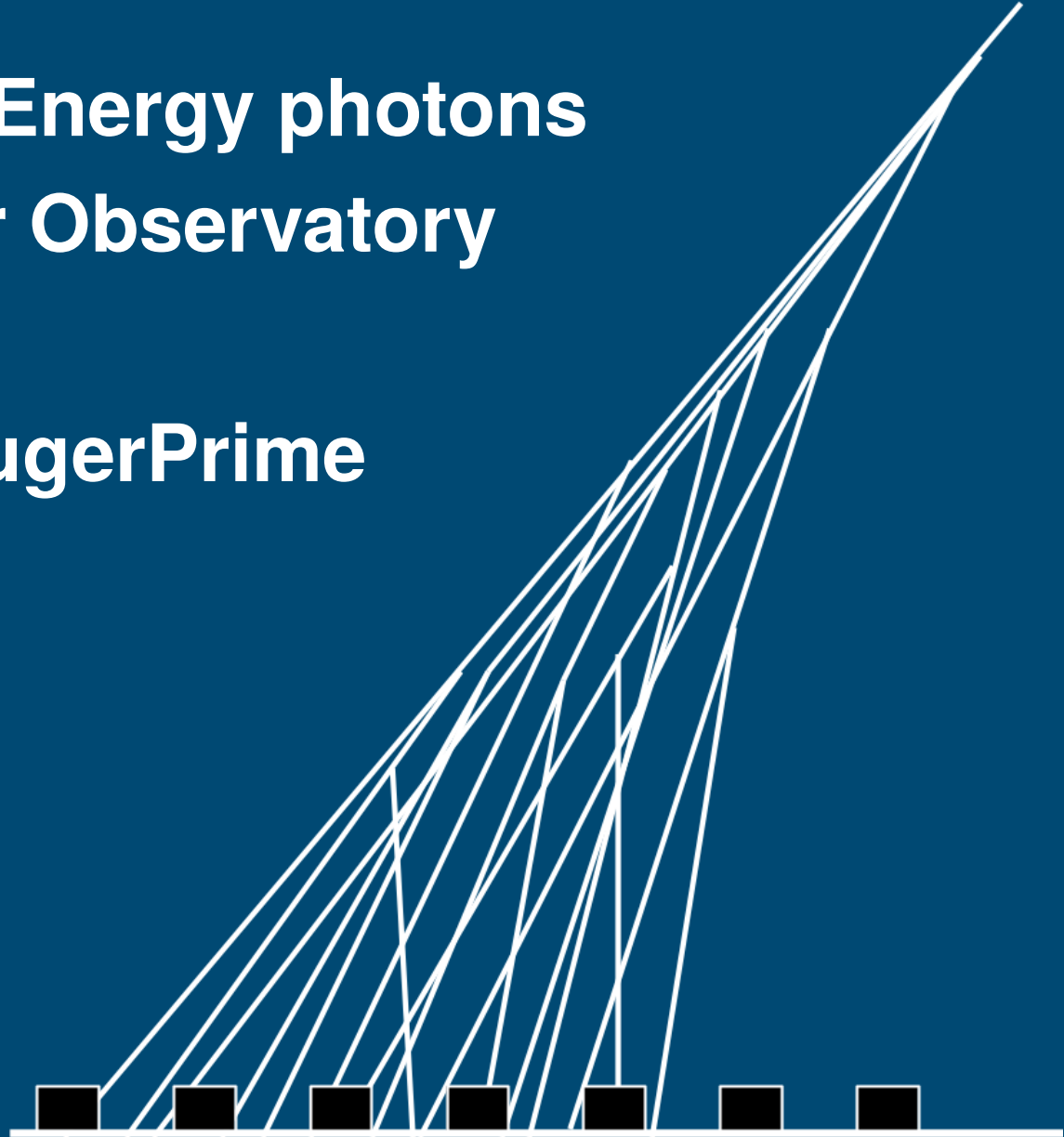


Search for **Ultra High Energy** photons at the **Pierre Auger Observatory** & contribution to **AugerPrime**

In the Auger group.

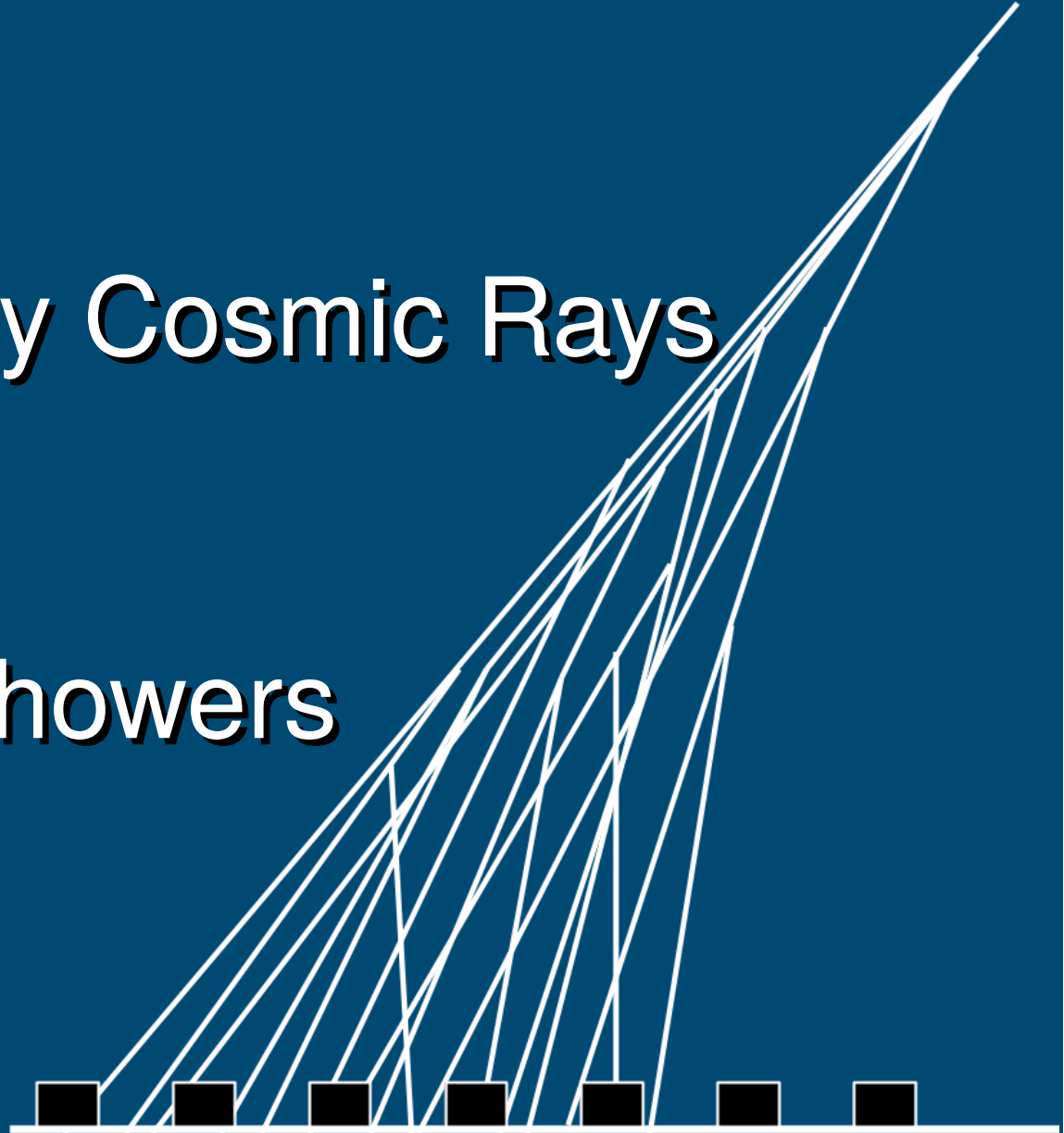
Thesis Supervisor : Corinne Berat



Outline

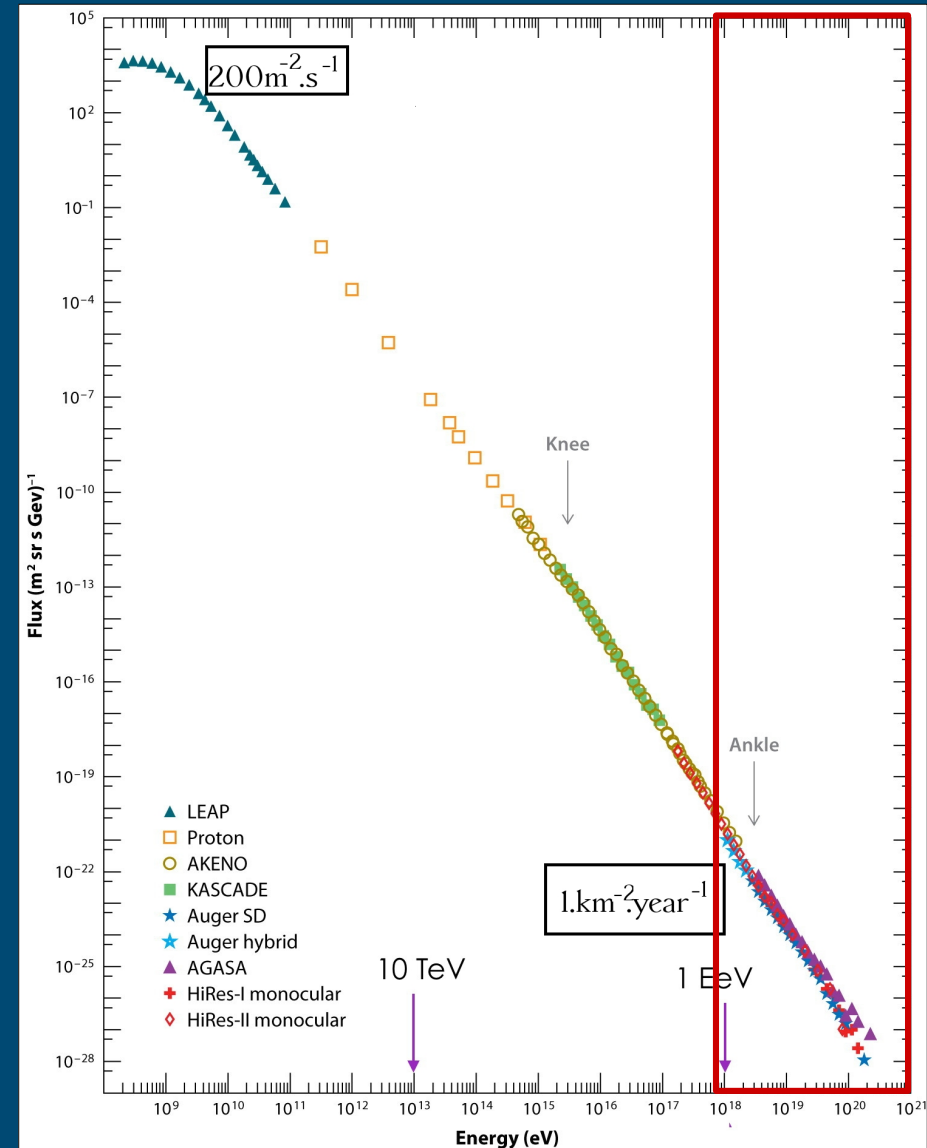
- Ultra High Energy Cosmic Rays & Extensive Air Showers
- The Pierre Auger Observatory & AugerPrime
- Scintillator Surface Detectors – Construction & Validation
- Search for Ultra-High Energy photon primaries – Motivations & Multi-Variate Analysis

Ultra-High Energy Cosmic Rays & Extensive Air Showers



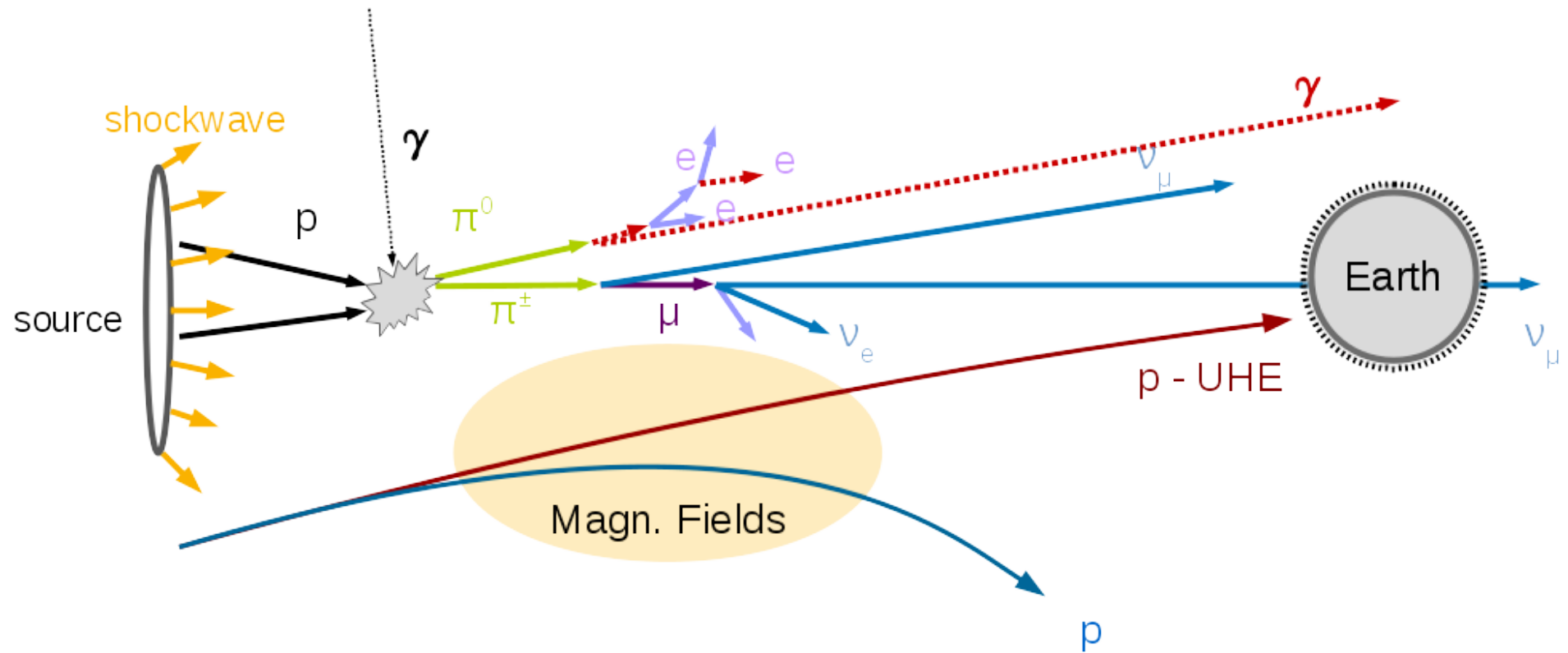
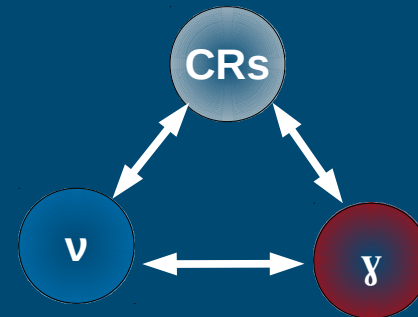
Ultra High Energy Cosmic Rays (UHECRs) :

- ultra high energies : $E > 10^{18}$ eV
- very limited flux : $< 1.\text{km}^{-2}.\text{year}^{-1}$
- features in the spectrum
- nucleus from H to Fe & neutrals ($n/\gamma/\nu$)



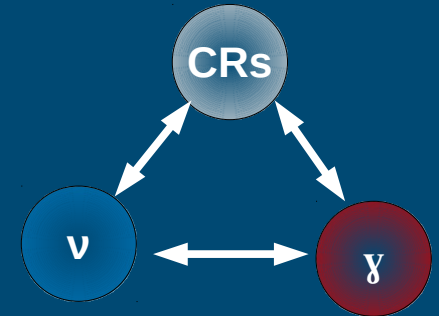
Beatty JJ, Westerhoff S. 2009.

Annu. Rev. Nucl. Part. Sci. 59:319–45



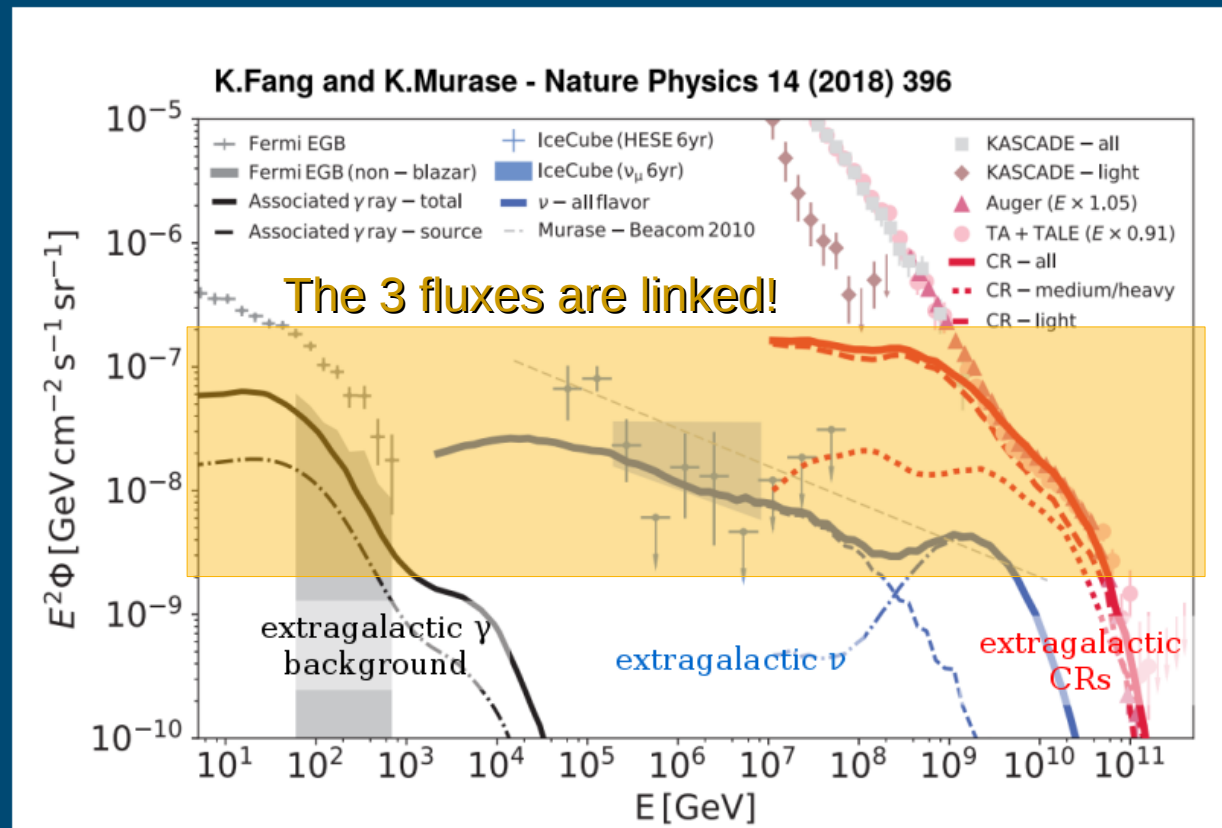
Multi-Messenger era of astrophysics :

- combine cosmic rays, gamma, neutrino and gravitational wave observations
- interplay between all these messengers



Complementarity between the observations

- Gamma-rays :
 - + : straight line
 - : UHE horizon < 10 Mpc
- Neutrinos :
 - + : straight line, no interaction
 - : isotropic diffuse background
- Cosmic-Rays :
 - + : direct accelerator probe
 - : deflected in magn. field



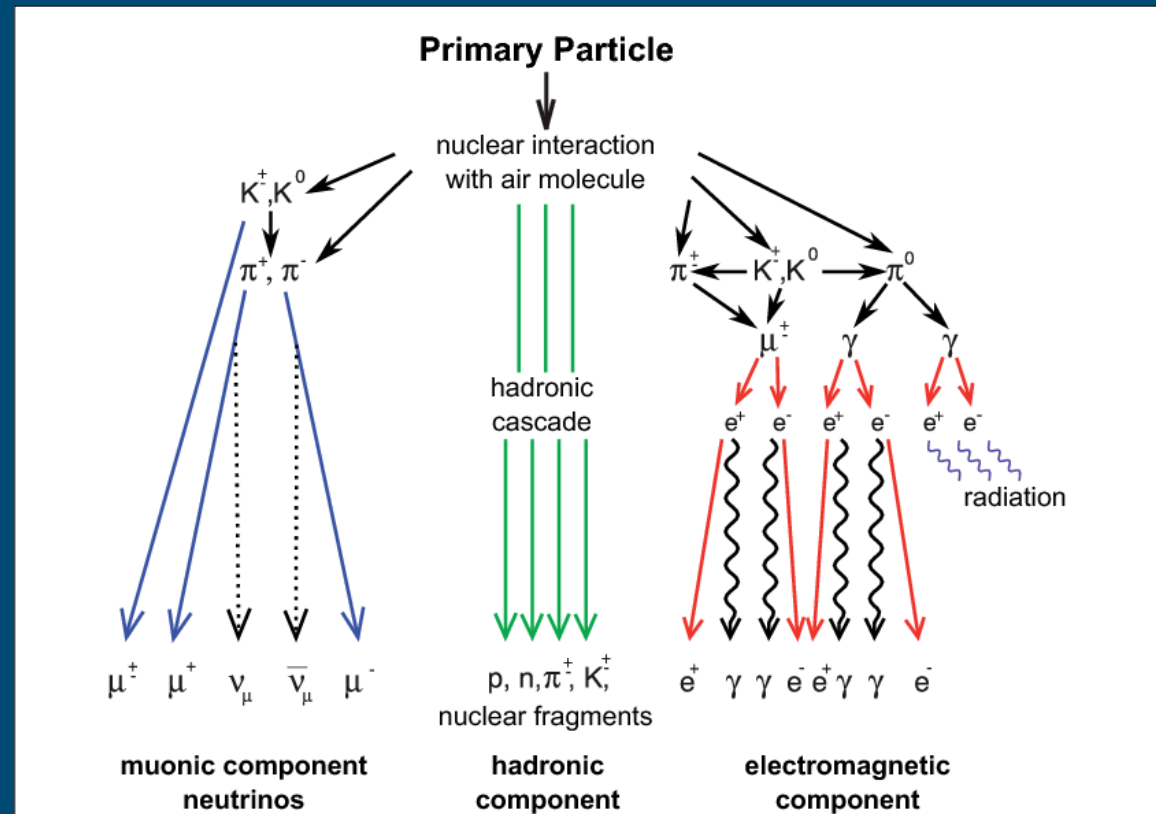
UHECRs interact with Earth's atmosphere :
→ generates an **Extensive Air Shower (EAS)**

3 main components :

- muonic component (~4%)
- hadronic component (~1%)
- electromagnetic component (95%)

At ground : $\sim 5 \cdot 10^{10}$ particles

(estimation for a 10^{19} eV p-shower)



UHECRs interact with Earth's atmosphere :
→ generates an **Extensive Air Shower (EAS)**

3 main components :

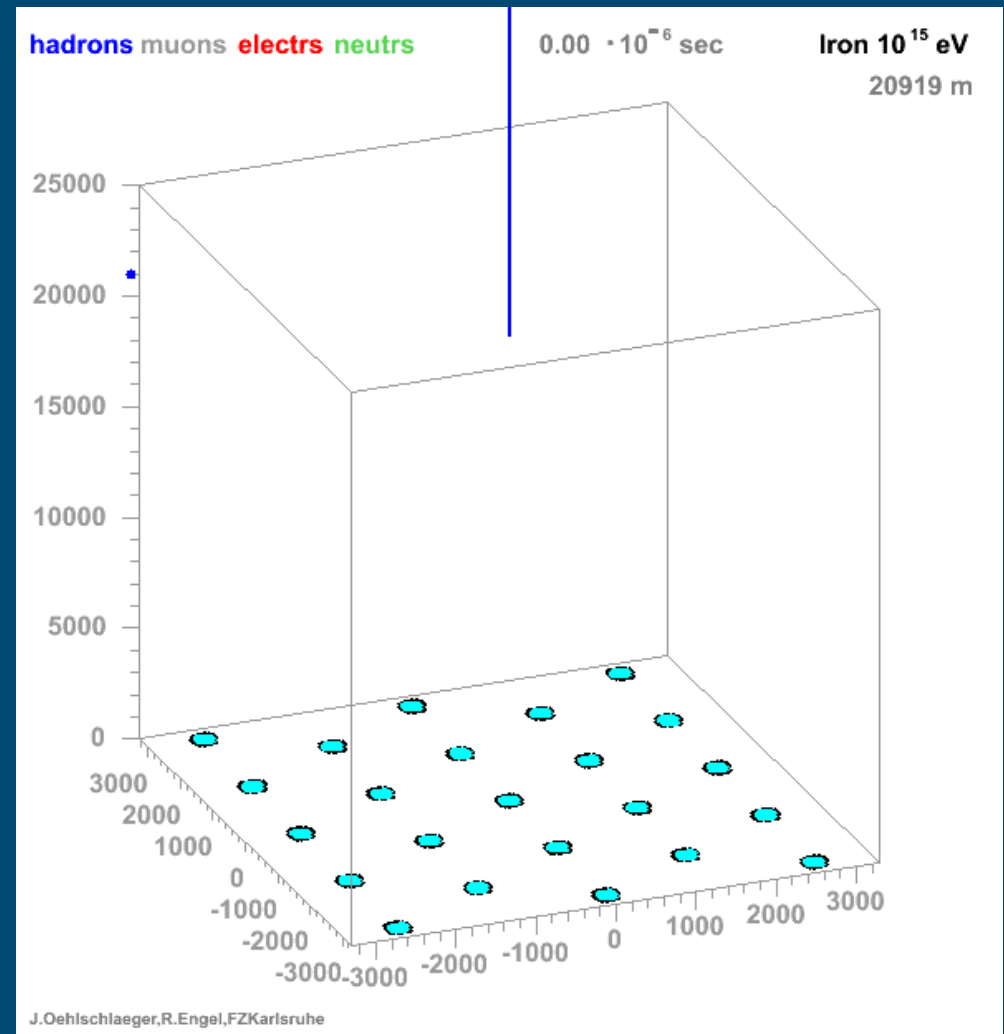
- muonic component
- hadronic component
- electromagnetic component

Advantages of the EAS :

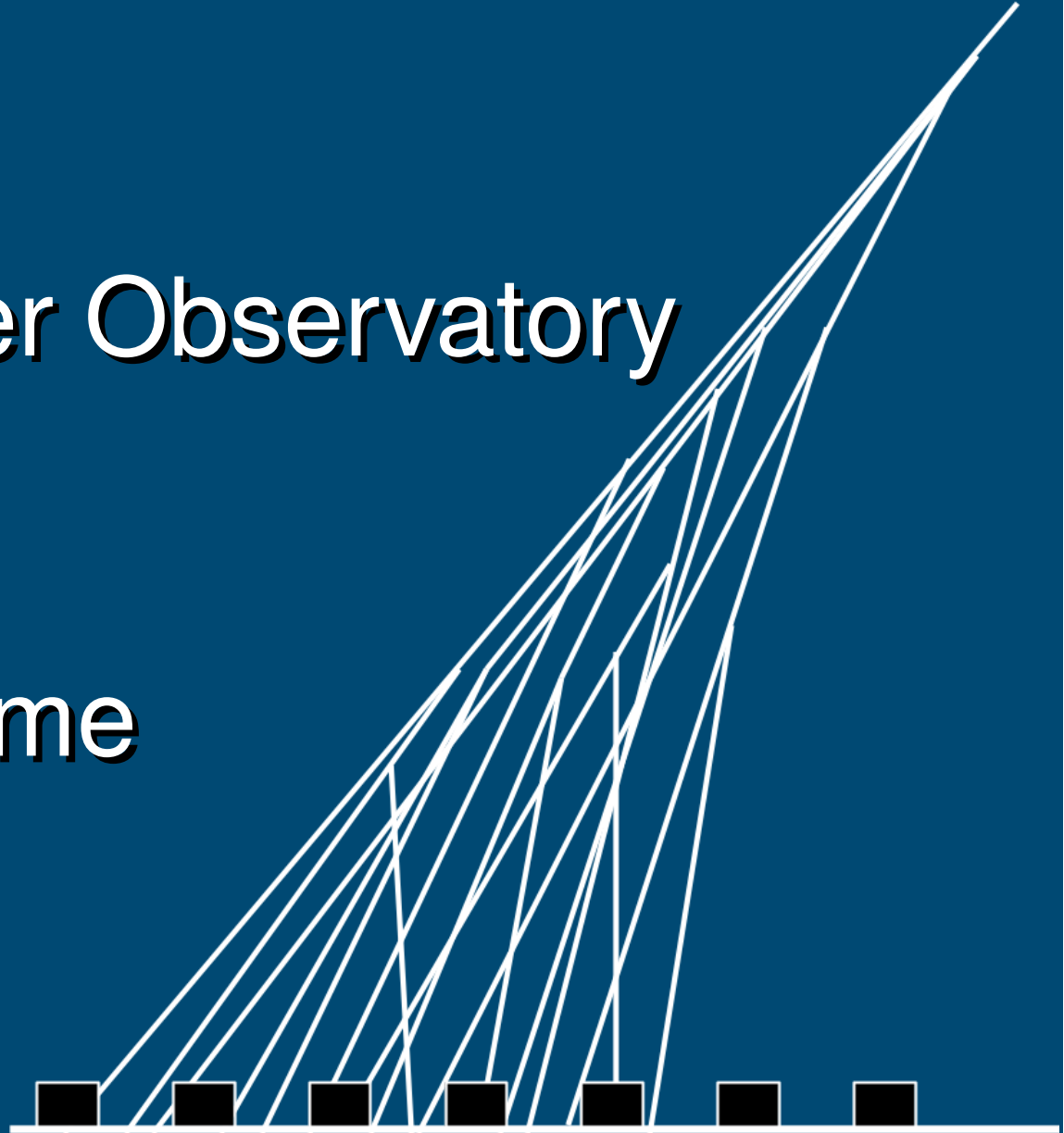
- large footprint (up to 15 km)
- multiple observations possibles
- UHE hadronic physics laboratory...

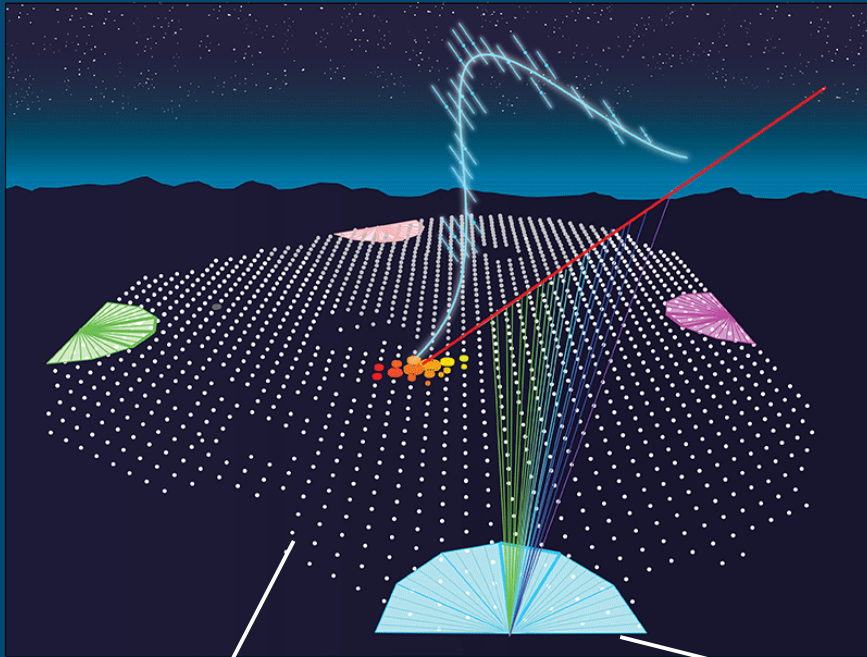
Disadvantages of the EAS :

- indirect information on primary's energy
- inhomogeneous calorimeter
- ...model dependent



The Pierre Auger Observatory & AugerPrime





The Pierre Auger Observatory (PAO) :

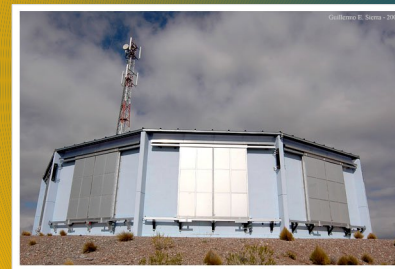
- Officially completed in 2008
 - started taking data in 2004
- 400 scientists from 18 countries
- Location : pampa near Malargüe, Argentina
- Altitude (mean) : 1400 m above sea-level
- Surface (SD) : 3000 km²

Surface Detector (SD) :

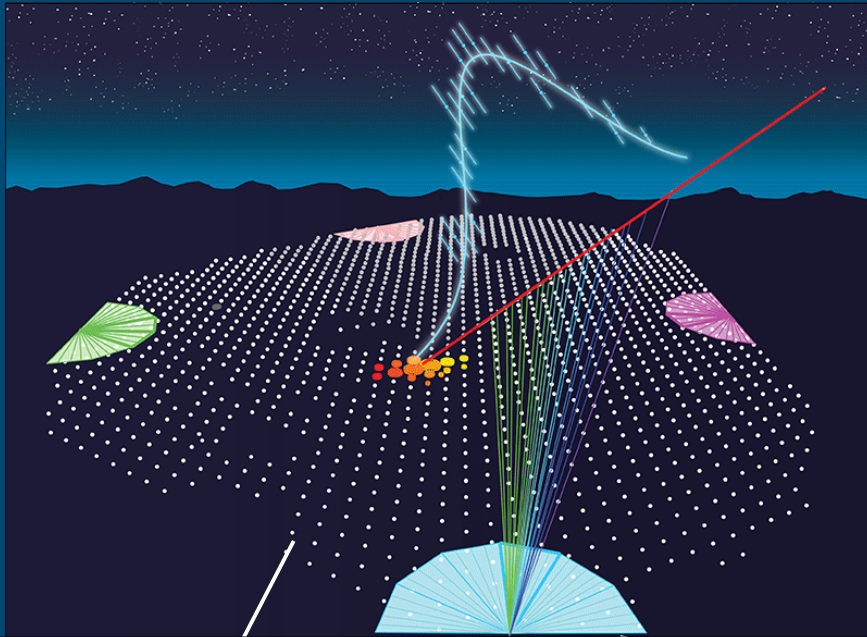


- 1660 Water Cherenkov Detector
- Triangular spacing of 1.5 km
- Duty-Cycle : 100%

Fluorescence Detector (FD) :



- 24 telescopes located in 4 buildings.
- Overlooking the atmosphere above the array
- Duty-Cycle : 14%



The Pierre Auger Observatory (PAO) :

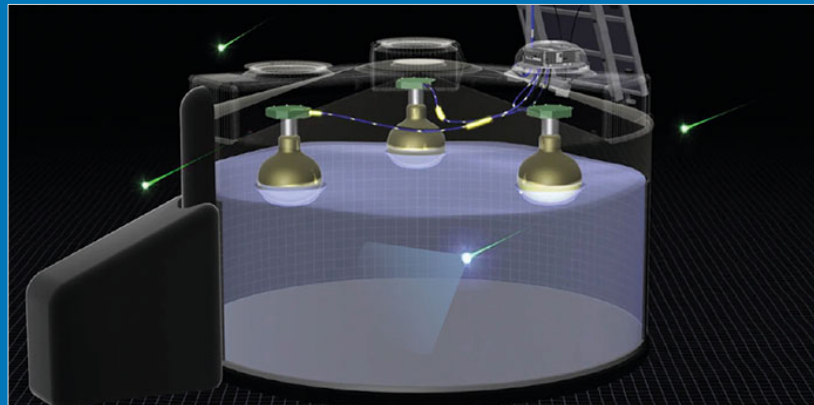
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- Location : pampa near Malargüe, Argentina
- Altitude (mean) : 1400 m above sea-level
- Surface (SD) : 3000 km²

Water Cherenkov Detector (WCD) :

Secondary particles (highly relativistic) going through the detector produce Cherenkov light.

Collect timing and signal to reconstruct the showers.

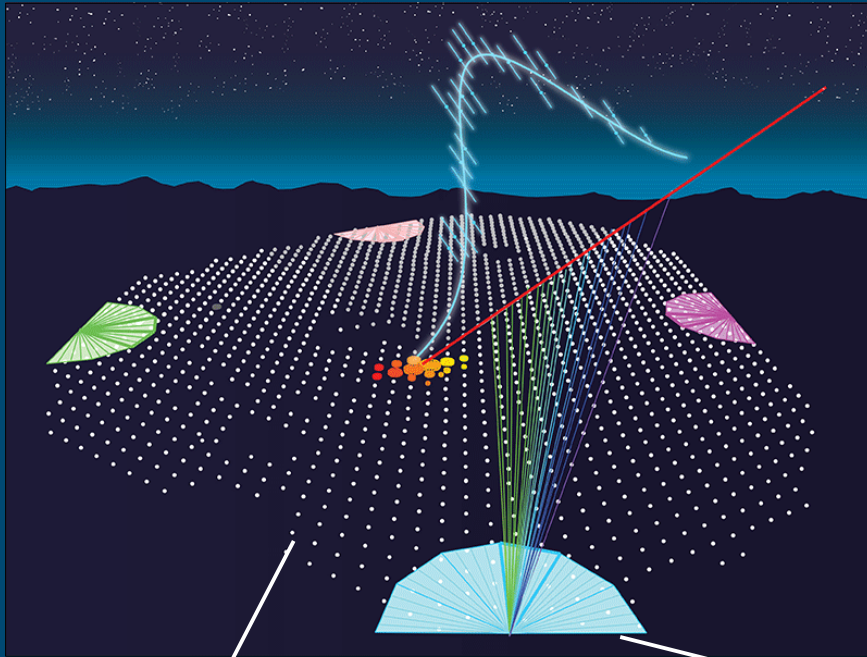
Sensitive to e^{\pm} , γ , μ



Fluorescence Detector (FD) :

- 24 telescopes located in 4 buildings.
- Overlooking the atmosphere above the array
- Duty-Cycle : 14%





The Pierre Auger Observatory (PAO) :

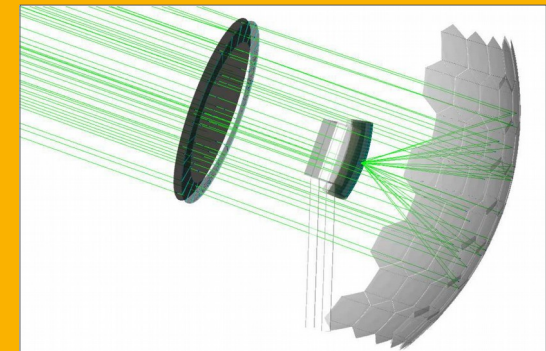
- Officially completed in 2008
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Fluorescence Telescope :

An EAS excite the nitrogen molecules in the atmosphere → Fluorescence Emission

Telescopes collect this UV light

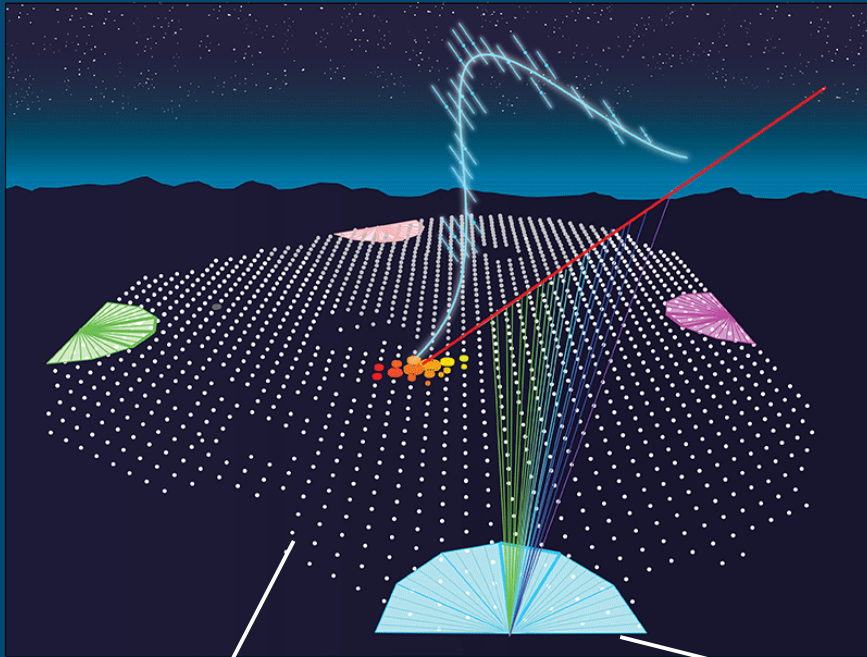
Direct measurement of the shower energy



Surface Detector (SD) :



- 1660 Water Cherenkov Detector
- Triangular spacing of 1.5 km
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The Pierre Auger Observatory (PAO) :

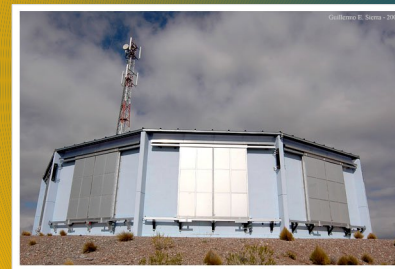
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Surface Detector (SD) :



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Fluorescence Detector (FD) :

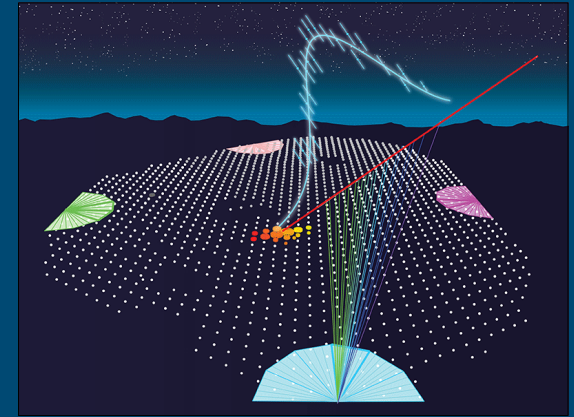


- 24 telescopes located in 4 buildings.
- Overlooking the atmosphere above the array
- Duty-Cycle : 14%

Hybrid Detection :

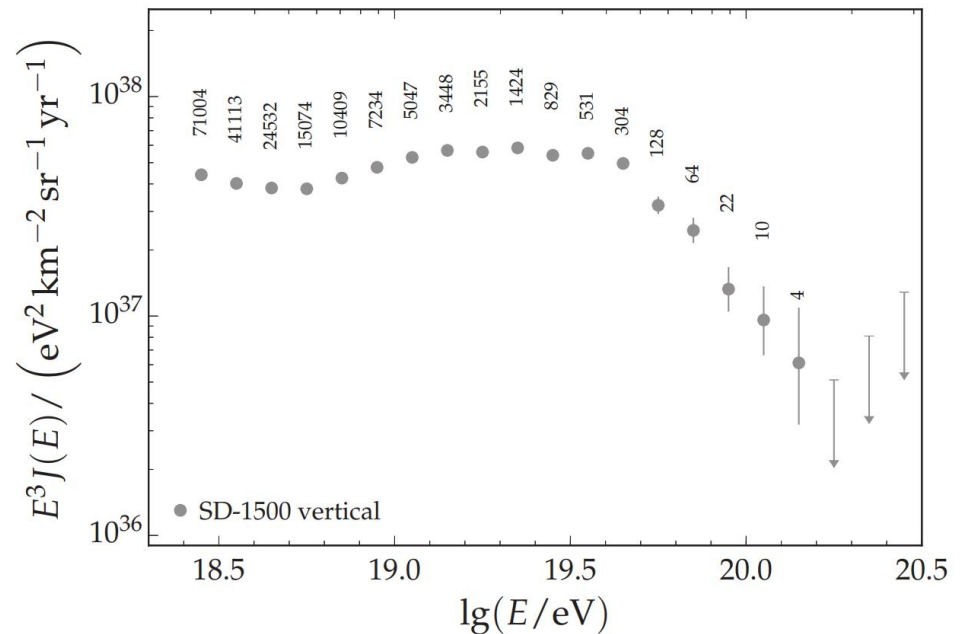
Able to use the FD to calibrate the SD's energy reconstruction

Other complementary detection possible...



Flux suppression around 10^{20}eV :
What is causing it ?

What particles are making up the
UHECRs flux ?



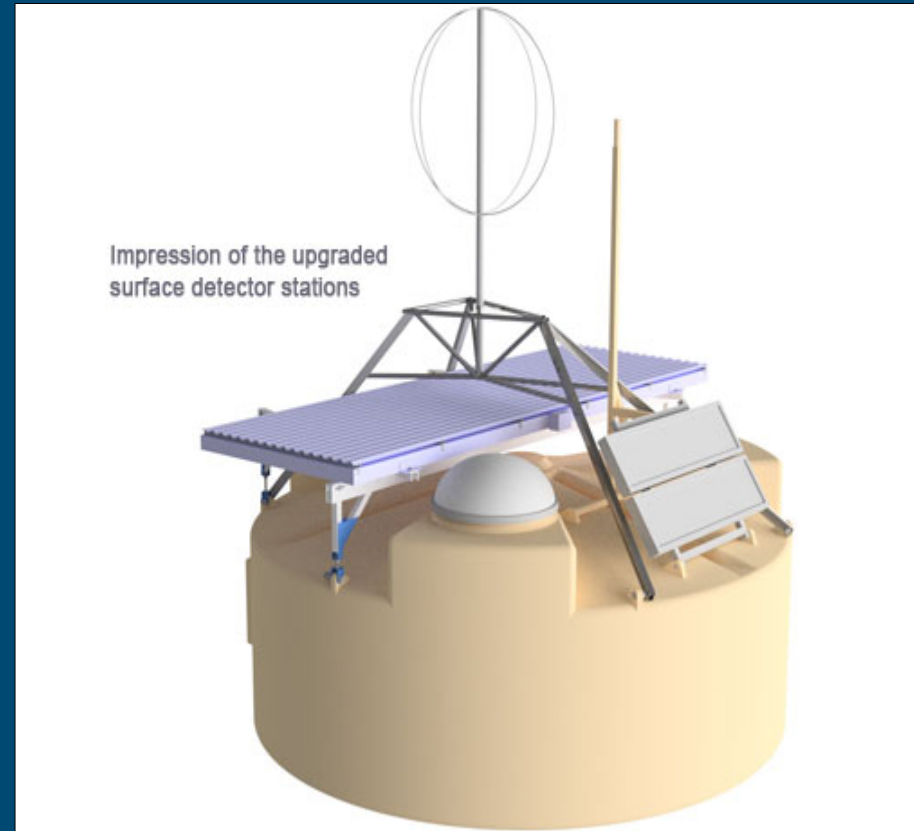
From Francesco Fenu, Contribution to the ICRC2017 : arXiv:1708.06592v2

Science Motivation :

- Probe the flux suppression
- Look at the flux composition at the highest energies
- UHE hadronic physics

AugerPrime :

- Add Scintillator Surface Detectors : on top of the WCD, to disentangle muon/EM components
- Upgraded electronics
- Radio Upgrade : add antennas on top of WCD to detect the showers radio-emissions



Scintillator Surface Detectors

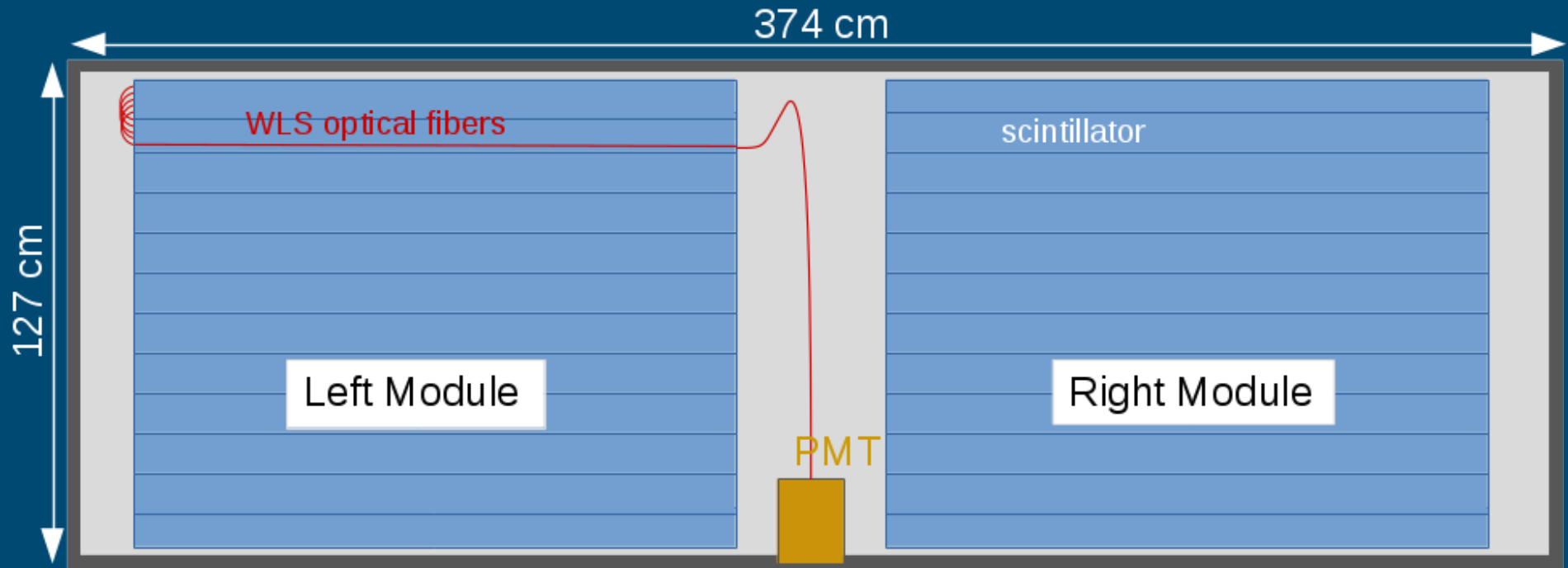
-

Construction & Validation



Objectives :

- add an independent and different measurement of the EAS' components, at the same place as the WCD
- reliable detector, with low maintenance



Detector's signal :

- the SSD's signal will be dominated by the shower's electrons, while the WCD's signal is dominated by the photons and muons.
- particle → scintillator → light → fibers → PMT → signal
- calibrated with atmospheric muons

SSD – Construction & Tests Setup

SSDs & Validation

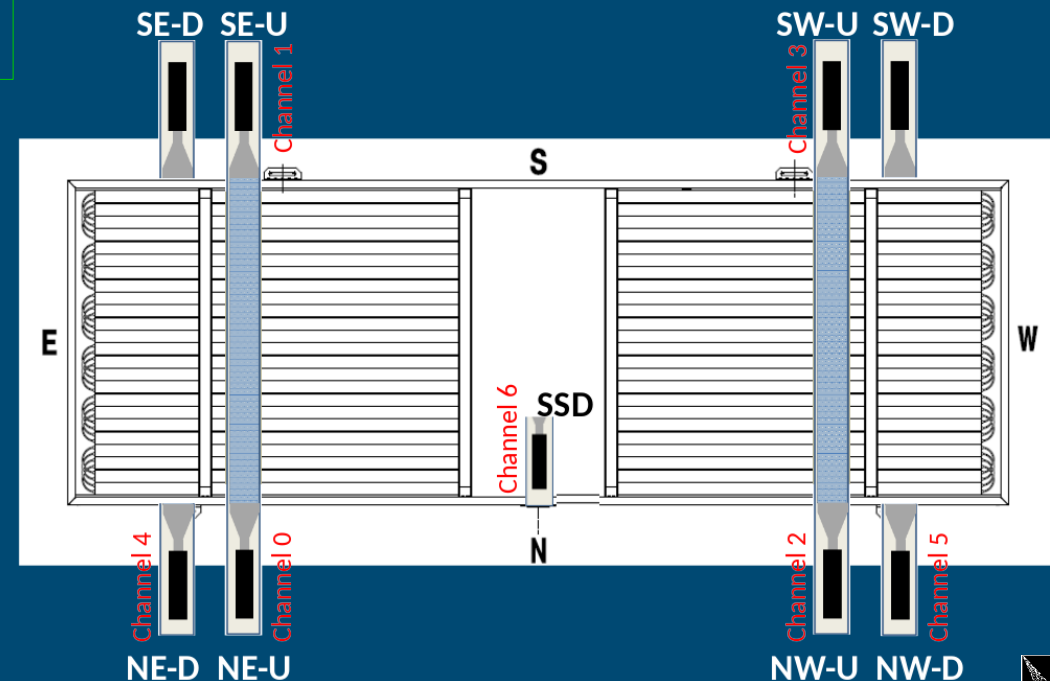
1200 SSDs built in 6 countries : 90 SSDs built at LPSC



Important involvement by the SDI, electronics and administrative departments

The scintillator boards are used as external triggers :

- a particle (muon) goes through both scintillators (up and down)
- read-out electronics : “trigger”
- record the signal from all PMTs inside a user-defined time window (*800 ns before trigger and 300 ns after trigger*)



Minimum Ionising Particle (MIP) :

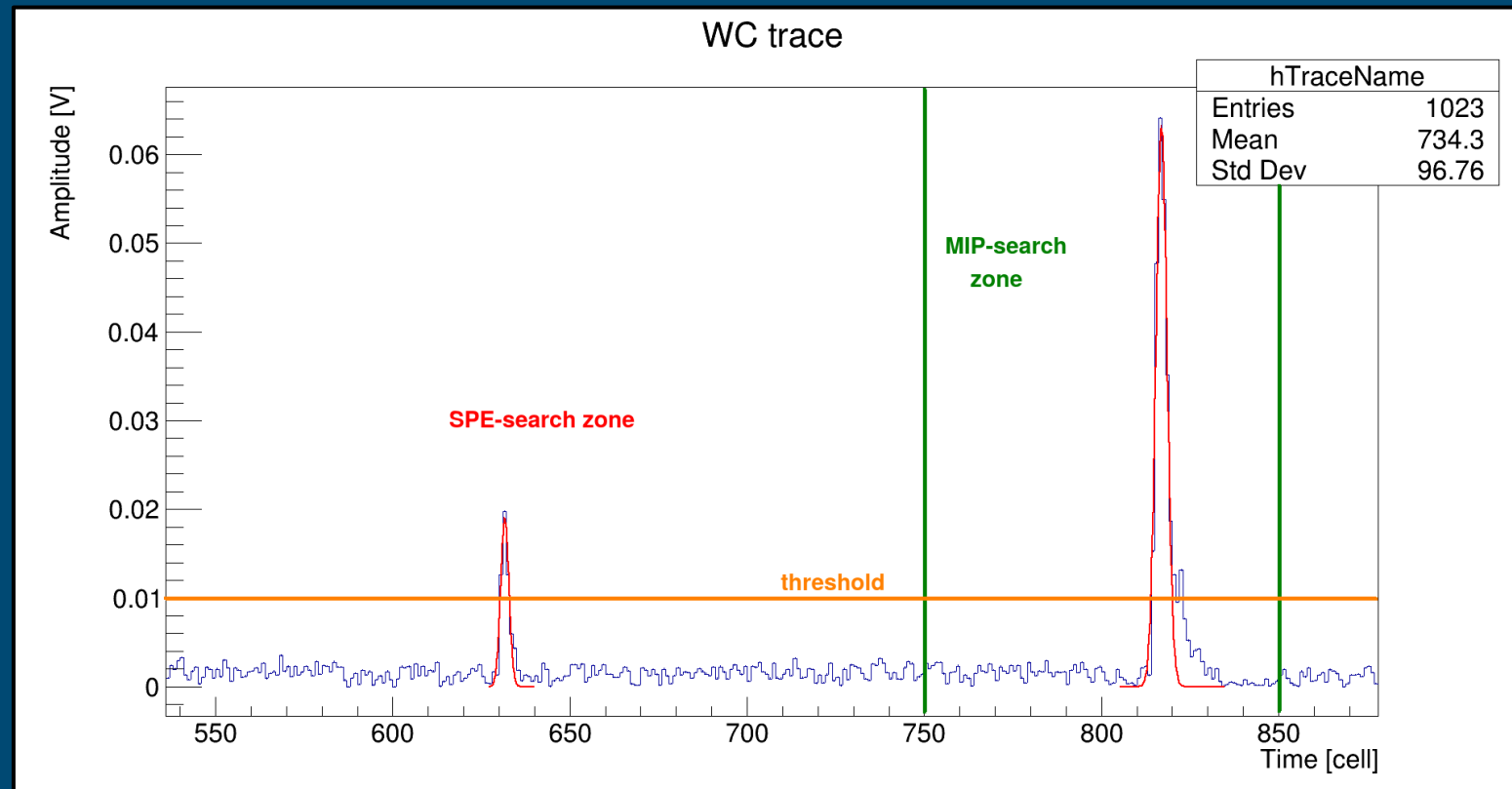
Minimum energy deposited by a through-going relativistic particle (i.e muon)

Single Photo-Electron (SPE) peak :

signal picked-up by the PMT for a single photoelectron inside the detector

For each triggered event (50k per run) :

- scan the SSD trace
- look for a MIP and/or SPE peak
- draw the distribution and fit
- use timing information on the external trigger to select vertical events → VMIP



Minimum Ionising Particle (MIP) :

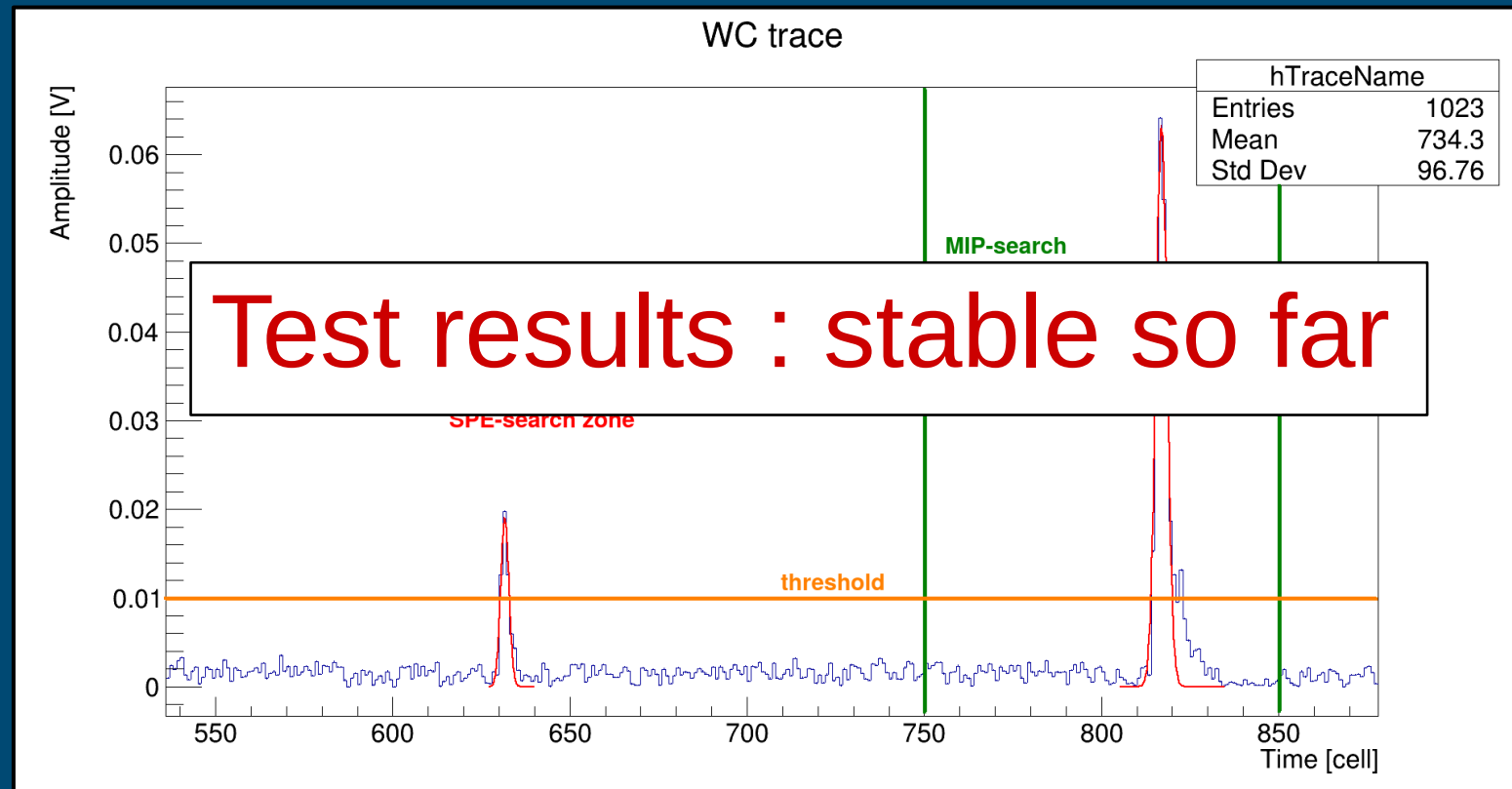
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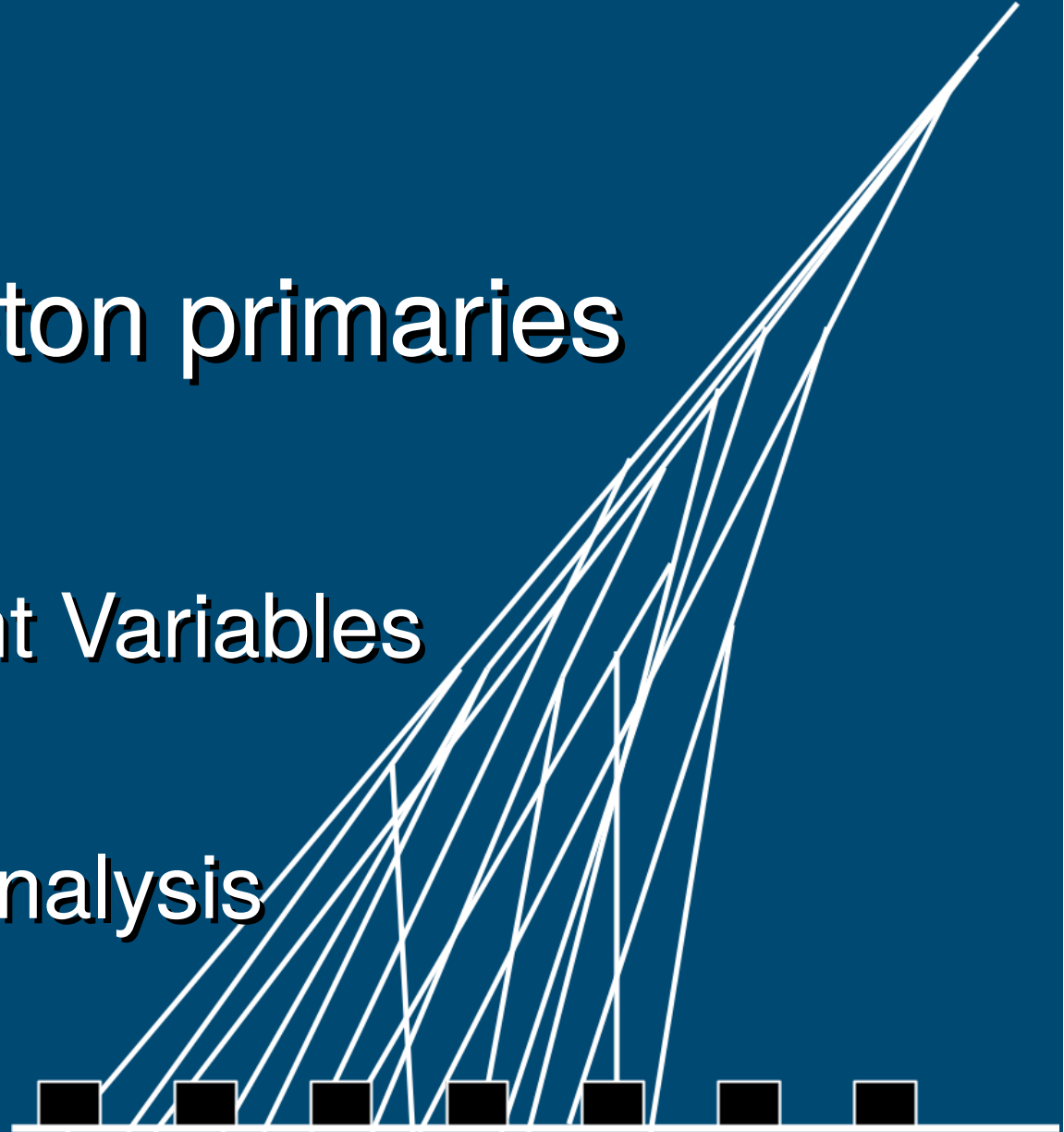
Search for photon primaries

-

Primary Dependent Variables

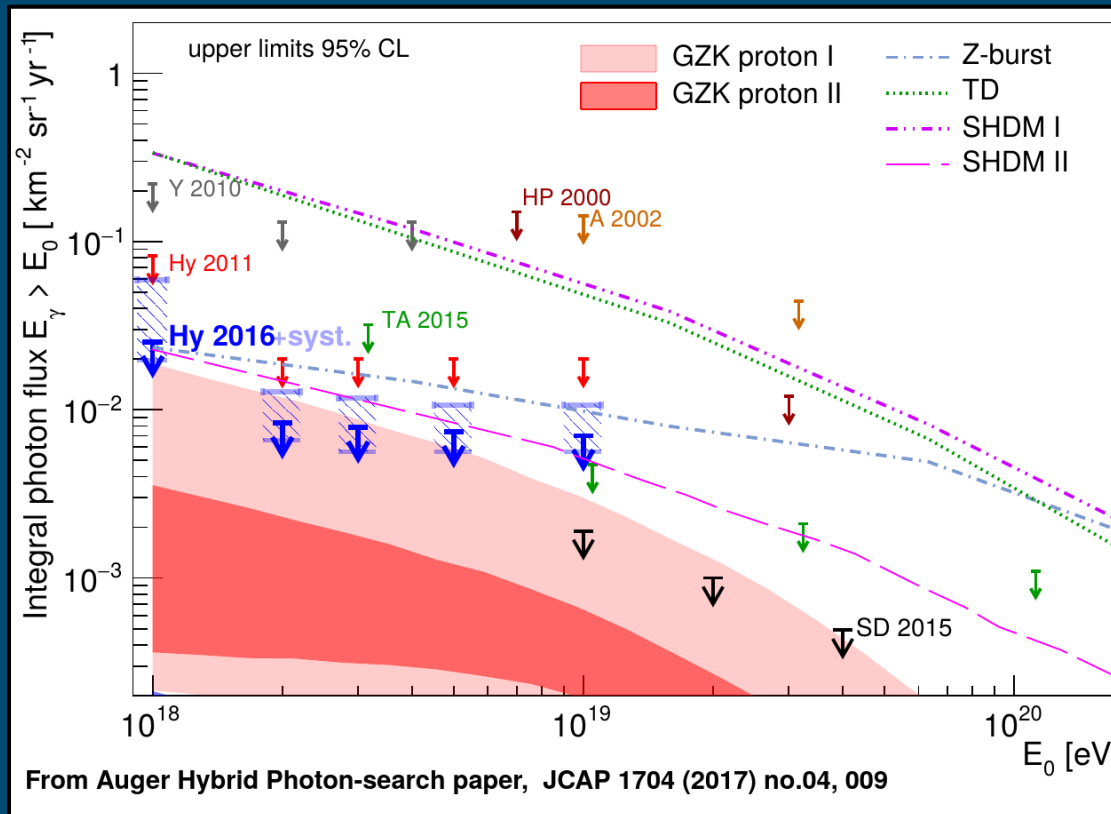
&

Multi-Variate Analysis



Why are photon primaries interesting? :

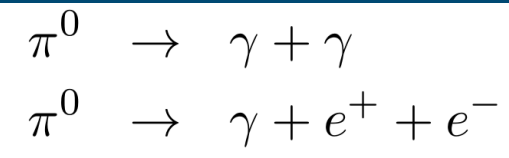
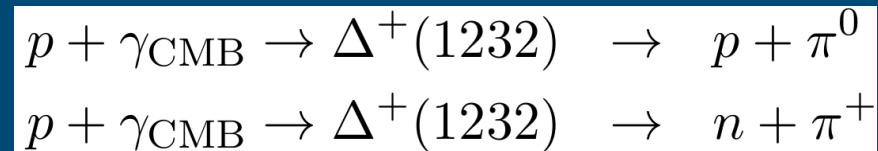
- point back to source directly
- UHE photons follow-up searches
- an excess of photons could independently confirm the GZK effect
- constrain astrophysical scenarios



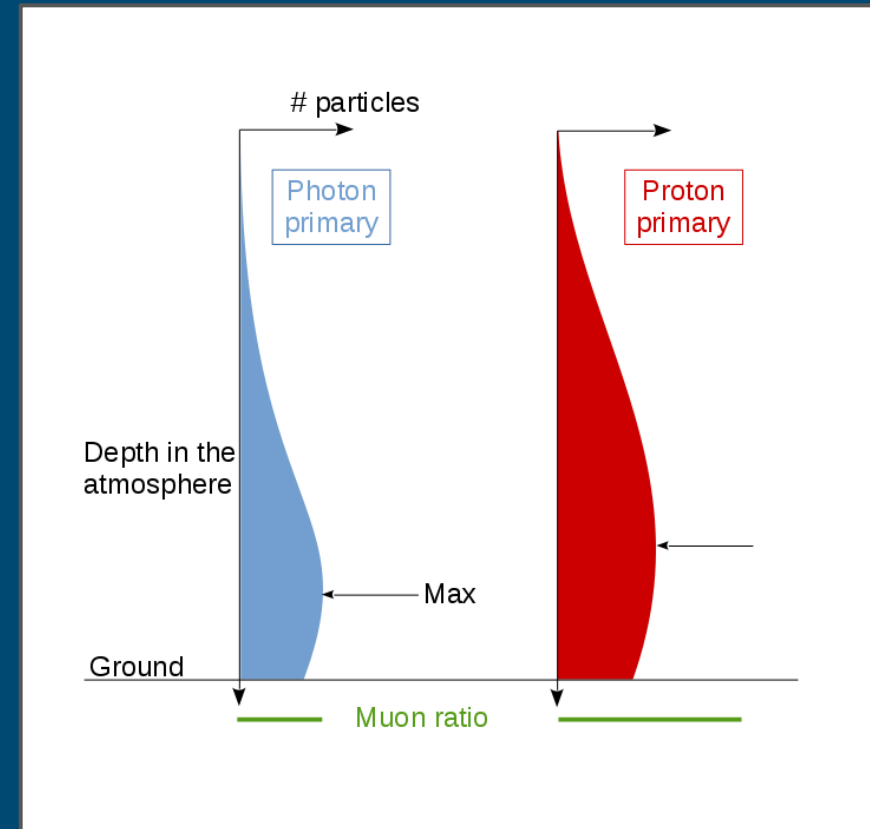
Greisen Zatsepin Kuzmin effect :

Interaction between UHECRs and Cosmic Microwave Background photons.

Above an energy threshold :
 $E_{\min} \sim 10^{19} \text{ eV}$



- Develop deeper into the atmosphere
- On average, more fluctuations of the shower maximum
- Less muons on ground



- Two official analyses in Auger collaboration :
- Hybrid (SD+FD) analysis : more observables
 - SD only analysis : *more data*

Aim of my analysis :

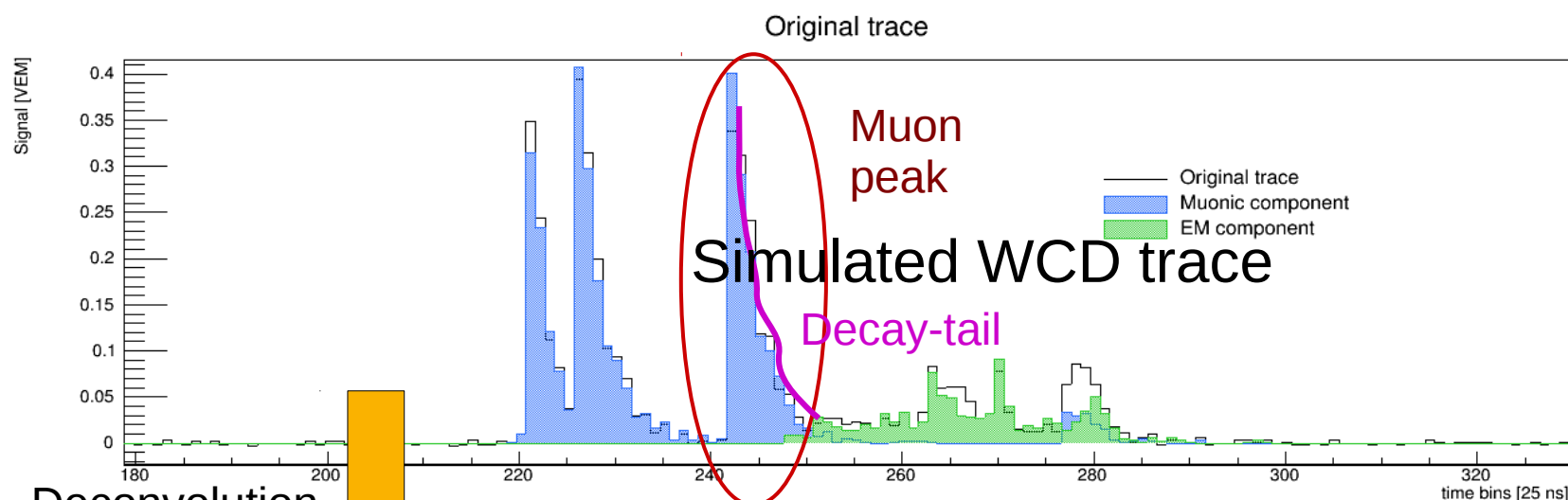
Use features inside the WCD signal to estimate the muonic content of the showers and thus differentiate between photon/proton primaries

Improve the discrimination power of the analysis

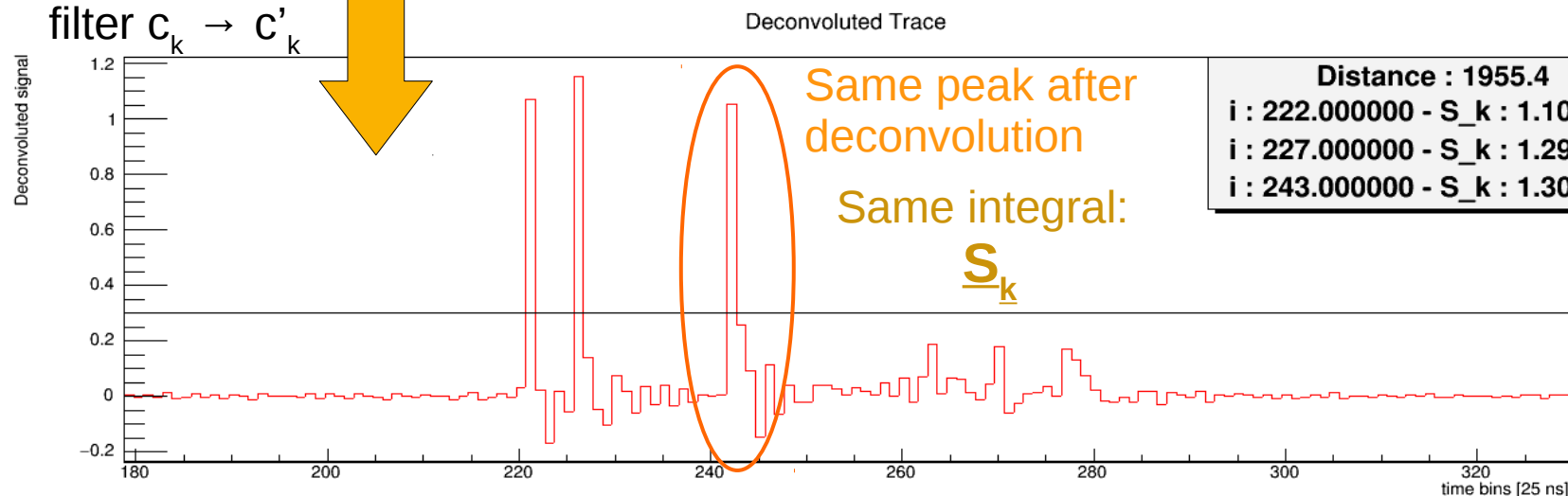
SD only analysis = 100% duty cycle

Trace = WCD signal

Core of the Muonicity Method : perform a linear deconvolution to remove the exponential decay-tail of a muon signal while integrating the total muon-signal.



Deconvolution
filter $c_k \rightarrow c'_k$

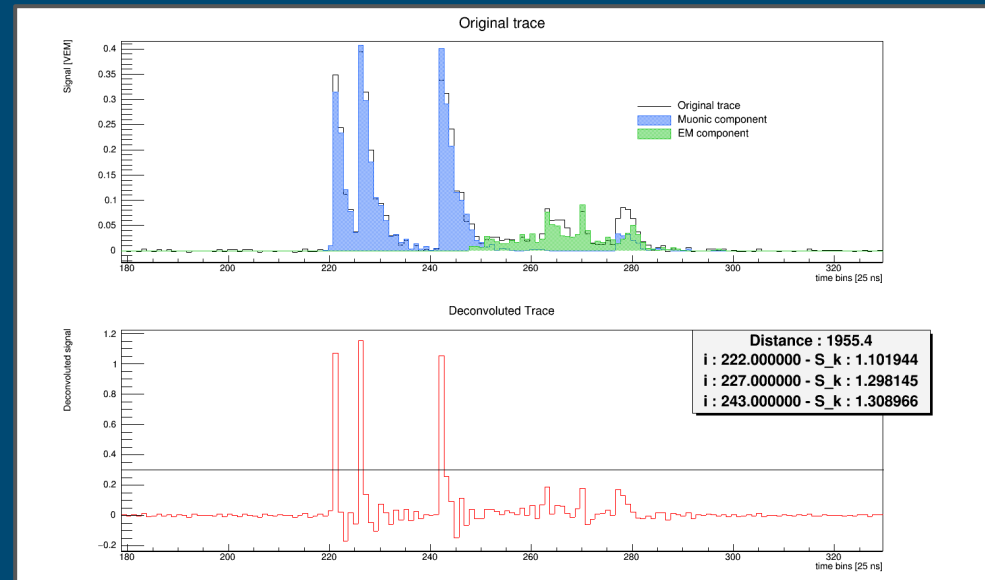


Core of the Muonicity Method : perform a linear deconvolution to remove the exponential decay-tail of a muon signal while integrating the total muon-signal.

Deconvolution Filter :

$$c'_k = \frac{c_k - \alpha \cdot c_{k-1}}{1 - \alpha}$$

with : $\alpha = \exp(-\Delta t / \tau)$



For each station j deconvolute the VEM trace, identify the peaks :

- Calculate S_k for each peak
- Sum S_k for each station : $\mathbf{S}_{\text{peaks}}$

$$S_{\text{peaks},j} = \sum_{k=0; S_k > 0.7 \text{ VEM}}^{N_{\text{peaks}}} S_k$$

Value calculated on trace, for
proton and photon showers :

S_{peaks}^{calc}

Training with proton simulations

Machine Learning Model :

- Parameters : Distance, Zenith, SD_Energy
- Predict S_{peaks}^{pred} values from parameters

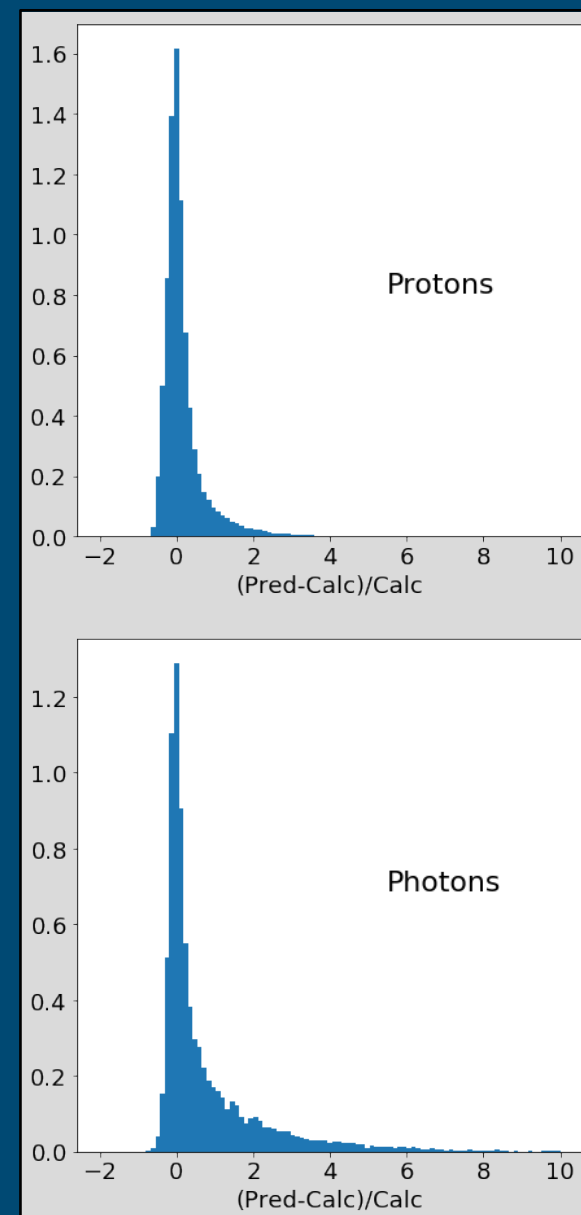
Predict a value from parameters

Value predicted by proton-trained
Machine Learning model :

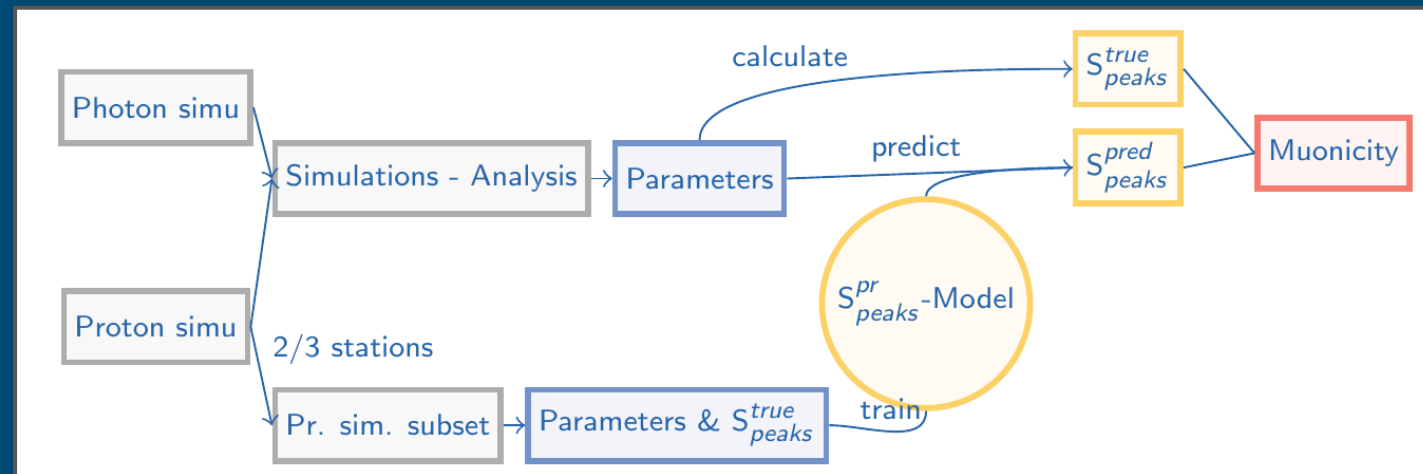
S_{peaks}^{pred}

→ the model is supposed to better reconstruct proton- S_{peaks}^{pred} (closer to S_{peaks}^{calc})

$$\mathcal{M} = \frac{1}{N} \sum_{j=0}^N \frac{S_{peaks,j}^{calc}}{S_{peaks,j}^{pred}}$$



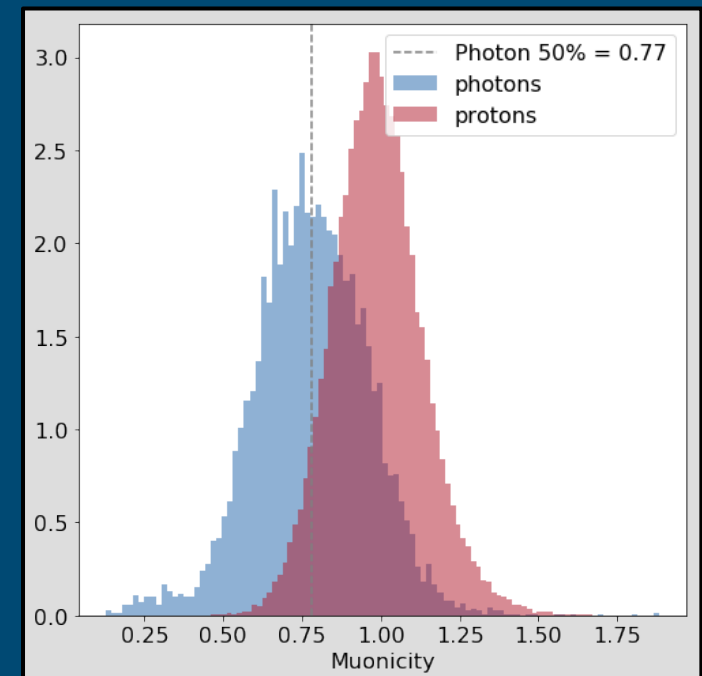
Simplified pipeline of the Muonicity Method →



On its own and without further parameter tuning, the Muonicity variable has some separation power

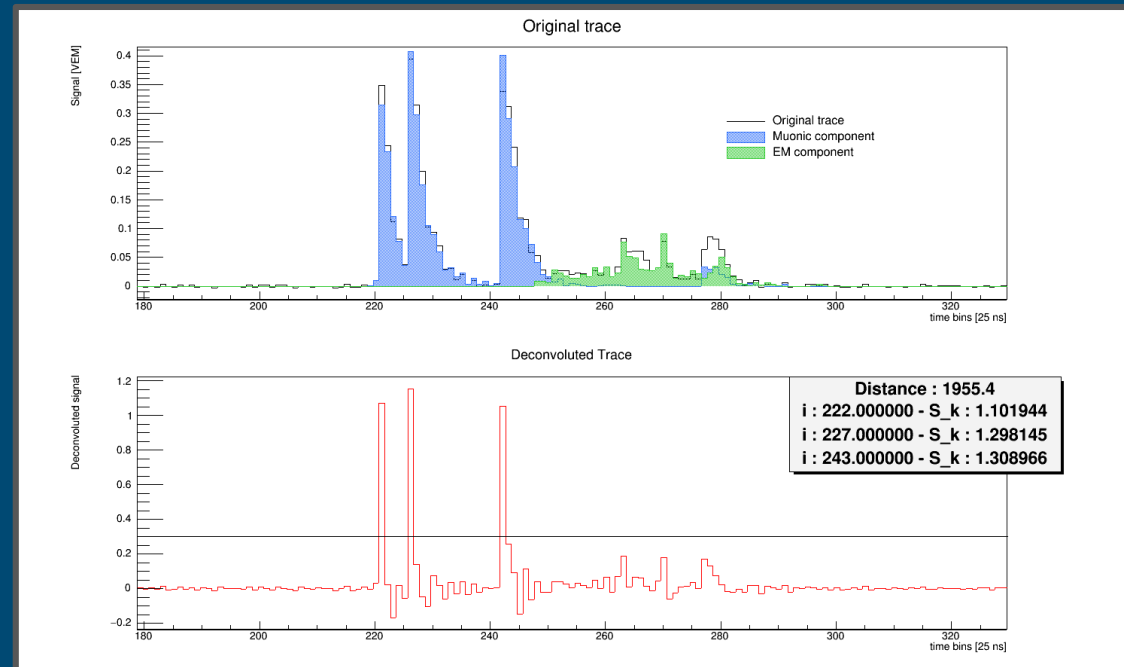
Merit Factor $\eta=0.91$

→ Can we extract more discrimination from the muonic component of the SD traces?

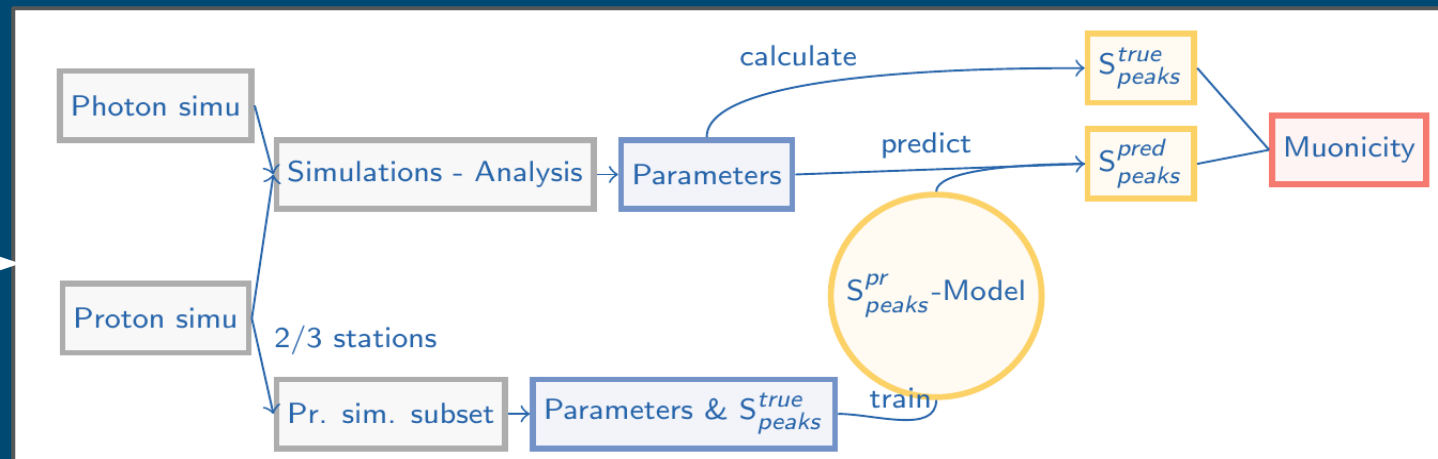


Muonicity :

- deconvolute muon peaks
 - sum peaks signal
- S_{peaks}



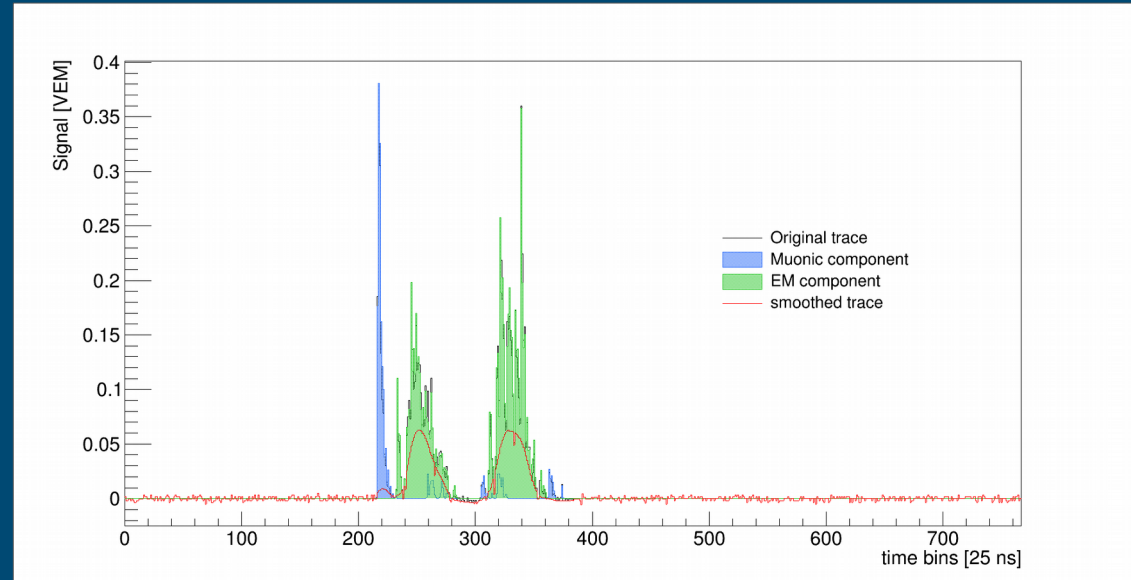
Simplified pipeline of the Muonicity Method →



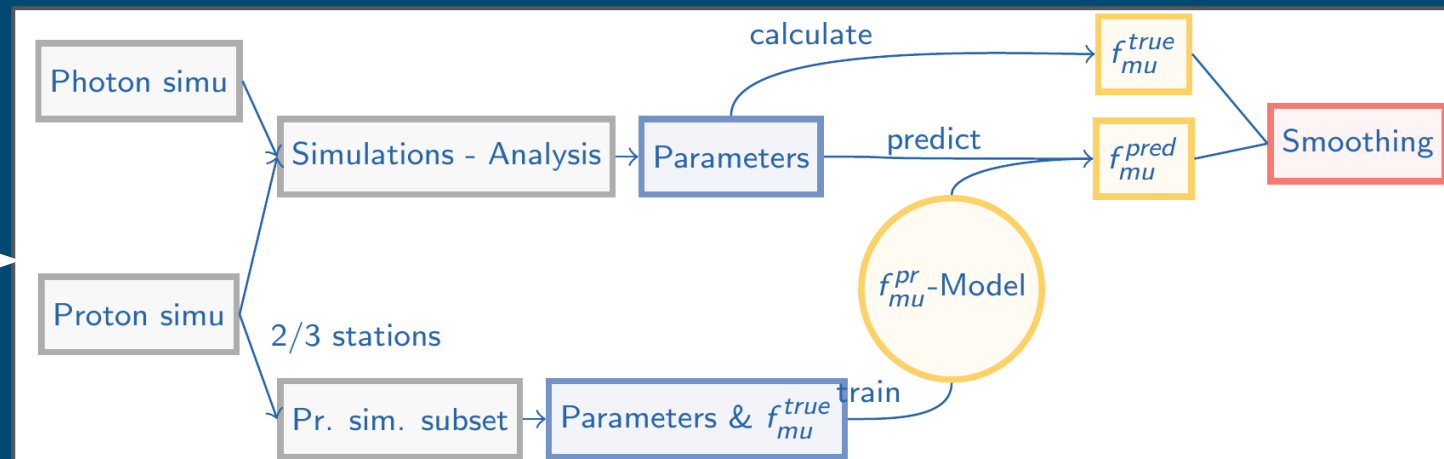
Smoothing :

- smoothen out the muon peaks
- estimate the EM signal

$$\rightarrow f_{\mu}$$



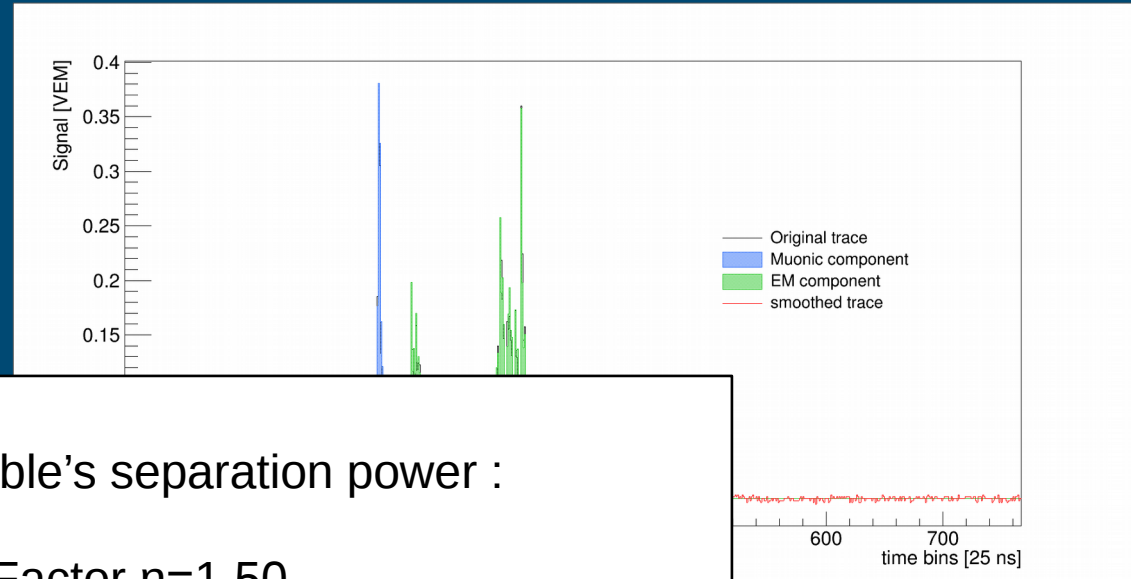
Simplified pipeline of the Smoothing Method



Smoothing :

- smoothen out the muon peaks
- estimate the EM signal

→ f

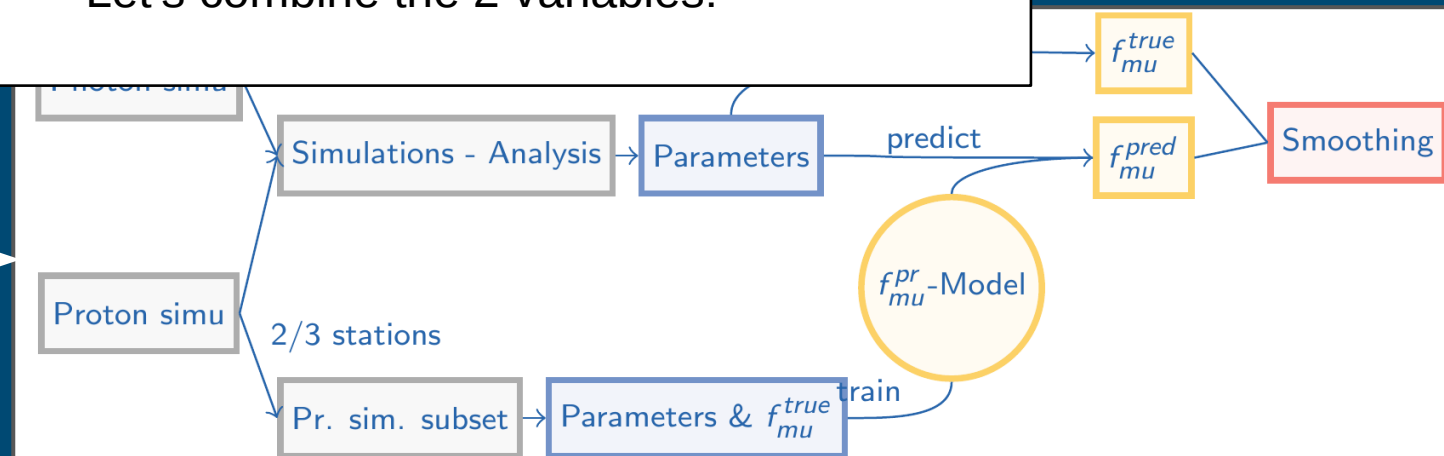


Smoothing variable's separation power :

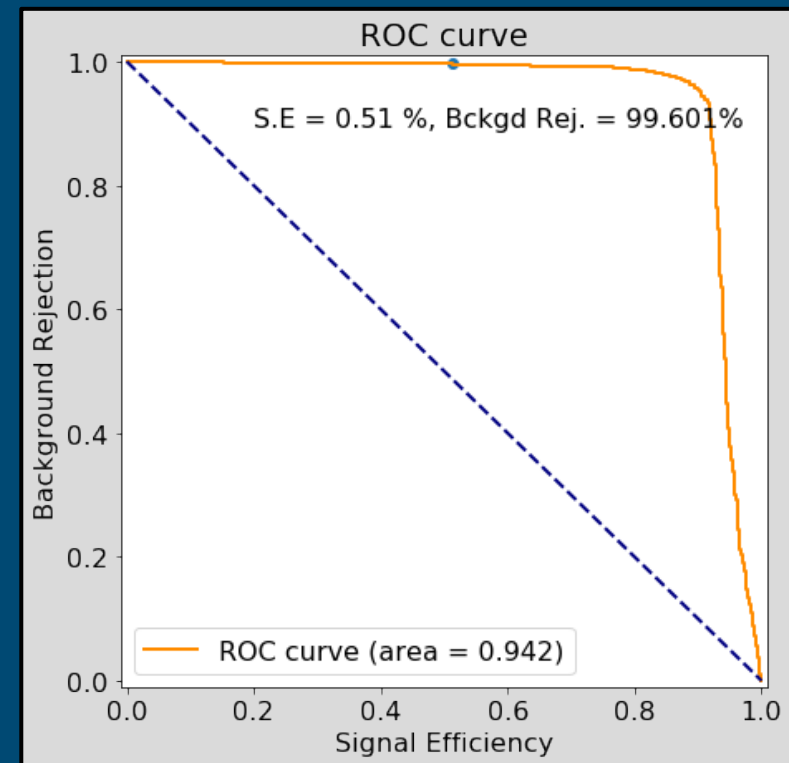
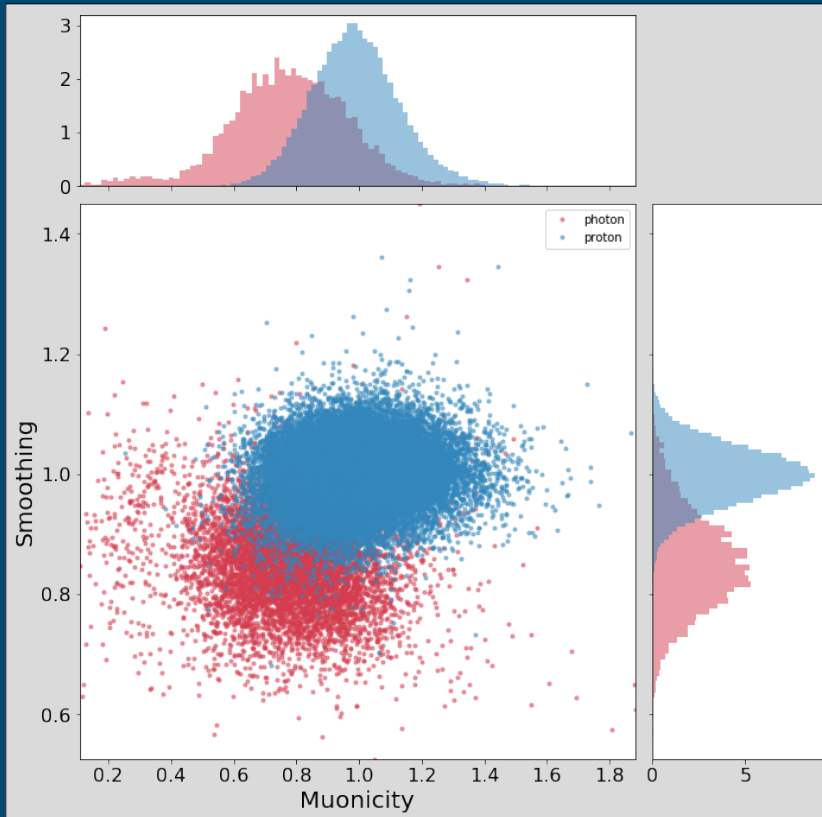
Merit Factor $\eta=1.50$

→ Let's combine the 2 variables!

Simplified pipeline of the Smoothing Method



- As expected the 2 variables are correlated
- But the separation power is still better by combining the two



- Using a Support Vector Machine classifier with RBF kernels
- At 50% signal efficiency, 99.6% background rejection

- SSDs assembly :
 - Wrote a procedure to standardize the SSDs construction process
 - Helped design and install the SSDs test setup
 - Performed the SSDs validations
- Photon-search :
 - Implemented discrimination observables calculation inside the Auger framework
 - Designed :
 - a flexible method for photon/proton discrimination
 - a pipeline for MVA based on machine learning
- Shifts, Formations & Outreach :
 - Participated to FD shifts and beta-tested the SD shifts
 - Outreach to scholars
 - Label REI
 - SOS school, ISAPP school

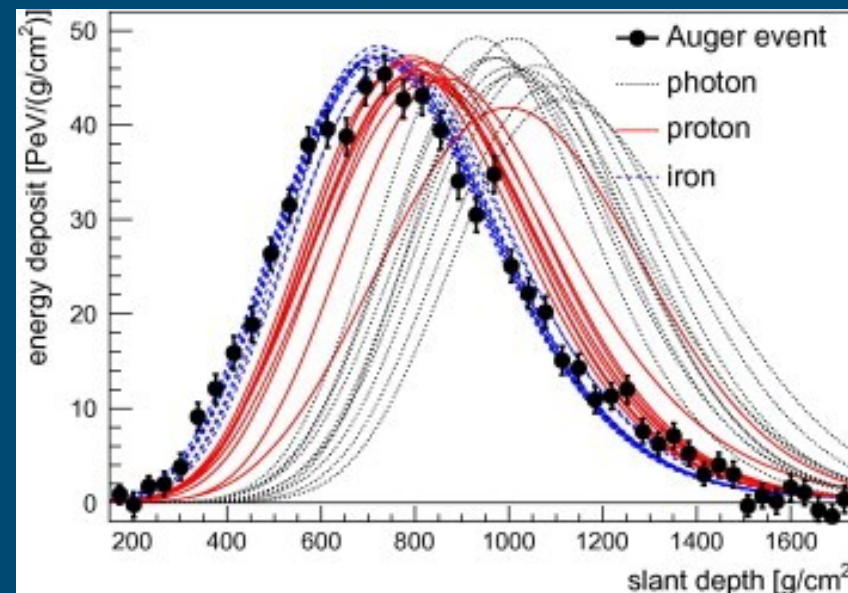
- SSDs tests :
 - Re-run the analysis on the whole dataset once the production is finished
- Muonicity & Smoothing methods :
 - Optimize the observables
 - Re-run the pipeline with tuned parameters, updated simulations and heavier primaries.
 - Try changing the ML input parameters
 - Add other observables?
- Apply the method to data
- Detect UHE photons or improve the limits on the flux

Thank you !



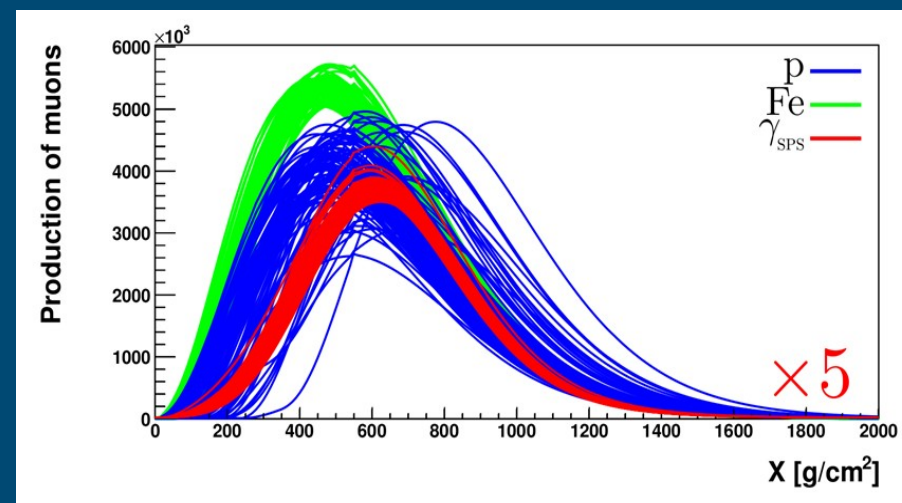
Differences in the “shape” of the showers :

- First interaction further down for light CRs
- Spread of the $z(N_{\max})$ tighter for heavier CRs



Differences in the composition of the showers :

- Heavier primary \rightarrow faster energy loss in the atmosphere
- Muon ratio $\propto A_{\text{primary}}$



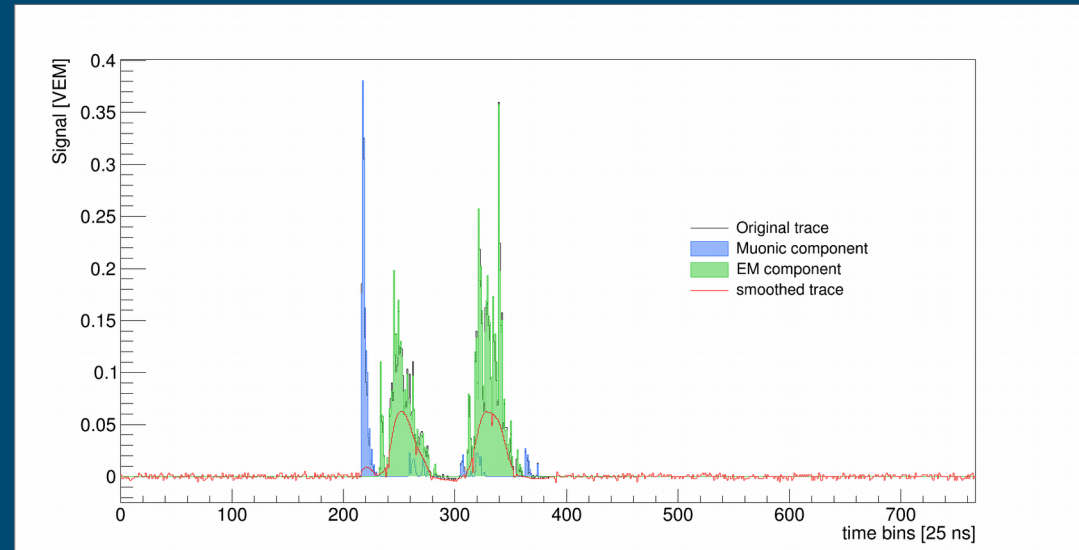
Core of the Smoothing Method : extract the muonic component of the trace by performing a sliding-window averaging to remove spikes

- $S^{sm}(t_i) = \sum_k \frac{S(t_k)}{2 \cdot N_{bin} + 1}$
with $k \in [i - N_{bin}, i + N_{bin}]$
- the muonic content is then :
 $S^\mu(t_i) = [S(t_i) - S^{sm}(t_i)]$
- This muonic content is subtracted from the trace and the process is repeated a number of times

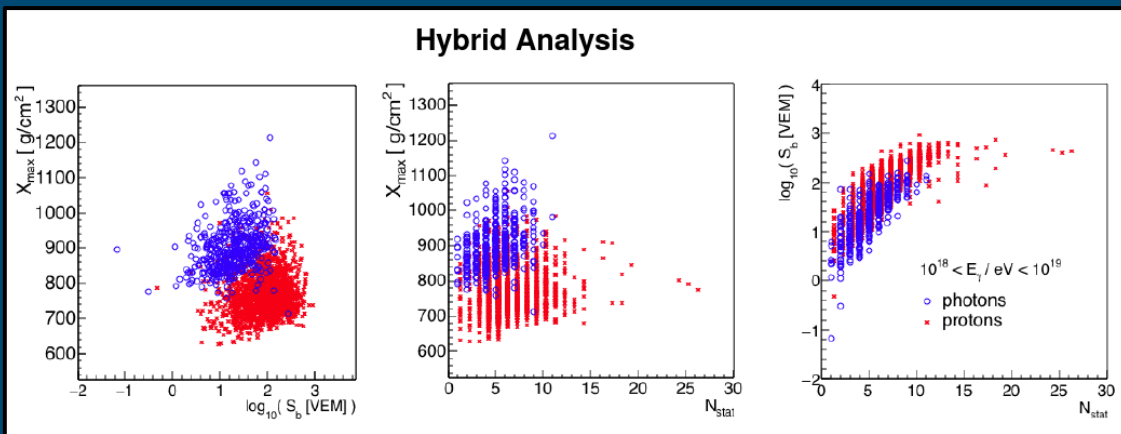
The smoothened trace is then compared to the original trace to obtain a st-level variable : f_{mu}

- $S_{tot}^\mu = \sum_i S(t_i) - S^{sm}(t_i)$
- $S_{tot}^{EM} = S_{tot} - S_{tot}^\mu$
- $f_{mu} = \frac{S_{tot}^\mu}{S_{tot}}$

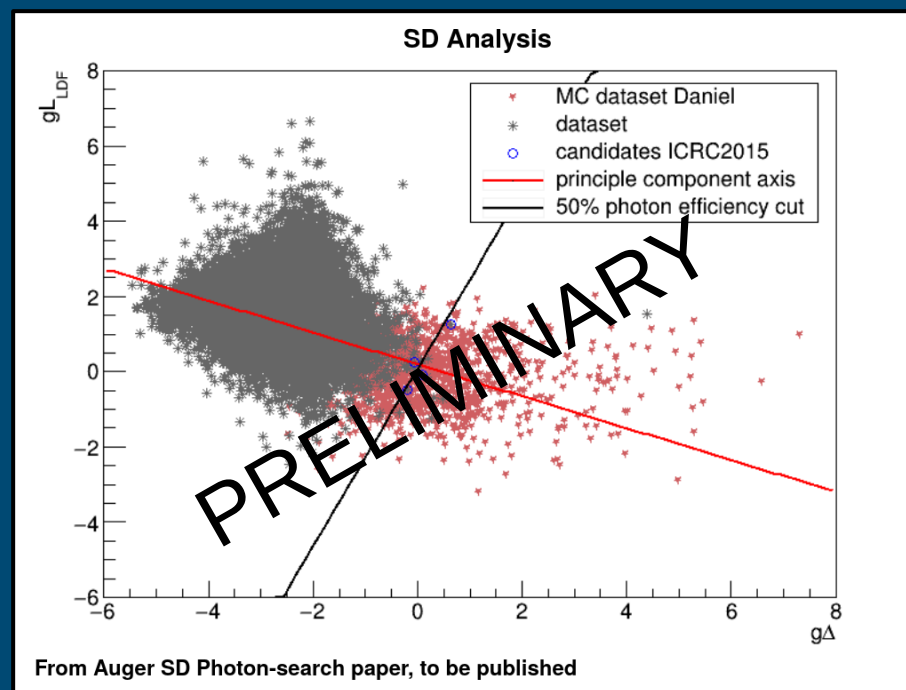
f_{mu} here, has the same role as S_{peaks} in the Muonicity Method



- Hybrid (SD+FD) analysis : more observables
- SD only analysis : *more data*



From Auger Hybrid Photon-search paper, JCAP 1704 (2017) no.04, 009



From Auger SD Photon-search paper, to be published

Aim of my analysis :

Use features inside the WCD signal to estimate the muonic content of the showers and thus differentiate between photon/proton primaries

SD only analysis = 100% duty cycle

Trace = WCD signal

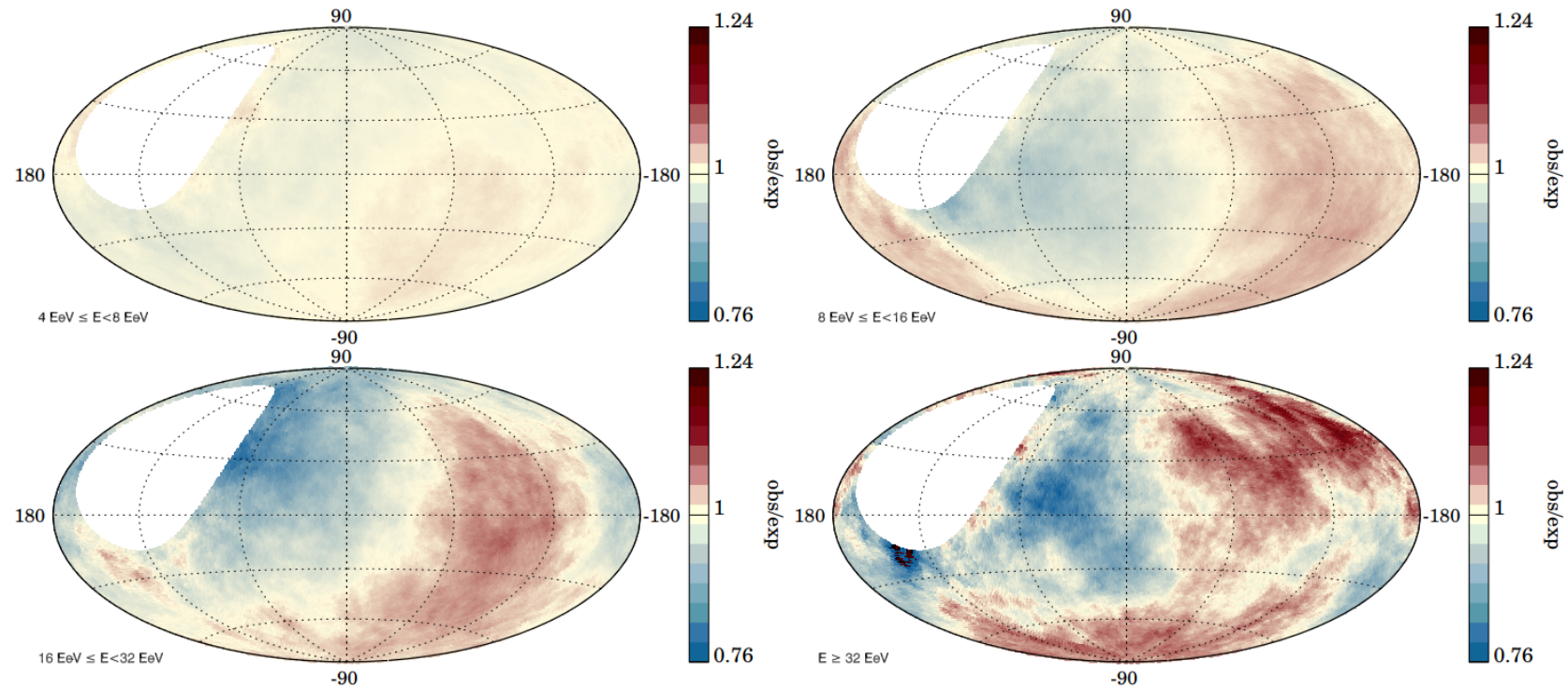
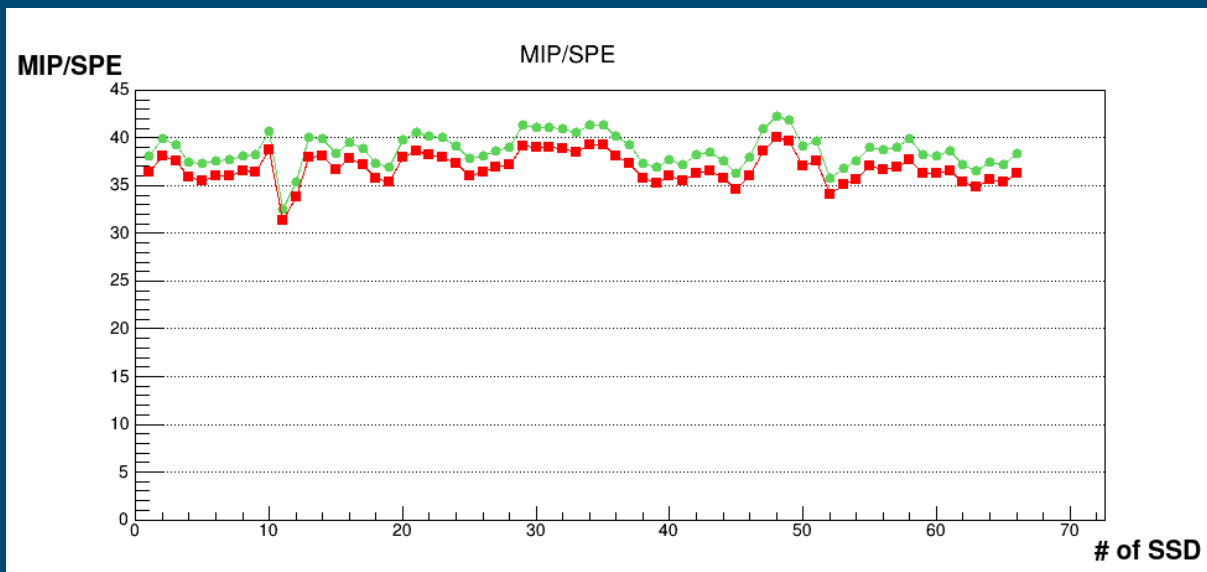
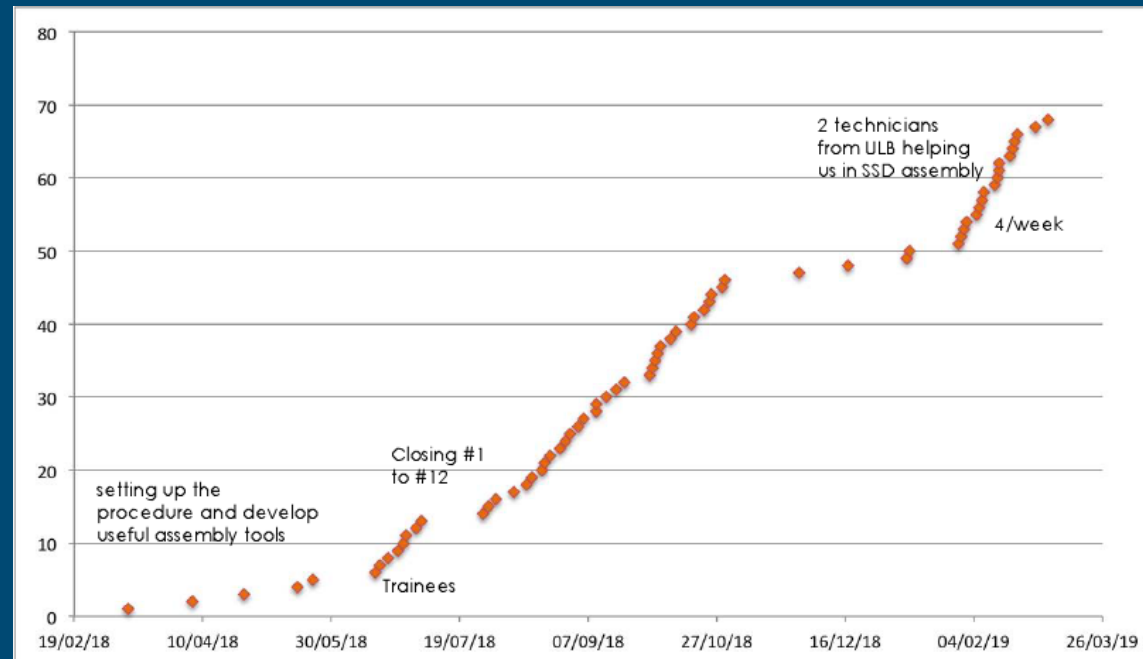
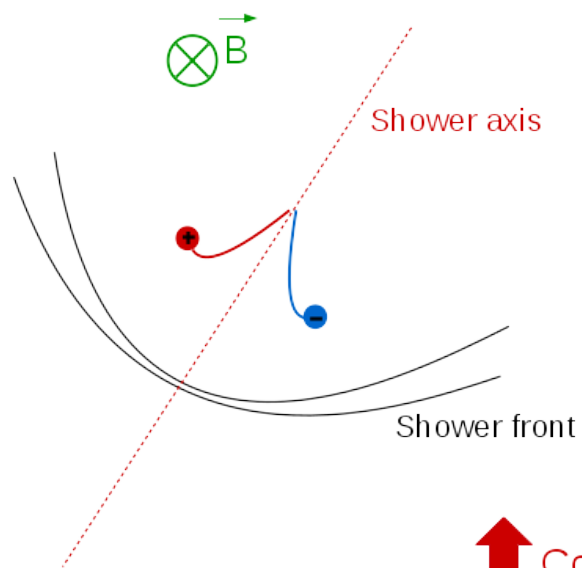


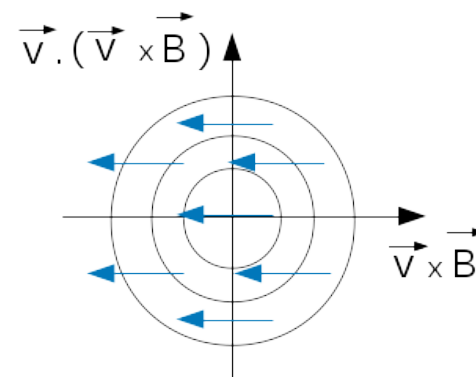
Figure 4. Maps in Galactic coordinates of the ratio between the number of observed events in windows of 45° over those expected for an isotropic distribution of arrival directions, for the four energy bins above 4 EeV.



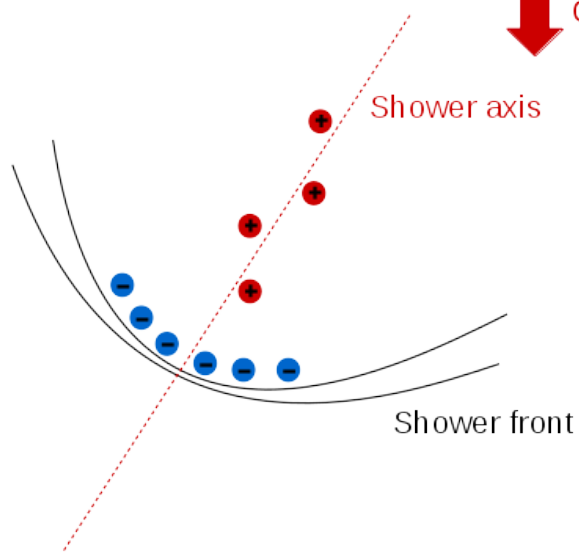


Primary effect :

Geomagnetic field induces a dipole in the shower front's charged particles.

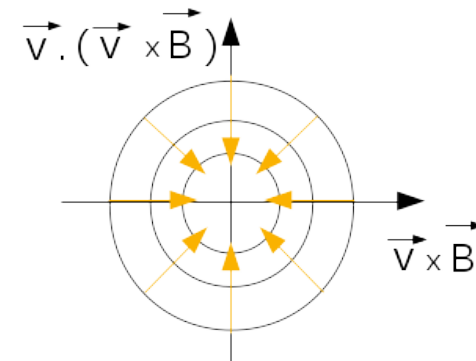


Combination
of both effects



Secondary effect :

Charge-excess in the shower front (more e^- than e^+).

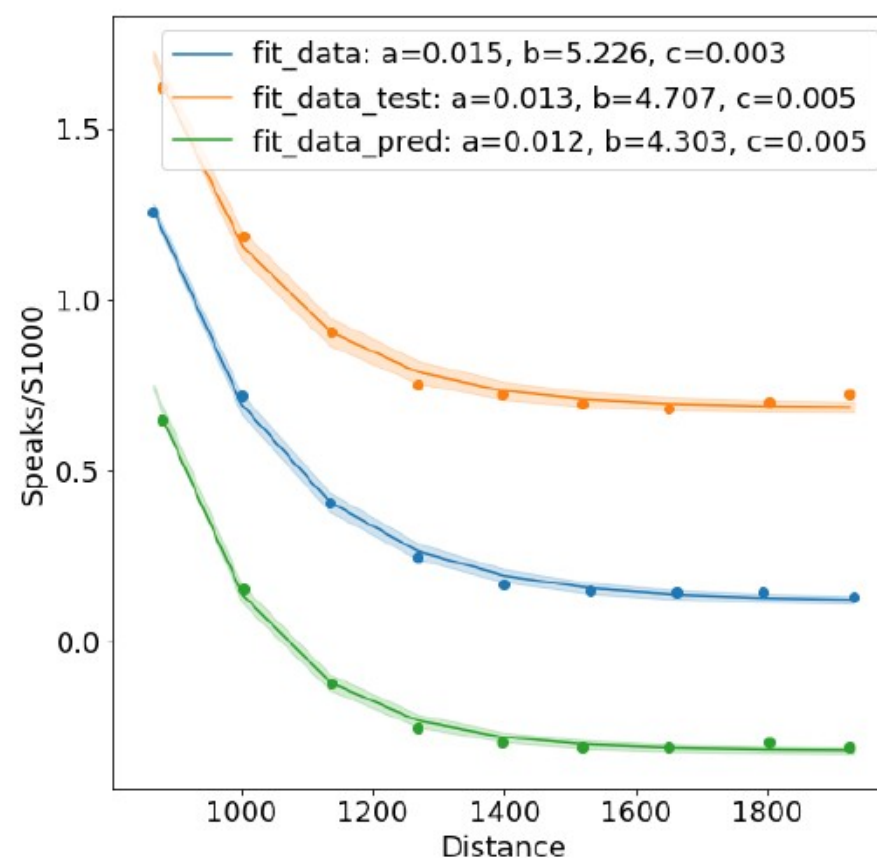
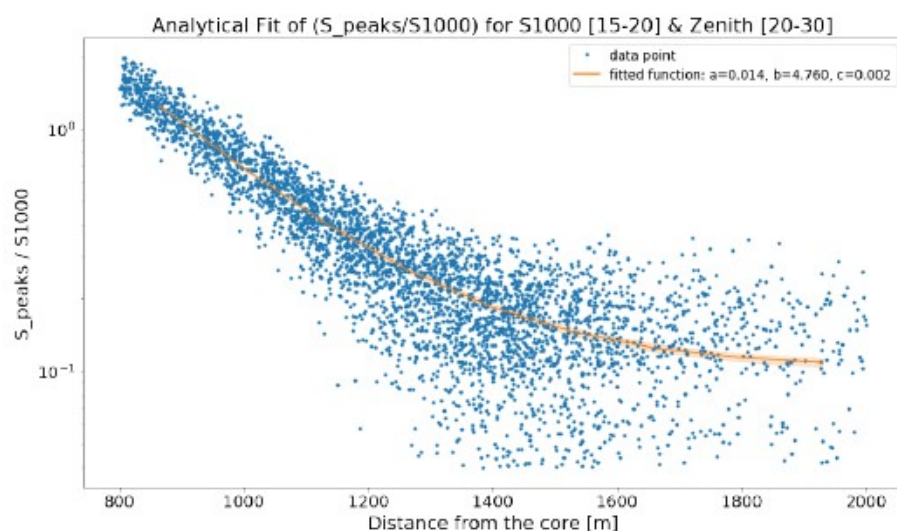


Reproduce analytical function with model

The analytical function fitted to predicted S_{peaks} is the same as the one fitted on data

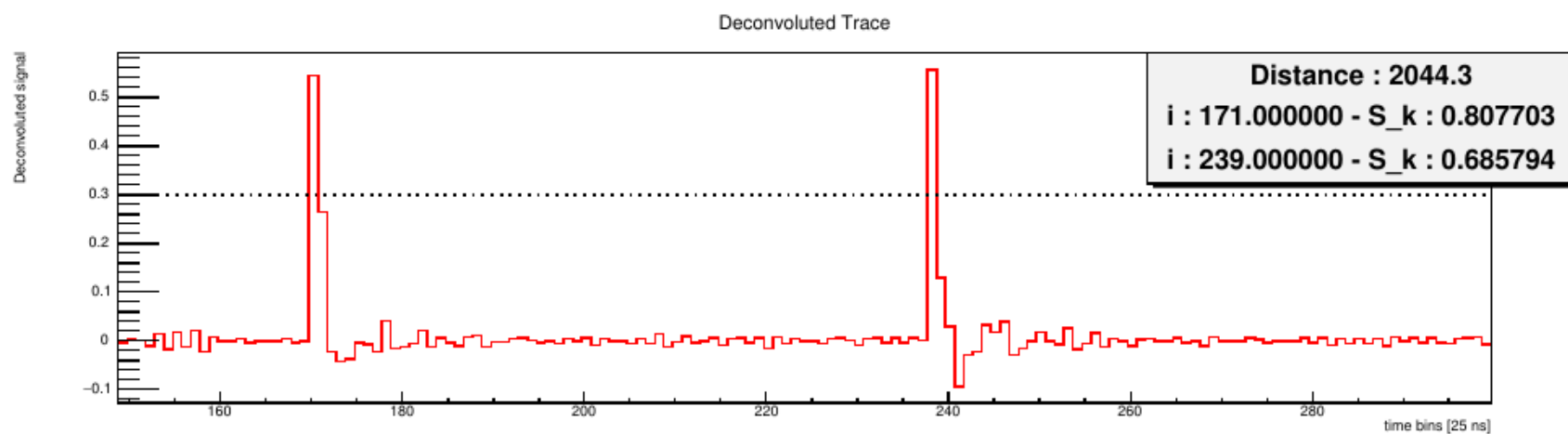
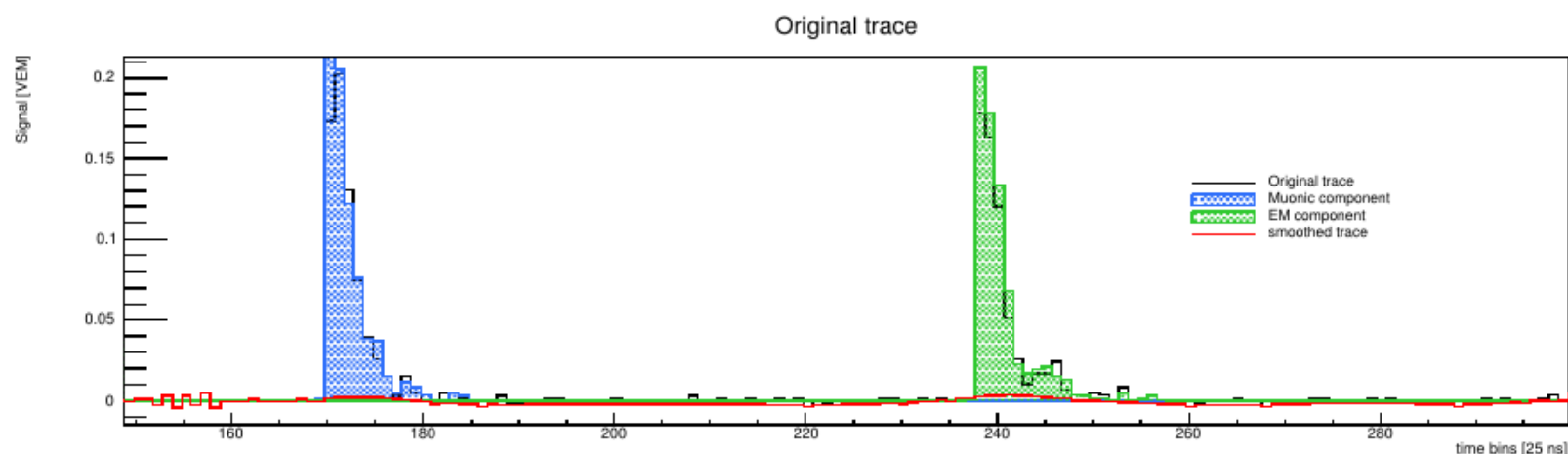
- Fitted function :
 $S_0 + A.e^{-(Dist-1000)/B}$
 where : $(A/B/S_0) = (a/b/c).(\theta, S1000)$
- Here *fit data pred* & *fit data test* are shifted for clarity

('Zenith : ', array([25.])) ('S1000 : ', array([12.5]))



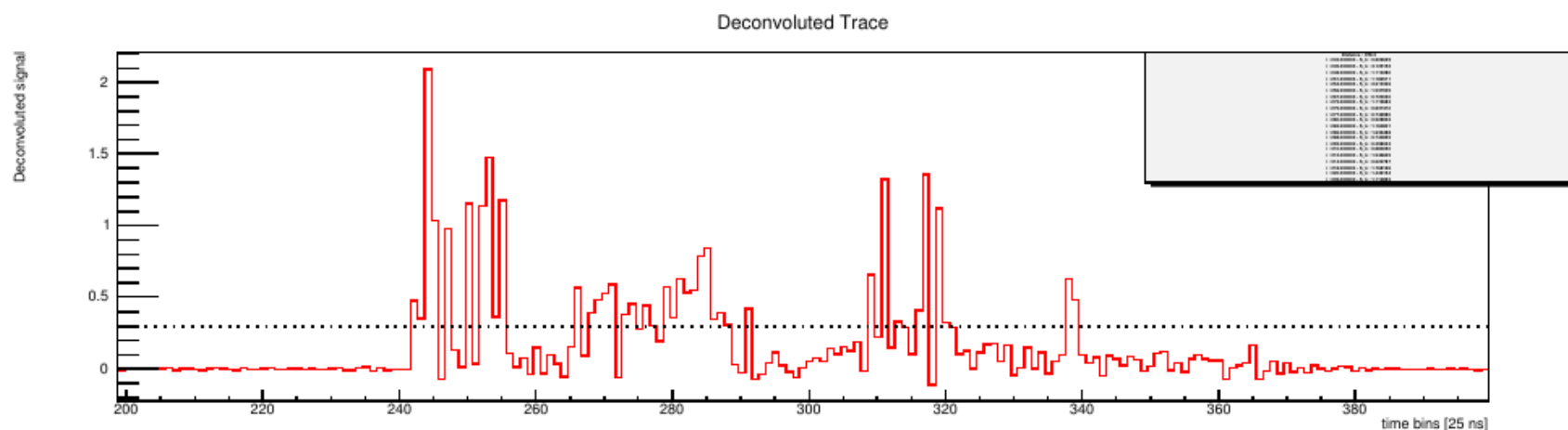
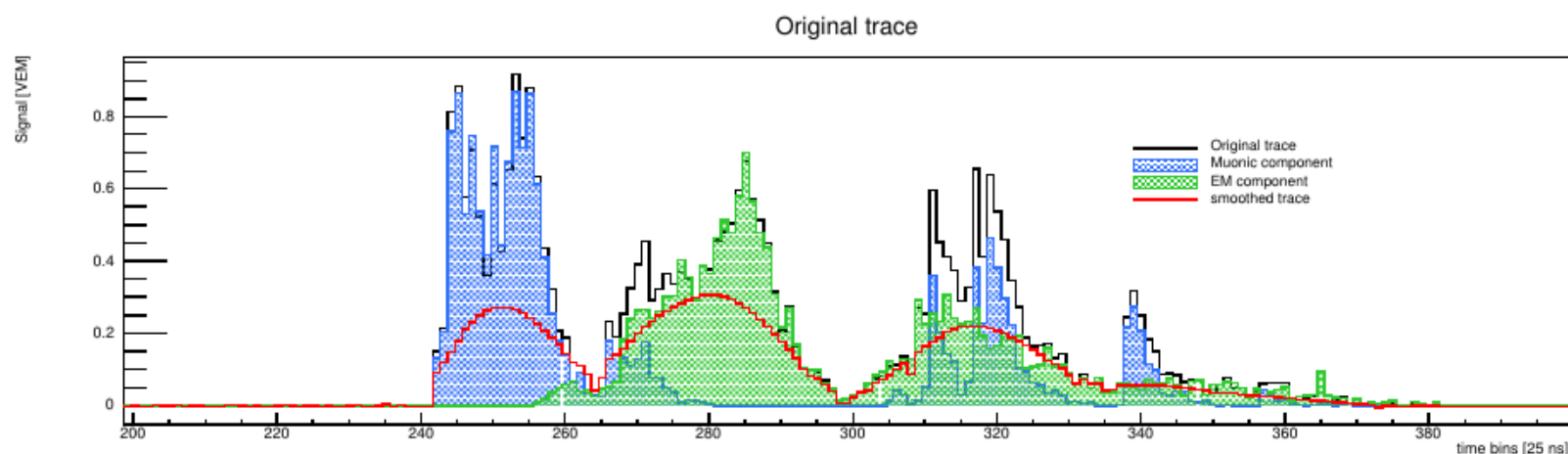
Not so convincing traces

Muon-like γ



Not so convincing traces

Overlapping peaks



RandomForestRegressor

A Random Forest Regressor trains several Decision Tree Regressor on data and parameter subsets. Then it combines those estimators to obtain a better one.

A Decision Tree recursively split the dataset to group identically labeled data.

- training vectors : $\vec{x}_i \in R^n$
with $i = 1, \dots, l$
- target value vector : $\vec{y} \in R^l$
- $y_m = \frac{1}{N_m} \sum_{i \in N_m} y_i$
- Mean Squared Error : $H(X_m) = \frac{1}{N_m} \sum_{i \in N_m} (y_i - y_m)^2$

At each node m , $H(X_m)$ is minimized to split dataset.

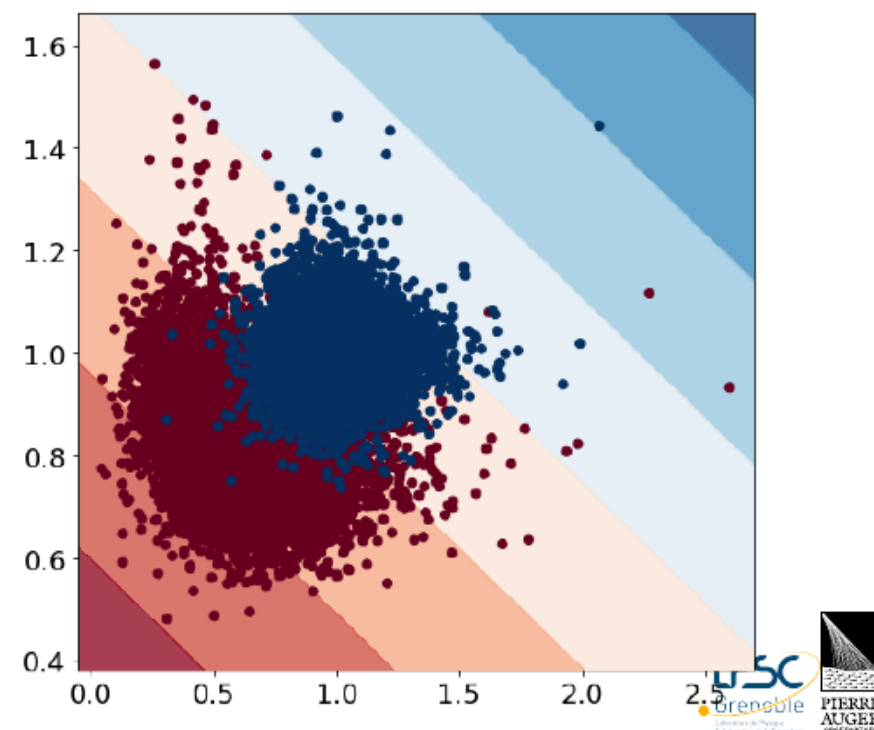
Support Vector Classification - Hyperplane

A **S**upport **V**ector **M**achine will construct a hyper-plane with the highest distance between two points of different classes.

$$\left[\frac{1}{n} \sum_{i=1}^n \max(0, 1 - y_i(\vec{w} \cdot \vec{x}_i - b)) \right] + \lambda \| \vec{w} \|^2$$

The aim is to minimize the above function given that :

- (\vec{x}_i, y_i) is a training dataset of n point.
 \vec{x}_i : parameters, y_i : (1 or -1) label
- hyperplane : $\vec{w} \cdot \vec{x} - b = 0$.
 if $y_i(\vec{w} \cdot \vec{x}_i - b) \geq 1$, then every data point is correctly predicted
- λ : tradeoff between margin-size and precision



Support Vector Classification - Kernels

For non-linearly separated data, it might be useful to project it in higher dimensions → **kernel functions**

Previous frame : linear kernel → no projections

Here : Radial Basis Function (RBF)

Mathematically, a kernel **K** applied to 2 data points can be written as :

$$\mathbf{K}(\vec{x}_i, \vec{x}_j) = \vec{x}_i \cdot \vec{x}_j : \text{linear kernel}$$

$$\mathbf{K}(\vec{x}_i, \vec{x}_j) = \exp(-\gamma \|\vec{x} - \vec{x}'\|^2) : \text{RBF kernel}$$

