The Regulatory Character of Boredom in AI – Towards a Self-Regulating System based on Spiking Neural Networks

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Abstract. Boredom is increasingly recognized as a functional emotion playing an important role in regulating human behavior. Despite continuous advances in the field of artificial intelligence, research on whether these models can enter emotional states such as boredom remains limited. However, emotions can be pivotal towards more human-like intelligence in AI. This paper transfers the regulatory function of boredom into a control loop modeled with spiking neural networks. Simulations demonstrate the successful replication of the regulatory mechanism of boredom based on simulated input. This work provides a foundation for future research and development towards a self-regulating system based on spiking neural networks capable of entering a state of boredom.

1 Introduction

The architecture and functioning of the human brain serves as a source of inspiration for the field of Artificial Intelligence (AI). Continuous technological progress has enabled the emergence of sophisticated Machine Learning (ML) models, which are capable of performing intricate tasks and processing an immense quantity of data. Nevertheless, emotions and related states remain a relatively underrepresented dimension in AI, despite their apparent significance in human information processing [1].

Boredom is an emotional state that almost everybody experiences from time to time. The phenomenon has been the subject of growing research interest in recent decades, particularly within the fields of psychology and philosophy. Given its recurring nature, boredom is regarded as a central component in the regulation of human behavior. However, only a few approaches have been proposed to incorporate the phenomenon in terms of information processing in an AI-based setting [2, 3, 4]. In the process of enhancing AI towards more human-like intelligence, emotional states such as boredom may play a central role [5]. Here we introduce a control loop that simulates the regulatory mechanism of boredom, modeled from a psychological perspective to replicate behaviors observed in humans. The paper is structured as follows: based on a functional theory of boredom, a control loop consisting of Spiking Neural Networks (SNNs) is constructed. Subsequently, the dynamic within the loop is investigated via simulations. Finally, we outline the modifications and adjustments to be addressed in the next steps.

2 The Functional Theory of Boredom

Despite extensive research, a universally accepted definition of boredom remains elusive. It is regarded as a multifaceted phenomenon, with its characterisation dependent on different theoretical frameworks and schools of thought [6]. Nevertheless, the experience of boredom seems to be a common occurrence among individuals, irrespective of their health status or cultural background.

Boredom can be considered within a functional framework, encompassing both an informative and a regulative component [7, 8]. First, boredom acts as a signal, indicating a mismatch between desired and actual levels of engagement [7, 9]. This discrepancy results in falling out of a zone of optimal cognitive engagement — a kind of *Goldilocks' Zone* [9]. As a result of the mismatch, boredom also represents a call-to-action, pushing the individual to explore for better options for engagement that would ultimately return them to the *Goldilocks' Zone*. Boredom thereby fulfills its regulatory role when the individual transitions from a suboptimal state back into a satisfying one [10].

3 Control Loop based on Spiking Neural Networks

SNNs aim to model information processing in a more biologically plausible manner compared to traditional Artificial Neural Networks (ANNs) or ML models. The individual units are spiking neurons, connected with each other through synapses. For both neurons and synapses, various models have been proposed, offering either higher biological accuracy or greater computational feasibility. SNNs provide insights into mechanisms observed in biological systems by modeling and subsequently analysing them. Furthermore, they can be applied in the context of classical ML problems [11].

The functional perspective on boredom described in the section above, is modeled as a control loop (see Fig 1) and implemented in this paper using the *NEST* simulator framework [12]. At its core are three spiking neuron populations representing the level of cognitive engagement, the level of boredom and the system's responsive behavior to boredom (control unit). Each spiking population is composed of arbitrary 75 *Leaky Integrate-and-Fire* neuron models [13] with identical initial parameters. To enable a dynamic behavior within the control loop, excitatory and inhibitory connections are established both within and between the populations through static synapses. For biological plausibility, 80 percent of the neurons within a population were defined as excitatory, while 20 percent were defined as inhibitory.

The expected dynamic flow is as follows: the CE population inhibits the boredom population (B), while the B population excites the control unit (CU).

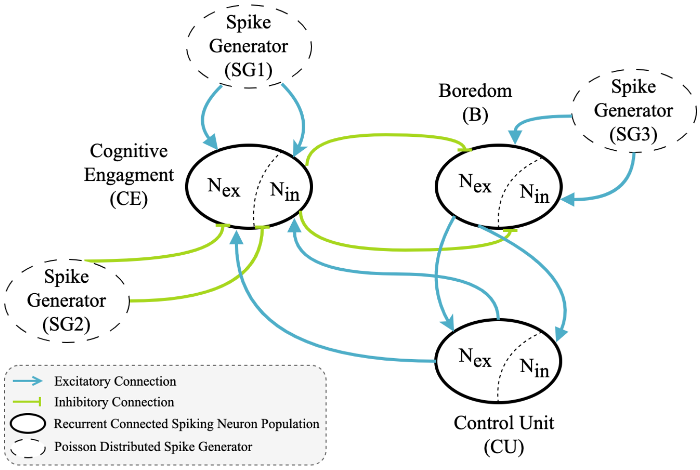

Fig. 1: Derived regulatory mechanism of boredom modeled as a control loop: It is constructed out of three spiking neuron populations (Cognitive Engagement, Boredom, Control Unit) consisting of excitatory (N_{ex}) and inhibitory (N_{in}) neurons. The populations are connected with each other by inhibitory and excitatory connections. To enable the dynamic, three spike generators are included (SG1, SG2, SG3).

In turn, CU provides excitatory input back to the CE population. This connectivity schema creates a feedback mechanism where high CE population activity suppresses boredom. When CE activity drops, it can no longer suppress boredom, which causes boredom to rise. This triggers the CU, which acts to restore the CE level back to the individual optimal *Goldilocks' Zone*. This dynamic mirrors the tendency to adapt behavior in search of an optimally engaging or satisfying situation to keep the CE level within the desired zone in a simplified way.

4 Simulation of the Control Loop

4.1 Setup

The dynamic of the control loop is initiated and sustained by the three included spike generators (see Fig 1), each consisting of 15 neurons that fire in accordance to a *Poisson* distribution. SG1 (excitatory) and SG2 (inhibitory) simulate inputs that modulate the level of CE. SG3 (excitatory) is responsible for continuously driving activity within the B population. This configuration is designed to emulate the mechanism by which, if CE activity falls below a certain threshold, boredom increases, prompting the CU to intervene and restore optimal engagement. We simulated the control loop for 2000 ms.

Initially, SG1 and SG2 are configured with identical firing rates (100 Hz), maintaining stable activity within the CE population and sufficiently suppressing the activity of the B population. To initiate the regulatory mechanism, the firing rate of SG1 is gradually reduced from $t = 500$ ms onward, leading to a decrease in excitatory input to the CE population, thereby creating an artificial mismatch in CE activity. As a consequence, the activity within the CE population declines progressively until it reaches a level where its inhibitory effect on the B population (constantly activated by SG3 with a firing rate of 90 Hz) is insufficient. At this point, the B population activates CU, which acts to return the system to the optimal equilibrium - the *Goldilocks' Zone*.

4.2 Simulation Results

In order to analyze and observe the behavior of the control loop due to the input, we examined both the raster plots of spiking events of the individual neurons within the populations and the overall population activity (see Fig 2). We interpret these pools of neurons as units, referring to the concept of population coding. For this, we calculated the population activity $A(t)$ as follows [14]:

$$A(t) = \frac{1}{\Delta t} \int_{t}^{t+\Delta t} \frac{1}{N} \sum_{j=1}^{N} \sum_{f} \delta(t - t_j^{(f)})\, \mathrm{d}t$$

The quantity $A(t)$ measures how many neurons in the individual populations are active, i.e., firing, in a defined time interval ($\Delta t = 10$ ms). The double sum accounts for the firing events $t_j^{(f)}$ of the neurons within the specified population of size N. The Dirac Delta function δ is used to denote a spike. The calculated activity of e.g. the CE population represents simultaneously the CE level.

We observed that, during periods when no mismatch occurred between SG1 and SG2, boredom was successfully suppressed. Additionally, the CE level decreased without the CU being activated. This outlines that the *Goldilocks' Zone* is a range of values and small deviations from a continuous CE level do not trigger a regulatory response. We defined the lower threshold of the *Goldilocks' Zone* retrospectively as the point at which the activity of the CU was greater than zero. This can be interpreted as the moment the system is trying to re-enter the zone as the level of boredom has breached a threshold. Once the CU had restored the CE level back to the *Goldilocks' Zone*, the level of boredom decreased, resulting in a reduction in the activation of the CU. However, as the firing rate of SG1 continued to decline, this resulted in a subsequent drop out of the *Goldilocks' Zone*, which in turn re-triggered the regulatory mechanism. At time point $t = 1200$ ms, the firing rate of SG1 was reset to its initial conditions, which results in the initial suppression of boredom and no further activity of CU. To complete the *Goldilocks' Zone*, the upper threshold was defined as being above the highest occurring CE level during the simulations. We successfully demonstrated that the psychological model of boredom can be simulated by means of SNNs.

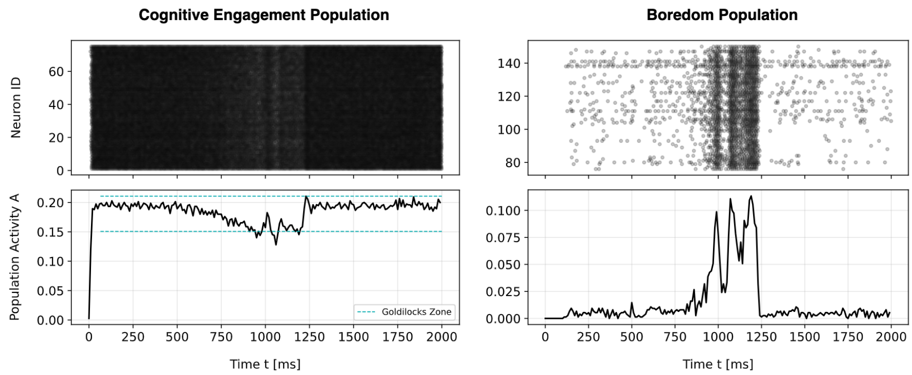

Fig. 2: Simulation behavior of the control loop. On the left-hand side, the raster plot and population activity of the CE population are displayed. The *Goldilocks' Zone* is illustrated by the two dashed blue lines. On the right, the raster plot and population activity of the B population are displayed.

5 Conclusion and Future Work

To the best of the authors knowledge, this work is the first incorporating the phenomenon of boredom in the field of AI by using SNNs. It models boredom functionally by translating a psychological theory of the phenomenon into a control loop based on spiking neuron populations. To investigate the behavior of this loop, three spike generators were introduced, successfully replicating a regulatory response driven by an input mismatch. This work presents a novel approach to modeling emotional states in AI as control loops with SNNs. It offers an approach for mimicking and studying the responsive behavior of humans to boredom (trait and state) from a psychological point of view. Furthermore, it provides a first basis for further developments towards a self-regulating system capable of entering a state of boredom.

We have not modeled differential inputs to the system - that is, different factors that may be more or less likely to promote either cognitive engagement or boredom. Nor have we modeled individual trait differences, most prominently boredom proneness. Here our aim was to begin with a model of the state of boredom. Future research could focus on input factors to provide conditions for the rise of boredom, based on inducing factors derived from experiments with humans. Furthermore, a mechanism that enables the model to autonomously identify the *Goldilocks' Zone*. This flexibility could mirror the subjective nature of boredom, where the experiences of individuals may differ. This also refers to the upper threshold, which is currently defined at the point of the highest CE level. That is, models of boredom suggest that the state can signal deviation from optimal engagement at both the upper and lower points of an optimal zone [9]. Deviations from the upper bounds of the *Goldilocks' Zone* were not directly tested here, but should evince the same behavior in the respective populations.

Lastly, further research will focus on how the model can respond to boredom, aiming to develop adaptive strategies for managing this state. This may also provide a foundation for further research exploring why some individuals experience greater challenges in eliminating boredom than others.

6 Acknowledgement

This work is partly supported by BMBF (Federal Ministry of Education and Research) in DAAD project 57616814 (SECAI, School of Embedded Composite AI, https://secai.org/). PFS is also affiliated with the MPI for Mathematics in the Sciences, the University of Vienna, the Santa Fe Institute, and the National University of Colombia.

References

[1] Carroll E. Izard. Emotion Theory and Research: Highlights, Unanswered Questions, and Emerging Issues. *Annual review of psychology*, 60:1–25, 2009.

[2] Mayank Agrawal, Marcelo G. Mattar, Jonathan D. Cohen, and Nathaniel D. Daw. The temporal dynamics of opportunity costs: A normative account of cognitive fatigue and boredom. *Psychological Review*, 129(3):564–585, April 2022.

[3] Jaime Gomez-Ramirez and Tommaso Costa. Boredom begets creativity: A solution to the exploitation-exploration trade-off in predictive coding. *Biosystems*, 162:168–176, December 2017.

[4] Yen Yu, Acer Y. C. Chang, and Ryota Kanai. Boredom-Driven Curious Learning by Homeo-Heterostatic Value Gradients. *Frontiers in Neurorobotics*, 12, January 2019. Publisher: Frontiers.

[5] Martin Bogdan. Is Boredom an Indicator on the way to Singularity of Artificial Intelligence? Hypotheses as Thought-Provoking Impulse. In *ESANN 2023 proceesdings*, pages 211–216, Bruges (Belgium) and online, 2023. Ciaco - i6doc.com.

[6] Quentin Raffaelli, Caitlin Mills, and Kalina Christoff. The knowns and unknowns of boredom: a review of the literature. *Experimental Brain Research*, 236(9):2451–2462, September 2018.

[7] Andreas Elpidorou. Boredom and Cognitive Engagement: A Functional Theory of Boredom. *Review of Philosophy and Psychology*, 14(3):959–988, September 2023.

[8] Shane W. Bench and Heather C. Lench. On the Function of Boredom. *Behavioral Sciences*, 3(3):459–472, September 2013. Number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

[9] James Danckert and Andreas Elpidorou. In search of boredom: beyond a functional account. *Trends in Cognitive Sciences*, 27(5):494–507, 2023.

[10] Andreas Elpidorou. The bored mind is a guiding mind: toward a regulatory theory of boredom. *Phenomenology and the Cognitive Sciences*, 17(3):455–484, July 2018.

[11] Kashu Yamazaki, Viet-Khoa Vo-Ho, Darshan Bulsara, and Ngan Le. Spiking Neural Networks and Their Applications: A Review. *Brain Sciences*, 12(7):863, June 2022.

[12] Marc-Oliver Gewaltig and Markus Diesmann. Nest (neural simulation tool). *Scholarpedia*, 2(4):1430, 2007.

[13] Wulfram Gerstner and Werner M. Kistler. *Formal spiking neuron models*, pages 93–146. Cambridge University Press, 2002.

[14] Wulfram Gerstner, Werner M. Kistler, Richard Naud, and Liam Paninski. *Neuronal Dynamics: From Single Neurons to Networks and Models of Cognition.* Cambridge University Press, 1 edition, July 2014.