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Procedia Computer Science 145 (2018) 471–480

Procedia Computer Science

www.elsevier.com/locate/procedia

Postproceedings of the 9th Annual International Conference on Biologically Inspired Cognitive Architectures, BICA 2018 (Ninth Annual Meeting of the BICA Society)

Meaningful-Based Cognitive Architecture

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Abstract

An overview is given of the cognitive architecture of the biologically inspired meaningful-based learning system (MBLS). The basic element of the MBLS is a reconfigurable Hopfield-like network (HLN) which can rapidly connect to other HLNs depending on the level of abstraction which yields a practical maximal "meaningfulness," defined as the reciprocal of the Shannon entropy of the HLNs. Without any external memory the MBLS synergistically processes external data (and internal data – "thoughts") with sensory processing abilities found in neural networks and some of the symbolic logical abilities found in human cognition. In practical applications the MBLS offers near-simultaneous pattern recognition and comprehension. In modeling the development of psychotic disorders in humans, the MBLS predicts that in many patients the etiology stems from the fragility of the working memory and the integration of additional reasoning mechanisms during adolescence.

Keywords: cognitive architecture; neural networks; cortical minicolumns

1. Introduction

At the time of this writing, despite the human-like performance of artificial neural networks (ANNs) in pattern recognition and reinforcement learning [1,2], such neural networks, trained with a very small quantity of examples, cannot causally make sense of their environment or information at the level a four-year old child can [3,4].

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10.1016/j.procs.2018.11.109

Recent models by Graves and colleagues help to narrow the neural-symbolic gap with an ANN which can read and write to an external memory, i.e., a hybrid system [5]. However, like the human brain, the meaningful-based learning system (MBLS), described below, can perform the sensory processing associated with ANNs and the efficient symbolic logic associated with human cognition, without the use of an external memory, i.e., it is not a physically hybrid system.

The basic functional unit of the MBLS is not an artificial neuron but a Hopfield-like network (HLN). The HLN contains a Hopfield neural network along with associated circuitry modifying convergence properties and allowing reconfiguration with other HLNs [6,7]. The HLN can learn and recognize patterns. While Hopfield networks are typically thought of as requiring stationary inputs they can be extended for sequential learning [8]. The weights of the connections between different HLNs can be adjusted gradually with learning as in a conventional ANN, can be adjusted more abruptly to form a more discrete logical relation between two HLNs, and as well can rapidly be reconfigured to on and off values to allow fast and extreme reconfiguration of the HLNs with each other. In rapid reconfigurations, there is an attempt by the HLNs to maximize meaningfulness, where this is defined as the reciprocal of the Shannon entropy, as described below.

2. MBLS Core Architecture

The MBLS makes use of reconfigurable topologies of Hopfield-like networks (HLNs). Figure 1 shows the output of, for example, HLN(2,3) going to the input of HLN(1,3). In this simplified figure, the MBLS appears as a stand-alone component communicating with the external world. However, in any practical implementation of the MBLS, as well as in the fuller MBLS Cognitive Architecture presented below and shown in Figure 4, the array of HLNs will receive data relating to a spectrum of goals, as well as core procedural memories, corresponding, for example, to the rules of the ACT-R cognitive architecture [9, 10].

HLNs can rapidly reconfigure with other HLNs. In Figure 1, HLN(1,2) is already connected to HLN(2,1) as shown by the dashed line. Sometimes HLN(1,2) is outputting to HLN(1,3) but other times it is connected to HLN(2,1). Reconfiguration of the HLNs can occur automatically by the HLN units themselves, as well as being influenced by other modules of the MBLS.

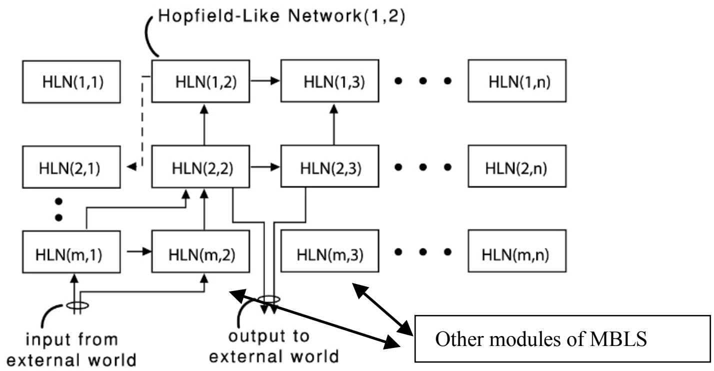

Figure 1: HLNs are basic elements of the MBLS

Figure 2 gives an overview of a Hopfield-*like* network (HLN) unit. An input vector goes to the auto-associative processor. Previous learning experiences have shaped the values of the weights of a given auto-associative processor. If the input vector is recognized, a stored pattern can be outputted to the vector processing unit, and then feeds into the abstraction addressor circuitry. The vector processing unit can be positioned both before and after the auto-associative processor to ensure valid convergence to an output that actually is related to the input vector. Based on the meaningfulness values of the feedback vector (which can be as simple as how many other related HLNs are activated, and will be discussed below), the abstraction addressor decides which of many possible output vectors wired up as inputs to other HLNs will have non-zero outputs. The abstraction addressor effectively allows the HLN to rapidly reconfigure its connections to other HLNs. (A variety of local algorithms relying on the feedback vector, e.g., an algorithm that tries to keep a high local meaningful value, as well as algorithms that also use computed system meaningful values, can decide on the next set of output vectors to activate. The feedback vector can also modulate when the auto-associative processor learns new patterns.)

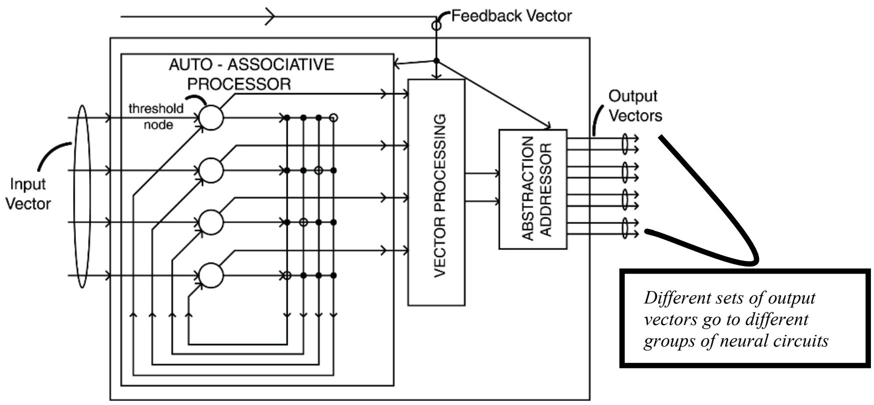

Figure 2: Overview of a Hopfield-like Network (HLN) unit

3. Properties of the MBLS

Hierarchies of pattern recognizers have previously been suggested in the literature, for example the hierarchical compositional network described by Lázaro-Gredilla, Liu, Phoenix and George [11]. Systems of pattern recognizers from the biological inspiration provided by the organization of the mammalian cortex have been popularized by Hawkins [12] and Kurzweil [13]. As well, the capsule neural network is inspired by the cortical minicolumn [14]. It has been shown that various hierarchies of pattern recognizers can recognize, for example, from lines to letters to words to ideas associated with those words. A feedback signal from higher-level hierarchical units will influence the pattern expected by a lower-level pattern recognizer. The MBLS, by virtue of a similar architecture possesses these same properties. However, the construction, operation and many of the properties of the MBLS, from its elementary units to its overall organization is significantly different than in these previous works.

HLNs are a form of memory, of course. Much of the MBLS memory, as shown in Figure 4, is represented by HLNs auto-configured as probabilistic causal memory, keeping track of which event follows another event, what spatial data follow previous spatial data, as well as causal details which actually form world models, and may include some of the other sensory or internally processed data occurring at the time. The intrinsic connections in the brain between hierarchical cortical columns may by default establish Bayesian inference [15], although such connections would not be sufficient to easily allow the higher-level inferences humans perform, without the use of HLN groups configured as logic/working memory units, discussed below.

The MBLS can be designed such that some HLNs can auto-configure into group(s) of HLNs which act as a working memory, and other HLNs can auto-configure into groups which act as logical processors (in theory, ranging from acting as small automatons to Church-Turing complete logical sub-systems) and operate on the working memory. It is important to realize that the representation of data in the MBLS is already quite causal and has meaning through the connections an HLN has via connections to other HLNs. The working memory need not convert the vectors from the HLN into some abstract symbolic data for the working memory to produce symbolic behavior, i.e., manipulation of the HLN vectors it receives suffices. In the simulation of the MBLS described below, it can be shown that HLNs auto-configured as relatively simple logic/working memory units are able to compare properties of vectors they receive, are able to choose one vector over another, are able to pattern match a vector from the entire MBLS memory and are able to direct the MBLS to output a vector.

From learning experiences, different HLNs' outputs form stronger and weaker weighted connections with other HLNs, as occurs in other pattern recognizer systems as well as in typical neural networks. However, in the MBLS each HLN has multiple sets of outputs wired to different sets of HLNs. The entire MBLS can rapidly reconfigure itself to allow different emergent output properties for a given set of inputs to the MBLS. A simple example of this is described below and illustrated in Figure 3. (In the current simulation, this pre-wiring of HLNs to other HLNs is topologically and locally based but allowing changes in the pre-wiring in response to HLNs' activity patterns is possible in future versions.)

The MBLS uses the property of what is defined here as "meaningfulness" to guide its reconfigurations – what reconfigurations are more meaningful in terms of recognizing and processing an input vector, for example, than other reconfigurations. One of the ways to compute meaningfulness is to simply count, in a given reconfiguration of the HLNs, how many HLNs become activated by the input vector (i.e., valid convergence of the auto-associative processor of an HLN when an input pattern is recognized). However, Shannon entropy gives a more realistic value of the information content of an input vector in terms of activating HLNs. Thus, meaningfulness M is defined as the reciprocal of the Shannon entropy (1,2):

$$H = -\sum_i P(x_i) \log_2 P(x_i) \quad (1)$$

$$M = 1/H \quad (2)$$

As can be seen in Figure 3 in Reconfiguration A, the input sensory vector causes activation of 5 HLNs in the path of the input vector, corresponding to a meaningfulness M=1.2, versus activation of 3 HLNs, corresponding to a meaningfulness M=1.0 in Reconfiguration B. In order to best make sense of the input vector, there is an attempt to maximize meaningfulness, and Reconfiguration A is chosen over Reconfiguration B, in this simple example.

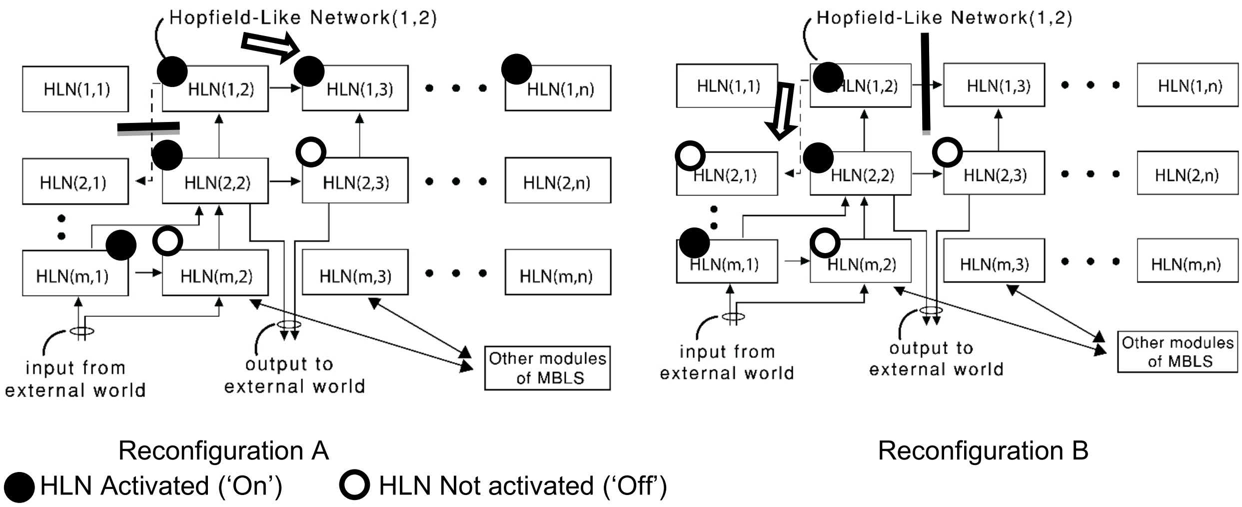

Figure 3: Same input vector gives Meaningfulness of M=1.2 (via Shannon entropy of 0.86) for Reconfiguration A versus Meaningfulness = 1.0 (via Shannon entropy of 1.0) for Reconfiguration B

Reconfiguring HLNs so as to maximize meaningfulness to yield an optimal output, is actually an intractable problem. However, a pragmatic reconfiguration of HLNs can allow polynomial-time solutions, reasonably sufficient for real-time applications:

- The general arrangement of hierarchical sub-systems for particular senses can be pre-configured ahead of time, via default weights and pre-wiring.
- The HLNs which will form other functional groups and modules can similarly be pre-configured ahead of time. (In addition, the internal properties of particular HLNs, for example HLNs used to process visual inputs versus HLNs used as building blocks of the working memory circuits, can similarly be pre-designed.)
- The scope of abstraction between HLNs, i.e., what set of outputs is activated (which determines the configuration of the HLNs with each other) can be varied in a limited algorithmic manner in searches for a practical maximal meaningfulness depending on the state of connected HLNs and the feedback vector to the HLNs, and if no reasonable solution is obtained after a limited number of reconfigurations of the HLNs, consider the sensory and external inputs again.
- A set of goals, default ones or changed with time, will prevent the MBLS from aimlessly reconfiguring its HLNs to mechanically maximize meaningfulness.

Automatically, over and over again, the MBLS looks at the local meaningfulness of the data in the sensory input vectors (via the feedback vector signal which can be as simple as the number of HLNs activated or more calculated such as a Shannon entropy value), and cycles through varying levels of abstraction so as to reconfigure the HLNs in a way to maximize local meaningfulness. After a number of reconfigurations, the "evaluation cycle" completes, system meaningfulness now is also fed back to the HLNs via the feedback vector (which can be used to decide to reconfigure again for the same sensory input vectors, to reconfigure other HLNs forming other units in the MBLS, or to go onto the next sensory input), and the next evaluation cycle starts again.

Note that the reconfigurations of the HLNs within the MBLS cause an extreme change in the weights between functional units, and thus is very different than, for example, the small changes in weights that, for example, occur with stochastic gradient descent in a differentiable feedforward neural network. Similar feedback-like processes also occur in the MBLS to cause learning of small changes in the weights between HLNs, but this is different than the reconfigurations.

Each evaluation cycle we describe the MBLS as evaluating the sensory data input vector. However, in an evaluation cycle, rather than evaluate the sensory data input vector, the MBLS can instead equally evaluate a data vector from the working memory subunit, i.e., the data vector output from the logic/working memory is considered as the input vector and feeds back into the MBLS like a sensory vector input, including back into the logic/working memory group of HLNs. In effect, information produced by the MBLS (the output of the logic/working memory group) is fed back into the MBLS to be processed again – essentially a "thought" occurs. "Thoughts" can be processed sequentially in a fashion to extract maximum meaningfulness from them leading to the next "thought" in the logic/working memory to be processed in the next evaluation cycle.

Let's consider an example, to see how all this works. An MBLS is controlling a search and rescue robot looking for a lost hiker in an uninhabited forest. The environment is full of noise with a variety of faint signals, only some of which will allow the MBLS to achieve its goal. The robot sends to the MBLS a flood of sensory inputs with representations of sounds, vibrations, visual images, odors, radio signals and navigation inputs. The MBLS starts looking for recognition of some of the input sensory vectors with patterns it has already seen (or been configured with) and related to the subject of the goal, a lost hiker. Any matches? It reconfigures some HLNs. Any better matches?

In this example, the MBLS detects two input sensory vectors with higher meaningfulness for signals that may indicate the presence of the lost hiker. One of these sensory input vectors is a sound from the southwest indicating a possible cry for help or a possible match with certain bird calls. The other sensory input vector is an odor coming from the north indicating a possible match with a commercial perfume/cologne. The processed sensory input vectors are sent to the logic/working memory unit. The logic/working memory unit can compare vectors and take subsequent actions depending on the results of comparisons such as changing vectors and outputting vectors to other modules of the MBLS. The MBLS is designed with basic procedures for acting on the logic/working memory (the preconfigured (instinctual) core goals module in Figure 4 below), and as well is able to learn procedures, essentially algorithms, from experience.

The logic/working memory unit and a basic algorithm find that a vector that is related uniquely to a vector of the goal, i.e., an odor that comes from a human which is related to the goal, is closer to the goal vector than a vector which could match other things, such as a sound which could come from some birds. Hence, the output of the logic/working memory unit is to focus on the odor input vector, and in the next evaluation cycle of the MBLS the output is to move in the direction of the odor sensory input vector. The search and rescue robot thus moves in a northerly direction towards the lost hiker.

The MBLS learns both declarative and procedural information from experience. The next time this MBLS is searching for a lost hiker in the forest and there is a perfume/cologne odor sensory input vector, this alone without the use of the more basic algorithms, is sufficient for directing the MBLS search and rescue robot towards the lost hiker. (However, the previous basic algorithms may still be used since other basic algorithms will direct the MBLS to process input sensory data using a variety of algorithms related to the problem at hand.)

4. Experimental Simulation of the MBLS

An experimental simulation was initially hand-coded in Python 2.7 without the use of ANN libraries, and made use of Shannon diversity [16]. In the new version the simulation now uses Python 3.6, Shannon entropy (as described above), and has added HLN-based causal memories and a full cognitive architecture. The sensory input vector is still simulated via keystrokes rather than have a more real-world sensor feed data into the MBLS. The input vector [/ \ — | |] would correspond to the segments in the letter “A” scanned by a video camera, for example.

At this point, the simulation, consisting of a few dozen simulated HLNs, is used to help with proof of concept of the MBLS cognitive architecture. For example, the input vector [— | | — | | —] can correspond, at this low pixel input resolution, to an input of “B” or to an “8”. For example, the weights of the MBLS have been adjusted by learning such that when this input vector goes into the MBLS and there are no other matching inputs occurring, this sensory input is recognized as a “B”. However, when certain other inputs are occurring, meaningfulness is maximized such that this input leads to the HLN indicating an output of “8” instead of “B”.

While the above toy example could easily be performed by just about any neural network model, consider a real-world system with a million input lines full of different sensory information, but the visual sensory input is from a poorly lit environment, so the visual inputs information content is still effectively low. If, for example, an ordinary feedforward ANN with backpropagation is used, then with enough examples the network could be trained to recognize the difference between a “B” and an “8”, from the associated non-visual sensory features when one occurs versus the other even though they both look similar with respect to the visual features in the poorly lit environment. Such learning can occur with the MBLS as well – weights between the HLNs can be trained gradually just as they are in a conventional neural network. However, the advantage of the reconfigurations is that extensive data and training otherwise required can be dramatically reduced. For example, when an “8” occurs versus a “B” there may be particular features here and there in the inputs, such that a rise in meaningfulness occurs in the visual inputs plus in certain other HLNs, and as a result there is activation of the HLNs leading to interpretation of the sensory input vector as an “8”. (If the increase in meaningfulness occurred in the HLNs which led to a “B” output even though the sensory input vector was an “8”, then a negative reward reinforcement/supervision value would occur, or should eventually occur, the increase in meaningfulness for “B” would be negated, weights would be changed, and “B” would be less likely to be chosen next time as the output.)

The processed sensory input vector is also sent to the MBLS logic/working memory unit, where it is processed at a more symbolic level based on the available algorithms and the content of the memories including world models, to better decide, continuing the example, if it is a “B” or an “8”. The symbolic processing can in many instances dramatically reduce the amount of training data required to satisfactorily train the MBLS compared to a conventional neural network.

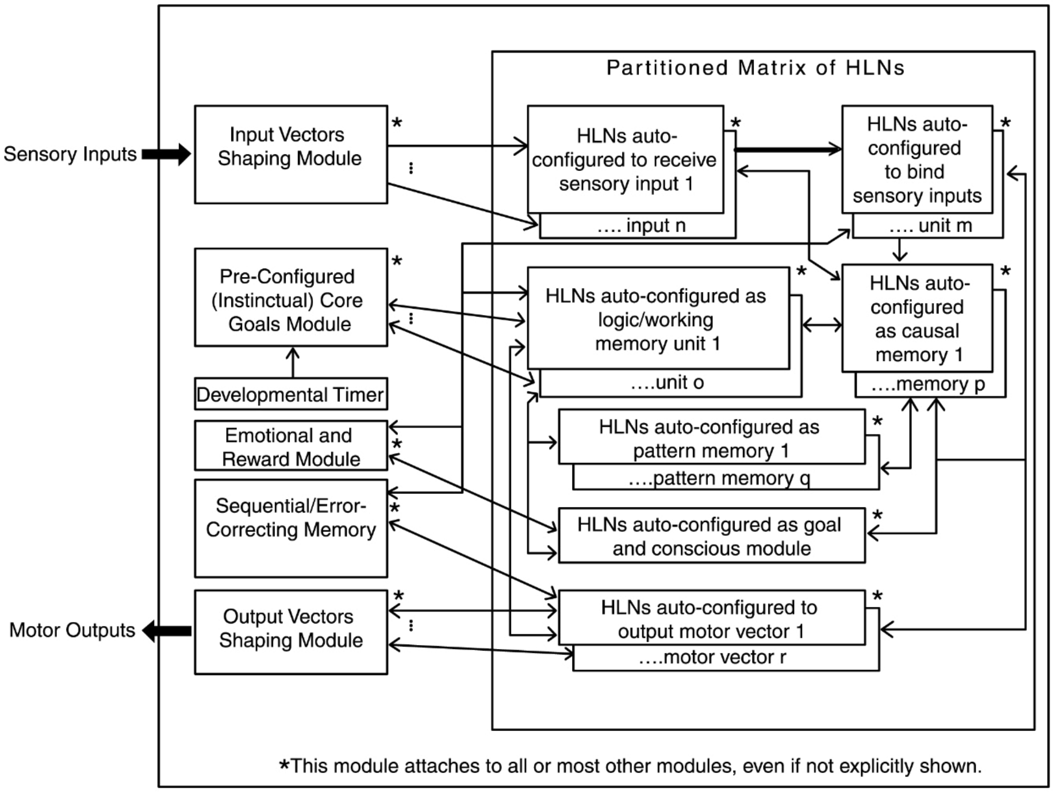

Figure 4: MBLS Cognitive Architecture

5. MBLS Cognitive Architecture

The key features of the MBLS cognitive architecture are shown in Figure 4. The MBLS is designed so that by default various HLNs auto-configure into different functional groups, and although not shown, the internal structure of the HLNs in different functional groups can be designed to be slightly different and optimized for the function they will be performing. The HLNs correspond roughly to the minicolumns of the mammalian cerebral cortex, which although tend to be similar to each other, do aggregate into different functional groups [17, 18].

Most of the modules and functional groups of the MBLS cognitive architecture *functionally* approximate to analogous aspects of the human central nervous system, but a neurophysiological mapping is beyond the scope of this paper. As well, although not explicitly shown, most modules and functional groups of HLNs connect to most other modules and functional groups, and most often these connections are bidirectional in some way. A complex of autonomic modules which perform straightforward computations on sensory inputs without the need of the HLNs matrix, and in turn produce motor outputs, are not shown in Figure 4, but could be useful for many applications.

Sensory inputs are pre-processed, then processed by functional units of HLNs, and then the varying senses are bound, along with data from the logic/working memory units and other functional units of HLNs. Sensory inputs at various levels of processing are fed to the sequential/error-correcting memory (a module useful for detecting changes in a spectrum of external and internal data, and learning sequences which can automatically be repeated later as needed), the HLN causal memory (keeps track of which event and associated data follows another event, what spatial feature leads to the next spatial feature, and as well holds causal details which actually form world models), the emotional and reward module, and other modules and functional units of HLNs. Data from the sequential/error-correcting memory, the HLN logic/working memory units, the HLN pattern and causal memory, and other modules and functional units, go to the HLNs auto-configured to output motor vectors, which in turn feeds into an output shaping module, and then produces the motor outputs which activate different actuators, as well as providing a data output to the external environment.

The pre-configured (instinctual) core goals module, which is affected by the maturity stage of the MBLS via the developmental timer, feeds default procedures into the HLNs auto-configured as logic/working memory. The goal and conscious module interacts with the emotional and reward module as well as the entire MBLS to provide some overall control of the MBLS' behavior. Causal memories of operations occurring in the logic/working memory are temporarily kept in the conscious module, allowing improved problem solving as well as providing more transparency to MBLS decision making. Rare events can sometimes be very important events to learn. The emotional module allows effective learning of infrequent events and obviates the class imbalance problem seen in conventional neural networks.

6. Expected Performance of the MBLS

It can be estimated that each "reconfiguration cycle" (i.e., attempt at a new reconfiguration in processing an input vector) of a hardware-based MBLS is approximately 10 times the 10 internal iterations the Hopfield network uses. We assume 10 "reconfiguration cycles" to process a given sensory input vector in each "evaluation cycle." Continuing this Fermi estimation, if we assume that the time of an internal iteration is approximately 10 times the length of a typical nanosecond clock cycle, then it takes on the order of 10 microseconds for the MBLS to process an input vector from the sensory inputs or from the working memory as a "thought" (as described above). If optimized hardware is used to construct the MBLS then a speed-up factor of 10 is expected, with a full "thought" therefore taking on the order of 1 microsecond. In comparison, a human brain can reactively process sensory inputs on the order of 50,000 microseconds, although to process a thought more fully takes the brain on the order of 1,000,000 – 3,000,000 microseconds [19].

7. MBLS Model of Psychotic Disorders

The HLNs are inspired by the biological mammalian minicolumns [17,18,20]. While the neurophysiological evidence does not support the exact same circuits which the HLN uses (e.g., an "abstraction addressor", etc.) the MBLS can functionally produce a variety of behaviors starting at the mesoscopic scale which can possibly help to better hypothesize and understand cortical function. In considering the design of large-scale brain models, Eliasmith and Trujillo note that perhaps the most important consideration is indeed the link to behavior [21].

In the MBLS, the auto-configurations of HLNs to create logic/memory working units and combine them with the procedures from the pre-configured (instinctual) core goals module, and shuffle working memory around and retrieve data from the HLNs and sequential/error-correcting memory and other functional groups, is an order of magnitude more complex than other operations of the MBLS. As the MBLS matures, and as shown in Figure 4 the developmental timer causes the pre-configured (instinctual) core goals module to feed even more algorithmically powerful procedures into the logic/working memory units, if there are small issues in the logic/working memory units or their connecting modules including the pre-configured (instinctual) core goals module, then the MBLS can fail in a psychotic fashion (cognitive dysfunction and retrieving memory vectors not corresponding with reality).

Models of schizophrenia, including neural network-based ones, have long been proposed, for example the work by Cohen and Servan-Schreiber in the 1990s [22] to the recent work at the time of this writing of Papanastasiou and colleagues [23]. However, in proof of concept simulation work on the MBLS, psychotic features seemed to emerge surprisingly easily when the logic/working memory HLN units had small flaws and were being overstressed. As well, the clinical literature indirectly seems to support the above MBLS model of psychotic disorders:

- It is possible to deplete the reserve capacity in non-psychotic persons' executive brain functions, more so than other brain functions [24].
- Over 4% of the population (18-64 years old) will experience psychotic symptoms (hallucinations and/or delusions) [25], and actually more than 10% of the population will experience less severe psychotic-like symptoms [23, 25], but just under 1% of the population suffers from schizophrenia (a psychotic disorder) – there are many causes why humans may experience psychotic-like symptoms.
- Clinically, psychotic disorders really only start to manifest as the brain gains additional algorithmic powers in the early teenage years, as would be expected by the MBLS model.
- These additionally gained mental powers distinguish the abilities of humans from other mammals, and indeed, while many psychological disorders are observed, as best as we can tell, naturally in other animals, psychosis is not, to the point where for research purposes heroic efforts are required to induce at best unreliable models of schizophrenia in animals [26].
- Non-psychotic relatives of persons with schizophrenia show deficits in working memory tests [27].

The MBLS cognitive architecture predicts that treatments, through a variety of modalities, which enhance or protect working memory functioning in the early teenage years may possibly prevent the development of psychotic disorders. Indeed, there is already some evidence for the latter [28, 29,30].

8. Discussion

The MBLS cognitive architecture, while not duplicating brain function down to the level of spiking neurons, is inspired by the mammalian brain. The MBLS uses reconfigurable Hopfield-*like* networks that can effectively connect to varying sets of other HLNs depending on the level of abstraction which yields what is defined above as the maximal meaningfulness. Every evaluation cycle, the MBLS looks at the meaningfulness of the data in the sensory input vectors, and cycles through varying levels of abstraction so as to reconfigure the HLNs in a way to pragmatically maximize local and system meaningfulness. Sensory data is further processed symbolically via the HLN-based logic/working memory units synergistically integrated with the entire MBLS architecture including causal memory units. The MBLS can process sensory input vectors or equivalently process the output of a logic/working memory unit as the next input, i.e., effectively a "thought" occurs.

The MBLS may serve as a practical enhanced neural network for analytic and control applications where it provides not just pattern recognition but comprehension. The MBLS may model the development of psychotic disorders in *Homo sapiens*, and if so predicts that in many patients the etiology stems from the fragility of the logic/working memory units and the integration of additional reasoning mechanisms during adolescence.

Future work, which has been started at the time of writing, includes a more comprehensive MBLS simulation, with the goal of obtaining reproducible quantitative data with regard to its properties.

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