From Cosmo-Seismic Correlations to a Weekly Effect in Global Seismicity

Magdalena Bochnak
Piotr Homola

From Cosmo-Seismic Correlations to a Weekly Effect in Global Seismicity

Cosmo-seismic correlation: an observed correlation between variations in the detection rate of secondary cosmic rays and changes in global seismic activity, with a maximum significance exceeding 6σ. The correlation significance varies with a period similar to that of the solar cycle.

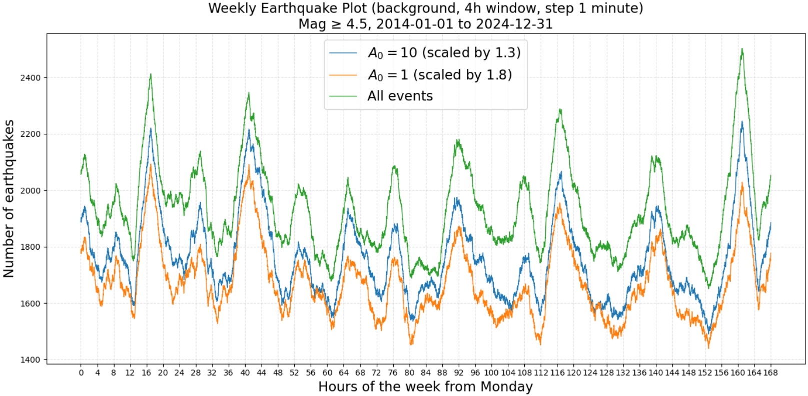
↓

Searching the analyzed datasets for periodicities potentially related to cosmo-seismic correlations

↓

Weekly effect in global seismicity, characterized by a pronounced Sunday peak in the number of earthquakes and a broader Sunday–Monday–Tuesday pattern.

Weekly Effect and Declustering



The cumulative weekly plot shows USGS earthquakes with $M \geq 4.5$ from 2014–2024; each point gives the event count in the preceding 4-hour window.

The green curve shows all events, while the blue and orange curves show those retained after nearest-neighbor declustering using two different values of the A_0 parameter. This method removes dependent events, such as aftershocks.

The weekly effect persists after declustering.

Questions and Next Steps

Questions addressed on the poster

1. How does the cosmo-seismic correlation significance vary across different cosmic-ray observatories?
2. What does declustering the earthquake catalog enable us to test?
3. Could the weekly effect arise due to statistical fluctuations?

Open Questions and Future Work

- Could the weekly effect arise from time-dependent deficits in earthquake detection?
- What physical mechanism could generate the observed weekly pattern?

We invite you to visit poster and join Piotr Homola's Friday lecture and hands-on workshop. :)

HAMILTONIANS WITH COMPLEX PERIODIC POTENTIALS BUT REAL ENERGY SPECTRA

JAKUB BORKOWSKI
UNIVERSITY OF WROCŁAW

OVERVIEW OF THE MODEL

We consider a modified Kronig–Penney potential with PT symmetry. The potential has the form:

$$V(x) = \sum_{n=-\infty}^{\infty} \alpha\, e^{(-1)^n i\theta}\, \delta\left(x - na - \frac{a}{2}\right).$$

For selected values of the phase θ, we analyze the resulting dispersion relations, eigenstates, and density of states.

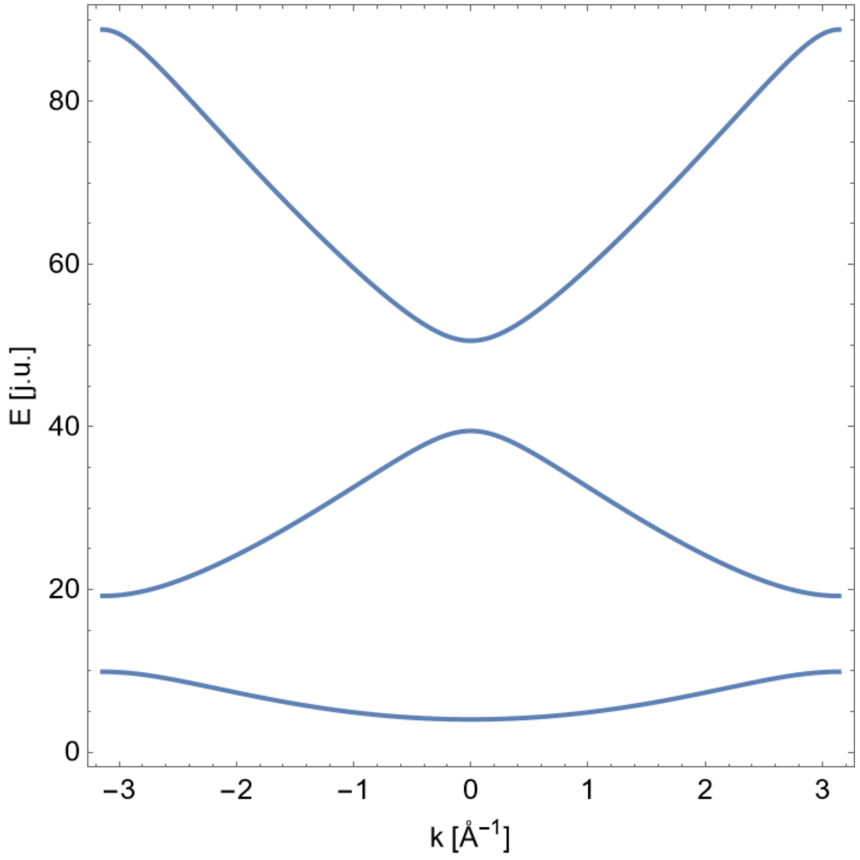


Figure 1. Example dispersion relations E = E(k) for an unmodified Kronig–Penney potential in the first Brillouin zone.

BAND STRUCTURE ANALYSIS

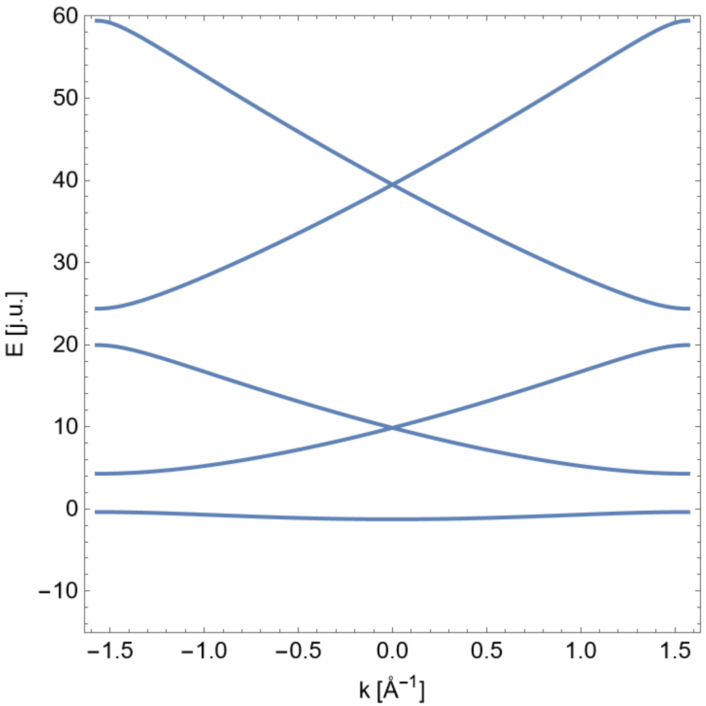


Figure 2. Example dispersion relations E = E(k) for an alternating real potential in the first Brillouin zone.

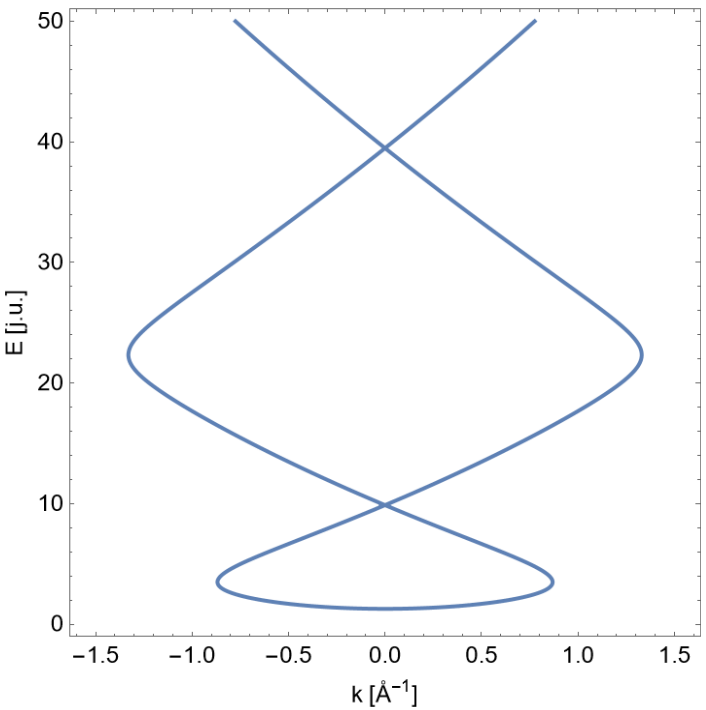


Figure 3. Example dispersion relations E = E(k) for a purely imaginary periodic potential in the first Brillouin zone.

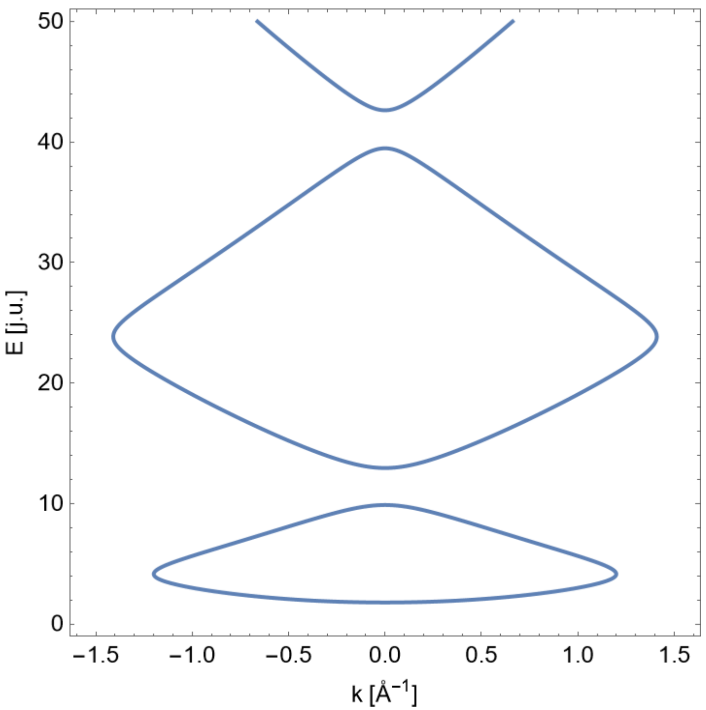


Figure 4. Example dispersion relations E = E(k) for a complex periodic potential with θ = π/4 in the first Brillouin zone.

Seismic Observations using Integrated Telecom Fibers

Daniele Caruana[1,2], Matthew Agius[2], André Xuereb[1], Cecilia Clivati[3], Simone Donadello[3]

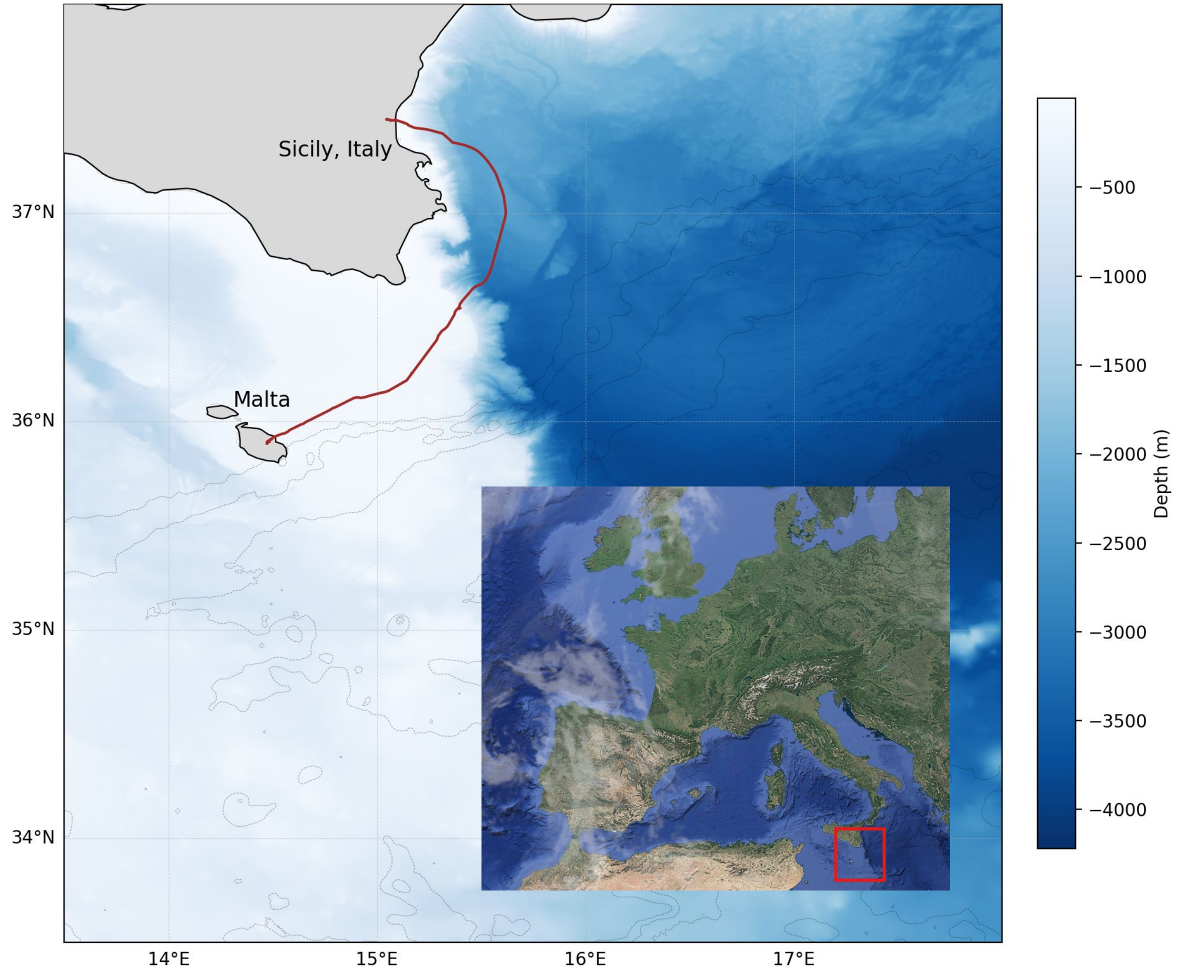
[1]Department of Physics, University of Malta, Malta
[2]Department of Geosciences, University of Malta, Malta
[3]INRIM- Italian National Institute of Metrology, Italy

L-Università ta' Malta

INRiM ISTITUTO NAZIONALE DI RICERCA METROLOGICA

SENSEI Smart European Networks for Sensing the Environment and Internet quality

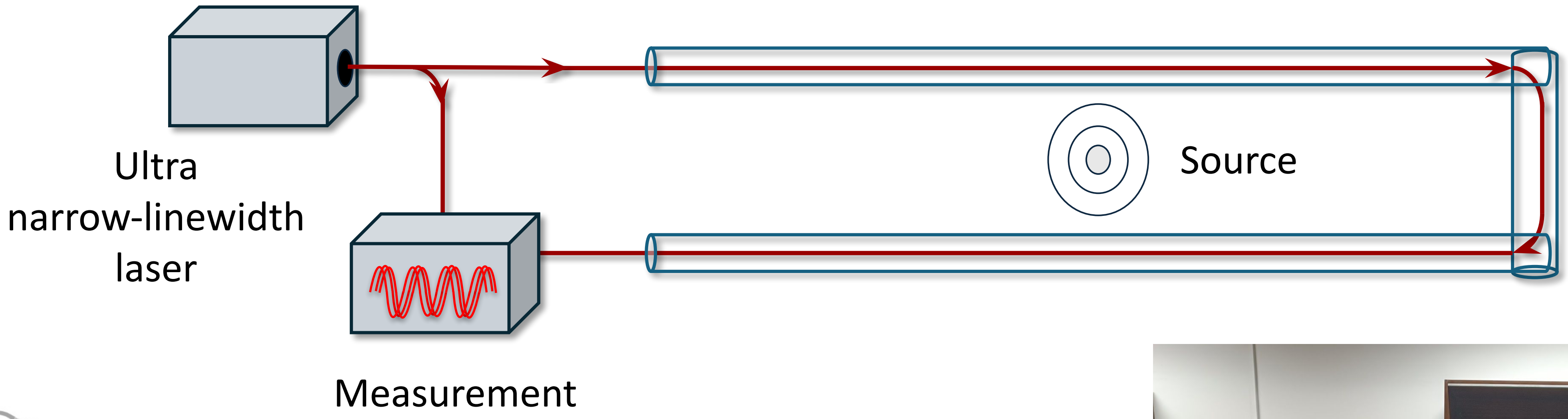
Our Testbed



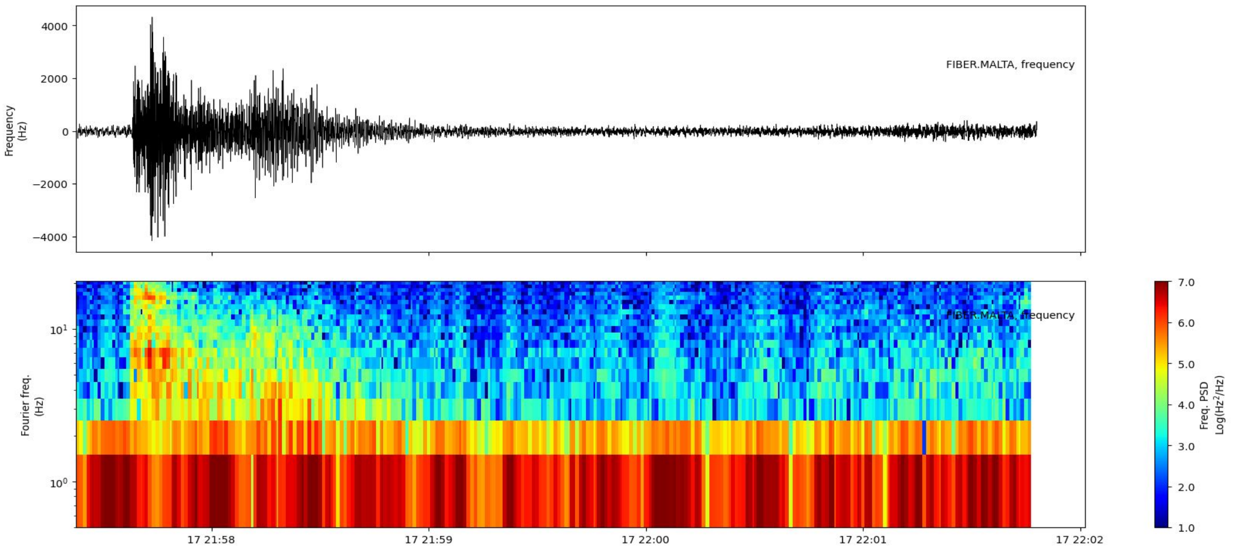
The area:

- Volcanically & seismically active
- Oceanographic interest
- Passes through an abyssal escarpment (water depth reaching ~4000 m)
- Well instrumented with other (onshore) sensing tools

Laser Interferometry

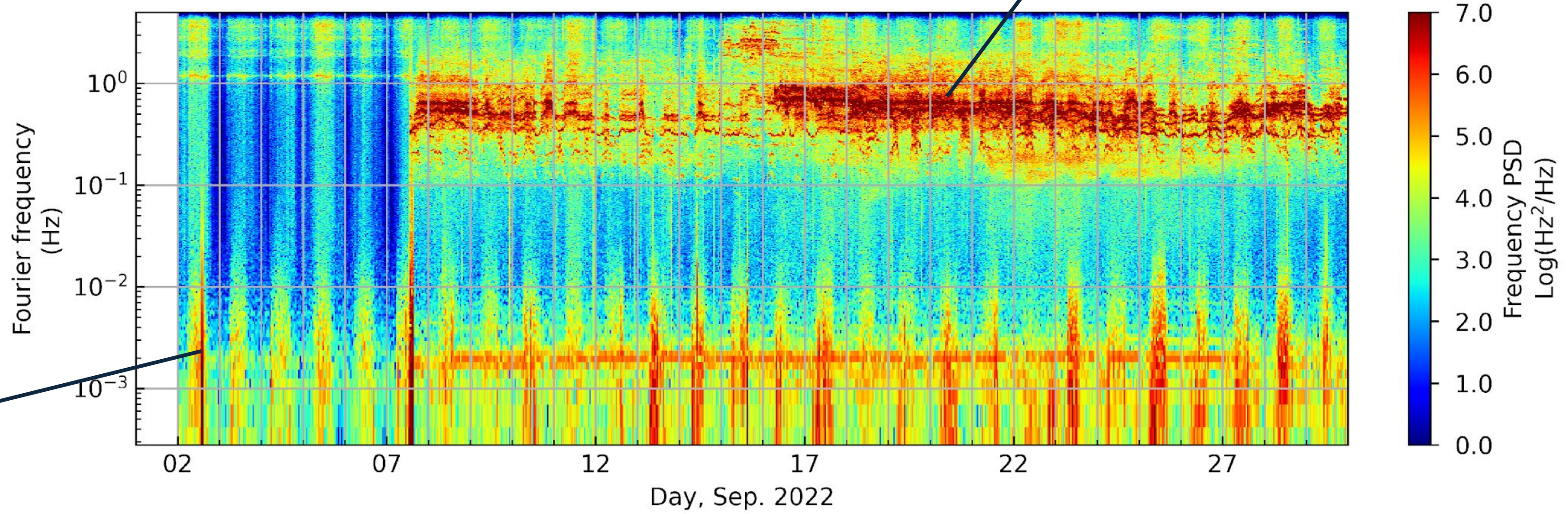


Our Data



- M5.3 Earthquake
- 120 km epicentral distance from fiber

Water shaking submarine range

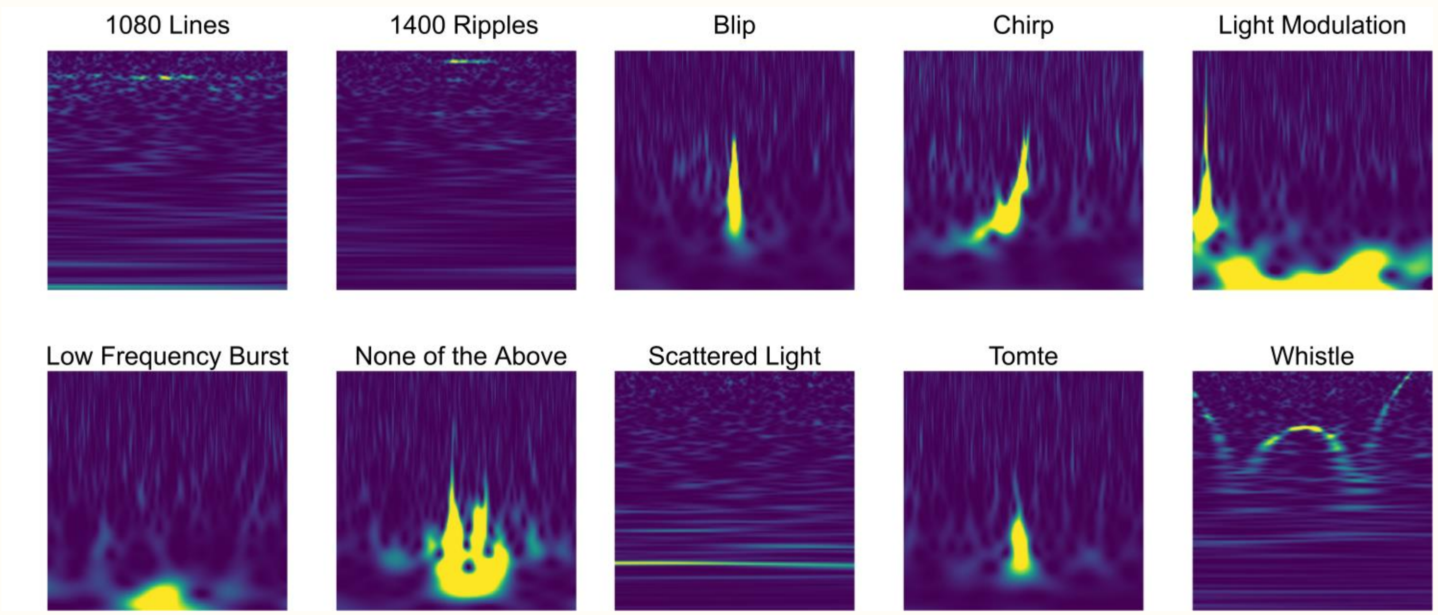


Anthropogenic noise

Efficient Glitch Classification in Gravitational-Wave Detector Data Using Deep Learning and Machine Learning

Deep visual features + lightweight machine learning

O. T. Bişkin · İ. Kırbaş · A. Çelik*



Representative time–frequency morphologies from the ten-class dataset

Motivation: retrain quickly as detector conditions and glitch populations evolve.

WHY GLITCHES MATTER

- Short, non-Gaussian detector transients
- Can resemble signal-like structures
- Degrade data quality and event validation

4,318 Gravity Spy samples

10 glitch classes

224x224 RGB Q-transforms

Research question

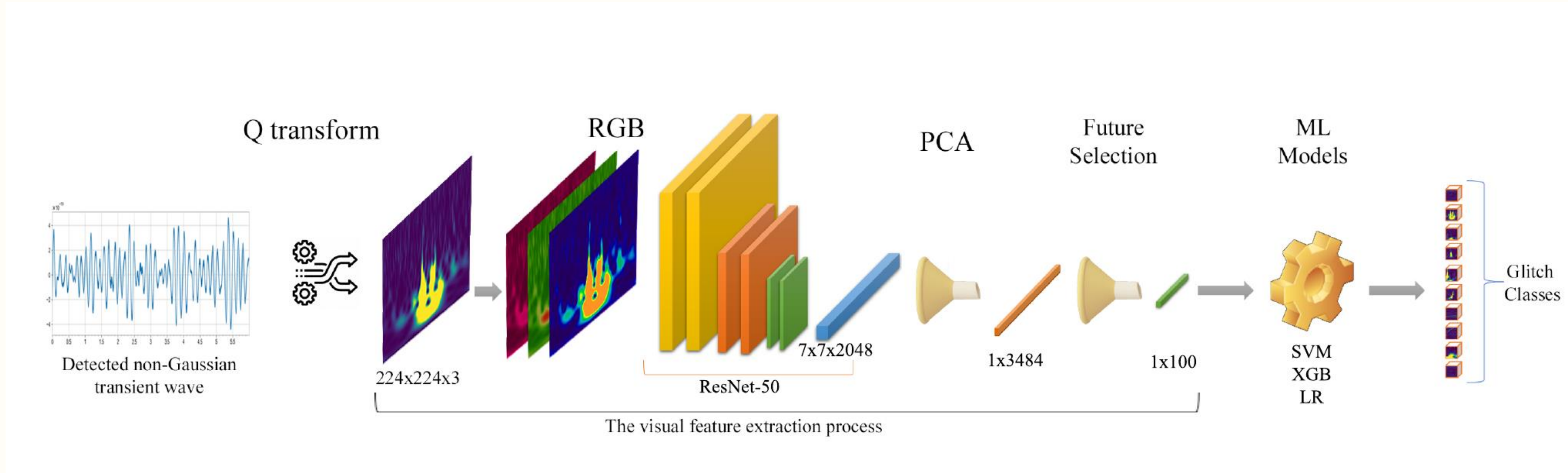
Can we retain high accuracy without repeatedly retraining the entire deep network?

STUDY DESIGN

70% train / 10% validation / 20% test
Five random realizations · no resampling

TWO-STAGE METHODOLOGY

Freeze the backbone; retrain only the classifier



Fine-tuning baseline: up to 100 epochs · patience 10 · learning rate 10^{-4}

DEEP VISUAL ENCODERS

Inception-v3

5 × 5 × 2,048 → 51,200 features

ResNet-50

7 × 7 × 2,048 → 100,352 features

ImageNet pretrained · convolutional weights fixed

→

COMPRESSION

51,200 / 100,352

↓

3,454 PCA components

↓

100 selected features

→

LIGHTWEIGHT CLASSIFIERS

LR · SVM · XGBoost

Only the downstream classifier is retrained

Optuna optimization
70% / 10% / 20% split
Five random realizations · no resampling

MAIN RESULT

Near-fine-tuned accuracy with 31.7× faster training

93.98%	37.6 s	F1 = 0.9111	31.7×
test accuracy	measured training time	selected frozen pipeline	faster than fine-tuning

INCEPTION-v3: ACCURACY–TIME TRADE-OFF

Frozen features + PCA + FS + LR	93.98%	37.6 s

Comparable fine-tuned pipeline	95.72%	1,191.8 s

Measured training-time scale

Trade-off: −1.74 percentage points accuracy · 31.7× faster training

THE TREND HOLDS BEYOND ONE SETTING

ResNet-50 frozen path

92.13% · 42.3 s · 23.9× faster

20-class scaling test

89.95% accuracy · F1 = 0.7983

Highest class-level F1

Scattered Light 0.9759
Blip 0.9713 · Chirp 0.9630

Hardest: None of the Above · F1 0.7097

Frozen deep features offer a practical accuracy–retraining-time trade-off.

Visit the poster for full class results, PCA sensitivity, and sample-scaling tests.

Score-based Neural Networks for Fokker-Planck Equation Solving

Nikolija Cuckić[1], **Velimir Ilić**[1,2]

[1] *Faculty of Sciences and Mathematics, University of Niš, Višegradska 33, 18000 Niš, Serbia*
[2] *Mathematical Institute of the Serbian Academy of Sciences and Arts, Kneza Mihaila 36, 11000 Beograd, Serbia*

- A d-dimensional stochastic process is described with probability density function $p_t(x)$
- PDF evolves over time in accordance with the Fokker–Planck equation:

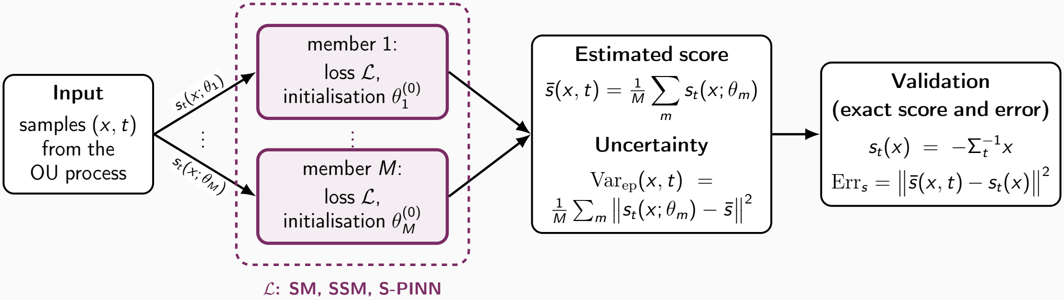
$$\frac{\partial p_t(x)}{\partial t} = -\sum_{i=1}^{d} \frac{\partial}{\partial x_i}[f_i(x,t)p_t(x)] + \frac{1}{2}\sum_{i=1}^{d}\sum_{j=1}^{d}\frac{\partial^2}{\partial x_i\,\partial x_j}\left[\sum_{k=1}^{d} G_{ik}(x,t)G_{jk}(x,t)\,p_t(x)\right],$$

  where $f(x,t)$ is the drift coefficient and $G(x,t)$ is the diffusion matrix
- Learning the PDF for large d: numerically unstable and difficult to normalise
- By learning the score instead, normalisation constraint is avoided:

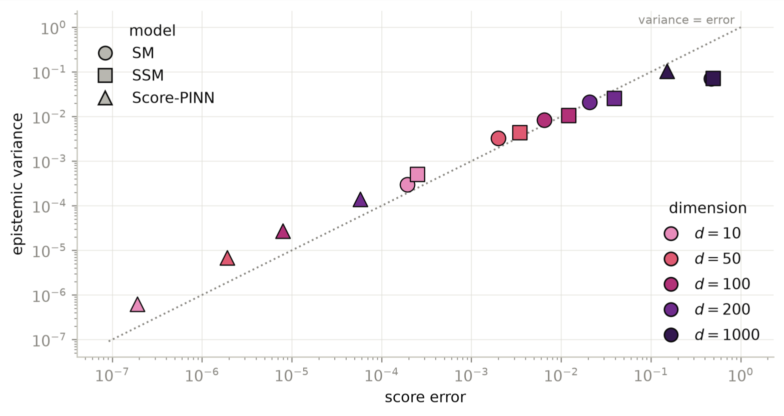
$$s_t(x) = \nabla_x \log p_t(x) = \nabla_x \log q_t(x)$$

Deep learning

- Neural network $s_t(x;\theta)$ approximates the score, where θ represents weights and biases
- Training is non-convex and starts from a random initialisation, so different runs on the same problem can reach different parameters θ, hence different predictions $s_t(x;\theta)$
- We compare methods that learn the score and study the relationship between the prediction error and the variance of several independently trained networks



Results



- As d grows, accuracy of all three methods degrades only slightly
- Strong correlation between ensemble variance and the prediction error
- Variance could indicate which prediction is better when analytical score isn't known

Nuclear equation of state modifications from spacetime structure

Anna Horváth, A. Wojnar, G.G. Barnaföldi, E . Forgács-Dajka

Nuclear equation of state modifications from spacetime structure

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Can we see extra dimensions in neutron stars?

Nuclear equation of state modifications from spacetime structure

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Can we see extra dimensions in neutron stars?

Can gravity affect the equation of state?

Nuclear equation of state modifications from spacetime structure

Anna Horváth, A. Wojnar, G.G. Barnaföldi, E . Forgács-Dajka

Can we see extra dimensions in neutron stars?

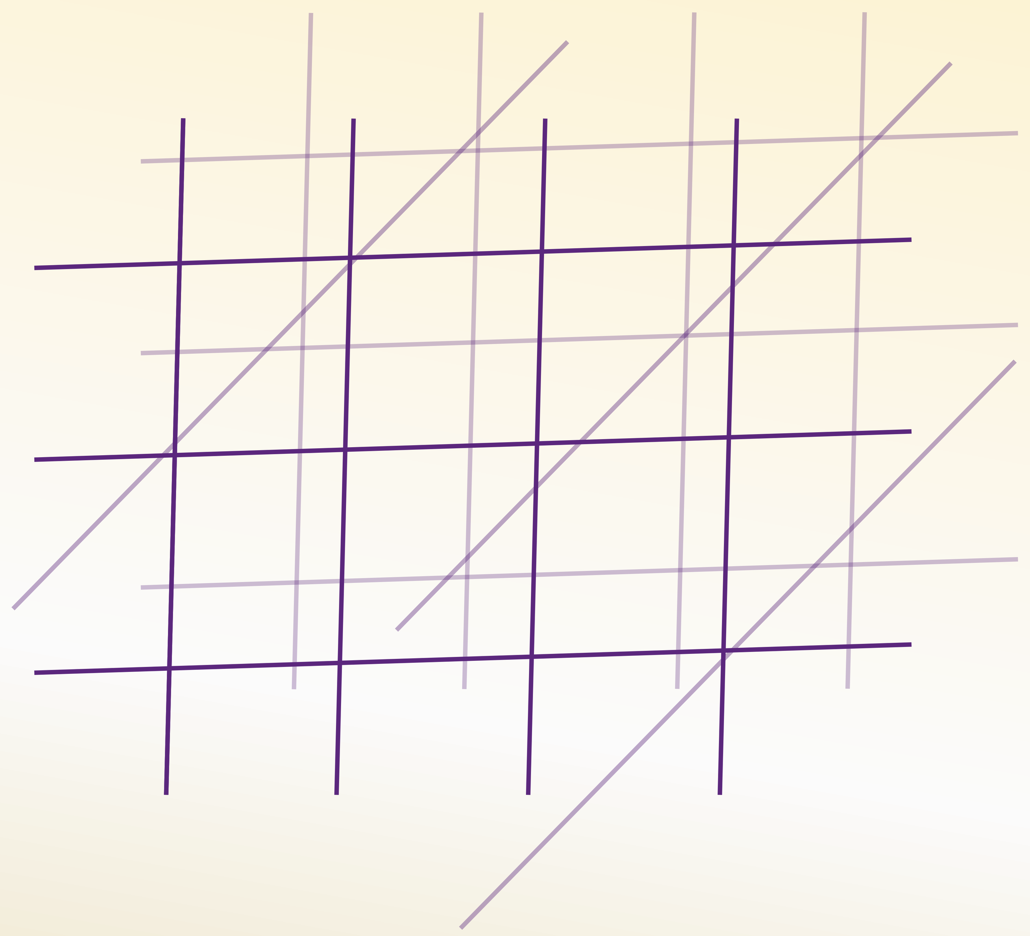
Can gravity affect the equation of state?

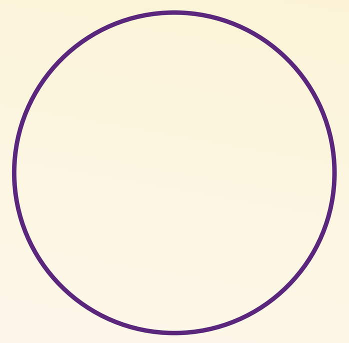
What about black holes?

Spatial dimension

$x = (t, \quad x_1, x_2, x_3, \quad x_5)$

1 **3** **1_C**





time **space** **extra dimension**

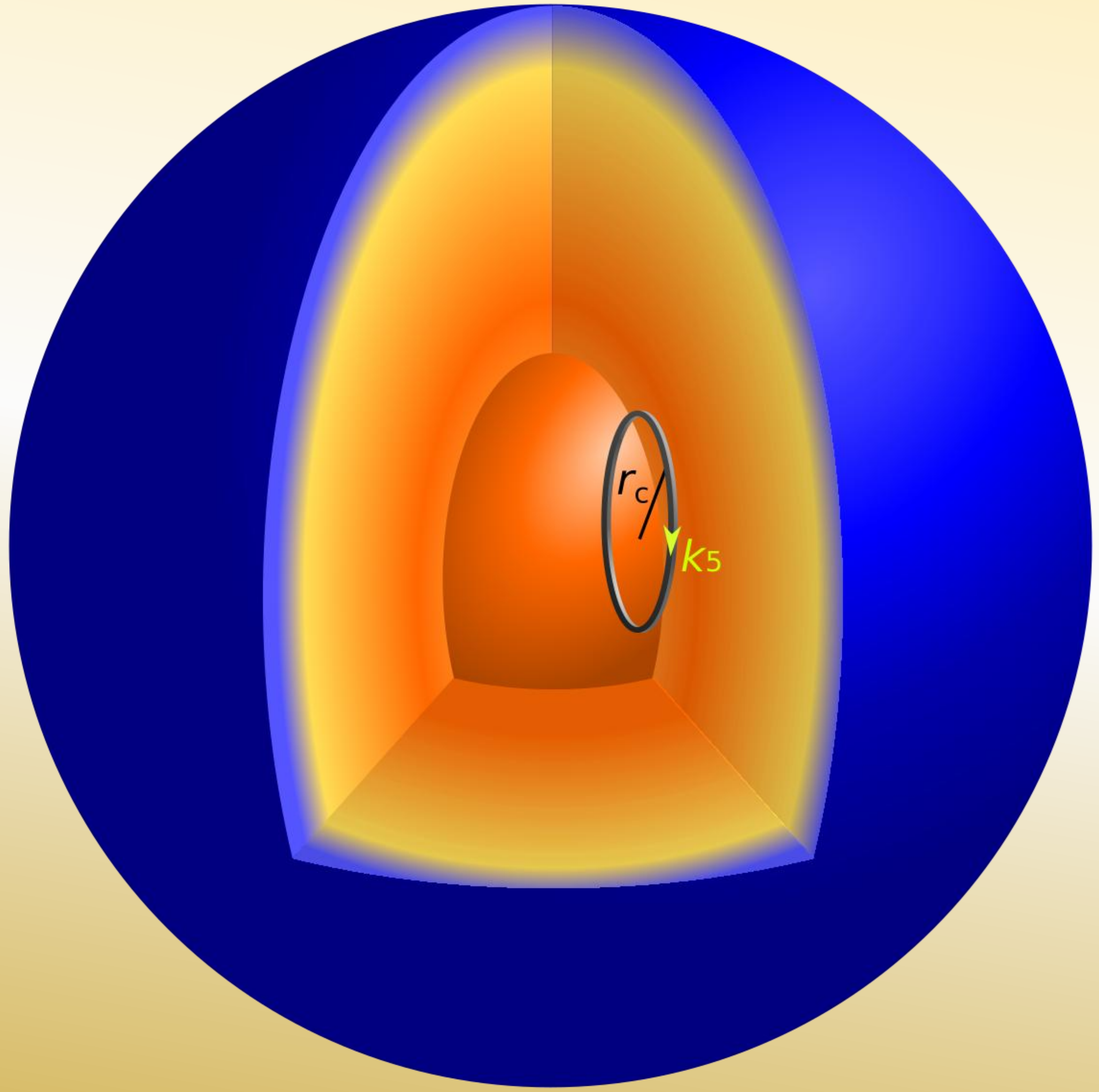
spacetime

5-dimensional spacetime

Compactified: curled up into a microscopic **circle**

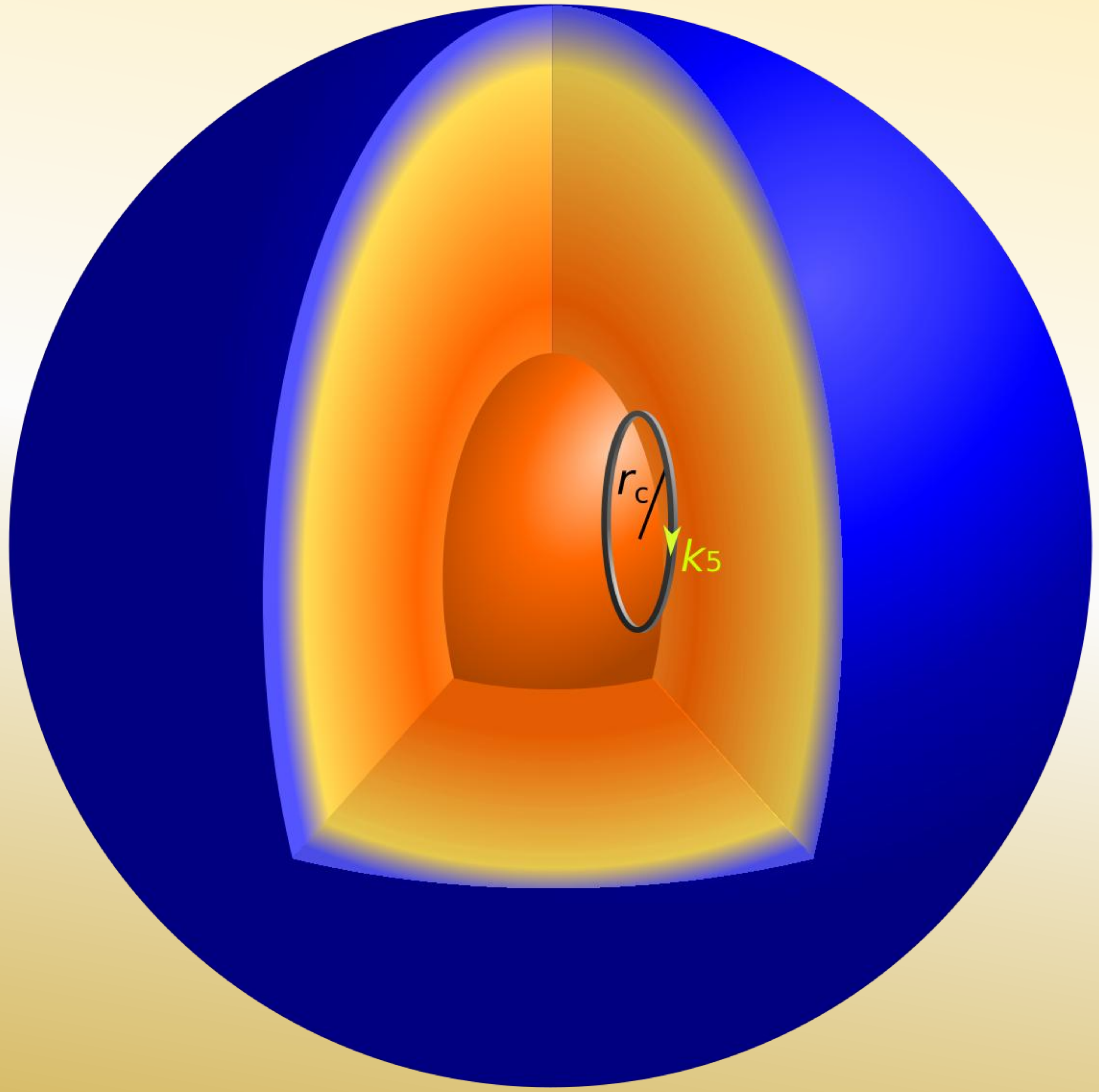
Too small to see

Modelling neutron stars



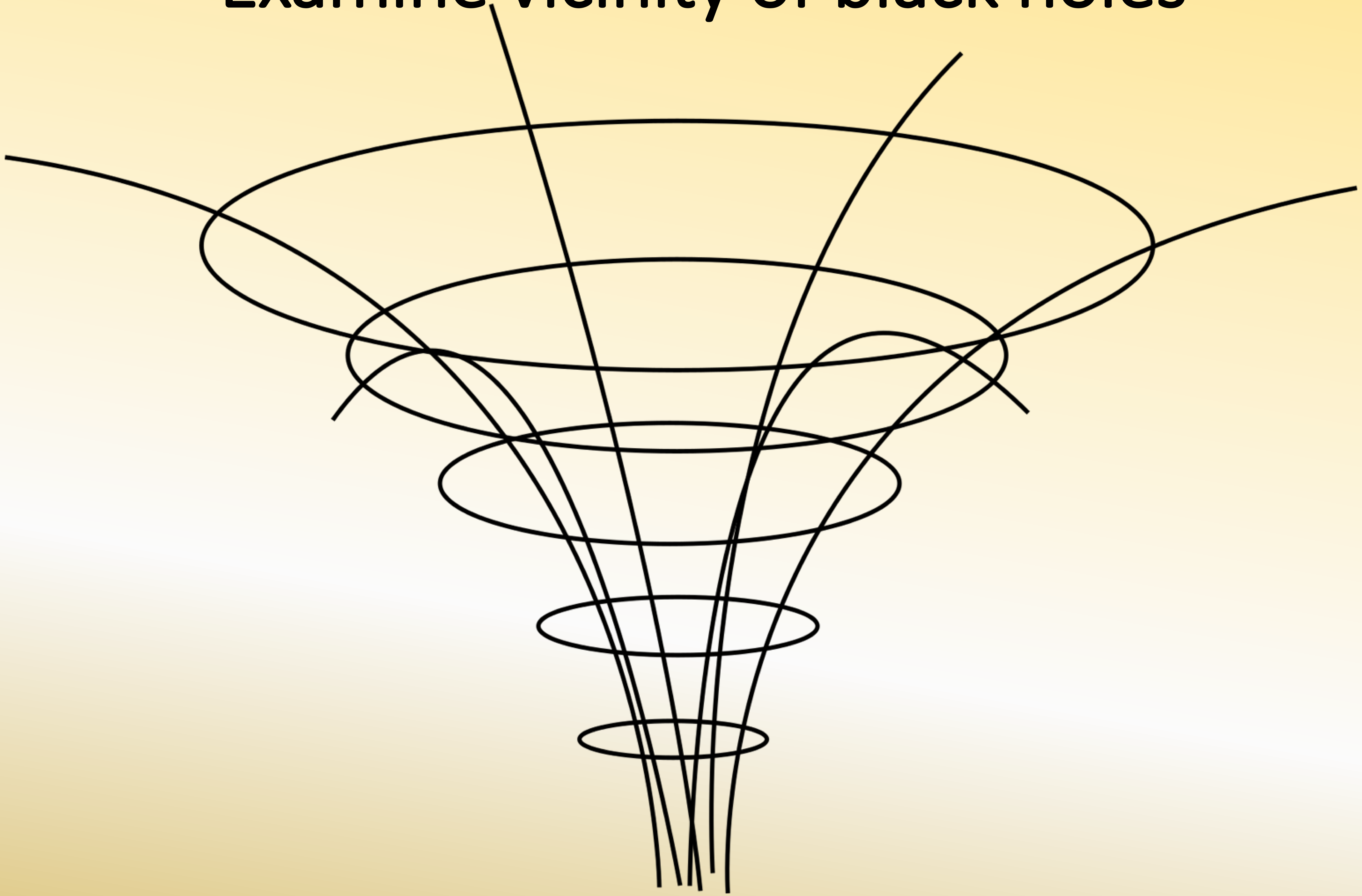
Building them up layer by layer

Modelling neutron stars



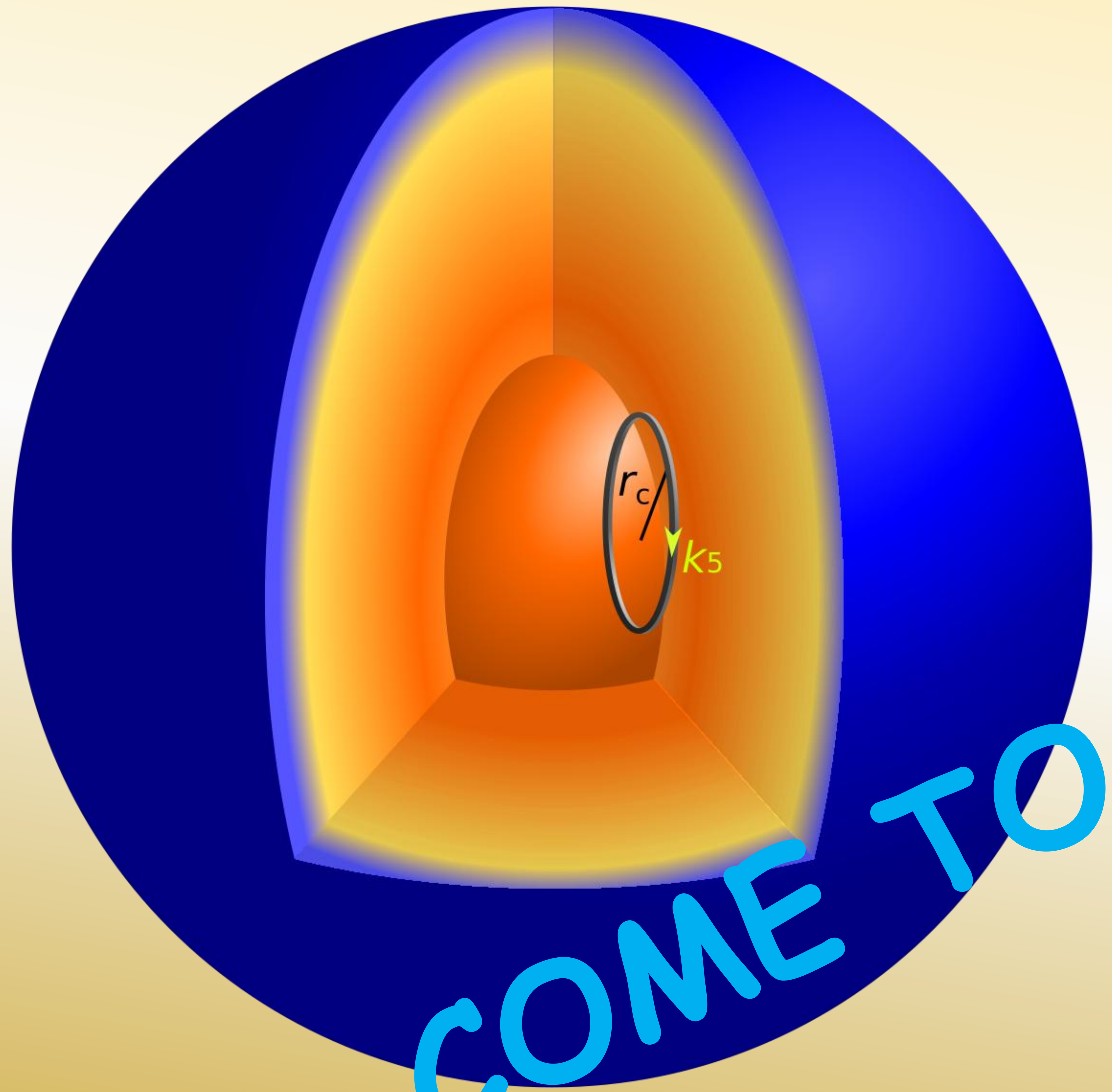
Building them up layer by layer

Examine vicinity of black holes



What happens at the horizon?

Modelling neutron stars



Building them up layer by layer

Examine vicinity of black holes

What happens at the horizon?

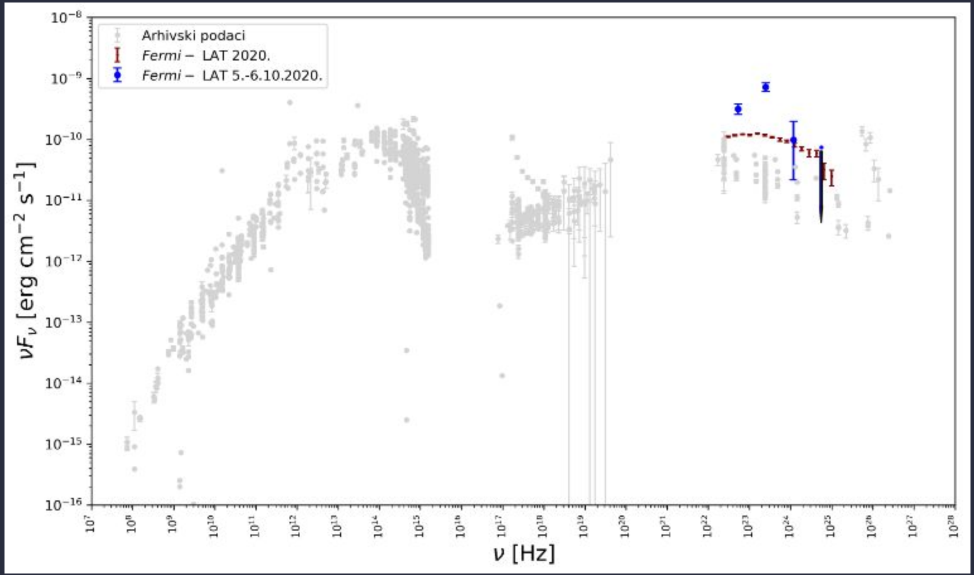
COME TO SEE MY POSTER!

Analysis and characterization of a single flare from the blazar BL Lacertae

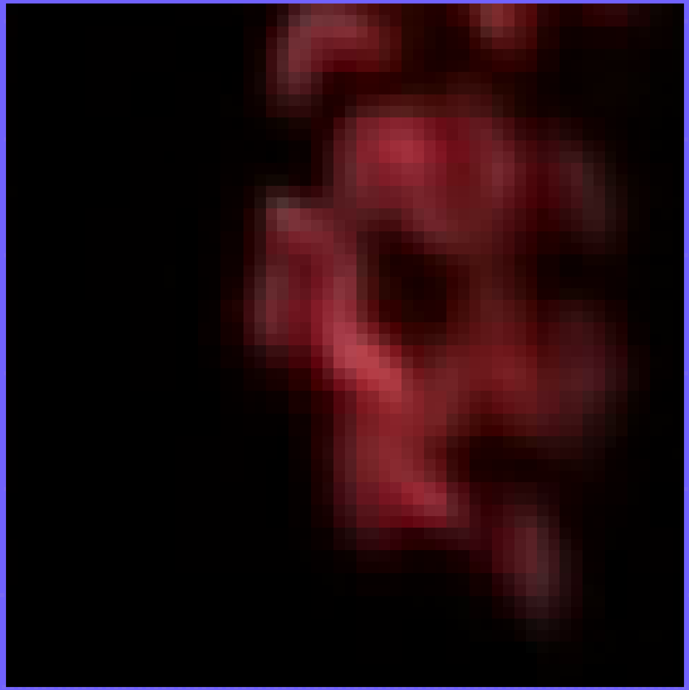
Rafaela Hujbert, Jelena Strišković
Contact: rhujbert@fizika.unios.hr, jstriskovic@fizika.unios.hr

What if ... ?

- What if one of the best laboratories for testing the laws of physics is not on Earth, but billions of light years away?



Machine-Learning-Based Data Cleaning for Anomaly Searches in the CREDO Smartphone Detector Network



Bartosz Izydorczyk

How to deal with clearly wrong detections?

Two Sciences, One Earth Event

SEISMOLOGY

- Ground Motion Records
- P-wave & S-wave Analysis
- Source Characterisation
- Site Attenuation Models

THE GAP

?

EARTHQUAKE ENGINEERING

- Structural Response Data
- Interstory Drift & Damage
- Site Amplification Effects
- Performance-Based Design

Data-Driven Interpretation of Structural Seismic Response for Interdisciplinary Seismology Applications

POSTER SESSION
Mazllum Kamberi
FuSe Training School 2026 — Tihany

Same earthquake — different data, different models, rarely integrated

The Data-Driven Framework

Integrating seismological and engineering datasets to uncover new physics

THE PIPELINE

1. **Multi-Source Data Ingestion** →
2. **Signal Processing** →
3. **Machine Learning Integration** →
4. **Cross-Domain Synthesis** →
5. **New Physical Insights**

INTERDISCIPLINARY COMMUNITY

S — **Seismologists**
Ground motion, source physics, wave propagation

AI — **Data Scientists**
Machine learning, feature extraction, integration

E — **Engineers**
Structural response, damage, vulnerability models

From Corfu to Tihany

C

Corfu

FuSe 2026 Conference
April 27–30, 2026

FOUNDATION

CONCEPTUAL & THEORETICAL BASIS

Identified the gap between seismological and earthquake-engineering interpretations of the same event, and argued for cross-disciplinary data integration as a path toward deeper physical understanding.

- Gap analysis: two sciences, one earthquake, separate data streams
- Conceptual case for a data-driven integration framework

NEXT STEP

→

POSTER SESSION

T

Tihany

FuSe Training School 2026
September 7–11, 2026

THIS WEEK

PROPOSED FRAMEWORK — EARLY STAGE

This poster proposes a structured data-driven pipeline (seismic input → ML/AI models → physics interpretation) as an early-stage research direction. No experimental results are reported.

- 5-step pipeline: data → features → ML → structural response → physics
- Roadmap: standardised protocols → data collection → monitoring networks

Come and See the Full Framework at the Poster

Conceptual pipeline, roadmap, and open questions — let's discuss and collaborate.

POSTER SESSION
Mazllum Kamberi
FuSe Training School 2026 — Tihany

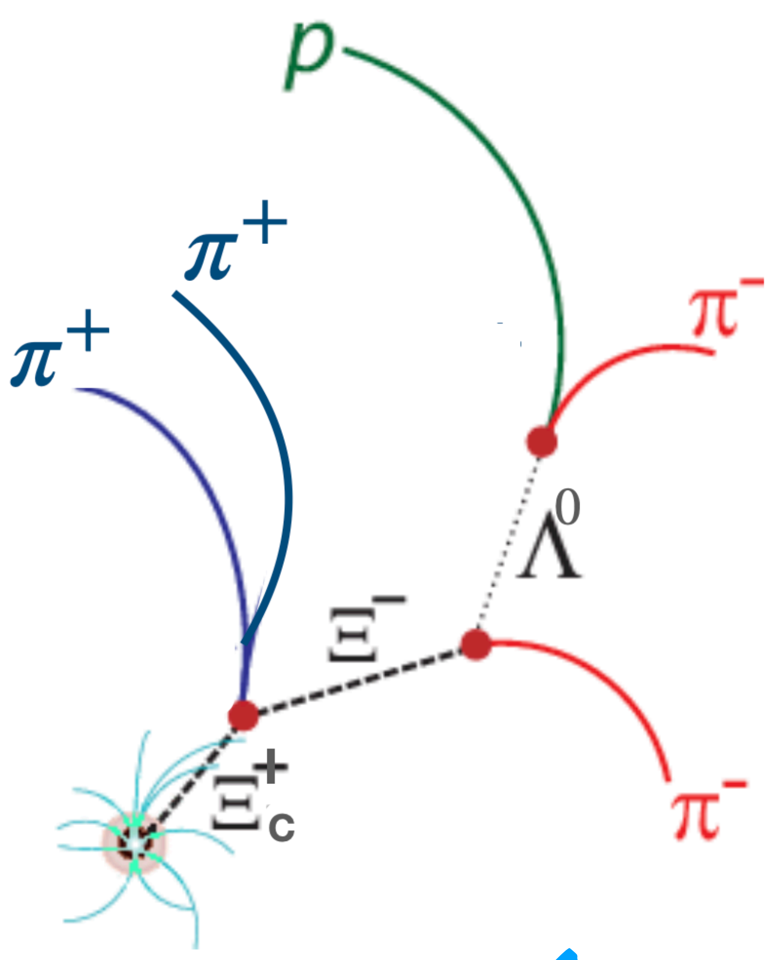
Generative AI for computational challenges in fundamental physics

Issue

Precision physics increasingly relies on large-scale simulations

- High-fidelity simulations can be computationally expensive
- Rare signals require very large simulated datasets
- Expensive CPU + storage requirements

Hundreds of millions of simulated events → only thousands of reconstructed signal candidates



Impact

Computational gain

- Training:
  - Takes minutes
- Generation:
  - < 1 minute for analysis-scale samples

👉 Reconstructed-level MC augmentation

👉 Preserve distributions and multidimensional correlations

👉 Validate against the original simulation

👉 A transferable strategy for simulation-limited physics

Idea

Huge MC campaign

↓

Tiny rare-signal statistics

↓

GAN augmentation

↓

Fast synthetic reconstructed samples

"Generative AI can learn more than images — it can learn the multidimensional output of scientific simulations."

Dr. Anisa Khatun

Physicist, ALICE Experiment/CERN

HUN-REN Wigner Research Centre for Physics

✉ anisa.khatun@cern.ch

[Poster]

arXiv:2602.12088 [hep-ex]

Constraining modified theories of gravity using seismic data

Aleksander Kozak, Aneta Wojnar

1st Training School on Testing Fundamental Physics with Seismology - FuSe School 2026, Tihany, 7-11.09.2026

Motivation

- Some modified gravity theories alter the weak-field limit of theory, leading to the inclusion of additional terms in the Poisson equation
- We have good knowledge of Earth's interior, e.g., thanks to the use of seismic waves' velocities. Velocities are related to the density at a given depth via hydrostatic equilibrium equation
- The goal of our research is therefore the determination of the extent to which possible modifications to the weak-field limit of general relativity can be constrained using seismic data

Methodology

1. Assume:
   - seismic waves' velocities as predicted by PREM
   - values of the free parameters related to the Earth's interior description: $(\rho_{\text{core}}, \rho_{\text{mantle}}, \Delta\rho)$;
   - value of the modified gravity parameter;
   - Earth is spherically symmetric, does not rotate.
2. Solve the hydrostatic equilibrium equation together with the mass formula given by $\frac{dM}{dr} = 4\pi r^2 \rho(r)$
3. Compute the polar moment of inertia, compare its value, together with the mass, with the ones predicted by PREM and use the experimentally determined uncertainties to assess the goodness of fit: $M_{\text{target}} = (5.9721 \pm 0.0006) \times 10^{24}\text{kg}$, $I_{\text{target}} = (8.01897 \pm 0.00097) \times 10^{37}\text{kg m}^2$.
4. If necessary, change values of the selected parameters and repeat the calculations, obtaining new mass and new polar moment of inertia.

Results

- bounds obtained: for Palatini $f(R)$ gravity: $-2 \times 10^9 \lesssim \beta \lesssim 10^9 \mathrm{m}^2$; for EiBI: $-8 \times 10^9 \lesssim \epsilon \lesssim 4 \times 10^9 \mathrm{m}^2$; for DHOST model, the constraint is: $-10^{-3} \lesssim \Upsilon \lesssim 10^{-3}$;
- theory sensitive to the value of ρ_{mantle}. If one increases the error in the determination of this parameter to about 50 kg/m^3, then the bounds for the Palatini parameter become worse by approximately two orders of magnitude;
- limitations of the model:
  1. assuming spherical symmetry, which fails to consider Earth's actual shape and its sensitivity to rotation;
  2. assuming lack of inhomogeneities in the density distribution;
  3. PREM does not consider seismic wave travel times sampling the boundaries of the outer and inner core, making it unsuitable to describe the deepest part of the planet;
  4. lack of the analysis of the impact of the density variation on the determination of the low eigenfrequency spheroidal modes.

Transfer learning (TL)

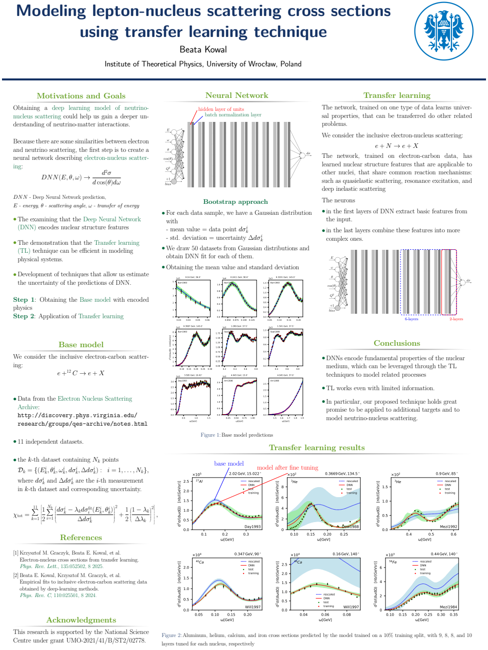
The ability of a person who has learned skills in one specific field to easily acquire skills needed in related areas of life.

TL can by applied in deep learning: The neural network learns the details of one kind of data, and after fine-tuning, it makes predictions for related problem.

We propose to use the TL technique in physics

Electron-nucleus cross sections from transfer learning
Phys. Rev. Lett. 135, 052502
K.Graczyk, B. Kowal, et al.

Empirical fits to inclusive electron-carbon scattering data obtained by deep-learning methods
Phys. Rev. C 110, 025501
B. Kowal, K.Graczyk, et al.



Modeling lepton-nucleus scattering cross sections using transfer learning technique

Beata Kowal
Institute of Theoretical Physics, University of Wrocław, Poland

Motivations and Goals

Obtaining a deep learning model of neutrino-nucleus scattering could help us gain a deeper understanding of neutrino-matter interactions.

Because there are some similarities between electron and neutrino scattering, the first step is to create a neural network describing electron-nucleus scattering:

$$DNN(E,\theta,\omega) \rightarrow \frac{d^2\sigma}{d\cos(\theta)d\omega}$$

DNN - Deep Neural Network prediction,
E - energy, θ - scattering angle, ω - transfer of energy

- The examining that the Deep Neural Network (DNN) encodes nuclear structure features
- The demonstration that the Transfer learning (TL) technique can be efficient in modeling physical systems.
- Development of techniques that allow us estimate the uncertainty of the predictions of DNN.

Step 1: Obtaining the Base model with encoded physics
Step 2: Application of Transfer learning

Base model

We consider the inclusive electron-carbon scattering:

$$e +^{12} C \rightarrow e + X$$

- Data from the Electron Nucleus Scattering Archive: `http://discovery.phys.virginia.edu/research/groups/qes-archive/notes.html`
- 11 independent datasets.
- the k-th dataset containing N_k points $\mathcal{D}_k = \{(E_k^i, \theta_k^i, \omega_k^i, d\sigma_k^i, \Delta d\sigma_k^i): \quad i = 1, \ldots, N_k\}$, where $d\sigma_k^i$ and $\Delta d\sigma_k^i$ are the i-th measurement in k-th dataset and corresponding uncertainty.

$$\chi_{\rm tot} = \sum_{k=1}^{11}\left[\frac{1}{2}\sum_{i=1}^{N_k}\left(\frac{d\sigma_k^i - \lambda_k d\sigma_i^{\rm fit}(E_k^i,\theta_k^i)}{\Delta d\sigma_k^i}\right)^2 + \frac{1}{2}\left(\frac{1-\lambda_k}{\Delta\lambda_k}\right)^2\right],$$

References

[1] Krzysztof M. Graczyk, Beata E. Kowal, et al. Electron-nucleus cross sections from transfer learning. *Phys. Rev. Lett.*, 135:052502, 8 2025.
[2] Beata E. Kowal, Krzysztof M. Graczyk, et al. Empirical fits to inclusive electron-carbon scattering data obtained by deep-learning methods. *Phys. Rev. C*, 110:025501, 8 2024.

Acknowledgments

This research is supported by the National Science Centre under grant UMO-2021/41/B/ST2/02778.

Neural Network

hidden layer of units
batch normalization layer

Bootstrap approach

- For each data sample, we have a Gaussian distribution with
  - mean value = data point $d\sigma_k^i$
  - std. deviation = uncertainty $\Delta d\sigma_k^i$
- We draw 50 datasets from Gaussian distributions and obtain DNN fit for each of them.
- Obtaining the mean value and standard deviation

Figure 1: Base model predictions

Transfer learning

The network, trained on one type of data learns universal properties, that can be transferred do other related problems.

We consider the inclusive electron-nucleus scattering:

$$e + N \rightarrow e + X$$

The network, trained on electron-carbon data, has learned nuclear structure features that are applicable to other nuclei, that share common reaction mechanisms: such as quasielastic scattering, resonance excitation, and deep inelastic scattering

The neurons

- in the first layers of DNN extract basic features from the input.
- in the last layers combine these features into more complex ones.

6-layers
2-layers

Conclusions

- DNNs encode fundamental properties of the nuclear medium, which can be leveraged through the TL techniques to model related processes
- TL works even with limited information.
- In particular, our proposed technique holds great promise to be applied to additional targets and to model neutrino-nucleus scattering.

Transfer learning results

base model
model after fine tuning

Figure 2: Aluminum, helium, calcium, and iron cross sections predicted by the model trained on a 10% training split, with 9, 8, 8, and 10 layers tuned for each nucleus, respectively

Goals

- The examining that the Deep Neural Network (DNN) encodes nuclear structure features

- The demonstration that the Transfer learning technique can be efficient in modeling physical systems.

- Obtaining a electron-nucleus scattering model using deep learning techniques

$$DNN(E,\theta,\omega) \rightarrow \frac{d^2\sigma}{d\cos(\theta)d\omega}$$

  DNN - Deep Neural Network prediction,
  E = Energy, θ = scattering angle, ω = transfer of energy

  - Step 1: Obtaining the Base model with encoded physics
    We consider the inclusive electron-carbon scattering:

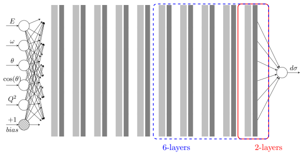
$$e +^{12} C \rightarrow e + X$$

  - Step 2: Application of Transfer learning
    Transfering physics from carbon to other targets
    We consider the inclusive electron-nucleus scattering:

$$e + N \rightarrow e + X$$

- Development of techniques that allow us estimate the uncertainty of the predictions of DNN.

We consider the situations in which some number of last layer is fine-tuned.



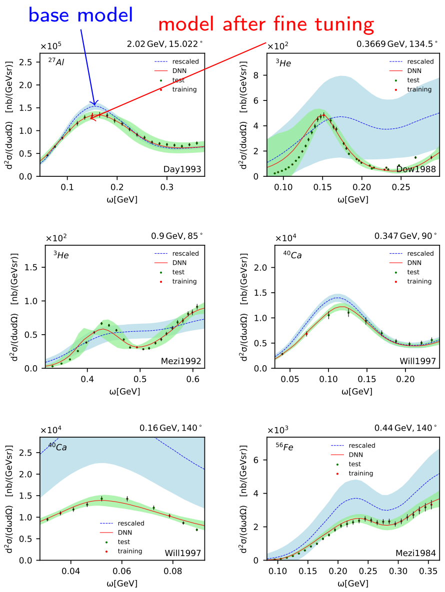
Bootstrap approach

i For each data sample, we have a Gaussian distribution with
- mean = data point $d\sigma_k^i$
- std. deviation = uncertainty $\Delta d\sigma_k^i$

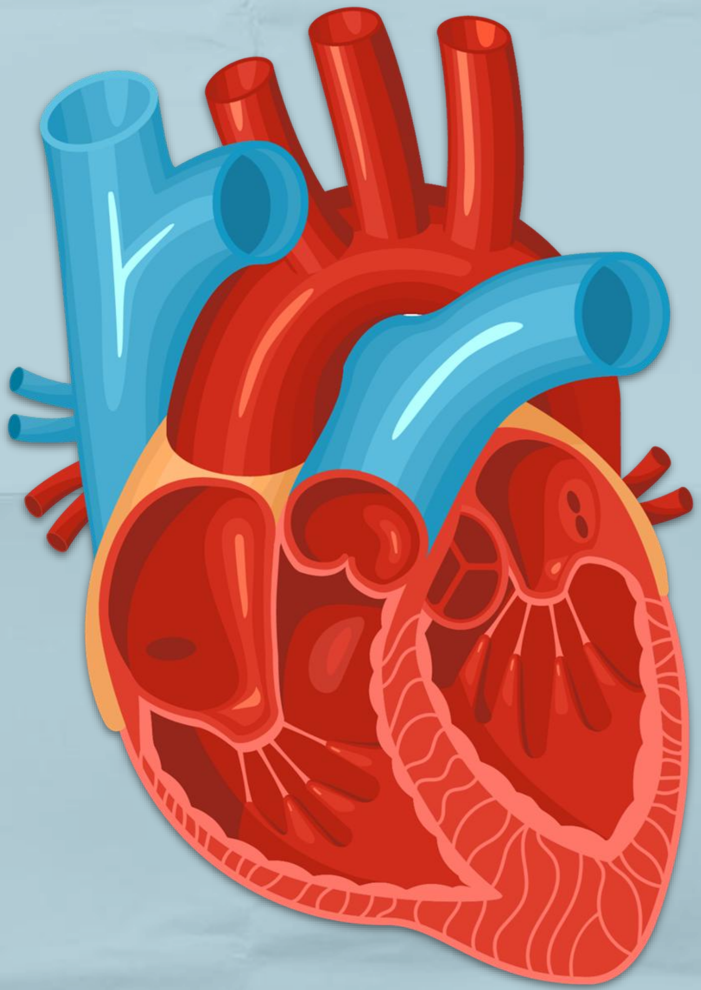
ii we draw 50 bootstrap (clone) datasets from Gaussian distributions

iii For each bootstrap (clone) data set, obtain DNN fit.

iv Obtaining the mean and standard deviation



Non linear dynamics and attractor reconstruction of complex physiological time series: an ECG analysis

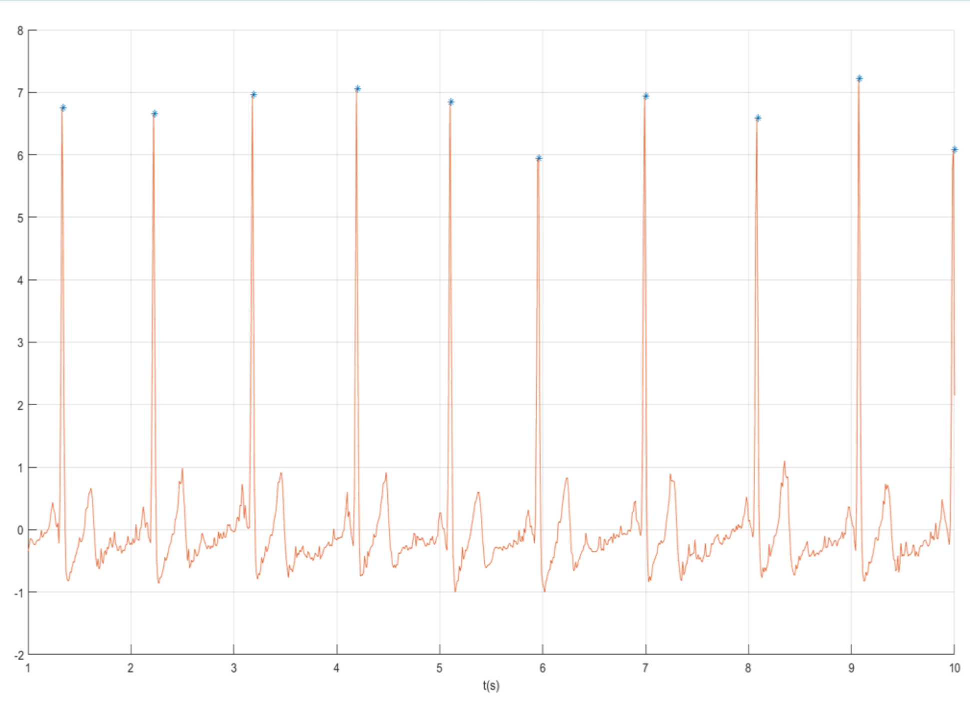


Giacomo Nasuti ed Elisabetta Ellettari

The Goal

Periodic component

Time series data



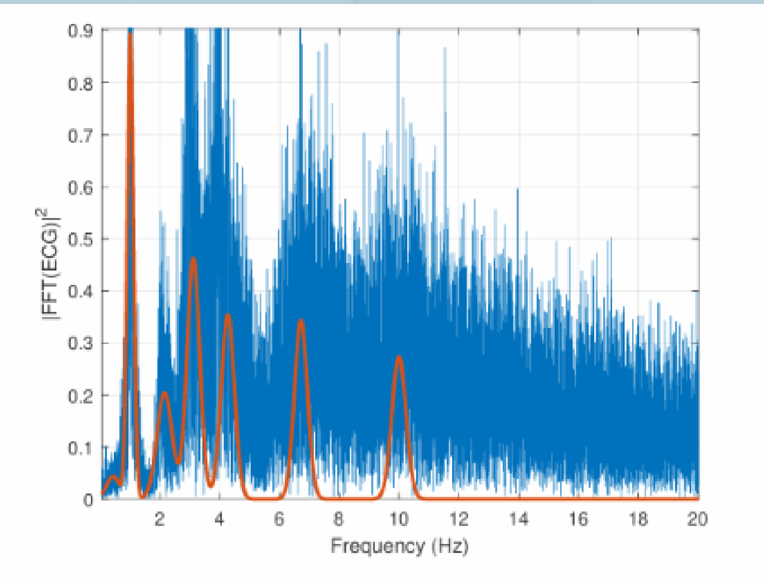


Figure 3. Fit with 7 Gaussians of the ECG signal Fourier transform

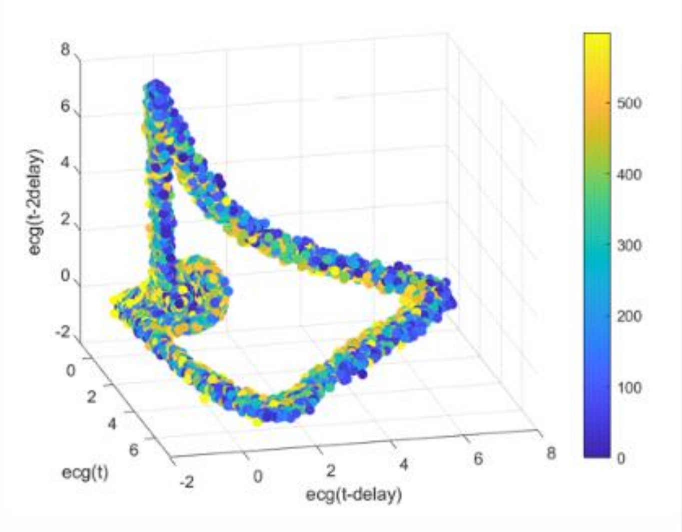


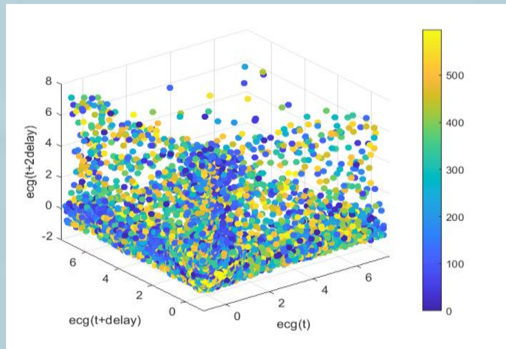
Figure 5. Reconstructed phase space attractor using an embedding dimension of $d = 3$ and a time delay $\tau = \frac{1}{30}$, determined by the minimum of the FFT.The data points are color-coded in chronological order.

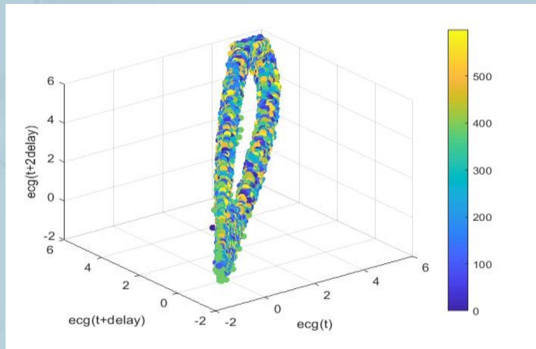
Chaotic component

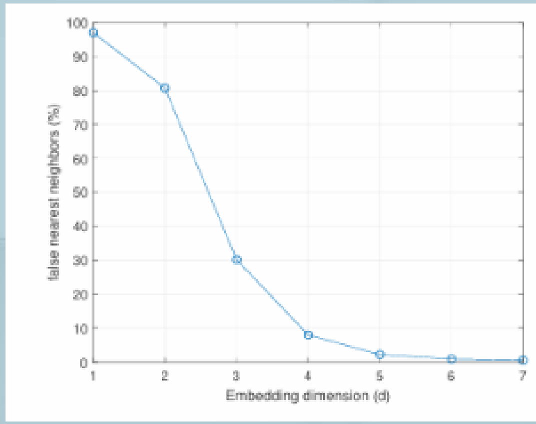
Main results

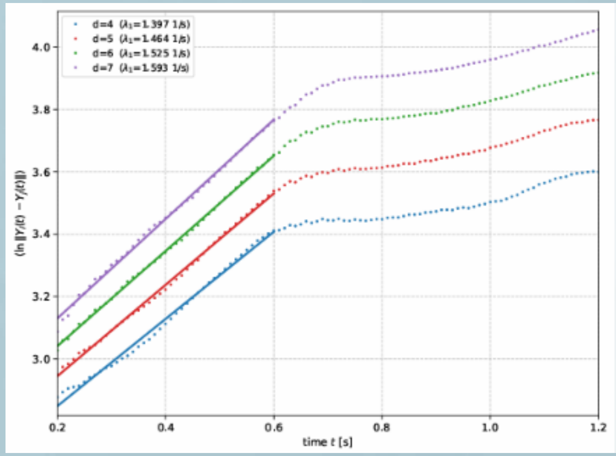
- We reconstructed the phase space using **Takens' embedding theorem** to recover the underlying strange attractor.
- The False Nearest Neighbors (FNN) algorithm determined a high-dimensional deterministic structure, requiring a minimum embedding dimension of: $d \geq 4$
- Rosenstein's algorithm yielded a positive maximal Lyapunov exponent, mathematically confirming high sensitivity to initial conditions: $L > 0$

With the wrong parameter...









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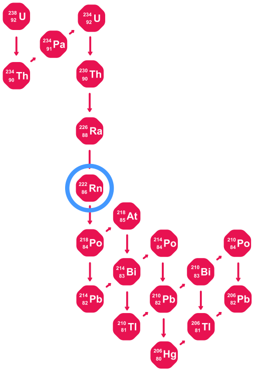
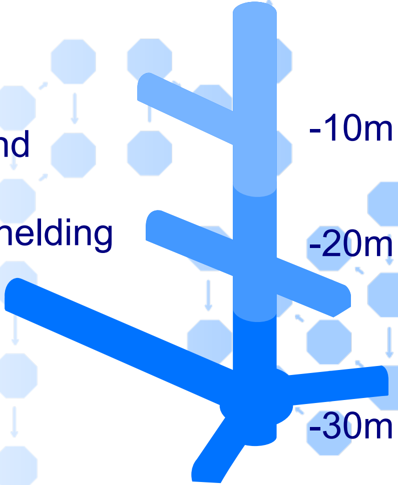
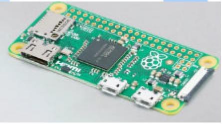


- Low radiation background experiments
- 40 cm reactor concret shelding
- Low seismic noise
- Low antropogenic noise
- Easily Accessible

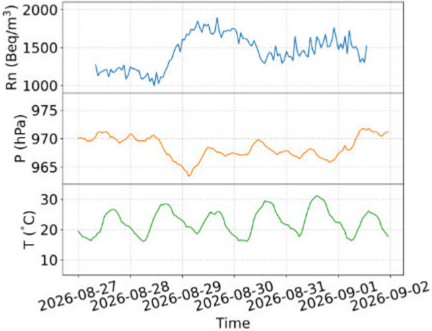


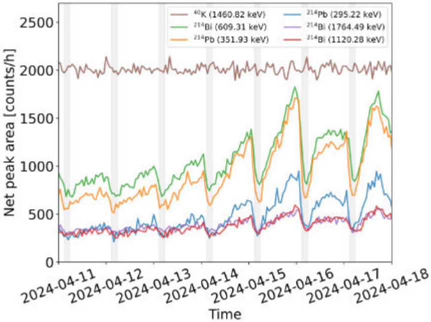
Radon Monitoring Network

Raspberry Pi



- Sensor System
- Predictive Model
  with Meteorogical Features
- Affordable Sensores





Higher-order nonlocal thermodynamic theories of gravity

Máté Pszota

in collaboration with

Péter Ván

HUN REN | WIGNER

ELTE EÖTVÖS LORÁND UNIVERSITY

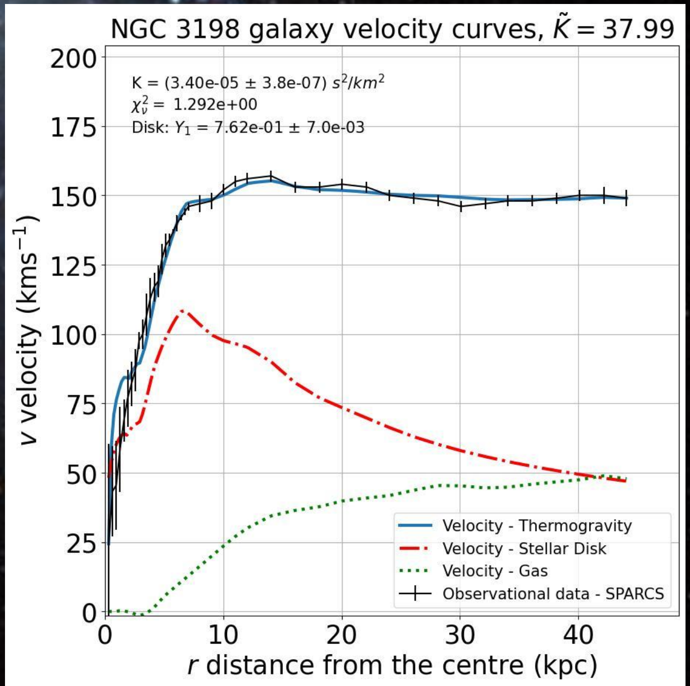
$$u = e - \frac{\varepsilon(\rho, \varphi, \nabla\varphi, \nabla^2\varphi, \nabla^3\varphi)}{\rho}$$

Short-scale modifications

Self-consistent, self-coupled gravity

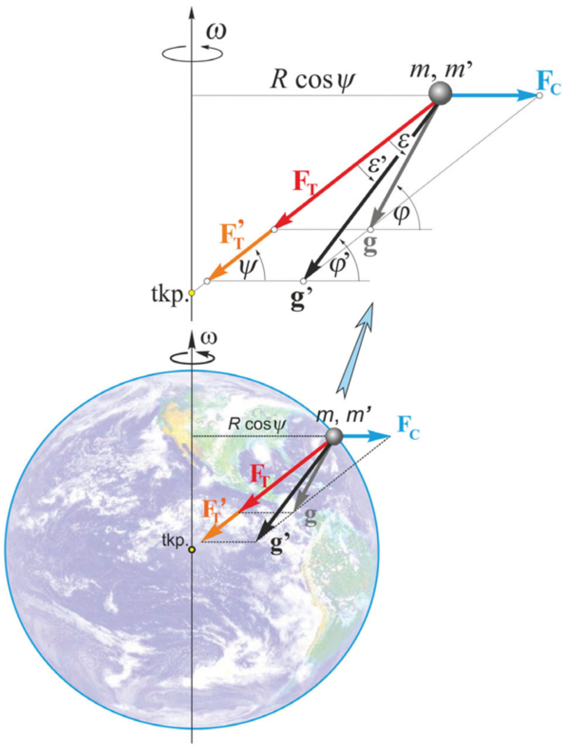
$$E = mc^2$$

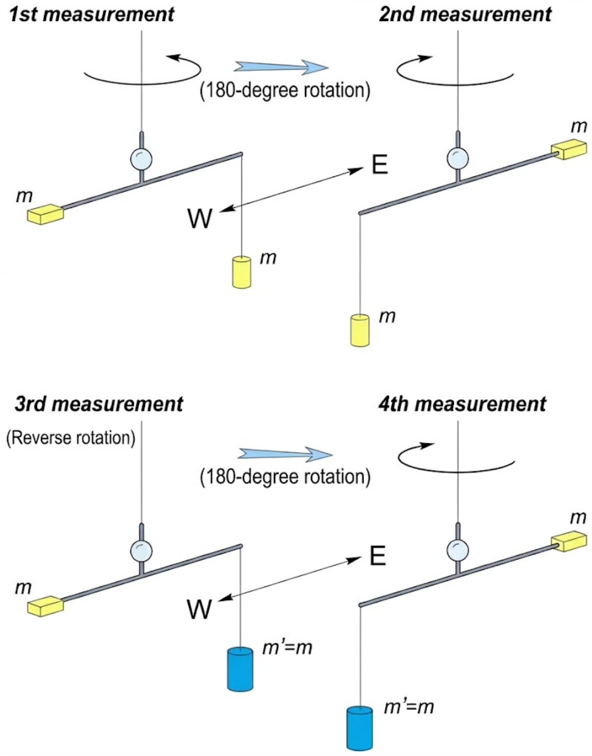
Galactic dynamics



$$\Delta\varphi = 4\pi G\rho + K(\nabla\varphi)^2$$

- Eötvös carried out his measurements between 1906 and 1909 testing the weak equivalence principle.
- 80 years later a correlation between the equivalence parameter and the barion number-to-mass ratio were found in his results.
- That’s what we want to explain.


ω
R cos ψ
m, m'
F_C
F_T
F_T'
ε
ε'
φ
φ'
ψ
g
g'
tkp.


1st measurement
2nd measurement
(180-degree rotation)
m
E
W
3rd measurement
(Reverse rotation)
4th measurement
m'=m

- Four methods are compared.
- The two methods neglecting the change of the gradients give approximately $-3.5 \cdot 10^{-9}$.
- The two methods allowing changing gradients give approximately $1.2 \cdot 10^{-8}$.