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Situatedness and Embodiment of Computational Systems

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Abstract: In this paper, the role of the environment and physical embodiment of computational systems for explanatory purposes will be analyzed. In particular, the focus will be on cognitive computational systems, understood in terms of mechanisms that manipulate semantic information. It will be argued that the role of the environment has long been appreciated, in particular in the work of Herbert A. Simon, which has inspired the mechanistic view on explanation. From Simon's perspective, the embodied view on cognition seems natural but it is nowhere near as critical as its proponents suggest. The only point of difference between Simon and embodied cognition is the significance of body-based off-line cognition; however, it will be argued that it is notoriously over-appreciated in the current debate. The new mechanistic view on explanation suggests that even if it is critical to situate a mechanism in its environment and study its physical composition, or realization, it is also stressed that not all detail counts, and that some bodily features of cognitive systems should be left out from explanations.

Keywords: cognitive mechanisms; informational interaction; mechanistic explanation; computational modeling

1. Introduction

A realistic approach to the computational explanation of cognitive processes assumes that they are adequately explained by computational models because they are computational. However, in the study of cognition, defenders of "embodied and embedded cognition", who claim that cognition depends essentially on interaction with the environment, have repeatedly criticized computational modeling for ignoring physical interaction, embodiment, and the role of environment, cf. [1–6]. The biological embodiment is supposed to exclude computational explanations. At the same time, such explanations predominate in theoretical papers published by major journals of cognitive science [7]. Is theory in cognitive science not up-to-date? Or maybe, the role of embodiment is actually overhyped, as some argue [8].

The aim of this paper is to answer the question of the role of the environment and physical embodiment in cognitive explanations of behavior, in particular when cognitive processes are considered to be sensitive to information. In answering this question, the role of environments as suppliers of information will be stressed, and it will be shown that current explanatory practices are not as revolutionary or radical as they are sometimes painted. The approach defended here belongs to the new mechanistic philosophy [9–12], which has long drawn heavily from the work of cognitive scientists, especially the late Herbert A. Simon. At the same time, the appeal to the mechanistic framework will be made only in the conclusion of the paper, and methodological insights could be phrased using another account of explanatory relevance preferred by the reader.

William Bechtel and Robert Richardson, in the second edition of their inspiring work on the discovery of mechanisms in scientific practice, re-emphasize their stress of Simon's work for the new mechanism:

> Simon shifted our attention to a recognition of bounded rationality as a fundamental feature of cognition. In decision contexts generally, he argued, human beings make choices between alternatives in light of goals, relying on incomplete information and limited resources. As a consequence, problem-solving cannot be exhaustive: we cannot explore all the possibilities that confront us, and the search must be constrained in ways that facilitate search efficiency, even at the expense of search effectiveness. [13] (p. xxii)

This paper will follow suit by stressing that Simon's methodological insights are not only connected to his account of bounded rationality but also can be elucidated in terms of learning driven by environments, in which cognitive mechanisms work. Although Simon's approach is based on symbolic models that have drifted out of fashion, and his hypotheses about conscious serial processing have turned out to be more controversial than he probably expected, there is an interesting methodological lesson to be drawn from his carefully planned studies. Moreover, he might have been one of the most radical proponents of both computational and environmentally-driven explanations of cognition [14]. Certainly not appreciated is the fact that if his approach fails because environments and cognitive problems are ill-structured [15], the situated account of cognition and ecological psychology fail for the same reason. If Simon's critics are right to say that there is not enough structure in the environment to solve cognitive problems, then they simply repeat the poverty of stimulus argument, which states that the structure of the environment is not sufficiently rich to drive solving certain cognitive problems [16]. Simon does not assume that all environments are not sufficient to solve problems, or to acquire the skills to solve them, and his approach is strikingly different from methodological solipsism [17]. I argue that his position is much more nuanced, and his arguments about the explanatory role of the external environment were not sufficiently analyzed in the debate on situatedness and embodiment. For example, proponents of embodiment claim that according to Simon "understanding people as behaving systems is going to be easier than we thought, because so much of the apparent complexity in their behavior is due to factors external to them, and hence external to our problem" [4] (p. 209). However, this is a huge simplification. In Simon's view, the environment and embodiment can play a role in cognitive explanations as long as they explain the phenomena in question. If performance levels of experimental subjects vary, bodily and environmental factors being equal, no amount of environmental interaction alone can explain these differences. In this paper, this argument will be further spelled out.

In Section 2, I develop the argument that the necessary (but not sufficient) condition of being cognitive is to be sensitive to and to process information, and show that it underlies computational explanations in cognitive science. In Section 3, it is shown that this role of environment is crucial in biologically plausible accounts of rationality, developed already by Simon in his theory of bounded rationality [18]. A classical study of human task solving, performed by Simon and Newell [19], is analyzed from the point of view of bounded rationality. Section 4 shows how Simon distinguished two kinds of environment—internal and external—and assigned them differing roles in explanation. It will be argued that Simon's view is largely compatible with contemporary views on embodied cognition—but in contrast to such views, it also focuses on what may be omitted from successful explanatory models. In Section 5, Simon's view on two environments will be further discussed in terms of the mechanistic account of explanation. The paper concludes with the claim that even if it is critical to situate a mechanism in its environment and study its physical composition, or realization, not all detail counts, and some bodily features of cognitive systems may and should be left out from explanations. Embodied and embedded cognition usually offers only a limited insight into cognitive functioning, and is not a cure-all in the study of cognitive processes. Instead of assuming that bodily and environmental factors are always crucial, one should include only those factors, external or internal, that make a difference to the cognitive process under study. Otherwise, one risks making embodied cognition a kind of ideological agenda rather than an empirical hypothesis to be confirmed.

2. Cognitive Mechanisms and Their Environment

What makes cognitive systems special among other physical systems is their ability to cognize their environments and adapt to them in a flexible manner. Still, it is difficult to say what makes a particular process cognitive without sparking a lively debate, see e.g., [20–22]. Moreover, different fields may study cognitive processes from distinct vantage points and by adopting different idealizations, so there can be no overarching definition of cognition for all these fields [23]. All these problems notwithstanding, partial insights are possible. For example, Buckner has plausibly argued that in comparative psychology, several properties of cognitive processes cluster together [24]. As he notices, the main property attributed to cognitive processes by comparative psychologists is behavioral flexibility, studied in more detail by devising tests that are supposed to tease out processes characterized by context-sensitivity, speed, class formation (in object recognition), higher-order and abstract learning, multi-modality of sensory perception, inhibition of behavioral strategies, monotonic integration (distinguishing dimensions along which stimuli can be ordered by increasing value), as well as expectation generation and monitoring. While the detailed characteristics are not important for my purposes here, one striking feature of all these processes is that they presuppose pickup and processing of information, especially about objects that cause sensory stimuli to appear.

Although one could describe behavioral flexibility in other terms, sensitivity to information about the environment and the organism itself is usually presupposed to underlie flexible behavioral strategies. What makes sensitivity to information particularly attractive in this context? The main reason is that while there could be some other reasons why behavioral strategies are not extremely stereotyped, flexibility is not unpredictability or chaotic behavior; flexible behavior is adapted to the current niche. It should be noted, however, that one could imagine flexibility underpinned by a non-informational causal interaction with the environment and some rich internal structure of a cognitive system. In such an explanation, it would remain, however, unclear why (and whether) this structure could be appropriately flexible, i.e., responsive to the environment. In particular, the more complex the behavior and its modifications vis-à-vis the environment, the less it is plausible to claim that it is not underpinned by some information transfer. One particular argument that this is highly unlikely can be found in the theorem that every good regulator must be a model of the controlled system, i.e., be informationally related to the goals achieved by the regulator, and these goals can be said to be situated in the environment [25] (I thank one of the anonymous reviewers for the suggestion to discuss the work of Conant and Ashby [25] as they also talk of models of the environment. However, a detailed comparison of their approach and Simon's goes beyond the scope of this paper).

Instead, it seems to be implied that there is a necessary but insufficient feature of cognitive processes: they require the processing of information. Elsewhere I have argued that as long as the function of such mechanisms is to process information, they should qualify as computational mechanisms [23]. Here, the mechanistic account of physical computation will only be summarily recapped. The goal of the account is to provide criteria to decide which physical systems, if any, qualify as computers. While there are some differences between the two mechanistic accounts of physical computation [23,26], both may be summarized by the following: The necessary condition for candidate physical systems is that they be mechanisms (in the sense of the new mechanistic view on causal explanation, cf. [9–11]) whose *function* is to compute. The mechanism's causal structure should correspond strictly to a mathematical model of computation over physical vehicles specified in a substrate-neutral way. Moreover, the computational explanation should essentially involve the processing of information (as I have described the condition) or be usable as information (as Piccinini has spelled it out). The rest of the conditions spelled out by mechanists simply follow from the general methodological norms of mechanistic explanation.

Mechanistic views on physical computation stress that not all computers process vehicles that bear semantic value. Quite the contrary, it is easy to produce a computer that processes vehicles which do not refer to anything outside the computer. Note: program-loaded computers process instructional information but it is not about anything *outside* the computational system; cf. [27]. In particular, the information in question may be merely *structural* (also called *logon-information* by MacKay, cf. [28]): the only requirement is that a physical vehicle has at least one degree of freedom and its state changes are recognized by some other physical entity. This kind of information need not be semantic, or *about* anything at all.

However, defenders of the mechanistic view on physical computation are not anti-representationalists; in other words, they do not deny that there is an important explanatory role for representation in cognitive explanations. For one, computational mechanisms embedded in larger control mechanisms may be tasked with processing feedback information from the environment in order to control ongoing environmental interaction. For another, probably one of the most important reasons why we view the brain as a computational system is that its function is to model, or represent, the world [29].

Some claim that there is no role for semantics in computational explanations of behavior; at most they are glosses on genuine computational explanations [30,31]. However, anti-representational accounts remain difficult to reconcile with a broader view on the role of computation in behavior—after all, what makes behavior adaptive, or appropriate in a given environment, is not *merely* computation. It is the sensitivity to information, and that is the linchpin of ecologically valid rationality. In the following sections, the focus will be therefore on the relationship between the use of information and rationality, and vexed questions about mental representation will be put to one side (but see [32–34] for mechanistic accounts of mental representation that go together well with the view presented below).

3. Simon, Ecologically Valid Rationality, and Cryptarithmetics

How do we study rationality in an ecologically valid way? Let us start with an extremely simple agent whose behavioral complexity depends on the environment. The ant navigates through the sand; as Herbert Simon notes, the route taken is quite complex, as he does not foresee the obstacles on his way home:

> He must adapt his course repeatedly to the difficulties he encounters and often detour uncrossable barriers. His horizons are very close, so that he deals with each obstacle as he comes to it; he probes for ways around or over it, without much thought for future obstacles. It is easy to trap him into deep detours. [35] (p. 51)

To navigate home, the ant uses simple rules which may be seen as rational—not ideally rational but rational enough to fulfill its goals. In other words, the ant may be said to display bounded rationality, which is one of Simon's key ideas.

In contrast to classical economics, with its highly idealized rationality of the *homo economicus*, Simon opted for a behaviorally and psychologically plausible alternative. The classical account of rationality in economics and decision theory assumes that decisions are determined by preferences over outcomes, which are known and fixed. Decision makers are supposed to maximize their net benefits, or utilities, by making choices that lead to the highest benefit. This model renders decision-making instantaneous, and idealizes away any learning or developmental processes. Moreover, the basic factors are the incentives, or the expected utilities of the outcomes [36].

In contrast, Simon claims that organisms "fall short of the ideal of 'maximizing' postulated in economic theory" [18]. Instead, they adapt well enough to "satisfice". Real decision-making in limited agents is strikingly constrained, and enabled by "the limitations upon the capacities and complexity of the organism" [18] (p. 129). Furthermore, the environments possess properties that permit further simplification of the choice mechanisms in organisms. In 1956, to argue for this claim Simon performed a systematic, mathematical exploration of two simple models that approximate ideal rationality in extremely simple agents. Here I skip the (fairly simple) mathematical detail and focus on a general specification.

The first model depicts an organism that has a single need, i.e., food, and is capable of three kinds of activity: resting, exploration, and food getting. The organism is able to see a circular portion of its environment, whose structure is almost completely bare but there are some isolated heaps of food. By exploring the environment, he is able to see more. The problem is how to choose a path that avoids starvation. According to Simon, one rational way to solve the problem is to behave in the following way: (a) explore the environment at random, watching for a food heap; (b) approach and eat the food when spotted; (c) rest if "the total consumption of energy during the average time required, per meal, for exploration and food getting is less than the energy of the food consumed in the meal" [18] (p. 130).

The second model involves multiple goals. For example, the agent is supposed to find not only food but also water. However, these goals can be attained in the same way; there is no complication if both water and food are randomly and independently distributed in the environment. Moreover, Simon notes that very simple preference mechanisms that could prioritize goals can be built into the agent (so that it would not die of thirst when satisfying its hunger). There might be environments in which one resource may be a clue for the location of another. The prioritization of mechanisms can be informed by the clues.

The models are not supposed to reflect real decision-making processes; they simply demonstrate the possibility that agents can make rational decisions thanks to the environmental constraints appropriately reflected in their choice mechanisms. At the same time, Simon believes that models characterize human rationality to some extent.

The criticisms of classical accounts of rationality underwrite Simon's negativity towards non-classical approaches to the study of cognition. In his joint work with Alonso Vera, Simon criticizes extreme versions of "situated action" approaches to the study of cognition [37]. In a nutshell, Vera and Simon declare the approaches that claim that one should study behavior only in complex real-world situations as question-begging, as no organism "ever deals with the real-world situation in its full complexity" [37] (p. 45). In other words, while there might be rich information out there to be picked up, organisms are only able to pick up and process a limited subset in an effective manner. This stands in stark contrast to John Haugeland's claim that environmental interactions are *always* "high-bandwidth", or causally very dense [4].

Simon's account of rationality as bound by the environment is accentuated in his empirical research on task solving, which is sometimes misleadingly characterized as "abstract" or "over-intellectualized" [15,38]. Whereas Simon indeed studied abstract problem solving, he did not maintain that experimental subjects solve their tasks solely by meditating on them. Quite the contrary, the task environment was designed to constrain the degrees of freedom in human behavior, which is necessary in order to perform replicable studies. It is worthwhile to cite five general claims made by Newell and Simon. These claims justify the design of their experimental studies and cognitive simulations:

1. Humans, when engaged in problem solving in the kinds of tasks we have considered, are representable as information processing systems.
2. This representation can be carried to great detail with fidelity in any specific instance of person and task.
3. Substantial subject differences exist among programs, which are not simply parametric variations but involve differences of program structure, method, and content.
4. Substantial task differences exist among programs, which also are not simply parametric variations but involve differences of structure and content.
5. The task environment (plus the intelligence of the problem solver) determines to a large extent the behavior of the problem solver, independently of the detailed internal structure of his information processing system [19] (p. 788).

Behavioral studies can be performed (and replicated) because the underlying cognitive mechanisms, according to Simon and Newell, manipulate cognitive representations (claim 2), although there are substantial individual differences among subjects (claim 3). The focus on individual differences makes the approach taken by Simon and Newell markedly distinct from the studies of reasoning performed by experimental psychologists such as Wason, who averaged the results of their studies over multiple experimental subjects [39]. However, as later studies have shown, the assumption that experimental subjects understand the instruction unambiguously and solve their tasks in the same way cannot be supported [40]. Moreover, it is well-known that in perceptual tasks, individual differences are rather small and may be limited to the attention span or the individual levels of sensory sensitivity, whereas the intellectual differences, as studied in intelligence research, are severe [41]. Simon and Newell have also focused on developmental differences owing to the individual learning histories of experimental subjects (claim 4). Additionally, crucially, they have claimed that the task environment determines, to a large extent, the behavior of the experimental subject, though it is not the *only* factor (claim 5). To sum up, Simon and Newell aim to explain individual differences in performance levels in similar task environments. This means that the focus on the task environment *alone* will be simply methodologically wrong: it cannot explain these differences, as it is kept equal among subjects.

This can be easily seen in the study of cryptarithmetic problems that consist of finding the Arabic decimal digits which correspond to letters in equations of the form SEND + MORE = MONEY or DONALD + GERALD = ROBERT. Solving the puzzle in a brute-force manner takes, on average, 30 min. Their explanation involved building a computer simulation that allowed them to explain and predict how individual problem solvers operated. The subject's performance is represented in terms of a model of an information-processing system (IPS). Its architecture embodies a number psychological hypotheses about human problem solving, including limited short-term memory and the serial, or sequential, nature of high-level processing. To solve a task, the IPS transforms input symbol structures into output symbol structures that are accepted as a solution. Symbols are understood as entities that can designate other symbol structures (rather than referring to things external to the system; this is admittedly the most controversial claim in the theory). Transformation of symbols is modeled in terms of production rules, expressed as conditionals whose antecedents give the criteria that have to be fulfilled, whereas the consequents are the actions to be performed.

Before analyzing a solver's individual performance on the task, Newell and Simon hypothesize about the possible problem space, or spaces, in which a solution to the problem might be sought. The problem space is a model of knowledge, in which particular locations can be attained by applying *operators* to existing knowledge states. Even vast spaces can be traversed quickly if there is an effective way of transforming knowledge states in order to achieve the goal state. As there are a number of ways in which problem spaces can be represented, the authors methodically consider various options, such as basic, augmented, algebraic, and so forth. These types of problem spaces correspond, as they claim, to differences caused by learning histories. Subjects without an engineering or mathematical background represent the problem in a simplistic way, in terms of one-to-one mapping between characters and digits, and do not notice that the Arabic numerical notation is positional, which would allow them to write an equation to solve. Instead, they try individual assignments one by one, which takes more time.

Interestingly, there are computationally more effective algorithms for solving cryptarithmetic puzzles but they are not used by human subjects because their execution is, according to Simon, impossible under the limitations of short-term memory. Instead, people are only boundedly rational, and commit mistakes, which means that they need to erase partial solutions, track back to previous states of their search, and so on.

The experimental data used to build a computer simulation are taken from verbal protocols: subjects are told to "think aloud", or to justify the steps they are taking. However, people fail to verbalize as fast as they think. Because of this, Newell and Simon also used eye-tracking, which delivered data that corresponded much closer to the proposed computational simulation. However, the computer simulation did not include perceptual processes; these differ from symbolic problem-solving in that that they are, according to Newell and Simon, parallel and not serial [19]. Nonetheless, subjects utilized a blackboard as an *external* memory, and this made problem solving observable. Newell and Simon state that the external memory needs to be interpreted in order to be useful (in contrast to an internal memory) but they do not explain what makes the external memory interpreted.

The theory proposed by Newell and Simon is summarized in terms of four propositions:

1. A few, and only a few, gross characteristics of the human IPS are invariant over the task and problem solver.
2. These characteristics are sufficient to determine that a task environment is represented (in the IPS) as a problem space, and that problem solving takes place in a problem space.
3. The structure of the task environment determines the possible structures of the problem space.
4. The structure of the problem space determines the possible programs that can be used for problem solving [19] (pp. 788–789).

In other words, according to Simon, one can model rational problem solving in an ecologically valid way by building computational models of a human IPS, which will include few characteristics invariant over tasks and subjects. The tasks are represented and solved by subjects who search for a solution in their problem spaces, which are determined by the structure of the task environment. In other words, one cannot abstract away from the structure of the environment in the study of problem-solving. Human rationality rests on responsiveness to the task environment, and while limited and bounded by scarce cognitive resources, it may be sufficient to solve tasks at hand.

4. Six Views on Embodied Cognition and Simon's Two Environments

Embodied cognition is a broad term that covers diverse approaches to the study of cognition. The basic claim is that the physical body of an agent is constitutively relevant to cognition; in other words, cognitive processing involves more than the brain [42,43]. Thus, core cognition, which essentially involves perception and action, depends on the features of the physical body.

Some proponents of embodied cognition reject computational or information-processing views on cognition, however, and this might make their position clearly incompatible with the account defended by Newell and Simon. For example, Lakoff states that computational models of the mind appeal to abstract and formal computations [1]. Similar claims are made by Barrett, who insists that human beings cannot be computers because cognition is adapted for action control [5,6]. Chemero, in his proposal of *radical embodied cognitive science*, denies that minds process information [44,45]. However, the first claim is outright implausible because physical computers are not abstract entities: for example, they can break or burn just like anything else (in contrast to abstractions such as number 1). The second claim is in no way incompatible with computationalism, and there are computers involved in the control of real-time interaction [46]. Chemero's claim is based on Gibson's account of information as picked out from the environment but not processed. What Chemero might have in mind (although he does not elucidate it at length) is that the stimulus information is rich, and that perception is not a process of enrichment of informationally-poor stimulus with some additional information stored in the brain, as suggested by Marr in his influential multi-stage account of visual processing [47]. However, computationalism is not committed to multi-stage processing and need not rely on integration of stored information with perceptual stimuli. So at the first glance, these rejections of information-processing models of the mind cannot be used to exclude a mechanistic view on physical computation as physical information-processing, already sketched above. (Proponents of embodied cognition may, of course, appeal to other arguments against the information-processing view. I review the most popular objections to computationalism in [48], and conclude that none of them are successful. One reason may be that cognition requires flexible action control, and that means that cognitive systems tend to be (sufficiently) good regulators. This cannot be achieved without some form of information-processing, as Conant and Ashby [25] have shown.)

What these proponents of embodied cognition may however have in their minds is the symbolic account of computation associated with Newell and Simon, as well as Fodor [49] and Pylyshyn [50] with their reliance of the symbolic language of thought. However, the claims about the role of the environment do not require the notion of symbol, so even Lakoff's or Barrett's version of embodied cognition may be compatible with the methodological views of Simon. Nevertheless, one should also stress that some proponents of embodied cognition are strongly committed to computationalism, for example Clark [51] or Barsalou [52]. At the same time, for my purposes, what is important is a common core in embodied cognition, accepted both by critics of (symbolic) computationalism and less radical defenders of the embodied and situated cognition. This core has been identified by Wilson who usefully distinguishes six views on embodied cognition: (1) cognition is situated; (2) cognition is time-pressured; (3) we off-load cognitive work onto the environment; (4) the environment is part of the cognitive system; (5) cognition is for action; (6) off-line cognition (or cognitive processes decoupled from the current environment) is body based [53]. The first three claims accentuate the role of the environment in cognitive processes; cognitive processing is always spatiotemporally embedded in some environment, and needs to be adequate vis-à-vis this environment. As should be now clear, this is also exactly what Newell and Simon claimed by saying that the structure of the task environment determined the possible structures of the problem space; the task environment may include external memory, which allows off-loading cognitive work onto the environment, just like the ant described by Simon. However, the tasks studied by Newell and Simon are not so strongly time-pressured. While problem solvers may feel pressure to solve the task as quickly as possible, it is not a matter of life and death.

The view that the environment is part of the cognitive system (claim 4) is closely connected to the idea of the *extended mind*, according to which parts of the environment that not only have causal but also constitutive relevance for cognitive processes [54], but see [55,56] for criticisms. It may be instructive to compare this view with the account defended by Simon. As I have already noted, symbols written by solvers on the blackboard are considered to be their external memory, which is distinguished from internal memory. However, it is also striking that Simon distinguishes two kinds of environment: *internal* and *external* [57].

The external environment is rarely modeled explicitly by Simon, although he mentions that robotic models are appropriate for the study of external environmental constraints; cf. [18]. It is rather included in his methodology: it is the structure of the task environment that lowers the degrees of freedom in human conduct under study [19]. However, it still leaves a lot of elbow room for the solver:

> Given all the invariant structures, a human IPS is still capable of almost arbitrary behavior in response to a task environment—everything from attempting the task to going to sleep, arguing with the presenter of the task, redefining the task, deliberately failing, ignoring the task, engaging in a sitdown strike for better working conditions, protesting over something not connected with the task—and so on. The structural limits provide only that he do these things in a certain style—not too fast, not remembering too much, using a goal structure to keep track of whatever goals he constructs and submits himself to, and using a problem space when the current goal confronts him with a problem he wishes to solve [19] (pp. 864–865).

This is why Haugeland's high-bandwidth interaction with the environment *alone* cannot explain individual performance. There is residual variance that needs to be explained with factors that go beyond physiological or bodily factors.

At the same time, on larger timescales, the external environment exerts influence on cognitive processing: namely, adaptive devices shape themselves to their environments [19]. This is a fairly metaphorical expression, which can be unpacked in the following way: over time, adaptive devices acquire capacities that allow them to solve their tasks effectively in their environments, which means that they are able to pick up relevant information from the external environment. Simon's metaphor is clearly related to evolutionary studies of animal morphology as determined by the environment. For example, Darwin famously studied finches and how their body shape was determined by the external environment. As he wrote: "Seeing this gradation and diversity of structure in one small, intimately related group of birds, one might really fancy that from an original paucity of birds in this archipelago, one species had been taken and modified for different ends" [58] (pp. 379–380).

Simon's metaphor may be thus interpreted in terms of embodied cognition quite straightforwardly by taking a clue from Darwin. For example, Lungarella and Sporns have studied the information flow between the shape of a robot's body and the environment [59]. In particular, they used mutual information and transfer entropy to discriminate non-directed and directed components of sensorimotor coupling, which allowed them to reconstruct the information flow between the environment and the system. Their findings are that the information flow is "(a) *quantifiable and variable in magnitude*; (b) *temporally specific*, i.e., restricted to short temporal delays between sensory and motor time series; (c) *spatially specific*, i.e., restricted to specific portions of the visual input capable of driving motor responses; (d) *modifiable with experience*, e.g., in the course of value-dependent learning of stimulus-response contingencies; and (e) *dependent upon morphology*, e.g., the density and distribution of visual sensors" [59].

However, the study cited above is limited to sensorimotor coupling and does not account for learning, so the focus of the study is the result of adapting to the environment, but not the process itself. To use the original metaphor, it shows that the shape of the solver is relevant to solving the problem, but not how the shape was attained. Simon has framed individual learning in the same terms as evolution, cf. also [60], so the same elucidation should be helpful in understanding both developmental and learning processes.

Simon stressed that the individual learning history explains why problem solvers use their preferred representations of a given problem. Unfortunately, there are no studies on the relationship between mathematical education and the ability to use more advanced problem spaces in solving cryptarithmetic problems. One could perform longitudinal studies on the same individual to test whether her puzzle-solving strategies change, and how. Advanced mathematical education allows some subjects to write up an algebraic equation, and solving it, for a skilled person, is much less error-prone than substituting letters one by one with digits. In more abstract terms, Simon would claim that the subject is able to represent the problem in a new way, and some representations make the solutions transparent.

The structure of the environment allows the solver to create new representational formats and heuristics that make problem-solving easier. The adaptation of an organism to the environment, which may occur as individual learning or as a result of natural selection, consists in structuring the internal processes of the organism so that they are capable of representing the structure of the environment well enough to solve their most important problems, at least on average (they need not be adapted ideally). While the question of how to model this process in terms of information flow remains open, at least two options are particularly popular in the current literature.

The first view has been forcefully defended by Friston in terms of the free energy principle [61]; in other words, organisms minimize their free energy (or entropy). Interestingly, the abovementioned good regulator theorem, proven by Conant and Ashby [25], also presupposes that a good regulator minimizes the entropy of the system that is regulated. Friston hypothesizes that biological systems become models of the causal structure in their local environment, which allows them to predict what happens next, thus countering surprising violations of those predictions. This preserves the homeostasis of biological systems: their states remain within certain bounds. While fairly abstract, Friston's account has straightforward applications to cognitive problems [62,63].

The second view is more developmental, and stresses the fact that both evolution and learning do not leave biological systems in their previous bounds [64]. One may view evolutionary transitions as being associated with novel means of information storage and transmission [65]. In such a view, information does not only allow organisms to remain within certain bounds; it helps them to do some physical work. For example, Terrence Deacon has defended an account of biological information that stresses the role of work, and physical energy, in the semantic role of information (interestingly, his account converges with some other pragmatic accounts of semantic information, cf. [28,66]).

These two views are not presented as an exhaustive taxonomy of all possible views (most probably the study of morphology performed by Lungarella and Sporns falls somewhere in between). Moreover, one may suppose that there is no single way that organisms may become informationally structured to reflect their environments, and that quite distinct strategies are possible. These, as a result, may require different mathematical models. For example, one can devise an artificial agent that relies on reinforcement learning implemented by predictive coding [67], and one that uses predictive error for reinforcement learning, but without predictive coding; one such example being the temporal difference algorithm [68]. Therefore, multiple learning algorithms, whose structure may reflect (sometimes slightly) differing informational relationships, may exist. Instead offering a single correct view on learning, therefore, these two views may still make Simon's suggestion less metaphorical.

Let me turn to the *internal* environment. Its role is framed in other terms. It constrains adaptivity, not problem solving itself. Simon proposes that the ability to learn natural language, for example, is not the result of innate constraints on language syntax, as Noam Chomsky would have it. He suggests that it depends, instead, on general-domain learning constraints of the information-processing architecture. While such claims remain very much debated, for my purposes the most important fact is that the internal environment remains invariant over multiple task environments. This makes it explanatorily highly relevant.

However, as long as morphology remains roughly constant, and temporal scales become larger, some other forms of learning may become more important for problem solving than mere sensorimotor coupling. After all, sensorimotor coupling cannot explain similar performances when the morphology and sensory abilities differ. Obese people may play chess as well as anorectics do; and short-sighted people as well as blind people do (e.g., if they have haptic stimuli).

Note that some proponents of the extended mind also stress that only parts of the environment that remain stably or constantly connected to the cognitive system could count as constituting the extended system [54]. However, their terminological choice is, in some way, opposite to Simon's, even if they appreciate Simon's description of the ant solving navigation problems in its environment [54]. Where Andy Clark and David Chalmers see the extended mind, Simon sees the environment; and he also considers the cognitive itself to be the (inner) environment. Even though he and Newell do not subscribe to the Skinnerian vision of an empty organism as a black box that merely responds to stimuli, they suggest that psychological mechanisms (constituted, in turn, by appropriate neurological mechanisms) work only in a certain environment, and as such, are just a part of a larger equation. These psychological mechanisms do not extend; they are complemented with sometimes ephemeral and highly variable task environments. Notice that the classical view that the mind is extended does not appreciate one-time or unstable contributions of the environment to cognitive tasks. Thus, methodologically speaking, the classical extended mind is not necessarily a step in an appropriate direction; it seems to lead one to ignore ephemeral structures that remain explanatorily and causally relevant to the explanation of certain cognitive processes. Not everything, after all, remains invariant in cognitive processing. (This insight has been appreciated by newer, more dynamical accounts of the extended mind that assert that the mind can include ephemeral structures, cf. [69,70].)

Notice also two other important differences. Whereas Simon would applaud that cognition is for action (claim 5) as long as the term *action* may also refer to highly intellectual activities (such as chess playing), he does not see a particularly important role for bodily processes in cognitive processes. Newell and Simon stress two facts: the importance of biology in understanding the constraints on cognition, and its relative explanatory triviality:

> Man is the mirror of the universe in which he lives, all that he knows shapes his psychology, not just in superficial ways but almost indefinitely and subject only to a few basic constraints. [. . .] The universe that man mirrors is more than his culture. It includes also a lawful physical universe, and a biological one—of which man's own body is not the least important part. [. . .] But a *normal situation* is precisely one in which these biological limits are not exceeded, and it is to such normal situations that the theory of this book applies. In this sense, the theory is a first approximation, which is to be refined by introduction of the sensory and other biological limits as additional constraints upon behavior. [19] (p. 866)

Here Newell and Simon claim something that seems to correspond to the recent survey of results obtained under the broad umbrella of the embodied cognition: even if embodied experimental designs lead to interesting discoveries, the embodied cognition has little or no role in explaining a number of cognitive processes [8]. It is precisely because in the weak sense, it is trivial that off-line cognition is body-based: people are not made of supernatural substance, after all; and in a strong sense, it is simply false: it is not *only* the body that is crucial in explaining most individual differences in solving cryptarithmetic tasks. It is the learning and developmental histories that explain certain representational preferences, which then lead to the choice of the problem space in a solver.

Simon stresses also that the distinction between the outer and inner environment is, to some extent, in the eye of beholder: "There is a certain arbitrariness in drawing the boundary between inner and outer environments of artificial systems" [35] (p. 86). The arbitrariness stems from the fact that the outer environment constrains the structure of the inner environment, which, in turn, constrains adaptivity. Although this may sound paradoxical or viciously circular, the idea is that at various timescales, inner and outer factors may exert their influence, and these factors are not entirely separable. Only by evaluating the factors that are explanatorily and predictively useful for the phenomenon at hand can one decide what to include in the explanatory models of cognition. However, whether the factor is purely inner or outer makes little contribution to the explanation at hand.

While the proponents of the embodied mind hold that including biological detail is crucial, Simon and Newell stress that this detail remains largely invariant, while individual performance varies. This simply means that some biological detail is explanatorily irrelevant and should normally be omitted from explanations; only if one discovers certain decidedly biological factors that would influence, say, the attention span of solvers, could it be included among crucial factors that are relevant (and today's neuroscience tries to discover such factors; cf. [41]). Even if the dictum "only what's relevant counts" seems hollow, it is actually much better methodological advice than assuming a priori that bodily detail always counts, or that it can be always abstracted from.

5. Looking Inside and Around: Not All Detail Counts

Let me summarize the methodological insights gained from the discussion of Simon's account of two environments in terms of the mechanistic view on explanation. In principle, one could also defend my conclusions in terms of the received view in the philosophy of science, namely, the covering-law account of explanation [71], or a functional account of explanation in cognitive sciences [72]. The reader may therefore rephrase my claims to her or his favorite account of explanation; at the same time, for the purposes of the study of cognition, the mechanistic framework seems not only easier to apply than the covering-law model (which would require rephrasing cognitive and neuroscientific models into sound deductive arguments citing exceptionless laws) but also closer to other normative practices in the current cognitive (neuro)science, which requires evidence from multiple levels of organization to be supplied [73]. However, my purpose is not to defend the mechanistic view here (but see [23]), but to use the account to further develop the methodological lessons.

The mechanistic account of explanation has drawn insight from scientific practice, and it has long stressed that mechanisms, which cannot be thought of as purely reactive systems, remain subject to modulation from the environment [74]. For this reason, the explanation has to include both the internal organization of the mechanism in question and the dependence of the behavior of mechanisms on the environmental regularities.

Craver has defended the most systematic account of mechanistic explanation and spelled out norms that satisfactory explanatory texts must satisfy [11]. The most important norm is completeness: Complete explanatory texts "represent all and only the relevant portions of the causal structure of the world" [11]. Subsequently, mechanists were understood to argue that "the more detail, the better" [75], and were criticized for adopting such an unrealistic standard [76]. However, such criticism is mistaken; mechanists defend the claim that only causally *relevant* detail counts [77,78]. Thus, for mechanists, not all possible detail is even *admissible* in explanatory texts. This implies that there might even be irrelevant causal interactions of a mechanism with its environment: they are irrelevant as long as they have no influence on the phenomenon to be explained. Explaining cognitive phenomena does not require including all detail about the situation in which the problem solver is found; some physiological information about the solver may turn out to be useless. For example, as far as we know, facial hair has no causal relevance for strategies adopted during solving cryptarithmetic tasks, even if facial hair may be evidence for some cultural trends, and hence may indicate that a solver belongs to a certain social group. However, there is no correlation between facial hair and the performance in cryptarithmetics. The same may be true of other bodily properties or processes. Not all of them, even if they support crucial metabolic processes, explain cognitive performance. As Newell and Simon phrased it, in *normal* situations, biological constraints exert little to no influence on cognition.

Only the properties, and in particular, regularities in the environment that are causally relevant for the performance of cognitive mechanisms, framed in terms of information processing mechanisms, should be included in explanatory texts about cognitive phenomena. Otherwise, they are just noise. In other words, it is crucial to include the interactions that modulate the computational mechanisms by causing certain inputs to appear.

The mechanistic explanation of cognition is typically situated because it needs to show how mechanisms are subject to environmental modulation. This is why researchers should look *around* the mechanism in order to understand its work. The work of the mechanism may be evolutionarily relevant: it may be an adaptation to the environment. Interestingly, for Simon, cognition is just adapting oneself to the milieu on a smaller temporal scale; as I have argued, adaptation in general may be understood in terms of learning, which, in turn, can be explained in terms of shaping informational relationships. This is why some constraints on the way that cognitive mechanisms work are informational: the information that is available and how it might be actively exploited is a constraint on the structure of the endogenous activity of internal mechanisms.

Furthermore, surrounding mechanisms may constitute a larger system. As the work in distributed cognition clearly shows [79,80], complex mechanisms that include both human agents, computational artifacts, and social organization may contribute to solving complex cognitive tasks that go beyond the capacities of a single problem solver.

The focus on how the mechanism is situated does not screen off the importance of the internal organization. Researchers have to determine how cognitive phenomena are constituted by internal processes and components of (neuro) cognitive mechanisms if the explanation is supposed to be causal and mechanistic. Unless the practitioners of embodied and embedded cognition can show that they can explain all individual differences in performance by appealing to the external environment and bodily structures, their reliance on environmental interaction as the *only* explanatory factor will count as mere ideology, whose poverty is already heavily criticized [8]. The mechanistic story, instead of recommending symbolic models of cognition, stresses that approaches to cognition must be flexible and pluralistic to be empirically valid. Efforts to explain all cognitive phenomena in a unified fashion by relying on bodily and environmental structures have turned out to be futile. It is time to face reality and embrace a radically boring hypothesis: cognition is not always as embodied and situated as it seems; but it is never entirely dis-embodied or isolated from external influence.

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