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Learning and memory phenomena in a complex sensory environment: a neuroheuristic approach

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Abstract—The concept of interdependent communications systems and Wiener's assertion that a machine that changes its responses based on feedback is a machine that learns, defines the brain as a cybernetic machine. Systems theory has traditionally focused on the structure of systems and their models, whereas cybernetics has focused on how systems function, how they control their actions, how they communicate with other systems or with their own components. However, structure and function of a system cannot be understood in separation and cybernetics and systems theory should be viewed as two facets of a single approach, defined as the neuroheuristic approach.

1. Introduction

Norbert Wiener, a mathematician, engineer and social philosopher, coined the word "cybernetics" from the Greek word meaning "steersman". He defined it as the science of control and communication in the animal and the machine [1]. Many other definitions have followed since then, but in general cybernetics takes as its domain the design or discovery and application of principles of regulation and communication. Early work sought to define and apply principles by which systems may be controlled. More recent work has attempted to understand how systems describe themselves, control themselves, and organize themselves.

The cerebral cortex is not a single entity but an impressive network formed by an order of tens of millions of neurons, most of them excitatory, and by about ten times more glial cells. Ninety percent of the inputs received by a cortical area come from other areas of the cerebral cortex. As a whole, the cerebral cortex can be viewed as a machine talking to itself and could be seen as one big feedback system subject to the relentless advance of entropy, which subverts the exchange of messages that is essential to continued existence (Wiener, 1954). This concept of interdependent communications systems, also known as systems theory, coupled with Wiener's assertion that a machine that changes its responses based on feedback is a machine that learns, defines the cerebral cortex as a cybernetic machine. Therefore, the focus of investigation is shifted from communication and control to interaction. Systems theory has traditionally focused more on the structure of systems and their models, whereas cybernetics has focused more on how systems function, that is to say how they control their actions, how they communicate with other systems or with their own components. However, structure and function of a system cannot be understood in separation and cybernetics and systems theory should be viewed as two facets of a single approach, defined as "the neuroheuristic approach".

2. Classical and Interactive Computation

McCulloch and Pitts [2] proposed a modelization of the nervous system as a finite interconnection of logical devices. For the first time, neural networks were considered as discrete abstract machines, and the issue of their computational capabilities investigated from the automata-theoretic perspective. Further developments of this perspective opened up the way to the theoretical approach to neural computation [3, 4, 5].

A *Turing machine* (TM) consists of a infinite tape, a head that can read and write on this tape, and a finite program which, according to the current computational state of the machine and the current symbol read by the head, determines the next symbol to be written by the head on the tape, the next move of the head (left or right), and the next computational state of the machine. The classical Turing paradigm of computation corresponds to the computational scenario where a system receives a finite input, processes this input, and either provides a corresponding output or never halts. According to the Church-Turing Thesis, the Turing machine model is capable of capturing all possible aspects of algorithmic computation [6].

The concept of a *Turing machine with advise* (TM/A) provides a model of computation beyond the Turing limits. It consists of a classical Turing machine provided with an additional advise function $\alpha : \mathbb{N} \longrightarrow \{0,1\}^+$ as well as an additional advise tape, and such that, on every input u of length n, the machine first copies the advise word $\alpha(n)$ on its advise tape and then continues its computation according to its finite Turing program. A *Turing machine with polynomial-bounded advise* (TM/poly(A)) consists of a TM/A whose advice length is bounded by some polynomial. Turing machines with (polynomial) advice are strictly more powerful than Turing machines.

In the brain, learning and memory phenomena must affect the perception of future inputs older memories themselves may change with response to new inputs. The general interactive computational paradigm consists of a step by step exchange of information between a system and its environment [7]. In order to capture the unpredictability of next inputs at any time step, the dynamically generated input streams need to be modeled by potentially infinite sequences of symbols [8] In most basic scenarios, the environment sends a non-empty input bit to the system at every time step (full environment activity condition), then the system updates its current state accordingly, and then it produces either a corresponding output bit, or remains silent for a while, thus expressing the need of some internal computational phase before generating a new output bit, or remains silent forever to express the fact that it died.

An *interactive Turing machine* (I-TM) consists of a classical Turing machine, yet provided with input and output ports rather than tapes in order to process the interactive sequential exchange of information between the device and its environment [9]. An *interactive Turing machine with advice* (I-TM/A) $\mathcal{M}$ consists of an interactive Turing machine provided with an advice mechanism which takes the form of an *advice function* $\alpha : \mathbb{N} \longrightarrow \{0,1\}^*$ [9]. The machine $\mathcal{M}$ uses two auxiliary special tapes, an *advice input tape* and an *advice output tape*, as well as a designated *advice state*. During its computation, $\mathcal{M}$ can write the binary representation of an integer m on its advice input tape, one bit at a time. Yet at time step n, the number m is not allowed to exceed n. Then, at any chosen time, the machine can enter its designated advice state and then have the finite string $\alpha(m)$ be written on the advice output tape in one time step, replacing the previous content of the tape. Interactive Turing machines with advice were proved to be strictly more powerful than interactive Turing machines [9].

3. Recurrent Neural Networks

A *recurrent neural network* (RNN) consists of a synchronous network of neurons (or processors) related together in a general architecture – not necessarily loop free or symmetric. The network contains a finite number of neurons $(x_j)_{j=1}^N$, as well as M parallel input lines carrying the input stream transmitted by the environment, and P designated output neurons among the N whose role is to communicate the output of the network to the environment. At each time step, the activation value of every neuron is updated by applying a linear-sigmoid function to some weighted affine combination of values of other neurons or inputs at previous time step. Formally, given the activation values of the internal and input neurons $(x_j)_{j=1}^N$ and $(u_j)_{j=1}^M$ at time t, the activation value of each neuron x_i at time $t+1$ is then updated by the following equation

$$x_i(t+1) = \sigma\left(\sum_{j=1}^{N} a_{ij} \cdot x_j(t) + \sum_{j=1}^{M} b_{ij} \cdot u_j(t) + c_i\right) \quad (1)$$

for $i = 1, \ldots, N$, where all a_{ij}, b_{ij}, and c_i are numbers describing the weighted synaptic connections and weighted bias of the network, and σ is the classical saturated-linear activation function defined by $\sigma(x) = 0$ if $x < 0$, $\sigma(x) = x$ if $0 \leq x \leq 1$, and $\sigma(x) = 1$ if $x > 1$.

A RNN is called *rational* (denoted by RNN[$\mathbb{Q}$]) if all its synaptic weights are rational numbers and *real* or *analog* (denoted by RNN[$\mathbb{R}$]) if all its synaptic weights are real numbers [10]. Since rational numbers are real, any rational network is a particular analog network by definition. In the case of dynamic synaptic weights, the dynamics of *evolving recurrent neural network* (Ev-RNN) [11] is defined by

$$x_i(t+1) = \sigma\left(\sum_{j=1}^{N} a_{ij}(t) \cdot x_j(t) + \sum_{j=1}^{M} b_{ij}(t) \cdot u_j(t) + c_i(t)\right) \quad (2)$$

for $i = 1, \ldots, N$, where all $a_{ij}(t)$, $b_{ij}(t)$, and $c_i(t)$ are *bounded* and *time-dependent* synaptic weights, and σ is the classical saturated-linear activation function. A significant breakthrough concerning the computational power of RNN was the demonstration that *rational RNN* are computationally equivalent to Turing machines [10]. The Turing universality of rational neural networks to a broader class of sigmoidal activation functions was further generalized [12]. Furthermore, it was recently demonstrated that *interactive rational recurrent neural networks* (I-RNN) are computationally equivalent to interactive Turing machines [11]. This result was generalized and it was proved that *interactive analog RNN* are computationally equivalent to interactive Turing machines with advice [11]. Analog [10] and evolving networks provide natural models of computation beyond the Turing limits, both in the classical as well as in the interactive computational frameworks [13, 14].

4. Neural Dynamics

In a different intereactive-like computational framework, the concept of an *ω-analog recurrent neural network* (ω-RNN[$\mathbb{R}$]) as an interactive RNN with real synaptic weights was generalized [15]. The network receives an infinite input stream of bits from its environment and produces a corresponding output stream of bits. The input stream is then said to be accepted by the network if the corresponding output remains forever active, i.e. never shuts down to 0 from some time step onwards. The language recognized by the network is then defined as the set of input streams that are accepted by the network. In this framework analog RNNs are strictly more expressive that deterministic and non-deterministic Turing machines equipped with Büchi or Muller accepting conditions. Such networks perform language recognition over the space of infinite streams of bits rather than ω-translations of infinite streams of bits [15].

The activity of each cell is necessarily related to the combined activity in the neurons that are afferent to it. In the cerebral cortex, due to the presence of reciprocal connections between cortical areas, re-entrant activity through chains of neurons is likely to occur in all brains. Developmental and/or learning processes are likely to potentiate or weaken certain pathways through the network by affecting the number or efficacy of synaptic interactions between the neurons [16]. Despite the plasticity of these phenomena it is rationale to suppose that whenever the same information is presented in the network the same pattern of activity is evoked in a circuit of functionally interconnected neurons, referred to as *cell assembly* [17]. In cell assemblies interconnected in this way some ordered sequences of interspike intervals will recur. Such recurring, ordered, and precise (in the order of few *ms*) interspike interval relationships are referred to as spatiotemporal patterns of discharges or preferred firing sequence. Several evidence exist of spatiotemporal firing patterns in behaving animals, from rats to primates [18, 19], where preferred firing sequences can be associated to specific types of stimuli or behaviors.

The whole time series of spike occurrences is assumed to be an expression of some fundamental process governing the activity of the neurons being analyzed. When a specific input pattern activates a cell assembly, the neurons are activated following a certain mode. Then, a *mode of activity* defines how an information is processed within a neural network and how it is associated to the output pattern of activity that is generated [20]. In this framework the *state* of the neural network is defined by a set of parameters characterizing the neural network at a certain time. Then, the state of the network at any given time is represented by the values of these parameters and a network state is fully determined if all parameters are known for each neuron. If we were able *ab absurdo* to set the same initial conditions for all elements we would obtain the same spike trains.

It is rationale to describe the activity of the network with the spike trains of all its elements, expressed by point-like processes. Let us consider a simple point process system, whose dynamics is characterized by discrete steps in time. Let $\{x_i\}, i = 1, \ldots, K$, be a time series with K points, where x represents the state of the system. In a *dynamical system* the subsequent state of the system is determined by its present state, e.g. a map defined by $x_{i+1} = ax_i$, where a is a control parameter. The expression $x_{i+1} = ax_i(1 - x_i)$, known as the logistic map, illustrates a simple dynamical system with a negative nonlinear feedback, defined for $x \in [0, 1]$. It is clear from this expression that the time arrow is non-reversible, because it is always possible for each x_i to obtain a value x_{i+1} but there are two possible x_i for each x_{i+1}. A dynamical system is *deterministic* if it is possible to predict precisely its evolution if one knows exactly the initial conditions. However, slight changes or incorrect measurement in the initial conditions results in a seemingly unpredictable evolution of the system.

A passage in time of a state defines a *process* and whenever it is completely deterministic at each step of its temporal evolution but unpredictable over the long term it is called *chaotic process*. Notice that analog RNNs are able to express the nonlinear dynamical properties characteristic of chaotic behaviors [21]. An equivalent definition of a process is a path over time, or *trajectory*, in the *space of states*. The points approached by the trajectory as the time increases to infinity are called *fixed points* and the set of these points forms an *attractor*.

Spike trains are treated as point process systems and a crucial requirement for a theoretical framework is to identify these point process systems without any assumption as to whether or not they are linear. Point process systems are said to be identified when an acceptable model is found. Notice that the goodness of fit of a certain kernel estimate as plausible is evaluated by means of a function f describing its mode of activity –the mode of activity being defined by how an information is processed within a neural network and how it is associated to the output pattern of activity that is generated. In formal terms, let us define a *probability function* f which describes how a state x' is mapped into the space of states. If the function is set by a control parameter μ we can write $f_\mu(x) = f(x, \mu)$. A *dynamical system* x' is a subset of the space of states and can be obtained by taking the gradient of the probability function with respect to the state variable, that is $x' = \mathrm{grad} f_\mu(x)$. Mathematically speaking, the space of states is a finite dimensional smooth manifold assuming that f is continuously differentiable and the system has a finite number of degrees of freedom [22]. Let us consider again the case of RNNs where the complexity of the system is such that several attractors may appear, moving in space and time across different areas of the network. Such complex spatio-temporal activity may be viewed more generally as an *attracting state*, instead of simply an attractor [23].

In the case of two control parameters, $x \in \mathbb{R}$, $\mu \in \mathbb{R}^2$, the probability function f is defined as the points μ of $\mathbb{R}^2$ with a structurally stable dynamics of $x' = \mathrm{grad} f_\mu(x)$. That means the qualitative dynamics x' is defined in a neighborhood of a pair (x_0, μ_0) at which f is in equilibrium (e.g. minima, maxima, saddle point). With these assumptions, the equilibrium surface is geometrically equivalent to the Riemann-Hugoniot or cusp catastrophe described by Thom [24]. According to this model the equilibrium surface could represent stable modes of activity with postsynaptic potential kinetics and the membrane excitability as control parameters [25]. Then, the same neural network may subserve several modes of activity through modulation of its connectivity, e.g. according to learning or pathological processes, or by modulation of its excitability [26], e.g. by modulation of the resting potential or of the synaptic time constants.

5. Discussion

The specific super-Turing model of a TM/A has a natural fit to capture the computational capabilities of basic brain-like models. The emergence of new concepts unbound by a restrictive definition of coding should include the investigation of the computing power of evolvable RNNs, the significance of preferred firing sequences and the mechanism of their generation and propagation. The open question of how structured information is represented in the brain cannot be avoided. [27]. As engineers increasingly are inclined to look for inspiration from biology, this question is also of general relevance for information technologies. To use a metaphor, we could state that "the neuroheuristic approach" observes the experimental results beyond the surrounding wall of the hypothesis by coupled conjecture and testing, similarly to a child playing in a garden while observing what happens beyond whatever enclosure surrounds him, which could be a hedge, a gate or a lattice. All of these are closures but they are all different and belong to distinct *topoï*. However, the complexity of problems presented to the researcher of today is of such a broad span that the database approach is unable of reducing its computational performance to a disciplinary dimension. The neuroheuristic approach to brain sciences attempts to promote a paradigm based upon synergy between Modelling and Experiments which parallels the synergy between Computer and Information Sciences with the Neurosciences.

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