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Particle ID in 3D calorimeters for space-borne applications

Claudio Brugnoni

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Università degli Studi di Perugia

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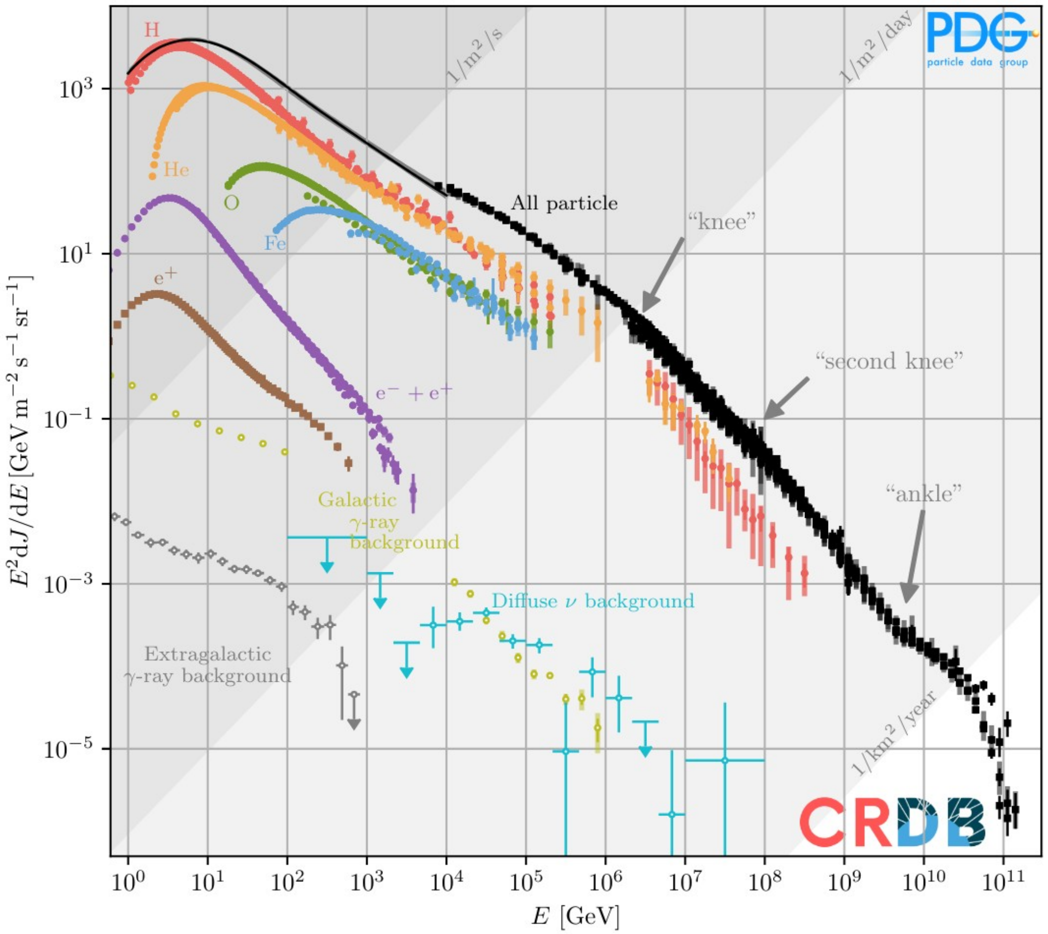
Cosmic rays

Population of high energy, **charged particles** (p, nuclei, e-, e+) incoming from both **galactic and extra-galactic sources**.

Can be detected **directly from space**, but size of detectors limited → impossible to study the lowest flux

Or **indirectly from ground experiments**, but information on single components is lost.



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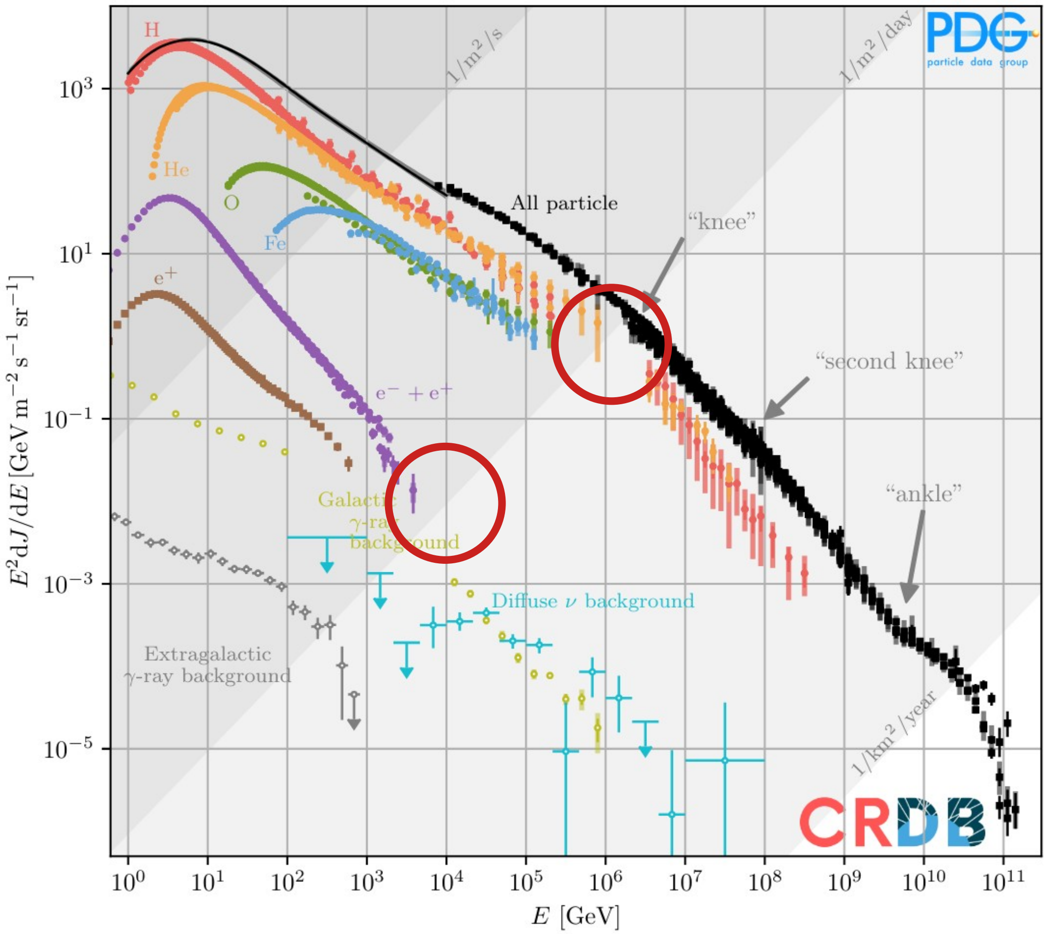
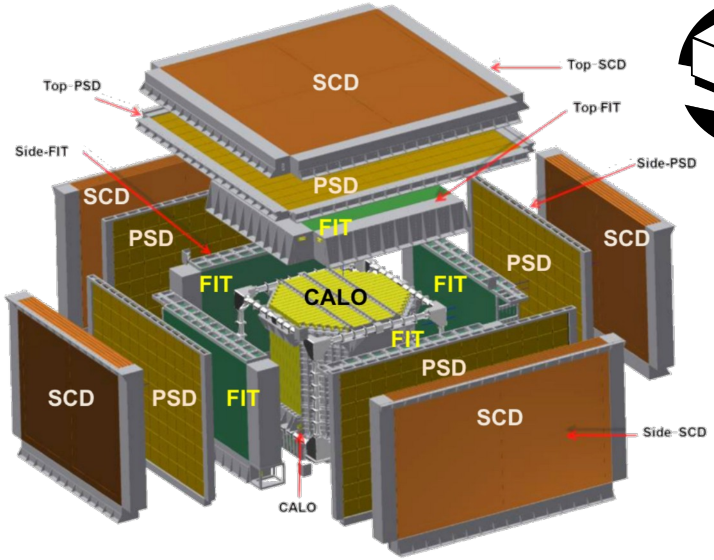
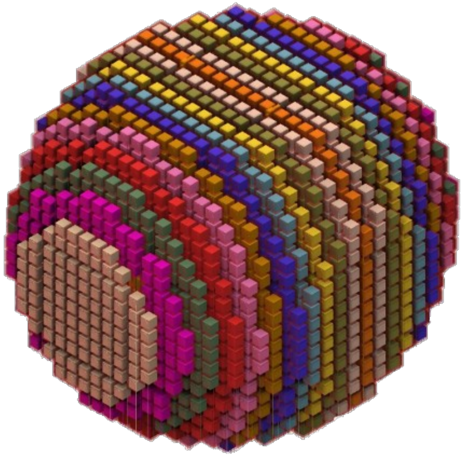


Isotropic experiments

Next generation experiments will utilize detectors as isotropic as possible in order to **maximize acceptance** at the same size.



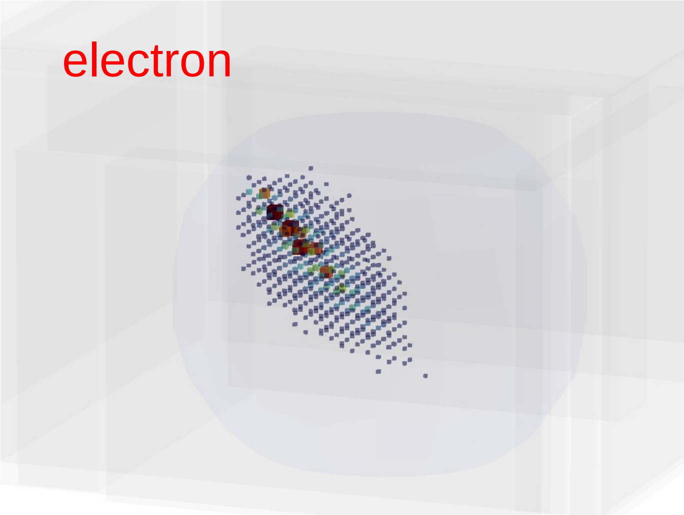


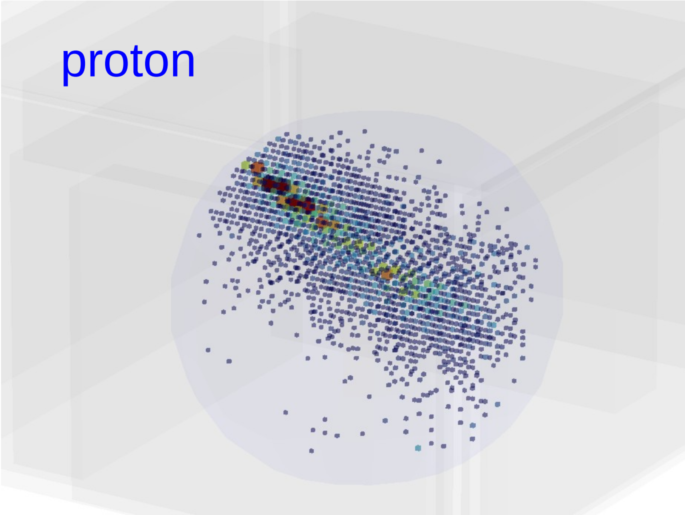
Pivotal **3D segmented calorimeters** as those designed for the upcoming **HERD** and **ALADInO** experiments.

Particle discrimination

We can't measure the sign of the charge, but electrons and hadrons **interact in different ways in calorimeters**

→ even at similar energy they produce **showers with clearly different shapes**





Thanks to **3D segmentation** we can **precisely acquire the shape** of showers.

Likelihood Test

Instead of single properties of showers (traditional approach) we look at the **whole shower development** and compare it to the **statistically expected shape** for an EM or hadronic event.

For each event we have N **energy deposit measurements** $\{x_i\}^N$.

If we have a probability density function *P(x)* associated with an *e* or *p* event we can **evaluate the likelihood *L*** of *e* or *p* hypothesis.

$$L^e = \Pi_i P(x_i|e)$$

$$L^p = \Pi_i P(x_i|p)$$

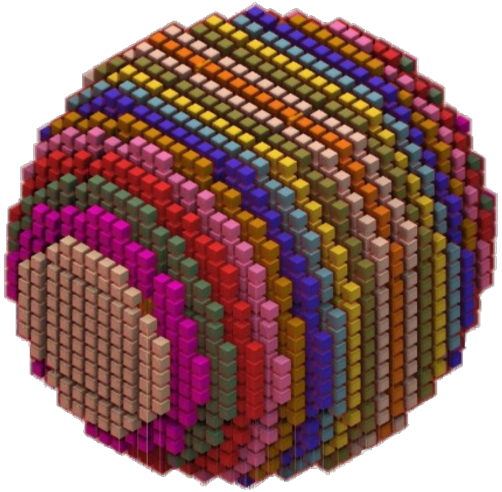
Let's approximate the pdf P(x) **modeling the average shower energy deposit and its variance.**

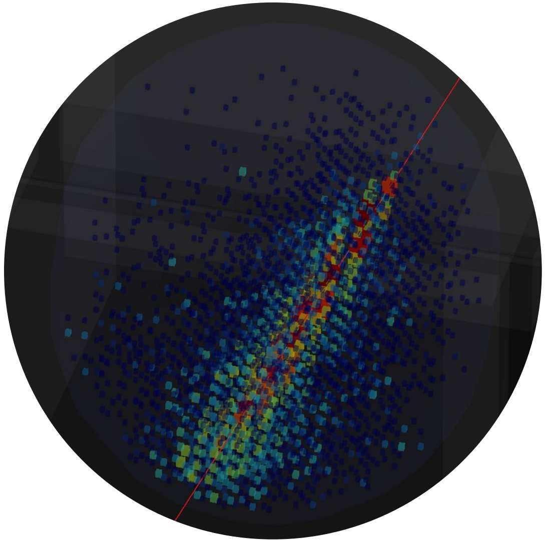
HERD case study

HERD spherical calorimeter:

7400 LYSO cubes 3x3x3 cm^3

Total depth **55 X_0 / 3 λ_I**





Simulated an E^{-1} spectrum of **isotropic electrons and protons** from 100 GeV to 100 TeV

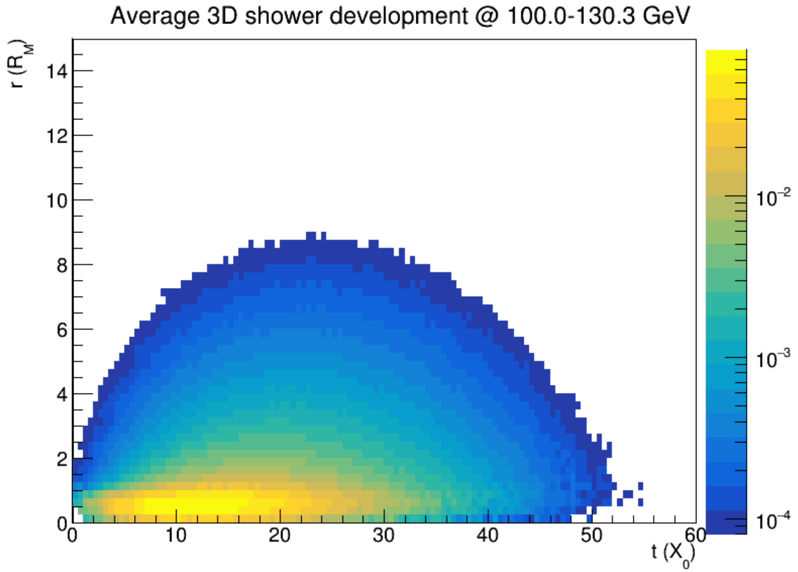
For quality of reconstruction selected events that develop for **at least 30 X_0 inside the LYSO**

About **10^6 electrons** and **10^6 protons**

Data preparation

Assuming **cylindrical symmetry** for the showers, the spatial development of the average deposit can be factorize in a **longitudinal (t)** and a **transversal (r)** component

$$\left\langle \frac{dE}{E_0 dt dr} \right\rangle = f(t, E_0) g(r, t, E_0)$$



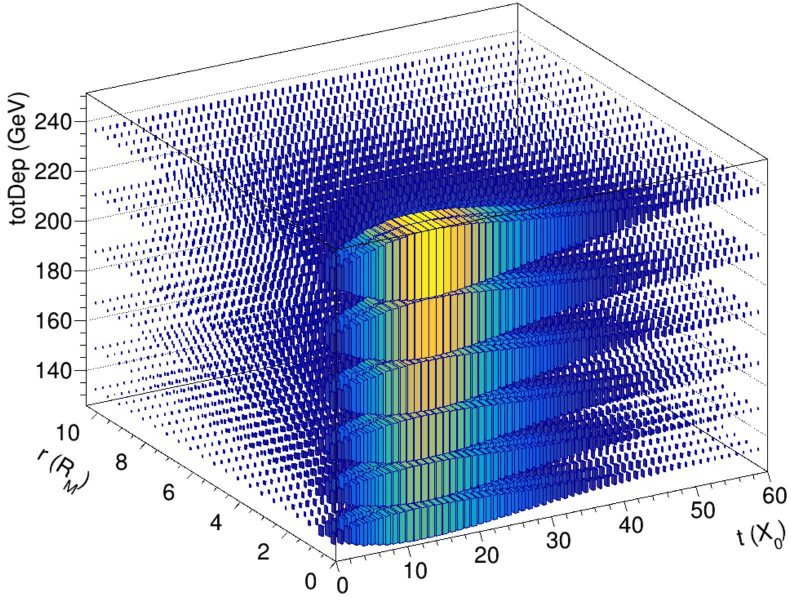
All events are projected in (t,r) reference frame and **binned for reconstructed energy** (totDep).

Longitudinal direction from MC for modeling, PCA on shower for testing

Modeling

Average development mapped for **both electrons and protons**.

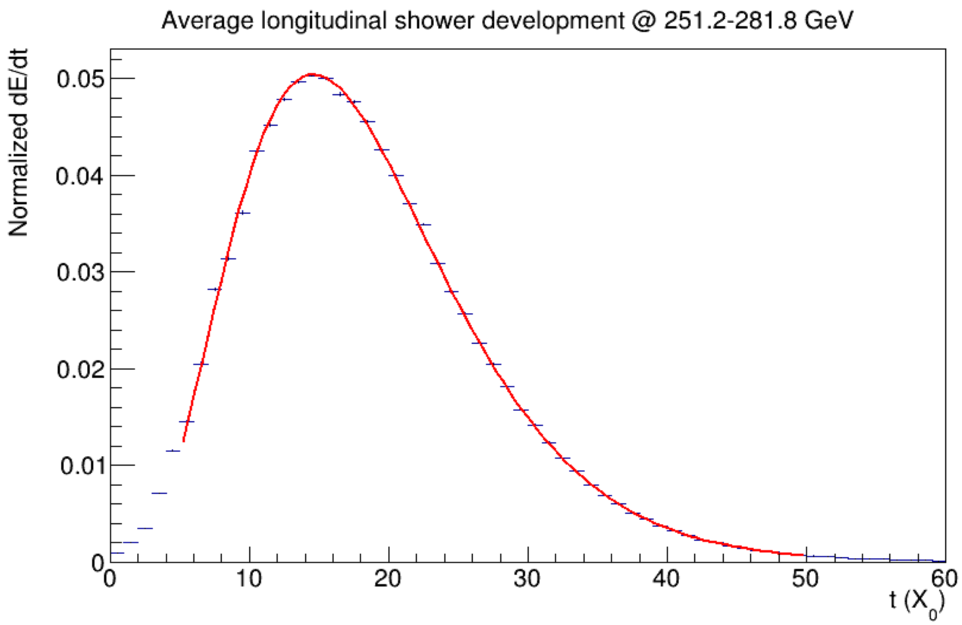
Average squared deposit development mapped too **to map variance** development.



This already enough to have a **first binned modeling** of the statistical behavior of particles.

For a step further we **fit the development components**

Longitudinal profile

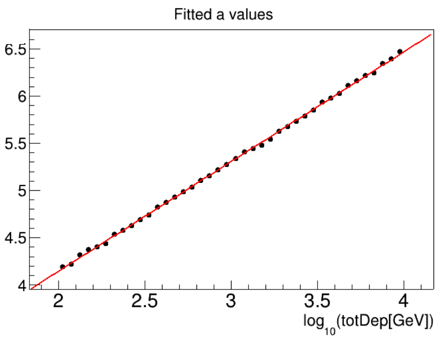


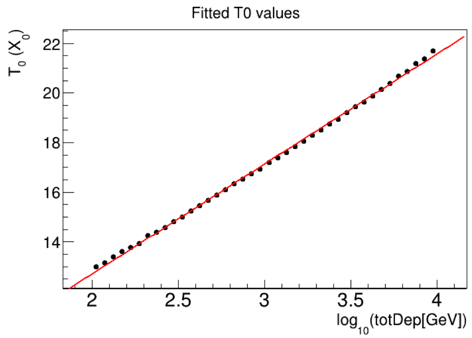
For **electrons**

$$f(t, E_0) = b\frac{(bt)^{a-1}e^{-bt}}{\Gamma(a)}$$

where $b = \dfrac{a-1}{T_0}$

Both parameters *a* and T_0 linearly depend on **log(totDep)**

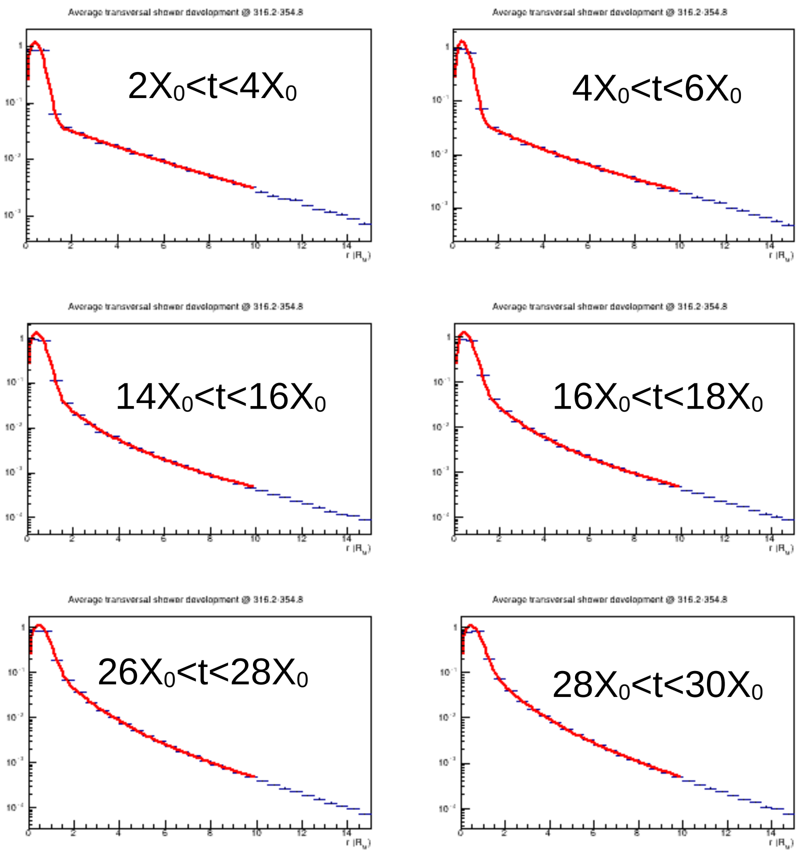




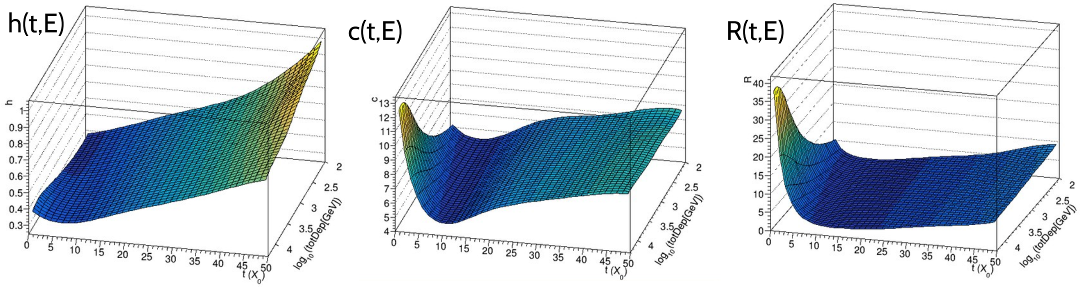
Transversal profile

Still for **electrons**

$$g(r,t,E_0) = r\left(2A\frac{e^{-r^2/h}}{h} + B\left(\frac{R}{R+r}\right)^c\right)$$



Parameters depend on **energy and *t*,** but relation is **not trivial**
→ Modeled using **2D splines**



Probability density function

Apply same procedure to model **average squared deposit**
→ We get a model for average and variance of the deposited energy

Approximation of pdf based on **modified Poisson function**

$$P(E_i^m|E_i^e,\eta_i) = N(E_i^e)\frac{e^{-E_i^e/\eta_i}(E_i^e/\eta_i)^{E_i^m/\eta_i}}{\eta_i\ \Gamma(E_i^m/\eta_i+1)}$$

$$E[E_i^m] = E_i^e$$

$$V[E_i^m] = E_i^e\eta_i$$

η parameter let both average and variance of pdf to fit to those simulated

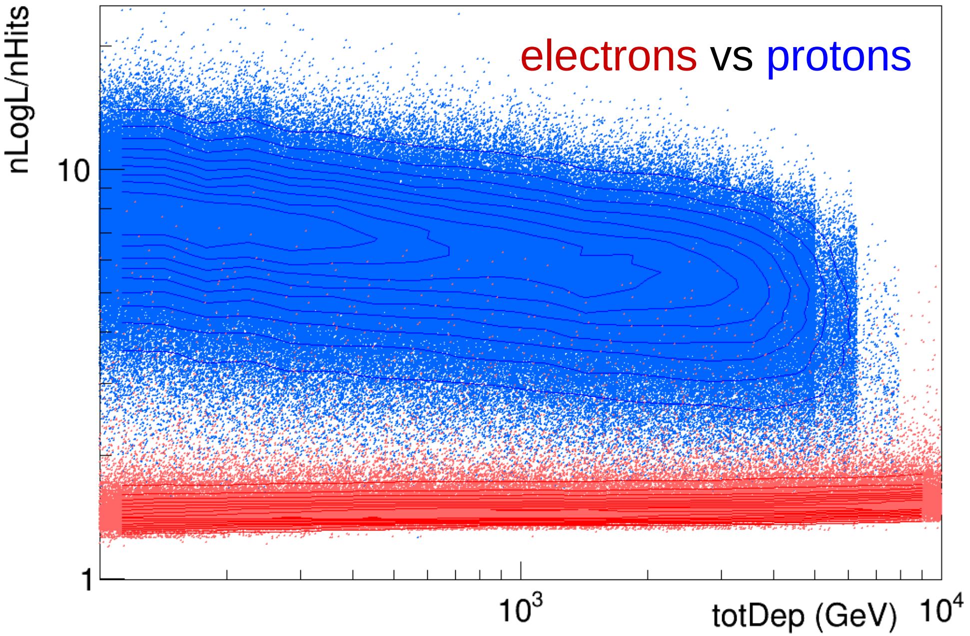
We can now evaluate the **likelihood of the electron hypothesis**

$$L = \Pi_i P(E_i^m|E_i^e,\eta_i)$$

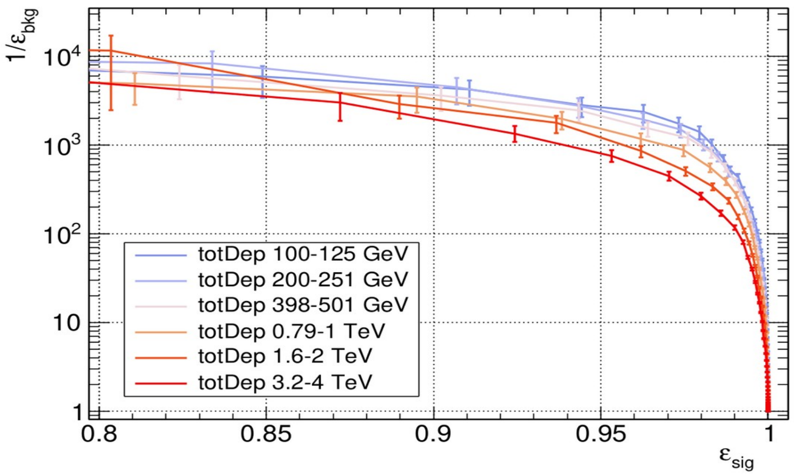
Product over deposited energy on every cube

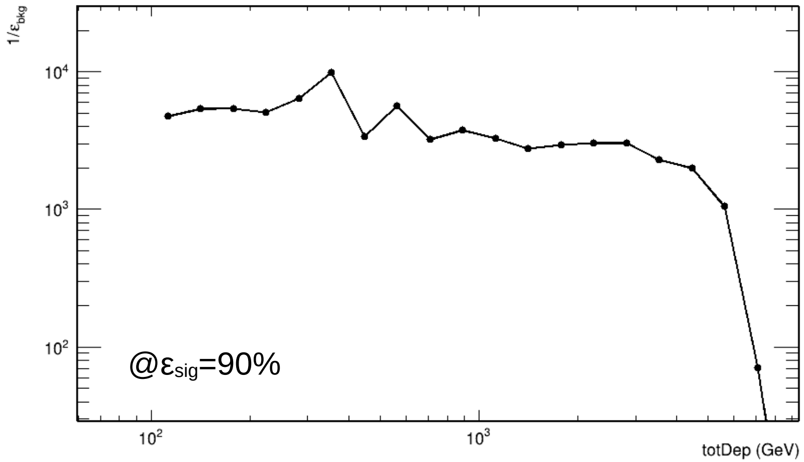
Rejection

$$nLogL = -log_{10}(L)$$



With this modeling we already obtain a **reduction of the protons background above 10^3** for a **90% signal efficiency**.





What if no fit?

Fitting might be **not necessary**.
Just by mapping we already have a model for **both electrons and protons.**

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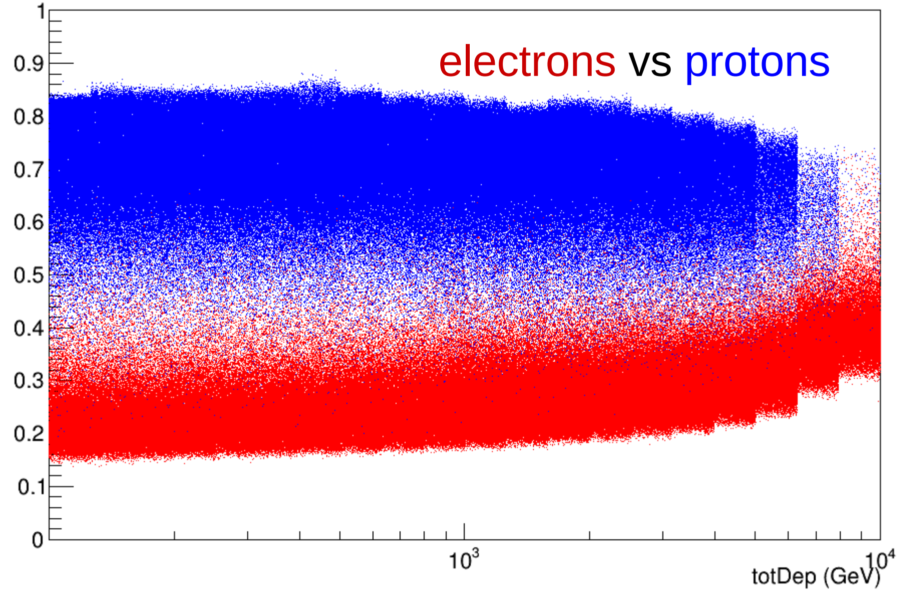
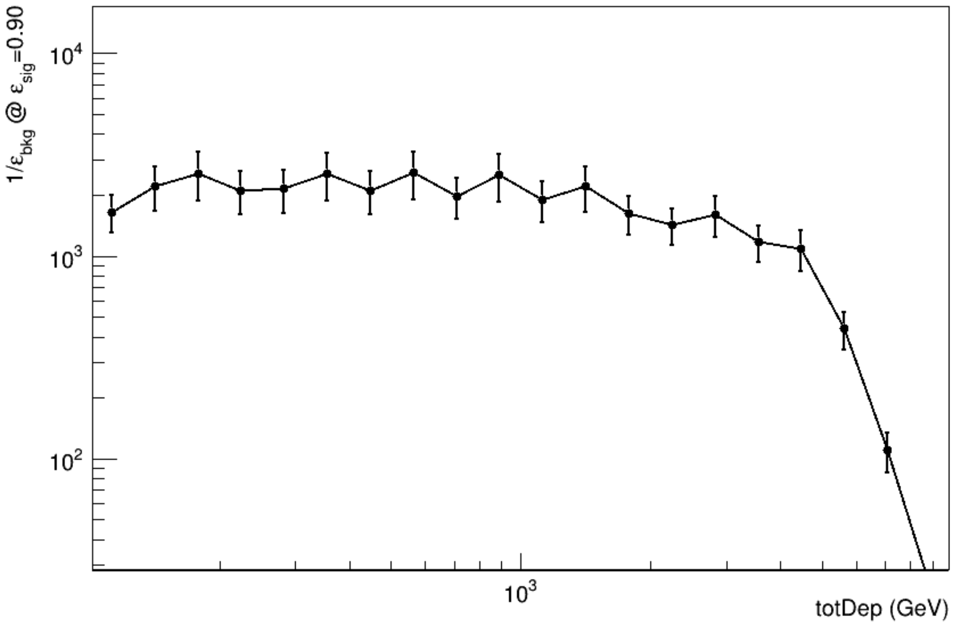
$$\frac{nLogL^e}{nLogL^e + nLogL^p}$$





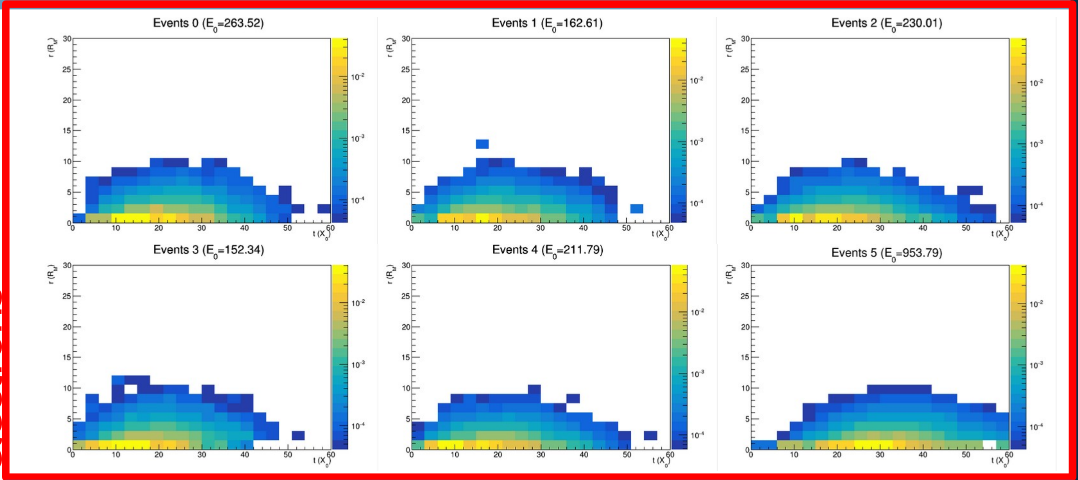
What if we use neural networks?

Showers projections on the (t,r) reference frame are pictures.

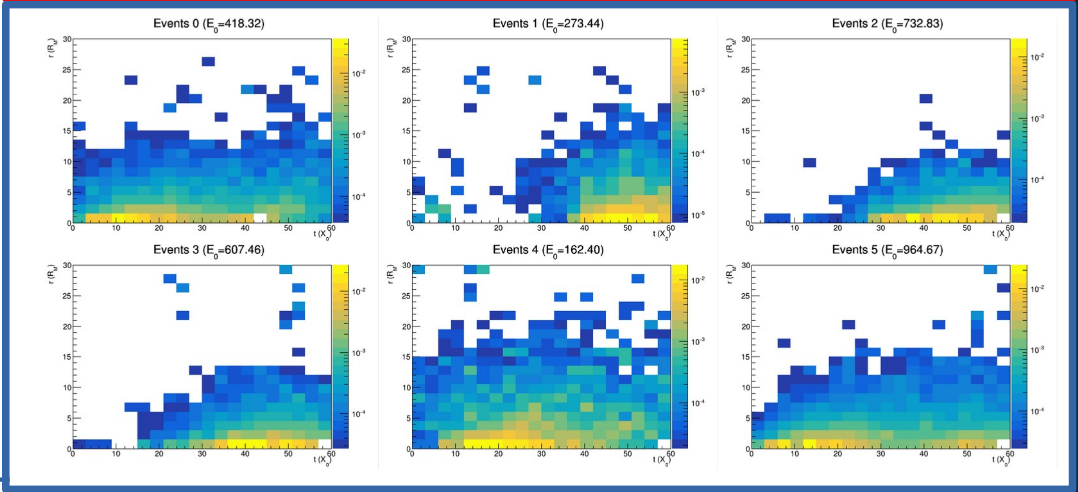
They can be studied with standard **computer vision techniques** like **convolutional neural networks.**

Not only shapes, but **also deposits correlations**

electrons



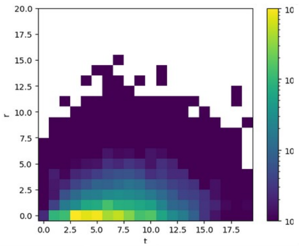
protons

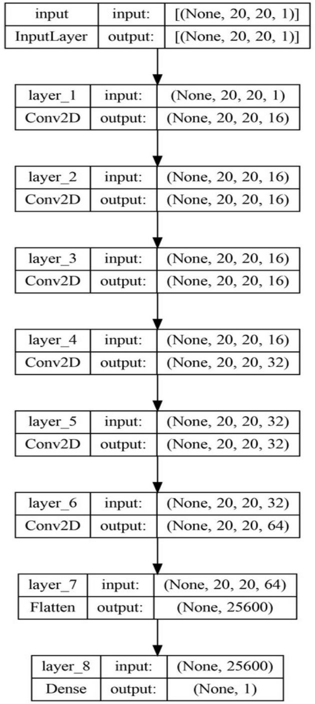


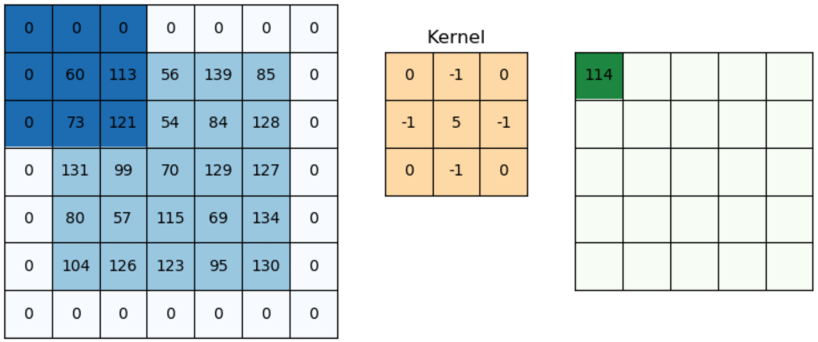
Convolutional Neural Network

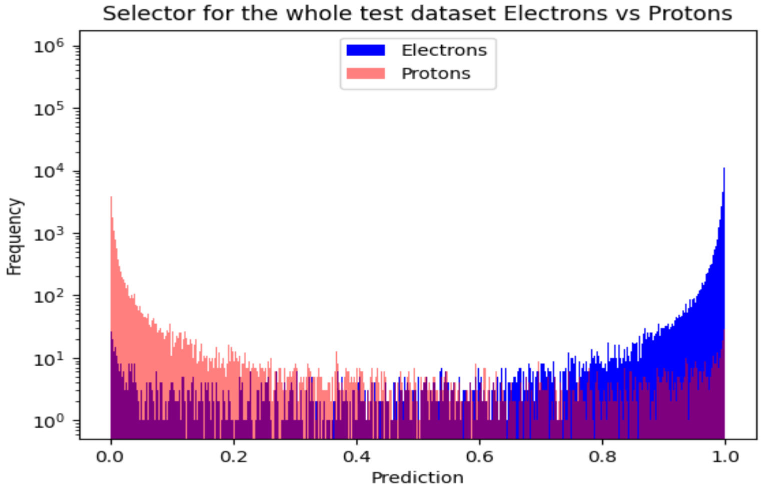
CNN by Luca Tabarroni
(Università Roma Tor Vergata)
based on the same dataset.

The final output is a single parameter used for the classification.



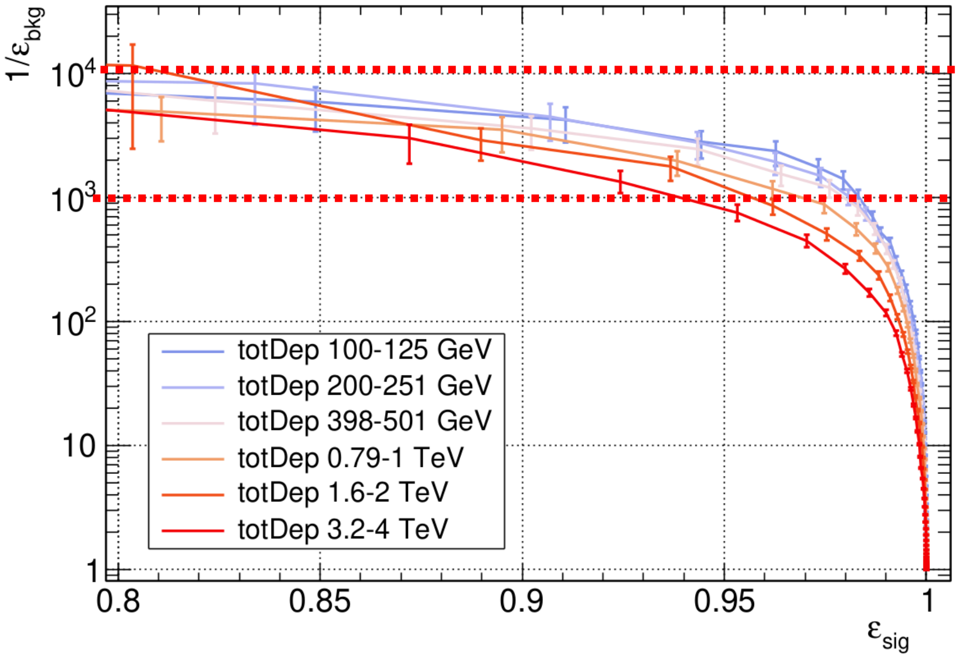




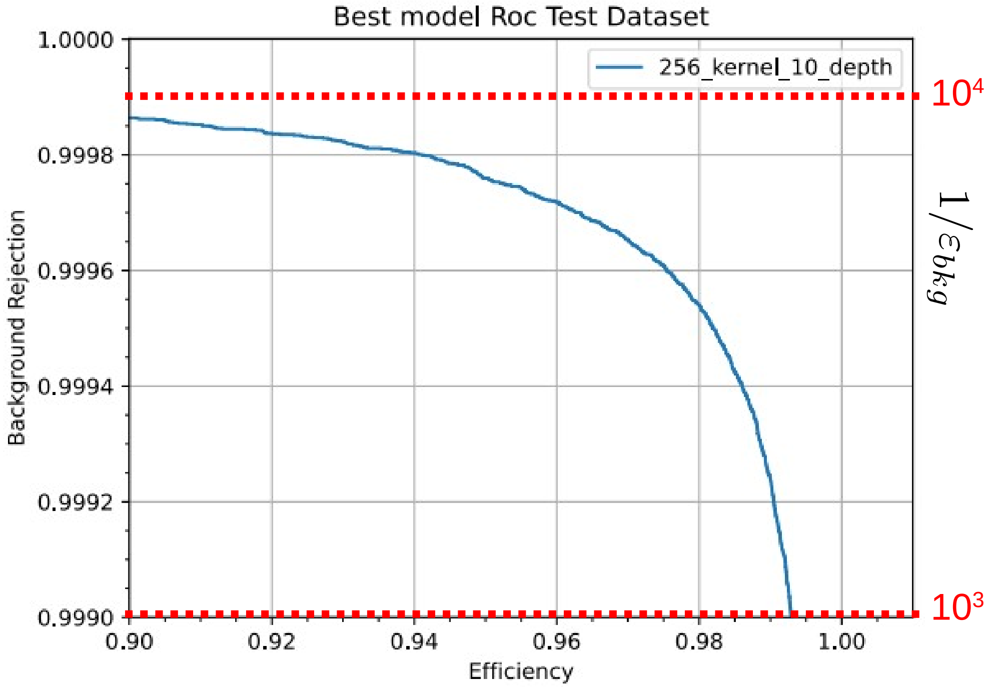


Performance comparison

Likelihood



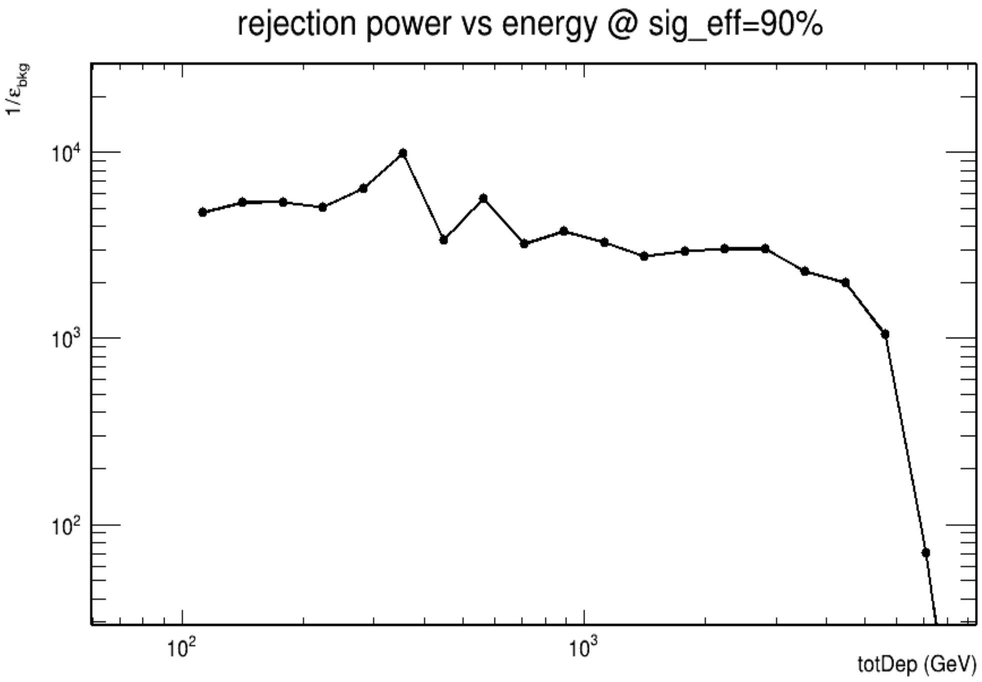
Neural Network



More powerful, but still comparable results

Performance comparison

Likelihood



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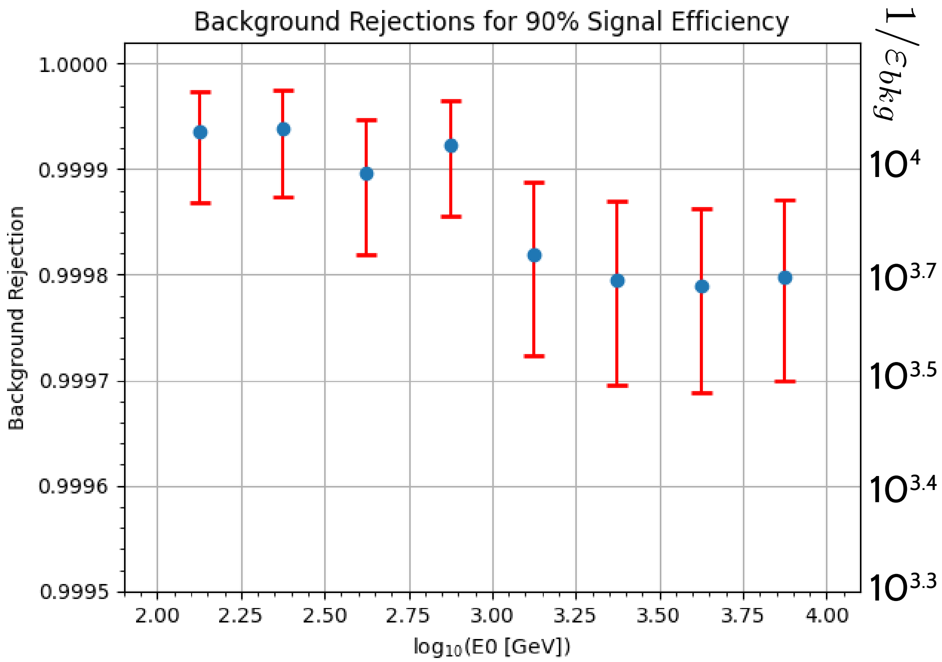

Performance comparison

Even if the performances are comparable, **CNN performs consistently better** than the likelihood at any tested energy.

CNN can **access information** that the model used for likelihood is not able to account for (e.g. local correlations).

Likelihood is still an **important way to validate the CNN** results through an explainable approach.

Future steps

- Test robustness at **higher energies**
- Study comparison of **computational cost** between CNN and Likelihood approach
- Test on actual **experimental data**

THANK YOU

Direct cosmic rays detection

Magnetic spectrometers: (AMS-02)

- measures the sign of the charge
- $$\frac{\sigma_p}{p} \propto p$$

Calorimeters: (DAMPE, CALET)

- No information on sign of charge
- $$\frac{\sigma_E}{E} \propto \frac{1}{\sqrt{E}}$$