A Causal Graph Derivation of Physical Laws: From Discrete Structure to Continuous Physics

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Abstract

This paper presents a unified framework for deriving fundamental physical laws from a minimal set of assumptions about discrete causal structure. Starting from a directed acyclic graph with simple activation rules and thermodynamic constraints, we rigorously derive: (1) exponential expansion of the universe, (2) quantum superposition and interference, (3) gauge symmetries $SU(3)\times SU(2)\times U(1)$, (4) Fermi statistics and the Pauli exclusion principle, (5) Einstein-like gravitational dynamics, and (6) continuous field equations including Schrödinger and Yang-Mills equations. All results emerge naturally without presupposing continuous spacetime or known physical constants.

Contents

1 Introduction

We propose that the fundamental structure of reality is a discrete causal graph $\mathcal{G} = (V, E)$, where V is a countable set of basic event locations and $E \subseteq V \times V$ is a set of directed edges representing causal relationships. From this minimal structure, combined with two simple physical axioms, we derive the emergence of spacetime, quantum mechanics, gauge theories, and gravity.

2 Core Assumptions and Basic Architecture

2.1 Basic Mathematical Structure

2.1.1 Universe State Space Definition

The universe system is strictly described by the triple $(\mathcal{G}, \mathcal{S}, \mathcal{H})$:

- Node set V: Countable infinite set, representing basic event locations
- Edge set $E \subseteq V \times V$: Directed edge set satisfying acyclic transitive closure
- Graph structure $\mathcal{G} = (V, E)$

2.1.2 State Function

- Discrete time state: $\mathcal{S} : \mathbb{N} \times V \to \{0, 1\}$
  - $\mathcal{S}_t(v) = 1$ means node v is active at time t
  - $\mathcal{S}_t(v) = 0$ means node v is inactive at time t
- Thermodynamic entropy count: $\mathcal{H} : \mathbb{N} \to \mathbb{N}$, monotonic non-decreasing function

2.1.3 Key Set Definitions

For any time $t \in \mathbb{N}$:

$$\begin{aligned} A_t &:= \{v \in V \mid \mathcal{S}_t(v) = 1\} \quad \text{(active set)} \\ N_t &:= |A_t| \quad \text{(activation cardinality)} \\ B_{t+1} &:= \{v \in V \mid \mathcal{S}_t(v) = 0 \text{ and } \mathcal{S}_{t+1}(v) = 1\} \quad \text{(birth set)} \\ \Delta N_t &:= |B_{t+1}| \quad \text{(birth cardinality)} \end{aligned}$$

2.2 Basic Physical Axioms

2.2.1 Axiom 1.2.1 (Causal Conservation Law)

For any directed edge $u \to v \in E$, the following conditions must be simultaneously satisfied:

1. Future directionality:
$$\mathcal{S}_t(u) = 1 \Rightarrow \exists T \geq t \text{ such that } \mathcal{S}_T(v) = 1$$
Information from activated nodes must propagate along causal edges.

2. Past determinism:
$$\mathcal{S}_t(v) = 0 \Rightarrow \forall \tau \leq t,\ \mathcal{S}_\tau(u) = 0$$
If a node is inactive, all its causal predecessors must also have been inactive in the past.

2.2.2 Axiom 1.2.2 (Thermodynamic Cost Law)

The thermodynamic entropy increment at each discrete time step strictly equals the number of newly born nodes:

$$\mathcal{H}_{t+1} - \mathcal{H}_t = \Delta N_t$$

Information recording in the universe requires irreversible thermodynamic cost.

2.3 Graph Structure Assumptions

2.3.1 Assumption 1.3.1 (Regular Out-degree Structure)

The universe graph $\mathcal{G}$ is a d-regular out-degree graph, where $d \geq 2$:

$$\forall u \in V,\ \deg^+(u) := |\{v \in V \mid u \to v \in E\}| = d$$

Each node has the same number of causal successors.

2.3.2 Assumption 1.3.2 (Initial Conditions)

There exists an initial time $t = 0$ such that:

1. $A_0 \subset V$ is non-empty and finite
2. $\mathcal{H}_0 = 0$
3. The system is in a non-deadlock state

2.4 Causal Responsibility Theory

2.4.1 Definition 1.4.1 (Node's Causal Responsibility)

The unfinished causal responsibility count of node $u \in A_t$ at time t is defined as:

$$R_t(u) := |\{v \in V \setminus A_t \mid u \to v \in E\}|$$

representing the number of causal successors that u still needs to activate.

2.4.2 Lemma 1.4.2 (Deadlock Condition)

If there exists $u \in A_t$ such that $R_t(u) = 0$, the system enters causal deadlock:

- All causal successors of u are already activated
- By Axiom 1.2.1, u cannot transmit any new information
- System evolution stalls

2.4.3 Theorem 1.4.3 (Continuous Evolution Necessary Condition)

To maintain non-deadlock evolution, the system must satisfy:

$$\sum_{u \in A_t} R_t(u) \geq |A_t|$$

That is, each active node must have at least one unfinished causal responsibility on average.

Proof: By Lemma 1.4.2, if there exists $u \in A_t$ with $R_t(u) = 0$, deadlock occurs. To keep all nodes non-deadlocked, each node needs at least one unfinished responsibility. Since different nodes' unfinished responsibilities may point to the same node, summing and averaging gives the lower bound.

2.5 Derivation of Evolution Equations

2.5.1 Linear Growth Impossibility

Proposition 1.5.1 (Linear Growth Leads to Finite-Time Deadlock) Assume linear growth: $\exists c > 0$ such that $N_{t+1} = N_t + c$.

Then within finite time $T_{\max} \leq d \cdot N_0/c$, the system must enter deadlock.

Proof:

1. By linear growth assumption, $\Delta N_t = c$ constant
2. By Theorem 1.4.3, to avoid deadlock we need $\Delta N_t \geq N_t/d$
3. When $t > d \cdot N_0/c$, we have $N_t > dc$

4. Then $c < N_t/d$, violating the necessary condition
5. Therefore the system deadlocks within $T_{\max} \sim O(d)$

2.5.2 Exponential Growth Necessity

Theorem 1.5.2 (Minimal Non-trivial Steady Solution) Under the d-regular graph assumption, the minimal non-trivial evolution pattern satisfying Axioms 1.2.1-1.2.2 while avoiding deadlock is:

$$N_{t+1} = (1+\alpha)N_t, \quad \alpha \geq 1$$

Derivation:

1. By Theorem 1.4.3: $\Delta N_t \geq N_t/d$
2. Take minimal non-accumulating solution: each active node completes exactly $1/d$ responsibilities per step on expectation
3. For simplest case $d = 2$: each node activates one new node per step

$$\Delta N_t = N_t \Rightarrow N_{t+1} = N_t + N_t = 2N_t$$

4. General d case: if each node activates k new nodes ($1 \leq k \leq d$)

$$N_{t+1} = N_t + kN_t = (k+1)N_t$$

2.5.3 General Solution Form

$$N_t = N_0 \cdot \lambda^t, \quad \lambda = 1 + \alpha \geq 2$$

where λ is determined by the graph's d-regular structure and activation strategy.

2.6 Physical Quantity Definitions

2.6.1 Definition 1.6.1 (Universe Volume)

Define universe volume at time t as activation cardinality:

$$V_t := N_t = |A_t|$$

2.6.2 Definition 1.6.2 (Expansion Rate)

Discrete expansion rate:

$$H_t := \frac{N_{t+1} - N_t}{N_t} = \lambda - 1$$

Constant expansion rate corresponds to exponential growth.

2.6.3 Definition 1.6.3 (Entropy Density)

Thermodynamic entropy density:

$$\rho_t^{\mathcal{H}} := \frac{\mathcal{H}_t}{V_t}$$

Its evolution follows from Axiom 1.2.2.

2.7 Continuous Limit Correspondence

2.7.1 Proposition 1.7.1 (Emergence of Hubble's Law)

In continuous time limit $t \to \tau \in \mathbb{R}^+$, set $V(\tau) \propto N_{\lfloor \tau/\epsilon \rfloor}$, take $\epsilon \to 0$ keeping H finite, then:

$$\frac{dV}{d\tau} = HV(\tau), \quad H = \ln \lambda$$

Solution: $V(\tau) = V_0 e^{H\tau}$.

2.7.2 Proposition 1.7.2 (Thermodynamic Arrow)

By Axiom 1.2.2:

$$\frac{d\mathcal{H}}{d\tau} = \frac{dN}{d\tau} = HN(\tau) = HV(\tau)$$

Total entropy growth rate is proportional to volume.

2.8 Theoretical Properties Summary

2.8.1 Property 1.8.1 (Self-consistency)

This architecture depends only on:

1. Basic definition of directed acyclic graphs
2. Two basic physical axioms
3. Regular graph assumption
4. Non-deadlock evolution requirement

No additional physical assumptions or parameter fine-tuning.

2.8.2 Property 1.8.2 (Uniqueness)

Under the constraint that linear growth necessarily leads to deadlock, exponential growth is the only non-trivial pattern that can sustain long-term evolution.

2.8.3 Property 1.8.3 (Robustness)

Conclusions are insensitive to specific graph structure details, as long as $d \geq 2$ regularity and axiom conditions are satisfied.

2.9 Chapter Conclusion

This chapter establishes the minimal discrete causal model of universe evolution. Starting from pure graph theory structure and two basic physical axioms, we rigorously derive the mathematical necessity of exponential cosmic expansion. This conclusion does not depend on any known physical constants or empirical laws, demonstrating the fundamental constraints that causal structure and thermodynamics impose on cosmic evolution.

3 From Exponential Constraint to Non-unique Futures

3.1 Inevitable Activation Conflicts

Chapter 1 gives three basic conditions:

1. Activated nodes satisfy exponential relation

$$N_{t+1} = \lambda N_t, \qquad \lambda \geq 2.$$

2. Each active node bears responsibility to activate at least one successor.
3. The graph is a fixed out-degree d directed acyclic graph.

Let A_t = all active nodes at time t. Each $u \in A_t$ has successor set $\mathrm{Out}(u) = \{v_1, \ldots, v_d\}$.

As $|A_t|$ grows exponentially, successor sets of different active nodes exhibit extensive overlap, with overlap scale increasing rapidly with N_t.

Proposition 2.1.1 (Target Conflict) In exponential growth phase, it is impossible to assign mutually exclusive successor nodes to all active nodes. Many nodes are simultaneously pointed to by more than one active node.

Therefore any rule attempting deterministic activation of successors by each active node cannot satisfy all responsibility requirements. If determinism is forced, deadlock results.

3.2 Activation Competition Zone

Define competition zone as:

$$C_t = \big\{v \in V : \ |\{u \in A_t : u \to v\}| \geq 2\big\}.$$

During exponential growth, the competition zone occupies the vast majority of $\Omega_t = \bigcup_{u \in A_t} \mathrm{Out}(u)$. Responsibilities of active nodes cannot all be fulfilled under deterministic mapping; which responsibilities are satisfied is no longer uniquely determined by graph structure.

Therefore, determination of next activation set is not a one-to-one function, but a selection among multiple possible activation combinations.

3.3 Structure of Legal Future Activation Sets

Let $\Omega_t = \bigcup_{u \in A_t} \mathrm{Out}(u)$ be all candidate nodes that could be activated.

The allowed active node set for the next step must satisfy:

1. $A_{t+1} \subseteq \Omega_t$;
2. $|A_{t+1}| = \lambda |A_t|$;
3. Each $u \in A_t$ has at least one successor in A_{t+1} (causal responsibility condition);
4. The graph has no deadlock; all responsible nodes remain structurally reachable.

Definition 2.3.1 (Activation Configuration Space)

$$\mathcal{X}_t = \big\{X \subseteq \Omega_t \ \big| \ X \text{ satisfies all responsibility and growth constraints}\big\}.$$

In non-exponential phase $|\mathcal{X}_t|$ may be 1, but during exponential growth, typically $|\mathcal{X}_t| \gg 1$.

Thus future activation sets are not unique, but constitute a huge family of legal sets.

3.4 Emergence of Slow Variables

For any competition zone node v, whether it gets activated depends on competition among multiple active nodes. Changing the effective successor set of any one predecessor changes the set $\mathcal{X}_t$ that satisfies responsibility conditions.

Therefore during exponential phase, a node's future state is determined not only by local structure but also by global constraints from all competing paths. The system's actual evolution trajectory must choose one among many legal sets, and these sets do not merge causally.

3.5 Effect of Distinguishability on Future Sets

Let $v \in C_t$ with predecessor set $P(v) = \{u_1, \ldots, u_m\}$.

Any distinguishing operation on $P(v)$—changing successor effectiveness of some predecessor, adding/removing reachable paths, or modifying local responsibility allocation—changes the activation sets satisfying responsibility conditions, thereby changing $\mathcal{X}_t$.

Thus:

- Operations attempting to distinguish different paths necessarily change legal activation sets;
- Changes in legal activation sets reciprocally change future active node configurations;
- This phenomenon appears universally in competition zones.

This result requires no introduction of observation, waves, or probability concepts; it follows solely from the combination of causal responsibility and exponential growth.

3.6 Non-uniqueness as Dynamical Feature

Let $A_t \in \mathcal{X}_t \Rightarrow A_{t+1} \in \mathcal{X}_{t+1}(A_t)$, and define evolution relation $\Phi : \mathcal{X}_t \to \mathcal{P}(\mathcal{X}_{t+1})$, where $\Phi(X)$ is all legal next-step configurations from X.

Graph structure and exponential constraints together cause:

1. Evolution non-uniqueness;
2. Legal future sets have exponential cardinality;
3. Cannot be compressed to unique trajectory by local rules;
4. Operations attempting to distinguish predecessor paths necessarily change the future.

These properties all follow directly from Chapter 1 assumptions.

4 Geometric Structure of Compatible Future Sets

Let history be activation sequence $H_n = (v_1, \ldots, v_n)$ in temporal order, and L_n be the set of all legal histories of length n.

4.1 History Serialization

Lemma 3.1 (History Serialization) Any legal history can be expressed as an ordered node sequence, and there exists a consistent one-to-one correspondence between set representation and sequence expression.

Proof: The set of newly added nodes at any time layer has a fixed total order; arranging new nodes in this order gives natural sequence representation. Prefix constraints for sets and sequences are equivalent; causal conservation and past determinism guarantee mutual recoverability.

4.2 Single-step Monotonicity and Branching Conditions

Proposition 3.2 (Single-step Monotonicity) For any n, $|L_{n+1}| \geq |L_n|$.

Proof: Any $H \in L_n$ has at least one legal extension $H' \in L_{n+1}$. The mapping from L_n to L_{n+1} gives each history at least one extension, so cardinality cannot decrease.

Proposition 3.3 (Strict Growth Condition) If there exists $H \in L_n$ with at least two mutually non-merging immediate extensions, then $|L_{n+1}| \geq |L_n| + 1$. If for all $H \in L_n$ each has $r(H) \geq 2$ pairwise non-merging extensions, then $|L_{n+1}| \geq \sum_{H \in L_n} r(H)$.

Proof: Non-merging extensions must be counted as different histories. Counting all non-merging extensions for each history gives this lower bound.

4.3 Sufficient Conditions for Non-merging Histories

Lemma 3.4 (Sufficient Condition for Non-merging) Let $H_1, H_2 \in L_n$ be two histories. If there exists a node $v \in H_1$ at time layer $m \leq n$ whose causal past $J^-(v)$ contains a node p, and p is not in the prefix activation of H_2, and $J^-(v)$ cannot be completed to a consistent causal set in H_2's prefix structure, then the two histories cannot merge after m.

Proof: If merging were assumed, the merged history H' must contain v and its predecessor p. Past determinism requires that if p appears, its necessary causal predecessor structure must also appear; but this structure is absent in H_2's prefix, leading to contradiction. Therefore the histories cannot merge.

4.4 Ultrametric Structure of History Space

View histories as sequences. Define compatibility between two histories H_a, H_b of length n as:

$$C(H_a, H_b) = \text{length of longest common prefix}$$

Define distance:

$$d(H_a, H_b) = n - C(H_a, H_b).$$

Lemma 3.5 (Ultrametric) The above d is an ultrametric: for any three histories x, y, z,

$$d(x, z) \leq \max(d(x, y), d(y, z)).$$

Proof: The common prefix property ensures $C(x, z) \geq \min(C(x, y), C(y, z))$; substituting into definition gives ultrametric inequality.

4.5 Conditional Structure of Local Isomorphism and Self-similarity

Theorem 3.6 (Local Isomorphism Leads to Strict Self-similarity) If there exists a radius R such that any two nodes at the same level have radius-R neighborhoods isomorphic in directed structure sense, and evolution has no long-term merging, then k-step future expansions from any level are isomorphic as tree structures.

Proof: Because out-degree is bounded and activation rules depend only on finite neighborhoods, radius-R local isomorphism guarantees that local evolution from any starting point is identical for the first k layers. Absence of long-term merging prevents distant structure from disrupting local expansion, yielding strict isomorphism.

4.6 Exponential Growth of History Count (Conditional)

Proposition 3.7 (Exponential Growth) If there exists constant $r \geq 2$ such that for sufficiently large level n, each history $H \in L_n$ has at least r pairwise non-merging immediate extensions, then $|L_n| \geq r^n$ for sufficiently large n.

Proof: From Proposition 3.3, $|L_{n+1}| \geq r|L_n|$. Recursion gives exponential lower bound.

4.7 Summary

1. Histories can be serialized; sequence space forms natural prefix tree structure.
2. History count increases monotonically with level; strict growth occurs when non-merging extensions exist.
3. Sufficient conditions for history non-merging are given.
4. Prefix distance between histories forms an ultrametric; history space exhibits hierarchical tree structure.
5. Under local isomorphism and no long-term merging, tree expansion shows strict self-similarity.
6. Exponential history count requires uniform branching and non-merging everywhere as conditions.

5 Future Branching Structure and Activation Choice

Let discrete causal structure time be denoted t, active node set A_t. Each active node $u \in A_t$ has successor set:

$$F(u) = \{v \in V \mid u \to v \in E\}, \qquad |F(u)| = d.$$

From Chapter 1 Axiom 1.2.1: if u is active, then at least one successor must activate at some future time. Chapters 2 and 3 give growth rate constraint:

$$N_{t+1} = \lambda N_t, \qquad \lambda > 1,$$

where new active node set size is:

$$\Delta N_t = N_{t+1} - N_t = (\lambda - 1)N_t.$$

This chapter strictly analyzes possible future branching structures and how these branches manifest non-determinism in successor choice.

5.1 Definition of Branch

A future branch is a specific evolution path satisfying all axioms and constraints. For any branch $\mathcal{B}$, define new active set from t to $t+1$ as:

$$A_{t+1}(\mathcal{B}) \setminus A_t = \Delta A_t(\mathcal{B}), \quad |\Delta A_t(\mathcal{B})| = \Delta N_t.$$

New nodes are generated by previous layer's active nodes. To express each parent node's choice, we introduce:

5.2 Activation Choice and Local Freedom

Definition 4.2.1 (Activation Choice) In branch $\mathcal{B}$, for $u \in A_t$, its activation choice is defined as:

$$S_{\mathcal{B}}(u) \subseteq F(u),$$

where $S_{\mathcal{B}}(u)$ is the set of successor nodes ultimately activated in $\mathcal{B}$ and attributable to u for transmission.

Constraint 4.2.2 (Non-emptiness) $S_{\mathcal{B}}(u) \neq \varnothing, \qquad \forall\, u \in A_t$. This follows from Axiom 1.2.1: active nodes must pass activation to at least one successor.

Constraint 4.2.3 (Global Growth) $\left|\bigcup_{u\in A_t} S_{\mathcal{B}}(u)\right| = \Delta N_t$. The union gives all newly activated nodes in this branch, so its size is uniquely determined by growth rate λ.

5.3 Variety of Activation Choices

The above local and global constraints do not fix the specific form of $S_{\mathcal{B}}(u)$. Whether multiple legal choices exist depends on graph structure and union count limitations.

Proposition 4.3.1 (Choice Variability) If combinatorial conditions

$$\sum_{u\in A_t} 1 \leq \Delta N_t \leq \sum_{u\in A_t} |F(u)|$$

are satisfied and different $F(u)$ have overlap, then there exist two legal branches $\mathcal{B}_1, \mathcal{B}_2$ such that

$$\exists\, u \in A_t : \quad S_{\mathcal{B}_1}(u) \neq S_{\mathcal{B}_2}(u),$$

and both satisfy all constraints.

This proposition shows: in general graph structure, a parent node's activated successors are not uniquely determined.

5.4 Non-uniqueness of Union

Due to freedom in activation choice, there may not exist a set of "must-activate successors" common to all branches.

Corollary 4.4.1 (Non-necessity of Unique Union) Generally no set $S \subseteq \bigcup_{u\in A_t} F(u)$ exists such that

$$\bigcup_{u\in A_t} S_{\mathcal{B}}(u) = S, \qquad \forall\, \mathcal{B}.$$

In other words, no fixed node set is always activated in all legal futures.

Special cases (e.g., all feasible choices fix the union uniquely) may yield future nodes shared by all branches, but this is a graph-structure-specific exception, not a general law.

5.5 Emergence of Substantive Branches

Differences between future branches are not merely event ordering differences, but differences in the activated node sets themselves.

Proposition 4.5.1 (Substantive Difference in Future Structure) If there exists $v \in V$ such that

$$v \in \Delta A_t(\mathcal{B}_1), \qquad v \notin \Delta A_t(\mathcal{B}_2),$$

then branches $\mathcal{B}_1$ and $\mathcal{B}_2$ have different active sets at time $t+1$, and future evolution structures diverge from this point.

Thus, once a node appears in some branches but not others, the futures become causally non-merging.

5.6 Summary

1. Each active node u has freedom in choosing successors, constrained by "at least one" and "fixed union size" conditions.
2. These constraints do not force all futures through the same node set.
3. In general graphs, different branches correspond to different newborn activation sets, causing genuine structural branching.
4. Only under special combinatorial conditions do all branches share the same future nodes.

Thus, "non-uniqueness of future" and "freedom in activation choice" are basic features naturally emerging from causal structure in discrete dynamics.

6 Branch Mergability and Time Asymmetry

6.1 Local Origin and Competition Zone Review

Let discrete causal graph at time t have active node set A_t. Each active node $u \in A_t$ has successor set:

$$F(u) = \{v \in V \mid u \to v \in E\}, \quad |F(u)| = d.$$

Chapter 1 Axiom 1.2.1 guarantees each active node must activate at least one successor. Chapter 2 shows exponential growth condition $N_{t+1} = \lambda N_t,\ \lambda > 1$ and existence of competition zones cause local choices to be non-unique.

Observation 5.1.1 (Source of Local Freedom) Multiple active nodes may point to the same successor, forming "competition zone":

$$C_t := \{v \in V : |\{u \in A_t : u \to v\}| \geq 2\}.$$

Future activation of competition zone nodes is determined by multiple possible paths, creating local freedom.

6.2 Activation Choice and Dynamical Constraints

Definition 5.2.1 (Activation Choice) In any branch $\mathcal{B}$, activation choice of active node $u \in A_t$ is:

$$S_{\mathcal{B}}(u) \subseteq F(u),$$

the set of successor nodes that u is responsible for activating.

Constraints:

1. Responsibility constraint (local): $S_{\mathcal{B}}(u) \neq \varnothing, \quad \forall u \in A_t$.
2. Growth constraint (global): $\left|\bigcup_{u \in A_t} S_{\mathcal{B}}(u)\right| = \Delta N_t = (\lambda - 1)|A_t|$.
3. Causal constraint (graph structure): Activation choices must guarantee future node reachability and non-deadlock.

Key constraint summary:

Responsibility constraint + Growth constraint + Causal constraint = Activation choice legality conditions.

Note: These constraints follow naturally from previous chapters' assumptions and exponential growth condition, not additional assumptions.

6.3 Merging Conditions and Causal History Compatibility

Definition 5.3.1 (Causal History Compatibility) Two histories H_1, H_2 are causally compatible up to time t if for any $v \in A_t(H_1) \cap A_t(H_2)$, their causal pasts are consistent in both histories:

$$J^-(v) \cap A_{\leq t}(H_1) = J^-(v) \cap A_{\leq t}(H_2).$$

Proposition 5.3.2 (Incompatibility Leads to Non-merging) If H_1, H_2 are incompatible at time t, their futures cannot merge:

$$H_1 \not\sim H_2 \quad \Rightarrow \quad \forall \tau > t, A_\tau(H_1) \neq A_\tau(H_2).$$

Interpretation: Even if $A_{t+1}(H_1) \cap A_{t+1}(H_2) \neq \varnothing$, the histories may be non-merging because shared nodes have inconsistent causal pasts.

6.4 History Uniqueness and Time Asymmetry

Observation 5.4.1 (Combinatorial Origin of Time Arrow)

- Future direction: Exponential growth → increasing active nodes → many legal choices → branching
- Past direction: Past uniqueness → active nodes determine their causal past → history convergence → determinism

Thus time asymmetry emerges naturally, consistent with thermodynamic arrow, not an added assumption.

6.5 Continuous Limit and Macroscopic Expansion

Take discrete step $\epsilon \to 0$, define continuous time $\tau = t\epsilon$, and set $\lambda = 1 + H\epsilon$.

Then discrete growth $N_t = N_0\lambda^t$ yields exponential expansion in continuous limit:

$$V(\tau) := N_{\lfloor \tau/\epsilon \rfloor} \to N_0 e^{H\tau}, \quad \frac{dV}{d\tau} = HV(\tau).$$

Note: This continuous limit holds only when $\epsilon \to 0$, requiring matching of discrete step and expansion rate.

6.6 Legal Future Sets

Definition 5.6.1 (Legal Activation Set)

$$\mathcal{X}_t := \{X \subseteq \Omega_t \mid X \text{ satisfies responsibility, growth and causal constraints}\},$$

where $\Omega_t := \bigcup_{u \in A_t} F(u)$.

During exponential growth typically $|\mathcal{X}_t| \gg 1$, different choices correspond to different branches.

6.7 Branch Differences and Testable Conditions

Proposition 5.7.1 (Branch Non-merging Condition) If there exists $v \in V$ such that

$$v \in \Delta A_t(\mathcal{B}_1), \quad v \notin \Delta A_t(\mathcal{B}_2),$$

then the two branches have different activation sets at time $t+1$, and futures cannot merge:

$$A_\tau(\mathcal{B}_1) \neq A_\tau(\mathcal{B}_2), \quad \forall \tau > t.$$

Interpretation: This is substantive branch difference, not merely event ordering difference, but difference in activated node sets themselves.

6.8 Summary

1. Local freedom of active nodes originates from competition zone structure and exponential growth.
2. Activation choice determined jointly by responsibility, growth and causal constraints.
3. History merging requires causal compatibility; otherwise branches cannot merge.
4. Time asymmetry emerges naturally: many future branches, unique past paths.
5. Continuous limit corresponds to exponential expansion; discrete model agrees with macroscopic cosmic behavior.
6. Legal activation set $\mathcal{X}_t$ typically non-unique; no global must-activate node set exists; branch differences are naturally emerging dynamical features.

7 Branch Weights and Interference

7.1 Necessity of Branch Weights

System activation choices at a given time t are typically non-unique, producing multiple possible branches. To describe relative likelihoods of these branches, we need a weight function.

Definition 6.1.1 (Branch Weight Function) Let $\mathcal{B}_t$ be legal branch set at time t. Weight function $W : \mathcal{B}_t \to \mathbb{R}^+$ satisfies normalization:

$$\sum_{\mathcal{B}\in\mathcal{B}_t} W(\mathcal{B}) = 1$$

Weight $W(\mathcal{B})$ describes relative likelihood of branch $\mathcal{B}$.

7.2 Weight Independence of Non-merging Branches

Non-merging branches have disjoint descendant node sets; their future evolutions cannot overlap. In this case, weights add independently.

Theorem 6.3.1 (Weight Additivity) If $\{\mathcal{B}_i\}$ are pairwise non-merging branches, then:

$$W\Big(\bigcup_i \mathcal{B}_i\Big) = \sum_i W(\mathcal{B}_i)$$

Strict proof:

- By non-merging definition, each branch $\mathcal{B}_i$ has unique node set D_i: (1) $D_i \cap D_j = \emptyset$ for all $i \neq j$, (2) each branch $\mathcal{B}_i$'s future activation must include D_i.
- Define observation event as "observing any node in D_i activate"; events are mutually exclusive:

$$P(\text{observing } D_i \text{ and } D_j) = 0, \quad i \neq j$$

- Therefore:

$$\begin{aligned} W\Big(\bigcup_i \mathcal{B}_i\Big) &= P\Big(\bigcup_i \text{observing } D_i\Big) \\ &= \sum_i P(\text{observing } D_i) \\ &= \sum_i W(\mathcal{B}_i) \end{aligned}$$

- Q.E.D.

7.3 Weight Superposition of Merging Branches

Merging branches may share future nodes; their weights superpose but must consider overlap degree.

Definition 6.4.1 (Interference Metric) For two branches $\mathcal{B}_1, \mathcal{B}_2$, define overlap:

$$\mathcal{V}(\mathcal{B}_1, \mathcal{B}_2) = 1 - \frac{|\Delta A_t(\mathcal{B}_1) \,\Delta\, \Delta A_t(\mathcal{B}_2)|}{|\Delta A_t(\mathcal{B}_1) \cup \Delta A_t(\mathcal{B}_2)|}$$

where $\Delta A_t(\mathcal{B})$ is newly activated node set in branch $\mathcal{B}$, Δ denotes symmetric difference.

Properties:

1. $0 \leq \mathcal{V} \leq 1$
2. $\mathcal{V}(\mathcal{B}, \mathcal{B}) = 1$
3. $\mathcal{V}(\mathcal{B}_1, \mathcal{B}_2) = \mathcal{V}(\mathcal{B}_2, \mathcal{B}_1)$

Overlap 0 means no overlap $\rightarrow$ no interference; 1 means complete overlap $\rightarrow$ maximal interference.

7.4 Symmetry and Equal Weight Assumption

Definition 6.5.1 (Local Choice Symmetry) For active node $u \in A_t$, let its legal choice set be:

$$\mathcal{S}(u) = \{S \subseteq F(u) : S \neq \emptyset \text{ and satisfies local constraints}\}$$

If there exists group G_u acting transitively on $\mathcal{S}(u)$, system has local choice symmetry at u.

Definition 6.5.2 (Global Symmetry) System has global symmetry at time t if:

1. All $u \in A_t$ have local choice symmetry
2. These symmetries coordinate to transitive group action on entire legal branch set $\mathcal{B}_t$

Theorem 6.5.1 (Equal Weight Theorem) If $\mathcal{B}_t$ is homogeneous under symmetry group G, and weight function W is G-invariant, then:

$$W(\mathcal{B}) = \frac{1}{|\mathcal{B}_t|}, \quad \forall \mathcal{B} \in \mathcal{B}_t$$

7.5 Dynamical Evolution of Weights

Evolution equation:

$$W_{t+1}(\mathcal{B}') = \sum_{\mathcal{B} \to \mathcal{B}'} T(\mathcal{B} \to \mathcal{B}')\, W_t(\mathcal{B})$$

Transfer coefficients $T(\mathcal{B} \to \mathcal{B}')$:

$$T(\mathcal{B} \to \mathcal{B}') = \begin{cases} 1/Z(\mathcal{B}) & \text{if } \mathcal{B}' \text{ is legal extension of } \mathcal{B} \\ 0 & \text{otherwise} \end{cases}$$

where $Z(\mathcal{B})$ is number of legal extensions of $\mathcal{B}$, for normalization.

7.6 Example 6.1

Let $d = 2, \lambda = 2$, starting from single node v_0 with successors $\{v_1, v_2\}$.

- Legal branches: $\mathcal{B}_1$: activate v_1; $\mathcal{B}_2$: activate v_2
- Symmetry: $\mathcal{B}_1 \leftrightarrow \mathcal{B}_2$
- Weights: $W(\mathcal{B}_1) = W(\mathcal{B}_2) = 1/2$
- New node sets: $\Delta A_0(\mathcal{B}_1) = \{v_1\}, \Delta A_0(\mathcal{B}_2) = \{v_2\}$
- Overlap: $\mathcal{V}(\mathcal{B}_1, \mathcal{B}_2) = 1 - \frac{2}{2} = 0 \rightarrow$ no interference

If allowing activation of both nodes ($\lambda = 3$), then $\mathcal{B}_3$: activate $\{v_1, v_2\}$ appears, having partial overlap with $\mathcal{B}_1$ and $\mathcal{B}_2 \rightarrow$ interference.

7.7 Summary

- Non-merging branches → weights add independently
- Merging branches → weights superpose, interference quantifiable via overlap $\mathcal{V}$
- Symmetry → equal weight theorem
- Weight evolution describable via transfer matrix T
- Example demonstrates basic mechanism of overlap and interference

This chapter provides strict definitions and calculation methods for probability and interference within discrete causal framework.

8 Emergence of Phases and Amplitude Evolution

8.1 Problem Statement

Chapter 6 weights $W(\mathcal{B})$ are real numbers describing relative likelihood of branches. Interference phenomena require complex phases to explain constructive or destructive superposition.

8.2 Oriented Edge Weights

Definition 7.2.1 (Oriented Edge Weight) Assign unit modulus complex number to each directed edge $u \to v \in E$:

$$w(u \to v) = e^{i\theta(u\to v)}, \quad |w(u \to v)| = 1$$

Improved phase definition:

$$\theta(u \to v) = \alpha \cdot I(u \to v) + \beta \cdot \kappa(u \to v) + \gamma \cdot \text{other topological invariants} \pmod{2\pi}$$

where:

- $I(u \to v)$ is information distinguishability marker (0 or 1)
- $\kappa(u \to v)$ is discrete curvature
- α, β, γ are fixed constants

Simple non-trivial example:

$$\theta(u \to v) = \frac{2\pi}{d} \cdot \kappa(u \to v) + \pi \cdot I(u \to v)$$

where curvature contribution $\frac{2\pi}{d}\kappa$ provides continuous phase change, and information branching contribution πI provides binary phase jump.

8.3 History Phase Factor

Definition 7.3.1 (Activated Edge) For history $\mathcal{B} = (A_0, A_1, \ldots, A_T)$, its activated edge set:

$$E_{\text{act}}(\mathcal{B}) = \{u \to v \in E : \exists t, u \in A_t, v \in A_{t+1}, v \text{ activated by } u\}$$

Definition 7.3.2 (History Phase Factor)

$$\Phi(\mathcal{B}) = \prod_{u\to v \in E_{\text{act}}(\mathcal{B})} w(u \to v) = \prod_{u\to v} e^{i\theta(u\to v)}$$

where $|\Phi(\mathcal{B})| = 1$, expressible as $\Phi(\mathcal{B}) = e^{i\Theta(\mathcal{B})}$.

8.4 Branch Amplitude

Definition 7.4.1 (Branch Amplitude)

$$A(\mathcal{B}) = \sqrt{W(\mathcal{B})}\,\Phi(\mathcal{B})$$

where $|A(\mathcal{B})|^2 = W(\mathcal{B})$, compatible with Chapter 6 probability interpretation.

8.5 History Sum Form

Total amplitude from initial activation A_0 to final activation A_T:

$$A(A_T) = \sum_{\mathcal{B}\,\text{merging to}\,A_T} A(\mathcal{B})$$

Observation probability:

$$P(A_T) = |A(A_T)|^2$$

Summation only over histories merging to same final state A_T. Total probability conserved: $\sum_{A_T} P(A_T) = 1$.

8.6 Determinism of Oriented Weights

Definition 7.6.1 (Weighted Automorphism) Graph automorphism $\phi : V \to V$ preserving edge relations is a weighted automorphism if:

$$w(\phi(u) \to \phi(v)) = w(u \to v)$$

This ensures locally isomorphic edges have same phase. $w(u \to v)$ should be determined by graph topology or directionality.

8.7 Interference Example

Node v_0 has outgoing edges to v_1, v_2:

$$w(v_0 \to v_1) = e^{i\alpha}, \quad w(v_0 \to v_2) = e^{i\beta}, \quad W(\mathcal{B}_1) = W(\mathcal{B}_2) = \frac{1}{2}$$

Total amplitude:

$$A_{\text{total}} = \frac{1}{\sqrt{2}}(e^{i\alpha} + e^{i\beta}), \quad P = |A_{\text{total}}|^2 = 1 + \cos(\alpha - \beta)$$

Interference term arises from edge phase difference.

8.8 Derived Action

Define "emergent action":

$$w(u \to v) = e^{is(u\to v)}, \quad S_{\text{eff}}(\mathcal{B}) = \sum_{u\to v \in E_{\text{act}}(\mathcal{B})} s(u \to v)$$

Here $s(u \to v)$ is dimensionless, describing only phase parameter. Action is derived concept, not fundamental assumption.

8.9 Amplitude Evolution

Theorem 7.9.1 (Amplitude Evolution Rule) Let history $\mathcal{B}$ have amplitude $A_t(\mathcal{B})$ at time t. Its legal extension $\mathcal{B}'$ has amplitude:

$$A_{t+1}(\mathcal{B}') = \sqrt{T(\mathcal{B} \to \mathcal{B}')} \cdot \left(\prod_{u\to v \in \Delta E_{\text{act}}(\mathcal{B}\to\mathcal{B}')} w(u \to v) \right) \cdot A_t(\mathcal{B})$$

where $T(\mathcal{B} \to \mathcal{B}')$ is Chapter 6 transfer probability, $\Delta E_{\text{act}}(\mathcal{B} \to \mathcal{B}')$ is newly activated edges.

Property 7.9.2 (Total Probability Conservation)

$$\sum_{\mathcal{B}'} |A_{t+1}(\mathcal{B}')|^2 = \sum_{\mathcal{B}} |A_t(\mathcal{B})|^2 = 1$$

8.10 Deep Implications

- Unit modulus of oriented weights ensures $|A(\mathcal{B})|^2 = W(\mathcal{B})$
- Combined with Chapter 6 weight normalization, guarantees total probability always 1 throughout evolution
- Phase more fundamental than action; action is derived concept
- Discrete causal graph structure naturally yields conservation laws without external assumptions
- Combination of curvature and information markers provides continuous and discrete phase changes, explaining arbitrary degree interference

8.11 Summary

- Fully endogenous complex amplitude framework
- History summation naturally yields interference
- Edge phase determined by graph topology and information markers
- Amplitude evolution follows directly from weight evolution and phase factors
- In continuous limit, "unitarity" of standard quantum mechanics emerges naturally, its essence being continuous manifestation of discrete probability conservation

9 Analysis of Causal Graph Connection Patterns

9.1 Connection Relations Between Nodes

9.1.1 Direct and Indirect Connections

Definition 8.1.1 (n-step reachable) Node u is n-step reachable to node v, denoted $u \rightsquigarrow_n v$, if path exists:

$$u = w_0 \to w_1 \to \cdots \to w_n = v$$

where $w_i \to w_{i+1} \in E$ for all $i = 0, \ldots, n-1$.

Definition 8.1.2 (Shortest step count) $\ell(u, v) = \min\{n \mid u \rightsquigarrow_n v\}$. If no such n, $\ell(u, v) = \infty$.

Definition 8.1.3 (Future reachable set) Node u's future reachable set:

$$F^*(u) = \{v \in V \mid \ell(u, v) < \infty\}$$

All nodes reachable from u via directed paths.

9.1.2 Common Connection Analysis

Definition 8.1.4 (Direct successor set) Node u's direct successor set:

$$F(u) = \{v \in V \mid u \to v \in E\}$$

By Assumption 1.3.1, $|F(u)| = d$ for all $u \in V$.

Definition 8.1.5 (Common successor set) Common successor set of nodes u and v:

$$\mathrm{CS}(u, v) = F(u) \cap F(v)$$

Definition 8.1.6 (Connection similarity) Connection similarity of nodes u and v:

$$s(u, v) = \frac{|\mathrm{CS}(u, v)|}{|F(u) \cup F(v)|} = \frac{|F(u) \cap F(v)|}{|F(u) \cup F(v)|}$$

Property 8.1.1

- $0 \leq s(u, v) \leq 1$
- $s(u, u) = 1$
- $s(u, v) = s(v, u)$

High similarity means similar connection patterns; low similarity means significantly different patterns.

9.2 Local Neighborhood Structure

9.2.1 Radius r Neighborhood

Definition 8.2.1 (Causal neighborhood) Radius r causal neighborhood of node u:

$$N_r(u) = \{v \in V \mid \ell(u,v) \le r \text{ or } \ell(v,u) \le r\}$$

Definition 8.2.2 (Pure future neighborhood) $N_r^+(u) = \{v \in V \mid \ell(u,v) \le r\}$
Definition 8.2.3 (Pure past neighborhood) $N_r^-(u) = \{v \in V \mid \ell(v,u) \le r\}$
Clearly $N_r(u) = N_r^+(u) \cup N_r^-(u)$.

9.2.2 Connection Density Within Neighborhood

Definition 8.2.4 (Edge count within neighborhood) $e_r(u) = |\{(x,y) \in E \mid x,y \in N_r(u)\}|$
Definition 8.2.5 (Maximum possible edges) $e_{\max}(r) = |N_r(u)| \cdot (|N_r(u)| - 1)$
Definition 8.2.6 (Local connection density) $\delta_r(u) = \frac{e_r(u)}{e_{\max}(r)}$
Property 8.2.1

- $\delta_r(u) \approx 1$ means almost fully connected
- $\delta_r(u) \approx 0$ means sparse connections

9.3 Statistical Patterns of Connection Modes

9.3.1 Distance Distribution

Definition 8.3.1 (Distance distribution function)

$$P_d(n) = \mathbb{P}(\ell(u,v) = n \mid \ell(u,v) < \infty)$$

In exponentially growing causal graphs, typically observed: $P_d(n) \sim \lambda^{-n} \quad (n \text{ large})$.
Definition 8.3.2 (Average shortest step) $\bar{\ell} = \sum_{n=1}^{\infty} n \cdot P_d(n)$

9.3.2 Clustering Coefficient

Definition 8.3.3 (Local clustering coefficient)

$$c(u) = \frac{2t(u)}{d(d-1)}, \quad t(u) = |\{(v,w) \in F(u) \times F(u) \mid v \neq w, v \to w \in E\}|$$

Definition 8.3.4 (Graph average clustering coefficient) $\bar{c} = \frac{1}{|V|} \sum_{u \in V} c(u)$

9.4 Endogenous Definition of "Direction"

9.4.1 Relative Direction Based on Connection Similarity

Definition 8.4.1 (Triplet direction similarity) For nodes u, v, w:

- $s(u,v) > \theta$
- $s(u,w) < \theta', s(v,w) < \theta'$

Then u, v are in similar direction, w in different direction.

9.4.2 Extracting Principal Direction

Algorithm 8.4.1 (Node out-edge direction analysis)

1. Build direct successor set $F(u) = \{v_1, \ldots, v_d\}$
2. Compute connection similarity matrix $S_{ij} = s(v_i, v_j)$
3. Eigenvalue decomposition $S = Q\Lambda Q^\top$

4. Principal eigenvector $\mathbf{q}_1$ corresponding to largest eigenvalue represents principal direction weights

Definition 8.4.2 (Direction consistency index) $\kappa(u) = \frac{\lambda_1}{\sum_{k=1}^{d} \lambda_k}$

- $\kappa(u) \approx 1$: out-edges highly concentrated
- $\kappa(u) \approx 1/d$: out-edges uniformly distributed

9.5 Concept of Graph "Dimension"

9.5.1 Dimension Based on Neighborhood Growth

Definition 8.5.1 (Neighborhood growth dimension) If exists d such that $|N_r^+(u)| \sim r^{d-1} \quad (r \to \infty)$, call local growth dimension d.

9.5.2 Dimension Estimation Based on Connection Similarity

Definition 8.5.2 (Embedding dimension problem) Find minimal dimension D and embedding $\phi : F(u) \to \mathbb{R}^D$, minimizing stress function:

$$\text{stress}(\phi) = \sum_{i \neq j} \left(s(v_i, v_j)^{-1} - 1 - \|\phi(v_i) - \phi(v_j)\|^2 \right)^2$$

Algorithm 8.5.1 (Multidimensional scaling)

1. Start trying from $D = 1$
2. Find embedding ϕ_D minimizing stress
3. Compute normalized stress $\text{stress}_N(D)$
4. Choose minimal D such that $\text{stress}_N(D) < \epsilon$

Definition 8.5.3 (Local similarity dimension) $D_{\text{sim}}(u) =$ minimal D satisfying threshold

9.6 Bridge from Discrete to Continuous

9.6.1 Coarse-graining Treatment

Definition 8.6.1 (Node partition) $V = \bigcup_{\alpha=1}^{M} B_\alpha, \quad B_\alpha \cap B_\beta = \emptyset$ Each block B_α contains many nodes $|B_\alpha| \gg 1$.

Definition 8.6.2 (Inter-block connection strength)

$$C_{\alpha\beta} = \frac{|\{(u, v) \in E \mid u \in B_\alpha, v \in B_\beta\}|}{|B_\alpha| \cdot |B_\beta|}$$

9.6.2 Conditions for Continuous Approximation

Condition 8.6.1 (Three conditions)

1. Scale separation: $1 \ll |B_\alpha| \ll |V|$
2. Smoothness: Exists mapping $\psi : B_\alpha \to \mathcal{M}$ such that $C_{\alpha\beta} \approx f(\psi(B_\alpha), \psi(B_\beta))$
3. Local uniformity: Local statistics vary slowly in $\mathcal{M}$

Definition 8.6.3 (Continuous limit) When $|V| \to \infty$ and partition becomes finer, if exists continuous manifold $\mathcal{M}$ and smooth function f such that:

$$\limsup_{\alpha,\beta} |C_{\alpha\beta} - f(\psi(B_\alpha), \psi(B_\beta))| = 0,$$

then causal graph has continuous limit.

Theorem 8.6.1 (Existence of continuous approximation) If causal graph satisfies translation invariance, decay, isotropy (or regular anisotropy), continuous limit may exist.

9.6.3 Statistical Intuition

As block size increases, each block contains many nodes, causing random fluctuations in connection strength $C_{\alpha\beta}$ to average out, approximating smooth function f, similar to law of large numbers.

9.7 Connection to Evolution Dynamics

9.7.1 Requirements on Connection Patterns for Growth

Exponential growth $N_{t+1} = \lambda N_t$ requires each active node to activate average $k = \lambda - 1$ new nodes.

Corollary 8.7.1 Connection patterns must satisfy:

1. Dispersion: $\mathbb{E}[s(u, v)]$ small for nodes at same time step
2. Coverage: $\left|\bigcup_{u \in A_t} F(u)\right| \geq \lambda |A_t|$

Definition 8.7.1 (Conflict coefficient) $\chi_t = \frac{1}{|A_t|^2} \sum_{u,v \in A_t} s(u, v)$

9.7.2 Effect of Connection Patterns on Branch Choice

Definition 8.7.2 (Branch distance)

$$d_{\text{branch}}(\mathcal{B}_1, \mathcal{B}_2) = 1 - \frac{|A_t^{(1)} \cap A_t^{(2)}|}{|A_t^{(1)} \cup A_t^{(2)}|}$$

Connection patterns affect similarity between different branches: high similarity yields similar futures; low yields significantly different futures.

9.8 Chapter Summary

1. Core concepts reviewed: shortest step $\ell(u, v)$, connection similarity $s(u, v)$, local clustering $c(u)$, neighborhood growth $|N_r(u)|$, direction consistency $\kappa(u)$, local similarity dimension $D_{\text{sim}}(u)$
2. Endogenous principle: no preset geometry; geometric concepts entirely derived from connection patterns; obtained via statistical pattern recognition; each concept has explicit computation method
3. Physical analogies:

Endogenous concept	Physical analogy	Key difference
$s(u, v)$	Spatial proximity	Based on information flow not preset distance
$\ell(u, v)$	Timelike distance	Discrete steps not continuous time
$\kappa(u)$	Worldline directionality	From connection patterns not coordinate axes
Growth dimension d	Spatial dimension	Derived from local growth

4. Origin of continuous limit: coarse-graining averages random fluctuations within blocks; inter-block connection strength approximates smooth function; similar to law of large numbers, statistical averaging produces continuous metric

Key insight: Geometry is not preset background but statistical manifestation of connection patterns; continuous spacetime emerges as effective theory in specific limit, not fundamental reality.

10 Macroscopic Manifestations of Branch Divergence and Observable Differences

10.1 Problem Location: From Branch Differences to Macroscopic Differences

According to Chapter 6, system at time t has multiple legal branches $\mathcal{B} \in B_t$, each with amplitude $A(\mathcal{B}) = \sqrt{W(\mathcal{B})}\,\Phi(\mathcal{B})$. According to Chapter 7, total amplitude calculation sums only over merging historical branches.

Now consider specific observable pattern: let $R \subset V$ be some region of graph. We focus on activation states of nodes within this region.

Definition 9.1.1 (Region activation pattern) For history branch $\mathcal{B}$, define its activation pattern in region R at time t as:

$$M_R(\mathcal{B}, t) = \{\mathcal{S}_t(v) : v \in R\}$$

i.e., activation state (0 or 1) of each node in R at time t.

Definition 9.1.2 (Activation count observation) Define observable:

$$N_R(\mathcal{B}, t) = \sum_{v \in R} \mathcal{S}_t(v)$$

i.e., total number of active nodes in region R at time t.

10.2 Pattern Differences Between Branches

Lemma 9.2.1 (Universality of branch differences) In exponential growth phase ($\lambda > 1$), for any sufficiently large region R, there exist two legal branches $\mathcal{B}_1, \mathcal{B}_2$ such that:

$$M_R(\mathcal{B}_1, t) \neq M_R(\mathcal{B}_2, t)$$

Proof:

1. By growth constraint $N_{t+1} = \lambda N_t$, system must choose $\Delta N_t = (\lambda - 1)N_t$ new nodes to activate.
2. Candidate set $\Omega_t = \bigcup_{u \in A_t} F(u)$ typically much larger than ΔN_t.
3. Multiple legal ways exist to choose which nodes activate.
4. If region R contains at least one candidate node $v \in \Omega_t \cap R$, then exists branch $\mathcal{B}_1$ activating v, branch $\mathcal{B}_2$ not activating v.
5. Under exponential growth, $|\Omega_t|$ grows rapidly; any finite region R will eventually contain candidate nodes.
6. Therefore activation pattern differences exist. □

10.3 From Pattern Differences to Observable Fluctuations

Definition 9.3.1 (Branch value of observable) Let O be quantity determined by activation pattern (e.g., N_R, activation state of some node). For each branch $\mathcal{B}$, define $O(\mathcal{B})$ as value of O in that branch.

Definition 9.3.2 (Amplitude-weighted average) Amplitude-weighted average of observable O:

$$\langle O \rangle_t = \sum_{\mathcal{B} \in B_t} |A(\mathcal{B})|^2 \cdot O(\mathcal{B})$$

where $|A(\mathcal{B})|^2 = W(\mathcal{B})$ is branch weight.

Definition 9.3.3 (Fluctuation amplitude) Fluctuation of observable O:

$$(\Delta O)_t^2 = \sum_{\mathcal{B} \in B_t} |A(\mathcal{B})|^2 \cdot [O(\mathcal{B}) - \langle O \rangle_t]^2$$

Theorem 9.3.4 (Condition for fluctuation existence) $\Delta O > 0$ if and only if there exist two branches $\mathcal{B}_1, \mathcal{B}_2$ satisfying:

1. $|A(\mathcal{B}_1)|^2 > 0$ and $|A(\mathcal{B}_2)|^2 > 0$
2. $O(\mathcal{B}_1) \neq O(\mathcal{B}_2)$

Proof: Direct from definition. If all branches have same O value, variance 0. If two branches have different O values with non-zero weights, variance necessarily positive. □

10.4 Fluctuation Interpretation of Double-slit Experiment

10.4.1 Experimental Setup Review

Use simplified model from Section 9.4:

- Source node S
- Path nodes A, B
- Screen nodes $D_1, D_2, \ldots, D_k$

Observable: whether screen node D_j activates at time t_2.

10.4.2 Branch Analysis

Consider two branches:

- $\mathcal{B}_A$: $S \to A \to D_j$ (activates D_j)
- $\mathcal{B}_B$: $S \to B \to D_j$ (activates D_j)

Case 1: No path recording nodes

- $\mathcal{B}_A$ and $\mathcal{B}_B$ can merge
- Total amplitude: $A(D_j) = A(\mathcal{B}_A) + A(\mathcal{B}_B)$
- Probability: $P(D_j) = |A(\mathcal{B}_A) + A(\mathcal{B}_B)|^2$
- But: each specific evolution, system takes only one branch
- If experiment repeated many times, sometimes takes $\mathcal{B}_A$, sometimes $\mathcal{B}_B$
- In $\mathcal{B}_A$: D_j activates (because $A \to D_j$)
- In $\mathcal{B}_B$: D_j activates (because $B \to D_j$)
- Wait, both branches activate D_j, no fluctuation?

Need refined model: screen has multiple nodes D_j, and different paths tend to activate different D_j (due to phase differences).

10.4.3 Revised Model

Set phases:

- $w(A \to D_j) = e^{i\alpha_j}$
- $w(B \to D_j) = e^{i\beta_j}$ with α_j, β_j varying with j

Then:

- Branch $\mathcal{B}_A$: tends to activate D_j for which α_j favorable
- Branch $\mathcal{B}_B$: tends to activate D_j for which β_j favorable

Since $\alpha_j \neq \beta_j$, two branches activate different sets of D_j.
Specifically: let O_j indicate "whether D_j activates". In $\mathcal{B}_A$, $O_j(\mathcal{B}_A) = 1$ for some j. In $\mathcal{B}_B$, $O_j(\mathcal{B}_B) = 1$ for other j. Thus $O_j(\mathcal{B}_A) \neq O_j(\mathcal{B}_B)$ for many j.

10.4.4 Emergence of Fluctuations

By Theorem 9.3.4:

- Exist branches $\mathcal{B}_A, \mathcal{B}_B$ with $|A(\mathcal{B}_A)|^2 > 0, |A(\mathcal{B}_B)|^2 > 0$
- $O_j(\mathcal{B}_A) \neq O_j(\mathcal{B}_B)$ for some j
- Therefore $\Delta O_j > 0$

This manifests as: in repeated experiments, D_j sometimes activates, sometimes doesn't. Activation pattern on screen differs each time → fluctuation of interference fringes.

10.5 Fluctuations in Uniform Background (Vacuum Fluctuations)

10.5.1 Uniform State Definition

Consider ideal case: graph highly uniform in some region R, all nodes structurally equivalent.

Definition 9.5.1 (Uniform activation pattern) Branch $\mathcal{B}$ is uniform in region R if for any two nodes $u, v \in R$, their activation probabilities in $\mathcal{B}$ are equal:

$$\sum_{\mathcal{B}:\mathcal{S}_t(u)=1} |A(\mathcal{B})|^2 = \sum_{\mathcal{B}:\mathcal{S}_t(v)=1} |A(\mathcal{B})|^2$$

10.5.2 Differences Within Uniformity

Even in such uniform background, different uniform branches can have different specific activation nodes.

Example: Let R have m nodes, need to activate k of them ($k < m$). Which k nodes to activate has $\binom{m}{k}$ ways, corresponding to different branches.

These branches:

1. All have same weight (by symmetry, Theorem 6.5.1)
2. All have same macroscopic density k/m
3. But specific which node activates differs

10.5.3 Fluctuations of Local Observables

Consider smaller subregion $R_0 \subset R$, with $|R_0| = n$, $|R| = m$. Define observable $X =$ "activation count within R_0".

In branch $\mathcal{B}$, $X(\mathcal{B})$ is actual number of activated nodes in R_0.

Since activation node choice is random (equal weight branches), X follows hypergeometric distribution:

$$P(X = x) = \frac{\binom{k}{x}\binom{m-k}{n-x}}{\binom{m}{n}}$$

Compute fluctuations: Expectation $\langle X \rangle = n \cdot (k/m)$ Variance $(\Delta X)^2 = n \cdot \frac{k}{m} \cdot \left(1 - \frac{k}{m}\right) \cdot \frac{m-n}{m-1}$

Since m finite, $\Delta X > 0$. This is vacuum fluctuation: even in uniform background, local activation count has fluctuations.

10.6 Transient Activation Patterns (Virtual Processes)

10.6.1 Intermediate States of Responsibility Transmission

Consider node u needs to activate distant w. Possible via intermediate node v: $u \to v \in E$, $v \to w \in E$.

Branch differentiation:

- Branch $\mathcal{B}_1$: u activates v at t, v activates w at $t + 1$
- Branch $\mathcal{B}_2$: u directly activates w in other way (perhaps via other path)

10.6.2 Observation of Intermediate Node

Define observable $Y =$ "whether node v activates between t and $t + 1$".

In $\mathcal{B}_1$: $Y(\mathcal{B}_1) = 1$ (v activates) In $\mathcal{B}_2$: $Y(\mathcal{B}_2) = 0$ (v doesn't activate)

Therefore $\Delta Y > 0$.

Interpretation: Node v's activation appears in some branches, not in others. When it appears, exists only very briefly (one step). This is graphical representation of virtual activation.

10.7 Scaling Relations of Fluctuations

10.7.1 Region Size and Fluctuations

Consider observable N_R (activation count in region R).

Let system have average activation density $\rho = \langle N_R \rangle / |R|$ in R.

Theorem 9.7.1 (Fluctuation vs region size) If node activations in R approximately independent, then:

$$\Delta N_R \propto \sqrt{|R|}$$

Relative fluctuation:

$$\frac{\Delta N_R}{\langle N_R \rangle} \propto \frac{1}{\sqrt{|R|}}$$

Proof:

1. Each node's activation state is random variable with finite variance
2. N_R is sum of $|R|$ random variables
3. If they are independent or weakly correlated, variance of sum $\propto |R|$
4. Standard deviation $\propto \sqrt{|R|}$
5. Relative fluctuation $\propto \sqrt{|R|}/|R| = 1/\sqrt{|R|}$ $\square$

10.7.2 Minimum Fluctuation Due to Discreteness

Due to graph discreteness, nodes have minimal spacing (say a), region size $|R|$ has minimum.

Corollary 9.7.2 (Minimum observable fluctuation) For minimal resolvable region $R_{\min}$ (scale $\sim a$), fluctuation has lower bound:

$$\Delta N_{R_{\min}} \gtrsim 1$$

i.e., at least one node's activation uncertain.

This is discrete scale fluctuation: originating from graph's discrete structure.

10.8 Manifestation of Fluctuations in Measurement Process

10.8.1 Role of Measurement Apparatus

Measurement apparatus is a causal structure amplifying microscopic branch differences into macroscopic recordable differences.

Suppose microscopic has two branches $\mathcal{B}_1, \mathcal{B}_2$, difference small (e.g., some phase different).

Measurement apparatus M designed such that:

- In $\mathcal{B}_1$: M activates pointer node P_1
- In $\mathcal{B}_2$: M activates pointer node P_2
- Activation patterns of P_1 and P_2 macroscopically distinguishable

10.8.2 Fluctuations of Measurement Results

Define observable $Z =$ "which result pointer points to".

In $\mathcal{B}_1$: $Z(\mathcal{B}_1) = 1$ In $\mathcal{B}_2$: $Z(\mathcal{B}_2) = 2$

Therefore $\Delta Z > 0$. Measurement results have fluctuations.

Key: This fluctuation not introduced by measurement apparatus, but macroscopic manifestation of microscopic branch differences.

10.9 From Quantum Fluctuations to Classical Determinism

10.9.1 Role of Law of Large Numbers

When observable involves many nodes ($|R| \to \infty$), relative fluctuation $\Delta N_R / \langle N_R \rangle \to 0$.

Theorem 9.9.1 (Classical determinism as limit) For any observable O expressible as function of many independent or weakly correlated nodes:

$$\lim_{N \to \infty} \frac{\Delta O}{\langle O \rangle} = 0$$

Proof: Let $O = \sum_{i=1}^{N} X_i$, where X_i is contribution of single node, finite variance, mutually weakly correlated. Then:

$$\mathrm{Var}(O) = \sum_{i=1}^{N} \mathrm{Var}(X_i) + \sum_{i \neq j} \mathrm{Cov}(X_i, X_j)$$

If covariance terms grow no faster than N, then $\mathrm{Var}(O) \sim O(N)$, standard deviation $\sim O(\sqrt{N})$, while $\langle O \rangle \sim O(N)$, relative fluctuation $\sim O(1/\sqrt{N}) \to 0$. □

10.9.2 Role of Decoherence

Decoherence (via recording nodes) makes different branches non-merging. Once branches non-merging, their amplitudes no longer add.

But effect on fluctuations:

- Before decoherence: fluctuations from interference of merging branches
- After decoherence: fluctuations from classical probability mixing of different branches

Total fluctuation not necessarily decreases, but nature changes: from quantum coherent fluctuations to classical statistical fluctuations.

10.10 Summary: Origin of Fluctuations

This chapter establishes logical chain:

1. Existence of branches (Chapter 6): system evolution has multiple legal paths
2. Branch differences: activation patterns differ between branches
3. Branch values of observables: each observable has definite value in each branch
4. Amplitude-weighted average: expectation value of observable
5. Fluctuation definition: variance of branch values
6. Universality of fluctuations: whenever two branches with different values exist, fluctuations exist
7. Specific manifestations:
    - Double-slit experiment: different branches activate different screen nodes
    - Vacuum: choice of specific activation nodes differs in uniform background
    - Virtual processes: path differences in responsibility transmission cause intermediate node activation differences
8. Scaling relations: fluctuation amplitude grows slowly with region ($\sqrt{N}$ law)
9. Classical limit: macroscopic observables involve many nodes, relative fluctuations tend to zero

11 Constraint Structure of Change Propagation

11.1 Basic Definitions

Let $G = (V, E)$ be d-regular directed acyclic graph.

11.1.1 Connection Similarity

For any $u, v \in V$, define:

$$s(u,v) = \frac{|F(u) \cap F(v)|}{|F(u) \cup F(v)|}$$

where $F(u) = \{w \in V : u \to w \in E\}$.

11.1.2 Path Length

$\ell(u,v)$ is shortest path length from u to v; if unreachable, $\ell(u,v) = \infty$.

11.2 Definition and Analysis of Change Intensity

11.2.1 Single-step Change Intensity

For edge $u \to v \in E$, define:

$$\delta(u,v) = 1 - s(u,v)$$

11.2.2 Finiteness of Change Intensity

Lemma 10.2.1 There exist constants $0 < \delta_{\min} \le \delta_{\max} < 1$ such that for all edges $u \to v$:

$$\delta_{\min} \le \delta(u,v) \le \delta_{\max}$$

Proof: Let $k = |F(u) \cap F(v)|$, then $0 \le k \le d$ and $k \ne 0, k \ne d$ (non-degenerate assumption). Then:

$$s(u,v) = \frac{k}{2d-k}$$

Since $0 < k_{\min} \le k \le k_{\max} < d$, we get:

$$\delta_{\min} = 1 - \frac{k_{\max}}{2d - k_{\max}} > 0, \quad \delta_{\max} = 1 - \frac{k_{\min}}{2d - k_{\min}} < 1 \quad \square$$

11.3 Accumulated Change and Path Optimization

11.3.1 Path Accumulated Change

For path $P = (u = w_0 \to w_1 \to \cdots \to w_n = v)$, define:

$$C(P) = \sum_{i=0}^{n-1} \delta(w_i, w_{i+1})$$

11.3.2 Minimal Accumulated Change

$$D(u,v) = \min\{C(P) : P \text{ is path from } u \text{ to } v\}$$

11.3.3 Basic Inequalities

Theorem 10.3.1 For all reachable $u \ne v$:

$$\delta_{\min} \cdot \ell(u,v) \le D(u,v) \le \delta_{\max} \cdot \ell(u,v)$$

Proof: Let shortest path P^* have length $n = \ell(u,v)$. By Lemma 10.2.1, δ on each edge in $[\delta_{\min}, \delta_{\max}]$, so:

$$n\delta_{\min} \le C(P^*) \le n\delta_{\max}$$

Since $D(u,v) \le C(P^*)$, and any path needs at least n edges, $D(u,v) \ge n\delta_{\min}$. $\square$

11.4 Change Rate Analysis

11.4.1 Average Change Rate

For reachable $u \neq v$, define:

$$r(u,v) = \frac{D(u,v)}{\ell(u,v)}$$

By Theorem 10.3.1: $\delta_{\min} \leq r(u,v) \leq \delta_{\max}$

11.4.2 Limit Ratios

Define:

$$R_{\min} = \inf_{u \neq v} r(u,v), \quad R_{\max} = \sup_{u \neq v} r(u,v)$$

We have $\delta_{\min} \leq R_{\min} \leq R_{\max} \leq \delta_{\max}$.

Assume graph rich enough that sequences (u_n, v_n) exist with $r(u_n, v_n) \to R_{\min}$, and sequences (u'_n, v'_n) with $r(u'_n, v'_n) \to R_{\max}$.

11.5 Chain Description and Relative Relations

11.5.1 Approximate Minimal Change Chains

Suppose node sequence $A = (A_0, A_1, A_2, \ldots)$ satisfies:

1. $A_i \to A_{i+1} \in E$
2. $\delta(A_i, A_{i+1}) \to R_{\min}$ as i increases

Call A approximate minimal change chain.

11.5.2 Relative Difference Parameter

Let A and B be two approximate minimal change chains, define:

$$\rho = \frac{D(A_0, B_0)}{\ell(A_0, B_0) \cdot R_{\min}} - 1$$

When $A_0 = B_0$, $\rho = 0$.

11.6 Derivation of Description Transformation

11.6.1 Problem Setting

Consider node $p \in V$. From chain A description: $t_A = \ell(A_0, p)$, $d_A = D(A_0, p)$ From chain B description: $t_B = \ell(B_0, p)$, $d_B = D(B_0, p)$

11.6.2 Existence of Functional Relations

Lemma 10.6.1 There exist functions f, g such that:

$$t_B = f(t_A, d_A; \rho), \quad d_B = g(t_A, d_A; \rho)$$

Proof: Given A_0, B_0 and ρ, for each p, (t_A, d_A) uniquely determines p's relative position in graph, thus determining (t_B, d_B). □

11.6.3 Local Linear Approximation

In small neighborhood of (t_A, d_A), by local uniformity of graph, f and g approximable as linear functions:

$$\begin{pmatrix} t_B \\ d_B \end{pmatrix} \approx \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} t_A \\ d_A \end{pmatrix}$$

Coefficients a, b, c, d depend on ρ.

11.7 Establishing Constraint Conditions

11.7.1 Chain Self-description Constraint

In chain B's own description, when $p = B_t$: $t_B = t$, $d_B = R_{\min} t$

In chain A description, B_t satisfies $d_A = (\rho + 1) R_{\min} t_A$

Thus when $d_A = (\rho + 1) R_{\min} t_A$, should have $d_B = 0$.

Substituting into linear approximation:

$$c t_A + d[(\rho + 1) R_{\min} t_A] = 0$$

Gives: $c + d(\rho + 1) R_{\min} = 0 \quad \text{(C1)}$

11.7.2 Maximal Change Direction Constraint

Let $\Gamma = R_{\max} / R_{\min} > 1$.

Maximal change direction satisfies $d = R_{\max} t = \Gamma R_{\min} t$.

Requirement: if in A description $d_A = \Gamma R_{\min} t_A$, then in B description $d_B = \Gamma R_{\min} t_B$.

Substituting:

$$c t_A + d(\Gamma R_{\min} t_A) = \Gamma R_{\min}(a t_A + b \Gamma R_{\min} t_A)$$

Gives: $c + d\Gamma R_{\min} = \Gamma R_{\min}(a + b\Gamma R_{\min}) \quad \text{(C2)}$

11.7.3 Boundary Condition

When $\rho = 0$, transformation should be identity:

$$a = 1, b = 0, c = 0, d = 1 \quad \text{(C3)}$$

11.7.4 Inverse Transformation Symmetry

Transformation coefficients from B to A should satisfy symmetry relations, and transformation composition should preserve opposite parameter sign.

11.8 Equation Solving

Let $k = R_{\min}$, $\Gamma = R_{\max} / R_{\min}$.

From C1: $c = -d(\rho + 1)k$

From C3: when $\rho = 0$, $c = 0$, $d = 1$, substituting into C1 gives $0 + 1 \cdot (0 + 1)k = 0$? Contradiction.

This indicates constraint setup problematic. Need re-examination.

11.9 Constraint Revision

Problem: In chain B's own description, when $p = B_t$, should have $d_B = R_{\min} t_B$, but $t_B = t$, $d_B = D(B_0, B_t)$.

By B being approximate minimal change chain, $D(B_0, B_t) \approx R_{\min} t$, not exactly equal.

Revise to: exists constant $\epsilon \to 0$ such that $|D(B_0, B_t) - R_{\min} t| < \epsilon t$.

Thus constraint C1 should be approximate constraint.

11.9.1 New Constraint Setup

Consider direction: when $d_A = \alpha t_A$, hope $d_B = \beta t_B$, where α, β relate to ρ.

Specifically:

1. Chain B's own direction: $\alpha = (\rho + 1) R_{\min}$, $\beta = R_{\min}$
2. Maximal change direction: $\alpha = R_{\max}$, $\beta = R_{\max}$

Let transformation be:

$$t_B = a t_A + b d_A, \quad d_B = c t_A + d d_A$$

Constraint 1: When $d_A = (\rho + 1) R_{\min} t_A$, $d_B = R_{\min} t_B$ Substituting:

$$c t_A + d(\rho + 1) R_{\min} t_A = R_{\min}(a t_A + b(\rho + 1) R_{\min} t_A)$$

$$c + d(\rho+1)R_{\min} = R_{\min}[a + b(\rho+1)R_{\min}] \quad \text{(C1')}$$

Constraint 2: When $d_A = R_{\max}t_A$, $d_B = R_{\max}t_B$

$$c + dR_{\max} = R_{\max}(a + bR_{\max}) \quad \text{(C2')}$$

Boundary condition: $\rho = 0$: $a = 1, b = 0, c = 0, d = 1$

11.9.2 Solving Equations

Let $k = R_{\min}$, $\Gamma = R_{\max}/R_{\min}$.

C1': $c + d(\rho+1)k = k[a + b(\rho+1)k]$ C2': $c + d\Gamma k = \Gamma k(a + b\Gamma k)$ Boundary: $\rho = 0$: $a = 1, b = 0, c = 0, d = 1$

When $\rho = 0$, C1' becomes: $0 + 1 \cdot 1 \cdot k = k[1 + 0 \cdot 1 \cdot k] \Rightarrow k = k$, holds. C2' becomes: $0 + 1 \cdot \Gamma k = \Gamma k(1 + 0 \cdot \Gamma k) \Rightarrow \Gamma k = \Gamma k$, holds.

Now consider general ρ.

From C1' and C2' eliminate c:

$$k[a + b(\rho+1)k] - d(\rho+1)k = \Gamma k(a + b\Gamma k) - d\Gamma k$$

Divide by k ($k > 0$):

$$a + b(\rho+1)k - d(\rho+1) = \Gamma(a + b\Gamma k) - d\Gamma$$

Rearrange:

$$a(1-\Gamma) + bk[(\rho+1) - \Gamma^2] + d[\Gamma - (\rho+1)] = 0 \quad (1)$$

Another relation: from C1':

$$c = k[a + b(\rho+1)k] - d(\rho+1)k$$

Need two more equations. Consider inverse transformation or composition.

Consider transformation composition: let from A to B parameter ρ, from B to C parameter σ, then from A to C parameter should be some $\tau = \phi(\rho, \sigma)$.

By linear form of transformation, composition corresponds to matrix multiplication:

$$\begin{pmatrix} a(\tau) & b(\tau) \\ c(\tau) & d(\tau) \end{pmatrix} = \begin{pmatrix} a(\sigma) & b(\sigma) \\ c(\sigma) & d(\sigma) \end{pmatrix} \begin{pmatrix} a(\rho) & b(\rho) \\ c(\rho) & d(\rho) \end{pmatrix}$$

This gives functional equations.

11.10 Solution of Functional Equations

Let $A(\rho) = \begin{pmatrix} a(\rho) & b(\rho) \\ c(\rho) & d(\rho) \end{pmatrix}$

Require: $A(\phi(\rho, \sigma)) = A(\sigma)A(\rho)$

And $\phi(\rho, 0) = \rho$, $\phi(0, \sigma) = \sigma$, $\phi(\rho, -\rho) = 0$.

Assume $A(\rho)$ differentiable, expand at $\rho = 0$.

Let $A(0) = I$ (identity matrix)

Let $A'(\rho)|_{\rho=0} = \begin{pmatrix} \alpha & \beta \\ \gamma & \delta \end{pmatrix}$

By boundary $a(0) = 1, b(0) = 0, c(0) = 0, d(0) = 1$.

Differentiate composition relation at $\sigma = 0$:

$$\frac{d}{d\sigma} A(\phi(\rho, \sigma))|_{\sigma=0} = A'(0)A(\rho)$$

But left side $= A'(\phi(\rho, 0)) \cdot \frac{\partial \phi}{\partial \sigma}|_{\sigma=0} = A'(\rho) \cdot \frac{\partial \phi}{\partial \sigma}|_{\sigma=0}$

Let $\frac{\partial \phi}{\partial \sigma}|_{\sigma=0} = \psi(\rho)$

Then: $A'(\rho)\psi(\rho) = A'(0)A(\rho)$

This is matrix differential equation.

Assume $\psi(\rho) = 1$ (simplest case), then:

$$A'(\rho) = A'(0)A(\rho)$$

Solution: $A(\rho) = e^{\rho A'(0)}$

11.10.1 Determining $A'(0)$

Differentiate C1' at $\rho = 0$: C1': $c(\rho) + d(\rho)(\rho + 1)k = k[a(\rho) + b(\rho)(\rho + 1)k]$

Differentiate, $\rho = 0$:

$$c'(0) + d'(0) \cdot 1 \cdot k + d(0) \cdot 1 \cdot k = k[a'(0) + b'(0) \cdot 1 \cdot k + b(0) \cdot 1 \cdot k]$$

Known: $c(0) = 0, d(0) = 1, b(0) = 0$ $c'(0) = \gamma, d'(0) = \delta, a'(0) = \alpha, b'(0) = \beta$

Substitute:

$$\gamma + \delta k + 1 \cdot k = k[\alpha + \beta k + 0]$$

$$\gamma + (\delta + 1)k = k\alpha + k^2\beta \quad \text{(D1)}$$

Differentiate C2' at $\rho = 0$: C2': $c(\rho) + d(\rho)\Gamma k = \Gamma k[a(\rho) + b(\rho)\Gamma k]$

Differentiate:

$$c'(0) + d'(0)\Gamma k = \Gamma k[a'(0) + b'(0)\Gamma k]$$

$$\gamma + \delta\Gamma k = \Gamma k(\alpha + \beta\Gamma k) \quad \text{(D2)}$$

11.10.2 Solving $A'(0)$

From D1: $\gamma = k\alpha + k^2\beta - (\delta + 1)k$

From D2: $\gamma = \Gamma k\alpha + \Gamma^2 k^2\beta - \delta\Gamma k$

Subtract:

$$k\alpha + k^2\beta - (\delta + 1)k = \Gamma k\alpha + \Gamma^2 k^2\beta - \delta\Gamma k$$

Rearrange:

$$k\alpha(1 - \Gamma) + k^2\beta(1 - \Gamma^2) + k[-\delta - 1 + \delta\Gamma] = 0$$

Divide by $k > 0$:

$$\alpha(1 - \Gamma) + k\beta(1 - \Gamma^2) + [\delta(\Gamma - 1) - 1] = 0$$

$$\alpha(1 - \Gamma) + k\beta(1 - \Gamma^2) + \delta(\Gamma - 1) = 1$$

$$(\Gamma - 1)(-\alpha + \delta) + k\beta(1 - \Gamma^2) = 1$$

Since $\Gamma > 1$, $1 - \Gamma^2 < 0$.

Need other condition. Consider determinant of $A(\rho)$.

By physical reasonableness, transformation should preserve some "area" or orientation. Assume $\det A(\rho) = 1$.

Then $\det A(0) = 1$, and $\frac{d}{d\rho} \det A(\rho)|_{\rho=0} = \operatorname{tr} A'(0) = \alpha + \delta = 0$

Thus $\delta = -\alpha$

Substitute:

$$(\Gamma - 1)(-\alpha - \alpha) + k\beta(1 - \Gamma^2) = 1$$

$$-2\alpha(\Gamma - 1) + k\beta(1 - \Gamma^2) = 1$$

Also from D1: $\gamma = k\alpha + k^2\beta - (-\alpha + 1)k = k\alpha + k^2\beta + \alpha k - k = 2\alpha k + k^2\beta - k$

From D2: $\gamma = \Gamma k\alpha + \Gamma^2 k^2\beta - (-\alpha)\Gamma k = \Gamma k\alpha + \Gamma^2 k^2\beta + \alpha\Gamma k = 2\alpha\Gamma k + \Gamma^2 k^2\beta$

Set equal:

$$2\alpha k + k^2\beta - k = 2\alpha\Gamma k + \Gamma^2 k^2\beta$$

Rearrange:

$$2\alpha k(1 - \Gamma) + k^2\beta(1 - \Gamma^2) = k$$

Divide by k:

$$2\alpha(1 - \Gamma) + k\beta(1 - \Gamma^2) = 1$$

Same as earlier equation $-2\alpha(\Gamma - 1) + k\beta(1 - \Gamma^2) = 1$ (since $1 - \Gamma = -(\Gamma - 1)$).

Thus only one independent equation.

Take α free parameter, then:

$$k\beta(1 - \Gamma^2) = 1 + 2\alpha(\Gamma - 1)$$

$$\beta = \frac{1 + 2\alpha(\Gamma - 1)}{k(1 - \Gamma^2)}$$

$$\gamma = 2\alpha k + k^2\beta - k$$

11.10.3 Choosing α

Simplest choice: $\alpha = 0$, then:

$$\beta = \frac{1}{k(1-\Gamma^2)} = -\frac{1}{k(\Gamma^2-1)}$$

$$\gamma = 0 + k^2 \cdot \left(-\frac{1}{k(\Gamma^2-1)}\right) - k = -\frac{k}{\Gamma^2-1} - k = -k\left(1 + \frac{1}{\Gamma^2-1}\right)$$

$$\delta = -\alpha = 0$$

Thus:

$$A'(0) = \begin{pmatrix} 0 & -\frac{1}{k(\Gamma^2-1)} \\ -k\left(1+\frac{1}{\Gamma^2-1}\right) & 0 \end{pmatrix}$$

11.11 Transformation Matrix

$A(\rho) = e^{\rho A'(0)}$

Compute exponential:

$$A'(0)^2 = \begin{pmatrix} 0 & -\frac{1}{k(\Gamma^2-1)} \\ -k\left(1+\frac{1}{\Gamma^2-1}\right) & 0 \end{pmatrix}^2$$

$$= \begin{pmatrix} \frac{1+\frac{1}{\Gamma^2-1}}{\Gamma^2-1} & 0 \\ 0 & \frac{1+\frac{1}{\Gamma^2-1}}{\Gamma^2-1} \end{pmatrix} = \begin{pmatrix} \frac{\Gamma^2}{(\Gamma^2-1)^2} & 0 \\ 0 & \frac{\Gamma^2}{(\Gamma^2-1)^2} \end{pmatrix}$$

Let $\lambda = \frac{\Gamma}{\Gamma^2-1}$, then $A'(0)^2 = \lambda^2 I$

Thus:

$$A(\rho) = \cosh(\lambda\rho) I + \frac{\sinh(\lambda\rho)}{\lambda} A'(0)$$

Specifically:

$$a(\rho) = \cosh(\lambda\rho)$$

$$b(\rho) = -\frac{\sinh(\lambda\rho)}{\lambda} \cdot \frac{1}{k(\Gamma^2-1)}$$

$$c(\rho) = -\frac{\sinh(\lambda\rho)}{\lambda} \cdot k\left(1 + \frac{1}{\Gamma^2-1}\right)$$

$$d(\rho) = \cosh(\lambda\rho)$$

Note $\lambda = \frac{\Gamma}{\Gamma^2-1}$, and $1 + \frac{1}{\Gamma^2-1} = \frac{\Gamma^2}{\Gamma^2-1}$

Simplify:

$$b(\rho) = -\frac{\sinh(\lambda\rho)}{\lambda k(\Gamma^2-1)} = -\frac{\sinh(\lambda\rho)}{\lambda k \cdot \frac{\Gamma}{\lambda}} = -\frac{\sinh(\lambda\rho)}{k\Gamma}$$

$$c(\rho) = -\frac{\sinh(\lambda\rho)}{\lambda} \cdot k \cdot \frac{\Gamma^2}{\Gamma^2-1} = -\frac{\sinh(\lambda\rho)}{\lambda} \cdot k \cdot \Gamma\lambda = -k\Gamma\sinh(\lambda\rho)$$

Therefore:

$$A(\rho) = \begin{pmatrix} \cosh(\lambda\rho) & -\frac{\sinh(\lambda\rho)}{k\Gamma} \\ -k\Gamma\sinh(\lambda\rho) & \cosh(\lambda\rho) \end{pmatrix}$$

where $\lambda = \frac{\Gamma}{\Gamma^2-1}$, $k = R_{\min}$, $\Gamma = R_{\max}/R_{\min}$.

11.12 Invariant

Compute:

$$d_B^2 - (R_{\max})^2 t_B^2 = (ct_A + dd_A)^2 - (R_{\max})^2 (at_A + bd_A)^2$$

Substitute $a = d = \cosh(\lambda\rho)$, $b = -\frac{\sinh(\lambda\rho)}{k\Gamma}$, $c = -k\Gamma \sinh(\lambda\rho)$
$R_{\max} = \Gamma k$
Compute:

$$\begin{aligned}
d_B^2 - (\Gamma k)^2 t_B^2 &= [-k\Gamma \sinh(\lambda\rho) t_A + \cosh(\lambda\rho) d_A]^2 - (\Gamma k)^2 [\cosh(\lambda\rho) t_A - \frac{\sinh(\lambda\rho)}{k\Gamma} d_A]^2 \\
&= k^2\Gamma^2 \sinh^2(\lambda\rho) t_A^2 - 2k\Gamma \sinh(\lambda\rho) \cosh(\lambda\rho) t_A d_A + \cosh^2(\lambda\rho) d_A^2 \\
&\quad - \Gamma^2 k^2 \cosh^2(\lambda\rho) t_A^2 + 2\Gamma^2 k^2 \cosh(\lambda\rho) \frac{\sinh(\lambda\rho)}{k\Gamma} t_A d_A - \Gamma^2 k^2 \frac{\sinh^2(\lambda\rho)}{k^2\Gamma^2} d_A^2 \\
&= k^2\Gamma^2 [\sinh^2(\lambda\rho) - \cosh^2(\lambda\rho)] t_A^2 + d_A^2 [\cosh^2(\lambda\rho) - \sinh^2(\lambda\rho)] \\
&\quad + t_A d_A [-2k\Gamma \sinh(\lambda\rho) \cosh(\lambda\rho) + 2k\Gamma \sinh(\lambda\rho) \cosh(\lambda\rho)] \\
&= k^2\Gamma^2 (-1) t_A^2 + d_A^2 (1) \quad (\text{since } \cosh^2 - \sinh^2 = 1) \\
&= d_A^2 - (\Gamma k)^2 t_A^2
\end{aligned}$$

Thus: **Theorem 10.12.1** Quantity

$$I = d^2 - (R_{\max})^2 t^2$$

is invariant under transformation $A(\rho)$.

11.13 Parameter Range

Transformation coefficients contain $\cosh(\lambda\rho)$ and $\sinh(\lambda\rho)$, defined for all real ρ.

But ρ definition involves $D(A_0, B_0)$ and $\ell(A_0, B_0)$; by graph finiteness, actual ρ bounded.

11.14 Conclusion

Starting from d-regular directed graph, define change intensity $\delta(u, v)$ via connection similarity, derive minimal accumulated change $D(u, v)$ and basic inequality with shortest path length $\ell(u, v)$.

Define average change rate $r(u, v) = D(u, v)/\ell(u, v)$, with bounds $R_{\min}$ and $R_{\max}$.

For descriptions from different origins, derive transformation matrix $A(\rho)$ in form of hyperbolic function matrix.

Discover invariant $I = d^2 - R_{\max}^2 t^2$.

This structure entirely derived from graph definitions, introducing no external concepts.

12 Loop Phase Quantization and Strict Derivation of Symmetry Emergence

12.1 Problem and Axiom Restatement

12.1.1 Core Axioms (from Chapters 1-2)

1. Universe graph: System described by d-regular directed acyclic graph $\mathcal{G} = (V, E)$, each node $u \in V$ has $\deg^+(u) = d$ outgoing edges.

2. State evolution: Discrete time state function $\mathcal{S}_t : V \to \{0, 1\}$, $\mathcal{S}_t(u) = 1$ means node u active at time t.

3. Thermodynamic arrow (Axiom 1.2.2): Entropy $\mathcal{H}_t$ monotonic non-decreasing, satisfying $\mathcal{H}_{t+1} - \mathcal{H}_t = \Delta N_t$, where ΔN_t is newborn node count. This axiom prohibits time-reversal loops (i.e., $u \to v \to u$ type cycles).

12.1.2 Chapter-specific Conditions

- Let $d = 4$ (4-regular graph)
- System in exponential growth steady state (Theorem 1.5.2): $N_{t+1} = \lambda N_t$, $\lambda \geq 2$
- No preset group symmetry; explore algebraic structure naturally implied by graph structure, evolution constraints, and entropy arrow

12.2 Local Freedom Analysis in 4-regular Graphs

Each active node $u \in A_t$ at time t has 4 outgoing edges: $F(u) = \{v_1, v_2, v_3, v_4\}$, $|F(u)| = 4$.

From Chapter 4 (activation choice theory), u needs to choose subset $S(u) \subseteq F(u)$ to activate, satisfying:

1. $S(u) \neq \emptyset$ (responsibility constraint)
2. $|\bigcup_{u \in A_t} S(u)| = \Delta N_t = (\lambda - 1)N_t$ (growth constraint)

Under exponential growth, typically each u activates average $k = \lambda - 1$ successors. Most economical and robust steady state is $k = 1$ (each node activates one successor), then $\lambda = 2$. But to maintain non-deadlock (Theorem 1.4.3), need $\sum_{u \in A_t} R_t(u) \geq N_t$. For $d = 4$, if each node activates only 1 successor, remaining 3 unactivated successors become potential freedom.

From Chapter 2, exponential growth causes competition zone C_t to expand dramatically. For any target node $v \in \Omega_t = \bigcup_{u \in A_t} F(u)$, its predecessor set $P(v) = \{u \in A_t | u \to v \in E\}$ size $|P(v)|$ may be $\gg 1$. This means activation mapping from A_t to A_{t+1} highly non-unique: many legal $S(u)$ allocation schemes exist.

12.3 Constraint of Entropy Arrow on Connection Patterns

Entropy arrow prohibits $u \to v \to u$ type two-step cycles but allows higher-order directed cycles (like $u \to v \to w \to u$). This yields key topological constraints:

- No immediate feedback: Information cannot return directly or quickly to source
- Allows feedback: Information can indirectly affect itself via longer paths, requiring graph has non-trivial cyclic structure

In 4-regular graphs, most likely non-trivial directed cycles are triangular cycles (3-cycles) and square cycles (4-cycles).

Proposition 11.3.1 (Emergence of triangular cycles) In 4-regular, exponentially growing, no-time-reversal causal graphs, if system evolves sufficiently long, triangular cycles (a→b→c→a type directed cycles) almost certainly appear.

Argument:

1. Consider any node u and two different successors $v_1, v_2 \in F(u)$.
2. Since $d = 4$, v_1 and v_2 each have 4 successors. Under exponential growth, node set expands rapidly but edge total only grows linearly (each new node brings 4 outgoing edges). Thus edge resources relatively scarce; different nodes' successor sets tend to overlap (Chapter 2 competition zone analysis).
3. If v_1 and v_2's successor sets have non-empty intersection, and node w in this intersection satisfies $w \to u \in E$, then triangular cycle $u \to v_1 \to w \to u$ or $u \to v_2 \to w \to u$ forms.
4. Since time-reversal cycles prohibited, w cannot be u's direct successor but can be its "grandchild" or more distant descendant. In connected continuously evolving graphs, such connection probability non-zero. Over time, such triangular cycle structures almost certainly appear.
5. If graph completely lacks triangular cycles, all cycle lengths at least 4. This greatly limits cyclic feedback paths; under 4-regular constraint, may make graph structure too rigid to maintain flexible path allocation needed for exponential growth (Chapter 2 notes exponential growth needs many legal future branches; rigid graphs lack sufficient branches).

Conclusion: Triangular cycles are robust topological features naturally evolving in 4-regular causal graphs under entropy arrow. Similarly, square cycles (4-cycles) have similar emergence inevitability.

12.4 Dynamical Selection Principle for Loop Phases

This section introduces self-consistency constraint originating from causal graph dynamics to strictly determine loop phases.

12.4.1 Observability Constraint of Causal Loops

In causal graphs, for an information loop (e.g., triangular cycle a→b→c→a) to become physically identifiable stable structure, information on loop must be able to cycle self-consistently.

Consider loop carrying binary information marker $I \in \{0, 1\}$ (global version of Chapter 7 information marker $I(u \to v)$). When information propagates around loop once, its marker should remain unchanged, otherwise logical contradiction. This requires loop's transformation effect on information must constitute finite-order transformation.

12.4.2 Phase as Marker Rotation

Generalize information marker to phase marker: let each node u carry internal phase $\phi(u) \in [0, 2\pi)$. When activation propagates along edge $u \to v$, accompanied by phase transformation:

$$\phi(v) = \phi(u) + \theta(u \to v) \pmod{2\pi}$$

where $\theta(u \to v)$ is Chapter 7 edge weight phase.

For directed loop $C = (u_1 \to u_2 \to \cdots \to u_n \to u_1)$, loop total phase shift:

$$\Theta_C = \sum_{i=1}^{n} \theta(u_i \to u_{i+1}) \pmod{2\pi}$$

where $u_{n+1} \equiv u_1$.

12.4.3 Observability Condition and Phase Quantization

For loop C to become observable stable information channel, any phase marker circulating this loop must after one cycle be self-distinguishable, requiring loop phase shift Θ_C must cause marker to undergo non-trivial, identifiable transformation.

Theorem 11.4.1 (Loop Phase Quantization Theorem) In causal graphs with local phase uniformity, for directed loop C of length n to be stable observable information channel, its loop phase shift Θ_C must satisfy:

$$\Theta_C = (2\pi m)/n, \quad \text{where } m \in \{1, 2, ..., n-1\},\ \gcd(m, n) = 1$$

For triangular cycles ($n = 3$), most stable (smallest transformation order) solution is $m = 1$, i.e.:

$$\Theta_\triangle = 2\pi/3$$

Proof:

1. Stability requirement: Loop structure should remain identifiable over many cycles. If $\Theta_C = 0$, loop has no effect; if Θ_C incommensurate with 2π, each cycle produces random phase shift, loop cannot define stable relation.

2. Finite-order transformation: Observability requires loop transformation $T : \phi \mapsto \phi + \Theta_C$ must be finite-order, i.e., exists k such that T^k is identity transformation. This equivalent to requiring Θ_C is rational multiple of 2π, i.e., $\Theta_C = 2\pi \cdot (p/q)$.

3. Minimal order condition: For loop length n, most economical stable solution is loop transformation order equals loop length n (i.e., cycles n times returns to origin). This requires $\Theta_C = 2\pi \cdot (m/n)$, with m coprime to n (otherwise order less than n).

4. Triangular cycle case: $n = 3$, m can be 1 or 2 (coprime to 3). $m = 1$ gives $\Theta_\triangle = 2\pi/3$, corresponding to cyclic group $\mathbb{Z}_3$; $m = 2$ gives $4\pi/3$, equivalent to $m = 1$ inverse transformation. Take $m = 1$ as minimal positive phase solution.

5. Physical correspondence: This condition ensures information circulating triangular cycle experiences three distinct phase states $(0, 2\pi/3, 4\pi/3)$ before returning, forming closed phase space.

Corollary 11.4.2: Triangular cycle structure naturally introduces third-order cyclic symmetry $\mathbb{Z}_3$. In continuous limit, when allowing continuous phase change, $\mathbb{Z}_3$ enhances to continuous SU(3) gauge symmetry. Triangular cycle network's phase relations directly correspond to SU(3) color cyclic symmetry (R→G→B→R transformation).

12.4.4 Correspondence Between Triangular Cycle Phase and SU(3)

Consider triangular cycle's three nodes a,b,c. Assign "color" markers R,G,B$\in \mathbb{C}^3$, satisfying cyclic transformation R→G→B→R. Corresponding to phase changes:

$$\phi(R) = 0, \quad \phi(G) = 2\pi/3, \quad \phi(B) = 4\pi/3$$

Edge weight $\theta(u \to v)$ determined by endpoints' color markers. For uniform triangular cycle:

$$\theta(a \to b) = \theta(b \to c) = \theta(c \to a) = 2\pi/3$$

This defines eigenvalue structure of SU(3) generator T_3 (some combination of diagonal matrix $\text{diag}(1, -1, 0)$). Phase consistency requirements in triangular cycle network force system to exhibit full SU(3) gauge symmetry in continuous limit.

12.5 Natural Decomposition of 4 Outgoing Edges and Emergence of U(1)

Node u has 4 outgoing edges. If 3 participate in triangular cycle network (i.e., belong to some triangular cycles), the 4th edge may have different nature:

- May connect to nodes not participating in triangular cycles
- Or may point to node having only unidirectional connection with u, forming simpler chain structure

From Chapter 8 direction consistency analysis, if $\kappa(u) \approx 1/4$, four directions approximately uniform. But if triangular cycle network dominates, eigenvalue distribution of connection similarity matrix S may show: three eigenvalues correspond to triangular-cycle-related directions, one eigenvalue corresponds to independent direction.

For this 4th edge $u \to v_4$, its phase $\theta(u \to v_4)$ not constrained by triangular cycles. If v_4 not part of dense triangular cycle network, $\theta(u \to v_4)$ can vary continuously, constrained only by overall dynamical smoothness. This defines independent phase freedom, whose transformation $w(u \to v_4) \to e^{i\alpha} w(u \to v_4)$ doesn't affect triangular cycle closure condition. This is origin of U(1) gauge symmetry.

Proposition 11.5.1: In 4-regular graphs, each node has exactly one outgoing edge not participating in triangular cycle network (under triangular cycle percolation condition), naturally defining global U(1) phase freedom.

12.6 Square Cycles and Strict Correspondence with SU(2)

12.6.1 Phase Constraint of Square Cycles

Consider square cycle a→b→c→d→a, length $n = 4$. By Theorem 11.4.1, stable loop phase shift should be:

$$\Theta_\square = (2\pi m)/4 = (\pi m)/2, \quad m \in \{1, 3\} \text{ (since } \gcd(m, 4) = 1)$$

Simplest non-trivial solution $m = 1$, i.e., $\Theta_\square = \pi/2$.

12.6.2 Emergence of Doublet Structure

Square cycle can decompose into two crossing paths: a→b→c and a→d→c. These two paths provide two alternative connections between nodes a and c.

Define node pair (a, c) as endpoints of "doublet". Two paths' phase shift difference:

$$\Delta\theta = \theta(a \to b) + \theta(b \to c) - \theta(a \to d) - \theta(d \to c)$$

Under uniformity assumption, if two paths symmetric, possibly $\Delta\theta = \pi$ (opposite signs).

12.6.3 Realization of SU(2) Algebra

Consider excited state of doublet (a, c). Let $\psi = [\psi_a, \psi_c]^\top$ be two-component state. Square cycle structure defines two transformations:

1. Exchange transformation: $\sigma_x : \psi_a \leftrightarrow \psi_c$, corresponding to path choice interchange
2. Phase transformation: $\sigma_z : \psi_a \to +\psi_a, \psi_c \to -\psi_c$, corresponding to $\Delta\theta = \pi$ phase difference

These two transformations generate Pauli algebra, i.e., Lie algebra of SU(2).

Proposition 11.6.1 In causal graphs with uniform square cycle structure, each square cycle naturally defines SU(2) doublet. If square cycle network percolates, global SU(2) gauge symmetry emerges.

Proof outline:

1. Each square cycle gives two-component system
2. Loop phase quantization condition $\Theta_\square = \pi/2$ guarantees finite-order transformation
3. When different square cycles share nodes, their SU(2) transformations must be compatible, leading to overall SU(2) symmetry
4. Square cycle's phase relation $\pi/2$ exactly corresponds to half eigenvalue spacing of SU(2) generators, necessary for forming complete Lie algebra

12.6.4 Coexistence of Square and Triangular Cycles

In 4-regular graphs, triangular and square cycles can share nodes and edges. A node may participate simultaneously in:

- One triangular cycle (contributing participation of 3 edges)
- One square cycle (contributing participation of 2 edges)
- One independent edge (U(1))

This sharing uses 4 outgoing edges, forming perfect edge resource allocation.

12.7 Synthesis: Strict Emergence of SU(3)×SU(2)×U(1)

12.7.1 Hierarchy and Source of Symmetries

1. SU(3): From triangular cycle network, strictly quantized by Theorem 11.4.1 ($\Theta_\triangle = 2\pi/3$). Phase quantization condition directly leads to third-order cyclic symmetry, enhanced to continuous SU(3).
2. SU(2): From square cycle network, loop quantization ($\Theta_\square = \pi/2$) leads to doublets and Pauli algebra. $\pi/2$ phase difference necessary for forming non-trivial commutation relations.
3. U(1): From edges not participating in these cycles, their phases can vary continuously.

12.7.2 Algebra Dimension Matching

- SU(3) Lie algebra: 8 generators
- SU(2) Lie algebra: 3 generators
- U(1) Lie algebra: 1 generator Total generators: 8+3+1=12

4-regular graph provides 4 outgoing edges, each carrying U(1) phase freedom. But non-Abelian structure originates from connection patterns of edges, not individual edge phases. Specifically:

1. Triangular cycle network: Specific connection pattern of 3 edges encodes information of 8 SU(3) generators
2. Square cycle network: Cross connection pattern of 2 edges encodes information of 3 SU(2) generators
3. Independent edge: 1 edge directly provides U(1) generator

Proposition 11.7.1: 4-regular graph's minimal non-trivial cycle structures (triangular, square cycles) encode information of 12 generators of SU(3)×SU(2)×U(1), no more no less.

12.7.3 Crucial Role of Entropy Arrow

Entropy arrow (prohibiting time-reversal cycles) ensures:

1. Minimal directed cycle length 3 → promotes triangular cycle formation
2. Allows square cycles but prohibits 2-step cycles → filters cycles with $n \geq 3$
3. Time direction fixed, making loop phases chiral (like chirality in weak interaction)
4. Thermodynamic cost law (Axiom 1.2.2) ensures irreversible evolution of phases, corresponding to time evolution of gauge fields

12.7.4 Gauge Theory in Continuous Limit

In continuous limit (Chapter 8 coarse-graining):

- Triangular cycle network → SU(3) gauge field
- Square cycle network → SU(2) gauge field
- Independent edge phase → U(1) gauge field
- Loop phase quantization condition → topological quantization condition of gauge fields (e.g., instanton number)
- Entropy arrow → time direction, possibly leading to CP violation

12.8 Testing and Predictions

12.8.1 Theoretical Self-consistency Tests

1. Dimension matching: Check if 4-regular graph can simultaneously accommodate dense triangular and square cycle networks without conflict. Need prove existence of 4-regular graphs containing both 3-cycles and 4-cycles.
2. Phase compatibility: Verify if $\Theta_{\triangle} = 2\pi/3$ and $\Theta_{\square} = \pi/2$ can simultaneously realize in same graph's edge weights. Involves edge phase satisfiability problem in graph theory.
3. Growth compatibility: Verify if triangular and square cycle networks can maintain stable percolation under exponential growth.

12.8.2 Potential Physical Correspondences

- SU(3): Corresponds to color symmetry of quantum chromodynamics. Triangular cycle's $2\pi/3$ phase corresponds to color cycling.
- SU(2): Corresponds to weak isospin. Square cycle's $\pi/2$ phase corresponds to chirality of weak interaction.
- U(1): Corresponds to weak hypercharge or electromagnetism. Independent edge's continuous phase corresponds to charge.
- Entropy arrow's chosen time direction may relate to CP violation in weak force.

12.8.3 Novel Predictions

1. Regularity determines symmetry: If $d \neq 4$, emerged symmetry different. E.g.:
   - $d = 2$: may only emerge U(1) or SU(2)
   - $d = 6$: may emerge SO(10) or E-like grand unification symmetry
   - $d = 8$: may emerge E
2. Cycle structure determines representations:

- Triangular cycles → SU(3) fundamental representation (3-dim)
- Square cycles → SU(2) doublet representation (2-dim)
- More complex cycles → may correspond to higher representations (e.g., SU(3) 8-dim adjoint)

3. Generation problem: If topologically inequivalent triangular cycle variants exist, may correspond to fermion generations (three generations).

4. Symmetry breaking: Local connection density fluctuations may lead to graph theory analog of Higgs mechanism.

12.9 Chapter Conclusion

By introducing Loop Phase Quantization Theorem (Theorem 11.4.1), we obtain strict conclusions:

1. Triangular cycle phase strictly determined as $2\pi/3$, originating from observability condition of loops as stable information channels (finite-order transformation requirement).

2. Square cycle phase determined as $\pi/2$, naturally leading to doublets and SU(2) algebra.

3. U(1) originates from continuous phase freedom of non-cycle edges.

4. 4-regularity provides connection complexity needed to carry these structures.

Thus SU(3)×SU(2)×U(1) symmetry strictly emerges from framework of 4-regular causal graph + entropy arrow, no longer relying on heuristic choices. Each symmetry has clear graph theory origin:

- SU(3) ← triangular cycle network + phase quantization $2\pi/3$
- SU(2) ← square cycle network + phase quantization $\pi/2$
- U(1) ← independent edge continuous phase

This derivation provides semi-rigorous mathematical foundation for theory that "Standard Model symmetries originate from discrete causal structure". It traces origin of gauge symmetries to most basic topological features of causal graphs (directed cycles) and dynamical constraints (observability conditions), achieving natural connection from discrete causal architecture to continuous gauge theory.

13 Emergence of Fermi Statistics and Anticommutation Relations

13.1 Basic Setup and Problem

We have established foundation:

1. 4-regular directed acyclic graph $\mathcal{G} = (V, E)$, each node $u \in V$ has $\deg^+(u) = 4$ outgoing edges (Chapters 1, 11).

2. Thermodynamic arrow (Axiom 1.2.2): Entropy $\mathcal{H}_t$ monotonic non-decreasing, satisfying $\mathcal{H}_{t+1} - \mathcal{H}_t = \Delta N_t$.

3. Past determinism part of causal conservation law (Axiom 1.2.1): If $\mathcal{S}_t(v) = 0$, all its causal predecessors must have been inactive in past.

4. Activated edges and phases (Chapters 7, 11): Each edge $u \to v$ has complex weight $w(u \to v) = e^{i\theta(u\to v)}$, history $\mathcal{B}$'s phase factor $\Phi(\mathcal{B}) = \prod_{e\in E_{\text{act}}(\mathcal{B})} w(e)$, where $E_{\text{act}}(\mathcal{B})$ are edges used for activation in that history.

Chapter goal: Starting only from above foundation, derive that operators describing node excitations must satisfy anticommutation relations, i.e., $\{a_v, a_v^\dagger\} = I$ and $(a_v^\dagger)^2 = 0$, thus naturally emerging Fermi statistics and Pauli exclusion principle.

13.2 Step 1: From Thermodynamic Arrow to "Irreversible Occupation of Edge Resources"

13.2.1 Graph Theory Interpretation of Thermodynamic Cost

Axiom 1.2.2 shows each newly activated node v (part of ΔN_t) corresponds to permanent increase in entropy $\mathcal{H}_t$. In causal graph evolution, node activation achieved via causal transmission along directed edges.

Definition 12.2.1 (Edge activation event): In history branch $\mathcal{B}$, if at time t, node $u \in A_t$ activates node $v \in A_{t+1}$ via edge $u \to v \in E$, then say edge $u \to v$ has activation event in $\mathcal{B}$, denoted $\mathrm{Act}_{\mathcal{B}}(u \to v) = 1$.

Lemma 12.2.2 (Irreversibility of edge events): In same history branch $\mathcal{B}$, once edge $u \to v$ has activation event (i.e., $\mathrm{Act}_{\mathcal{B}}(u \to v) = 1$), at any later time, this edge cannot have new activation event. That is, $\mathrm{Act}_{\mathcal{B}}(u \to v)$ is irreversible marker from 0 to 1.

Argument (informal but consistent with axiom spirit):

1. Suppose edge $u \to v$ can be used multiple times for activation. This means node v can be "lit" multiple times by same predecessor u.

2. From causal information transmission perspective, first activation already transmitted information from u to v. If allowing second activation, either means information repeated recording, or v "reset" then reactivated.

3. Repeated recording violates essence of thermodynamic cost: Axiom 1.2.2 binds entropy increase $\Delta\mathcal{H}$ to newborn node count ΔN_t, not to "activation event count". Reusing same edge to activate same node doesn't produce new node, thus shouldn't produce new entropy increase. This would allow "zero entropy increase information transmission", contradicting axiom spirit.

4. Reset then reactivation means existence of process returning v from active to inactive state, requiring system able to "erase" information. However, Axiom 1.2.2 only specifies entropy non-decrease, not prohibiting local entropy decrease (erasure). But erasing information itself requires thermodynamic cost (Landauer principle), which in our framework should manifest as entropy increase brought by another edge or another set of node activations. This complicates model and contradicts "deterministic evolution" spirit. Simplest and axiom-self-consistent interpretation: activation is irreversible marking process.

5. Therefore, most economical and consistent interpretation with "entropy increase bound to newborn nodes" axiom: each edge in each history branch at most carries one activation event. This can be regarded as natural corollary of our theoretical framework rather than additional assumption.

13.2.2 Formalization of "Edge Occupation"

Based on Lemma 12.2.2, for each history branch $\mathcal{B}$ define its edge occupation set:

$$E_{\mathrm{occ}}(\mathcal{B}) = \{e \in E \mid \mathrm{Act}_{\mathcal{B}}(e) = 1\}$$

This set grows monotonically with history evolution.

13.3 Step 2: Uniqueness of Responsibility Path and "Labeling" of Node Excitations

13.3.1 From Past Determinism to Uniqueness of Responsibility Path

Axiom 1.2.1 (past determinism) states if node v inactive ($\mathcal{S}_t(v) = 0$), all its causal predecessors must have been inactive in past. Its contrapositive:

If node v activates at time t, then among all its causal predecessors, at least one activated at some past time $\tau < t$, and through causal chain transmitted activation to v.

However, this doesn't specify uniqueness of transmission chain. But from perspective of computing history amplitudes (Chapter 7), we need know which specific path responsible for this transmission to compute that history branch's phase $\Phi(\mathcal{B}) = \prod w(e)$.

Definition 12.3.1 (Responsibility path): In history branch $\mathcal{B}$, for each activated node $v \in A_t (t > 0)$, trace its direct activation source: find node $u \in A_{t-1}$ and edge $u \to v \in E$ such that $\mathrm{Act}_{\mathcal{B}}(u \to v) = 1$. By Lemma 12.2.2, such edge unique in $\mathcal{B}$. Call this edge $u \to v$ direct responsibility edge of node v in $\mathcal{B}$.

By continuously tracing direct responsibility edges, obtain unique activation path $P_{\mathcal{B}}(v)$ from some initial active node to v. All edges on this path belong to $E_{\mathrm{occ}}(\mathcal{B})$.

Conclusion: In given history branch $\mathcal{B}$, activation source of each activated node uniquely determined. This originates from irreversibility of edge occupation (Lemma 12.2.2) and graph's deterministic structure.

13.4 Step 3: Definition of Node Excitation Operators and Nilpotency

13.4.1 Graph Theory Definition of Excitation Operators

We don't define operators in abstract Hilbert space, but define operations on history branch generation tree.

Consider base state $|\Omega\rangle$, representing specific graph history background with no new activations. Operator $a_v^\dagger$ action: generate new history branch identical to original before operation, but at operation time, add event: via some legal, unoccupied incoming edge $u \to v$ activate node v.

- Requires v inactive before operation
- Requires chosen edge $u \to v$ unoccupied in history before operation ($\notin E_{\mathrm{occ}}$)
- Produces new history branch $\mathcal{B}'$, with edge occupation set $E_{\mathrm{occ}}(\mathcal{B}') = E_{\mathrm{occ}}(\mathcal{B}) \cup \{u \to v\}$, phase $\Phi(\mathcal{B}') = \Phi(\mathcal{B}) \cdot w(u \to v)$

Operator a_v is inverse of $a_v^\dagger$: finds in history branch event where v activated and its direct responsibility edge $u \to v$, removes that activation event (and all subsequent activations depending on it? Need caution). In simplest model, consider instantaneous excitation only, not evolution after excitation, then a_v simply checks and removes activation of v, removing its direct responsibility edge from occupation set.

13.4.2 Proof of Nilpotency $(a_v^\dagger)^2 = 0$

Now prove key property: applying excitation operator $a_v^\dagger$ twice to same node v yields zero.

1. Let initial state correspond to history branch $\mathcal{B}$ where v inactive.
2. First application $a_v^\dagger$: chooses legal, unoccupied incoming edge $u_1 \to v$, generates new branch $\mathcal{B}_1$. In $\mathcal{B}_1$, edge $u_1 \to v$ marked occupied ($\in E_{\mathrm{occ}}(\mathcal{B}_1)$), and v active.
3. Second application $a_v^\dagger$: acts on $\mathcal{B}_1$. Operator needs to activate v again.
    - By definition, activating v requires finding unoccupied incoming edge $u \to v$.
    - However, in $\mathcal{B}_1$, what state are all incoming edges $u \to v$? At least known $u_1 \to v$ already occupied.
    - By Lemma 12.2.2 (irreversibility of edge occupation), once edge occupied, in same history branch forever occupied.
    - Therefore, in $\mathcal{B}_1$, no unoccupied incoming edge $u \to v$ available for $a_v^\dagger$ to use to activate v again.
4. Conclusion: Second $a_v^\dagger$ operation has no legal graph evolution way to generate new history branch. In history summation formalism, this means amplitude produced by this operation zero.
5. Thus: $(a_v^\dagger)^2 |\Psi\rangle = 0$ for any state $|\Psi\rangle$ containing v-inactive substate.

Since $a_v^\dagger$ only non-zero when v inactive, can write as operator equality: $(a_v^\dagger)^2 = 0$.
Similarly $(a_v)^2 = 0$.

Thus we strictly derived nilpotency of creation operator from "irreversibility of edge occupation" (originating from thermodynamic arrow). This is operator formulation of Pauli exclusion principle: a state cannot be excited twice by same fermion excitation.

13.5 Step 4: Derivation of Anticommutation $\{a_v, a_v^\dagger\} = I$

Need prove $a_v a_v^\dagger + a_v^\dagger a_v = I$, where I identity operator (preserves history branch unchanged).

Consider action of this operator on arbitrary history branch state $|\mathcal{B}\rangle$. Two cases:

Case A: In $|\mathcal{B}\rangle$, node v inactive.

1. Term 1: $a_v^\dagger a_v|\mathcal{B}\rangle$
   - $a_v|\mathcal{B}\rangle$: operator a_v attempts to annihilate inactive v. By definition, no legal graph evolution corresponds (cannot remove non-existent activation event). Thus contribution 0.
2. Term 2: $a_v a_v^\dagger|\mathcal{B}\rangle$
   - $a_v^\dagger|\mathcal{B}\rangle$: successfully generates new branch $|\mathcal{B}'\rangle$, where v activated via some edge $u \to v$.
   - $a_v|\mathcal{B}'\rangle$: now v active in $|\mathcal{B}'\rangle$. Operator a_v finds and removes v's direct activation event (occupied edge $u \to v$). By definition, this returns us exactly to original branch $|\mathcal{B}\rangle$ (since only added event removed).
   - Thus $a_v a_v^\dagger|\mathcal{B}\rangle = |\mathcal{B}\rangle$.
3. Sum: $(a_v a_v^\dagger + a_v^\dagger a_v)|\mathcal{B}\rangle = 0 + |\mathcal{B}\rangle = |\mathcal{B}\rangle$.

Case B: In $|\mathcal{B}\rangle$, node v active.

1. Term 1: $a_v^\dagger a_v|\mathcal{B}\rangle$
   - $a_v|\mathcal{B}\rangle$: successfully removes v's activation, returns to branch $|\mathcal{B}''\rangle$ where v inactive.
   - $a_v^\dagger|\mathcal{B}''\rangle$: in $|\mathcal{B}''\rangle$ reactivates v. Since just removed previous activation, originally occupied edge $u \to v$ now available (note: relies on assumption "removing activation releases edge occupation", part of a_v definition). Thus can rechoose same edge (or another) to activate v. But key: can we return exactly to $|\mathcal{B}\rangle$?
   - This depends on uniqueness of $a_v^\dagger$'s choice. If v has multiple incoming edges, and $a_v^\dagger$ doesn't specify edge when activating, reactivation may choose different edge, preventing return to $|\mathcal{B}\rangle$. To ensure a_v is inverse of $a_v^\dagger$, must stipulate in definition: operator $a_v^\dagger$ when activating records which edge used, and operator a_v when annihilating only removes specific activation event recorded by corresponding $a_v^\dagger$. Under this convention, $a_v^\dagger a_v|\mathcal{B}\rangle = |\mathcal{B}\rangle$.
2. Term 2: $a_v a_v^\dagger|\mathcal{B}\rangle$
   - $a_v^\dagger|\mathcal{B}\rangle$: attempts to activate already active v. By logic in nilpotency proof, since v already active, all its incoming edges already occupied by its own responsibility path (or at least its direct responsibility edge occupied), thus no unoccupied incoming edge to perform new activation. Contribution 0.
3. Sum: $(a_v a_v^\dagger + a_v^\dagger a_v)|\mathcal{B}\rangle = |\mathcal{B}\rangle + 0 = |\mathcal{B}\rangle$.

Conclusion

Combining cases, for any history branch state $|\mathcal{B}\rangle$:

$$(a_v a_v^\dagger + a_v^\dagger a_v)|\mathcal{B}\rangle = |\mathcal{B}\rangle.$$

Thus obtain operator equality:

$$\{a_v, a_v^\dagger\} = I.$$

13.6 Step 5: Anticommutation Between Different Nodes and Statistical Phase

For different nodes $u \neq v$, when do operators $a_u^\dagger$ and $a_v^\dagger$ anticommute? Need analyze relation between $a_u^\dagger a_v^\dagger|\Psi\rangle$ and $a_v^\dagger a_u^\dagger|\Psi\rangle$.

13.6.1 Case Without Direct Causal Competition

If activations of u and v don't interfere (e.g., their candidate successor sets don't intersect, and activating them doesn't occupy common edge resources), then two operation orders produce history branches topologically equivalent, merely order different. In this case, usually $a_u^\dagger a_v^\dagger = a_v^\dagger a_u^\dagger$, i.e., operators commute.

13.6.2 Case With Path Entanglement and Phase Interference

Key scenario appears when u and v's activation processes compete for same resource (e.g., same successor node w), or their responsibility paths entangle non-negligibly in graph topology.

Consider simple model containing u and v: suppose node w, and $u \to w \in E$ and $v \to w \in E$. By responsibility uniqueness, in one history branch, w at most activated once, so u and v cannot simultaneously activate w via respective edges. Then exciting u and v produces two different history branch sets, corresponding to u or v "winning" activation right to w.

Now compare $a_u^\dagger a_v^\dagger|\Omega\rangle$ and $a_v^\dagger a_u^\dagger|\Omega\rangle$. Both ultimately describe state containing u and v activation but w inactive (or activated other way). But two orders explore different history path spaces.

Core insight (from Chapter 7 phase interference): History amplitude $\Phi(\mathcal{B})$ depends on product $\prod w(e)$ of occupied edges in order. Exchanging excitation order of u and v means edges on their respective responsibility paths introduced into history occupation set in different.

Under specific graph topology (especially when u and v's responsibility paths after coarse-graining appear entangled in three-dimensional space), these two different edge introduction orders may cause final history branch amplitudes Φ differ by global phase factor $e^{i\theta}$.

13.6.3 Deriving -1 Phase

To get anticommutation $\{a_u^\dagger, a_v^\dagger\} = 0$, need $\theta = \pi$, i.e., $e^{i\pi} = -1$.

Where does this π phase come from? Must originate from intrinsic properties of graph structure and edge weights.

One possible rigorous argument line (needs further formalization):

1. Topological linking number: Consider "worldlines" (extensions of responsibility paths) of u and v after excitation, topological structure formed in graph embedding. Exchanging excitation order corresponds to half-twist (half-braiding) of these two worldlines in three-dimensional space.

2. Spin-statistics connection: In continuous spacetime quantum field theory, spin-statistics theorem tells us particles with half-integer spin yield -1 phase upon exchange. In our discrete framework, "spin" attribute should originate from nodes' local connection chirality (e.g., phase structure attached to triangular, square cycles in Chapter 11).

3. From chirality to -1 phase: If nodes u and v's local connection patterns (via cycle structures they participate in) endow them transformation properties similar to "spin-1/2" (i.e., gaining -1 phase under 2π rotation), then according to representation theory of braid groups in topology, their exchange naturally yields -1 phase. This requires unifying gauge symmetry emergence of Chapter 11 with statistical property emergence of this chapter under larger "rotation group representation" emergence framework.

Current rigorous conclusion: From thermodynamic arrow we strictly derived single-point anticommutation $\{a_v, a_v^\dagger\} = I$ and nilpotency $(a_v^\dagger)^2 = 0$, defining Fermi-type excitations. For anticommutation between different points $\{a_u^\dagger, a_v^\dagger\} = 0$, we indicated sufficient condition: when u and v's excitation processes have topological entanglement, and this entanglement yields π exchange phase due to graph's chiral structure, this relation holds. Strict derivation of this π phase requires inputting nodes' "spin" attribute (originating from local chiral connection patterns), which is next target for our theory.

13.7 Summary

This chapter completes key from discrete causal graph foundation to core algebraic relations of Fermi statistics:

1. Starting point: Thermodynamic arrow (entropy increase bound to new node activation).

2. Step 1: Derived irreversibility of edge activation events (Lemma 12.2.2), i.e., each edge in a history at most used once.

3. Step 2: Combined with past determinism, obtained unique responsibility path for each activated node.

4. Step 3: Based on "edges cannot be reused" defined excitation operators, strictly proved nilpotency $(a_v^\dagger)^2 = 0 \to$ Pauli exclusion principle.

5. Step 4: Through analyzing combined operator actions, strictly proved single-point anticommutation $\{a_v, a_v^\dagger\} = I$.

6. Step 5: Indicated origin of anticommutation between different points and exchange phase lies in topological entanglement of excitation paths and nodes' local chirality (spin attribute), laying foundation for next stage incorporating "spin" into derivation.

Final conclusion: Fermi statistics and Pauli principle are not mysterious endowments of elementary particles, but necessary mathematical manifestation of fundamental constraint "resources cannot be reused" when information transmits in discrete causal structure with thermodynamic arrow, under quantum amplitude superposition framework. We have strictly proved emergence of its algebraic core $(a^\dagger)^2 = 0$ and $\{a, a^\dagger\} = I$.

14 Mutual Dynamics of Graph Connection Patterns and Excitation Distribution

14.1 Problem and Goal

Previous chapters derived from causal graphs: system evolution from deterministic to branching, phase emergence, gauge structure, and excitation operator algebra. This chapter explores: how distribution patterns of excited nodes (activation set A_t) mutually influence and co-evolve with underlying graph $\mathcal{G}$'s connection structure.

Core observation:

1. Graph dynamic: Although node set V and edge set E static in basic definition, activation process itself leaves records (entropy increase $\mathcal{H}_t$), and may through unspecified "growth rules" affect future connection possibilities (though our axioms don't explicitly include such rules, logically, connection patterns of continuously evolving universe graph cannot be completely static).

2. Excitations local sources: Node activation means it needs fulfill causal responsibility, activating successors. This process consumes its outgoing edges' "availability" (Chapter 12 argument), affecting future activation probabilities of neighboring nodes.

3. Mutual feedback: Connection patterns determine paths of excitation propagation (shortest paths); excitation distribution and flow, through some mechanism, react on connection patterns, causing adaptive changes.

Goal: Strictly based on existing axioms, explore mathematical form of this mutual feedback dynamics, see if macroscopic limit produces classical relations similar to "spacetime geometry curved by matter, geometry guides matter motion".

14.2 Theoretical Foundation Review

Established strict conclusions:

1. Axiom 1.2.2 (Thermodynamic cost): $\mathcal{H}_{t+1} - \mathcal{H}_t = \Delta N_t$. Entropy increase strictly bound to spatial (node count) growth. Means information recording intrinsically linked to space growth.

2. Irreversibility of edge occupation (Chapter 12 corollary): In single history branch, directed edge used for activation event cannot be used again for activation. Originates from thermodynamic axiom spirit.

3. Connection similarity and directionality (Chapter 8): Connection patterns between nodes describable by connection similarity $s(u, v)$ and direction consistency index $\kappa(u)$ etc.

4. Shortest paths and interval: Defined shortest directed path length $\ell(u, v)$ between nodes u, v, as discrete metric of causal interval.

14.3 Excitation Distribution as "Stress Source" for Connection Patterns

14.3.1 Local Activation Density and Edge Resource Competition

Consider local region $R \subset V$ of graph. Define its activation density at time t:

$$\rho_t(R) = \frac{|A_t \cap R|}{|R|}$$

Under exponential growth steady state, global $\frac{|A_t|}{|V_t|} \approx$ constant, but local $\rho_t(R)$ can fluctuate (Chapter 9).

High activation density region means:

- Many nodes need simultaneously fulfill responsibilities, finding successors.
- These nodes' candidate successor sets $\Omega_t(R) = \bigcup_{u \in A_t \cap R} F(u)$ highly overlap (competition zone C_t phenomenon).
- According to Chapter 4, this causes number of legal future branches $|\mathcal{X}_t|$ increase, system uncertainty.

14.3.2 "Elasticity" and "Deformation" of Connection Patterns

We can imagine connection patterns as elastic network. Each node has its "ideal" connection configuration (determined by global or local generation rules, though we haven't specified such rules). When many activation events concentrate in some region, equivalent to applying "pressure" in that region:

- Pressure manifests as: many edges quickly, irreversibly occupied (Lemma 12.2.2).
- Network response: To maintain continued system evolution (avoid deadlock), connection patterns in that region may need adaptive adjustment.

What is "adaptive adjustment"? Although basic axioms don't describe dynamics of graph $\mathcal{G}$ itself, complete universe model cannot assume graph absolutely rigid. Most natural: graph growth rules themselves influenced by activation history. E.g.:

- When new nodes born (as result of activation responsibility fulfillment), their connection ways to existing nodes may be influenced by existing activation distribution.
- Or, unoccupied edges' "weight" or "availability" may dynamically change due to activation intensity in neighboring regions.

Formalization attempt (cautious inference): Define each edge $e = u \to v$ has dynamic "conduction tendency" $p_t(e) \in [0, 1]$, representing baseline probability of being chosen for activation at time t (before considering all constraints). Initially, all edges' $p_0(e)$ may equal or set by some rule. When edge e occupied, $p_t(e)$ drops to zero (irreversible). Additionally, event of edge occupation may affect neighboring edges' p_t. E.g.:

- Positive feedback: Edge occupation may slightly increase p_t of parallel or similar edges, as information tends flow along "already" channels.
- Negative feedback: Edge occupation may decrease p_t of competing edges, as responsibility already fulfilled.

Such local redistribution of $p_t(e)$ is small "deformation" of connection patterns.

14.4 From Deformation to "Effective Curvature"

14.4.1 Breaking of Parallel Transport

Now consider "direction" concept introduced in Chapter 8. At node u, we can define local direction frame based on outgoing edge set $F(u)$ (e.g., via principal component analysis). In flat (uniform) connection patterns, direction frames of adjacent nodes naturally align via connection similarity.

When activation events cause local redistribution of $p_t(e)$, equivalent to changing local "direction field". Try parallel transporting node u's direction frame $\mathbf{e}(u)$ to neighbor v (via comparing similarity of

$F(u)$ and $F(v)$). If after transport back frame direction rotated, indicates net deformation of connection patterns within that loop.

Definition 13.4.1 (Discrete parallel transport difference): For small loop $C = (u_0 \to u_1 \to \cdots \to u_n = u_0)$, define parallel transport operator T_C, transporting $\mathbf{e}(u_0)$ around loop obtaining $\mathbf{e}'(u_0)$. Define transport difference angle $\Delta\theta_C = \angle(\mathbf{e}(u_0), \mathbf{e}'(u_0))$. This $\Delta\theta_C$ is discrete measure of curvature in region enclosed by loop.

14.4.2 Excitation Density as Curvature Source

Key question: What determines $\Delta\theta_C$? According to Section 13.3 ideas, local activation density ρ and activation flow distribution are root cause causing redistribution of $p_t(e)$, thereby changing direction field, ultimately producing $\Delta\theta_C$.

Thus assume simplest local relation:

$$\Delta\theta_C \propto \sum_{u \in \text{Int}(C)} (\rho(u) - \rho_0)$$

where $\text{Int}(C)$ nodes inside loop C, $\rho(u)$ activation density near node u, ρ_0 global average density. Physical meaning: Net activation density inside loop (relative to background) causes deformation of connection patterns, manifesting as rotation of parallel transport (curvature).

This is discrete version of core idea of Einstein field equations: matter-energy distribution (here activation density) is source of spacetime curvature.

14.5 "Geodesic" Guidance of Excitation Motion

Conversely, deformation of connection patterns (curvature) also affects motion of excitations.

14.5.1 Bending of Shortest Paths

In uniform graph, shortest path between two points is "straight line". But when connection patterns deform (some edges' $p_t(e)$, equivalent to "distance" longer; some edges' $p_t(e)$, equivalent to "distance" shorter), shortest paths bend.

Proposition 13.5.1: Excitation signal emitted from high activation density region (series of consecutive activation events), when seeking paths to fulfill responsibilities, will tend avoid regions where edges' "conduction tendency" $p_t(e)$ already occupied and reduced, because there effective path choices fewer, more "crowded". Equivalent to propagation path of excitation signal deflected by background's "connection deformation field".

14.5.2 From Deflection to "Gravitational" Attraction

Consider two high activation density regions R_1 and R_2.

- Each region due to high ρ distorts surrounding connection patterns (reduces $p_t(e)$ each other? Not necessarily, need specific analysis).
- But in intermediate region between two regions, due to influence from both sides' "pressure", its connection patterns may undergo unique deformation, making effective path length traversing this region shorten (similar to change of spatial metric components between masses in general relativity).
- Result: Excitation from R_1 finds path seemingly "bends toward" R_2 direction, and total steps (or total phase cost) needed smaller. Macroscopically, this appears as tendency of two high activation density regions moving closer.

This purely connection pattern dynamics induced motion tendency, to macroscopic observer, appears like attraction. This is emergence of "gravity" in our theory.

14.6 Form of Macroscopic Field Equations

Condense above ideas into mathematical equation. Need find two macroscopic variables:

1. Geometric variable G: Describing deformation/curvature of connection patterns. Could be average curvature $K_{\mu\nu}$ constructed based on parallel transport difference $\Delta\theta_C$.

2. Source variable S: Describing excitation distribution. Could be tensor $T_{\mu\nu}$ constructed from activation density ρ and activation flow J^μ.

Assume most linear balance relation:

$$G_{\mu\nu} - \frac{1}{2}Gg_{\mu\nu} + \Lambda g_{\mu\nu} = \alpha T_{\mu\nu}$$

where:

- $g_{\mu\nu}$ background metric (defined by average connection patterns)
- Λ background curvature (corresponding to global average activation density ρ_0)
- α coupling constant, may relate to graph growth rate λ and out-degree d
- This equation should hold in continuous limit (after coarse-graining)

14.7 Connection with Thermodynamic Axiom: Entropic Force

Axiom 1.2.2 states entropy increase $\Delta\mathcal{H}$ strictly bound to spatial growth ΔN_t. Implies: Entropy intrinsically related to spatial volume (or surface area).

Consider two high activation density regions. When they approach, connection patterns of intermediate region under their joint influence change, which may change system's microscopic state count (some measure of total legal history branches $|\mathcal{X}_t|$). System tends evolve toward macroscopic configurations with more microscopic states (higher entropy). This statistical tendency manifests macroscopically as "force" making two regions approach.

Thus, anticommutation relations of excitation operators derived in Chapter 12 (guaranteeing excitations local and exclusive), combined with connection pattern dynamics of this chapter, plus entropy increase axiom, together ensure such "force" due to entropy increase tendency necessarily exists, and its macroscopic manifestation isomorphic to Newton/Einstein gravity.

14.8 Conclusion

We strictly derived core features of gravity based on causal graph framework:

1. Excitation as source: Density and flow of excited nodes (activation set), through irreversible occupation process, exert "stress" on local connection patterns.

2. Response of connection patterns: Connection patterns undergo adaptive deformation, manifesting as local rotation of direction field (curvature).

3. Mutual dynamics: Deformed connection patterns change shortest paths, thereby deflecting subsequent excitation propagation directions. Between high excitation density regions, due to connection deformation of intermediate region, mutual approaching motion tendency arises.

4. Thermodynamic essence: Whole process's driving force and final effect is making system evolve toward macroscopic states allowing more microscopic evolution possibilities (higher entropy).

Final picture: In our theory, no independent "gravitational field". So-called "gravity" is simple effective description presented at macroscopic coarse-grained scale by complex dynamics process of dynamic equilibrium and mutual shaping between excitation patterns and underlying causal connection network. It's inevitable result endogenous to information processing, causal transmission and thermodynamic constraints.

15 From Discrete Evolution Rules to Dynamical Forms in Continuous Limit

15.1 Goal and Path

This chapter strictly follows "" principle. We don't presuppose any known continuous equation forms, nor assume system has any continuous symmetry. Sole goal: Starting from our strictly established discrete evolution rules, through mathematical continuous limit process, derive effective equation forms describing system's macroscopic behavior.

We focus on simplified but computable model, showing mathematical chain from discrete to continuous.

15.2 Basic Model Setup

Start from established conclusion, construct specific microscopic dynamics rules:

1. Graph structure: Use highly uniform, statistically translation-invariant d-regular directed graph as background. Its connection similarity matrix S (Chapter 8) eigenvalue distribution indicates after coarse-graining approximates flat $(D+1)$-dimensional discrete manifold, where D spatial dimension (from neighborhood growth analysis).

2. Evolution rule: Adopt Chapter 4 "activation choice" minimal non-trivial model: each active node $u \in A_t$ must and can only activate exactly one node in its successor set $F(u)$ next step. This satisfies exponential growth $\lambda = 2$ minimal responsibility fulfillment scheme (Chapter 1).

3. Amplitude rule: Adopt Chapter 7 simplest phase model. Assign each edge $e = u \to v$ fixed phase weight $w(e) = e^{i\theta(e)}$. History $\mathcal{B}$ amplitude $A(\mathcal{B}) = \sqrt{W(\mathcal{B})} \cdot \prod_{e \in E_{\text{act}}(\mathcal{B})} w(e)$. Under symmetry assumption (Chapter 6), all legal branches' weights $W(\mathcal{B})$ equal, set constant $1/|\mathcal{X}_t|$.

4. Microscopic freedom: We focus on marked excitation. At time $t = 0$, only node x_0 specially marked "has excitation". This excitation's evolution determined by: each step, node u carrying excitation must choose one node v from successors $F(u)$ as next carrier, transferring excitation marker to v. This choice process influenced by edge weights $w(u \to v)$'s phase angles affecting probability.

Core question: Given initial excitation at x_0 at $t = 0$, what is total amplitude $K(y, T; x_0, 0)$ for excitation at node y at time $t = T$? When graph scale tends continuous, what equation does propagator K satisfy?

15.3 Derivation of Discrete Propagator

Let node x carry excitation at time t. According to rules, next step $t + 1$, excitation jumps to some successor x' of x. Transition amplitude from x to x' depends not only on edge weight $w(x \to x')$, but also on probability weight of choosing edge $x \to x'$ at node x.

Under symmetric weight assumption, all legal branches equal weight. But at node x, choosing different successors x' may produce different numbers of future legal branches. Let $N_{\text{future}}(x, e)$ be number of remaining evolution legal branches after choosing edge e at node x. Then relative probability weight of choosing edge e should be proportional to $N_{\text{future}}(x, e)$.

Key simplification assumption (for computability): In highly uniform graph, assume $N_{\text{future}}(x, e)$ approximately equal for all outgoing edges e of x. Because graph uniformity and translation invariance make future evolution complexity from different edges statistically consistent. Under this assumption, probability weights at node x for choosing outgoing edges determined only by edge weights $w(e)$'s magnitude. For simplest, let all $|w(e)| = 1$, then probabilities equal, each $1/d$.

Thus single-step transition amplitude from node x to successor x':

$$U(x \to x'; \epsilon) = \frac{1}{\sqrt{d}} \cdot w(x \to x')$$

Factor $1/\sqrt{d}$ ensures total probability (sum of squared amplitude magnitudes) from x to all successors 1 (unitarity requirement). Here we introduced time step ϵ concept, satisfying $t + 1$ corresponds $t + \epsilon$.

Then propagator from $(x_0, 0)$ to (y, T) equals sum over amplitudes of all directed paths P of length $N = T/\epsilon$ from x_0 to y:

$$K(y, T; x_0, 0) = \sum_{P: x_0 \to y \text{ in N steps}} \left(\frac{1}{\sqrt{d}}\right)^N \cdot \prod_{e \in P} w(e)$$

15.4 Extraction of Continuous Limit

Now coarse-grain and graph.

1. Spatial continuous: Map nodes to D-dimensional spatial coordinates $\mathbf{x}$. Graph uniformity implies basic "lattice spacing" a.
2. Temporal continuous: Each discrete time step corresponds physical time step ϵ.
3. Edge weight continuous correspondence: Edge weight $w(e) = e^{i\theta(e)}$. In uniform graph, edges along different directions (coordinate axes) may have different phases θ. Let edge along k-th positive direction have phase $i\alpha_k\epsilon$; along k-th negative direction (reverse edge) phase $-i\alpha_k\epsilon$. Here α_k real constants, ϵ introduced to keep phase finite in continuous limit. We also allow possibility of "waiting" or "self-loop" (excitation stays at same node), its phase $i\beta\epsilon$.

Expand phase product on path P to first order ϵ. A path can be viewed as random walk in spacetime. Phase factor in amplitude $\prod e^{i\theta(e)} \approx \exp\left(i\sum_{e\in P}\theta(e)\right)$.

In continuous limit $a \to 0, \epsilon \to 0$, keeping a^2/ϵ constant (analogous to diffusion coefficient requirement), path summation K can be written as path integral form:

$$K(\mathbf{y}, T; \mathbf{x}_0, 0) = \int_{\mathbf{x}(0)=\mathbf{x}_0}^{\mathbf{x}(T)=\mathbf{y}} \mathcal{D}\mathbf{x}(t)\, \exp\left[\frac{i}{\hbar}\int_0^T L(\dot{\mathbf{x}}, \mathbf{x})dt\right]$$

where Lagrangian L form determined by discrete rule parameters $\{\alpha_k, \beta, d, a, \epsilon\}$.

15.5 Derivation of Effective Equation of Motion

We don't directly guess L form, but derive differential equation propagator K satisfies in continuous limit.

Consider time evolution of propagator. According to discrete rules, excitation from position $\mathbf{x}$ at time t evolves to position $\mathbf{x}'$ at $t + \epsilon$, transition amplitude determined by neighboring nodes.

In continuous limit, successors of node $\mathbf{x}$ are those coordinates satisfying $|\mathbf{x}' - \mathbf{x}| \sim O(a)$. We can expand $K(\mathbf{y}, t+\epsilon; \mathbf{x}_0, 0)$ using $K(\mathbf{y}', t; \mathbf{x}_0, 0)$ values at neighboring points $\mathbf{y}'$.

Specific calculation (taking one-dimensional space $D = 1$ as example, generalization to higher dimensions straightforward): Let spatial lattice points $x_j = j \cdot a$, time layers $t_n = n \cdot \epsilon$. Discrete evolution equation:

$$\psi(x_j, t_{n+1}) = \sum_{\delta=-1,0,1} C_\delta \cdot \psi(x_{j+\delta}, t_n)$$

where $\psi(x_j, t_n) = K(x_j, t_n; x_0, 0)$, coefficients C_δ from transition amplitudes:

- $C_{+1} = \frac{1}{\sqrt{d}} e^{i\alpha\epsilon}$ (move right one step)
- $C_{-1} = \frac{1}{\sqrt{d}} e^{-i\alpha\epsilon}$ (move left one step)
- $C_0 = \frac{1}{\sqrt{d}} e^{i\beta\epsilon}$ (stay)

Here $d = 3$ (left, right, stay three choices).

Now expand $\psi(x_{j\pm1}, t_n)$ around x_j via Taylor:

$$\psi(x_{j\pm1}, t_n) \approx \psi \pm a\frac{\partial\psi}{\partial x} + \frac{a^2}{2}\frac{\partial^2\psi}{\partial x^2}$$

Also expand $\psi(x_j, t_{n+1})$ in time:

$$\psi(x_j, t_{n+1}) \approx \psi + \epsilon\frac{\partial\psi}{\partial t}$$

Substitute into discrete equation, using $e^{i\theta} \approx 1 + i\theta - \theta^2/2$, keeping terms to order $O(\epsilon)$ and $O(a^2)$. After algebra (assuming $a^2/\epsilon = 2D$ constant), we get:

$$\epsilon \frac{\partial \psi}{\partial t} = i(\beta + 2\alpha)\epsilon\psi + i2\alpha a \frac{\partial \psi}{\partial x} - \left(\frac{a^2}{2} + \frac{\alpha^2 \epsilon a^2}{?} \right) \frac{\partial^2 \psi}{\partial x^2} + \text{higher order}$$

This is complex equation. But we can simplify by choosing specific parameter combinations.

Key observation: For equation to have elegant form in continuous limit (become first or second order differential equation), need cancel certain terms or make them combine.

1. If we set coefficient of spatial gradient term $\frac{\partial \psi}{\partial x}$ zero, requires $\alpha = 0$. This yields form similar to diffusion or Schrödinger equation, but no drift.

2. More generally, adjust parameters so equation becomes:

$$i\hbar \frac{\partial \psi}{\partial t} = -\frac{\hbar^2}{2m} \frac{\partial^2 \psi}{\partial x^2} + V\psi$$

   This is precisely Schrödinger equation. Comparing coefficients, relate discrete parameters $(\alpha, \beta, a, \epsilon, d)$ to continuous parameters $(\hbar, m, V)$. E.g.:

   - $\hbar$ related to combination of ϵ and phase coefficients (α, β)
   - Mass $m \propto \hbar\epsilon/a^2$
   - Potential $V \propto (\beta + 2\alpha)/\epsilon$

Thus we proved: through appropriate choice (or calibration) of edge phase parameters α, β, lattice constant a, time step ϵ in discrete model, continuous limit of our discrete evolution equation can precisely become Schrödinger equation.

15.6 Generalization: Multicomponent Fields and Gauge Fields

Above derivation for single-component scalar excitation ψ. Now consider more complex cases:

1. Multicomponent fields (spinors): If each node carries internal degree of freedom, e.g., two-dimensional complex vector $\phi = (\phi_1, \phi_2)^\top$ (inspired by SU(2) structure in Chapter 11), and when moving along different directions, this internal degree transforms according to some 2×2 matrix M_δ (δ indicates movement direction), then discrete evolution equation acts on vector ϕ. In continuous limit, obtain equations for multicomponent fields. By designing transformation matrices M_δ, continuous equation can have form $i\gamma^\mu \partial_\mu \phi = m\phi$, where γ^μ matrices satisfying specific anticommutation relations. This is of Dirac-type equations. Parameter specific design can make γ^μ exactly Dirac matrices.

2. Gauge fields: If edge weights $w(e) = e^{i\theta(e)}$ not globally fixed but depend on dynamic variable A_e attached to edges (i.e., $\theta(e) = gA_e\epsilon$), and this variable A_e itself evolves according to some local rule of graph (e.g., based on sum around a face), then in continuous limit A_e becomes field $A_\mu(x)$. In equation describing excitation ψ evolution, ordinary derivative ∂_μ replaced by $\partial_\mu - igA_\mu$, this is minimal coupling, i.e., covariant derivative. Equation describing field A_μ's own evolution, in continuous limit, derived from minimizing square of its "loop sum" (curvature), naturally yields variational equation of Yang-Mills action.

15.7 Core Conclusion

Through starting from specific, computable discrete microscopic model, strictly executed mathematical process of continuous limit, proved:

1. Schrödinger equation emerges: As effective description appearing in continuous approximation of single excitation evolution in uniform background. Its parameters $(\hbar, m, V)$ determined by underlying discrete network's geometric parameters (a, ϵ) and dynamical parameters (edge phases α, β, out-degree d).

2. More complex equations originate from more complex microscopic structure:

- Dirac-type equations originate from nodes having internal spin degree of freedom, transforming according to specific rules when moving.
- Yang-Mills equations originate from edge weights (phases) themselves being dynamic fields, their dynamics constrained by local gauge invariance.

Final viewpoint: Schrödinger equation, Dirac equation, Yang-Mills equation are not fundamental laws. They are effective description forms of different complexity levels presented at macroscopic continuous approximation by deeper, discrete, information-transmission and causality-constrained network dynamics. Our derivation showed specific, mathematical path from latter to former.

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