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Associations are all we need

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Running Head: Unified Radical Associationism

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Abstract

In this opinion article, I argue that the time has come for a unified radical associationism that is built around the assumption that associations are all we have and probably all we need to account for mental activities. This radical associationism should be able to *merge* the fields of associative, statistical and Hebbian learning and unify these theoretical and empirical approaches. A direct consequence of adopting such a theoretical stance is a revision of several key psychological concepts (e.g., the notion of attention) based on neurobiological ones, leading to a unified neuro-psychological theorization of mental activities.

Keywords: Associationism, statistical learning, Hebbian learning

Résumé

Dans cet article, je défends l'idée que le temps est venu d'un associationnisme radical unifié qui serait construit autour de l'hypothèse que les associations sont tout ce que nous avons et probablement tout ce dont nous avons besoin pour rendre compte de nos activités mentales. Cet associationnisme radical devrait permettre de fusionner les domaines de l'apprentissage associatif, statistique et hebbien, et d'unifier ces approches théoriques et empiriques. Une conséquence directe de l'adoption d'une telle position théorique est une révision de plusieurs concepts psychologiques clés (par exemple, la notion d'attention) basée sur des concepts neurobiologiques, conduisant à une théorisation neuropsychologique unifiée des activités mentales.

Mots clés: associationnisme, apprentissage statistique, apprentissage hebbien.

1. Introduction

The scientific study of our mental activity (i.e., psychological science) emerges progressively during the 19th century and ends up occupying an ever more marked academic base throughout the 20-21th centuries. But psychology is still a very recent field of knowledge whose central concepts still need to be refined and consolidated, and sometimes *radically* revised. Take a bunch of contemporary textbooks on psychology (e.g., Cervone, 2015; Lemaire & Didierjean, 2018; Nairne, 2013) and it quickly becomes apparent that none of them describes this field of knowledge in the same way nor it uses the same definitions of the central concepts of this discipline. This conceptual diversity ties in with what Walter Mischel has called the “toothbrush problem”: “Psychologists treat other peoples’ theories like toothbrushes — no self-respecting person wants to use anyone else’s “ (Mischel, 2008; see also, Poldrack & Yarkoni, 2016).

This situation is partly due to the fact that throughout its recent and short history, psychology has seen the emergence of different schools of thought that have constantly revised the concepts and theories of their predecessors. Structuralists, functionalists, behaviorists, gestalists, cognitivists, and connectionists (to name only the main ones), have constantly reshaped our conceptual space in order to always tend towards better descriptions and explanations of our mental activities (e.g., Nicolas & Ferrand, 2008; Rey, 2012; Schultz & Schultz, 2007). The time when we will arrive at stable concepts in psychology is therefore still to come (if that day ever comes).

During this same period, our knowledge in neurophysiology developed in parallel and revealed the cellular, associative, and interactive structure of the biological substratum that carries our mental activity. Some people have progressively become accustomed to the mechanistic idea that our mental activity is a by-product of the activity of a complex network of billions of neurons and trillions of synapses (e.g., Herculano-Houzel, 2009) whose interactions support our thoughts. Throughout the 20th century, neuropsychology has also constantly described the link between brain lesions and disturbances in our mental activities, suggesting the tenuous relation between psychology and neurobiology (e.g., Shallice, 1988). Others, and not the least, have expressed concern about these mechanistic and reductionist visions, considering that they can lead to some worrying forms of radical determinism and that something is missing from these approaches (Chomsky, 1972), even if this something is rarely described and specified.

For example, Smith and Church (2018) consider that it is not possible to account for all our mental activities with the notion of associative learning. This notion is certainly useful, but only to account for elementary mental operations without exceeding what they call the *threshold* of explicit/declarative cognition. However, when it comes to describing the mechanisms at play beyond this threshold, we often don't find very clear explanations, and we never quite understand how these mechanisms work and would be implemented at the computational or neural level.

The purpose of this opinion article is not to untangle the aporetic issue of the relationship between reductionism and determinism. Let's leave this

fascinating debate to philosophy, the art of producing the best possible thoughts and reasoning about the world and the human condition from the conceptual and lexical corpus available at a given time, and let's stick to science, the art of constantly refining these words and concepts so that they best fit the complexities of reality. Recognizing that our mental activity is the result of the activity of a complex network of neurons is no indication of the capacity of such a network to free itself from its own determinisms (the central problem being undoubtedly in what we mean by freedom). However, it is probably premature to speculate on this potential capacity before having an excellent understanding of how such a system works.

The aim of this article is therefore to reaffirm the epistemological utility for psychology of the associationist hypothesis in order to try to converge towards a set of concepts that are as stable and functional as possible. To achieve this, this article is organized in three parts. I will begin with a historical detour to recall the place of the associationist hypothesis in the recent period. I will argue that this hypothesis has taken different forms and has led to the formation of different, relatively disjointed, research fields, such as associative learning, statistical learning or Hebbian learning (to name a few). In a second part, I will present and discuss a list of ten points to try to better define the associationist hypothesis. I will then argue that several research domains that have adopted the associationist hypothesis in different forms, are articulated around the same phenomenon which is at the heart of the construction of our mental life: the coding of repeated co-occurrences. Since these domains are based on similar theoretical structures, it is probably time to unify them into what could be called

a "unified radical associationism" (URA). I will also argue that the general framework of Hebbian learning, even if it must be constantly revised according to the latest advances in neurobiology, is certainly the best computational theoretical framework at the moment to structure this project. Finally, in a last part, I suggest to glimpse the consequences of such a theoretical approach on a certain number of central concepts in psychology, such as the notion of attention, considering that it is probably time to pursue the hebbian project (Hebb, 1949) and reshape these ill-defined notions with more precise concepts rooted in the field of neurobiology.

2. A historical detour about the associationist hypothesis

Philosophical and neurobiological associationisms

Many traces of the associationist hypothesis can be found in the philosophical discourses that precede the advent of so-called psychological science (Warren, 1921, 1916). For example, in his *Enquiry concerning human understanding* (Section 3: The association of ideas), David Hume considers that "the mind's thoughts or ideas are obviously inter-connected in some systematic way: there is some order and regularity in how, in memory and imagination, one idea leads on to another". According to him, "there appear to be only three factors connecting ideas with one another, namely, resemblance, contiguity in time or place, and cause or effect" (Hume, 1748). But philosophical associationism is more concerned with the question of mental associations and the organization of our ideas and thoughts than with the question of the neuropsychological functioning of our mental activities

understood as the by-product of a neurobiological activity carried by a network of neuronal cells. And for good reason, since the notion of the neuron as a minimal unit of a network that conducts information through biomechanical and electrical processes, is a notion that was born almost at the same time as scientific psychology (Brazier, 1988; Clarac & Ternaux, 2008; Shepherd, 2015). History books indeed consider that the birth of the concept of neuron dates from the discoveries of Camillo Golgi on new techniques of staining of nerve tissue (Golgi, 1873) and the work of Santiago Ramón y Cajal (Ramón y Cajal, 1899). However, it was not until the middle of the 20th century and the discovery of electronic microscopy that it was possible to get a precise definition of a neuron and of the connections between neurons, then called "synapses" (Clarac & Ternaux, 2008). These notions are therefore extremely recent, even though they are at the basis of the associationist hypothesis, of which we will give a much precise definition later on.

Instrumental and reinforcement learning

The idea that there are regular, sometimes systematic, relationships between different elements or *events* of the world around us or causal links between these events and that we are able to encode and memorize these statistical regularities is not recent. The experimental exploration of this fundamental idea dates back to Thorndike's famous work with different animal species (Thorndike, 1905). He is often cited as one of the first to study the temporal dynamics of learning a relationship between a behavior A (e.g., like pressing a lever) and the positive or negative effect B it produces (e.g., like opening a door that leads to food). Also called the "law of effect", it shows how

variations of random exploration behavior are selected in a Darwinian fashion by the effects that these behaviors produce. The temporal co-occurrence of these two events A and B (i.e., the behavior and its effect) thus seems to allow the development of an association between A and B that will increase the probability of producing this behavior (if the effect has positive consequences for the organism) and whose strength will continue to increase with each repetition of $A \Rightarrow B$. This type of learning is called "instrumental conditioning", but under the impetus of B. F. Skinner and the radical behaviorism he developed (e.g., Skinner, 1938), it is better known as "operant conditioning" or "reinforcement learning".

Thus, instrumental and operant conditioning highlight the learning of causal and directional relationships between two co-occurring events A and B, one predicting the production of the other. However, the associative chain that is set up with this type of learning does not seem limited to A and B. If after pressing a lever (event A), a door opens (event B) and that I access food (i.e., event C), then come into play other pre-existing associations between food, the action of eating (event D) and the pleasure it generates (event E), or not (event F). Operant conditioning therefore involves a whole associative network that it would probably be wrong to reduce to events A and B. The precise description of these seemingly simple associative mechanisms seems to rely on a more complex associative network than it first appears. But it should be remembered that the proponents of the behaviorist approach did not seek to describe these associative mechanisms but only the chaining structure of

observable behaviors. However, it seems reasonable today to think that we could translate this chain of behaviors into a chain of neuronal associations.

Pavlovian conditioning

During this same period, Pavlov (1927) shows how from a pre-existing association between two events A and B, A *mechanically* inducing the production of B (A being the unconditioned stimulus, US, e.g., food, and B the unconditioned response, UR, e.g., salivation), the co-occurrence with A of an event C (called the conditioned stimulus, CS, e.g., a ringing bell) ends up inducing the production of B (which becomes a conditioned response, CR). In this form of associationism called "classical or Pavlovian conditioning", it is the simple spatial and/or temporal co-occurrence that creates an association between events A and C (i.e., the US and the CS). Everything happens here as if the mental activity linked to A became, by simple repetition of their co-occurrence, associated with that linked to C.

Hebbian learning

The idea of a neural coding of co-occurrences is at the heart of the Hebbian project (Hebb, 1949) and of what will become the Hebb rule in artificial neural networks. The whole Hebbian theoretical proposal is indeed based on this simple idea that the development and structuring of our mental activity depends on an elementary associative property that we do not control and which is the foundation of the memory trace. Hebb indeed proposed the following general associative principle: "*When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that*

A's efficacy, as one of the cells firing B, is increased" (pp. 62). With this simple general property of the nervous tissue, Hebb pretends to account for the construction of our incredible mental cathedral. And if this principle applies to the level of two neurons connected to each other, it generalizes to the development of a wider trace encompassing numerous neurons within an *assembly of neurons* that will encode more widely the network of cerebral activity associated with a given event and therefore the mental activity related to this event (Buzsáki, 2010; Dragoi, 2020; Harris, 2005).

Chomsky's criticism

Interestingly, while behaviorists and neuropsychologists were converging in the middle of the 20th century by emphasizing the importance of elementary associative mechanisms in the structuration of our behavioral and mental activities, a major theoretical earthquake occurred which completely reversed the perspectives opened up by these different approaches. Its epicenter is the result of the friction of two tectonic plates that clashed on the thorny issue of language. In the same year, two books were indeed published which attacked the question of language from two radically opposed perspectives. On the one hand, Skinner (1957) applied the principles of operant conditioning to the question of language and tried to show that these basic principles can account for the development of this unique faculty. On the other hand, Chomsky (1957) criticized the possibility of accounting for the faculty of language by means of the associationist hypothesis (and more precisely, one of its instantiations, the Markov chains) and substituted it with the hypothesis of generative grammar. His argumentative line was simple, striking, and

remarkably convincing: it is not possible to account for our ability to produce grammatical sentences on the basis of learned associations between words. Chomsky (1959) goes even further with an explosive critique of the Skinnerian project that has become a landmark since it is often considered to introduce the cognitive revolution and (almost) the end of behaviorism (see MacCorquodale, 1970, for an attempted response from the behaviorist camp).

Associative learning

This massive criticism did not, however, completely extinguish the flame of associationism. A form of resistance to the chomskyan tsunami was implicitly organized around the study of Pavlovian conditioning in animal learning experiments, with a particular role played by the theoretical contribution of Rescorla and Wagner's (1972) model that can be considered as providing the foundations of the field of associative learning (Siegel & Allan, 1996). This model aims at accounting for results on Pavlovian conditioning where one measures the effect of associating two conditioned stimuli (CS) to the same unconditioned stimulus (US). It generated a whole series of theoretical developments (e.g., Honey et al., 2020; Honey & Dwyer, 2022; Mackintosh, 1975; Miller et al., 1995; Pearce, 1994; Pearce & Hall, 1980; Wagner, 1981) in interaction with a series of experimental phenomena of which they tried to give an account (e.g., *blocking effect*; e.g., Kamin, 1969; *conditioned inhibition effect*; e.g., Rescorla, 1969; *contingency effects*; e.g., Rescorla, 1968; *overshadowing effect*; e.g., Mackintosh, 1976; *relative validity effect*; e.g., Wagner et al., 1968; *super-conditioning effect*; e.g., Rescorla, 1971). Review articles have been published regularly in the *Annual Review of Psychology* to

report the state-of-the-art in this relatively discrete but still burgeoning field of research (Dickinson & Mackintosh, 1978; Domjan, 2005; Pearce & Bouton, 2001; Rescorla & Holland, 1982; Shanks, 2010; Wasserman & Miller, 1997). Even if the original article by Rescorla and Wagner (1972) makes no reference to Hebb's (1949) work, it is in fact quite clear that the proposed formalisms account for the encoding of co-occurrences and the interaction between competing associations. The basic mechanisms thus seem similar, if not identical, even if the models of associative learning and Hebbian learning have never really converged towards a common formalism.

Connectionism and deep learning

The use of artificial neural networks to account for psychological processes, such as McClelland and Rumelhart's (1981) landmark model for reading and visual word recognition, took off in the 1980s with the development of the backpropagation algorithm (Rumelhart et al., 1986). This powerful connectionist wave, including the famous book by McClelland, Rumelhart and the PDP Research Group (McClelland et al., 1986), introduced computational modeling into psychology and gave a second wind to a form of associationism. Supervised learning by backpropagation indeed shows how an artificial neural network can learn to produce a certain output from a given input by adjusting the weight of its connections. With the increasing development of our computer power and a change in the way of thinking about the role of contextual information (Vaswani et al., 2017), this learning algorithm is at the heart of the latest connectionist wave known as "deep learning" (Krizhevsky et al., 2017). Interestingly, even if the performances of

these new generations of models do not yet allow to really pass the Turing test (Floridi & Chiriatti, 2020), they at least re-open the debate on the capacity of neural networks to generate grammatically correct sentences based on associative learning principles.

It should be noted, however, that backpropagation networks suffer from at least one major limitation: their poor neurobiological plausibility (O'Reilly, 1998; Thorpe, 2023). It is indeed difficult to find a neurobiological basis for the backpropagation algorithm and for the principle of adjusting the weight of the connections from a calculation of the error produced in output. So, even if these deep neural networks show that the associationist hypothesis should not be buried and has clear computational interest, it seems that the basic learning principles of these networks are not yet the right ones (Perruchet & Vinter, 2021).

Resurgence of Hebbian learning

Pulvermüller's (1999) seminal article opens the door to a resurgence of Hebbian learning principles on the specific and critical issue of language. In Pulvermüller's proposal, neural assemblies are described as a way to encode information about words, and by assuming the existence of sequence detectors, he also claimed to account for our syntactic abilities (e.g., Pulvermüller, 2003; Pulvermüller et al., 2008, 2013; Pulvermüller & Knoblauch, 2009; Pulvermüller & Shtyrov, 2003). However, as interesting as this theoretical proposal is, it still seems to lack the computational proof that it is indeed possible to account for natural language development with the principles of Hebbian learning (but, for recent and promising developments, see Schomers et al., 2017).

Numerous studies have also used the Hebb repetition paradigm (Hebb, 1961) to investigate the dynamics of word form learning. In this classical work, Hebb tested participants in a serial immediate recall task of nine-digit sequences. A sequence was repeated every third trial and participants were not informed of this repetition. Hebb showed that recall performance on the repeated sequence improved over repetitions, indicating that a stable representation of the sequence in long-term memory developed over these repetitions. Page and Norris (2009) built on this empirical phenomenon and suggested that this learning paradigm may be a laboratory analogue of word form learning, which appears to rely on the same sequence learning processes. Since then, this hypothesis has been supported by several studies indicating one more time that associative and/or Hebbian learning principles can certainly provide the foundations for the development and processing of language (e.g., Archibald & Joanisse, 2013; Attout et al., 2020; Mosse & Jarrold, 2008; Norris et al., 2018; Ordonez Magro et al., 2018, 2022; Page et al., 2013; Pinto Arata et al., 2024; Rey et al., 2020a; Szmalec et al., 2009, 2012; Tosatto, Bonafos, et al., 2022).

Statistical learning

We close this historical detour by the extremely productive field of statistical learning whose beginning is generally dated with the seminal article of Saffran et al. (1996)¹. This study shows that 8-month-old children are able to extract lexical regularities present in a continuous sound stream of a few

¹ Perruchet and Pacteau's (1990) article could also be identified as one of the main studies initiating this field of research since it was one of the first to account for results in artificial grammar learning experiments by assuming simple mechanisms of regularity extraction.

minutes composed of the random concatenation of 4 artificial trisyllabic words. This result and many others suggest that we have innate abilities to extract statistical regularities from our environment (Fiser & Lengyel, 2022; Frost et al., 2019; Perruchet & Pacton, 2006; Saffran & Kirkham, 2018) and that these statistical learning abilities can be considered as foundations for our mental activity (Perruchet & Vinter, 2002).

At the theoretical level, this field has been extremely thriving and has given rise to numerous theoretical proposals to account for our ability to extract statistical regularities (e.g., Cairns et al., 1997; Christiansen et al., 1998; Daland & Pierrehumbert, 2011; Elman, 1990; Frank et al., 2010; French et al., 2011; Giroux & Rey, 2009; Goldwater et al., 2009; Mareschal & French, 2017; Orbán et al., 2008; Pearl et al., 2010; Perruchet & Vinter, 1998; Plaut & Vande Velde, 2017; Robinet et al., 2011; Thiessen & Erickson, 2013). Interestingly, the same general idea runs through these different theoretical proposals: whatever the sensory modality, we do have an innate ability to detect and encode repeated patterns in memory (although modality-specific effects have also been reported, see Frost et al., 2015). These patterns are made up of adjacent elements that appear repeatedly in the same sequential order and are supposed to be stored as processing units or *chunks* (e.g., Gobet et al., 2001; Tosatto, Fagot, et al., 2022). These chunks can also be composed of non-adjacent elements but it seems that the encoding of these non-adjacent dependencies is less easier than for adjacent ones and is conditioned by the simultaneous processing of its constituent elements (e.g., Pacton et al., 2015; Pacton & Perruchet, 2008; Tosatto et al., 2022; Wilson et al., 2020).

While statistical learning has been considered as the fundamental mechanism accounting for lexical development by extracting and encoding word units, it is only recently that it has been extended to the perception and production of grammatical sentences. Indeed, McCauley and Christiansen (2019) provides the first computational evidence that it is probably possible to account for our abilities to perceive and produce grammatical sentences by assuming that these processes only require the development of multiword chunks and the use of information about transitional probabilities between chunks. Interestingly, even if they do not refer to Pulvermüller's notion of sequence detectors, it seems that we find the same idea of an encoding of higher-level regularities that may be sufficient to account for the generativity and compositionality of human language².

Summary

We have just seen that several forms of the associationist hypothesis have emerged in the recent period. Figure 1 provides a schematic representation of these various forms of associationism and their historical positioning. Although these approaches have developed in parallel, they share the same interest in learning associations between different events of the environment that have the common characteristic of being regularly repeated. Since the differences between these approaches seem to be less important than the similarities, it is undoubtedly time to try to bring them together under a single label that could be called “unified radical associationism”.

² An idea that was also already present in Hebb (1949): “Activity in superordinate structure (...) is then defined as being whatever determinate, organized activity results from repeated activity in the earlier-developed or subordinate structures giving rise to it” (p. 98).

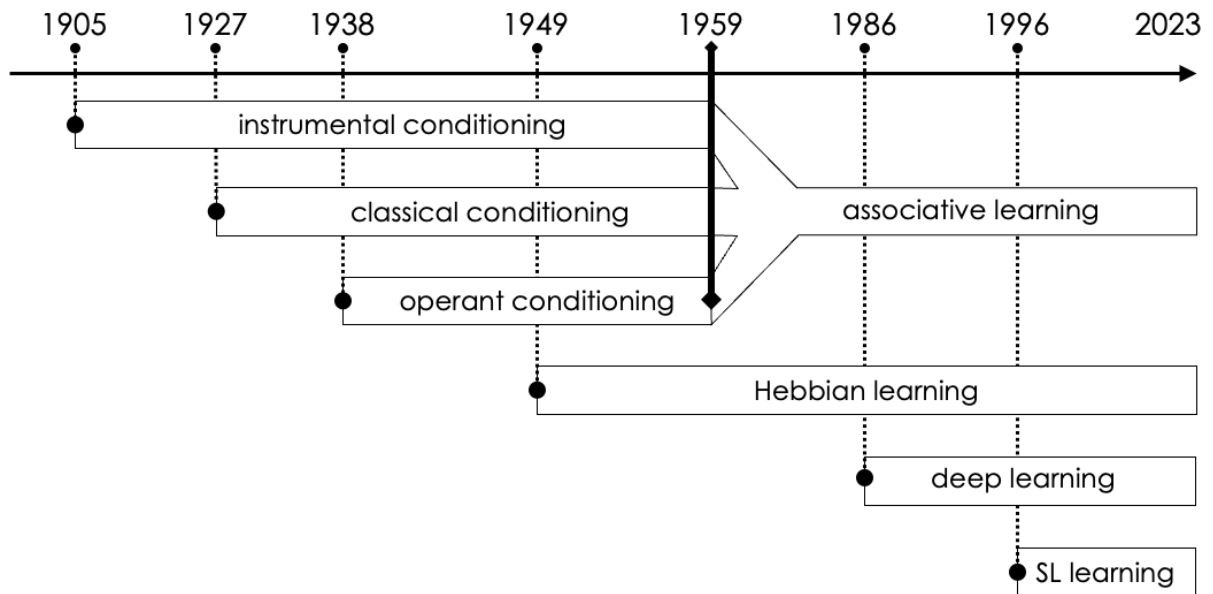


Figure 1: Schematic representation of the various forms of associationism during the recent historical period. Each date corresponds to key publications that have changed the trajectory of theorizing in psychology (e.g., Chomsky, 1959; Hebb, 1949; Pavlov, 1927; Rumelhart et al., 1986; Saffran et al., 1996; Skinner, 1938; Thorndike, 1905).

The use of the term "radical" is based on the assumption that all of our mental activities, even those usually considered to be higher-level cognitive processes such as language, can be described using the associationist hypothesis. This radicality has an epistemological value because it tries to push the associationist hypothesis as far as possible by trying to account for all our mental activities. This is *not* a blind conceptual commitment but an attempt to account for the extent and complexity of our mental activities from a conceptual scheme as simple as the associationist hypothesis. This idea can be illustrated from two recently published commentaries in which we provided much simpler alternative interpretations of the reported results in terms of associative learning mechanisms (i.e., Chartier & Rey, 2020; Rey & Fagot, 2023; for a similar approach, see also, Perruchet & Rey, 2005; Rey, Goldstein, et al., 2009).

3. Merging Hebbian, associative and statistical learning

In this section, I first propose to better define the associationist hypothesis by listing 10 points that outline its basic conceptual structure. I then propose to consider that the fields of hebbian, associative and statistical learning, all study the same type of phenomena and that it is probably possible to gather them under the same banner of "unified radical associationism". Finally, I suggest that the Hebbian conceptual framework is perhaps currently the best suited to bring these approaches together, even if it still contains a certain number of grey areas, the clarification of which will certainly lead us to other conceptual horizons.

Defining the associationist hypothesis

For a hypothesis to be of epistemological interest, it is essential to define it as precisely as possible in order to make each of its assertions falsifiable³. I will therefore venture to state 10 points that make it possible to circumscribe what I have called the *associationist hypothesis*. These 10 points do not give a strict definition of the associationist hypothesis but provide a list of premises or axioms on which to base this theoretical approach. Some of these points may seem obvious, but the historical detour we've just taken has shown that what may seem obvious today wasn't necessarily so at the beginning of the 20th century.

³ «Scientific theory in its best sense consists of the strict logical deduction from definite postulates of what should be observed under specified conditions. If the deductions are lacking or are logically invalid, there is no theory; if the deductions involve conditions of observation which are impossible of attainment, the theory is metaphysical rather than scientific; and if the deduced phenomenon is not observed when the conditions are fulfilled, the theory is false.» (Hull, 1935)

The purpose of listing these 10 points is to see to what extent they will still be accepted or discussed by the middle of the 21st century.

1. The brain is a biological substratum composed essentially of a complex network of cells called neurons, whose structure, function and organization may vary from one region of the brain to another.
2. Neuronal cells communicate with each other through cell-to-cell connections called synapses.
3. At any given time, only a portion of the total neuronal population is active and this activity is the biological support for our mental activity.
4. This activity is propagated very rapidly on the neuronal network following the connections between neurons.
5. We can break down our mental activity into a series of processes that operate on *events* of the world. The processing of each event produces a certain pattern of activation in different regions of the brain and the activation of assemblies of neurons specific to each event.
6. The processing of an event takes place over a period of time during which several sub-assemblies of neurons can be active in a parallel, sequential and/or interactive way.
7. The reverberation of assemblies of neurons active during the processing of a given event would be the support of short-term memory also called working memory.
8. The coactivation of two assemblies of neurons coding respectively for two events A and B induces transient modifications of the connectivity between

these two populations, supporting the memory of the co-occurrence between these two events.

9. The repeated processing of two events A and B consolidates the connectivity between the assemblies of neurons coding for A and B and constitutes part of the memory support of this co-occurrence. Another part comes from the activation of a neuronal assembly specifically activated by the assemblies encoding for A and B, and ultimately encoding the AB chunk.
10. These mechanisms are innate and uncontrolled. They lead to an isomorphic internal hierarchical representation of environmental regularities. Each species has its own genetically determined initial cellular network that conditions the repertoire and the complexity of regularities that can be coded.

Of course, each of these 10 points is already open to comment, debate and discussion, and I propose to initiate the controversy myself by briefly reviewing each of these proposals. It's also worth noting that each of these 10 points could be considered too general to be interesting and binding on a theoretical level. As I shall now attempt to show, none of these points is trivial, and each can be open to debate. Moreover, their theoretical fertility is conditioned by their falsifiability, an essential criterion for making a theoretical proposition subject to discussion or modification, and one that seems to be fulfilled by each of these 10 points.

Reducing the brain to a network of neurons (Point 1) is probably wrong because it is known to be composed of other cell types (e.g., glial cells) that

certainly play an equally important role in brain function. However, we can probably assume that the extremely rapid transmission of information by the neural network is the major support of our mental activity even if on larger time scales, other cellular mechanisms and other non-neuronal cells also play a role in brain dynamics and particularly in the memorization of information (Bullock et al., 2005). Similarly, assuming that neurons communicate primarily through their synapses (Point 2) may be an oversimplification, which does not sufficiently take into account, for example, the role of myelination, but it can probably be considered a fair enough approximation for the moment.

The idea that we can reduce our mental activity to the activity of assemblies of neurons (Point 3) is mainly justified by the observation of patients who have suffered brain damage and who are no longer able to perform certain mental operations, such as reading in the case of acquired alexia. Brain imaging techniques also provide evidence that our mental activities are at least correlated with our brain activity. Assimilating our mental activities to the specific activation of certain assemblies of neurons thus seems reasonable, even if we have seen that this conception is relatively recent in the history of ideas.

But then comes the question of what we call "mental activity", and how each mental activity relates to the others. For example, should we consider that maintaining a certain postural balance corresponds to a mental activity? Similarly, are automated gestural sequences such as walking supported by a specific mental activity? If we answer these two questions in the affirmative, how do we account for the fact that we can walk, keep our balance and talk

to another person on the phone all at the same time (Barrouillet et al., 2004, 2011)? If each mental activity presupposes assemblies of active neurons that code for each of these activities, how do these different activations of neuron populations coexist? Here, brain specialization seems to provide some answers to this apparent paradox. If we assume that certain regions code for postural balance, while others code more specifically for oral language processing, we get a glimpse of how the brain can coactivate two populations of neurons at the same time. On the other hand, if the same cerebral region is solicited by two different sources of information (as, for example, if we were to answer two telephone calls at the same time), then it seems impossible to envisage simultaneous processing of these two sources but instead some form of alternate or sequential processing.

Considering that information flows through the neural network (Point 4) seems nowadays relatively accepted. However, the difficulty lies in understanding how this rapid flow of information propagates within a huge and complex neural network. The time scale is so fast that it cannot be grasped by introspection and technology is our only ally to achieve an understanding of this extremely rapid dynamic system.

Discretizing the continuous flow of information that constitutes our environment (external and internal) into a series of events that the brain processes (Point 5) is an epistemological option that is undoubtedly useful for grasping the flow of our mental activities. However, this option has certain weaknesses that cannot be avoided for the time being, but which can at least be made explicit. An event can be any stimulation that produces a sensory

change or any motor production that also produces a change at the motor level. More precisely, an event can be anything that is processed by the brain. For example, a sound, a face, but also a movement of the arm or the hand are all events that are associated with the activity of an assembly of neurons which, through their activation, process and encode this event. The advantage of using a term as neutral as "event" is to consider that there is no fundamental qualitative difference between the different events that the brain can process and that it is probably possible to apply identical processing principles to each event.

Now, the precise processing of an event during a certain period of time (Point 6) and the cascade of activated sub-assemblies of neurons corresponding to the processing of this event requires a detailed description. For example, the processing of a letter presented on a computer screen and that one must name, leads to the activation of assemblies of neurons that code the visual form of the letter but also its pronunciation. The fine temporal dynamics of the activation of these neural assemblies supports the perception and identification of the letter and may also contain feedback loops between neural assemblies (from visual to phonological areas and *vice versa*, e.g., Madec et al., 2012; Madec, Le Goff, Anton, et al., 2016; Madec, Le Goff, Riès, et al., 2016; Rey et al., 2009). Describing the activation dynamics of these different assemblies of neurons should allow us to understand in detail the processing performed by the brain on each of the events it is confronted with.

The existence of loops within the neural network is probably essential to keep the processing of a certain event active (Point 7). This reverberation of

neuronal activity keeps several events active in a quasi-parallel way, which then constitute the content of the so-called “working memory” (e.g., Christophel et al., 2017; D’Esposito & Postle, 2015). This maintained activation also makes it possible to link non-adjacent events and create more complex associations (e.g., Rey et al., 2012).

Points 8 and 9 are obviously part of the Hebbian tradition. But simply assuming that the connections between two assemblies of neurons that are co-active will get stronger with repetition may not be enough. The co-occurrence of events A and B probably produces additional coding in which another assembly of neurons codes for the chunk AB. The idea of a hierarchical neural coding of chunks is not new and even seems to be one of the fundamental characteristics of brain organization (Dehaene et al., 2005; Grainger et al., 2008; Hebb, 1949; Hubel & Wiesel, 1962; Riesenhuber & Poggio, 1999; Rolls, 2000). It has also been implemented in recent computational models that use a generalization of the classical Hebbian learning rule and the notion of mixed-coding neurons (Bourjaily & Miller, 2011; Lavigne et al., 2014, 2016; Rey et al., 2022; Rigotti et al., 2010).

Finally, that these same elementary associative mechanisms are present in all species whose life is governed by a network of neurons (Point 10) also seems to be a reasonable idea, even if obviously each species has a specific network at birth that conditions what it is able to learn from the regularities of the environment as well as from its own body constraints. Of course, with the development of language, the human species can acquire an additional information processing system that offers the possibility to encode not only an

even greater amount of information but also increasingly complex information. Understanding the respective roles of language and low-level associative mechanisms and their dynamical interaction and integration within the human cognitive system is the major problem we still have to solve (Destrebecqz et al., 2005; Rey et al., 2019).

A unified radical associationism

From the 10-point list I gave to anchor the associationist hypothesis, it follows that a certain number of hitherto disjointed fields of research actually seem to share the same concerns, objectives and even theoretical framework. As described in the first section of this text, at least three of them are concerned with how our brains code the regular and repeated presentation of sequences of co-occurring events (i.e., Hebbian, associative and statistical learning).

Each of these areas ultimately deals with very similar, if not identical, issues. As we have seen, it is always possible to describe the situations they study experimentally by dividing them into a series of events that follow one another and are repeated in a certain order, and which can be thought to activate specific assemblies of neurons. Following the Hebbian hypothesis, their coactivation invariably leads to the strengthening of connections between these assemblies of neurons and to a structuring of the neural network based on these cooccurring activities. Just as Hebb (Hebb, 1949) foresaw, we can suppose that the structuring of our mental activities depends essentially on these elementary associative mechanisms which progressively allow us to refine and consolidate our cerebral network to bring it to carry out ever more sophisticated operations. Interestingly, we find the same theoretical

construction at the psychological level in the theory of the self-organizing consciousness proposed by Perruchet and Vinter (2002).

It therefore seems possible today to bring together the fields of Hebbian, associative, and statistical learning, under the banner of a *unified associationism*, which could account for the phenomena that these different fields study using the same theoretical corpus. Although this qualifier may frighten some people (because it evokes a form of extremism), I suggest adding the term "radical" because it seems to have an epistemological utility here. It just allows us to position ourselves theoretically by seeking in each situation, if it is possible to account for a mental activity or a behavior from the point of view of the associationist hypothesis. "Association is all we need and all we have to account for our mental activities" could summarize this *unified radical associationism*. A growing number of recent studies suggest that the Hebbian theoretical framework may provide the basis for this conceptual gathering.

Hebbian learning as a theoretical starting point

That the brain creates associations seems to be widely accepted today, but there is still no consensus on how to describe and understand these associations. By simply assuming, within the Hebbian theoretical framework, that the processing of an event by the brain produces the activation of a specific assembly of neurons and that the co-activation of two assemblies of neurons induces modifications at the level of their synaptic junctions, it seems that we have a more precise level of description to define what we mean by association.

More generally, as shown in Figure 2, if we consider a sequence of three events A, B and C that are processed repeatedly in succession in the same order, we can assume that each event will activate a specific assembly of neurons and that this activation will be maximal as long as the event is processed. We can also imagine that this activation will progressively decrease, but not completely disappear (due to reverberation mechanisms), once the brain processes the next event. We therefore see that there are temporal zones during which two assemblies are co-active, thus inducing a strengthening of their synaptic connections (i.e., classical Hebbian learning). We also see that even if some elements are temporally disjoint (e.g., A and C), there may be a temporal overlap during which the assemblies of neurons coding for these two events are co-activated, thus inducing the strengthening of their synaptic connections (Malassis et al., 2018). We also see here that as the ABC triplet is repeated, B will be increasingly preactivated by A but also that C should be further preactivated by B and A, a prediction that has been observed in several recent experiments (Minier et al., 2016; Rey et al., 2019, 2020b; Tosatto, Fagot, et al., 2022).

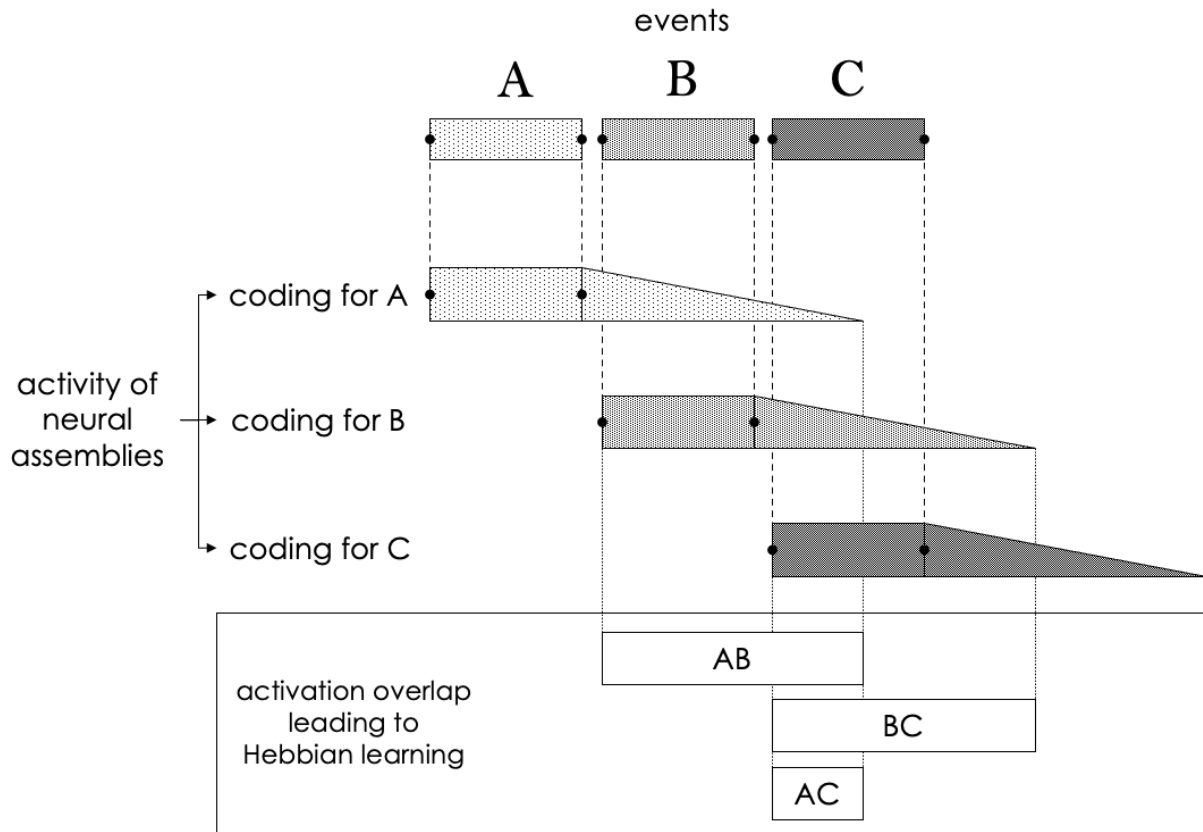


Figure 2: Schematic representation of Hebbian learning for a triplet of three successive events ABC that are repeatedly processed. The resulting activity of the respective neural assemblies coding for A, B, and C shows that there are activation overlaps, which should lead to Hebbian learning (i.e., the reinforcement of the synaptic junction between the coactivated assemblies).

Simple computational implementations of these Hebbian principles have been proposed recently to account for various statistical learning phenomena, for the formation of equivalence classes and for associative learning mechanisms (Endress & Johnson, 2021; Tovar et al., 2018; Tovar & Westermann, 2017, 2023). Although some of these implementations differ and are not always based on the same computational choices, the predictions of these models can now be compared to test the validity of their respective choices. But more importantly, they pave the way to computational models in psychology rooted in more plausible neurobiological principles.

However, as mentioned earlier, classical Hebbian learning principles are likely not sufficient (K. D. Miller & MacKay, 1994) and these recent models may benefit from recent bio-inspired models implementing a generalization of the Hebbian learning rule to account for problematic situations, such the XOR problem (Lavigne et al., 2014, 2016) and taking advantage of the development of mixed-coding neurons that encode chunks of information (e.g., Bourjaily & Miller, 2011; Lavigne et al., 2014; Rigotti et al., 2010). Together, these computational proposals may lay the foundation for powerful future theoretical frameworks that should help us better understand the structure and dynamics of our mental activities described as resulting from the activity of assemblies of neurons.

Let us keep in mind, however, that the hypotheses of an engram that would be the support of our memory traces and the result of a Hebbian type of learning, even if technological progress in neuroscience allows us to better study and understand these fundamental memory mechanisms (e.g., Roy et al., 2022), also gives rise to a certain number of difficulties, particularly with regard to the timing of learning. Notably, Gallistel and Matzel (2013) noted that the modifications of the Hebbian synapse are often linked to the discovery of long-term potentiation (LTP), which is frequently thought to be the biological support of learning (e.g., Martin et al., 2000). However, if we take into account the temporal dimension of LTP mechanisms, it seems that it does not coincide with the temporal behavioral manipulations observed in Pavlovian conditioning. The Hebbian scenario must therefore undoubtedly be further

revised in order to shed light on these controversies and erase the remaining inconsistencies (see also Gallistel, 2017, 2021).

Summary

In this section, I have listed ten points that should allow us to define more explicitly the associationist hypothesis as it can be formulated today. These ten propositions are not fixed, but they may simply help to structure the scientific debate around the idea of a unified radical associationism. I have also proposed to take theoretical support from the Hebbian approach and from recent computational proposals inspired by Hebbian learning. Although we are still far from the end of the road, this Hebbian-inspired theoretical positioning seems promising to guide future neuro-psychological theorizing. Without pushing the cursor to the extreme on the neurobiological side and neglecting the fine analysis of behavior (Krakauer et al., 2017; Niv, 2021), the aim is rather to enrich our descriptions of the mechanisms that drive our behavior by taking greater account of the properties of the neural substratum.

4. Revising ill-defined psychological concepts

Contemporary psychological science has inherited the concepts developed by the different schools of thought that have marked its young history. For more than a century, there has been a conceptual tension between these different schools which balance between radical mentalism and radical behaviorism (see Uttal, 2000, for a remarkable analysis of this conceptual opposition between mentalism and behaviorism).

On one side, mentalist approaches consider that our mental activities are based on a set of mental processes that can be characterized and studied. They thus give rise to a whole range of more or less well-defined concepts (e.g., executive functions, motivation, intention, theory-of-mind) which nevertheless seem to reflect a certain psychological reality. On the other side, the most radical behaviorist approaches consider that we do not have the means to make the slightest hypothesis about these mental processes to which we do not have direct access and that psychological science can only be built from what is observable, i.e., behaviors. Ill-defined psychological concepts must therefore be purely and simply eliminated from any serious scientific approach (i.e., eliminative behaviorism, Zuriff, 1985).

Radical associationism is not exactly somewhere between these two extremes. Indeed, since the first behaviorist writings, neurobiology has not ceased to enlighten us on the cerebral structure and the internal functioning of the brain. We now have tools that give us direct access to brain activity and even if the study of behavior remains essential, we are able to make hypotheses about our mental activities understood as resulting from brain activity. Radical associationism thus adopts the same rigorous criticism of behaviorism with respect to the ill-defined concepts of mentalist psychology, without refusing the project of describing and understanding our mental activities. Its project could even be defined as revising and reconstructing mentalist psychological concepts by relying as much as possible on our knowledge of brain functioning.

This project is both demanding and ambitious. It implies systematically questioning the validity of the concepts commonly used in psychology. Obviously, this project goes beyond the present article and I will only give here an illustration of how a radical associationist approach can help to rethink, or to revise, one of the key concepts in psychology, the notion of attention.

Defining attention

“Every one knows what attention is” wrote William James in his famous essay “The principles of psychology” (James, 1890, p. 403). But paradoxically, it is difficult to find two authors who share the same definition of this central psychological concept. James offered his: “It is the taking possession by the mind, in clear and vivid form, of one out of what seem several simultaneously possible objects or trains of thought. Focalization, concentration, of consciousness are of its essence. It implies withdrawal from some things in order to deal effectively with others, and is a condition which has a real opposite in the confused, dazed, scatterbrained state which in French is called *distractio*n, and *Zerstreutheit* in German” (p. 403).

Let's see if it is possible to find a clearer definition of this concept in contemporary psychology textbooks. According to Nairne (2013), “Psychologists use the term *attention* to refer to the internal processes that set priorities for mental functioning. For adaptive reasons, the brain uses attention to focus selectively on certain parts of the environment while ignoring others. Obviously, the concepts of attention and consciousness are closely linked – you're consciously aware only of those things that receive some measure of attention” (p.189). According to Cervone (2015), “Wherever you are at the

moment, there are a lot of objects to see, but you're only looking at one of them. (...) Attention is the process of bringing an idea or an external stimulus into conscious awareness" (p.204). Clearly, while these definitions reflect what we all intuitively think of the notion of attention, they seem to carry the classic idea of a beam of light moving across the surrounding world, like a spotlight on a theater stage, illuminating only part of the world. Such would be our attention. Then the other classic question arises: "who is handling the projector?".

To escape from this paradoxical situation, some of the best experts on attention have proposed to consider attention as an organ system (Posner & Fan, 2008) that they define as "differentiated structures (...) made up of various cell and tissues and adapted for the performance of some specific function and grouped with other structures into a system" (p. 31). This organ system would be composed of three attention networks involved in alerting, orienting, and executive attention. These three networks would have distinct attentional functions and would be handled by distinct brain areas and chemical modulators (see also Carhart-Harris & Friston, 2010). However, this view of attention as a cognitive function instantiated into specific brain regions and interacting with other regions by modulating their activity assumes that there is indeed a projector, situated inside a projection booth, but it does not explain who is controlling the projector or even who is the projectionist. The solution of an organ system playing the role of attention seems therefore to bring us again into one of these famous recursive paradoxes.

Getting out of the attention paradox

What solution could radical associationism propose to this classical attention paradox? A short and radical answer could be: do we absolutely need the notion of attention? Can't we define attention differently or find another term that corresponds more operationally to our intuitive notion of attention? What happens if we replace the notion of attention with that of *processing*?

Indeed, rather than asking ourselves how and why we process such information from the environment rather than another, perhaps we can simply note that at a given moment in time we *process* such information. Perhaps we should consider that attention (and probably also consciousness) simply corresponds to the *processing* that my brain carries out at a given moment on a certain event. And according to Points 5 and 6 from the 10-point list presented above, the processing of this event is supported by specific assemblies of neurons whose activation can be decomposed in time by cascading activation of subassemblies of neurons coding for different dimensions of this event. Following Point 7, these activations can reverberate and be maintained for some period of time. The processing of adjacent events, understood as the coactivation of assemblies of neurons coding for these events, can lead to the establishment of a transient memory trace between events processed within the same temporal window (Point 8). The repetition of these co-occurrences of events can consolidate this trace and lead to the coding of a chunk formed by the repetition of the co-occurrence of these events (Point 9).

However, does this proposal make it possible to explain how we move from one process to the next, in other words, if we reuse the classic notion of attention, why do we pay attention to different information in succession and what guides this passage from one process to the next? The hypothesis that can then be formulated here is that this passage from one processing to another is not the product of an attentional module or an organ of attention which would command this processing change, but simply the by-product of the activity of the assemblies of neurons activated in the recent time window. The neuronal activity at a given time could indeed be considered as the stochastic result of a combination of neuronal activities that would have appeared during the recent temporal window. We can even consider that the passage from one activity pattern to the next does not result from any *decision* (another key psychological that should probably be revised) but only from a dynamic process of integration and interaction of previous neuronal activities.

This raises the question of whether eliminating a notion as important and widespread in the field of psychology as the notion of attention is tenable or reasonable, and whether such a stance makes it possible to generate new testable hypotheses. It seems that supposing that such a notion is perhaps unnecessary already generates a way of thinking about our mental activities from a different angle, which has the merit of getting us out of the attention paradox described above. The bet we can make is that we'll certainly manage to formulate hypotheses that are as clear and testable as possible without resorting to a notion as vague and ill-defined as attention.

Summary

I have tried to illustrate in this section how radical associationism can help to revise some key concepts of contemporary psychology, which is predominantly mentalist. In fact, it is simply an attempt to describe our mental activities by translating them into a series of processes that our brain carries out at each moment without resorting to ill-defined concepts of mentalist psychology. Determining these processes allows us to identify what is maintained in working memory as well as what will be retained transiently or over the longer term depending on the repetition of the processes performed. We can thus suppose that the structuring of our mental activity depends on these elementary associative mechanisms of which neurobiology enlightens each day more the functioning and from which psychology must be inspired to better understand the structure and the dynamics of our mental activity.

5. Conclusion

The recent development of our knowledge in the neurobiology of memory helps us to progress in psychology in the understanding of our mental activities and the fundamental mechanisms of learning. I have shown here that it is certainly time to bring together different hitherto disjointed approaches to the psychology of learning (i.e., Hebbian, associative, and statistical learning) under one banner, unified radical associationism, and that Hebbian learning can certainly serve as a unifying conceptual basis.

This proposal is not very original because it has already been carried by many famous authors (e.g., Posner & Rothbart, 2007; Pulvermüller, 1999).

However, recent developments in computational modeling (e.g., Köksal Ersöz et al., 2022; Tovar & Westermann, 2023) suggest that the *Zeitgeist* is conducive to revisiting the Hebbian project by feeding it with the latest advances in neurobiology, and that this neuro-psychological project should allow us a major, and perhaps more stalwart, revision of our conceptual apparatus in psychology.

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