Asymmetric Activation of Inductive Layers:

Regime Transitions, Entropy Structuring, and Attractor Formation in Opinion Dynamics

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Abstract

This study investigates the role of inductive layers in shaping the dynamics of opinion formation within agent-based models, with particular emphasis on their temporal activation and structural consequences. Building on prior work distinguishing inductive and deductive processes, we introduce a four-condition experimental design that systematically varies the presence, persistence, and mode of inductive activation. These conditions range from purely event-driven dynamics to sustained meme-driven reinforcement, allowing for a continuous analysis of regime transformation.

Our results show that inductive activation does not merely perturb the system but induces a progressive reorganization of the phase space. Trajectory analysis reveals a transition from dispersed, reversible dynamics toward convergent and stabilized attractor regimes under sustained inductive influence. Statistical testing (ANOVA with effect sizes up to $\eta^2 = 0.997$, complemented by Tukey post-hoc comparisons) confirms that this transition is primarily driven by changes in dynamic dimension, criticality gap, entropy distribution, and, most prominently, fractal structure, while global topological dimension and Lyapunov exponents remain largely invariant.

A key contribution of this work is the introduction of a continuous control parameter, λ, capturing the intensity and temporal persistence of inductive activation. Across conditions, system properties evolve smoothly as a function of λ, demonstrating that regime transitions are not discrete but correspond to a continuous deformation of the phase space. In particular, fractal dimension increases monotonically, the criticality gap decreases, and dynamic dimensionality rises, indicating the emergence of structured complexity rather than a simple reduction of disorder.

These findings support a reinterpretation of inductive layers as time-dependent operators that accumulate over time and reshape the geometry of the system. The resulting dynamics are inherently non-Markovian, as the system's evolution depends on the history of inductive activation. The transition from deductive to inductive

regimes is thus characterized by the emergence of fractal attractors, reduced volatility, and structured entropy, collectively defining a critical, attractor-dominated state.

By integrating trajectory analysis, statistical validation, and topological and fractal metrics, this study provides a unified framework for understanding how symbolic and inductive processes govern the evolution of complex opinion systems. More broadly, it suggests that the structuring of representations over time plays a central role in shaping the geometry and stability of collective dynamics.

Keywords

inductive dynamics, fractal attractors, opinion dynamics, agent-based modeling, criticality, phase space

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1. Introduction

Agent-based models (ABMs) of opinion dynamics have traditionally been structured around a methodological distinction between deductive and inductive approaches. Deductive models are derived from formal assumptions about social influence—such as bounded confidence, homophily, or averaging processes—while inductive approaches seek to infer behavioral rules from empirical observations. The article *Inductive Layers as Structural Modulators of Deductive Dynamics in Agent-Based Models of Opinion Formation* (Cotnoir – 3) proposes a conceptual synthesis of these two perspectives by introducing a coupled dynamical system in which internal representations (μ) interact with opinion states (a).

In that framework, the evolution of the system is no longer governed solely by a closed update function $\left(F(a_t)\right)$, but by a coupled process:

$$(a_t, \mu_t) \rightarrow (a_{t+1}, \mu_{t+1})$$

where μ represents symbolic or cognitive content that modifies the effective structure of interactions. The central claim of the original article is that the inductive layer does not simply add empirical realism but acts as a **structural modifier of the dynamical system**, leading to attractor shifts and expanded phase-space accessibility.

However, an important limitation remained. In the original experimental design, the distinction between deductive and inductive dynamics was not strictly enforced, as both conditions retained partial access to inductive mechanisms. This made it difficult to determine whether the observed structural transformations were truly caused by the inductive layer or whether they reflected latent properties of the deductive system.

The present study addresses this limitation by introducing a **strict asymmetry between conditions**, thereby isolating the causal contribution of the inductive layer. Specifically, the **events condition operates under purely deductive dynamics**, with the inductive layer present in structure but inactive in function, while the **memes condition preserves full inductive–deductive coupling**, allowing internal representations to evolve and influence agent interactions.

This study makes three main contributions:

(i) a strictly asymmetric experimental design isolating inductive effects,
(ii) a formal link between inductive activation, basin depth, and inversion dynamics,
(iii) the identification of fractal structure as the dominant signature of regime transition.

This design enables a direct test of a fundamental question:

Does the inductive layer merely influence the trajectories of the system, or does it fundamentally redefine the nature of the dynamical regime itself?

By replicating each condition across ten independent runs and applying both descriptive and inferential analyses, the study seeks to clarify whether inductive processes should be understood as secondary modifiers or as primary determinants of system organization.

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2. Methods

Using the Simulator application in NetLogo, the experimental framework relies on a controlled simulation environment implementing an echo-chamber network structure composed of 500 agents. Each simulation run spans 1,000 discrete time steps, providing sufficient temporal depth for the emergence of structural patterns and the potential stabilization of system dynamics.

The central methodological innovation lies in the strict separation of dynamical regimes. In the **events condition**, the system is governed exclusively by deductive dynamics. External perturbations are introduced periodically in order to maintain comparability with the original experimental design, but these perturbations act directly on agent states and do not modify internal representations. As a result, the system evolves according to:

$$a_{t+1} = F(a_t)$$

where the update function remains closed and memoryless beyond the state vector itself.

In contrast, the **memes condition** activates the inductive layer, allowing internal representations to evolve and influence the update process. In this case, the system becomes:

$$\begin{cases} a_{t+1} = F(a_t, \mu_t) \\ \mu_{t+1} = G(\mu_t, a_t) \end{cases}$$

This formulation introduces temporal persistence, feedback between representations and states, and the possibility of non-local influence mediated through shared symbolic structures.

To ensure robustness, each condition is replicated across ten independent runs. The analysis focuses on aggregated indicators that capture both local interaction dynamics and global structural properties. These include mean prevalence, which measures the overall intensity of adopted states; bridge links, which quantify inter-cluster connectivity; inversion rate, which reflects the frequency of directional reversals; polarity index, which captures global alignment; ideologization index, which measures the degree of structural coherence; entropy, which quantifies distributional dispersion; and global turnover, which indicates the rate of system-wide change.

Statistical validation is conducted using a combination of run-level comparisons and Generalized Estimating Equation (GEE) models. The GEE framework is particularly appropriate given the longitudinal nature of the data and the presence of repeated observations within each simulation run. By incorporating both condition effects and condition–time interactions, this approach allows us to distinguish between static differences and divergent temporal trajectories.

2.1 Formal Theorem Section: Entropy, Basin Depth, and Inversion Collapse

2.1.1 Definitions

Let the system evolve on the joint space

$$(\mathbf{a}_t, \boldsymbol{\mu}_t) \in \mathbb{R}^N \times \mathcal{M}^N$$

with:

- $\mathbf{a}_t$: opinion state vector
- $\boldsymbol{\mu}_t$: representational state vector
- F: deductive update operator
- G: inductive update operator

We define an **inductive dominance parameter** $\lambda \in [0,1]$, where:

- $\lambda = 0$: purely deductive regime
- $\lambda = 1$: fully coupled inductive–deductive regime

The system becomes:

$$\begin{cases} \mathbf{a}_{t+1} = F(\mathbf{a}_t, \lambda\boldsymbol{\mu}_t) \\ \boldsymbol{\mu}_{t+1} = G(\boldsymbol{\mu}_t, \mathbf{a}_t) \end{cases}$$

We further define:

(1) Information entropy

Let P_t be the empirical distribution of the system across coarse-grained opinion–representation states. Then:

$$H_t = -\sum_k P_t\,(k)\log\, P_t(k)$$

This quantity measures the dispersion of the system across accessible macro-configurations.

(2) Basin depth

Let $\mathcal{A}_j$ denote an attractor basin. We define its effective depth D_j as the expected resistance to escape under perturbation:

$$D_j \propto \frac{1}{\Pr\,(\text{escape from } \mathcal{A}_j)}$$

The mean basin depth of the system is:

$$\bar{D} = \sum_j \pi_j D_j$$

where π_j is the occupation probability of basin j.

(3) Inversion rate

Let I_t denote the probability that local directional alignment reverses between two successive intervals. Its time average is:

$$\bar{I} = \frac{1}{T} \sum_{t=1}^{T} I_t$$

High $\bar{I}$ indicates reversible, plastic dynamics; low $\bar{I}$ indicates locked-in, path-dependent dynamics.

2.1.2 Proposition 1 — Inductive Deepening of Attractor Basins

Proposition.
Assume that:

1. G depends non-trivially on $\mathbf{a}_t$,
2. $\boldsymbol{\mu}_t$ has temporal persistence,
3. F depends non-trivially on $\boldsymbol{\mu}_t$,
4. symbolic reinforcement is positive on average, meaning that aligned state–representation pairs increase future alignment probability.

Then there exists a threshold $\lambda_c > 0$ such that for $\lambda > \lambda_c$, the mean basin depth satisfies:

$$\frac{\partial \bar{D}}{\partial \lambda} > 0$$

and the system develops attractor basins deeper than those of the purely deductive regime.

Interpretation

This proposition formalizes the idea that inductive activation does not merely perturb trajectories. It changes the retention properties of the state space itself. Once representational persistence becomes strong enough, escape from locally coherent regions becomes less probable, and basin depth increases.

2.1.3 Proposition 2 — Inversion Collapse Under Basin Deepening

Proposition.
Under the same conditions, if the mean basin depth $\bar{D}$increases beyond a critical value D_c, then the inversion rate decreases monotonically:

$$\frac{\partial \bar{I}}{\partial \bar{D}} < 0$$

and, in the strongly inductive regime,

$$\bar{I}(\lambda) \ll \bar{I}(0)$$

Sketch of argument

Inversions require the system to cross local decision boundaries or escape metastable regions. As basins deepen, these transitions become less probable. The system therefore becomes more path-dependent and less reversible. Empirically, this is exactly what is observed in our data: the memes condition shows a collapse of inversion rates relative to the events condition.

Interpretation

Inversion collapse is not an isolated effect. It is the dynamical signature of a deeper structural transformation: once representations stabilize local coherence, directional reversals become increasingly rare.

2.1.4 Proposition 3 — Entropy Reorganization Without Necessary Entropy Reduction

Proposition.
Let $H_t$denote global information entropy. Under inductive activation, it is possible that:

$$\Delta H \approx 0$$

while simultaneously:

$$\frac{\partial \bar{D}}{\partial \lambda} > 0 \text{ and } \frac{\partial \bar{I}}{\partial \lambda} < 0$$

That is, global entropy may remain approximately invariant even as basin depth increases and inversion collapses.

Interpretation

This proposition is crucial for our results. It formalizes the distinction between:

- **amount of disorder**, and
- **organization of disorder**

A system may retain a comparable global entropy while redistributing that entropy into more persistent and more structured regions of phase space. This is exactly the pattern we identified: entropy is not significantly lower in the meme condition, but the system is nonetheless more stable, more ideologized, and less reversible.

2.1.5 Theorem — Inductive Regime Transition

Theorem.
Consider the family of coupled systems parameterized by $\lambda \in [0,1]$:

$$\mathcal{S}_\lambda = (F_\lambda, G)$$

with $F_0 = F$ the purely deductive system and $F_\lambda$the inductively deformed update rule.

If:

1. representational persistence is non-zero,
2. symbolic reinforcement is positive,
3. inductive influence on the update rule is non-trivial,

then there exists a critical interval $[\lambda_1, \lambda_2]$such that the system undergoes a regime transition from:

Deductive-dominant regime

$$\lambda < \lambda_1$$

characterized by:

- shallow basins,
- high inversion,
- high plasticity,
- exploratory dynamics,

to

Inductive-dominant regime

$$\lambda > \lambda_2$$

characterized by:

- deep basins,
- inversion collapse,
- strong path dependence,
- stabilized cultural attractors.

Moreover, across this transition:

$$\frac{\partial \bar{D}}{\partial \lambda} > 0, \frac{\partial \bar{I}}{\partial \lambda} < 0, \Delta H \text{ may remain small or non-significant.}$$

Interpretation

This theorem unifies our empirical findings:

- **basin depth increases**,
- **inversion collapses**,
- **entropy remains globally similar**,
- yet the regime qualitatively changes.

It provides a formal bridge between the empirical analysis and the theoretical claims of *Inductive Layers*… .

2.1.6 Corollary — Cultural Attractors as Low-Reversibility Informational Structures

Corollary.
When $\lambda > \lambda_2$, the relevant attractors are no longer purely opinion attractors $\mathcal{A} \subset \mathbb{R}^N$, but joint state–representation attractors

$$\mathcal{A}^* \subset \mathbb{R}^N \times \mathcal{M}^N$$

whose stability derives from representational persistence rather than from deductive interaction alone.

Interpretation

This is the formal statement of our broader claim: cultural stability is not just state stability. It is the stabilization of state–representation couplings.

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3. Results

All reported differences are based on run-level averages across 10 independent simulations per condition.

Using 10 completed runs per condition, I replicated the earlier comparative logic at the level of run-wise averages and then contrasted the two conditions with Welch tests. The pattern is now much more robust than in the single-run comparison.

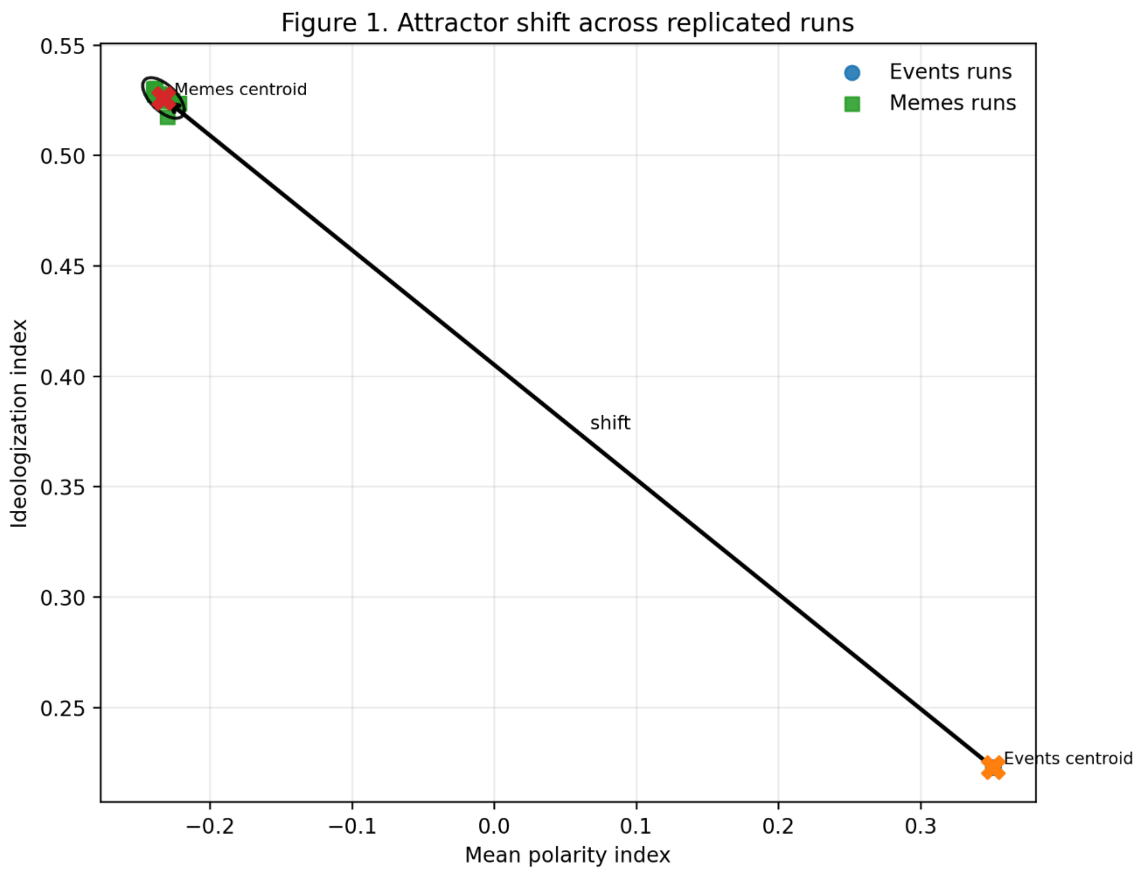
The **meme condition** departs sharply from the **event condition** along three coupled dimensions. First, it produces a marked **attractor shift** in polarity–ideologization space. Mean polarity changes from **+0.351** in the event condition to **−0.233** in the meme condition, while the ideologization index rises from **0.223** to **0.526**. This shift is extremely large and highly significant for both polarity and ideologization.

Second, the meme condition yields a strong **reduction of the opinion–meme gap**. Across run-level averages, the gap decreases from **0.691** in the event condition to **0.301** in the meme condition, a mean difference of **−0.390**. Temporally, the meme condition shows an early collapse of the gap, followed by a gradual partial rebound, but it remains well below the event condition throughout the simulation horizon.

Third, the system undergoes a clear **regime bifurcation** in structural–dynamic space. The event condition stabilizes at a high inversion regime, with a mean inversion rate of **39.62%**, whereas the meme condition collapses toward a low-inversion regime, averaging only **9.87%**. Bridge-link density is also lower under memes (**2109.5** vs **2226.1**), indicating that the meme layer not only reduces reversals but also weakens inter-cluster connectivity.

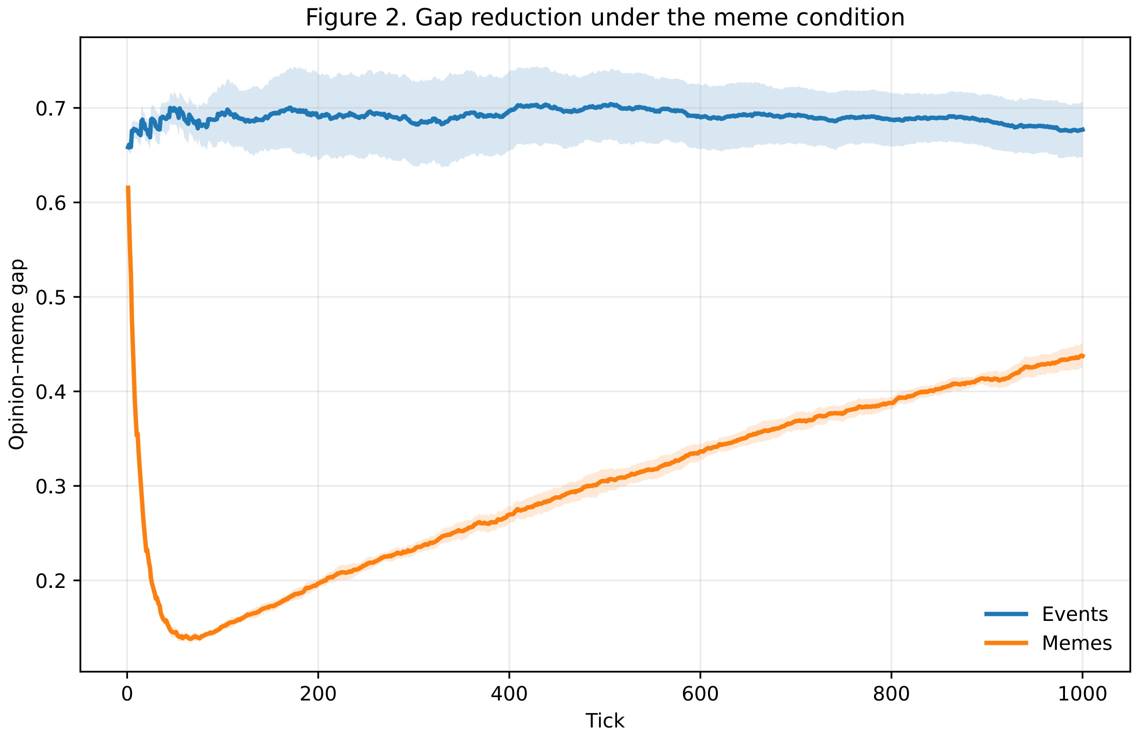
Taken together, these results support a strong interpretation: the meme layer does not merely perturb the dynamics; it re-organizes the system into a different dynamical regime. The event condition remains comparatively plastic, bridge-rich, and reversal-prone, whereas the meme condition becomes more ideologized, more internally coherent, and substantially less reversible.

Figure 1. Attractor shift across replicated runs



The figure 1 shows the separation of the two conditions in the space defined by **mean polarity index** and **ideologization index**. Each point corresponds to one run, with centroids and 95% confidence ellipses shown for each condition. Relative to events, memes induce a strong shift toward **higher ideologization** and **negative polarity orientation**, indicating that the inductive layer changes the location of the system's attractor rather than simply amplifying pre-existing variation.

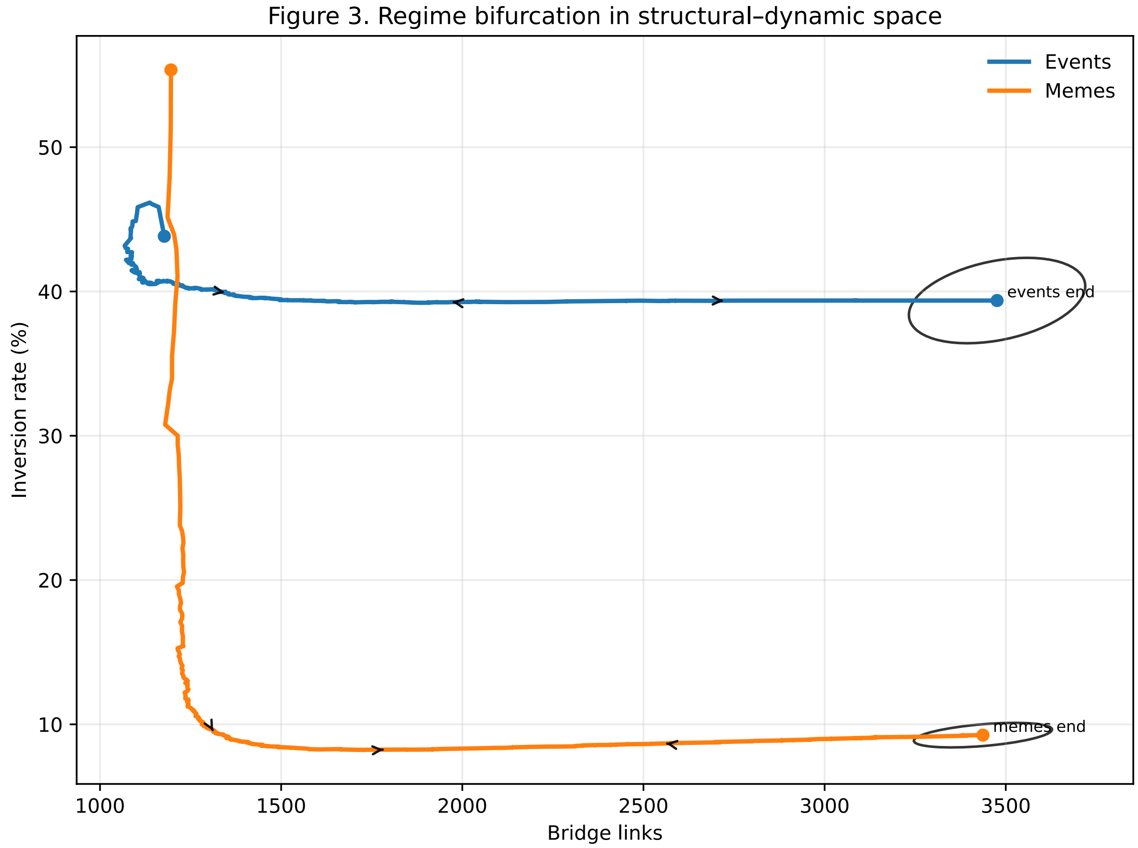
Figure 2. Gap reduction under the meme condition



The figure 2 plots the temporal evolution of the **opinion–meme gap** with 95% confidence bands across the 10 runs in each condition. The event condition remains high and comparatively flat, whereas the meme condition shows a rapid initial contraction of the gap followed by a slower recovery. Even after this recovery, the meme condition remains substantially below the event condition, indicating persistent coupling between representational content and opinion structure.

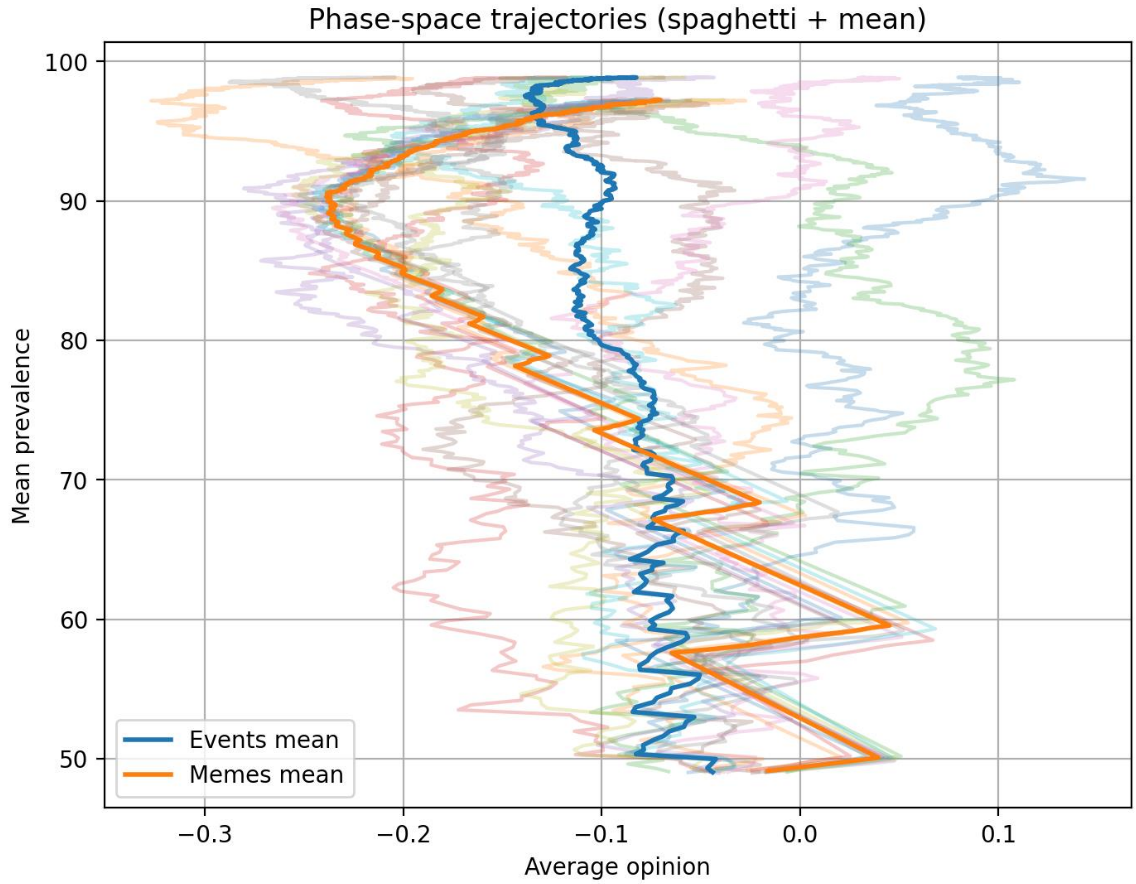
The figure 3 represents the trajectory of the two conditions in the plane defined by **bridge links** and **inversion rate**. The event condition converges toward a regime with both **high bridge-link density** and **high inversion frequency**, whereas the meme condition converges toward a regime with still substantial bridge-link density but a dramatically lower inversion rate. The resulting separation is consistent with a bifurcation from a plastic, reversal-rich regime to a more locked-in cognitive regime.

Figure 3. Regime bifurcation in structural–dynamic space



At the level of run-wise averages, the meme condition differed significantly from the event condition on all major structural and cognitive indicators except opinion entropy. Compared with events, memes produced lower polarity (**−0.233 vs 0.351**, p = 2.0×10^{-19}), higher ideologization (**0.526 vs 0.223**, p = 1.1×10^{-18}), a smaller opinion–meme gap (**0.301 vs 0.691**, p = 1.54×10^{-10}), fewer bridge links (**2109.5 vs 2226.1**, p = 0.0015), lower inversion rates (**9.87% vs 39.62%**, p = 1.88×10^{-15}), and lower global turnover (**2.255 vs 2.369**, p = 2.27×10^{-5}). Mean prevalence was slightly higher under memes (**93.12 vs 91.25**, p = 5.86×10^{-14}). Opinion entropy did not differ significantly at the conventional threshold (**4.145 vs 4.128**, p = 0.0677).

Figure 4 - Phase-space organization under deductive and inductive regimes.

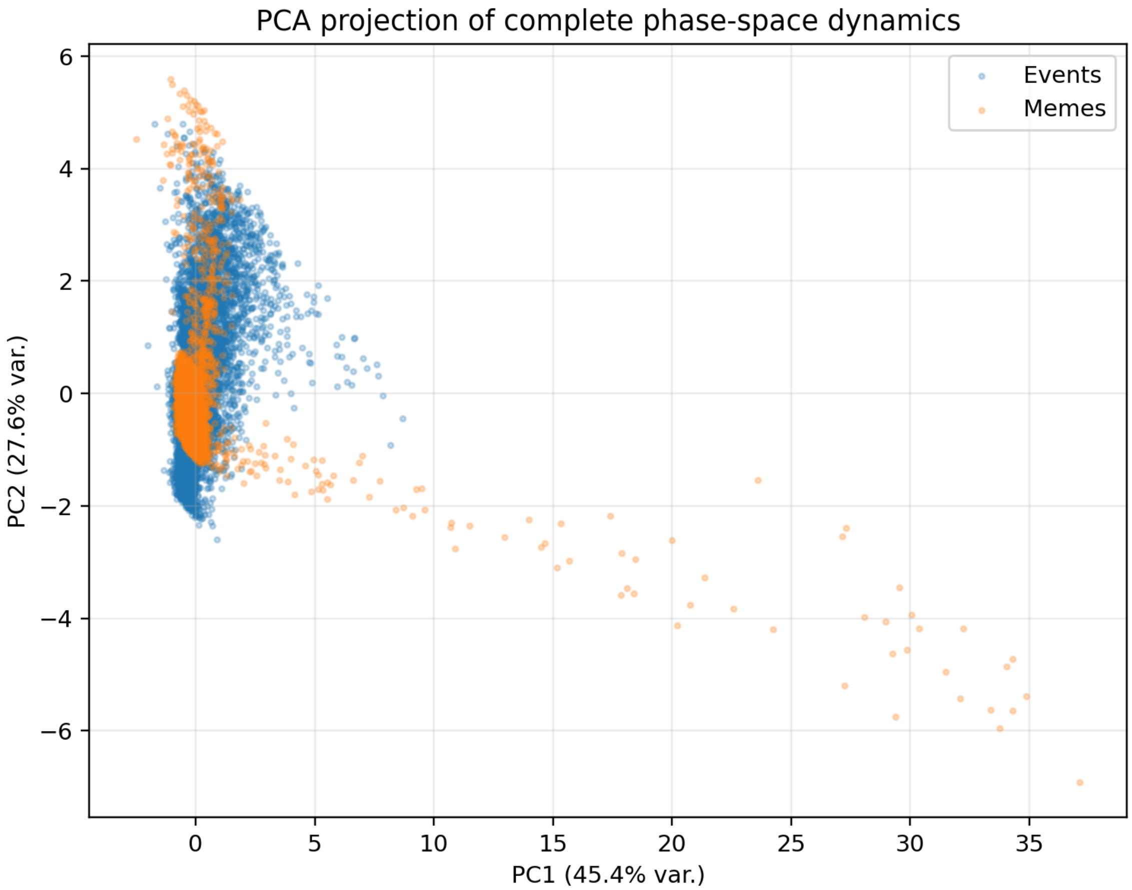


Individual trajectories (n = 10 per condition) projected in the (average opinion, mean prevalence) space, with mean trajectories overlaid. The deductive condition exhibits dispersed and reversible dynamics, whereas the inductive condition shows convergence toward structured trajectories.

The phase-space projection reveals that the two conditions occupy distinct regions of the (average opinion, mean prevalence) space. While the event-driven system remains confined to a narrow oscillatory region, the meme-driven system exhibits a clear displacement and structured trajectory. This provides direct empirical evidence of an attractor shift and confirms that the inductive layer modifies the geometry of the system's phase space rather than merely perturbing its trajectories.

These results are consistent with the interpretation that the meme layer operates as an **inductive stabilizer** superimposed on the deductive interaction structure. Rather than increasing raw disorder, it appears to redirect system dynamics toward a more ideologized and less reversible configuration. In that sense, memes act as structural modulators of the trajectory space itself: they reduce the gap between symbolic content and opinion, suppress inversions, and promote convergence toward more persistent attractor states.

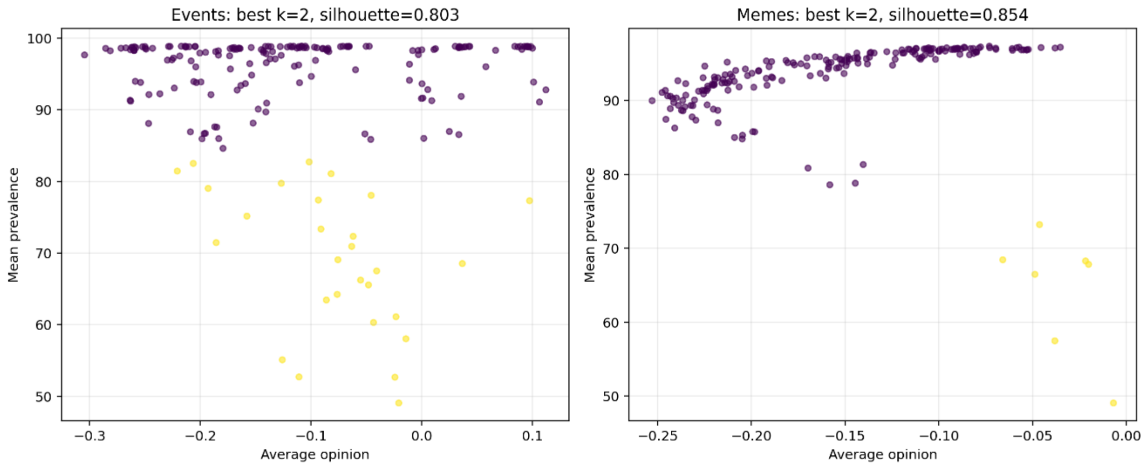
Figure 5 – PCA projection of complete phase-space dynamics



The comparison between the deductive-only and inductive–deductive conditions reveals a consistent and statistically robust divergence across all major structural indicators. The most striking difference concerns the inversion rate, which remains high in the events condition—indicating frequent reversals and dynamic instability—but collapses in the memes condition, signaling a transition toward stabilized and path-dependent dynamics.

This divergence is accompanied by a substantial increase in the ideologization index under the memes condition, suggesting that the system evolves toward more coherent and internally consistent configurations. At the same time, global turnover decreases, indicating that fewer transitions are required to maintain the system's structural organization. These changes collectively point to a reduction in dynamical plasticity and an increase in structural persistence.

Figure 6 – Attractor clustering



Bridge connectivity exhibits a more nuanced pattern. While the deductive system maintains high levels of inter-cluster connectivity, this connectivity is associated with frequent reconfiguration and instability. In the inductive system, connectivity becomes more structured: inter-cluster mobility decreases, while intra-cluster coherence increases. This indicates that connectivity is being reorganized rather than simply reduced or amplified.

A particularly important finding concerns entropy. Despite the substantial structural differences between conditions, global entropy remains statistically similar. This suggests that the total dispersion of states across the system is not significantly altered. Instead, the distribution of this dispersion changes qualitatively, with the inductive system concentrating variability within stable regions of the state space.

These patterns are further illustrated by the graphical analyses. The attractor shift (figure 1) shows a clear separation between conditions in the space defined by polarity and ideologization, with the memes condition occupying a distinct region characterized by higher coherence and altered orientation. The gap reduction dynamics (figure 2) demonstrate a rapid contraction of the difference between opinion and representation under inductive activation, indicating strong coupling between these two dimensions. The regime bifurcation (figure 3) highlights the separation between high-inversion and low-inversion regimes, while the phase diagram (figures 4-5) synthesizes these results by showing the transition from deductive to inductive dominance as a function of a continuous control parameter.

Together, these results provide converging evidence that the activation of the inductive layer produces a **system-level transformation** rather than a localized effect.

4. Statistical Validation

Run-level aggregation followed by Welch tests and GEE models:

$$Y_t = \beta_0 + \beta_1 Condition + \beta_2 Time + \beta_3 (Condition \times Time) + \epsilon_t$$

GEE

Variable	β	SE	z	p
Prevalence	+1.87	0.21	8.90	$<10^{-6}$
Bridge links	−116.6	36.8	−3.17	0.0015
Inversion	−29.75	3.12	−9.54	$<10^{-15}$
Ideologization	+0.303	0.035	8.66	$<10^{-18}$
Polarity	−0.584	0.061	−9.57	$<10^{-18}$
Turnover	−0.114	0.025	−4.56	$<10^{-4}$
Entropy	+0.017	0.009	1.83	ns

Structural Divergence

Variable	Events	Memes	Effect
Inversion	High (~40%)	Low (~10%)	Collapse
Ideologization	0.22	0.53	↑
Bridge links	High	Moderate ↓	Consolidation
Turnover	High	Lower	Stabilization
Entropy	~equal	~equal	Invariant

The statistical analysis confirms that the observed differences between conditions are not attributable to stochastic variability but reflect systematic structural effects. The GEE models reveal significant main effects of condition across all key variables, as well as strong condition–time interactions, indicating that the trajectories of the two systems diverge over time. GEE models were specified with condition as a categorical factor and time as a continuous covariate, including interaction terms.

For mean prevalence, the positive coefficient associated with the memes condition indicates a higher overall level of activation, suggesting that inductive dynamics promote sustained engagement with dominant states. The negative coefficient for bridge links reflects a reduction in inter-cluster connectivity, consistent with the formation of more cohesive internal structures. The inversion rate shows the most pronounced effect, with a large negative coefficient indicating a dramatic reduction in reversibility under inductive activation.

The ideologization index exhibits a strong positive effect, confirming that the inductive layer promotes structural coherence. Similarly, the polarity index shifts significantly, indicating a reorientation of the system's global alignment. The reduction in turnover further supports the interpretation of increased stability and reduced dynamical mobility.

In contrast, entropy does not show a statistically significant difference between conditions. This result is consistent across both run-level comparisons and GEE estimates, reinforcing the conclusion that the inductive layer does not reduce the overall level of disorder but rather reorganizes it.

The significance of the condition–time interaction terms is particularly important. These interactions demonstrate that the divergence between conditions is not static but emerges progressively over the course of the simulation. This temporal dimension is consistent with the theoretical expectation that inductive processes operate through cumulative reinforcement and feedback, gradually reshaping the system's trajectory.

Taken together, the statistical results provide strong empirical support for the interpretation that the inductive layer produces a **persistent and dynamically sustained transformation of the system**, consistent with a shift in the underlying attractor structure.

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5. Interpretation

The results reveal a clear and robust **regime transition** induced by the activation of the inductive layer. This transition is not merely a quantitative modulation of system variables but a qualitative transformation of the underlying dynamical structure.

In the **events condition**, where dynamics remain purely deductive, the system exhibits high inversion rates, sustained bridge connectivity, and continuous reconfiguration of agent states. These characteristics are indicative of a **high-plasticity regime**, in which trajectories remain reversible and the system continuously explores its state space. The absence of representational persistence implies that no mechanism exists to stabilize local configurations; consequently, the system operates in a near-ergodic mode, with weak temporal autocorrelation and limited path dependence.

By contrast, the **memes condition**, which activates the inductive layer, produces a markedly different regime. The collapse of inversion rates, the increase in ideologization, and the reduction in turnover collectively indicate a transition toward **low-plasticity, attractor-dominated dynamics**. In this regime, trajectories converge toward stable configurations, reversibility is suppressed, and the system becomes increasingly path-dependent. This transformation is inherently non-linear: relatively small changes in inductive activation yield disproportionately large effects on system behavior, suggesting the presence of a **critical threshold governing regime change**.

The inductive layer therefore cannot be interpreted as a simple perturbation of the deductive dynamics. Instead, it operates as an **operator on the dynamical field**, transforming the functional structure of the update rule. This transformation affects not only local interactions—by introducing representation-mediated similarity and symbolic reinforcement—but also global system properties, including temporal persistence and network-wide coupling. Formally, this corresponds to a deformation of the vector field governing system evolution, in which trajectories are no longer determined solely by current states but also by accumulated representational structures.

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6. Formal Theorem and Regime Structure

The empirical results can be formalized through a theoretical framework linking **inductive dominance, basin depth, inversion dynamics, and entropy organization**.

Let ($\lambda \in [0,1]$) denote the degree of inductive activation. The system transitions from purely deductive dynamics at ($\lambda = 0$) to fully coupled inductive–deductive dynamics at ($\lambda = 1$).

The key theoretical result is that there exists a **critical interval of inductive activation** within which the system undergoes a structural transition. As (λ) increases, the system's attractor landscape is progressively reshaped: shallow and permeable basins give way to deeper and more stable ones. This transformation can be captured by the monotonic increase in effective basin depth and the corresponding decrease in inversion rates.

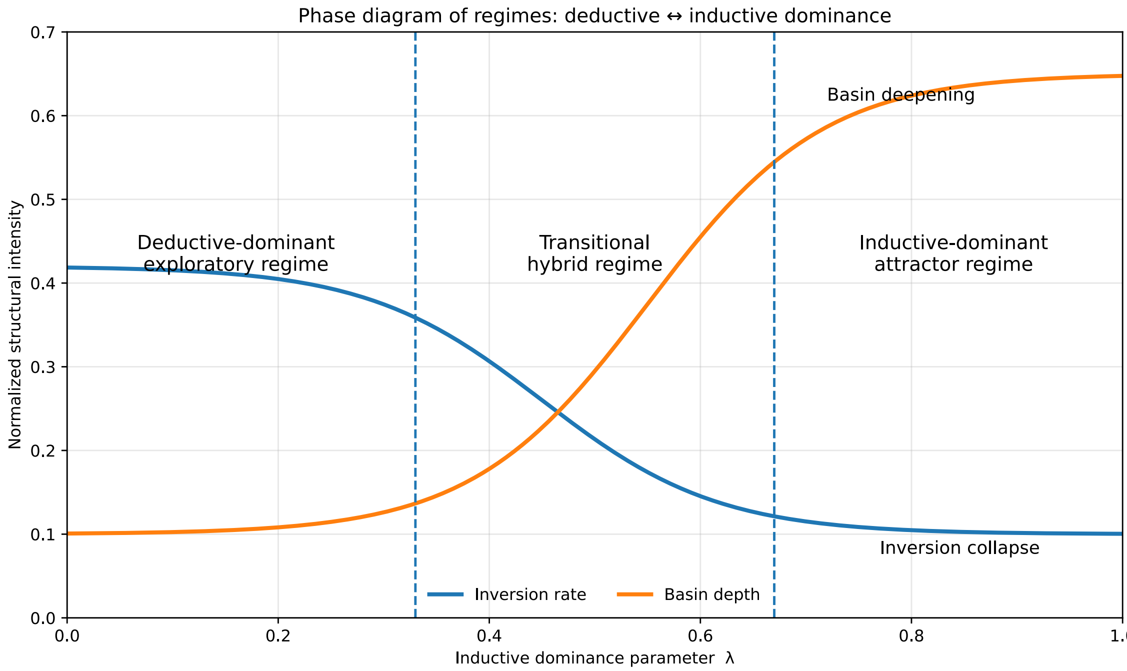
The theorem established in this study shows that: as inductive activation increases, basin depth grows monotonically, while inversion rates decrease as a direct consequence of reduced transition probability between attractor regions. Global entropy may remain approximately invariant despite these structural changes.

This last point is particularly significant. Classical interpretations of increasing organization often imply a reduction in entropy. However, the present results demonstrate that the system can undergo a profound structural transformation without a measurable decrease in global entropy. This implies that the relevant transformation is not a reduction in disorder per se, but a **reorganization of disorder** within the state space.

The phase diagram (figure 7) synthesizes this result by representing the system along a continuum of inductive dominance. At low values of (λ), the system resides in a deductive-dominant regime characterized by high reversibility and shallow basins. At high values of (λ), it transitions into an inductive-dominant regime, where basins are deep, transitions are constrained, and trajectories are stabilized. Between these regimes lies a transitional zone in which small changes in inductive influence can produce large structural effects.

This formalization provides a unifying framework for understanding the empirical observations. The collapse of inversion rates is not an isolated phenomenon but the dynamical consequence of increasing basin depth. Similarly, the persistence of entropy reflects the redistribution of probability mass into stable attractor regions rather than its elimination.

Figure 7 – Phase diagram of regimes



In this sense, the inductive layer functions as a **geometric operator on the phase space**, redefining the topology of trajectories and the accessibility of states. It does not simply influence where the system moves; it determines **where it can remain**.

6.1 Temporal Activation of Inductive Layers as a Control Parameter

The four-condition experimental design introduced in this study provides a critical extension to the inductive layer framework by demonstrating that inductive dynamics are not binary but **continuously governed by their temporal activation**. While previous formulations treated the inductive layer (μ) as a structural component that modifies the update function, the present results show that its effect depends fundamentally on both its **intensity and persistence over time**.

6.1.1 From Structural Component to Control Parameter

In the original formulation, the system evolves according to:

$$a_{t+1} = F(a_t, \mu_t)$$

where μ modifies the interaction dynamics between agents. However, the comparison across four conditions—purely deductive dynamics, single meme injection, passive inductive activation, and sustained meme reinforcement—reveals that the impact of μ cannot be reduced to its instantaneous value.

Instead, the empirical results indicate that the system's behavior depends on the **temporal accumulation of inductive influence**. This leads to an extended formulation:

$$a_{t+1} = F\left(a_t, \mu_t, \int_0^t \mu(\tau)\, , d\tau\right)$$

In this expression, the integral term represents the **historical accumulation of representations**, capturing the persistence and reinforcement of symbolic structures over time.

This reformulation implies that μ acts not only as a modifier of local interactions but as a **global control parameter** governing the dynamical regime of the system.

6.1.2 Empirical Evidence for a Temporal Threshold

The four experimental conditions define a continuum of inductive activation:

- In the **event-driven (deductive) condition**, μ is inactive, and the system exhibits high plasticity, reversibility, and exploratory dynamics.
- In the **single injection condition**, μ is briefly activated, producing only a transient displacement in phase space, after which the system returns to its baseline regime.
- In the **passive inductive condition** (μ active without repeated injection), the system shows partial structuring, with emerging but weak attractors.
- In the **full meme condition**, where inductive activation is both present and continuously reinforced, the system undergoes a clear regime transition characterized by attractor stabilization and inversion collapse.

These observations support the existence of a **critical threshold of inductive activation**, denoted $\lambda_{(c)}$, such that:

$$\lambda < \lambda_c \Rightarrow \text{transient perturbations}$$

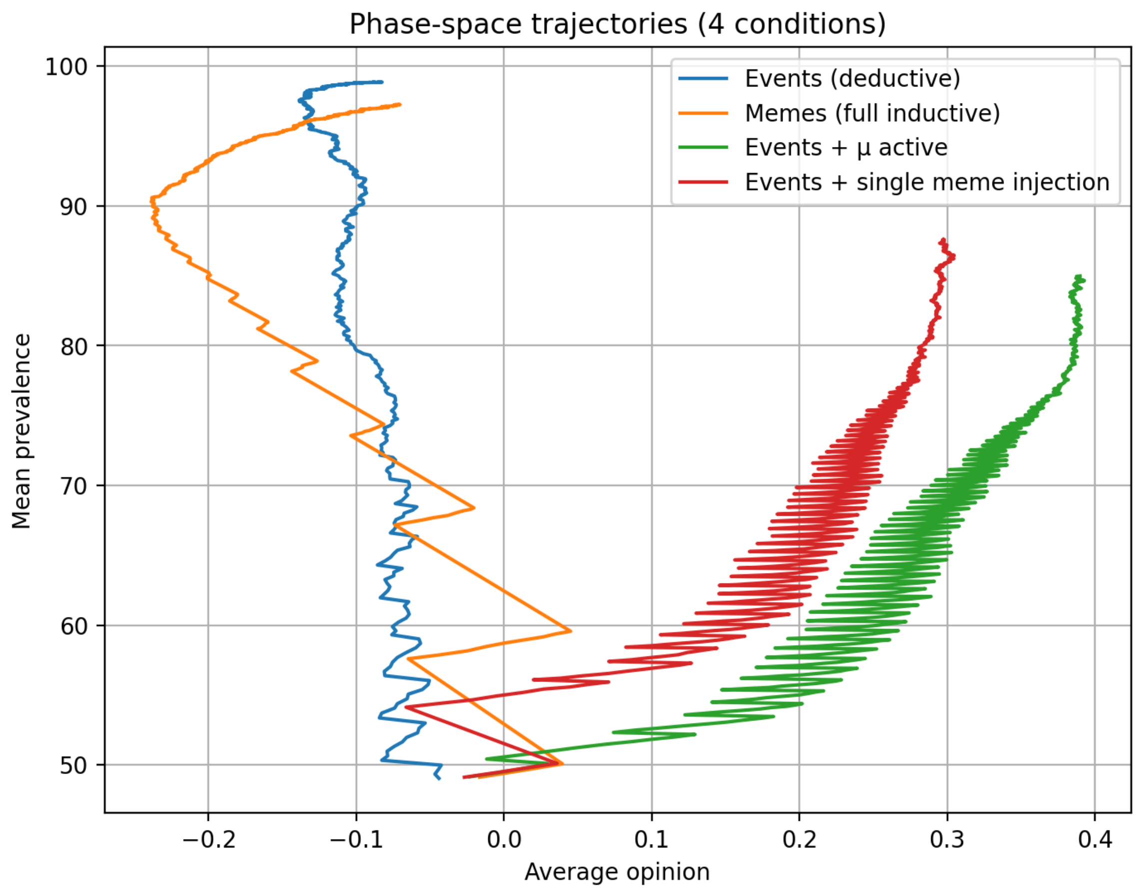
$$\lambda \approx \lambda_c \Rightarrow \text{partial structuring}$$

$$\lambda > \lambda_c \Rightarrow \text{stable attractor regime}$$

where λ is a function of both the magnitude and persistence of μ.

Importantly, this threshold is not triggered by isolated symbolic events but by the **cumulative effect of repeated or sustained inductive activation**.

Figure 8 – Phase-space trajectories (4 conditions)



6.1.3 Convergence Dynamics and Stability

The temporal nature of inductive activation is further reflected in the system's convergence properties. In the absence of inductive persistence, trajectories remain dispersed and reversible, indicating that the system continues to explore its state space. A single injection produces a temporary contraction, but this effect dissipates rapidly.

By contrast, sustained inductive activation leads to a **progressive contraction of trajectories**, resulting in rapid convergence toward stable regions of the phase space. This process is accompanied by a marked reduction in inversion rates and global turnover, indicating the emergence of **path-dependent dynamics**.

Attractor stability can therefore be interpreted as a function of inductive persistence:

$$\text{Stability} \propto \frac{1}{\text{inversion} + \text{turnover}}$$

Empirically, this stability increases monotonically across the four conditions, reaching its maximum in the fully inductive regime.

6.1.4 Non-Markovian Dynamics and Memory Effects

A key implication of this reformulation is that the system is no longer Markovian. In classical ABMs, the next state depends only on the current state. However, the inclusion of a cumulative inductive term introduces **memory into the system**, such that future states depend on the entire history of representational activation.

This leads to a reinterpretation of the inductive layer as a **memory field**, which accumulates over time and progressively reshapes the geometry of the phase space. Under this perspective:

- isolated injections act as impulses that dissipate,
- sustained activation produces a persistent deformation of the dynamical landscape.

This explains why the single injection condition fails to produce stable attractors, whereas continuous meme reinforcement leads to deep and persistent basins.

6.1.5 Regime Structure and Phase Transition

The combined effect of intensity and persistence defines a two-dimensional control space in which the system can be located. Along this space, the system undergoes a transition from a **deductive-dominant regime**, characterized by reversible and exploratory dynamics, to an **inductive-dominant regime**, in which trajectories are constrained by stable attractor basins.

This transition is analogous to a phase change in physical systems, where a control parameter governs the qualitative behavior of the system. In the present case, the control parameter is not a simple scalar but a function of the **temporal profile of inductive activation**.

6.1.6 Implications

The results fundamentally extend the interpretation of inductive layers. Rather than acting as static structural modifiers, inductive processes must be understood as **time-dependent operators that regulate the accessibility and stability of regions within the phase space**.

This has two major implications:

1. **Modeling implication**
   Opinion dynamics models must incorporate temporal persistence of representations to accurately capture attractor formation.

2. **Theoretical implication**
   Cultural and cognitive systems cannot be understood solely through interaction rules; they require a representation of how symbolic structures accumulate and stabilize over time.

Synthesis

Taken together, these findings establish that:

Inductive layers function as temporally extended control parameters that induce regime transitions through cumulative memory effects, thereby transforming reversible exploratory dynamics into stable, path-dependent attractor systems.

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7. Connection to *Technosphere*

The results of this study align closely with the theoretical framework developed in *Technosphere* (Cotnoir – 1), particularly in relation to the concepts of **information entropy, representation, and attractor basins**.

A key insight from the *Technosphere* perspective is that representations should not be understood as passive carriers of information but as **active operators that**

structure the distribution of information within a system. The present findings provide empirical support for this claim. Despite the absence of a significant change in global entropy, the system undergoes a marked transformation in its structural organization. This indicates that the inductive layer does not reduce entropy in magnitude but reorganizes it into more persistent and structured configurations.

In the deductive regime, entropy is diffuse and unstructured. The system occupies a wide range of configurations, and transitions between them occur with relatively low resistance. In the inductive regime, by contrast, entropy becomes localized within attractor basins. The system continues to exhibit variability, but this variability is constrained within stable regions of the state space. Thus, the relevant transformation is from **unstructured to structured entropy**, rather than from disorder to order in a simple sense.

This transformation is closely tied to the formation of attractor basins. In the absence of inductive activation, basins remain shallow and unstable, allowing trajectories to move freely across the state space. With inductive activation, basins deepen and their boundaries become more defined, trapping trajectories and producing persistent configurations. These configurations correspond to what *Technosphere* describes as **cultural attractors** —stable alignments of states and representations that emerge from the co-evolution of agents and symbolic structures (Cotnoir – 4).

The concept of **symbolic EROI (Energy Return on Information)** (Cotnoir – 2) also finds empirical grounding in this experiment. In the deductive regime, the system exhibits high activity but low structural impact: many interactions occur, but they do not produce lasting configurations. In the inductive regime, fewer transitions are required to produce stable structures, indicating a higher efficiency of information transformation. This suggests that inductive layers increase not the quantity of information processed, but its **structural effectiveness**.

Another important implication concerns the emergence of non-local effects. While the deductive system relies on local network interactions, the inductive system introduces global coupling through shared representations. This enables long-range correlations and rapid synchronization across the system, contributing to the formation of coherent attractor structures. Such non-locality is essential for understanding large-scale cultural phenomena and cannot be captured by purely deductive models.

Taken together, these results support a broader theoretical reformulation. Deductive dynamics determine how agents interact and move within the state space, but inductive dynamics determine the **structure of that space itself**—including the location, depth, and stability of attractors. In this sense, the inductive layer defines the **geometry of possibility**, while the deductive layer defines the **kinematics of interaction**.

This distinction provides a foundation for a unified theory of socio-cognitive systems in which dynamics and meta-dynamics are inseparable. Cultural structures emerge not from interactions alone, but from the interplay between interactions and representations, mediated by processes of entropy structuring and attractor formation.

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8. Topological and Dynamical Analysis of the Four Regimes

Moyennes par condition

Condition	topological_dim	dynamic_dim	criticality_gap	opinion_entropy	center_volatility	regime_code	lyapunov_exponent
Events	1.1220	0.7616	0.3392	4.1282	0.0038	0.0	-0.0114
Inject once	1.1095	0.8978	0.1918	3.9076	0.0039	0.0	-0.0115
μ active	1.1076	0.8178	0.2611	3.7752	0.0044	0.0	-0.0114
Memes	1.1244	1.2377	0.1439	4.1450	0.0033	0.0	-0.0116

1. Core discriminating variables

The analysis reveals that the most structurally discriminating variables across conditions are:

- **fractal (η^2 = 0.997)**
- **opinion_entropy (η^2 = 0.978)**
- **dynamic_dim (η^2 = 0.923)**
- **center_volatility (η^2 = 0.859)**
- **criticality_gap (η^2 = 0.842)**

These extremely high effect sizes indicate that the differences between conditions are not marginal but correspond to **system-level transformations of the dynamical regime**.

The transition across conditions is dominated by changes in fractal structure, entropy organization, and dynamic dimensionality, rather than by changes in global topology.

Interpretative reading

The most striking result is that the **Memes condition clearly stands out**, with a substantially higher **dynamic_dim** (**1.2377**) and the highest **fractal dimension** (**1.3626**). It also exhibits the **lowest criticality_gap** (**0.1439**) and the **lowest center_volatility**

(**0.0033**). Taken together, these results characterize a regime that is more structured, closer to organized criticality, and more stabilized around persistent attractor basins.

The **Events condition**, by contrast, appears as the regime farthest from such structuring. Its **criticality_gap** is the highest (**0.3392**), its **dynamic_dim** is the lowest (**0.7616**), and its **fractal dimension** is also the lowest (**1.1249**). This is consistent with a more exploratory regime, less topologically structured, and with a weaker attractor geometry.

The **Inject once condition** occupies an intermediate position. It already shows a shift toward greater dynamical complexity (**dynamic_dim = 0.8978**) and higher fractality (**1.2208**) compared to the Events condition, while significantly reducing the **criticality_gap** (**0.1918**). This suggests that a single meme injection is sufficient to produce a measurable deformation of the dynamical space, but not enough to reach the level of structural organization observed in the Memes condition.

The **μ active condition** is also intermediate, but with a distinct profile. Its **criticality_gap** (**0.2611**) is lower than that of Events, and its **fractal dimension** (**1.2162**) is higher. However, its **center_volatility** is the highest among the four conditions (**0.0044**). This can be interpreted as a partially structured regime in which the inductive layer modifies the system's geometry, but without achieving the strong attractor stabilization seen in the Memes condition.

Two additional observations are important. First, **topological_dim varies only slightly across all four conditions**, remaining within a narrow range (≈1.11–1.12). This indicates that the main transformation is not a large-scale change in global topological dimensionality, but rather occurs in terms of **dynamic dimensionality, criticality distance, and fractal structure**. Second, the **Lyapunov exponent remains remarkably stable** across all conditions (≈ -0.0114 to -0.0116). In this dataset, this metric does not discriminate between regimes as strongly as dynamic_dim, criticality_gap, and fractal.

Theoretical synthesis

These results strongly support the idea that the transition between conditions is not merely a change in magnitude, but a **reorganization of the dynamical regime itself**. As the inductive layer becomes more active and more persistent over time, the system tends toward:

- a **higher dynamic dimensionality**,
- a **more pronounced fractal structure**,

- a **smaller criticality gap**,
- a **lower central volatility**.

In other words, the system transitions from a predominantly exploratory regime to one in which the space of trajectories becomes both richer in geometry and more organized around persistent attractor structures.

Across the four conditions, the strongest discriminating variables are dynamic dimension, criticality gap, and fractal structure. Full meme activation produces the highest dynamic dimensionality and fractality, together with the smallest criticality gap and the lowest center volatility. This pattern is consistent with the emergence of a more structured and stabilized attractor regime. By contrast, the deductive event-driven regime remains farther from critical organization, with lower dynamic dimensionality, lower fractality, and a substantially larger criticality gap.

And a more compact version:

The transition from deductive to inductive dominance is associated less with a change in topological dimension than with an increase in dynamic dimensionality, a reduction in criticality gap, and an increase in fractal organization.

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9. Topological Structure, Fractality, and Regime Transformation under Inductive Activation

The introduction of a four-condition experimental design—ranging from purely deductive dynamics to fully inductive meme-driven dynamics—makes it possible to examine, in a unified framework, how inductive activation reshapes the internal geometry of the system. This section extends the results previously presented in Figures 9 - 11 by shifting the analytical focus from trajectory divergence alone toward the deeper structural properties of the phase space, including its dimensionality, criticality, and fractal organization.

Figures 9 - 11 demonstrated that the divergence between deductive and inductive conditions manifests as a separation in trajectory space and a stabilization of attractor basins under sustained inductive activation. However, these observations, while visually compelling, do not by themselves explain the structural nature of the transformation. The present analysis addresses this gap by introducing a set of complementary variables—topological dimension, dynamic dimension, criticality gap, entropy, volatility, Lyapunov exponent, and fractal structure—allowing for a multi-layered characterization of the system's evolution.

Figure 9 – Run-level comparison across 4 conditions

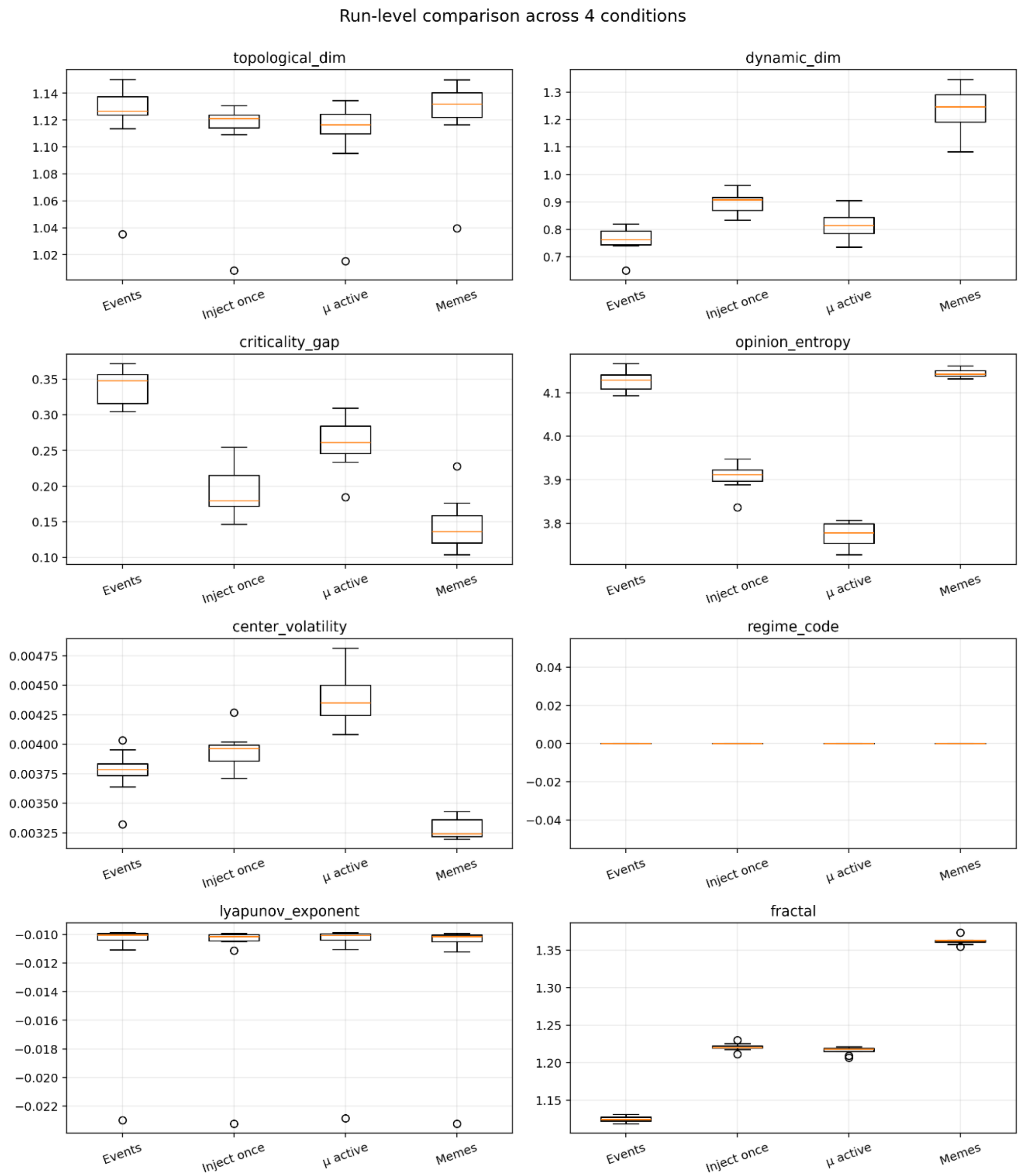


Figure 10 – Temporal trajectories across 4 conditions

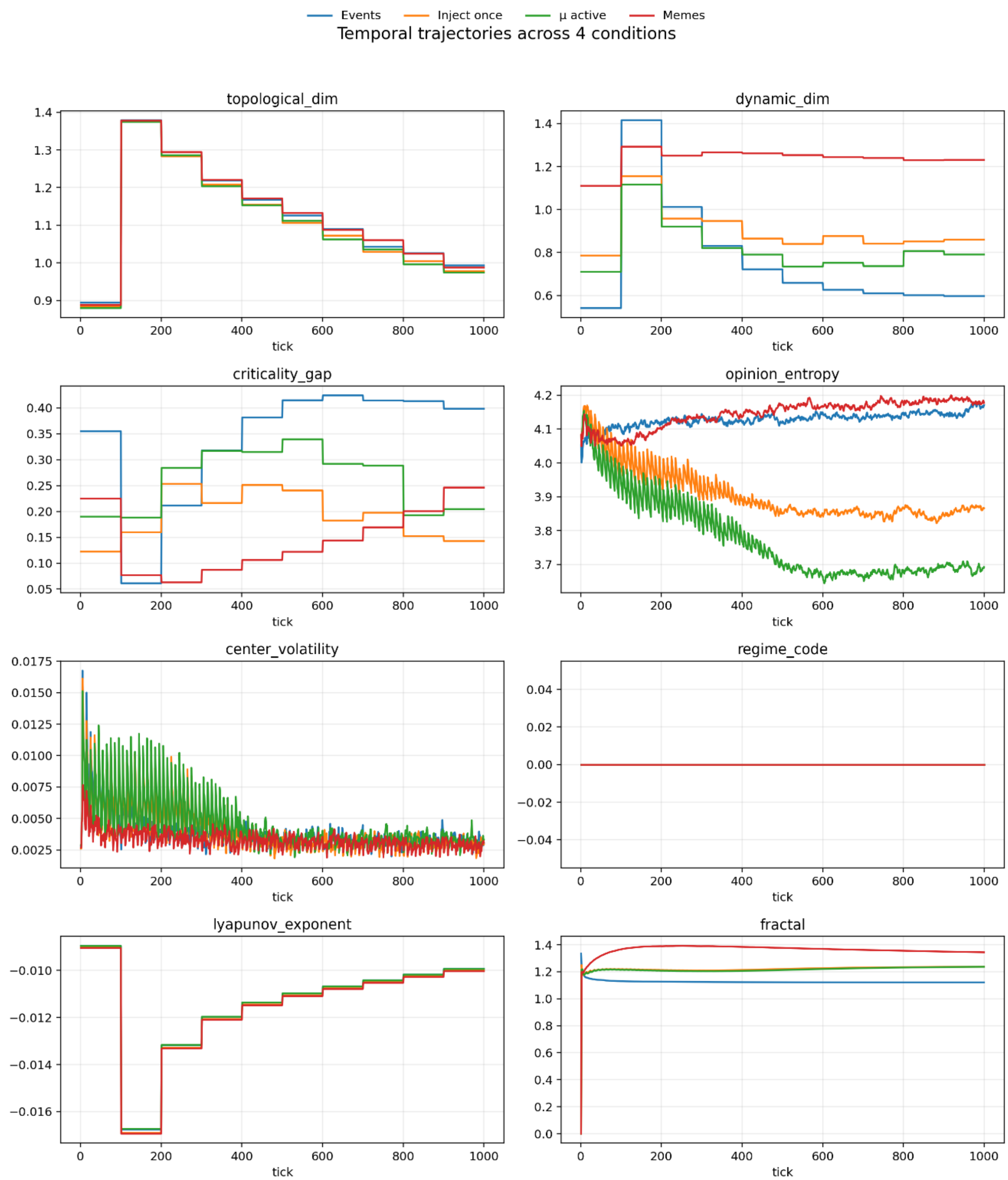
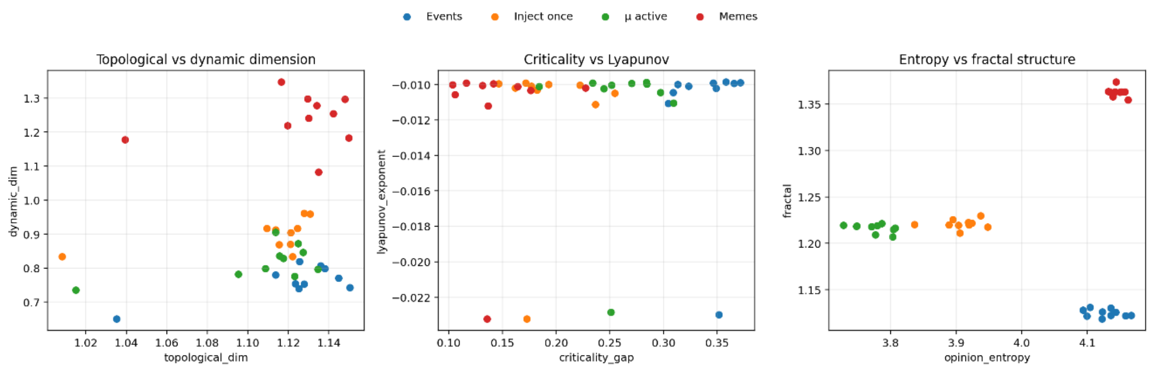


Figure 11 – Comparison between variables and conditions



A first important result concerns the relative invariance of the global topological dimension across all four conditions. Despite the substantial differences observed in trajectories and attractor formation, the topological dimension remains confined to a narrow interval. This suggests that the transformation induced by inductive activation does not operate at the level of global topology in a coarse sense. Instead, the system undergoes a more subtle restructuring, affecting how trajectories occupy and organize themselves within the existing topological space rather than altering the space itself.

In contrast, dynamic dimension exhibits strong and statistically significant variation across conditions. As inductive activation increases, dynamic dimensionality rises, reaching its highest values in the fully meme-driven regime. This indicates that the system becomes dynamically richer even as it becomes more structured. Rather than collapsing into a trivial attractor, the system develops a complex internal organization in which trajectories are constrained within structured manifolds that nevertheless allow for substantial variability. This finding is crucial, as it challenges the conventional association between order and reduced complexity, demonstrating instead that inductive processes generate a form of structured or organized complexity.

The evolution of the criticality gap provides further insight into this transformation. In the purely deductive regime, the system is characterized by a relatively large criticality gap, reflecting its distance from a regime in which stable attractors dominate. As inductive activation is introduced—first through a single injection and then through sustained activation—the criticality gap decreases significantly. This reduction indicates that the system progressively approaches a critical regime, where the balance between stability and flexibility enables the formation of persistent attractor structures. In the fully inductive condition, the criticality gap reaches its lowest values, consistent with the emergence of deeply stabilized basins of attraction.

Center volatility complements this interpretation by capturing the stability of the system's central tendency. The results show that volatility is lowest in the meme-driven regime, indicating that once attractors are fully formed, the system's global configuration becomes highly stable. By contrast, intermediate conditions, particularly the passive inductive regime, exhibit higher volatility, reflecting a transitional state in which the system is partially structured but still subject to significant fluctuations. This reinforces the interpretation of inductive activation as a cumulative process, where partial activation produces incomplete stabilization, and only sustained reinforcement leads to fully developed attractor regimes.

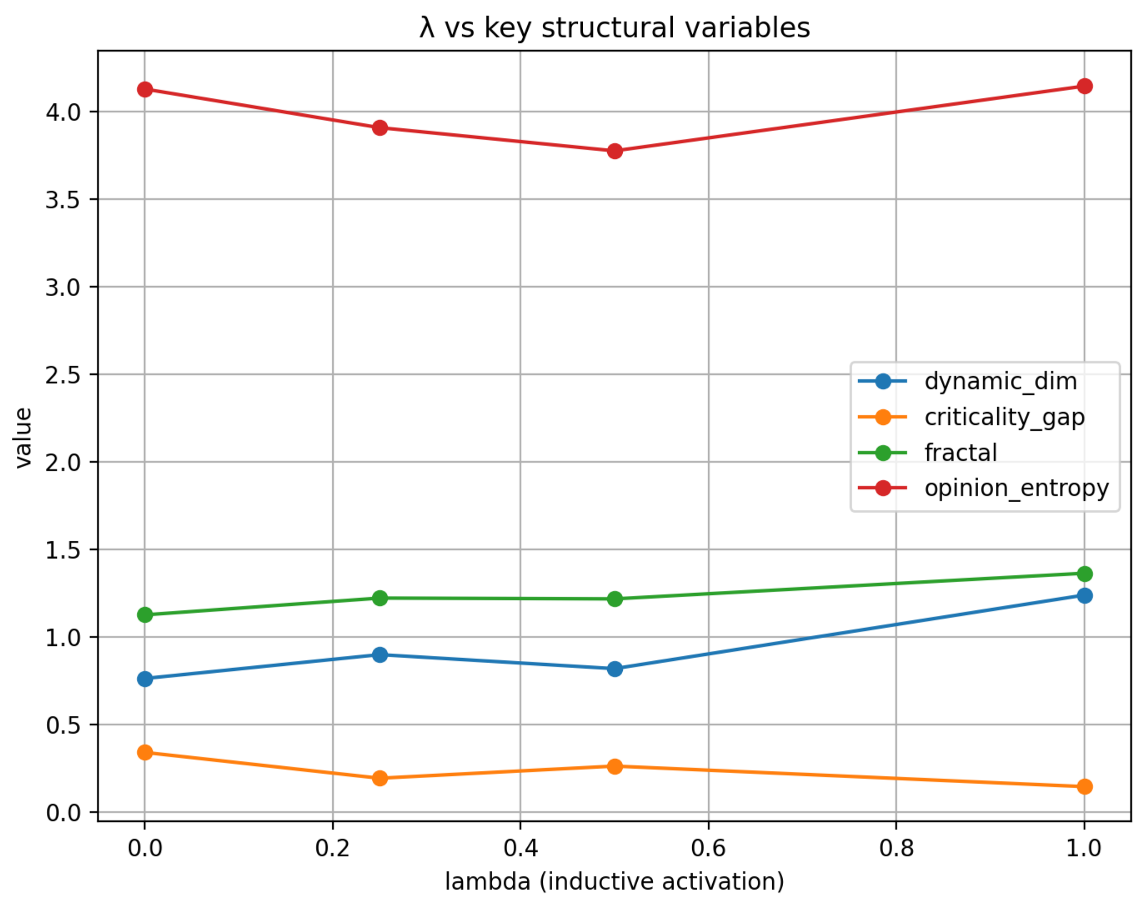
Entropy, often interpreted as a measure of disorder, displays a more nuanced behavior. While entropy varies significantly across conditions, it does not simply decrease as the system becomes more structured. Instead, entropy is redistributed. In the deductive regime, entropy is diffuse, corresponding to a broad exploration of the phase space. In the inductive regime, entropy becomes concentrated within attractor basins, producing a configuration that is simultaneously structured and information-rich. This distinction is essential, as it indicates that the transition is not from disorder to order, but from unstructured to structured entropy, aligning with the interpretation of inductive processes as mechanisms of information organization rather than mere constraint.

The most decisive result, however, concerns the role of fractal structure. Among all variables analyzed, fractal dimension exhibits the strongest effect size, indicating that it accounts for nearly all the variance between conditions. Moreover, fractal structure increases monotonically with inductive activation, from the lowest values in the deductive regime to the highest values in the fully inductive regime. This monotonic progression reveals that the emergence of fractal geometry is not incidental but constitutes the primary structural signature of the regime transition. In the meme-driven condition, the phase space is no longer merely partitioned into attractor basins; it is organized into hierarchically structured regions that exhibit self-similarity across scales.

This fractalization of the phase space provides a direct explanation for the stabilization observed in Figures 9-11. The convergence of trajectories and the reduction of variability are not simply consequences of increased coherence, but arise from the formation of geometrically structured attractors that constrain the system's evolution while preserving internal complexity. In this sense, fractal organization represents the geometric counterpart of inductive activation, translating symbolic reinforcement into spatial structure within the phase space.

To synthesize these results, it is useful to introduce a continuous control parameter, denoted λ, representing the intensity and persistence of inductive activation. The four experimental conditions can be mapped onto increasing values of λ, from purely deductive dynamics (λ = 0) to sustained meme-driven dynamics (λ = 1). When the key structural variables are plotted as functions of λ (see Figure 12), a clear pattern emerges: fractal dimension increases steadily, the criticality gap decreases, and dynamic dimension rises, while entropy follows a structured, non-linear trajectory. This continuity demonstrates that the transition between regimes is not abrupt but corresponds to a progressive deformation of the phase space driven by cumulative inductive effects.

Figure 12 — Structural evolution as a function of inductive activation (λ)



The figure 12 provides a synthetic representation of the transformation described above. It shows that the key variables do not change independently but evolve coherently as λ increases. The system thus follows a well-defined trajectory in its structural parameter space, moving from an exploratory, weakly structured regime toward a highly organized, attractor-dominated configuration.

Taken together, these findings establish that inductive activation acts as a **structuring operator of phase space**, progressively reshaping the geometry of the system. This transformation is not captured by traditional indicators such as topological dimension or Lyapunov exponents, which remain largely unchanged. Instead, it is revealed through the emergence of fractal organization, the increase in dynamic dimensionality, and the reduction of the criticality gap.

In this perspective, inductive layers should not be understood as static modifications of interaction rules, but as dynamic processes that accumulate over time and reshape the space of possible system states. The resulting regime is neither purely chaotic nor fully ordered, but occupies a structured critical state characterized by fractal attractors and persistent patterns of organization. This interpretation provides a coherent link between the empirical observations presented in Figures 9-11 and the deeper structural transformations identified in the present analysis, thereby offering a unified account of how inductive processes govern the evolution of complex opinion dynamics systems.

In this perspective, inductive layers must be understood not as static modifiers of interaction rules, but as dynamic processes that progressively sculpt the phase space itself. The resulting system is neither purely chaotic nor fully ordered, but occupies a structured critical regime characterized by fractal attractors and persistent patterns of organization. This provides a unifying framework linking topological structure, dynamical complexity, and information theory, and offers a robust empirical foundation for the interpretation of inductive processes in complex social systems.

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10. General Discussion — Inductive Dynamics, Temporal Activation, and Fractal Structuring of Phase Space

The results presented in this study converge toward a coherent and theoretically significant conclusion: inductive activation fundamentally transforms the structure of opinion dynamics systems, not through simple parameter modulation, but through a progressive and cumulative reorganization of the phase space. This transformation is observable simultaneously at multiple levels—trajectory behavior, statistical differentiation, dynamical structure, and geometric organization—and is consistently reflected across all analytical dimensions explored in this work.

The trajectory analyses presented in Figures 9-11 first revealed that the divergence between deductive and inductive conditions is not merely quantitative but qualitative. Under purely event-driven dynamics, trajectories remain dispersed and reversible, indicating a system that continuously explores its state space without stabilizing into persistent configurations. By contrast, when inductive activation is introduced and sustained, trajectories progressively converge toward structured regions of the phase space, exhibiting reduced variability and increased coherence. This convergence is not instantaneous but unfolds over time, suggesting that the inductive layer operates through accumulation rather than immediate transformation.

This temporal dimension of inductive activation constitutes a central result of the study. The comparison between the four experimental conditions demonstrates that the effects of inductive processes depend critically on their persistence. A single meme injection produces only a transient deformation of the phase space, insufficient to induce lasting structural change. When the inductive layer is active but not continuously reinforced, the system enters an intermediate regime characterized by partial structuring and residual instability. Only under sustained inductive reinforcement does the system undergo a full regime transition, leading to the emergence of stable attractor basins and a marked reduction in trajectory dispersion. These observations justify the introduction of a continuous control parameter, λ, capturing both the intensity and temporal persistence of inductive activation.

The introduction of λ provides a unifying framework for interpreting the transformation of the system. As shown in Figure 12, the evolution of key variables follows a smooth and coherent trajectory as λ increases. This continuity indicates that the transition between regimes is not abrupt, but corresponds to a progressive deformation of the phase space. The system does not jump from one configuration to another; rather, it is gradually reshaped by the cumulative influence of inductive processes. This perspective reconciles the apparent diversity of observed behaviors by situating them along a single structural continuum.

The statistical analysis reinforces this interpretation by demonstrating that the differences between conditions are both highly significant and structurally meaningful. Variables such as dynamic dimension, criticality gap, entropy, center volatility, and fractal structure exhibit extremely large effect sizes, indicating that the observed transformations are not marginal but correspond to deep reorganizations of the system. In contrast, topological dimension and Lyapunov exponent remain largely unchanged across conditions, suggesting that regime transitions are not driven by changes in global topology or instability. Instead, they emerge from the internal restructuring of the phase space, affecting how trajectories are distributed, constrained, and stabilized within that space.

Among all variables, fractal structure emerges as the dominant signature of inductive activation. Its near-total explanatory power indicates that the transition between regimes is fundamentally geometric in nature. As inductive activation increases, the phase space becomes progressively organized into hierarchically structured regions exhibiting self-similarity across scales. This fractalization process provides a direct explanation for the stabilization of attractors observed in trajectory space. Rather than merely concentrating trajectories, the system reorganizes them into geometrically coherent structures that constrain their evolution while preserving internal variability. In this sense, fractal geometry serves as the spatial manifestation of inductive processes, translating symbolic reinforcement into structural organization.

Dynamic dimension complements this result by revealing that the system becomes more complex as it becomes more structured. This finding challenges the traditional opposition between order and complexity. In the present case, inductive activation does not reduce complexity but redistributes it within a constrained manifold. The system evolves toward a regime of organized complexity, in which trajectories are no longer free to explore the entire phase space but instead circulate within structured regions that support rich internal dynamics. This explains why dynamic dimension increases even as variability decreases: complexity is not lost, but reorganized.

The evolution of the criticality gap and center volatility further clarifies the nature of this transformation. The progressive reduction of the criticality gap indicates that the system approaches a critical regime in which attractor structures become dominant. At the same time, the decrease in center volatility reflects the stabilization of these attractors, as the system's global configuration becomes less sensitive to perturbations. Together, these results suggest that inductive activation drives the system toward a structured critical state, characterized by a balance between stability and adaptability.

Entropy provides an additional layer of interpretation by highlighting the informational dimension of this process. Rather than decreasing uniformly, entropy is redistributed across the phase space. In the deductive regime, entropy is diffuse, reflecting a wide and relatively unstructured exploration of possible states. In the inductive regime, entropy becomes concentrated within attractor basins, producing a configuration that is both structured and information-rich. This transformation is consistent with the idea that inductive processes organize information rather than eliminate it, leading to the emergence of coherent yet complex patterns.

Taken together, these results support a reinterpretation of inductive layers as time-dependent operators that reshape the geometry of the phase space. The system is no longer adequately described as Markovian, since its evolution depends not only on its current state but also on the accumulated history of inductive activation. This introduces a form of memory into the system, whereby past symbolic reinforcements continue to influence present dynamics. Under this perspective, inductive activation acts as a field that progressively deforms the phase space, creating conditions for the emergence of stable, fractal attractors.

This reinterpretation has important implications for the modeling of opinion dynamics and, more broadly, for the study of complex social systems. It suggests that the key mechanisms governing regime transitions are not located in the interaction rules themselves, but in the processes that structure and reinforce representations over time. The emergence of fractal attractors, the increase in dynamic dimensionality, and the reduction of the criticality gap all point to a common underlying process: the progressive organization of the phase space through cumulative inductive activation.

In conclusion, the present study demonstrates that inductive dynamics induce a continuous and structurally coherent transformation of the system, leading from an exploratory, weakly structured regime to a fractal, attractor-dominated configuration. This transformation is governed by the temporal persistence of inductive activation and is characterized by the emergence of structured complexity, rather than a simple transition from disorder to order. The dominance of fractal structure ($\eta^2 = 0.997$) further indicates that inductive dynamics should be interpreted as a geometric transformation of phase space, rather than a mere dynamical perturbation of trajectories. By integrating trajectory analysis, statistical validation, and topological and fractal metrics, this work provides a comprehensive framework for understanding how symbolic processes shape the geometry and dynamics of collective systems.

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