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If the representation of the  $(L + 1)$ th stimulus is a repetition of a representation already in consciousness, there is no reason (apart from temporal context) why the representation of the repetition should not overwrite the representation already in consciousness. It was noted above that, before the  $(L + 1)$ th stimulus is added to a list of  $L$  stimuli differing in content, the total number of representations in consciousness that differ in content approximates  $L$ . After the addition of an  $(L + 1)$ th stimulus that is not a repetition of a list stimulus' content, the total number of representations differing in content will be increased to  $(L + 1)$ . But if the  $(L + 1)$ th stimulus does repeat a content, and then the representation of that  $(L + 1)$ th stimulus overwrites the representation whose content it repeats, the total number of representations differing in content will remain at  $L$ .

Now, a participant would be helped to detect the fact that the  $(L + 1)$ th stimulus repeats a content if he or she notices that the addition of the  $(L + 1)$ th stimulus causes no observable change in the total number of *differing* contents represented in consciousness. Let P&V's effortlessness be denoted by  $E$ . We hypothesize that  $E$  varies directly with the contrast between a change and no change in that number. So  $E$  will be defined, relative to  $L$ , as:

$$E = [(L + 1)/L] - [(L + 0)/L] = (1/L) \tag{3}$$

Let  $D$  denote the time required to detect that the  $(L + 1)$ th stimulus is a repetition, and let  $D$  vary inversely with  $E$ . The greater the effortlessness, the shorter the detection time. Then:

$$D = (a/E) = [a/(1/L)] = La \tag{4}$$

The reason the constant of proportionality in Equation 4 is assumed to equal  $a$  is that Equations 4 and 2 are thereby consistent because, when  $L = 1$ ,  $D = a$  in both equations. Furthermore, when  $L > 1$ , Equation 4 specifies that  $D = (La)$ . The term  $(La)$  is conventionally called the "decision latency" component of the Sternberg function and is contrasted with a "residual latency" determined by routine response processes.

Next, we turn to the memory span task. Following the presentation of  $L$  differing list stimuli, the participant must recall all  $L$  stimuli in correct serial order. In a Sternberg task using digit-triple material, the probability that a representation of a particular list stimulus would still be in consciousness after the presentation of the final list stimulus, but prior to the onset of the  $(L + 1)$ th stimulus, was specified by Murray et al. (1998, p. 1199) to be  $(1 - m)^i$ . Here,  $i$  is the number of list stimuli intervening between that list stimulus and the end of the list; usually  $i = (L - 1)$ . In a memory span task, the equivalent would be the number of stimuli (including both list stimuli and the recalls of those list stimuli) intervening between the presentation of a particular list stimulus and the recall of that stimulus. Here too, this number equals  $(L - 1)$ .

The probability,  $P$ , that *all* of the  $L$  list stimuli will be correctly recalled in order, is:

$$P = (1 - m)^{L(L-1)} \tag{5}$$

Cavanagh (1972, p. 527) defined the memory span,  $S$ , as being that  $L$  value associated with a probability of 0.5 of being correctly recalled in order. Dividing both sides of Equation 5 by  $2P$ , and substituting  $S$  for  $L$  in Equation 5, yields:

$$0.5 = [(1 - m)^{S(S-1)}]/(2P) \tag{6}$$

Taking natural logarithms and rearranging terms of Equation 6 gives:

$$-\ln(1 - m) = \{-\ln[0.5(2P)]/(S - 1)\}(1/S) \tag{7}$$

From Equation 2, the left side of Equation 7 equals  $(a - u)$ , so Equation 7 becomes:

$$a - [(-\ln P)/(S - 1)](1/S) + u \tag{8}$$

Equation 8 is Cavanagh's function expressing  $a$  (the slope of the Sternberg function) as a linear function of  $(1/S)$  (the reciprocal of

the memory span). Its intercept is  $u$  and its slope is  $[(-\ln P)/(S - 1)]$ . Cavanagh's estimated value of the intercept was 0.0028s, and his estimated value of the slope was 0.2432s.

Cavanagh also reported the obtained values of  $a$  and of  $S$  associated with each of seven materials. The estimated values of  $m$  for the seven materials ranged from 0.0301 (for single digits) to 0.0678 (for nonsense syllables). The mean value of the seven estimates of the slope of the Cavanagh function, derived by calculating  $[(-\ln P)/(S - 1)]$  for each material, was 0.2431s.

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The computational baby, the classical bathwater, and the middle way

Gerard O'Brien and Jon Opie

Department of Philosophy, University of Adelaide, South Australia 5005.  
 gerard.obrien@adelaide.edu.au jon.opie@adelaide.edu.au  
<http://www.arts.adelaide.edu.au/philosophy/gobrien.htm>  
<http://www.arts.adelaide.edu.au/philosophy/jopie.htm>

**Abstract:** We are sympathetic with the broad aims of Perruchet & Vinter's "mentalistic" framework. But it is implausible to claim, as they do, that human cognition can be understood without recourse to unconsciously represented information. In our view, this strategy forsakes the only available mechanistic understanding of intelligent behaviour. Our purpose here is to plot a course midway between the classical unconscious and Perruchet & Vinter's own noncomputational associationism.

We are sympathetic with the general thrust of Perruchet & Vinter's (P&V's) "mentalistic" framework. In particular, we endorse their attempt to establish a principled connection between mental representation and conscious experience (see, e.g., O'Brien & Opie 1999a). And, like them, we are suspicious of orthodox, intellectualist approaches to the cognitive unconscious. Nonetheless, in developing the notion of a "self-organizing consciousness," P&V go too far when they contend that unconsciously represented information plays no role in human cognition. As we explain shortly, this thesis throws out the computational baby with the classical bathwater, and thereby forsakes the only available mechanistic understanding of intelligent behaviour. Our purpose in this commentary is to plot a course midway between the classical unconscious and P&V's own noncomputational associationism.

At the heart of P&V's project is the claim that (unconscious, noncomputational) associative processes of learning and memory are sufficient to generate conscious mental representations whose contents are isomorphic with the world. This is a very bold claim. It flies in the face of the classical computational program in cognitive science, which assumes that conscious representations are the product of a vast amount of unconscious symbol manipulation governed by unconscious rules. It is therefore incumbent on P&V to provide a detailed account of the kinds of associative processes they have in mind.

Yet, as far as we can determine, P&V directly address the nature of mental association in just three relatively short passages of the target article. First, they briefly discuss how associative learning can explain classical conditioning (sect.1.3.3). Second, in response to the apparent inability of associative processes to account for the full complexity of human cognition and conscious mental life, they suggest that such processes are not limited to acting on elementary stimuli but can be extended to complex representations (sect. 2.2.2). And third, they claim that primitive represen-

tations that are repeatedly linked in attention “tend to pool together and form a new primitive,” which is then available as a unitary representation in subsequent processing (sect. 3.2). All of the ensuing discussion presupposes that mental association has been adequately explained, and P&V concentrate on showing how the complex conscious representations it produces can account for human behaviour in various domains.

What we are suggesting is that P&V’s discussion of mental association is insufficiently developed to bear the burden of their principal thesis. This becomes especially apparent in section 6.4, where P&V help themselves to representations with increasingly abstract contents. These, they explain, can be formed by iteration of the same basic associative processes already described. Yet, because they have said so little about these processes, it is difficult for the reader to assess the plausibility of this claim.

It is not surprising that P&V fail to specify associative processes adequate to the complexities of human cognition. Associationism, in various guises, has been around for a long time, and its shortcomings are well known. Two of these deserve mention here.

The first concerns the raw materials on which associative processes putatively operate, specifically, conscious representations. Whatever the status of the claim that the conscious states produced in the course of processing linguistic input are the result of associative processes,<sup>1</sup> the same cannot be said of other perceptual modalities, especially vision. This is because visual experience is radically underdetermined by the data available in the proximal stimulus (the dynamic array of light falling on the retinae). The conclusion most theorists find inescapable is that visual perception is an inferential, rather than associative, process – one that constructs visual representations by combining stimulus data with internally represented assumptions about the structure of the environment. Because we are not aware of this process, visual inference, and the representations it implicates, must be unconscious (see Fodor & Pylyshyn 1981; and for a more recent statement, Palmer 1999, pp. 55–59).

The second problem runs even deeper and concerns the physical implementation of cognitive processes. What is required to explain cognition is a physical mechanism that can account for the parallelism between the content of mental representations and their causal relations (see, e.g., Fodor 1987, Ch.1). This challenge stumped proponents of associationism in the eighteenth and nineteenth centuries, who only permitted contiguity and co-occurrence of ideas as ultimate explanatory principles. Behaviourism, essentially a nonmentalistic version of associationism, was likewise explanatorily impoverished. It was only the emergence of the classical computational theory of mind, inspired by the power of digital computers, that saw the first serious contender for a mechanistic account of cognition. Classicism offers a story as to how the causal interactions between mental representations (in the form of symbol structures) preserve their semantic relations. But this story is distinctly nonassociationist, given that it depends on the operation of unconscious, structure-sensitive rules. Because these rules, and much of the information they implicate, are not consciously available, classicism delivers the sophisticated cognitive unconscious P&V are at pains to avoid.

In short, as things currently stand, the only idea we have of how cognitive processes might be physically implemented in the brain assumes that these processes are computational in form. To abandon computationalism in favour of a mentalistic form of associationism, as P&V exhort, is thus to embrace mystery.

But P&V need not despair. There is a path that runs midway between classical computationalism and mentalistic associationism; a path that avoids the classical unconscious *without* abandoning computationalism. We finish by plotting this middle way.

The middle way is to reject classicism, with its commitment to a symbol crunching unconscious, in favour of the *connectionist* computational theory of mind. As we have explained at length in this journal (O’Brien & Opie 1999a), connectionism permits a distinction between explicit (activation pattern) representation and inexplicit (connection weight) representation that is perfectly

crafted for P&V’s mentalistic framework. Instead of claiming that unconscious information plays no role whatever in human cognition, they should restrict this claim to unconscious, *explicitly represented* information. Even if all explicitly represented information is conscious, inexplicit representation is still free to carry the burden of the cognitive unconscious. In this story, the links between conscious representations are computational, rather than merely associative, because they are mediated by connection weight representations. Such representations embody, for example, unconscious assumptions about the visual world, but in non-symbolic form. Thus, the unconscious one ends up with is very different from its classical counterpart. Moreover, the conscious (explicit) and unconscious (inexplicit) are intrinsically and deeply connected, because activation pattern representations are shaped by inter-unit connections. To use P&V’s own metaphor (sect. 1.3.1), they are like the two sides of a coin, inseparable, yet distinct.

NOTE

1. P&V’s work on this topic is, we think, highly significant, and does much to undermine traditional models of word segmentation, grammar learning, and so on, which help themselves to an implausibly rich cognitive unconscious.

## Oral and visual language are not processed in like fashion: Constraints on the products of the SOC

Christophe Parisse<sup>a</sup> and Henri Cohen<sup>b</sup>

<sup>a</sup>INSERM-Laboratoire de Neuropsychopathologie du Langage et de la Cognition, Batiment Pharmacie, Hopital de la Salpetriere, Paris, France;

<sup>b</sup>Cognitive Neuroscience Center and Department of Psychology, Université du Québec à Montréal, Montreal, QC, Canada.

parisse@ext.jussieu.fr henri.cohen@uqam.ca

<http://www.plpc.chups.jussieu.fr/christophe.html>

<http://www.unites.uqam.ca/sirp/experts/6593.html>

**Abstract:** The SOC framework does not take into account the fact that the oral modality consists of purely transient data, which is not the case for the other modalities. This, however, has important consequences on the nature of oral and written language, on language consciousness, on child language development, and on the history of linguistics.

In section 2.1, Perruchet & Vinter (P&V) posit the existence of an isomorphism between “the actual and the represented world,” and explain that “complex representations account for seemingly rule-governed behavior.” This is made possible by the existence of the self-organizing consciousness (SOC), the principles of which are exemplified in PARSER. The power of PARSER was put to the test on a computer by replicating a learning situation tested with infants and adults by Saffran and collaborators (Saffran et al. 1996a; 1997). The situation corresponds to the extraction of words from raw phonetic input.

The performance of PARSER is very impressive – as is that of infants and adults – but maybe not so much so when one considers the characteristics of the input signal. All syllables in the input are of the same duration, the same height, share the same structure, and are repeated more than a thousand times in the same situation. In such contexts, primitives such as syllable segmentation and syllable identification work so well that the problem to be solved becomes too simple and does not adequately represent real life situations. Of course, there is a lot of information other than word regularities that helps children get the job done in real life situations (see target article, sect. 4.1; Johnson & Juszyk 2001; Perruchet & Vinter 1998b). Nonetheless, this affects the working context of PARSER and undermines the demonstration of P&V.

A second problem is that stimuli in the oral modality are always transient. This limits the possibility of an “outside memory,” (O’Regan 1992) and makes it more difficult to create an isomorphic representation. Conscious reanalysis of the signal is impossible or