

PRD 29: Chemical Reaction Networks and the Origin of Life

Pure Thought AI Challenge 29

Pure Thought AI Challenges Project

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Abstract

This document presents a comprehensive Product Requirement Document (PRD) for implementing a pure-thought computational challenge. The problem can be tackled using only symbolic mathematics, exact arithmetic, and fresh code—no experimental data or materials databases required until final verification. All results must be accompanied by machine-checkable certificates.

Contents

Domain: Biology Systems Chemistry

Timeline: 6-9 months

Difficulty: High

Prerequisites: Chemical kinetics, graph theory, dynamical systems, information theory, thermodynamics

0.1 1. Problem Statement

0.1.1 Scientific Context

The **origin of life** is one of science's deepest mysteries: how did non-living chemistry give rise to self-replicating, evolving systems capable of Darwinian evolution? A leading hypothesis posits that life emerged from **autocatalytic reaction networks**—collections of molecules that catalyze their own production from simple precursors. This framework, pioneered by Stuart Kauffman, Manfred Eigen, and others, treats the origin of life as a phase transition in chemical space.

Key concepts:

- **Autocatalytic sets:** Chemical reaction networks where every reaction is catalyzed by molecules within the set, and all molecules can be produced from a simple "food set" of externally supplied compounds
- **RAF sets** (Reflexively Autocatalytic and Food-generated): Formal mathematical definition requiring closure and catalytic completeness
- **Hypercycles:** Eigen's model of catalytic cycles forming stable coexistence states
- **Molecular evolution:** Once autocatalytic sets emerge, natural selection operates on variation and heredity

The formose reaction (autocatalytic synthesis of sugars from formaldehyde) and the metabolic pathways of modern cells provide empirical evidence for autocatalytic chemistry's central role in biology.

0.1.2 Core Question

Can we algorithmically detect minimal autocatalytic sets in realistic chemical reaction networks and characterize their emergence from combinatorial chemistry?

Key challenges:

- **RAF detection:** Given a network with 100+ species and 1000+ reactions, find all minimal autocatalytic subsets (NP-hard in general)
- **Catalytic closure:** Verify that every reaction has a catalyst from within the set
- **Food-generation:** Prove all molecules are reachable from the food set via catalyzed reactions
- **Thermodynamic viability:** Check $G < 0$ for all reactions under given conditions
- **Dynamical stability:** Verify hypercycle coexistence against parasites and fluctuations
- **Information content:** Quantify emergence of complexity via Shannon entropy and mutual information

0.1.3 Why This Matters

- **Origin of life:** Provides testable hypotheses for abiogenesis in primordial soup or hydrothermal vents
- **Synthetic biology:** Guide design of minimal autocatalytic reaction sets for artificial cells
- **Astrobiology:** Predict probability of life emergence on exoplanets with different chemistries
- **Evolutionary theory:** Understand pre-Darwinian selection at the chemical level
- **Complex systems:** General principles for emergence of self-organization

0.1.4 Pure Thought Advantages

Autocatalytic sets are **ideal for pure thought investigation**:

- Based on **graph algorithms** (reachability, closure)
 - Thermodynamics computable from **standard free energies** (database lookup)
 - Dynamics solvable via **ODE integration** (deterministic kinetics)
 - Information theory **exact** (Shannon entropy formulas)
 - All results **certified via symbolic computation**
 - NO wet lab experiments until validation phase
 - NO empirical reaction rate measurements initially
-

0.2 2. Mathematical Formulation

0.2.1 Chemical Reaction Networks

Reaction network: Tuple (S, R, C, F) where:

- $S = s, \dots, s$: species (molecules)
- $R = r, \dots, r$: reactions $r: a_s \rightarrow b_s$
- $C: S \times R \rightarrow \{0,1\}$: catalysis relation ($C(s,r) = 1$ if s catalyzes r)
- $F \subseteq S$: food set (externally supplied)

Reaction graph: Directed hypergraph where nodes are species, hyperedges are reactions.

Stoichiometry matrix: where $\sigma_{ij} = b_i - a_i$ (net production of species i in reaction j).

0.2.2 RAF Sets (Hordijk Steel)

Definition: Subset $R' \subseteq R$ is a RAF set if:

- **Reflexively Autocatalytic:** $\forall r \in R', \exists s \in \text{cl}_F(R') \text{ such that } C(s, r) = 1$

(Every reaction is catalyzed by something producible in the set)

- **Food-generated:** All reactants in R' are either in F or produced by reactions in R'

$\text{cl}_F(R') = \text{closure of } F \text{ under reactions in } R'$

Minimal RAF (maxRAF): A RAF set with no proper subset that is also RAF.

Theorem (Hordijk-Steel 2004): For random catalytic networks with sufficient connectivity, RAF sets emerge with high probability above a critical complexity threshold.

0.2.3 Hypercycles (Eigen Schuster)

Hypercycle: n species forming catalytic cycle: $s \rightarrow s \rightarrow \dots \rightarrow s \rightarrow s$ where s catalyzes production of s .

Dynamics:

$$\frac{dx}{dt} = k_{xx}x - d x - x$$

where k_{xx} (selection flux).

Coexistence condition: All species maintain positive concentration at steady state.

Theorem (Eigen): Hypercycles are stable against competitive exclusion if cycle length $n \geq 5$.

0.2.4 Thermodynamic Constraints

Gibbs free energy: For reaction $aA + bB \rightarrow cC + dD$,

$$G = G + RT \ln \left(\frac{[C]^c [D]^d}{[A]^a [B]^b} \right)$$

Thermodynamic viability: Reaction proceeds forward if $G < 0$.

Constraint on RAF: All reactions in set must satisfy $G < 0$ under specified concentrations.

0.2.5 Information Theory

Shannon entropy: $H(X) = - \sum p \log p$ (bits) where p = concentration of species i .

Mutual information: $I(X;Y) = H(X) + H(Y) - H(X,Y)$ quantifies correlation between species.

Information emergence: RAF sets exhibit $I(X;Y) > 0$, indicating functional relationships.

0.2.6 Certificates

All results must come with **machine-checkable certificates**:

- **RAF certificate:** Reachability graph proving all molecules producible from food
- **Catalytic closure certificate:** Witness $s \in \text{cl}_F(R')$ for each reaction r
- **Thermodynamic certificate:** $G < 0$ verified for all reactions
- **Stability certificate:** Jacobian eigenvalues of steady state all negative

Export format: JSON with reaction network and RAF set:

```

1 {
2   "network": {"species": ["A", "B", "C"], "reactions": [...], "food":
3     ["A"]},
4   "raf_set": {"reactions": [0, 2, 5], "species": ["A", "B", "C"]},
5   "is_minimal": true,
6   "thermodynamically_viable": true,
7   "hypercycle_stable": true
8 }

```

0.3 3. Implementation Approach

0.3.1 Phase 1 (Months 1-2): RAF Detection Algorithms

Goal: Implement efficient RAF detection for networks with 50-100 species.

```

1 import networkx as nx
2 from typing import Set, List, Tuple
3 import numpy as np
4
5 class ReactionNetwork:
6     """Chemical reaction network with catalysis."""
7
8     def __init__(self, species: List[str], reactions: List[dict],
9       food_set: Set[str]):
10         """
11         Args:
12             species: List of molecule names
13             reactions: [{reactants: [s1,s2], products: [s3], catalyst:
14               s4}, ...]
15             food_set: Externally supplied molecules
16         """
17         self.species = species
18         self.reactions = reactions
19         self.food_set = food_set
20
21         # Build indices
22         self.species_to_idx = {s: i for i, s in enumerate(species)}
23
24         # Build catalysis graph
25         self.catalysis_graph = self._build_catalysis_graph()
26
27     def _build_catalysis_graph(self) -> nx.DiGraph:
28         """Build graph where edges s -> r mean s catalyzes reaction
29           r."""
30         G = nx.DiGraph()
31
32         # Add nodes for species and reactions
33         for s in self.species:
34             G.add_node(('species', s))
35
36         for i, rxn in enumerate(self.reactions):
37             G.add_node(('reaction', i))

```

```

36         # Add edge from catalyst to reaction
37         if 'catalyst' in rxn and rxn['catalyst']:
38             G.add_edge(('species', rxn['catalyst']), ('reaction',
39                 i))
40
41     return G
42
43
44 def find_all_raf_sets(network: ReactionNetwork, max_size: int = None)
45     -> List[Set[int]]:
46     """
47     Find all RAF sets in network.
48
49     Algorithm (Hordijk & Steel):
50     1. Compute closure cl_F = all species producible from food
51     2. For each subset R' ⊆ R, check if RAF
52     3. Prune search using reachability constraints
53
54     Returns:
55     List of RAF sets (as sets of reaction indices)
56     """
57     # Compute reachable species from food
58     reachable = compute_food_closure(network,
59         set(range(len(network.reactions))))
60
61     # Only consider reactions using reachable species
62     viable_reactions = [
63         i for i, rxn in enumerate(network.reactions)
64         if all(r in reachable for r in rxn['reactants'])]
65
66     raf_sets = []
67
68     # Search over subsets (exponential use heuristics for large
69     # networks)
70     if max_size is None:
71         max_size = min(10, len(viable_reactions))
72
73     for size in range(1, max_size + 1):
74         for candidate in combinations(viable_reactions, size):
75             candidate_set = set(candidate)
76             if is_raf_set(network, candidate_set):
77                 raf_sets.append(candidate_set)
78
79     return raf_sets
80
81 def is_raf_set(network: ReactionNetwork, reaction_subset: Set[int]) ->
82     bool:
83     """
84     Check if reaction subset forms a RAF set.
85
86     Conditions:
87     1. Reflexively autocatalytic: every reaction catalyzed by molecule
88         in closure

```

```

86     2. Food-generated: all reactants producible from food
87     """
88     # Compute closure
89     closure = compute_food_closure(network, reaction_subset)
90
91     # Check catalysis for each reaction
92     for rxn_idx in reaction_subset:
93         rxn = network.reactions[rxn_idx]
94
95         catalyst = rxn.get('catalyst')
96         if catalyst is None:
97             return False # No catalyst assigned
98
99         if catalyst not in closure:
100             return False # Catalyst not producible
101
102     # Check all reactants are in closure
103     for rxn_idx in reaction_subset:
104         rxn = network.reactions[rxn_idx]
105         for reactant in rxn['reactants']:
106             if reactant not in closure:
107                 return False
108
109     return True
110
111
112 def compute_food_closure(network: ReactionNetwork, reaction_subset:
113     Set[int]) -> Set[str]:
114     """
115     Compute cl_F(R'): all species producible from food using reactions
116     in subset.
117
118     Fixed-point iteration.
119     """
120     closure = set(network.food_set)
121
122     changed = True
123     while changed:
124         changed = False
125
126         for rxn_idx in reaction_subset:
127             rxn = network.reactions[rxn_idx]
128
129             # Check if all reactants available
130             if all(r in closure for r in rxn['reactants']):
131                 # Add products to closure
132                 for product in rxn['products']:
133                     if product not in closure:
134                         closure.add(product)
135                         changed = True
136
137     return closure
138
139 def find_minimal_raf_sets(network: ReactionNetwork) -> List[Set[int]]:
140     """

```



```
140     Find all maxRAF sets (minimal RAF sets with no proper subset being
        RAF).
141     """
142     all_rafs = find_all_raf_sets(network)
143
144     # Filter to minimal ones
145     minimal_rafs = []
146
147     for raf in all_rafs:
148         is_minimal = True
149
150         # Check if any proper subset is also RAF
151         for other_raf in all_rafs:
152             if other_raf < raf: # Proper subset
153                 is_minimal = False
154                 break
155
156         if is_minimal:
157             minimal_rafs.append(raf)
158
159     return minimal_rafs
160
161
162 from itertools import combinations
163
164 def raf_detection_exhaustive(network: ReactionNetwork) -> dict:
165     """
166     Exhaustive RAF detection with certificates.
167     """
168     minimal_rafs = find_minimal_raf_sets(network)
169
170     # Generate certificates
171     certificates = []
172     for raf_set in minimal_rafs:
173         closure = compute_food_closure(network, raf_set)
174
175         cert = {
176             'raf_reactions': list(raf_set),
177             'raf_species': list(closure),
178             'is_minimal': True,
179             'size': len(raf_set),
180             'catalysis_verified': verify_catalysis(network, raf_set,
181                                                    closure)
182         }
183         certificates.append(cert)
184
185     return {
186         'n_minimal_rafs': len(minimal_rafs),
187         'minimal_rafs': minimal_rafs,
188         'certificates': certificates
189     }
190
191 def verify_catalysis(network: ReactionNetwork, raf_set: Set[int],
192                     closure: Set[str]) -> bool:
193     """Verify every reaction has catalyst in closure."""
```

```

193     for rxn_idx in raf_set:
194         catalyst = network.reactions[rxn_idx].get('catalyst')
195         if catalyst not in closure:
196             return False
197     return True

```

Validation: Test on formose reaction network (Breslow 1959).

0.3.2 Phase 2 (Months 2-4): Hypercycle Dynamics

Goal: Simulate hypercycle ODEs and analyze stability.

```

1  from scipy.integrate import odeint
2  from scipy.linalg import eig
3
4  def hypercycle_ode(n_species: int, catalysis_rates: np.ndarray,
5                    decay_rates: np.ndarray) -> dict:
6      """
7      Simulate n-species hypercycle dynamics.
8
9      
$$\frac{dx_i}{dt} = k_i x_{i-1} x_i - d_i x_i - \phi x_i$$

10     where  $\phi = \sum_j k_j x_{j-1} x_j$  (selection flux).
11     """
12     def dydt(x, t):
13         dxdt = np.zeros(n_species)
14
15         # Compute selection flux
16         phi = sum(catalysis_rates[i] * x[(i-1) % n_species] * x[i]
17                  for i in range(n_species))
18
19         for i in range(n_species):
20             i_prev = (i - 1) % n_species
21
22             production = catalysis_rates[i] * x[i_prev] * x[i]
23             decay = decay_rates[i] * x[i]
24             dilution = phi * x[i]
25
26             dxdt[i] = production - decay - dilution
27
28         return dxdt
29
30     # Initial conditions (small random perturbation)
31     x0 = np.ones(n_species) / n_species + 0.01 *
32         np.random.randn(n_species)
33     x0 = np.maximum(x0, 0.001) # Ensure positive
34
35     # Integrate
36     t = np.linspace(0, 1000, 10000)
37     sol = odeint(dydt, x0, t)
38
39     # Check coexistence
40     final_state = sol[-1]
41     coexists = all(final_state > 1e-3)
42
43     # Compute stability (Jacobian at equilibrium)

```

```

43     if coexists:
44         J = compute_hypercycle_jacobian(final_state, catalysis_rates,
45                                         decay_rates)
46         eigenvalues = eig(J)[0]
47         is_stable = all(np.real(eigenvalues) < 0)
48     else:
49         is_stable = False
50         eigenvalues = None
51
52     return {
53         'trajectory': sol,
54         'time': t,
55         'coexists': coexists,
56         'final_state': final_state,
57         'is_stable': is_stable,
58         'eigenvalues': eigenvalues
59     }
60
61 def compute_hypercycle_jacobian(x_eq: np.ndarray, k: np.ndarray, d:
62     np.ndarray) -> np.ndarray:
63     """
64     Compute Jacobian matrix at equilibrium.
65
66     J_ij = (dx_i/dt) / x_j
67
68     n = len(x_eq)
69     J = np.zeros((n, n))
70
71     for i in range(n):
72         i_prev = (i - 1) % n
73
74         # Diagonal term
75         J[i, i] = k[i] * x_eq[i_prev] - d[i] - sum(k[j] * x_eq[(j-1) %
76             n] for j in range(n))
77
78         # Off-diagonal (coupling through catalysis)
79         J[i, i_prev] = k[i] * x_eq[i]
80
81         # Selection flux coupling
82         for j in range(n):
83             j_prev = (j - 1) % n
84             J[i, j] -= k[j] * x_eq[j_prev] * x_eq[i] / n # Approximate
85
86     return J
87
88 def test_hypercycle_stability(n_range: range = range(2, 10)) -> dict:
89     """
90     Test Eigen's conjecture: hypercycles stable only for n = 5.
91
92     results = {}
93
94     for n in n_range:
95         # Random catalysis and decay rates
96         k = np.random.uniform(0.5, 2.0, n)

```

```

96     d = np.random.uniform(0.1, 0.5, n)
97
98     hypercycle_result = hypercycle_ode(n, k, d)
99
100    results[n] = {
101        'coexists': hypercycle_result['coexists'],
102        'stable': hypercycle_result['is_stable']
103    }
104
105    return results

```

Validation: Reproduce Eigen Schuster (1979) stability threshold $n \approx 5$.

0.3.3 Phase 3 (Months 4-5): Thermodynamic Constraints

Goal: Verify $G < 0$ for all reactions in RAF sets.

```

1  def compute_reaction_free_energy(reaction: dict,
2                                  concentrations: dict,
3                                  standard_free_energies: dict,
4                                  T: float = 298.15) -> float:
5
6      """
7      Compute Gibbs free energy change for reaction.
8
9       $G = G^\circ + RT \ln(Q)$ 
10
11      where  $Q = [\text{products}] / [\text{reactants}]$  (reaction quotient).
12      """
13
14      R = 8.314 # J/(mol K)
15
16      # Compute  $G^\circ$ 
17      delta_G_standard = 0
18      for product in reaction['products']:
19          delta_G_standard += standard_free_energies.get(product, 0)
20      for reactant in reaction['reactants']:
21          delta_G_standard -= standard_free_energies.get(reactant, 0)
22
23      # Compute reaction quotient Q
24      Q = 1.0
25      for product in reaction['products']:
26          Q *= concentrations.get(product, 1e-6)
27      for reactant in reaction['reactants']:
28          Q /= max(concentrations.get(reactant, 1e-6), 1e-10)
29
30      # Gibbs free energy
31      delta_G = delta_G_standard + R * T * np.log(Q)
32
33      return delta_G
34
35  def verify_thermodynamic_viability(network: ReactionNetwork,
36                                     raf_set: Set[int],
37                                     concentrations: dict,
38                                     standard_free_energies: dict) -> dict:
39
40      """
41      Verify all reactions in RAF set have  $G < 0$ .

```

```

40     """
41     viable = True
42     delta_Gs = []
43
44     for rxn_idx in raf_set:
45         rxn = network.reactions[rxn_idx]
46
47         delta_G = compute_reaction_free_energy(rxn, concentrations,
48         standard_free_energies)
49         delta_Gs.append(delta_G)
50
51         if delta_G >= 0:
52             viable = False
53
54     return {
55         'thermodynamically_viable': viable,
56         'delta_Gs': delta_Gs,
57         'max_delta_G': max(delta_Gs) if delta_Gs else 0,
58         'mean_delta_G': np.mean(delta_Gs) if delta_Gs else 0
59     }

```

Validation: Check formose reaction G values against literature.

0.3.4 Phase 4 (Months 5-7): Information-Theoretic Analysis

Goal: Quantify information emergence in autocatalytic sets.

```

1  from scipy.stats import entropy
2
3  def compute_shannon_entropy(concentrations: np.ndarray) -> float:
4      """
5      Shannon entropy  $H(X) = - \sum p_i \log_2(p_i)$ .
6
7      Measures diversity of molecular species.
8      """
9      # Normalize to probabilities
10     probs = concentrations / np.sum(concentrations)
11     probs = probs[probs > 0] # Remove zeros
12
13     H = entropy(probs, base=2) # bits
14
15     return H
16
17
18  def compute_mutual_information(conc_X: np.ndarray, conc_Y: np.ndarray)
19  -> float:
20      """
21      Mutual information  $I(X;Y)$  between two molecular species.
22
23       $I(X;Y) = H(X) + H(Y) - H(X,Y)$ 
24      """
25      # Joint distribution (discretize concentrations)
26     hist_2d, _, _ = np.histogram2d(conc_X, conc_Y, bins=10)
27     hist_2d = hist_2d / np.sum(hist_2d) # Normalize
28
29     # Marginals

```

```

29 hist_X = np.sum(hist_2d, axis=1)
30 hist_Y = np.sum(hist_2d, axis=0)
31
32 # Entropies
33 H_X = entropy(hist_X[hist_X > 0], base=2)
34 H_Y = entropy(hist_Y[hist_Y > 0], base=2)
35 H_XY = entropy(hist_2d[hist_2d > 0].flatten(), base=2)
36
37 I_XY = H_X + H_Y - H_XY
38
39 return I_XY
40
41
42 def information_analysis_raf(network: ReactionNetwork,
43                             raf_set: Set[int],
44                             trajectory: np.ndarray) -> dict:
45     """
46     Compute information-theoretic properties of RAF dynamics.
47     """
48     n_species = len(network.species)
49
50     # Shannon entropy over time
51     entropies = [compute_shannon_entropy(trajectory[t]) for t in
52                  range(len(trajectory))]
53
54     # Mutual information matrix
55     I_matrix = np.zeros((n_species, n_species))
56
57     for i in range(n_species):
58         for j in range(i+1, n_species):
59             I_matrix[i, j] = compute_mutual_information(trajectory[:,
60                                                         i], trajectory[:, j])
61             I_matrix[j, i] = I_matrix[i, j]
62
63     return {
64         'entropy_trajectory': entropies,
65         'final_entropy': entropies[-1],
66         'entropy_increase': entropies[-1] - entropies[0],
67         'mutual_information_matrix': I_matrix,
68         'mean_mutual_information': np.mean(I_matrix[I_matrix > 0])
69     }

```

Validation: Verify $H(X)$ increases as RAF set emerges from simple precursors.

0.3.5 Phase 5 (Months 7-8): Origin of Life Scenarios

Goal: Apply RAF theory to prebiotic chemistry (formose, amino acids, nucleotides).

```

1 def formose_reaction_network() -> ReactionNetwork:
2     """
3     Construct formose reaction network (autocatalytic sugar synthesis).
4
5     HCHO      glycolaldehyde      glyceraldehyde      ...      sugars
6     """
7     species = [
8         'HCHO', # Formaldehyde (food)

```

```
9         'glycolaldehyde',
10         'glyceraldehyde',
11         'dihydroxyacetone',
12         'erythrose',
13         'ribose'
14     ]
15
16     reactions = [
17         {'reactants': ['HCHO', 'HCHO'], 'products': ['glycolaldehyde'],
18          'catalyst': 'glycolaldehyde'}, # Autocatalytic
19         {'reactants': ['HCHO', 'glycolaldehyde'], 'products':
20          ['glyceraldehyde'],
21          'catalyst': 'glyceraldehyde'},
22         {'reactants': ['glyceraldehyde', 'HCHO'], 'products':
23          ['erythrose'],
24          'catalyst': 'erythrose'},
25         {'reactants': ['erythrose', 'HCHO'], 'products': ['ribose'],
26          'catalyst': 'ribose'}
27     ]
28
29     food_set = {'HCHO'}
30
31     return ReactionNetwork(species, reactions, food_set)
32
33 def amino_acid_network() -> ReactionNetwork:
34     """
35     Simplified amino acid synthesis from HCN, NH3, H2O.
36     """
37     # ... (similar construction)
38     pass
39
40 def origin_of_life_analysis(network: ReactionNetwork) -> dict:
41     """
42     Complete origin of life analysis pipeline.
43     """
44     # 1. Find RAF sets
45     raf_result = raf_detection_exhaustive(network)
46
47     # 2. Thermodynamic viability
48     concentrations = {s: 0.001 for s in network.species} # 1 mM
49     concentrations.update({s: 1.0 for s in network.food_set}) # 1 M
50     food
51
52     standard_free_energies =
53         estimate_standard_free_energies(network.species)
54
55     thermo_results = []
56     for raf_set in raf_result['minimal_rafs']:
57         thermo = verify_thermodynamic_viability(network, raf_set,
58          concentrations, standard_free_energies)
59         thermo_results.append(thermo)
60
61     # 3. Hypercycle stability (if applicable)
62     # ... (check if RAF forms hypercycle structure)
```

```

60
61     # 4. Information emergence
62     # ... (simulate dynamics and compute entropy)
63
64     return {
65         'raf_detection': raf_result,
66         'thermodynamics': thermo_results,
67         'conclusion': 'VIABLE' if any(t['thermodynamically_viable'] for
68                                     t in thermo_results) else 'NOT_VIABLE'
69     }
70
71 def estimate_standard_free_energies(species: List[str]) -> dict:
72     """
73     Estimate G from group contribution methods or database lookup.
74     """
75     # Placeholder: use Benson group additivity or lookup tables
76     free_energies = {}
77
78     for s in species:
79         # Approximate: small organic molecules ~ -100 to -200 kJ/mol
80         free_energies[s] = -150.0 + 50.0 * np.random.randn()
81
82     return free_energies

```

Validation: Reproduce Kauffman's autocatalytic set emergence threshold.

0.3.6 Phase 6 (Months 8-9): Certificate Generation

Goal: Generate complete certificates for all RAF sets found.

```

1 from dataclasses import dataclass, asdict
2 import json
3
4 @dataclass
5 class RAFCertificate:
6     """Complete certificate for RAF set."""
7
8     network_name: str
9     n_species: int
10    n_reactions: int
11    food_set: List[str]
12
13    # RAF properties
14    raf_reactions: List[int]
15    raf_species: List[str]
16    is_minimal: bool
17
18    # Verification
19    catalytic_closure_verified: bool
20    food_generation_verified: bool
21    thermodynamically_viable: bool
22    mean_delta_G: float
23
24    # Dynamics
25    hypercycle_stable: bool

```



```

26
27     # Information
28     shannon_entropy: float
29     mutual_information_mean: float
30
31     # Metadata
32     computation_date: str
33
34     def export_json(self, filename: str):
35         with open(filename, 'w') as f:
36             json.dump(asdict(self), f, indent=2)
37
38     def verify(self) -> bool:
39         checks = [
40             len(self.raf_reactions) > 0,
41             len(self.raf_species) >= len(self.food_set),
42             self.catalytic_closure_verified,
43             self.food_generation_verified
44         ]
45         return all(checks)
46
47
48     def generate_raf_certificate(network: ReactionNetwork, raf_set:
49         Set[int]) -> RAFCertificate:
50         """Generate complete certificate for RAF set."""
51         closure = compute_food_closure(network, raf_set)
52
53         # Thermodynamics
54         concentrations = {s: 0.001 for s in network.species}
55         standard_free_energies =
56             estimate_standard_free_energies(network.species)
57         thermo = verify_thermodynamic_viability(network, raf_set,
58             concentrations, standard_free_energies)
59
60         cert = RAFCertificate(
61             network_name='Formose',
62             n_species=len(network.species),
63             n_reactions=len(network.reactions),
64             food_set=list(network.food_set),
65             raf_reactions=list(raf_set),
66             raf_species=list(closure),
67             is_minimal=True,
68             catalytic_closure_verified=verify_catalysis(network, raf_set,
69                 closure),
70             food_generation_verified=(closure.issuperset(
71                 set(r for rxn_idx in raf_set for r in
72                     network.reactions[rxn_idx]['reactants'])))
73             ),
74             thermodynamically_viable=thermo['thermodynamically_viable'],
75             mean_delta_G=thermo['mean_delta_G'],
76             hypercycle_stable=False, # Would require dynamics
77             shannon_entropy=0.0, # Would require simulation
78             mutual_information_mean=0.0,
79             computation_date='2026-01-17'
80         )

```

```
77 | return cert
```

0.4 4. Example Starting Prompt

Prompt for AI System:

You are tasked with finding autocatalytic sets in chemical reaction networks to model the origin of life. Your goals:

- **RAF Detection (Months 1-2):**
 - Implement formose reaction network (6 species, 10 reactions)
 - Find all minimal RAF sets
 - Verify catalytic closure and food-generation
- **Hypercycle Dynamics (Months 2-4):**
 - Simulate n-species hypercycles for $n = 2, \dots, 10$
 - Verify Eigen's stability threshold ($n > 5$)
 - Compute Jacobian eigenvalues
- **Thermodynamics (Months 4-5):**
 - Compute G for all reactions
 - Verify viability: $G < 0$
 - Use group contribution methods
- **Information Theory (Months 5-7):**
 - Compute Shannon entropy $H(X)$
 - Compute mutual information $I(X;Y)$
 - Track entropy increase over time
- **Origin of Life (Months 7-8):**
 - Apply to formose, amino acids, nucleotides
 - Find minimal autocatalytic sets
 - Compare to literature thresholds
- **Certificates (Months 8-9):**
 - Generate RAFCertificate for each set
 - Export to JSON
 - Verify all certificates

Success Criteria:

- MVR (2-4 months): RAF detection for toy networks
- Strong (6-8 months): Formose analysis, hypercycle stability
- Publication (9 months): Complete origin-of-life scenario

References:

- Kauffman (1986): Autocatalytic sets
- Eigen Schuster (1979): Hypercycle theory
- Hordijk Steel (2004): RAF algorithm

Begin by implementing RAF detection for formose network.

0.5 5. Success Criteria**0.5.1 Minimum Viable Result (Months 1-4)****Core Achievements:**

- RAF detection for networks with 10-20 species
- Catalytic closure verification
- Basic hypercycle simulation (n = 5)
- Certificate generation

Validation:

- Find RAF in formose network
- Reproduce Eigen stability threshold

Deliverables:

- Python module `raf_detection.py`
- Jupyter notebook: formose analysis
- JSON certificates for 3+ RAF sets

0.5.2 Strong Result (Months 4-8)

Extended Capabilities:

- Thermodynamic viability checks
- Information-theoretic analysis
- Hypercycle stability for $n \geq 10$
- Multiple prebiotic networks

Publications Benchmark:

- Reproduce Hordijk Steel (2004) results
- Match thermodynamic thresholds

Deliverables:

- Database of 10+ networks
- Entropy vs time plots
- Stability phase diagrams

0.5.3 Publication-Quality Result (Months 8-9)

Novel Contributions:

- Novel RAF sets in unexplored chemistry
- Thermodynamic-information tradeoffs
- Predictive model for RAF emergence
- Experimental predictions

Deliverables:

- Arxiv preprint on origin of life
 - Public database of RAF sets
 - Web tool for RAF detection
-

0.6 6. Verification Protocol

```
1 def verify_raf_certificate(cert: RAFCertificate) -> dict:
2     results = {
3         'catalysis_verified': cert.catalytic_closure_verified,
4         'food_generation_verified': cert.food_generation_verified,
5         'thermodynamically_viable': cert.thermodynamically_viable,
6         'certificate_valid': cert.verify()
7     }
8
9     results['all_checks_passed'] = all(v for v in results.values()
10         if isinstance(v, bool))
11
12     return results
```

0.7 7. Resources and Milestones

0.7.1 Essential References

- **Foundational Papers:**
- Kauffman (1986): "Autocatalytic sets of proteins"
- Eigen Schuster (1979): *The Hypercycle*
- Hordijk Steel (2004): "Detecting autocatalytic, self-sustaining sets"
- **Modern Work:**
- Xavier et al. (2020): "Autocatalytic chemical networks at the origin of life"
- Vasas et al. (2012): "Evolution before genes"

0.7.2 Milestone Checklist

Month 1: RAF detection implemented

Month 2: Formose network analyzed

Month 3: Hypercycle simulations working

Month 4: Thermodynamic checks complete

Month 5: Information theory implemented

Month 6: 5+ networks analyzed

Month 7: Origin-of-life scenarios tested

Month 8: Certificates generated

Month 9: Database exported

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