

Background suppression with machine learning in volcano muography



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MODE workshop

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Eötvös Loránd
University



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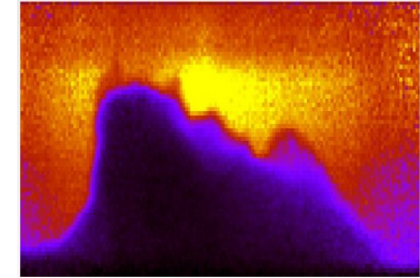
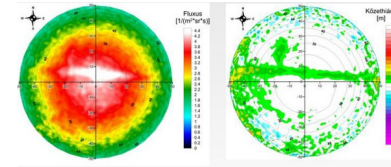
Outline of the talk

- Background for volcano muography
- Geant4 simulation of the Muography Observatory System
- With the G4 simulation:
 - Testing the “classic” χ^2 algorithm currently being used
 - Teaching a deep neural network to suppress background
- Can we use deep learning to enhance signal to noise ratio?
 - Especially important for volcano muography
- Applying the machine learning algorithm to MOS-08 measurements @ Sakurajima

What can cosmic muons be used for?

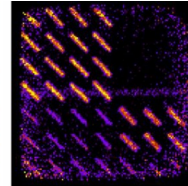
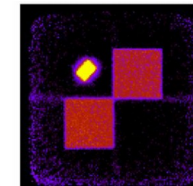
- **Attenuation muography:**

- Cosmic muon flux attenuated by material (density-length)
- Directional measurement : muogram \rightarrow density map of large objects
- Geophysics, archeology, industrial, meteorology



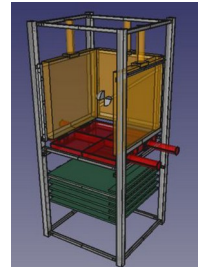
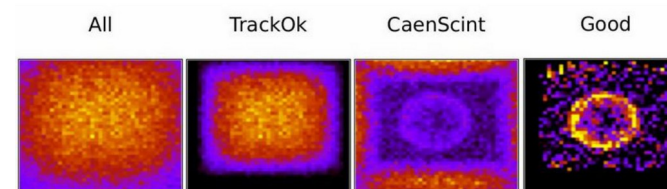
- **Muon scattering tomography**

- Multiple scattering on high-Z material
- Two tracklet matching :
scatter map \rightarrow high-Z materials
- Disclose hidden objects, homeland security



- **Muon induced secondaries**

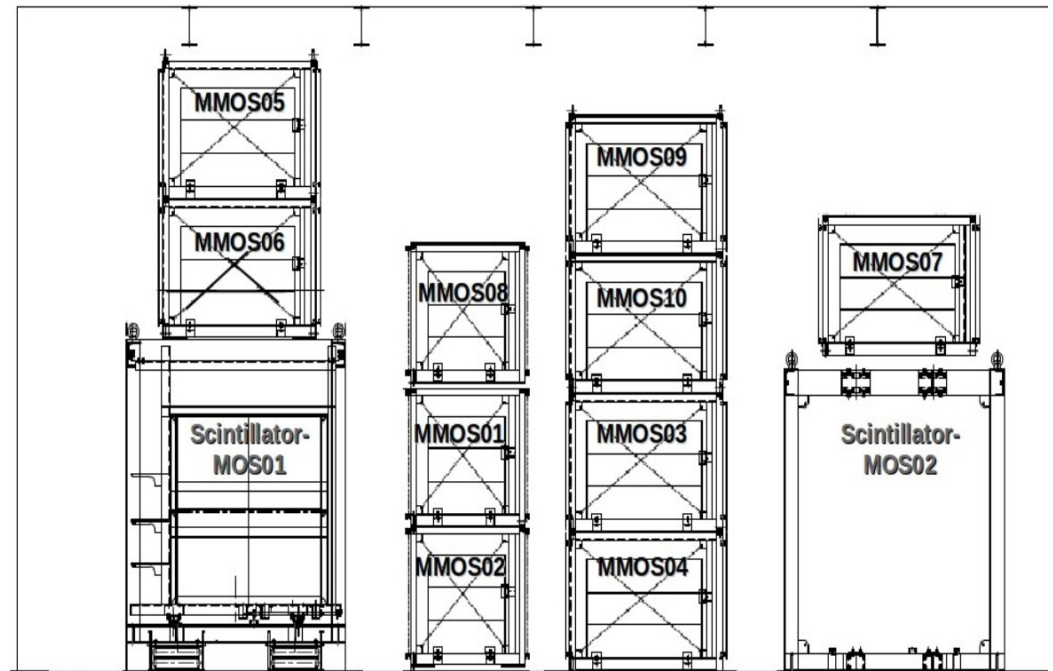
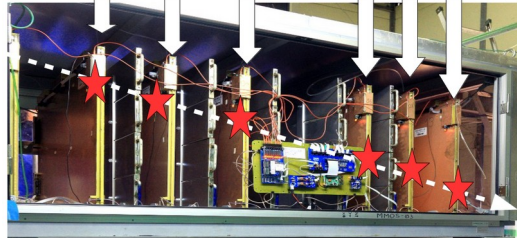
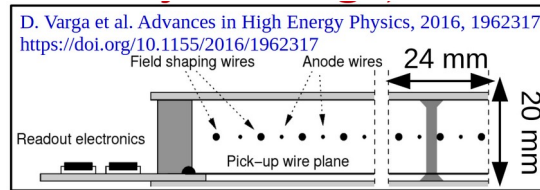
- The type of secondaries that are created, absorbed and exit depends strongly on the material



Our detectors @ Sakurajima volcano

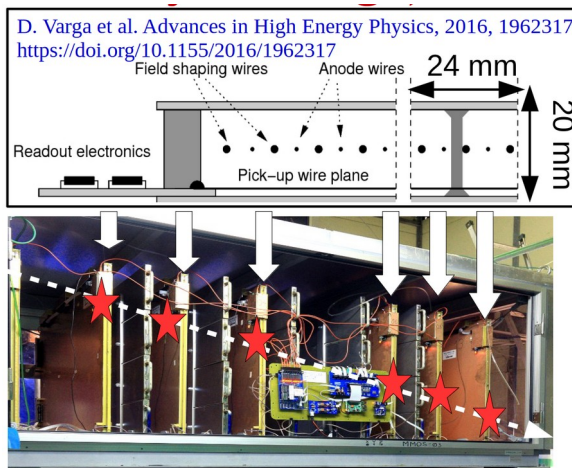
~ 10 m² sensitive area

- Low signal (3 Hz) for a detector
- MWPC detectors
- Cost effective



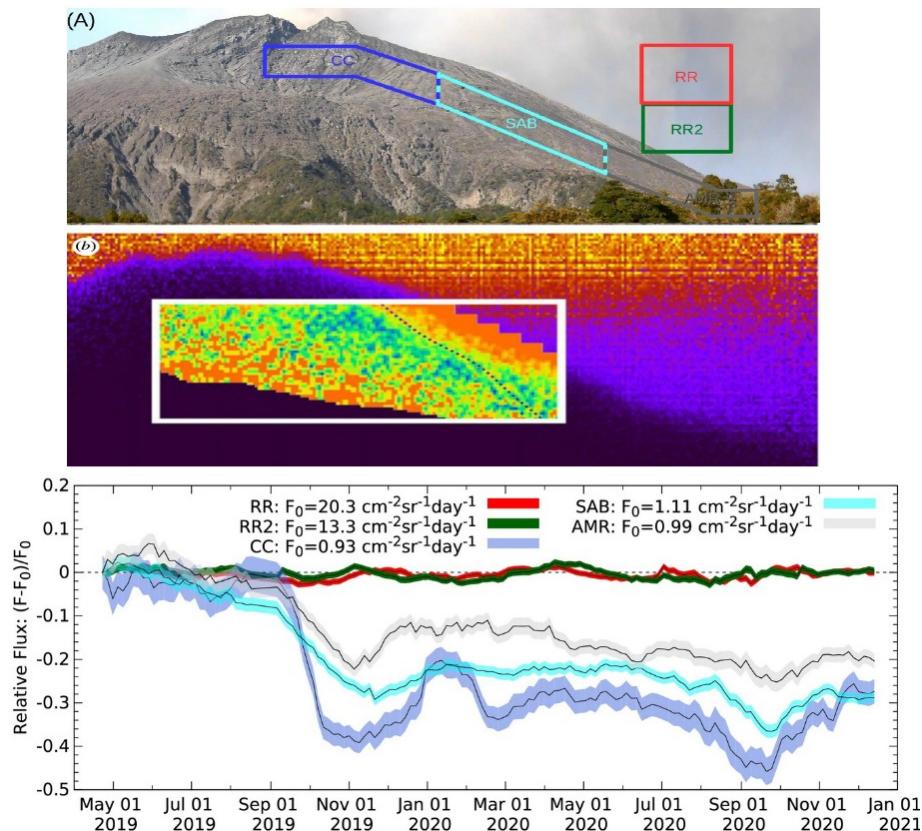
Our detectors @ Sakurajima volcano

- 4 years of data
- Challenge: no spectrometer
- ~10 m resolution @ volcano



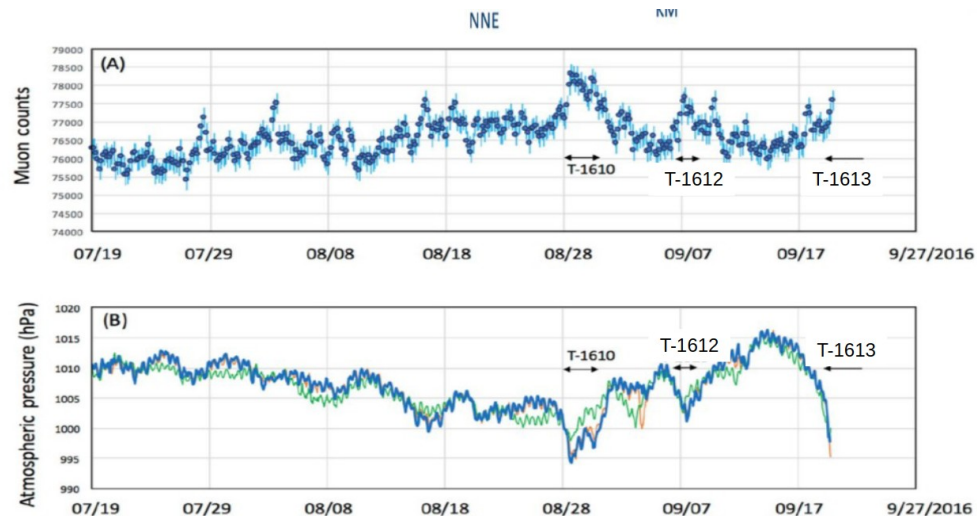
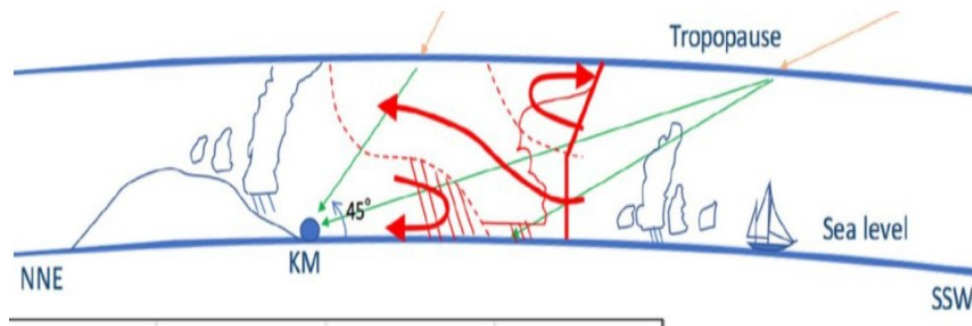
L. Oláh et al. *Scientific Reports*, 8, 3207, 2018,

<https://doi.org/10.1038/s41598-018-21423-9>



Muography of cyclones

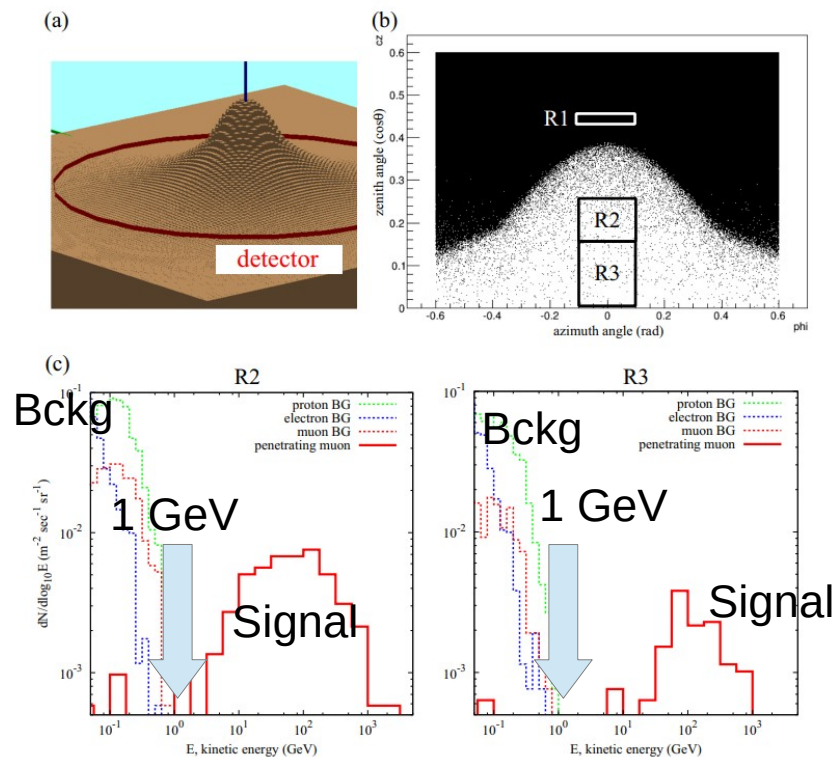
- Increased pressure yields more μ decaying
- Low pressure \rightarrow more μ
- 1 % pressure drop result in 2 % flux increase



Tanaka et al. (2022) Sci. Rep. 12, 16710 <https://doi.org/10.1038/s41598-022-20039-4>

Backgrounds in volcano muography

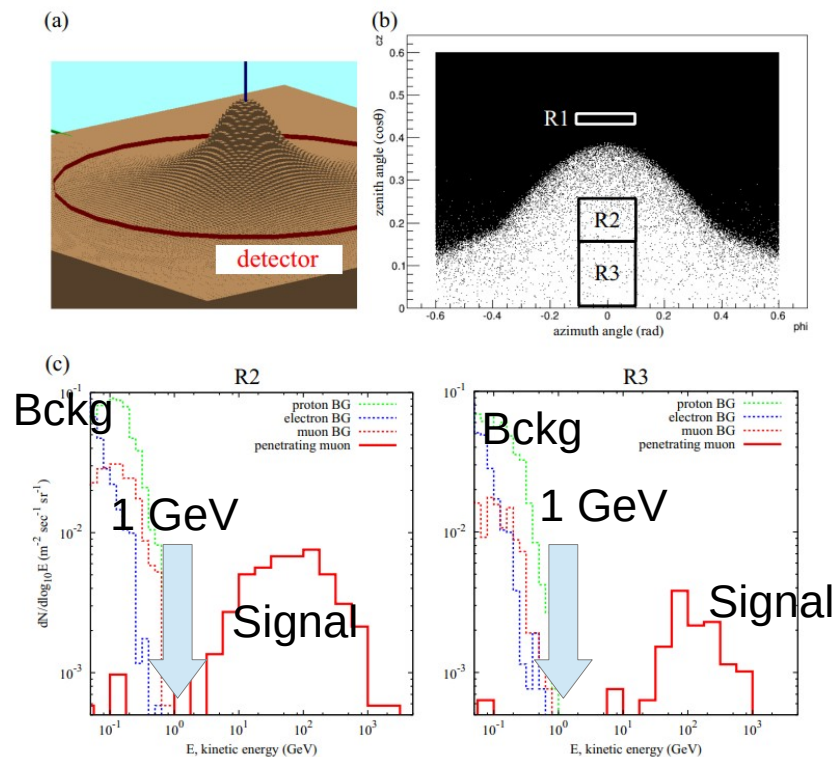
- Background depends on
 - Detector
 - Thickness of volcano
 - Elevation angle
- R. Nishiyama et al. (2016) simulated a realistic background for a volcano
- R2: 300-600 m rock
- R3: 600-900 m rock



R. Nishiyama et al. (2016)

Backgrounds in volcano muography

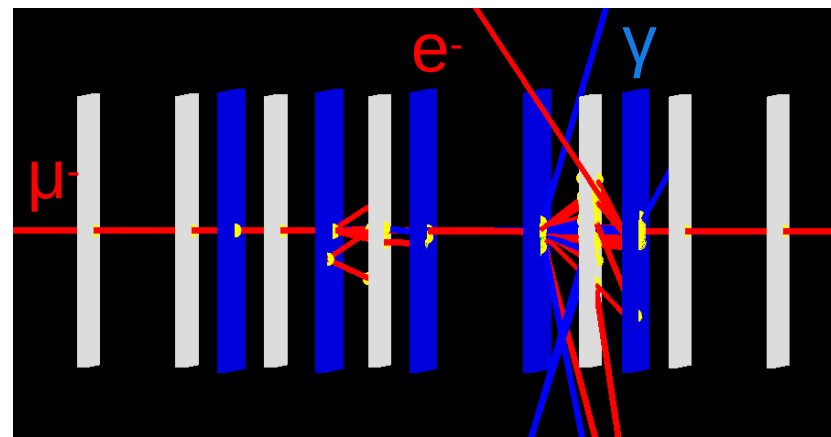
- Background: protons, electrons and **muons** (hadronic origin)
- IF we could use a cut at ~ 1 GeV there would be almost no background!
- In our detectors due to absorbers very suppressed total background:
 - ~~Electrons~~
 - Protons
 - **Scattered muons**



R. Nishiyama et al. (2016)

Geant4 simulation of the MOS-08

- Dedicated simulation developed
- Gas volume voxelized
- Output of simulation is in same format as the measurement pipeline
 - Important for testing the tracking algorithm
- Output analyzed with same tracking algorithm (N-1 point χ^2)
- Some “detector” effects are very hard to simulate → take the distribution from measurements

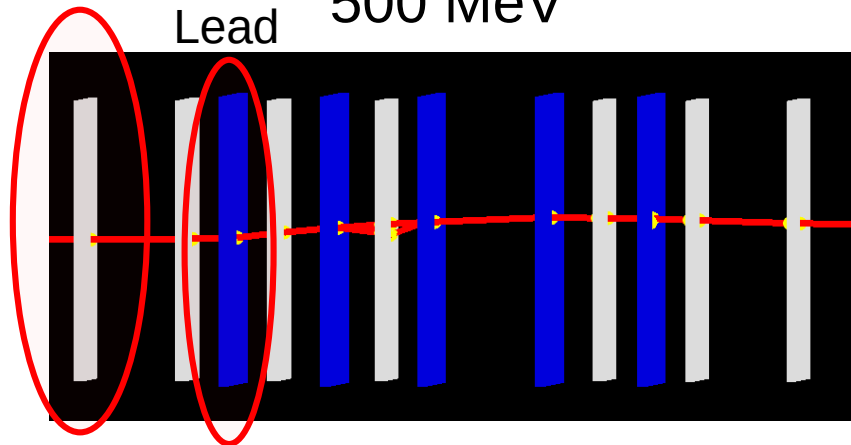


Muon energy dependent features

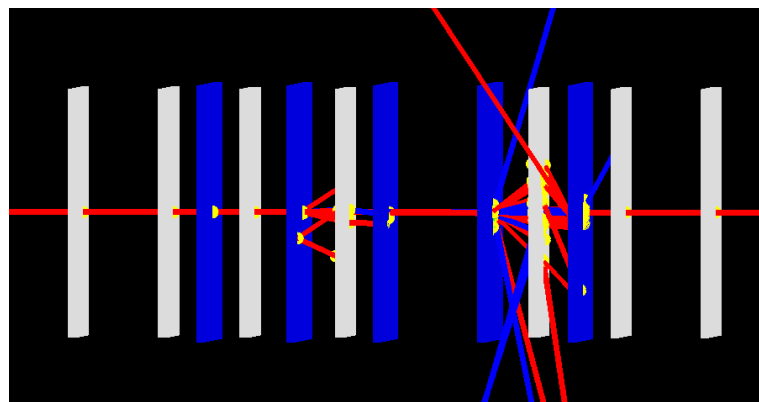
Detector

Lead

500 MeV



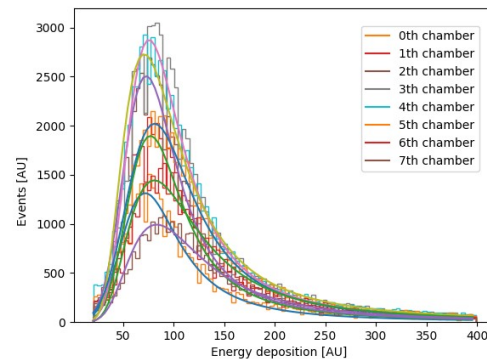
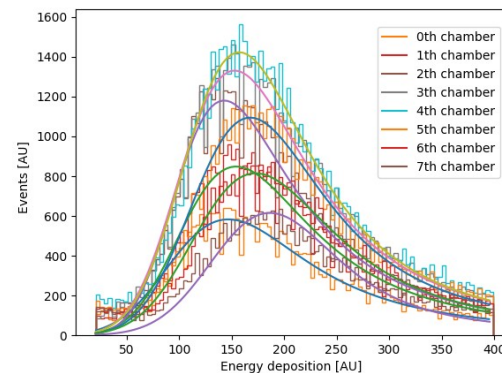
50 GeV



- Scattering (used by χ^2 algorithm)
- Secondary creation:
 - Energy deposition (NOT used by χ^2 algorithm)
 - Lots of clusters (NOT used by χ^2 algorithm as input)

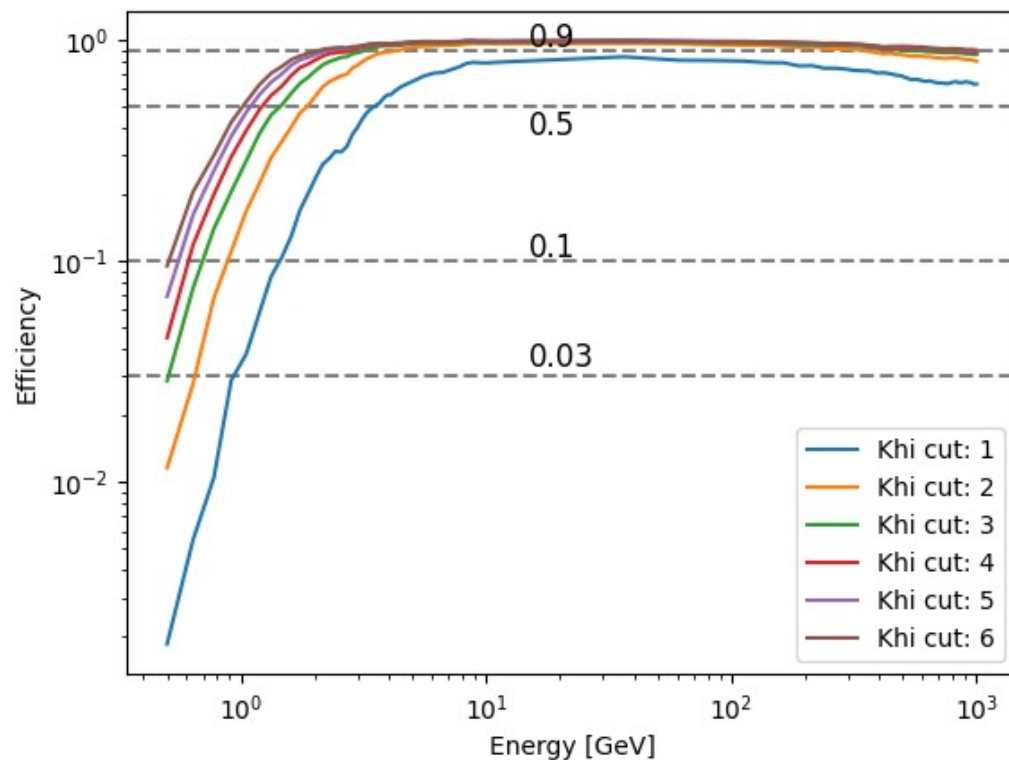
Detector effects

- Need to include these in the simulation to reproduce measurements
- Cluster size
- Gain changes:
 - Changing weather
 - Non homogenous gain (due to wires)
- Important for Machine Learning!



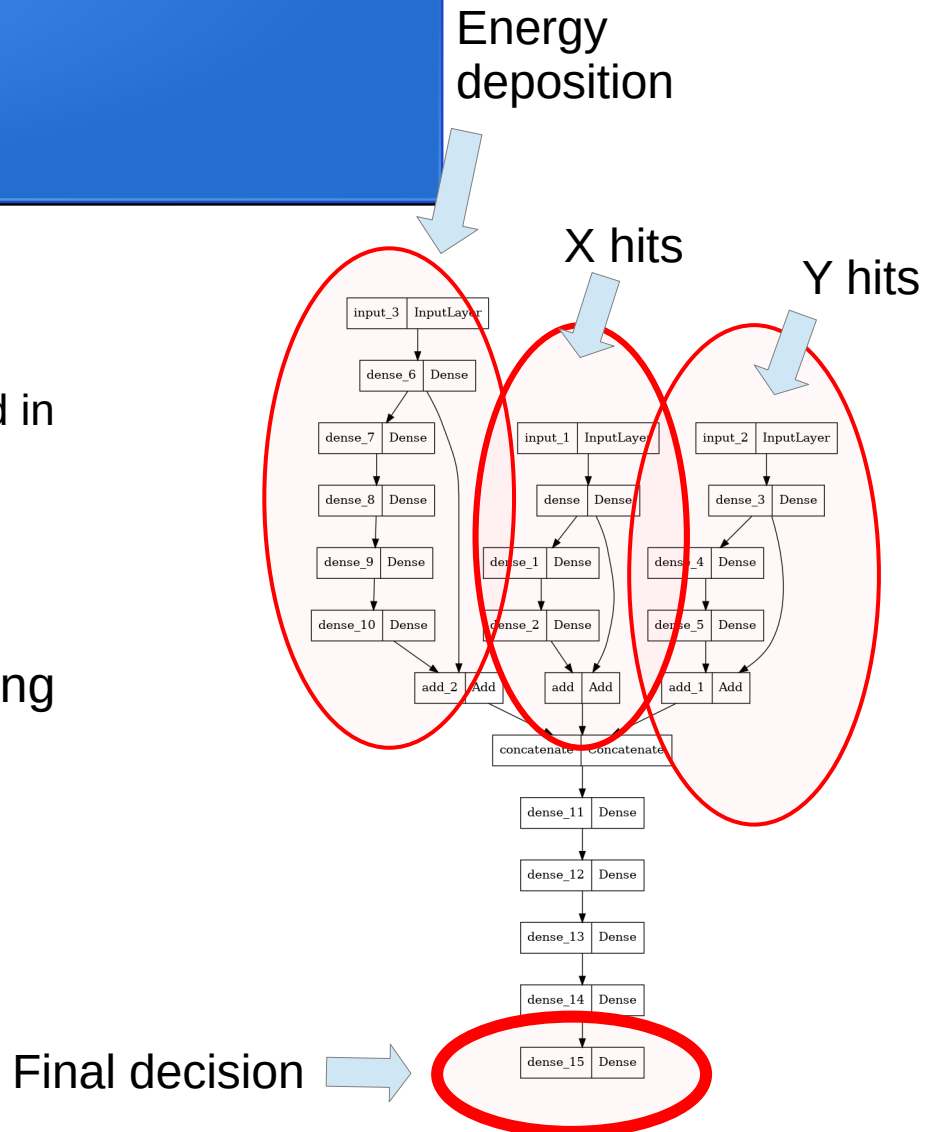
Testing the tracking algorithm

- Simulation data
- Different χ^2 cuts shown
- $\chi^2 < 4$ cut is used in this talk
- Suppresses 0.5 GeV muons with 95% chance
- ~98% efficiency @ 5 GeV
- ~90% efficiency @ 1 TeV



Neural network

- Used together with χ^2 algorithm → Direction
- Binary classification:
 - Was the muon above a certain energy (5 GeV used in this presentation)
- Residual layers for robustness
- Decouple the information sources
- Output: score (1 double) ~ probability of belonging to one class (it's mapping)
- Three subnetworks:
 - X direction (8 x 64 wires, 0 or 1 – hit or not)
 - Y direction (8 x 64 wires, 0 or 1 – hit or not)
 - Energy deposition (8 double)

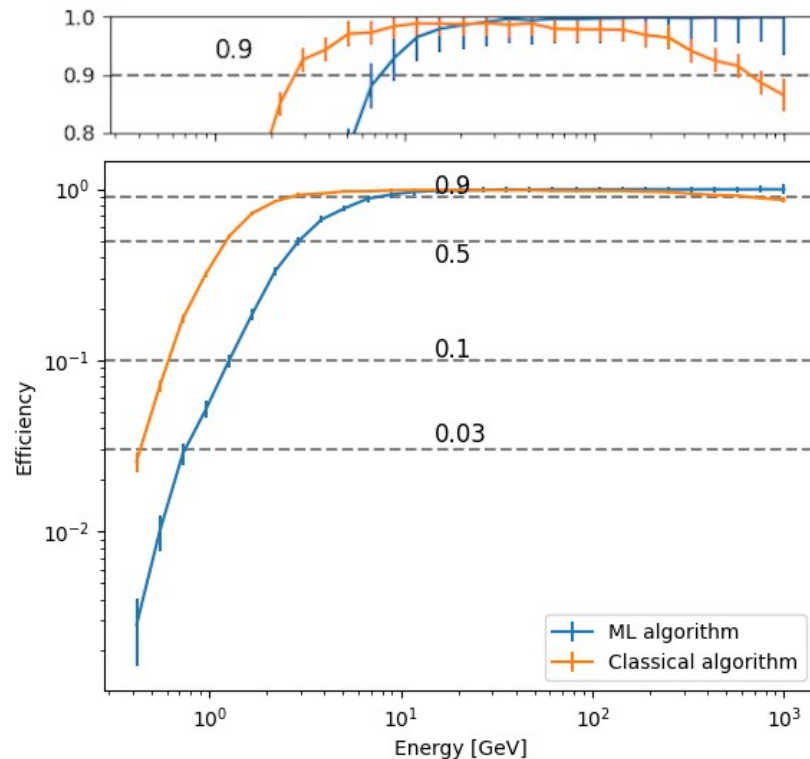


Teaching the ML

- ~ 1 day on a single GPU
- 20 million muons
- 12 GB of events data
- Accuracy: 0.900
- Most used metric for classification $AUC = 0.952$

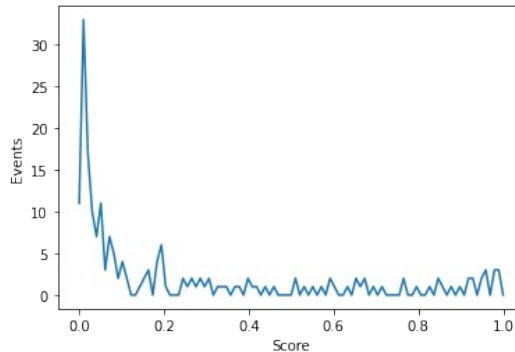
Results of the ML

- Cut at score 0.4
- Cut can be tuned on demand
- Suppresses 1 GeV protons
 - 6x more than $\chi^2 < 4$ algorithm
- ~99.5% efficiency @ 1 TeV

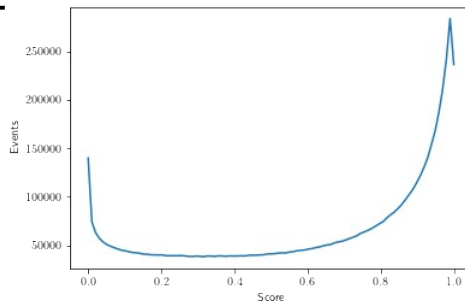


What does the ML predict to measurements?

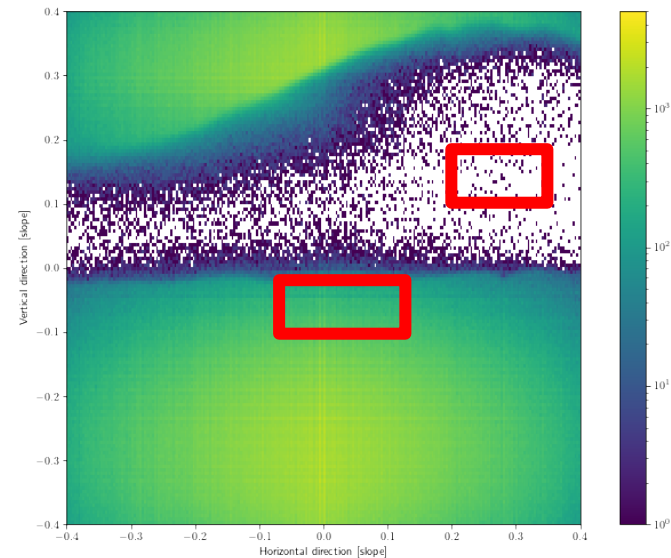
- Measurements taken
 - @Sakurajima
- Score distribution for different regions
- Middle of the mountain
 - 7 km of rock → Only low E
- Open sky ~ horizont
 - High E



Middle of mountain



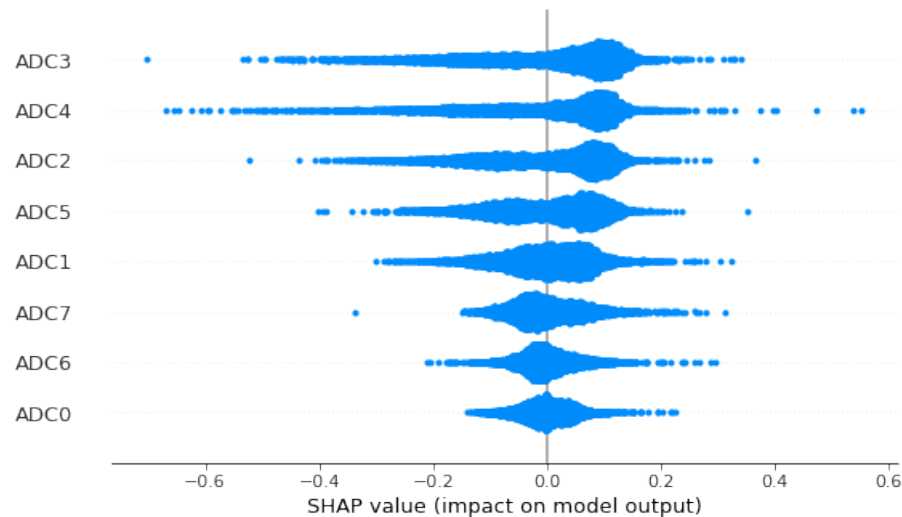
Open sky → High energy



3.5 years of data analysed with χ^2
MOS-08@Sakurajima

Interpretability – SHAP values

- Tool to understand most ML algorithms
- From game theory
- Lloyd Shapley, Nobel prize
- Remove a subset of inputs
calculate the output of the model
- Additive values
- Energy deposition after lead absorbers
are used mostly



$$\Phi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} (v(S \cup \{i\}) - v(S))$$

Conclusion

- Designed a detailed Geant4 simulation of MOS system
 - Included detector effects (changing gain, cluster size)
 - Tested the classical tracking algorithm
- Designed a dedicated Deep Neural Network to classify low vs. high E muons
 - Taught the network with simulation data
- The neural network:
 - Suppresses low energy muons better than χ^2
 - Identifies high energy muons with complicated clusters better than χ^2
- Applied the ML to measurements taken at Sakurajima:
 - The preliminary results agree with the expected tendencies

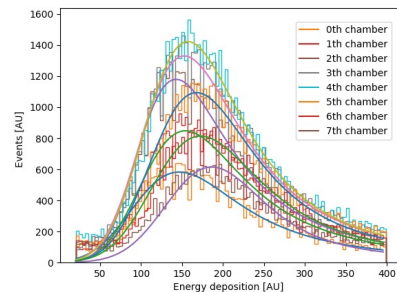
Outlook

- Try additional models:
 - GNN (working @ IceCube)
 - Vision transformers
- Optimize the geometry!
- Test the machine learning with **measurements**:
 - Dedicated measurements to collect muons with known **energy bands**
- Could the lessons learned from ML be used in classical tracking?
 - E.g. Use cut on number of wires fired besides using χ^2
- Perform anomaly detection on Sakurajima data to look for volcanological events in the last 4 years

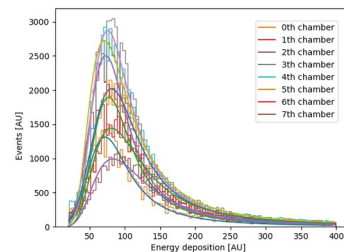
That's all Folks!

Simulations, detector effects

- Need to include these in the simulation to reproduce measurements
- Important for Machine Learning!
- Read out electronics:
 - 2 or 3 wires / pads connected for cheaper readout
- Gain changes:
 - Changing weather
 - Non homogenous gain (due to wires)



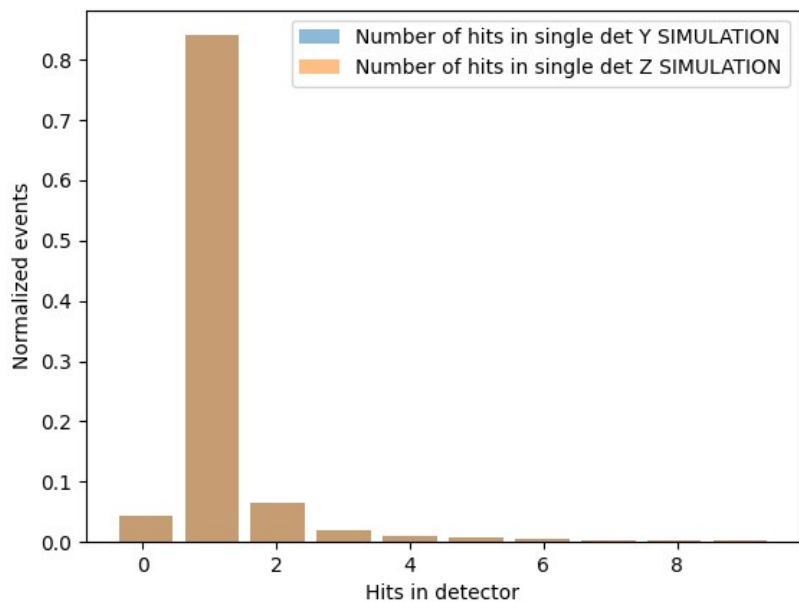
26/10/2022



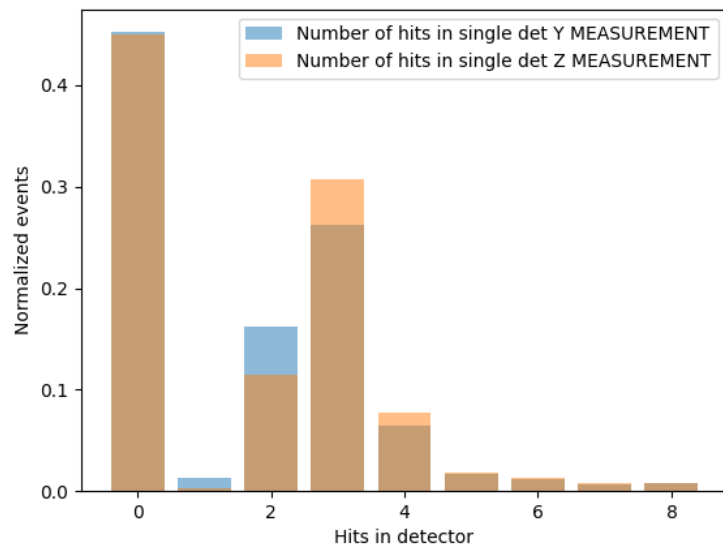
16/11/2019

Number of fired wires per layer

Simulation before including detector effects

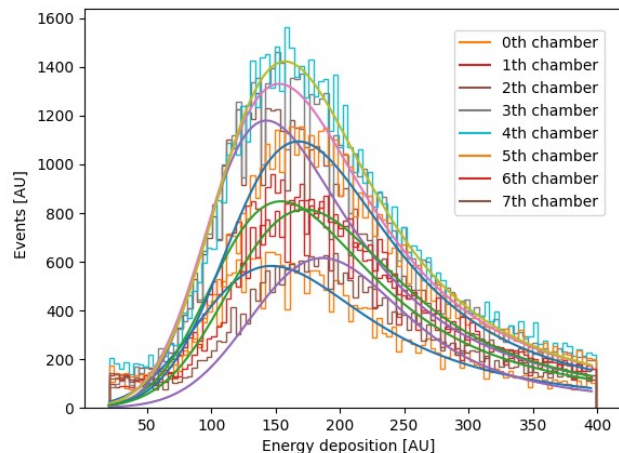


Measurements

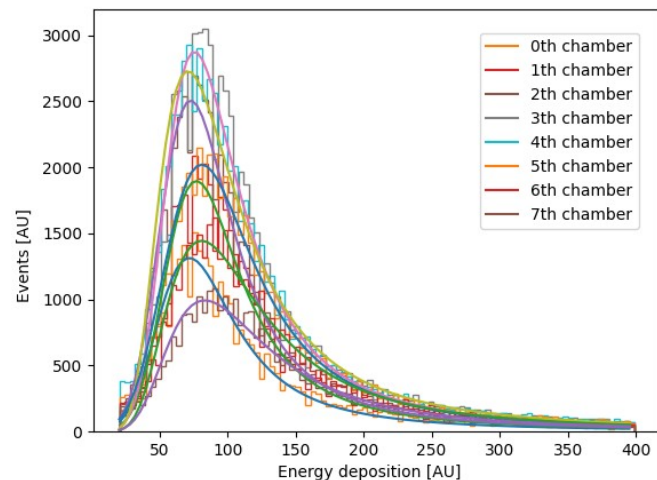


Changing gain

- Fitted Landau distribution to the energy deposition for every ~ 2 hour
- Scaled measurements to simulation for ML



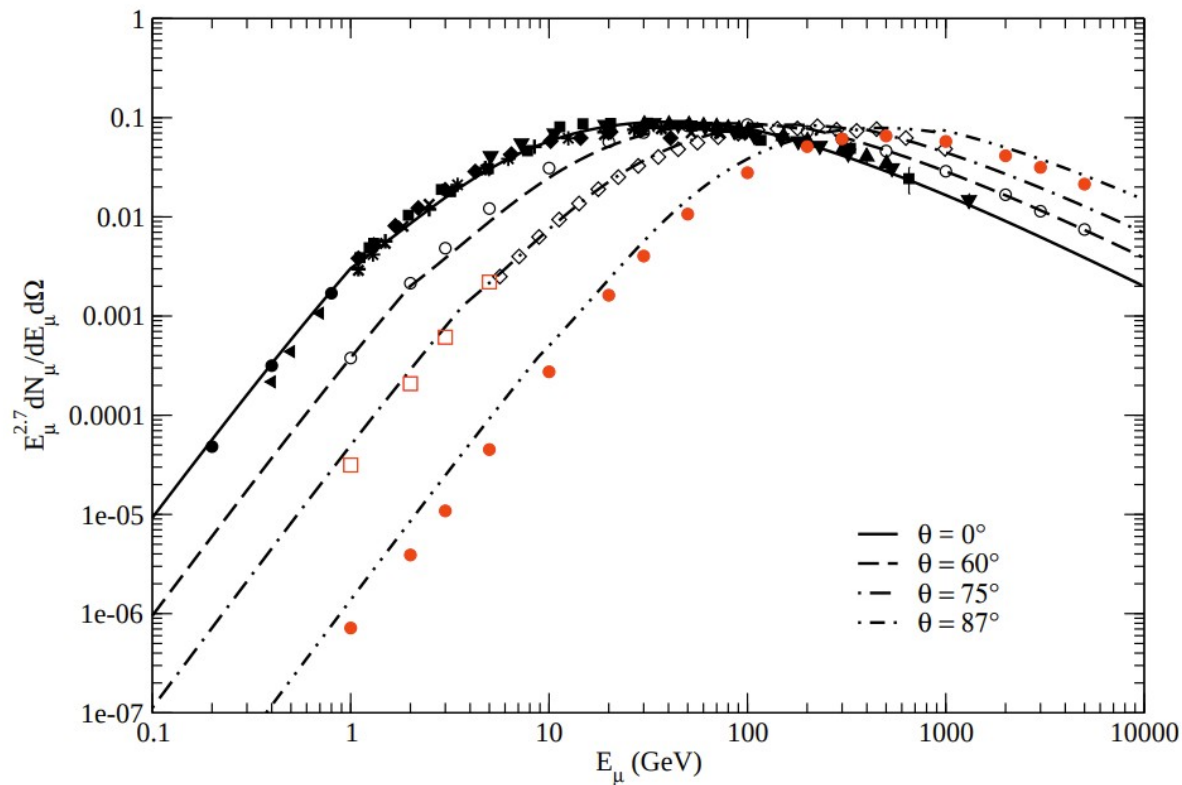
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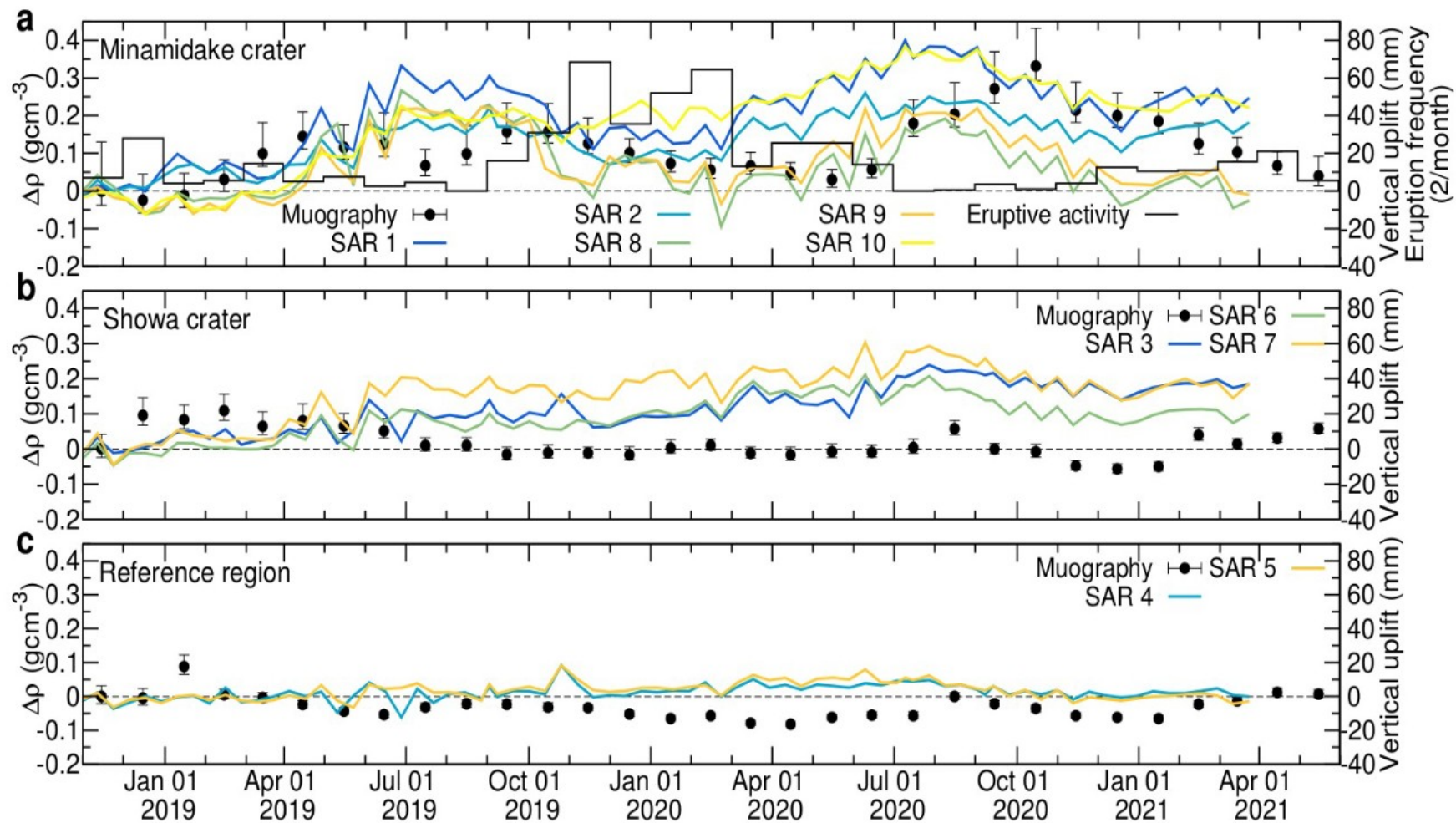


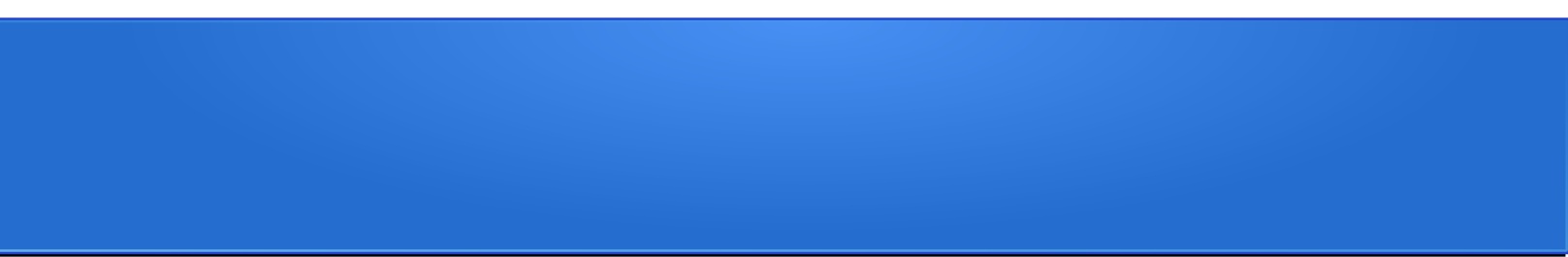
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Modified Gaisser dist.

- Muon flux for diff. E

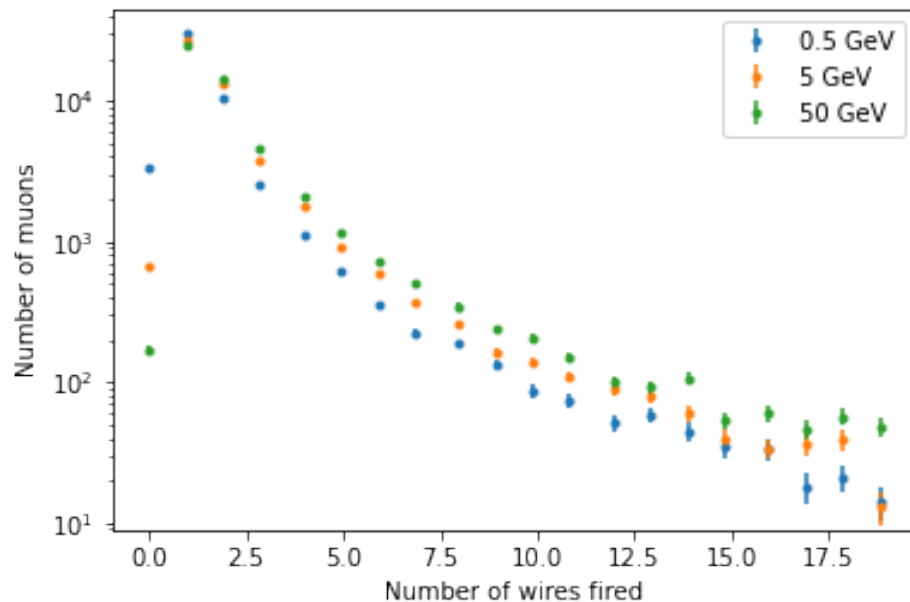






Muon energy dependent features

- A dedicated simulation to understand effect of muon E on secondary detection
 - One 2 cm lead and 1 detector
- Secondary creation:
 - Number of fired wires
- For high E many clusters
 - “Bad” for χ^2 algorithm (lot of clusters)
 - “Good” for ML

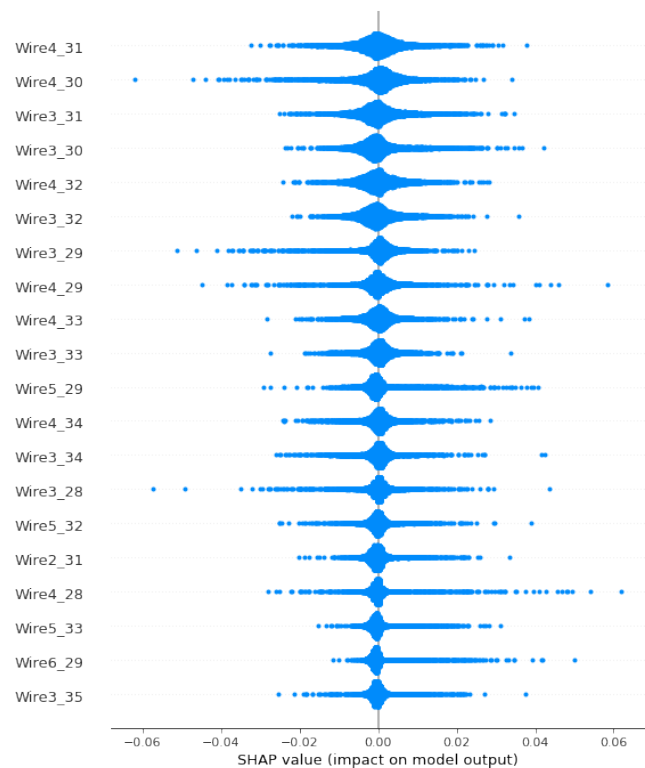


Highlights

- The ML presented is used for volcano muography
 - Special use case: signal is very low for ~ 200 m rock thickness
- Pros:
 - Lots of data: ~ 4 years measurements 10 m^2 at Sakurajima volcano alone
- Cons:
 - No Measurements with KNOWN primary muon energy not taken
- Personal experience:
 - detector effects are very important

SHAP values for wires

Y wires



Y wires

