Neural Simulation-Based Inference for the keV-scale Sterile Neutrino Search with TRISTAN at KATRIN

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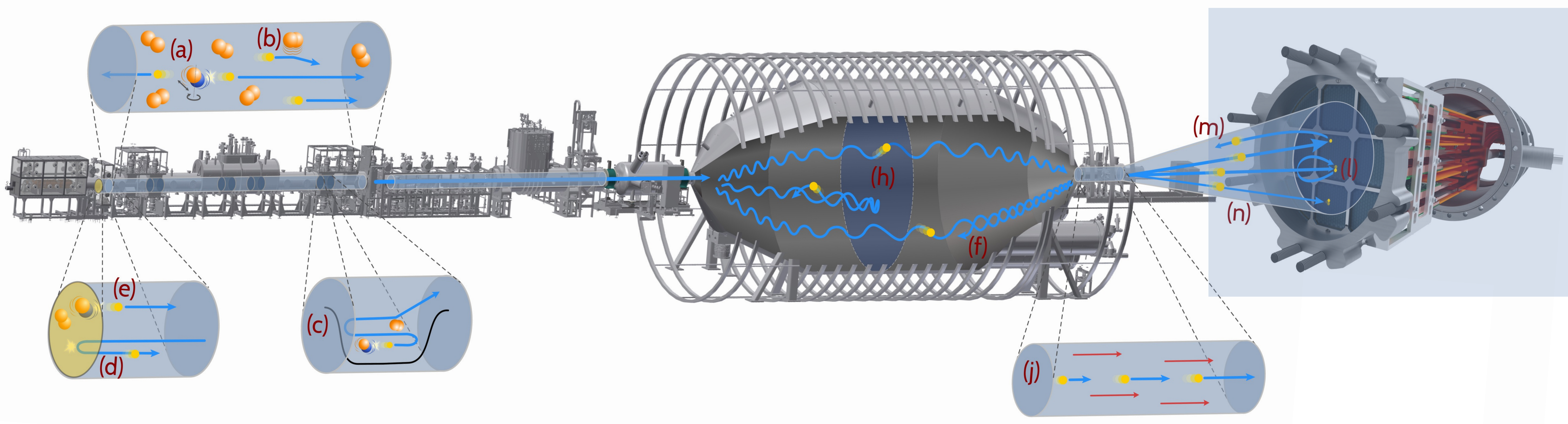
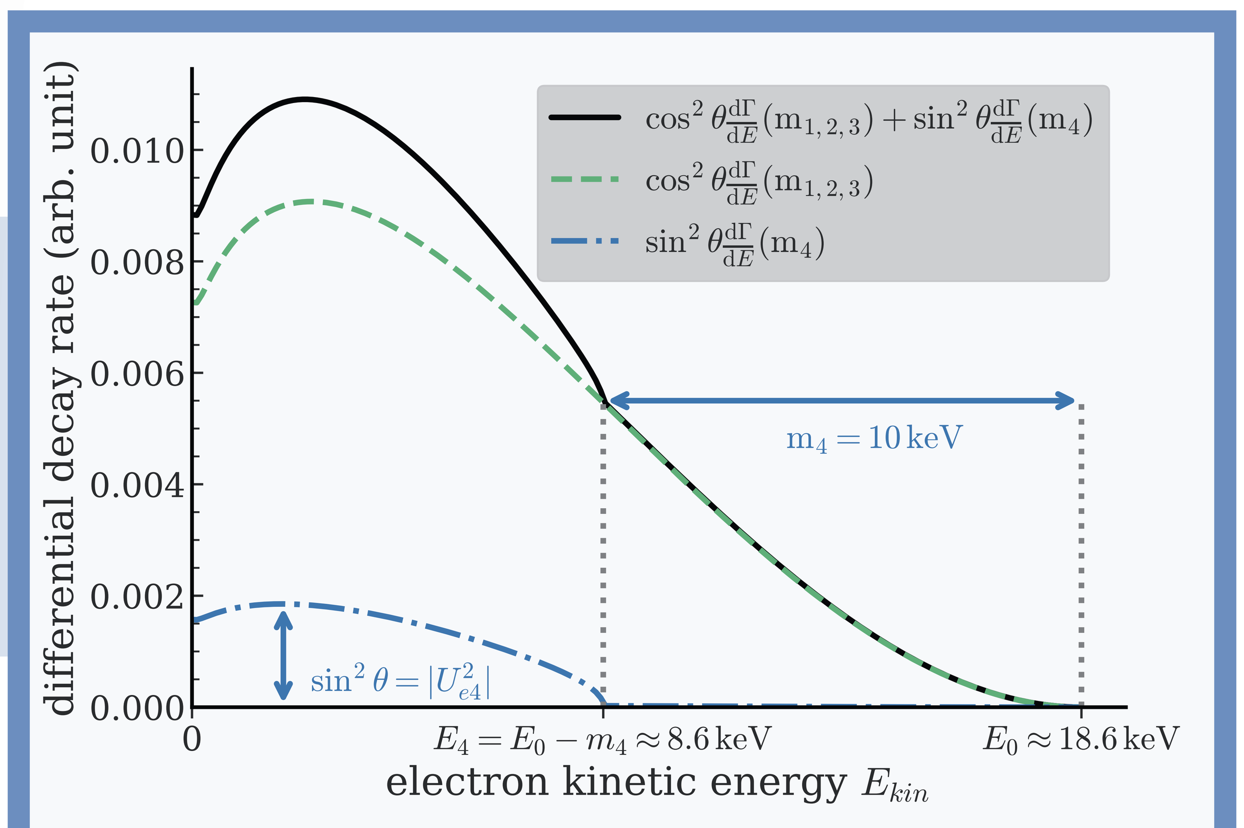
Starting 2026: KeV-scale sterile neutrino search

TRISTAN Detector





keV-sterile-neutrino search:

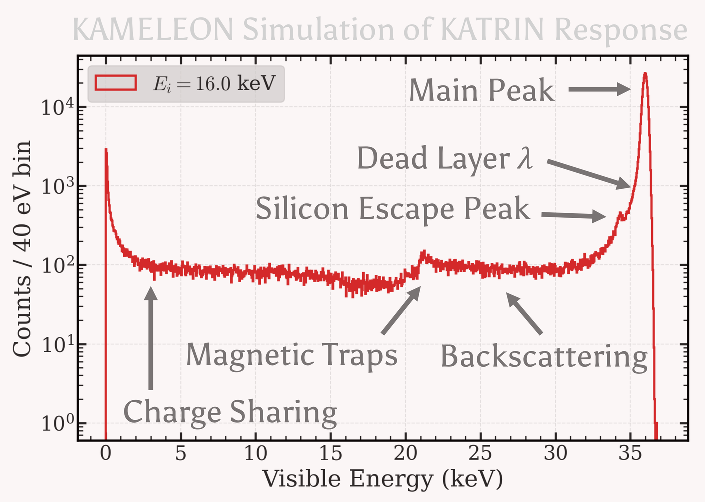
- Kink-like sterile neutrino signature
- Deep into the **differential** T_2 β-decay spectrum
- Extremely high rates ($\sim 10^8$cps)
- With silicon drift detector array with ~1k pixels
- **Designed to be sensitive to ppm-level $\sin^2\theta$**

Analysis Goal: Fit Prediction to Data

„Response Function"

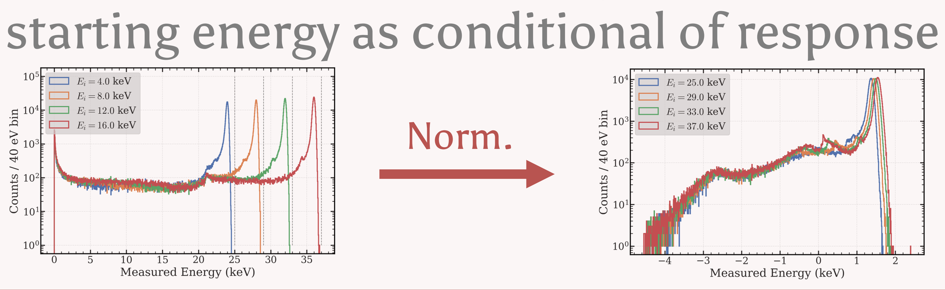
$$\text{Prediction} = A \times \Gamma_{vis}(E, m_4, \sin^2\theta, y_{nuis}) = A \times \int R(E', E, y_{nuis})\, \Gamma_{theo}(E, m_4, \sin^2\theta)\, dE'$$

Modelling Challenge: Systematic Effects (a – l)



Challenges:

- Some systematic effects act at the percent level on the spectrum (vs. possibly ppm-level signal)
- Many systematic effects have to be simulated
- Systematic uncertainties (systematic effects need to be conditionals of response)
- e^- starting energy as conditional of response

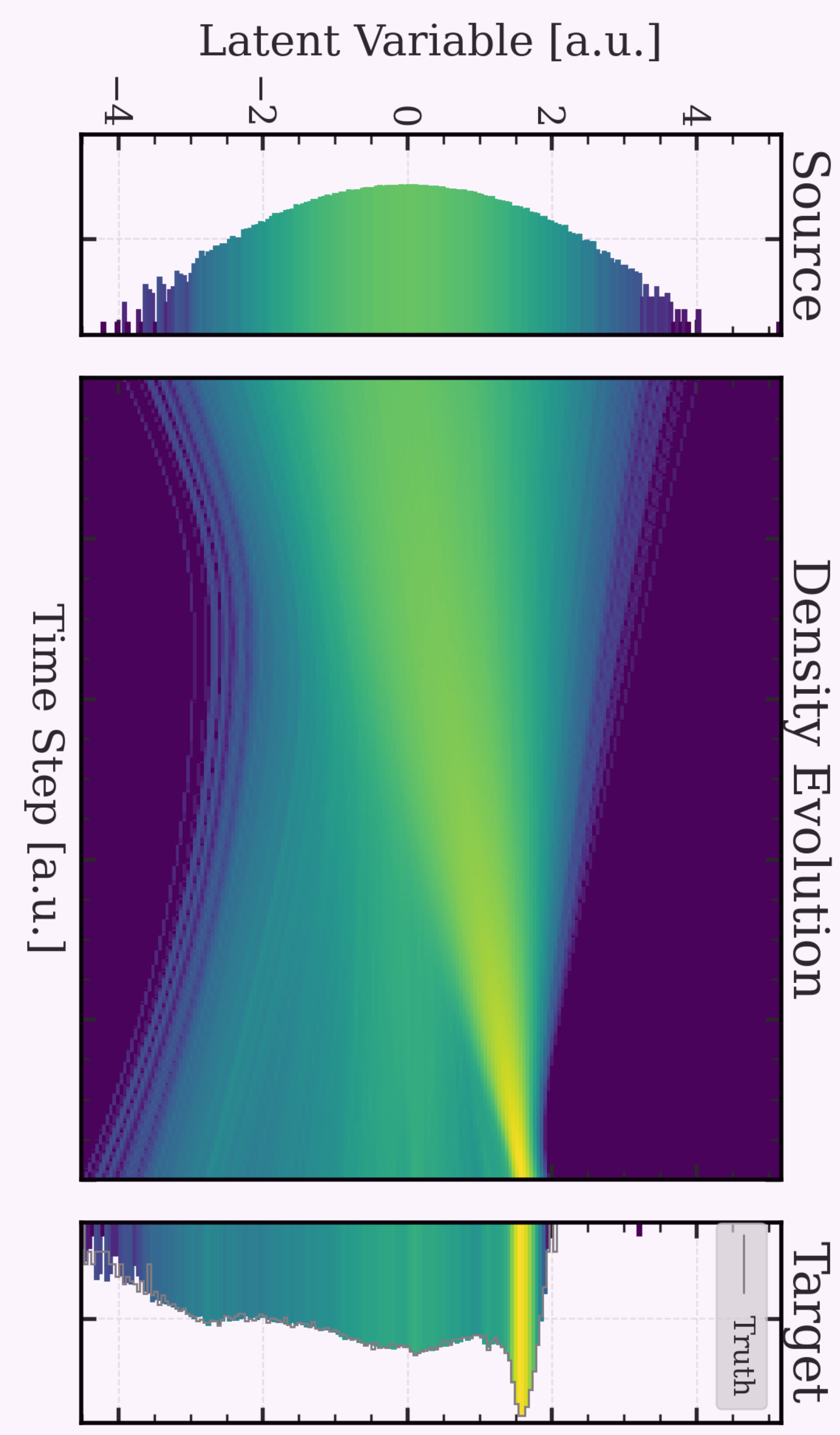


Modelling Approaches

	Empirical Model (by hand / symbolic regression)	Normalizing Flows → Focus of this poster
Precise and accurate at high stat.	Expensive (high stat. simultations for each E_{in}, y_{nuis})	✓
Conditioned on E_{in}, y_{nuis}	Very hard	✓
unbinned	✓	✓

Continuous Normalizing Flow

Trained via Flow Matching



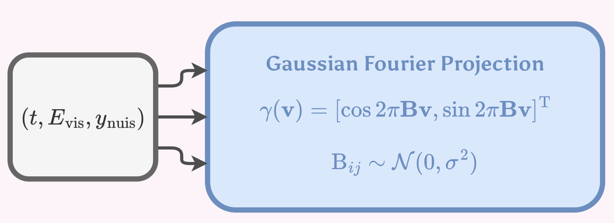
Flow Matching:

- NN learns to predict the „probability flow" vector field connecting a simple distribution to the target distribution (i.e. the response)
- Is trained only using samples
- **Provides an unbinned conditional response**

Difficulties and Solutions for Continuous Normalizing Flows

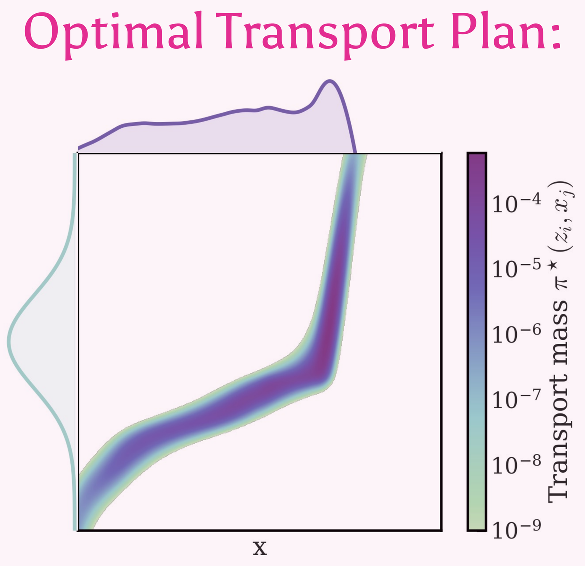
High peak with long tail containing high frequency features	1	Adding Gaussian Fourier Features
High variance in probability flow vector field due to conditionals and crossing paths	2	Conditonal Optimal Transport
Large Number of Samples	3	Amortizing Optimal Transport

1 & 2 Gaussian Fourier Projection:

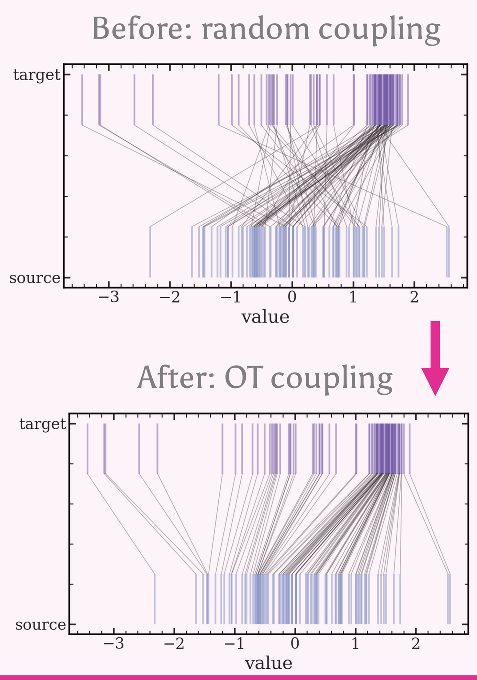


Overcomes NNs natural bias towards learning low frequencies first

Optimal Transport Plan:



Using Euclidean and Conditional Cost



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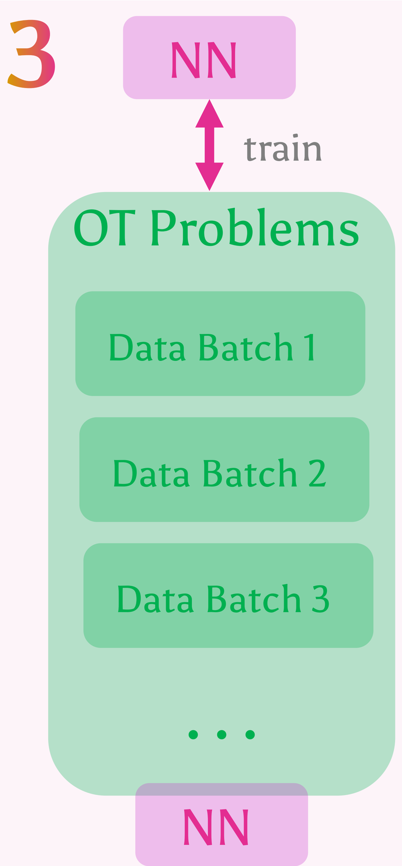

Inference 20x faster than numerical solver

Results (preliminary)

Takeaway: Good first step, need to extend to more y_{nuis} and fine-tune hyperparameters