An Early PDP Connectionist Model for Describing the Behavioral Phenomenon

Um Modelo Inicial do Conexionismo PDP para Descrever o Fenômeno Comportamental

Un Modelo Conexionista PDP Inicial para Describir els Fenómeno del Comportamiento

Ricardo Tiosso Panassiol[1]
Universidade Católica Dom Bosco

Abstract

The focus of modern neuroscience on cognitive processes has relegated to behavior the epiphenomenal status of neural processing and the difficulties generated by this interpretation have encouraged the use of computational models. However, the implementation based on inferred cognitive constructs has been inefficient. The objective of this work was to review the concept of behavior by a selectionist approach and propose a connectionist computational model that operates integrally with its neurophysiological bases. The behavioral phenomenon was functionally defined and described at different levels of analysis. Functional levels make it possible to understand *why* behavioral phenomena exist, while topographic levels describe *how* morphophysiological mechanisms implement the response. The connectionist notions of PDP ANNs formalizes the proposal. The model stands out for contextualizing neural processing as part of the response, addressing the behavioral phenomenon as a whole that needs to be explained in its most different levels of analysis.

Keywords: Neuroscience, behavioral sciences, behavior, connectionism, artificial neural networks

Resumo

O enfoque das neurociências modernas nos processos cognitivos tem relegado ao comportamento o status de epifenômeno do processamento neural e as dificuldades geradas por essa interpretação incentivaram o uso de modelos computacionais. Entretanto, a implementação pautada em construtos cognitivos inferidos tem sido ineficiente. Foi objetivo desse trabalho revisar o conceito de comportamento pelo viés selecionista para se propor um modelo computacional conexionista que opere integradamente com suas bases neurofisiológicas. O fenômeno comportamental foi definido funcionalmente e descrito em diferentes níveis de análise. Os níveis funcionais possibilitam entender o *porquê* do fenômeno comportamental, enquanto que os níveis topográficos descrevem *como* os mecanismos morfofisiológicos implementam a resposta. A formalização do modelo foi realizada com noções conexionistas de RNAs de PDP. O modelo se destaca por contextualizar o processamento neural como parte da resposta, tratando o fenômeno comportamental como um todo que precisa ser explicado em seus mais diferentes níveis de análise.

Palavras-chave: Neurociência, ciências comportamentais, comportamento, conexionismo, redes neurais artificiais

Resumen

El enfoque de las neurociencias modernas en los procesos ha relegado al comportamiento el status de epifenómeno del procesamiento neural y las dificultades generadas por esa interpretación incentivaron el uso de modelos computacionales. Sin embargo, la implementación pautada en construcciones cognoscitivas inferidas ha sido ineficiente. Fue objetivo de ese trabajo revisar el concepto de conducta por el sesgo seleccionista para proponer un modelo computacional conexionista que opere íntegramente con sus bases neurofisiológicas. El fenómeno conductual fue definió funcionalmente y descrito en diferentes niveles de análisis. Los niveles funcionales posibilitan entender el *porqué* del fenómeno conductual, mientras que los niveles topográficos describen *cómo* los mecanismos morfofisiológicos implementan la respuesta. La formalización del modelo fue realizada con nociones conectivistas de RNAs de PDP. El modelo se destaca por contextualizar el procesamiento neural como parte de la respuesta, tratando el fenómeno conductual como un todo que necesita ser explicado en sus más diferentes niveles de análisis.

Palabras-clave: Neurociencia, ciencias comportamentales, conducta, conexionismo, redes neuronales artificiales

[1] **Contact address**: Rua Vitório Zeolla, 1228, CEP 79032-360, Carandá Bosque I, Campo Grande, MS, Brasil. Tel: (67) 99123-4660. E-mail: ricardo.tiosso@gmail.com

Programa de Mestrado e Doutorado em Psicologia, UCDB - Campo Grande, MS

Introduction

Multidisciplinarity is at the heart of the origins of modern neuroscience, consisting of three complementary historical moments. Focused on the basic understanding of the structures and functions of the nervous system, in the late 1950s the area took shape with the interdisciplinary convergence of the fields of physiology, anatomy, biochemistry and behavioral sciences. In the 1980s, molecular biology and genetics techniques were introduced to promote the refinement of molecular description of the neural substrates involved in complex behavior and its disorders (Cowan, Harter, & Kandel, 2000). In this period, occurred the removal of the classic basis of behavioral sciences and the approach of Cognitive Psychology, implementing Information Theory as a way to describe the processes that mediate the transformation of the sensorial information of the environmental stimulation into perception, memory and behavior (Baars & Gage, 2010). Finally, in the 1990s, the fusion with computational sciences was motivated by the interests of the cognitive bases, promoting the use of computational models to formally describe mental activity and giving the field an unrivaled breath (e.g. Dayan & Abbot, 2001; Koch & Segev, 1998; Kriegeskorte & Douglas, 2018; Sejnowski, 1992).

Cognitive Neuroscience emerged as a metatheory that came from the need to understanding the relationship between the nervous system and the behavioral phenomenon (Schaal, 2013) and a strong conceptual heritage from Cognitive Psychology. Seeking to combine experimental techniques and approaches from the brain sciences with those of the behavioral sciences, its main objective is to examine the biological bases of higher cognitive functions (Bickle, Mandik, & Anthony, 2012; Cowan *et al.*, 2000; Frank & Badre, 2015). With the focus on cognitive processes, behavior has come to be explained only as an epiphenomenon of neural processing from which, after repeated observations, the explanatory constructs that would causally explain the origins of behavior will be inferred (Baars & Gage, 2010; Bickle, 2016).

However, since the late 1990s, this overly focused inferential approach to cognition has bumped into criticism for constantly disregarding the effects of functional relations between environment and behavior (Overskeid, 2008). In addition, the need for theoretical and experimental understanding of the behavioral phenomenon as an instance that would explain the function of neural activity has been repeatedly addressed by the scientific community (Cooper & Peebles, 2015; Donahoe & Palmer, 1994; Engel & Schneiderman, 1994; Marr, 2010; Schlinger, 2015; Ward, Simpson, Kandel, & Balsam, 2012). Even if current neuroscientific methods can accurately reveal the structure and functioning of neural cells and circuits, there are indications that they do not produce a hierarchical and structural description of information processing in the neural system sufficiently complete to causally explain behavior (Jonas & Kording, 2017). For this, the implementation of computational models has been fundamental and prolific in the description and formalization of these neural mechanisms, however it has proved fruitless when implemented as a function of verbally defined cognitive constructs (Kriegeskorte & Douglas, 2018).

As already pointed out in other works (Donahoe & Palmer, 1994; Krakauer *et al.*, 2017), the *a priori* study of behavior has been shown to be fundamental for the functional understanding of neural activity. The problem of implementation and interpretation of neuroscientific data in computational models seems to arise from the misunderstanding of

Programa de Mestrado e Doutorado em Psicologia, UCDB - Campo Grande, MS

behavioral phenomenon and a consequent limited experimental design, lacking context to interpret the meaning of the data. The lack of a conceptual framework based on robust behavioral studies impairs the mapping of the relationship between the behavioral data and the neural data, making it difficult to elaborate experimental hypotheses and to align different levels of description in a single functional explanation.

Being a bridge between theory and practice, the conceptual framework guides the researcher's choice about how to move to still unexplored themes or how to revisit old issues under new perspective (Ravitch & Riggan, 2012). In this sense, the treatment of cognition as an independent causal variable and behavior as a mere consequent epiphenomenon guides and targets the researcher in the visualization and delimitation of the problem (Zilio, 2013). This understanding theoretically aligns the choices of tools and analytical methods, especially how to interpret the experimental data.

Considering the importance of reassessing the concept of behavior, the first part of this study will revisit the behavioral sciences, seeking theoretical, methodological and experimental subsidies for the functional understanding of the concept of behavior in the neuroscientific endeavor. This reflection agrees with previous works that affirm the great capacity of formal description of computational models (Donahoe & Palmer, 1994; Donahoe, 1997; Kriegeskorte & Douglas, 2018). Thus, the second part will turn to the preliminary description of an artificial neural network (ANN)- based connectionism model that operates with the functional notions of behavior and its neurophysiological bases. The scope is to outline an explanatory model that includes ANNs as plausible proximal causal mechanisms consistent with a selective view of behavior, so that there is no need to resort to unverifiable explanatory constructs.

Exploring Alternatives for a Functional Definition of Behavior

A functional relation consists in conceiving the notion of cause and effect as only the description of the relation between an independent variable and a dependent variable. In this relationship, manipulations in the dependent variable tend to be accompanied by changes in the dependent variable (Skinner, 2003). It is a probabilistic definition that does not imply the cause producing an effect, leaving implicit in the identification of these regularities the manipulacionist notion and the necessity of verifiability of the phenomenon (Craver, 2007). Thus, behavior can be functionally described as the relation between environmental events (independent variables) and the actions of the organism (dependent variables), or as Skinner describes elsewhere (Skinner, 1966), as being specifically all that an organism do as a function of the environment.

In a functional definition of behavior, cognition would not be a causal instance, but a set of actions of the organism. In this sense, we leave the structural notion of cognition that occupies a causal function behind and move to a relational definition that contextualize the cognitive phenomenon as a behavioral event. In this way, we avoid the competition between environment and cognition for the causality of the behavior, simplifying parsimoniously the understanding of the phenomenon.

Combining evolutionary sciences and the selective notion as a form of causal explanation, it is possible to identify three levels of behavioral selection in relation to context (Skinner, 1966). The phylogenetic level establishes the own structure of the organism that behaves, selecting the species with a relatively low adaptive speed. The ontogenetic level establishes the repertoire developed throughout the life by means of the selection of the behavior in the interaction of the individual with the environment. A last level, most recent in the temporal scale, is the cultural one. It acts strongly on the selection of a specific type of behavioral repertoire that is social or verbal, and establishes cultural practices of the subject with a very high adaptive speed (Figure 1). It is important to emphasize that all these levels exert selective pressure concomitantly, but with distinct mechanisms of operation and time scales.

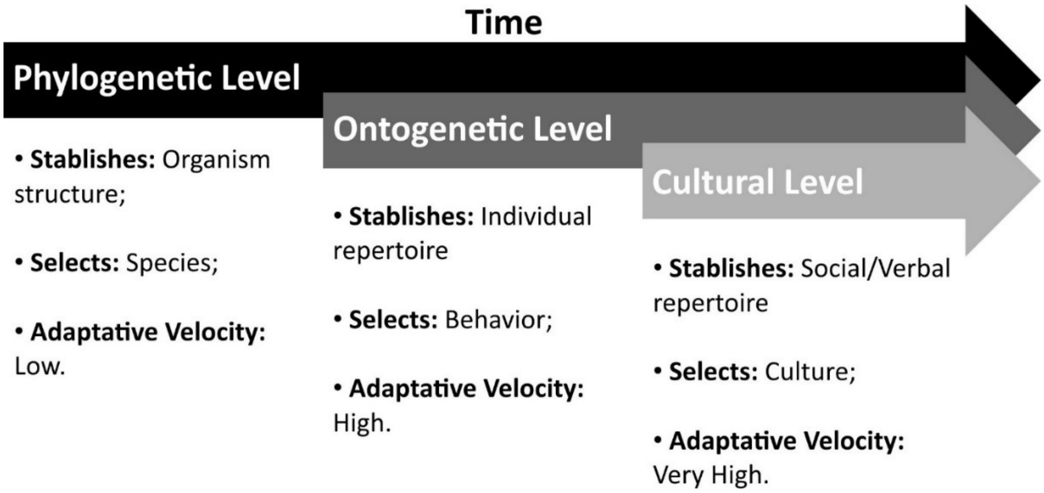

Figure 1. The Three Levels of Behavioral Selection

The phylogenetic level is particularly interesting for this work, because it is at this level that is established the entire anatomical and physiological structure that will behave. It is the very matter selected at the phylogenetic level that will undergo the selective pressures of the other levels and will be shaped by the function established in the relation with the context. In this sense, the phylogenetic level delimits the topographical possibilities of the behavior, that is, how it will take shape. Thus, the behavior function describes *why* it occurs, while the topography describes *how* it occurs (Skinner, 2003).

Limiting the analysis to a purely topographical level of behavior does not make it possible to understand the relation between form and context. Still, however, what is selected in the relationship of the organism with the environment is the very set of behavioral topographies that are functionally matched to a context. For example, we can hold a glass in various ways, describe all movement of the involved muscles and the neural processing responsible for the action, however, if we do not identify the contextual relations of this response, it is practically impossible to say why it happens. At the same time, the very form of the response is directly related to its effectiveness. The response to holding a glass with the left arm is either disabled or severely compromised if the structural components involved in this action are damaged or absent.

In a behavioral episode (Figure 2) there is a chronological order of events: 1) There is an antecedent environmental event that is able to stimulate the organism; 2) The organism responds to the environmental stimulus with a set of neurophysiological, homeostatic and motor events; 3) Homeostatic and motor events generate changes in the environment that lead to response. These consequences affect the organism by altering the probability of similar past responses occurring in similar contexts in the future. If the probability of the emission of the response increases in relation to that consequence, we say that the behavior had its response reinforced (Catania, 1999). In this sense, learning is understood as the very process of structural modifications of the organism according to the consequences that directly affect the probabilities of the occurrence of the responses (Skinner, 1966). Empirical evidence has shown that learning involves changes in synaptic processes of long-term potentiation (LTP) and depression (LTD). In addition, gene expression of DNA segments results in protein synthesis and consequent structural changes in neurons (Kalat, 2015; Kandel, 1989, 1991; Kolb & Whishaw, 2015).

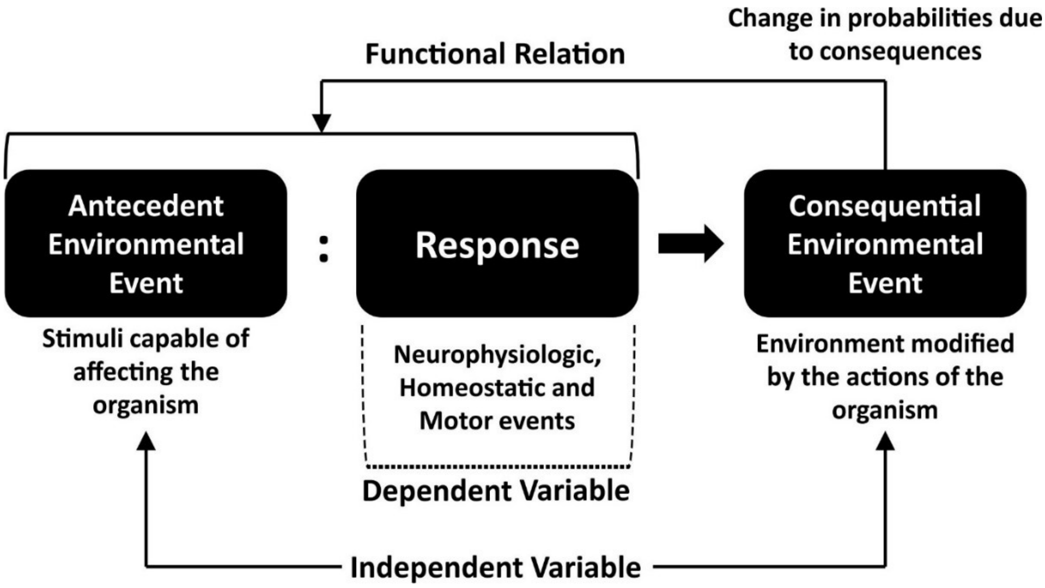

Figure 2. The Elements of Functional Analysis of a Behavioral Episode

The level of functional analysis of behavior is sufficiently described when the regularity relations between events 1, 2 and 3 are identified. The topographic level of analysis occurs in the description of the mechanisms involved in the neurophysiological, homeostatic and motor events that the organism presents as a function of environmental events. As Craver (Craver, 2005) defines, a mechanism is the collection of organized *entities* and *activities* to do something. Entities are the structural components of a mechanism, whereas activities are the functions performed by components in the context of a particular mechanism. At the topographical level of the response, entities are all those structures described by morphology while physiology describes its activities.

Behavioral sciences are interested in the functional levels of behavior. They present a certain independence of the neurosciences precisely because they seek to identify regularities in the relationship between antecedents, responses and consequences, by taking the answer as an indivisible whole (Skinner, 1989). The neurosciences, in turn, are interested in the mechanisms underlying the responses, and may or may not contextualize them functionally in the environment (Cowan *et al.*, 2000). In Behavioral Neuroscience, the traffic between levels of topographic analysis is what will delimit the explanatory capacity of the behavioral phenomenon (Krakauer *et al.*, 2017). Therfore, the importance of the neuromorphophysiological substrate is proportional to the level of deepening in the relationship between topography and function demanded by the research question.

Programa de Mestrado e Doutorado em Psicologia, UCDB - Campo Grande, MS

With the implementation of the selection in a functional description of the topographical aspescts of a response, Behavioral Neurosciences evades the problems that the inferential method has generated. However, this description of the topographical aspects of the response demands a formalism not found among the behavioral sciences. The biological mechanism that implements the funcitonal principle of behaviroal selection is already described by neurosciences. In turn, the set of formal techniques to delineate the cumulative effects of this principle are best described by the artificial neural network models found among connectionist systems (Donahoe, 1997).

Implementing the Connectionism in an Integrated Model

The term connectionism was first attributed to E. L. Thorndike's theory of animal intelligence (Thorndike, 1898) which describes the associations learned between stimuli and responses as connections that would be strengthened or weakened according to the construction or loss of habits. The seminal work on the Law of Effect (Thorndike, 1933) initiated a prototypical neural network theory with strong inferential aspects. However, the main idea raised by this theory was that reinforcement not only automatically influenced the connections of the specific stimulus-response relationship, but would also influence adjacent temporary connections that occurred before or shortly after the availability of the reinforcer.

This premise gave rise to the various types of modern connectionisms that, for the most of them, are strongly based on cognitive theories. Particularly interesting for this work is Distributed Parallel Processing (PDP) connectionism (McClelland & Rumelhart, 1986a, 1986b). This type of connectionism has a formal basis based on Artificial Neural Networks (ANNs), which are parallel processing models with great learning capacity and pattern recognition inspired by biological neural systems (Dayan & Abbot, 2001). PDP connectionism has a great affinity with the selective notions of behavior by approaching the learning processes of its ANNs by the consequetiation of its processing as a function of result. In this way, as pointed by at other works, this kind of connectionism is able to simulate complex behavior (Donahoe & Palmer, 1994; Donahoe, 1997; Donahoe, Burgos, & Palmer, 1993; Donahoe & Dorsel, 1997; Donahoe, 1991; Donahoe & Palmer, 1989; Tryon, 2002).

ANNs (Figure 3) are typically described by simple processing units (*artificial neurons*) arranged in interconnected layers by which excitatory and inhibitory signals propagate via weighted connections, which have their weights adjusted as a function of a result. The *network environment* is the input patterns that specify external vector values for the first units of an ANN or *input layer*, and by the target or *output patterns*, which specify the desired activation values for the intermediate units in the *hidden layers* or to the end units in the output layer. Processing usually takes place in cycles of iterations in which the signals propagate consecutively through the input, hidden and output layers. Each receiving unit will multiply the signals received by the synaptic weights of its connections that are in function of the emitting units. The receiving unit sum the weighted inputs and this total adjusts the values of its activation function, which will transmit the transformed signal to the next layer or emit the output pattern. The adjustments of the synaptic weights that will determine the next iterations and, consequently, the learning of the network, are performed according to the rules pre-established by the learning function, and can occur in a supervised or unsupervised way (McClelland, 2015).

Programa de Mestrado e Doutorado em Psicologia, UCDB - Campo Grande, MS

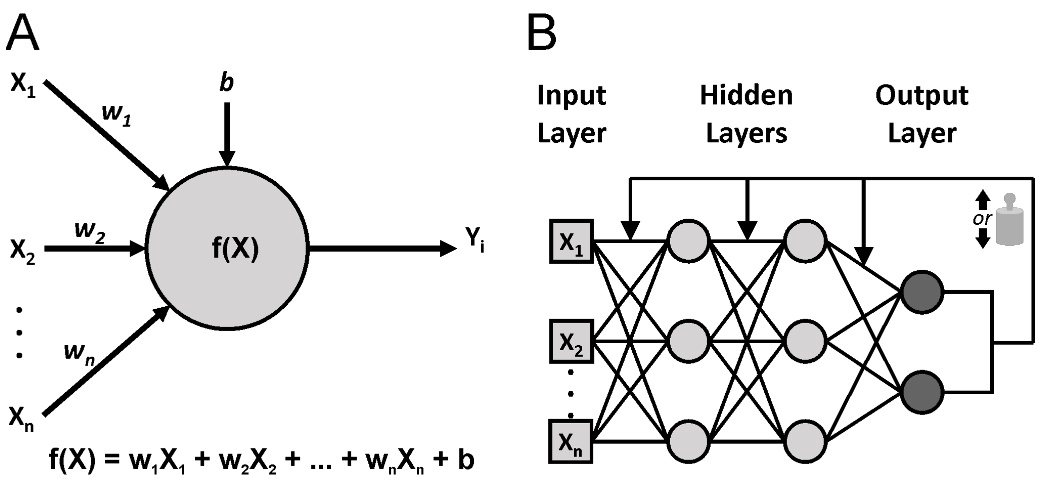

Figure 3. Artificial Neuron and the Artificial Neural Network

Despite the inspiration in biology, the ANNs were developed mainly in the technological environment of engineering. Because of this pragmatic problem-solving context, ANNs rely on simplifications and arbitrariness such as reduced number of parameters, layered topology, synchronized work, limited learning algorithms, inefficiently power consumption and static stages of training and test that does not correspond to the biological networks that inspired them. While these characteristics may generate difficulties in some direct comparisons (Rajalingham *et al.*, 2018), they offered practical solutions that help explain the biological networks in other works (Majaj, Hong, Solomon, & DiCarlo, 2015). In PDP connectionism, the ANNs models could help in describing the proximal mechanisms underlying the response of a behavioral event precisely because they offer a common formal language for the description of the patterns of neuronal activation. Although the limitations imposed by those arbitrariness, they can enable the construction of computational models that maintain more biological and behavioral trustworthiness (Barrett, Morcos, & Macke, 2018; Kietzmann, McClure, & Kriegeskorte, 2019; Ullman, 2019).

In the study of Artificial Intelligence, the best models that meets those reliability criteria are those from deep learning (Kriegeskorte & Douglas, 2018). As an area of machine learning, deep learning consists of obtaining increasingly higher levels of representations in data and raw patterns by implementing supervised or unsupervised learning methods in models with several layers of nonlinear information processing (Deng & Yu, 2014; Marsland, 2015). The traditional architecture of a Deep ANN (DANN) can be basically divide into a pre-processing stage of the input pattern that performs feature extraction, followed by an ANN with more than one hidden layer responsible for categorizing these patterns. The pre-processing structure allows feeding the posterior ANN with already digested information, which facilitates the probability of correct categorization and consequent adjustment weights in favor of learning (Kriegeskorte, 2015).

The proposed system (Figure 4) integrates the PDP connectionism to the theoretical behavioral framework according to the levels of analysis. Behavior is understood as a relation between environmental events and the actions of the organism. At its functional level, the regularities of the organism's responses are objectively described in relation to the contextual disposition of antecedent and consequent stimuli. The main advantage of this approach is the possibility of assessment, manipulation and replication of the phenomenon, which require less inference about the data. These descriptions will make it possible to interpret the *reason* for the behavioral phenomenon without the appeal to inferred hypothetical constructs, since the regularity of the phenomenon occurs gradually and selectively.

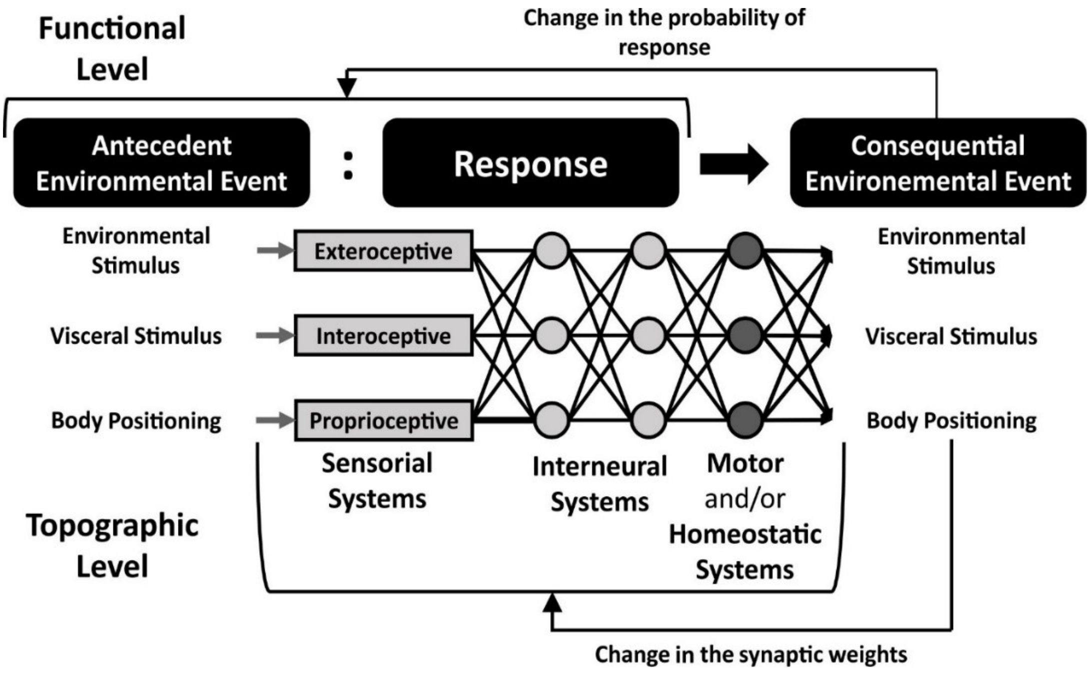

Figure 4. PDP connectionist model for the behavioral phenomenon and it neurophysiological basis

As we delve deeper into the topographic level, we can describe more precisely how the organism responds to the environment through the biological mechanisms already identified by the neurosciences, formally organizing the system with PDP ANNs models. Environmental stimulations are organized according to the types of sensory receptors of the organism, being limited to the following formal classes: *environment*, *visceral* and *proprioceptive*. Due to phylogenetic pressures, the sensory system of the organism is structurally organized to respond to these formal classes, and is organized in *exteroceptive*, *interoceptive* and *proprioceptive* pathways. A vector containing sensory elements of the three pathways topographically describes the functional definition of environmental stimulus. Damage to an organism's sensory system limits its sensitivity to the context, and functionally impairs the development of the response.

With the transduction of the environmental stimuli into neural code by the receptors of the sensory systems, the processing of this information will occur in several layers, following an architecture compatible with the biological network. These neurophysiological processing steps will eventually result in the effector pathways of the motor and homeostatic systems. The effectuation of these two systems leads to a physical change in the environmental stimuli that will result in a consequentiation of the response by weighting the synaptic connections responsible for the output via back propagation and modifying the future probability of that effectuation occurring again in relation to similar context.

Discussion

The proposed model differs from the conventional one (e.g. Donahoe & Dorsel, 1997) because it considers neural processing as part of the behavioral response. In this way, behavior is understood by the definitions of behavioral theories themselves. It would not only be the output of the network or an epiphenomenon of neural processing. The behavioral phenomenon is the whole that needs to be explained in its most different levels of analysis. All that the organism does as a function of context is behavior – neural processing; motor and homeostatic effectuation – are descriptions at the topographical/formal levels of behavioral response. They are all part of the phenomenon.

In a big picture, this proposal ends up helping to resolve many questions based on the inferential process of causal constructs in a parsimoniously way. The theoretical framework points out the steps to be investigated precisely for reference in the physical, manipulative and replicable context. Even in studies on ANNs, which are mostly theoretical, the hypotheses raised are based directly on morphophysiological data from the nervous system, and there is little room for metaphors or conjectures that go beyond the data.

This model is intrinsically multidisciplinary. Although the behavioral sciences devote greater efforts to the level of functional analysis, the interface with the neurosciences has become increasingly urgent. Functional descriptions have progressively demanded for their neurophysiological bases and there is a great need for the development of descriptive and theoretical accuracy. PDP connectionism emerges as an already formalized mathematical arsenal for describing the underlying networks of behavior. However, the historical separation during the formation of the behavioral sciences and the neurosciences generated different theoretical contexts. Therefore, the concepts implemented in this study have intrinsic epistemological limitations, despite considering what is new in both areas. This is an initial attempt to revise the main concepts and theoretical models from both areas in which the formal mediation that PDP connectionism offers creates a timely context of collaboration.

Conclusion

As pointed out, deep learning techniques has the potential to help the development of computational models that maintain more biological and behavioral trustworthiness. By looking for models that substitute non-biological arbitrariness for more biocompatible ones, future research could deepen the formalization of the biological networks that corresponds to the pre-processing and the classification stages. The thalamo-cortical circuits are a good candidate for these studies (Pelaez, 1997; Pelaez & Simoes, 1999). The thalamus integrates the exteroceptive, interoceptive and proprioceptive processing, working as a gateway to the cortex, which will abstracts refined responses from the input patterns.

The proposal can be further refined with the advances of deep reinforcement learning (DRL), an area of machine learning which combines the DANNs with reinforcement learning to solve sequential decision making problems (Sutton & Barto, 2017). However, despite sharing similar names, there is not much concern for the theoretical rigor of behavioral theories in this area. By using the functional definition of behavior proposed here, behavioral science, AI research and neurosciences can achieve mutual benefits from this endeavor.

Programa de Mestrado e Doutorado em Psicologia, UCDB - Campo Grande, MS

References

Baars, B. J., & Gage, N. M. (2010). Cognition, brain and consciousness: Introduction to cognitive neuroscience. *Journal of Chemical Information and Modeling* (2nd ed., Vol. 53). Oxford: Elsevier.

Barrett, D. G. T., Morcos, A. S., & Macke, J. H. (2018). Analyzing biological and artificial neural networks: Challenges with opportunities for synergy? *Current Opinion in Neurobiology*, *55*, 55-64.

Bickle, J. (2016). Revolutions in Neuroscience: Tool development. *Frontiers in Systems Neuroscience*, *10*, 24.

Bickle, J., Mandik, P., & Anthony, L. (2012). The Philosophy of Neuroscience. In E. N. Zalta (Ed.), *The stanford encyclopedia of Philosophy* (Summer 201). Stanford: Metaphysics Research Lab, Stanford University.

Catania, A. C. (1999). *Aprendizagem: Comportamento, linguagem e cognição*. Porto Alegre: Artmed.

Cooper, R. P., & Peebles, D. (2015). Beyond single-level accounts: The role of cognitive architectures in cognitive scientific explanation. *Topics in Cognitive Science*, *7*(2), 243-258.

Cowan, W. M., Harter, D. H., & Kandel, E. R. (2000). The emergence of modern neuroscience: Some implications for neurology and psychiatry. *Annual Review of Neuroscience, 23*, 343-391.

Craver, C. F. (2005). Beyond reduction: Mechanisms, multifield integration and the unity of neuroscience. *Studies in History and Philosophy of Science part C :Studies in History and Philosophy of Biological and Biomedical Sciences*, *36*(2 Spec. Iss.), 373-395.

Craver, C. F. (2007). *Explaining the brain: Mechanisms and the mosaic unity of neuroscience*. Oxford: Clarendon Press.

Dayan, P., & Abbot, L. F. (2001). *Theoretical Neuroscience: Computational and mathematical modeling of neural systems*. Cambridge, Massachusetts: The MIT Press.

Deng, L., & Yu, D. (2014). Deep Learning: Methods and applications. *Foundations and Trends® in Signal Processing*, *7*(3-4), 197-387.

Donahoe, J. W. (1991). The selectionist approach to verbal behavior: Potential contributions of neuropsychology and connectionism. In L. J. Hayes & P. N. Chase (Eds.), *Dialogues on verbal behavior: The first international institute on verbal relations* (pp. 119-145). Reno: Context Press.

Donahoe, J. W. (1997). The necessity of neural networks. In J. W. Donahoe (Ed.), *Neural-Networks models of cognition* (pp. 422-435). Amsterdan: Dorsel, Vivian Packard.

Donahoe, J. W., Burgos, J. E., & Palmer, D. C. (1993). A selectionist approach to reinforcement. *Journal of the Experimental Analysis of Behavior*, *60*(1), 17-40.

Donahoe, J. W., & Dorsel, V. P. (1997). *Neural-Network models of cognition: Biobehavioral foundations*. (G. E. Stelmach & P . Vroon, Eds.), *Advances in psychology* (Vol. 121). Amsterdan: Elsevier.

Donahoe, J. W., & Palmer, D. C. (1989). The interpretation of complex human behavior: Some reactions to Parallel Distributed Processing, edited by J. L. McClelland, D. E. Rumelhart, and the PDP Research Group. *Journal of the Experimental Analysis of Behavior*, *51*(3), 399-416.

Programa de Mestrado e Doutorado em Psicologia, UCDB - Campo Grande, MS

Donahoe, J. W., & Palmer, D. C. (1994). *Learning and complex behavior*. Boston: Allyn& Bacon.

Engel, B. T., & Schneiderman, N. (1994). Operant Conditioning and the Modulation of Cardiovascular Function. *Annu. Rev. Physiol*, *46*, 199-210.

Frank, M. J., & Badre, D. (2015). How cognitive theory guides neuroscience, *Cognition*, *135*, 14-20.

Jonas, E., & Kording, K. P. (2017). Could a neuroscientist understand a microprocessor? *PLOS Computational Biology*, *13*(1), e1005268.

Kalat, J. W. (2015). *Biological psychology* (12th ed.). Boston: Cengage Learning.

Kandel, E. R. (1989). Genes, nerve cells, and the remembrance of things past. *Journal of Neuropsychiatry*, *1*, 103-125.

Kandel, E. R. (1991). Cellular mechanisms of learning and the biological basis of individuality. In E. R. Kandel, J. H. Schawartz, & T. M. Jessel (Eds.), *Principles of neural science* (pp. 1009-1031). Norwalk: Appleton & Lange.

Kietzmann, T. C., McClure, P., & Kriegeskorte, N. (2019). Deep neural networks in computational neuroscience. *Oxford Research Encyclopedia of Neuroscience*.

Koch, C., & Segev, I. (1998). *Methods in neuronal modeling: From ions to networks*. Cambridge, Massachusetts: The MIT Press.

Kolb, B., & Whishaw, I. Q. (2015). *Fundamentals of Human Neuropsychology* (7th ed.). New York: Worth Publishers.

Krakauer, J. W., Ghazanfar, A. A., Gomez-Marin, A., MacIver, M. A., Poeppel, D., Holmes, P., . . . Dudman, J. T. (2017). Neuroscience needs behavior: Correcting a reductionist bias. *Neuron*, *93*(3), 480-490.

Kriegeskorte, N. (2015). Deep neural networks: A new framework for modeling biological vision and brain information processing. *Annual Review of Vision Science*, *1*(1), 417-446.

Kriegeskorte, N., & Douglas, P. K. (2018). Cognitive computational neuroscience. *Nature Neuroscience*.

Majaj, N. J., Hong, H., Solomon, E. A., & DiCarlo, J. J. (2015). Simple learned weighted sums of inferior temporal neuronal firing rates accurately predict human core object recognition performance. *Journal of Neuroscience*, *35*(39), 13402-13418.

Marr, D. (2010). *Vision: A computational investigation into the human representation and processing of visual information*. Cambridge: MIT Press.

Marsland, S. (2015). *Machine learning: An algorithmic perspective*. (R. Herbrich & T. Graepel, Eds.) (2nd ed.). Boca Raton: Chapman and Hall/CRC.

McClelland, J. L. (2015). *Explorations in parallel distributed processing: A handbook of models , programs , and exercises* (2nd ed.). Stanford: Stanford Psychology Department.

McClelland, J. L., & Rumelhart, D. E. (1986a). *Parallel distributed processing: Explorations in the microstructure of cognition*. (Vol. 1). Cambridge, Massachusetts: MIT Press.

McClelland, J. L., & Rumelhart, D. E. (1986b). *Parallel distributed processing: Explorations in the microstructure of cognition* (Vol. 2). Cambridge, Massachusetts: MIT Press.

Overskeid, G. (2008). They should have thought about the consequences: The crisis of cognitivism and a second chance for behavior analysis. *The Psychological Record*, *58*(1), 131-151.

Pelaez, J. R. (1997). Plato' s theory of ideas revisited. *Neural Networks*, *10*(7), 1269-1288.

Pelaez, J. R., & Simoes, M. G. (1999). Pattern completion through thalamo-cortical interaction. In *IJCNN'99. International joint conference on neural networks. Proceedings* (Vol. 1, pp. 125-130). IEEE.

Rajalingham, R., Kar, K., Issa, E. B., Schmidt, K., DiCarlo, J. J., & Bashivan, P. (2018). Large-scale, high-resolution comparison of the core visual object recognition behavior of humans, monkeys, and state-of-the-art deep artificial neural networks. *The Journal of Neuroscience*, *38*(33), 7255-7269.

Ravitch, S. M., & Riggan, M. (2012). *Reason & rigor: How conceptual frameworks guide research*.Whashington. Califórnia: Sage Publications.

Schaal, D. W. (2013). Behavioral neuroscience. *APA Handbook of Behavior Analysis, Vol. 1: Methods and Principles.*, *1*, 339-350.

Schlinger, H. D. (2015). Behavior analysis and behavioral neuroscience. *Frontiers in Human Neuroscience*, *9*, 210.

Sejnowski, P. C. T. J. (1992). *The computational brain*. Cambridge, Massachusetts: The MIT Press.

Skinner, B. F. (1966). *The behavior of organisms: An experimental analysis*. *1938*. New York: Appleton-Century-Crofts.

Skinner, B. F. (1989). The behavior of organisms at 50. In B. F. Skinner (Ed.), *Recent Issues in the Analysis fo Behavior* (pp. 121-136). Ohio: Merril Publishin Company.

Skinner, B. F. (2003). *Ciência e comportamento humano* (11th ed.). São Paulo: Martins Fontes.

Sutton, R. S., & Barto, A. G. (2017). *Reinforcement learning: An introduction* (4th ed.). Cambridge, Massachusetts: The MIT Press.

Thorndike, E. L. (1898). Animal intelligence: An experimental study of the associative processes in animals. *The Psychological Review*, *II*(4), 1-107.

Thorndike, E. L. (1933). A proof of the Law of Effect. *Science*, (77), 173-175.

Tryon, W. W. (2002). Expanding the explanatory base of Behavior Analysis via modern connectionims: Selectionism as a common explanatory core. *The Behavior Analyst Today*, *3*(1), 104-118.

Ullman, B. S. (2019). Using neuroscience to develop artificial intelligence, *363*(6428), 692-694.

Ward, R. D., Simpson, E. H., Kandel, E. R., & Balsam, P. D. (2012). Schizophrenia : Behavior analysis as a guide for neuroscience. *Behav Processes*, *87*(1), 149-156.

Zilio, D. A. (2013). Behavioral unit of selection and the operant-respondent distinction: The role of neurophysiological events in controlling the verbal behavior of theorizing about behavior. *The Psychological Record*, *63*, 895-918.

Received in: 12/11/2018
Revision received: 07/03/2019
Accepted in: 13/03/2019

About the author:

Ricardo Tiosso Panassiol – Doctoral student in Neurosciences and Behavior and master in Experimental Psychology, both at the Institute of Psychology of the University of São Paulo (USP). Graduated in Psychology at the Federal University of Mato Grosso do Sul (UFMS). Currently, he researches the computational processes of the thalamo-cortical circuits involved in the pattern completion of afferent and efferent information through the artificial neural network modeling of deep learning. Works as a clinical behavioral psychologist and develops studies in the areas of Behavior Analysis, Neuroscience, Neuroengineering and Brain-Machine Interface. E-mail: ricardo.tiosso@gmail.com, Orcid: http://orcid.org/0000-0002-3614-2735