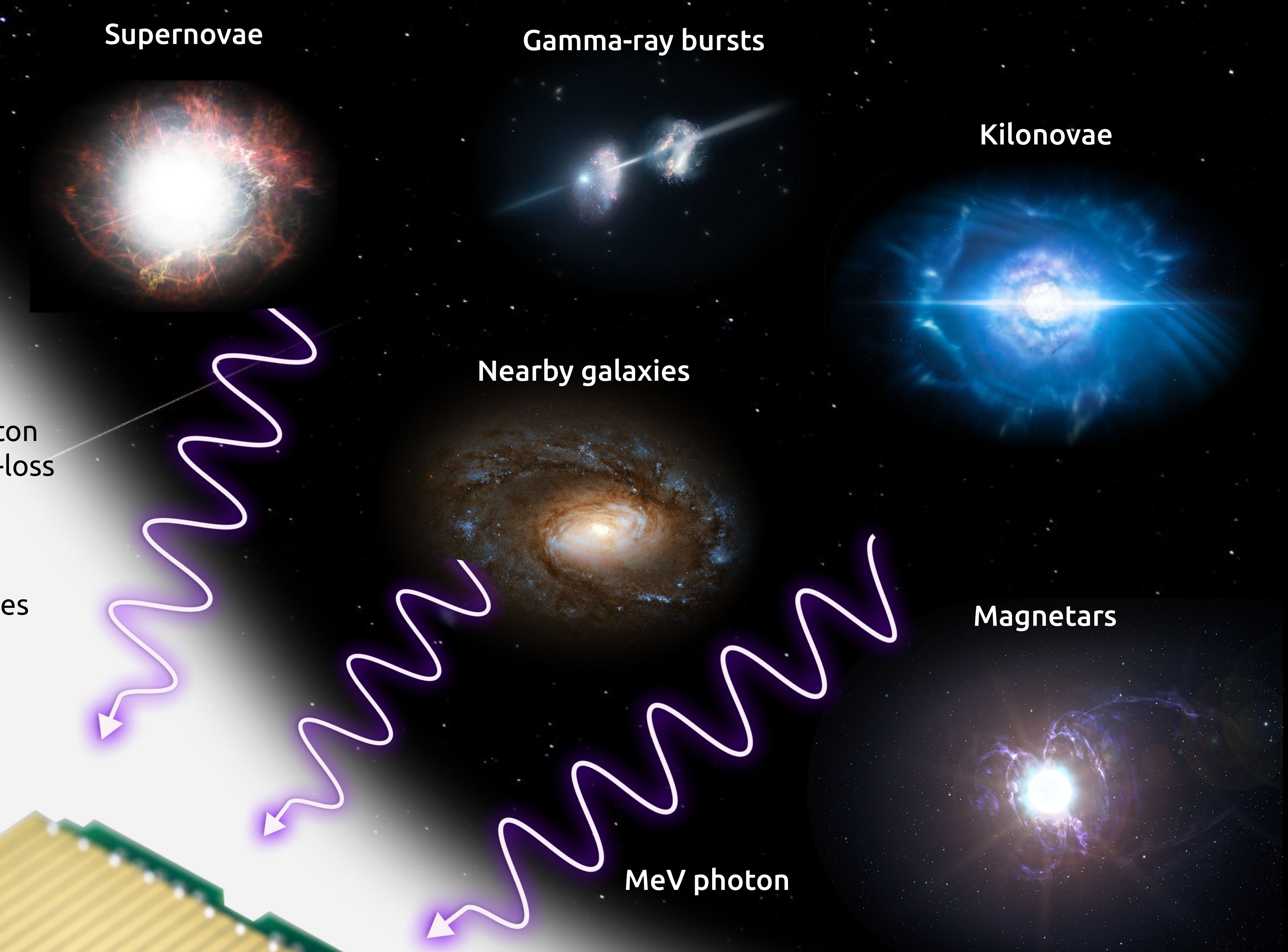
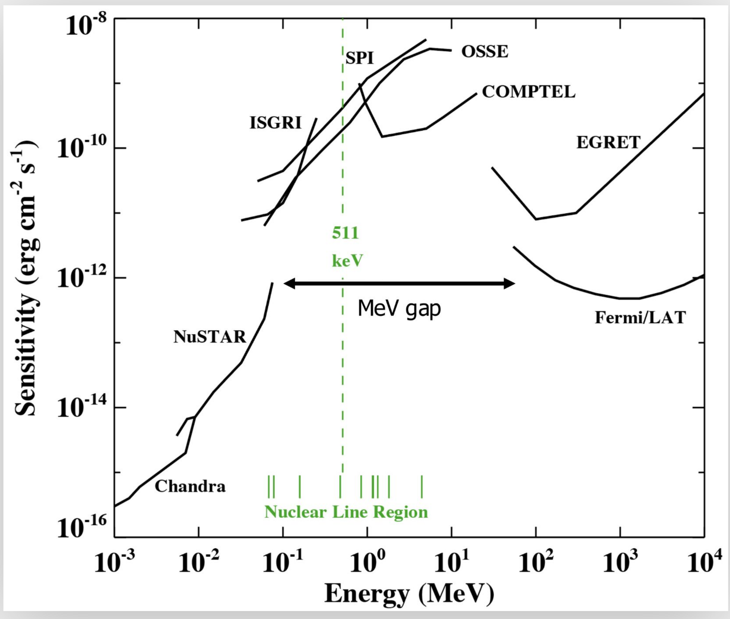
Unlocking the MeV Spectrum: Advancing Detector Technology with AI

Funded by the European Union



1 The MeV spectrum



Plot from John Tomsick, "Compton Polarimetry and the Compton Spectrometer and Imager", FiXPAcademy 2025

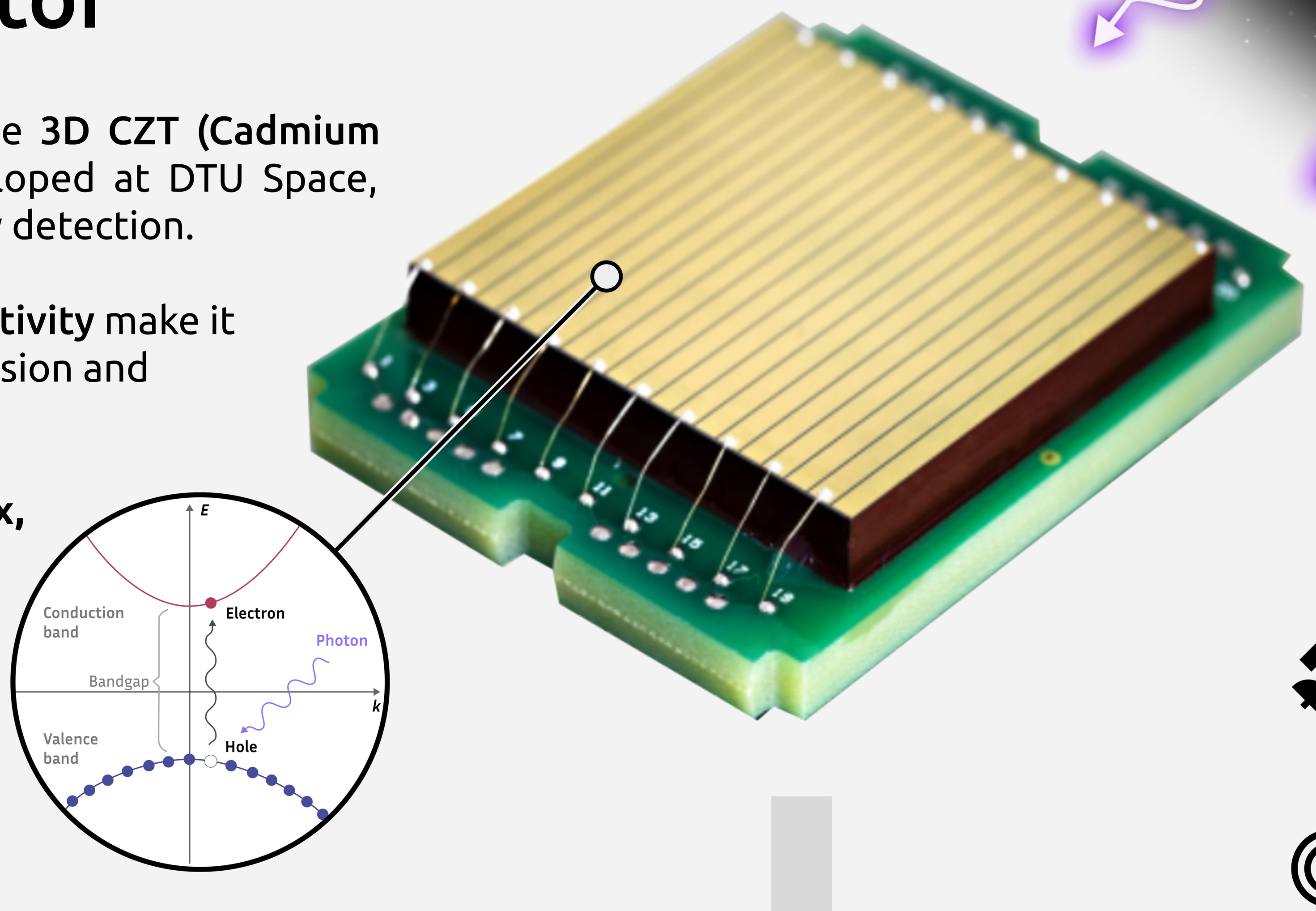
- **Medium-energy X- and gamma-ray (~0.1-100 MeV)** emitted by cosmic events such as gamma-ray bursts or Supernovae
- **Difficult to detect** due to low flux, low photon interaction probability and complex energy-loss processes.
- **The MeV Gap** - a significant gap in sensitivity due to limited detector capabilities compared to adjacent energy bands.

2 Radiation detector

Advanced detector technology such as the **3D CZT (Cadmium Zinc Telluride) drift strip detector**, developed at DTU Space, offers high-resolution X-ray and gamma-ray detection.

The detector's **compact size and high sensitivity** make it promising for applications future space mission and medical imaging.

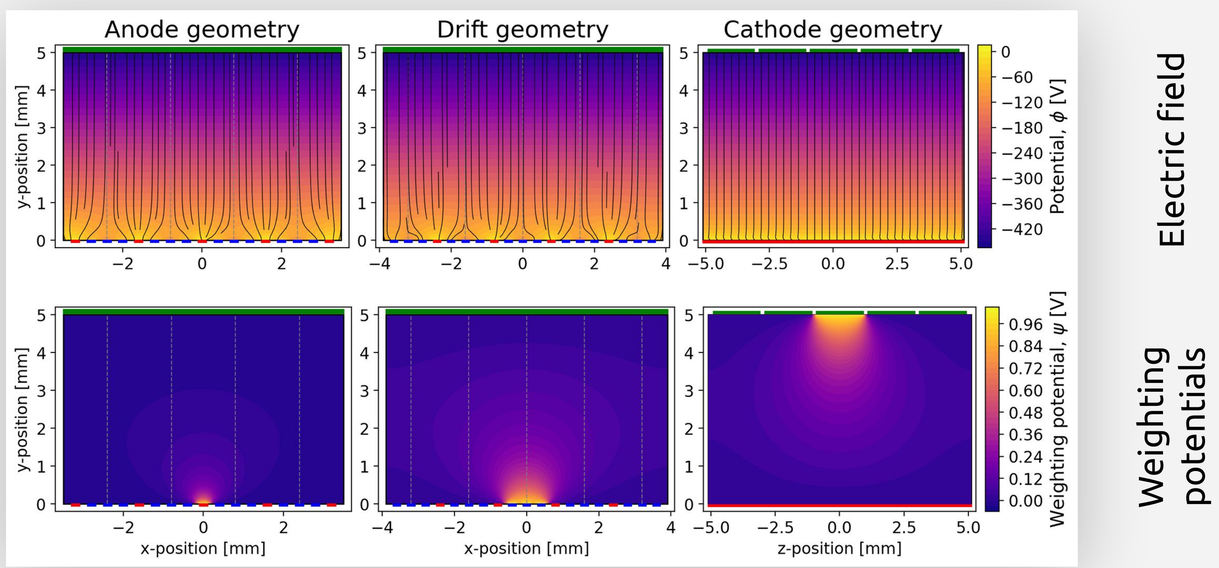
Each photon interaction generates **complex, high-dimensional data** (pulse shapes), encoding the radiation trace through underlying physical reactions.



3 Simulations

Detailed **modeling of the detector's internal physics**, including electric fields and charge transport, is used to generate synthetic detector output (pulse-shaped signals). This, in turn, is used to train Neural Networks, ensuring data-efficient learning.

- Simulated electric field and weighting potentials

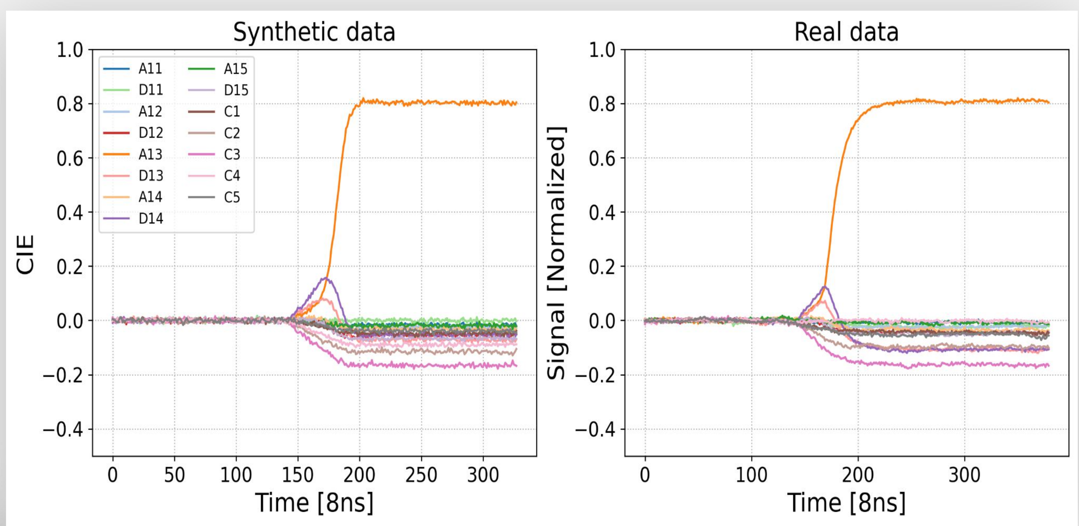


- Charge transport model

$$\underbrace{\mu_n \nabla\phi \cdot n^+}_{\text{drift}} + \underbrace{\nabla \cdot (D_n \nabla n^+)}_{\text{diffusion}} - \underbrace{\frac{n^+}{\tau_n}}_{\text{trapping}} + \underbrace{\mu_n \nabla\phi \cdot \nabla\psi_k}_{\text{generation}} = \frac{\partial n^+}{\partial t}$$

Charge Induction Efficiency (CIE)

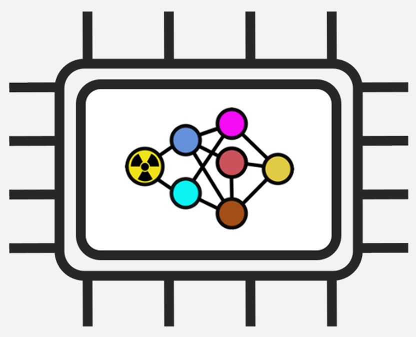
- Generated detector output



The better the match, the better the performance of Neural Network models.

Signal converters

Real-time signal processing



Incident radiation information (photon-by-photon)

Time

Energy

Position

Type

Key takeaways 5

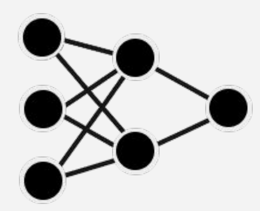
- **AI-driven signal processing enables compact, high-performance instrumentation** for future space missions and MeV astrophysics.
- **Neural networks trained on simulated data** can outperform conventional algorithms especially near the boundary regions of the detector allowing more accurate reconstruction of photon interaction events.

Neural Networks 4

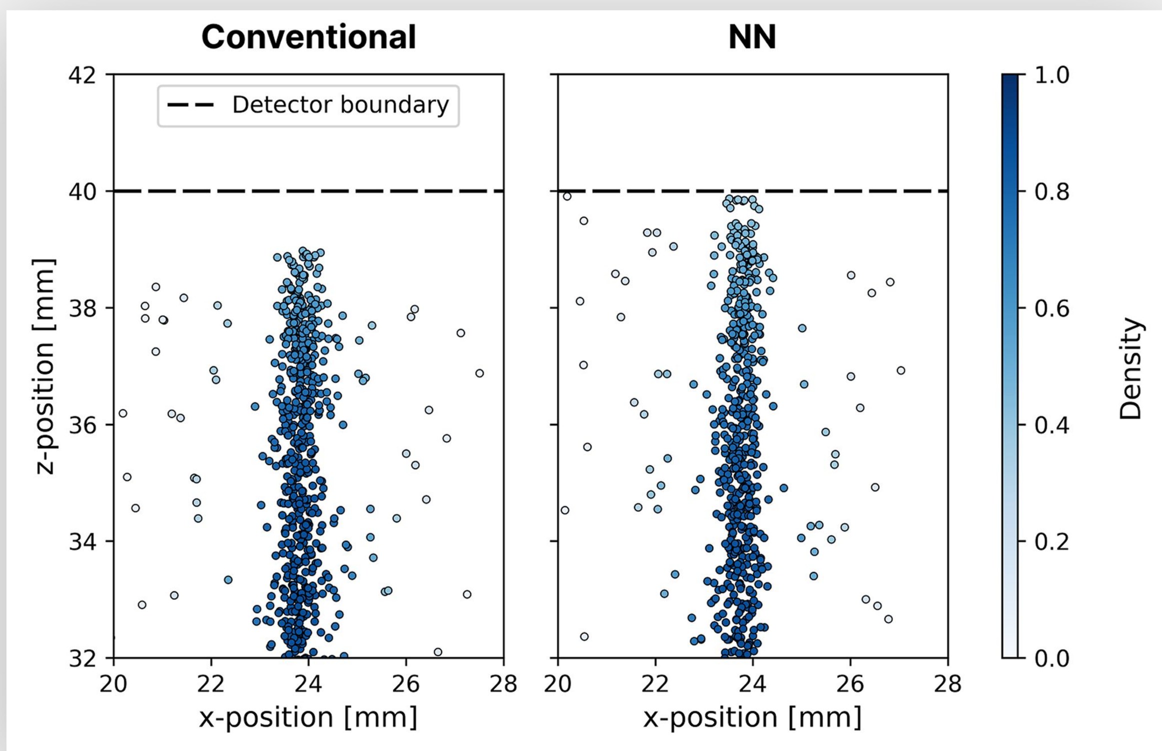
Neural networks learn complex relationships between input pulse shapes and physical quantities like interaction position, energy, and time. They **enable fast, accurate reconstruction** of photon events.

- **Training:** supervised learning on **simulated data**

FFNN, CNN

Event signals →  → Interaction position (x, y, z)

- **Results:** predicted interaction positions on **real data**



Neural Networks show increased performance near the edges of the detector, thanks to learning from data.

Want to learn more about the project?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