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HUMAN LEARNING *VERSUS* MACHINE LEARNING: ANALOGIES THAT CAN BE USED TO APPROACH COGNITIVE NEUROSCIENCE IN CONTINUING EDUCATION FOR BASIC EDUCATION TEACHERS

Edson Urubatan

Patrícia Libório

Abstract: Teacher training must be geared towards a better understanding of the multiplicity of factors that interfere with learning, in order to enhance the educational process. Understanding the factors that govern learning requires an understanding of the development of cognitive neuroscience. From a neuroscientific perspective, the argument about the effectiveness of the learning process can take place as follows: when we learn, what changes occur in the brain so that we can later recall a piece of knowledge or perform a rehearsed behavior? The answer to this question involves knowledge related to the process of acquiring information. Cognitive neuroscience studies how information is processed in the brain. In order to facilitate understanding of the learning process in the human brain, analogies can be drawn with the learning process developed in machines. The aim of this paper is to relate some concepts from the field of computing and the development of machine learning to the learning process in the human brain. Nowadays, people have more and more knowledge about computer science concepts and analogies with neuroscience concepts can facilitate the dissemination of essential neuroscience concepts in the educational sphere. In some examples it is appropriate to use analogies to compare the learning process in artificial and human systems. Many brain processes, such as the process of acquiring information, are similar to computer processes and the use of analogies can facilitate understanding. However, there are factors that greatly differentiate these learning processes, so these analogies must be used carefully.

INTRODUCTION

In the classroom, there has been a greater number of extrinsic and intrinsic distractions that hinder the process of building knowledge. That's why it's important for teachers to be increasingly able to work taking into account the different demands of today. Teacher training must be geared towards a better understanding of the multiplicity of factors that interfere with learning, in order to enhance the process. In order to understand the factors that govern learning, it is necessary to understand the development of Cognitive Neuroscience. From a neuroscientific perspective, the argument about the effectiveness of the learning process can take place as follows: when we learn, what changes occur in the brain so that we can later recall a piece of knowledge or perform a rehearsed behavior? The answer to this question involves knowledge related to the process of acquiring information (Geake and Cooper, 2003).

Understanding the concepts of Cognitive Neuroscience related to the process of acquiring information allows educators to develop greater skills in understanding the process of constructing knowledge and assessing the functioning of the cognitive functions responsible for learning, directing their classroom practice towards developing adaptations, interventions and activities that provide students with a more dynamic reading of the world (Geake and Cooper, 2003).

Cognitive Neuroscience studies how information is processed in the brain. In order to facilitate understanding of the learning process in the human brain, analogies can be made with the learning process developed in machines. Nowadays, people have more and more knowledge about computer science concepts and analogies with neuroscience concepts can facilitate the dissemination of essential neuroscience concepts in the educational sphere (Geake and Cooper, 2003).

COGNITIVE NEUROSCIENCE

Information processing in the brain takes place in stages. After the information is entered, it is perceived and analyzed, then assigned a meaning. The information is then stored in the memory, which will enable the process of recall when information retrieval is required. Storing information guides decision-making, deductions regarding future demands, actions (motor control) and the transmission of information to another person through communication. Comparisons can be made between the brain and a computer, because in both we can enter data, store it and retrieve it whenever necessary. This data enables the development of basic operations that we use every day. However, these comparisons need to be used with caution, because computers are programmable machines. Brains are not, at least not literally. Many scientists believe that this comparison can lead to erroneous conclusions, because on closer examination the brain is not just an information processor (processing and intelligence are not equivalent concepts). Furthermore, this comparison can also limit and bias the way we see brain processes, especially in relation to consciousness and perception. Explicit formal comparisons with computers should only aim to contextualize certain brain processes, describing them using terms borrowed from the lexical field of computing (algorithms, computation, hardware, software, among others) (Romain, 2022).

The brain acts like a computer in which information is transmitted through nerve cells by means of electrical impulses called action potentials (AP), making the communication of neurons similar to a network of electronic circuits. In addition, the brain has a way of processing information similar to the decision-making process of machine algorithms, which generate standardized responses. In computing, an algorithm is a sequence of computational steps that transform input into output. There are different ways of defining these steps, but it has to be a procedure reducible to a finite set of elementary operations applied in a certain order. All of the brain's functioning processes, not necessarily , resemble the process of using an algorithm, but some are comparable, such as synaptic networks. Each neuron is defined as a binary function and a feedforward network transforms an input into an output through a composition of such functions. The same applies to information acquisition models (Romain, 2022).

ACTION POTENTIAL

Many studies show that the action potential is the main source of information transmission in the brain. Neurons in a resting state have a difference in electrical potential between the inner and outer phases of the membrane due to the existence of ion channels that allow the passage of Na ions^{+} , Ca^{2+}, K^{+} and Cl^{-}. The membrane has an electrical potential due to the concentration of positive and negative charges in the intra- and extracellular phases. The membrane potential of a neuronal cell at rest is approximately - 70mV. The electrical potential of a neuronal cell membrane at rest is called the resting potential. The resting potential of nerve cells, squid giant axons, permeable to K ions^{+} is - 75mV. This value is calculated using the Nernst equation (Kandel, 2014).

$$E_x = \frac{RT}{zF} \ln \frac{[X]_o}{[X]_i} \text{ Nernst equation}$$

Where R is the gas constant (8.314J/mol.K), T is the temperature (in Kelvin), z is the valence of the ion, F is the Faraday constant (96485.34 C/mol) and $[X]_o$ and $[X]_i$ are the concentrations of the ions inside and outside the cell (Kandel, 2014). AT 25°C:

$$E_x = \frac{58\ mV}{z} \log \frac{[X]_o}{[X]_i}$$

For K^+ , where z=+1 and the concentrations inside and outside the cell medium are 20 and 400, respectively.

$$E_x = \frac{58\,mV}{z}\,log\frac{200}{400} = 75\,mV$$

The Na equilibrium potential$^+$ of nerve cells, the giant squid axon, is +55mV.

$$E_x = \frac{58\,mV}{z}\,log\frac{440}{50} = +55mV$$

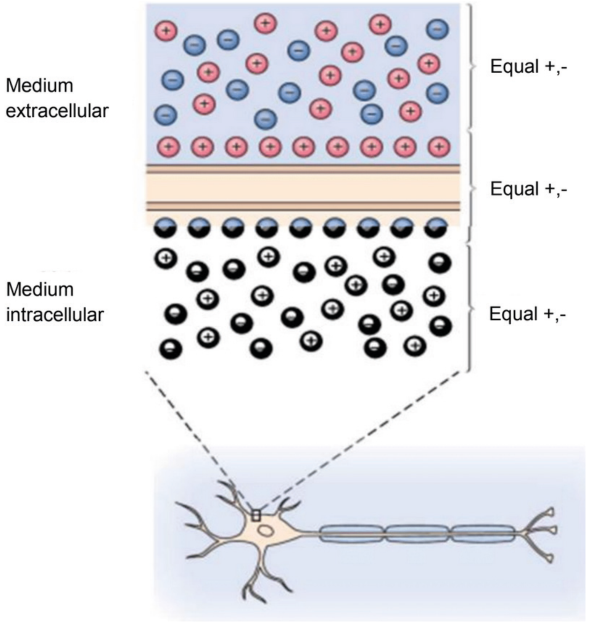

Figure 1: Representation of membrane potential (Kandel, 2014)

The resting potential of the membrane is characterized by the flow of positive and negative charges that occur through resting channels, leak channels (which are always open) and gated channels (which are opened when they are activated at a characteristic voltage). The opening and closing of channels generates the action potential. Ions do not have the same concentration in the intra- and extracellular media. The Na^+ and Cl^- ions are more concentrated in the extracellular medium and the K^+ and Ca^{2+} ions are more concentrated in the intracellular medium (Krueger *et al.*, 2011).

Table 1 shows the concentrations of these ions in the extra- and intracellular environment of a nerve cell, the squid giant axon (Krueger *et al.*, 2011).

Ion	Intracellular environment		Extracellular medium	
	mM	mEq/L	mM	mEq/L
[Na+]	50	10	440	142
[K+]	400	140	20	4
[Cl-]	52	4	560	103

Table 1. Concentration of sodium, potassium and chlorine in the intra- and extracellular medium of squid giant axons (Krueger *et al.*, 2011).

An action potential is generated due to a disturbance in the resting state of the cell membrane, generating a flow of ions through the membrane with a consequent change in the ionic concentration in the intra- and extracellular media (Krueger *et al.*, 2011).

The ionic balance characteristic of the membrane at rest is destabilized during the action potential. The contribution of each ion in generating the action potential can be quantified by Goldman's equation. Analysis of this equation shows the dependence of the membrane potential on the permeability and ionic concentration of Na^+ , K^+ and Cl^- (Krueger *et al.*, 2011).

$$V_m = \frac{RT}{F}\,ln\frac{P_k[K^+]_0 + P_{Na}[Na^+]_0 + P_{Cl}[Cl^-]_i}{P_k[K^+]_i + P_{Na}[Na^+]_i + P_{Cl}[Cl^-]_0}$$

Goldman equation

Where P_k, P_{Na} and P_{Cl} are the permeabilities of potassium, sodium and chlorine ions. This equation determines that the greater the concentration and permeability of the membrane to an ionic species, the greater its participation in determining the membrane potential (Krueger *et al.*, 2011). Membrane potential can also be defined as:

$$V_m = V_{in} - V_{out}$$

Where V_{in} is the potential of the internal part and V_{out} is the potential of the external

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part. By convention, the extracellular potential is assigned a value of zero, so the resting potential is equal to V_{in} (Kandel, 2014).

Cell membranes are semi-permeable to the passage of specific substances such as Na^+, K^+, Cl^-, Ca^{+2}, proteins and glucose. Applying the Nernst equation, it can be seen that each substance has a difference in potential between the intra- and extracellular phases due to the difference in concentration between the media. This difference in concentration and the effect known as Gibbs-Donnan equilibrium allow the polarization of the cell membrane to be maintained (Kandel, 2014).

In many nerve cells, the membrane behaves like a resistor in response to small pulses of hyperpolarizing or depolarizing current. There is a gradual variation in the voltage of the membrane as a function of the size of the current (following Ohm's law; $\Delta V = \Delta I \ x \ R$). As the current increases, there is a tendency to reach the voltage threshold (close to -50mV for the sodium ion), at which point the action potential is generated. The action potential is an all-or-nothing event. According to the all--or-nothing law, the nerve impulse is always equal in amplitude, duration and waveform. The action potential is a phenomenon that involves a sequence of firings and can be represented by a sequence of zeros and ones. There is evidence that neural coding and information processing in the brain are the result of the interaction between the firing sequences of its billions of neurons (Kandel, 2014).

The functional properties of neurons can be represented as an equivalent circuit. Neurons have three fundamental passive electrical properties, which are: membrane conductance at rest ($g_r=1/R_r$), membrane electrical capacitance (C_m) and intracellular axial resistance (r_{α}) (Kandel, 2014).

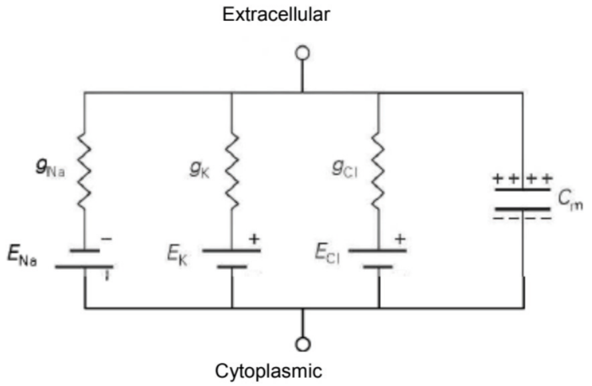

Figure 2: Neuronal membrane equivalent circuit in which the circuit elements are the ion channels Na^+, K^+ and Cl^- (Kandel, 2014)

The fundamental passive electrical properties of the neuron determine the time course of the change in synaptic potential generated by the synaptic current and whether the synaptic potential generated in the dendrites will sufficiently depolarize the trigger zone in the initial segment of the axon to promote the generation of the action potential. The changes that occur in the resting state of the neuronal membrane voltage in response to a subliminal current are similar to the operation of a simple resistor. However, a resistor shows similar responses to changes in voltage due to sudden changes in current. In the neuronal membrane, on the other hand, the potential varies more slowly as a result of changes in current (Kandel, 2014).

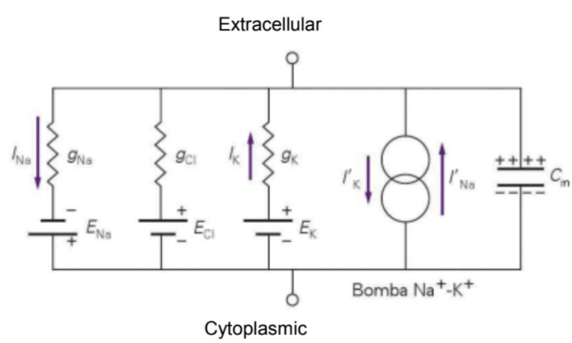

Figure 3: Illustration of a passive and active current equivalent circuit in a neuron (Kandel, 2014)

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The voltage across a capacitor is proportional to the stored charge. The change in voltage is due to the addition or removal of charge (Q) in the capacitor (Kandel, 2014).

$$\Delta V = \frac{\Delta Q}{C}$$

The current is equivalent to the flow of charge per unit of time (Kandel, 2014).

$$I_c = \frac{\Delta Q}{C}$$

The change in voltage of a capacitor can then be described as:

$$\Delta V = I_c \, x \frac{\Delta t}{C}$$

The voltage variation will depend on the charge flow per unit time. For a neuronal membrane of a neuron with a spherical cell body, the voltage variation will be described as:

$$\Delta V_m(t) = I_m \, R_m(1 - e^{-\frac{1}{T}})$$

Where e is the base of the natural logarithm system with an approximate value of 2.72 and T is the time constant of the membrane (obtained by the product: $R_m C_{m)}$ (Kandel, 2014).

FORMATION OF SYNAPTIC NETWORKS

Neurons are cells specialized in transmitting and processing signals. In other words, they are responsible for processing information. Neurons are the cells responsible for conducting nerve impulses. Figure 4 shows the structure of a neuron. It shows the presence of a cell body, which contains the cell nucleus, responsible for controlling cell metabolism. The cell body has two types of extensions: dendrites and axons. The dendrites are branched, which makes it possible to increase the surface area for stimulus capture (Cosenza and Guerra, 2011; Izquierdo, 2011).

Axons have branches that establish contact with another neuron, gland or muscle. Axons can be surrounded by Schwann cells, which contain large amounts of lipids and form the myelin sheath. The purpose of the myelin sheath is to insulate the axons. Regions that are not covered by the myelin sheath are called Ranvier nodules. When dendrites receive stimuli, they trigger nerve impulses, which are transmitted to the cell body, which transmits these impulses to the axon and its branches. The nerve impulse jumps from one Ranvier node to another through variations in the electric field (Cosenza and Guerra, 2011; Izquierdo, 2011).

There is a tiny gap between the axon branches and the structure they are associated with, this region is known as the synaptic cleft. From this gap, the axon branches release chemical substances in response to the nerve impulse. These substances are neurotransmitters. Neurotransmitters are substances synthesized by neurons and present at the end of nerve cells. Neurotransmitters are released by the synaptic clefts in sufficient quantity to exert a defined action on a particular effector organ or on another neuron. Neurotransmitters bind to specific chemical receptors on the post-synaptic cell, provoking a response which can be a nerve impulse or a muscle contraction. The emission of neurotransmitters across the synaptic cleft is called a nerve synapse. Neurons transmit information to other neurons until the information reaches its final destination via the axons, thus characterizing synaptic transmission (Terman, 2010).

A neuron can be compared to a digital processor whose purpose is to modulate information received in the form of action potentials. Neurons have a structure that allows them to form networks. Networks represent more complex processing structures that are able to integrate information received through somatosensory stimuli with visual and auditory

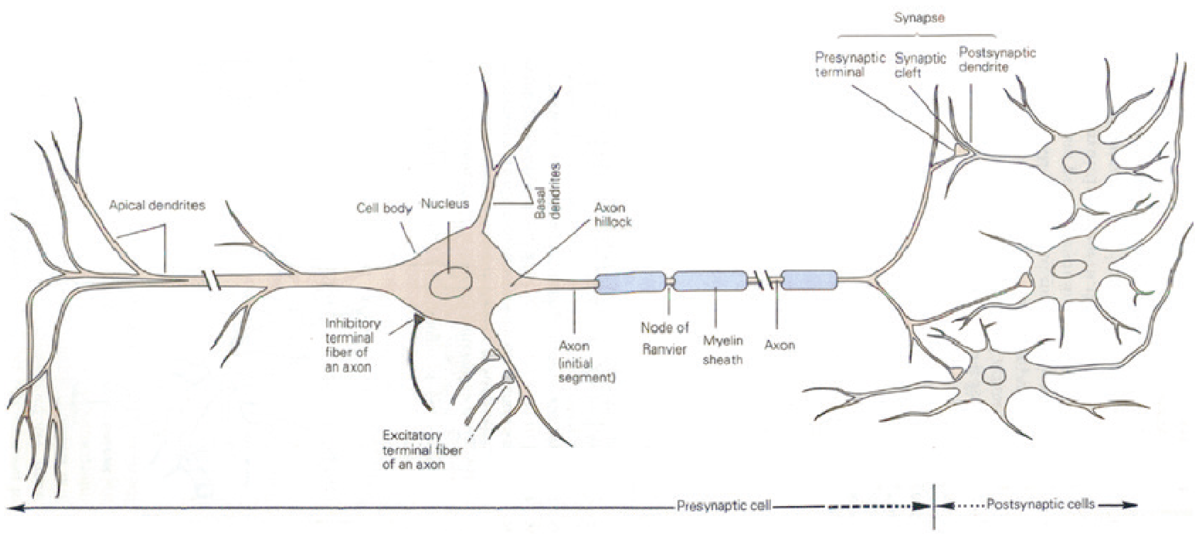

Figure 4: Representation of a neuron (Kandel, 2014)

information and also with previously stored information. From this integration, the brain is able to trigger decision-making, an analysis of future action plans, among other actions. In a synaptic network, a neuron receives inputs from several other neurons and sends outputs to several other neurons (Terman, 2010)

A synaptic network is made up of three basic components, which are the neurons within the network, the synaptic connections between the cells and the architecture of the network. Each of these components can be analyzed using mathematical foundations. The brain is equivalent to a digital computing machine made up of millions of relays called neurons (Terman, 2010). For neurons, we can relate two variables:

$$\frac{dv}{dt} = f(v,w)$$
$$\frac{dw}{dt} = \epsilon g(v,w)$$

Where v is the cell's membrane potential, w is a channel activation variable, being a positive parameter. Thus, w is equivalent to a channel state variable that is activated or inactivated on a slower time scale than other processes. The synapse is the unit that promotes the transportation of information in the nervous system and the contact between a neuron and another cell for the transmission of messages (Terman, 2010). For the chemical synapse, the synaptic current can be written as:

$$I_{syn} = g_{syn}s(V_{post} - v_{syn})$$

Where g_{syn} is a constant maximum conductance, V_{post} is the cell's membrane potential and v_{syn} is the synaptic reversal potential. The dependent variable s represents the fraction of open channels and depends on the pre synaptic membrane potential (Terman, 2010). Generally, we assume that s satisfies the first-order equation described below.

$$\frac{ds}{dt} = \alpha(1-s)H_\infty(V_{pre} - V_T) - \beta_s$$

Where α and β represent the rates at which the synapse turns on and off, respectively (Terman, 2010). The model for a pair of neurons (assuming that the cells are identical so that the non-linear functions f and g do not depend on the cell) mutually coupled is then:

$$\frac{dv_i}{dt} = f(v_i, w_i) - g_{syn}s_j(v_i - v_{syn}),$$
$$\frac{dw_i}{dt} = \epsilon g(v_i, w_i),$$
$$\frac{ds_i}{dt} = \alpha(1-s_i)H_\infty(v_i - V_T) - \beta s_i.$$

INFORMATION ACQUISITION AND STORAGE

The brain, like a computer, stores information through memory formation. To form memories, a set of signals, modeled after a signal input, is transported to the central nervous system by electrical signals (action potentials) via afferent pathways. In the central nervous system, the information can be transformed into biochemical signals (when long-term memory is formed). These signals are stored and self-reproduced for periods of time that can be differentiated (Matassi and Martinez, 2022; Bongard and Levin, 2021; Martinez and Sprecher, 2020; Brette, 2020).

MACHINE LEARNING

Machine learning is the ability of computers to develop the learning process autonomously, due to interaction with the user. Machine learning aims to analyze data in order to learn internal patterns by applying statistical and mathematical calculations that allow a machine to process and understand the patterns (Harrison, 2019).

An algorithm is a sequence of instructions that helps a machine develop its commands. Computers are made up of billions of transistors, and algorithms turn transistors on and off. Learning algorithms are algorithms that create other algorithms. Through machine learning, computers are able to develop their own programs and action commands (Harrison, 2019). The machine learning process can be classified into three categories:

- Supervised learning: the computer receives a previous set of data that offers a solution to a problem (called labeled data). The algorithm then understands the rules that map the inputs and outputs (Harrison, 2019).
- Unsupervised learning: the computer receives unlabeled data. This data does not provide the solution to a problem, so the algorithm needs to develop a structure for processing the inputs (Harrison, 2019).
- Semi-supervised learning: the computer receives labeled and unlabeled data. This data is used to help solve a problem (Harrison, 2019).
- Reinforcement learning: the computer does not receive any set of prior data. The algorithm interacts with a dynamic environment with a targeted goal, such as winning a game or developing a search pattern. The algorithm develops a solution to a problem based on a process of trial and error (Harrison, 2019).

HUMAN BRAIN VERSUS MACHINE LEARNING

Brain processes can be described using words borrowed from the lexical field of computing (algorithms, computation, hardware, software, etc.). Just as the functioning of computers can be described using analogies with terms from Neuroscience (memory, acquisition and storage of information). From a functional point of view, the brain is an information processing device, i.e. a device capable of computing information. The term computer refers to a programmable machine that can store, retrieve and process data, usually an electronic device, which processes data according to a set of instructions. The chemical and electrical connections between neurons forming synaptic networks reinforces the relationship with an electrical device with multiple and complex mechanisms (Matassi and Martinez, 2022; Bongard and Levin, 2021; Martinez and Sprecher, 2020; Brette, 2020).

In some examples it is appropriate to use analogies to compare the learning process in artificial and human systems. Many brain processes such as the process of acquiring information are similar to computer processes and the use of analogies can facilitate understanding. However, there are factors that make these learning processes very different. Human learning is related to cognition, which means that our learning is developed through interaction with the environment. Cognitive development involves information processing, conceptualization, image formation and mental representations, but it also involves perception and sensation (Leporace, 2023).

Many authors are working on developing mathematical models to describe the functioning of the neuronal networks that make up the brain. But the accuracy of these models has yet to be confirmed. Ideas about how information is processed, the speed of neuronal communication, the role of the neuron in integrating inputs, the routing of information and the correlation between firing patterns and brain activities (i.e. mental activities) show some similarities to the processes described in the field of computing (Matassi and Martinez, 2022; Bongard and Levin, 2021; Martinez and Sprecher, 2020, Brette, 2020).

Nicolelis says that human learning is not comparable to the learning of a computer system. And human intelligence is not transferable to a mathematical formula. Intelligence is a characteristic of living beings that is developed and improved through interaction with the environment and with other living beings. The development of skills such as intuition, creativity, intelligence and empathy does not occur through sequences of one and zero. There are many variations between one and zero, so not all brain processes can be related to the functioning of a machine. Artificial intelligence, for example, will never reproduce a human brain. However, the human brain is capable of transforming itself and imitating a digital system (Nicolelis, 2020).

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