GANIL

Internship in data science for accelerator physics

Smart isotope identification with causal state observers at the SPIRAL1 GANIL facility

SPIRAL1 produces exotic radioactive ion beams via the ISOL method. Identifying isotopes relies on β–γ decay spectroscopy, which is challenged by complex decay schemes, overlapping peaks, detector background, and beam-induced fluctuations. Traditionally, isotope assignment is based on expert analysis and calibration, but the increasing diversity of isotopes and noise conditions calls for AI assistance [1].

In system and control theory, state observers are used to model hidden dynamics such as release kinetics and decay profiles. Their prediction residuals capture mismatches between expected and measured spectra. These residuals can then serve as features for anomaly detection and isotope classification [2,3]. Linking causal observers with machine learning classifiers creates an interpretable framework: predictions explain why a spectrum is assigned to a specific isotope, while residual analysis highlights discrepancies due to noise or background [4,5].

Recent AI research emphasizes combining physics-informed models with semi-supervised or self-supervised classifiers to tackle scarce or noisy labels [1-3]. This internship will test such hybrid methods on SPIRAL1 spectra, setting up a proof-of-concept that a full PhD project can generalize and industrialize.

Explainability focus: Depending on progress, this internship will also explore causal explainability, linking observed β–γ spectra to latent isotope states estimated by the observer. Simple causal graphs [6] and uncertainty bands will be used to show why an isotope ID decision was made, distinguishing genuine isotope signatures from noise or background. This reflects state-of-the-art approaches where causal inference is key for interpreting anomalies in multivariate time series under uncertainty [7].

Objectives

- Develop a basic state observer for isotope release and decay curves.
- Use observer residuals as inputs to classifiers (semi/self-supervised learning).
- Explore causal graphs and uncertainty as interpretability tools.
- Focus case: robust isotope ID under background noise.

Expected outcome

- Proof-of-concept observer-assisted classifier for isotope identification.
- Clear roadmap for deeper PhD-level work (advanced causal observers, generalisation, large-scale benchmarking).

Expected skills

Python, ML, control/observer basics, spectrum analysis, nuclear physics interest. Optional: C++, Root

This work leads to a PhD-thesis.

Contact: Adnan Ghribi
Phone: +33 (0)2 31 45 46 80
mail: adnan.ghribi@ganil.fr

References

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