Neural-Network-Based Event Reconstruction for the RadMap Telescope

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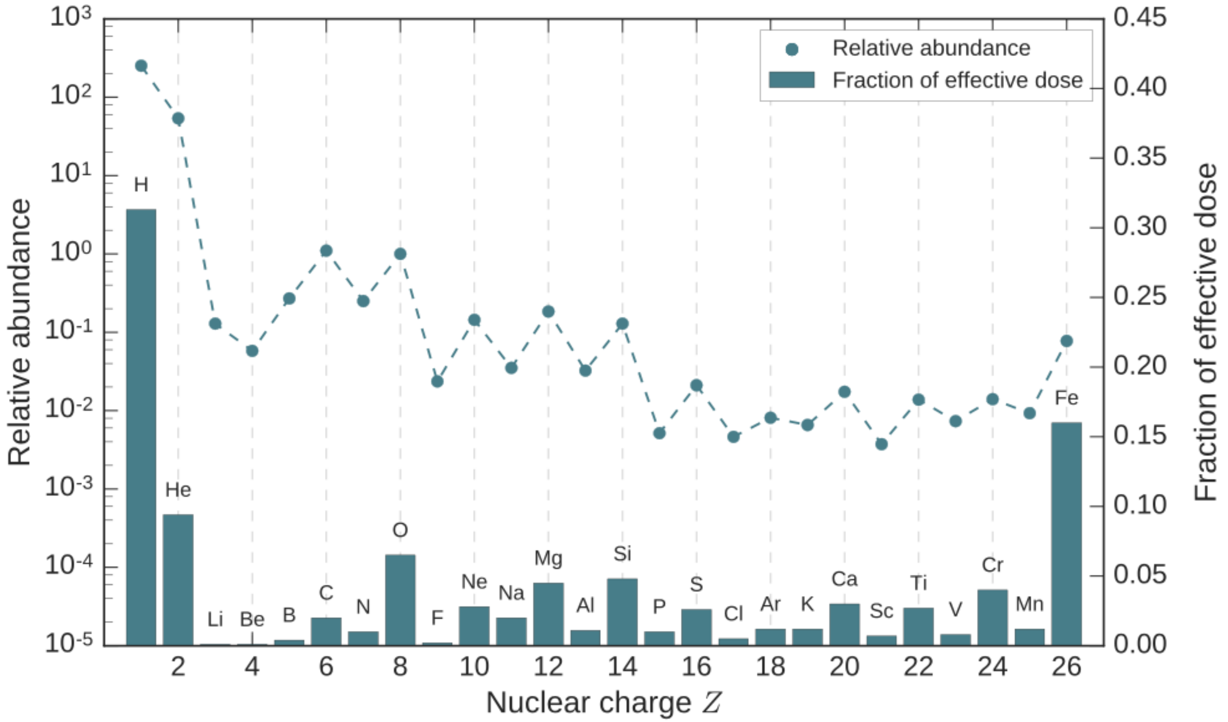
The Space Radiation Environment

Composition and Effects

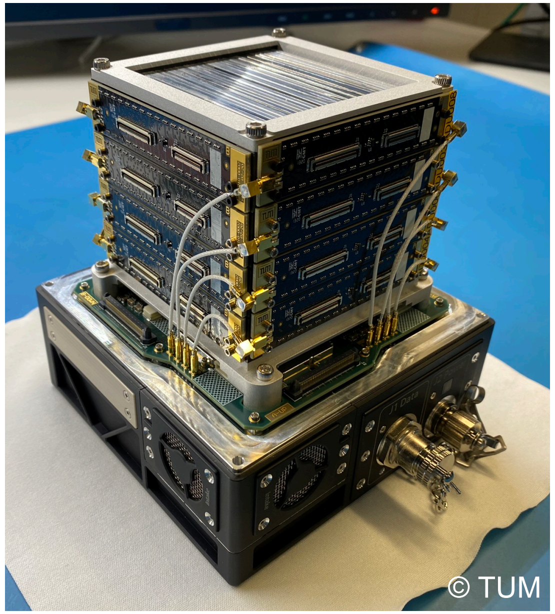


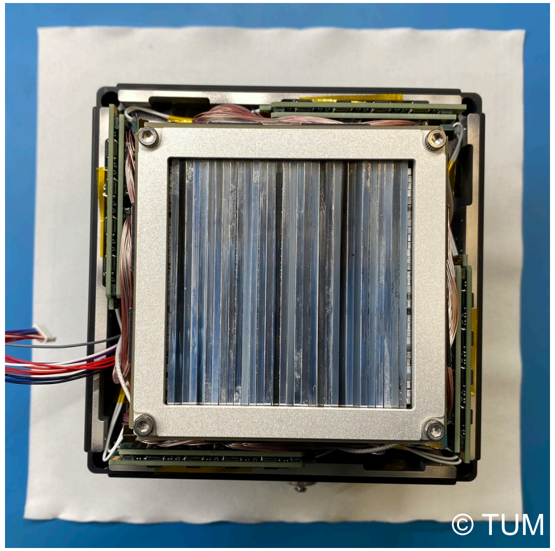
- **Composition**
  1. Galactic cosmic rays: 2% electrons, **98% protons and high-energy heavy ions**
  2. Solar energetic particles and solar wind: **protons**, electrons, and alpha particles
- Earth and low Earth orbit shielded from primary cosmic rays by Earth's atmosphere and magnetosphere
- Regions with increased flux of particles at orbits close to Earth (*South Atlantic Anomaly*)

Objective: Assess shielding requirements and their temporal variations to minimize exposure to damaging radiation on future manned and un-manned space missions

The RadMap Telescope

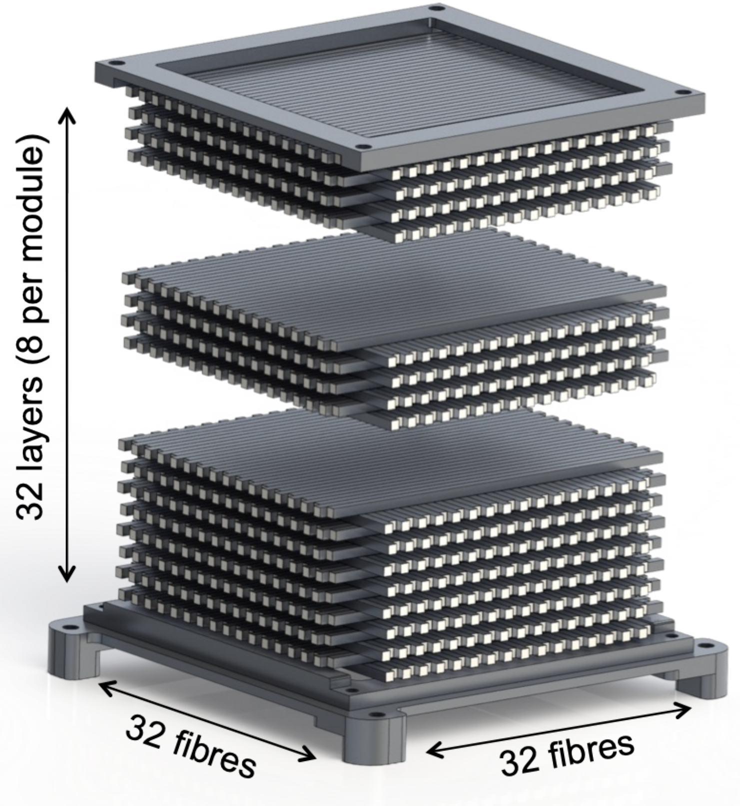
Capabilities & ADU Detector Concept





Main Detector Unit | ADU

- Detector Setup
  - Active tracking volume of ~ 8 x 8 x 8 cm^3
  - 1024 scintillating-plastic fibres organised in 32 layers of 32 fibres each
  - Output: two-dimensional projections of energy depositions
- Precise Tracking & Particle Identification
  - Energy Range: > ~70 MeV/n
  - Angular Resolution: < 2°
  - Coverage: Full solid angle

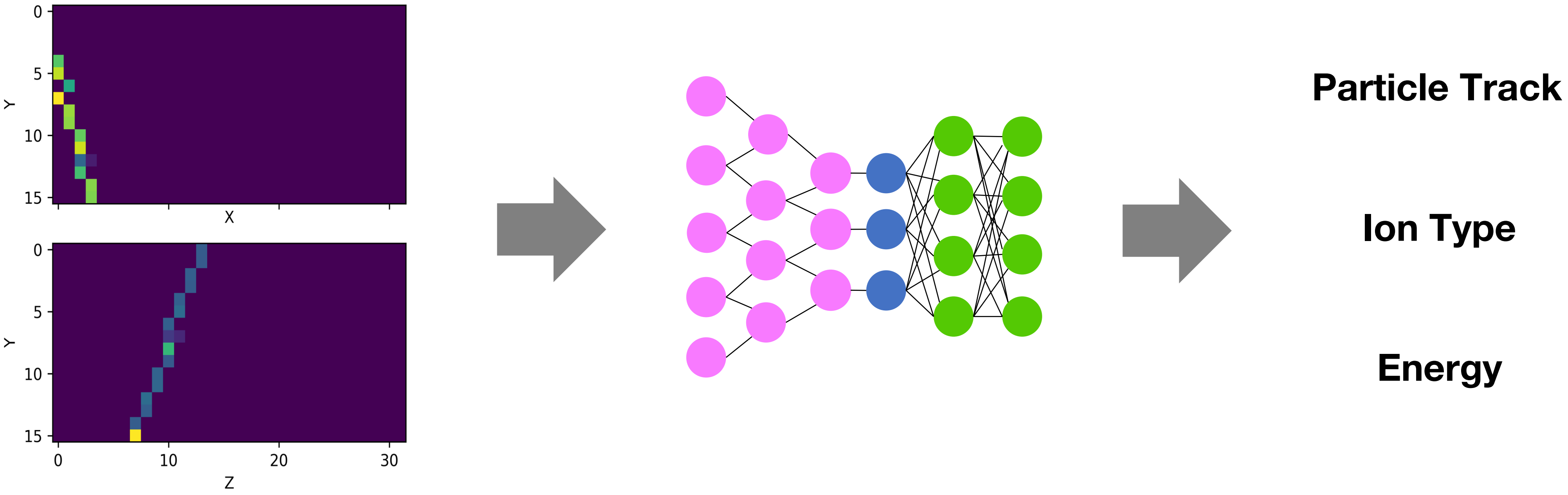


Advantages

- Single, general-purpose radiation monitor adapted to applications in space
- Collection of spatially and time-resolved radiation-flux data
- Monitoring of particle-type resolved, biologically meaningful dose rates on the ISS (and beyond)

The RadMap Telescope

Reconstruction Tasks

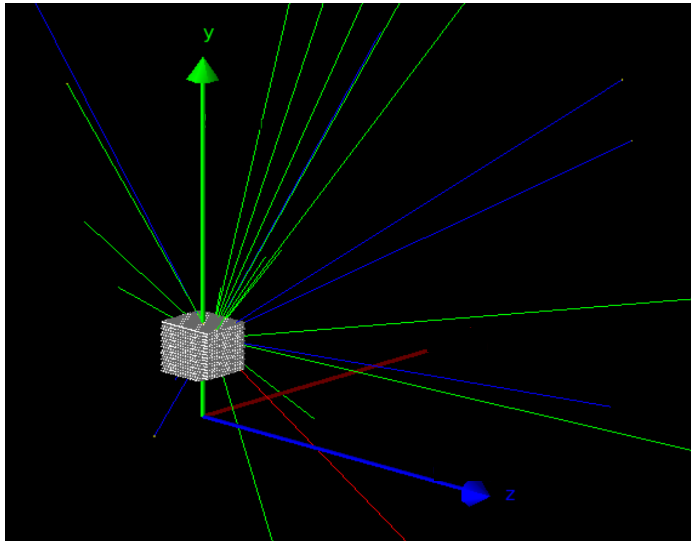


- Objective: evaluation of events in near-real time and in-orbit using neural networks
- Ground-based training of neural networks and subsequential deployment onto on-board computer to comply with computational restrictions to in-orbit analysis
- Separate neural-network framework for each of the three reconstruction tasks

Training Data

Simulation and Composition

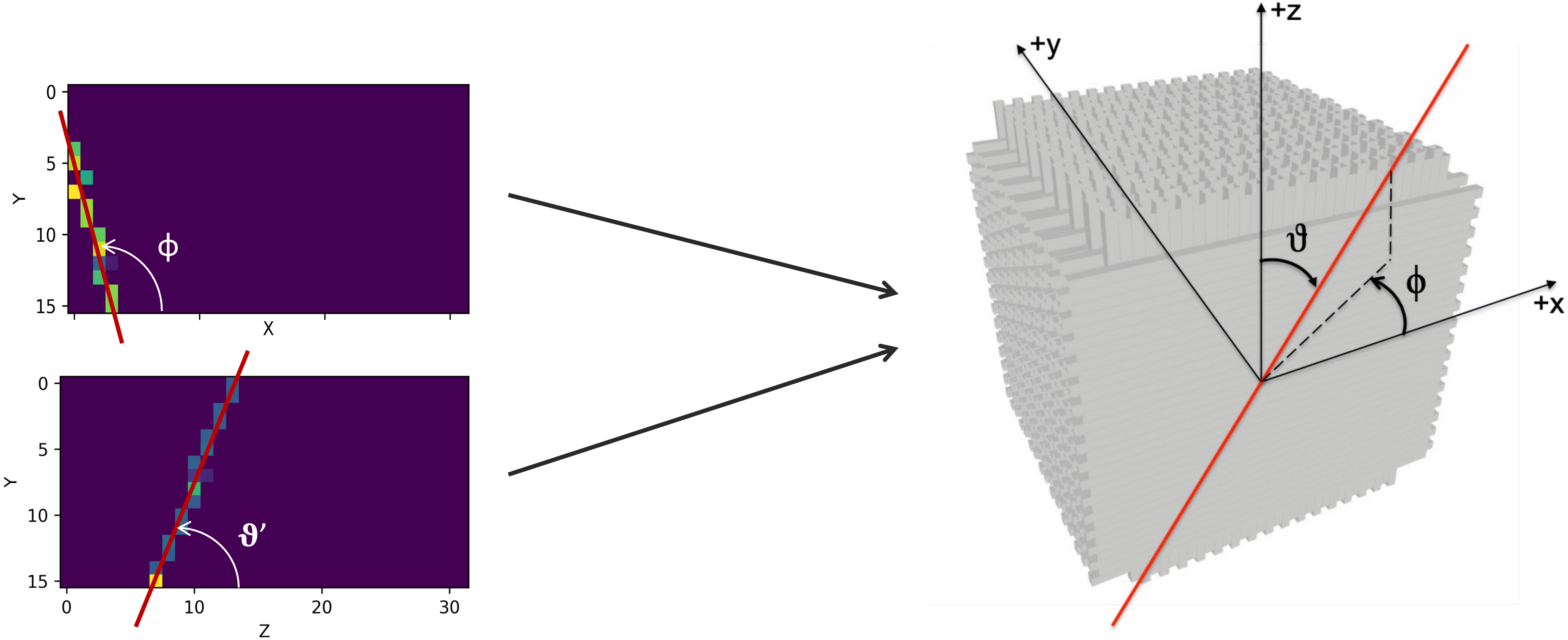
- Training data simulated with Geant4
- Distributions modeled to cosmic ray abundances **but** adapted to optimize training of neural networks
  - Particle types
    - **Nuclei** of elements from hydrogen to iron as they appear in cosmic rays
    - Uniform distribution of ion types
  - Angles of incidence
    - **Isotropic distribution**
  - Particle energies
    - 70 MeV to 50 TeV
    - **Power-law distribution**
- Minimum of **3 fiberhits** in each projection



Neural-Network-Based Event Reconstruction

Particle-Track Reconstruction – Parametrisation

- **Parametrisation** of three-dimensional track
  - $\vartheta \in [0, 180)$ deg
  - $\phi \in [-180, 180)$ deg



Neural-Network-Based Event Reconstruction

Particle-Track Reconstruction – Neural Network Architecture

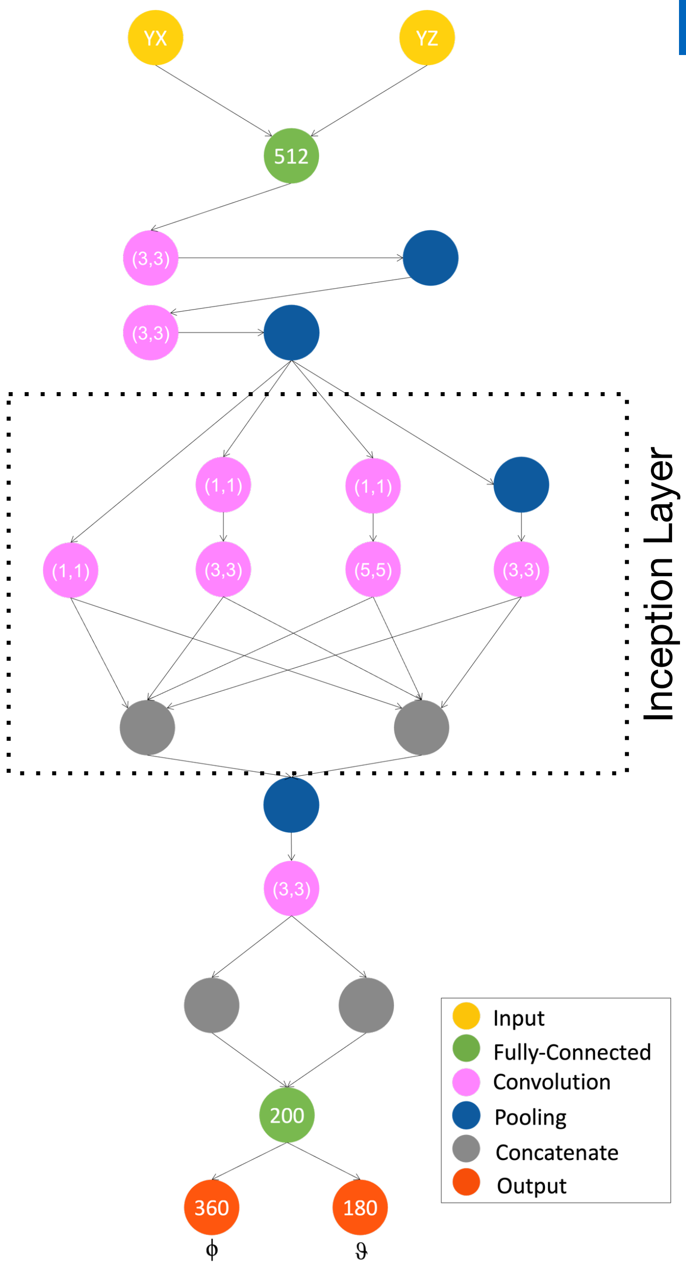
- **Parametrisation** of three-dimensional track
  - $\vartheta \in [0, 180)$ deg
  - $\phi \in [-180, 180)$ deg

- Core architecture component: **Inception layer** [Szegedy et al, 2014]
  - Multiple convolutional layers of different sizes in parallel
  - Goal: learn the scale of structures of interest

- Task:

  Dual **classification** over 180 resp. 360 classes
  ≙ Binning resolution of 1°

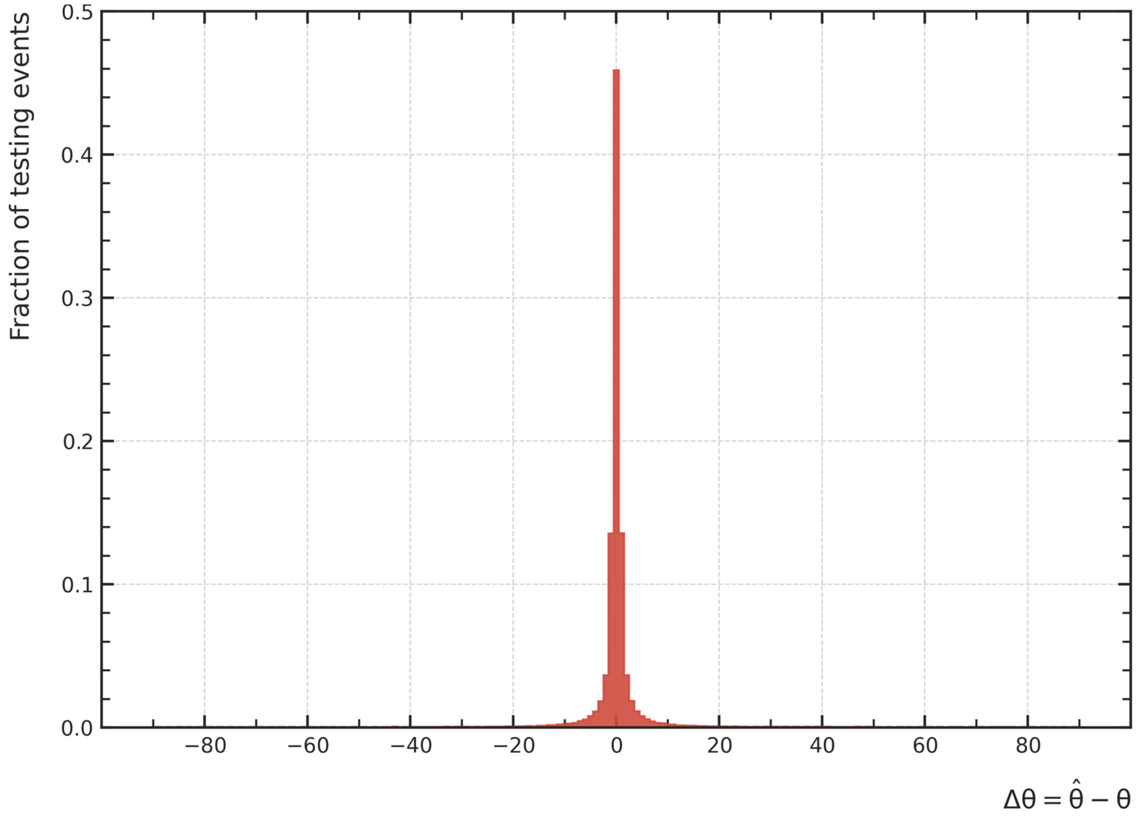
- Training parameters:
  - Nb. of trainable parameters: 3 million
  - 10M training events
  - 400+ training epochs



Neural-Network-Based Event Reconstruction

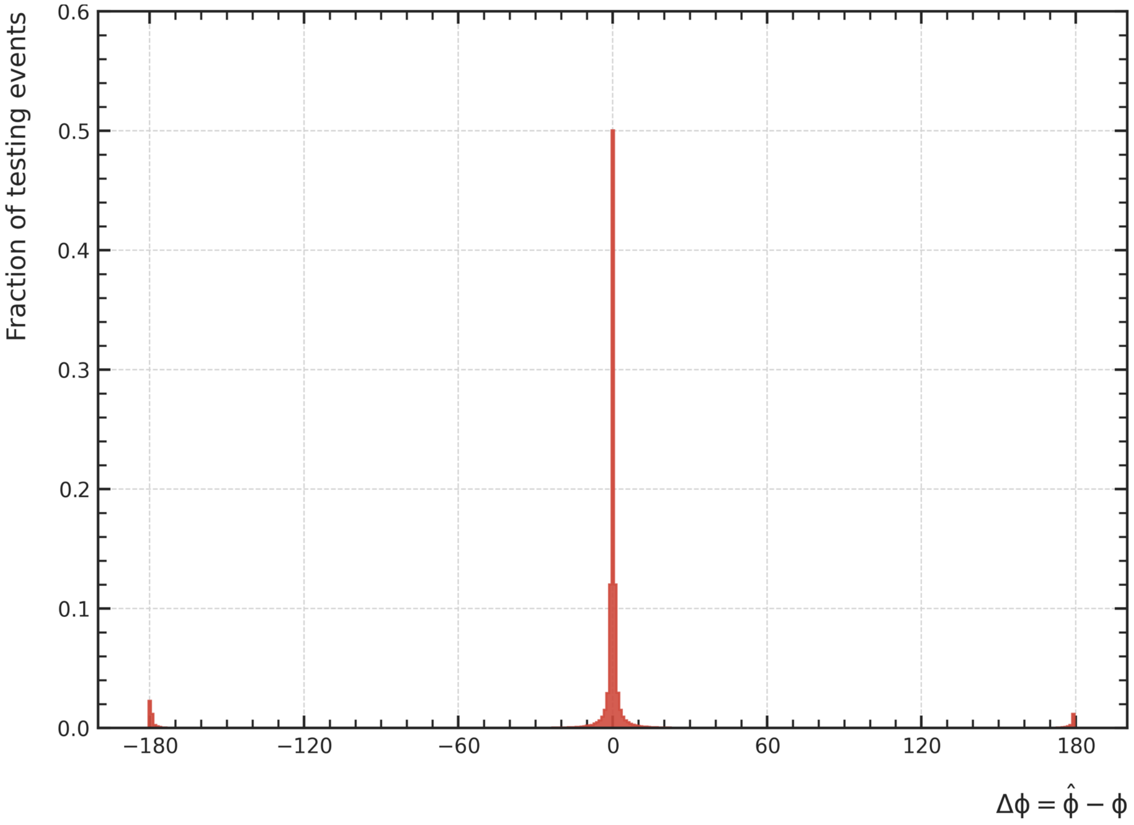
Particle-Track Reconstruction – Results

Theta



$$\sigma_\theta = 1.15 \text{ deg}$$

Phi

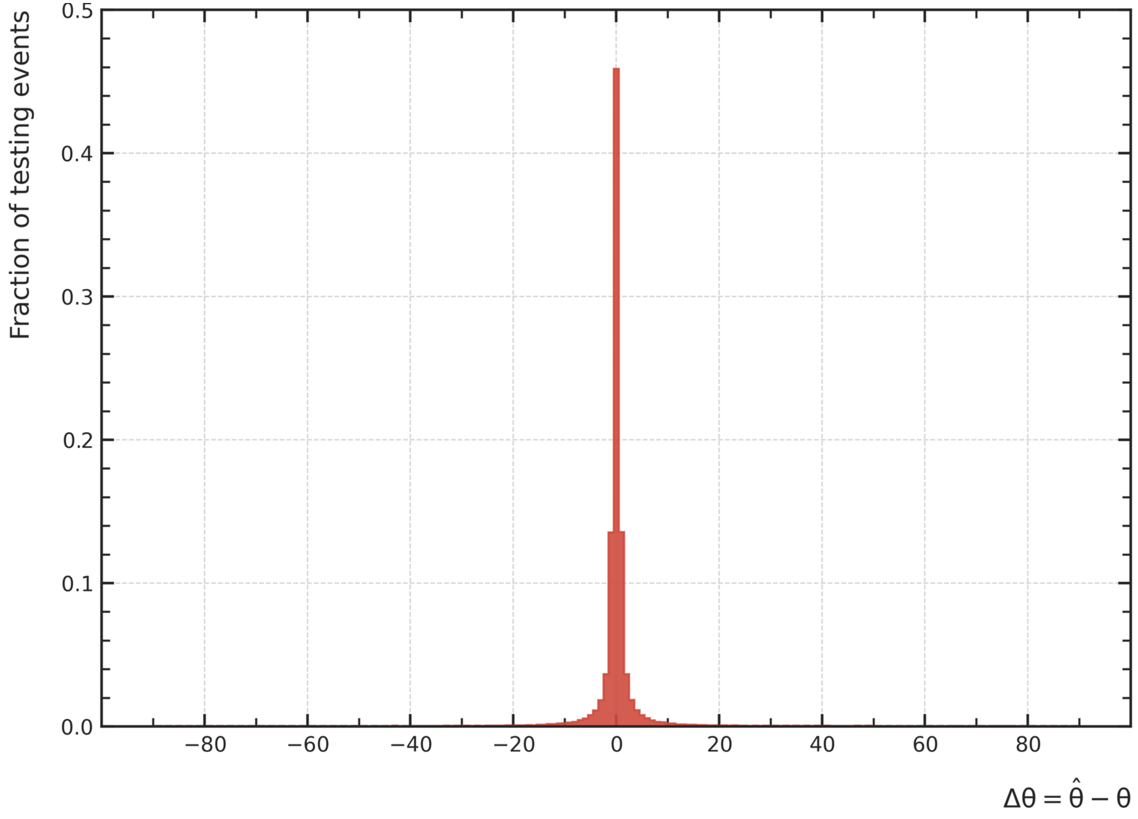


$$\sigma_\Phi = 1.02 \text{ deg}$$

Neural-Network-Based Event Reconstruction

Particle-Track Reconstruction – Results

Theta



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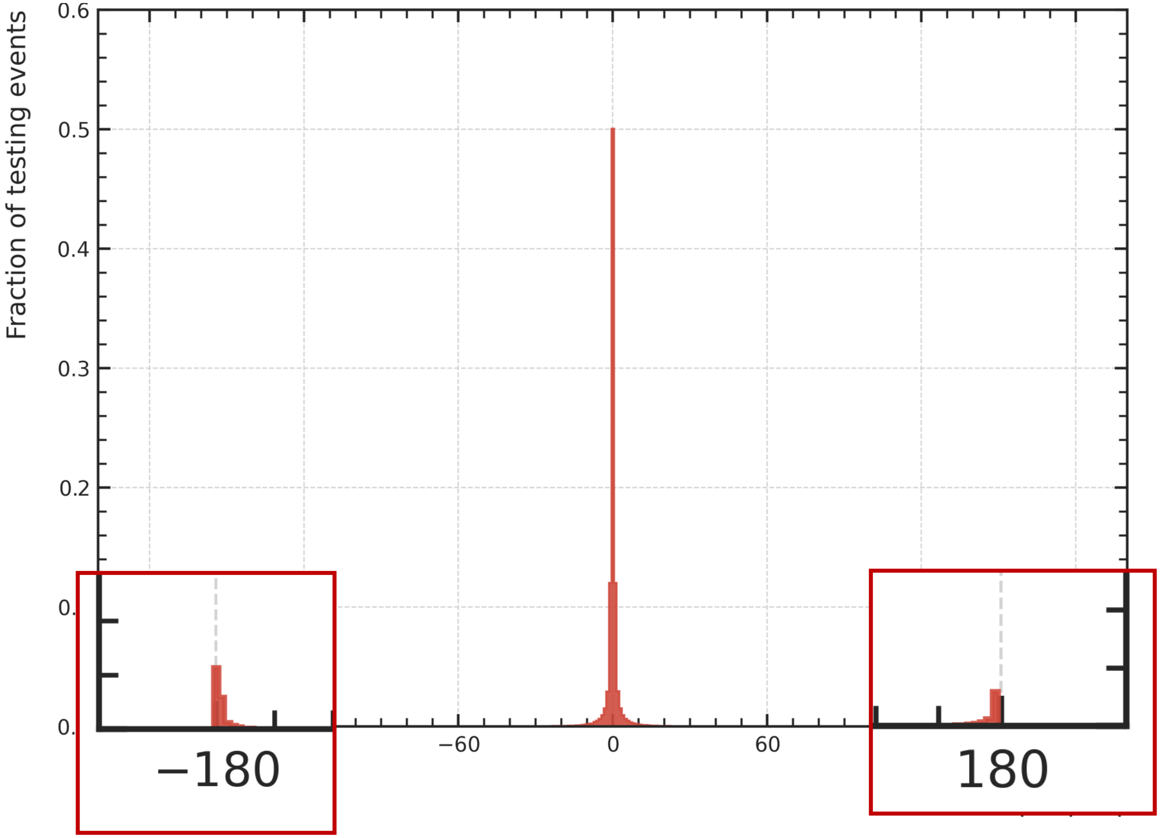

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Neural-Network-Based Event Reconstruction

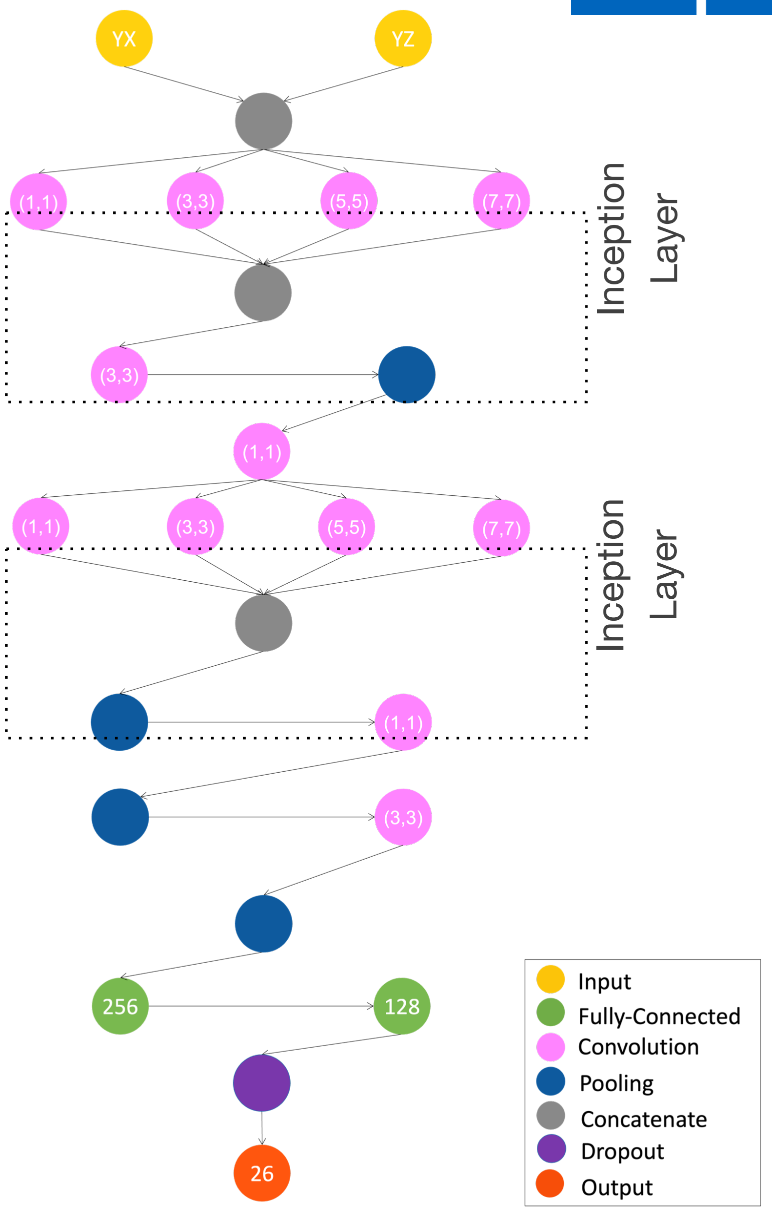
Particle Identification – Network Architecture

- Identification of nuclei of elements from H to Fe

- Increased complexity of the task

  → Multiple inception layers

- Training parameters:
  - Nb. of trainable parameters: 2 million
  - 10M training events
  - 100+ training epochs



Neural-Network-Based Event Reconstruction

Particle Identification – Network Architecture

- Identification of nuclei of elements from H to Fe

- Increased complexity of the task

  → Multiple inception layers

- Training parameters:
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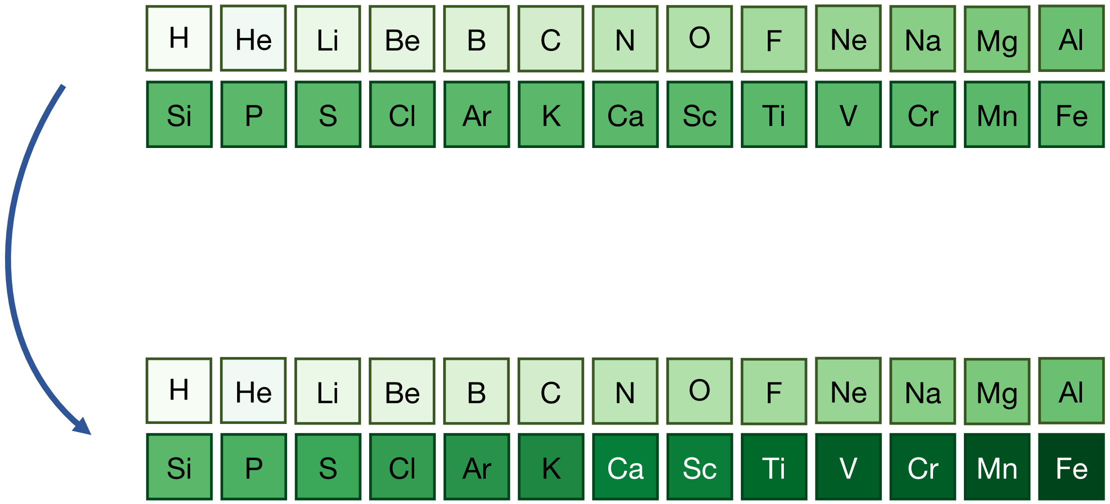
  - 100+ training epochs

- **Two-step classification**

1 Identify lighter ions from H to Al and sort out heavier ions

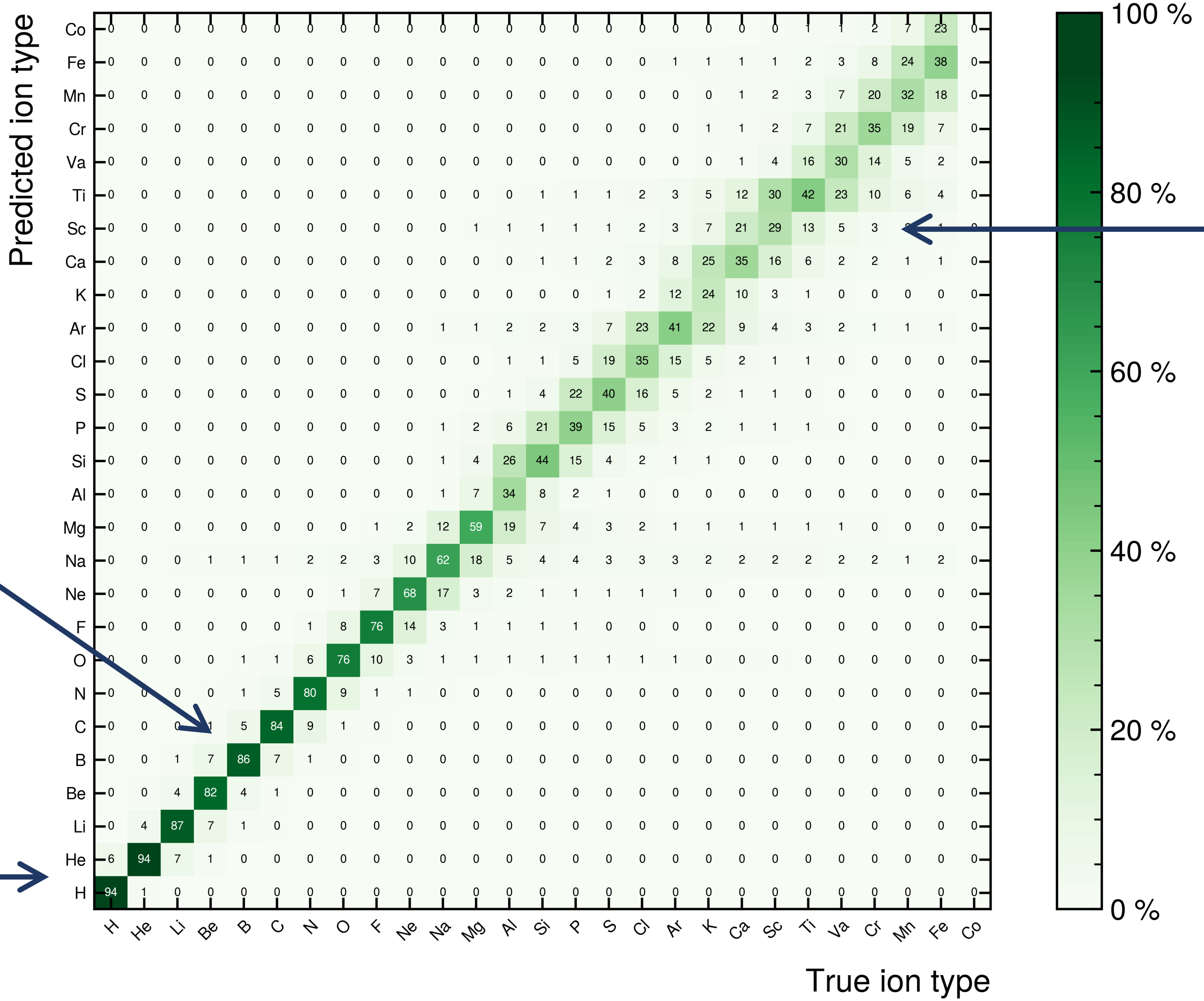


2 Identify heavier ions from Si to Fe with specialized network

Neural-Network-Based Event Reconstruction

Particle Identification – Results

Accuracies



Heavier ions: < 50%

Lighter ions: > 80%

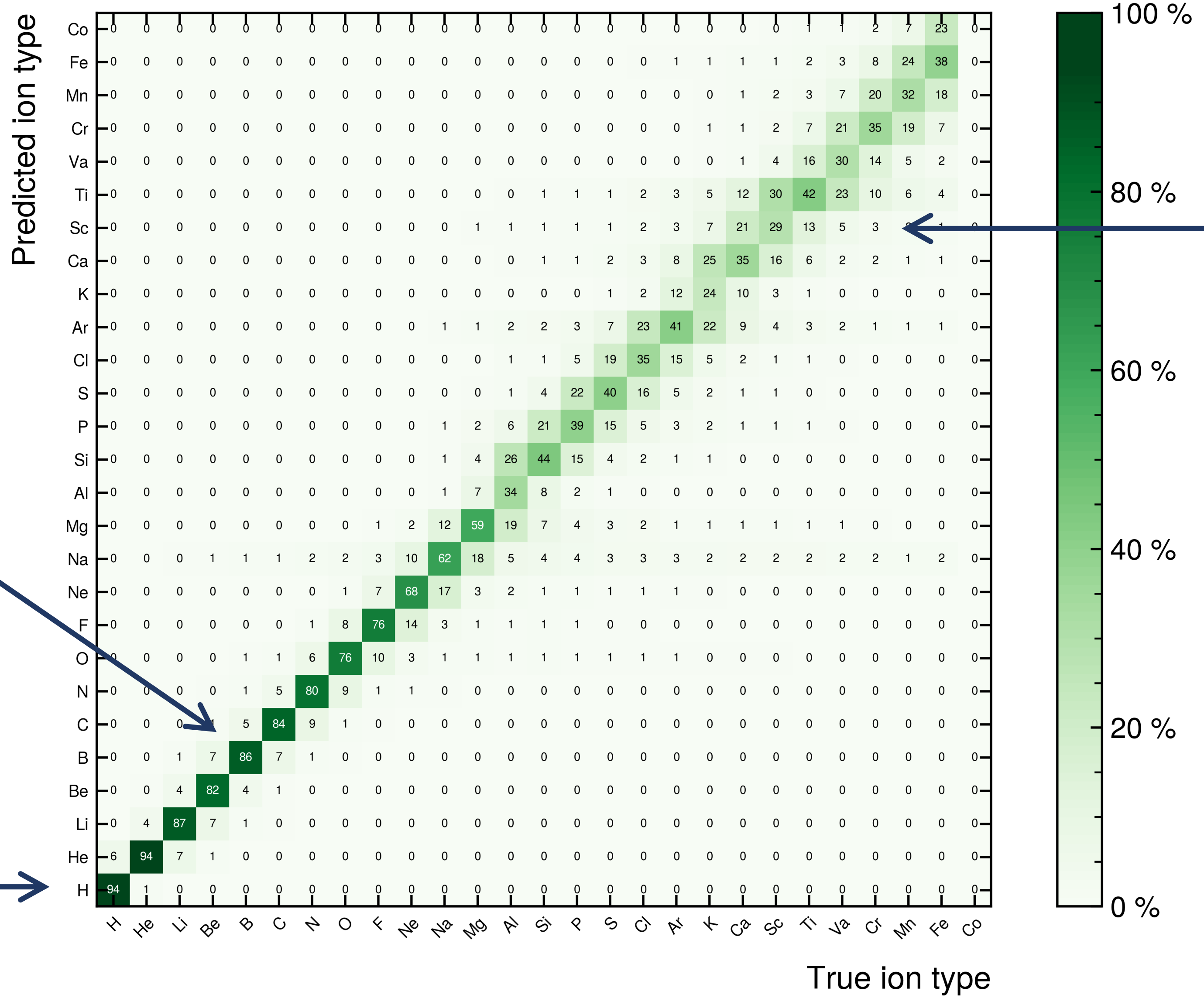
H & He: 94%

Overall: 54%

Neural-Network-Based Event Reconstruction

Particle Identification – Results

Accuracies



Heavier ions: < 50%
Z ± 2: ***> 85%***

Lighter ions: > 80%
Z ± 2: ***> 98%***

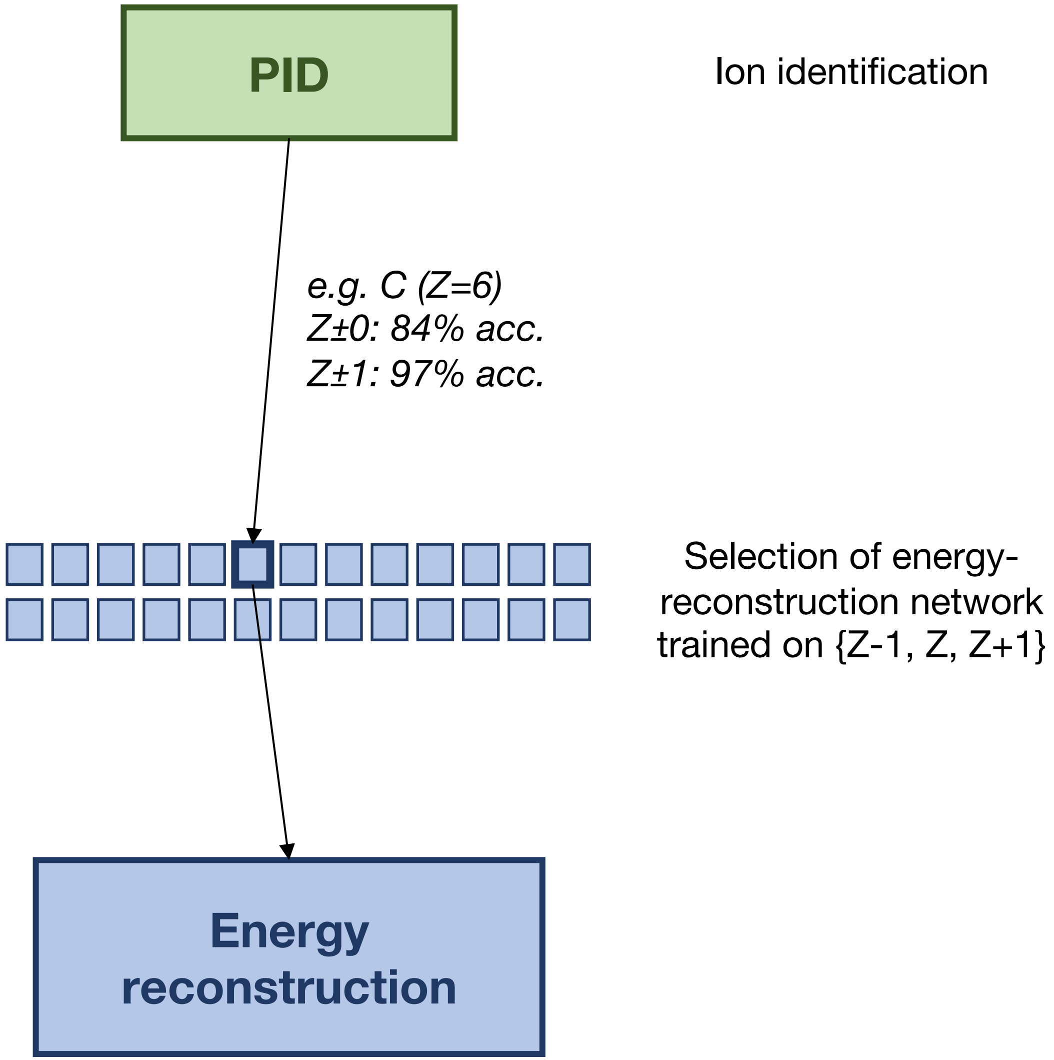
H & He: 94%
Z ± 2: ***99%***

Overall: 54%
Z ± 2: ***90%***

Neural-Network-Based Event Reconstruction

Energy Reconstruction

- Ion-type dependent reconstruction of **energy per nucleon**
- **Energy range** of the particles: 50 MeV/n to 1 GeV/n
- Similar network architecture as for particle identification
- Training parameters:
  - **Regression** task: real-valued energy prediction
  - Nb. of trainable parameters: 2 million
  - 10M training events for PID
  - 1M training events for each energy reconstruction network
  - 100+ training epochs on average

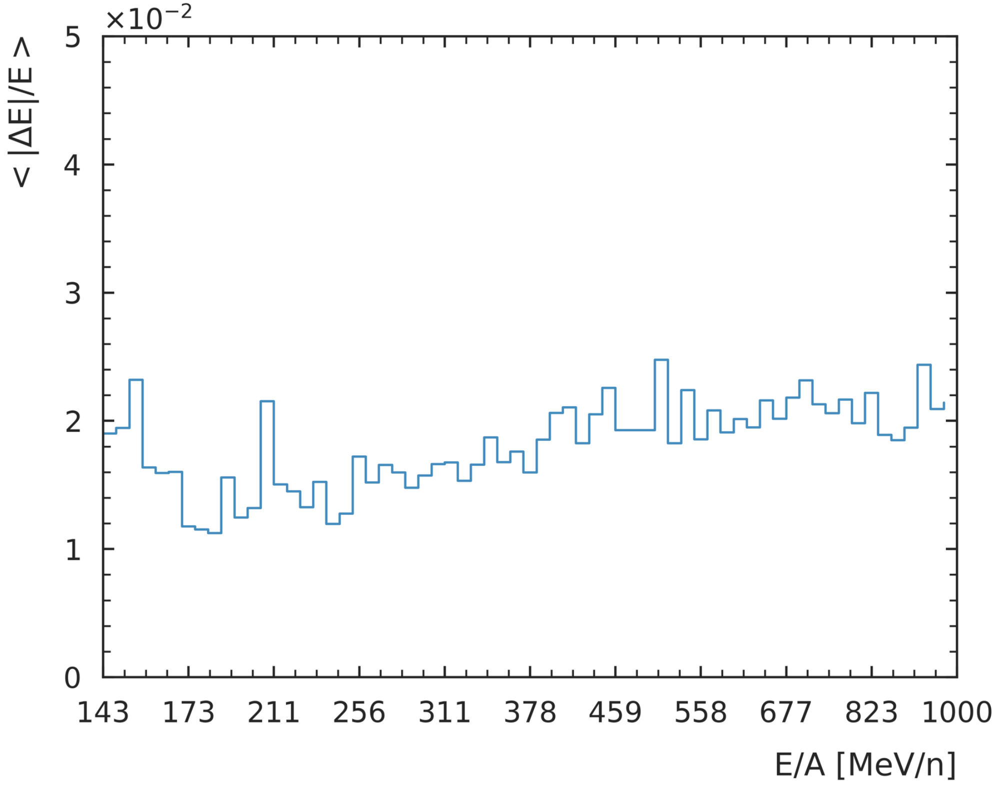


Neural-Network-Based Event Reconstruction

Energy Reconstruction – Results

- Ion-type dependent reconstruction of **energy per nucleon**
- In total, mean energy resolution for each ion type: $< {}^{|\Delta E|}/_{E} > \leq 10\%$

Protons



Conclusion and Outlook

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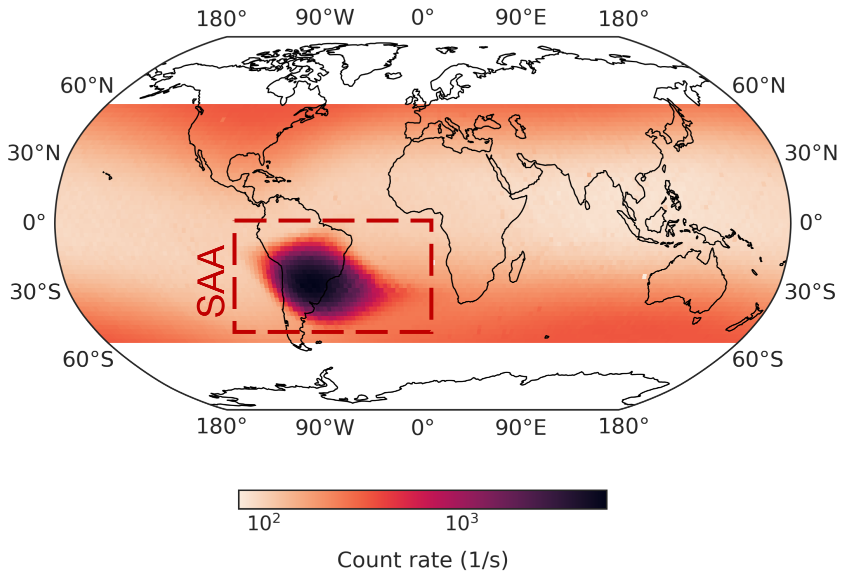
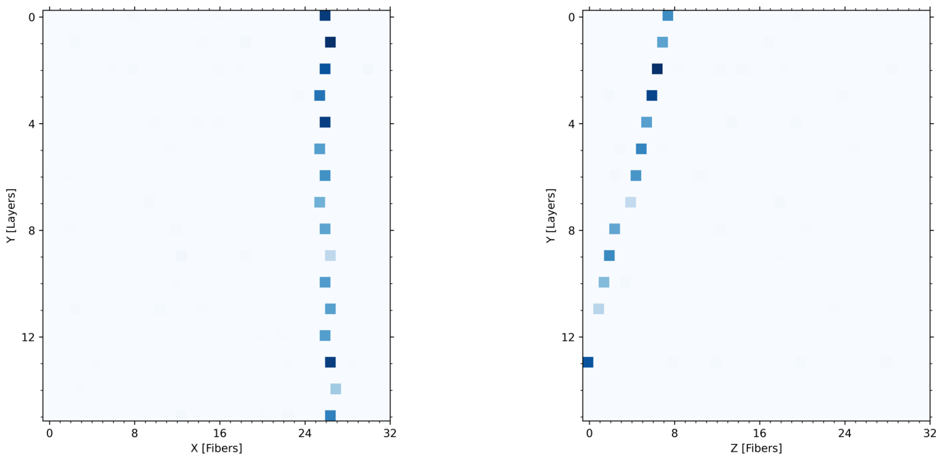
- So far…

  Very promising results for all three reconstruction tasks using simulated data

- But what about real data?
  - Launch of RadMap to the ISS and data taking since Summer 2023
  - On-going steps:
    - First evaluation of networks' performance on real data
    - Understand detector effects and 'noise patterns'
    - Improve simulation and optimize training data based on findings





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