Multi-scale Resolution of Cognitive Architectures: *A Paradigm for Simulating Minds and Society*

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Abstract. We put forth a thesis, the *Resolution Thesis*, that suggests that cognitive science and generative social science are interdependent and should thus be mutually informative. The thesis invokes a paradigm, the reciprocal constraints paradigm, that was designed to leverage the interdependence between the social and cognitive levels of scale for the purpose of building cognitive and social simulations with better resolution. In addition to explaining our thesis, we provide the current research context, a set of issues with the thesis and some parting thoughts to provoke discussion. We see this work as an initial step to motivate both social and cognitive sciences in a new direction, one that represents some unity of purpose and interdependence of theory and methods.

1 Introduction

The degree of overlap between cognitive science and generative social science is small despite a shared interest in human behavior and a reliance on computer simulation. The former focuses, largely, on developing computational and formal accounts of human thought, action, performance and behavior with non-trivial incorporation of neurophysiological principles when warranted. The latter approaches the question of understanding social structure and dynamics using computational and formal accounts that implement simple agents (what we call *sans cognitive*) in social contexts. We submit that the dearth of interdisciplinary

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work between these disciplines does not serve either well. Our central thesis, the *Resolution Thesis*, is this: *the correct resolution of both cognitive and social systems depends on mutual constraints between them in the sense that the dynamics and structure of one system should inform the theoretical nature of the other.* We mean this in the context of theory development and related applications in both cognitive science and generative social science. The method implied by this thesis is what we call the reciprocal constraints paradigm–a bi-directional dependence across levels of scale w.r.t. their respective parameter specifications.[1]

Our thesis implies two claims. First, cognitive models should be able to match and predict the real world dynamics of social systems when embedded in social simulation, and, if not, the cognitive model should be questioned. Second, if an agent-based simulation is not informed by cognitive first principles, it will fail to generalize its account of the dynamics of social system to new situations.

In what follows, we will (1) flesh out the details of the reciprocal constraints paradigm, (2) provide some prior work that is directly relevant to our thesis and puts it in context of recent research, (3) address issues and their potential mitigation, and, (4) close with some brief, but potentially provocative suggestions. We deliberately exercised a narrow focus using the ACT-R cognitive architecture as our vehicle of rhetoric, partly because it reflects our expertise, and partly because this architecture is comparatively well suited for integration of both neural and social constraints. Cognitive architectures, as opposed to any cognitive model, capture what agents, in the scheme of generative social science, are supposed to do–make adaptive decisions that affect the environment.

2 The Reciprocal Constraints Paradigm

Figure 1 captures the core components of the reciprocal constraints paradigm: multiple levels of scale, multiple potentials for model types at each level, and, the constraints among levels. To understand the paradigm, it will be useful to imagine a potential implementation. Consider a modeling problem in which there is a simple social system (e.g., a multi-player repeated economic game). The cognitive model is developed, with some consideration for key neural processes, call this CM [1], and without direct comparison to newly generated individual-level data sources (e.g., running single-subject experiments in pseudo-game like contexts). CM [1] is then implemented in a social network graph that controls information flow (e.g., knowing past decisions of other players) and, given some other parameterizations, a simulation of the multi-player repeated game is conducted; call this SM [1]. Then, SM [1] data is aggregated in some way isomorphic to human data in a similar experimental paradigm and an accuracy/error/confidence metric is computed, call it Constraint [1] to map onto Fig. 1. (Notice, at this point, the only direct comparison to human data was at the social system level.) Constraint [1] would then be used–in an undefined way at this point–to change

[1] Because cognitive systems are sometimes tightly yoked to neurophysiology, we consider three levels as central to our thesis: neurophysiology, cognitive architecture, and social systems.

some aspect of the cognitive model, either directly within the cognitive level or, potentially, through the neurophysiological level. Let's imagine that it makes sense to consider neurophysiological processes as the next step, a step we call Interpret [1] to map onto Fig. 1. Now, a set of targeted neurophysiological measurements are captured by running single-subject experiments in pseudo-game like contexts which yields insight into a potential missing abstraction of neurophysiological process in the cognitive model, which we call Abstraction [1]. The cognitive model is then refactored to incorporate Abstraction [1] and the process is repeated by another simulation using the next generation of the cognitive model CM [2]. Note, this example provides only one of an infinite set of paths; the paths may be consequential to the final model and could include integration of human data at one or more points.

A fundamental part of the paradigm is the acknowledgment that scaling up from the cognitive level to the social level is different, in principle, compared to the scaling up from the neural to cognitive level. The former transition instantiates multiple isomorphic and interdependent cognitive models as a simulated system. The latter, in contrast, abstracts information processing functionalities that are assumed to be interdependent but different in nature (i.e., different functions). This is an important difference in light of what a constraint actually means.

3 Relevant Prior Work

In cognitive science, there are several relevant threads of work that address aspects that are important for the *Resolution Thesis*, e.g., on multi-agent systems [1], computational organizational theory [2], computational social psychology [3]. These efforts, however, were not directly concerned with the *Resolution Thesis*. Instead, these efforts, in the main, attempted to provide both more accurate predictions of social system level behavior and explanations that were grounded in cognitive first principles. In this section, we focus on ACT-R to illustrate efforts to either inform ACT-R from neurophysiology or use implementations of ACT-R as the agent definitions in a social simulation. These efforts, we hope, will illustrate how the state-of-the-art in infusing social simulation with cognition contrasts with the *reciprocal constraint paradigm*. Further, we offer a glimpse into how generative social science has conceptualized the integration of cognitive first principles into the behavior of agents to date.

3.1 The ACT-R Cognitive Architecture

Computational modeling aims to quantitatively capture human cognitive abilities in a principled manner. Cognitive architectures are computational instantiations of unified theories of cognition that specify the structures, representations and mechanisms of the human mind. Cognitive models of any given task can be developed using a cognitive architecture as a principled implementation

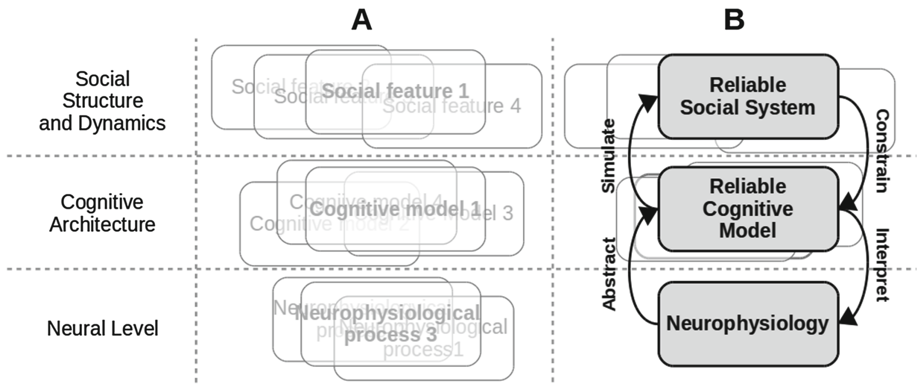

Fig. 1. ***The Architecture and Implementation of the Reciprocal Constraints Paradigm*** Each row represents a level of scale (as labeled in the left-most column). Column A is notational for the degree of variety of potential types of neural processes and cognitive models that could be constructed to capture a phenomenon and the types of features in the social space (e.g., peer-network)–i.e., it captures the feature/model space of a particular implementation. Column B shows the implementation of the reciprocal constraints paradigm; each arrow represents a kind of constraint: *Abstract*–abstraction of neural processes to cognitive processes; *Simulate*–simulating social systems in which humans behavior is defined as a cognitive architecture; *Constrain*–the feedback signal from the accuracy of the social simulation w.r.t. to empirical measurements on human systems; and, *Interpret*–refinement of the selection of neural processes that are implicated in the cognitive model. The former two constraints we call *upward constraints*; the latter are called *downward constraints*. Implementation of the paradigm will require iteration between the feature/model space and the simulation of social and cognitive models. There may be potential for automation of this paradigm once it is well developed.

platform constraining performance to the powers and limitations of human cognition. Cognitive models are not normative but represent Simon's (1991) theory of bounded rationality [4], and can also represent individual differences in knowledge and capacity such as working memory. Cognitive models can be used to generate quantitative predictions in any field of human endeavor.

ACT-R is a highly modular cognitive architecture, composed of a number of modules (e.g., working memory, procedural and declarative memory, perception and action) that operate in parallel asynchronously through capacity-limited buffer interfaces. Each module in turn consists of a number of independent mechanisms, typically including symbolic information processing structures combined with equations that represent specific phenomena and regularities (e.g., power law of practice and forgetting, reinforcement learning). Most notably, the architecture includes a number of learning mechanisms to adapt its processing to the structure of the environment. ACT-R has been applied to model human behavior across a wide range of applications (see ACT-R web site for over a thousand publications), ranging from basic experimental psychology paradigms to language, complex decision making, and rich dynamic task environments. The combination of powerful computational mechanisms and human capacity limitations (e.g., working memory, attention, etc.) provides a principled account of both human information processing capabilities as well as cognitive biases and limitations.

3.2 Neurophysiogical Constraints in ACT-R

The development of ACT-R has been guided and informed, in recent years, by the increased understanding of the computational mechanisms of the brain. For example, independent modules have been associated to specific brain regions and circuits, and this correspondence has been validated multiple times through fMRI experiments. The detailed computations of crucial ACT-R components can also be derived from the neural mechanisms they abstract. For instance, the latency to retrieve declarative information from long-term memory can be derived from the dynamics of the integrate-and-fire neural model [5], and the mechanisms for skill acquisition can be derived from reinforcement learning [5] as well as from the simulation of the large-scale effects of dopamine release in the fronto-striatal circuits [6]. In fact, the modularity of ACT-R permits to easily abstract and integrate lower-level neural principles within the architecture. While this approach does not grant the full flexibility of large-scale neural simulations, it has been repeatedly shown to be very effective in capturing features of human behavior that would otherwise have remained unexplained, while at the same time maintaining the computational parsimony of a cognitive symbolic architecture. For example, implementing the dynamics of memory retrieval permits to capture a variety of decision-making effects and paradoxes, beyond those explained by current mathematical models [7]. The modularity of ACT-R also permits to regulate the degree of fidelity of a module to its biological counterpart, without affecting the entire architecture. As an example, Stocco [8] has shown that the competition between the direct and indirect pathways of the basal ganglia can be captured by splitting production rules into opposing pairs. This procedure captures the cognitive effects of Parkinson's disease, and provides a way to model individual differences in decision-making [8] and cognitive control [9] that are due to individual differences in dopamine receptors in the two pathways. See Fig. 2. This is an example of additional mechanisms that can be added to ACT-R to incorporate further biological details (i.e., the *abstract* constraint in Fig. 1).

3.3 Social Simulation with ACT-R Agents

To study the dynamics of simple systems, work using ACT-R has focused on iterated two-player games, including both adversarial games (e.g., paper-rock-scissors, pitcher-batter in baseball) and social dilemmas allowing both cooperation and competition dynamics such as Prisoner's Dilemma and Chicken Game [10–12]. Even in such simple systems, we have observed the emergence of complex effects such as bifurcations and stochastic resonance [13]. To scale up to

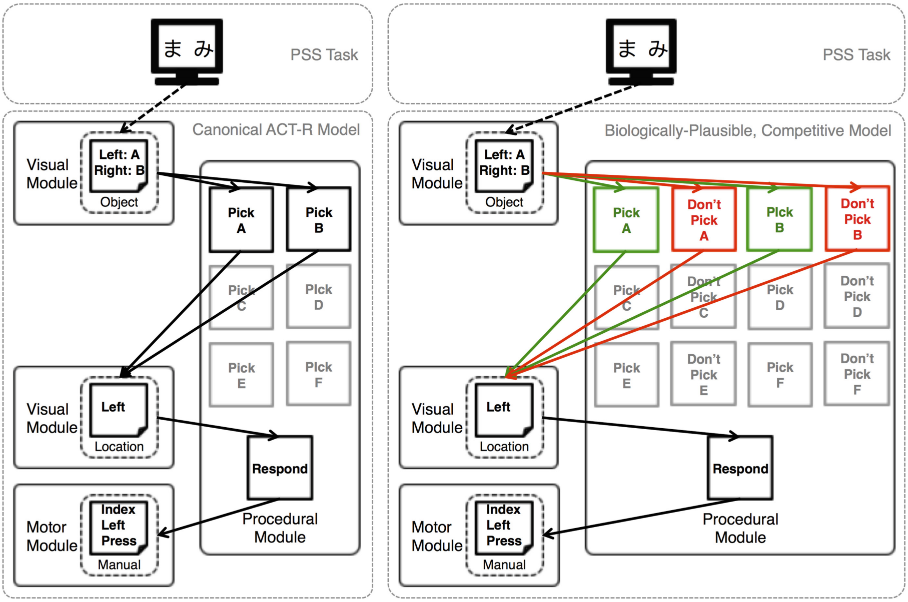

Fig. 2. ***An example (taken from [8] with permission) of how neurobiological constraints can be incorporated in a cognitive architecture.*** The two panels illustrate two alternative ways to implement a forced choice task with six possible options (A through F) in ACT-R. **(Left Panel)** A canonical ACT-R model, in which each option A . . . F is associated with a single, corresponding production rule (Pick A Pick F). In this model, the expected value of the different options is encoded as the expected utility of each production rule. The utility of each rule is learned through reinforcement learning in ACT-R's procedural module, which is associated with the basal ganglia. However, the lack of biological plausibility in ACT-R's procedural module prevents the model from capturing the results of the original study. **(Right Panel)** A biologically-plausible version of the same model, in each of the original production rules is split into two opposite actions (Pick A Pick F and Don't Pick A Don't Pick F), whose utilities are learned separately. This new version abstracts the competition between the direct and indirect pathways of the basal ganglia circuit. When equipped with this biologically-plausible version of production rules, the model can successfully reproduce the results in the neuropsychological literature, as well as capture individual differences in genetics [8] and even correctly predict new findings [9].

more complex yet regular systems, we have modeled the emergence of group consensus and choice differentiation in networks of a few dozen nodes on tasks such as consensus voting and map coloring, respectively, and observed phenomena such as sensitivity to network rewiring parameters [14]. To study complex cognition in complex systems, we have designed and implemented an information foraging task called the Geogame that involves cooperative and competitive problem solving and have observed effects including sensitivity to network topology and tradeoffs between perceptual and memory strategies [15]. Clearly, this work represents well the *simulate* constraint in Fig. 1.

A common pattern in models of social interaction using ACT-R has been to ground agent decisions in previous experiences, whether explicitly in the form of memories or implicitly by reinforcement of existing strategies, as mentioned in the previous section. We will focus here on an example using the former approach, because it has been both more common and more flexible. Models of adversarial interaction usually involve a core capability of detecting patterns in the opponent behavior and exploiting them until they disappear. For instance, playing paper rock scissors involve exploiting the human limitation in generating purely random behavior (the standard game theory solution) by detecting statistical patterns in move sequences. An expectation of an opponent's next move can be generated by matching his most recent moves against previous sequences using statistical memory mechanisms. Once a pattern is being exploited, the opponent is likely to move away from it and in turn exhibit new ones, requiring a cognitive system that constantly unlearns previous patterns and learns emerging ones, rather than traditional machine learning systems that are training on a fixed set of inputs and then frozen. In that sense, social simulation is the ultimate requirement for online learning: unlike physical environments which change relatively slowly and can be mastered in a relatively static way, social interactions (especially competitive and adversarial interactions), as they involve other cognitive entities, are endlessly evolving and require constant learning and adaptivity.

3.4 Comparison to the Generative Social Science Approach

Generative social simulation has historically been concerned with the simulation of interacting agents according to simple behavioral rules. We can often equate the outcome behavior of agents to a simple binary action (e.g., you either riot or don't riot) and the behavioral rules that produce this outcome to simple mathematical and logical formulations (e.g., if/else statements, threshold values). We are in debt to the many classic models that made computational social science the field it is today [16–18]. However, there has been some acknowledgment that to gain further insight into social systems, we need to decompose behavior into its underlying cognitive, emotional, and social (interactions) processes. With this, we are beginning to see a slight shift to developing models with more complex agents [19].

In this vein, an approach that has gained some traction is the use of conceptual frameworks that integrate the varied components of agent decision-making processes [20–23]. Such frameworks include BDI (Beliefs, Desires, and Intentions) and PECS (Physical conditions, Emotional state, Cognitive capabilities, and Social status) [24]. In the BDI framework, beliefs are said to be the individual's knowledge about the environment, desires contain information about the priorities and payoffs associated with the current objective, and intentions represent the chosen course of action [25]. BDI agents use a decision tree process which relies on payoff and utility maximizing functions to select goals and to determine the optimal action sequence for which to achieve those goals. The focus on optimality, however, may pose limits on its ability to model the boundedly rational agent and has been criticized for being too restrictive [25]. PECS views agents as a psychosomatic unit with cognitive capabilities residing in a social environment [26]. The PECS framework is flexible due to its ability to model a full spectrum of behaviors, from simple stimulus-response behaviors to more intricate reflective behaviors, which requires a construction of self that necessitates the agent be fully aware of its internal model. By example, Pires and Crooks [23] used the PECS framework to guide implementation of the underlying processes behind the decision to riot, applying theory from social psychology to create the agent's internal model and to simulate social influence processes that heightened certain emotions and drove the agent's towards certain actions. These frameworks, while helpful for guiding implementation, are not to be considered substitutes for cognitive architectures such as ACT-R. They can, however, provide a meta-framework (sometimes called a macro-architecture) to organize knowledge and skill content in respect to a cognitive architecture (e.g., [27]).

Cognitive architectures and meta-frameworks are fundamentally complementary [28]. Cognitive architectures precisely specify the basic cognitive acts that can be used to compose complex models in a bottom up approach, but provide few constraints to guide those complex structures. Meta-frameworks provide a top down methodology to decompose complex tasks into simpler ones and structure the knowledge required, but do not include a principled grounding for that process. The combination of the two approaches can be achieved in a number of different ways. One approach is to develop integrated environments allowing modelers to flexibly leverage the two methodologies in a way that is best suited to the specific requirements of each application [29]. An alternative is to provide high-level patterns and abstractions that can be formally compiled into cognitive models in a target cognitive architecture [30].

4 Issues and Their Mitigation

4.1 Downward Constraints

Social to Cognitive. This issue was laid out plain by Allen Newell about three decades ago [31] in reference to the *social band* (bands in geometric time of $> 10^4$ seconds that represent organizational behavior and other social systems). Newell, thinking in terms of the strength of a system's levels, hypothesized that social bands should be characterized as having weak strength, and therefore may not be computing much at all, in a systematic way. If Newell's surmises are correct, then constraining cognitive architectures from the social band makes little sense. Anderson's Relevance Thesis [32], put forth about a decade later, does not address the operation of social systems in terms of constraining cognitive models; his thesis is more focused on the degree to which understanding lower bands, especially the cognitive (10^{-1} to 10^1 time scale), are implicated in qualities of higher bands, e.g., educational outcomes. So, from the cognitive perspective, there might not be much signal from the social band that could serve as a useful constraint on cognitive architectures.

However, there are potential approaches towards mitigation of this problem, Newell's thesis notwithstanding. Online social communities often exhibit emergent empirical regularities. For instance, the World Wide Web exhibits many regularities including the small world organization of link structure and the distribution of the lengths of browsing paths that users exhibit. The latter has been called the "Law of Surfing"?. Many of these regularities have been modeled at the social level using variants of statistical mechanics. The Law of Surfing [33] observes that the frequency distribution of path lengths (number of Web pages visited) is well fit by an Inverse Gaussian Distribution, that has a long positive tail. The key insight at the social level is that a Web surfer can be viewed as moving around in a kind of space analogous to the Brownian motion of a small particle on a liquid surface. In the case of the Web surfer, the movement is in the dimension of expected utility that will be received (or not) when visiting a Web page, where the expected utility from continuing on to the next page is stochastically related to the expected utility of the current page, and the Web surfer continues until a threshold expected utility is reached. This is modeled as a stochastic Wiener process. But, the Law of Surfing can also be predicted from Monte Carlo simulations with ACT-R agents [34]. In contrast to the stochastic social models, these finer-grained ACT-R agents can make predictions for specific Web tasks at specific Web sites, which can be used to predict and engineer improvements [35]. However, the emergence of the Law of Surfing from the ACT-R agent simulations is seen as constraint on the cognitive models.

In short, the social band, at least in some domains, does have structure that could constraint cognitive modeling efforts. A question that remains is to what degree will it be possible to develop general methods across the varieties of social domains for the purpose of constraining cognitive models.

Cognitive to Neurophysiology. The downward "Interpret"? arrow in Fig. 1 could seem paradoxical, given that the underlying neural level is often taken as the ground truth of the entire system. Neurophysiological findings, however, are often only imperfectly understood. For instance, the existence of basal ganglia projections outside of the frontal lobe was considered impossible for a long time until recently [36]. Even when our grasp of neurophysiology is solid, cognitive architectures can be helpful in providing a functional interpretation to existing data by focusing on the computational integration of different circuits, that is, answering the question of "what does this circuit do"?. The most famous example in this sense is the interpretation of the activity of dopamine neurons in terms of reward prediction error signals in reinforcement learning (RL)[37]–an interpretation that borrowed from a decades-old AI theory (temporal difference learning: [38]) to solve decades of seemingly inconsistent empirical findings on the role of dopamine [39,40]. Incidentally, this example perfectly illustrates how the Interpretation is further aided by the use of a comprehensive architecture on an agent's behavior, such as that provided by RL agents. In our case, the adoption of a single architecture (such as ACT-R) to create multiple models provides the unifying framework to interpret neurophysiological data. The fact that the activity of the same neuronal process must be interpreted in the same way across multiple models of different tasks provides additional constraints to maintain the interpretation consistent.

4.2 Upward Constraints

Parsimony and Generative Social Science. By uncovering some new relationship or testing some stylized hypothesis of social phenomena many classic agent-based models (e.g., [16,18]) have demonstrated the value of modeling simple (*sans cognitive*) agents. For instance, Reynolds [41] illustrates how three simple rules of behaviors can result in the emergence of the collective behavior of a flock of birds – what looks like the highly coordinated actions of a "leader" is actually the result of three simple rules.[2] These models and many others in the computational social sciences adhere to parsimony, or keeping the model simple such that the model has just enough of right features and no more, as a main guiding principle [42]. Arguments for this approach stress the intuitive and interpretive appeal of such models [42,43]. The purpose of the model may also dictate that the model be parsimonious (e.g., [41]). In short, parsimony in respect to simple agents has served well as a strategy in generative social science. It is natural, then, to ask if cognitive modeling breaks with this notion of parsimony in modeling social systems.

We think the issue of parsimony in generative social science does not imply anything particular about the use of cognitive architectures in social simulations. Parsimony implies that model simplicity is considered in conjunction with how well a model matches empirical findings. Thus, the issue of whether to include cognitive agents, as defined in the reciprocal constraints paradigm, is largely an empirical issue. We offer that cognitive constraints may provide the right model and thus improve the degree to which a social simulation matches empirical findings. Moreover, because cognitive models inherit mechanistic constraints from cognitive architectures, they might actually end up being more parsimonious than agent-based models without such constraints.

4.3 Mere Parameter Optimization?

To deal with the challenges of scaling up cognitive models beyond the scale of tasks in the cognitive band (seconds to minutes) to tasks in the social band (weeks to months), Reitter and Lebiere [44] formulated a methodology called *accountable modeling*. That approach is not only a technical solution to scaling up the cognitive architecture but also a scientific commitment to an approach

[2] ABMs, however, can range in abstraction, from the stylized models just described to empirically-driven models; although the latter in no way implies incorporation of cognitive constraints.

that explicitly states which aspects of the model are constrained by the architecture and which are free parameters to be estimated from data. This commitment helps determine which aspects of the social-scale simulation reflect the cognitive mechanisms and can be assumed to generalize, and which have been parameterized to reflect aspects of the situation not constrained by first principles, and thus will need to be estimated from data in new situations. Such an approach actually results in simpler, more transparent models that are explicit about their parameters rather than trying to camouflage them under a mechanistic veneer.

5 Closing Thoughts

Crossing levels of scale or analysis inevitably takes one near to deep scientific issues that echo notions pointed out 50+ years ago in Simon's "Architecture of Complexity" paper [45] (see also [46] for similar early example). Our thesis goes counter to Simon's notion of near decomposability in that it puts social structure and dynamics in the realm of convergent evidence for a cognitive theory. In this spirit, we will leave the reader with one final comment.

We see social systems as distributed and symbolic. Thus, insight into them and predictions about them should come through a distributed symbolic system–i.e., a social simulation of interacting cognitive architectures. This argument is not meant to imply that sub-symbolic processes are not part of human information processing, but only to mean that social interactions operate via symbols. For the purposes of simulating social systems, observed social structure and dynamics should be generated from the first principles of interactive artificial symbol systems.

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