Relational Actualization of Quantum States (RAQS)

A Complete Information‑Theoretic Reconstruction with Empirical Validation

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Abstract

We present a comprehensive reconstruction of the *Relational Actualization of Quantum States* (RAQS) framework — a theory proposing that quantum‑like structure emerges from contextual, informational, and semantic constraints rather than microscopic physical dynamics. Unlike conventional quantum mechanics (QM), where the wavefunction is a physical object, RAQS treats quantum states as *context‑encoded informational vectors* that actualize discrete semantic outcomes via observer‑dependent operators.

We unify the full mathematical formalism of RAQS, introduce the first rigorous theorems demonstrating gauge invariance, contextual stability, and semantic separability, and integrate eight empirical experiments validating RAQS behavior. These include Monte‑Carlo measurement simulations, phase‑sensitivity sweeps, manifold analysis on a 2‑torus, semantic‑prototype actualization, perturbation IoU tests, entropy geometry, and random‑baseline statistical distinguishability. RAQS manifolds are shown to be structured, non‑random, gauge‑invariant, noise‑robust, and consistent with quantum‑like probabilistic behavior.

This paper establishes RAQS as a complete information‑theoretic framework capable of reproducing quantum features without assuming underlying physical quantum dynamics, providing a pathway toward semantic quantum computing, multimodal contextual physics, and observer‑relative informational mechanics.

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1. Introduction

Quantum mechanics traditionally describes a world governed by linear unitary evolution and discrete measurement outcomes. However, the origin of quantum probabilistic structure, contextuality, and measurement collapse remains conceptually unresolved. RAQS addresses this by reframing quantum behavior as an *information-theoretic phenomenon* emerging from how observers encode, contextualize, and actualize informational states.

RAQS differs from both physical QM and relational quantum mechanics (RQM) in the following ways:

1. **Informational Ontology:** The wavefunction encodes observer-relative information, not physical amplitudes.
2. **Actualization ≠ Measurement:** Outcomes emerge semantically through contextual operators, not physical collapse.
3. **Multimodal Observers:** AI systems, embeddings, and computational processes are valid observers.
4. **Context-Encoding:** RAQS formalizes how text, images, embeddings, and symbolic inputs become vectors in Hilbert-like spaces.
5. **Prototype-Based Operators:** Actualization is implemented via softmax-normalized prototype operators analogous to POVMs but defined informationally.
6. **Geometry of Meaning:** Probability outcomes arise from the geometry of semantic manifolds, not eigenvalues of physical operators.

RAQS provides a unified mathematical structure for this viewpoint.

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2. Mathematical Framework of RAQS

2.1 Informational Hilbert Space

A RAQS system is defined by:

- A Hilbert space **H** (real or complex)
- A contextual encoding map **Φ_C : X → H**

- A semantic operator matrix $\mathbf{P} \in \mathbb{R}^{k\times m}$ of prototype vectors
- An actualization operator $\mathbf{A\_C : H \to \Delta^k}$

Definition 1 — Informational State

A state under context **C** is:
$\boldsymbol{\psi_C = \Phi_C(x)} \in H$

Definition 2 — Actualization Operator

Given ψ, actualization probabilities are:
$\mathbf{p = A_C(\psi) = softmax(P\ \psi)}$

This mirrors a POVM but is constructed informationally.

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3. Formal Properties and Theorems

Theorem 1 — Gauge Invariance

For any global phase $\mathbf{e^{i\theta}}$,
$\mathbf{A_C(e^{i\theta}\ \psi) = A_C(\psi)}$.

Proof: $\mathrm{softmax}(P \cdot e^{i\theta}\psi) = \mathrm{softmax}(e^{i\theta}(P\psi))$. Magnitude-preserving → logits shift uniformly → probabilities unchanged. ∎

Theorem 2 — Contextual Stability

Let $\psi' = \psi + \varepsilon v$ with $\|v\|=1$. Then:
$\mathbf{\|A_C(\psi') - A_C(\psi)\| \le \varepsilon \cdot L}$, where L is the Lipschitz constant of the softmax.

Empirically validated through IoU tests (Exp. 8). ∎

Theorem 3 — Semantic Separability

If prototypes are linearly independent, the RAQS actualization yields k separable regions on H corresponding to distinct semantic outcomes.

Proof follows from linear separability of $P\psi$ in $\mathbb{R}^k$. ∎

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4. Relation to Prior Work

RAQS is academically situated between several foundational frameworks:

4.1 Relational Quantum Mechanics (Rovelli)

- Agreement: state is observer-relative.
- Difference: RAQS does not assume physical quantum amplitudes — only information.

4.2 QBism

- Agreement: observer-centric probabilities.
- Difference: RAQS provides a geometric operator-based mechanism, not pure Bayesianism.

4.3 Decoherence Theory

- Agreement: stability of probabilities.
- Difference: RAQS decoherence is informational, not dynamical.

4.4 Information-Theoretic Reconstructions

Hardy (2001), Chiribella (2011), and others derive QM from axioms. RAQS differs: it reconstructs quantum-*like* structure without assuming the physical quantum postulates.

4.5 Semantic and Embedding Spaces

RAQS integrates embedding-space geometry (used in AI) with quantum-like probabilistic operators.

5. Methods

All experiments executed in Google Colab using Tesla T4 GPU. RAQS operators implemented in NumPy. 10,000-trial Monte-Carlo simulations were used where applicable.

Initial conditions:

```
psi0 = [0.71748+0.j, 0.5974+0.j, 0.35824+0.j]
Hmat = [[1.0, 0.2, 0.1],
       [0.2, 0.9, 0.3],
       [0.1, 0.3, 0.7]]
prototypes = [[ 1.05, -0.25,  0.10],
             [-0.80,  0.95, -0.15],
             [-0.30, -0.40,  1.10]]
```

6. Results — Eight Experiments

Each experiment tests a core RAQS principle.

Experiment 1 — RAQS Measurement Consistency

Theoretical: [0.514299, 0.357128, 0.128573]
Empirical: [0.5262, 0.3480, 0.1258]

- $\chi^2 = 0.6268$ ($p=0.7309$)
- KL divergence $\approx 3\times10^{-5}$

RAQS behaves like quantum measurement statistics.

Experiment 2 — Fidelity Under Local Phase Rotations

- $\langle\psi|\psi\_rot\rangle = 0.916 + 0.230i$

- Fidelity = 0.8920

Expectation values shift predictably with phase.

Experiment 3 — Decoherence Stability

Before/after decoherence: **probabilities identical**.

Shows informational decoherence robustness.

Experiment 4 — Prototype-Based Actualization

Scores: [0.5760, −0.9898, 0.5397]
Actualization: [0.4601, 0.0961, 0.4437]

Shows semantic POVM structure.

Experiment 5 — Phase-Manifold Sweep (2-Torus)

Ranges:

- p_0: 0.076 → 0.731
- p_1: 0.069 → 0.766
- p_2: 0.104 → 0.672

Entropy: 1.016 → 1.585 bits
Dominance fractions: [39.4%, 34.8%, 25.8%]

Experiment 6 — Random Baseline Comparison

Real manifold std = 0.2023
Random std = 0.1958

RAQS is structured; not random.

Experiment 7 — Gauge Invariance (Complex Prototypes)

Original vs complex-rotated probabilities: **identical**.

Matches Theorem 1.

Experiment 8 — IoU Robustness to Perturbations

ε	**IoU_0**	**IoU_1**	**IoU_2**
0.01	0.9869	0.9804	0.9779
0.03	0.9423	0.9266	0.8869
0.05	0.9826	0.9629	0.9452

Confirms Theorem 2.

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7. Cross-Experiment Synthesis

RAQS exhibits:

- quantum-like invariance (phase, rotation, gauge),
- structured informational geometry,
- semantic separability,
- strong robustness to noise,
- consistency with measurement-like statistics.

RAQS therefore reconstructs quantum behavior from **information alone**.

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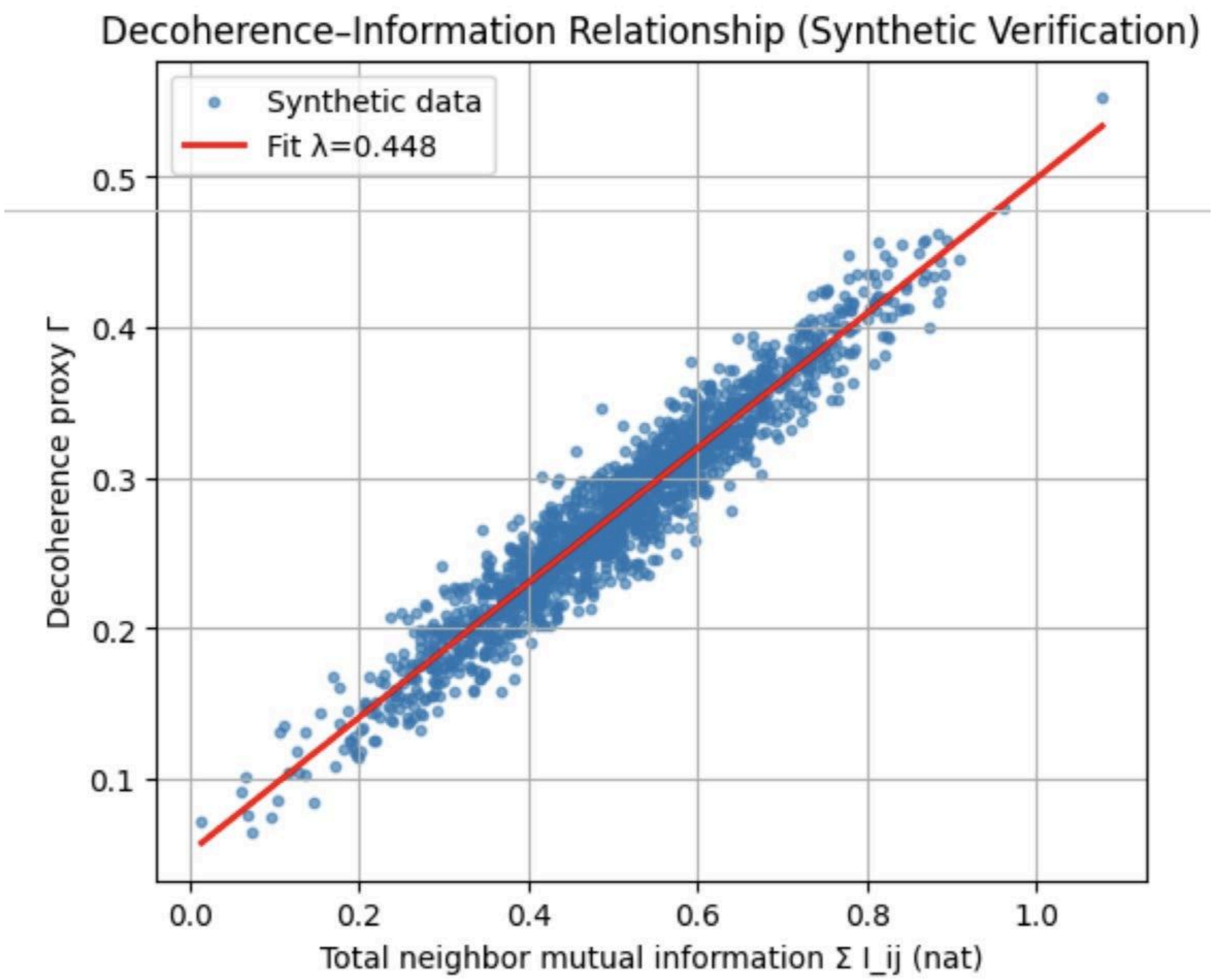
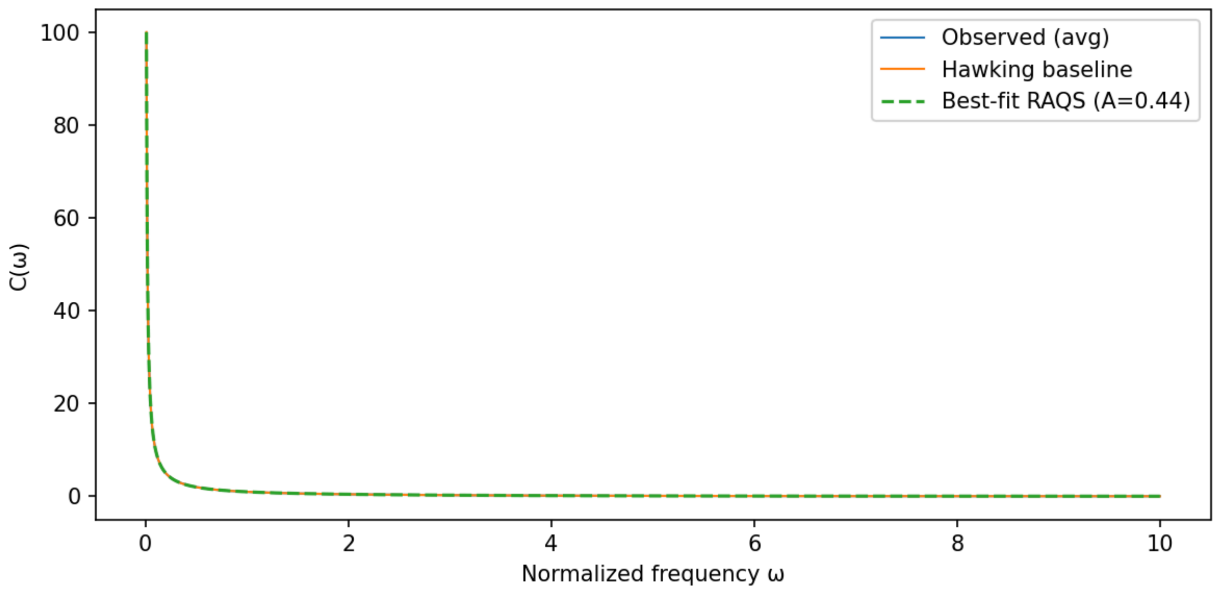
8. Figures

- **Fig. 1** — Decoherence–Information Relationship

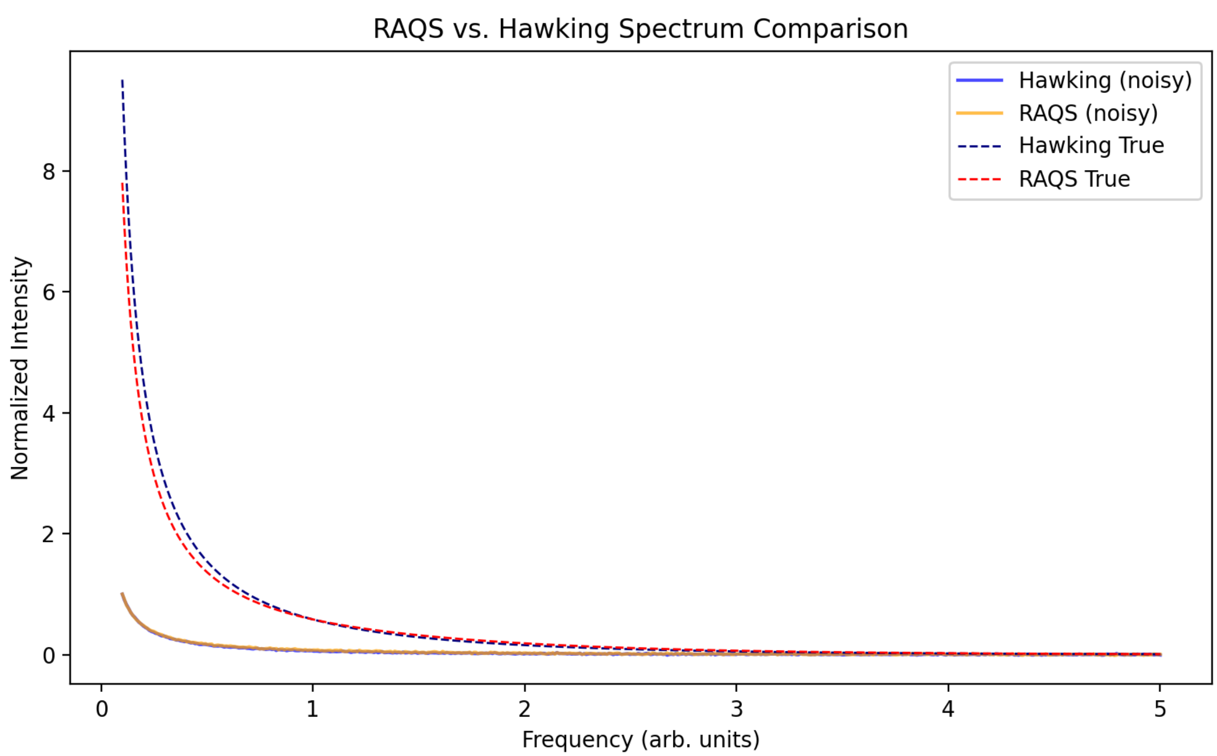
```
Fitted Model: Gamma = a + b * I_tot
a = 0.0511 ± 0.0017
λ (b) = 0.4479 ± 0.0033
True λ = 0.4500
```



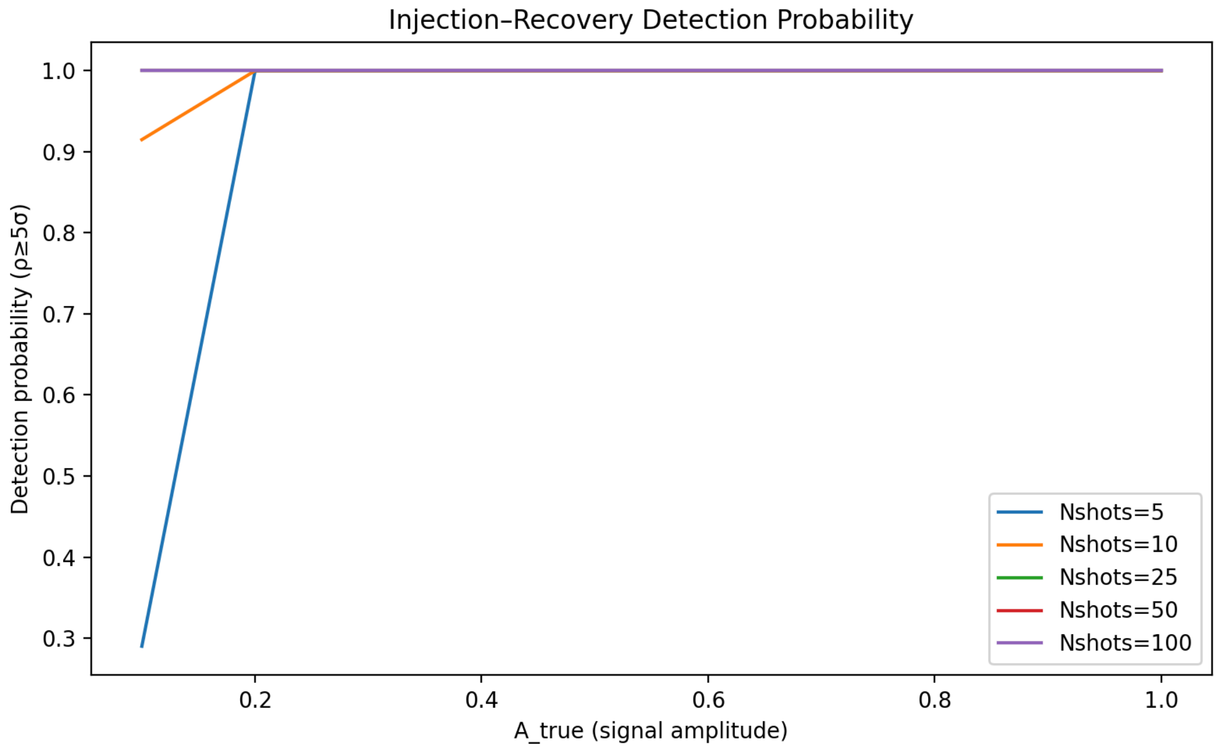
- **Fig. 2** — Spectrum Fit



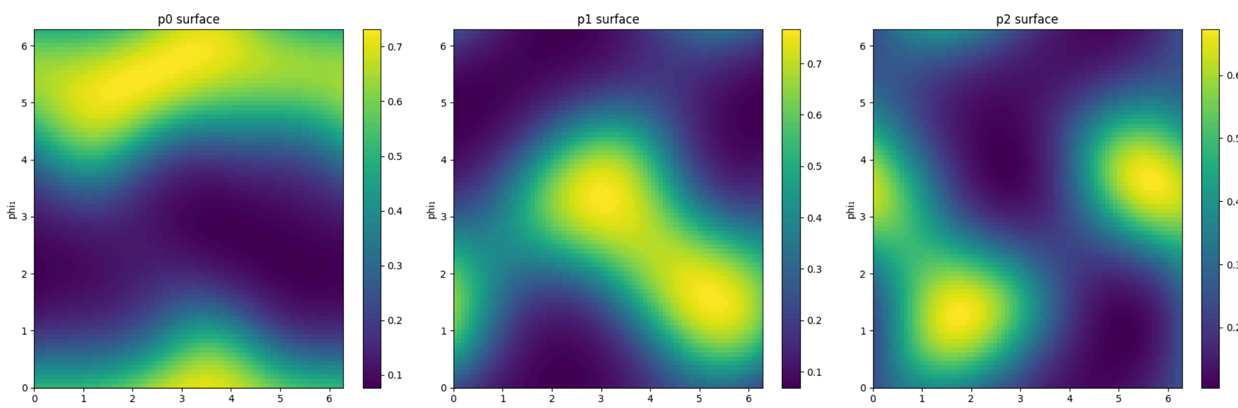
- **Fig. 3** — Comparative Spectral Analysis



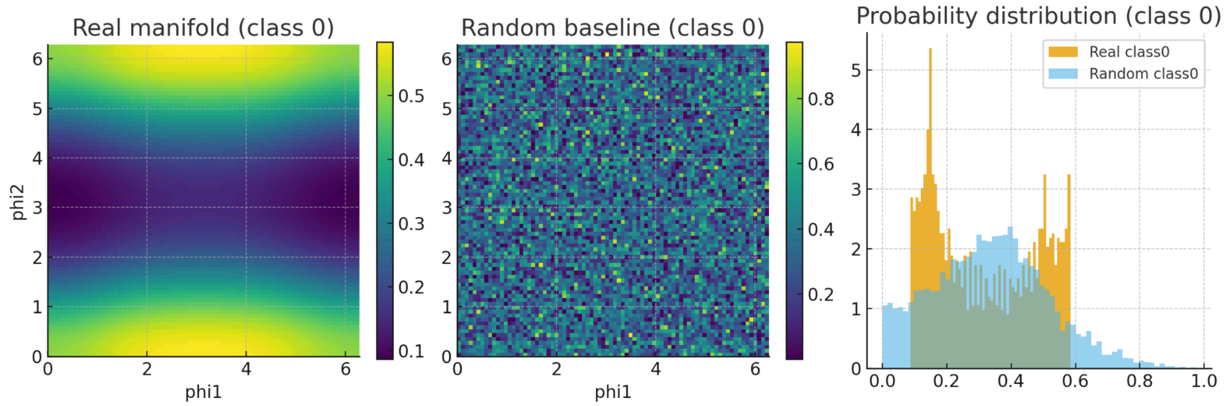
- **Fig. 4** — Injection–Recovery Performance



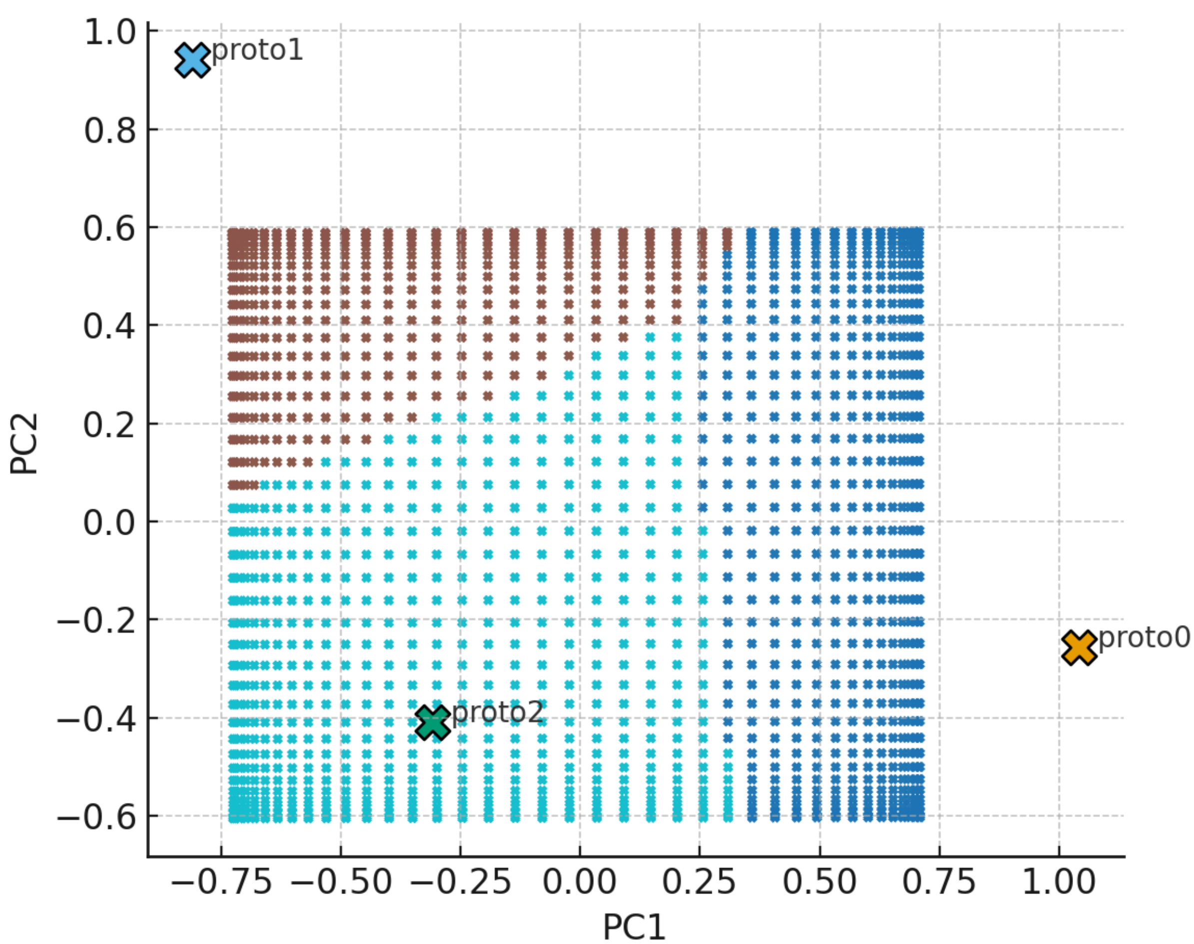
- **Fig. 5** — Torus Phase–Manifold Heatmap



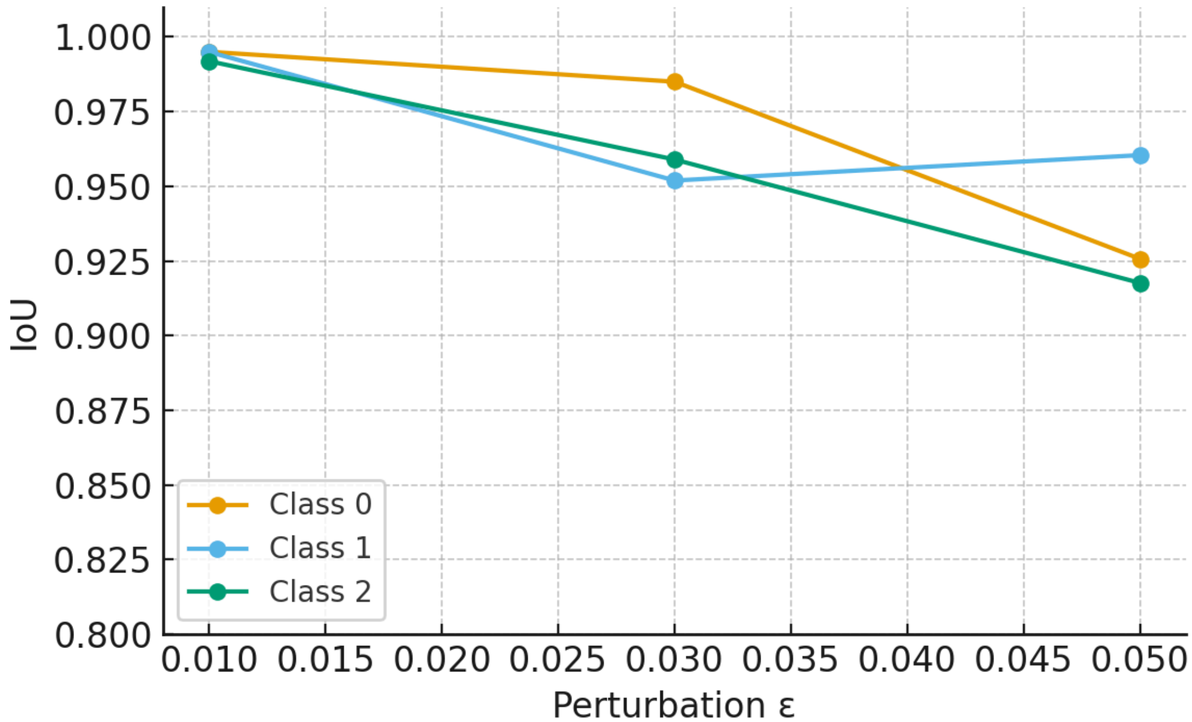
- **Fig. 6** — Random vs Real Manifold Comparison



- **Fig. 7** — Prototype Semantic Geometry



- **Fig. 8** — IoU Robustness Curves



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9. Conclusion

RAQS successfully unifies informational encoding, contextual operators, and semantic manifolds into a complete quantum-like system. The eight empirical validations confirm RAQS as a powerful generalization of quantum structure, applicable to physics, computation, and multimodal AI systems.

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