Ricostruzione degli eventi di Limadou-HEPD con tecniche di Deep Learning

14-18 September 2020 - Congresso SIF

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on behalf of the Limadou Collaboration

Event Reconstruction based on Deep Learning

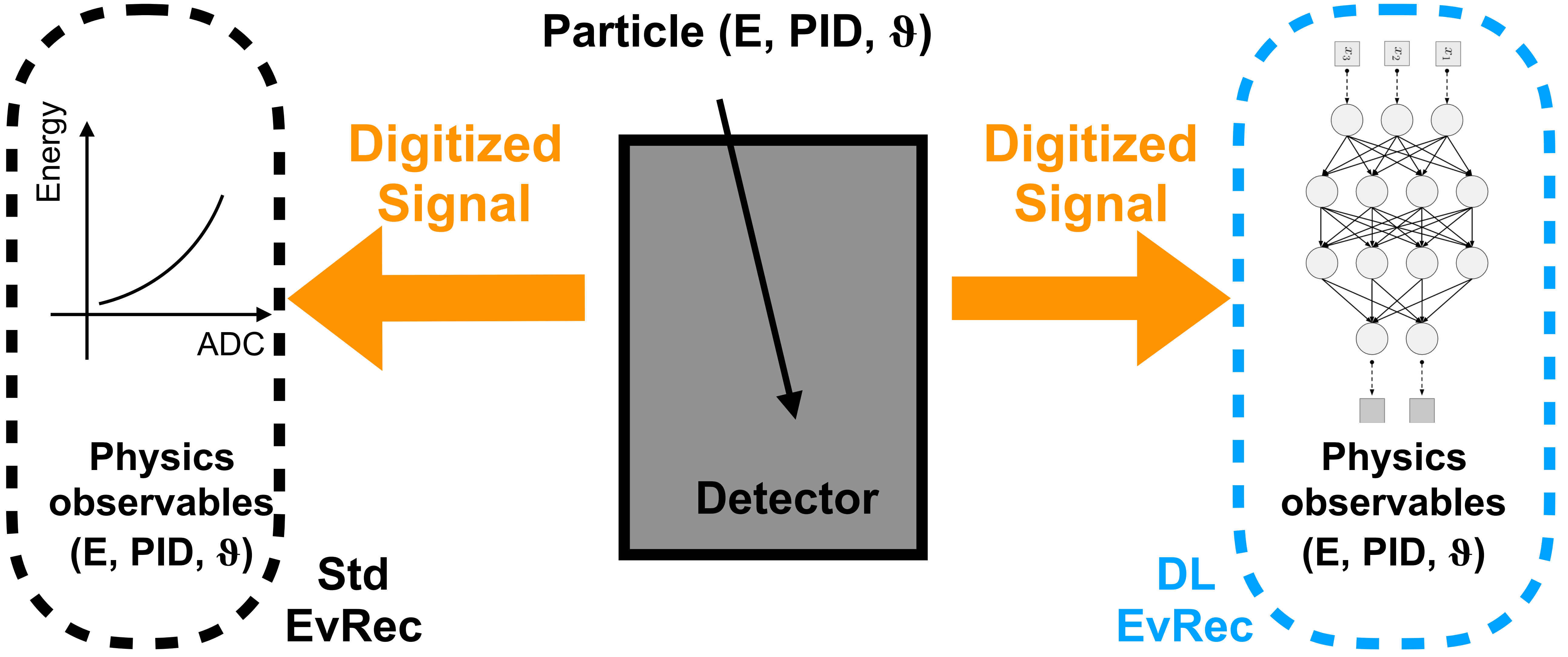
Deep learning algorithms play a **key role in the event reconstruction** of most modern particle physics experiments (particle identification, tracking, correction of the observables, etc…) . They offer advantages and show very few drawbacks:

Advantages:

- They **account for all correlations between the variables**, which are hidden or not easy to model;
- They can **compensate for and exploit the detector asymmetries and data inhomogeneities** to improve reconstruction performances;

Limits:

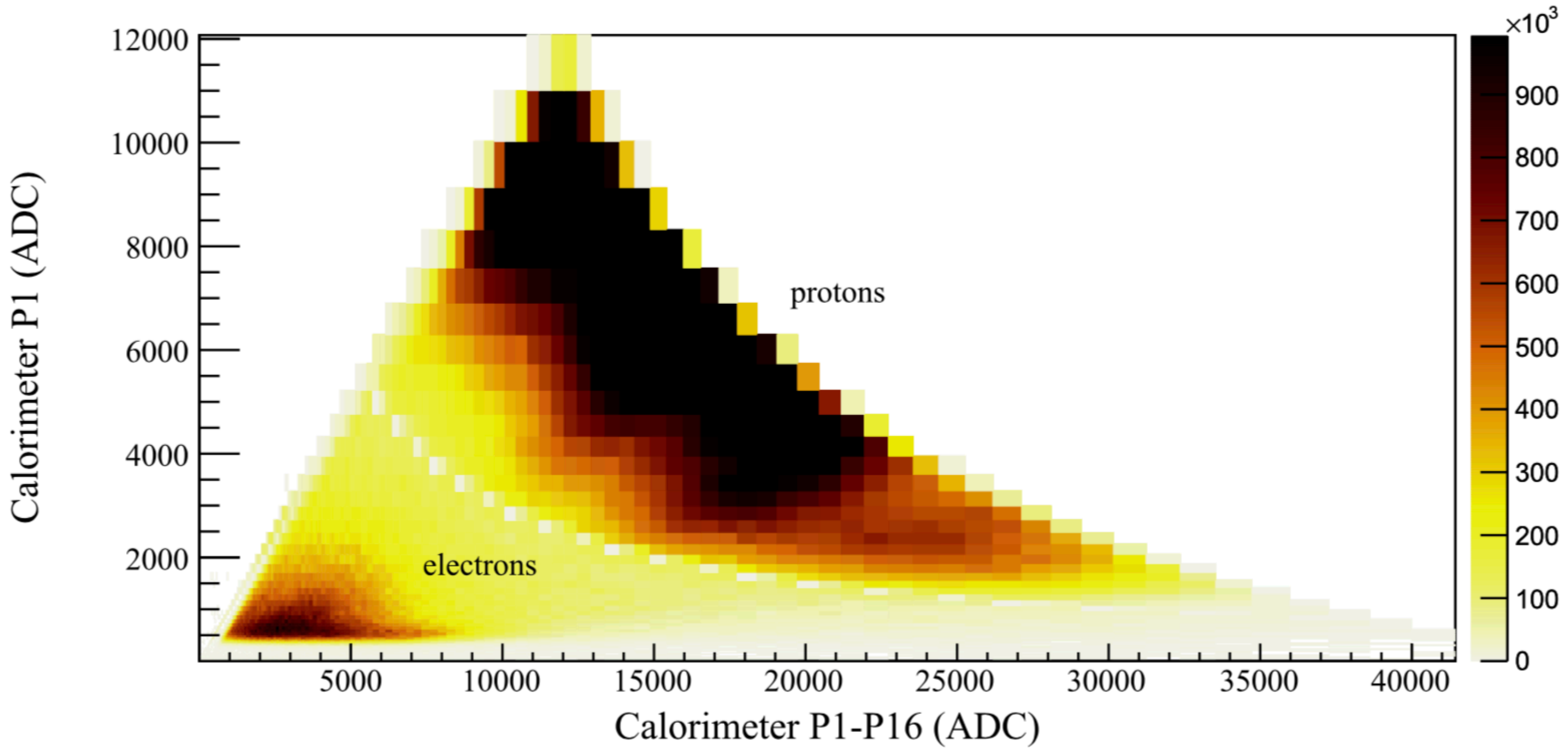
- They **rely on simulations (training dataset)**: MC ➔ DATA **not trivial**.

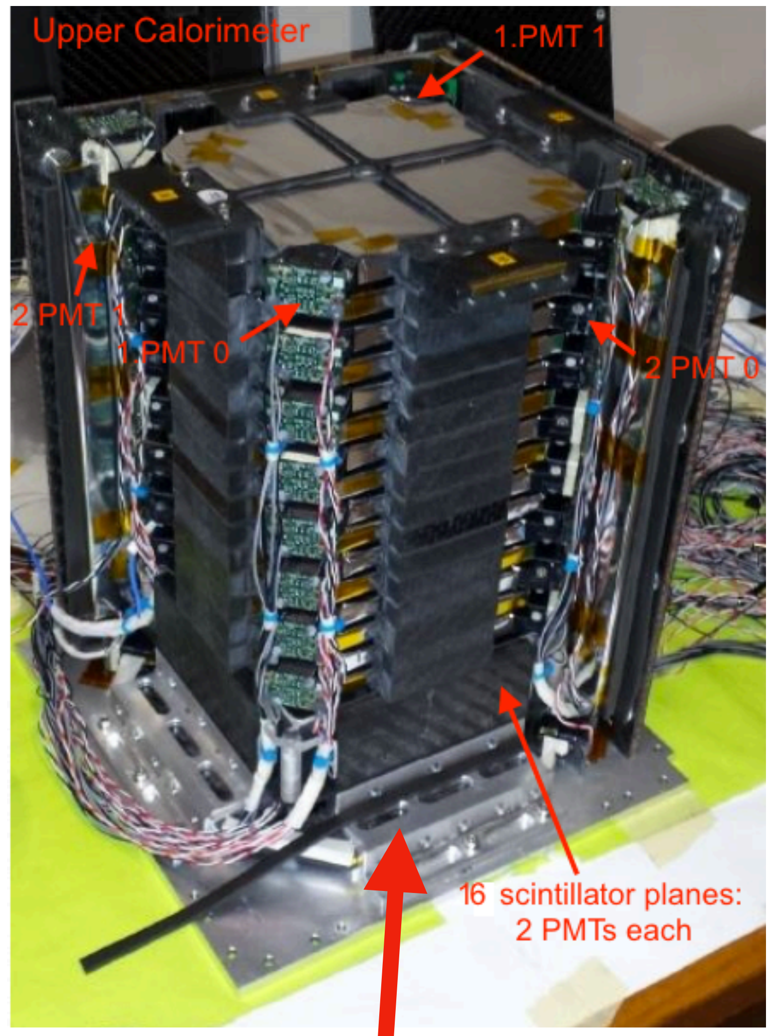


Reference case - Limadou HEPD

The **Limadou** High Energy Particle Detector **(HEPD)** is an Italian payload on board of the China Seismo Electromagnetic Satellite **(CSES)** [1].

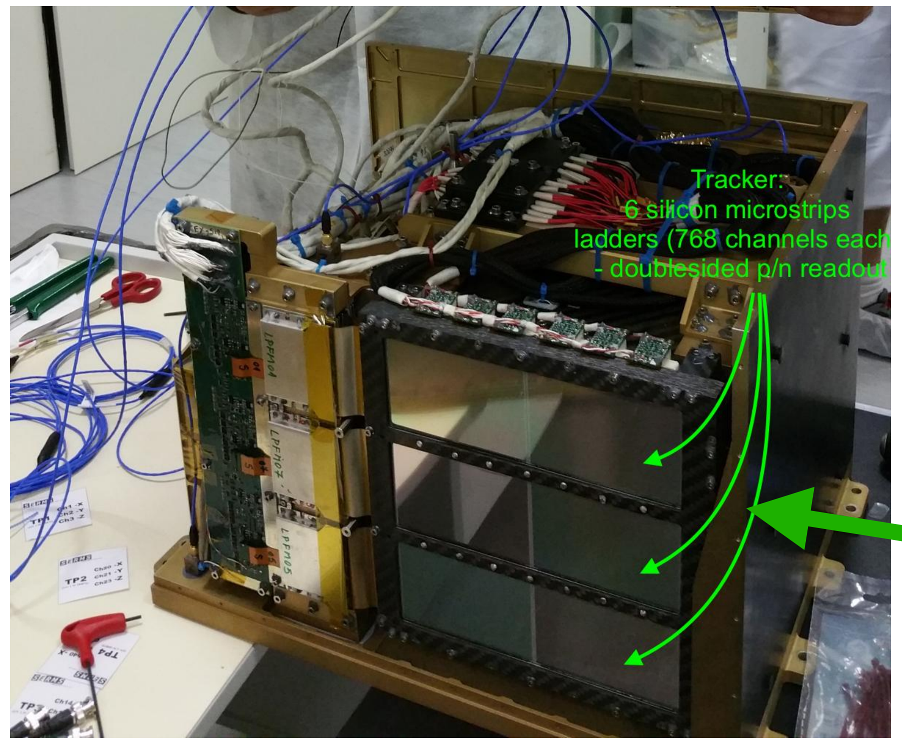
- **Measure fluxes of charged particles;**
- **Electrons** (3-100 MeV) and **protons** (30-300 MeV);

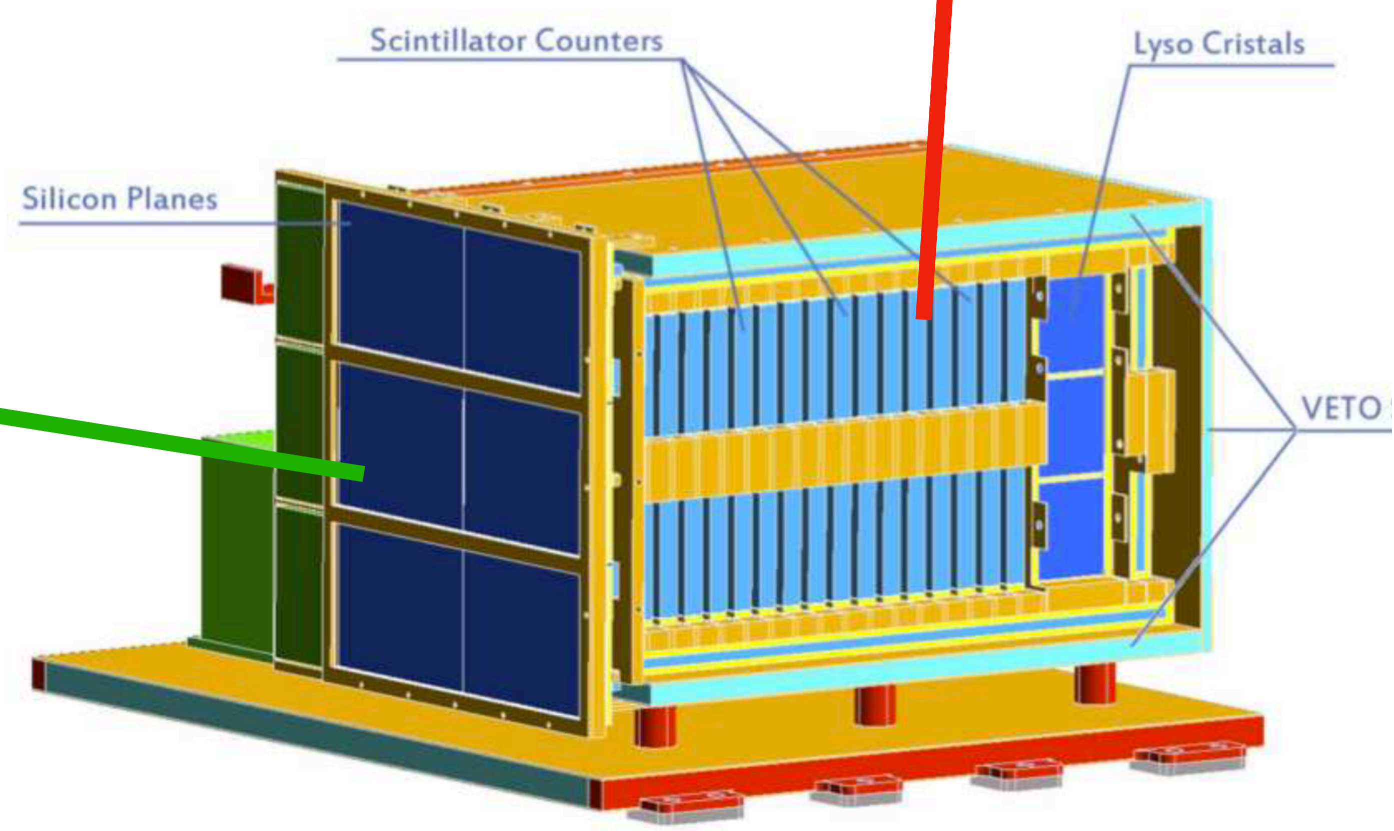




HEPD Detector:

- a **trigger plane** made of plastic scintillator, segmented into **6 paddles**;
- A tracker made by **2 planes of silicon microstrip detectors**;
- a **calorimeter** made by **16 planes of plastic scintillator** and **3 x 3 matrix of** an inorganic scintillator **(LYSO)**;
- **a veto** system which consists of **5 plastic scintillators**.



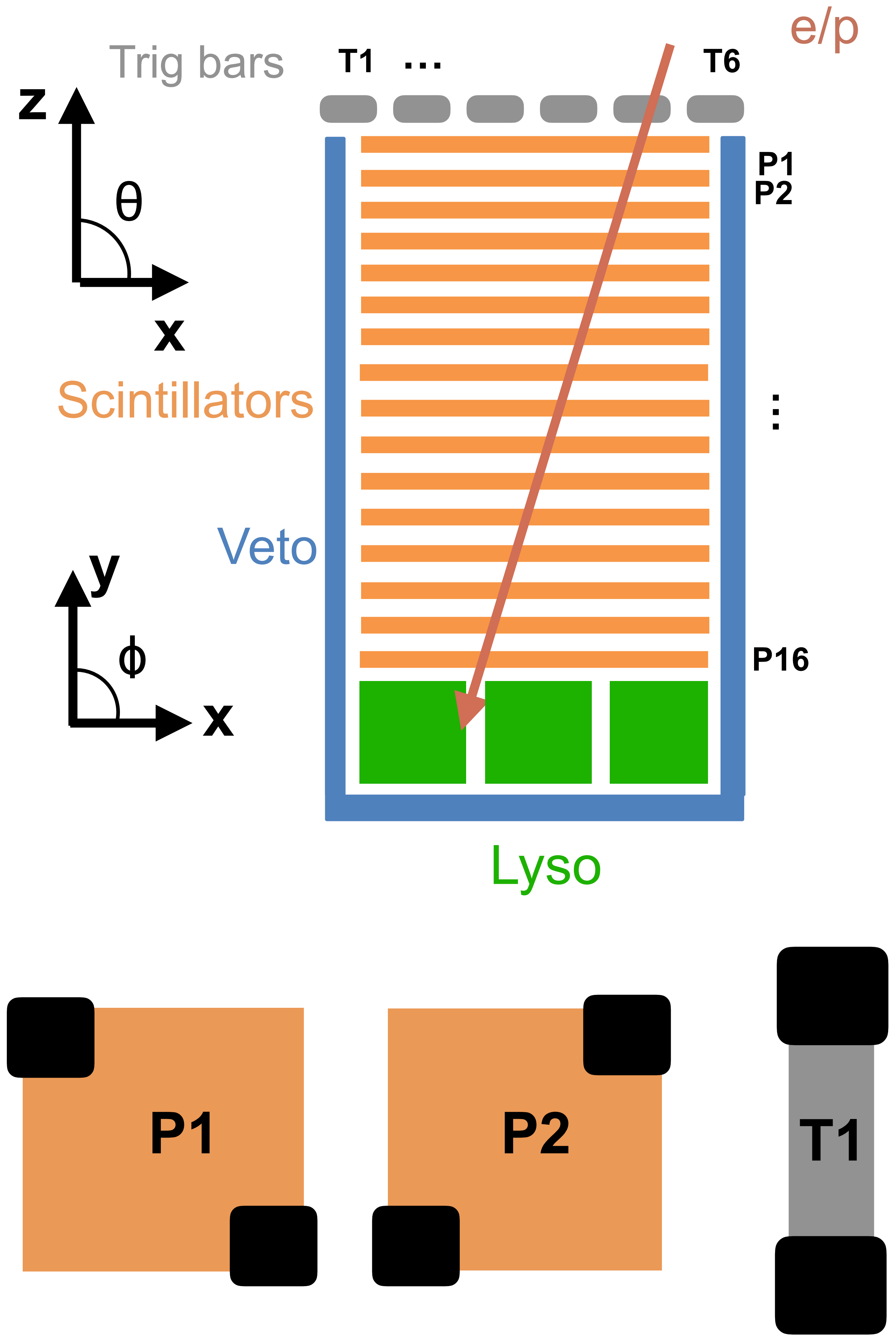


[1] "The HEPD particle detector of the CSES satellite mission", Science China Technological Sciences

[2] "Scientific Goals and In-orbit Performance of the High-energy Particle Detector on Board the CSES ", APJS 2019

Simulation: detector and data

We used Geant4 to **simulate** particles (electrons and protons) interacting with a **detector like limadou HEPD:** trigger bars (2 PMTs), 16 scintillator planes (PMT evenly distributed at the edges of each plane) and an array of 9 Lyso cubes (1 PMT).

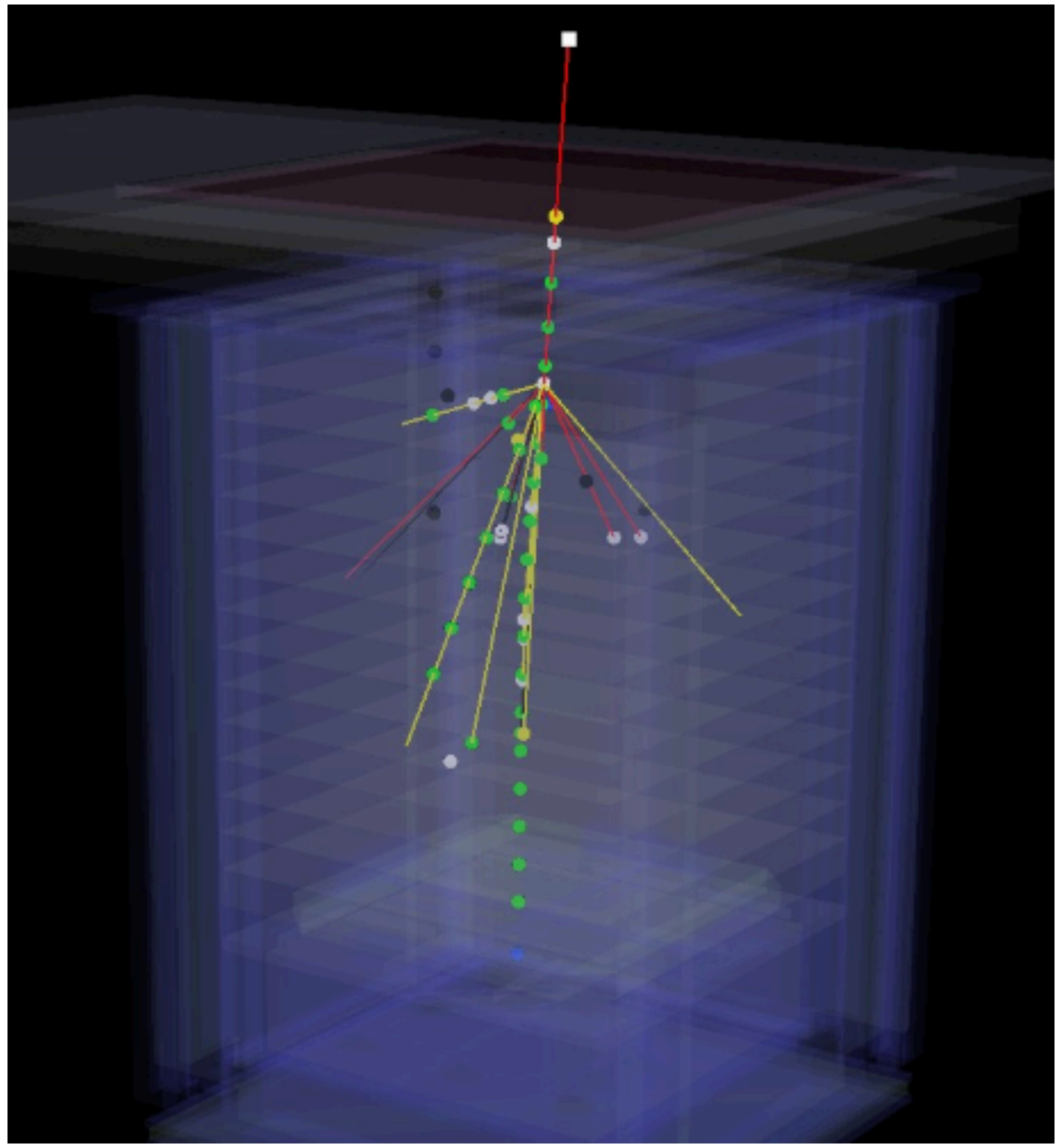


Protons and **electrons** simulated:
(5 million events each)

- 0° < θ < 90°;
- 0°< ϕ < 360°;
- 30 MeV< E_K < 1000 MeV (protons)
  1 MeV< E_K < 200 MeV (electrons)

Selection:

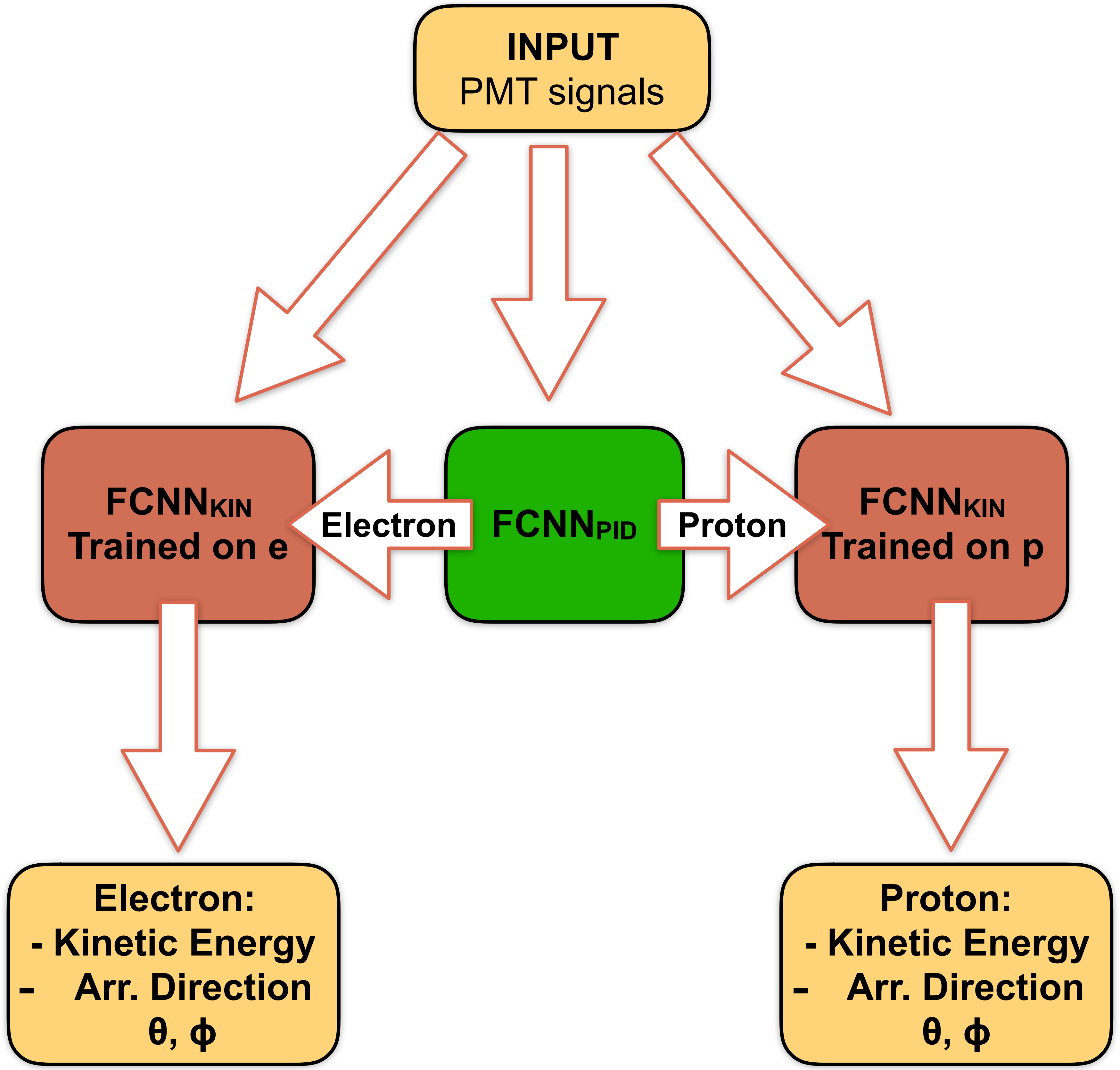
- Traversing P1 and P2, but not hitting the lateral Veto (passing);



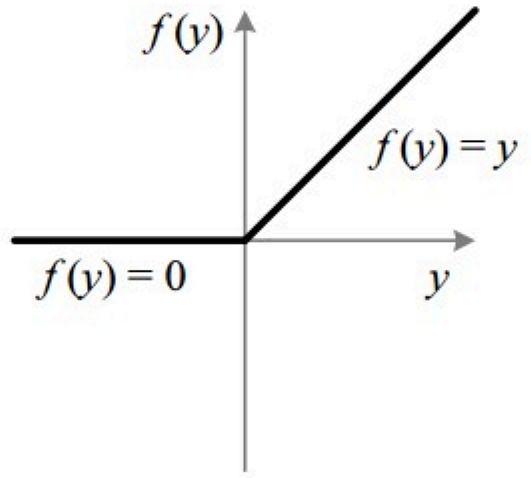
Deep Learning reconstruction strategy

The main elements of the reconstruction chain are **two Fully Connected Neural Networks (FCNNs)** taking as input the signal of photo-multiplier tubes and **giving as output particle-type flag,** polar and azimuthal **angles** in the local frame and **energy of the particle**.

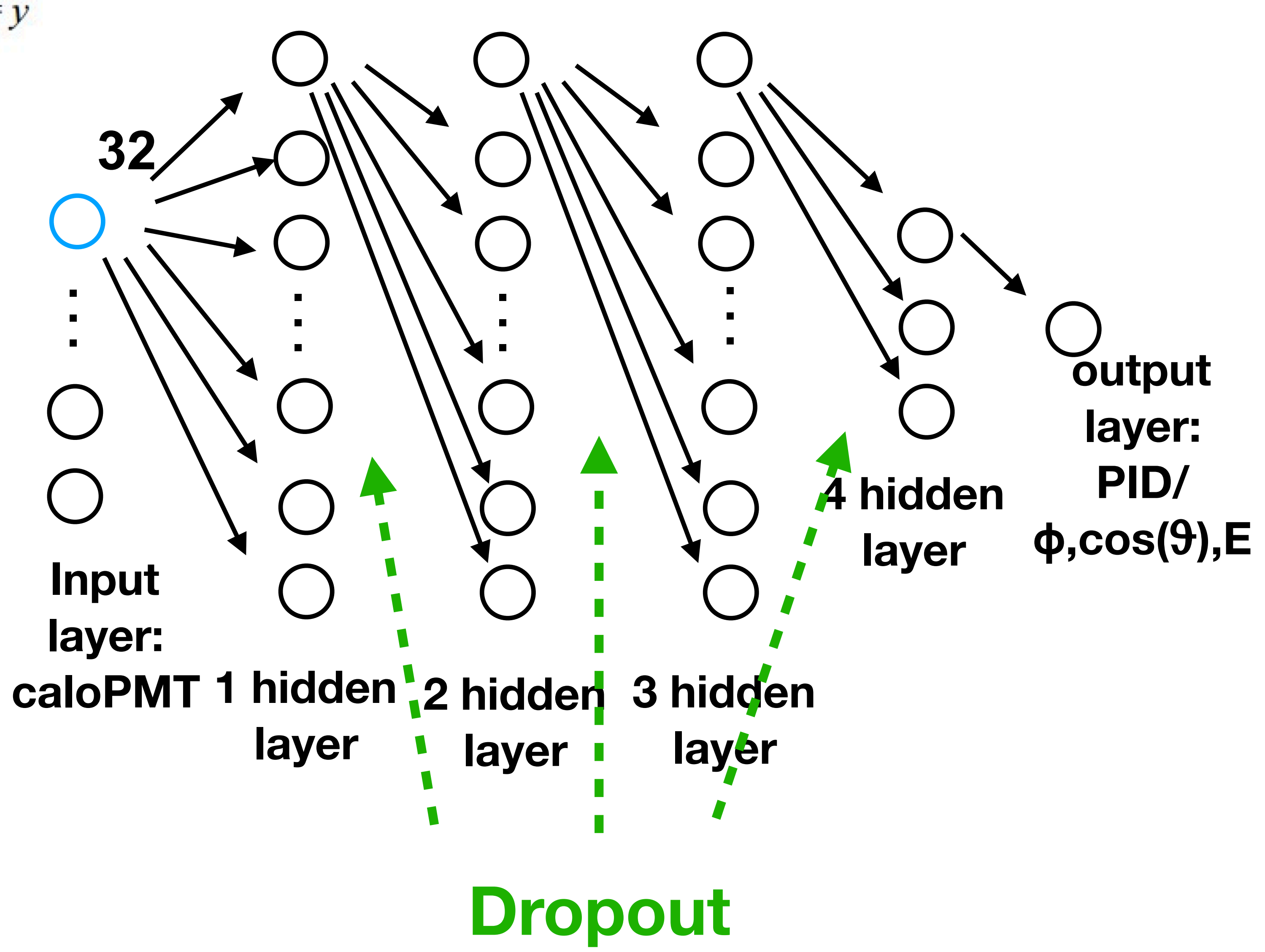
Ev reco chain



Activation “Relu”

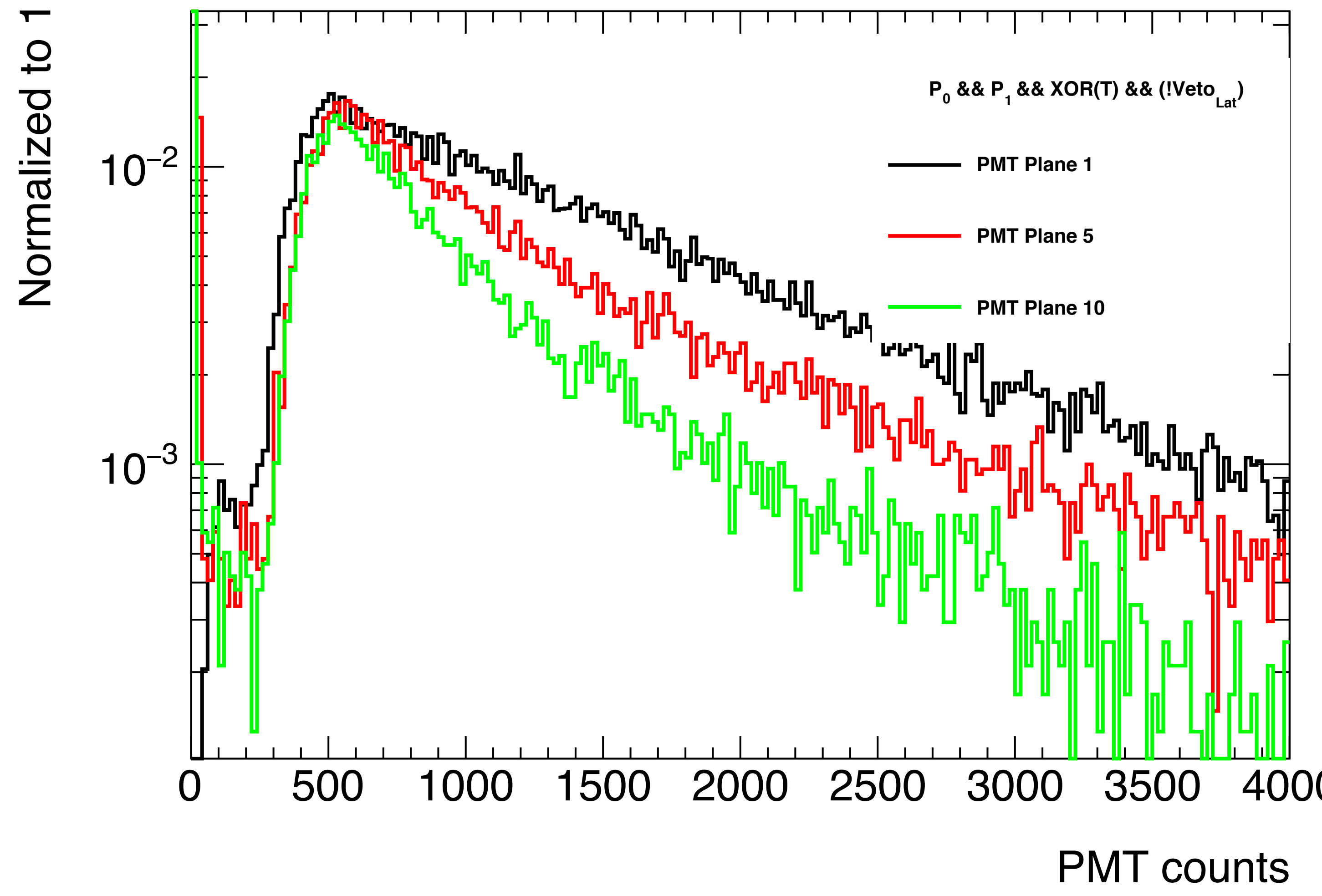


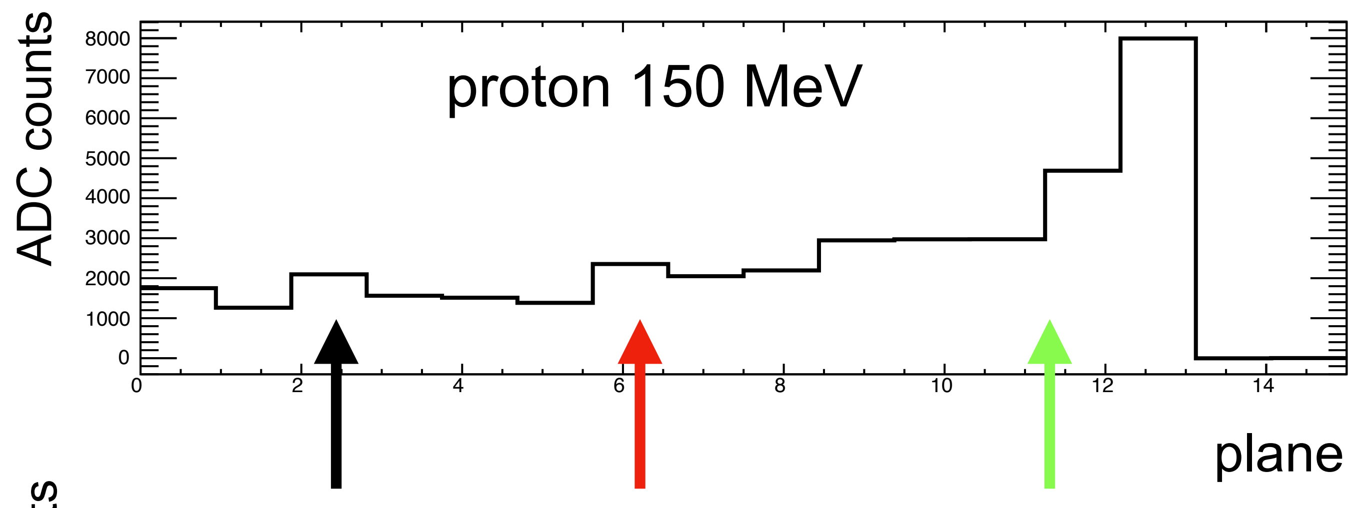
FCNN architecture
(KIN and Pid similar)

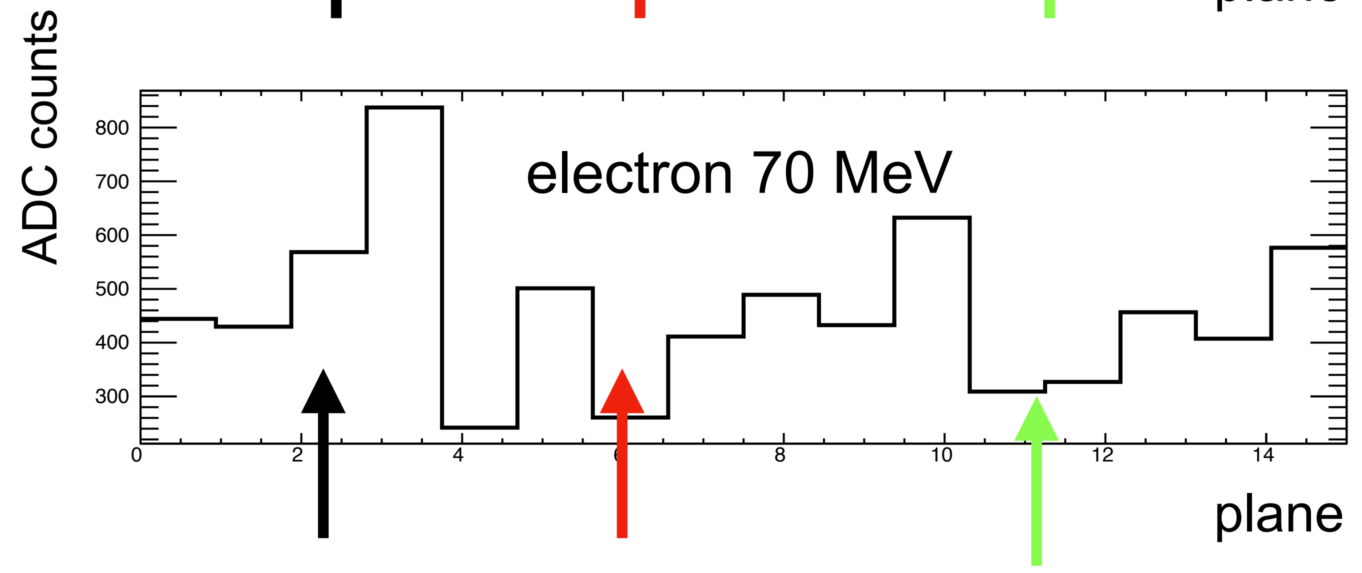


Input and Target distributions

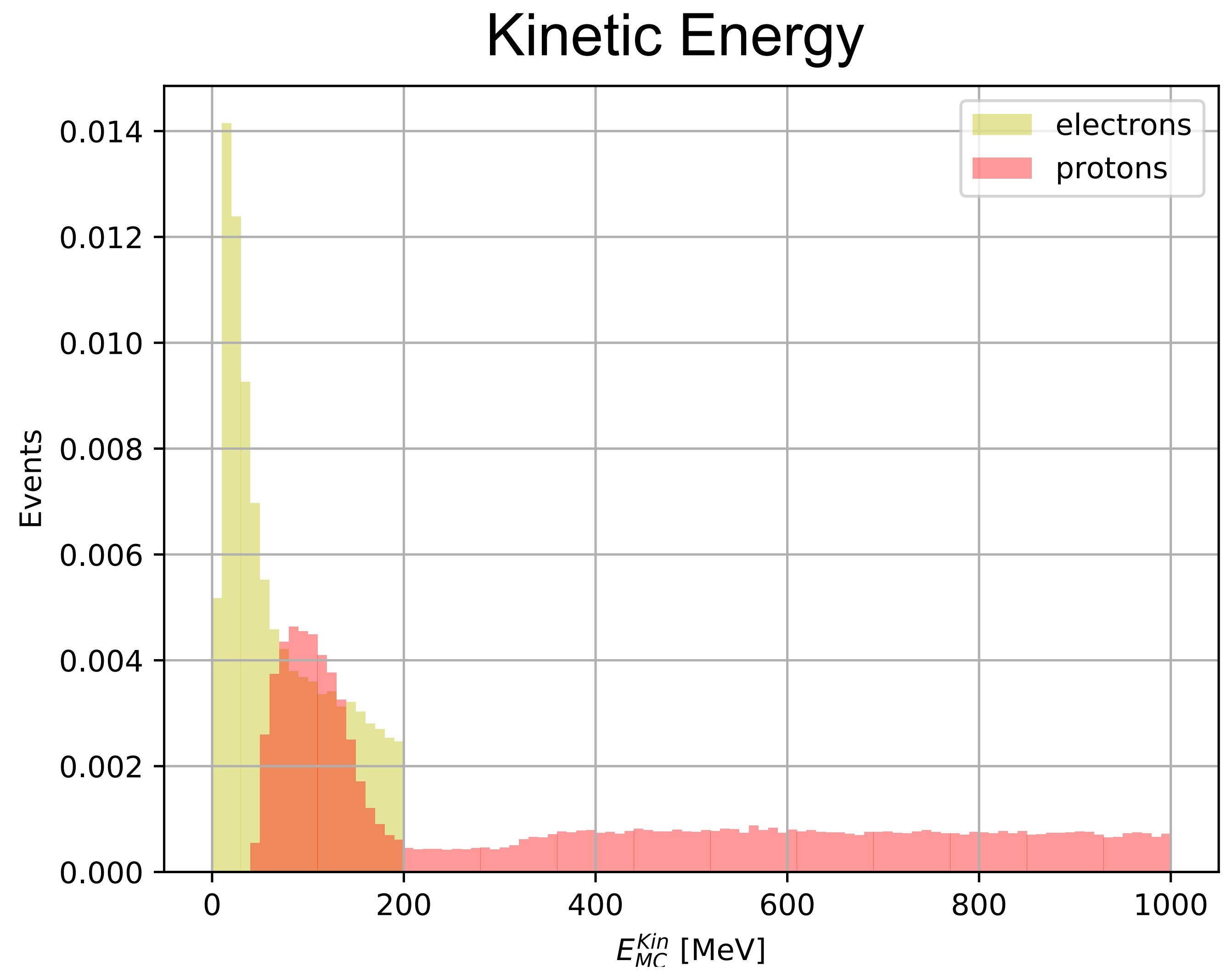
Input variables: PMT signals

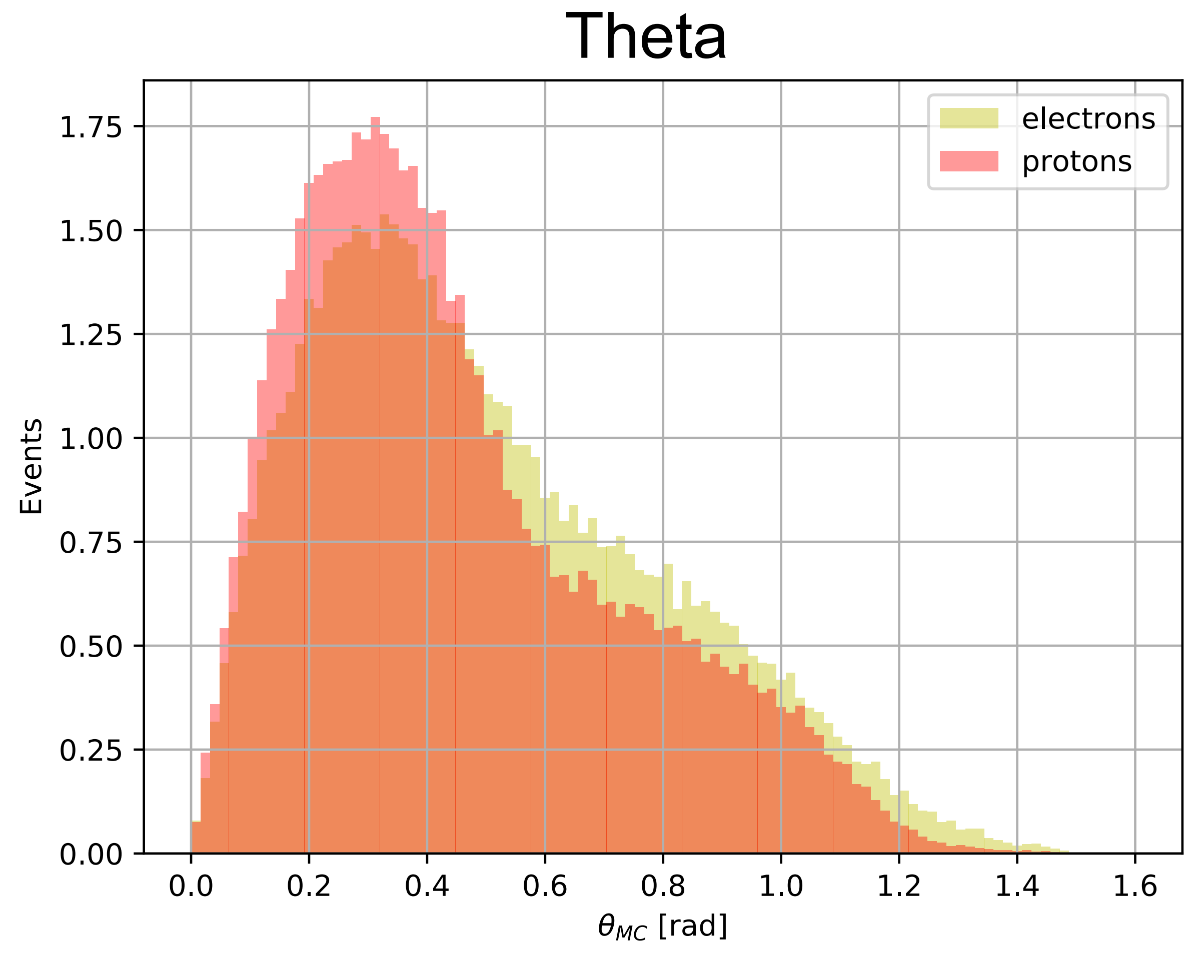


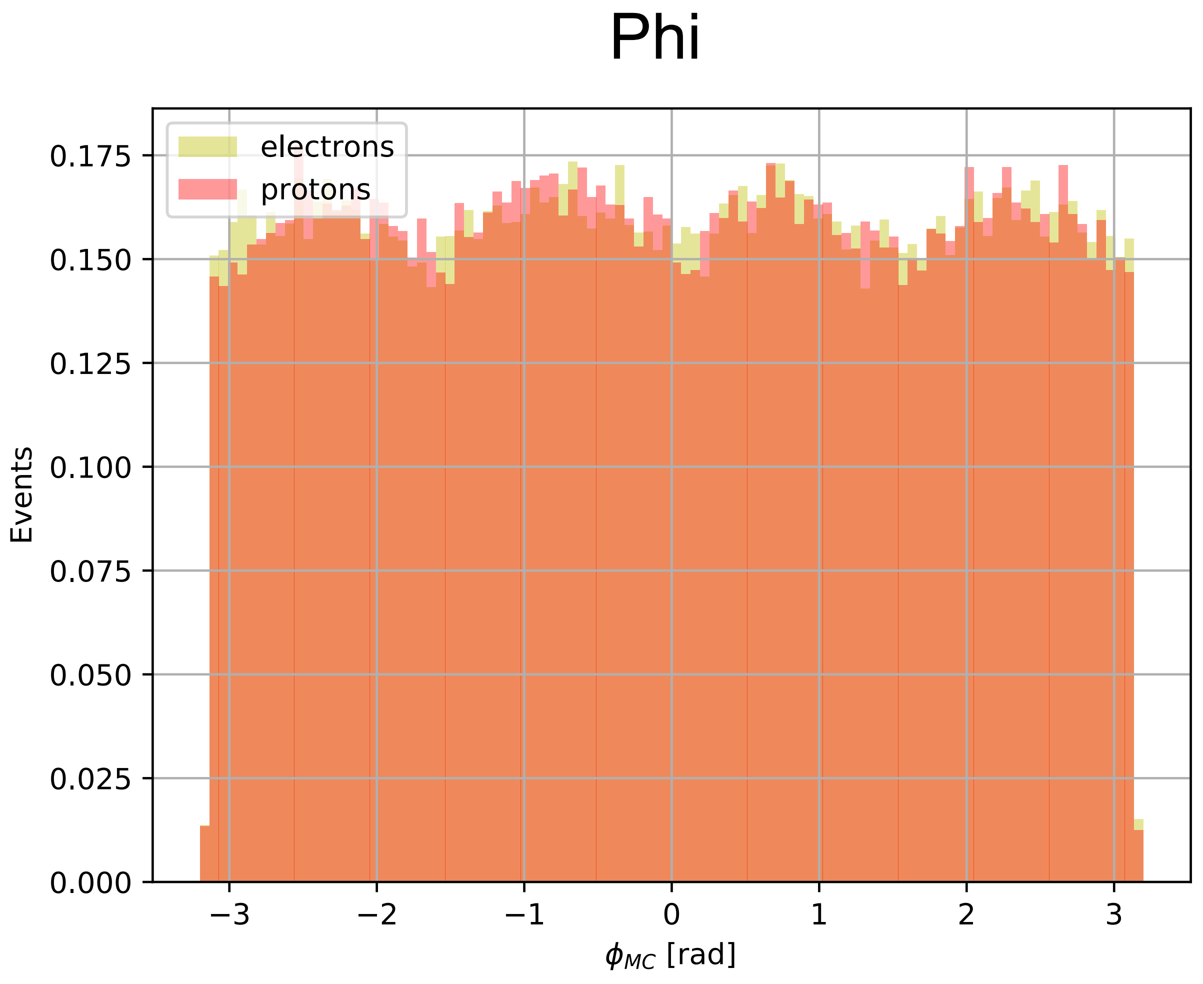




Target distributions: ϕ, θ, E_{kin}



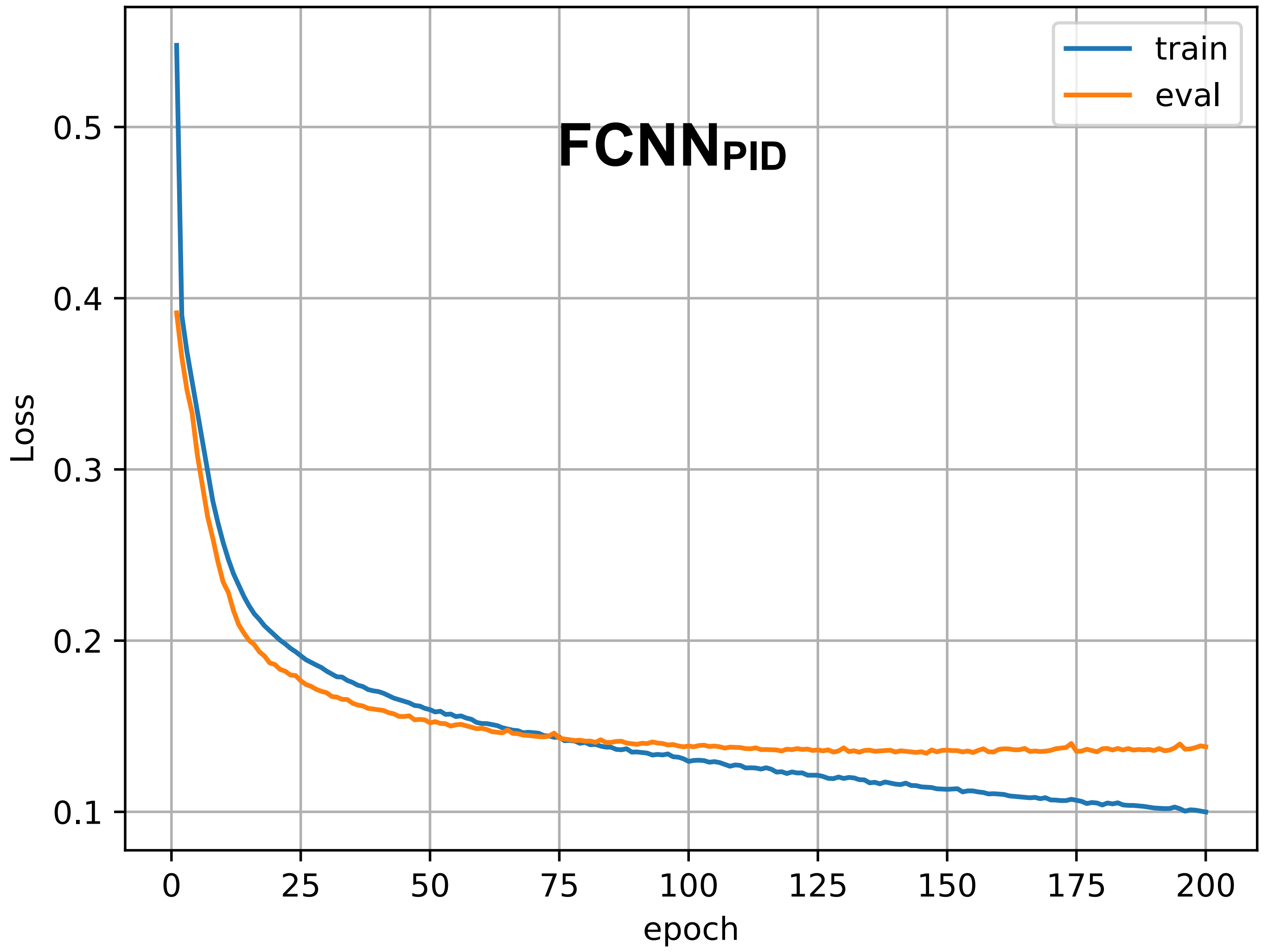


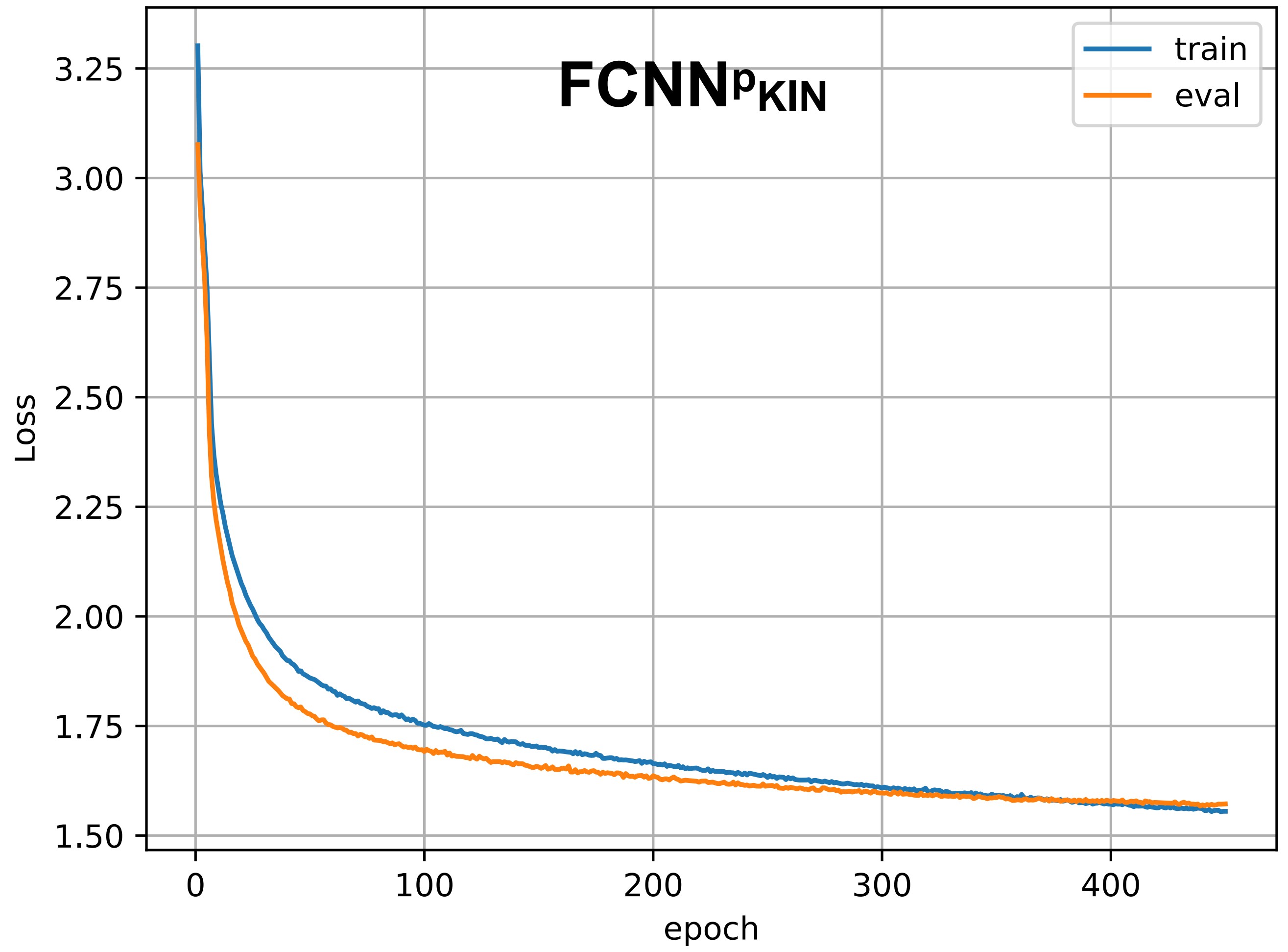


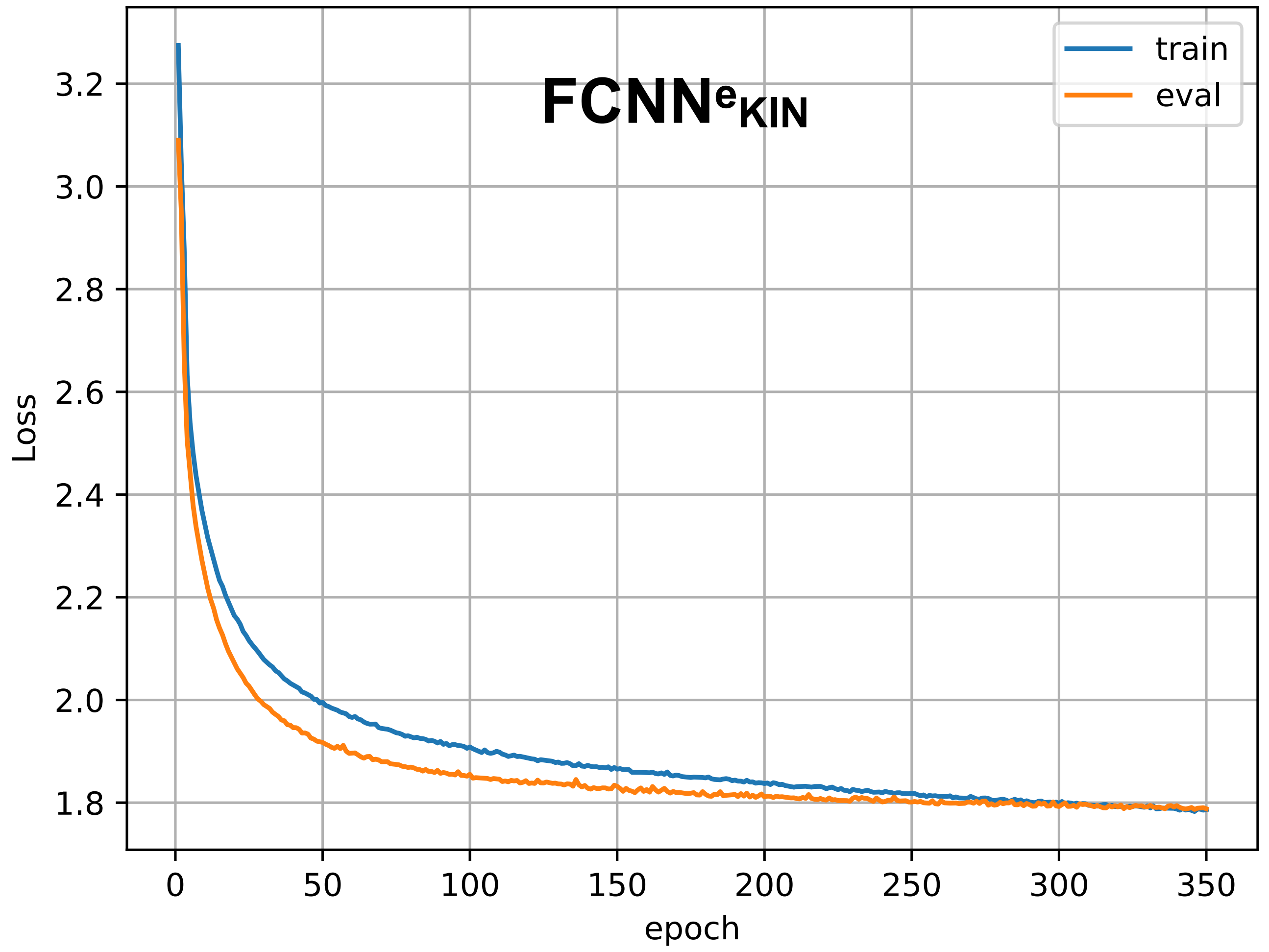
Training procedure

The two **FCNNs are trained independently** to keep their prediction (PID and Kin) uncorrelated as much as possible. Therefore, we get **independent predictions at each step** of the reconstruction chain.

- Training dataset split in two parts: **80% for training and 20% for evaluation** (cross validation [3] was used).
- An additional and statistically independent test sample was used to check the FCNNs performance.
- **Number of epochs** ranged between **200-450** and **hyperparameters (**batch size, learning rate, etc…**) optimized**;
- Loss functions: combination of losses (i.e. L1, L2) for $FCNN_{Kin}$ (regression) and BCE for $FCNN_{PID}$ (classification);





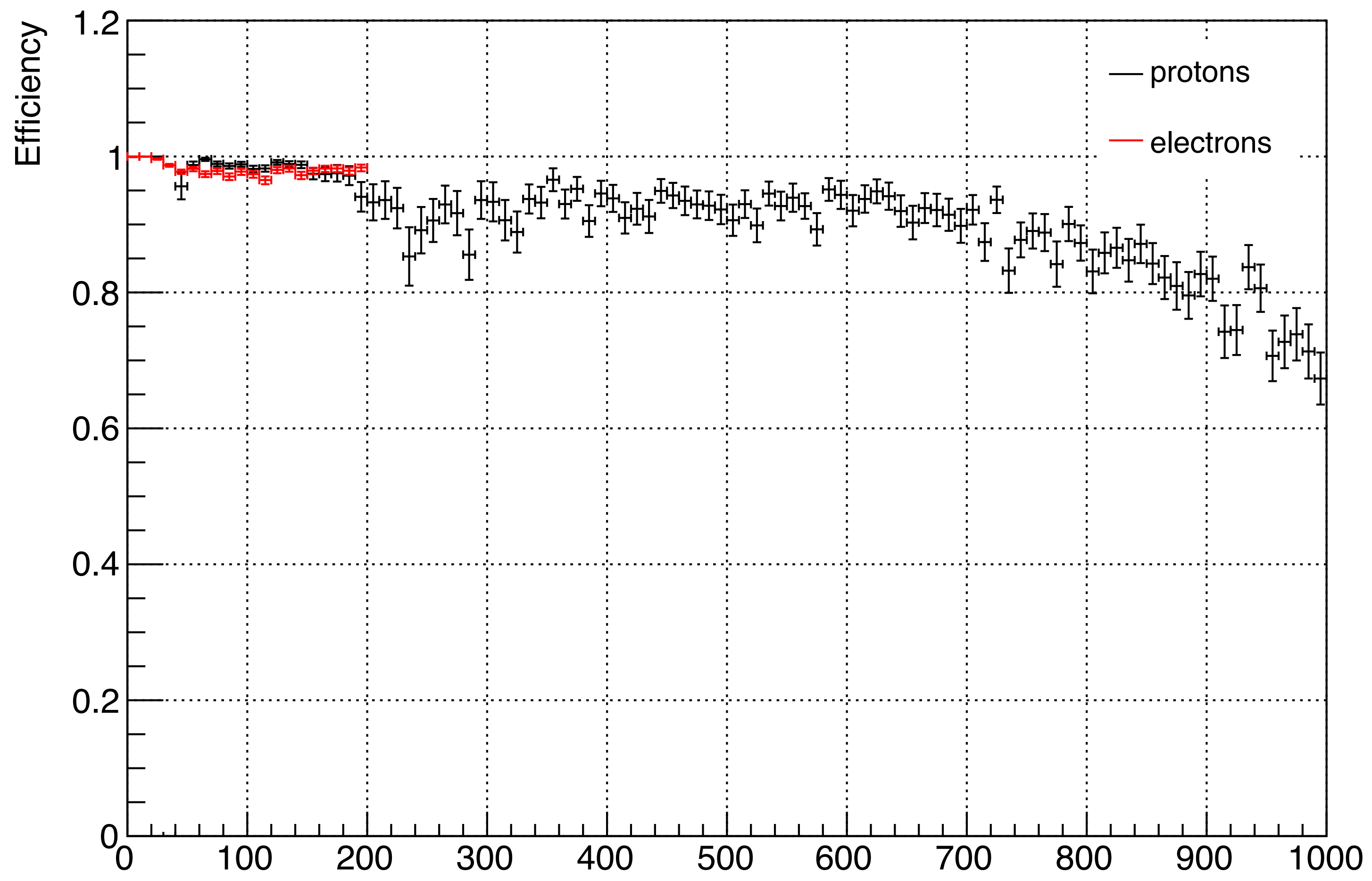


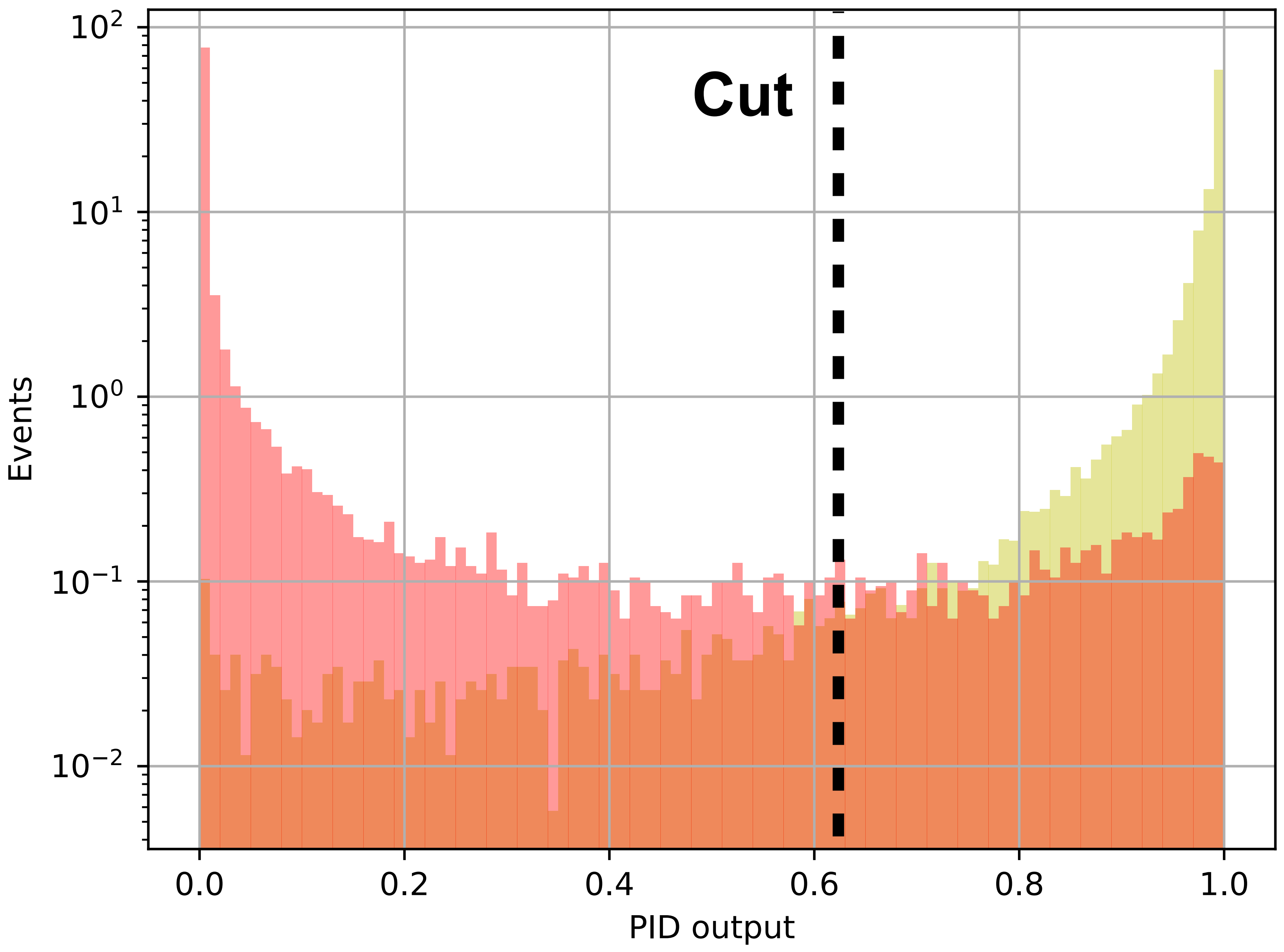
[3] "A Study of CrossValidation and Bootstrap for Accuracy Estimation and Model Selection ", http://ai.stanford.edu/~ronnyk/accEst.pdf

Particle Identification

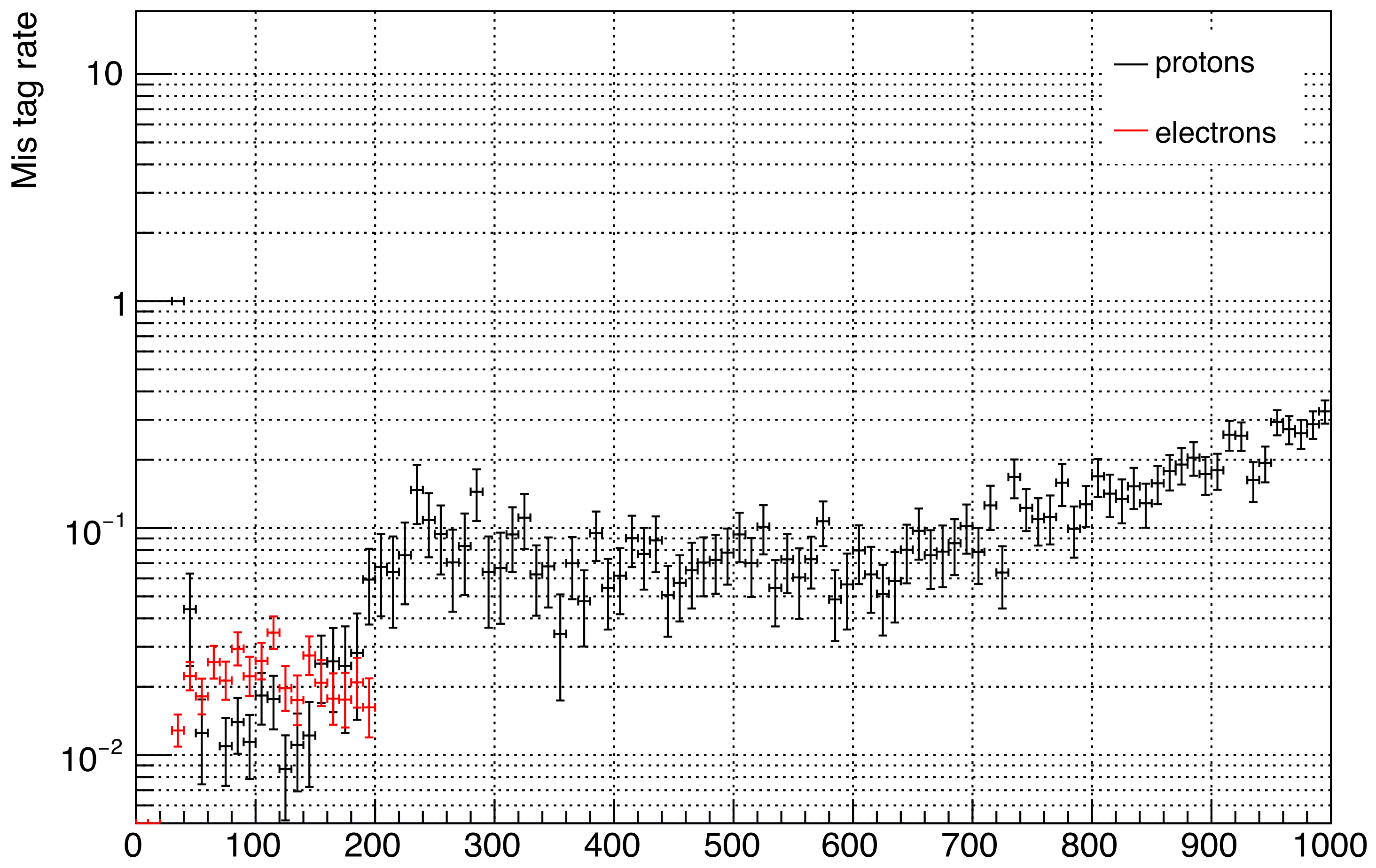
After the training procedure **the accuracy of the PID** based on DL **is ~ 96 %** (accuracy with standard methods 5-10% lower).
Efficiency and **mistag rate** have been estimated for electrons and protons.

$$Eff_{part} = \frac{N_{ev}(PID = part)}{N_{ev}(TRUTH = part)}$$





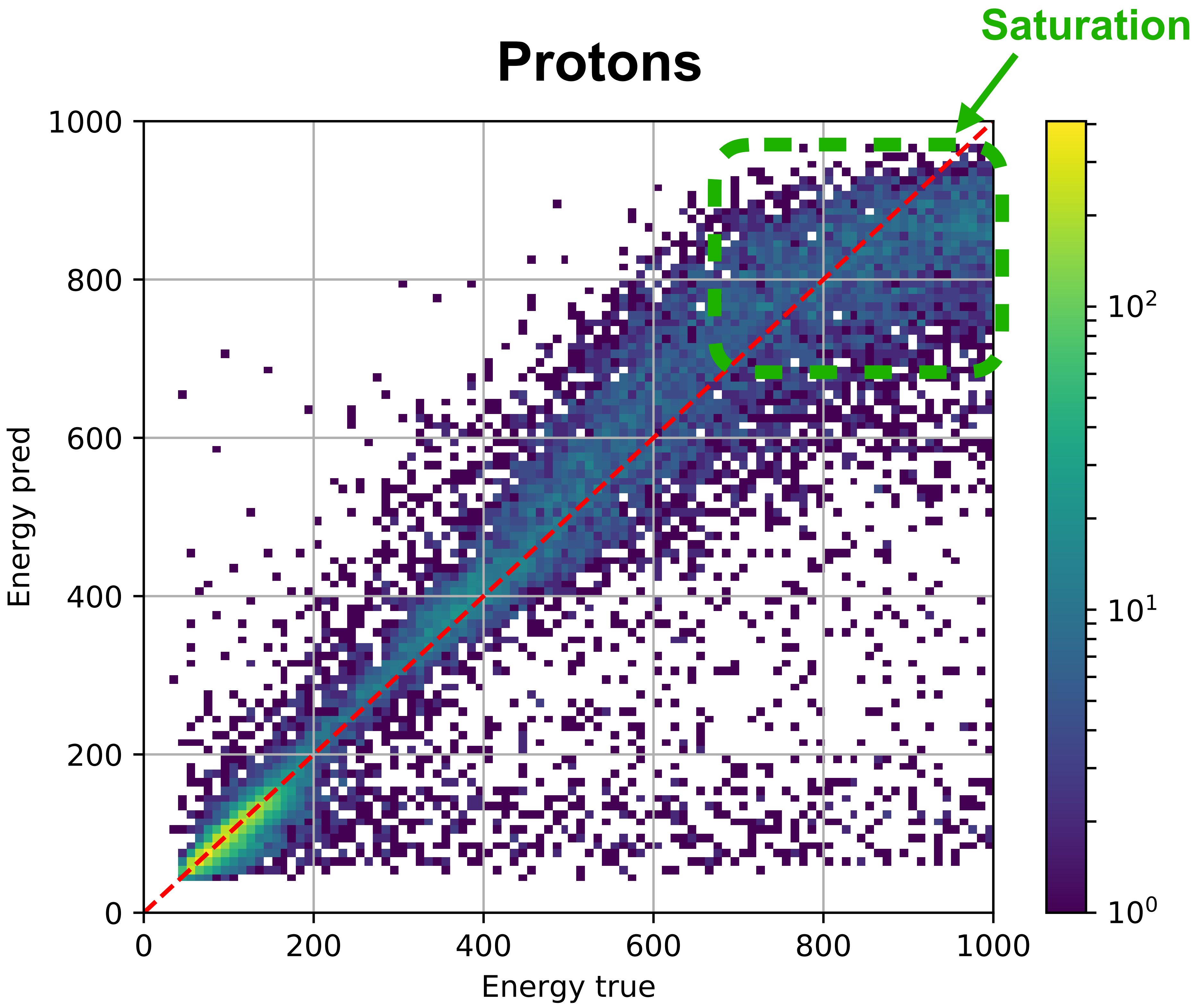
$$Mis_{part} = \frac{N_{ev}(PID != part)}{N_{ev}(TRUTH = part)}$$

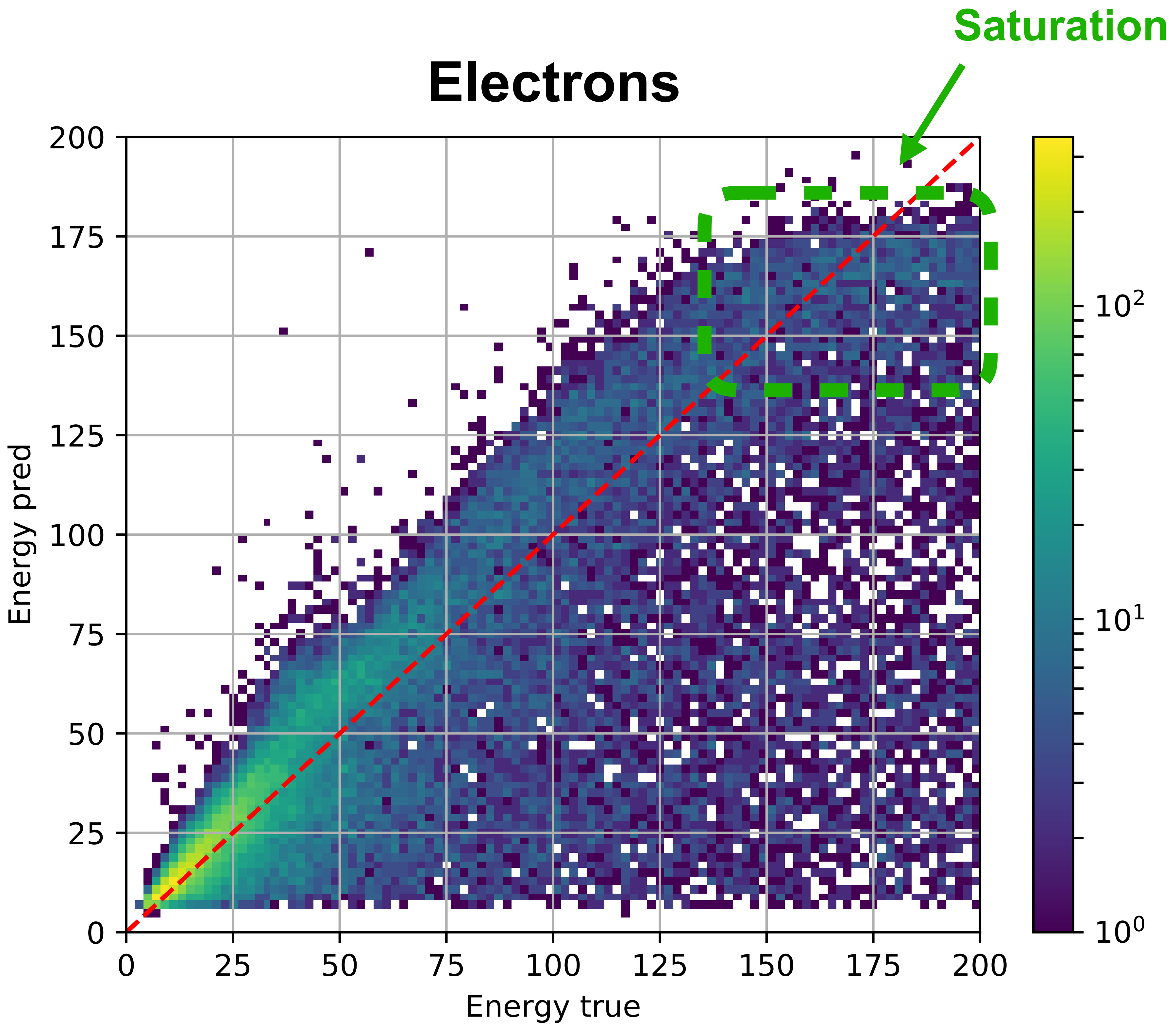


The **cut on the FCNN$_{PID}$ output is optimized to improve the separation** between electrons and protons overall all the energies.

Kinetic Energy reconstruction

Deep Learning algorithms can **extend the energy reconstruction also for not contained particle** exploiting the charge deposit profiles. When the particle starts to be MIP-like this information is not more available and the reconstruction less accurate.

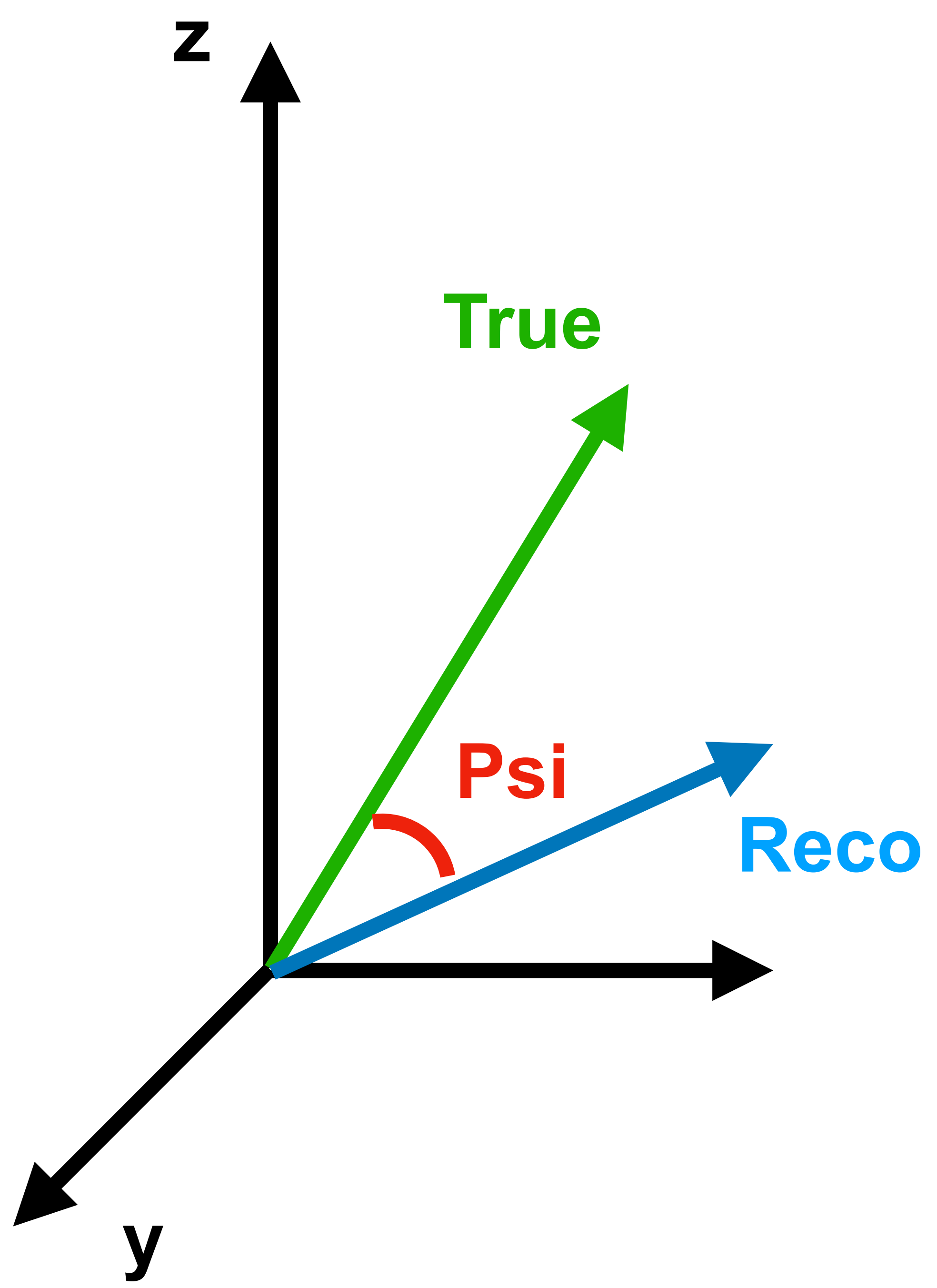




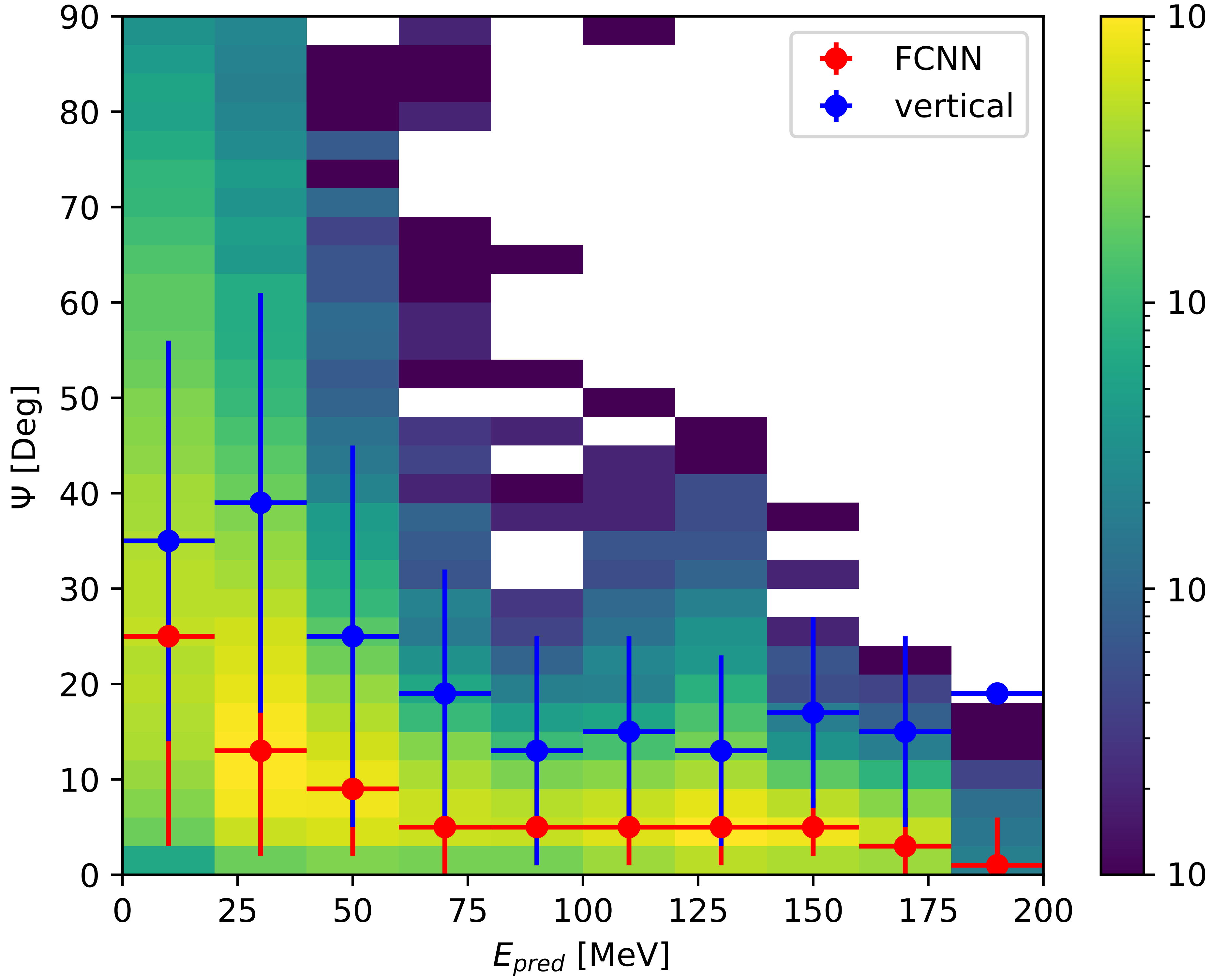
Electrons are much more problematic than the protons as **they are MIPs** for the energies for which this experiment has been designed.

Arrival direction

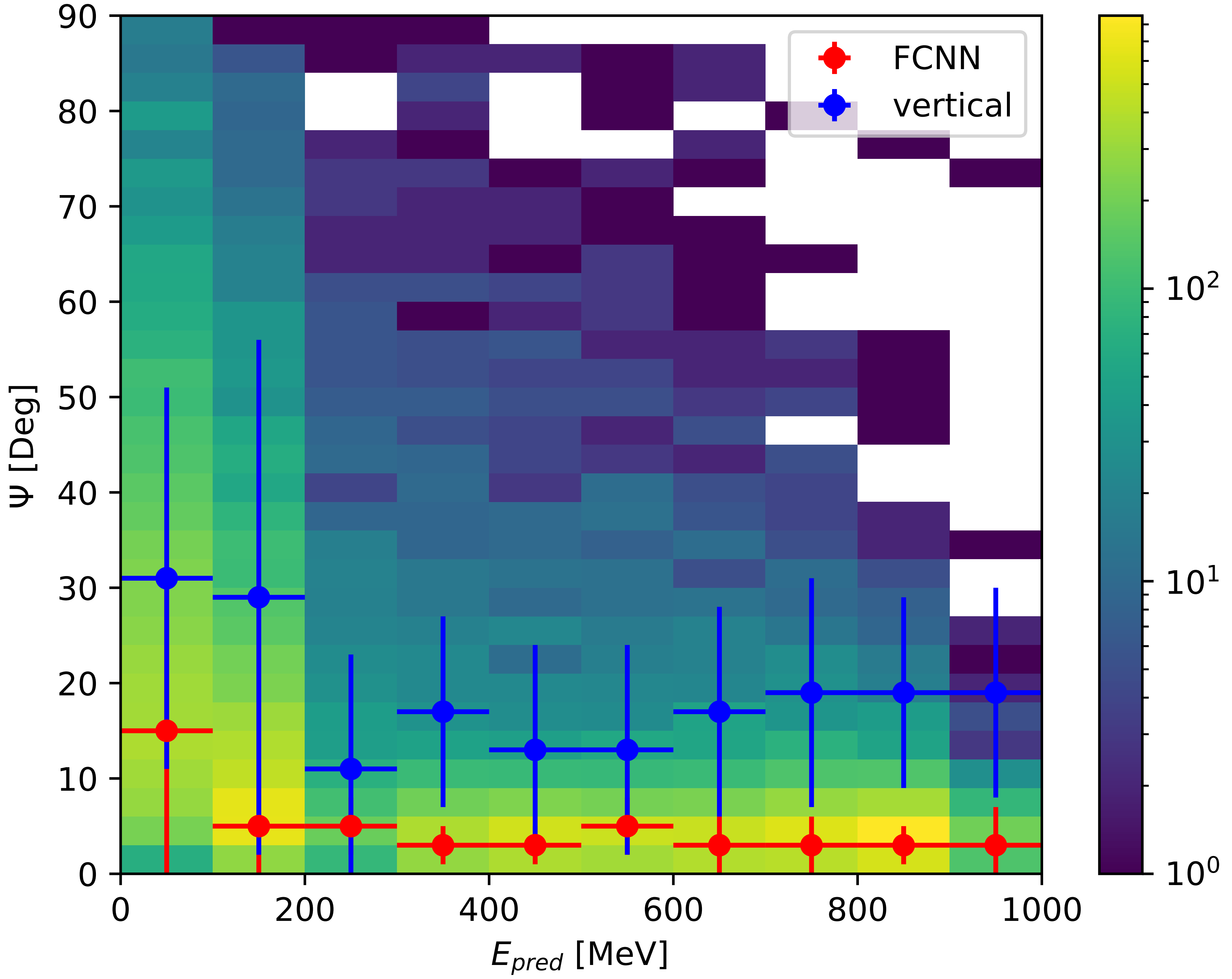
It is **most challenging task using just the calorimeter information**. The more the energy of a particle the more it traverses the detector, providing useful information for the angular reconstruction. For that reason **the error on the arrival direction decreases when the kinetic energy increases.**



Electrons



Protons



The **FCNN reconstruction outperforms the random pointing** (always vertical, 0°) over all the energy range.

Summary and conclusions

A new and pioneering **DL-based event reconstruction** has been presented.

The performance of this set of algorithms on **simulated events** have been shown and the **results are promising**:

- The DL chain successfully reconstruct **PID, energy and arrival direction** of the incoming charged particle;
- This method exploits the **correlation between energy and arrival direction** to improve both the predictions;
- DL efficiently **reconstructs the energy for not contained particle** (allows not contained analysis);
- **Further developments and studies ongoing;**