composed of individuals and individuals who internalize society.

« 6 » I suggest that within all of these examples, circularity both exists and does not exist in time. For this reason, it becomes problematic to invoke the notion of causality within the concept of circularity. Füllsack is interested in what he terms "circular causation." As he notes in §18, the very notion of causality implies temporal indexing, including first causes. But what are the first causes in the making of an individual self? The dynamics are continual and ever shifting, as they operate on multiple time scales. Füllsack's argument in §18 regarding interlocked nonaction as the causal glue for eventual crowd unrest seems clumsy. The role of expectation in macro-scale dynamics also holds for how the stock market operates and for what people project upon others when deciding how to act themselves.

« 7 » Whether it results in action or nonaction, to perceive others' intentions is a forward-looking arc that is built right into our nervous systems. The mirror neuron system, including the perception of intentionality, has been identified as an implicit part in understanding the actions of others by simulating them inside ourselves (e.g., Gallese 2009). From the perspective of brain dynamics, the future becomes embedded inside the present, and all within the context of the past. A nonlinear conception of time is hardwired into our very brains, and it underlies the psychological/experiential level of our perspective as observers. It seems arbitrary to assert we can understand causality only retrospectively in terms of first causes and actions, as if past, present, and future can be clearly separated from one another.

« 8 » The beauty of a nonlinear dynamical approach is that patterns of interaction can be examined independent of time, space, or particular material composition. Perhaps confusion emerges from the fact that paradox characterizes so many nonlinear phenomena. Consider the action of the stock market, whose turbulent complexity of interlocking expectation is now understood to operate according to fractal attractors (Mandelbrot 2006). This means that self-similar patterns of ups and downs exist simultaneously on all temporal scales, such that the characteristic fractal pattern manifests both in and out of time. When Füllsack asserts in §29 that computer iterations follow each other in time and so can be indexed in time, this is a misleading, if not faulty, claim. Yes, the computer's operations are ordered in succession, and yes, the computer code does take time to calculate. Yet, the computer would come up with the same calculations no matter what speed it moved at. So too with the brain. While timing is important in brain processes, interconnectivity and succession are most critical, which is why the emergent level of thought can take on a life of its own to exist somewhat independent of the precise timing of brain events underneath.

« 9 » An important distinction needs to be made between time as a lived quantity and succession as an abstract quality. This distinction between time and succession are meaningful both in computation and in the realm of mathematics, where, for example, mathematician Louis Kauffman has recently teamed up with computer scientist Joel Isaacson (2016) to posit a circular model of recursive distinctioning. Their model relies upon the most basic act of distinguishing same from different at the boundary between successive elements in a one-dimensional line, a two-dimensional grid, etc.

« 10 » Isaacson and Kauffman's system relates to George Spencer Brown's (1969) calculus of indications, where space comes first, and time emerges out of recrossing the same boundary in space. These systems imply that succession is deeper than time, such that time is a quantity that emerges out of succession as a quality of experience and observation. In light of this thinking, I have asserted that fractal geometry exists both in and outside of time, partly by melding quality with quantity and observer with observed (Marks-Tarlow 2015).

« 11 » Due to the paradoxical complication of such dynamics, I suggest it is more useful to think acausally about circularity. Within realms far from equilibrium, where nonlinear dynamics hold, perhaps we should use the language of triggers, acausal dynamics, and unpredictable emergence in the shifts between equilibria states. "Causal" is too narrow, classical, and time-bound a word to describe circular influence, especially when it occurs within nonlinear, statistical, and paradoxical realms.

Terry Marks-Tarlow is a clinical psychologist in private practice in Santa Monica, California. She studies and researches how nonlinear dynamics – including chaos theory, complexity theory, and fractal geometry – apply to human growth and development. She takes special interest in areas related to interpersonal neurobiology, creativity, and clinical intuition.

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Circular Constitution of Observation in the Absence of Ontological Data

Olivier L. Georgeon
University Lyon 1, France
olivier.georgeon/at/liris.cnrs.fr

Piotr Boltuc
University of Illinois, Springfield, USA
epetebolt/at/gmail.com

> Upshot • We join Füllsack in his effort to untangle the concepts of circular causation, macro states, and observation by reanalyzing one of our own simulations in the light of these concepts. This simulation presents an example agent that keeps track of its own macro states. We examine how human observers (experimenters and readers of this commentary) can consider such an agent as an observing agent on its own.

« 1 » Manfred Füllsack examines how circular interactions among the constitutive elements of a complex system can generate system states observable at the macro level. He discusses several examples to illustrate this phenomenon: traffic jams, the physical states of water, the authoritarian regime of the Soviet Union (§5), and the public good game computer simulation (§37). For the observer of the system, these macro states seem to "emerge from another domain of observation" (§34); the causes of their emergence are to be found in circular interactions among elements of the system – a kind of causation Füllsack refers to as "circular causation" (§2).

« 2 » In Füllsack's target article, only an external observer identifies the macro states of the systems. These systems themselves do not identify the set of macro states in which they can be, nor do they detect their own transitions from one macro state to another. In this commentary, we wish to complement Füllsack's discussion by reanalyzing a simulation first reported in Georgeon & Hassas (2013). It features an example system that indexes its possible macro states and detects its own transitions among them. We hope that this commentary will enrich the contribution to "the observation of observing systems" mentioned in the target article's abstract.

« 3 » Our simulation implements a mutable string of 11 digits arbitrarily initialized with $E_0 = [1, 7, 3, 2, 9, 3, 5, 6, 7, 8, 9]$, plus an integer p in the interval $[0, 9]$, initialized with $p_0 = 0$. E_t constitutes the *environment* at time t. p_t is the *position* of the agent in the string at time t. $E_t[p_t]$ denotes the digit at position p_t at time t.

« 4 » The agent has three actions at its disposal: *feel*, *swap*, and *move forward*. The *feel* action returns a bit of information (explained in §5 below) without changing the environment. The *swap* action swaps the digit $E_t[p_t]$ (current digit) with the digit $E_t[p_t + 1]$ (next digit in the string). The *move forward* action moves the agent to the next position ($p_{t+1} = p_t + 1$) unless the agent was in position 9, in which case it returns to position 0. The programmer of the agent's algorithm does not know the signification of the actions. Actions are randomly assigned on each experiment run to prevent the programmer from hard-coding their interpretation in the algorithm.

« 5 » On each interaction cycle, the agent's algorithm selects an action a, and then receives a single bit r of information in return. The value of r indicates whether the current digit was greater than the next before the action. The programmer does not know which value of r corresponds to what: for example, *move forward* may return $r = 0$ if $E_t[p_t] > E_t[p_t + 1]$, and $r = 1$ otherwise, and *feel* may return the opposite. This precaution prevents the programmer from hard-coding the interpretation of r.

« 6 » The input bit r is not a function of the state of the environment only; in a given state of the environment, r may vary depending on the action a; r thus does not constitute a *representation* or an *image* of the state of the environment. In this case, the programmer cannot consider the algorithm's input data as the agent's *perception*. This is similar to Füllsack's agents, whose input data (the dividend) is not a function of their environment only either. Agreeing with Füllsack's §25, the "access" to the state of the agent's environment "is blocked, as we have known since Immanuel Kant." In a previous paper, we referred to such agents as *agents without ontological data about a presupposed reality* (Georgeon, Mille & Gay 2016). Note that this design choice contrasts with many authors' choices to provide the agent's algorithm with input data that do represent the state of the environment, for example Russell & Norvig, for whom "the problem of AI is to build agents that receive percepts from the environment and perform actions" (Russell & Norvig 2003: iv).

« 7 » We call *event of interaction*, or, in short, *event*, the association $e = \langle a, r \rangle$ of an action with its returned bit. Our events are similar to Füllsack's *rounds* (§37) in that *rounds* also associate the agents' actions (the investment) with returned information (the dividend). We also associate a numerical *valence* $v(e)$ with each type of event e just as Füllsack associates payoff with *rounds*. The valences are parameterized by the *experimenter*, who knows the signification of events, contrary to the programmer.

« 8 » In the experiment reported below, the experimenter defined the valences as follows: v(*move forward to a greater digit*) $= +1$, v(*move forward to a lower digit*) $= -1$, v(all other events) $= 0$. These valences intend to simulate an agent that enjoys *moving up*, dislikes *moving down*, and is indifferent to *feeling* and *swapping*. We expect this agent to learn to use the *feel* action to observe whether the next digit is greater or lower than the current digit. Depending on the result, the agent should swap these digits or not, and then move upward onto a greater digit. After a learning phase, the agent should carry on this conditional scheme of behavior indefinitely, as if it understood that the *feel* action allowed it to observe the phenomenon present in its environment and helped it decide what subsequent series of actions is best in regard to its motivation defined by the experimenter through the valences of events.

« 9 » When designing the agent's algorithm, the programmer is facing a puzzling circularity problem. The algorithm must learn, in parallel, that the agent may be interacting with phenomena of two kinds (which we call the *upward* and the *downward* phenomena) while learning that the *feel* action tells them apart without changing the state of the environment, as opposed to the two other actions. This circularity problem can be expressed more generally as follows: *to observe, the agent must know what actions tell phenomena apart, but to know what categories of phenomena even exist, the agent must observe.*

« 10 » Our algorithm addresses the circularity problem of observation by indexing macro states with nodes in a Petri net. Arcs in this Petri net represent transitions from one macro state to another. On the start, the Petri net is initialized with only one node labeled *ignorant*, which indexes the initial macro state of the agent. When the token of the Petri net is on the *ignorant* node, the algorithm selects the next action without making assumptions about the category of the phenomenon with which the agent is interacting. In this macro state, the experimenter can thus consider that the agent *ignores* the category of phenomenon with which it is interacting.

« 11 » We refer the reader to Georgeon, Bernard & Cordier (2015) for details on the agent's algorithm. In essence, when the algorithm finds an event of interaction e that can be generated several times in a row, it constructs a new self-loop (an arc that originates from, and points to, the same node), and a new node N_n attached to it. The node N_n represents a new hypothetical possible macro state and is associated with a new hypothetical category of phenomenon P_n observable through the event e. Later, as the agent experiments more with its environment, the algorithm confirms or disconfirms this hypothesis, and progressively constructs the set S_n of events that can be enacted when the agent is in macro state N_n. When the token is on node N_n, the algorithm anticipates that the agent can enact events belonging to the set S_n. The experimenter can then consider that the agent *knows* that it is interacting with a phenomenon of the category P_n. Figure 1 shows the Petri net constructed over time.

« 12 » Figure 2 reports a trace of the agent's behavior. It shows that the agent progressively learned to categorize the phenomena present in its environment and learned to observe the environment to tell the category of phenomenon with which it was interacting. The observational behavior was active; it consisted of performing a *feel* action and interpreting the information received in return as we expected (see §8 above). Notably, this observational behavior emerged only because it helped the agent satisfy its motivation defined by the valence of events. For example, when the experimenter sets the valences of all events to 0, the agent keeps selecting actions randomly without observing its environment as if it did not care about the events resulting from its actions.

« 13 » In summary, we support Füllsack's move to handle circular causation by identifying two levels of generality: the micro and the macro levels. We imagine that the circular problem of observation generally arises in simulations that do not provide the agent's algorithm with data that would represent the state of the agent's environment (i.e., when the algorithm receives no ontological data about the environment). In this case, the agent's *perception* does not assimilate to the input data of the agent's algorithm; perception rather emerges out of circular causation between events of interaction. We show the emergence of macro states through a methodology similar to Füllsack's: the analysis of the system's behavior using time charts, see Füllsack's Figures 5 and 6 (top) and our Figure 2.

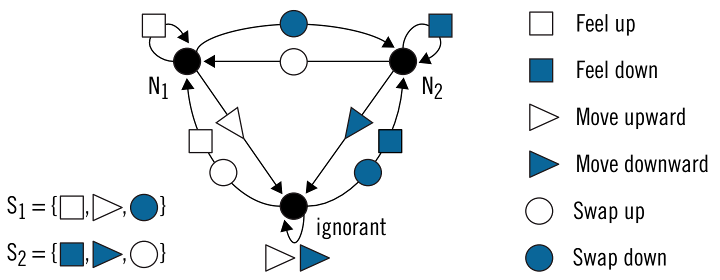

Figure 1 • Center: Petri net constructed by the agent after Time 41. Nodes represent macro states of the agent; arcs represent transitions between macro states. Left: learned sets S_1 and S_2 of events afforded by phenomena of categories P_1 and P_2. When the token is on node N_n, $n \in \{1,2\}$, the algorithm assumes that the agent is interacting with a phenomenon of category Pn and anticipates that it can enact events that belong to the set S_n. When the agent enacts an event associated with an arc, the algorithm moves the token from the origin node to the destination node of this arc.

« 14 » Our simulation complements Füllsack's by providing the agent's algorithm with the capacity to identify the agent's macro states. In so doing, our simulation exemplifies a situation of second-order cybernetics in which human observers (experimenters and readers of this commentary) observe an *observing agent*. Füllsack's analysis on how observation relates to circular causation and macro states helped us argue that this agent was indeed an observing agent.

Olivier L. Georgeon is an associate researcher in computer science with the LIRIS laboratory, and a pedagogical engineer at Université Claude Bernard Lyon 1. He has an interdisciplinary background with a master of engineering in computer science from L'École Centrale de Marseille (1988) and a PhD in cognitive psychology from Université Lumière Lyon 2 (2008). His research focuses on the implementation of developmental learning mechanisms in intrinsically motivated agents.

Piotr (Peter) Boltuc is a philosopher who formulated the Engineering Thesis in machine consciousness, the view that first-person consciousness could be engineered in robots. He presented the Church-Turing Lover, an argument that even if consciousness is epiphenomenal, we have reasons to care whether our loved ones are first-person conscious. Also, he argued that first-person consciousness is analogous to hardware rather than software. Furthermore, he developed a deflationary theory of non-reductive consciousness. Boltuc has held fellowships at Oxford, Princeton, ANU, and Canterbury and works now at the University of Illinois–Springfield where he holds an endowed professorship, and at the Warsaw School of Economics.

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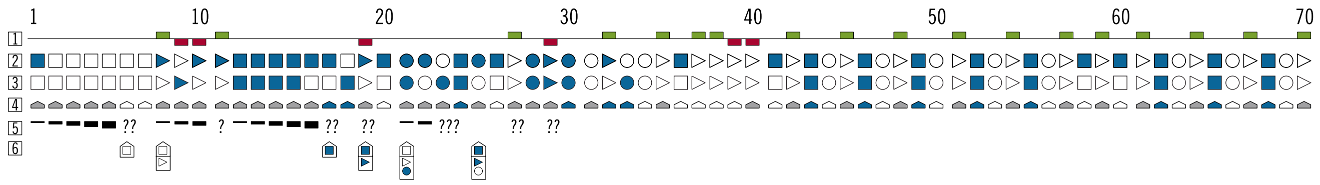

Figure 2 • Activity trace of the agent (from Georgeon, Bernard, & Cordier 2015). Line 1: valences of the enacted events represented as a bar graph: +1 (green), –1 (red), or 0. Line 2: anticipated events. Line 3: enacted events. Line 4: current macro states: ignorant (gray), upward phenomenon (white), downward phenomenon (blue). Line 6: progressive learning of sets S_1 and S_2; the agent initialized set S_1 with the feel up event on Time 6, while creating node N_1, and set S_2 with the feel down event on Time 17, while creating node N_2. From Time 41 on, the trace shows the enaction of the observational behavior: observing an upward phenomenon (white square) followed by moving upward (white triangle), or observing a downward phenomenon (blue square) followed by swapping up (white circle) and moving upward, and then repeating this conditional scheme.