic paired associate experiment performed by Kleinsmith and Kaplan (1963) revealed this impact of arousal on memory by performing memory tests on subjects while monitoring arousal levels. The details of the experiment are summarized below:

- 48 subjects were divided into 6 groups of 8.
- Each subject participated in a single learning trial of 8 words with a paired association of a number between 2 and 9. The words used were *kiss, rape, vomit, exam, dance, money, love, and swim*.
- The ordering of the stimulus was unique to each member in a group.
- A stimulus was first presented for 4 seconds followed by the presentation of the paired number with the stimulus.
- This was repeated eight times and color slides were presented to the subject in between each test. The subjects were not told that they would be tested for paired associate recall.
- A galvanic skin response (GSR) recording device was attached to each subject during the experiment. The levels were recorded during display of the stimulus. This level was used to determine which words caused high arousal during encoding. The three highest arousal words were grouped into a high arousal category. The three lowest arousal words were grouped into a low arousal category. The results of the middle two words were discarded.
- Each group was later tested for recall at different times: 1 week, 1 day, 45 minutes, 20 minutes, and 2 groups at 2 minutes. The order of stimulus presentation during recall was varied.

Figure 5 shows the recall performance from the experiment for the high arousal word group and low arousal word group. The results for the low arousal word group show a familiar forgetting / decay curve; however, the results for the high arousal word group show that recall actually improved with time. For the first 20 minutes, a blocking effect can be observed relative to the low arousal group but then the recall performance improves drastically and approaches the short duration recall performance of the low arousal group. These results demonstrate the aforementioned effects of short-term blocking and long-term reminiscence due to high arousal.

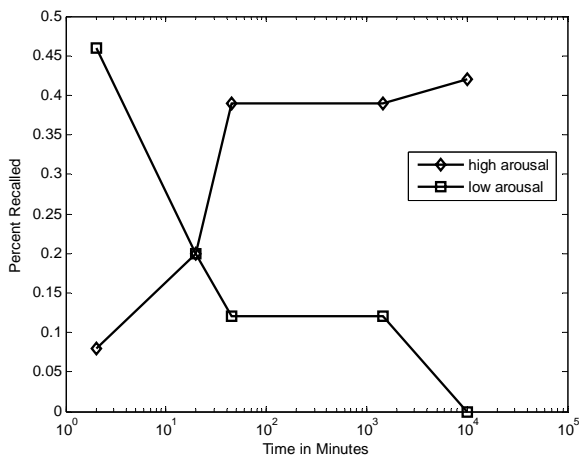


Figure 5: Results of Experimental Study

Kleinsmith and Kaplan (1964) later replicated the study using nonsense syllables instead of emotionally charged stimulus and documented similar results to the original study. These effects were also seen by Levonian (1967) in a study of 83 high school students who were presented continuous material while being monitored by GSR sensors. It was found again that high arousal (deflection from nominal) facilitated short term forgetting and long term (one week) remembering. Low arousal showed the converse effect. Gray, Braver, and Raichle (2001) recently studied the impact of arousal accompanied by pleasure and pain and found that an unpleasant, highly aroused emotional state impaired short term verbal memory. They also found that a stronger emotional induction led to a stronger performance effect.

Model

Our goal is to model the results of the Kleinsmith and Kaplan experiment utilizing a model that can predict both the low arousal and high arousal results. The simulation environment utilized is Matlab, and the memory model utilized is from ACT-R (Anderson & Lebiere, 1998).

It is important to note that there have been other efforts to add elements of emotion to ACT-R through manipulation of the parameters within the conflict resolution algorithm¹. Ritter, Avraamides, Council et al., (2002) have shown that emotional labels such as threatened and worried can be modeled by varying parameters as a way to model the level of motivation and clarity of thought. Belavkin (2001) provided an explanation of the aforementioned inverted U curve. Performance was in terms of speed of learning and arousal was modeled by varying parameters within the conflict resolution algorithm.

Within ACT-R, (declarative) memory is represented by chunks. Every chunk in ACT-R has associated with it an activation level. When a retrieval request is made of the memory system, the chunk with the greatest activation among those that match a retrieval specification is retrieved. However, there is a retrieval threshold that specifies the minimum activation level of a chunk for retrieval. If the chunk with the highest activation among those that match the request has an activation level less than the retrieval threshold, then a failure to retrieve will occur.

The equation for the activation A_i of a chunk i is defined as²:

$$A_i = B_i + \varepsilon$$

B_i : The base-level activation.

¹ Conflict resolution is embedded in the procedural module, and the memory model is embedded in the declarative module.

² Similarity and Source Activation are ignored

ϵ : Noise. The noise is composed of two components: a permanent noise associated with each chunk and an instantaneous noise computed at the time of retrieval.

The equation for base-level activation for chunk i is:

$$B_i = \ln\left(\sum_{j=1}^n t_j^{-d}\right)$$

n : Number of presentations for chunk i .

t_j : Time since presentation j .

d : Decay parameter

This equation describes a process in which each time an item is presented there is an increase in its base-level activation, which decays away as a power function of the time since that presentation³.

Note that arousal is not a parameter to the activation equation; therefore, it is somewhat intuitive that this existing formula will not be adequate for modeling both the low arousal and high arousal performance curves. Figure 6 compares the ACT-R activation curve from a single encoding (presentation) with the Kleinsmith and Kaplan results⁴. The ACT-R decay parameter (d) is set to 0.05 for the simulation.

As might be expected, the ACT-R activation slope closely follows the low arousal group curve, which might be as expected for a decay based model. The high arousal recall performance is shown to be drastically different. The high arousal words were poorly recalled at 2 minutes and 20 minutes (short term) but were recalled at a much higher percentage at 45 minutes, 1 day, and 1 week (long term).

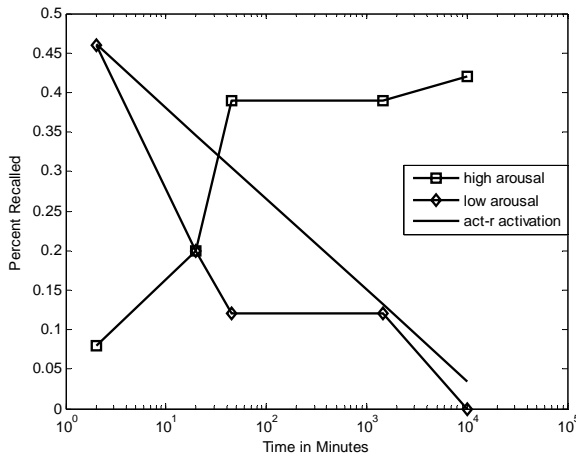


Figure 6: Experimental Results vs. ACT-R

³ There are three types of events that are considered a presentation of a chunk: creation, merging, and retrieval.

⁴ 0.5 is added to the ACT-R activation for display purposes

As Figure 6 shows, the current ACT-R memory model is not adequate for predicting the recall results of the high arousal word grouping. In order to do so, a memory model that increases activation with time is needed. This can be accomplished by replacing the decay parameter with a growth parameter (negative decay rate) and implementing a ceiling for activation after 45 minutes. This ceiling represents that the memory no longer continues to increase or decrease (at least at the same rate) once it is deeply encoded and the short term blocking effect has dissipated. The growth parameter generates an increase in memory activation as time proceeds between encoding and attempted recall. Figure 7 shows a simulation of memory encoding and recall using the modified activation equation with the growth parameter ($-d$) set to 0.04. 500 memory encoding and recall cycles were simulated using a noise variance of 0.1⁵. Also, a base level constant (BLC) of -4.5 was added in the activation equation.

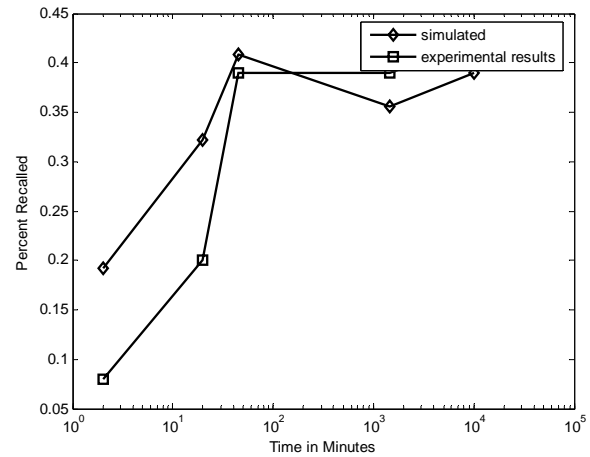


Figure 7: Simulation Results

It is interesting to note that this function utilizing a growth parameter (negative decay) closely follows the experimental results and that the growth parameter (0.04) is very close to the negative of the decay (0.05) that was used previously to follow the low arousal group curve.

Discussion

Additional data on specific arousal levels (relative to a baseline) during encoding and retrieval are needed for the specification of a robust general memory model. However, we sketch a model proposal using the previous results and the findings from Gray, Braver, and Raichle (2002) that show that a stronger affect facilitates a more pronounced behavioral effect. It is important to note that one of the goals of this general model is that it will simplify to the original ACT-R equation when arousal is set to its nominal level.

⁵ A normal distribution is utilized instead of a logistic distribution (as utilized in ACT-R).

We first propose that the base level activation decay parameter (d) should be some function of arousal at time of encoding. The decay rate should increase for lower arousal levels and turn into a growth parameter ($g = -d$) for higher arousal levels.

$$B_i = \ln\left(\sum_{j=1}^n t_j^{-d(a)}\right)$$

Next, we propose a definition of $d(a)$ as a linear function of arousal (a), a high arousal threshold (a_h), and a scale parameter (s):

$$B_i = \ln\left(\sum_{j=1}^n t_j^{-d_s(1-a/a_h)}\right) - (a - a_n)$$

d_s : scaled decay (growth) parameter: $s * d$

a : arousal at the time of encoding; $0 \leq a \leq 1$

a_n : nominal arousal

a_h : high arousal threshold

Arousal (a) can vary between 0 (e.g., sleep) and 1 (full arousal). The exponent to t_j becomes a growth parameter when arousal is high ($a > a_h$), and the decay accelerates when arousal is low ($a < a_h$). The equation defaults to the ACT-R activation equation when arousal is set to its nominal level and decay is scaled to the inverse of the $(1-a/a_h)$ term. The term outside the log function ($a - a_n$) provides initial blocking for high arousal levels.

For example, we set the parameters as follows: $d_s = 3*d$; $a_n = 0.5$; $a_h = 0.75$, which gives us the following equation:

$$B_i = \ln\left(\sum_{j=1}^n t_j^{-3*d(1-a/0.75)}\right) - (a - 0.5)$$

Figure 8 depicts a simulation of this general activation function over time for three levels of a using a decay rate of 0.05. This model provides considerable blocking for high arousal in the first few minutes and relatively strong activation after 20 minutes. A ceiling function was not utilized in this simulation but could be easily added.

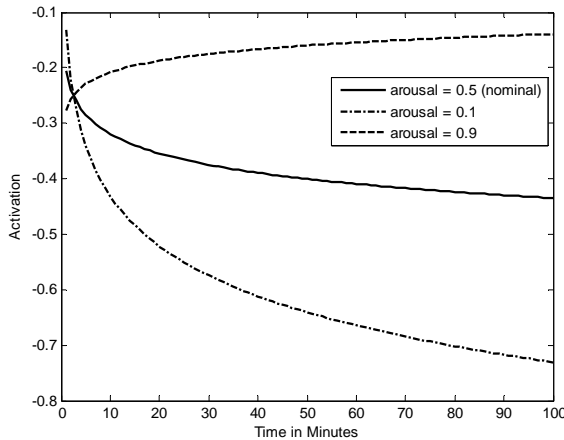


Figure 8: General Model, Three Levels of Arousal

Figure 9 depicts one hundred simulations with arousal normally distributed about 0.5 utilizing a standard deviation of 0.2.

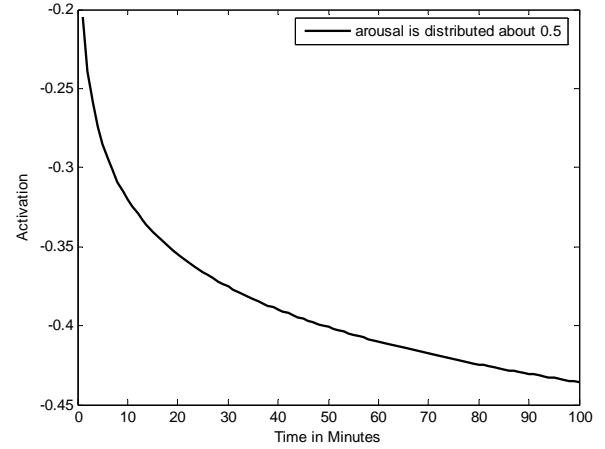


Figure 9: General Model

As stated previously, the modeling of arousal is an early step in an effort to develop a comprehensive computational model of emotion integrated within a theory of cognition. Arousal is one way in which the emotional system provides automatic direction of behavior. Arousal can be seen as a kind of importance gage, which is discussed more thoroughly in a companion paper (Chown, 2006).

Important events should be remembered, and different behavioral strategies should be employed based upon the level of importance. The next steps will be to expand and refine the work on arousal and examine computationally the impact of pleasure and pain.

Pleasure and pain provide an organism with a measure of valence – pleasurable outcomes are preferred over painful results. This suggests that organisms will work to stop feeling pain and avoid future pain while trying to continue to feel pleasure and seeking to get pleasure in the future. Of the three parts of the emotional system proposed in our model the pleasure/pain system is the most highly studied both within cognitive science and also mathematically (most machine learning systems can be cast in terms of pleasure and pain, and reinforcement learning is directly inspired by the relationship of pleasure and pain to behavior).

The final part of our emotional model is the least well understood in terms of mechanism. Clarity and confusion are important to decision making agents because they provide a rough measure of competence (Kaplan, 1991). When the world and one's model of the world are in sync then one's model is likely to provide the basis of sound decisions. It is relatively simple to see how such a mechanism would work at the neural level – focused neural

activity that results from the confluence of internal and external input should correspond to clarity. On the other hand, when internal and external signals are at odds neural activity should be more diffuse. It is relatively more difficult to cast this in symbolic terms because it requires constantly and explicitly monitoring the state of the agents knowledge structures as measured against what the agent is perceiving.

Summary

Emotion is a critical element to being human, and it impacts cognitive functions like performance, memory, and behavior. Computer systems that emulate intelligence as well as cognitive models typically lack this important element and therefore have difficulty modeling and predicting human behavior when real-life emotions are at work outside a laboratory setting.

This paper reviewed a classic experimental psychology study on arousal and memory, compared its results to what would be predicted by a memory model typically found in a cognitive architecture, and then modified the model to provide a better match against the data. A general memory model that accounts for arousal was also proposed.

Acknowledgments

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References

Anderson, J. R., & Lebiere, C. (1998). *The Atomic Components of Thought*. Mahwah, NJ: LEA.

Belavkin, R. V. (2001). Modelling the inverted-U effect with ACT-R. *Proceedings of ICCM*, 4.

Chown, E. (2006). Emotions as Adaptive Behavior. *Submitted to Cognitive Science '06*

Damasio, A. (2003). *Looking for Spinoza, Joy, Sorrow, and the Feeling Brain*. Orlando FL: Harcourt Books.

Gray, J. R., Braver, T. S., & Raichle, M. E. (2002). Integration of emotion and cognition in the lateral prefrontal cortex. *Proceedings of the National Academy of Sciences USA*, 99, 4115 - 4120.

Kaplan, S. (1991). Beyond rationality: Clarity based decision-making. In Garling, T. and Evans, G.W., (Eds.) *Environment, Cognition and Action: An Integrated Approach*, pages 171-190. Oxford University Press, New York

Kleinsmith, L. J. & Kaplan, S. (1963). Paired-associate learning as a function of arousal and interpolated interval. *Journal of Experimental Psychology*, 65, 190-193.

Kleinsmith, L. J. & Kaplan, S. (1964). The interaction of arousal and recall interval in nonsense syllable paired associate learning. *Journal of Experimental Psychology*, 67, 124-126.

Levonian, E. (1967). Retention of Information in Relation to Arousal During Continuously-Presented Material. *American Educational Research Journal*, 4, 103-116

Ritter, F. E., Avraamides, M. N., Councill, I. G., Karen S. Quigley, K. S., and Klein, L. C. (2002) Modeling the Effects of Two Behavior Moderators in ACT-R. *Workshop on ACT-R Models of Human-System Interaction*.

Sherwood, J. J. (1965). A Relation Between Arousal And Performance. *The American Journal of Psychology*, 78, 461-465

Yerkes, R. M. & Dodson, J. D. (1908), The relation of strength of stimulus to rapidity of habit formation, *Journal of Comparative Neurology and Psychology*, 18, 459-482.