Background suppression with machine learning in vulcano muography

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REGARD
INNOVATIVE GASEOUS DETECTORS

Eötvös Loránd University

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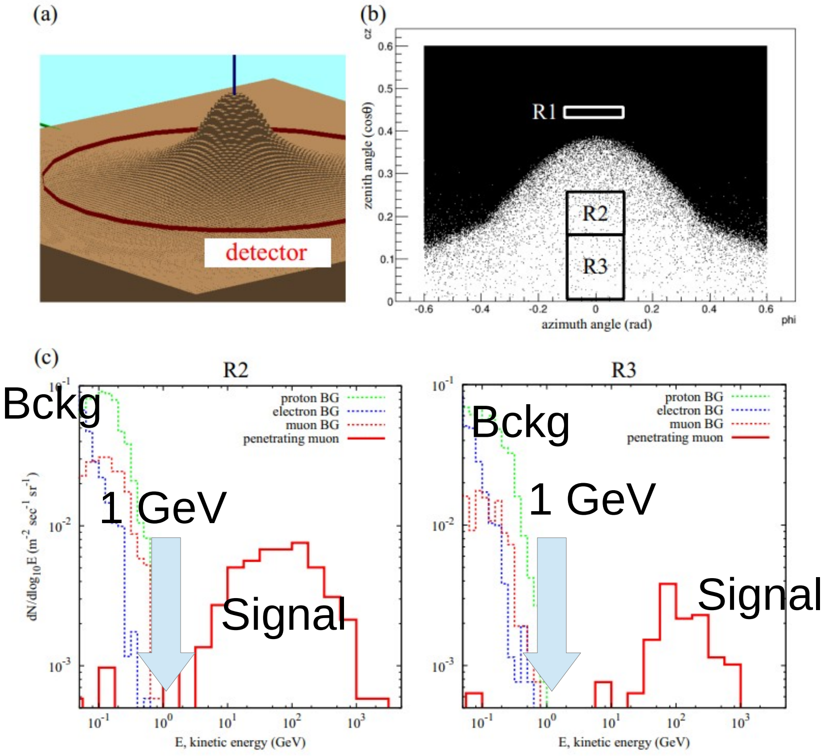
Outline of the talk

- Can we use deep learning to enhance signal to noise ratio?
  - Especially important for vulcano muography
- Background for vulcano 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
- Applying the machine learning algorithm to MOS-08 measurements @ Sakurajima
- Outlook – further validation and applications

Backgrounds in vulcano muography

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

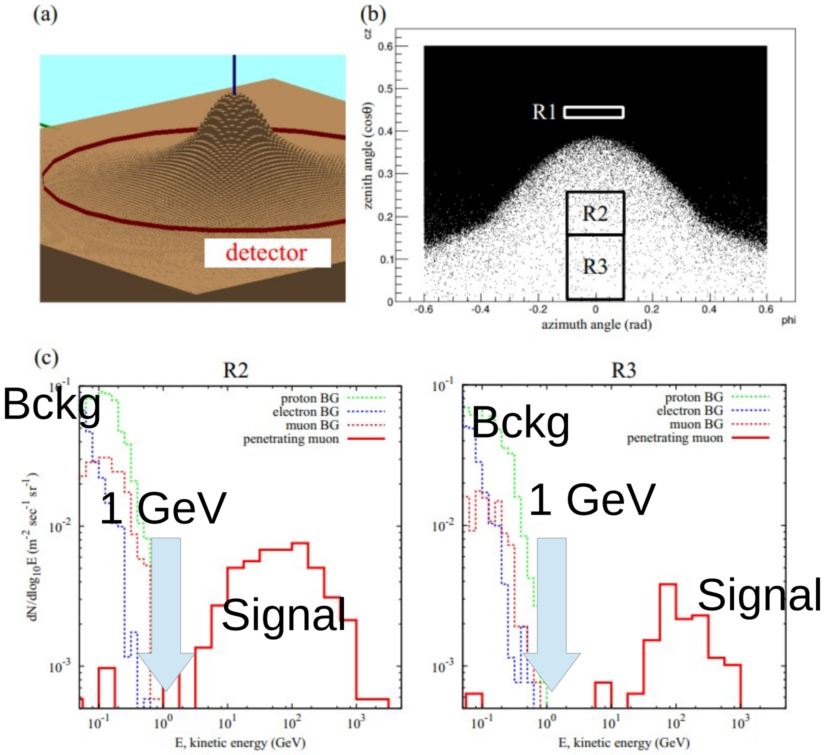


R. Nishiyama et al. (2016)

Backgrounds in vulcano muography

- Background: protons, electrons and muons (hadronic origin)
- IF we could use a cut at ~1 GeV

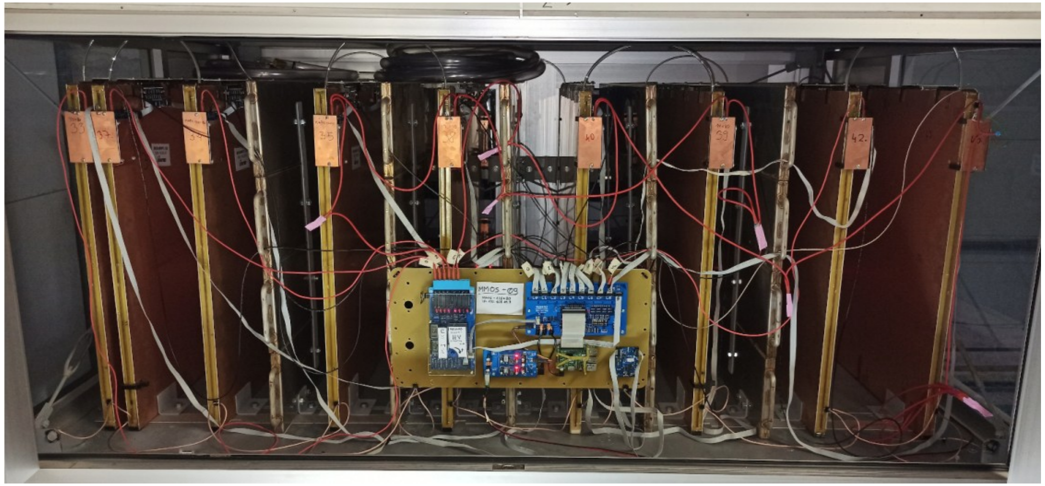
  there would be almost no background!



R. Nishiyama et al. (2016)

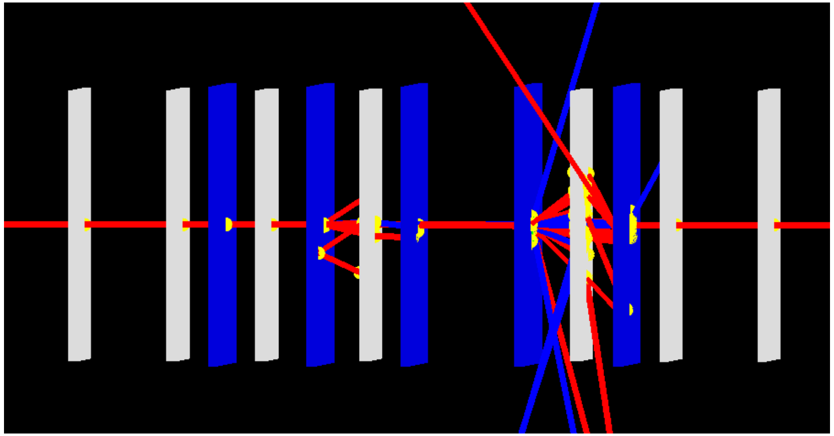
MWPC-based Muography Observation System (MOS)

- Introduced by talk of Oláh László on Tuesday
- Sakurajima vulcano in Japan
- 12 modules online
- MWPC detectors + lead absorbers
- Due to absorbers very suppressed total background:
  - ~~Electrons~~
  - Protons
  - Scattered muons

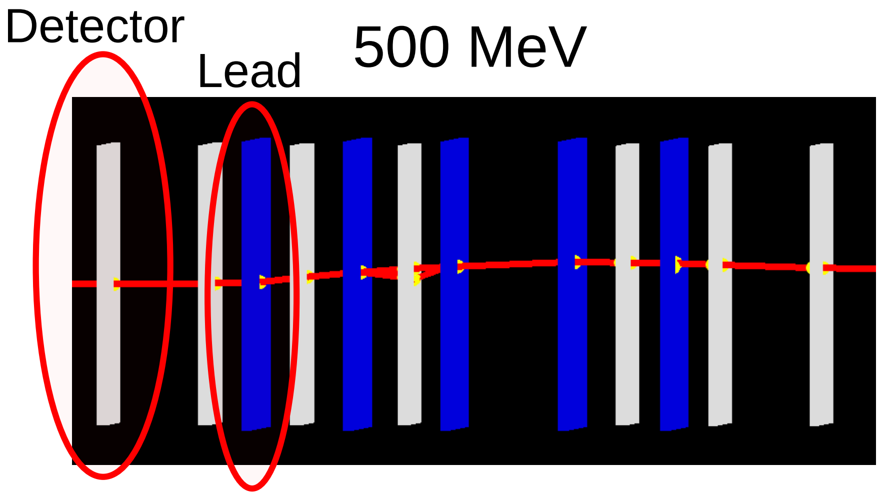


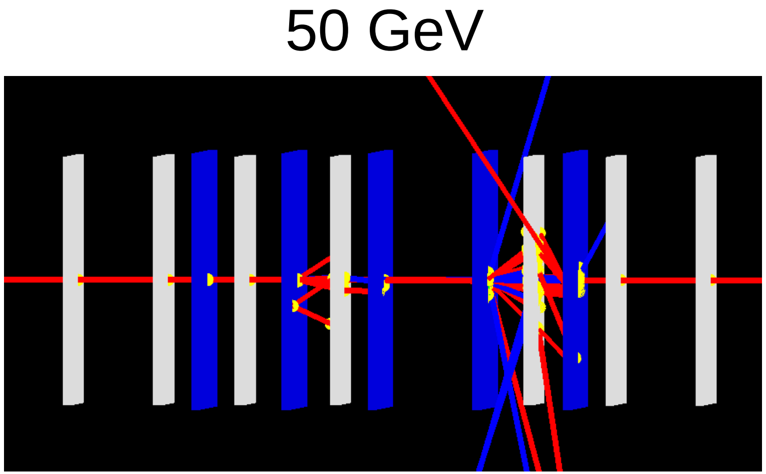
Geant4 simulation of the MOS-08

- 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

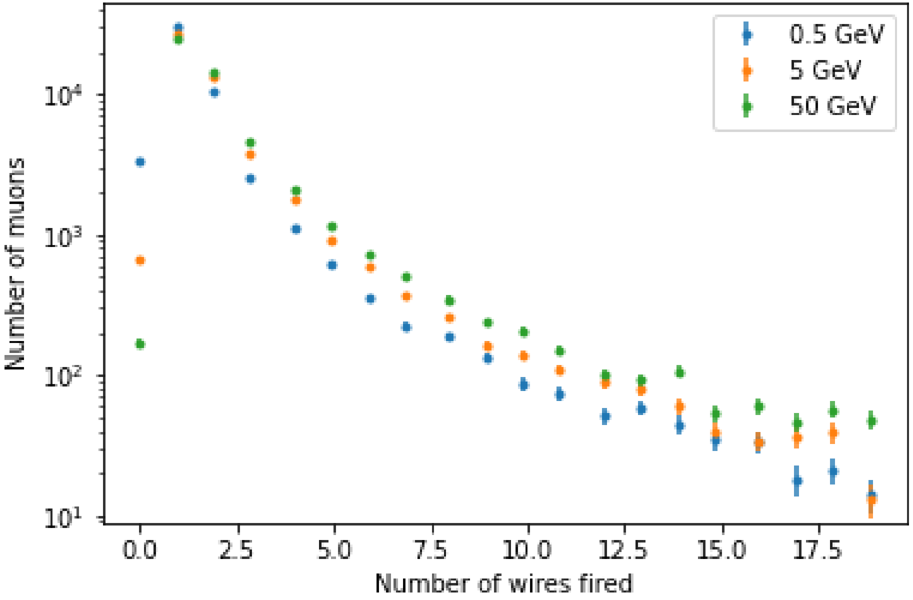




- Scattering (used by χ^2 algorithm)
- Secondary creation:
  - Energy deposition (NOT used by χ^2 algorithm)
  - Lots of clusters (NOT used by χ^2 algorithm as input)

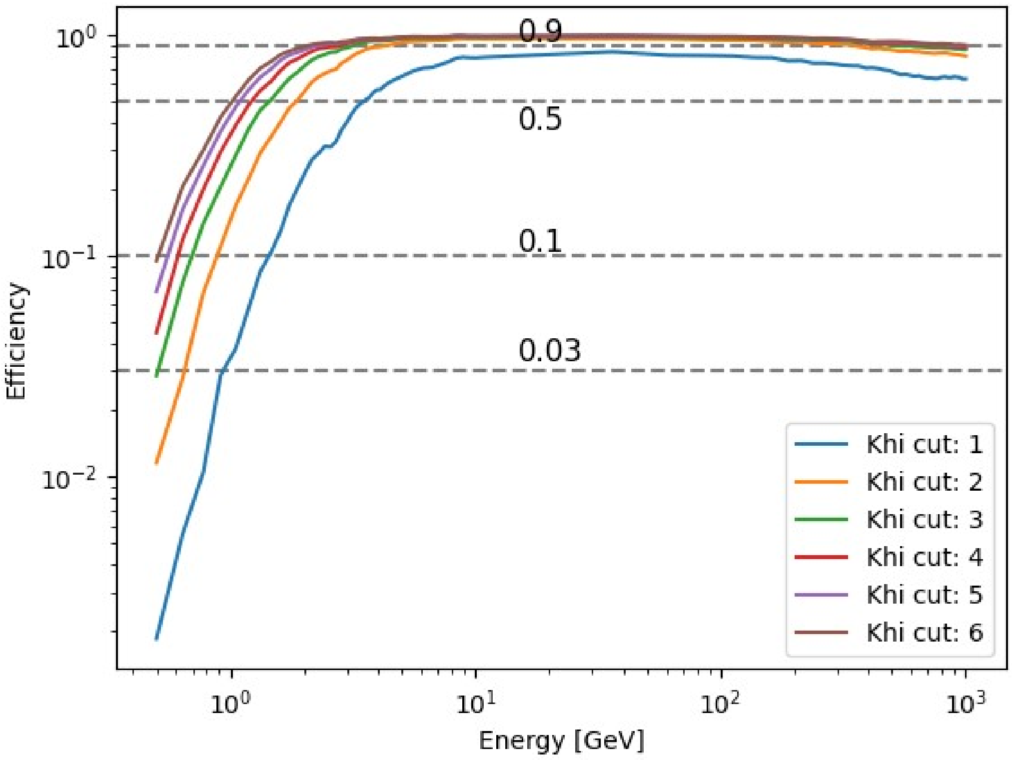
Muon energy dependent features

- 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



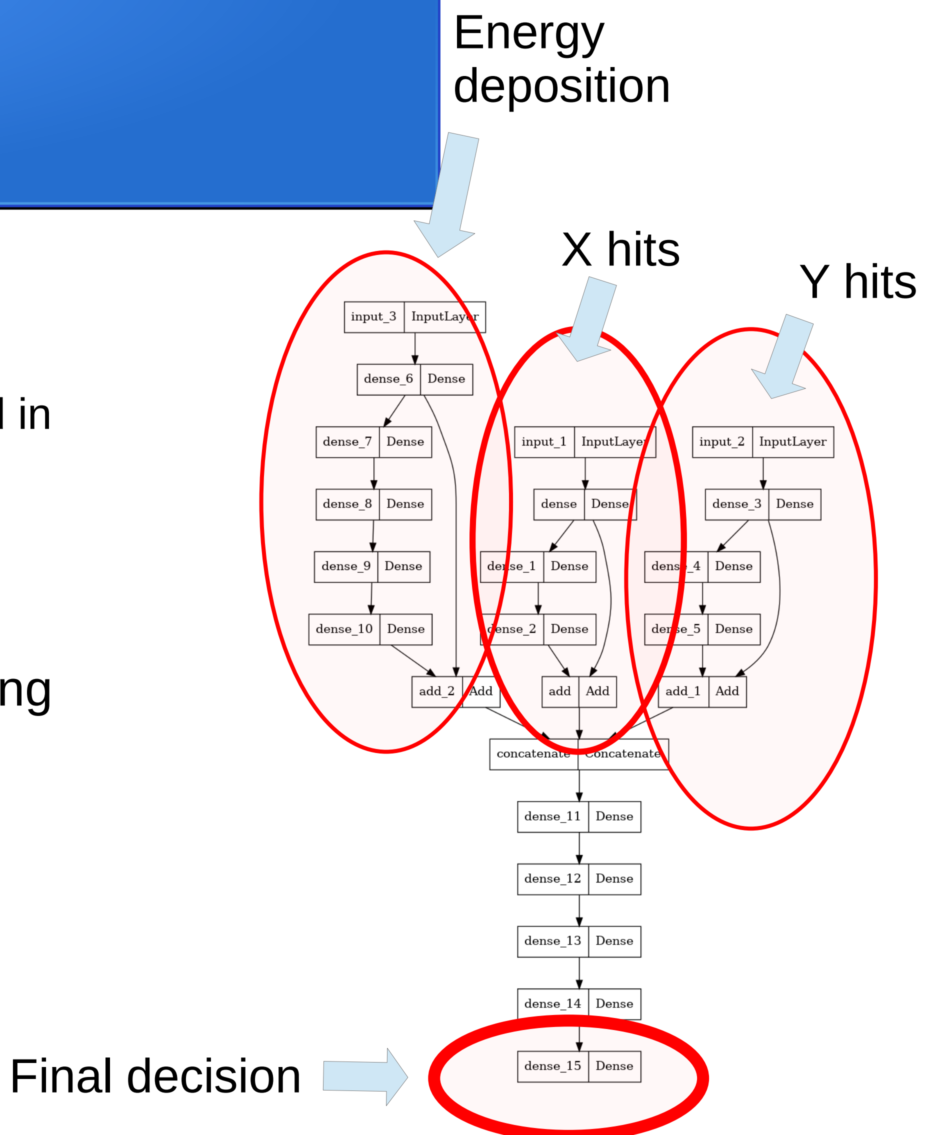
Testing the tracking algorithm

- 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 to 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)

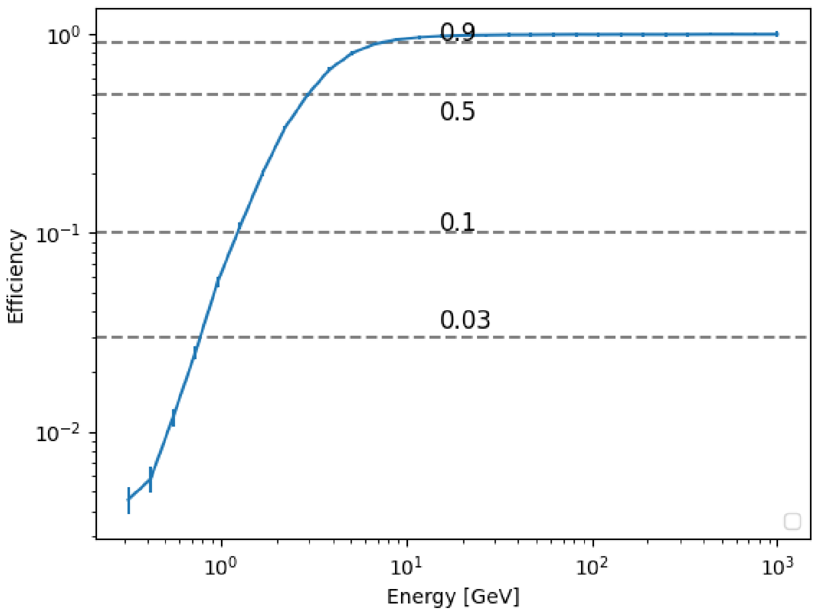


Teaching the ML

- ~ 1 day on a single GPU
- 20 million muons
- 12 GB of events data
- Accuracy: 0.900
- Most used metric for “goodness” of classification
  AUC = 0.952
- AUC above 0.9 it is considered exceptional

Results of the ML

- Cut at score 0.4 (info on next slide)
- Cut can be tuned on demand
- Suppresses 1 GeV protons
  - 4x more then $\chi^2<4$ algorithm
- ~99.5% efficiency @ 1 TeV

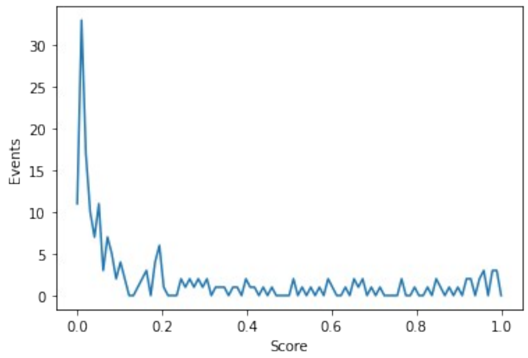


What does the ML predict to measurements?

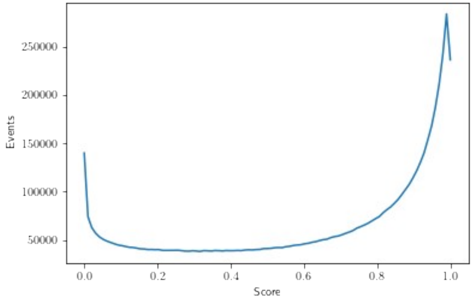
- Measurements taken

  @Sakurajima
- Score distribution

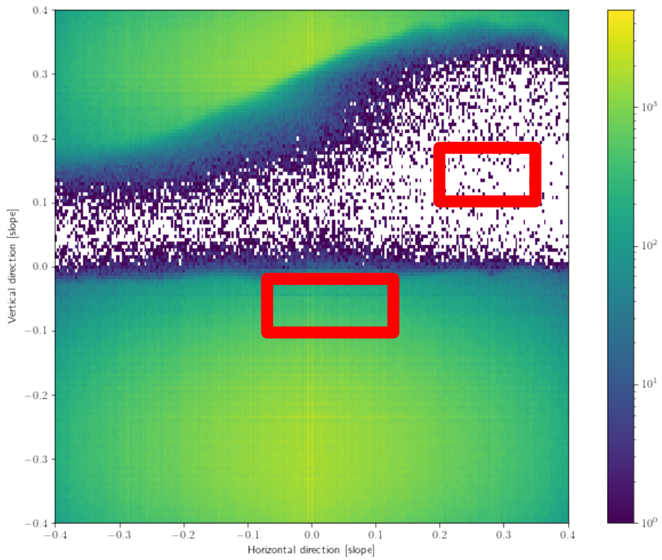
  for different regions
- Middle of the mountain
  - 7km of rock → Only low E
- Open sky ~ horizont
  - High E



Middle of mountain

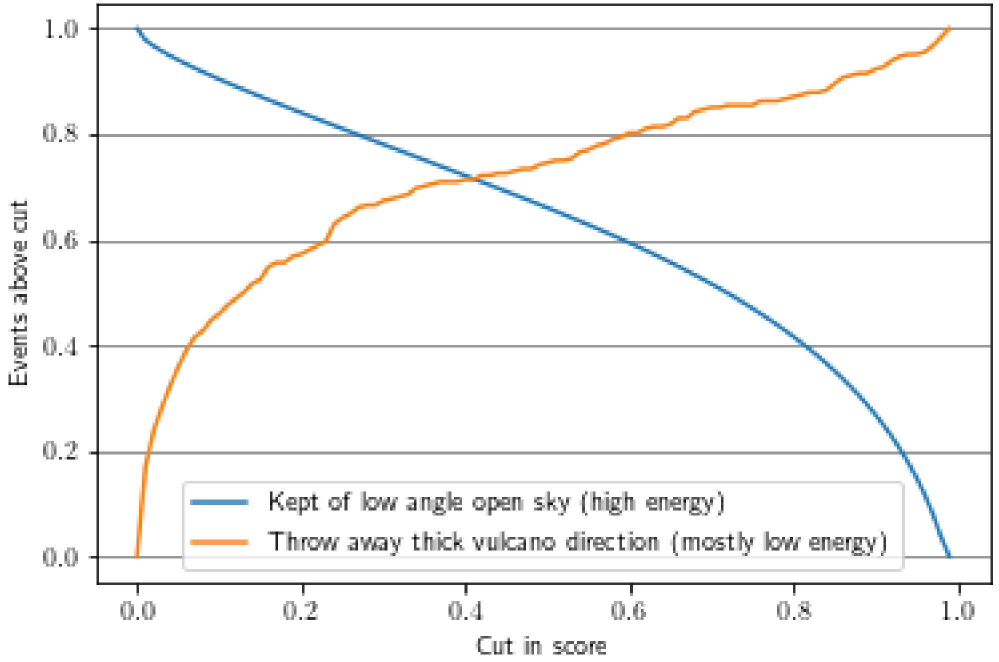


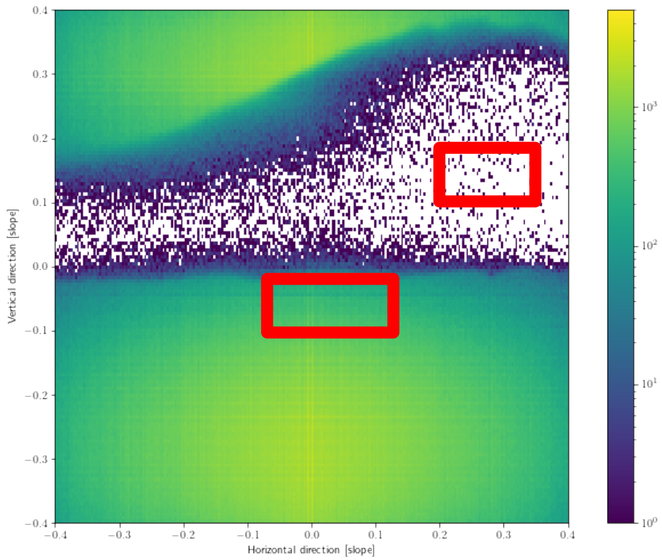
Open sky → High energy



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

Where to put the cut in score?



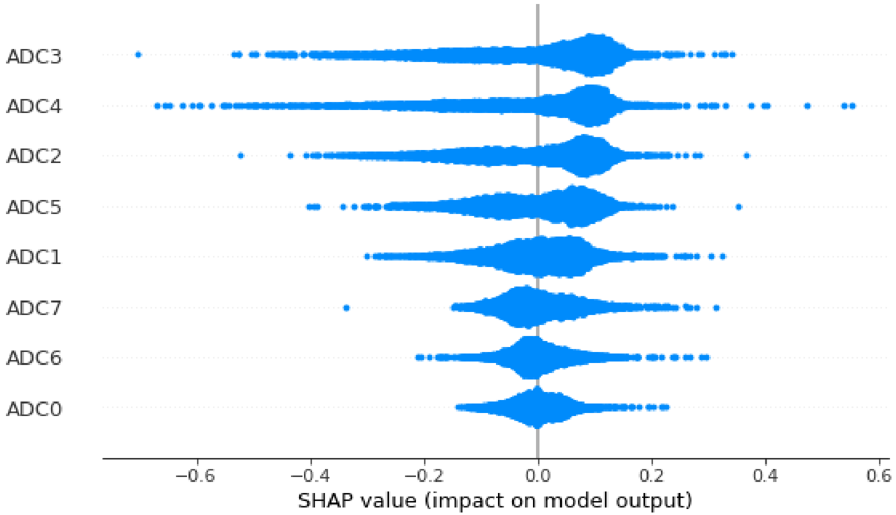


25.08.2019 to 22.01.2023
MOS-08 system muography
Sakurajima

SHAP values

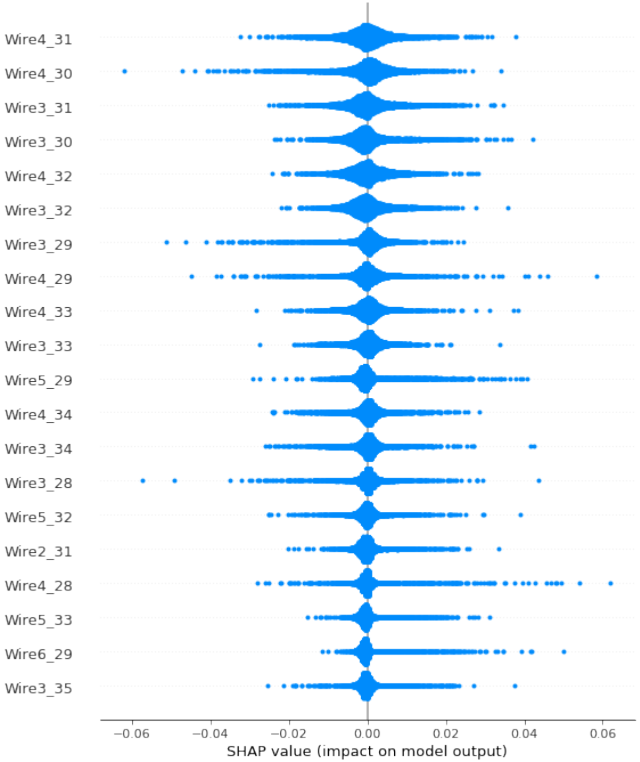
- Tool to understand the neural network
- From game theory
- Lloyd Shapley, Nobel prize
- Remove a subset of inputs

  calculate the output of the model
- Additive values
- Energy deposition after lead absorbers are used mostly

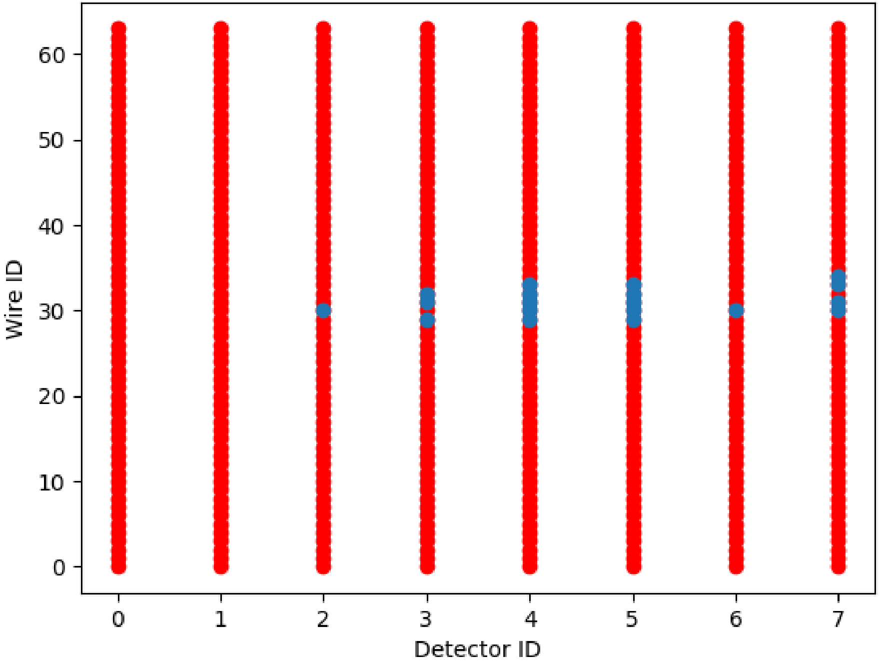


SHAP values for wires

Y wires



Y wires



Conclusion

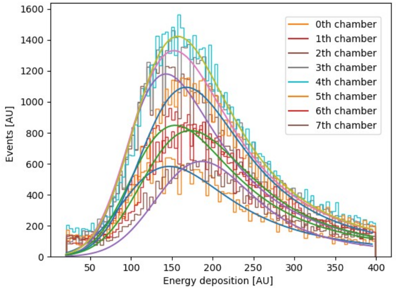
- Designed a detailed Geant4 simulation of MOS system
  - Included detector effects (changing gain, cluster size)
  - Tested the classical tracking algorithm
- Designed a dedicated Deep Neural Network to classify low vs. high E muons
  - Taught the network with simulation data
- The neural network:
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

Outlook

- 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 vulcanological events in the last 4 years

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)



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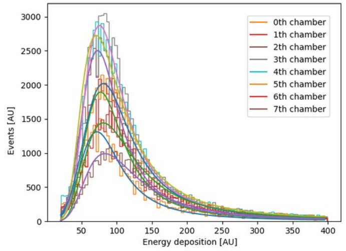

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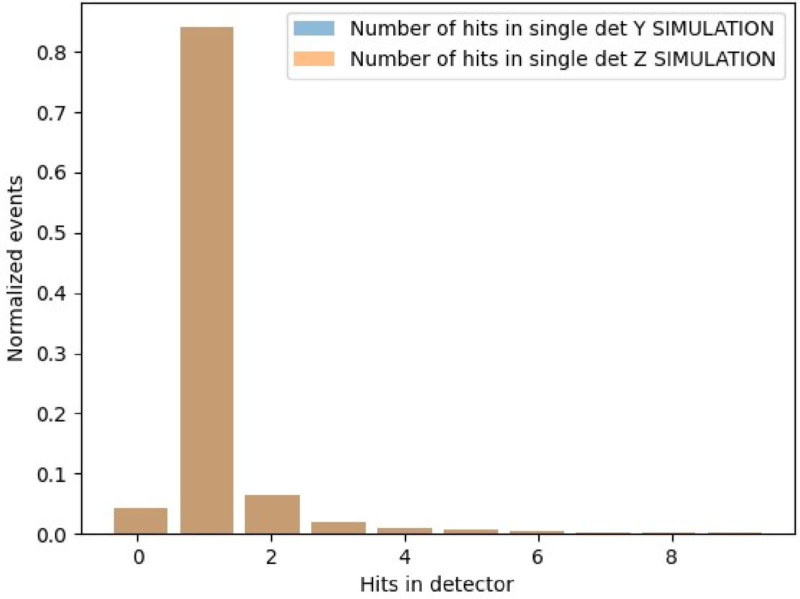
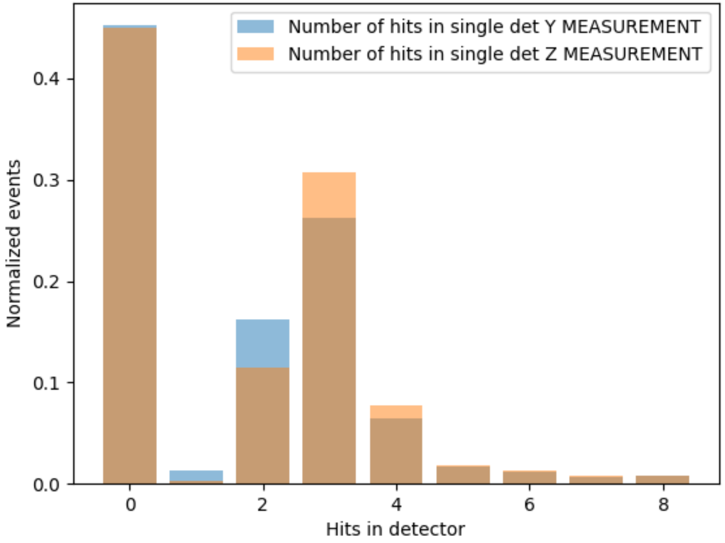
Number of fired wires per layer

Simulation before including detector effects

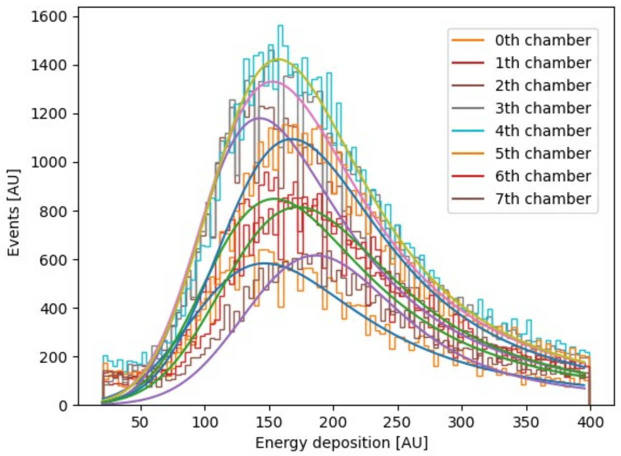


Measurements



Changing gain

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



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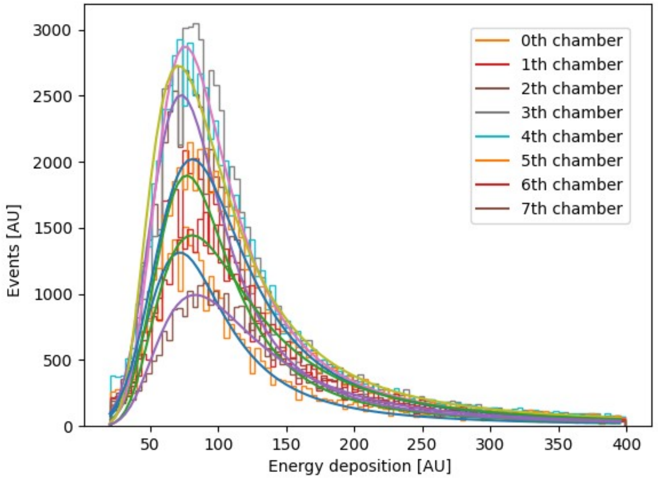

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Modified Gaisser dist.

- Muon flux for diff. E