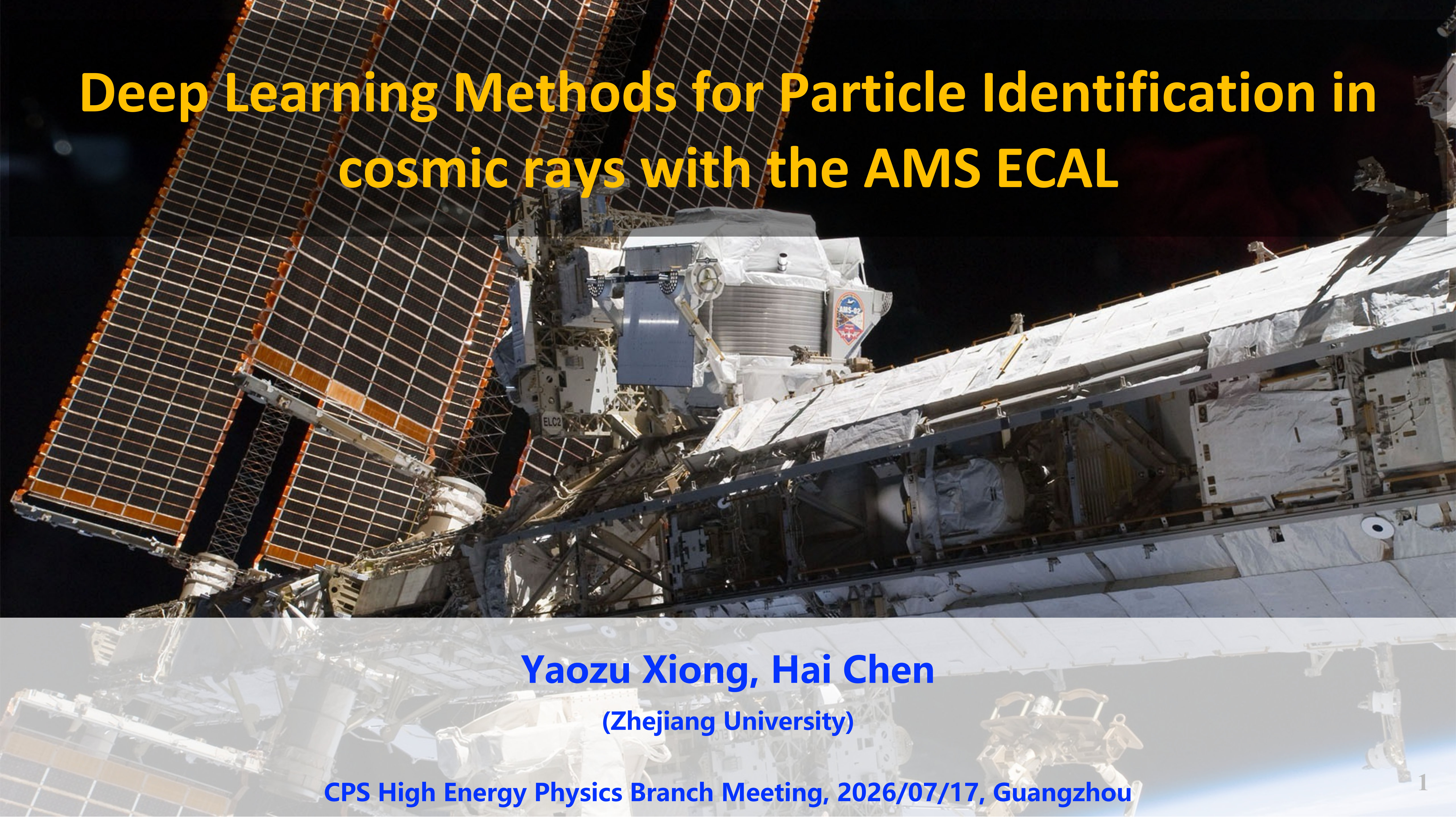

Deep Learning Methods for Particle Identification in cosmic rays with the AMS ECAL

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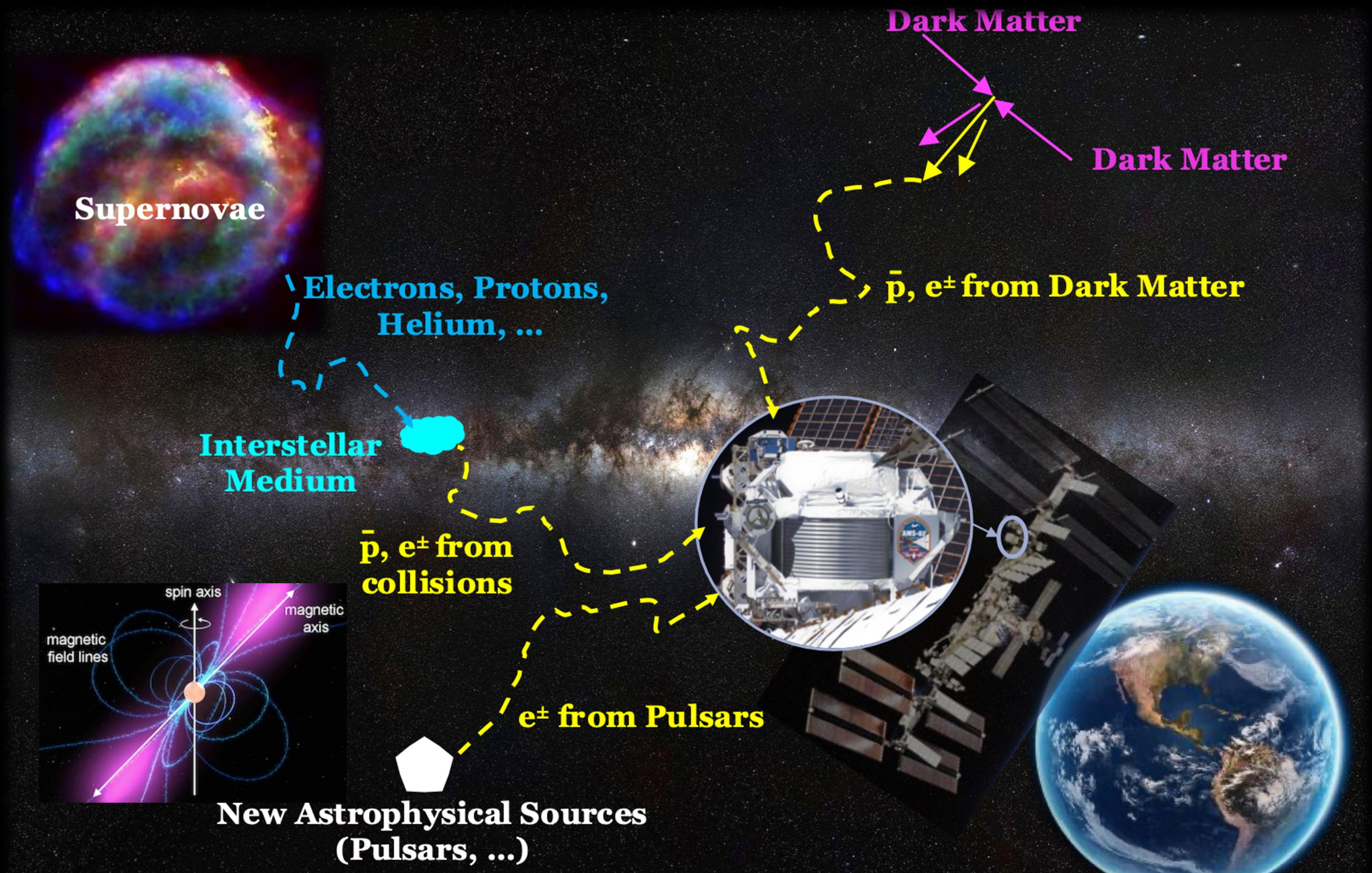
CPS High Energy Physics Branch Meeting, 2026/07/17, Guangzhou

The origins of cosmic electrons and positrons

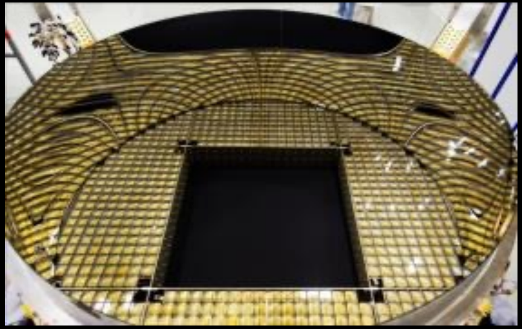


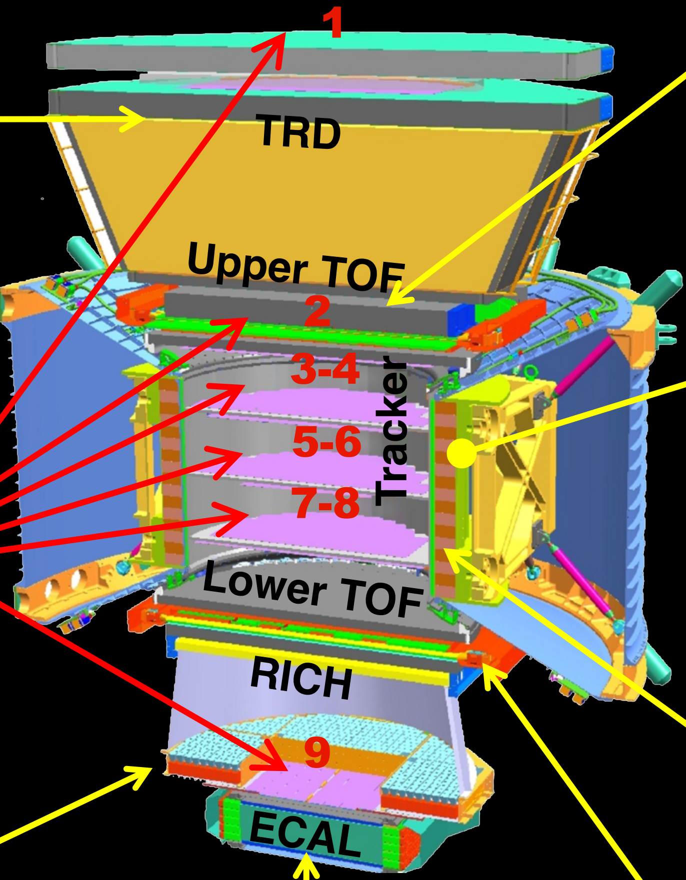
AMS : a unique magnetic spectrometer

Transition Radiation Detector (TRD)
identify e^+, e^-

Silicon Tracker
measure Z, P

Ring Imaging Cerenkov (RICH)
measure Z, E





Electromagnetic Calorimeter (ECAL)
measure E of e^+, e^-

Upper TOF measure Z, E

Magnet identify ±Z, P

Anticoincidence Counters (ACC)
reject particles from the side

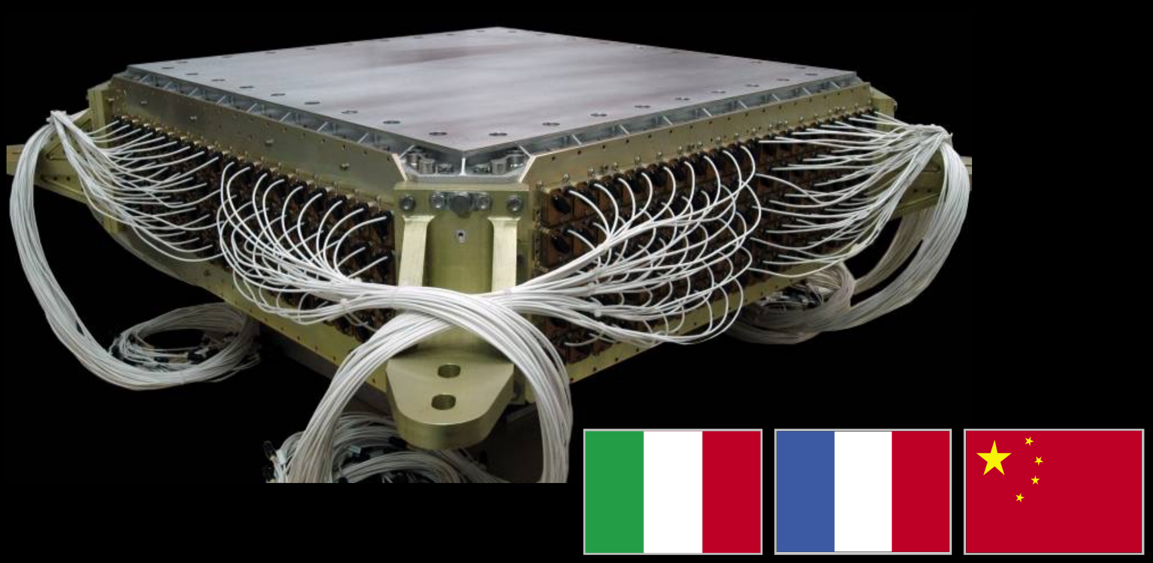
Lower TOF measure Z, E

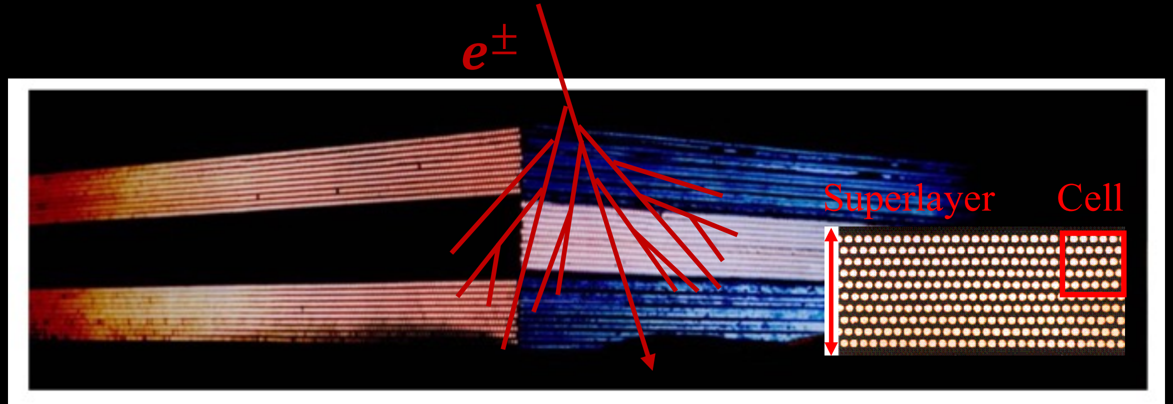
A 3D Imaging Electromagnetic Calorimeter

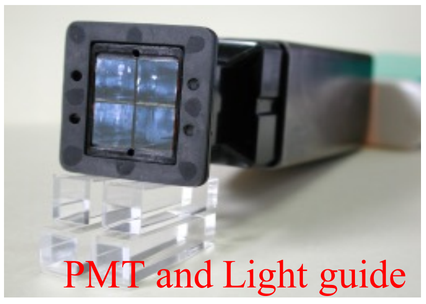
ECAL provides precise three-dimensional measurements of the directions and energies of electrons and positrons up to TeV energy range.

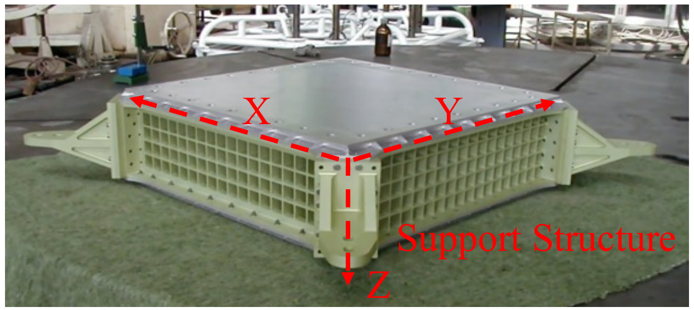
- It consists of 9 superlayers of lead foils and scintillating fibers, arranged alternately parallel to the x and y axis.
- Each superlayer is consisted by two layers and read out by 36 PMTs. Each PMT has four anodes, and each anode covers an area of 9 × 9 mm^2 called "cell".

In total, ECAL has 18x72 cells.





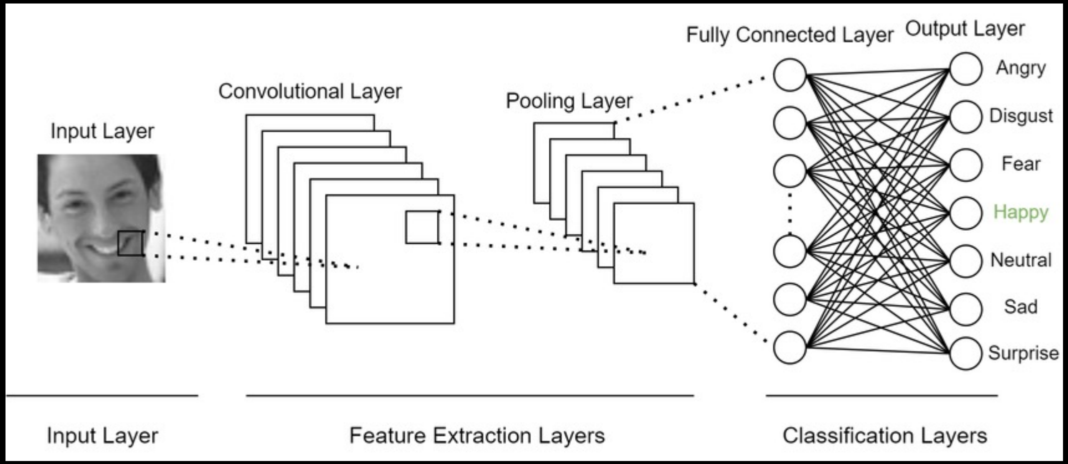




Deep Learning in ECAL

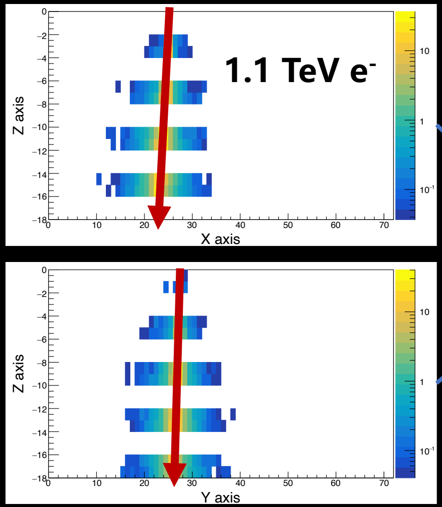
Deep learning can be used for particle classification in ECAL images, analogous to its use in computer vision.

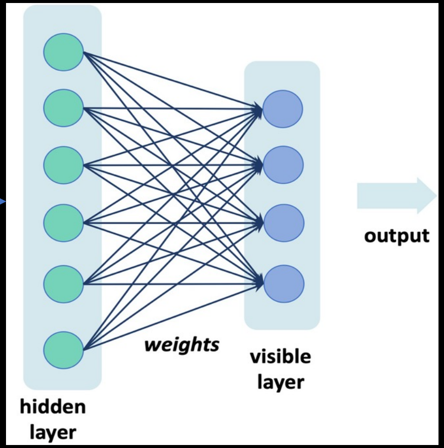
Input:
A smiling face image



Output:
Facial emotion classification

Input:
ECAL image

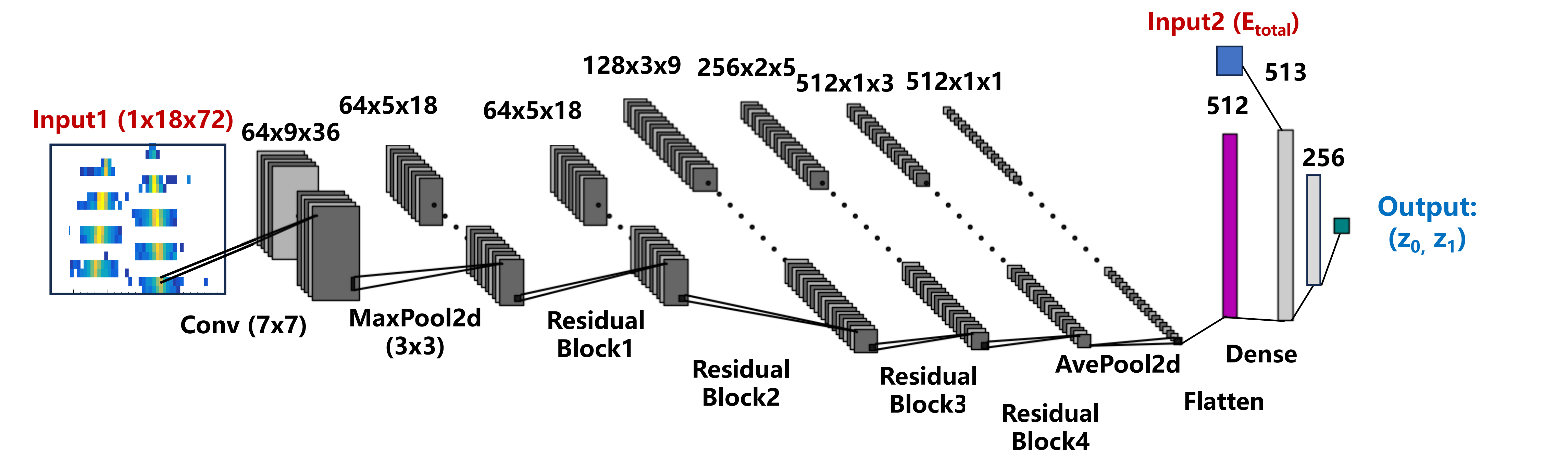




Output:
E/P Classifier

The ResNet Model

- Residual neural networks, or ResNets, are state-of-the-art deep learning architectures widely used in computer vision, with excellent performance across diverse tasks.
- For the 18x72 ECAL energy deposition format, the ResNet18 model is chosen due to its lightweight architecture, which is composed of 17 convolutional layers and two single dense layers.



Loss Function Definition

- **Challenge:** abundant Monte Carlo simulation is available, but pure electron and positron samples in ISS data are limited.
- We utilize a **weighted Cross-Entropy** loss function for model learning:

$$Loss = -\frac{1}{N}\sum_{i} \log \frac{w_E \, e^{z_{i,y}}}{e^{z_{i,0}} + e^{z_{i,1}}}$$

  - ✓ (z_0, z_1) are the output of the ResNet model;
  - ✓ y is the truth value at 0 (electron signal) or 1 (proton background) given by the event label;
  - ✓ $p_0 = \frac{e^{z_0}}{e^{z_0}+e^{z_1}}$ is the *Softmax probability* for each event to be an electron signal;
  - ✓ w_E is the weight factor which is determined by the relative ratio of MC/ISS events in the training dataset.

Dataset

- The datasets are divided into four energy bins from 100 GeV to 1600 GeV
- The ISS data samples are selected with strict TRD and Tracker cuts to achieve high purity
- To reduce the performance difference between MC and ISS, mixed MC-ISS samples are used for training.

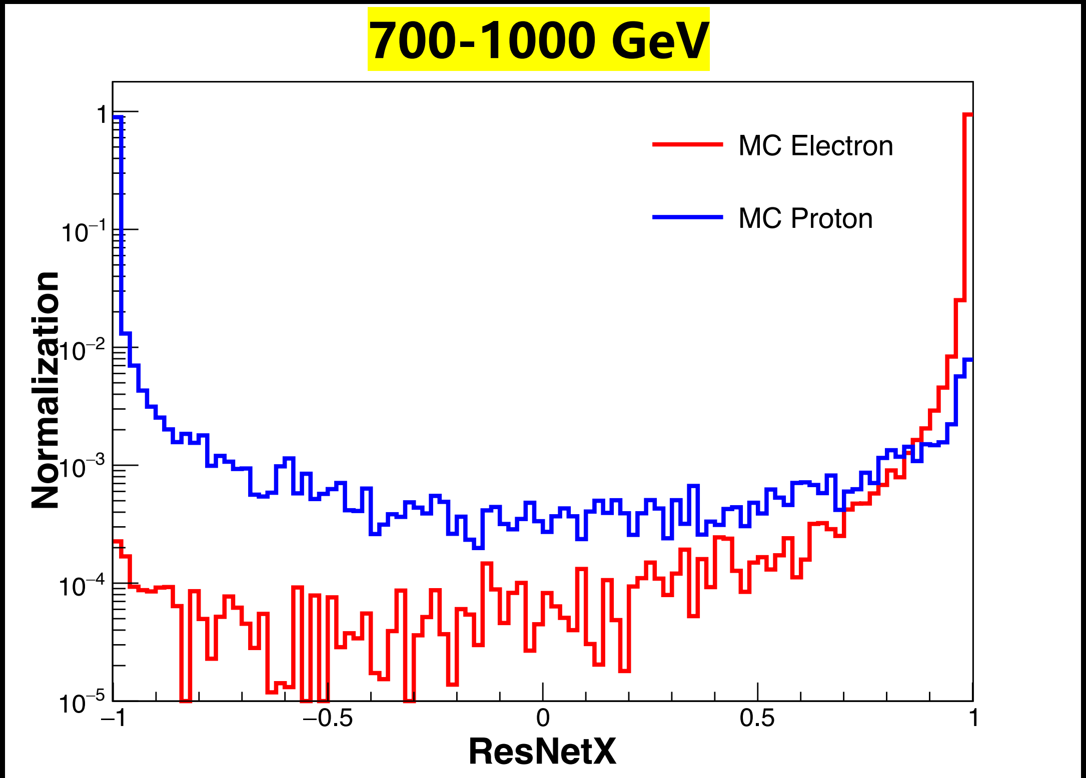
	Training				Testing			
Energy (GeV)	Electron MC	Electron ISS	Proton MC	Proton ISS	Electron MC	Electron ISS	Proton MC	Proton ISS
100-200	$1.3*10^4$	$2.0*10^3$	$3.0*10^3$	$1.2*10^4$	$5.8*10^5$	$3*10^3$	$9.8*10^5$	$1.7*10^5$
200-400	$1.3*10^4$	$2.0*10^3$	$3.0*10^3$	$1.2*10^4$	$6.1*10^5$	$3*10^3$	$9.3*10^5$	$5.0*10^4$
400-800	$1.3*10^4$	$4.0*10^2$	$3.0*10^3$	$1.2*10^4$	$6.1*10^5$	$6*10^2$	$8.3*10^5$	$1.3*10^4$
800-1600	$1.3*10^4$	60	$3.0*10^3$	$1.2*10^4$	$5.5*10^5$	89	$6.2*10^5$	$8.0*10^3$

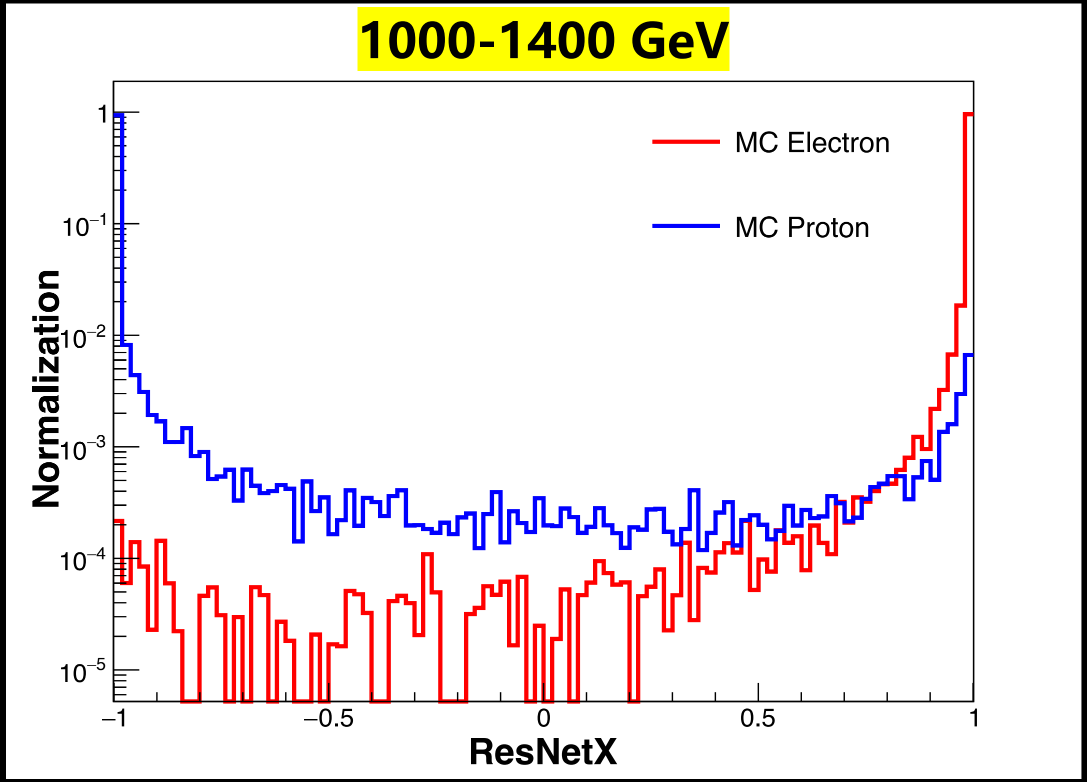
Model Performance with MC

- We define the final estimator as:

$$\mathbf{ResNetX} = \frac{e^{Z_0} - e^{Z_1}}{e^{Z_0} + e^{Z_1}}$$

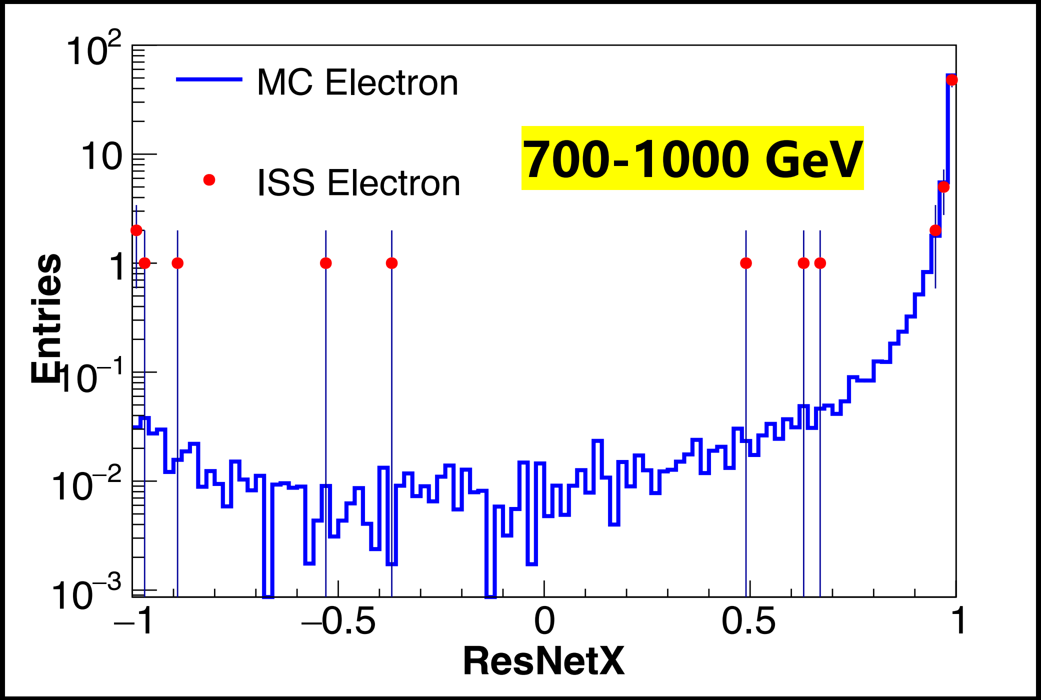
- We firstly use Monte Carlo simulation as performance estimation.

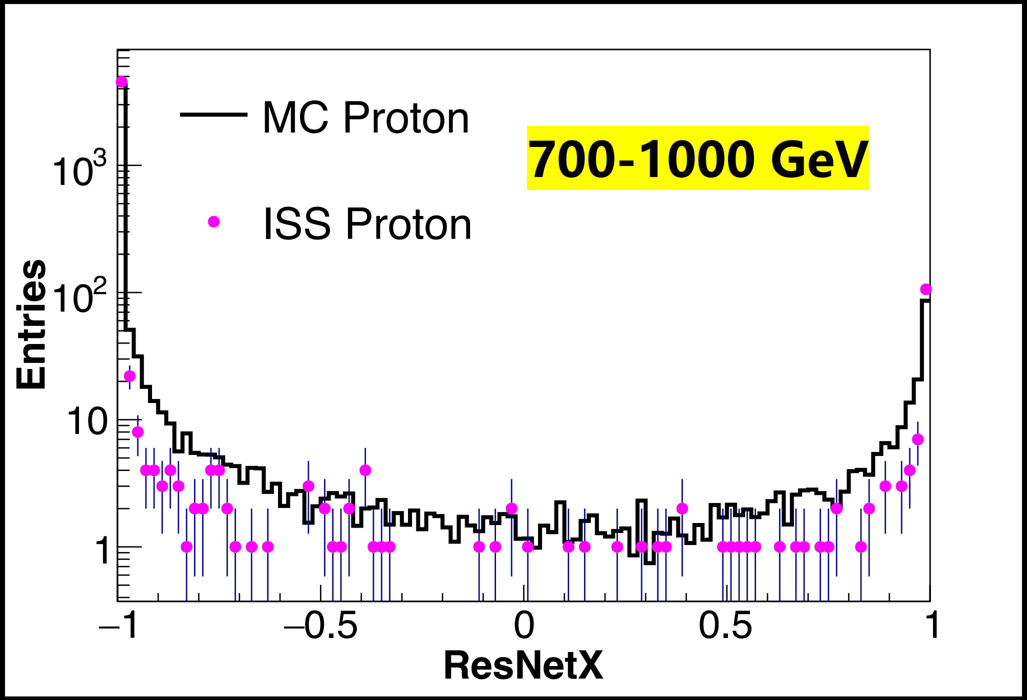




ISS and MC Consistency

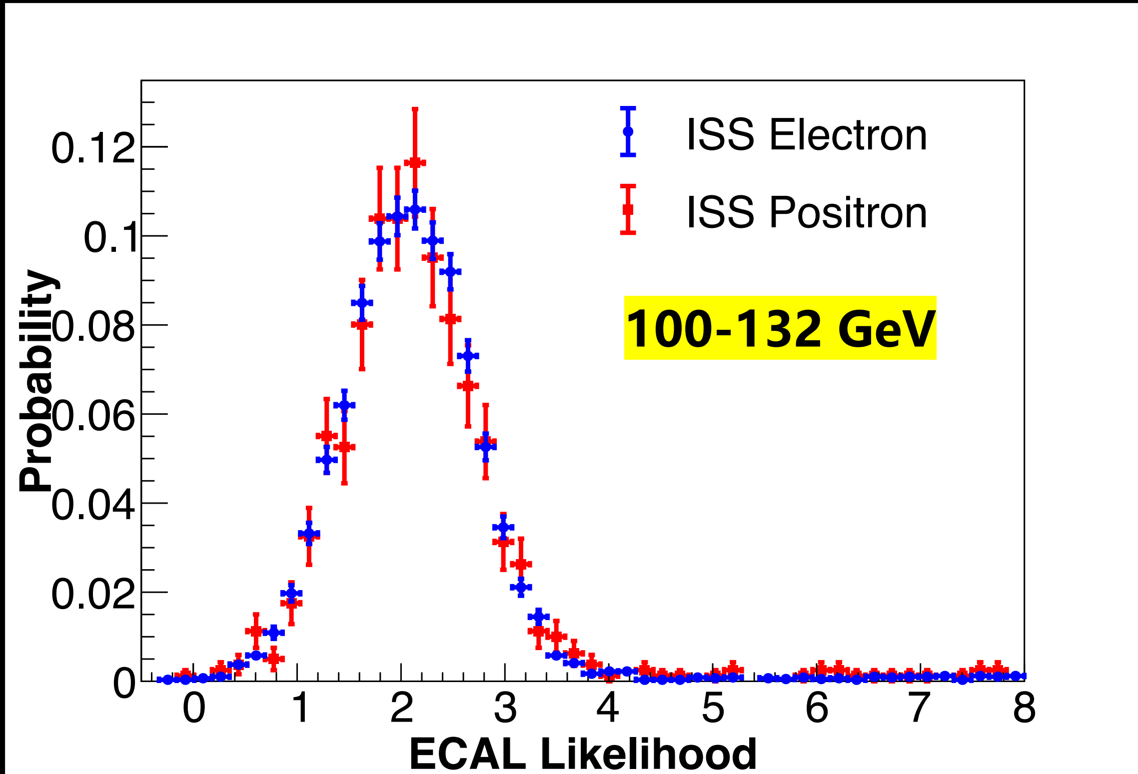
- The available ISS electron and proton samples are limited by statistics.
- Within statistical uncertainties, MC and ISS electron samples exhibit good agreement at TeV energies.
- For ISS electrons, residual proton background from the control-sample selection is visible in the left panel.

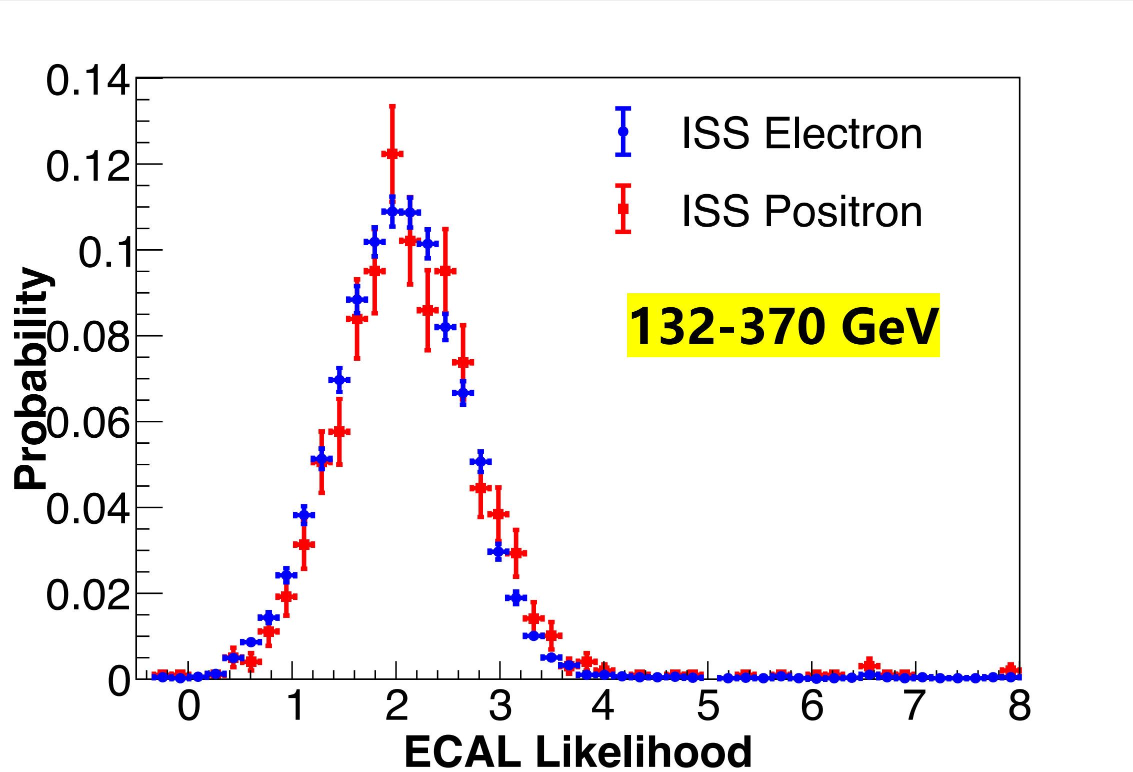




Performance with ISS Electron/Positron

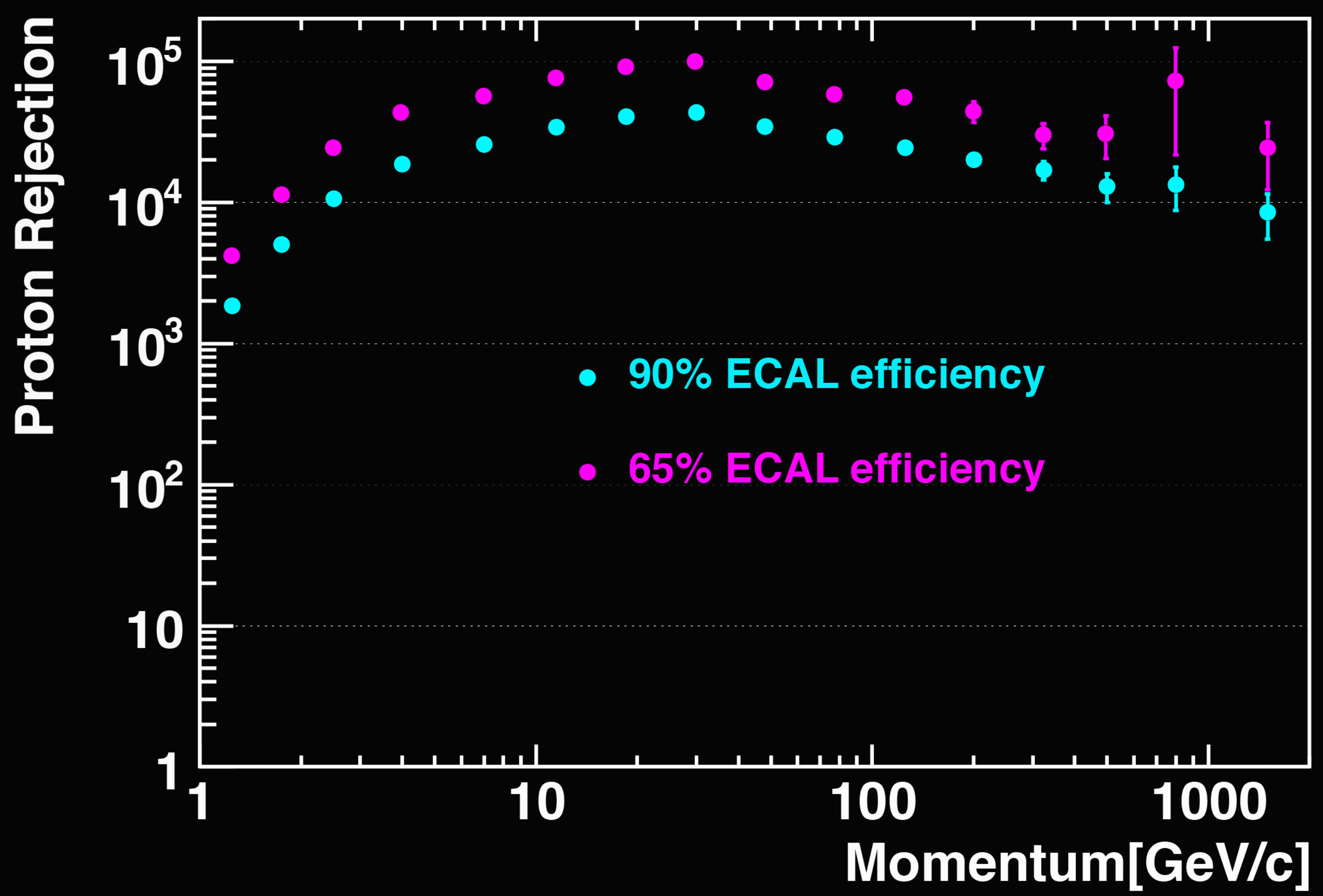
- The ResNetX selection enables high-purity ISS electron and positron samples to be selected;
- The resulting distributions show excellent consistency between the two charge signs.





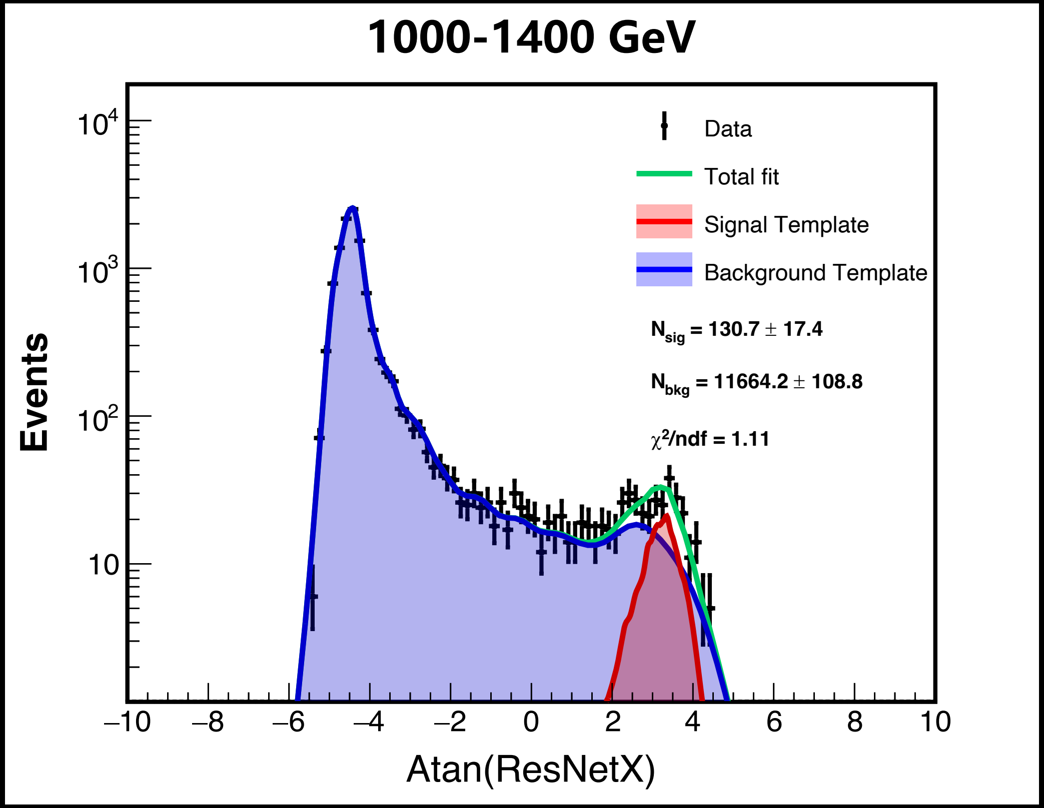
Model Performance

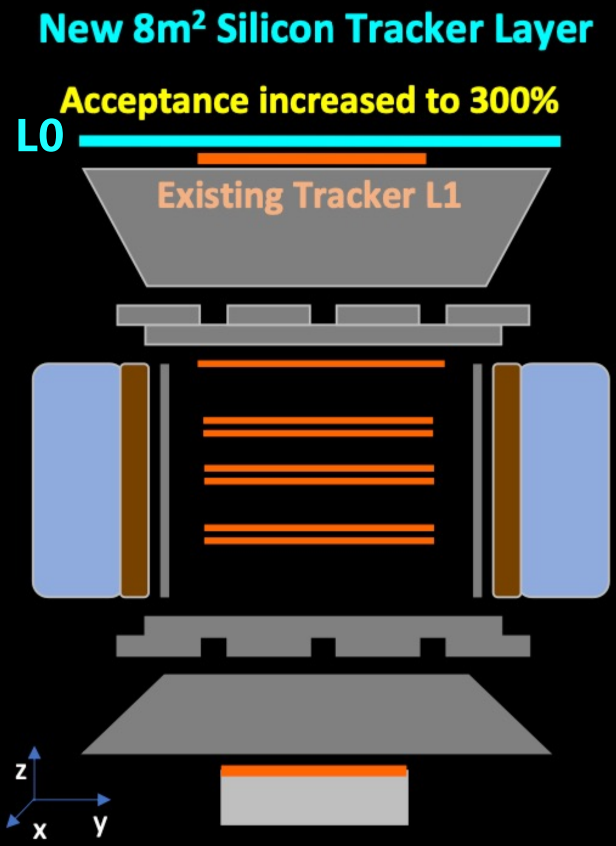
- The rejection ability as a function of energy



Applications in Lepton Analysis

- In the 1–1.4 TeV energy bin, ResNetX clearly separates signal events from proton background, enabling future studies at higher energies;
- For events with large incident angles, the conventional three-dimensional shower-fit method becomes computationally inefficient, whereas the deep-learning approach remains robust.





Summary

- Cosmic-ray electron and positron measurements are essential for understanding cosmic-ray origin, dark matter, and antimatter.
- At TeV energies, limited signal statistics and overwhelming proton background require highly efficient particle identification.
- We developed ResNetX, a deep-learning-based tool, which shows excellent performance compared with conventional estimators, providing complementary capability for proton rejection.
- This method can be applied after the upcoming AMS upgrade.

Thank you for your attention!