

Extending Iterated, Spatialized Prisoner's Dilemma to Understand Multicellularity: Game Theory With Self-Scaling Players

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Abstract—Evolutionary developmental biology, biomedicine, neuroscience, and many aspects of the social sciences are impacted by insight into forces that facilitate the merging of active subunits into an emergent collective. The dynamics of interaction between agents are often studied in game theory, such as the popular Prisoner's Dilemma (PD) paradigm, but the impact of these models on higher scales of organization, and their contributions to questions of how agents distinguish borders between themselves and the outside world, are not clear. Here we applied a spatialized, iterated PD model to understand the dynamics of the formation of large-scale tissues (colonies that act as one) out of single cell agents. In particular, we broke a standard assumption of PD: instead of a fixed number of players which can *Cooperate* or *Defect* on each round, we let the borders of individuality remain fluid, enabling agents to also *Merge* or *Split*. The consequences of enabling agents' actions to change the number of agents in the world result in non-linear dynamics that are not known in advance: would higher-level (composite) individuals emerge? We characterized changes in collective formation as a function of memory size of the subunits. Our results show that when the number of agents is determined by the agents' behavior, PD dynamics favor multicellularity, including the emergence of structured cell-groups, eventually leading to one single fully-merged tissue. These larger agents were found to have higher causal emergence than smaller ones. Moreover, we observed different spatial distributions of merged connectivity vs. of similar behavioral propensities, revealing that rich but distinct structures can coexist at the level of physical structure and the space of behavioral propensities. These dynamics raise a number of interesting and deep questions about decision-making in a self-modifying system that transitions from a metabolic to a morphological problem space, and how collective intelligences emerge, scale, and pattern.

Index Terms—Collective intelligence, game theory, iterated Prisoner's Dilemma.

Received 9 March 2025; accepted 31 March 2025. Date of publication 18 April 2025; date of current version 17 June 2025. The work of Michael Levin was supported in part by John Templeton Foundation under Grant 62212, and in part by Templeton World Charity Foundation under Grant TWCF0606. The associate editor coordinating the review of this article and approving it for publication was S. Balasubramaniam. (*Corresponding author: Michael Levin.*)

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Code and simulation data are made available at <https://github.com/lksshw/IPDm>

This article has supplementary downloadable material available at <https://doi.org/10.1109/TMBMC.2025.3562358>.

Digital Object Identifier 10.1109/TMBMC.2025.3562358

I. INTRODUCTION

A. Emergent Agents and the Scaling of Collective Intelligence

INTELLIGENCE is fundamentally a collective phenomenon because all problem-solving agents are made of parts that must work together toward goals that belong to the collective [1]. In addition to well-known collective intelligences such as ant and bee colonies [2], [3], [4], [5], [6], and robot swarms [7], [8], [9], [10], even seemingly-unified intelligences such as human beings are composed of cells which must integrate their activity toward emergent adaptive behavior. An exciting research program at the intersection of complexity, information, and cognitive sciences seeks to understand how the decision-making that guides cooperative and competitive interactions of active subunits gives rise to new collective minds [11], [12], [13], [14], [15].

Importantly, the dynamics of collective intelligence are not limited to behavior of adult organisms during their lifetime. As recognized by Turing [16], the understanding of the autopoiesis of minds is tightly linked with that of the self-assembly of bodies during embryogenesis. Both on a developmental timescale [17], and on an evolutionary one [18], [19], [20], [21], the dynamics that drive multicellularity are a critical feature of understanding life and mind. Rational agents self-assemble from cellular components (which themselves assemble from chemical networks that have learning capacity [22], [23]), as embryos result from a physical and behavioral alignment of cellular collectives navigating the space of anatomical configurations. While the mechanisms of these processes are beginning to be understood, many important questions abound with respect to how the decision-making of individual cells and their local physiological/metabolic goals give rise to emergent problem-solving in anatomical space and eventual intelligence in behavioral space [24].

While game theory [25], [26] studies the forces that shape interactions between agents, it has not been sufficiently integrated with formalisms that describe the origin and scaling of agents out of their constituent parts [27], [28]. What allows us to recognize an embryo (an individual) vs. a large collection of independent cells? During embryogenesis, every cell has some other cell as a neighbor, but embryos arise when cells merge into physiological signaling networks that cooperate toward morphogenetic goals (creating the correct species-specific anatomy) because of shared memories and stress landscapes [17], [29].

This however is a very active process: the number of individuals (and “selves”, in the sense of “self-interest” in economic and game theoretic formalisms, and in the behavioral science sense of a centralized, unitary agent that makes decisions) within an embryonic blastoderm is not fixed by the genetics: it can be 0, 1 (singleton), or a few (conjoined twins, triplets, etc.) depending on physiological factors that regionalize the blastoderm into some number of autonomous but internally-coherent morphogenetic zones. The actual number and the boundaries between agents are a dynamic result of cell decisions with respect to the connections they make and maintain [27]. Game theory is an important tool with which to begin to unravel the decision-making of subunits that need to optimize local self-interest with global, long-term goals. Most game-theoretic formalisms feature a fixed, known number of players which perform actions that impact their well-being but not their essential nature. This limits the applicability of game-theoretic approaches in scenarios (such as embryogenesis, cancer, and other contexts) where the size, scale, and composition of agents is not only plastic but can be affected by their actions.

To unify approaches of economics and game theory with questions of the evolution of multicellularity and dynamics of collective intelligence, we built and analyzed a computational simulation of a self-referential system of rational selfishness in which agents can merge or split, controlling the size of the boundary between self and world as one of the behaviors they can execute. We softened the conventional boundary between fixed agents and possible behaviors, and analyzed a simulated world in which the borders between agents and their world was not fixed, modifying a workhorse formalism from economics and game theory known as Prisoner’s Dilemma.

B. Prisoner’s Dilemma and Its Variants

Prisoner’s Dilemma (PD) is a theoretical framework in game theory which describes the evolution of cooperation and competition between two players dealing with a decision-making problem at a specific instance in time [30], [31]. Realistic scenarios in biology and economics unroll over longer periods during which agents find themselves in similar situations with multiple interaction partners. This situation, with various degrees of historicity (player-specific memories of interaction), has been studied via the Iterated Prisoner’s Dilemma (IPD) [32]. In an IPD setting, agents account for the uncertainty in their possible future interactions with other agents, and develop time-dependent strategies accordingly to receive a better payoff score [33], [34]. The kinds of strategies in IPD become interesting if one considers the role of memory: for instance, if agents are allowed to remember their opponents’ previous action, a diverse set of strategies with traits of hostility, forgiveness, altruism, envy, and reciprocation appears [35]. If instead of a single timestep, such strategies are allowed to depend on N moves into the past (“N-memory strategies”), they assume a probabilistic flavor, with strategies being functions of an agent’s past “N” encounters with its opponent [36], [37].

IPD games are not necessarily restricted to two player settings, and can also involve multiple agents distributed across space. In such spatialized settings, positional information characterizes an agent’s interactivity and consequently its behavior, introducing yet another factor of complexity to the dynamic of the collective [38], [39]. Given the combination of iterative interactions an agent encounters in such a setting, analytical tools need to be more complex than in the non-spatialized case [40]. As such, dynamic strategies have been explored by adopting a Reinforcement Learning (RL) framework. An agent can now be treated as an independent entity seeking to maximize its payoff score by optimizing its strategy over long time horizons [32], [41], [42]. While this provides additional modeling power, most works in literature assume a fixed number of agents interacting with one another.

Here we consider a multi-agent, stochastic, memory based IPD formulation with a varying number of agents: cells within a 2-dimensional world, which can choose to connect to (or disconnect from) their neighbors in the way that real biological cells can link via gap junctions and other ways with which to share metabolic, informational, and other aspects of their function. Such variation in numerosity is brought about in this work by the inclusion, within each PD game, of the possibility of merging or splitting. Numerosity over the course of simulation decreases or increases through merges or splits respectively: agents choosing to *merge* coalesce into a new agent; alternatively, merged agents choosing to *split* reduce into their constituent agents. The fluctuating numerosity in IPD games is an important part of the puzzle in understanding cooperative dynamics in fields as varied as biology (self-organized behavior in embryogenesis, regeneration, and cancer [1], [43], [44], [45]), economics (mergers, acquisitions, splits, and their impact on the economy [31], [46]), and psychology (decision-making behavior between multiple selves within a human [47]).

II. METHODS

We simulated spatialized Iterated Prisoner’s Dilemma (IPD) games between multiple agents with memory. In contrast to traditional Prisoner’s Dilemma (PD) games, our agents’ action space was expanded to include two additional options: *Merge*, and *Split*, with the payoff matrix expanded accordingly (Fig. 1A.II). An agent choosing to play the *Merge* action with another conjoined with it to form a single whole. Alternatively, a merged agent choosing to *Split*, broke down into its constituent agents. Due to these two operations, the number of active, game-playing agents varied over the duration of simulation. We observed the impact of merges and splits on the behavior of agents, recording their memories, fitness scores, and their tendency to form multi-agent clusters.

A. World State

Each simulation involved games played between agents placed in a rectangular grid of size $N \times M$ (Fig. 1A.I). Agents in the World State took discrete positions corresponding to a single $(i, j)^{th}$ cell in the grid (where $i = 1 \dots N$, and $j = 1 \dots M$). Each agent carried with it: a) its own memory

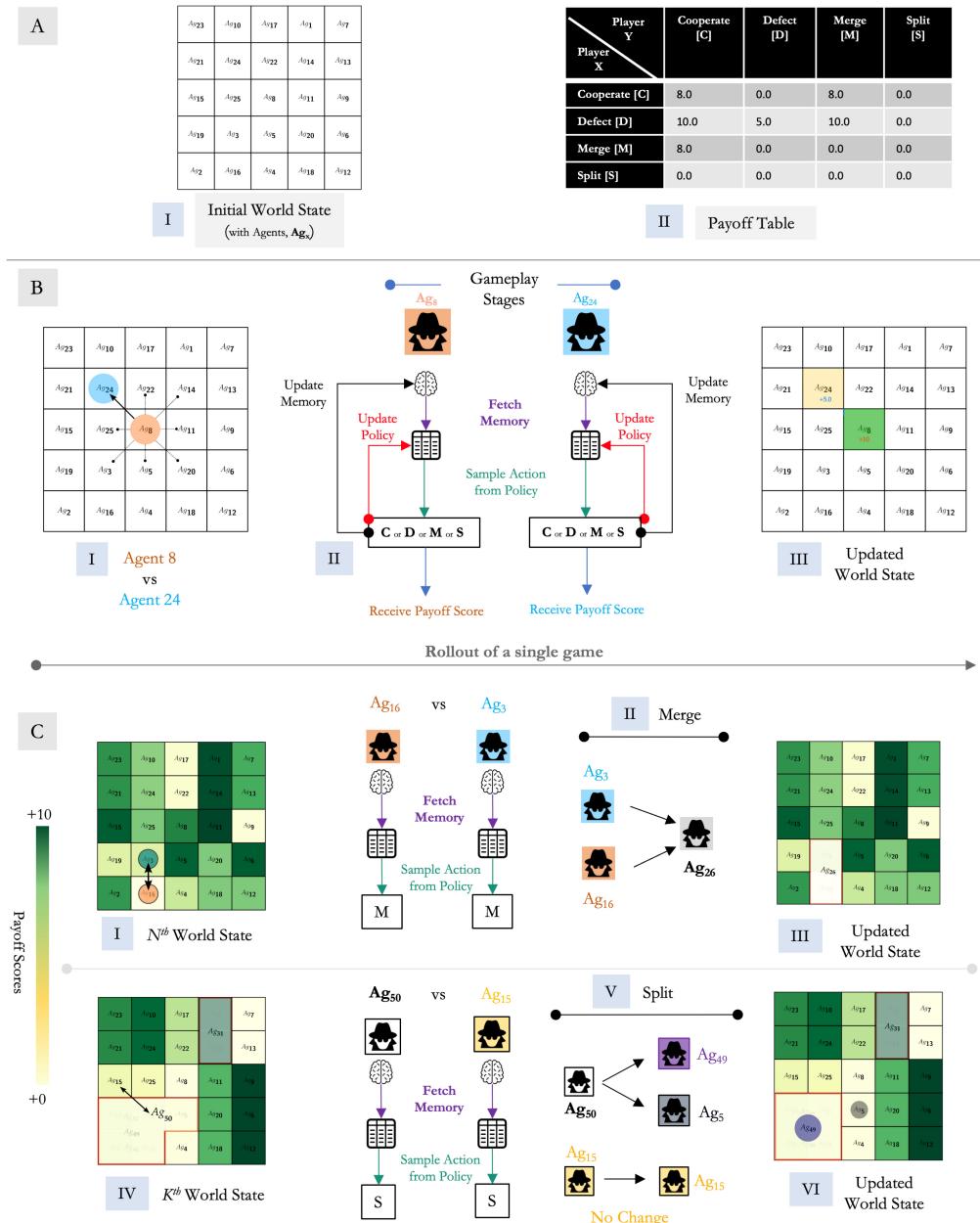


Fig. 1. Schematic of experimental setup (IPD-ms). **Panel A, Game World Description:** Agents are arranged at discrete positions in a rectangular matrix (the World State, A.I). In each round, an agent and a neighbor are selected at random to play a game of Prisoner's Dilemma (PD). Agents maintain memory of their past, and use it to sample actions from a policy table. **Panel A.II, Payoff table:** Agents play one of four actions (*Cooperate*, *Defect*, *Merge*, or *Split*). During a game, either player can initiate a merge by playing the *Merge* action; similarly, either agent can play the *Split* action to break into constituent units (provided they can be broken down into simpler parts). **Panel B, Rollout of a single PD game:** A game is played between two agents. Each agent assesses the state it is in by consulting its memory and uses the resulting state to sample one of four actions: *Cooperate*, *Defect*, *Merge*, or *Split* using its policy table. Once both agents play an action, the payoff table is consulted and corresponding rewards are stored (A.II). Policy tables are updated using the *Q*-learning rule, and sampled actions are appended to players' memories. Finally, the World State is updated to reflect these changes. **Panel C, Concept of Merge and Split:** During any game, two special situations exist: if at the *Nth* game between two agents, either of them select *Merge* as their intended action, then these agents are allowed to coalesce into a single new agent. The new agent derives its memory, policy, and payoff score from the best performing constituent agent. Once merged, the constituent agents cease to exist, and the new agent functions by occupying the constituents' positions on the grid (C.III). A second unique situation concerns splitting. If during any game, either of the agents choose the *Split* action, then they have the optionality to split. For a split to occur, an agent must be a composite (eg: Agent-50 in C.IV), else the *Split* action does nothing. In case a split occurs, the composite agent splits, transferring its policy, memory, and payoff scores to each constituent. For instance: if after *K* rounds of IPD-ms, Agent-50 chooses to split during a game with Agent-15, it splits into its parental constituents (Agent-49 and Agent-5 in this case) transferring its policy, memory, and payoff-scores to each. The constituent agents assume their original positions on the grid, and continue to play IPD-ms games. Agent-50 is destroyed.

(initially empty), and b) a policy table mapping memory states to actions, initialized to random values. Agents were by design restricted to play IPD games with their neighbors, including on diagonals (Moore neighborhood).

A single game unfolded as follows: An agent (say, the *Challenger*) and one of its neighbors (say, the *Opponent*) were chosen at random (Fig. 1B.I). To determine which action to play, the *Challenger* constructed a “memory state”, and

used such a state to sample an action from its policy table. Simultaneously, the *Opponent* constructed its own “memory state” and used it to sample an action from its own policy table. Based on their respective actions, each agent received a payoff score (Fig. 1B.II), which was used by the *Challenger* and the *Opponent* to update their memory and policy tables. Finally, the World State was updated to reflect these changes (Fig. 1B.III).

B. Agent Memory

An agent’s memory was a historical record of its actions taken with different opponents, the size of which was determined by a hyperparameter termed memory size. Given the role memory size played in determining the extent to which an agent could “consult” its past to make decisions in the present, we used it as a proxy for the degree of “intelligence” an agent possessed.

C. Memory State

The memory state of an agent was a consolidated record of its past behavior with other agents providing information about its present condition. We illustrate its construction with an example: consider a game played between two agents: the *Challenger*, and one of its neighbors the *Opponent*. After a few rounds k let the *Challenger*’s memories be a list:

$$C = [c_0, c_1, c_2, \dots, c_k], \quad (1)$$

constrained in length by its memory size hyperparameter, M_c .

Correspondingly, let the *Opponent*’s memories be:

$$O = [o_0, o_1, o_2, \dots, o_k], \quad (2)$$

constrained in length by its own memory size hyperparameter, M_o .

The *Challenger*’s memory state was constructed as:

$$C_{\text{state}} = \left[c_{(k-M_c)} o_{(k-M_c)}, c_{(k-M_c+1)} o_{(k-M_c+1)}, \dots, c_k o_k \right] \quad (3)$$

assuming $k > M_c$.

Similarly, the *Opponent*’s memory state was constructed as:

$$O_{\text{state}} = \left[o_{(k-M_o)} c_{(k-M_o)}, o_{(k-M_o+1)} c_{(k-M_o+1)}, \dots, o_k c_k \right] \quad (4)$$

assuming $k > M_o$.

This manner of memory state construction accounted for the *Challenger*’s as well as the *Opponent*’s past actions, providing agents with a state-representation from which they could take subsequent actions. It was introduced by [32] and we use it here unchanged.

D. Policy Tables

Along with memories, each agent carried with it a policy table mapping memory states to actions. Given the presence of a policy table and memory, we treated the setup of each agent within a reinforcement learning framework employing a

similar methodology to that in [32]. The update rule for the policy table was based on the Q-learning algorithm:

$$\Delta Q(s, a) = \alpha * (r + \gamma * \max_b Q(s', b) - Q(s, a)) \quad (5)$$

where Q represented the policy table, s the current memory state, s' the next memory state, b the action space (*Cooperate*, *Defect*, *Merge*, or *Split*), a the specific action within the action space, r the payoff score received, α the learning rate, and γ the discount factor.

E. Merge Operator

Two agents (say, the *Challenger* and *Opponent*) could merge into a single composite if either of them chose to play the *Merge* action. The resulting agent acquired a new identifier (Fig. 1C. II); its memories, policy tables, and hyperparameters were derived from either the *Challenger* or *Opponent* based on whichever agent carried the highest time-averaged payoff score (we also experimented with other mechanisms: selecting the memories, policy tables, and hyperparameters of the lower fitness constituent, or a constituent chosen at random. We elaborate on these results in the Discussions section and in Supplement 1). Post the merge process, the merged agent assumed the physical positions of its constituents (Fig. 1C.III).

F. Split Operator

Merged agents could also break into their constituents (Fig. 1C. IV). If during a game, two agents (say the *Composite* or the *Singleton-Opponent*) chose to play the *Split* action, then the agent playing the *Split* action could break down into its constituents provided that it could be broken down into simpler parts. For example, the *Composite* choosing to split could be broken down into its immediate constituent agents (i.e., those two agents responsible for its existence), with the constituents inheriting its memories, policies and hyperparameters. Whereas, if during the same game, the *Singleton-Opponent* (a single agent which could not be broken down further) played the *Split* action, its intention was ignored. (Fig. 1C. VI).

G. Fitness Score

An agent’s fitness score was its game-time averaged payoff score:

$$f = \frac{1}{T} \sum_{t=0}^T R(t) \quad (6)$$

where $R(t)$ was the payoff score received at game round t , with T being the total number of games played at the time of assessment.

H. Selection

With a pre-determined probability, an agent A in the World State performing worse (as measured by its fitness score) than each of its neighbors contained in the set P was replaced by a new agent with a policy equal to that of the policy of the best performing agent in P.

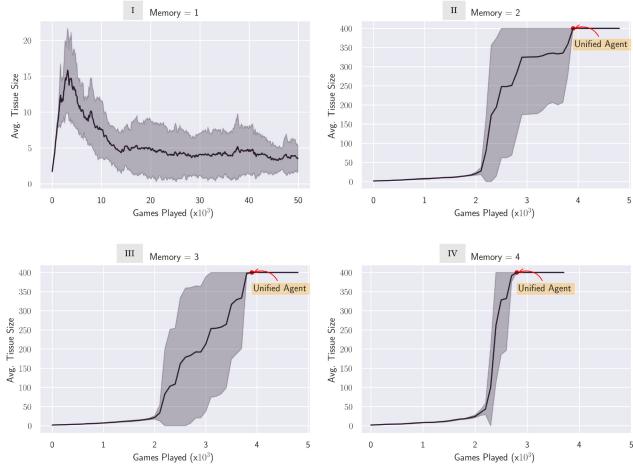


Fig. 2. Higher memory sizes permit aggressive merging. Panels (I, II, III, IV) show IPD-ms simulations of 400 agents, arranged in a 20x20 grid, each with a fixed memory size of 1, 2, 3, or 4 run over 50 k games. The average sizes (i.e., Avg. Tissue size) of agents in a population were plotted over time. Shaded areas indicate 1-standard deviation above and below the mean over five simulation runs. A unique situation was found to emerge when progressive merges resulted in a fully-merged unified agent (panels II, III, and IV). Such an agent constituted every other agent in the World State and consequently could no longer play. We termed this the “unified-agent” point.

III. RESULTS

We ran a series of experiments involving IPD games with *Merge* and *Split* operators (termed “IPD-ms”), by which the boundaries of each agent could be modified. In our investigation of factors that bear on the resulting dynamics, we prioritized examination of the role of memory size, since agents’ decision to make or break borders were expected to be a function of their past experience. Consequently, our experiments were aimed at studying the impact of *Merge* or *Split* operations as a function of agents’ memory size. We began with simulations where agents were homogeneously allocated with fixed memory sizes, eventually moving on to simulations with a heterogenous mixture of memory sizes.

A. Higher Memory Sizes Permit Aggressive Merging

First, to probe the extent to which agents preferred merging or splitting (to either increase or decrease their border size respectively), we simulated IPD-ms games and monitored the average size of agents throughout simulation (Fig. 2). Specifically, we ran four IPD-ms simulations, each consisting of 400 agents placed in a 20x20 grid, initialized with a fixed memory size (of 1, 2, 3 or 4) for a duration of 50 k Games. In each simulation, we plotted the average size of each agent (“Avg. Tissue size”), which owing to the presence of *Merge* or *Split* operators could either increase or decrease in value respectively to integer values between [1, 400].

From our simulations, we observed that agents with a memory size of 1 exhibited a low average tissue size, with the maximum value reaching 16 (± 6) at game $\approx 2 k$ and reducing to $\approx 4 (\pm 2)$ towards the end of simulation (Fig. 2.I). In contrast, agents with a memory size of 2, 3, and 4 managed to reach the maximum possible tissue size of 400 well within 5 k games. The reason why simulations don’t proceed beyond

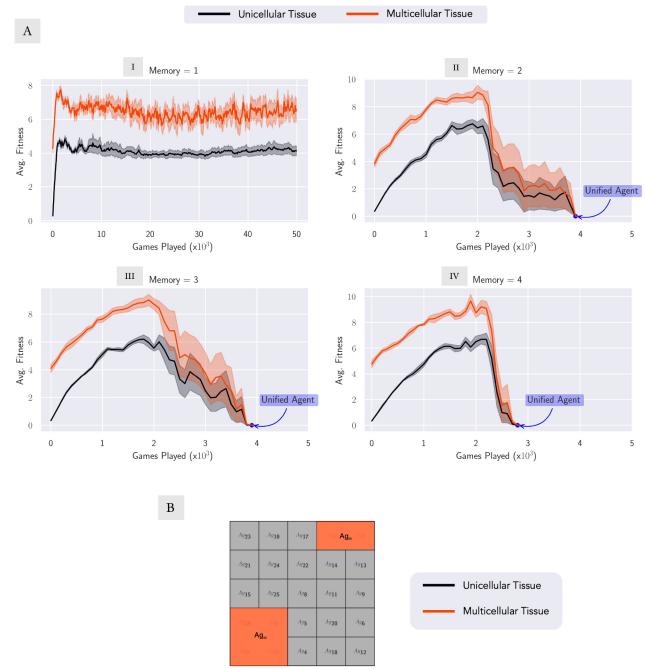


Fig. 3. Multicellular tissues outperform unicellular tissues across different memory sizes. *Panel A:* Four IPD-ms simulations each consisting of 400 agents, arranged in a 20x20 grid, with memory size fixed to values of 1, 2, 3, or 4 (corresponding to Panels I, II, III, or IV) were run for 50 k games. Merged agents were treated as “multicellular tissue” and individual agents were treated as “unicellular tissue”. Average fitness values for each tissue (unicellular or multicellular) were plotted over time. Shaded areas indicate 1-standard deviation above and below the mean over five simulation runs. *Panel B:* A schematic depicting unicellular (shaded black) and multicellular (shaded orange) tissue in the World State.

this point has to do with the lack of opponents: a tissue size of 400 indicates the presence of a fully-merged unified agent of size 400 with no other agents available to play games against.

This drive towards a fully-merged unified agent was observed to take place with periods of rapid rise in tissue size followed by constant equilibrium in a cyclic manner. For instance, in simulations with a memory size of 2 (Fig. 2.II) we observed three cycles of the rise-equilibrium dynamic; five cycles in simulations with a memory size of 3 (Fig. 2.III), and two cycles in simulations with a memory size of 4 (Fig. 2.IV).

Further, we observed that the time taken to reach the unified agent status decreased with increasing memory size. For instance, memory-sized-2 agents required $\approx 3.9 k$ games to grow into a unified agent; memory-sized-3 agents required 100 games fewer, and memory-sized-4 agents required ≈ 1100 games fewer. We conclude that agents with a memory size of 1 maintain relatively low tissue sizes throughout simulation without a drive towards formation of large clusters. Agents with memory sizes in the range of [2, 4] exhibit cyclic patterns of rise-equilibrium phases in their tissue size, with the time taken by these agents to grow into a unified agent decreasing with increasing memory size.

B. Multicellular Tissues Outperform Unicellular Tissues

Second, to check whether merged agents with larger constituents received higher scores than individual agents, we simulated IPD-ms games where we compared the fitness

values of single sized agents (“unicellular tissue”) and merged multi-sized agents (“multicellular tissue”) throughout simulation (Fig. 3B). Similar to our previous experiment, we simulated four independent IPD-ms experiments each consisting of a population of 400 agents, placed in a 20x20 grid, initialized with a fixed memory size (1, 2, 3, or 4), and run for 50 k games. We plotted the average fitness of unicellular agents and the average fitness of multicellular agents at each time step.

Our simulations revealed that multicellular tissues on average perform better than unicellular tissues across different memory sizes (Fig. 3A; panels I, II, III, and IV). In memory-sized-1 agents, the dominance was found to be consistent (an average gap of 2.0 fitness points) throughout 50 k games ($p \ll 0.01$; measured at several game steps). In memory-sized-2 agents, multicellular dominance was observed for a duration of 2 k games (an average gap of ≈ 4.0 fitness points) ($p \ll 0.01$); but thereafter we noticed a sharp decrease in the fitness of both tissues (avg. gap of 0.5 fitness points), with their values tending to converge over the remaining 1.9 k games at the end of which a singular agent emerged (Fig. 3A.II). A similar pattern was noticed in agents with memory sizes of 3 and 4: a period of multicellular dominance lasting 2 k timesteps, followed by a convergence in fitness values lasting for 1.8 k games and 0.7 k games respectively (Fig. 3A.III, 3A.IV).

We conclude that multicellular tissues dominate over unicellular tissues throughout simulation in a population of memory size 1. At higher memory sizes, two phases exist: an initial duration where multicellular tissues dominate over unicellular tissues, and a subsequent later stage where their fitness values converge and eventually reduce to 0, indicating the presence of a fully-merged, unified agent.

C. High Intra-Group Cooperation Does Not Lead to High Inter-Group Cooperation

Third, we checked the cooperative tendency of unicellular and multicellular clusters at different memory sizes. We did so by simulating IPD-ms games and observing the inter-agent cooperation exhibited by unicellular and multicellular agents throughout simulation (Fig. 4). To this end, we ran four IPD-ms simulations, each consisting of 400 agents, placed in a 20x20 grid, initialized with a fixed memory size (1, 2, 3 or 4) for a duration of 50k games. In each simulation, we grouped agents into two groups: 1. merged agents (multicellular tissue), and 2. individual unmerged agents (unicellular tissue). Simulations began with the World State composed of unicellular tissues; but, owing to *Merge* and *Split* actions, this cluster ceded (or gained) its numbers to (or from) the multicellular tissue cluster. At any point in simulation, we checked the number of unicellular tissues cooperating with other tissues (unicellular or multicellular) and similarly we checked the number of multicellular tissues cooperating with other tissues (unicellular or multicellular). This value was plotted as a proportion of their respective population size.

When testing the effects of memory on resulting dynamics, we checked “tendency to cooperate” as a function of memory size (not fitness, just behavioral cooperation). We observed that

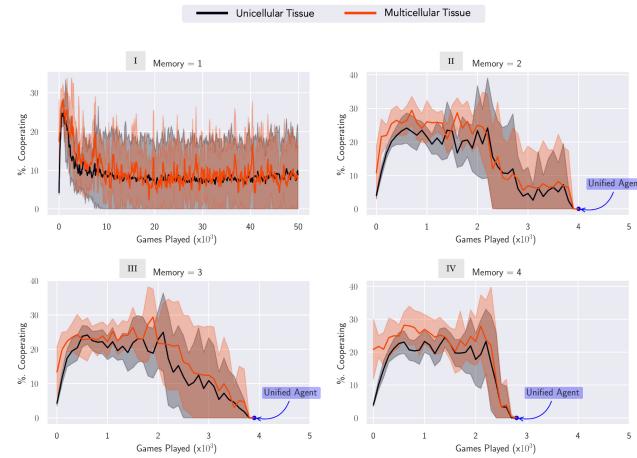


Fig. 4. High intra-group cooperation does not lead to high inter-group cooperation. Panels (I, II, III, IV) show IPD-ms simulations of 400 agents, arranged in a 20x20 grid, each with a fixed memory size 1, 2, 3, or 4 run over 50 k games. A “unicellular tissue” was treated as an agent composed of itself, whereas a “multicellular tissue” was treated as an agent composed of one or several other unicellular or multicellular agents. Each panel indicates the percentage of unicellular (black) or multicellular (orange) agents cooperating with other agents over the course of simulation. Shaded areas indicate 1-standard deviation above and below the mean over five simulation runs.

across all four memory sizes, multicellular tissues cooperated in a way identical to that of unicellular tissues. For instance, unicellular and multicellular agents with a memory size of 1 exhibited no difference in cooperation across all 50k games ($p = 0.92$, Fig. 4.I). Similar dynamics were found in simulations with memory sizes 2, 3, and 4 (corresponding p values of 0.8, 0.91, and 0.86 respectively; Fig. 4.II, 4.III, and 4.IV). Further, across all four memory sizes, tissue groups were found to reach a peak cooperation of 40% of their proportion but remained at a value well below 30% during a majority of their simulation duration.

In addition, we observed fluctuating stability across memory sizes: tissue groups with a memory size of 1 exhibited large instability with a standard deviation of ≈ 10 throughout simulation (Fig. 4.I). Higher stability was noticed in tissue groups with memory sizes 2, 3 and 4 with agents exhibiting relatively lower standard deviation until the 2 k^{th} game, increasing briefly, and decreasing thereafter as agents coalesced into a fully-merged unified agent.

We conclude that the tendency of agents to form large sized clusters does not lead to an increase in their tendency to cooperate better with other agents as compared to smaller sized clusters. Further, increasing an agent’s memory size has no statistically significant effect in inducing inter-agent cooperation among large clusters.

D. Merging/Splitting Skews the Memory Distribution of a Population Towards Lower Sizes

Next, we studied the memory preferences of agents when they were allowed to play games of traditional IPD versus IPD-ms. In contrast to previous experiments, populations were initialized with a heterogenous mixture of memory sizes, chosen uniformly at random between 0 and 4 inclusive. Given the heterogeneous content of a population, agents had yet another avenue to gain a fitness advantage over others: the

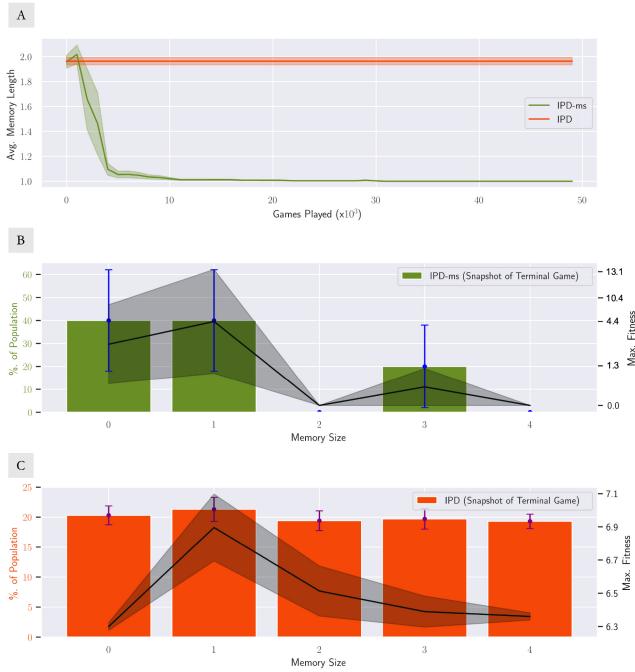


Fig. 5. Enabling *Merge/Split* skews the memory distribution of a population towards lower sizes. Two populations - one where agents played traditional *Cooperate, Defect* IPD (the “IPD” population), and one, where agents played four-action: *Cooperate, Defect, Merge, Split* IPD (the IPD-ms population) - were initialized uniformly with memory sizes in [0, 4] and their memory size distribution was monitored throughout simulation. *Panel A*: Average memory size over time in the IPD-ms and the IPD populations. *Panel B*: Snapshot of the histogram of the IPD-ms population at the final ($50 k^{th}$) game. Error bars (blue) indicate 1-standard deviation over and below the mean over five simulation runs. The maximum fitness of agents binned in a specific memory size were plotted over each bar (Black Trace, right hand side, y-axis); shaded areas indicate 1-standard deviation over and below the mean over five runs. *Panel C*: Snapshot of the histogram of the IPD population ($50 k^{th}$) game. Error bars (purple) indicate 1-standard deviation over and below the mean over five runs. The maximum fitness of agents binned in a specific memory size were plotted over each bar (Black Trace, right hand side y-axis); shaded areas indicate 1-std deviation over and below the mean over five simulation runs.

utilization of larger or shorter memory sizes to develop better strategies.

The memory sizes within a population playing IPD-ms could fluctuate because of the presence of *Merge* and *Split* operators whose roles allowed for the “weeding” away of low-performing memory sizes: as an example, consider two agents A1 and A2 with memory size 1 and 4, carrying fitness values 2.0 and 10.0 respectively, choosing to merge during a certain game during simulation; the resulting agent (say A3) will carry the memory size of the higher fitness agent A2, thereby “weeding” away the “traits” of the low performant agent A1.

Our goal was to observe how the *Merge* and *Split* operators played a role in influencing the memory size distribution of a population over time. To this end, we simulated two experiments over $100 k$ games: a) where agents played traditional, cooperate-defect IPD, and b) where agents played four action IPD-ms games (Fig. 5). In each experiment 400 agents, placed in a 20×20 grid, were initialized uniformly with memory sizes in the interval 0 to 4 inclusive, with our objective being to monitor the distribution of memory sizes throughout simulation.

We observed that the average memory size in the IPD population remained constant (with no variation) throughout simulation, whereas the IPD-ms population exhibited a minor increase in its average memory size at Game $\approx 2k$, followed by a steep decrease to a value of 1.0, suggesting a preference for agents with lower memory sizes (Fig. 5A). We verified this behavior by observing a histogram of the memory size distribution at the final ($50 k^{th}$) game, which revealed the preference of the IPD-ms population to sample from low memory sizes (Fig. 5B). Specifically, 80% of the population consisted of agents with a memory size of 0 (playing a random policy without memory), or a memory size of 1. The remaining 20% of the population was found to be composed of agents with a memory size of 3. We attributed this disproportion to the higher fitness values carried by agents with memory sizes 0 and 1 (fitness = 4.4) as opposed to those with a memory size of 3 (fitness = 1.3) (Fig. 5B; black trace, RHS y-axis).

In the case of the IPD population, we noticed a uniform distribution of memory sizes post $50 k$ games of simulation (Fig. 5C) with an approximately uniform distribution of fitness values in the range of 6.3 and 7.0 with low variance (Fig. 5C, black trace, RHS y-axis).

We conclude that the ability to merge/split confers agents with lower memories (including even those without memories) a fitness advantage during IPD-ms games. Such a fitness advantage allows agents with lower memory sizes to outperform their higher memory counterparts, allowing them to dominate the population over time. In contrast, agents playing games of traditional cooperate/defect IPD exhibit no such disproportionality, maintaining roughly similar fitness values throughout simulation.

E. Morphological Patterns Emerge as a Result of Successive Merges

To visualize the spatial distribution of merged clusters, we color coded tissues of different sizes in the World State and visualized their evolution throughout simulation. Specifically, we evolved a single IPD-ms population composed of 400 agents, each with a fixed memory size of 2, arranged in a 20×20 grid. At each step of our simulation, the World State was visualized by spatially coloring agents based on their size (“cluster size”) (Fig. 6). As agents played games of IPD-ms, we observed the emergence of an increasing diversity of patterns: starting from an evenly distributed World State, a complex cluster of tissues emerged (tracing left to right, top to bottom in Fig. 6A) with the spatial distribution eventually becoming uniform with the emergence of a fully-merged unified agent (Fig. 6A.IX).

A peculiar feature of the patterns that emerged was the apparent clustering of similar sized tissues close to one other, with smaller sized tissues aggregating on the periphery of larger ones. To quantify the distribution of a particular tissue size next to another, we measured the probability with which one could expect to find an agent of size X , next to another agent of size Y . A result of this quantification was a heatmap (Fig. 6B), where the rows spanned over sizes X , and the

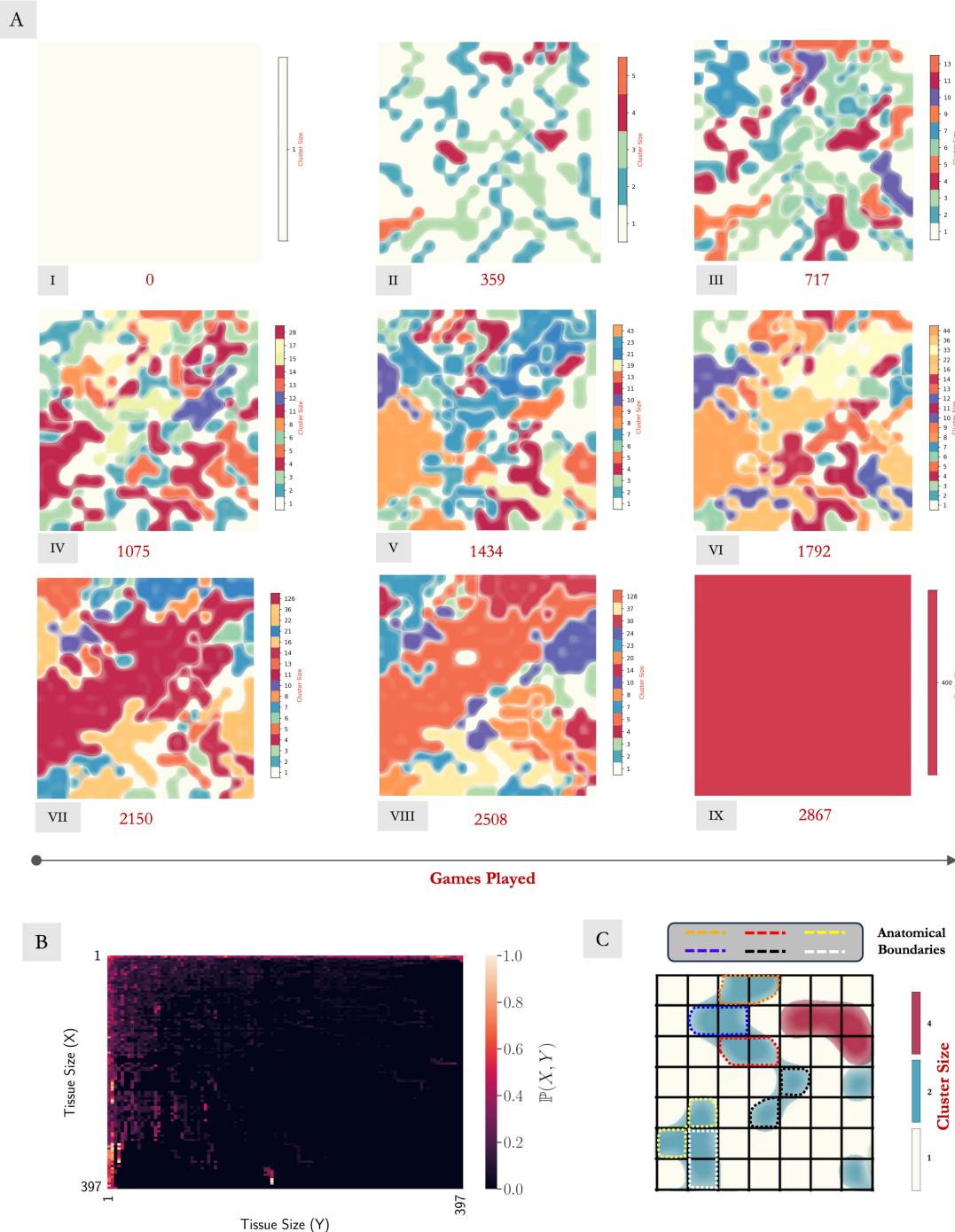


Fig. 6. Morphological Patterns emerge as a result of Successive Merges. Snapshots of the World State at different periods during gameplay in an IPD-ms simulation of 400 agents arranged in a 20×20 grid, each with a fixed memory size of 2. Colors denote merged tissues of different tissue sizes (“cluster size”). *Panel A:* Initially (A.I), the World State was composed of agents of tissue-size 1; tissue sizes increased or decreased owing to *Merge* or *Split* actions taken by agents respectively. Patterns shown here are the result of Lanczos interpolation [48] of each agent considered separately. *Panel B:* Heatmap of the probability of finding a combination of tissue sizes next to one another. Rows and columns depict tissue sizes. A cell (X, Y) within the heatmap indicates the probability of finding an agent with tissue size X , next to a separate agent with tissue size Y . *Panel C:* Snapshot of a region within the World State depicting the obfuscation of agentical borders. Colors denote tissues of a specific size as represented by the color bar. Grid lines are drawn to visually assist the reader in accounting for merged agents. Dashed, cilia-like, colored borders denote ground truth anatomical boundaries, without which the illusory presence of a coherent whole (blue blobs on the upper part of the snapshot) becomes a convincing deception.

columns over sizes Y , with any (X, Y) combination taken to be the probability of finding a cluster of size X next to a cluster of size Y . We observed that small sized tissues (with sizes in the range of 1 – 50) (Y variable in Fig. 6B) tended to cluster

around agents of every possible anatomical-size (X variable in Fig. 6B), indicating that irrespective of the tissue size of an agent, a smaller sized agent (with a tissue size less than 50) could be expected in its neighborhood with high probability.

A consequence of proximal organization is the question of boundaries: if two similar sized clusters were next to one another, how would an external observer demarcate their individual boundaries? How likely would it be for an observer to mistake them for a single continuous agent? For instance, consider a section of the World State (with grid lines drawn for visual support) as shown in Fig. 6.C. The snapshot shown contains multiple agents of similar size, grouped close to one other. We draw attention of the reader to two such groups marked by dashed-boundaries on the left hand side of the grid. Without explicitly drawn ground-truth information on their agential boundaries, it would be natural for an external observer looking at a snapshot of the population at a specific timestep to treat these adjacently placed agents as a single agent, while in fact they are multiple agents with independent policies. Such misattribution illustrates the difficulty of trying to ascertain the boundaries between goal-directed autonomous agents (and the outside world) from structural observations of a multiscale complex system. In effect, this illustrates the emergence of structurally contiguous tissues with physiological regionalizations that are not apparent at the anatomical level.

We conclude that IPD dynamics allowing fluid agent boundaries progressively result in the emergence of clusters, with relatively smaller sized “tissues” clustering around relatively larger sized aggregates. Thus, IPD dynamics give rise to rich emergent spatial (morphological) patterning reminiscent of biological organization, but the attribution of behavioral coherence within and between clusters cannot be made exclusively from this topological information.

F. Integrated Information Theory highlights That Larger Agents are More Integrated With the Environment Than Smaller Ones

Having identified emergent spatial structure in this system, we investigated one other crucial component of larger-scale clusters: information integration. A significant literature [49], [50], [51], [52], [53], [54], [55], [56], [57], [58] shows how higher levels of organization, in some architectures, acquire integrated autonomy and become agents that significantly supervene over their parts. Is there a sense in which the organization induced by multicellular merged clusters exhibits significant information integration?

To this end, we checked whether large sized agents possessed a greater degree of cohesiveness with their environment compared to smaller sized agents as they played games of IPD-ms (Fig. 7). Specifically, we simulated an IPD-ms population consisting of 400 agents, arranged in a 20x20 grid, each with a fixed memory size of 4, run until the emergence of a fully-merged unified agent (which was found to be at ≈ 2.7 k games). At each game step, we recorded agents’ tissue size and used it to calculate their aggregate information integration with their environment using the Integrated Information Decomposition metric, ϕ^r [59]. Specifically, we considered an IPD-ms population of N agents, denoting A_n as the n^{th} agent ($n \in N$) surrounded by the set of other agents (termed collectively as the environment, E). The overall World State

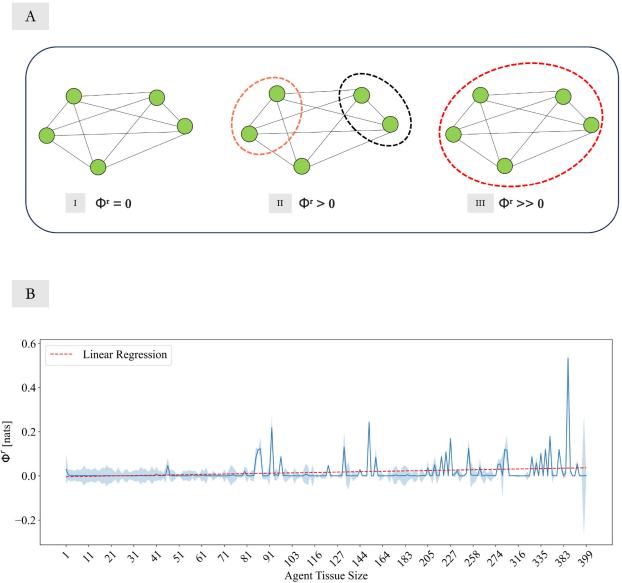


Fig. 7. Integrated Information Theory highlights that larger agents are more integrated with the environment than smaller ones. In Integrated Information Theory, ϕ^r measures the degree to which a system's elements are integrated. A system with high ϕ^r implies agents with high interconnectivity, with the system as a whole behaving in a way that can't be explained by the sum of its parts. *Panel A:* In our framework, nodes represent agents, and the edges represent actions. Nodes grouped under dashed ellipses (as in A.II or A.III) are representative of merged agents behaving as a single unit. Merged groups behaving as a whole (red ellipse in A.II) carry a higher ϕ^r value compared to those merged groups with fewer agents (orange and black ellipses in A.II). *Panel B:* Blue fluctuating graph: median \pm standard deviation (across random seeds) of ϕ^r for different agent sizes. Dashed red line: the least-squares linear regression fit, with a significantly positive slope ($p \ll 0.01$) indicating that as agent-size increases, integration between the agent and the rest of the environment increases, suggesting that larger subunits make the whole game behave in a way that the single parts cannot fully explain.

at any timestep t , could then be expressed as a variable, $X = (A_n, E)$, and ϕ^r could be calculated as:

$$\begin{aligned} \phi^r = & I(X(t), X(t+1)) - I(A_n(t), A_n(t+1)) \\ & - I(E(t), E(t+1)) \end{aligned} \quad (7)$$

where I is the Shannon mutual information.

In essence, ϕ^r computed the information that the whole carried about its future minus the information that the parts carried about themselves. Intuitively, a high ϕ^r implied that the system behaved in a manner which could not be completely explained by the sum of its parts.

In our case, we observed that an increase in the size of an agent led to a corresponding increase in the fluctuation of ϕ^r . A linear regression fit over these fluctuations yielded a positive slope (red dotted line, Fig. 7B). The slope of the regression line was found to be significantly positive ($p \ll 0.01$), indicating that as an agent's size increased, integration between the agent and the rest of the environment increased as well. Our result suggests that larger subunits influence future IPD-ms dynamics in a way that single parts cannot completely explain, and demonstrates quantitatively that higher sized agents tend to causally emerge from lower sized agents during IPD-ms games.

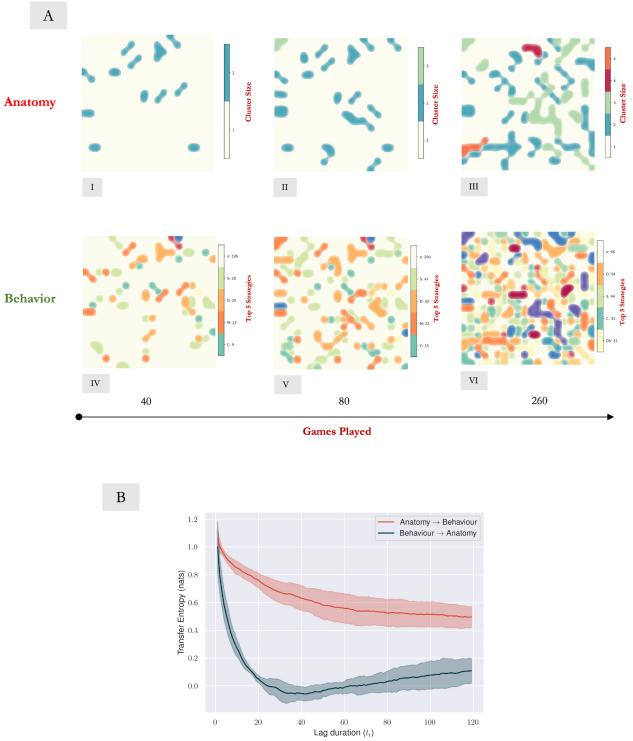


Fig. 8. Agential boundaries can be anatomical or behavioral. *Panel A*: Anatomical and behavioral boundaries over the course of simulation within the two-dimensional World State. Top row sub-panels (A.I, A.II, A.III) depict anatomical boundaries color-coded by their respective tissue-size. Bottom row sub-panels depict behavioral boundaries (A.IV, A.V, A.VI), color-coded by agents' playing strategies. Strategies are defined as memory sequences of size less than or equal to three. The color bar (in A.IV, A.V, A.VI) indicates color-strategy relationships of the five most frequent options played at any point in time. Strategy “x” is assumed to represent those agents which have not played IPD-ms games so far. *Panel B*: Relationship between Transfer Entropy and Lag Duration (t_t). Transfer Entropy from a sequence $X \rightarrow Y$ is the degree of uncertainty reduced in future values of Y , given past values of X and Y from an instant in the present. The length of the past is based on the Lag-period duration t_t , and is set here to values ranging from [1, 120] game steps. Transfer Entropy between sequences of Anatomy → Behavior (red trace) or Behavior → Anatomy (black trace) was calculated at each lag-duration (t_t) and was reported as a spatially averaged value over all agents. Shaded areas are indicative of standard deviation over 5 independent runs of IPD-ms experiments initialized with 400 agents each with a fixed memory size of 2.

G. Agential Boundaries Can be Anatomical or Behavioral

Agents are commonly treated as goal-directed entities occupying physical space. However, self-reinforcing persistent dynamical states (patterns in an excitable medium) can exist in other spaces as well [60], [61], [62], [63], and it has been pointed out that agential biological systems also are temporary patterns of metabolism, genetic information, and memory [64], [65], [66], [67], and that different observers focused on measuring different quantities in a system might see very different patterns and draw boundaries between active agents very differently [68]. Thus, it becomes interesting to track not only the physical pattern of connectivity (ground truth of which agents are merged with which other agents), but also the informational patterns that could persist and spread through the population in a way that doesn't respect physical boundaries between agents [69]. Behavioral space, for instance, is the space of all possible strategies for managing sensing/actuation mappings of an agent during its lifetime. Multiple agents

depicting identical behaviors can appear “merged” to an external observer, who sees behavior but not the internal states of agents, despite their physical boundaries remaining intact. Thus, to check the extent to which the behavioral space became patterned differently from anatomical space in this model, we analyzed instances of the same simulation: one where we color-coded agents by their physical boundaries, and a second where we color-coded agents by their personalities (the strategies they chose to play) (Fig. 8A).

To this end, four hundred agents, each with a fixed memory size of 2, arranged in a 20×20 grid, played games of IPD-ms. We investigated patterns of agent borders and groupings in two different spaces by visualizing agents according to (1) physical boundaries (anatomical contours) and (2) by the strategies played by agents (behavioral contours) (see Supplement 1 for details). We observed that agential boundaries revealed by these two perspectives differed dramatically. Early during simulation (by game number 40), we found agents grouped into common behavioral boundaries despite not having physically merged (Fig. 8A.I, 8A.IV). As simulation progressed this effect increased, to an extent that by game number 260, behavioral boundaries were unrecognizable from their anatomical boundaries, their complexity outrunning the pace of anatomical merges (Fig. 8A.III, 8A.VI). We conclude that emergent patterns and boundaries between agents (which differ in physical connectivity or in behavior) can be different, depending on what observables are analyzed in the population.

Given these two different perspectives on the boundaries of agents in this system, we sought to characterize their respective causality: whether the anatomical, or the behavioral, patterns influenced each other. Specifically, we characterized how much of the past of one variable, (anatomy or behavior) influenced the future values of the other, testing different lengths of possible lag in the causality. To quantify this, we calculated the Transfer Entropy (TE) [70], [71], [72], [73] between anatomy and behavior for each of the 400 agents at different lagged intervals (t_t), by recording sequences of cluster-size and behavior during simulation (see Supplement 1 for details).

We observed that TE values from anatomy to behavior (A-B) were higher than the TE from behavior to anatomy (B-A) across Lag Durations ranging from 1 up to 120 games (Fig. 8B). At a Lag Duration of 1, a strong bidirectional relationship between anatomy and behavior was observed. With an increase in Lag Duration, TE in either direction decreased, with TE from B-A decreasing at a relatively higher rate. Interestingly, over Lag Durations spanning 20 to 60 games, TE from B-A was found to be negative, indicating that behavioral patterns increased (rather than decreased) future uncertainty in anatomical patterns, playing a negative role in its causal influence. But reverse-causality did not persist, and post a Lag Duration of 60, TE from B-A progressively increased. We note however that, despite such an increase, its absolute values remained significantly below that of its reciprocal relationship (A-B) through Lag Durations up to 120 games.

Our observations suggest a coupled influence between behavioral and anatomical patterns on multiple time scales;

bi-directional causality exists between patterns of connectivity and behavior, with emerging anatomical patterns from as far back as 120 game steps in the past influencing the distribution of behavioral propensities in the present to a greater extent than vice-versa.

IV. DISCUSSION

Most interesting things are made of parts; this is especially true of living agents (biological beings composed of organs, which are in turn composed of tissues, cells, and molecular networks) [74]. Thus, it becomes important to understand how the interactions of those parts give rise to the behavioral properties of a larger-scale system. This extends well beyond biology to questions of origin and stewardship of ecosystems, financial systems, social structures, etc. A considerable literature that spans across evolution, human behavior, and economics focuses on the emergent consequences of self-interest [75], [76]. However, that presupposes a single, unitary, persistent “Self” that is able to at least reap the consequences of its decisions, and often, to also deliberate and follow specific policies to maximize certain outcomes. Models in the field have studied agents that can change their policies, but generally not the borders between agents. That is, there is typically no question of where one agent ends and another begins. Likewise, aside from studies of hyperbolic discounting [46], [77], [78], there are few frameworks for understanding what happens when one’s actions radically change one’s structure and thus the perceived payoff matrix of future decisions. While historical approaches have the benefit of tractability, they limit the real-world applicability of models and contribute to the poor fit between dynamics of living systems and formalisms that make a sharp distinction between machine/data, structure/function, etc. [68].

Two biological systems illustrate the kind of questions that are raised by loosening the assumption of fixed agents. One is the caterpillar-butterfly metamorphosis example – these are genetically identical beings but occur in two configurations with radically different requirements for food and interesting evolutionary dynamics of competition. Indeed, enabling agents to change over time provides an interesting twist on memories and predictions as communication with past and future selves [65], by enabling competition and cooperation with past and future selves which are not the same as the current self in terms of preferences, vulnerabilities, capabilities, etc.

Another biological example is the slime mold *Physarum*, which is a multi-nucleated but unicellular organism that has been used to understand basal cognition and many other relevant aspects of behavior and resource allocation [79], [80], [81], [82]. Consider a *Physarum* extending toward an oat flake [83], when a razor blade separates the leading 10% from the larger mass behind. At that moment, the leading 10% has a choice to make: continue toward the flake and consume the resource without having to share it with the rest of the colony, or flow backwards and merge with the collective. Note that this question, and the payoff matrix, did not exist prior to the amputation, and it will not exist again if the fragment chooses to merge first – all the self-interest of the fragment will vanish once it’s part of the collective. From the perspective of that

potential future, there is no choice to be made, and there is no I, only We. *Physarum* can execute splits and merges routinely, but even advanced organisms’ cells can do this during embryogenesis, resulting in chimeras and monozygotic twins. How can we think about actions which will change the context of all future actions?

There is a dearth of results of game theory in scenarios where the actions of the agents feed back to change the nature, number, and composition of the agents themselves. Here, we addressed this fascinating “strange loop” [84] by analyzing a simulation in which the payoff table and interaction landscape can itself be changed, in real-time, by the decisions made by an agent. We used the workhorse Prisoner’s Dilemma paradigm [30], [85], iterated and spatialized, but added an important feature: the borders of the agents were not fixed, and agents could decide to merge or split just as they could decide to cooperate or defect in each interaction. This connects the questions of cooperation and competition with a thriving field of research into the scaling of cognition: the developmental and evolutionary processes by which single cells join into organs and organisms that have competencies, goals, preferences, and memories that none of their parts have [20], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98]. This builds on our previous work examining processes of up- and down-scaling of Selves and the biological processes that enabled this plasticity in the context of embryogenesis [27], [28], [74], which pointed out that it is these dynamics that break down and lead to the defections from the bodyplan known as cancer [99], [100]: a dissociative disorder of morphogenesis that arises not from more selfish cells but from smaller Selves.

A. Multicellularity Arises in the Context of Merge Based IPD

Our data in this paper revealed that given the opportunity for agents to change their boundaries, large scale multi-agent clusters emerge (Fig. 2, Fig. 6). We particularly investigated the impact of memory on the dynamics of cluster formation: memory is traditionally used in game theory simulations to provide a history of play against specific opponents so that reciprocity, punishment, revenge, trust, etc. can be modeled. As such, we used memory as a proxy for the “intelligence” of the agents, simulating diverse degrees of information processing capacity seen across scales, from molecular pathways in cells to whole organisms and swarms, in Biology. Our results showed that higher memory sized agents tended to merge aggressively towards a singular agent (Fig. 2). We also observed that merged clusters possessed a higher fitness than un-merged, singleton agents, across memory sizes (Fig. 3).

One could interpret these two results as the consequence of a selection-like process (that the merge operation permitted propagation of the best performant constituent’s policies and memories). This would potentially explain why merged agents possess higher fitness values over singleton-agents (Fig. 3). However, we note that this cannot be the only explanation, as evidenced by a control experiment in which we designed the merge operator to permit the propagation of the policy, and memories of the least fit constituent and continued to observe aggressive merge behavior as well as the dominant

fitness of merged clusters (Supplement 1). While it is clear that memory size influences merge behavior, the tendency for the dominance of merged clusters does not have a clear factor of influence. We speculated that merged agents might have cooperated better with their also-merged peers, but such a hypothesis also proved false as we discovered that merged agents cooperated roughly similarly to that of singleton agents (Fig. 4).

B. Population Dynamics

A few observations can be made about the overall trends in how populations develop over time. First, we observed a kind of “punctuated equilibrium” dynamic with respect to tissue size, much as seen in the evolutionary record [101]: at fixed memory sizes greater than or equal to 2, long periods of stagnation followed by rapid rises were noticed (Fig. 2).

Next, when memory size was under evolutionary control (Fig. 5), we found a surprising tendency for agents in simulations of IPD-ms to settle on lower memory sizes, a large proportion even choosing to make decisions with no memory of the past (i.e., using a memory of 0) (Fig. 5B). One reason why low memory agents persist over high memory agents could be because of the capacity to experience their environment better: low memory agents act by considering fewer memories (in fact, exponentially fewer in our framework compared to higher memory agents). Thus, despite playing over long durations, lower memory agents require keeping track of less compared to higher memory agents who require learning to act from a vast array of states. A key consequence is that low memory agents outplay large memory agents; before large memory agents experience enough games to learn from their actions, they will have been outplayed by lower-memory agents.

A second curious result we noticed in this variable memory experiment (Fig. 5) is the absence of agents with a memory size of 2, even though agents with a memory size of 1 and 3 exist. This behavior cannot be attributed to chance as it occurred reliably over five different runs of the simulation. We have been unable to identify any discrete, localizable cause of this outcome and provisionally consider it to be an emergent feature of this complex system, perhaps like properties of certain cellular automata [102].

C. Graded Structures: Emergent “Tissues”

One remarkable finding is that of the emergence of “clustered” tissues (Fig. 6C). The rules of physics of this simulated world only provide 2 levels of organization: single cell agents and merging into larger groups. However, we observed an unexpected outcome: spontaneous aggregation of smaller sized individuals around larger sized agents (Fig. 6B). This reveals a causal link between competitive payoff dynamics and morphological organization: these structures did not need to be programmed into the simulation, nor did our agents have any mechanisms for morphogenesis whatsoever. It appears that structural organization – not merely unicellularity vs. multicellular syncytium – can arise spontaneously due to metabolic competition.

Further, these multicellular clusters were found to possess a higher degree of cohesiveness. When measured by tools from integrated information theory [59], these large-scale clusters exhibited a higher degree of integration with their environment (Fig. 7B). Their cohesiveness is suggestive of their complexity: encompassing a tendency to encode policies with greater coherent complexity than those possessed by unicellular agents. It is striking that simple competitive games (metabolic dynamics with limited resources) can lead to the emergence of morphological complexity, as well as a rise in causal emergence (Fig. 7) which has been proposed as a metric of cognitive capacity [56], [103], [104], [105], [106], [107]. This could perhaps shed light on how evolution pivots competencies across metabolic, physiological, transcriptional, anatomical, behavioral, and linguistic spaces [24].

D. Patterns Emerging in Multiple Spaces

An alien observer, who did not share our specific assumptions about spatio-temporal scale at which agency must occur, would have an interesting challenge when observing our planet. Should the relevant level of analysis (and communication) be the molecules, cells, organs, organisms, swarms/colonies, ecological niches, or perhaps the entire ecosystem? Multiscale agents are defined by alignment and similarity among their parts, but are the relevant agents demarcated by boundaries of physical objects (skin and other embodiments that determine degree of connectivity), or are more useful maps drawn based on isolines of more subtle patterns of thermodynamics or behavioral tendencies? Our attempts at exobiology will have the same difficulty: it is not obvious which scale, and in which space/substrate, relevant patterns are to be sought. Most work on agent-based dynamics assumes discrete agents whose number is fixed and whose definition is set from an agreed-upon perspective of observables. Here, we expanded this tradition in two directions. First, we studied the dynamics of shifting boundaries of active agents; for the analyses in Figs. 2-7, the boundaries of agents were fluid (and controlled by the agents’ own behavior), but we treated it as an objective fact as to what metric determined the definition of an agent’s borders – physical ground truth of connectivity in decision-making. But then (Fig. 8), we loosened even that requirement and examined two different perspectives on this in silico world: patterns of “physical” connectivity vs. behavioral tendencies (roughly corresponding to the genetically-encoded protein hardware of a body and the physiological dynamics that can occur during lifetime at the level of signaling pathways, ion channels opening and closing in place, etc.).

We sought to establish a minimal model for asking questions about detection of novel patterns in biologically-relevant processes. We observed that a perspective based on the ground truth of who was actually connected to whom (as a result of mergers) provides very different information than a perspective based on “which elements actually act alike”. We do not believe it is possible to say which of those perspectives is “better” than the other, consistent with the principle of no privileged level of causation in biology [108]. This can perhaps become an important minimal model system for the

difficult task of biomedical personnel who must integrate not only histological (anatomical) patterns but also those of temperature, stress, metabolism, biomechanical properties, gene expression, epigenetic age, bioelectric state, and many others, into models from which to derive interventions. It is clear that many system-level disorders, such as cancer and immune conditions, are driven by dynamic, not easily observed patterns of information, state, and energy that do not neatly map onto physical boundaries of tissues and organs [109], [110], [111], [112]. It has been argued that it is essential to begin to transition biomedical approaches toward models of management of not just physical objects, such as cells and organs, but of motile, causally-important, self-reinforcing patterns of energy, stress, physiological state, and information [113], [114].

Another important aspect here is that we observed homogeneous agents grouped into common behavioral boundaries despite not having physically merged (Fig. 8A). Given that two very different pictures of boundaries coexist in this system, what is their causal relationship – does one drive or influence the other? Our data are consistent with a bi-directional relationship in which patterns of anatomical connectivity and patterns of behavioral propensities influence each other – changes in tissue architecture appear to alter behavior of specific regions while patterns of behavior feed back to alter the structure. This reciprocal relationship between the “software” and “hardware” aspects of the system on multiple temporal scales are a hallmark of the self-modifying architecture of biology at the evolutionary, developmental, and cognitive scales. While it is difficult to quantify statistical significance of absolute levels of Transfer Entropy, we found that the anatomical pattern is more likely to affect the behavioral map to a greater extent across several Lag Durations than the reverse (Fig. 8B). Future work will characterize deeper aspects of the causality, and examine possible analogies of this phenomenon in biology, in which a subtle pattern eventually becomes canalized into physical form, perhaps including such phenomena as genetic assimilation of behavioral patterns [115], [116], [117], [118], short-term memories becoming encoded into long-term engrams, and mind-body effects in which patterns of thought influence gene expression and eventually synaptic structure [118], [119]

E. Endgame: a Minimal Model of Eschatology

One of the most interesting aspects of the model was the precipitous drop of fitness (Fig. 3A.II, 3III, 3IV) occurring during the late stages of each run. At first this was very puzzling to us, but analysis showed the reason: when the population merged into a very few agents, there were not enough games being played to support sufficient incoming credit from IPD-ms payoffs: agents played merge actions frequently, which carrying a payoff score of 0.0, caused a drop of everyone’s fitness. This raised a question we had not considered before: what happens after the whole population is merged into a unified being and there is no one to compete or cooperate with? This connects to similar ideas about the fitness of the ecosystem as a whole, and the singularities that

appear in conventional models of ecology and evolution based relative frequencies within a large population competing for resources. We thought of several general approaches to this problem. One is to say that when a life form expands to the edges of its world, there are no more resources to be had, and everything dies (a kind of heat death of the universe).

Another way to think about it is as a set of cycles of fragmentation and reunification. This roughly corresponds to some spiritual traditions in which the world begins as a dissociation of a universal singular mind (perhaps due to boredom) into individual agents, followed by a lengthy climb as the fragments join into progressively bigger minds (scaling of the cognitive light cone as described in [27]) and eventually achieve union with the Absolute. The cycle can then continue indefinitely. We did not model this phase in our system, but future work can explore such models by adding various proto-cognitive drives within the agents (and possibly emergent ones in groups) for stimulation (infotaxis) which could implement stress- or uncertainty-driven fragmentation and re-association. Such work offers the possibility of a generic framework for scaling of agency that works across metabolic, morphological, and cognitive spaces.

The final and perhaps most exciting possibility is that systems that reach the boundaries of their world could try to project their newfound competencies into a new problem space. Issues of agents escaping from one environment to exploit another are relevant to evolution of novel competencies (e.g., from physiological problem-solving in single cells to navigating anatomical morphospace), the logic and limitations of formal systems [120], [121], and concerns over AI software agents escaping from their virtual machines [122]. A future roadmap for this work concerns implementing additional spaces in our model (to allow open-ended discovery [123], [124], [125], [126]) and identifying the minimal properties that agents need to have to exploit their multicellularity to find new problems to solve in new problem spaces. In parallel, it would be important to study the question of how an external observer can detect (and ideally, predict) when and how a given system would transcend its initial environment.

F. Limitations of the Study

There were a number of limitations of this study that serve as the basis for future work. First, there are other ways to handle conditions upon which merge, split, and agent replacements happen – it will be interesting to explore the consequences of other policies. Second, our framework is spatially restricted to two dimensions with agents occupying discrete grid positions. This constraint restricts agents’ interactivity, and it will be interesting to see whether expanding to 3D or allowing movement (akin to Solé’s liquid brains, such as ant colonies [127], [128]), alters outcomes. Third, the number of memory states (and consequently, the size of the policy table) grows exponentially with memory size, preventing scaling up to memory sizes >10. Fourth, at memory sizes >2, a large number of memory states remain unvisited, with action probabilities in the policy-map changing little if any from their initialized state, rendering convergence impossible.

G. Future Work

A promising area for investigation is a better use of memory within agents. In the current model, high memory agents are always at a disadvantage relative to low memory agents because their world isn't stable enough to be modeled internally: they simply don't experience enough "states" from their vast memory to take advantage of it. It would be interesting to implement a kind of coarse-graining mechanism that would focus less on the exact specifics of move history for each player and more on general categories of "friend vs. foe" or some other automatically-inferred classifications. This would drastically reduce the size of the space of specific actions that need to be looked up to determine how to act in any given situation. One specific mechanism that could be added is the Active Inference framework, which has begun to be studied in the context of collective intelligence [129], [130]. Also, a useful extension of the work might be to explicitly examine the use of Cooperate/Defect behaviors as messages between agents that become exploited for communication [131], [132], [133]. A final extension concerns the analysis of the emergent dynamics. It would be interesting and important to ask what an external observer, who did not know the ground truth of which agents were merged with which neighbors, would conclude – where would they draw the lines of apparent agents? Knowing how to draw borders between higher-level emergent entities, within a sea of subunits, is a challenging open question in areas ranging across developmental biology, exobiology, and social sciences. Where are the emergent virtual governors [134], [135] and how does one recognize them? We envision a parallel system of observers evolving, which can do observational and perturbational experiments to optimize its model of where the causal agency is to be found in this multiscale system [50], [51], [52], [53], [54], [55], [56], as a future roadmap for evolving our understanding of detection of emergent beings in unfamiliar substrates [136].

V. CONCLUSION

The origins of complexity, agency, and multi-scale organization in the biosphere is an exciting and active topic of research. Its relevance spans evolutionary developmental biology, regenerative medicine of birth defects and cancer, and the cognitive science of the scaling of behavior from basal origins in simple agents. Combining game theory dynamics with agents' control over shifting self-world boundaries revealed a number of surprising emergent features observed in the biological world. This may be the beginning of an exciting roadmap that reveals minimal metabolic dynamics sufficient for the appearance and scale-up of key structural, functional, and informational properties. This in turn may lead to improved ability to detect, repair, and create such systems in a plethora of diverse embodiments.

ACKNOWLEDGMENT

The authors thank Julia Poirier for assistance with the manuscript.

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