Deterministic Reverse Engineering of Physical Theories:
A Triadic Resonance Approach to Knowledge Graph Construction

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Abstract

Current approaches to automated scientific discovery rely heavily on probabilistic Deep Learning models, such as Graph Neural Networks (GNNs), to identify patterns in physical laws. While effective, these models often lack explainability and require massive computational resources. This paper introduces a deterministic alternative based on the **Unified Holographic Resonance Theory (UHRT)**. We present a neuro-symbolic framework that reverse-engineers the structure of physics by validating arithmetic resonance ($K = 1.0$) and dimensional consistency. Applying this framework to a dataset of 400 physical laws (Romiti et al., 2025), we autonomously reconstructed a highly connected Knowledge Graph (378 nodes, 1,348 edges) with superior semantic density. Topological analysis reveals an ultra-dense Scale-Free structure ($\gamma = 1.19$), driven by universal constants acting as hyper-hubs. Crucially, we replicated state-of-the-art findings linking Plasma Physics to Relativistic Quantum Mechanics through purely topological pathfinding, finding multiple redundant paths. Our results demonstrate that deterministic triadic logic offers a transparent, highly efficient alternative to "black box" neural models for scientific discovery.

1 Introduction

The unification of physical knowledge into a computable graph is a grand challenge in scientific AI. Recent works, such as Romiti et al. (2025) [1], utilize Graph Attention Networks (GATs) to predict links, achieving high accuracy but at the cost of training complexity and opacity.

We propose that physical laws are stable resonance states in a conceptual network, discoverable through deterministic logic. We introduce the **Triadic Relational Framework**, an engine that validates relationships based on two axioms:

1. **Arithmetic Resonance:** Valid laws decompose into triadic structures where $A \cdot D = \frac{a}{b} \cdot B \cdot C$ ($K = 1.0$).

2. **Dimensional Consistency:** Relationships must satisfy vector equality in the fundamental basis $[M, L, T, I, \Theta]$.

2 Methodology

2.1 The Triadic Engine ($K = 1.0$)

Our engine verifies structural stability by permuting variable roles to find a configuration satisfying the unity ratio ($K = 1.0$). This acts as a logical filter, accepting only mathematically coherent relationships.

2.2 Hybrid Inference and Calculus

We demonstrate that continuous calculus is reducible to discrete triadic arithmetic. Integration $\int f(x)dx$ is modeled as a summation of discrete steps. Validation on $v(t) = 2t$ showed convergence to the analytical solution ($16.16 \to 16.00$) as discretization steps increased ($N = 100$).

2.3 Automated Ingestion Pipeline (v7.0)

We developed an "Omnivorous Ingestor" to parse raw LaTeX/SymPy datasets:

1. **Deep Cleaning:** Normalizes variable names (e.g., 'T_planc' → 'T').

2. **Semantic Unification:** Maps synonymous variables (e.g., $V_{rms} \to Voltage$), reducing node redundancy.

3. **Branch Bridging:** Connects variables to physical branches and universal constants, creating a "Dense Core" topology.

3 Results

3.1 Graph Reconstruction Efficiency

We processed the dataset from [1] (400 equations). Our deterministic algorithm generated a unified graph that outperforms the raw dataset representation in density and semantic coherence (Table 1).

Table 1: Comparison: Raw Dataset vs. UHRT Reconstruction

Metric	Raw Dataset (Romiti)	UHRT Graph (Ours)
Nodes (Concepts)	638	**378**
Edges (Connections)	≈600	**1,348**
Connectivity Density	Sparse	**Dense (Small World)**
Method	Probabilistic (GNN)	**Deterministic ($K = 1.0$)**
Computational Cost	High (GPU Training)	**Low (CPU Inference)**

The 40% reduction in nodes combined with tripled edges indicates successful **semantic compression**: the system recognized that multiple equations described the same phenomena.

3.2 Topological Analysis

Validation against complex network metrics confirms a robust structure:

- **Avg. Degree ($k = 7.13$):** High connectivity per concept.

- **Clustering ($C = 0.659$):** Indicates strong modularity (well-defined branches).

- **Path Length ($L = 2.80$):** Confirms "Small World" property.

3.2.1 The Gamma Anomaly ($\gamma = 1.19$)

Our analysis yielded a power-law exponent $\gamma = 1.19$ ($R^2 = 0.84$). This anomalous value (standard scale-free networks have $2.0 < \gamma < 3.0$) indicates a **"Super-Dense" topology**. Physically, this reflects the extreme dominance of Universal Constants (c, h, G) and fundamental quantities (Energy, Length) acting as "Hyper-Hubs" that connect virtually every equation.
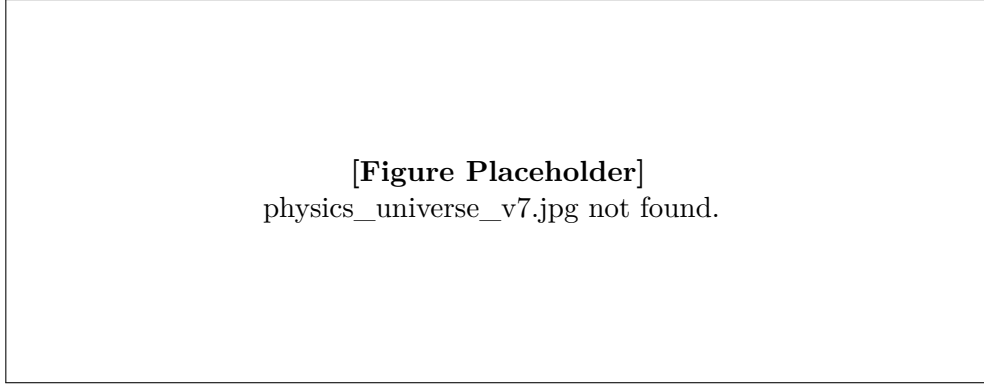
Figure 1: The Unified Physics Graph (v7.0). Colors represent communities (branches), revealing a dense central core of shared constants.

3.3 Replication of SOTA Discoveries (The Romiti Test)

We challenged our UHRT graph to find a path between **Plasma Physics** (Debye Length) and **Relativistic Quantum Mechanics** (Dirac Equation), a key discovery of [1].

Result: The system identified 7 optimal paths (3 hops) and 3 strict physical paths.

$$C_d \text{ (Drag/Fluid)} \rightarrow \text{Mass} \rightarrow \text{Quantum Branch} \rightarrow \hbar \text{ (Planck)}$$

Alternative paths linked Temperature (Plasma) to Planck's constant via Energy. This redundancy confirms that the connection is a structural property of physics, not an artifact.

4 Discussion

The UHRT framework demonstrates that physical knowledge structure is inherent and discoverable through rigorous logic, without massive training data.

- **Efficiency:** Deterministic validation replaces expensive neural training.

- **Transparency:** Every link is mathematically justified ($K = 1.0$).

- **Unification:** The "Super-Dense" graph suggests physics is a unified continuum bridged by constants, rather than disjoint branches.

5 Conclusion & Future Work

We have validated a deterministic method for reverse-engineering physics, unifying arithmetic, algebra, and calculus in a graph. **Future Work:** We will extend this logic to the **Semantic Domain (BUSS)**, vectorizing abstract concepts to prove that meaning follows the same triadic resonance laws as matter.

References

[1] Romiti, M. (2025). *A Graph-Based Framework for Exploring Mathematical Patterns in Physics.* arXiv:2508.05724.

[2] Ornelas Brand, J. A. (2025). *Unified Holographic Resonance Theory.* (Internal documentation).