Pushing the Bounds of Bounded Optimality and Rationality

Sebastian Musslick[*,1,2] and Javier Masís[*,3]

[1]Department of Cognitive, Linguistic, and Psychological Sciences,
Brown University, Providence, RI 02912, USA.
[2]Carney Institute for Brain Science, Brown University, Providence, RI 02906, USA.
[3]Princeton Neuroscience Institute, Princeton University, Princeton, NJ 08544, USA.
[*] Equal Contribution, Corresponding Author: sebastian@musslick.de

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Abstract

All forms of cognition, whether natural or artificial, are subject to constraints of their computing architecture. This assumption forms the tenet of virtually all general theories of cognition, including those deriving from bounded optimality and bounded rationality. In this letter, we highlight an unresolved puzzle related to this premise: what are these constraints, and why are cognitive architectures subject to cognitive constraints in the first place? First, we lay out some pieces along the puzzle edge, such as computational tradeoffs inherent to neural architectures that give rise to rational bounds of cognition. We then outline critical next steps for characterizing cognitive bounds, proposing that some of these bounds can be subject to modification by cognition and, as such, are part of what is being optimized when cognitive agents decide how to allocate cognitive resources. We conclude that these emerging views may contribute to a more holistic perspective on the nature of cognitive bounds, as well as their alteration subject to cognition.

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Cognitive bounds form a tenet of general theories of cognition

All forms of cognition, whether natural or artificial, are subject to constraints of the computing architecture, such as the inability to carry out an infinite number of computations in parallel (Miller, 1956; Petri et al., 2021; Russell & Subramanian, 1994). This assumption forms the tenet of all general theories of cognition, including those deriving from bounded optimality and bounded rationality. Bounded optimality assumes that cognitive agents maximize expected utility given limitations of their computational architecture and environment (Russell & Subramanian, 1994). Relatedly, bounded rationality (Gigerenzer, 2008; Simon, 1957; Todd & Gigerenzer, 2012) posits that suboptimalities in human behavior arise from the use of heuristics rather than full deliberation because of bounds on processing capacity and limited information. From this point of view, the bounds of cognition can be considered the axioms of cognitive theories. However, cognitive scientists lack consensus on what these bounds are and, perhaps more importantly, why biological architectures are subject to these bounds in the first place—a puzzle that poses significant challenges to a unifying theory of cognition. In this letter, we seek to lay out some pieces along the puzzle edge by examining the role of cognitive bounds for theories of cognition and propose a more holistic perspective: Although cognition likely resides within a set of bounds, those bounds may not all be fixed. Moreover, we argue that an important and still overlooked part of cognition is its role in modifying some of those bounds.

Bounded optimality (Russell & Subramanian, 1994), including its extensions to biological cognition (e.g., Gershman, Horvitz, & Tenenbaum, 2015; Griffiths, Lieder, & Goodman, 2015; Kahneman, 2002; Lewis, Howes, & Singh, 2014; Lieder & Griffiths, 2020; Shenhav, Botvinick, & Cohen, 2013; Silvestrini, Musslick, Berry, & Vassena, 2022) and behavioral economics (Caplin & Dean, 2015; Hébert & Woodford, 2019; Sims, 2003), are based on the principle that optimality in a computational system should be evaluated in the context of the resources available to it. For instance, Russell and Subramanian (1994) assume that bounded-optimal agents select a program of cognitive operations c^*,

$$c^* = \underset{c}{\operatorname{argmax}}\, V(c, B, \mathbf{E}) \tag{1}$$

such that an agent maximizes their outcome value $V(c, B, \mathbf{E})$ subject to the bounds of their cognitive architecture B for a set of environments $\mathbf{E}$. In artificial systems (e.g., based on the von Neumann architecture; von Neumann, 1958), the computational bounds B derive from resources with definable capacity, such as memory, processing speed, or parallelization. These bounds characterize a landscape of tradeoffs to be navigated, which amount to competing opportunity costs between, for example, processing one task versus another. In biological systems, however, what the bounds are, and perhaps more importantly, why they are there, remains unclear.

Cognitive bounds can reflect a rational response to computational tradeoffs

Following the structural constraints in the von Neumann architecture, one may reasonably posit that the cognitive bounds of the brain reflect similar limitations. However, the vast amount of structural capacity that the brain holds for processing—billions of neurons operating in parallel—is unlikely to account for some stark limitations, such as the inability to follow two conversations simultaneously. Alternatively, resource theories argue that energetic costs (Attwell & Laughlin, 2001; Lennie, 2003), often reflected in terms of limited metabolic resources (Gailliot et al., 2007; Baumeister, Vohs, & Tice, 2007), underlie cognitive bounds. Yet, these models have suffered strong critiques (Kurzban, Duckworth, Kable, & Myers, 2013; Shenhav et al., 2017), and meta-analyses have failed to provide evidence in their favor (Carter, Kofler, Forster, & McCullough, 2015; Friese, Loschelder, Gieseler, Frankenbach, & Inzlicht, 2019; Hagger, Wood, Stiff, & Chatzisarantis, 2010). Moreover, accounts based on structural or resource limitations struggle to explain why different types of cognition are subject to different bounds. Why can the brain—unlike the von Neumann architecture—effortlessly perform face recognition while it struggles with two-digit arithmetic?

A recent point of view, buttressed on the analysis of neural network architectures, suggests that cognitive limitations do not reflect a bound on rational processing, but rather a rational bound on processing (Musslick & Cohen, 2021). General theories of cognition typically assume bounds on the number of computations that can be carried out in parallel. Theories of human multitasking (i.e., parallel processing) attribute these bounds to processing interference that arises if two or more cognitive processes call upon the same local resources for different purposes (Allport, Antonis, & Reynolds, 1972; Feng, Schwemmer, Gershman, & Cohen, 2014; Meyer & Kieras, 1997; Musslick, Saxe, Hoskin, Reichman, & Cohen, 2020; Navon & Gopher, 1979; Salvucci & Taatgen, 2008; Wickens, 1991). For example, following two conversations simultaneously may require engaging the same neural resource representing language for different purposes, yielding processing interference. But if the sharing of resources among cognitive processes imposes a limitation in multitasking, then why would a cognitive system not rely on separate resources for each cognitive process, thereby enabling interference-free multitasking? (Imagine, for instance, each ear mapping onto a separate language area, allowing the decoding of two conversations in parallel.)

The theoretical study of neural network architectures suggests that the sharing of resources can facilitate learning and transfer (Baxter, 1995; Caruana, 1997; Musslick et al., 2017). In fact, the benefit of faster learning can outweigh the costs of limitations in parallel processing (Sagiv, Musslick, Niv, & Cohen, 2018; Ravi, Musslick, Hamin, Willke, & Cohen, 2020). This tradeoff between learning efficacy through shared representations, and processing efficiency through separated representations depends upon the demands and statistics of the environment. Indeed, for language, the balance seems to tip in favor of a shared representation, perhaps because our need to quickly learn language surpasses our need to decode two conversations simultaneously (which may not happen very often). However, in some cases, such as in visual object recognition, where faces, places, and objects must all be simultaneously decoded on a regular basis, the benefits of parallel processing may instead warrant the development of separated, specialized representations. Thus, it can sometimes be rational, however counter-intuitive, for a cognitive architecture to adopt limitations in parallel processing—a bound that can be considered as a result of the cognitive architecture rather than an unexplained constant—precisely to capitalize on the learning benefits that come with shared (capacity-limiting) resources.

Despite its ability to rationalize parallel processing limitations, rational boundedness theory requires additional pieces to accommodate other bounds of human cognition, such as limited working memory and cognitive fatigue. Auspiciously, recent studies have begun to provide rational accounts of such limitations. For instance, an emerging line of work suggests that cognitive fatigue may reflect the opportunity cost of attending to one task at a time (Agrawal, Mattar, Cohen, & Daw, 2021; Kurzban et al., 2013), or that the limit on attention allocated to a single task reflects a tradeoff between cognitive stability and flexibility (Musslick, Jang, Shvartsman, Shenhav, & Cohen, 2018; Ueltzhöffer, Armbruster-Genç, & Fiebach, 2015). This recent work notwithstanding, it remains an open puzzle of how rational explanations for cognitive bounds integrate with accounts proposing structural or metabolic limitations of the brain.[1]

Cognitive bounds can be subject to modification by cognition

The potential rationality of cognitive bounds does not, however, mean that the bounds are fixed. Cognitive agents have the capability to change cognitive bounds as seen with skill acquisition (Newell & Rosenbloom, 1981; Taatgen & Lee, 2003). Parallel distributed processing models suggest that higher "automaticity" of a cognitive process arises from decreased interference with other cognitive processes, resulting in greater parallel processing capacity (Cohen, Dunbar, & McClelland, 1990; MacLeod & Dunbar, 1988; Posner & Snyder, 1975; Shiffrin & Schneider, 1977). Under this view, learning can be regarded as an agent pushing the bounds of its own cognition. Thus, the

[1] One potential avenue for conciliation may be that metabolic resources, such as extracellular glutamate in the lateral prefrontal cortex, which was elevated in subjects enduring more cognitively demanding tasks (Wiehler, Branzoli, Adanyeguh, Mochel, & Pessiglione, 2022), serve to indirectly signal imbalances in competing computational demands rather than constituting a limited resource in and of themselves—much like hormones indirectly signal imbalances in homeostasis rather than constituting the primary limit of biological function.

optimization problem posed by Russell and Subramanian (1994, Eq. (1)) becomes one in which the bounds B_{t+1} at a future point in time $t+1$ can be expressed as a function of cognitive operations applied at present time t,

$$B_{t+1} = L(c_t, B_t, \mathbf{E}) \tag{2}$$

where L corresponds to a learning function describing how cognitive operations affect bounds of the computing architecture. For instance, recent neuroimaging and computational work suggests that participants can push the bounds of their multitasking capability by learning to separate representations between tasks (K. Garner & Dux, 2015; K. G. Garner & Dux, 2022; Musslick & Cohen, 2019). Similarly, learning to chunk visual features has been found to increase the effective storage capacity of working memory, albeit at a loss in recall precision (Nassar, Helmers, & Frank, 2018).

Cognitive agents may consider the modification of cognitive bounds when allocating cognitive resources

The benefits of learning are clear, but what is less clear is how an agent decides whether it is worthwhile to invest in learning. Practice and learning require an opportunity cost of time and reward over prolonged periods. Nonetheless, people do choose to learn despite these costs (e.g. mastering the piano). This phenomenon suggests that people engage in managing their own cognitive bounds through learning. This view comports with accounts that operationalize effort and information as inherently rewarding, to explain seemingly irrational behavior (Inzlicht, Shenhav, & Olivola, 2018). Furthermore, accounts on flow (Csikszentmihalyi, 1990; Melnikoff, Carlson, & Stillman, 2022; Wilson, Shenhav, Straccia, & Cohen, 2019), boredom (Geana, Wilson, Daw, & Cohen, 2016), curiosity (Schmidhuber, 1991), and fatigue (Agrawal et al., 2021) suggest mechanisms for investing cognitive resources not only to accommodate current bounds, but to optimally change those bounds. In line with normative theories of learning (Dubey & Griffiths, 2020; Kidd & Hayden, 2015), human infants and macaques will allocate attention to stimuli that are intermediately surprising (Cubit, Canale, Handsman, Kidd, & Bennetto, 2021; Wu et al., 2021), and adults will self-organize their curricula to maximize learning and reward (e.g., Ten, Kaushik, Oudeyer, & Gottlieb, 2021). This research extends to other organisms, such as rats which have been found to manage their learning strategically, trading instant rewards for faster learning (Masís, Chapman, Rhee, Cox, & Saxe, 2020).

As highlighted above, changing the bounds of cognition carries opportunity costs. Recent work on rational boundedness proposes meta-cognitive processes that consider these opportunity costs, e.g., when deciding between instant learning and future parallel processing (Sagiv et al., 2018; Ravi et al., 2020; Musslick & Cohen, 2021). Such meta-cognitive processes manage learning through the use of cognitive control, e.g., to increase task automaticity (Masís, Musslick, & Cohen, 2021), or to adjust the granularity of task representations (Ho et al., 2022). The nature of such meta-cognitive processes, and their role in changing the bounds of cognition, remains an important question in the pursuit of general theories of cognition.

Conclusion

The puzzle pieces outlined in this article point to a novel "rational boundedness" perspective on bounded optimality and bounded rationality: Cognitive bounds can reflect a rational response to computational tradeoffs inherent to the computing architecture. Importantly, however, cognition is not just acting within these bounds, but also shaping those bounds in a rational way over time. These emerging views may aid in the development of a more holistic perspective on the nature of cognitive bounds, as well as their alteration subject to cognition.

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