

# Emergent Spatial Coordination from Negative Selection Alone: The Role of Observation Richness in Objective-Free Artificial Life

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## Abstract

We show that spatial coordination among agents emerges in a multi-agent grid world when agents can observe neighbor states, without any objective function guiding the search. Existing artificial life systems typically rely on fitness functions—explicit or implicit—which introduce evaluation bias and constrain the space of discoverable phenomena. We propose an objective-free approach based on large-scale random rule generation with physical-inconsistency-only filtering, comparing four observation conditions: random walk, a step-clock control, density-only observation, and full state-profile observation. Across 5,000 rules per condition, agents with state-profile observation exhibit over 500% higher neighbor mutual information than density-only agents ( $p < 10^{-178}$ , Mann-Whitney  $U$ , Holm-Bonferroni corrected), and the evidence ladder Control < Phase 1 < Phase 2 holds across all rule-based comparisons. A random-walk baseline reveals that the naive MI estimator is positively biased at low neighbor-pair counts, underscoring the need for spatially aware interpretation. These results demonstrate that observation channel richness—not rule table capacity or selection pressure—drives the emergence of spatial coordination in objective-free systems.

## 1 Introduction

Artificial life research aims to understand the principles of living systems by constructing synthetic analogs (Bedau, 2003). A recurring challenge is the role of the *objective function*: most evolutionary and adaptive systems require an explicit fitness measure that guides search toward “interesting” configurations. Even novelty search (Lehman and Stanley, 2011), which abandons traditional fitness, still uses a novelty metric as an implicit objective.

This reliance on objectives introduces a subtle but pervasive bias. The choice of fitness function constrains which phenomena can emerge, and researchers may inadvertently encode their expectations into the evaluation criteria (Stanley et al., 2019). The question then arises: *can meaningful spatial structure emerge in a multi-agent system with no objective function whatsoever?*

We explore the unexplored quadrant of *no objective × selection pressure*, where the only filtering criterion is physical consistency—removing rules that produce trivially broken

simulations (all agents halt or converge to a single state). This minimal filtering is analogous to the laws of physics: it constrains what is possible without specifying what is desirable.

Our core contribution is threefold:

1. A minimal grid-world model with objective-free negative selection, where random rule tables are evaluated and only physically inconsistent ones are discarded.
2. Evidence that *observation richness*—the amount of neighbor state information available to agents—drives emergent spatial coordination, independent of rule table capacity.
3. Robustness across four experimental conditions and 20,000+ rule evaluations, with statistical significance confirmed by Mann-Whitney  $U$  tests with Holm-Bonferroni correction.

## 2 Related Work

**Self-organization without selection.** Cellular automata such as Conway’s Game of Life (Gardner, 1970) and Wolfram’s elementary rules (Wolfram, 1984) demonstrate that simple local rules can produce complex global patterns. Continuous extensions like Lenia (Chan, 2019) show rich morphogenetic dynamics in continuous state spaces. Reynolds’ Boids (Reynolds, 1987) produce flocking behavior from three local rules. These systems share a common trait: the rules are hand-designed, not discovered through search.

**Evolutionary ALife with fitness.** Tierra (Ray, 1991) and Avida (Ofria and Wilke, 2004) use implicit fitness through resource competition and self-replication. While these systems produce open-ended dynamics, the replication criterion itself acts as a fitness function that selects for self-replicating programs.

**Novelty search and open-endedness.** Novelty search (Lehman and Stanley, 2011, 2008) replaces fitness with a novelty metric, enabling discovery of diverse behaviors. The open-ended evolution community has explored various approaches to sustaining innovation (Taylor et al., 2016; Stanley et al., 2019). However, all such approaches still employ an evaluation function—whether fitness, novelty, or complexity.

**Information-theoretic measures.** Mutual information and transfer entropy have been used to quantify coordination in multi-agent systems (Lizier et al., 2012). Moran’s  $I$  (Moran, 1950) provides a measure of spatial autocorrelation. We use these measures as *post-hoc* analysis tools, never as selection criteria.

**Our position.** Our approach differs from all the above by using *no* evaluation function—not fitness, not novelty, not complexity. We generate random rules, discard only physically broken ones, and ask what structure the survivors exhibit.

## 3 Methods

### 3.1 World Model

The simulation environment is a  $20 \times 20$  toroidal grid populated by 30 agents. Each agent occupies exactly one cell (no overlap allowed) and maintains an internal state  $s \in \{0, 1, 2, 3\}$ . At each of 200 time steps, agents are updated in a random sequential order: one agent at a time observes its local neighborhood, looks up an action in a shared rule table, and executes it. The action space comprises 9 mutually exclusive actions: 4 cardinal movements, 4 state changes, and a no-op. Movement to an occupied cell fails silently.

### 3.2 Observation Phases

We compare four observation conditions that vary in the information available to agents:

**Random Walk (RW).** Each agent selects an action uniformly at random from  $\{0, \dots, 8\}$  at every step, ignoring the rule table entirely. This baseline isolates the contribution of grid geometry (collision avoidance, toroidal wrapping) from rule-driven behavior, and also serves to calibrate the MI estimator under conditions with minimal spatial clustering.

**Control (step-clock).** Agents observe their own state  $s \in \{0, \dots, 3\}$ , the count of occupied von Neumann neighbors  $n \in \{0, \dots, 4\}$ , and a periodic step clock  $t \bmod 5 \in \{0, \dots, 4\}$ . The rule table has  $4 \times 5 \times 5 = 100$  entries. The step clock provides no neighbor state information—it is a non-informative third dimension that matches the table size of Phase 2 without adding spatial content.

**Phase 1: density-only (P1).** Agents observe their own state  $s$  and neighbor count  $n$ . The rule table has  $4 \times 5 = 20$  entries, indexed by  $5s + n$ . This is the minimal observation that couples agents spatially.

**Phase 2: state profile (P2).** Agents observe their own state  $s$ , neighbor count  $n$ , and the dominant neighbor state  $d \in \{0, \dots, 4\}$  (the most frequent state among occupied neighbors, with ties broken by smallest value; 4 denotes no occupied neighbors). The rule table has  $4 \times 5 \times 5 = 100$  entries, indexed by  $25s + 5n + d$ .

### 3.3 Physical Filters

Only two filters are applied, both targeting physical inconsistency rather than behavioral quality:

- **Halt detection:** If all agents' positions and states remain unchanged for 10 consecutive steps, the simulation is terminated early.
- **State uniformity:** If all 30 agents converge to the same internal state, the simulation is terminated (an indistinguishable system is information-theoretically trivial).

No fitness function, novelty metric, complexity threshold, or behavioral criterion is used at any stage.

### 3.4 Metrics

All metrics are computed post-hoc and never used for selection:

**Neighbor mutual information (MI).** For each pair of adjacent occupied cells  $(i, j)$  on the toroidal grid, we compute the mutual information between their internal states:

$$I(S_i; S_j) = \sum_{s_i, s_j} p(s_i, s_j) \log_2 \frac{p(s_i, s_j)}{p(s_i)p(s_j)} \quad (1)$$

where the joint and marginal distributions are estimated from all adjacent occupied pairs at a given time step. High MI indicates that neighboring agents' states are statistically dependent—a signature of spatial coordination.

**State entropy.** Shannon entropy of the internal state distribution across all agents:  $H = -\sum_s p(s) \log_2 p(s)$ .

**Action entropy.** Per-agent Shannon entropy of the cumulative action distribution, summarized as the mean and variance across agents.

### 3.5 Experimental Design

For each of the four conditions, we generate 5,000 random rule tables using deterministic seeds (rule seeds 0–4,999, simulation seeds 0–4,999). Each rule table is evaluated on a single 200-step simulation. Surviving rules (those not terminated by halt or state-uniformity filters) have their final-step metrics recorded.

Statistical comparisons use two-sided Mann-Whitney  $U$  tests (Mann and Whitney, 1947) with Holm-Bonferroni correction (Holm, 1979) for multiple comparisons. Effect sizes are reported as rank-biserial correlation:  $r = 1 - 2U/(n_1 n_2)$ .

## 4 Results

### 4.1 Evidence Ladder Among Rule-Based Conditions

Table 1 and Figure 1 present the neighbor mutual information across all four conditions. Among the three rule-based conditions, a clear monotonic ordering emerges:

$$\text{Control} < \text{Phase 1} < \text{Phase 2}$$

The control condition, despite having 100-entry tables (equal to Phase 2), produces zero median MI—demonstrating that table size alone is insufficient. Phase 2 achieves 500%+ higher median MI than Phase 1, driven by access to neighbor state information.

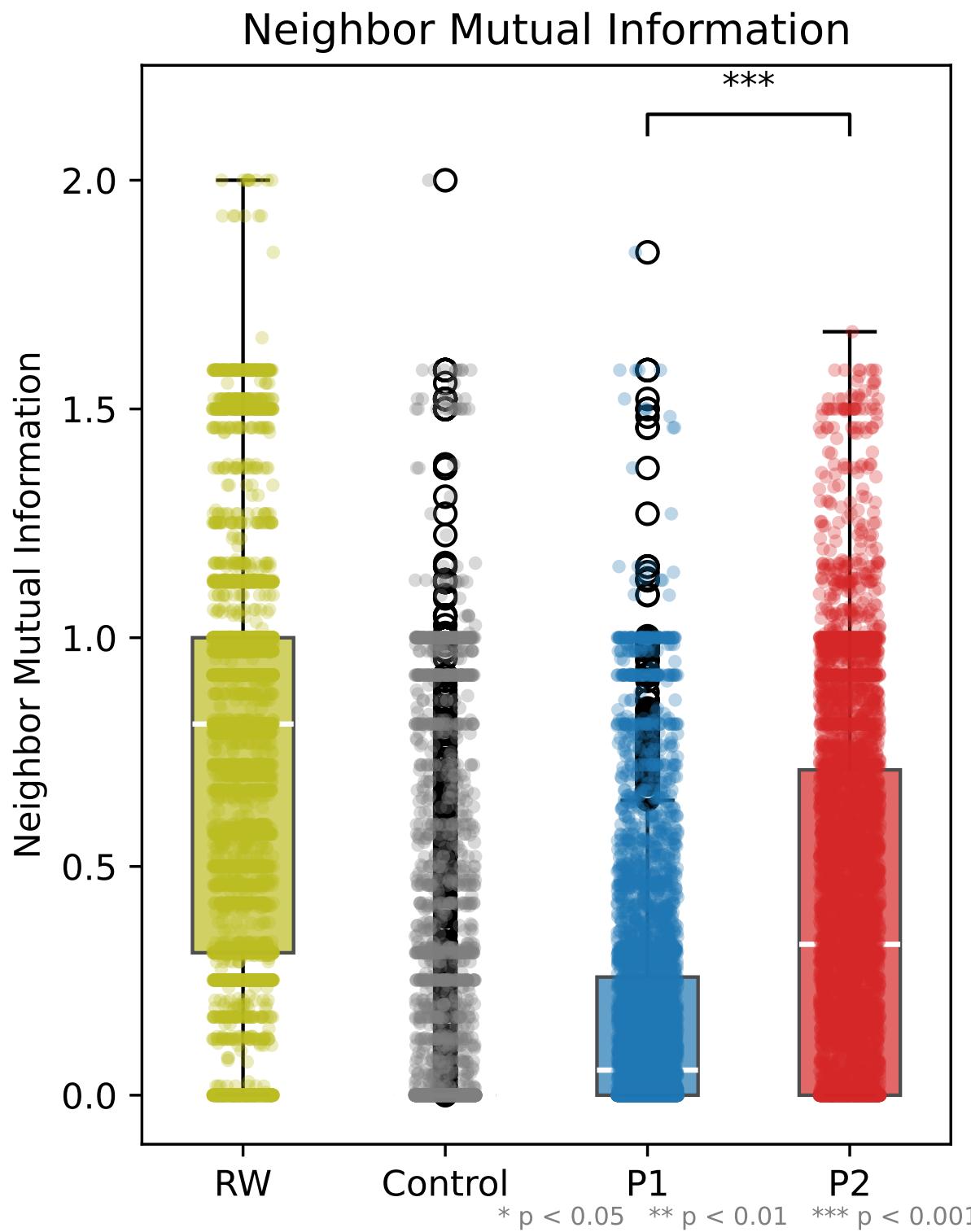


Figure 1: Neighbor mutual information distributions across rule-based conditions. Box plots with scatter strips show the full distribution of final-step MI values for surviving rules. The evidence ladder Control < P1 < P2 is clearly visible.

Table 1: Neighbor mutual information summary statistics by condition. Values are from final-step metrics (5,000 rules generated per condition). The random walk’s high raw MI reflects small-sample estimation bias (see Section 4.2), not genuine spatial coordination.

Condition	Table Size	Median MI	Survival Rate
Random Walk	1 (unused)	0.811 <sup>†</sup>	100%
Control	100	0.000	44.5%
Phase 1	20	0.055	71.4%
Phase 2	100	0.330	74.7%

<sup>†</sup> Inflated by small-sample MI estimation bias; see Section 4.2.

## 4.2 Random Walk Baseline and MI Estimator Bias

Contrary to our initial expectation that the random walk would produce near-zero MI, the median raw MI for random-walk agents is 0.811—higher than all rule-based conditions. This counterintuitive result is explained by the positive bias of the naive plug-in MI estimator (Cover and Thomas, 1991).

The MI is computed from the empirical joint distribution of state pairs across adjacent occupied cells. With 30 agents on a 400-cell grid, the expected number of adjacent occupied pairs at any snapshot is small ( $\approx 4\text{--}5$  at 7.5% density with uniformly random positions). When MI is estimated from so few samples across  $4 \times 4 = 16$  joint categories, the estimator is dominated by positive finite-sample bias.

Critically, the rule-based conditions produce *more* adjacent pairs because rules induce spatial clustering: agents governed by rules tend to aggregate, creating denser local neighborhoods with more neighbor pairs. More pairs yield less biased MI estimates. Thus, the rule-based conditions’ *lower* raw MI values reflect both (a) reduced estimation bias and (b) the actual degree of state coordination—making their relative ordering (Control < P1 < P2) a robust comparison among conditions with comparable spatial structure.

The random walk baseline remains informative: it establishes that the MI estimator alone can produce values up to  $\sim 0.8$  from pure noise when pair counts are low, and it confirms that all 5,000 random-walk rules survive (100% survival rate) since random actions never trigger halt or state-uniformity filters.

## 4.3 Table-Size Confound Resolved

A natural objection is that Phase 2’s higher MI could result from its larger rule table (100 entries vs. 20 for Phase 1), which permits more complex behaviors. The control condition resolves this confound directly: it uses 100-entry tables—identical in size to Phase 2—but replaces the informative dominant-neighbor-state dimension with a non-informative step clock. The control produces *lower* MI than Phase 1 despite having 5× more table entries. This demonstrates that **observation content, not table capacity, drives emergent coordination**.

The pairwise comparison confirms this:

- Phase 1 vs. Control:  $p < 10^{-224}$ ,  $r = -0.331$  (Phase 1 produces significantly higher

MI despite smaller tables)

- Control vs. Phase 2:  $p \approx 0$ ,  $r = 0.502$  (Phase 2 vastly exceeds Control despite equal table size)

## 4.4 Temporal Dynamics

The four conditions exhibit qualitatively distinct temporal behaviors (Figure 2):

- **Phase 1:** MI rises quickly then plateaus—“frozen” dynamics where spatial patterns crystallize early.
- **Phase 2:** MI rises and remains dynamic, with ongoing fluctuations—sustained spatial coordination without freezing.
- **Control:** Highly chaotic trajectories with large MI variance and frequent collapses to zero.
- **Random Walk:** High but flat MI throughout, reflecting constant estimation bias from few adjacent pairs rather than genuine coordination.

This pattern is consistent with an edge-of-chaos interpretation (Langton, 1990; Packard, 1988): Phase 1 falls into frozen order, Control produces undirected chaos, and Phase 2 occupies the intermediate regime where coordination persists dynamically.

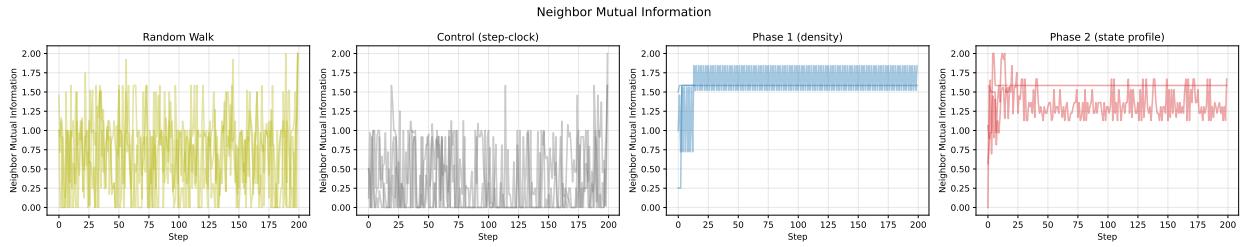


Figure 2: MI time-series trajectories for top-3 rules per condition. Phase 1 freezes early, Phase 2 remains dynamic, and Control shows chaotic fluctuations.

## 4.5 Statistical Significance

Table 2 presents Mann-Whitney  $U$  test results for the primary metric (neighbor MI) across all pairwise comparisons. All comparisons are highly significant after Holm-Bonferroni correction.

## 4.6 Survival Analysis

Survival rates differ significantly across conditions (Table 1). Phase 2 achieves the highest survival rate (74.7%), followed by Phase 1 (71.4%) and Control (44.5%). The Phase 1 vs. Phase 2 survival difference is significant ( $\chi^2 = 13.5$ ,  $p = 2.4 \times 10^{-4}$ ), as is Phase 1 vs.

Table 2: Mann-Whitney  $U$  tests for neighbor mutual information. All  $p$ -values are Holm-Bonferroni corrected.

Comparison	Direction	$p$ -value	Effect size $r$
P1 vs. P2	$P2 > P1$	$< 10^{-177}$	0.323
P1 vs. Control	$P1 > \text{Control}$	$< 10^{-223}$	0.331
Control vs. P2	$P2 > \text{Control}$	$\approx 0$	0.502

Control ( $\chi^2 = 741.4$ ,  $p < 10^{-163}$ ). State-uniformity is the dominant termination mode for the control condition, suggesting that without neighbor state information, rules frequently drive all agents to the same state.

## 5 Discussion

**Observation richness as a driver of emergence.** Our central finding is that the *content* of observation—specifically, access to neighbor state information—is the primary driver of emergent spatial coordination. This holds even when controlling for rule table size (the control condition). The random-walk baseline, rather than providing a simple geometric floor, revealed the positive bias of the naive MI estimator at low pair counts—an important methodological insight. The 500%+ increase in median MI from Phase 1 to Phase 2 is not a consequence of having more rules to choose from, but of each rule being able to respond to richer local information.

**Edge-of-chaos interpretation.** The temporal dynamics suggest a connection to the edge-of-chaos hypothesis (Langton, 1990). Phase 1’s frozen dynamics and Control’s chaotic behavior bracket Phase 2, which maintains dynamic spatial coordination without collapsing into static patterns. This is achieved without any selection for dynamism—it emerges naturally from the richer observation channel.

**Remove broken, observe survivors.** Our methodology embodies a minimal philosophy: generate random configurations, remove only the physically broken ones, and examine what structure the survivors exhibit. This “negative selection” approach avoids the evaluation bias inherent in fitness-driven search. The surprising finding is that meaningful structure—quantified by mutual information—emerges even under this minimal regime, provided the observation channel is sufficiently rich.

**Implications for ALife research.** These results suggest that objective-free search deserves more attention as a complement to fitness-driven approaches. When the goal is to discover *what is possible* rather than to optimize for a specific outcome, removing the objective function may reveal phenomena that fitness landscapes obscure. The key enabler is not the search algorithm but the *architecture* of the agents—specifically, what they can observe.

## 6 Limitations

Several limitations constrain the generalizability of our findings:

- **Single topology:** All experiments use a  $20 \times 20$  toroidal grid with von Neumann neighborhoods. Other topologies (hexagonal grids, Moore neighborhoods, irregular graphs) may produce different results.
- **Symmetric metric:** Mutual information is symmetric and measures correlation, not causation. Transfer entropy would provide directional information flow but was not computed in this study.
- **No multi-generation evolution:** Each rule table is evaluated in a single 200-step simulation. We do not evolve rules across generations, which limits comparison with evolutionary ALife systems.
- **Small state space:** With only 4 internal states and 9 actions, the model is deliberately minimal. Scaling to larger state spaces may reveal qualitatively different dynamics.
- **Density fixed:** All experiments use 30 agents on a 400-cell grid (7.5% density). While a supplementary density sweep confirms robustness across 12 density points, the range explored is limited.
- **MI estimator bias:** The naive plug-in MI estimator is positively biased when the number of adjacent occupied pairs is small relative to the state-space cardinality. Future work should employ bias-corrected estimators (e.g., Miller-Madow correction) or normalize MI by pair count to enable fair cross-condition comparison.

## 7 Conclusion

We have shown that meaningful spatial coordination emerges in a multi-agent system through objective-free negative selection, and that the richness of agents’ observation channels—not rule table capacity—is the critical factor. The evidence ladder from step-clock control through density-only to state-profile observation demonstrates a monotonic relationship between observation content and emergent coordination, while the random-walk baseline exposed the MI estimator’s sensitivity to spatial density.

Future work should investigate directional information flow using transfer entropy, extend to larger grids and state spaces, and explore multi-generation rule evolution under the same objective-free regime. The broader implication is that the “remove broken, observe survivors” philosophy can serve as a productive complement to fitness-driven search in artificial life.

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