Funded by the European Union
European Research Council

V Gravi-Gamma-Nu Workshop 2024

AI for cosmic ray detection in space at high-energy frontier

Andrii Tykhonov
UNIVERSITÉ DE GENÈVE

Disclaimer:

This talks is NOT aimed as a review of AI in the field. It is heavily biased by presenter's own research experience, focused on DAMPE and HERD experiments.

Science motivated:

We do not aim at AI for sake of AI. We ask ourselves first – what do we need to achieve with AI in terms of science?

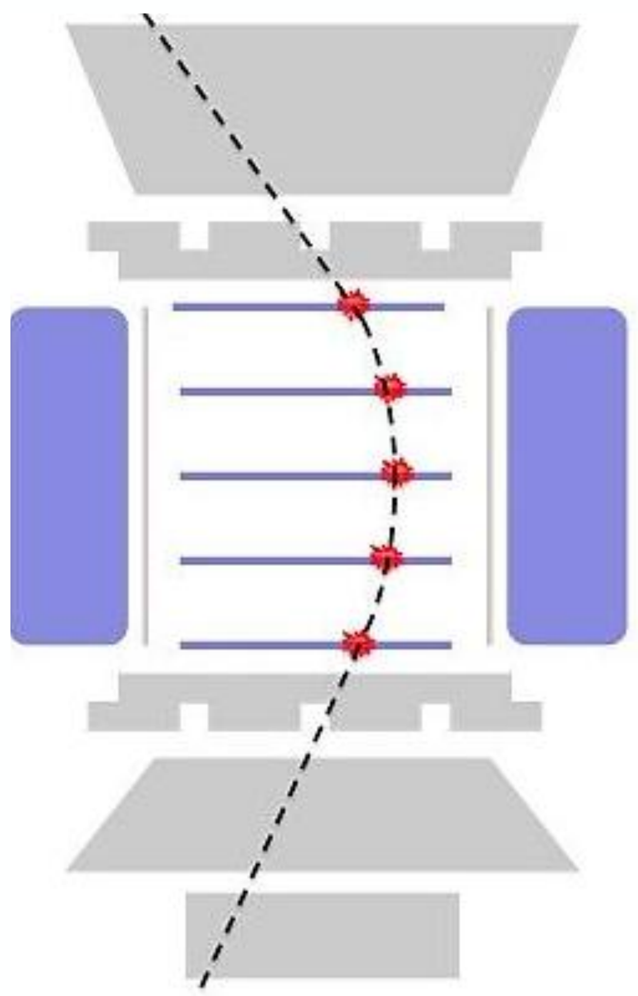
Part I: Cosmic Ray Detection in Space at High Energies — Rationale for AI and (some) Motivation

Cosmic Ray Detection in Space

Magnetic Spectrometers

- **PAMELA**: Payload for Antimatter Matter Exploration and Light-nuclei Astrophysics (**2006**)
- **AMS-02**: Alpha Magnetic Spectrometer (launch to ISS **2011**)

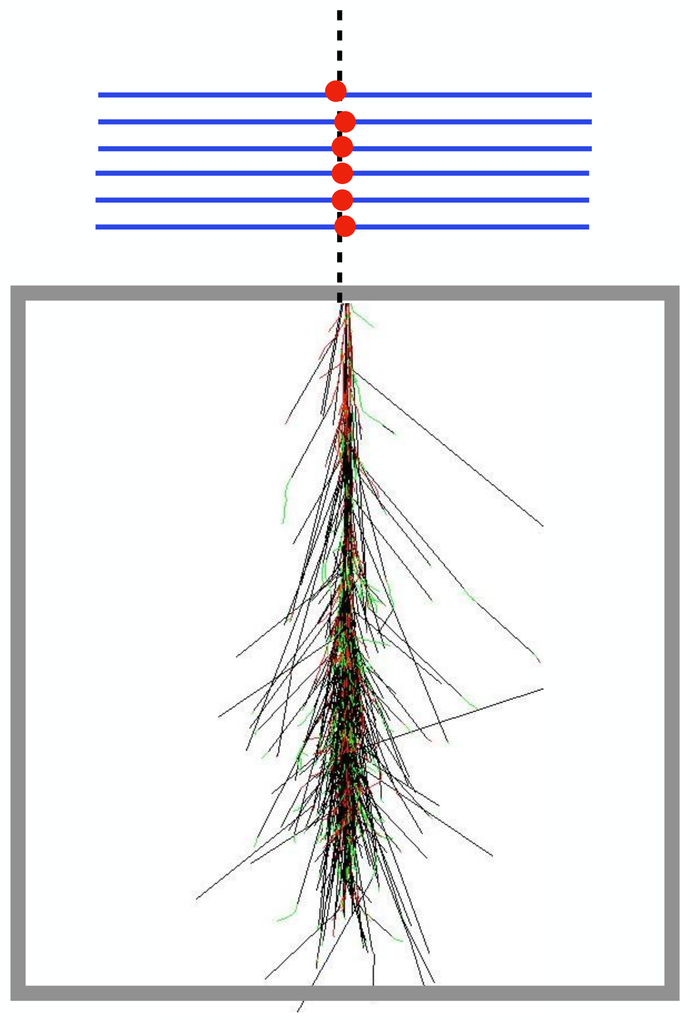
… difficult to go beyond few TeV with spectrometers



Calorimeters

- **CALET**: Calorimetric Electron Telescope (launch **2015**)
- **ISS-CREAM**: on ISS since **2017**
- **DAMPE**: DArk Matter Particle Explorer (launch **2015**)
- **HERD**: High Energy cosmic Radiation Detection experiment (~**2028**)

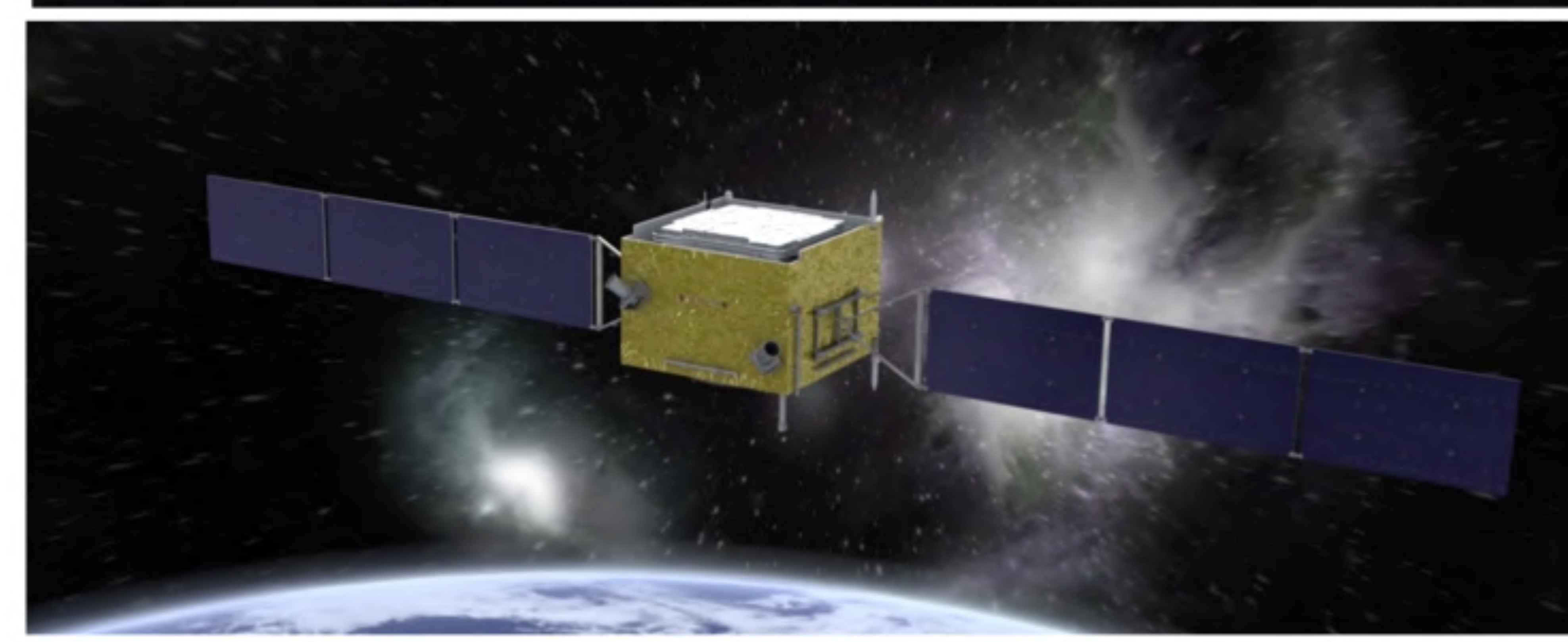
mostly covered in this talk…

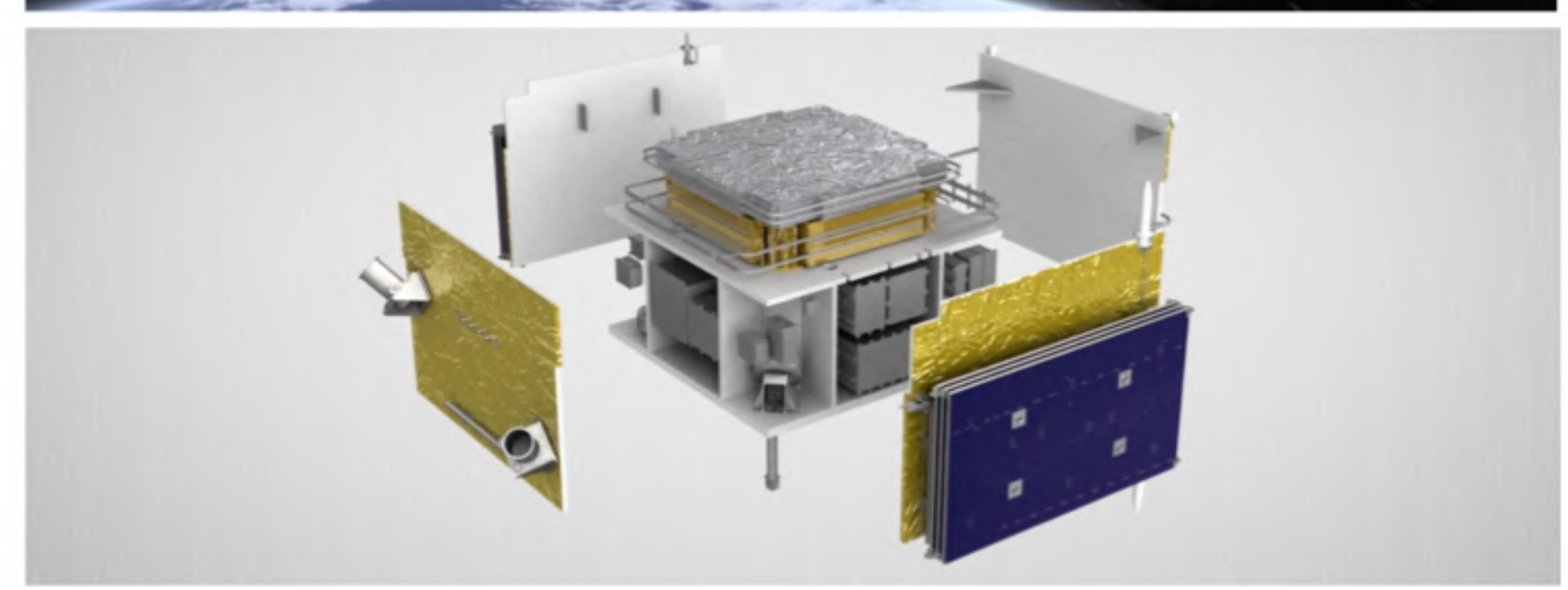


DArk Matter Particle Explorer (DAMPE)

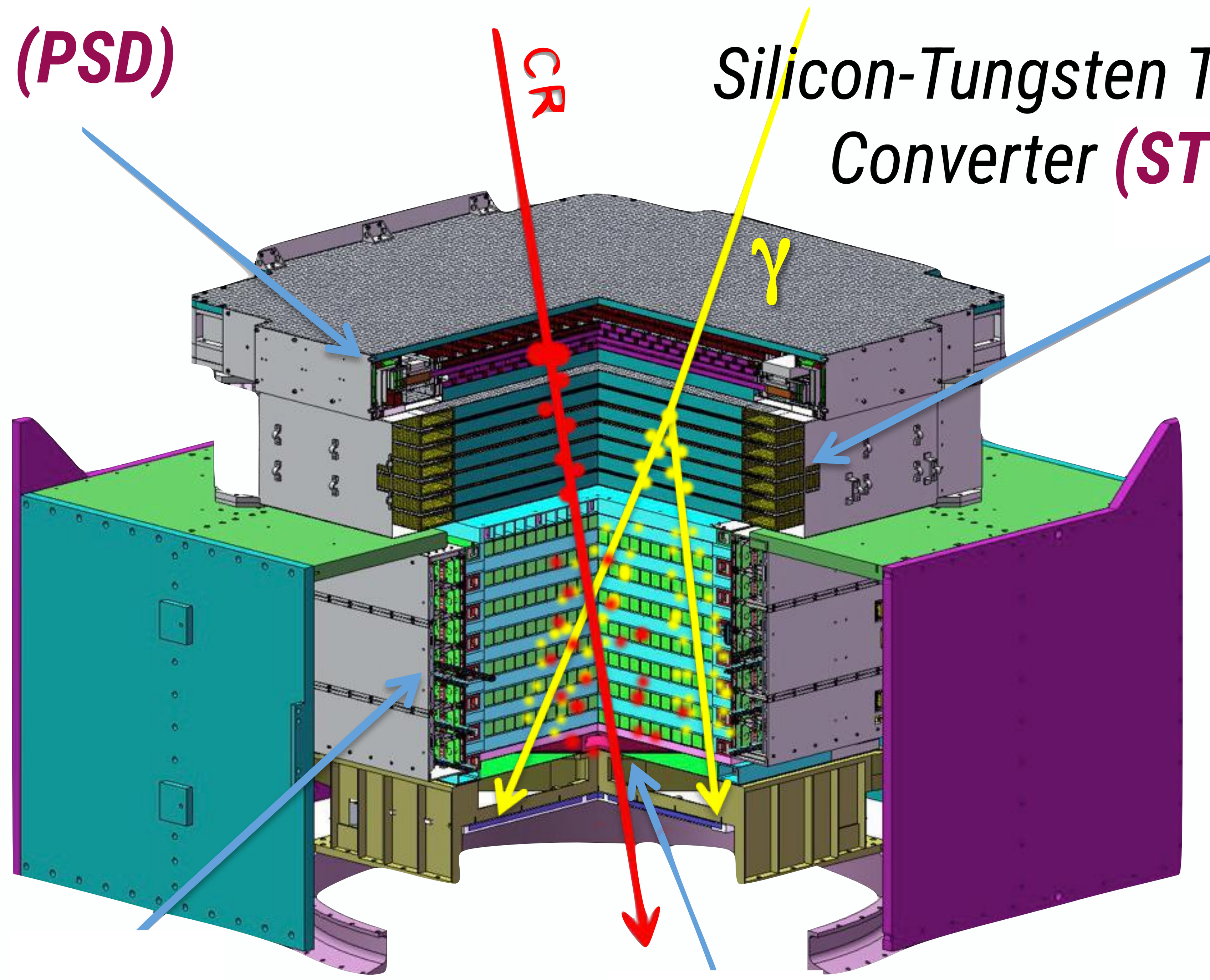
- Launched in **Dec 2015**
- Orbit: sun-synchronous, **500 km**
- Period: **95 min**
- Payload: **1.4 Tonn**
- Power: ~ **400 W**
- Data: ~ **12 GByte / day**

Collaboration





DArk Matter Particle Explorer (DAMPE)



PSD

- Z identification up to *Ni* (Z=28)
- γ anti-coincidence signal

STK

- Position solution ***~50 micron***
- γ-ray angular resolution ***0.5°–0.1°***
- Absolute Charge (Z) identification

BGO

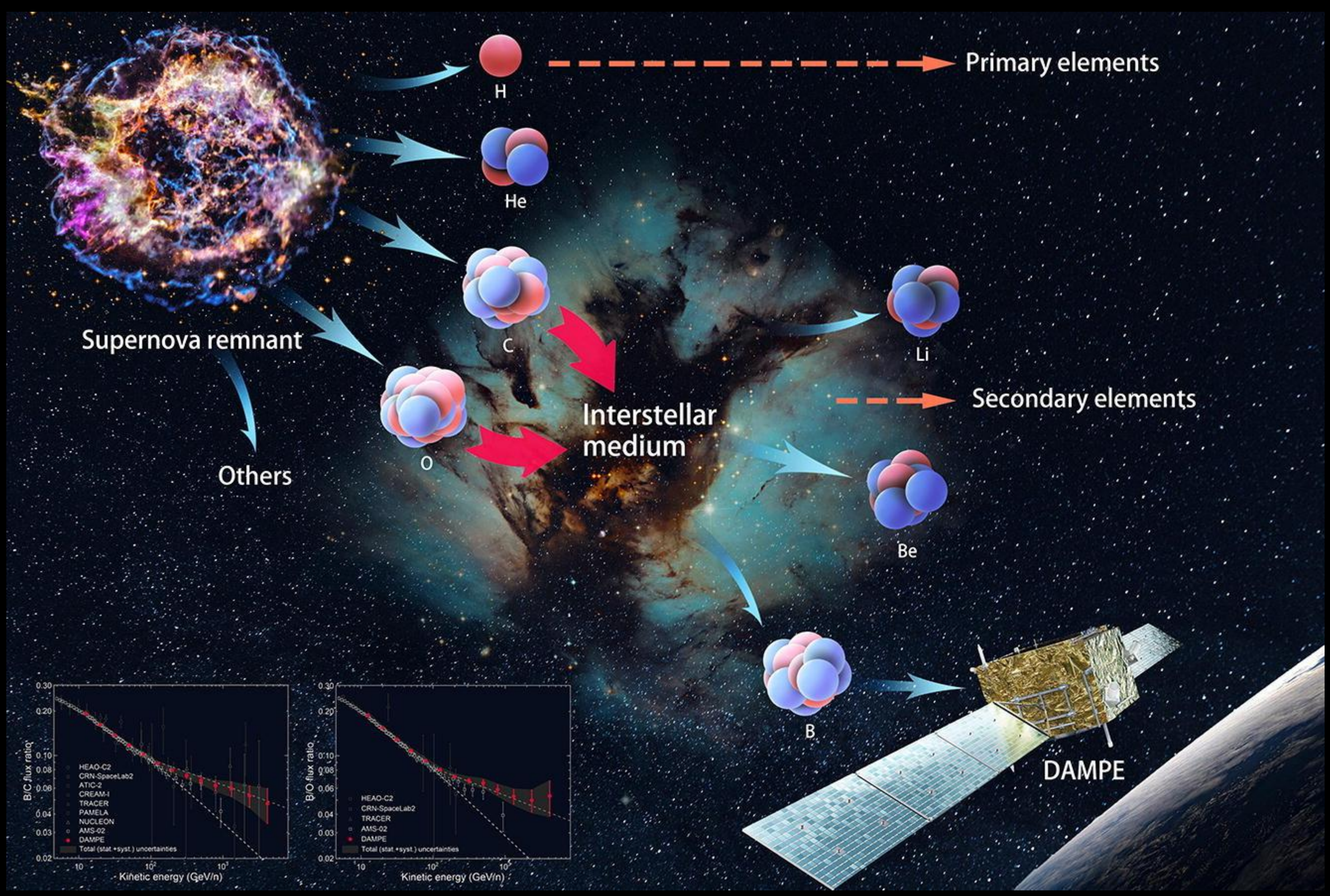
- 31 X_0 – thickest in space
- e/γ detection **GeV – 10 TeV**
- *p*/ions: **50 GeV – PeV**

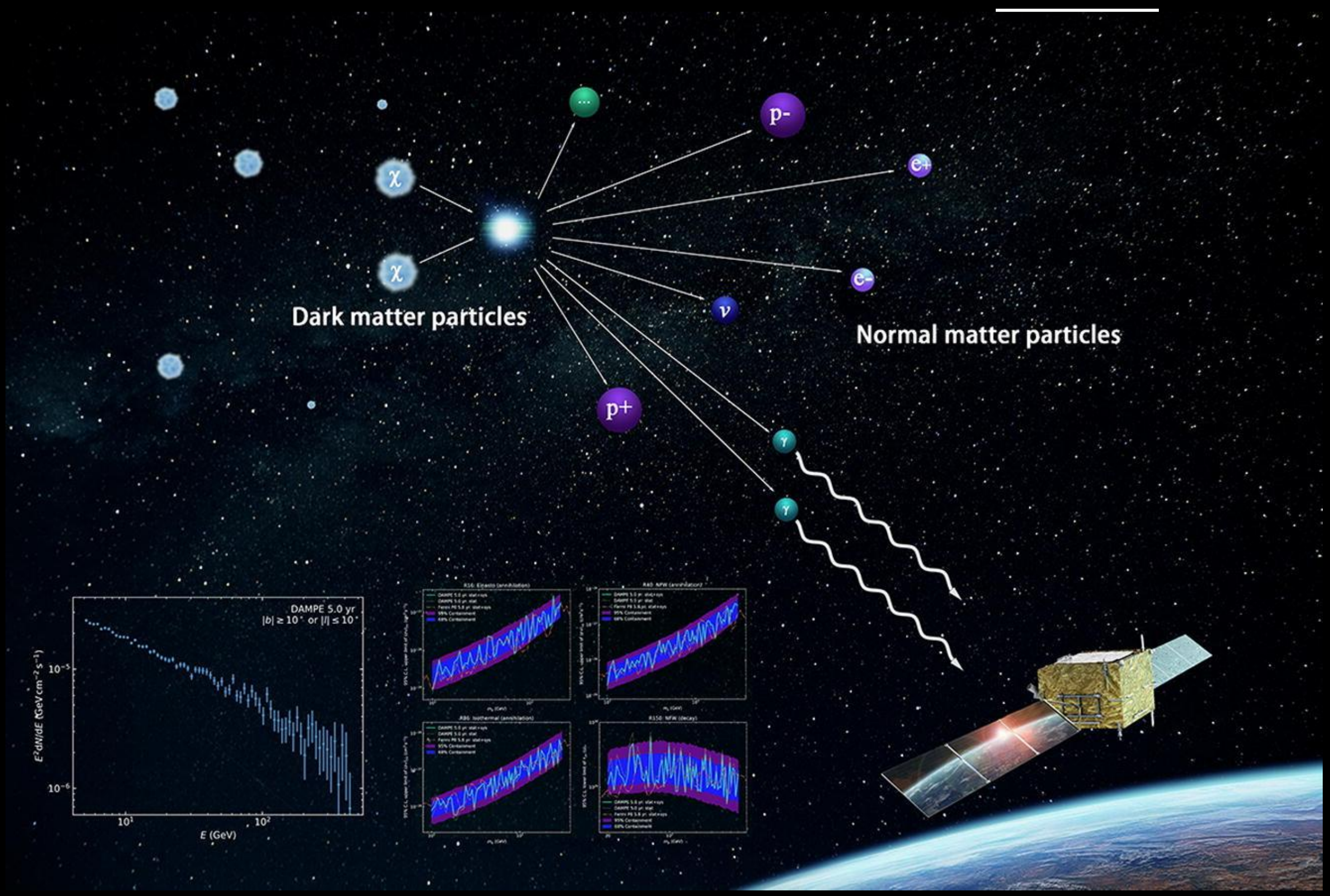
NUD

- Additional e/p rejection power

DAMPE on orbit

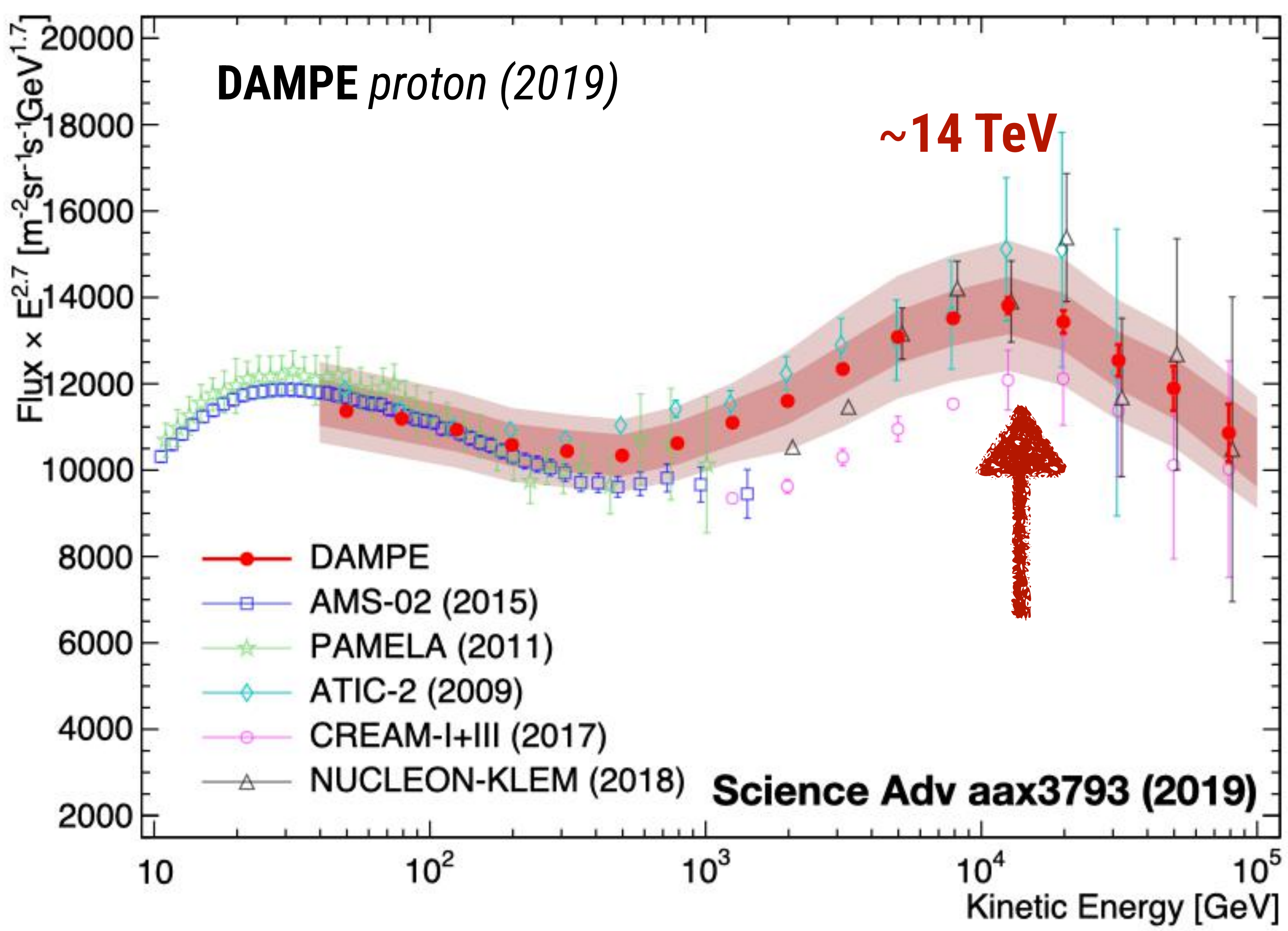
- Many exciting results published since 2015: electrons, protons, helium, B/C and B/O, γ-rays, solar physics
- More in progress (C,O, Ne-Mg-Si, Fe)

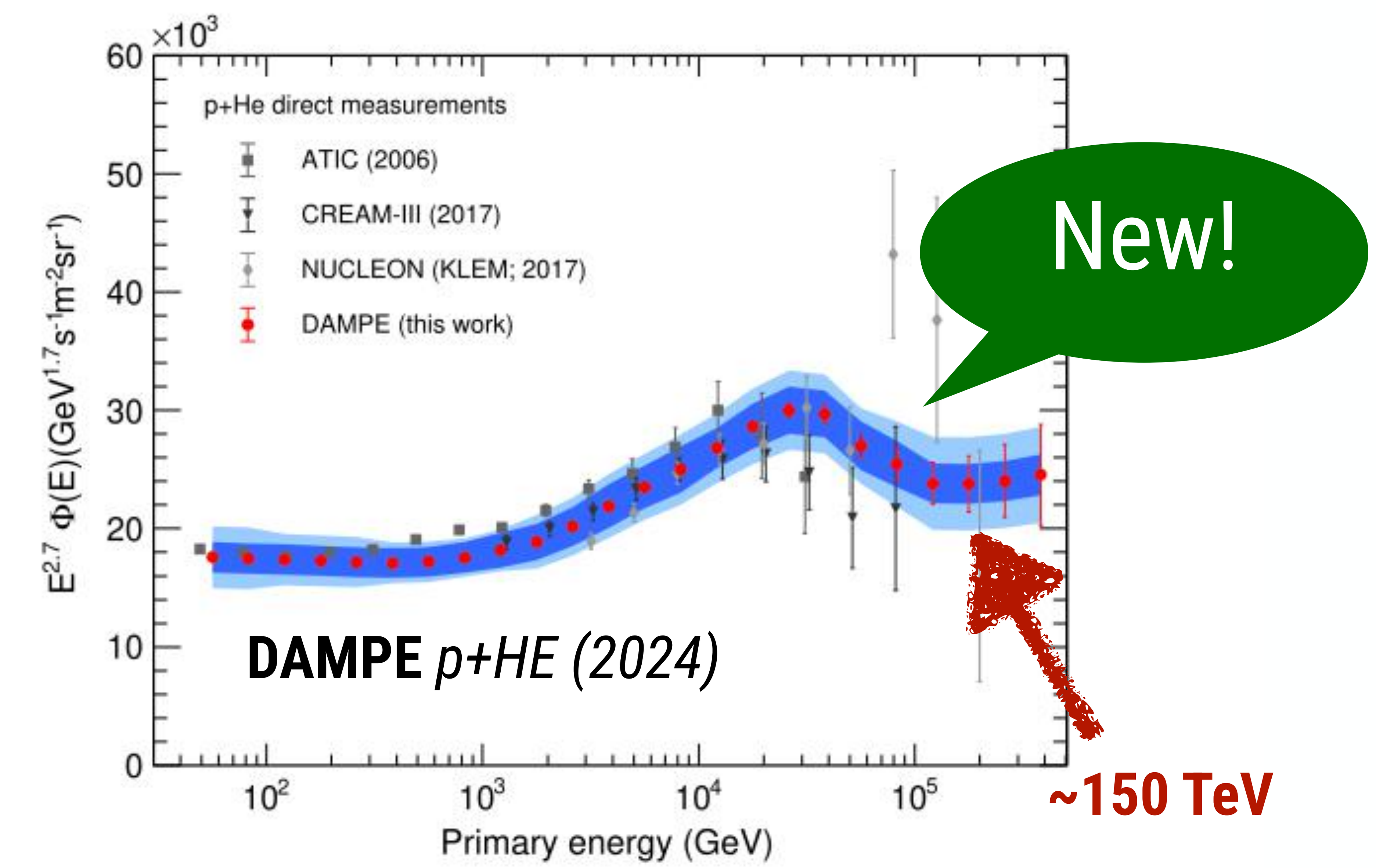


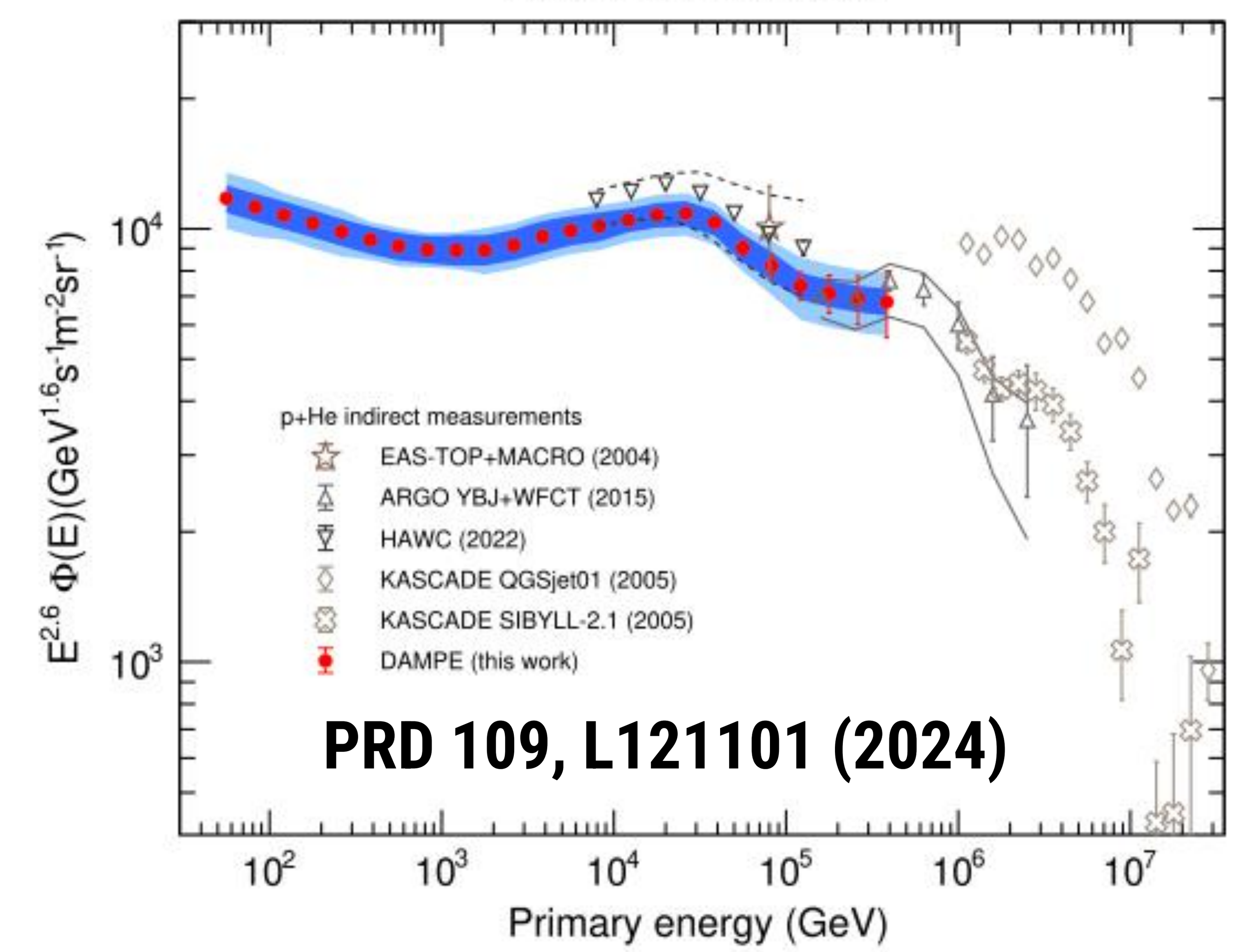


See talk of ***Elisabetta Casilli***

Motivation — reaching PeV energies in Space



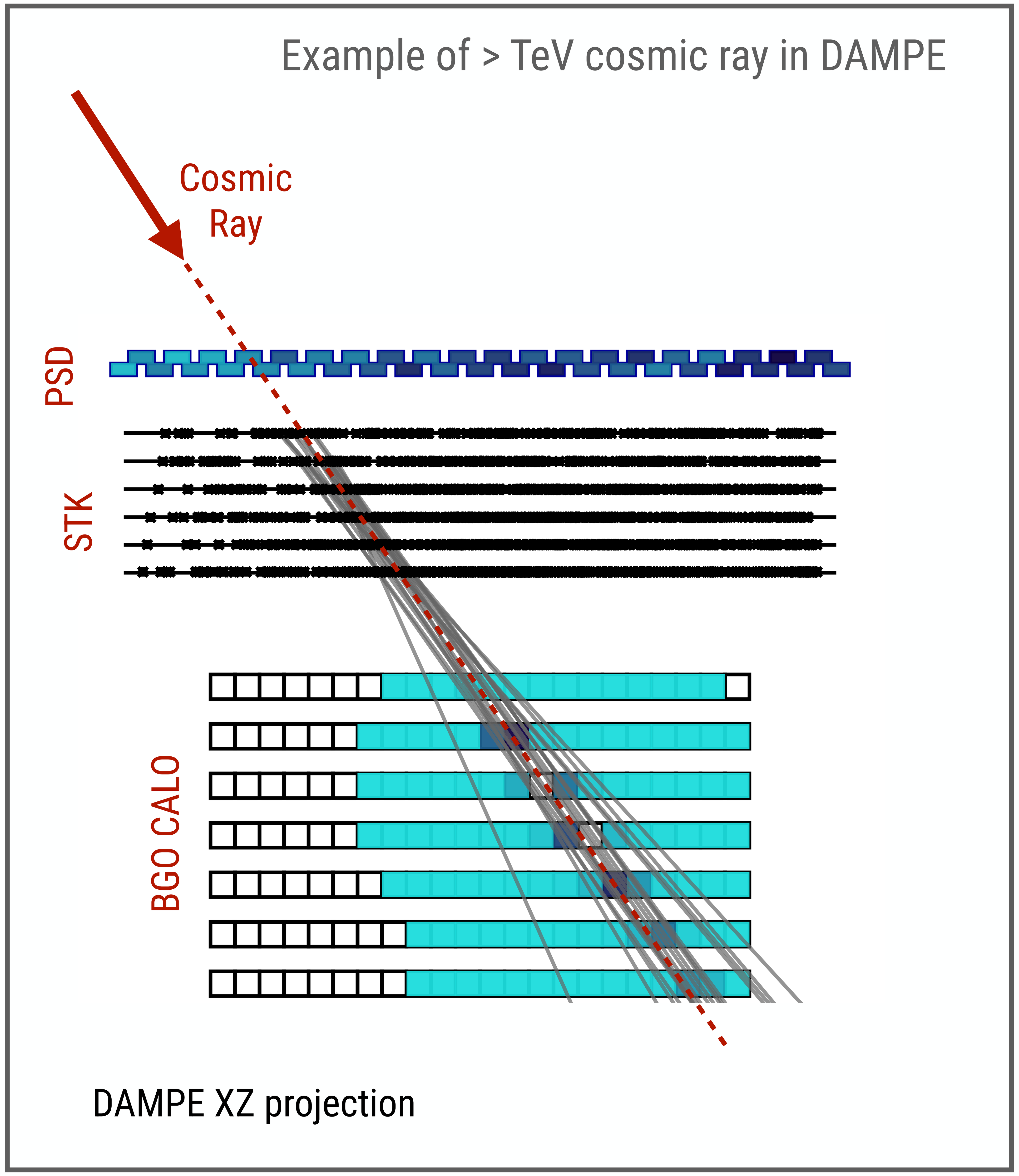




- Proton — most abundant CR and the only CR with Z=A
- Previous individual CR proton measurement reaching 100 TeV
  → limited by statistics and particle identification
- p+He spectrum (2024) suggests a **new hardening at ~ 150 TeV**

→ **<u>What about individual proton (and helium) spectra?</u>**

Challenge of CR reconstruction



Conventional track reconstruction:

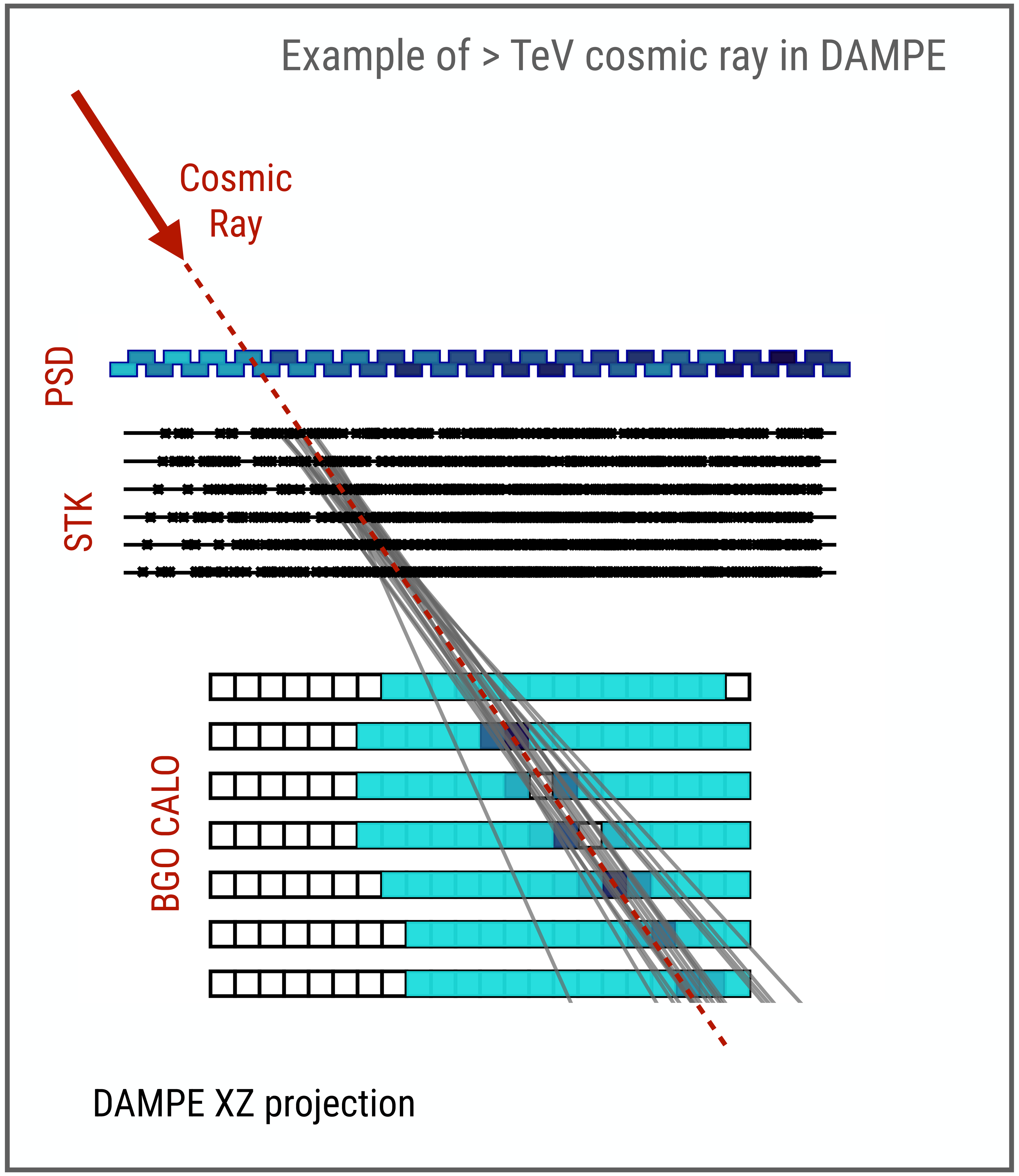
- Shower axis from CALO as a seed
- Kalman fitting
- Combinatorial track finding
- XZ and YZ fitted separately,
- … then combined in 3D tracks

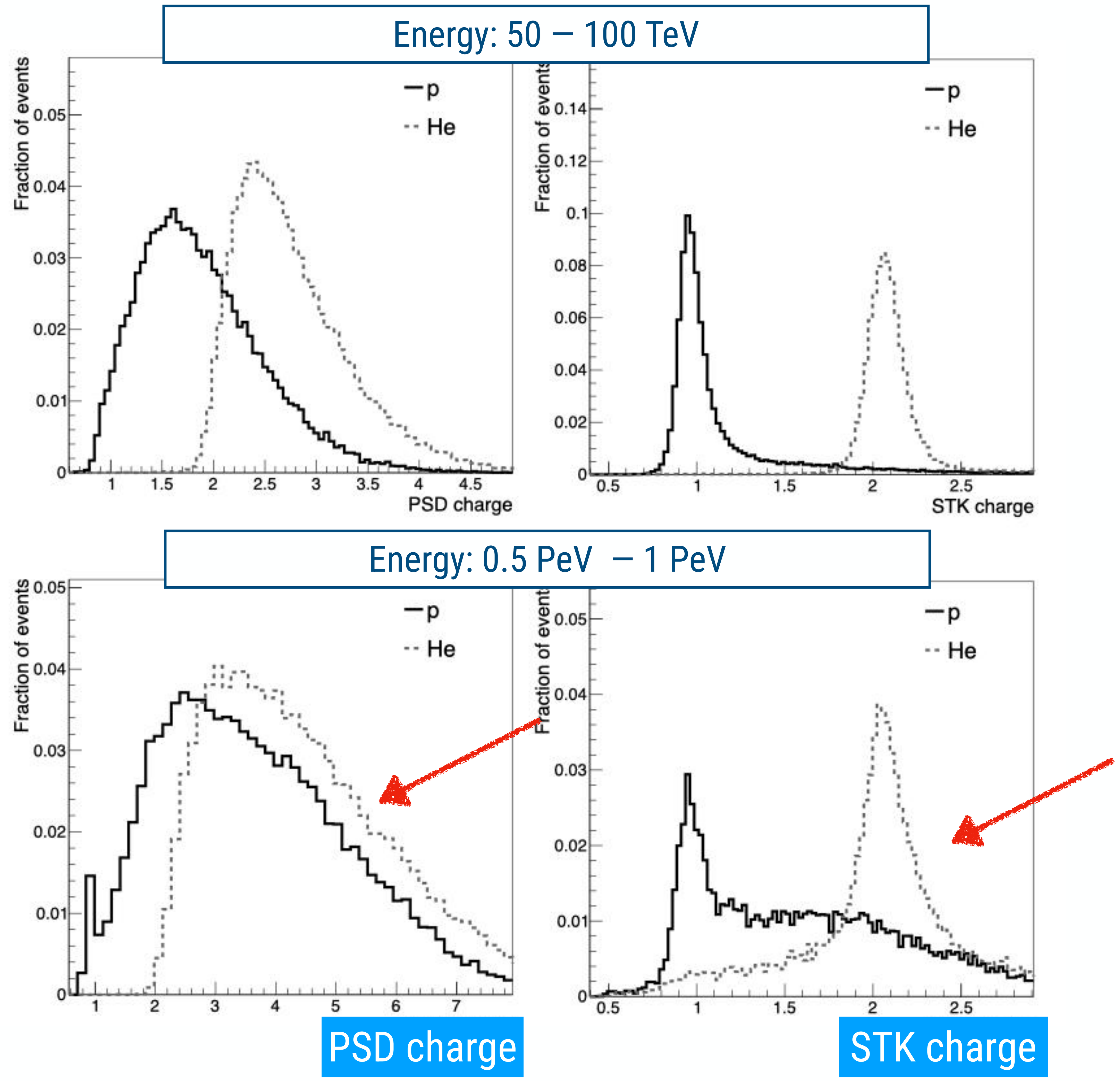
Problems:

- Selection needed to find **the ONLY track**
- Efficiency drops at high hit multiplicity

At TeV– PeV hit multiplicity increases dramatically →
Track reconstruction & identification is a key challenge!

Challenge of CR reconstruction

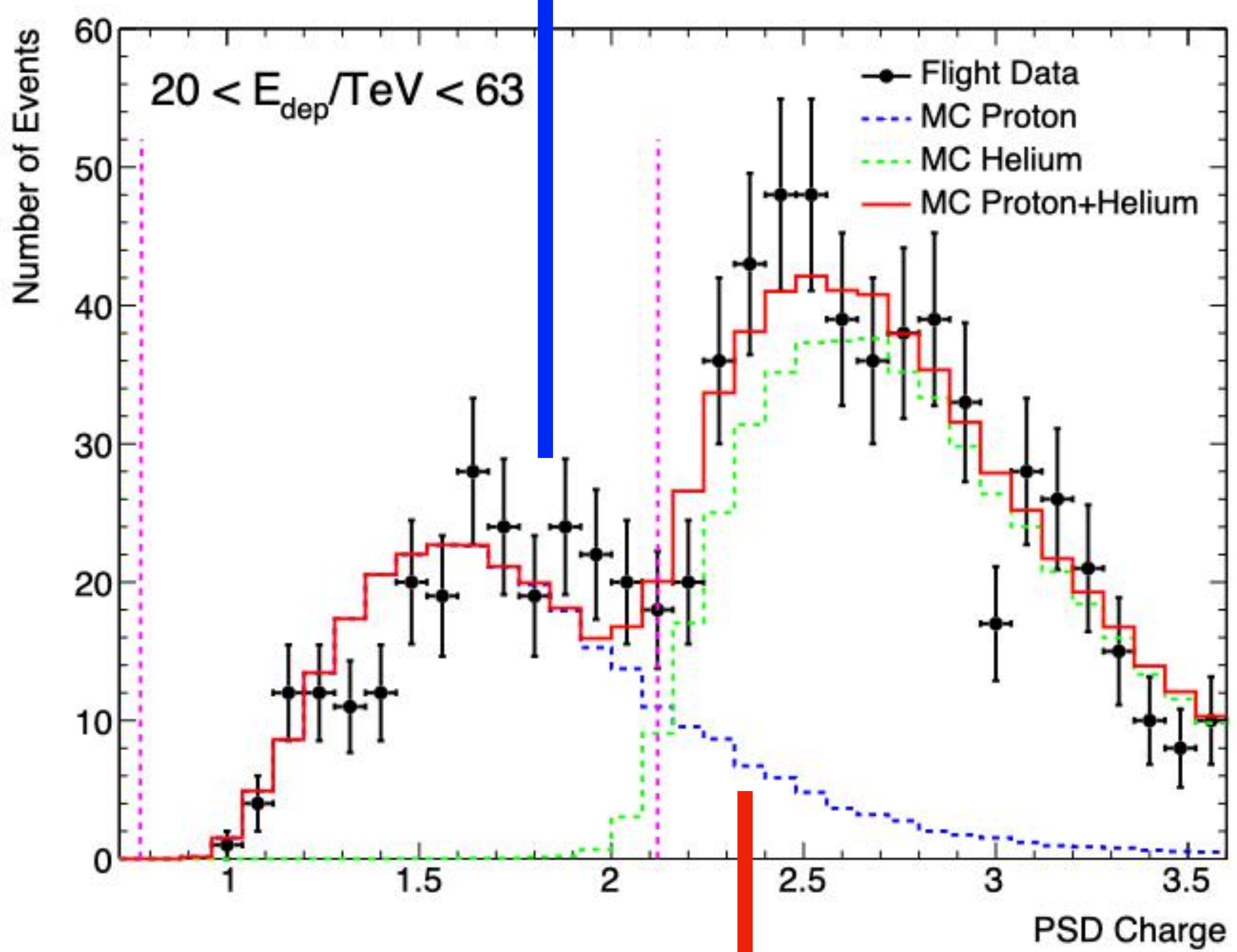




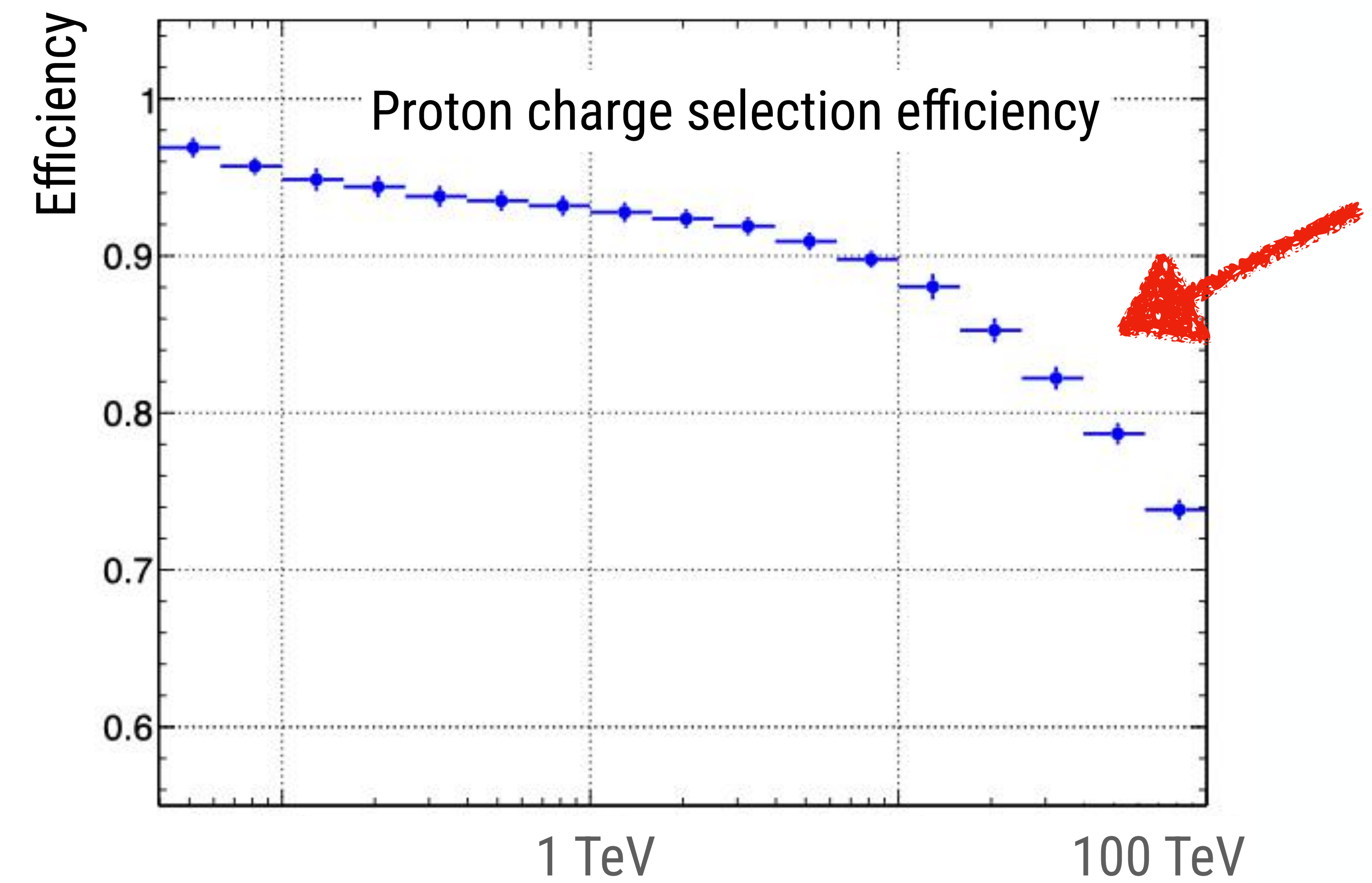
Charge identification in PSD — track used as a pointer:

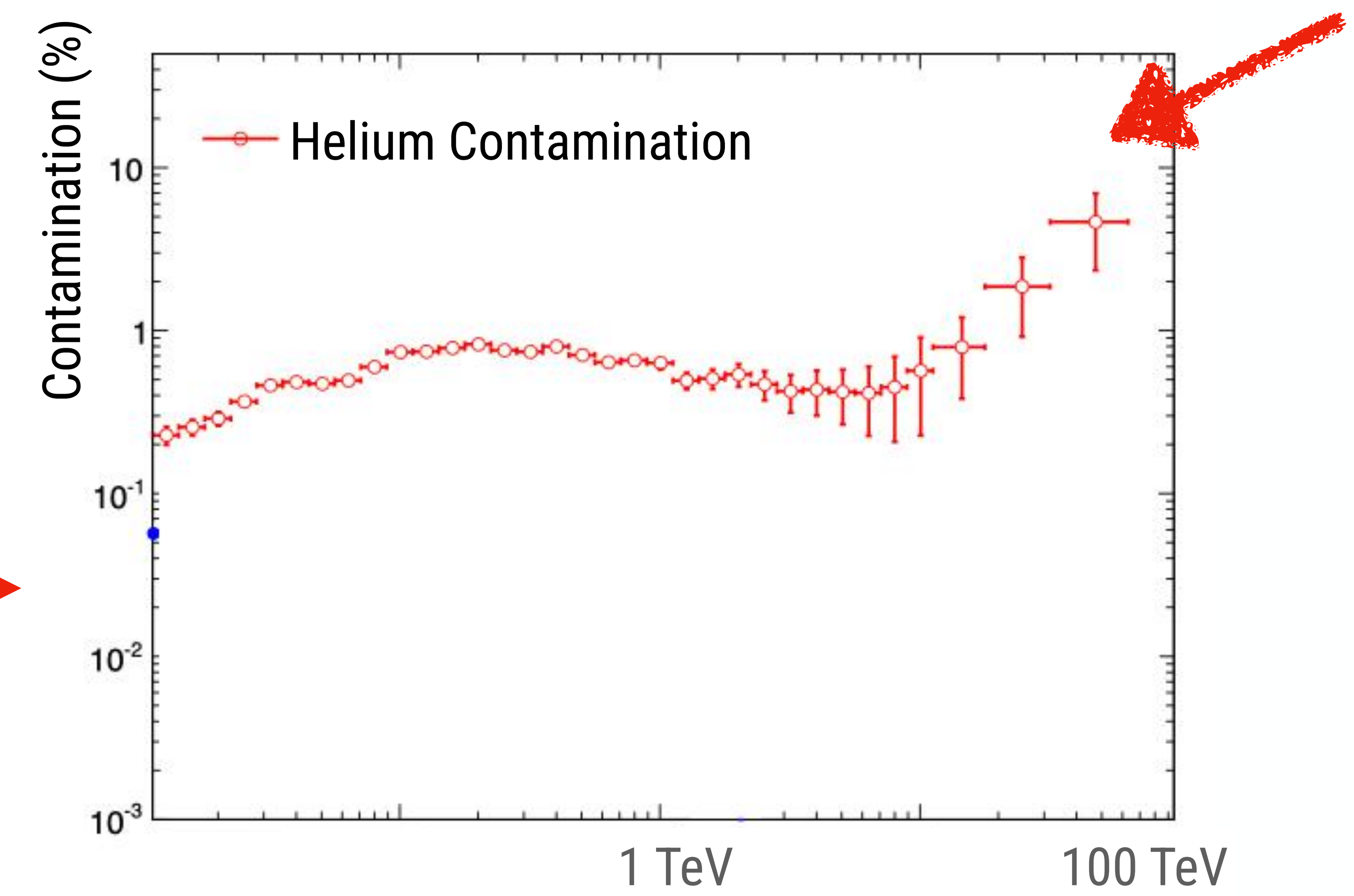
- Tolerant to track mis-identification
- However, **p and He peaks "washed out" at high energies!**

Limit of classical CR reconstruction methods…



DAMPE collaboration,
Science Advances 5/9 (2019)

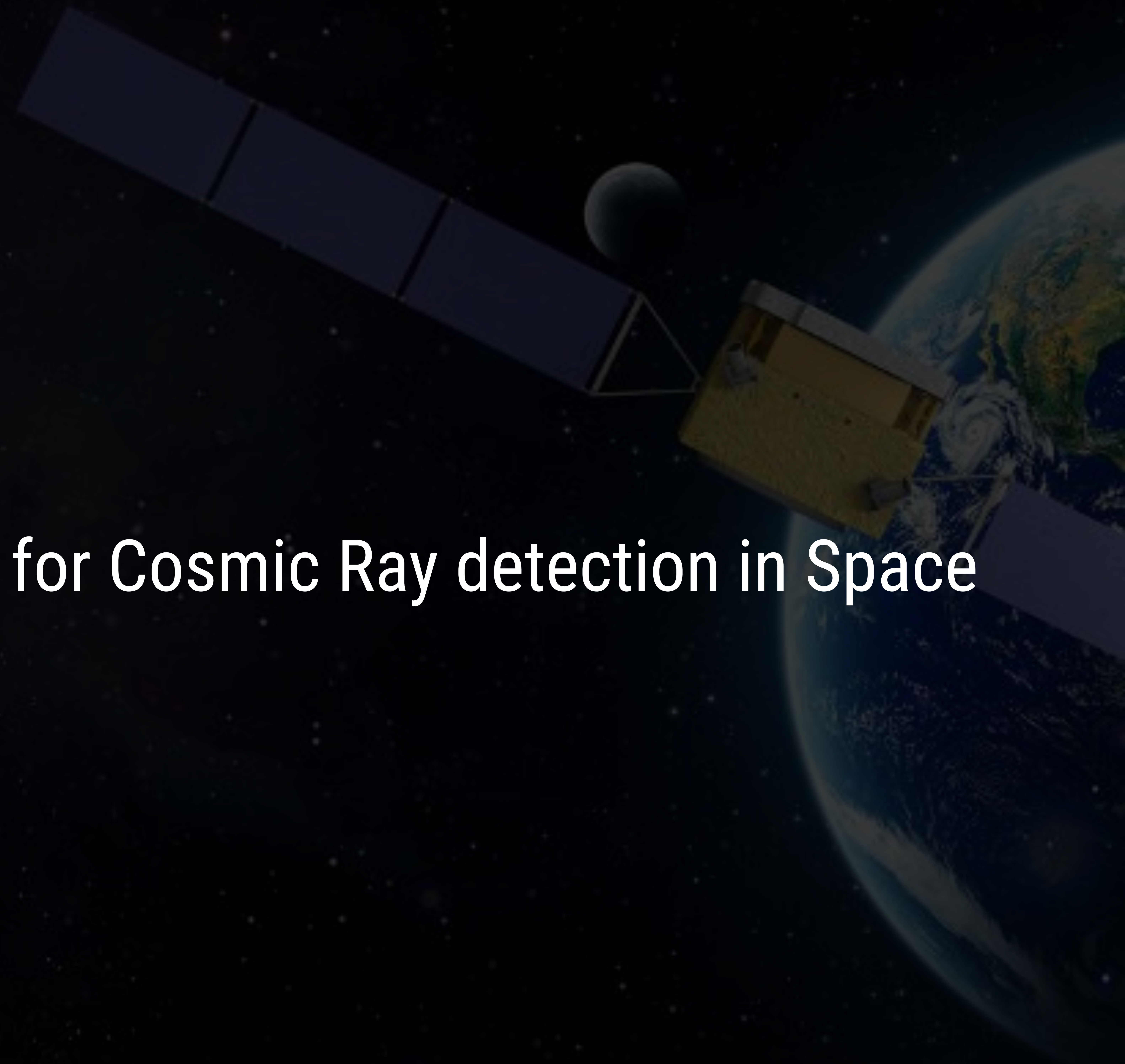




Track reconstruction + proton charge identification – limiting energy reach and drastically decreasing the precision at > 100 TeV

We need new tracking algorithm for > 100 TeV measurements!

Part II: AI applications for Cosmic Ray detection in Space



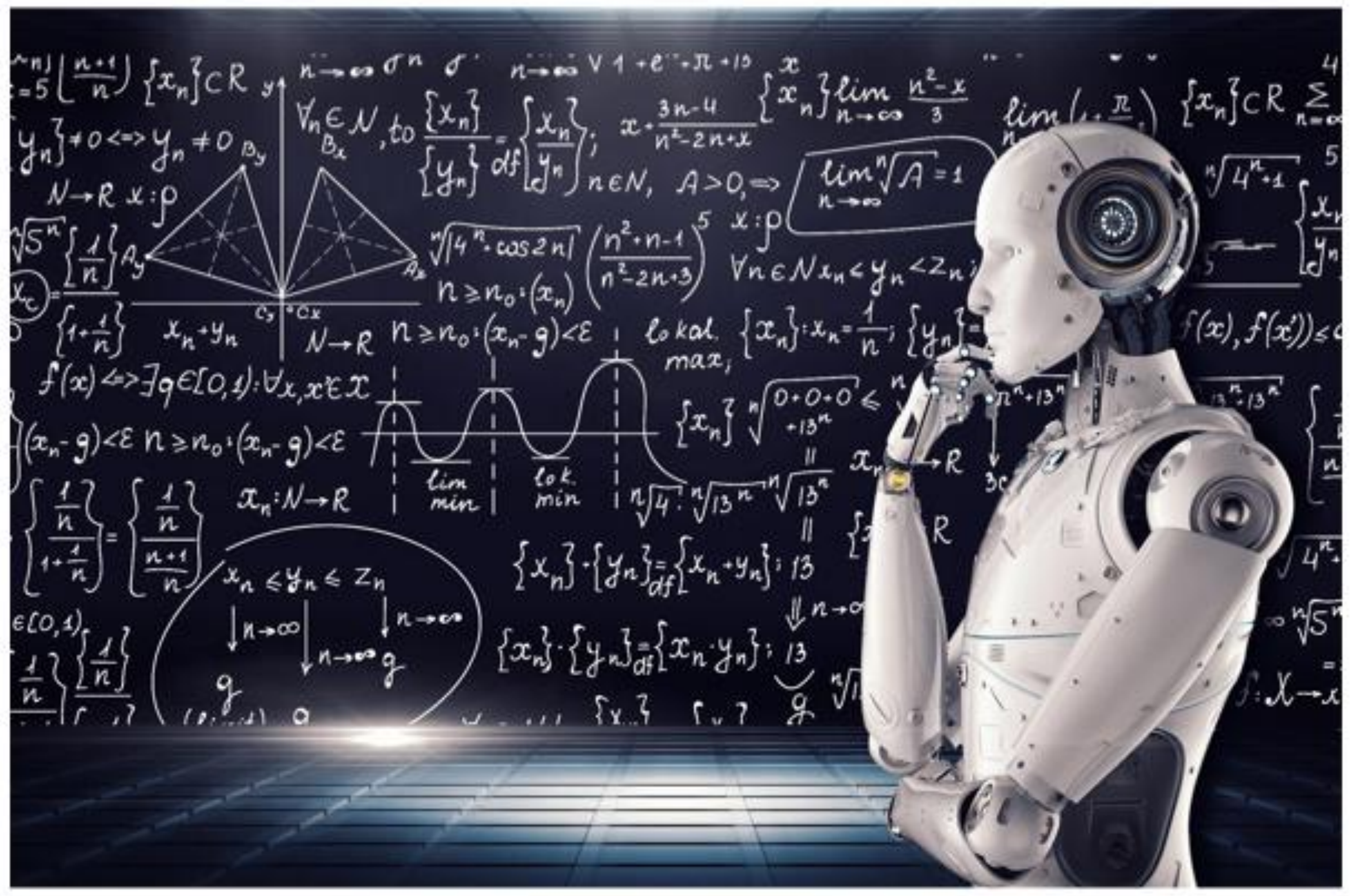
AI terminology

Artificial Intelligence

Human Intelligence
Exhibited by Machines

Machine Learning

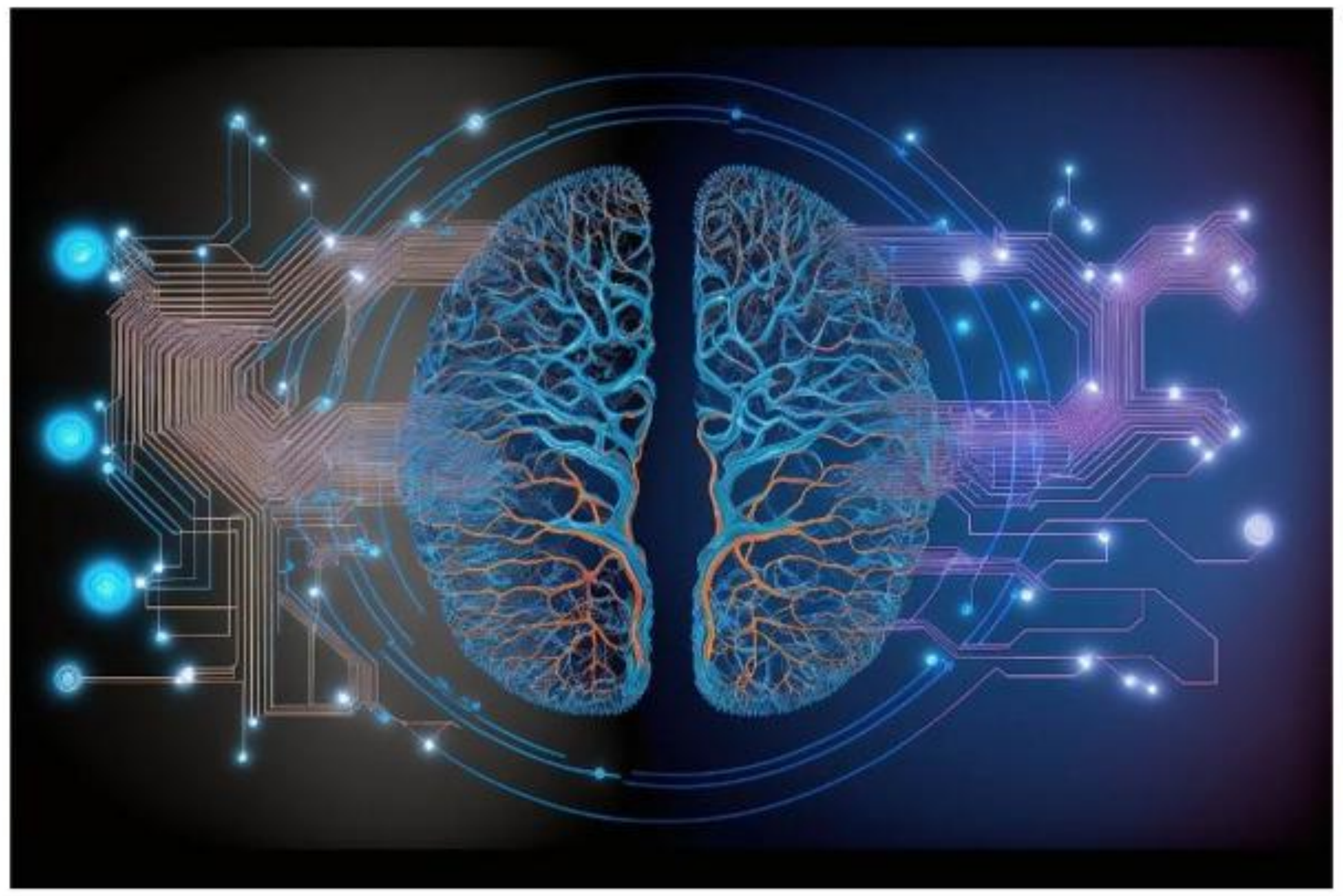
An Approach to Achieve
Artificial Intelligence



We focus mostly on deep learning applications in this talk

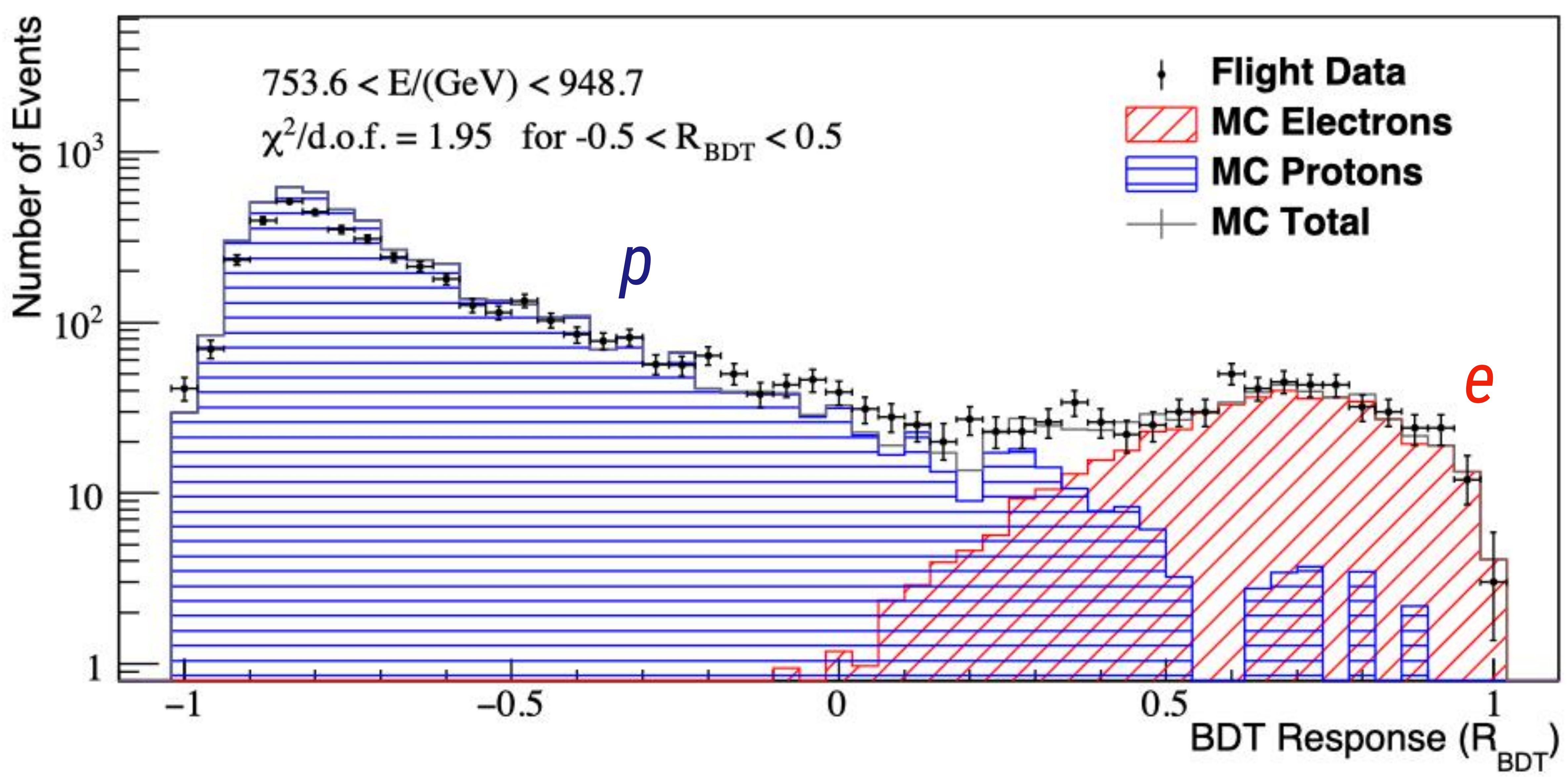
Deep Learning

A Technique for Implementing
Machine Learning

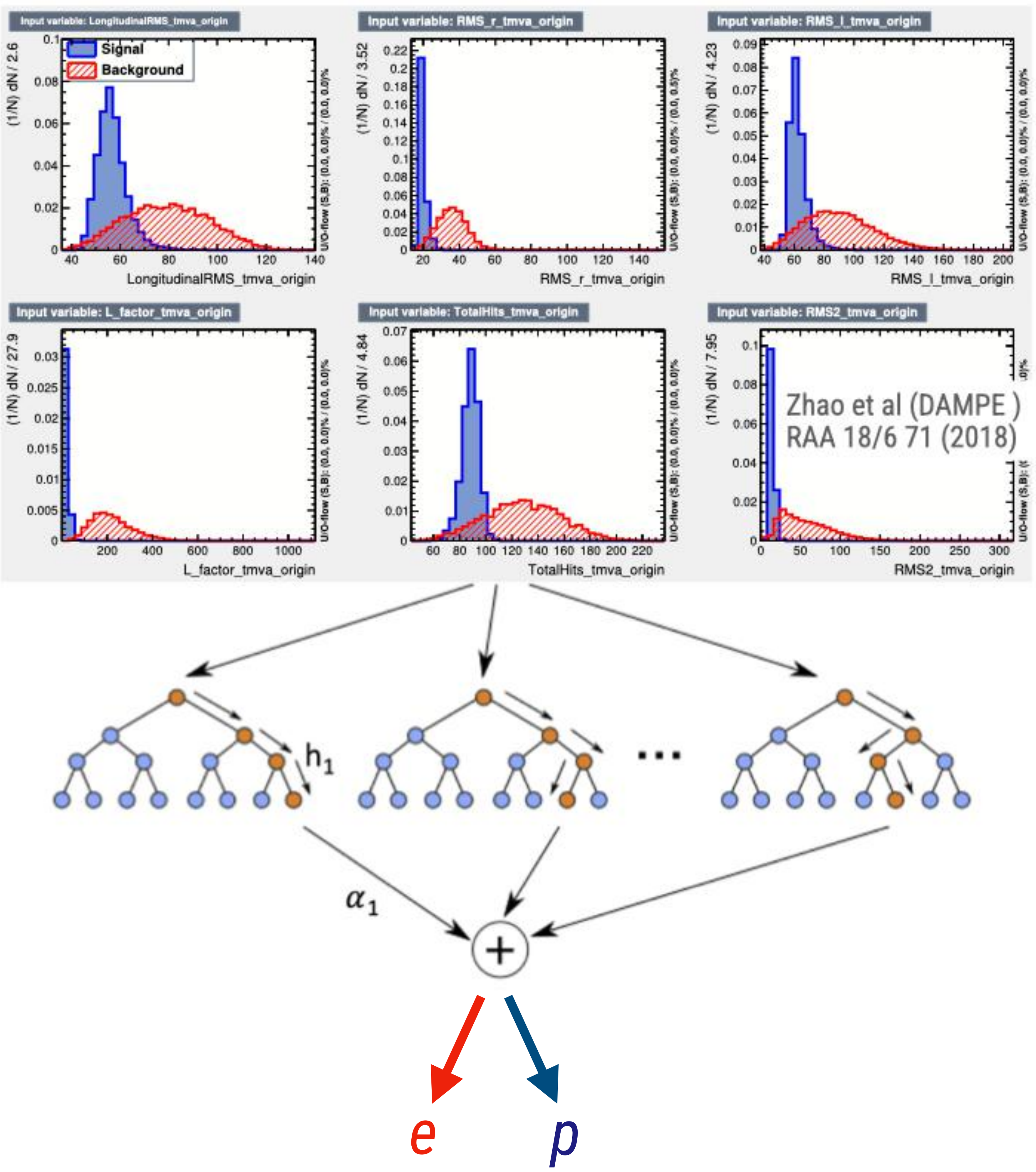


On Boosted Decision Trees (BDTs)…

- Powerful technique for classification
- Well-known/studied since pre-LHC era
- Commonly used in space experiments (AMS-02, CALET, DAMPE)



Adriani et al. (CALET Collaboration)
PRL 131, 191001(2023)

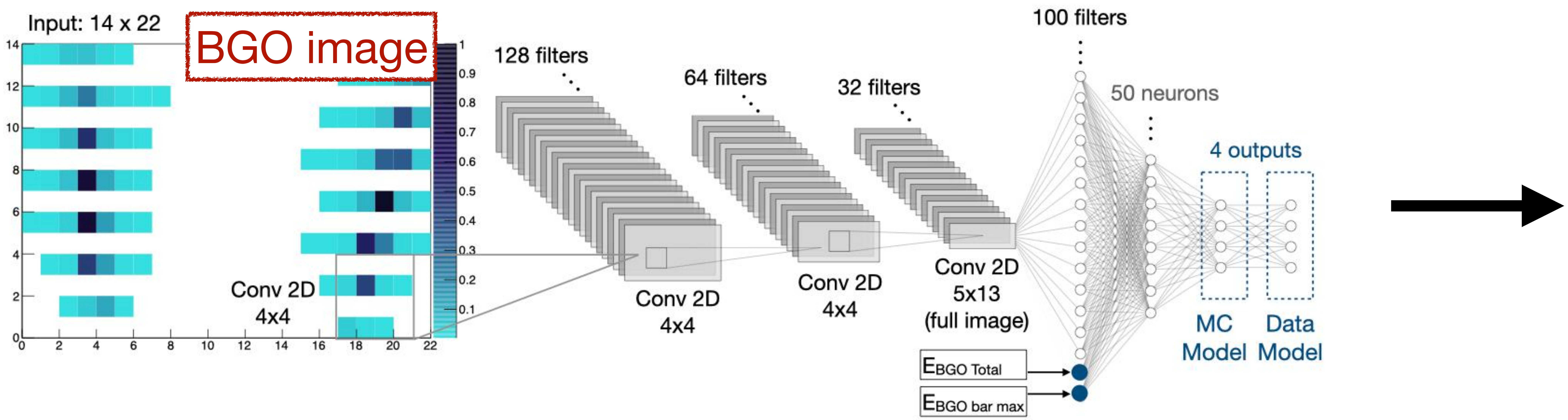


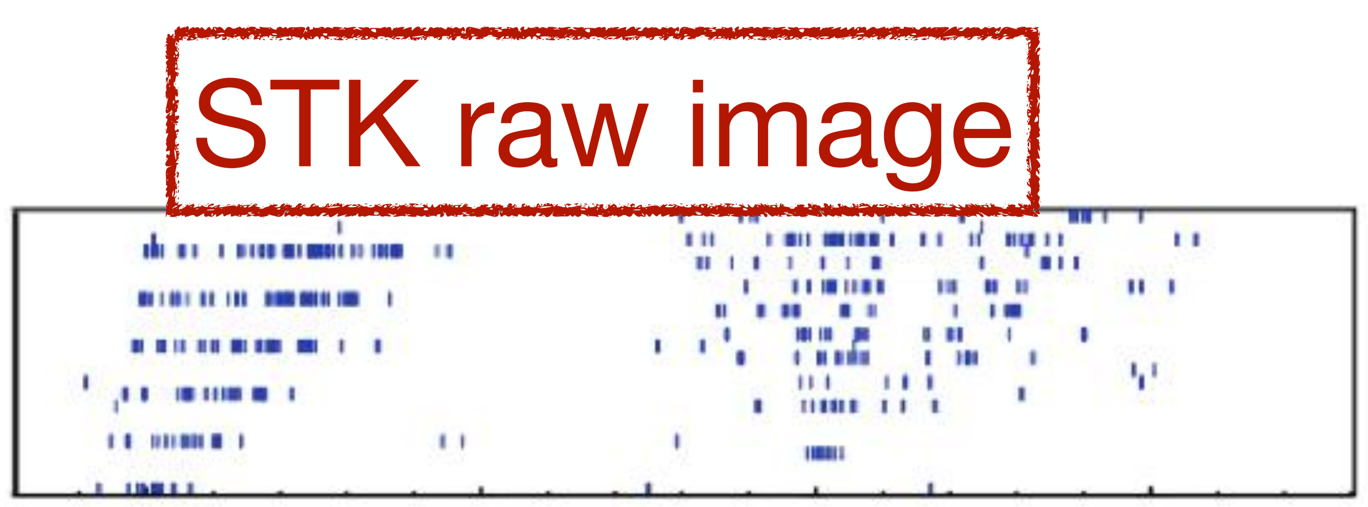
Classical use case: combination of correlated high-level variables each having some classification power (number of hits in the detector, energy-per-layer etc.)

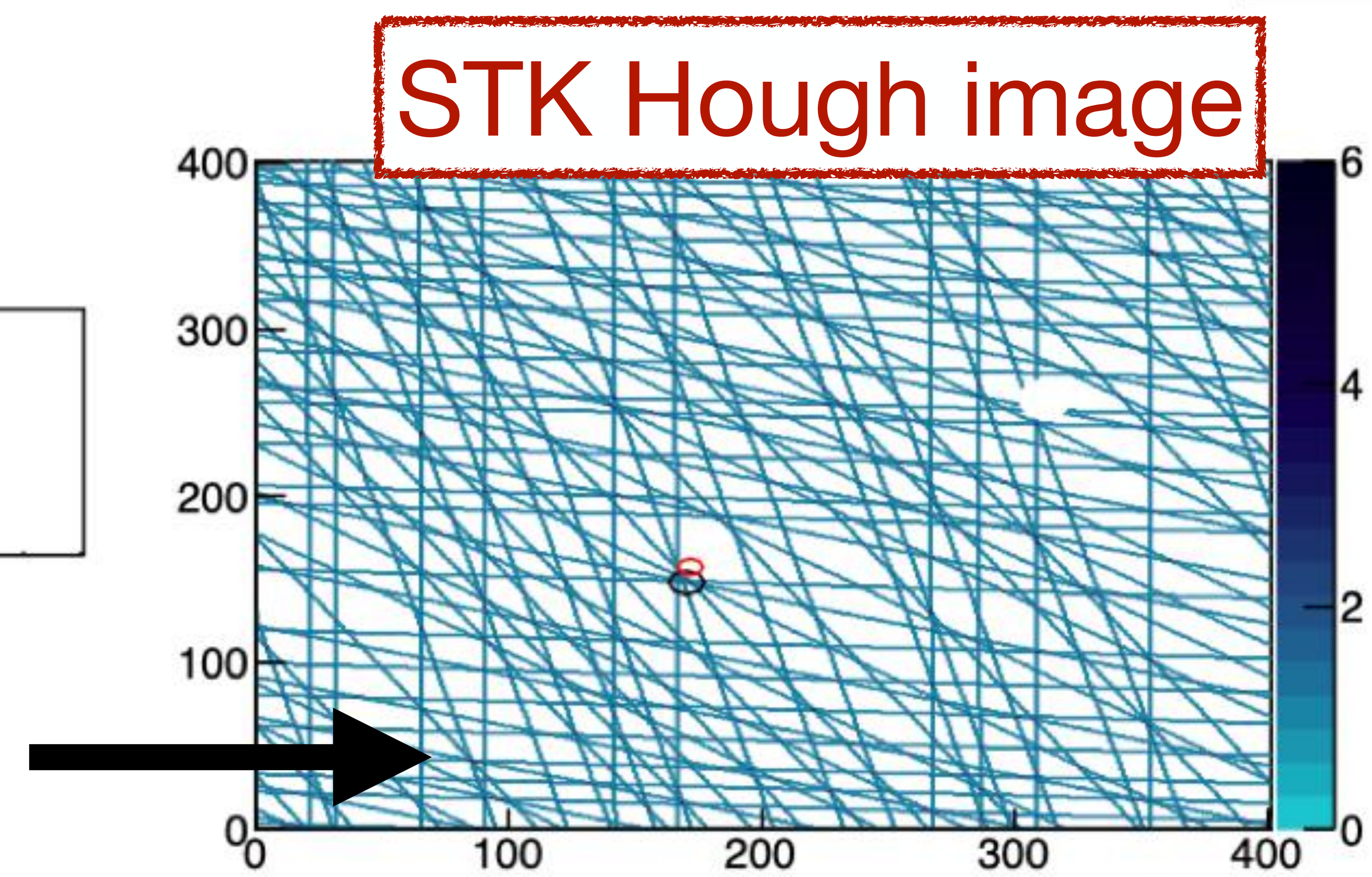
BDTs not designed for high-dimensional low-level data *(images, arrays of detector read-out signals, etc.)*

Towards PeV: CNNs Tracking Algorithm in DAMPE

Convolutional Neural Networks (CNNs) for cosmic ray trajectory reconstruction:





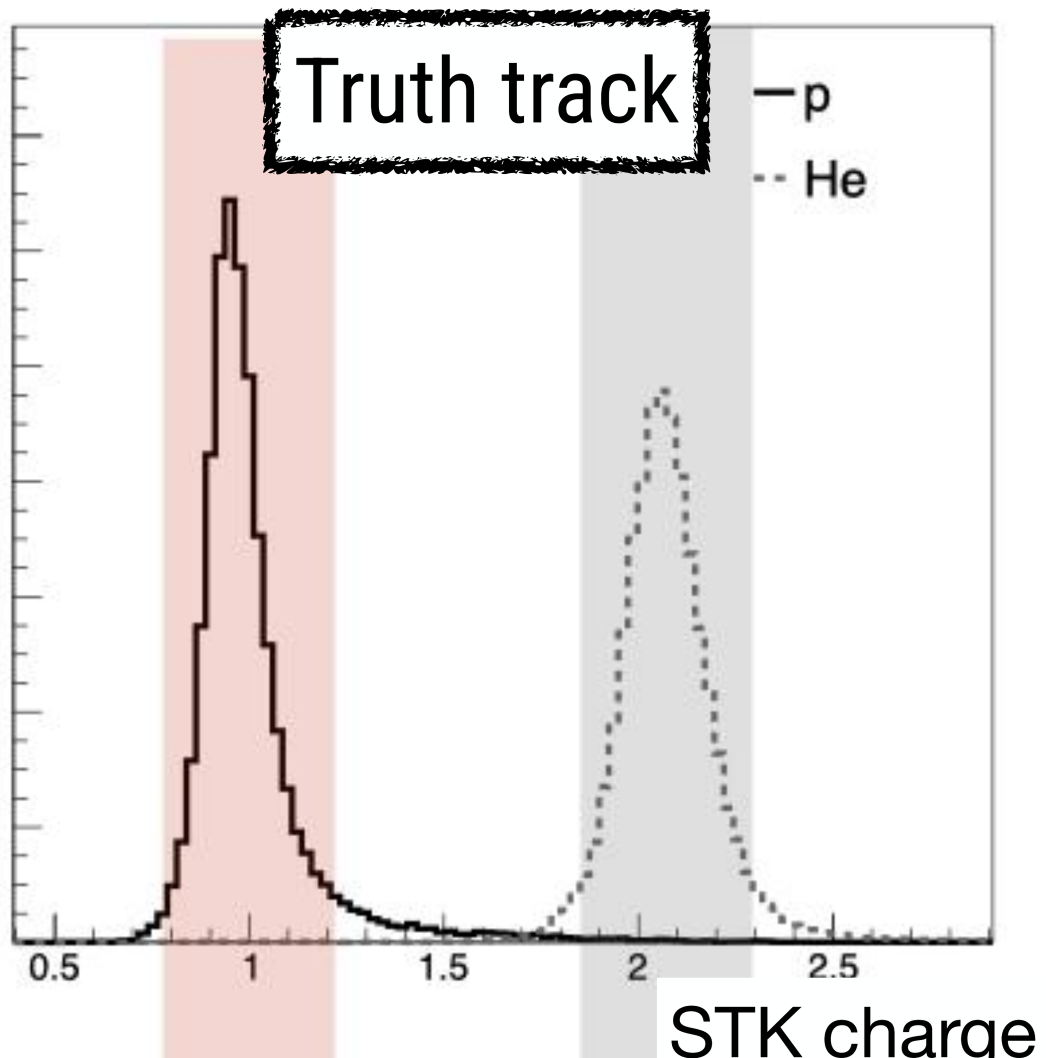


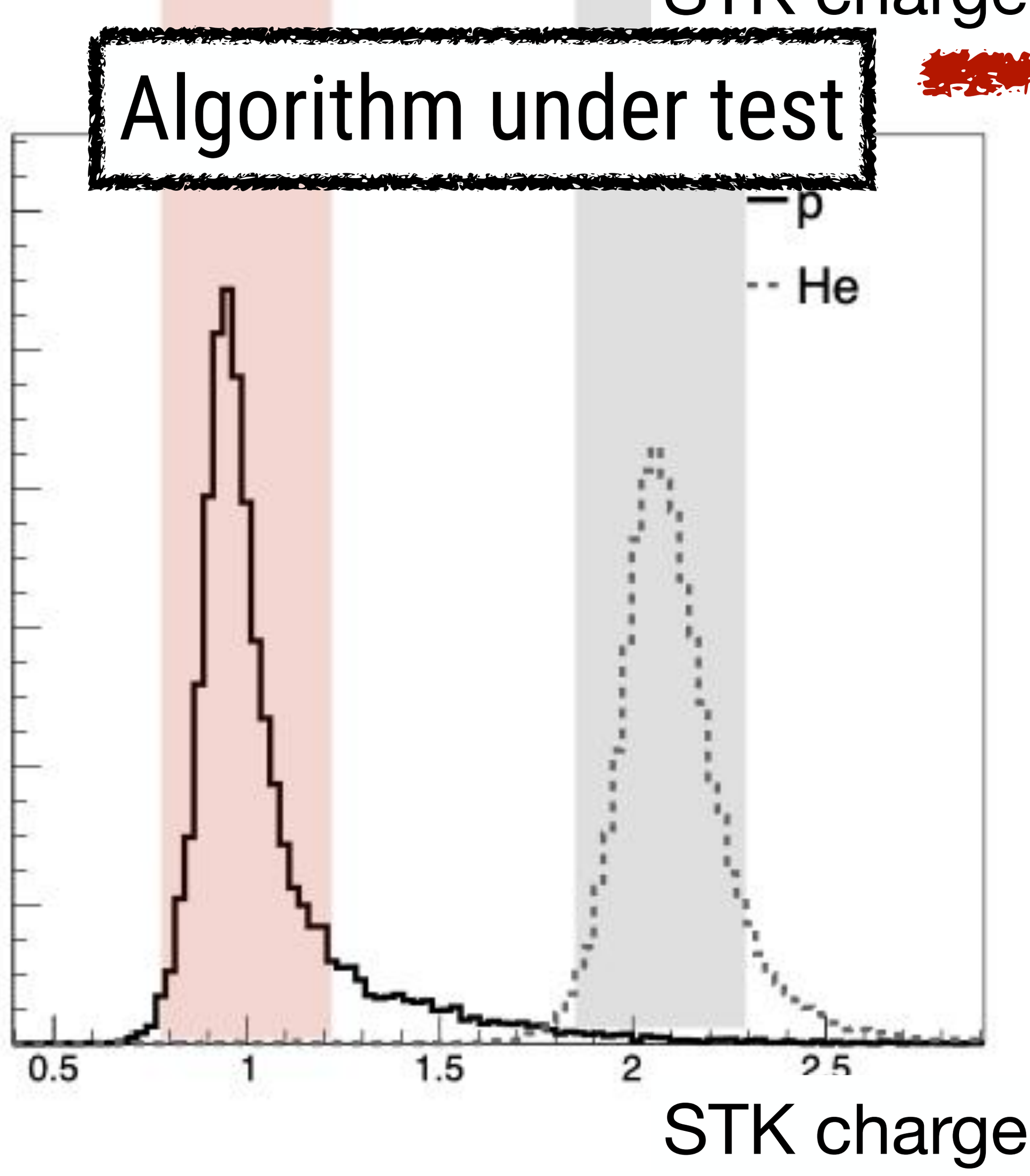
Tykhonov et al. Astropart. Phys. 146 (2023)

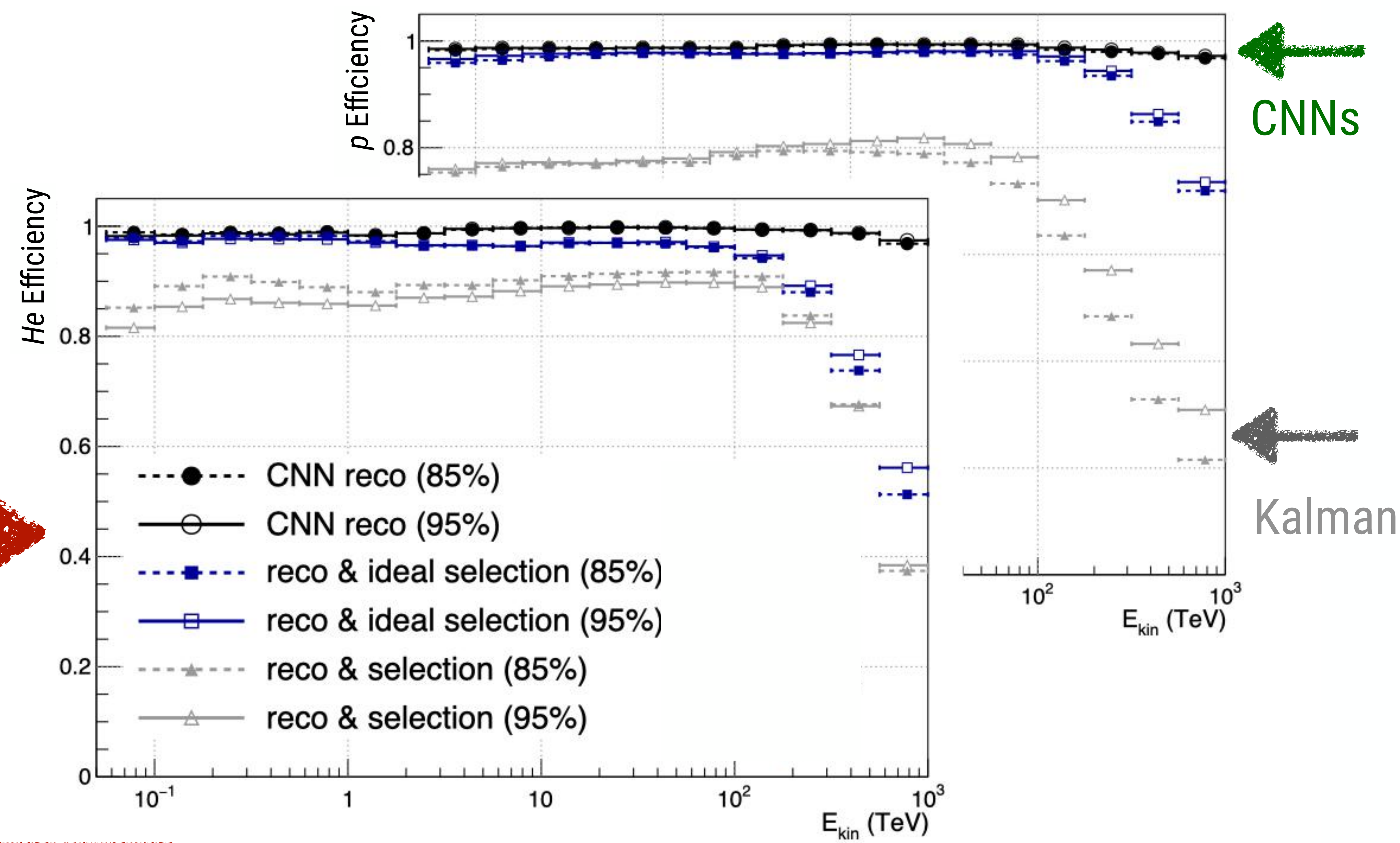
- CALO image used as input for CNN
- Returns particle direction as an output
- Region of interest created in the tracker
- Another CNN processes STK image
- Returns high-precision particle direction
- Also used for vertex prediction

Towards PeV: CNNs Tracking Algorithm in DAMPE

Performance evaluation:





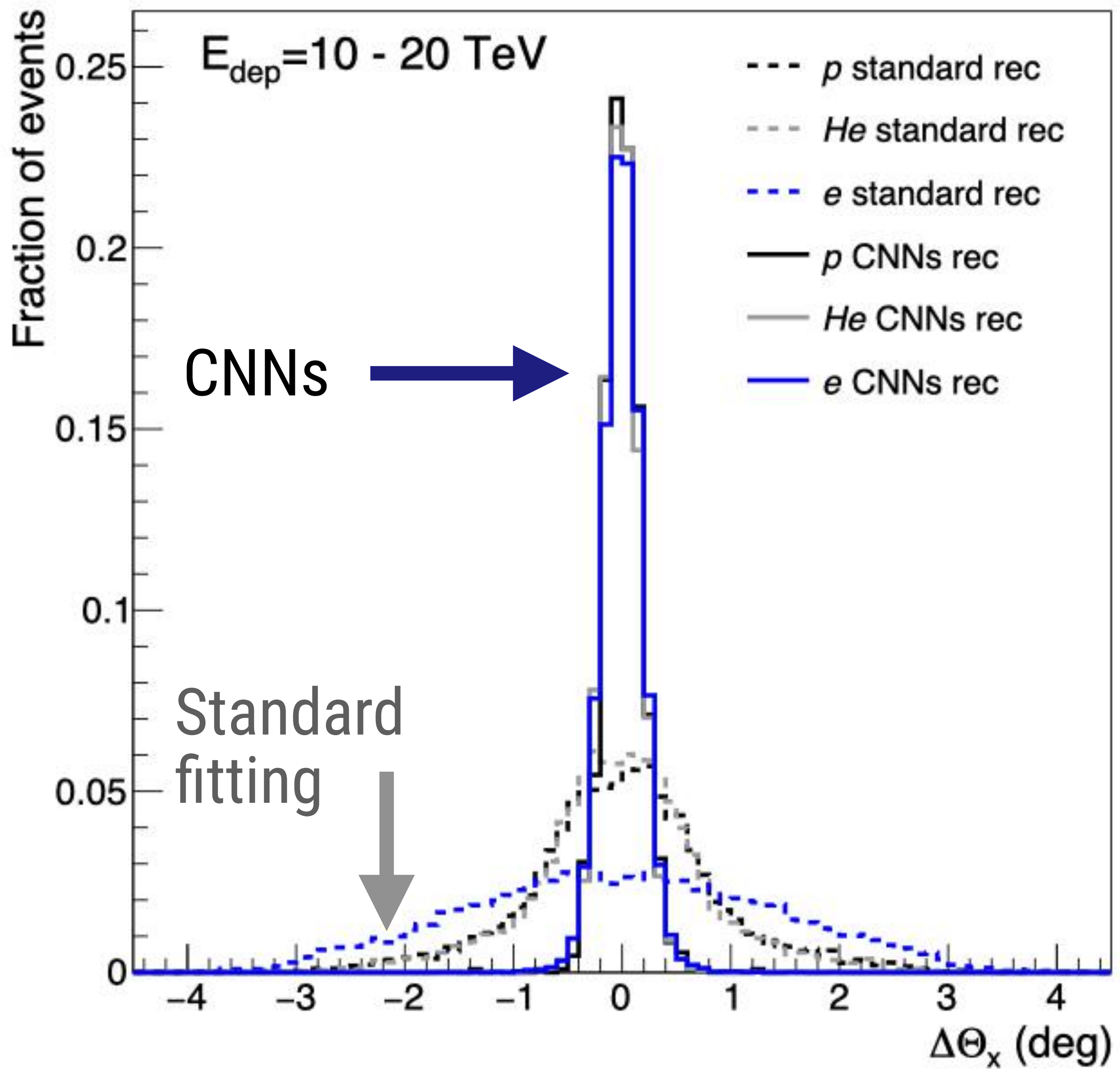


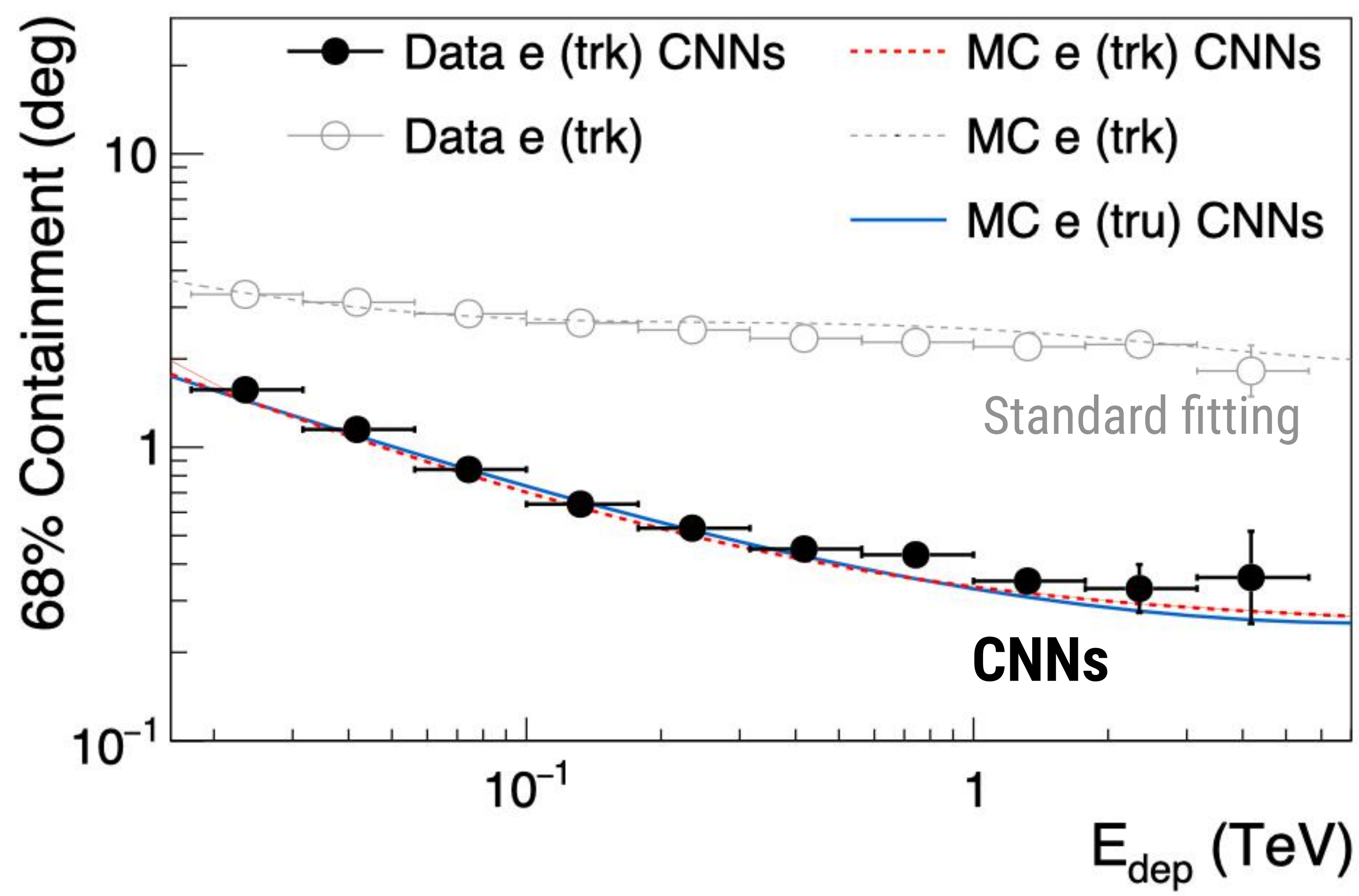
$$\text{Eff} = \frac{N_{\text{algorithm}}}{N_{\text{true}}}$$

<u>CNN tracking efficiency > **96%** up to PeV</u>

Towards PeV: CNNs Tracking Algorithm in DAMPE

CNNs — extremely powerful tool for shower axis reconstruction:

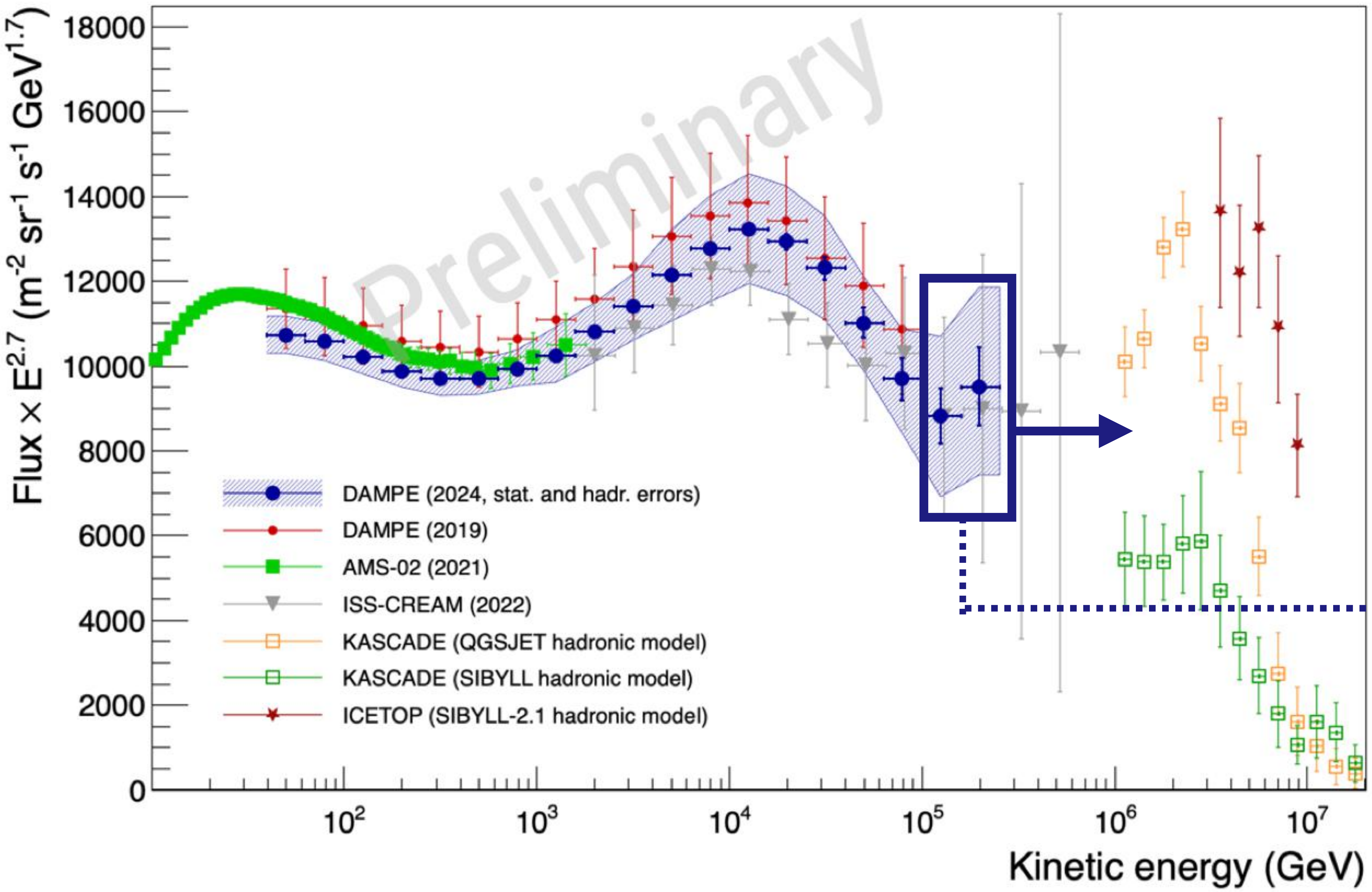


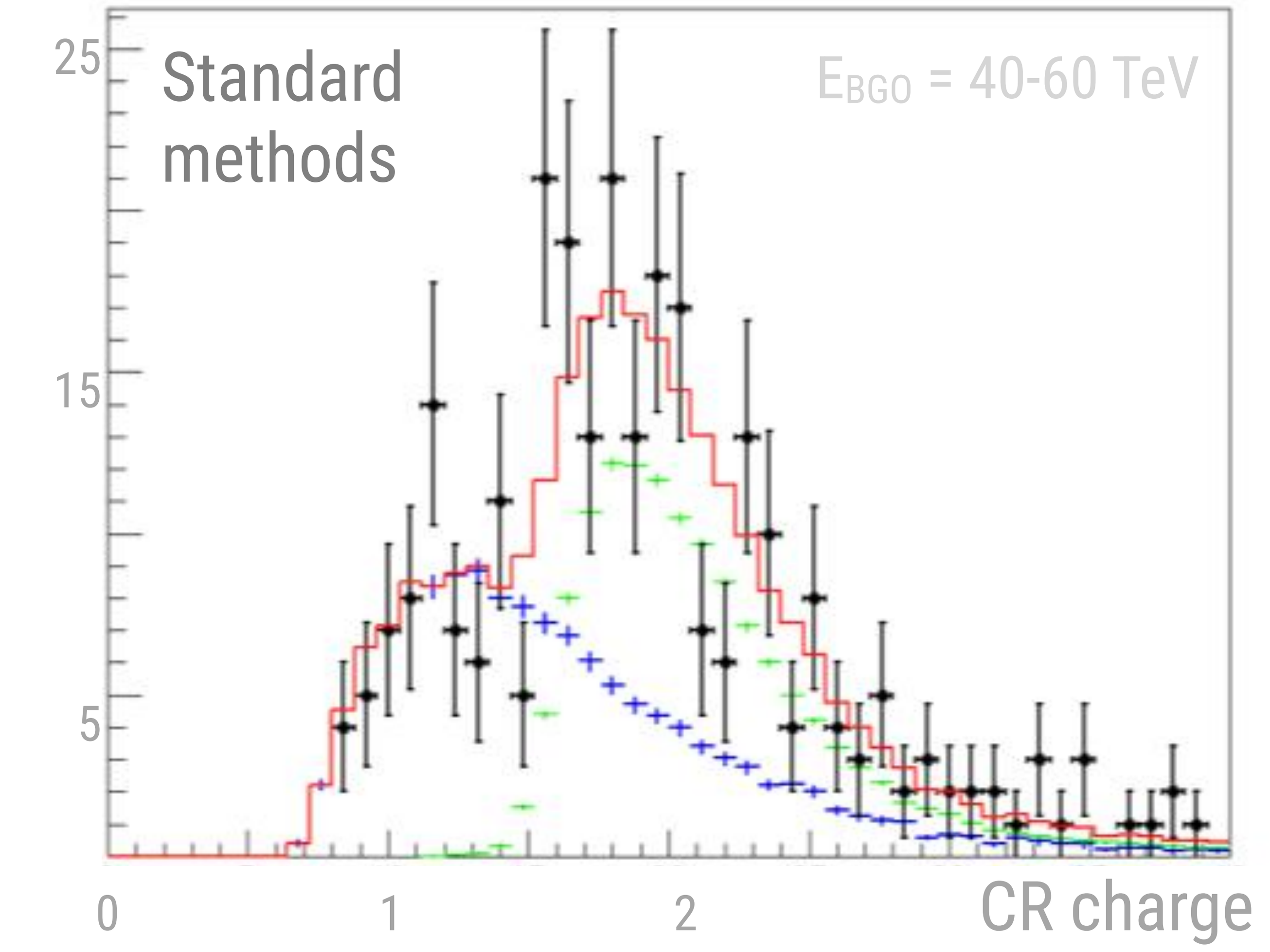


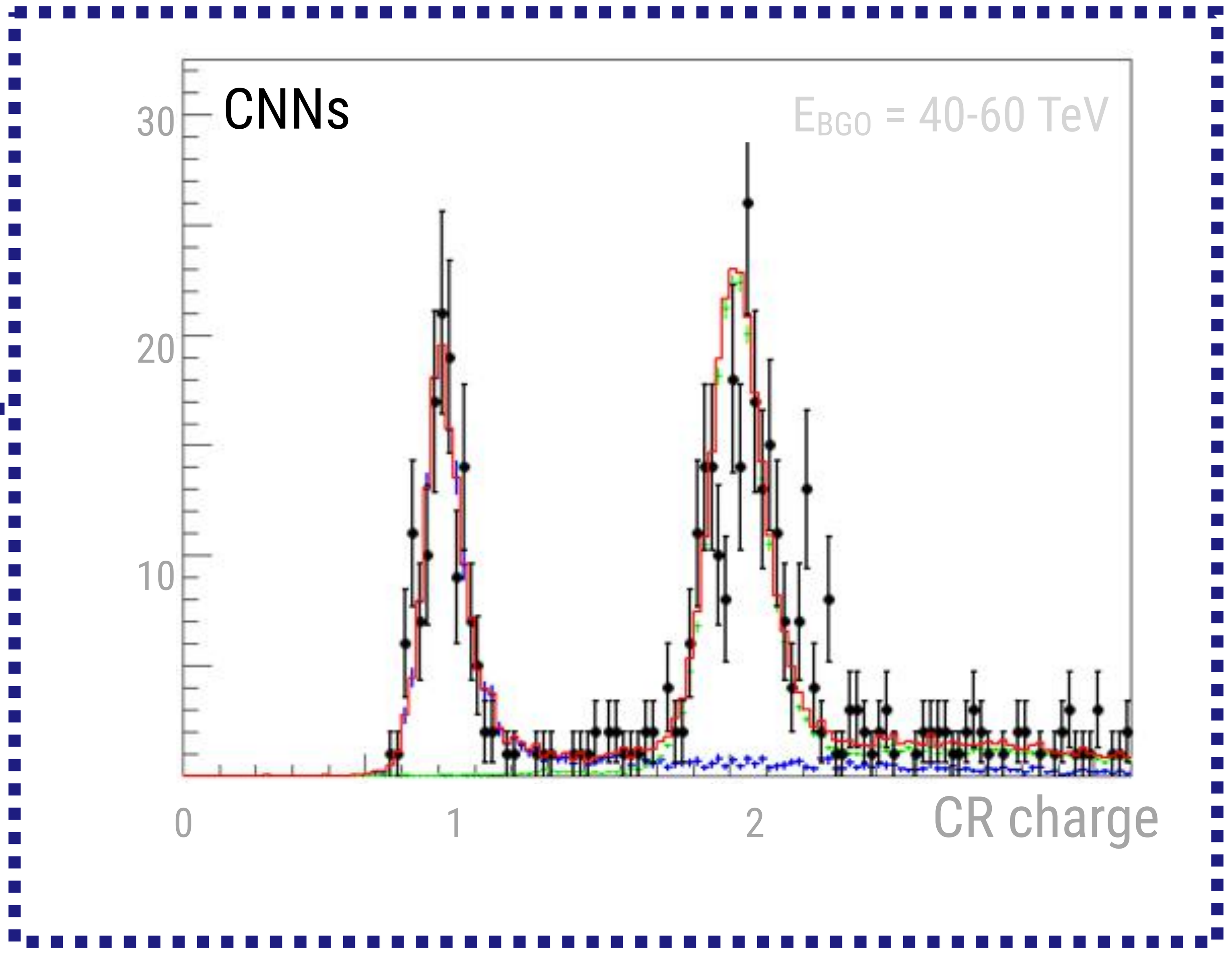
$\Theta_{68\%}$ ~ 0.4° — six times better than with conventional shower-axis fitting!

Physics applications: DAMPE Proton Spectrum

Using the CNNs track reconstruction algorithm, DAMPE Proton spectrum currently extended from 100 TeV to 250 TeV:

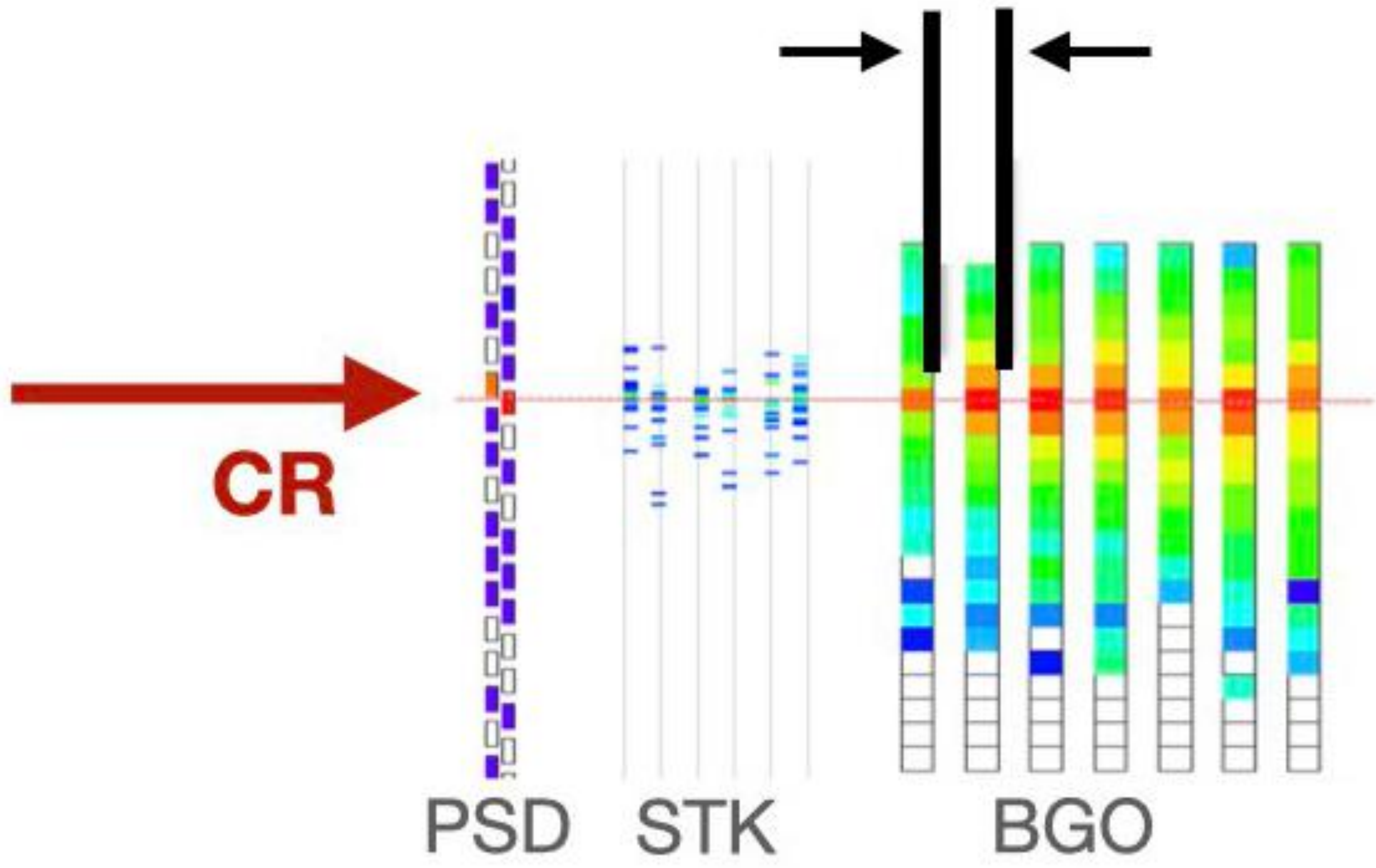






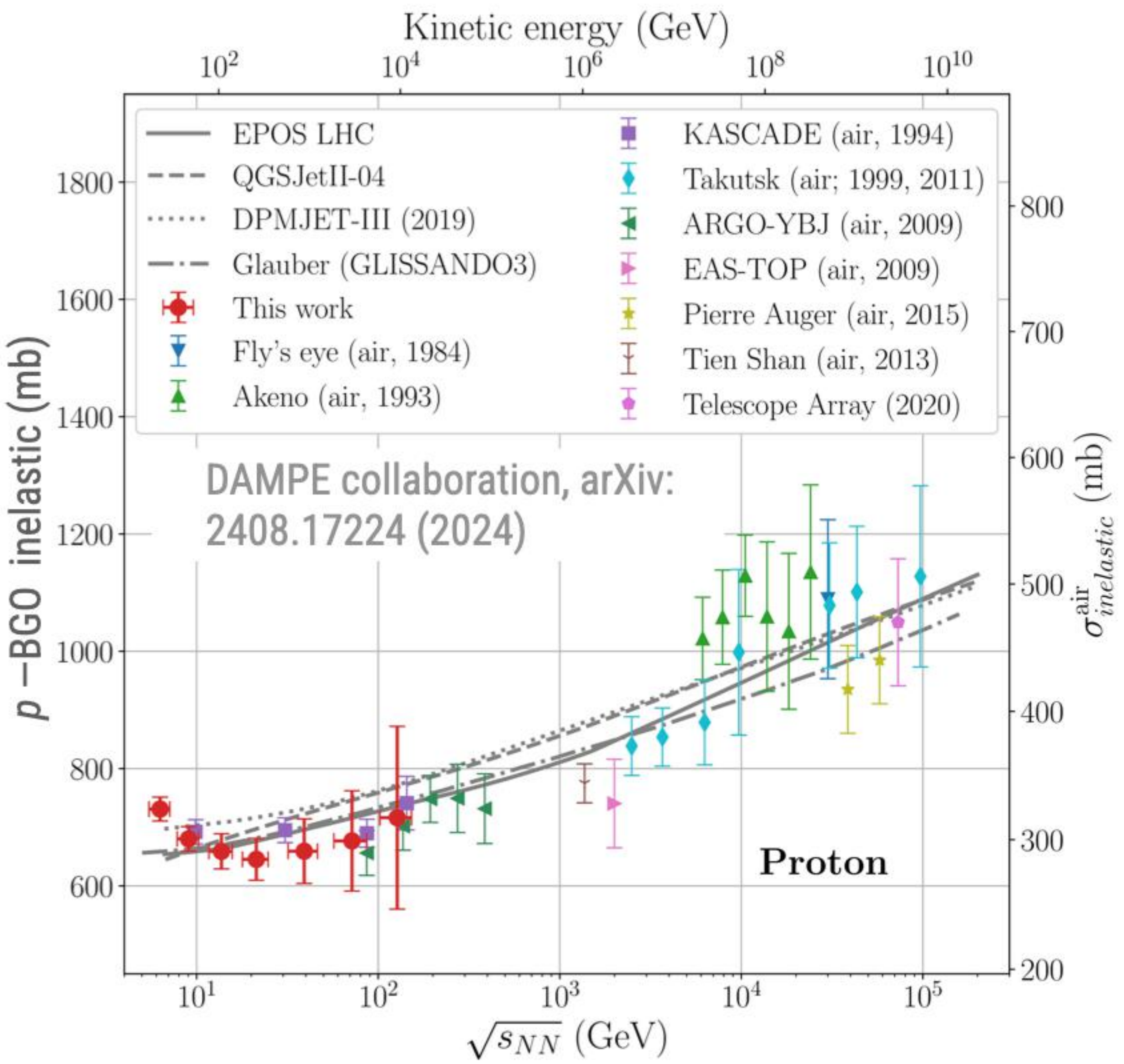
Physics applications: Hadronic Cross Sections

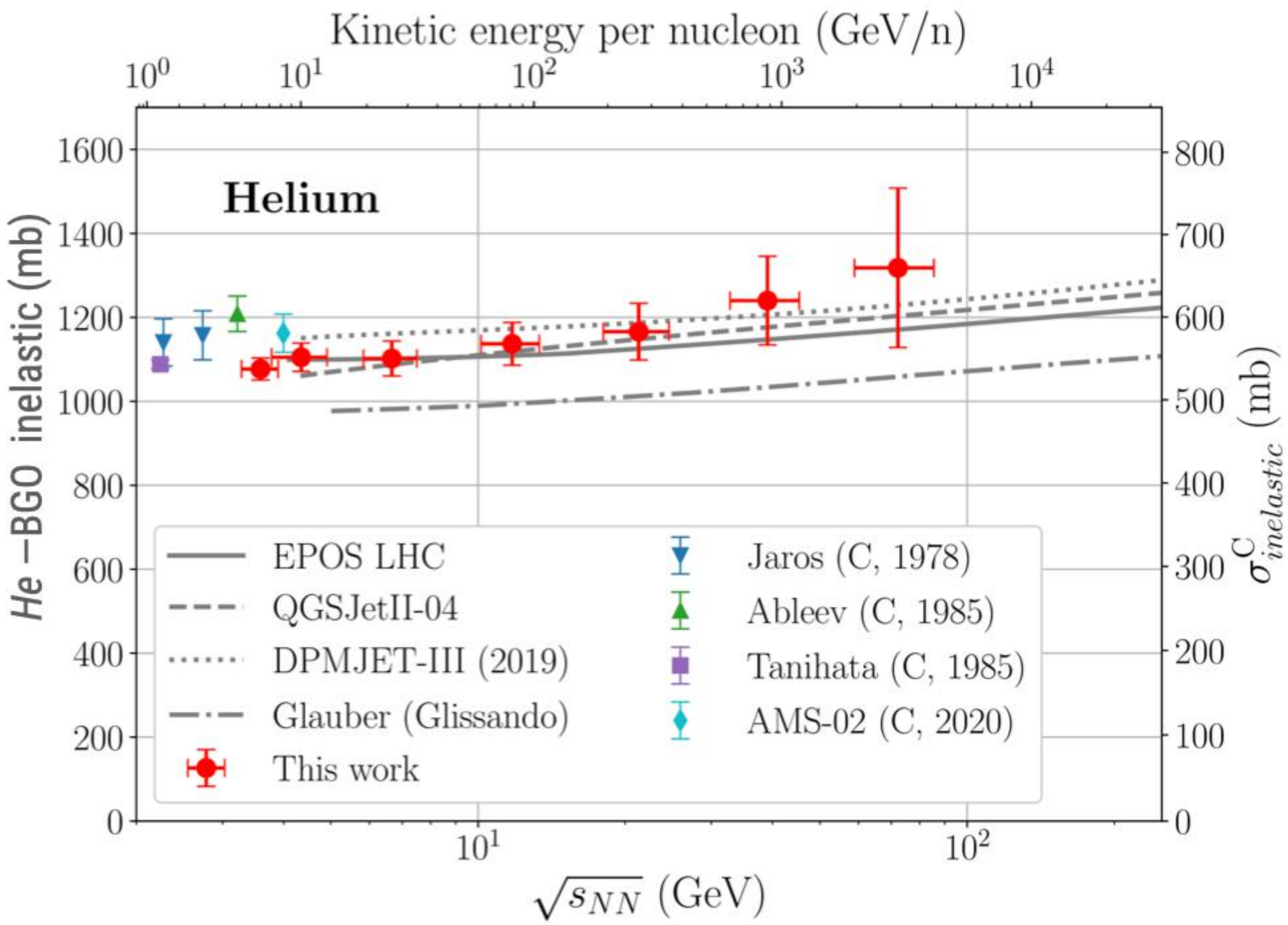
CNNs based tracking enables **clean and unbiased particle identification**
– critical for hadronic **cross section measurement** with DAMPE:



Physics applications: Hadronic Cross Sections

CNNs based tracking enables **clean and unbiased particle identification** – critical for hadronic **cross section measurement** with DAMPE:



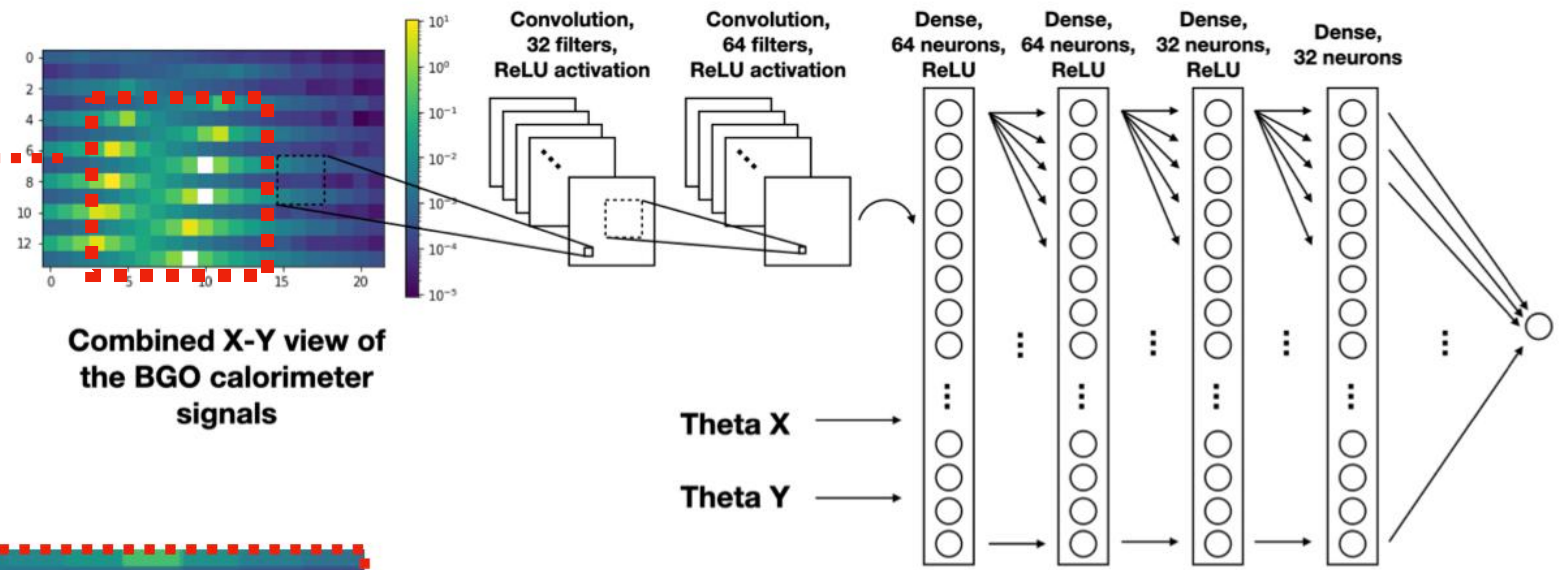


BDTs & CNNs also used for the reconstruction of the hadronic inelastic interaction point in calorimeter

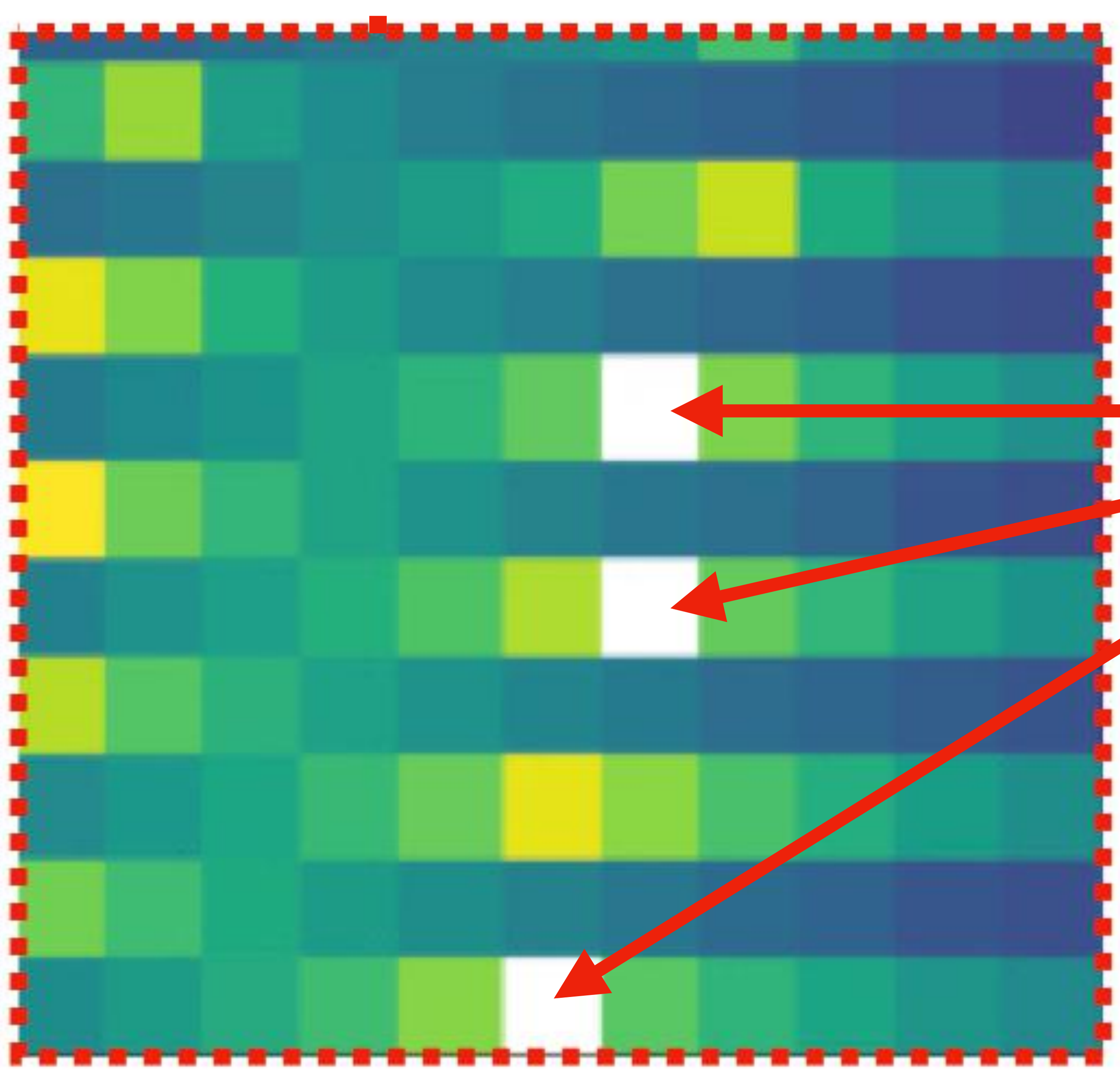
Credit: ***Paul Coppin (UniGeneva)***

Physics applications: Energy Reconstruction

CNNs correct for saturation in calorimeter and infer the truth particle energy in the DAMPE calorimeter:

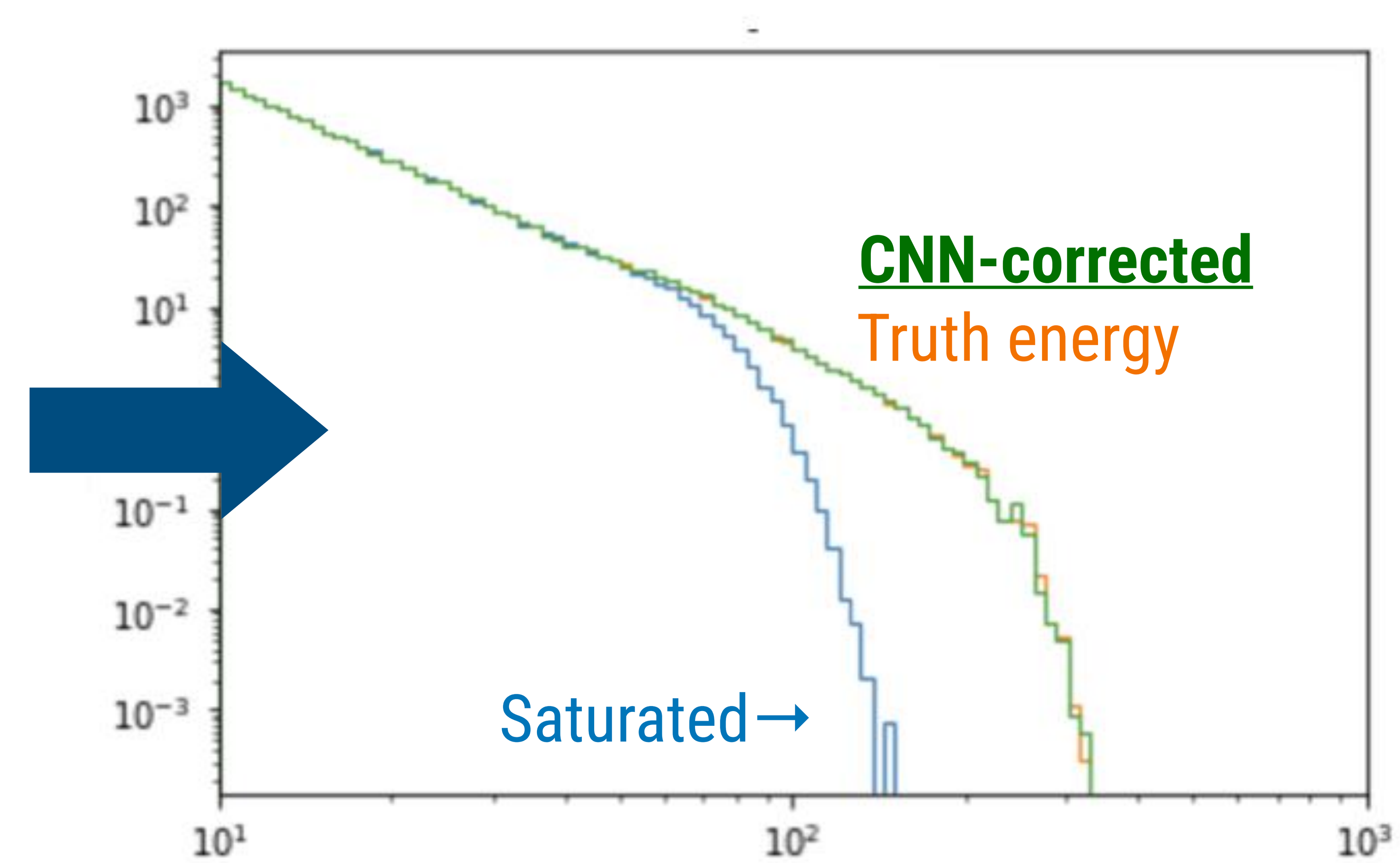


Prediction of particle energy



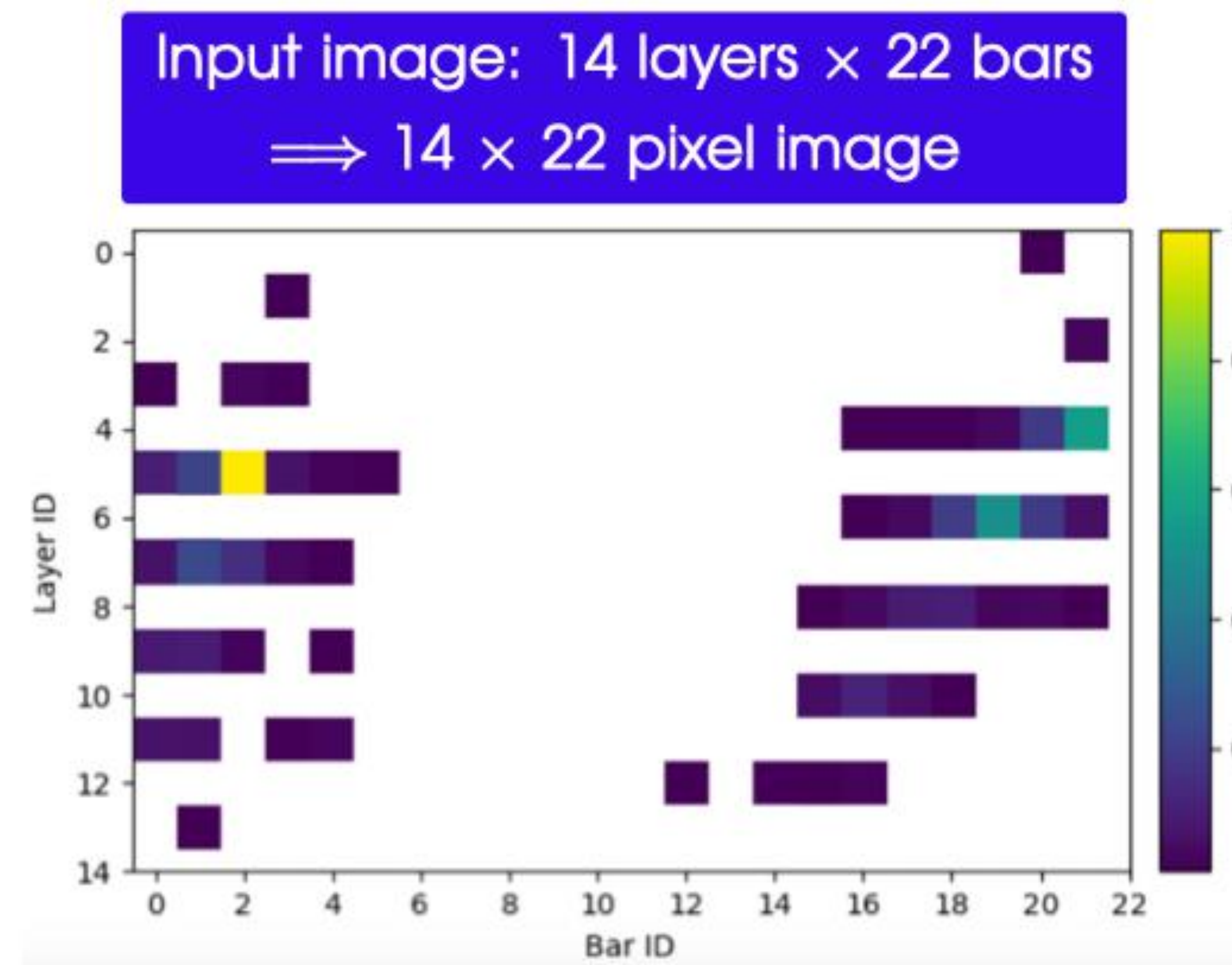
Saturated BGO bars

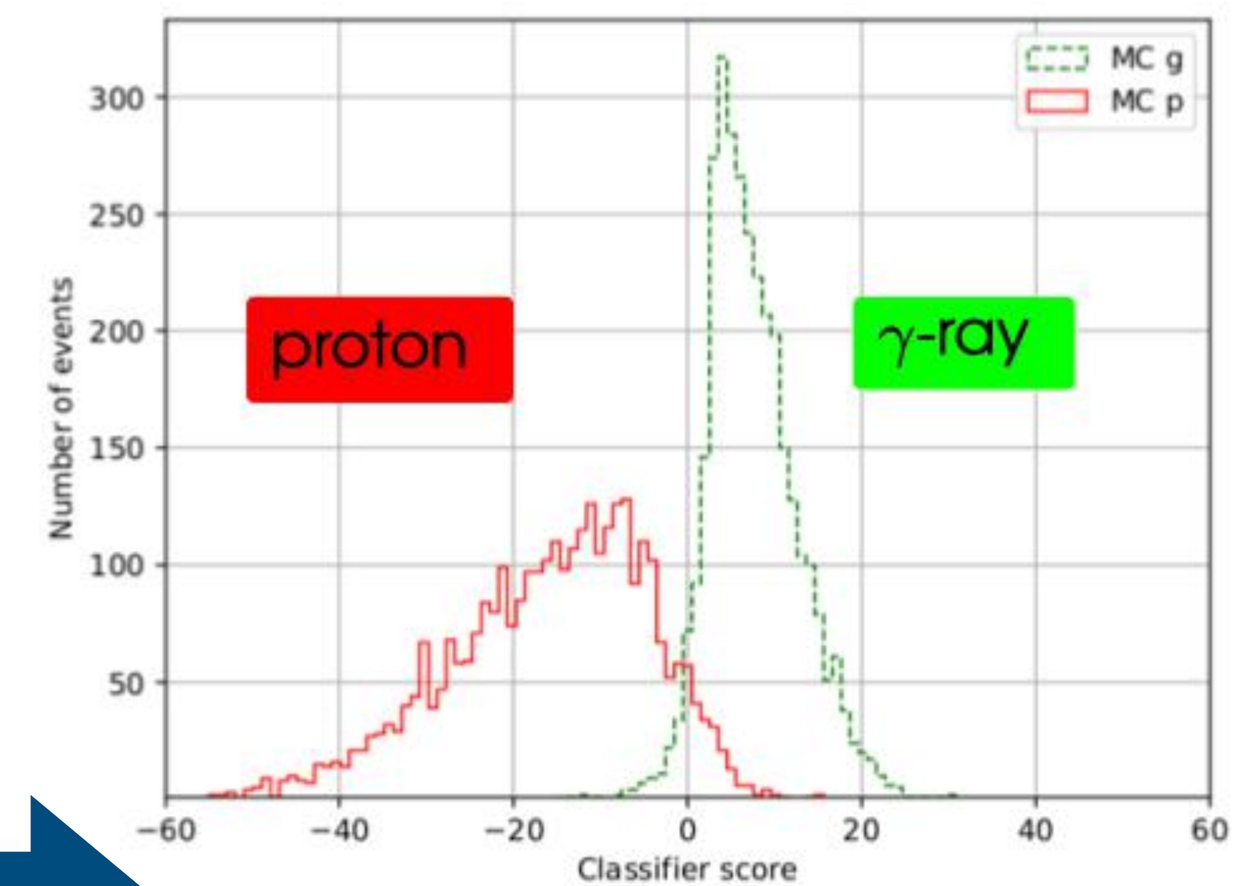
Data structure is important!
“Mixed” image structure works better than two independent projections

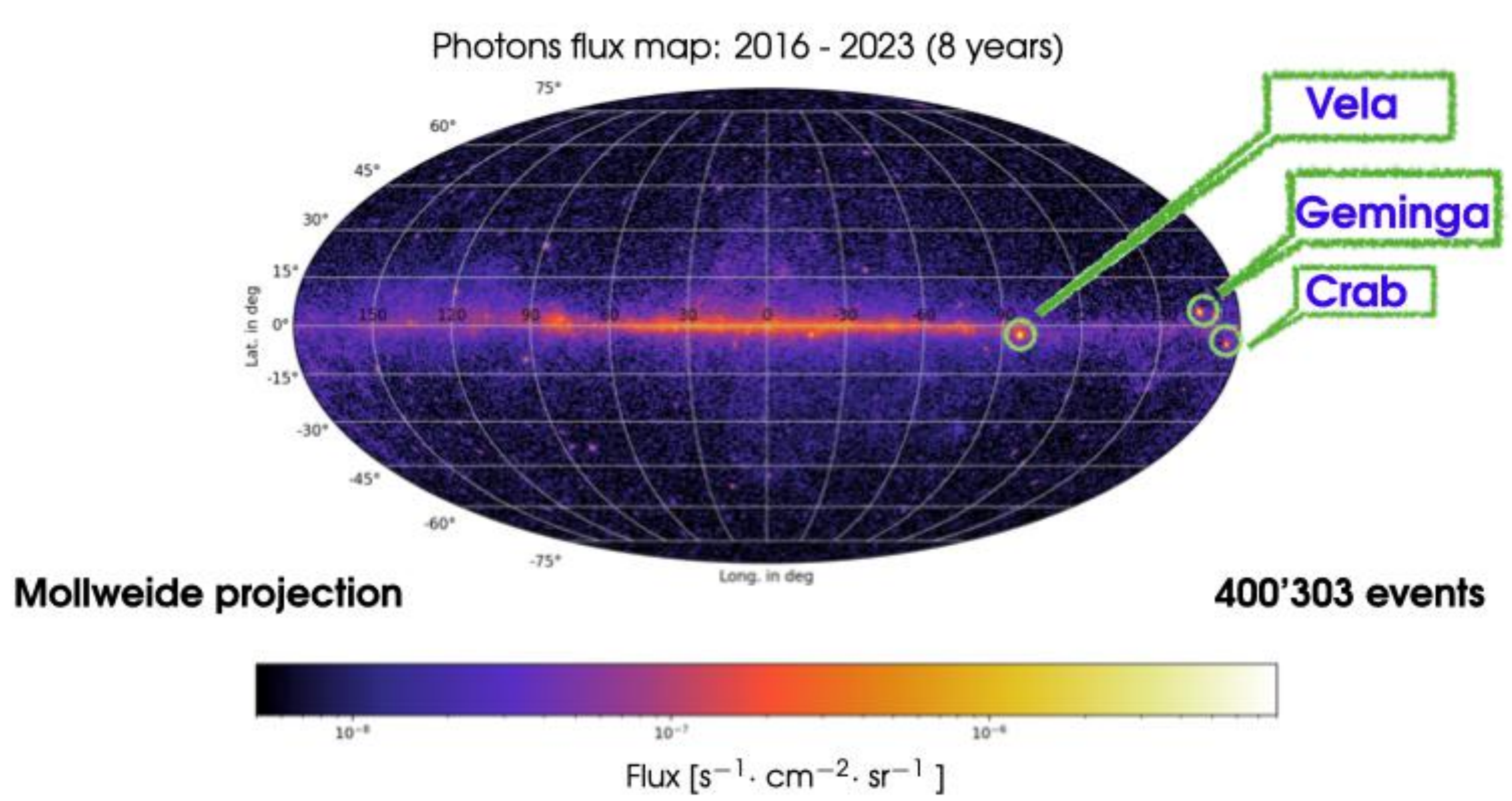


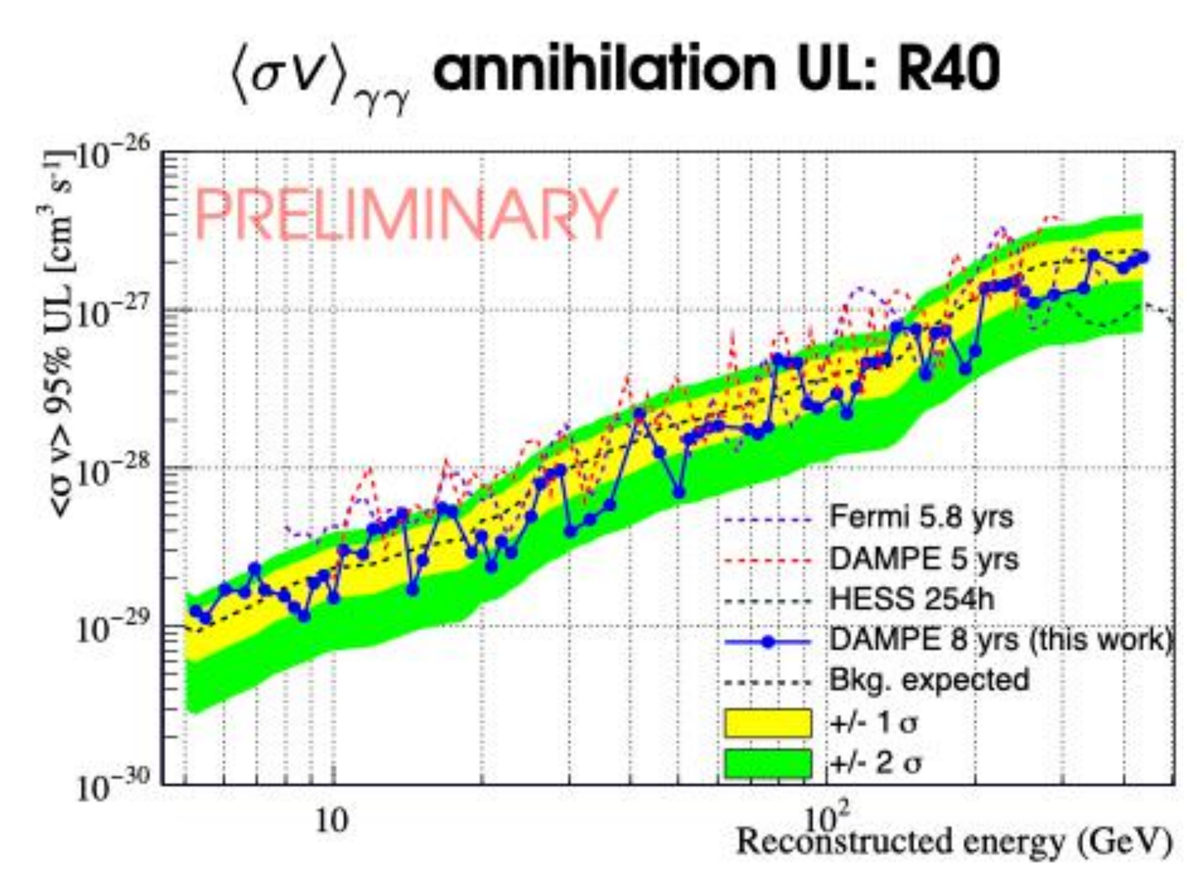
Stolpovskiy et al. JINST 17 (2022) 06, P06031

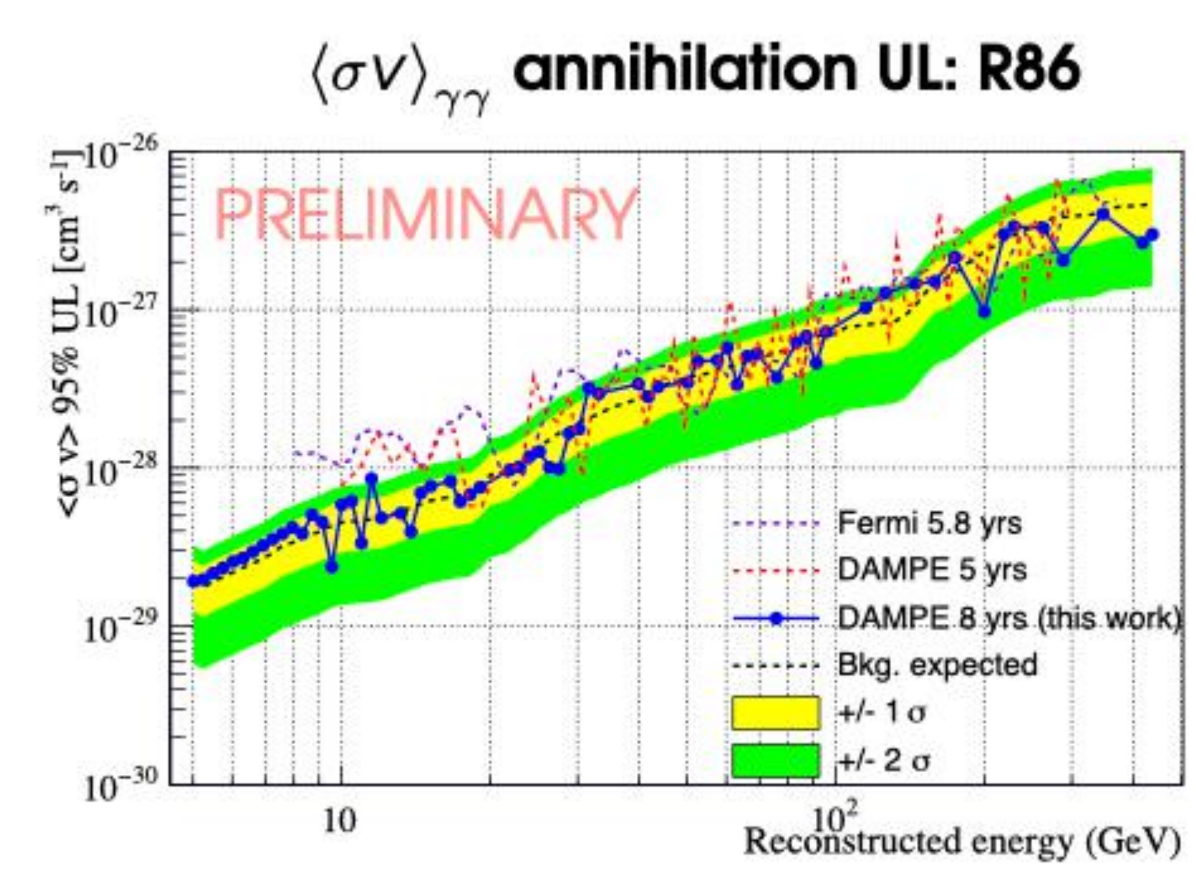
CNNs for γ-ray and proton separation in DAMPE:









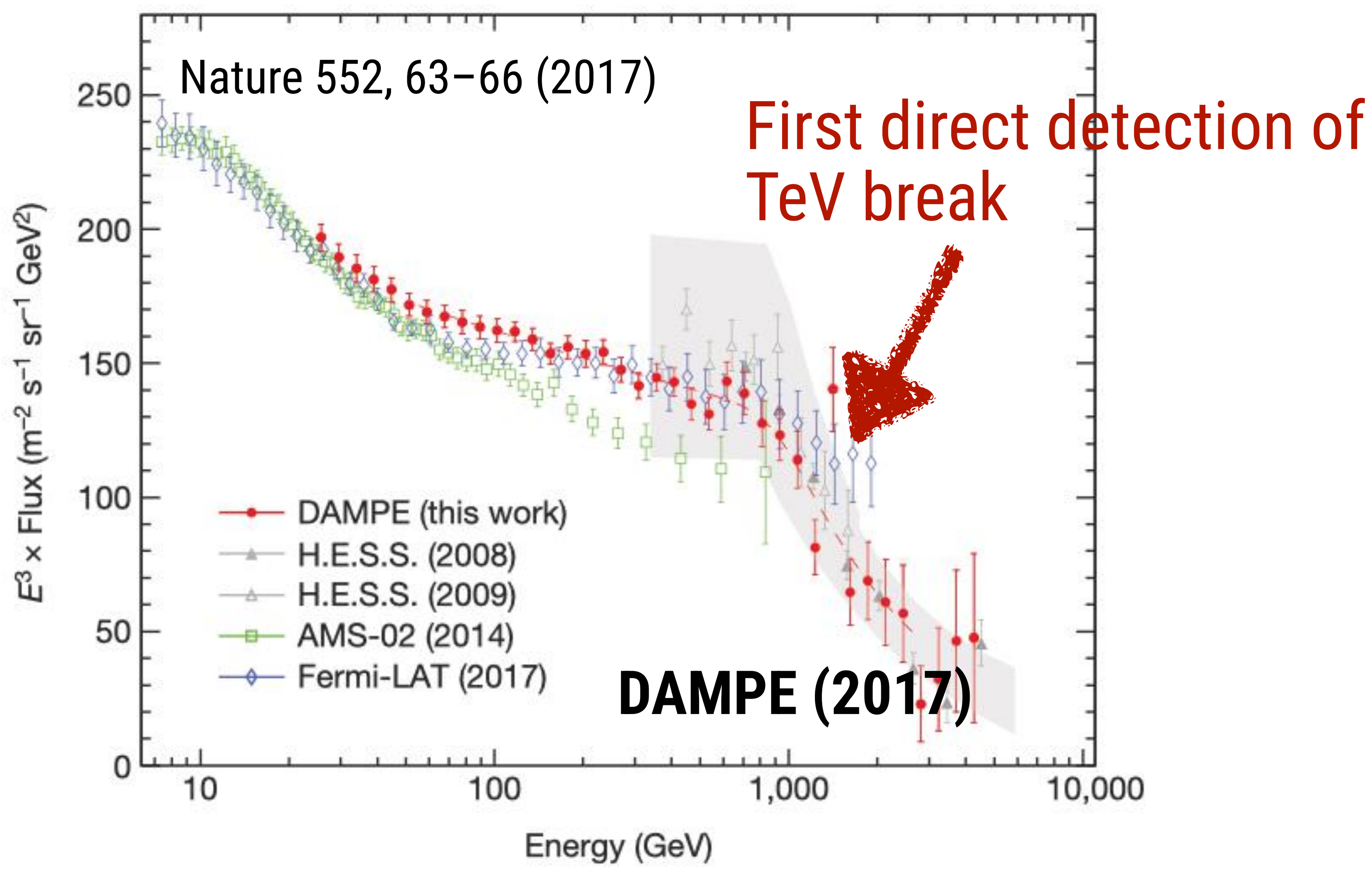


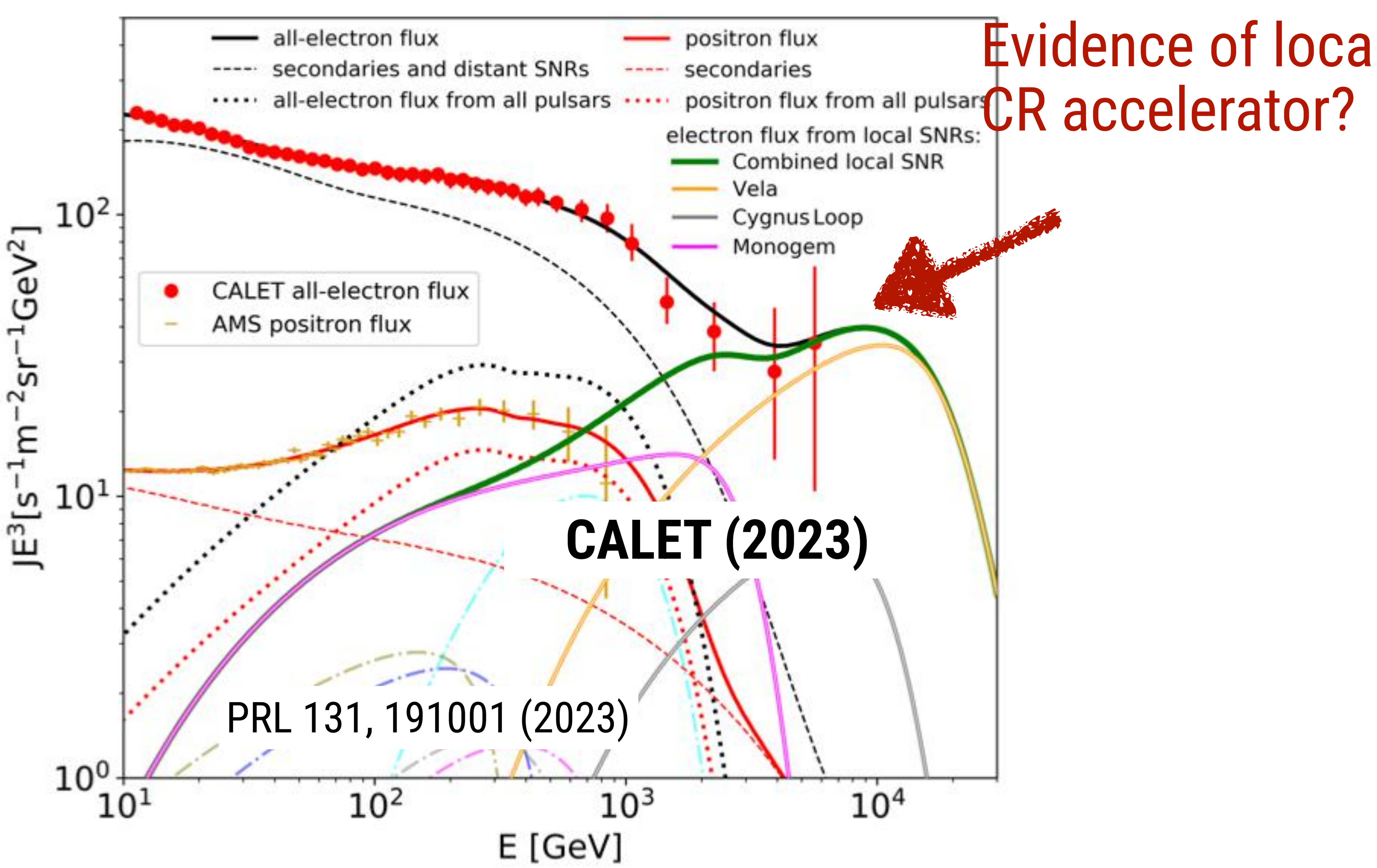
Improved sensitivity for dark matter searches!

Credit: ***Jennifer M. Frieden (EPFL)***

https://agenda.infn.it/event/35353/contributions/239308/

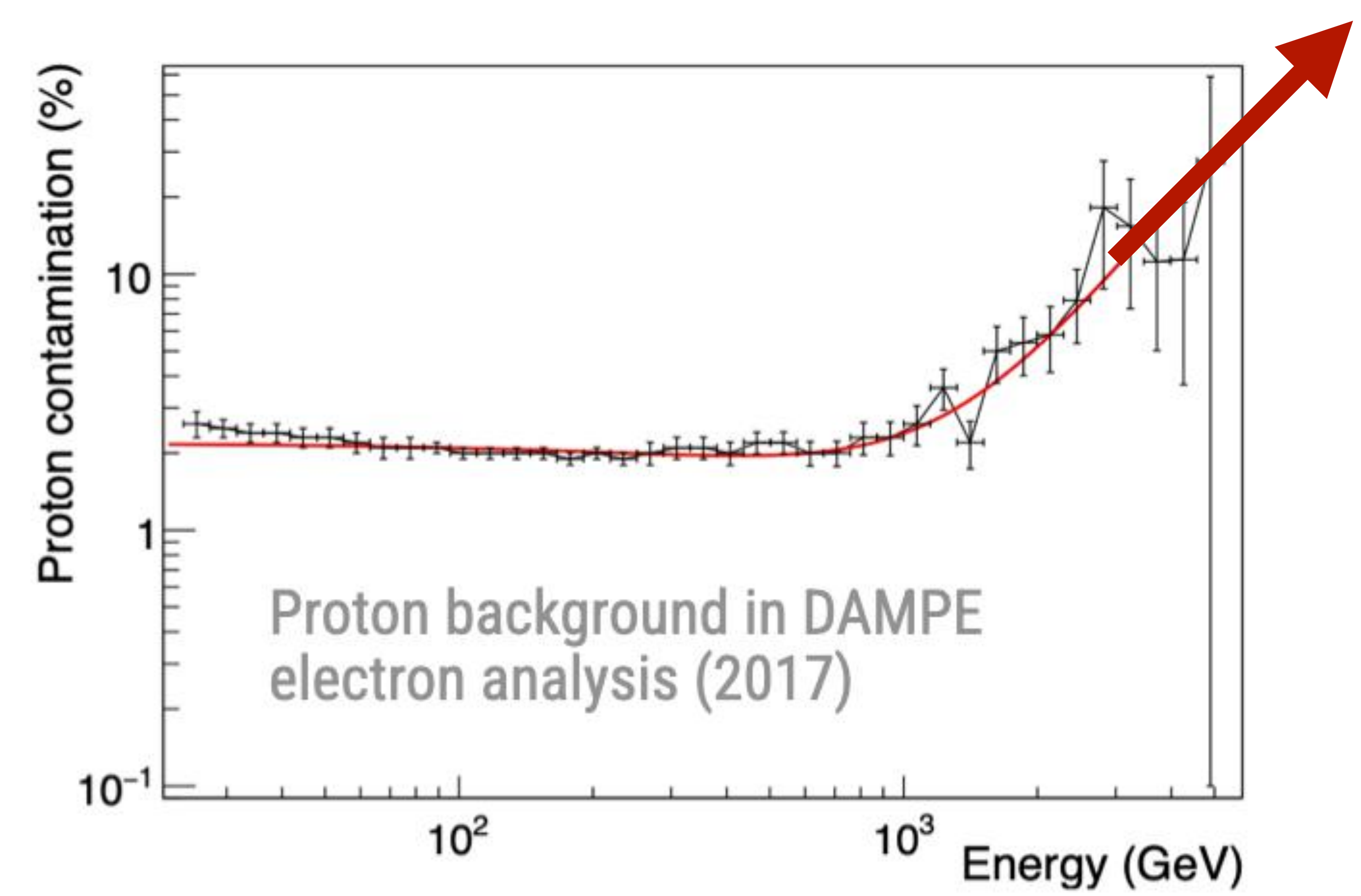
Physics applications: Electron flux





CR electrons:

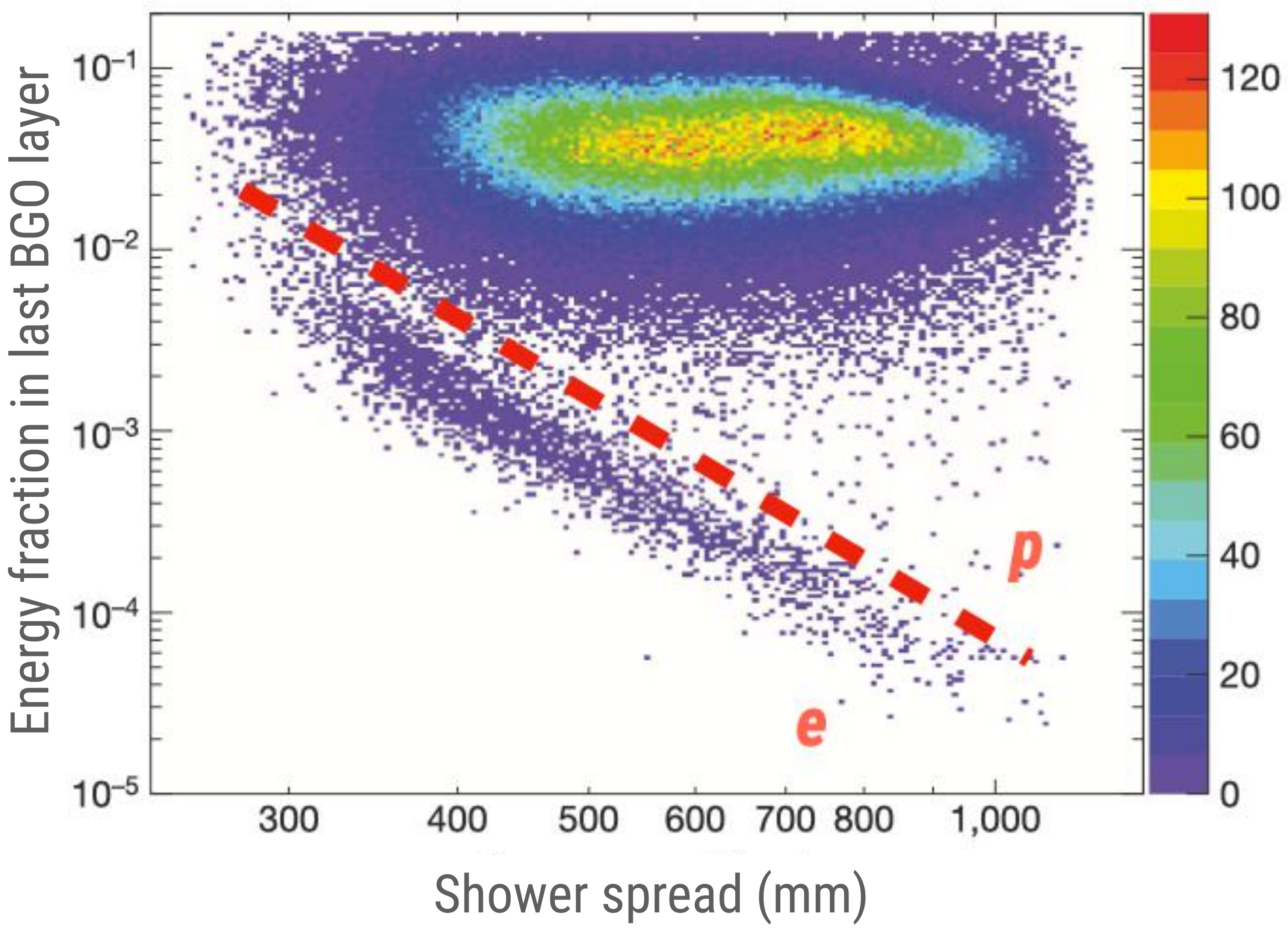
- First direct detection of ~TeV break: 2017
- CALET: hint of hardening towards ~10 TeV
- CALET measurement reaches 7.5 TeV
- DAMPE measurement reaches 4.6 TeV
- **What is out there at > ~ 10 TeV energies?**

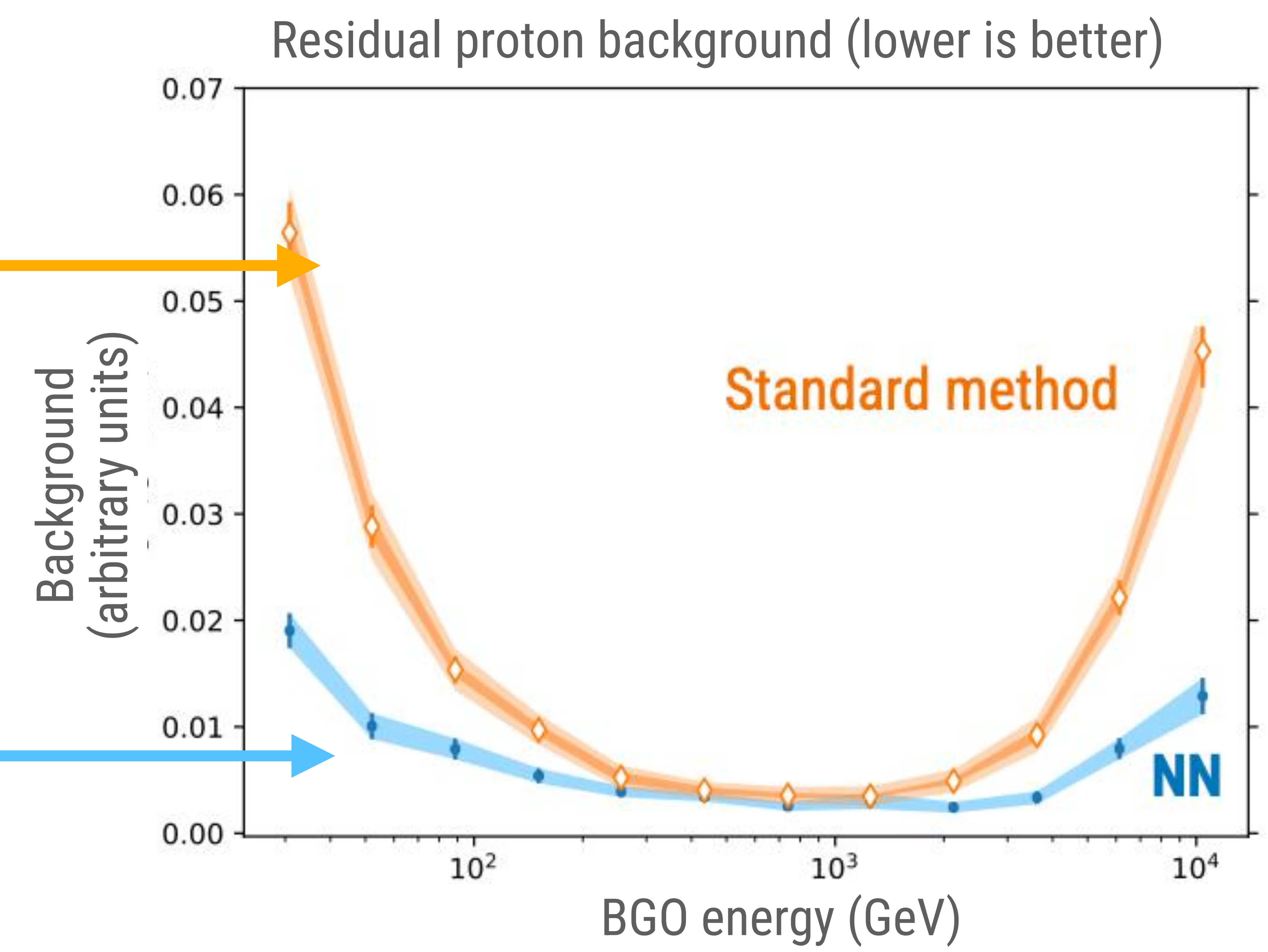


Protons are 10^4—10^5 times more than electrons at > TeV energies — **we need more powerful e/p separation!**

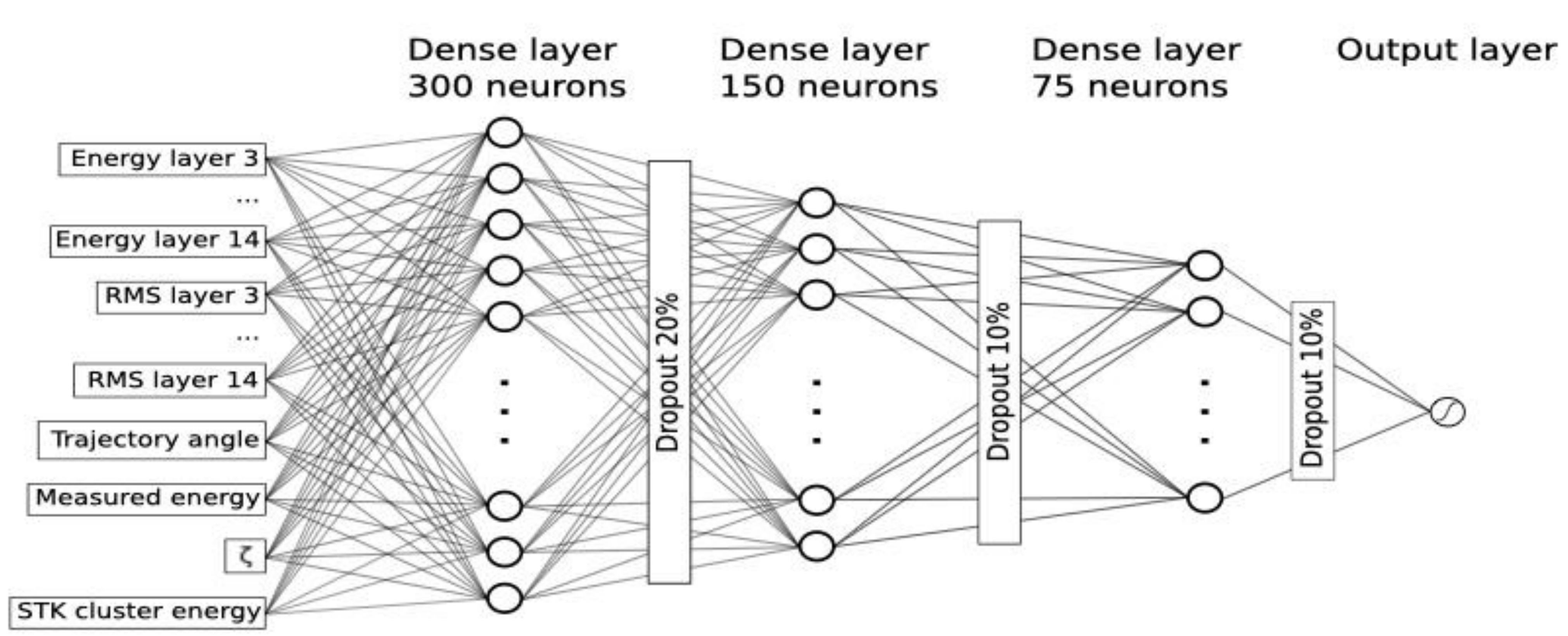
Physics applications: *e/p* separation (DAMPE)

Standard method (shower-shape):





Neural Network classifier:



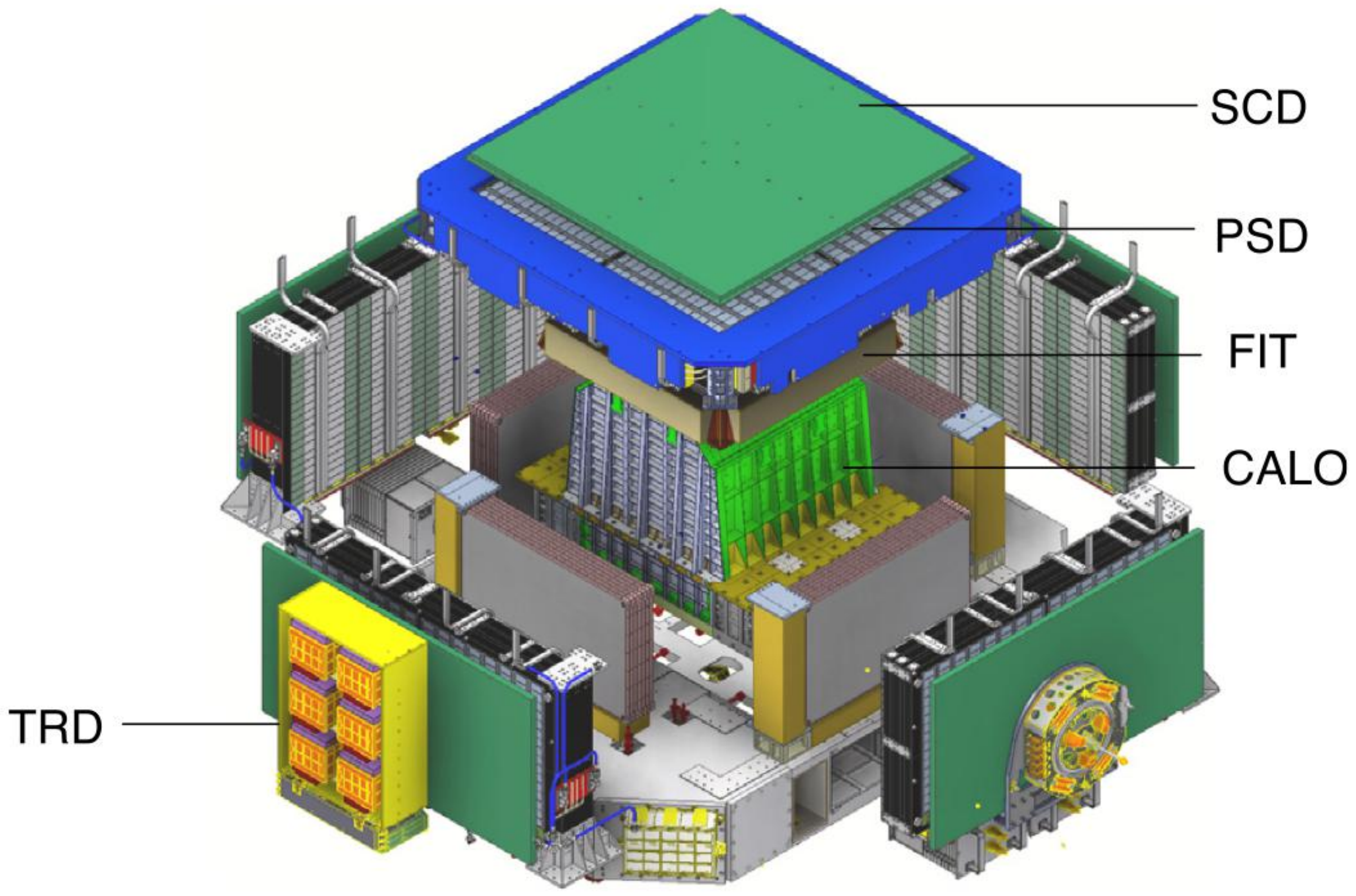
- Neural Network (NN) classifier: 3—4 times better proton background rejection at > 10 TeV!
- CNNs also investigated: potential factor ~2 enhancement of proton rejection over NNs

Droz et al. JINST 16 P07036 (2021)

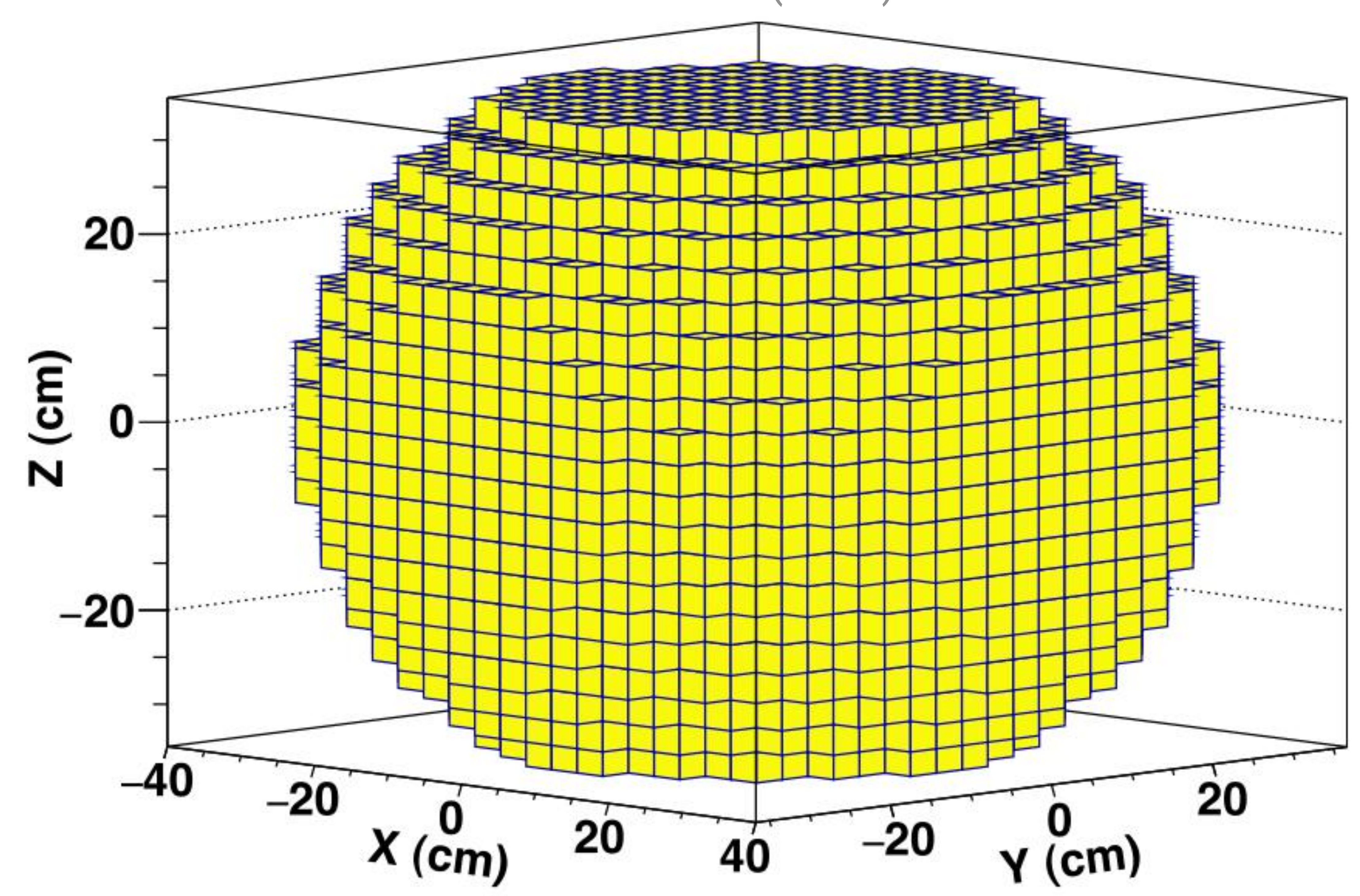
Part III: Quick Look in Near Future

High Energy cosmic Radiation Detection facility (HERD)

- Launch > 2027
- First 3D calorimeter in Space (~55 X_0 / ~3Λ_0 - twice as thick as DAMPE calorimeter)



Yang et al. NIM A 1066 (2024) 169571

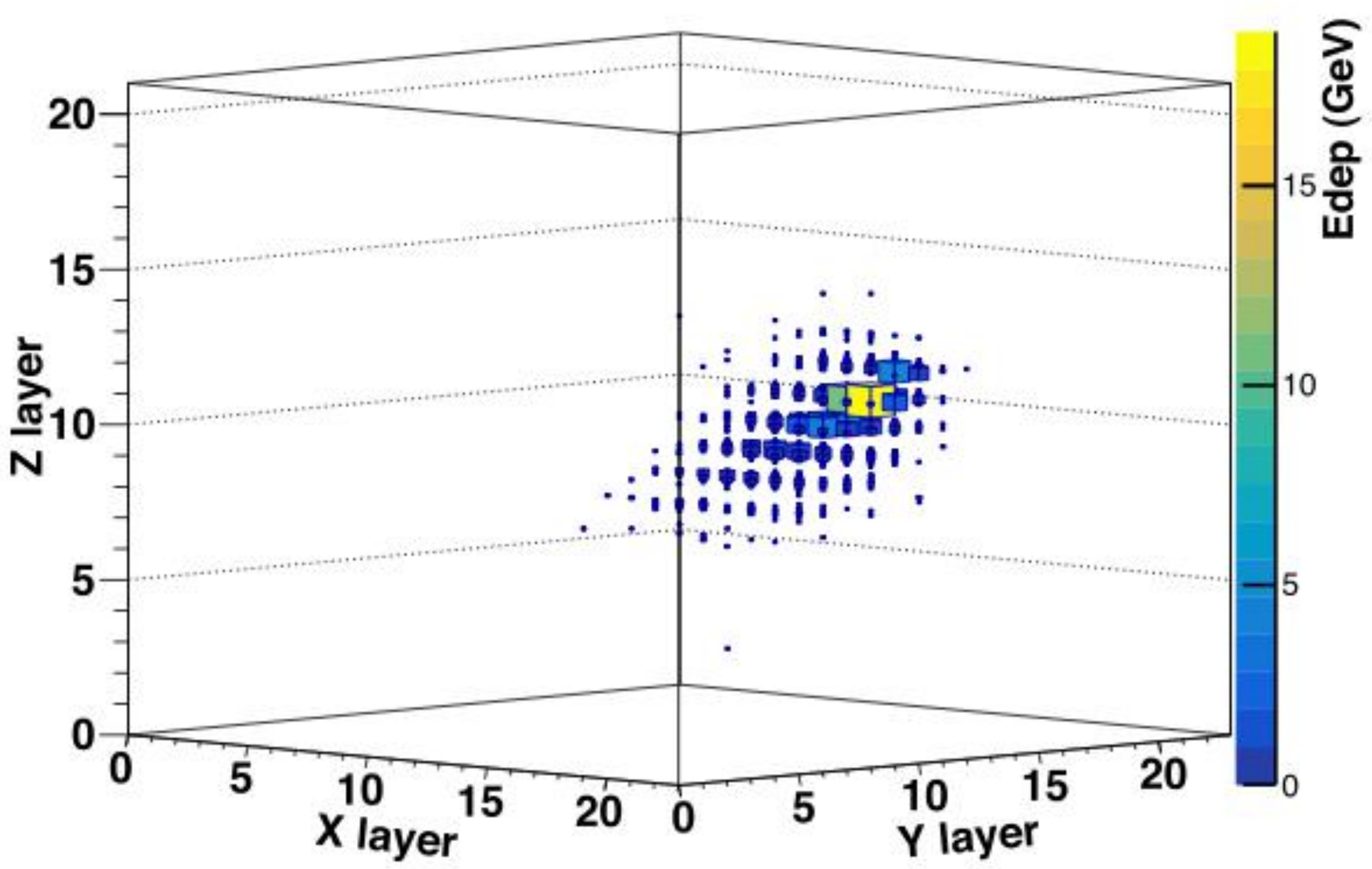


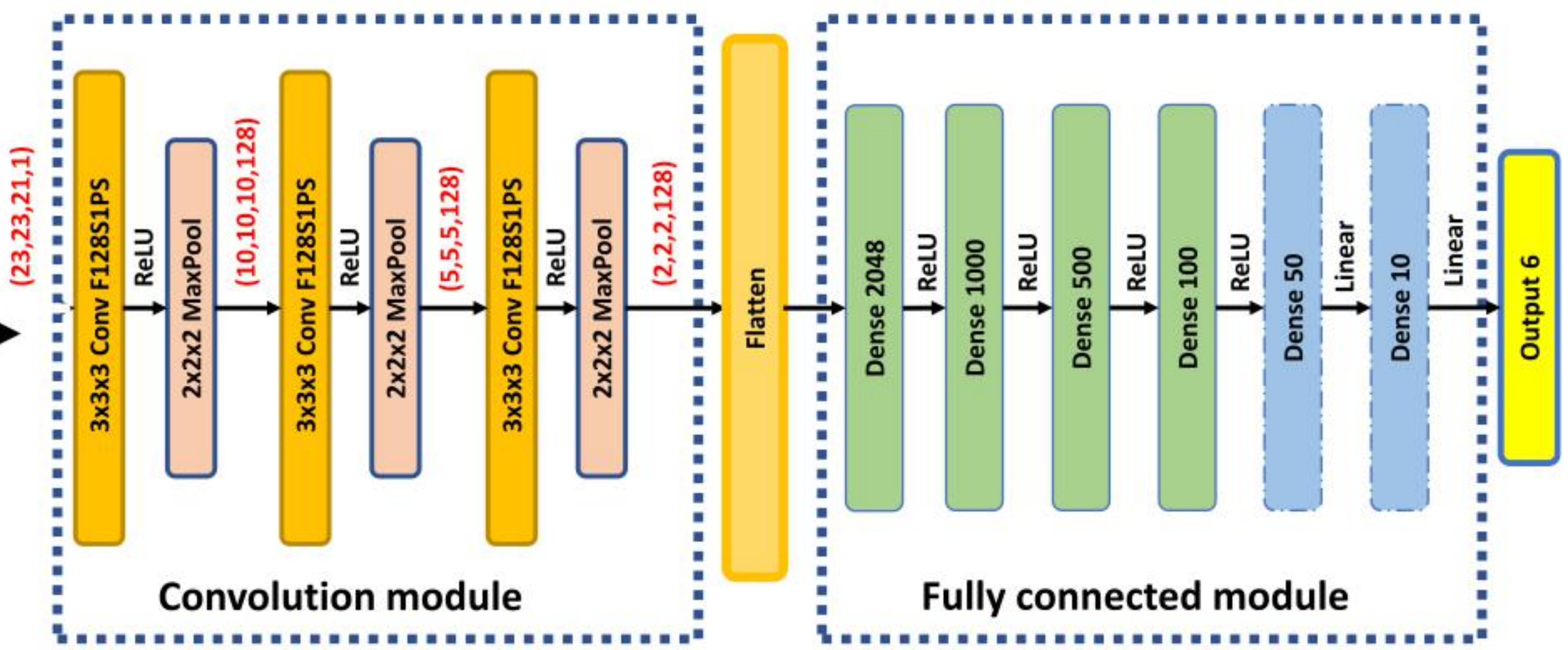
> one **order of magnitude higher complexity** of the detector (compared to DAMPE) — ideal "playground" for deep learning ...

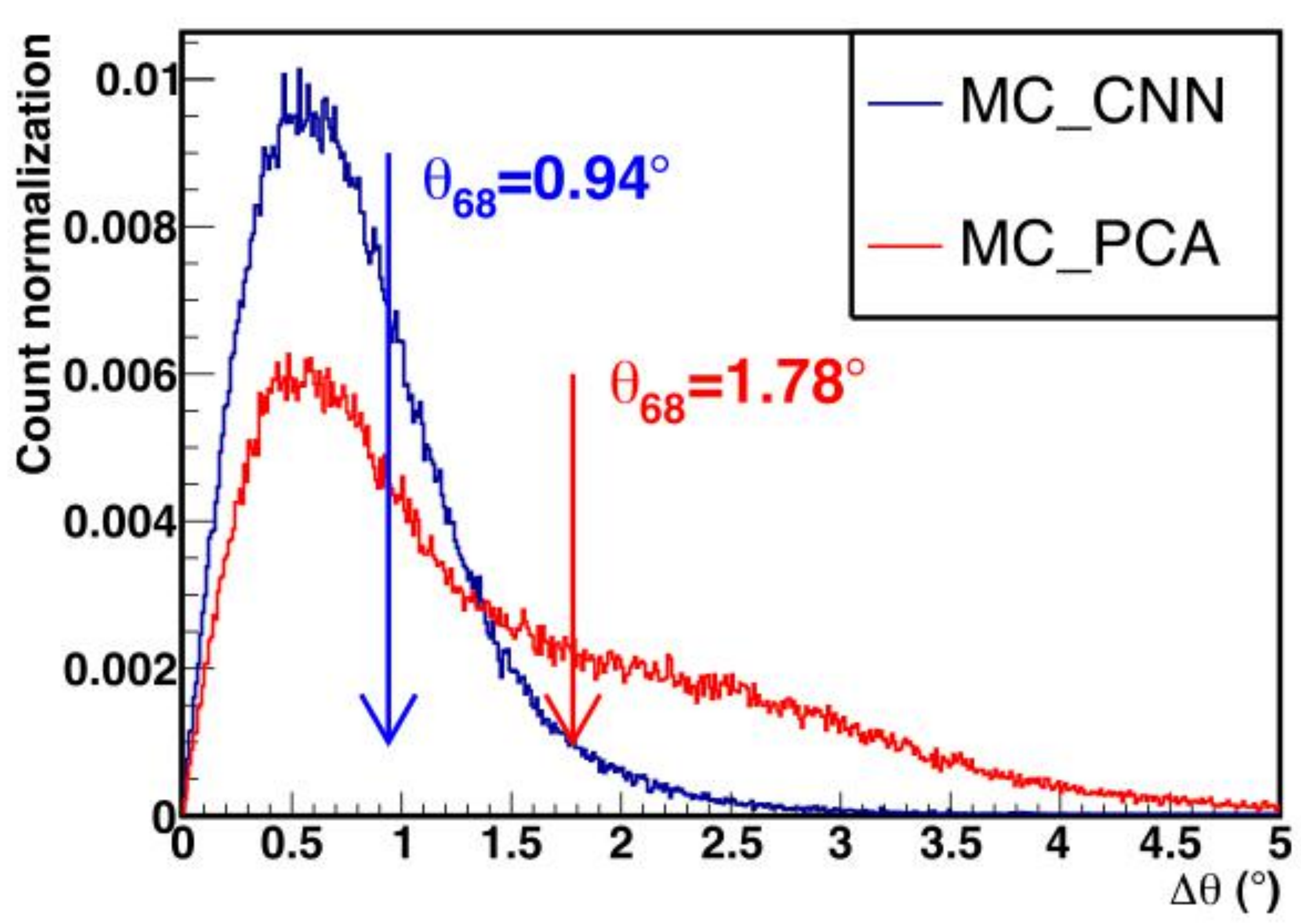
Deep Learning in HERD

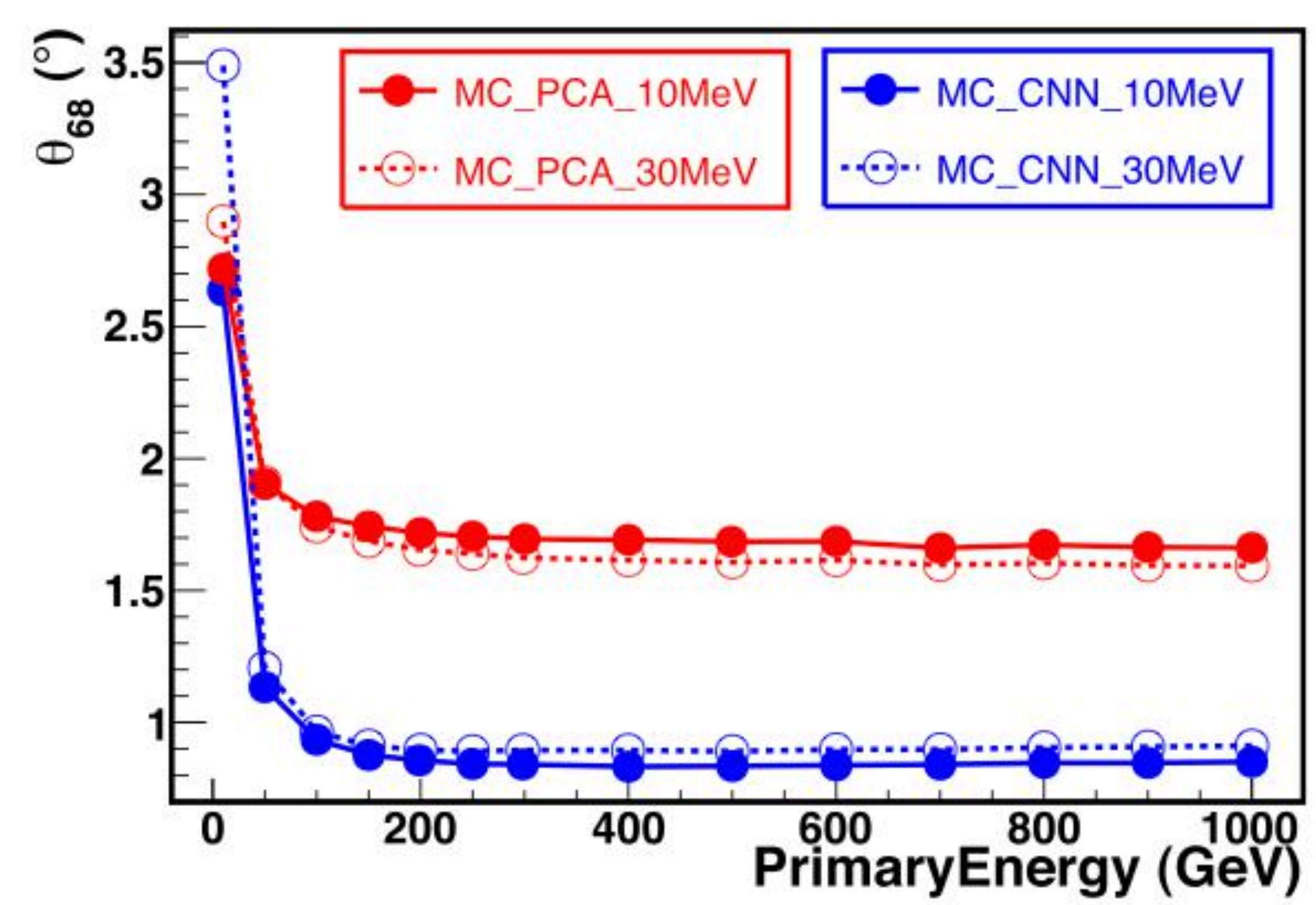
Yang et al. NIM A 1066 (2024) 169571

100 GeV electron in HERD calorimeter:







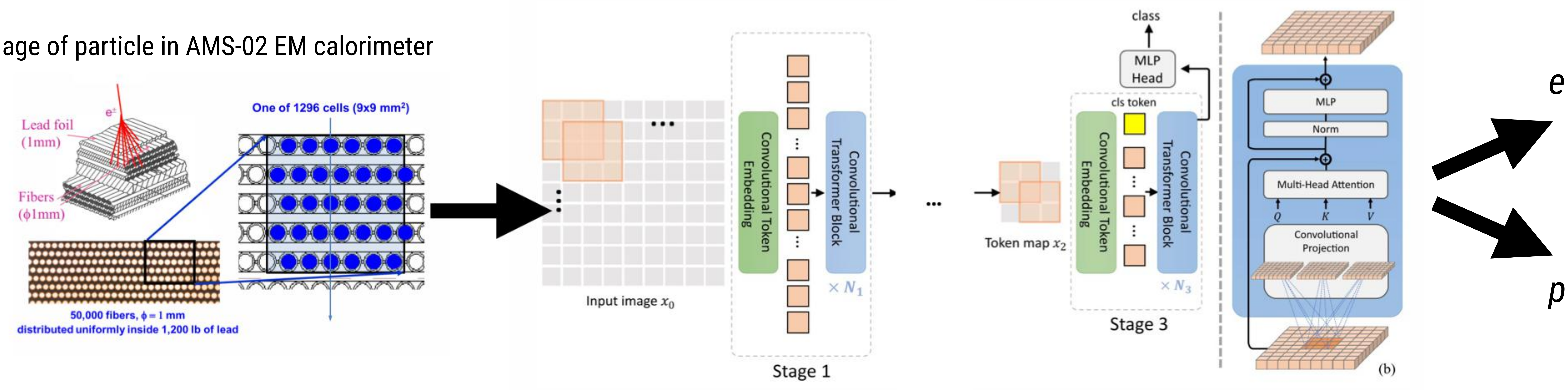


$\Theta_{68\%}$ ~ 0.8° above 200 GeV —twice higher than DAMPE, does not improve with energy

→**more complex AI architecture needed?**

Transformers @ AMS-02

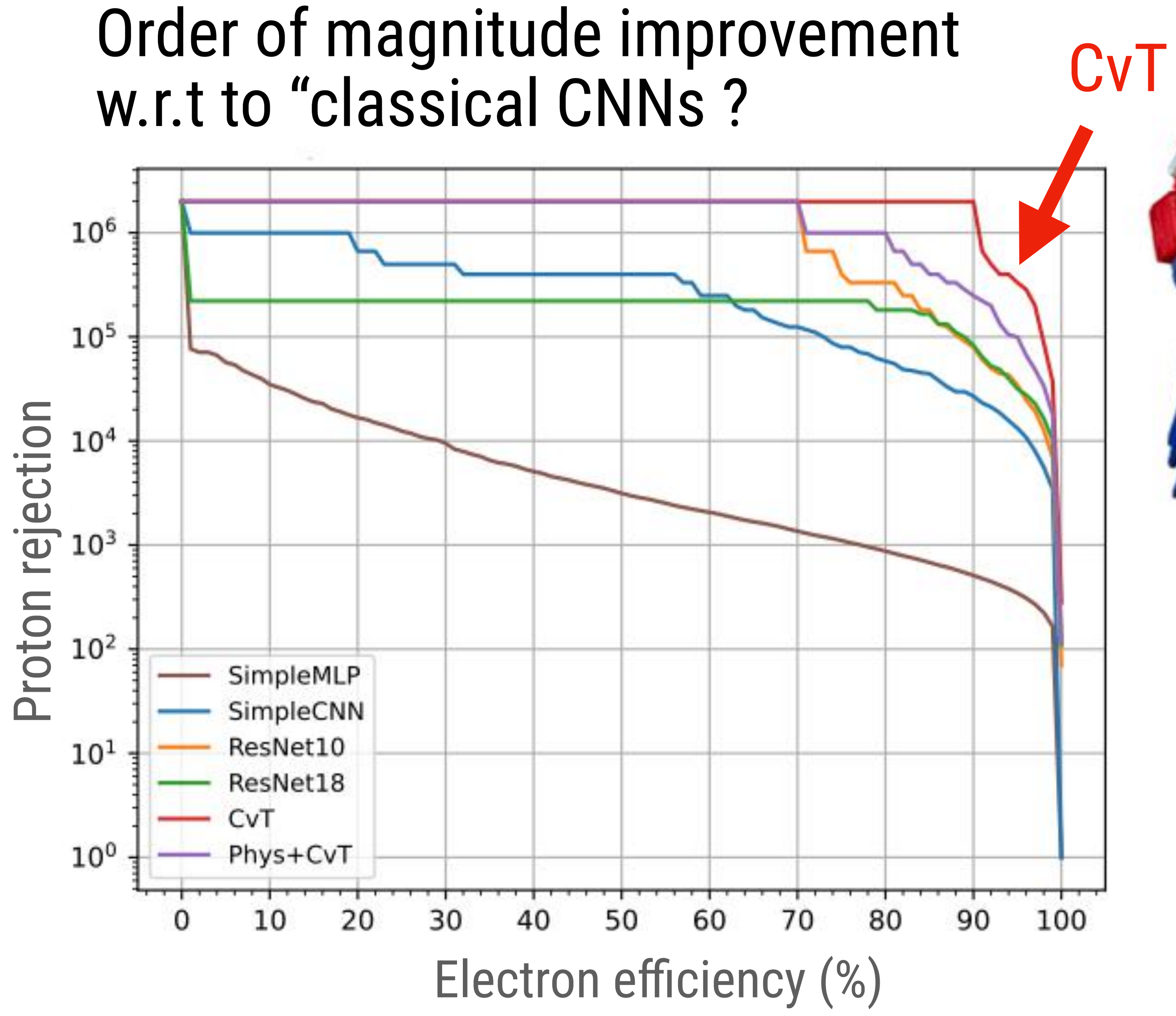
Image of particle in AMS-02 EM calorimeter



Experience from large language processing models

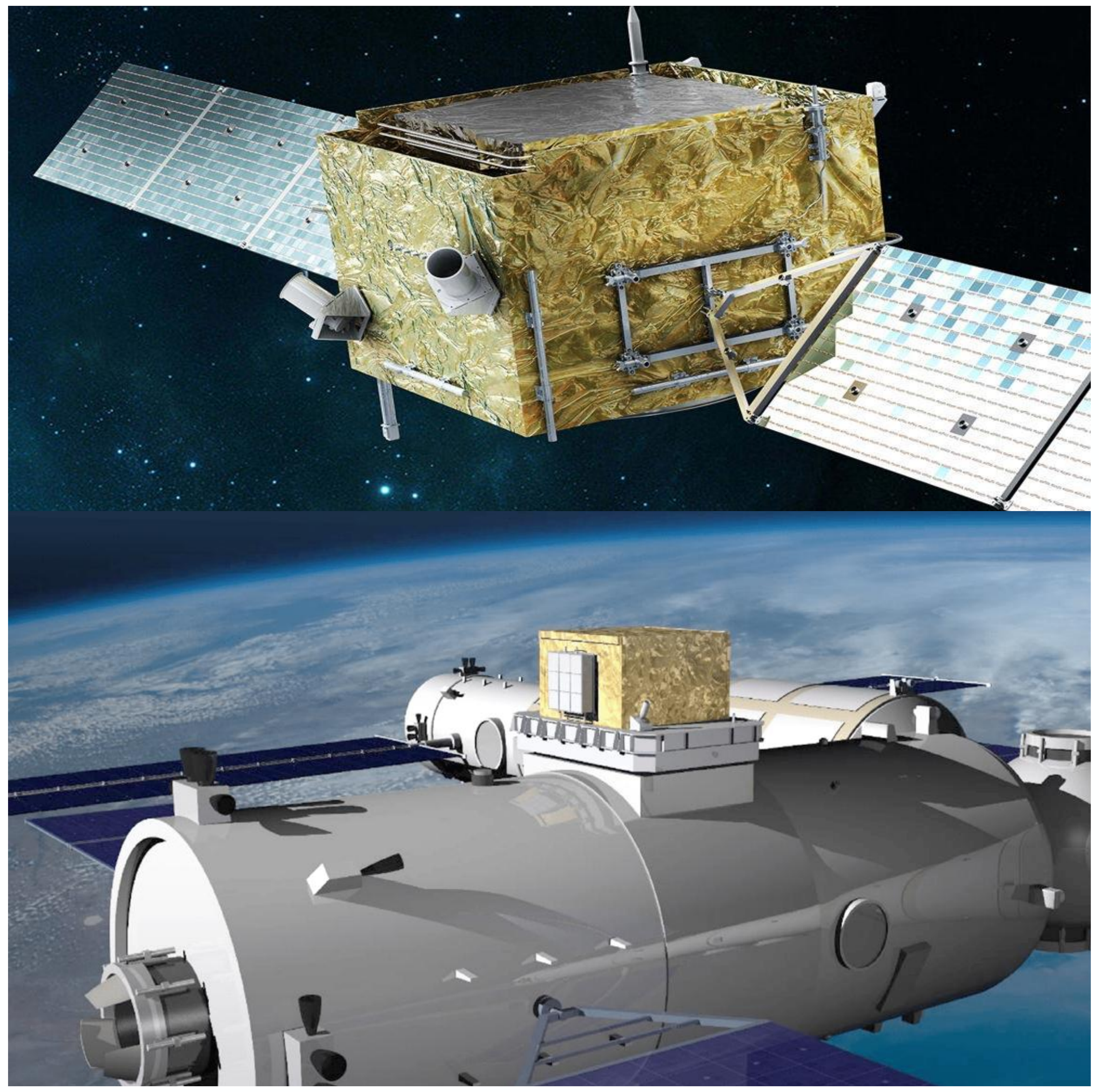
- **Attention**: method that dynamically highlights the most relevant parts of an input (key words in a sentence, key parts of an image)
- Convolutional vision Transformers (CvT): **better generalization**, better focus on key areas, and global context

Order of magnitude improvement w.r.t to "classical CNNs ?



Hashmani et al.
arXiv:2402.16285v1 (2024)

Conclusions



Some physics motivations & use cases for AI

- Extension of measurements to higher energies
- Background reduction for electron/γ-ray detection
- Trajectory/vertex reconstruction & hadronic physics

...

What we learned so far?

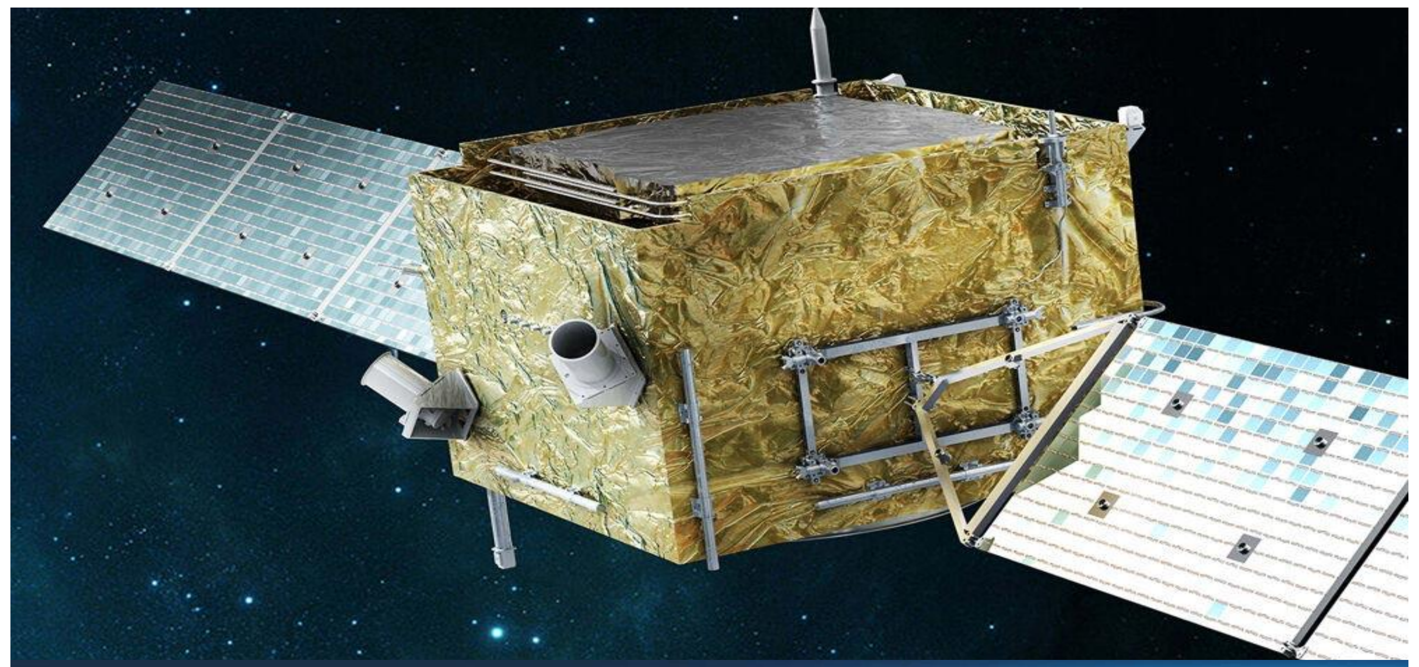
- BDTs still good for many classification problems
- CNNs "revolution" – treat everything as "images"
- Validation with data is difficult
- Structuring input data is important
- Next: state-of-the-art AI (large language models experience...)

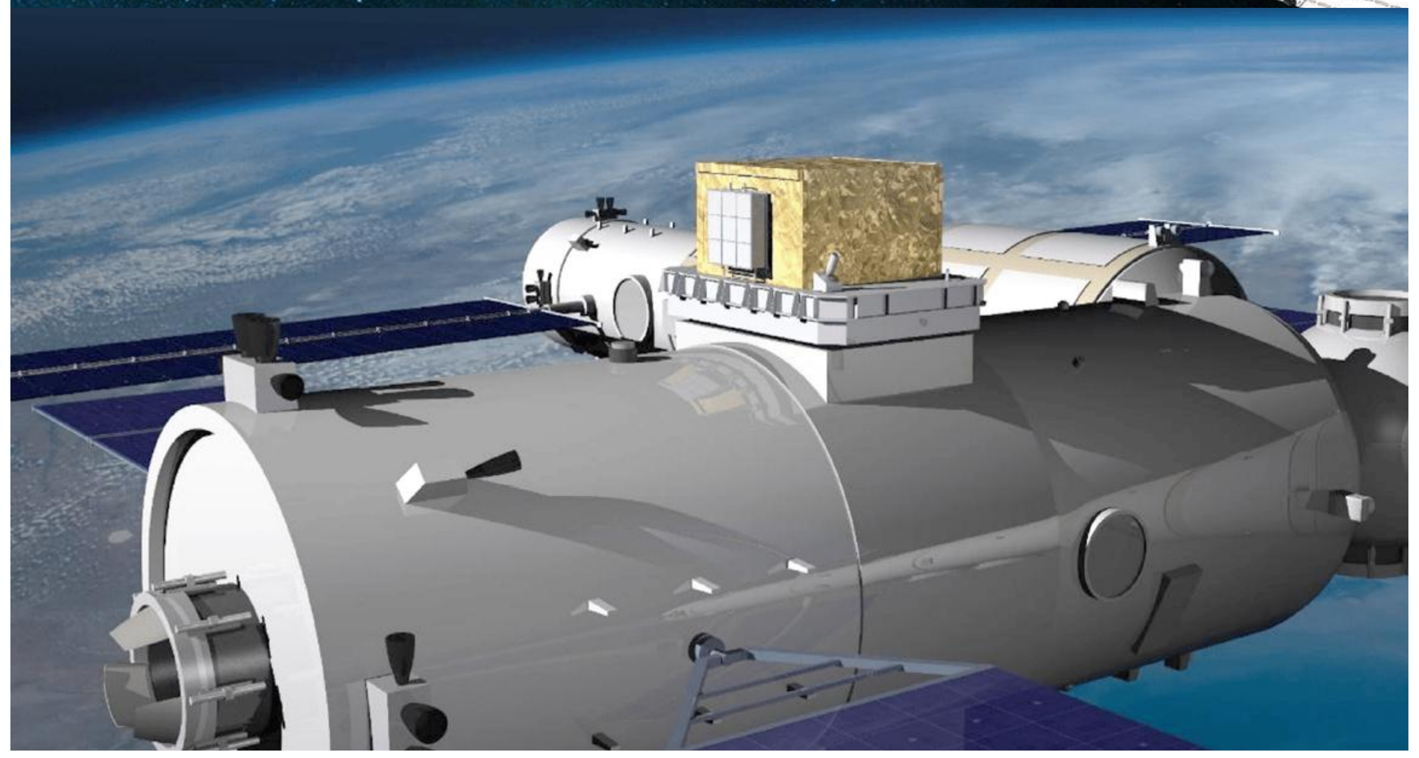
Conclusions

Some physics motivations & use cases for AI

- Extension of measurements to higher energies
- Background reduction for electron/γ-ray detection
- Trajectory/vertex reconstruction & hadronic physics

...





What we learned so far?

- BDTs still good for many classification problems
- CNNs “revolution” – treat everything as “images”
- Validation with data is difficult
- Structuring input data is important
- Next: state-of-the-art AI (large language models experience...)

Thank You!