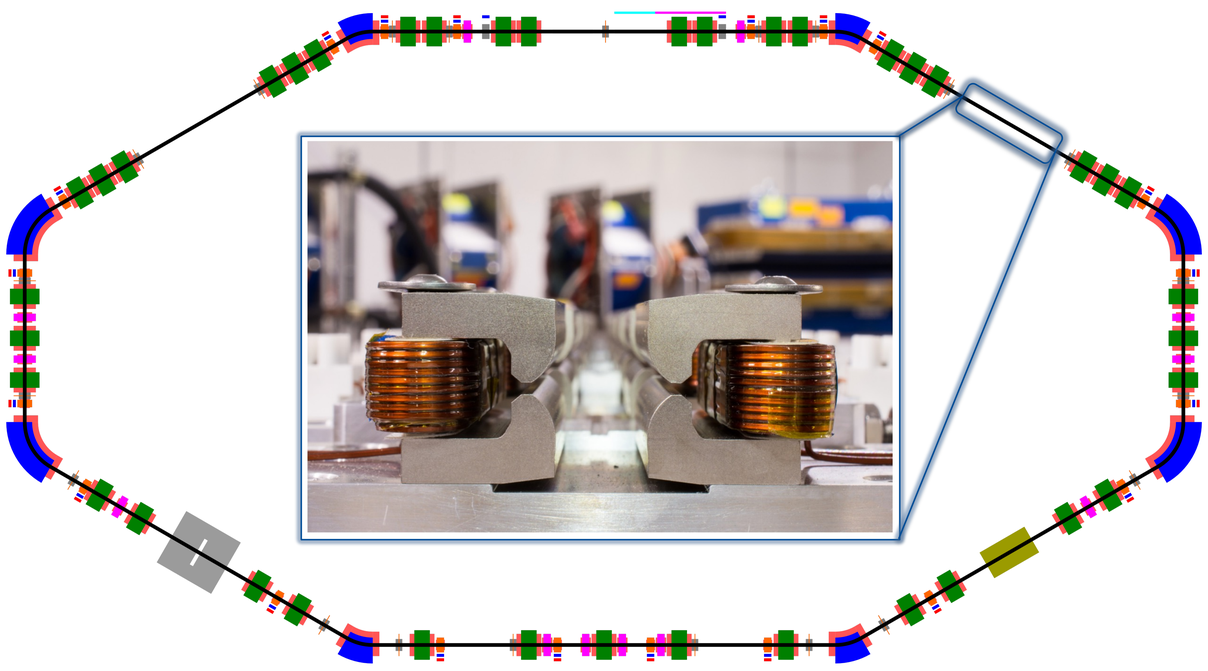
FERMILAB-POSTER-24-0030-AD

Experimental verification of integrability in a Danilov-Nagaitsev lattice using machine learning

N. Banerjee, A. Romanov, G. Stancari, A. Valishev, J. Wieland, Fermi National Accelerator Laboratory
N. Kuklev, Argonne National Laboratory

IPAC24

We used machine learning to verify conservation laws in turn-by-turn beam data obtained from experiments at the Integrable Optics Test Accelerator in Fermilab.

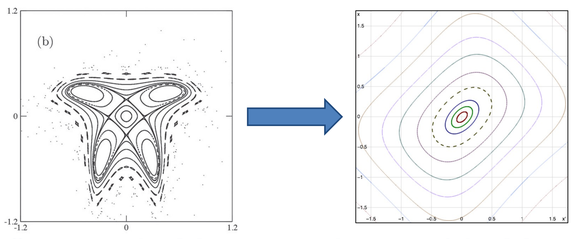


The Integrable Optics Test Accelerator is dedicated to research in beam physics. Non-linear Integrable Optics, Optical Stochastic Cooling, quantum statistics of undulator radiation, single electron studies, electron lens and many more. **See posters MOPG05, MOPG06, MOPS57, TUPC28, TUPR48, WEPG39, WEPR48, THPC20, THPC21, THPC68, THPR32 and talks MOZD1, WEBN1.**

Non-linear Integrable Optics using the Danilov-Nagaitsev magnet

Integrable System

Number of conservation laws = Number of degrees of freedom
Avoids chaos and resonances.

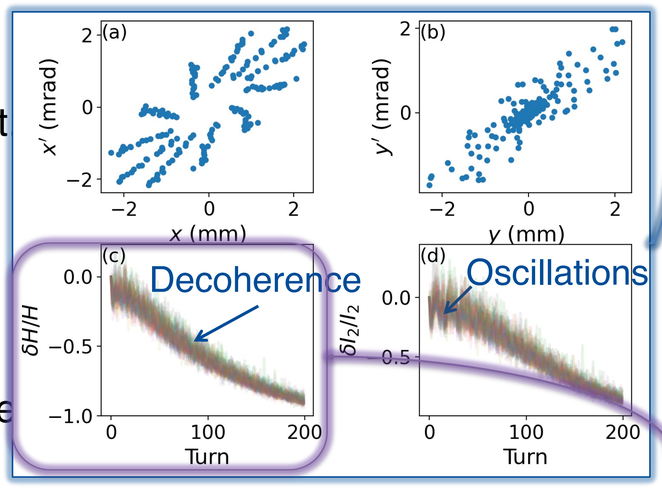


Sextupole Map → Integrable Map

Concentric invariant tori in phase-space avoids chaos

Experimental Procedure

- Capture 150 MeV electrons into one bucket
- Kick particles.
- Measure turn-by-turn transverse positions on multiple Beam Position Monitors.
- Reconstruct phase-space positions.

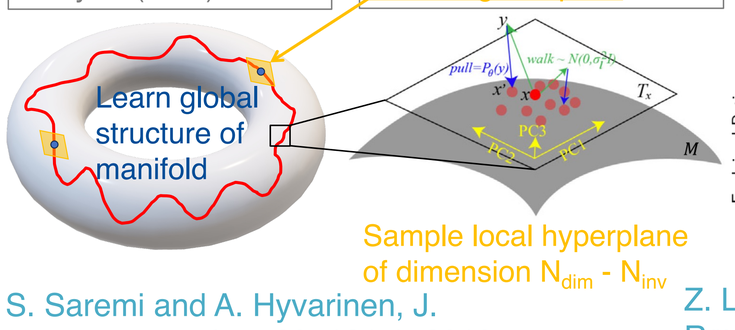


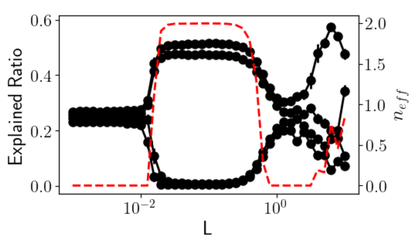
See poster THPC20 for details on the experiment.

V. Danilov and S. Nagaitsev, Phys. Rev. ST Accel. Beams **13**, 084002, 2010.

Manifold learning with AI Poincaré

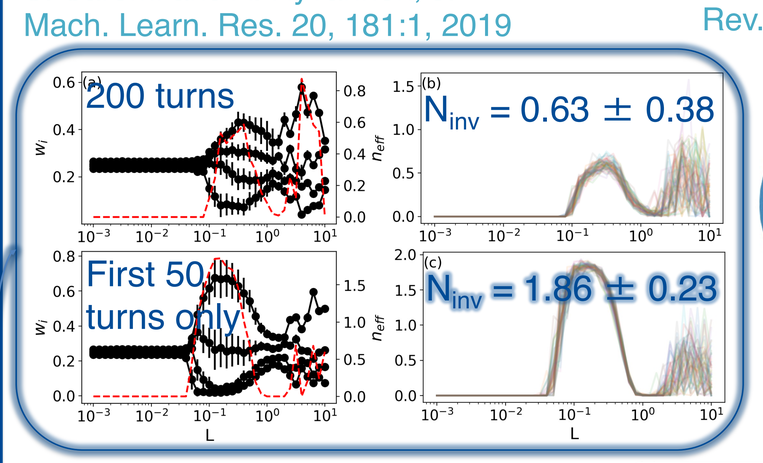
Scale, center, filter out linear invariants using Principal Component Analysis (PCA) → Train pull network (Neural Empirical Bayes), Monte Carlo sampling of local tangent space → Dimensionality determination using Principal Component Analysis (PCA)

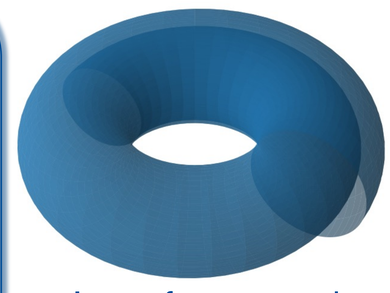




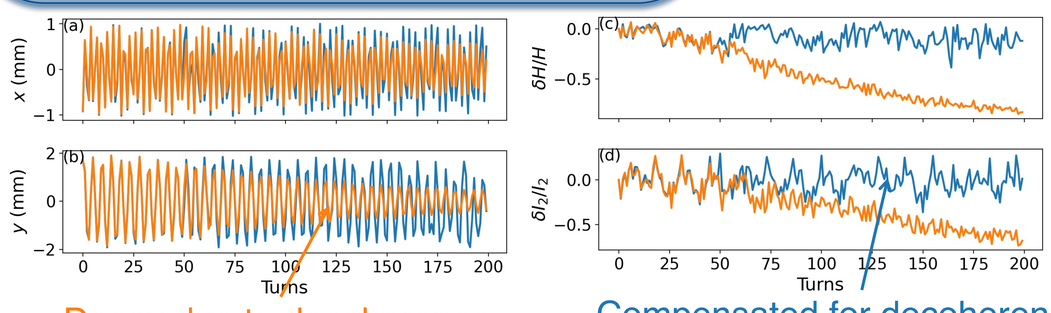
S. Saremi and A. Hyvarinen, J. Mach. Learn. Res. 20, 181:1, 2019

Z. Liu and M. Tegmark, Phys. Rev. Lett. 126, 180604, 2021





Imperfect torus due to decoherence



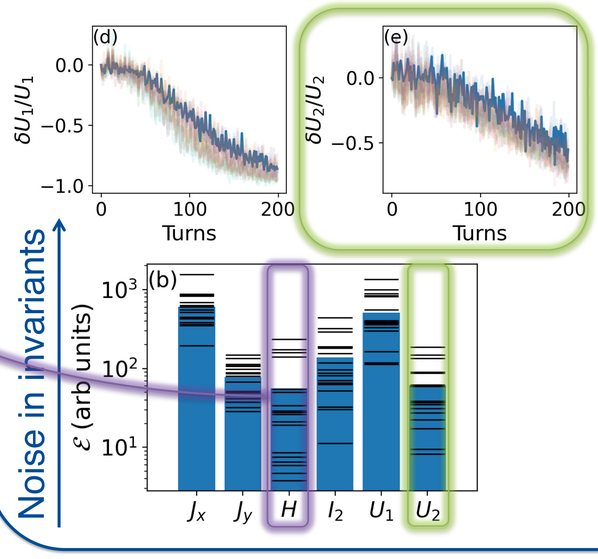
Learning invariants from data

Train a neural network which takes $\{x, x', y, y'\}$ as input and calculates two quantities U_1 and U_2.

$$L\{\phi\} = \sum_{p=1}^{P}\left\{\frac{\alpha_1}{2}\sum_{i=1}^{2}\left|U_i(\vec{Z}_p) - \overline{U}_i\right|^2\right\} + \sum_{q=1}^{Q}\left\{\alpha_2\left|\vec{\nabla}U_1(\vec{Z}_q)\cdot\vec{\nabla}U_2(\vec{Z}_q)\right|^2\right\} + \frac{\alpha_3}{2}\sum_{i=1}^{2}\left|U_i(\vec{O})\right|^2$$

Constant value on manifold — Gradients must be orthogonal — 0 at origin

Z. Liu, V. Madhavan, and M. Tegmark, Phys. Rev. E. vol. 106, 045307, 2022.



Learned invariant U_2 shows comparable or better conservation than the theoretical invariants.

This manuscript has been authored by Fermi Research Alliance, LLC under Contract No. DE-AC02-07CH11359 with the U.S. Department of Energy, Office of Science, Office of High Energy Physics.