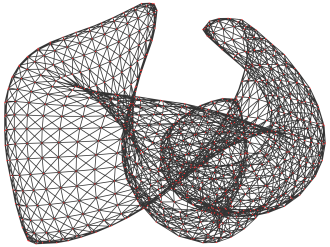
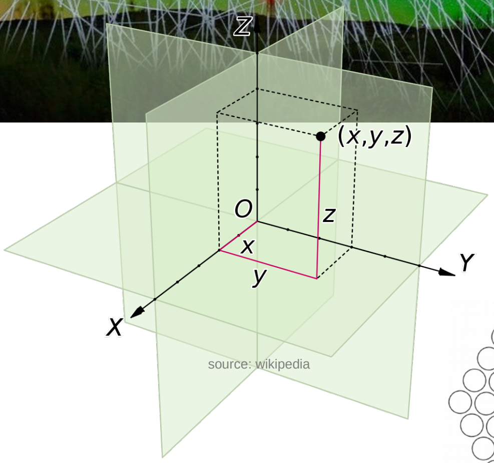
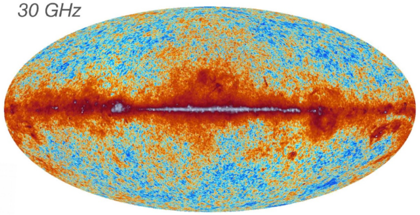
Friedrich-Alexander-Universität
Erlangen-Nürnberg

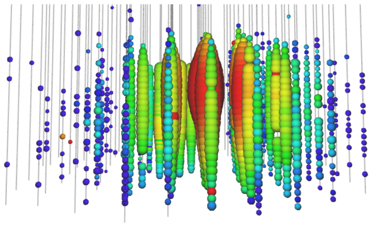
# Machine Learning for Astroparticle Physics






Astronomy and Astrophysics 641, p. 1 (2018)



https://arxiv.org/abs/1309.7003

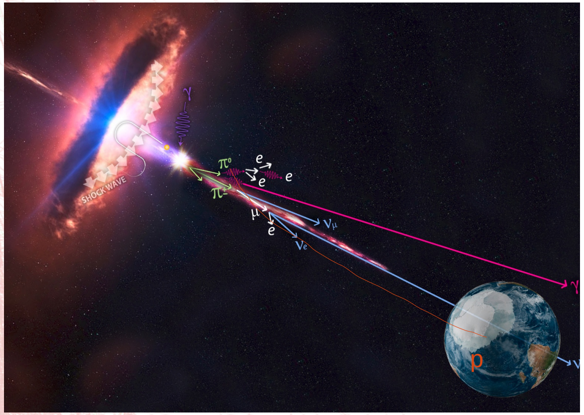

Jonas Glombitza

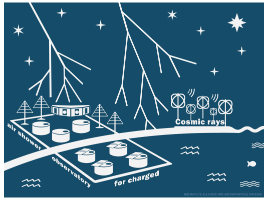

April 8, 2024 São Carlos Institute of Physics

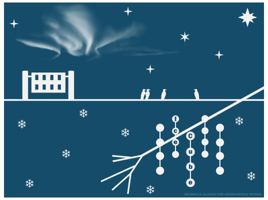

SPONSORED BY THE
Federal Ministry of Education and Research

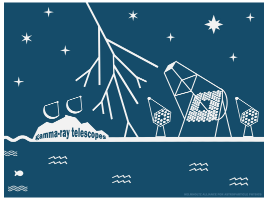
ERLANGEN CENTRE FOR ASTROPARTICLE PHYSICS

# Astroparticle Physics and AI






Study of particles with astronomical origin

- arrival direction, energy, particle type

Reconstructions

- *basic:* fits, parameterizations, observables
- *advanced:* MC templates, ML & observables
- **Aim: exploit all available information**

→ needed: algorithm able to analyze complex high dimensional data)

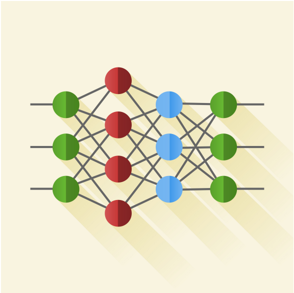
**Great progress in AI (last 15yrs)**

Deep neural networks (DNNs)

→ new state-of-the-art

- Lots of training data
- Parallelized training (GPUs)
- New techniques/architectures

**Able to exploit complex patterns in high dimensional data**

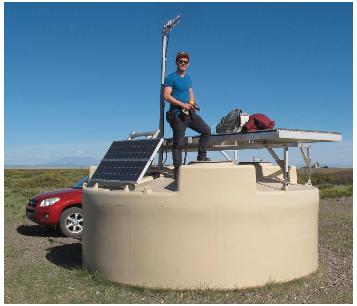


# Recap: Last workshop

*old* (2023)
***new* (2024)**

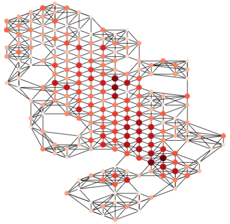
## Mass composition of UHECRs

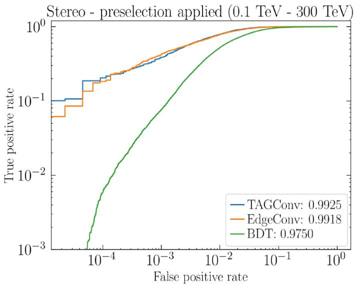
- Composition measurements using water-Cherenkov detectors
- Shower reconstruction using deep learning
- **Preliminary results on data**



## DNNs: Event reconstruction for IACTs

- Graph networks: very promising on MC
- To be verified on data



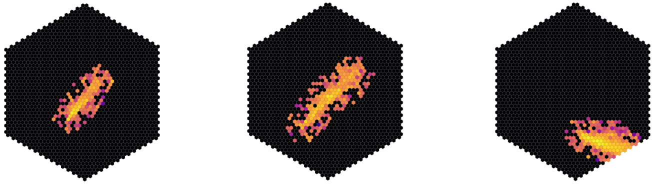


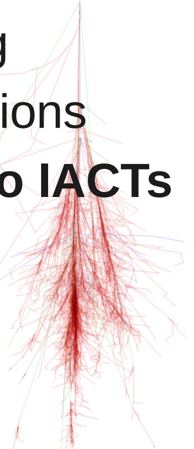

## DNNs: Event Reconstruction SWGO

- Design of a future water-Cherenkov based gamma-ray detector
- **ɣ/hadron separation** (Martin)
- **Event reconstruction** (Franziska)

## Generative Models for IACTs

- Simulations very time consuming
  - accelerate (air) shower simulations
  - **first successful application to IACTs**
- Investigate anomaly detection





# Generative models

Learn to generate new samples


"Albert Einstein using a mobile phone while watching TV"


"A penguin flies in the sky and overtakes other birds. Clouds are seen in the background"

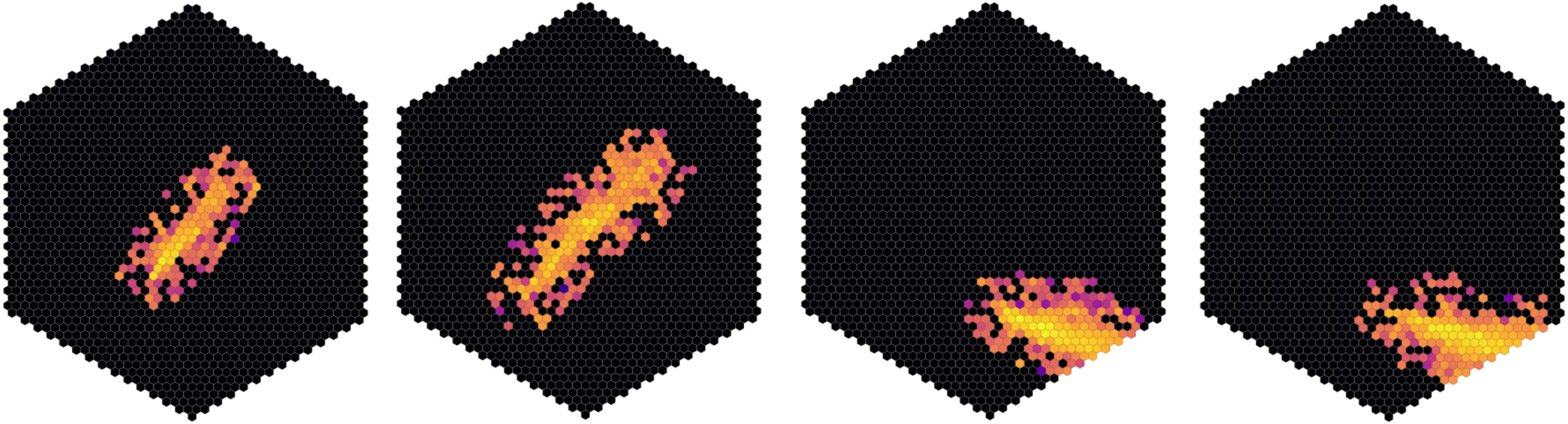
Breakthrough in generative machine learning

- generation of realistic images
- image feature local and global coherence
- realistic image super resolution

# Which face is real?

Play the game:
https://www.whichfaceisreal.com

# Which generated IACT image is real?



Imaging Air Cherenkov Telescope
Example simulated / generated for the CT5 telescope of the H.E.S.S. array

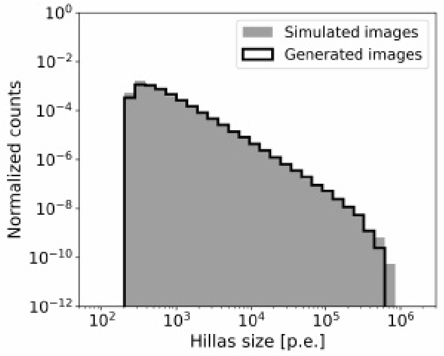


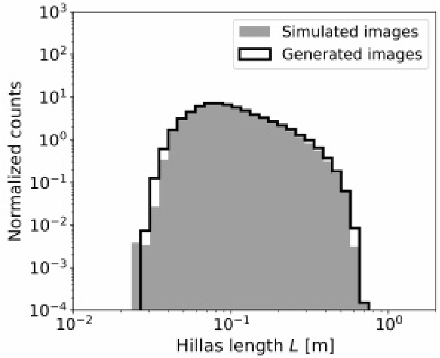
C.Elfein, S.Funk, J.G. arXiv:2311.01385

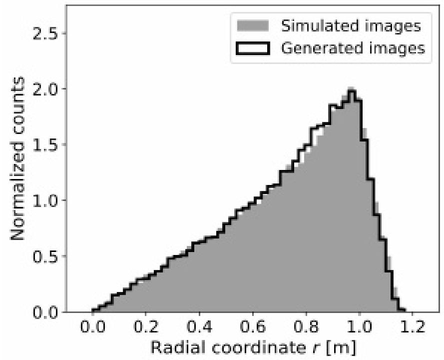
# Hillas Parameter

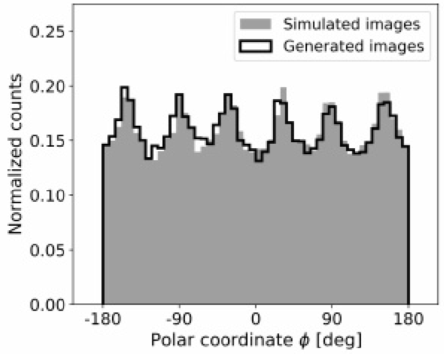
**Distributions agree very well → over large range of magnitude!**
**Very different showers are generated!**

**Promising prospects:**
**accelerate simulations by $10^5$!**



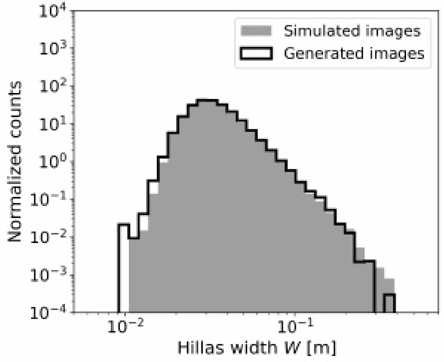
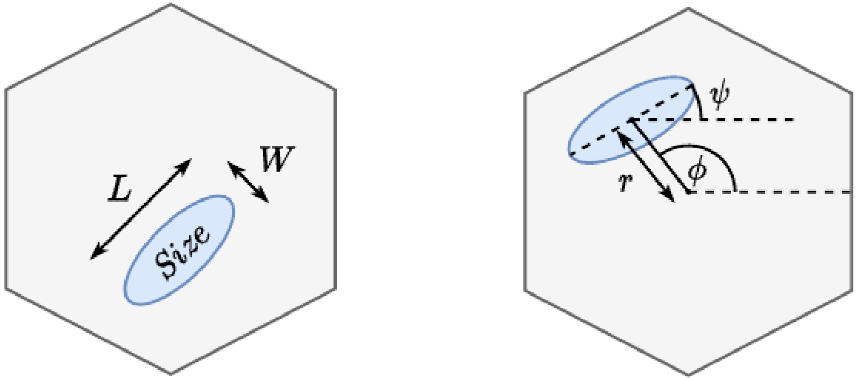
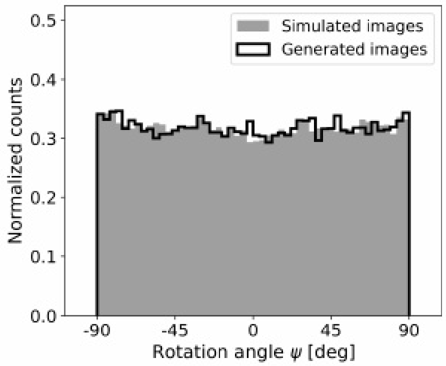




**Image shape modeled well!**



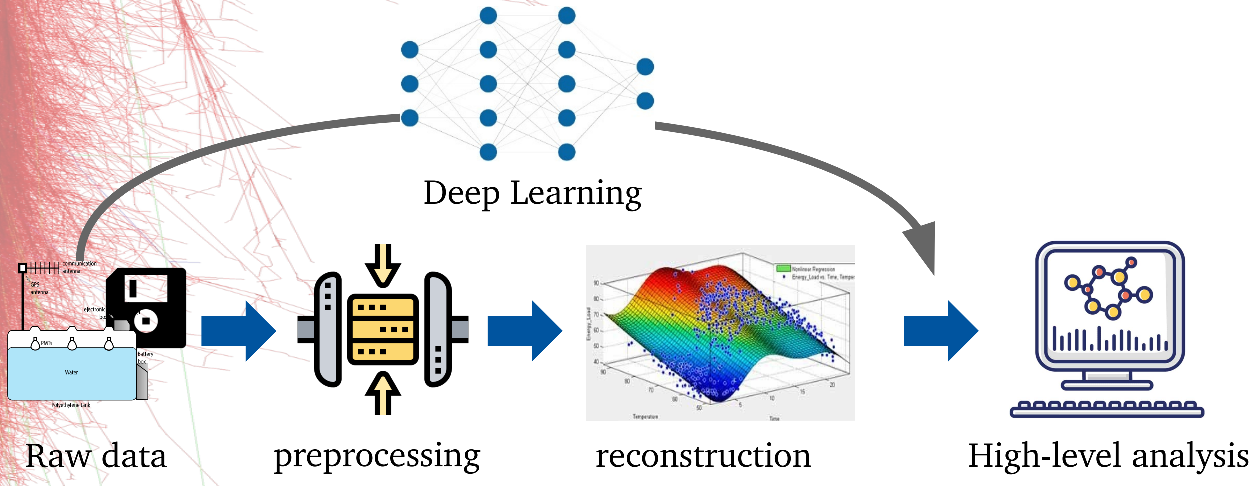

Investigate Hillas parametrization
→ traditionally used for event reconstruction

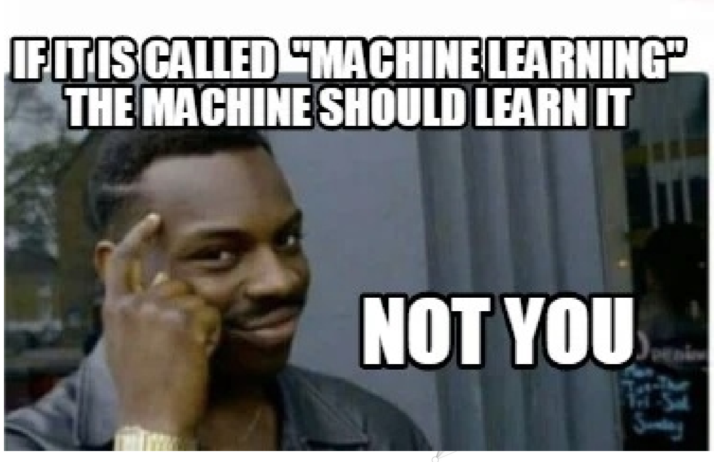



**Full camera used**
**→ Very different geometries**

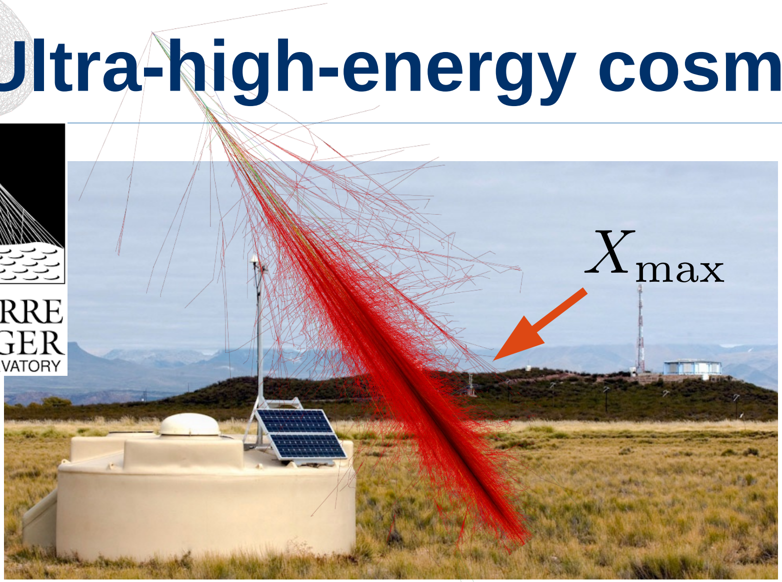
C.Elfein, S.Funk, J.G. arXiv:2311.01385, accepted by JINST

# Physics Results
# & DNNs applied to data



# Ultra-high-energy cosmic rays (UHECRs)

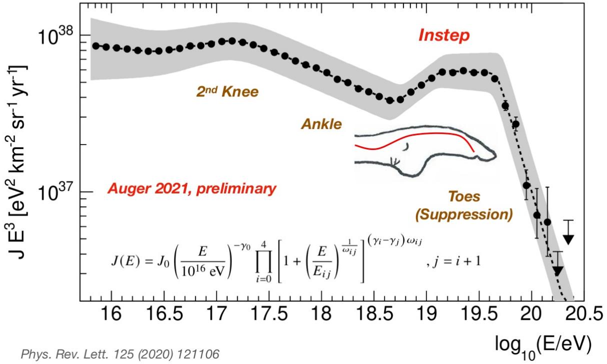



## The Pierre Auger Observatory

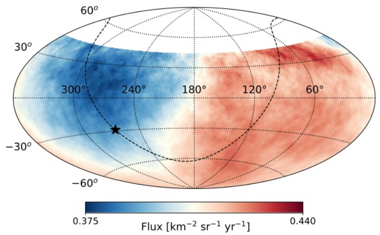
- world’s largest observatory to study ultra-high-energy cosmic rays
- hybrid detection of air showers
  - 1,660 water-Cherenkov detectors
  - 27 fluorescence telescopes
    - can precisely observe Xmax

## Key findings

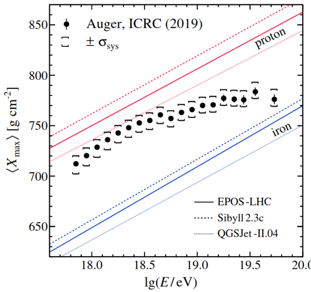
<u>Characteristics of the energy spectrum</u>

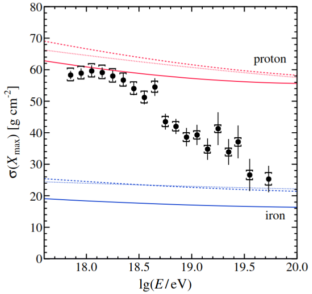



Phys. Rev. Lett. 125 (2020) 121106




Discovery: <u>large-scale anisotropy</u> pointing away from galactic center
Hint: UHECRs are extragalactic



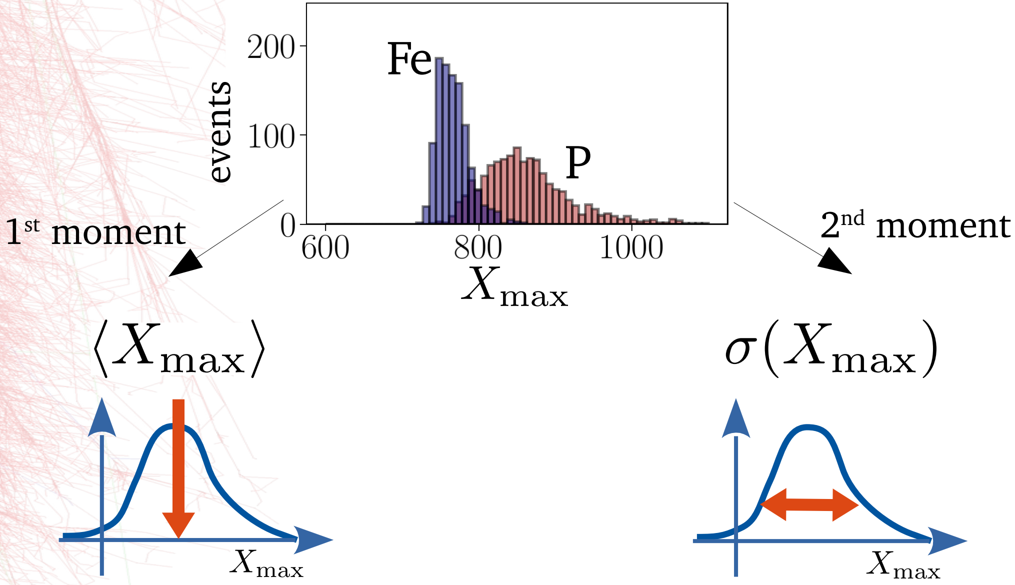

<u>Mass composition</u>
Towards heavier and purer composition

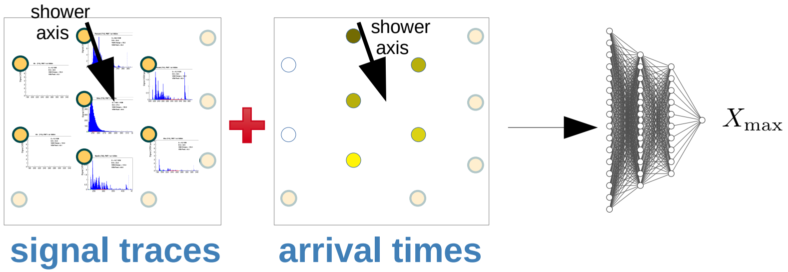
No GZK protons!

# Xmax reconstructed with SD data

## Mass composition of UHECRs

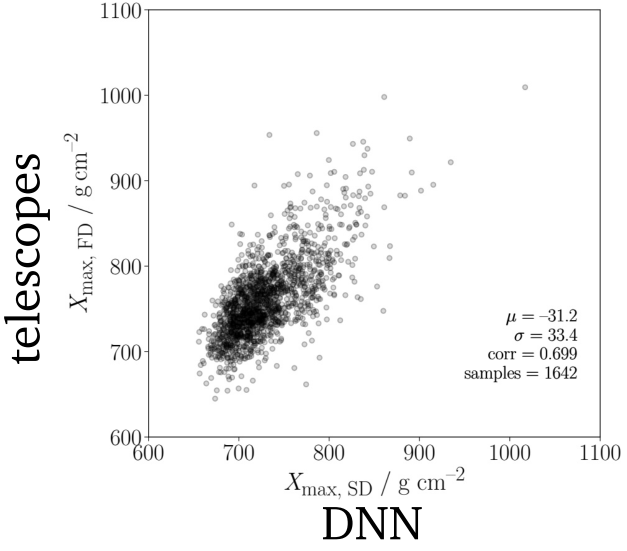
- currently: most precise mass estimator by reconstructing shower maximum $X_{\mathrm{max}}$
- determine composition by studying the measured $X_{\mathrm{max}}$ distributions




## DNN-based Xmax reconstruction

- Reconstruct Xmax using SD signals
- Calibrate and crosscheck using telescope (hybrid) data




State last year

# Evidence for breaks in the elongation rate

Critical for understanding astrophysical sources

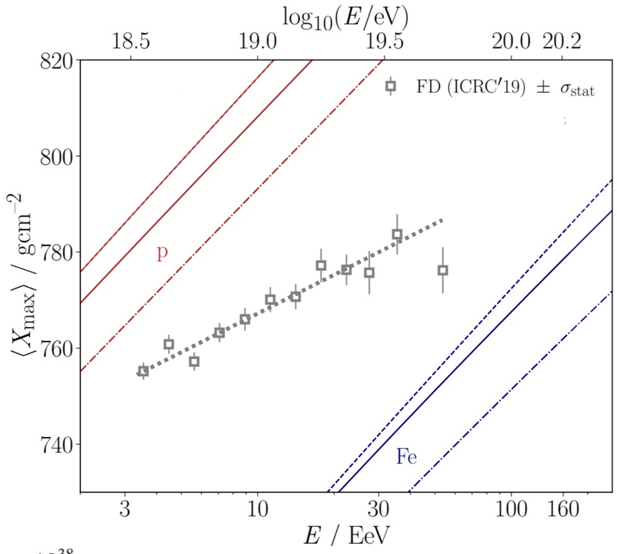
- Energy spectrum feature (deviations from simple power law)
- Evolution of mass composition

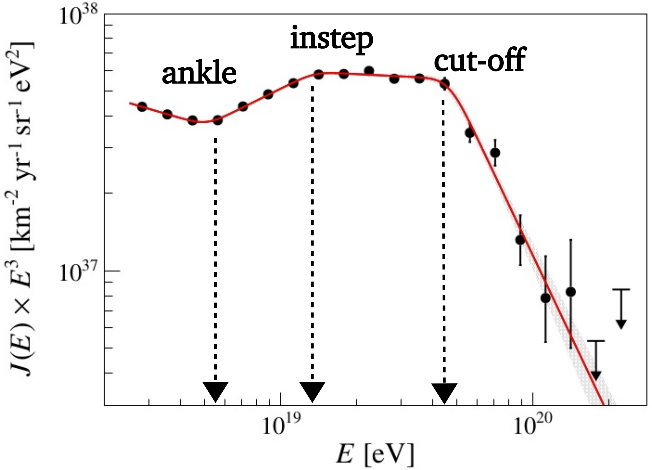
Telescope-based measurements:

- Linear model describes transition from light to heavy composition

**Current interpretation:**

- Ankle: transition from galactic to extra galactic
- Cut-off: maximum injection energy accelerator & propagation?




Preliminary: PoS(ICRC2023)278

# Evidence for breaks in the elongation rate

Critical for understanding astrophysical sources

- Energy spectrum feature (deviations from simple power law)
- Evolution of mass composition

Telescope-based measurements:

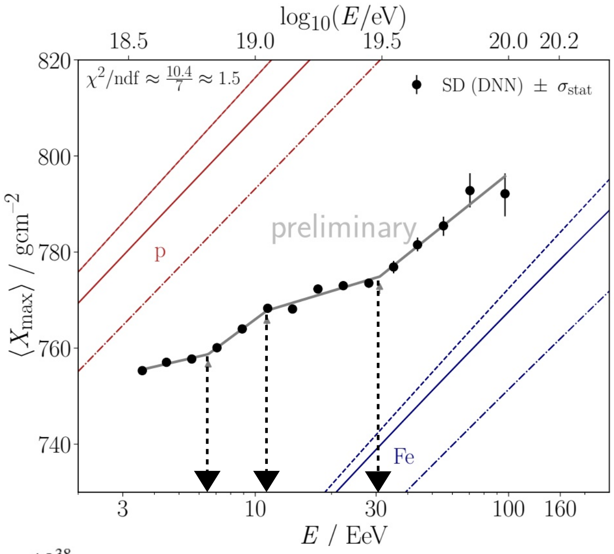
- Linear model describes transition from light to heavy composition

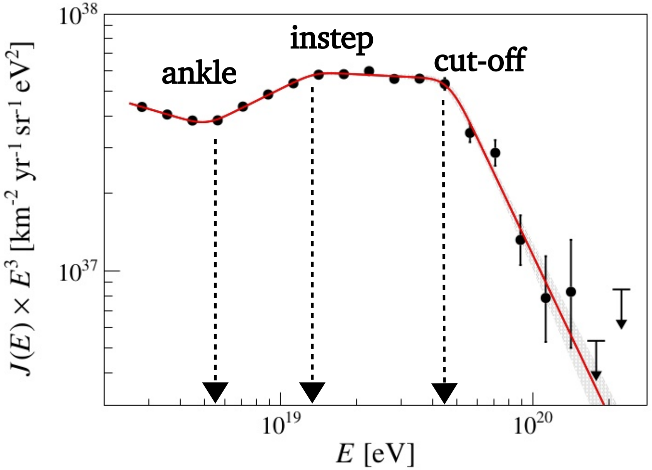
Surface-detector based (utilizing **deep learning**): statistics x10

- Evidence for three breaks, coinciding with spectrum features

**Current interpretation:**

- Ankle: transition from galactic to extra galactic
- Cut-off: maximum injection energy accelerator & propagation?




Preliminary: PoS(ICRC2023)278

# Summary

Advent deep learning (AI) offers new tools for astroparticle physics
→ Novel opportunities to analyze large amounts of <u>raw</u> data

- Event reconstruction
- Background rejection

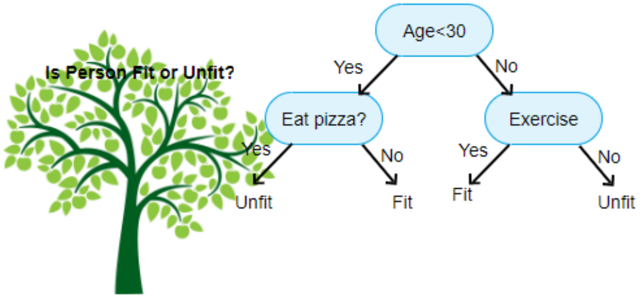
- Central challenge: transfer performance from MC to data
  - ‘refinement’ of simulated data (domain adaption)

- studies at ECAP:
  - event reconstruction: IACTs (H.E.S.S. / CTA), WCD-based (Auger, SWGO)
  - Unsupervised learning applications
    - acceleration of physics simulations
    - search for anomalies

# Machine Learning and Deep Learning

## Machine Learning

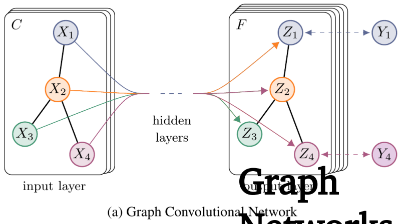
- applications across many physics domains, e.g., for (background rejection, multi-class classifications)
- BDTs, random forest, shallow NNs




https://www.aitimejournal.com/@akshay.chavan/a-comprehensive-guide-to-decision-tree-learning

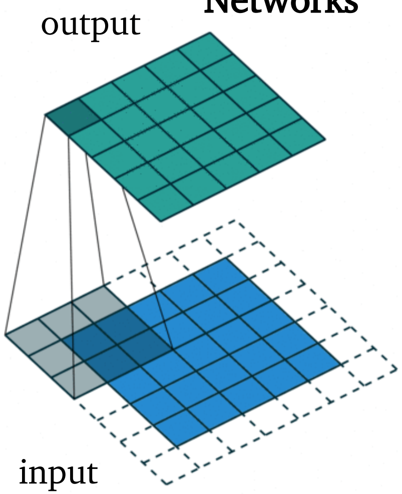
## Deep Learning

- driven by computer science (BigTechs)
- major improvements in:
  - speech recognition, NLP
  - pattern recognition, CV
- (usually) requires huge amounts of data

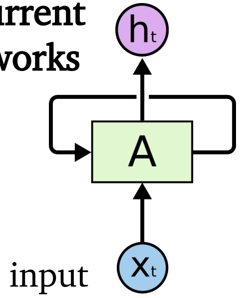



Graph Networks

Convolutional Networks



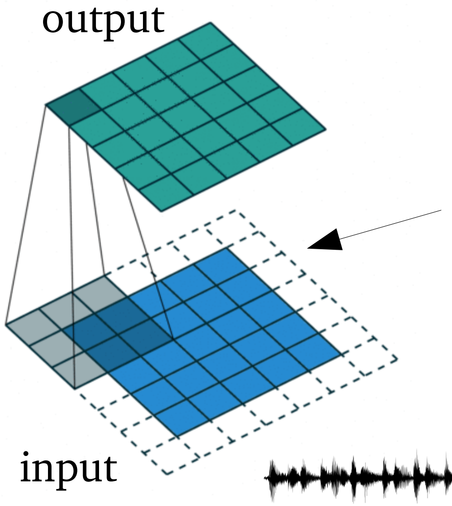

Recurrent Networks



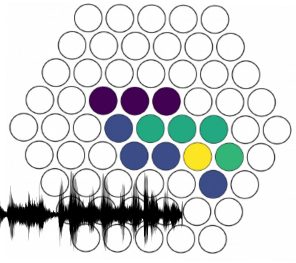
# Deep Learning: RNNs & CNNs

## Convolutional Networks (CNNs)

- analyze image-like data
- **filter** exploits image
  - features translational invariance
  - prior on local correlations

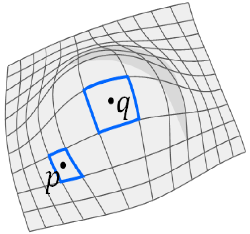



adaptive parameters of **filter**



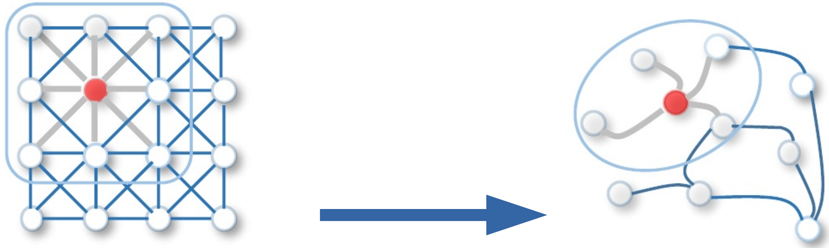
## Graph Network

- For data with spatial correlations
  - Local proximity important prior
- Extent concept of CNNs to
  - Non-regular grids
  - Non-Euclidean Manifolds



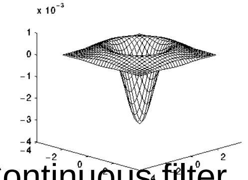

CNN

Graph Network



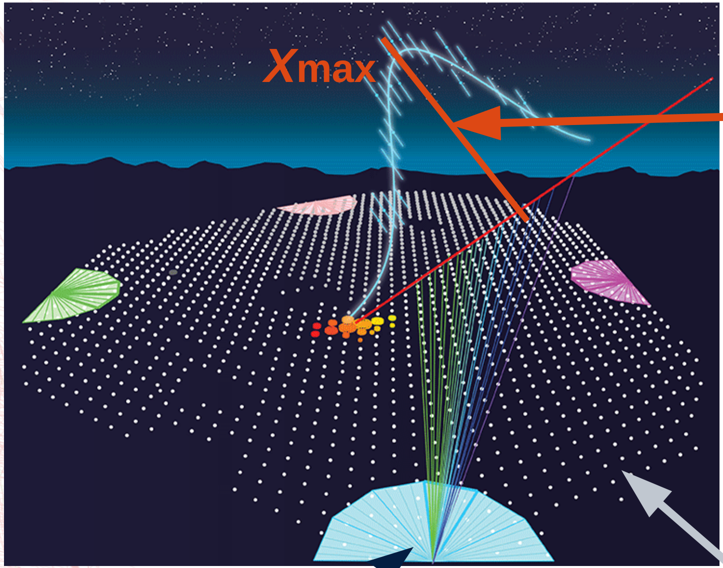
$$\mathbf{D}^2_{xy} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

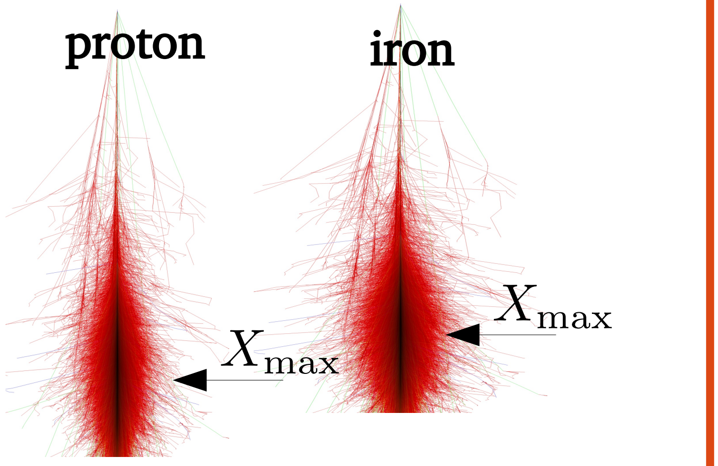
Discrete filter



Continuous filter

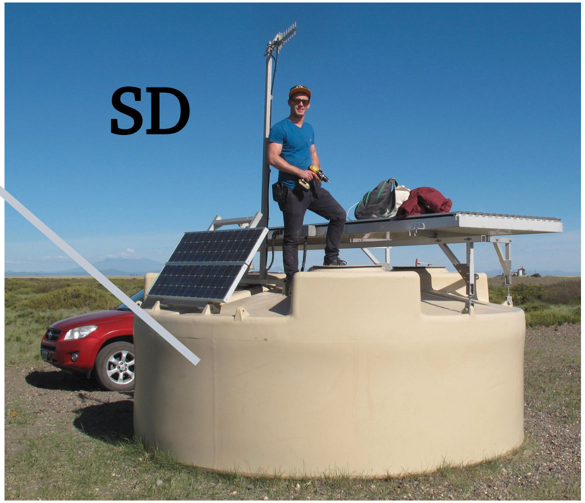
# Pierre Auger Observatory




shower maximum sensitive to mass


- 27 telescopes
- 15% duty cycle
- overlook array
- directly observe Xmax




- ~1600 detectors
- 3000 km²
- cannot directly access Xmax
- 100% duty cycle

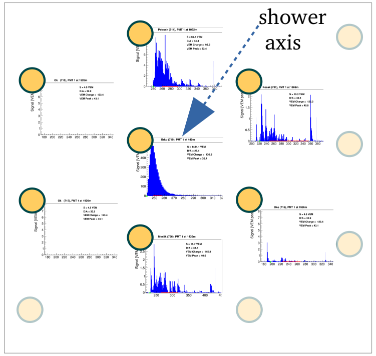
→ use Deep Learning

# Air Shower Reconstruction

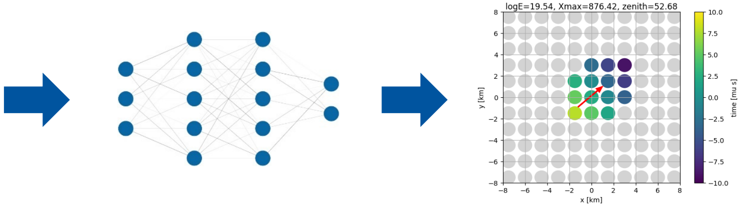
- Train neural network on simulated detector signals

- Verify reconstruction using hybrid events
  - ➔ precise observations of shower maximum using FD
- ML approach outperforms physicist's designed algorithm on **MC and data**

➔ potential for new insights into UHECR composition

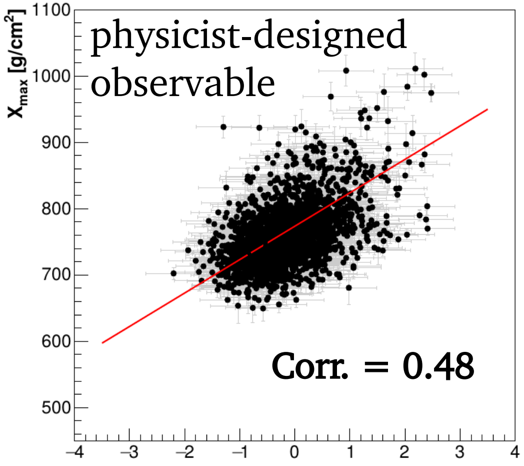



signal traces

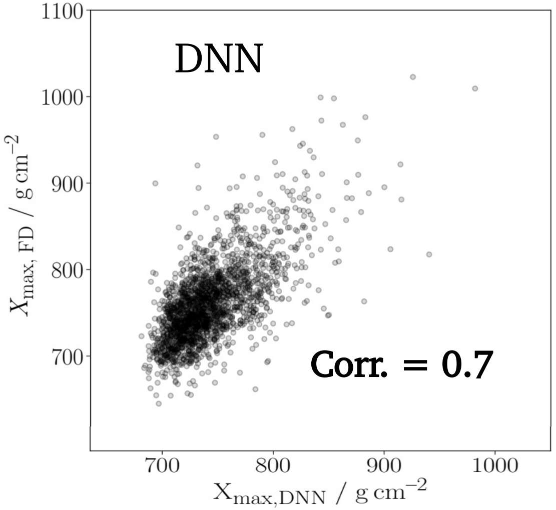



Deep neural network

Reconstruction




ArXiv/1710.07249




The Pierre Auger Collaboration, JINST 16 P07019 (2021)

# Summary

The advent of deep learning offers new tools for astroparticle physics
→ novel opportunities to analyze large amounts of data

- Event reconstruction
- Background rejection

- unsupervised learning models
  - ‘refinement’ of simulated data (domain adaption)

- studies at ECAP:
  - event reconstruction: IACTs (H.E.S.S. / CTA), WCD-based (Auger, SWGO)
  - acceleration of physics simulations

# Generalization Capacities on Data

## DNNs and Domain Adaption

- models are trained using physics simulations
- trained models are applied to data
  - ➔ can lead to reconstruction biases


https://bair.berkeley.edu/static/blog/humans-cyclegan/

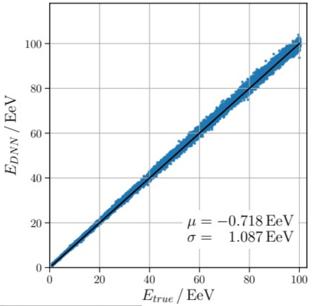
# Simulation Refinement

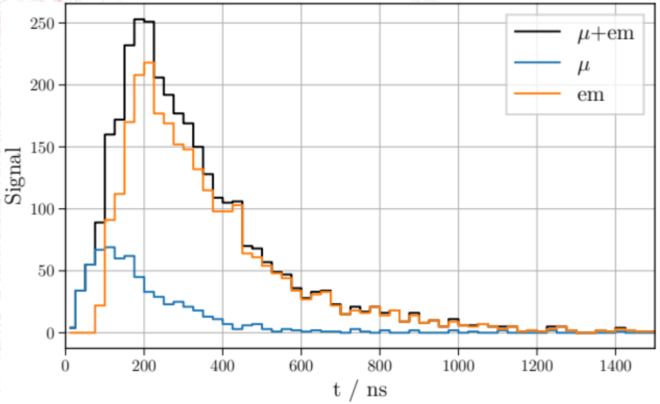
Erdmann et al.
Comput Softw Big Sci (2018) 2: 4

- Training on **simulations** but application on **data**
  - Model can be sensitive to artifacts / mismatches existing in simulation

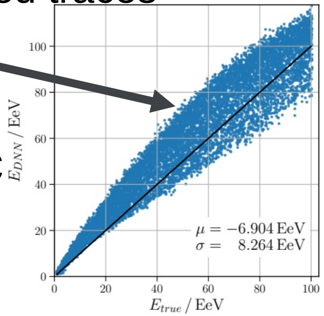
Neural network can not handle modified traces

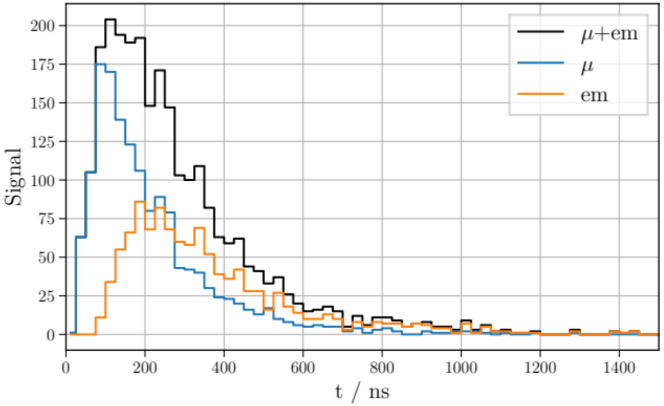
**Simulation**
**70%** electromagnetic
**30%** muonic



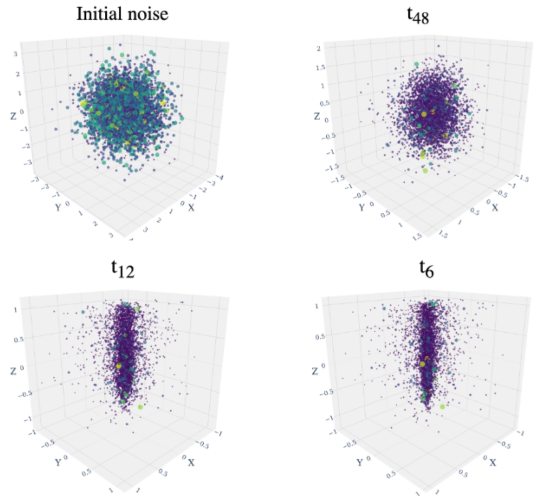

**Data**
**30%** electromagnetic
**70%** muonic
+ Increased noise



# Application in Particle Physics

- Detector simulation are very time consuming
  - accelerated ($10^3$–$10^5$) using generative models
- Conditioned on the physics observables
  - e.g., (energy, particle type, arrival direction)
- Samples must comply with physics laws
- Samples have to follow phase space density $\rightarrow$ usually no cherry-picking

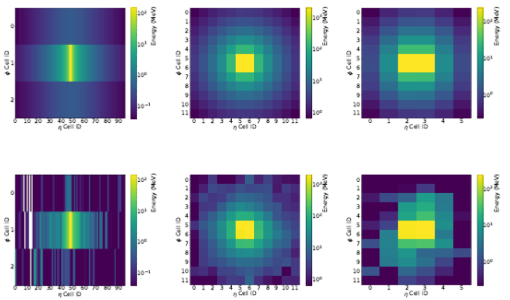



Buhmann et al., ArXiv/2305.04847

Layer

Geant4

GAN

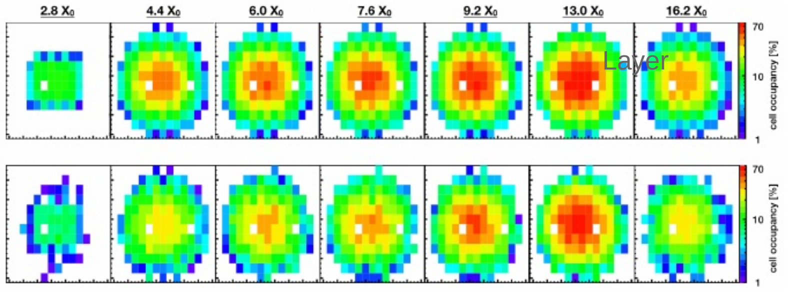


Paganini, Oliviera, Nachman - Phys. Rev. D 97, 014021 (2018)

Layer

Geant4

WGAN




Erdmann, Glombitza, Quast - T. Comput Softw Big Sci (2019) 3: 4

# Simulation Refinement

Erdmann et al.
Comput Softw Big Sci (2018) 2: 4

mitigate data / simulation mismatches → train *refiner* to refine simulated data

- feedback given by adversarial *critic* network, rating the refined simulation quality
  - refiner uses feedback to improve performance
- improved performance when training with refined simulation