Building a Brain,
Considerations on non-deterministic learning networks and deterministic control from a neuropsychological perspective

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Introduction

Many attempts have been made to build an artificial brain. This paper aims to contribute to the conceptualization of an artificial learning system that functionally resembles an organic brain in a number of important neuropsychological aspects. Probably the techniques (algorithms) required are already available in various fields of artificial intelligence. However, the question is how to combine those techniques. The combination of truly autonomous learning, in which "accidental" findings (serendipity) can be used without supervision, with supervised learning from both the surrounding and previous knowledge, is still very challenging. In the event of changed circumstances, network models that can not utilize previously acquired knowledge must be completely reset, while in representation-driven networks, new formation will remain outside the scope, as we will argue. In this paper considerations to make artificial learning functionally similar to organic learning, and the type of algorithm that is necessary in the different hierarchical layers of the brain are discussed. To this end, algorithms are divided into two types: conditional algorithms (CA) and completely unsupervised learning. It will be argued that in a conceptualisation of an artificial device that is functional similar to an organic learning system, both conditional learning (by applying CA's), and non-conditional (supervised) learning must be applied. If attempts are made to make artificial learning functionally similar to organic learning, no Conditional Algorithm's should be used in the bottom-up processes, while higher-order top-down processes should be established by using categorically and thus conditionally algorithmically. Logical aspects of both (algorithmic) learning, and organic learning (neuropsychology and the brain) will be discussed.

1 Conditional algorithms in AI

In their basic architecture, many cognitive computational models of both perception and action are someway critically based on conditional algorithms (CAs, see Román-González et al., 2017; Lu et al., 2018). In the most simple form of conditional algorithms, decisions are made by, for example, applying (and solving) equations that make comparisons in an inverted branching tree structure: If-then-else. However, such equations cannot explain the recognition of *new* patterns. *If* a pattern found corresponds to an already present pattern, for example in a matrix, *then* a decision is made. Because of this conditional algorithmic, it is therefore a selection process instead of a new learning process. A number of properties irrevocably coincide with conditional algorithms. The most important are that CAs do not concern learning mechanisms. Instead they embody selection mechanisms, CAs cannot deal with novelty and, thirdly, they are strictly entropic (the degree of complex cohesion within the system can only decrease, as a result of which the chaos in the system increases). Contrary to this, in real life *organic learning* is negative entropic (negentropic: for example in the evolution from single-cell to complex mammal, there is a huge increase in the complexity of the structure). Concretely, in CAs the in advance available (a priori) patterns present in the matrices on which basis the conditional algorithms shape their selection process, can only be disturbed; no new patterns can be added by the "learning process" (selection process) itself. CAs are only redundant if an a priori multiple-select "learning content" is coded, so that if one such item is disturbed or damaged, it is possible to switch to a *spare item*. Incidentally, with smart algorithms, the matrices can be continuously updated by, for example, the audience searching on the internet. However, the public then lends her "life" (negentropy) to the mechanism, which therefor stays just a selection mechanism. Both learning and novelty stay out of the process!

Classic decision trees are obviously based on conditional algorithms. However, in fact, much more current "explanatory models" and forms of machine learning are also based on conditional algorithms. Evolution, conceived as selection of random mutation in function of adaptivity, is an example of a conditional algorithm. If an accidental mutation (an exploration) leads to a survival advantage, it remains in the species and will eventually dominate, otherwise it does not matter. Also operant conditioning in behaviourism is an example of a conditional algorithm. If an accidental behaviour (an operant) is desired, then reward will follow and the organism will learn to keep repeating this behaviour to achieve the desired effects. More formally, learning is conceived as selection of accidental operators (explorations) in function of punishment and reward. Both examples - evolution and learning according to behaviourism - are based on selection and do not explain how the complexity of, for example, a single-cell organism to a complex mammal can increase. Or how practically infant is able to understand and communicate with a complex language that is shaped by punishing and rewarding the random baby sounds.

Reinforcement learning is a good example of a far more advanced instance of conditional algorithmic learning. In fact it is a form of evolutionary learning or learning by operant conditioning. The learning network, the agent, explores - performs action. On basis of knowledge in the environment, the connections in the network are strengthened if the exploration is correct. If the weights between the cells are strengthened, this "supervising" knowledge is as it were injected in the network. In further exploration, the network departs by both exploiting the knowledge that has emerged from the reinforced connections, and new exploration in the network. These composite actions are then reinforced again if they are found to be correct. So, the conditional algorithm is selection of accidental explorations in function of reward from the environment. If an action is correct, strengthen the connections, otherwise continue exploration (trial and error). If something is learned, take it with you (exploit the reinforced knowledge) and repeat learning, now to even more correct behaviours. The reinforcement requires a priori knowledge, the trainer, supervisor, or whatever you call it. Of course this is a great strategy, but it falls within the class of what we call CAs, and therefore it cannot explain novelty, learning without selecting pre-existing knowledge. In the following we depart from a functional point of view (see Clark, 2008 for a powerful plea).

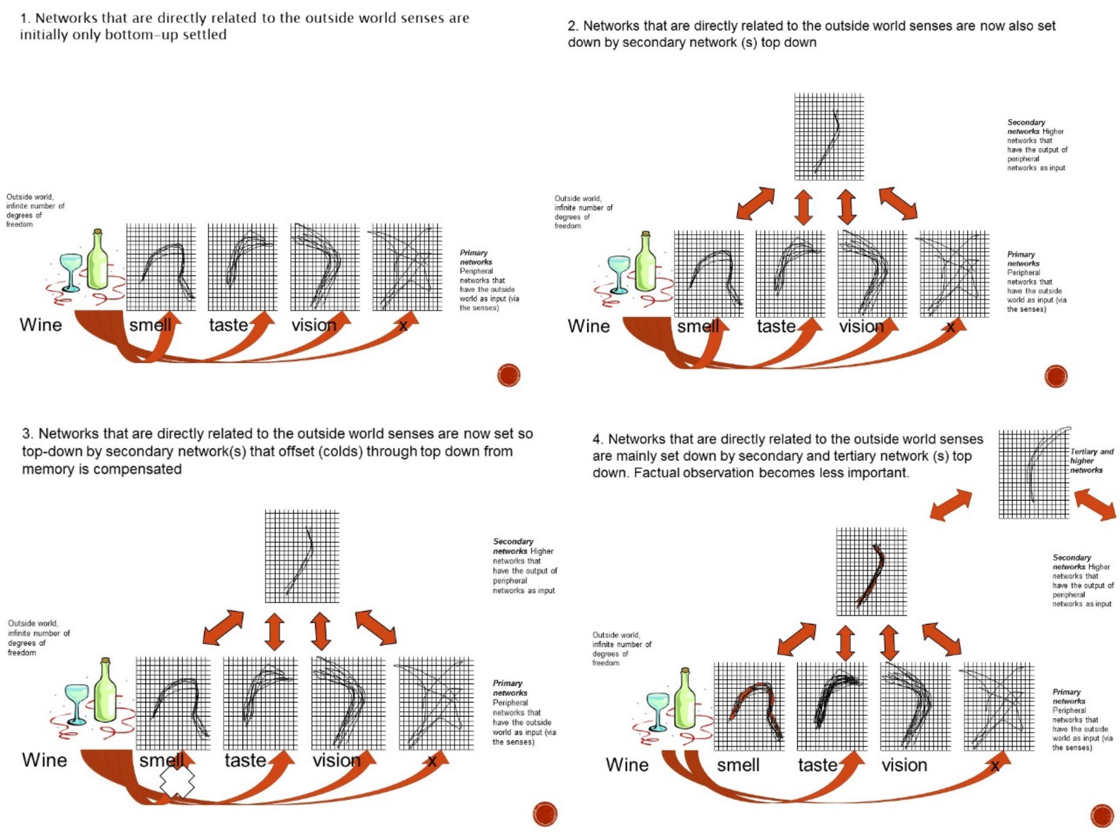
2 Lessons from neuropsychology

2.1 Functional learning similar to organic learning

Organic perception is always based on invariant analysis (Gibson et al., 1979). Everything flows, nothing remains the same, but if events seem to repeat (the sun goes down again the next day, and the next day after, etc.), then the repeating aspects form invariants. These invariants form a memory trace in our brain, according to the Hebbian rule: cells that fire together, wire together! The formation of memory traces is comparable with the channelling of a river; when the meltwater from the snow on the mountain top flows downwards in the same way, a channel will emerge, so that even if the wind is different, water will still go through this “guiding” channel. A practically infinite number of watercourses down the hill has thus been reduced to only one emerged channel (or perhaps a channel with a few side branches). The channel emerges in a bottom-up manner. That is, it was not present in advance as a selectable representation. Back to invariants in the brain, a "medium" is necessary. Such a medium consists of a large number of more or less "autonomous" elements: the neurons. In the case of our mountain example, these autonomous elements that form traces consist of stones, or (grains of) sand, which are organized in a bottom-up manner by the repetition of the water flow. If it were decided that a channel would be dug from behind a drawing board, that channel would have been created in advance, on a top-down basis. However, even then the channelling would be further established by the water streaming in a bottom-up manner. The top-down planning and construction of a channel can be compared to CAs, there is deterministic identification. After all, a pre-existing plan (a matrix) is present with the channel, and this plan is updated through planned excavation activities. However, if a medium, irrespective of whether it is a brain or a sandy bottom of a hill, emerges in a bottom-up manner, there is *contingency* (instead of pre-existing determinacy) between the repeating patterns and the resulting structure. The emergent structure is not equal to (an aspect of) the repetition, it is "only" related and thus contingent to it. Network learning (like reinforcement learning) does not inject an one to one identification between the outer world and the internal representation of it, while applying decisions in a branching tree representation do depend on such an deterministic identification.

2.2 The hierarchical brain: primary, secondary and tertiary networks.

Although everything in our reality is in fact one-off (variant), we constantly experience/observe repetition (invariance). For example, in the experience "*drinking wine*", connected networks associated with our perceptual sensors channel various patterns: visually (the viscosity of the wine to the glass, the colour, the reflection and light transmission, etc.), smell, taste, context, etc. Each of these networks can be compared to the sandy bottom of a hill or mountain that channels the meltwater. In each network a memory trace is formed on basis of exposure to more *wine experiences* with more or less "the same" wine. In the long run, if all different memory traces have become entrenched, the total configuration of these traces at the level of all primary networks (networks that are directly related to the outside world), will be the same per type of wine, or per type of wine experience. For a secondary network that does not have the outside world but the primary networks as its input, the configurations of all primary networks form the actual input. As a consequence, redundancy occurs automatically, because in the case of poor input from one of the primary networks (for example because someone has caught a cold in the "wine experience") the other primary networks together form a configuration that result in a specific trace in the secondary network. From there, this secondary pattern can *update* the disturbed primary network in a "top-down" manner (from secondary to the disturbed primary network). Phantom pains and effects can also be understood in this way.



The Russian neuropsychologist Luria was one of the pioneers in thinking in terms of a hierarchical brain. He distinguished three levels (zones) of networks: primary, secondary and tertiary networks. For example, on the primary zone (v1) that is involved in visual perception (located within the occipital cortex), there are cells that only respond to partial aspects of perception. Some cells, for example, only respond to the direction of a line, or only to a certain type of contrast. The input at the primary level is the outside world through the sensory systems. In other words, the cells in these networks are directly connected to the sensory systems (and therefor to the outside world). Only in the secondary networks, which is in case of vision still located in the occipital cortex, all activation patterns in the primary networks (who al together form the primary zone) are merged. The output of the primary networks form the input of the networks in the secondary zone. At this level the composite patterns arise. Only in the tertiary zones, where the output of the secondary zones of the occipital cortex coincides with, among other things, the output of the auditory secondary zones (temporally), the higher order forms emerge. Luria called the tertiary zones also the association areas (Luria, 2012). If there is a disturbance in the bottom-up signal while someone already has a lot of experience with the observed “reality”, the missing bottom-up information will be filled in (completed) from the secondary or even from the tertiary zones. So there are two simultaneous processes: bottom-up (primary-secondary-tertiary) and top-down (starting from the tertiary or association areas back to the secondary and primary areas). In figure 1 this is demonstrated in the case of experiencing wine in a viticulturist. Even without the ability to smell because of rheum, the viticulturist is often perfectly able to decide what wine is tasted. In an experienced brain, bottom-up disruptions can be bypassed by exploiting top-down cohesions and thus redundancy. In the next paragraph, psychological illusions will be explained by combining (partly) impoverished bottom-up formation and compensating top-down processes between the three zones.

2.3 Topdown bottom-up (mis)matches; a few examples

A few examples from neuropsychology can clarify how the two directions of information flow influence or even shape each other. The McGurk experiment (McGurk & MacDonald, 1976) is a famous example, in which a test person in front of the camera says "BA, BA, BA". However, the image is manipulated in such a way that you do not see the lips shooting of each other at the B sound. In fact you see a French G sound. The result is baffling. If you close your eyes you hear BA, BA, BA, but when you look, you hear GA, GA, GA (some persons hear actually DA, DA, DA). Learning experiences with the contingency between hearing the B and seeing the lips that come apart, has a strong top down accent ("expectancy") on the visual signal, a B cannot be heard when seeing other exactly timed action of the lips. As a result, the vision interferes (DA, DA, DA) or in some persons even dominates (GA, GA, GA) the hearing.

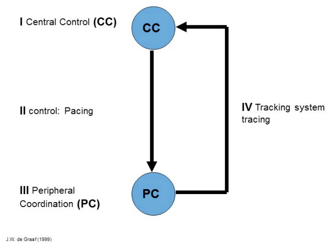
A second example is the well-known cube of Lotto and Purves (Lotto & Purves, 2002). Lotto and Purves showed two identical cubes that resemble the famous Rubik's cubes, but with many more coloured squires. The left cube is visible through a yellow filter and the right cube is visible through a blue filter. The special feature is that the blue squires in the left cube physically (in terms of wavelength) have exactly the same colour as the yellow squires in the right cube: grey. Yet, on the basis of top-down knowledge that has been created by a lot of bottom-up perception experience, everyone sees both the left and the right cube squires as blue and yellow respectively! In addition, the red squires on the left are when seen separately in fact ochre yellow and the red squires on the right purple. However, in the context of the coloured cubes with the filters it's impossible to see them any other colour than red. In addition, in fact all illusions are based on a mismatch between bottom-up experience and top-down corrections. This also applies to the McGurk illusion.

A third example lies in the fact that with aging, sometimes reinforced by disorders, the factual perception often gets worse. It is known that musicians in orchestras often suffer hearing damage. Yet conductors are often only able to perform at the top of their abilities from the age of 45 to 50. In fact, "redundancy" also plays an important role here. Only with very little bottom-up information the conductor top-down is able to compare the whole orchestral sound with his desired "expectation" and he / she learns to conduct it in the desired direction. Even people who physically only have a 10% view, are often able to expand over time to sometimes 35 to 40%. Shortages in the senses are compensated by learning how to use the memory tracks that have been created in a top-down manner.

Finally, another interesting observation from neuropsychology in this context. Some children, including Ben Underwood, who have no eyes at all, learn through contingency to orientate and move spatially in the world through echolocation. Ben made clicking sounds with his tongue and learned spontaneously (bottom-up) to interpret the echo of the sound. If he stood in front of a wall, for example, the signal came back much earlier than when he was standing in a completely open field. In this way his brain interpreted all the sound, which Ben could cycle, play basketball and many other things that a blind person could never (Draaisma, 2017). When scans were made of the signal processing in his brain, the auditory signal was partly directed at the visual cortex (occipital), where it reached the primary, secondary and tertiary zones (including the parietal cortex). Bats, for example, orient themselves in a similar way.

2.4 Two brains in one: procedural versus declarative processing

Finally, on top of the secondary networks, tertiary networks can be placed, which have as input the output of secondary networks. At this level, abstract knowledge emerges, which is, once settled, unchangeable relative to the primary networks and their input. This level of the networks explains why, for example, a top conductor with a relatively poor hearing (with aging the sensory systems become relatively worse, and because of a lot of exposure to sound, this goes especially for the musicians): they have enough information on a very small basis! The networks form the building blocks of the artificial brain. Mathematical techniques such as backward- and forward propagation can be used to shape the medium that needs to be channelled (the river sand). Also network AI learning techniques like (un) supervised (reinforcement) learning are available. However, a lot of research will have to be done to produce artificial brains that are "free of representation" at the level of Peripheral Coordination and at the same time able to be controlled by both learned, and self-organized representations at the level of the Central Control.



An organic brain is dual, in the sense that there is a procedural system and a declarative system (Pezzulo, 2011). The declarative system can be seen neuro-psychologically as conditional algorithmic. The procedural system is the automatic (contingent) perception-response machinery. The procedural systems (responses, actions, etc.) come into operation on the basis of both bottom-up incentives and top down "commands" in broad lines. Typing has taught many people letter by letter (top down, letter by letter, declarative), but once it is controlled, it goes (almost) completely on autopilot (procedural system). Practically nobody can say where, for example, the "b" is on the keyboard, but tapping the word library is automatic. Our procedural system does not always require a lot of practice (data). Sometimes an unpleasant consequence (for example spitting out after eating a certain vegetable) can be sufficient to have an aversion to the vegetable in question.

3. Possibilities of joining non-supervised and CA learning: Kauffman's autocatalyst theory

When designing an artificial brain, account must be taken of the contingent networks (procedural system) and the possibilities to send them top down (declarative system). The Russian neurologist Bernstein was one of the first scientists to describe both systems separately: central control (CS, Declarative system) and peripheral coordination (PC, Procedural system, see Latash, 1996). We can understand CS in terms of CAs. All our formal (scientific) knowledge can be summarized in terms of CAs. PC, on the other hand, cannot be understood in terms of CAs.

In the bottom-up networks, therefore, no CAs should be used as argued. Reinforcement learnings might be used while unsupervised learning techniques could be used even better, but in both techniques a major drawback is that there is a lot of data available on the input side, while an organism can sometimes present structural connections on the basis of relatively few data. could be used, but it should be prevented that at this level isomorphic relationships between the reinforcers and the aspects of the outside world are formed.

In organic learning, exploring (bottom-up unsupervised exploration) and exploiting already present knowledge (top-down supervision) occurs in an iterative manner. In other words, a complex knowledge system is created based on a combination of bottom-up self-organization and top-down application of knowledge, or values. So indeed the two components of reinforcement learning - exploration and exploitation – are involved. However, the value (correct or incorrect) of the explorations (self-organization) is not present in advance. As was previously stated, learning and evolution are in of the very same order. Therefore it is possible to look for solutions found in evolutionary biology to escape the entropy inherent in conditional algorithmic systems. The autocatalyst theory of Stuart Kauffman(1996) is such a theory.

Stuart Kauffman stated that (neo) Darwinian theory is a selection theory and as such it does not lead to the emergence of complex order. Stuart Kauffman determined that (neo-) Darwinian evolution based on the selection of natural selection and mutation (historical accidents) is insufficient to explain the order of the living world: cells, organisms, ecosystems. In fact, he states that much of the order in organisms may not be the result of selection at all. The motor of negative entropy (increase of complexity) is, according to him, based on the origin of spontaneous order or self-organized systems (autocatalytic sets). However, he does not deny the importance of selection processes (conditional algorithms). Natural Selection acts upon natural order. Kauffman: "We stand by the need for an evolutionary process in which self-organization, selection and historical accident find their natural places with one another." (p 150). According to Kauffman, in Darwinism biology is based on chance, on an improbable accident. He argues that many traits or organisms are not a historical history: "If life is bound to arise, not as an incalculable improbable accident, but as an expected fulfilment of natural order, then we truly are at home in the universe." (p.20). If we are able to find these laws, we could explain the origin of life. In an artificial brain, if we could explain the origin of novelty, we could possibly create a real artificial intelligence!

In a recently published paper, Fazeli et al. (2019) show how they developed a robot at MIT, bottom-up in which bottom-up acquired tactile information and visual information (via a camera) is used in hierarchical reasoning and multisensory fusion. The robot learns to play Jenga. Jenga is a complex game that requires physical interaction to be played effectively. This is very promising in the context of the combination of peripheral coordination and central control. In fact, the robot learns a new task only partly due to the training (supervision), and that is a big step forward. Learning is in fact partly negentropic!

4. Concluding remarks

An artificial learning system that is functional similar to an organic learning system, must embody both conditional learning (by applying CA's), and non-conditional (supervised) learning. Logical aspects of both (algorithmic) learning, and organic learning (neuropsychology and the brain) are discussed. If attempts are made to make artificial learning functionally similar to organic learning, no prior knowledge should be injected in the bottom-up processes, while higher-order top-down processes should be established by using categorically and thus conditionally algorithmically. An artificial brain that both is capable of generating novelty (new knowledge), and can also learn from internally or externally generated categories, can in principle become intelligent just in a similar way as organic brains are. Also in organic brains a lot of knowledge is not necessarily present. On the contrary, often people think they understand a simple device while in fact we do not really know exactly how it works. The knowledge is present in others (experts, or even they don't know exactly how it works), and largely distributed in the outside world. This is what Andy Clark calls HEC, the hypothesis or extended cognition. An artificial system that can generate new implicit knowledge, make it explicit and can function as a hybrid on both non-supervised learning, and conditional algorithms offers unprecedented possibilities as a medium between man and machine!

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