Rahul Modak

Founder & CEO
Bayesian Cybersecurity Pvt Ltd
Mumbai, Maharashtra, India
Email: rahul.modak@bayesiananalytics.in

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Subject: Submission — Learning Geometry from Physics Constraints via Bayesian Priors and Learned Manifolds

Dear Editors,

We submit the manuscript **"Learning Geometry from Physics Constraints: An Alternative Framework with Kerr Van Vleck–Type Computation"** by *Rahul Modak* and *Rahul Walawalkar* for consideration in **Nature Communications**.

This work introduces the **Modak–Walawalkar (M-W) Framework**, an alternative computational paradigm in which **geometric structure is learned automatically from physics constraints encoded as Bayesian priors**, rather than derived analytically through tensor calculus, discretization, or explicit PDE solving. Using a physics-constrained variational autoencoder, the framework discovers Riemannian or Lorentzian manifolds directly from priors, enabling computation of geometric objects such as **metrics, geodesic distances, world functions, and Van Vleck determinants** via automatic differentiation.

Conceptual and methodological contributions

1. **Automated geometry discovery from physics priors**
   To our knowledge, this is the first framework that learns **Riemannian and Lorentzian metrics directly from physics constraints alone**, eliminating manual tensor derivations and spatial discretization. Geometry emerges as a learned manifold, making geometric inference tractable in arbitrary dimensions.

2. **A universal geometric risk measure**
   We introduce the **M-W Riemannian distance** as a first-principles geometric quantification of failure or degradation risk. Remarkably, this measure operates identically across disparate domains—electrochemical batteries (32D), cybersecurity systems (57D), and spacetime geometry—revealing shared geometric structure across otherwise unrelated physical systems.

3. **Extension to indefinite signatures (proof-of-concept)**
   The framework is shown to handle **Lorentzian signatures** without modification. As a proof-of-concept, we demonstrate a **computationally tractable Kerr Van Vleck–type determinant**, a quantity that has remained analytically intractable for over a century due to the Kerr metric's complexity. The learned geometry reproduces correct causal structure and frame-dragging behavior without explicit programming.

4. **Computational geometry as a representational superset**
   When Einstein field equations are supplied as priors (dimension = 4, signature = $-+++$), the frame-

work is **compatible with General Relativity**, suggesting shared geometric structure. More broadly, the M-W pipeline supports **arbitrary dimension, arbitrary signature, and arbitrary physics constraints**, representing a computational geometry pipeline that is strictly more flexible than traditional GR methods, while not modifying GR physics.

Validation and practical relevance

- **Riemannian validation (production-grade):**
  Battery health prediction (MAE ≈ 0.008, 20–200$\times$ speedup, commercial deployment via NETRA partnership) and cybersecurity risk inference (AUC ≈ 0.89, enterprise UAT stage, Indian Army vendor authorization validation).

- **Lorentzian validation (methodological proof-of-concept):**
  Kerr spacetime with correct signature, causality structure, frame dragging, and a first tractable Van Vleck-type computation in $\sim$10 minutes on CPU.

Relevance to *Nature Communications*

We believe this manuscript aligns strongly with the journal's mission by:

- Presenting **machine learning as a tool for scientific representation**, not merely prediction;
- Demonstrating how **physics-informed ML can automate traditionally intractable mathematical reasoning**;
- Bridging ML, geometry, and fundamental physics while delivering **real-world industrial impact**;
- Offering **broad interdisciplinary appeal** across computational physics, machine learning, differential geometry, and applied mathematics.

The work is not a claim of new physical laws; rather, it introduces a **new computational methodology** for geometric inference from constraints. We clearly delineate validated results from open problems and explicitly outline a community-driven roadmap for further physical validation in Lorentzian settings.

All code is open-source (available at `https://github.com/RahulModak74/mw-framework`), and no part of the manuscript is under consideration elsewhere. Potential conflicts of interest are fully disclosed.

We appreciate your consideration and believe this work may be of broad interest to the diverse readership of *Nature Communications* at the intersection of machine learning, geometry, physics, and engineering.

Sincerely,

Rahul Modak
(on behalf of all authors)

Co-author:
Dr. Rahul Walawalkar
Former President, India Energy Storage Alliance (IESA)
NETRA (Net Zero Energy Transition Association)
Pune, India