Towards Emotion in Sigma: From Appraisal to Attention

Paul S. Rosenbloom[1,2], Jonathan Gratch[1,2], and Volkan Ustun[1]

[1] Institute for Creative Technologies, [2] Department of Computer Science, University of Southern California
12015 Waterfront Drive, Playa Vista, CA 90094

Abstract. A first step is taken towards incorporating emotional processing into *Sigma*, a cognitive architecture that is grounded in graphical models, with the addition of appraisal variables for *expectedness* and *desirability* plus their initial implications for *attention* at two levels of the control hierarchy. The results leverage many of Sigma's existing capabilities but with a few key additions.

Keywords: Sigma, cognitive architecture, emotion, appraisal, surprise, attention, evaluation.

1 Introduction

Sigma [1] is a cognitive architecture/system that is based on combining what has been learned from over three decades worth of independent work in cognitive architectures [2] and graphical models [3]. Its development is being guided by a trio of desiderata: (1) *grand unification* (expanding beyond strictly cognitive processing to all of the capabilities required for intelligent behavior in complex real worlds); (2) *functional elegance* (deriving the full range of necessary capabilities from the interactions among a small general set of mechanisms); and (3) *sufficient efficiency* (executing at a speed sufficient for anticipated applications). We have recently begun exploring the incorporation of emotion into Sigma, driven by: the theoretical desideratum of grand unification; the practical goal of building virtual humans for applications in education, training, counseling, entertainment, etc.; and the hypothesis that emotion is critical for general intelligences to survive and thrive in complex physical and social worlds.

A major focus of this effort concerns what aspects of emotion are properly architectural – that is, fixed parts of the mind – versus enabled primarily by learned knowledge and skills. A large fragment of emotion is non-voluntary and immutable, providing hard-to-ignore input to cognition and behavior from what could be called *the wisdom of evolution*. It also makes direct contact with bodily processes, to the extent such exist, to yield the *heat* in emotion. Thus, significant fractions of it must be grounded architecturally even with knowledge clearly being critical at higher levels.

Driven by functional elegance, there is also a major emphasis here on reusing as much as possible the capabilities provided by the existing architecture, rather than simply building a separate emotion module. One obvious example is leveraging Sigma's *hybrid* (discrete + continuous) *mixed* (symbolic + probabilistic) nature to support both the low-level subsymbolic aspects of emotion and the high-level symbolic aspects. Another such example is the seamless mapping of Sigma's tri-level cognitive control [4] – as inherited from Soar [5] and comprising *reactive*, *deliberative* and *reflective* levels – onto tri-level theories of emotion [6], suggesting a more unified tri-level model of *emotocognitive processing*.

A less obvious example is the essential role that Sigma's gradient-descent learning mechanism [7] has turned out to play in *appraisal* [8]. Appraisal is typically considered the initial stage of emotional processing, capturing emotionally and behaviorally relevant assessments of situations in terms of a relatively small set of variables, such as *relevance*, *desirability*, *likelihood*, *expectedness*, *causal attribution*, *controllability* and *changeability* in the EMA theory [9]. These ground appraisals, or combinations thereof, may then lead to higher-order appraisals, transient emotional states, and a variety of important impacts on thought and behavior.

Still, extensions to Sigma's architecture are clearly necessary to fully support emotional processing. Prior to this work, Sigma had no emotions. Yet, the immutable and mandatory nature of emotions implies they must be deeply rooted in the architecture. Central to this effort is understanding the architectural extensions necessary to (1) enable the ground appraisals that initiate emotional processing, and (2) yield the appropriate emotional modulations of thought and behavior.

This article provides an initial report on work towards emotion in Sigma, focused on architectural variants of *desirability* and *expectedness*, along with their initial impacts on *attention*. Key to both appraisals is a new architectural mechanism for *comparing distributions*, with *desirability* based on comparing the distributions over the current state and the goal, and *expectedness* based on comparing the distributions over a fragment of memory before and after learning. *Attention* then leverages these appraisals to focus processing at multiple levels of control. This is the first architectural model of low-level attention that stretches all of the way from appraisal to its impact on thought. It also demonstrates a complementary impact on higher-level attention.

There is considerable recent work on emotion in cognitive architectures – e.g., in Soar [10], PsychSim [11], FAtiMA [12], EmoCog [13], MicroPsi [14], ACT-R [15], BICA [16], and CLARION [17] – but Sigma's unique aspects shed new light on how this can be done. Section 2 provides the basics of Sigma needed for this work. Sections 3 and 4 cover expectedness and desirability. Attention is covered in Section 5, with a wrap up in Section 6.

0	1	.5	.3
1	.6	0	1
.7	.6	0	1

Fig. 1: A *piecewise-constant function*, the special case of piecewise linear functions used here. Dimension spanning *slices* exist wherever there are adjacent regions with different functions.

2 Sigma

Sigma is based on *factor graphs* [18] – undirected graphical models with variable and factor nodes – and hybrid mixed *piecewise-linear functions* [19] (Fig. 1) stored at factor nodes and sent as messages via the *summary product algorithm* [18] (Fig. 2). Sigma's factor graphs are compiled from a high-level language that is based on *predicates* with typed arguments plus *conditionals* embodying patterns over predicates. Predicates specify relations over continuous, discrete and/or symbolic arguments. They may be *closed world* – assuming, as in production systems, that unspecified values are false – or *open world* – assuming, as in probabilistic reasoning, that unspecified values are unknown.

Each predicate has a portion of working memory (WM) allocated to it that forms part of the full factor graph. Predicates may also have perception and/or long-term memory (LTM) functions. For perceptual predicates, factor nodes for *perceptual buffers* are connected to the WM subgraphs. For memorial predicates, *function factor nodes* (FFNs) are likewise connected. Messages into FFNs provide the gradient for learning the nodes' functions. Conditionals structure LTM and basic reasoning, compiling into more extended subgraphs that also connect to the appropriate WM subgraphs.

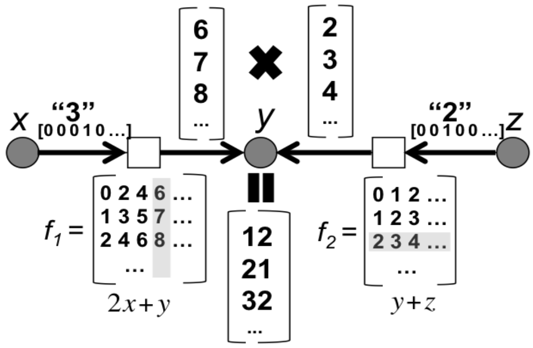


Fig. 2: Summary product computation over the factor graph for $f(x,y,z) = y^2+yz+2yx+2xz = (2x+y)(y+z) = f_1(x,y)f_2(y,z)$ of the marginal on y given evidence concerning x and z.

Processing in Sigma is driven by a *cognitive cycle* that comprises input, graph solution, decisions (selection of best elements from distributions), learning, and output. Graph solution occurs by *product* of the messages coming into a node – including the node's function when it is a factor node – and then *summarization* out, via integration or maximum, of unneeded variables from outgoing messages. Most of perception and action is to occur within graph solution in Sigma, rather than within external modules [20]. Reactive processing occurs within individual cycles, whereas deliberative processing occurs across a sequence of cycles. As in Soar, *impasses* occur when decisions cannot be made, leading to reflective processing.

3 Expectedness

Expectedness concerns whether an event is predicted by past knowledge. Its inverse maps naturally, as *unexpectedness*, onto the notion of *surprise* that underlies the bottom-up aspects of today's leading models of visual attention. In other words, attention is drawn to what is surprising or unexpected; e.g., the *Bayesian Theory of Surprise* compares the *prior distribution* over the visual field – i.e., the model that has previously been learned for it – with the *posterior distribution* derived via Bayesian belief updating of the prior given the image [21]. The size of the difference correlates with how poorly past knowledge predicts the image. This comparison is computed by the *Kullback-Leibler (KL) divergence*, with M the current model and D the new data:

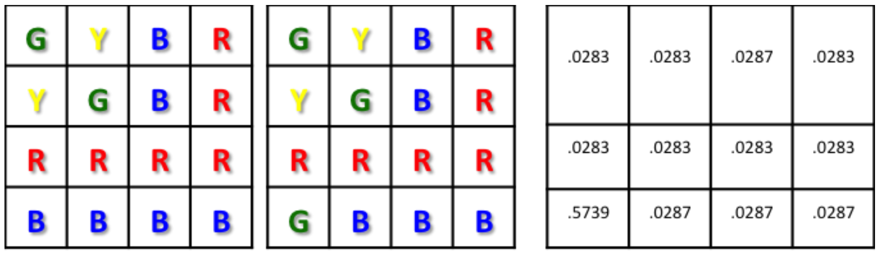
$$S(D,M) = KL(P(M \mid D), P(M)) = \int_M P(M \mid D) \log \frac{P(M \mid D)}{P(M)} dM. \qquad (1)$$

The computation of surprise in Sigma tracks this approach, but differs in several details. Distribution updating is mediated by Sigma's gradient-descent learning mechanism – as applied at FFNs – with the functions before and after learning compared ere the prior is replaced by the posterior as the node's function. Also, rather than basing the comparison on KL divergence it is based on *Hellinger distance*:

$$S'(D,M) = HD(P(M \mid D), P(M)) = \sqrt{1 - \int \sqrt{P(M \mid D)(x) P(M)(x)} dx}. \qquad (2)$$

While both measure the difference between two distributions, KL divergence is non-symmetric – and thus not a metric – and undefined for 0s in the second distribution. The Hellinger distance was chosen primarily because it can deal with these 0s.

Fig. 3 shows the computation of surprise in a simple visual field, represented by a three-argument predicate: `image(x:[0:4), y:[0:4), color:[red, yellow, green, blue, black]%)`. The first two dimensions are modeled as discrete numeric, while color is symbolic. The `%` denotes that there is a distribution over the color given the location. Fig. 3(a) shows the initial visual field. It remains this way for ~20 cycles to learn a model. Then, the bottom-left location is switched from blue to green, as in Fig. 3(b). Fig. 3(c) shows the (normalized) *surprise map*, which highlights the changed location. The surprise map is a form of architectural self-perception [22], and therefore stored in the perceptual buffer of an automatically created *surprise predicate* – `image*surprise(x:[0:4)%, y:[0:4)%)` – that embodies a joint distribution over the conditioning variables in the original predicate.



(a) Initial field (b) Changed field (c) Surprise map

Fig. 3: Visual field before and after change in bottom left cell, plus the resulting surprise map. Each cell has a (Boolean) distribution over colors, but just the argmaxes are shown.

Surprise has also been explored in more complex pre-existing tasks, such as Simultaneous Localization and Mapping (SLAM) [7]. In SLAM surprise is computed over the learned map, a fragment of mental imagery [23] rather than direct perception, with local input focusing surprise on the current and previous locations in the map. In all, the work to date has moved Sigma from where it had no measure of surprise to where it is computable over any memorial predicate, whether perceptual or cognitive.

4 Desirability

Desirability concerns whether or not an event facilitates or thwarts what is wanted. In Sigma it is modeled as a relationship between the current state and the goal. The former is in working memory; however, until recently, Sigma did not have goals that the architecture could comprehend. Although Sigma, like Soar, has deep roots in search and problem solving, neither natively embodied declarative goals that would enable automated comparisons. Driven by the needs of emotion, a goal function can now be specified for each predicate in Sigma, leading to an automatically created *goal predicate* whose WM represents the goal function; e.g., a pattern of tiles to be reached in the Eight Puzzle can be stored in the WM of the `board*goal` predicate. Thus, investigating appraisal has led to the resolution of a decades-long issue in problem-solving architectures. In principle, this shouldn't be too surprising – if emotions exist for functional reasons, they ought to support gains in other system capabilities.

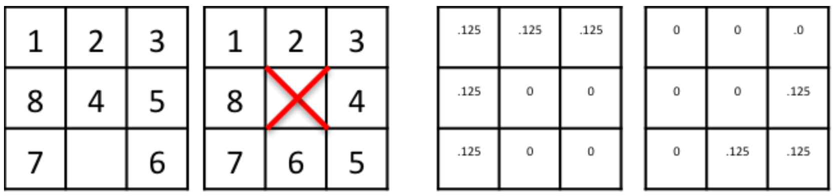
Given a predicate's state and goal, *desirability* amounts to how similar/different the state is to/from the goal. Although similarity in Sigma was first implemented as the dot product of the state and goal functions, once surprise was implemented it became clear that the Hellinger distance could directly yield a difference measure here, while the *Bhattacharyya coefficient,* a key subpart of the Hellinger distance, could replace the dot product in computing similarity:

$$Difference(S,G) = HD(S,G) = \sqrt{1 - \int \sqrt{s(x)g(x)}dx}. \tag{3}$$

$$Similarity(S,G) = BC(S,G) = \int \sqrt{s(x)g(x)}dx. \tag{4}$$

Thus, only one difference measure is needed for both expectedness and desirability, with a similarity measure computed for free. Both variants of desirability are now computed and stored, as a *progress map* (for similarity) and a *difference map*, in the perceptual buffers for automatically created *progress* and *difference predicates*.

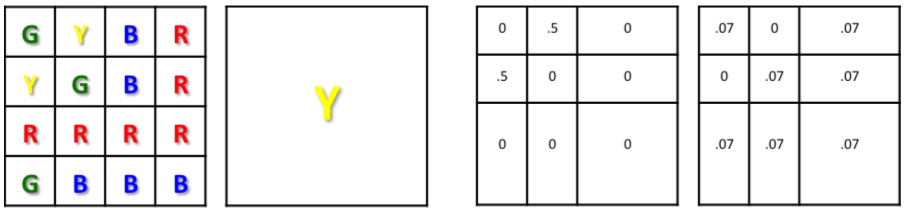
Progress yields a region-by-region map of how similar the two distributions are. With Boolean goal and state distributions, what is computed corresponds to the fraction of the goal conjuncts achieved. With a Boolean goal and a more general state distribution, this more closely resembles the probability that the goal has been achieved. A full distribution over the goal corresponds more to a utility or heuristic function than a goal. Fig. 4 shows a sample state and goal for the Eight Puzzle, plus the progress and difference maps (normalized by the number of goal regions).



(a) State (b) Goal (c) Progress Map (d) Difference Map

Fig. 4: Eight Puzzle state and goal configurations, plus the resulting desirability maps. The first two show argmaxes over (Boolean) distributions. No goal has been set for the center cell.

Beyond problem solving, desirability is also relevant to quite different sorts of problems, such as a *visual search* that, e.g., is to find the *yellow* locations in the visual field. For complex visual searches, human processing is slow and sequential, but for simple searches like this one, detection occurs in time that is nearly independent of the number of distractors. In Sigma, goals for visual search are specified just like those for problem-solving search – yielding an `image*goal` predicate here – with *progress* comparing the image with this goal. However, instead of expressing a desire to change the existing image, it specifies what is to be found in it. Fig. 5 shows sample states and goals for visual search, plus the progress and difference maps.



(a) Visual field (b) Goal (c) Progress Map (d) Difference Map

Fig. 5: Visual field state and goal (argmaxes), plus the resulting desirability maps.

5 Attention

Attention broadly concerns the effective allocation of limited resources. Standard dichotomies for it include *perceptual* (e.g., visual) versus *cognitive* (or central), *overt* (e.g., involving eye movements) versus *covert* (sans observable changes), and *top down* (i.e., task relevant) versus *bottom up* (i.e., stimulus driven) [24, 25]. Yet, from Sigma's perspective, the first two of these dichotomies are best reconceptualized in terms of: (1) *physical* versus *computational*, and (2) the level of control involved (i.e., *reactive*, *deliberative* or *reflective*). The first relates to overt versus covert, since allocating a physical resource such as the eye is overt; however, both covert perceptual attention and cognitive attention are computational, so the pie is cut a bit differently. Within computational attention, quite different mechanisms may then operate at different levels of control. For example, at the deliberative level, the decision procedure is a canonical means of allocating resources – and thus of focusing attention – but it is too slow, at ~50 msec per decision, to allocate reactive resources.

The work here focuses on two levels of *computational attention* – *reactive* and *deliberative* – and in particular on how expectedness and desirability impact them. Computational attention is more difficult to evaluate than overt perceptual attention, but it is critical in cognitive architectures and likely also underlies physical attention. *Reactive attention* spans both covert perceptual attention and low-level cognitive attention. It should largely be architectural given the timings, although architecturally accessible knowledge – such as is provided by appraisals – is still fair game. Top-down versus bottom-up is less a distinction among types of attention than types of input to it. Here both factor into attention to reduce the cost of reactive processing.

The primary reactive cost in Sigma is message processing at nodes in the factor graph; i.e., computing message products and summarizing out unneeded dimensions from them. Many optimizations have already been introduced into Sigma to reduce the number of messages passed [26] and the cost per message [27]. Simulated parallelism has also been explored [26]. Yet, attention may support further non-correctness-preserving optimizations that still yield *good enough* answers.

A range of attentional approaches have been considered that reduce the number of messages sent and/or the cost of processing individual messages, with one form of the latter chosen for initial experiments. The basic idea is to use an *attention map* for each predicate in guiding *abstraction of messages* out of FFNs. The intent is to yield smaller messages that are cheaper to process yet still maintain the information critical for effective performance. The approach is analogous to attention-based image compression [28], but here it reduces inner-loop costs within a cognitive architecture.

The attention map for a predicate is automatically computed from its surprise map and/or its progress/difference map. When there is a learned function for a predicate, a surprise map exists and provides the bottom-up input to attention. This makes sense conceptually – what is expected is not informative, and has little utility unless relevant to goals (making it a top-down factor) – and has a strong grounding in human cognition [21]. When a predicate has a goal, progress and difference maps exist, and one of them is reused as the top-down input to the attention map. Again this makes sense conceptually, as top-down input is goal/task related, but there is some subtlety required in determining which of the two desirability maps to use.

In problem solving, the focus should be on those parts of the state that differ from the goal – i.e., the *difference map* – as this is where problem-solving resources are most needed. However, in visual search, what matters are the regions that match the goal – i.e., the *progress map* – as they correspond to what is being sought. One way of dealing with this conundrum is to invert the sense of the goal in visual search so that it would seek differences from *not yellow* rather than similarities to *yellow*. An alternative is to identify a fundamental distinction between the two problem classes that would enable *difference* to be used for the first and *progress* for the second.

.014	.261	.015	.014
.261	.014	.015	.014
.014	.014	.014	.014
.291	.015	.015	.015

Fig. 6: Normalized attention map for visual search.

A variant of the second approach has been implemented, based on closed-world predicates – as seen in the more stable, all-or-none, states found in problem solving – versus open-world predicates – as seen in perception and other forms of more transient distributional information. The attention map for a predicate is therefore a combination of surprise and difference for closed-world predicates, and surprise and progress for open-world predicates. If either map in the pair doesn't exist, the attention map is simply the one that does exist. If neither exists, there is no attention map. When both maps exist, they are combined via an approximation to *probabilistic or* that enables both to contribute while their combination remains ≤1:

$$P(A \vee B) = P(A) + P(B) - P(A \wedge B) \approx P(A) + P(B) - P(A)P(B). \qquad (5)$$

Fig. 6 shows the attention map for visual search after the change in Fig. 3(b), based on the surprise map in Fig. 3(c) and the progress map in Fig. 5(c). Bottom-up attention boosts the single changed region, while top-down boosts the two yellow regions.

Given such an attention map, message abstraction out of FFNs then leverages the piecewise-linear nature of Sigma's functions via an existing mechanism that minimizes the number of regions in functions by eliminating slices, and thus region boundaries, when the difference between the functions in each pair of regions spanning a slice is below a threshold. In particular, at an FFN the attention map for the predicate is first scaled and then exponentiated to increase the contrast between large and small values (the scale is set so that the maximum value is 1 after exponentiation). This exponentiated attention map is then multiplied times the factor function, and slices in the original function are removed if the differences are below threshold in this modified version. In contrast to normal slice removal, where the functions across the slice are similar enough for either to be used for the new expanded region, here the functions contributing to the new region are averaged. Fig. 7 shows the resulting message in the visual-search task. Only 4 regions are removed here, but many more can be removed for larger images; for example, with a 200×200 image the reduction is from 160,000 regions to 12. Significant cost savings can accrue as well, with a factor of ~3 seen with large images.

Fig. 7: Abstracted outgoing message with two mixed blue-red cells.

In addition to visual search, reactive attention has also been explored in SLAM. We were able to verify that a correct map could still be learned, and that the messages from the FFNs are smaller, but so far these reductions have not been sufficient for significant cost savings in this task.

Moving up the emotocognitive hierarchy to the deliberative level, it should be clear that a huge amount is already known about attention at this level, just mostly not under this name. Decision-making, planning and problem solving are all concerned with deciding what to do next, which is the essence of deliberative attention. However, with the notable exception of [29], tying this to appraisals is rare. To date in Sigma, *desirability* – and, in particular, *progress* – has been explored as an automatic evaluation function for (reflective) hill climbing in the Eight Puzzle. When all of the map's dimensions are summarized out via integration, the result is a single number in [0, 1] specifying the fraction of the tiles that are in their desired locations. The result here is an *evaluation function* that enables successful solution of many Eight Puzzle problems without the task-specific control knowledge previously added by hand.

Further attentional extensions within easy reach include: bottom-up inputs to decisions [29], *progress* as a reward function in reinforcement learning [30], *difference* as a guide in means-ends analysis (as in GPS [31]), and reflective attention.

6 Wrap Up

This work contributes novel architectural models of the *expectedness* and *desirability* appraisal variables, along with an initial investigation of their architectural implications for *computational attention*, both *reactive* (in aid of reducing message computation) and *deliberative* (in aid of guiding decisions). The approach to reactive attention particularly breaks new ground, while also contributing an extension of existing ideas about perceptual attention to explain low-level cognitive attention.

These results leverage many of Sigma's existing capabilities – including its (1) hybrid mixed function representation, (2) predicate factor graphs (particularly including working memories, perceptual buffers, and factor functions), (3) gradient-descent learning mechanism, (4) ability to remove unnecessary slices from functions, and (5) reflective problem solving. Added to the architecture were (1) a mechanism for comparing two distributions, (2) an architectural representation of declarative goals, (3) predicates for appraisal variables, and (4) a mechanism for abstracting graph messages based on an attention map. Rather than forming a distinct emotion module, these largely just amount to more reusable architectural fragments.

Still, this work just scratches the surface of all that is needed to implement emotion fully within Sigma. More appraisal variables are clearly needed, such as *controllability* – with its close ties to decision-making – and *social appraisals*, with their potential grounding in recent work on Theory of Mind in Sigma [4]. It also makes sense to explore aggregation of appraisals across predicates. Much more is also needed concerning the impact of appraisals on thought and behavior. Here we began exploring the impact on attention. We have also begun investigating the impact of the approach on *drives* and *moods*, based on further leveraging of distribution comparisons and learning. Beyond this are also the broad topic of *coping* and the larger question of the relationship of emotions to embodiment. Sigma has recently been connected to a virtual human body [32], but this is still just a beginning.

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