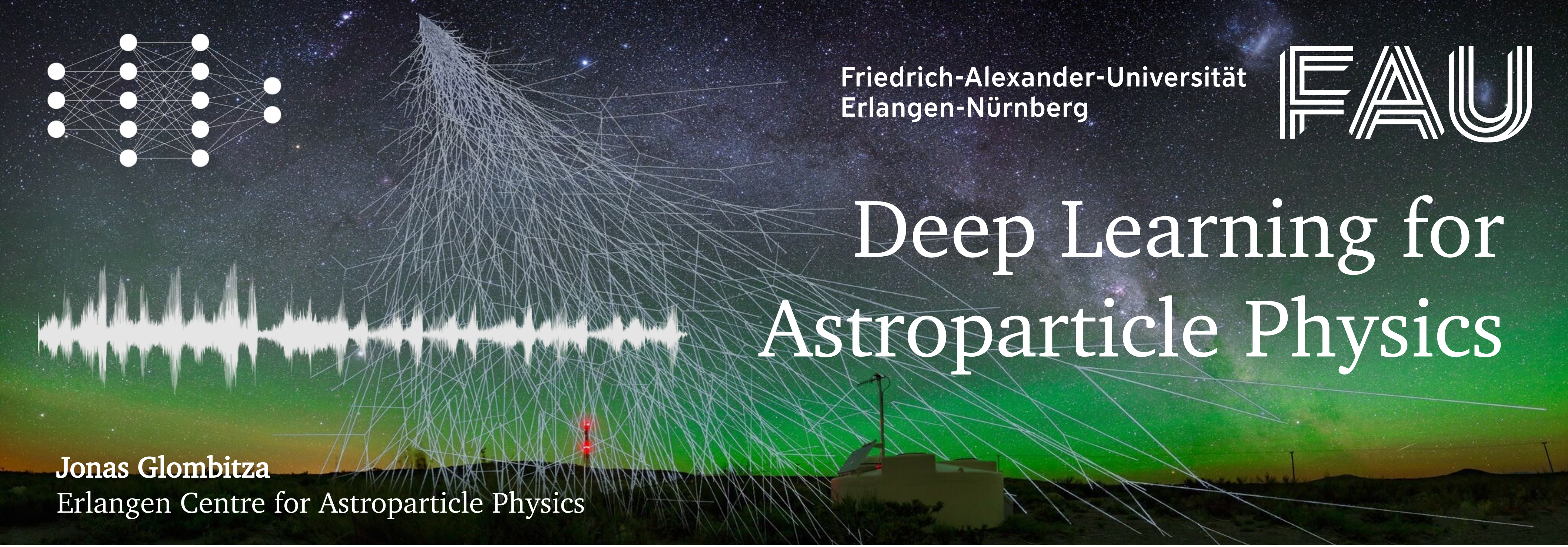
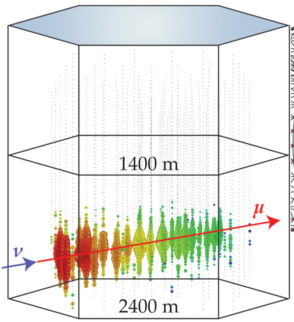
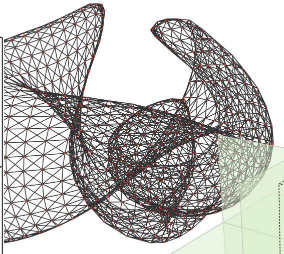


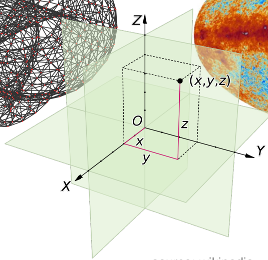
Friedrich-Alexander-Universität Erlangen-Nürnberg

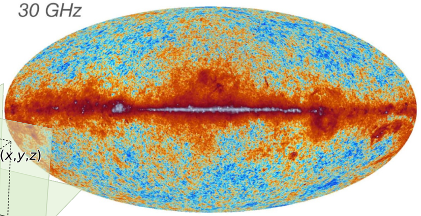
Deep Learning for Astroparticle Physics

Jonas Glombitza
Erlangen Centre for Astroparticle Physics

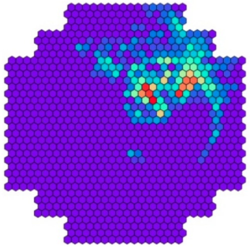


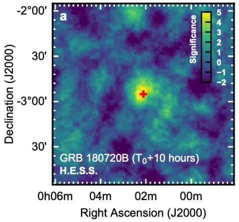






source: wikipedia





June 20, 2024

ERLANGEN CENTRE FOR ASTROPARTICLE PHYSICS
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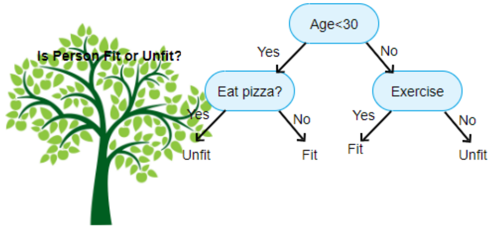
Federal Ministry of Education and Research

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

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

KÜNSTLICHE INTELLIGENZ

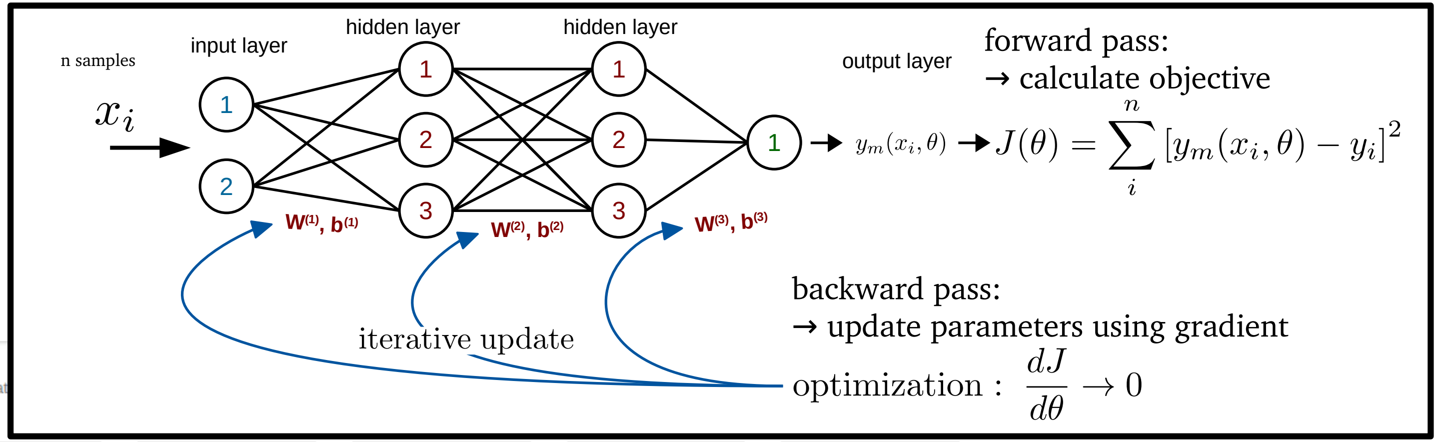
Schlau in zwei Stunden

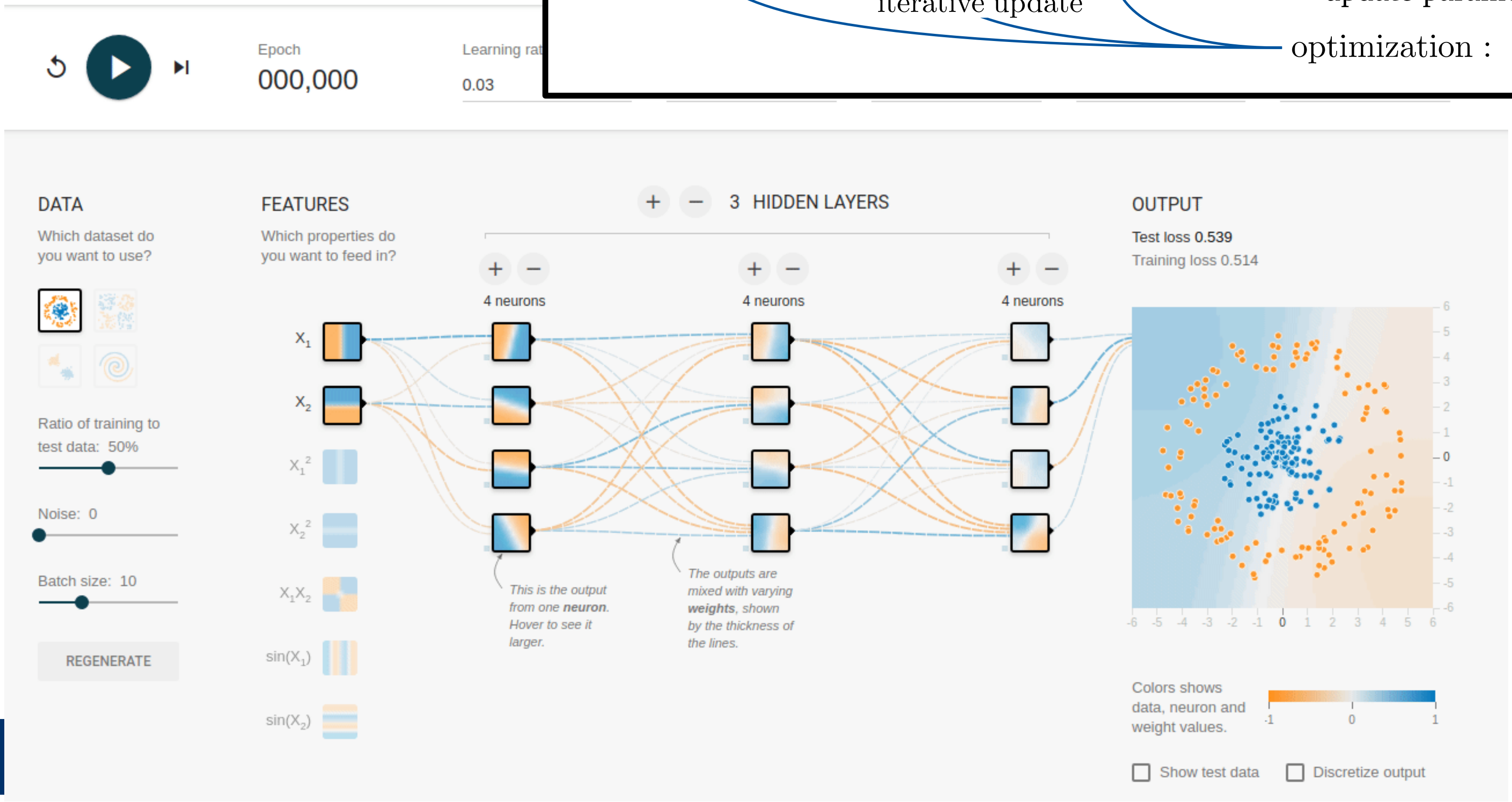
VON ALEXANDER ARMBRUSTER - AKTUALISIERT AM 27.09.2017

www.faz.net

© nature

Neural network training in a nutshell





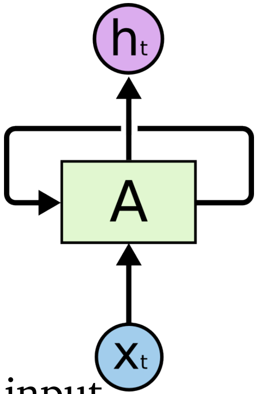
https://playground.tensorflow.org

Deep Learning: RNNs & CNNs

Recurrent Networks (RNNs)

- analyze sequential data (translation)
- recurrent definition of transformation

$$h^{(t)} = A(h^{(t-1)}, x^{(t)})$$



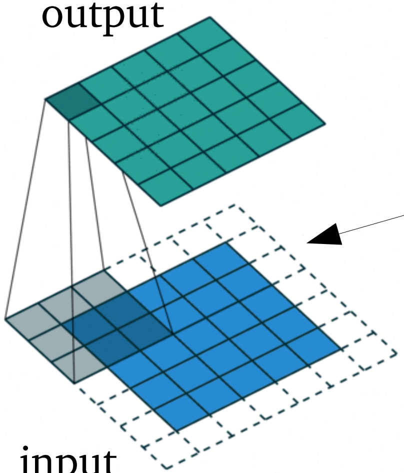
Advanced concept: LSTM

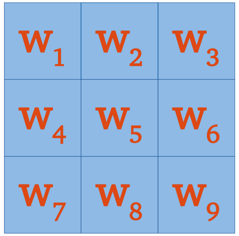
features memory

- long-rate correlations

Convolutional Networks (CNNs)

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

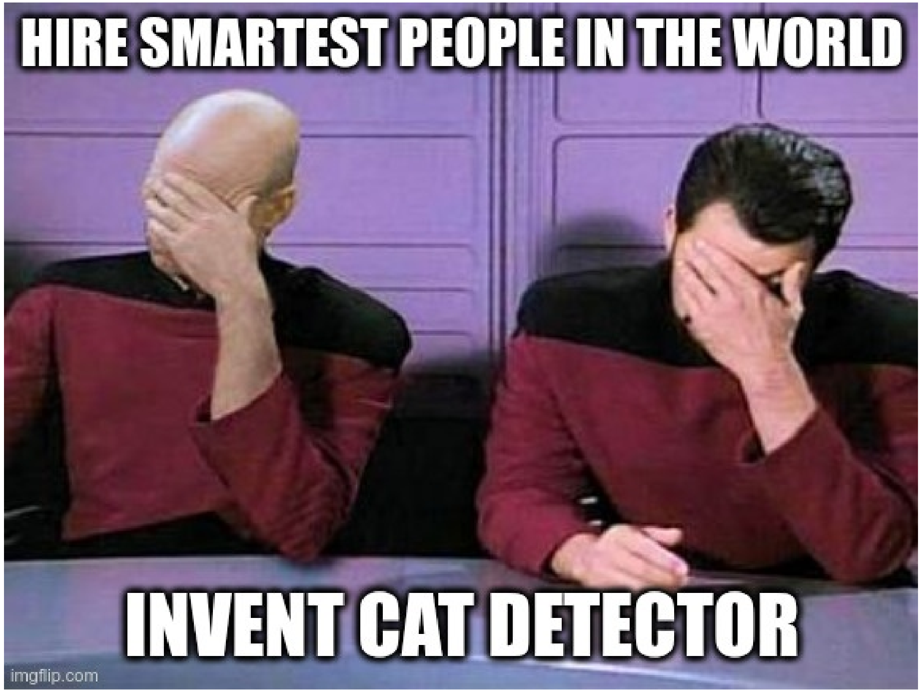




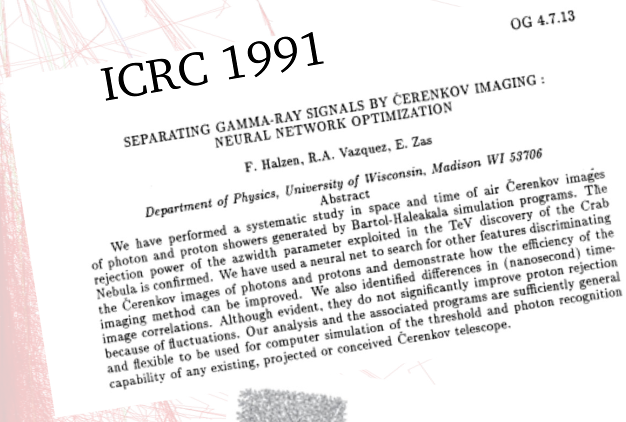
adaptive parameters of **filter**

What deep learning reached so far?

- Superhuman Go playing
- Improved add targeting
- Human-level image classification
- Improved search results on the web
- Realistic image generation
- Very improved chatbots



Machine Learning in Astroparticle Physics


ICRC 1991

OG 4.7.13

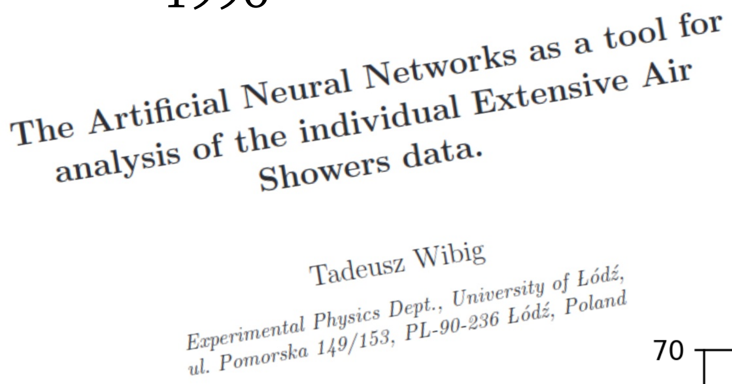
SEPARATING GAMMA-RAY SIGNALS BY ČERENKOV IMAGING : NEURAL NETWORK OPTIMIZATION

F. Halzen, R.A. Vazquez, E. Zas

Department of Physics, University of Wisconsin, Madison WI 53706

Abstract

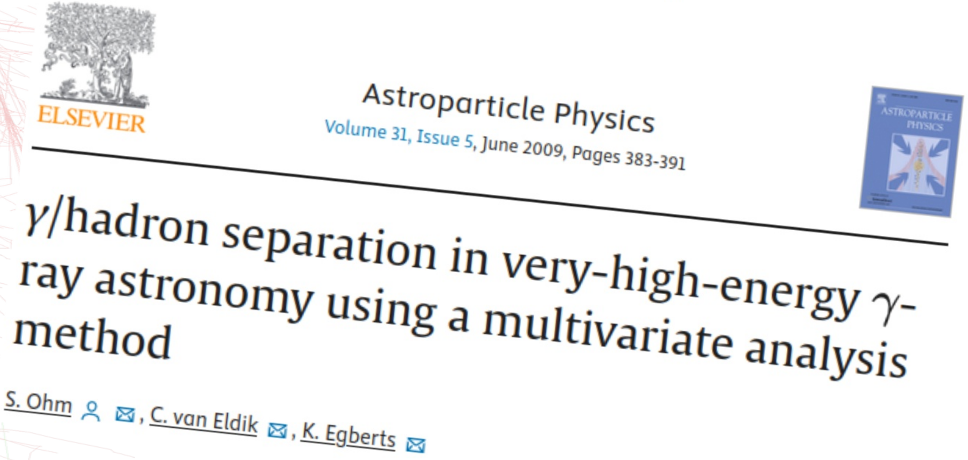
We have performed a systematic study in space and time of air Čerenkov images of photon and proton showers generated by Bartol-Haleakala simulation programs. The rejection power of the azwidth parameter exploited in the TeV discovery of the Crab Nebula is confirmed. We have used a neural net to search for other features discriminating the Čerenkov images of photons and protons and demonstrate how the efficiency of the imaging method can be improved. We also identified differences in (nanosecond) time-image correlations. Although evident, they do not significantly improve proton rejection because of fluctuations. Our analysis and the associated programs are sufficiently general and flexible to be used for computer simulation of the threshold and photon recognition capability of any existing, projected or conceived Čerenkov telescope.


1996

The Artificial Neural Networks as a tool for analysis of the individual Extensive Air Showers data.

Tadeusz Wibig

Experimental Physics Dept., University of Łódź, ul. Pomorska 149/153, PL-90-236 Łódź, Poland


ELSEVIER

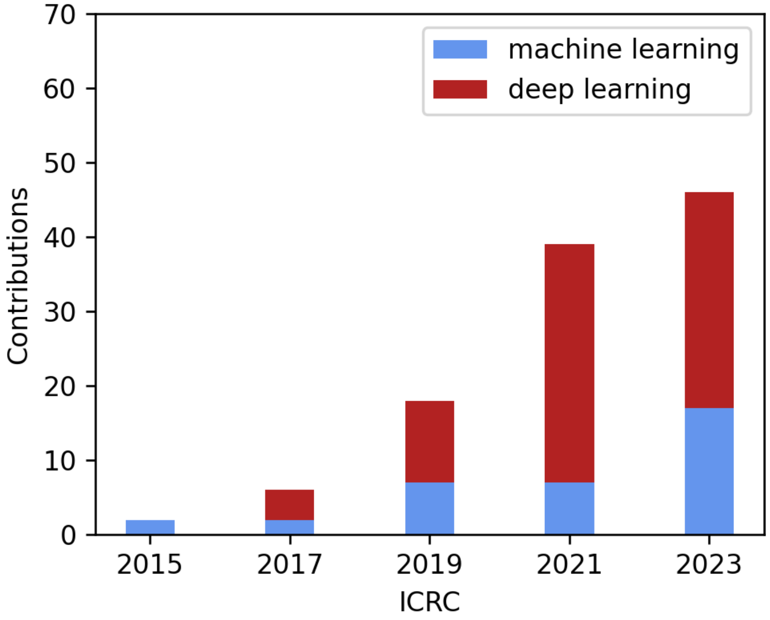
Astroparticle Physics

Volume 31, Issue 5, June 2009, Pages 383-391

γ/hadron separation in very-high-energy γ-ray astronomy using a multivariate analysis method

S. Ohm, C. van Eldik, K. Egberts

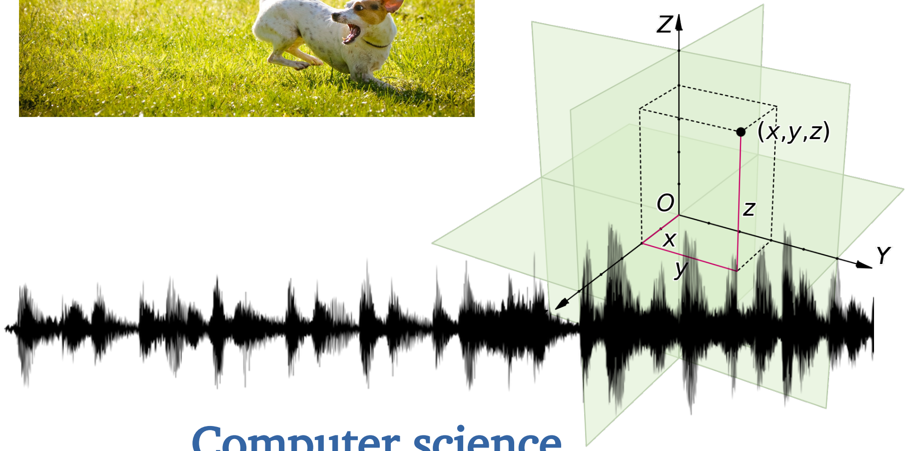
- Dates back to the 90s
- Recently became very popular



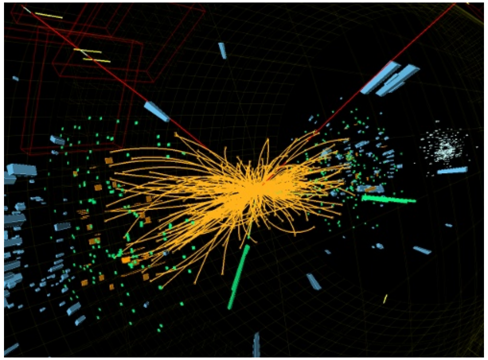
Application in Physics

Physics feature different data
Challenge: adapt algorithms from computer science to physics research

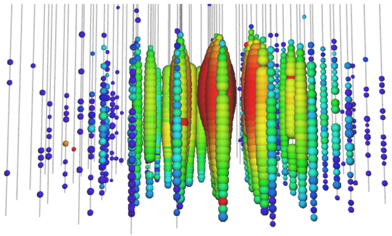
source: wikipedia



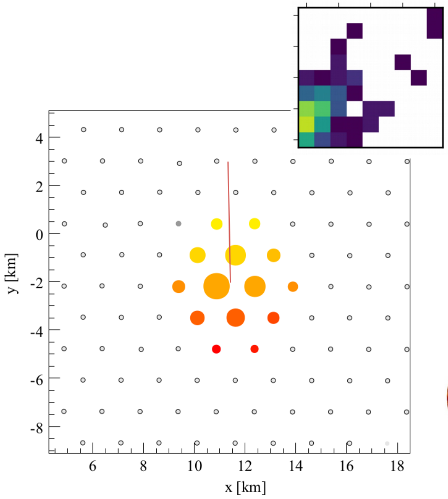
Computer science



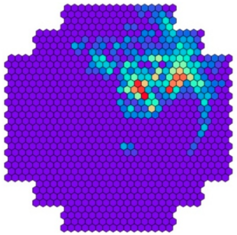
https://cds.cern.ch/record/2711418



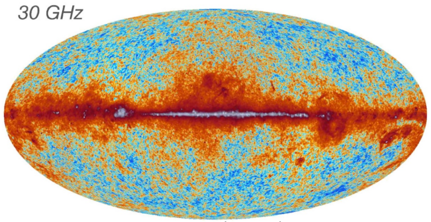
https://arxiv.org/abs/1309.7003



10.1016/j.nima.2015.06.058



10.1016/j.astropartphys.2018.10.003

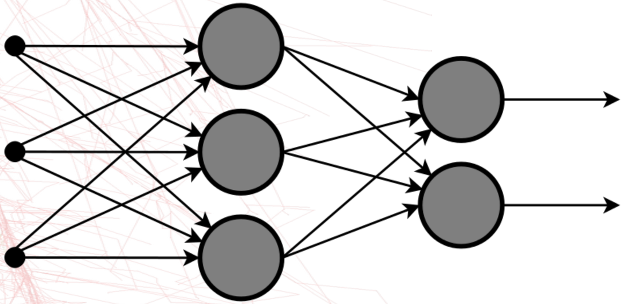


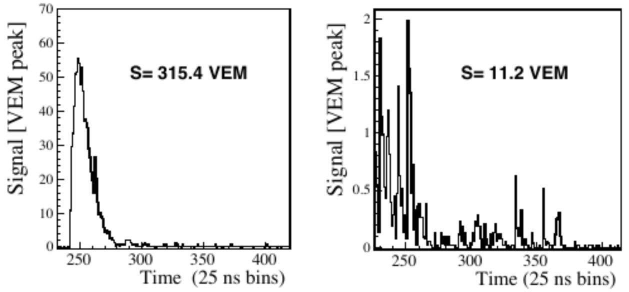
Astronomy and Astrophysics 641, p. 1 (2018)

Physics

Machine Learning to Deep Learning

- Air shower signals measured by surface detectors
  - disentangle muonic and em part at station level





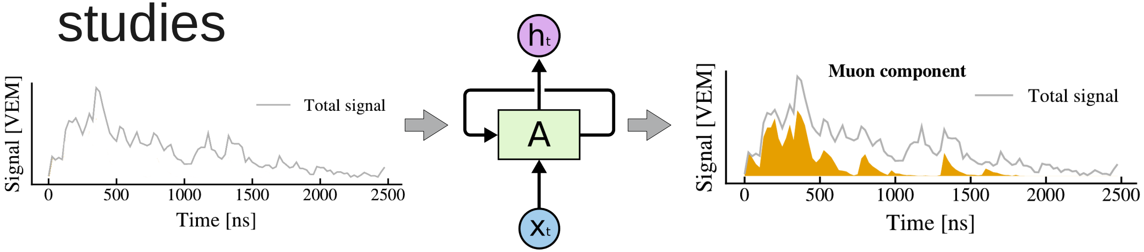
Traditional ML approach

- Extract <u>fraction</u> of muons measured by single station
- Feed physicist observables into a neural network

A. Gulillen et al., 10.1016/j.astropartphys.2019.03.001

Deep learning version

- Use RNN to extract <u>time-dependent signals</u> induced by muons
- Promising results for mass composition studies



Pierre Auger Collaboration, JINST 16 P07016 (2021)

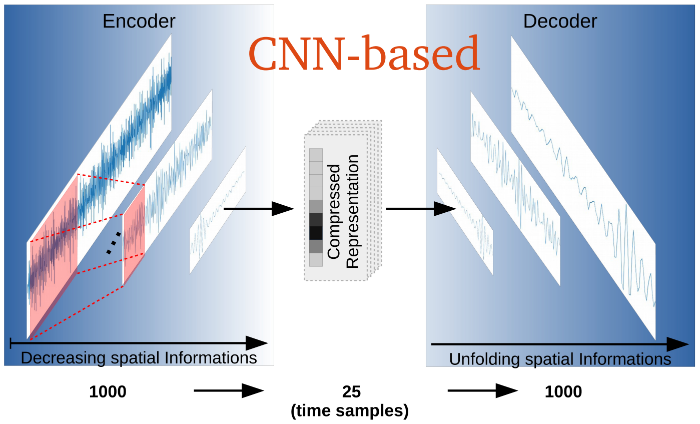
Denoising of Signal Traces (1D)

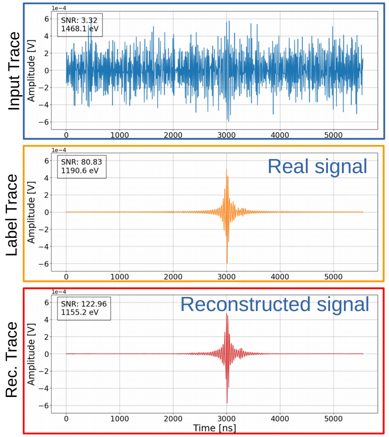
Supervised training of denoising autoencoders

- feature compressed space in between encoder and decoder
- ➔ encodes only relevant information in compressed space

Future application: bringing ML close to the sensor

Denoising of cosmic ray radio signals

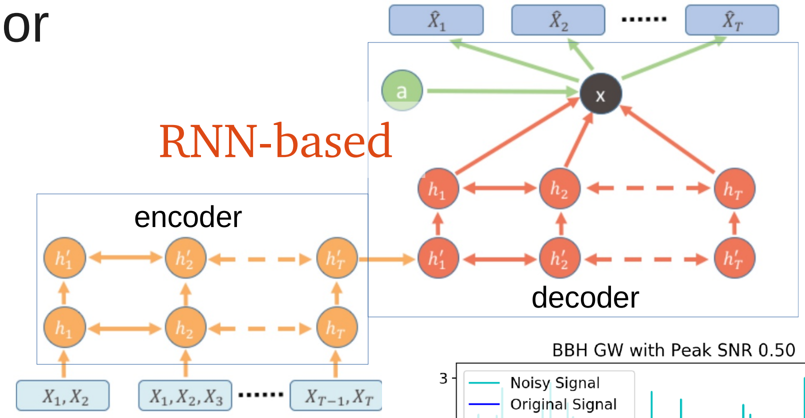


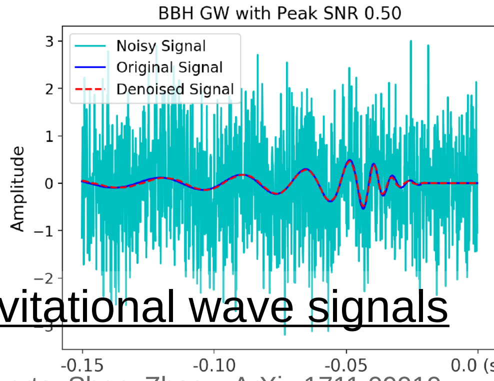


M. Erdmann et al. - 10.1088/1748-0221/14/04/P04005

A. Rehman et al., PoS ICRC2021 417

P. Bezyazeekov et al., ArXiv/2101.02943 & D. Shipilov et al., EPJ (2019) 02003

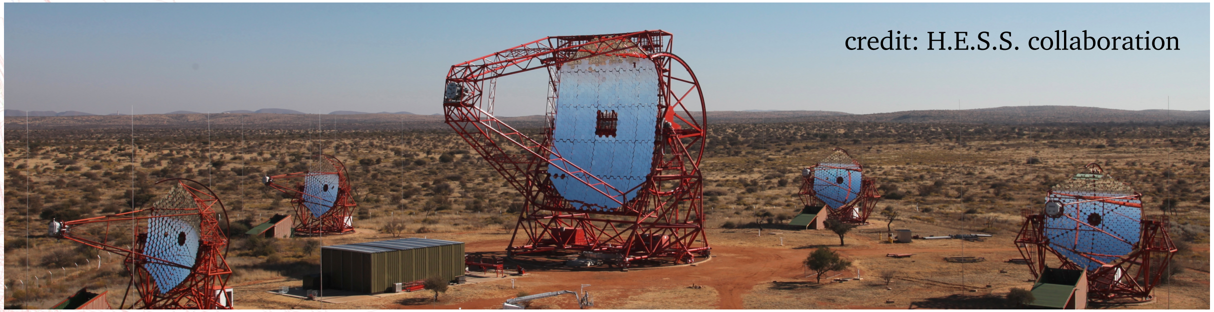


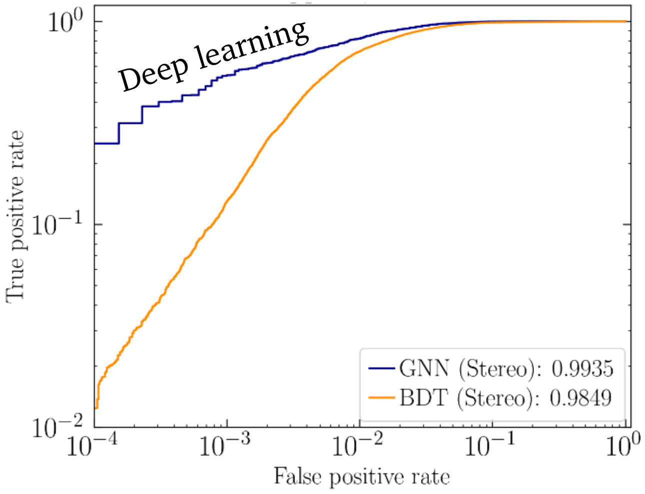


Denoising of gravitational wave signals

George, Huerta, Shen, Zhao – ArXiv 1711.09919

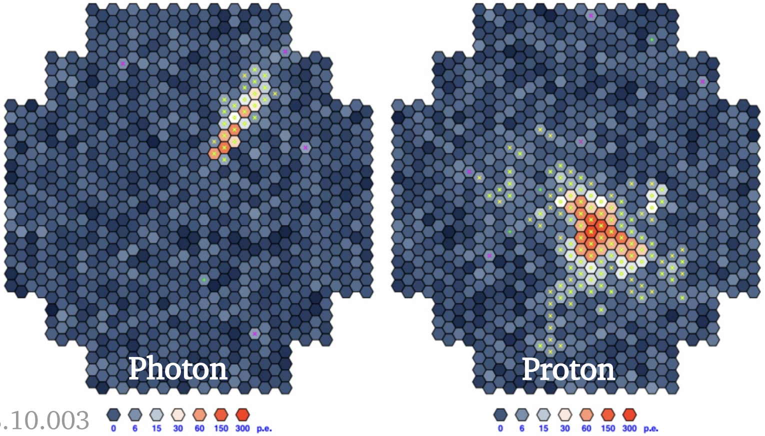
Deep Learning for IACTs





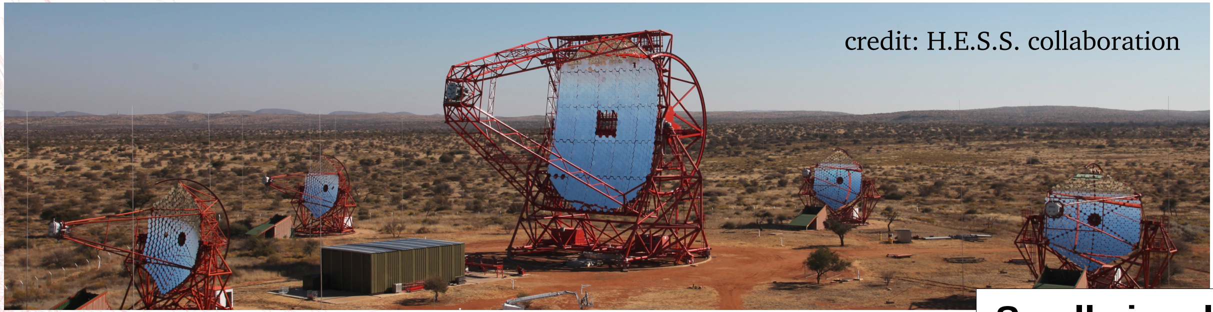
- Gamma ray telescopes in Namibia
- For each photon ~ $10^3 \rightarrow 10^4$ protons
  - Powerful rejection needed
- First promising results on simulations
  - Neural networks outperforms BDTs

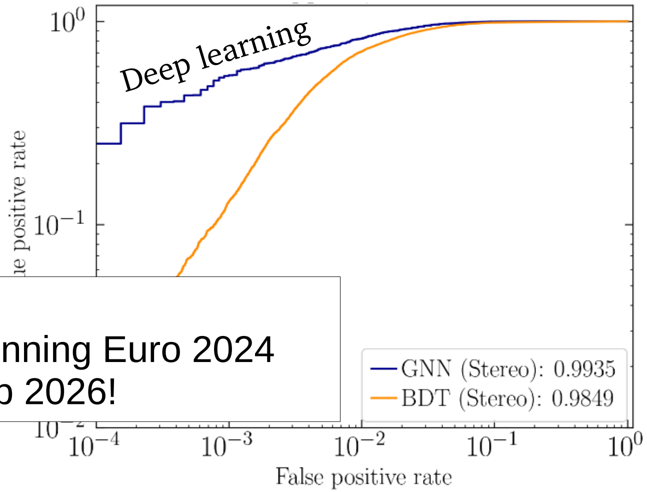
- Currently investigating stereoscopic models exploit telescope-telescope correlations
  - Standard reconstructions outperform DNNs



Shilon et al., 10.1016/j.astropartphys.2018.10.003
Glombitza et al, PoS(ICRC2023)715

Deep Learning for IACTs





Small signal!
Odds of of Italy winning Euro 2024 and the World Cup 2026!

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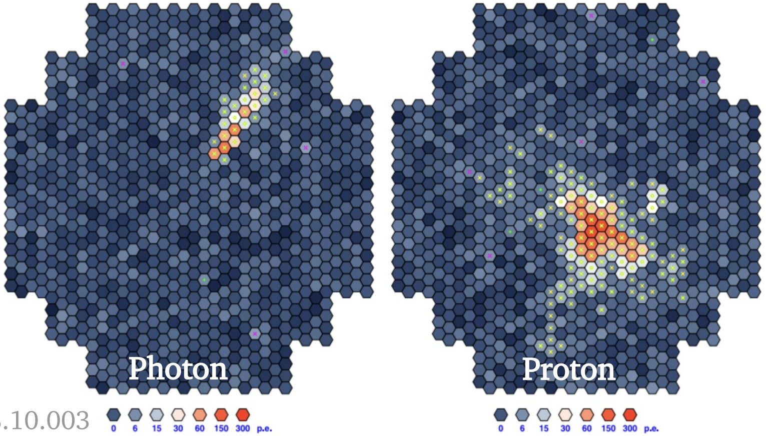
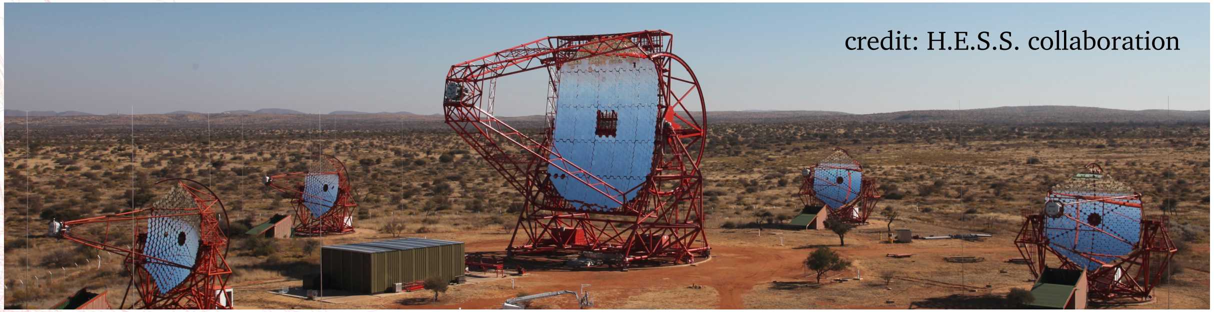
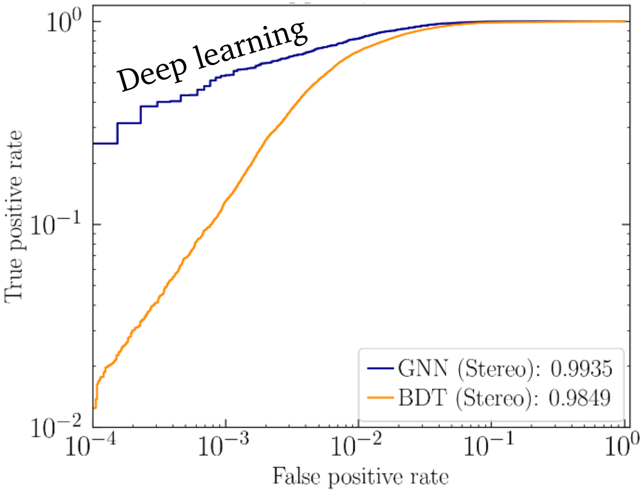


Shilon et al., 10.1016/j.astropartphys.2018.10.003
Glombitza et al, PoS(ICRC2023)715

Deep Learning for IACTs





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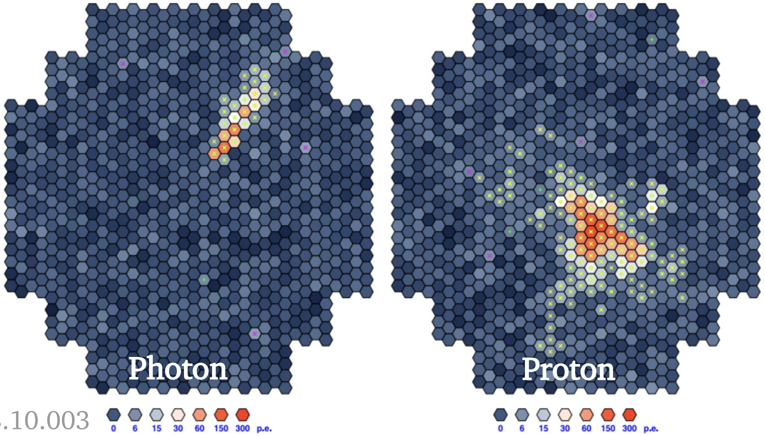
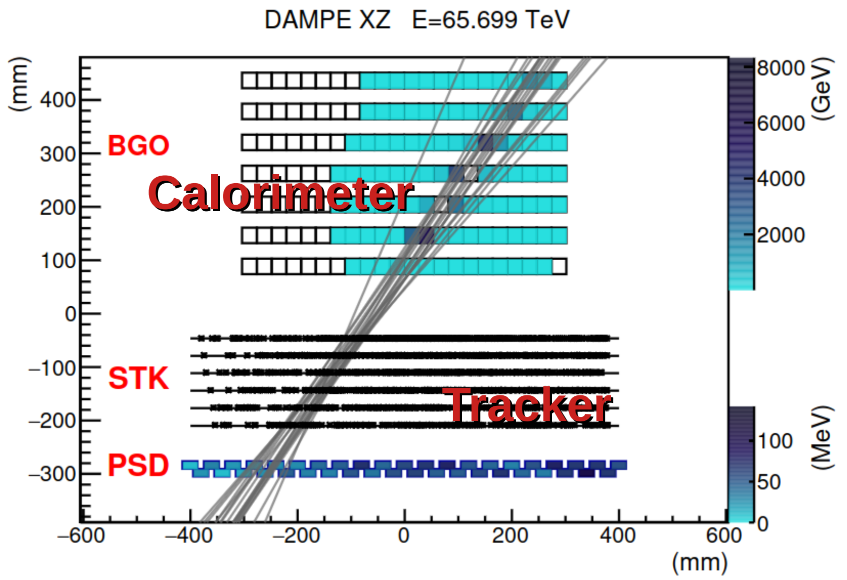


Shilon et al., 10.1016/j.astropartphys.2018.10.003
Glombitza et al, PoS(ICRC2023)715

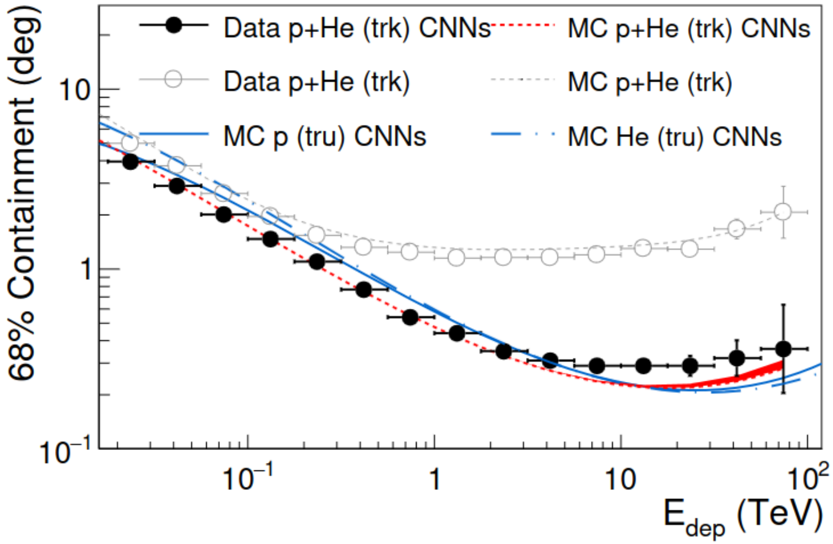
Tracking using DNNs at DAMPE

- DAMPE: cosmic-ray space mission
- Challenge: At high E calorimeter particles back-scatter into tracking
- Use calorimeter data and CNN to perform tracking (+ seed for tracker)



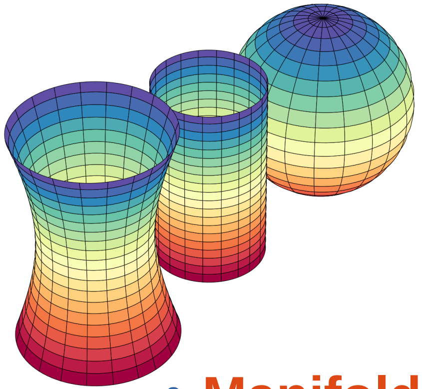
A. Tykhonov et al, Astropart. Phys. 146, 102795 (2023)

- Validation using events with clear tracker
- Significant improvement over classical method
- Increase tracking efficiency using tracker



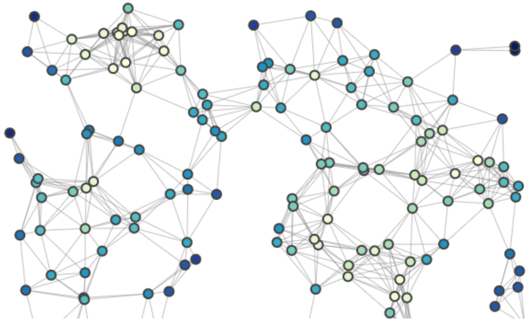
Non-Euclidean Domains

- Defining convolutions, challenging on non-euclidean domains
  - Deformation of filters, changing neighbor relations
  - Non-isometric connections on graphs



- **Manifolds**

source: wikipedia



- **Graphs**

source: Cody Marie Wild, Towards Data Science

How can we generalize convolutions?

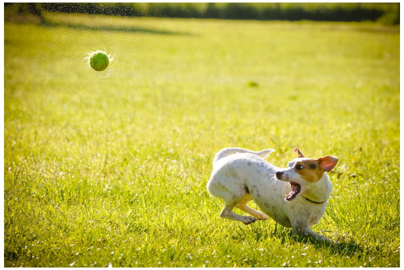
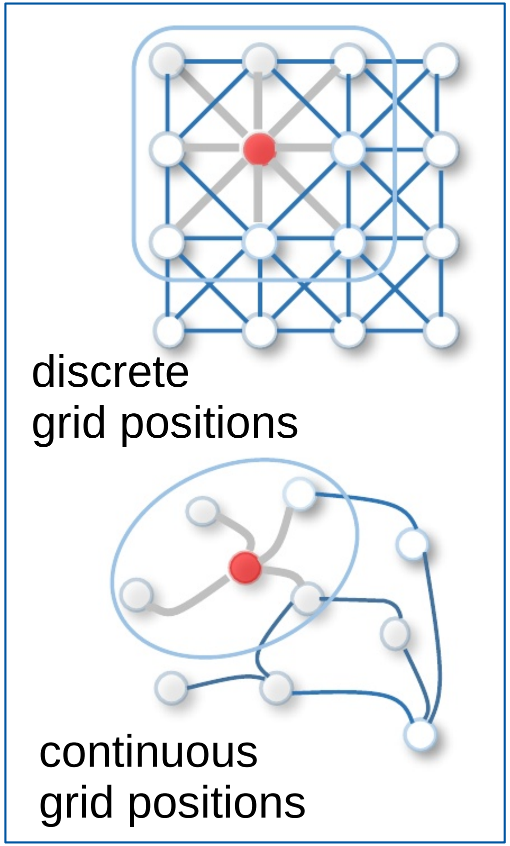


Image-like data

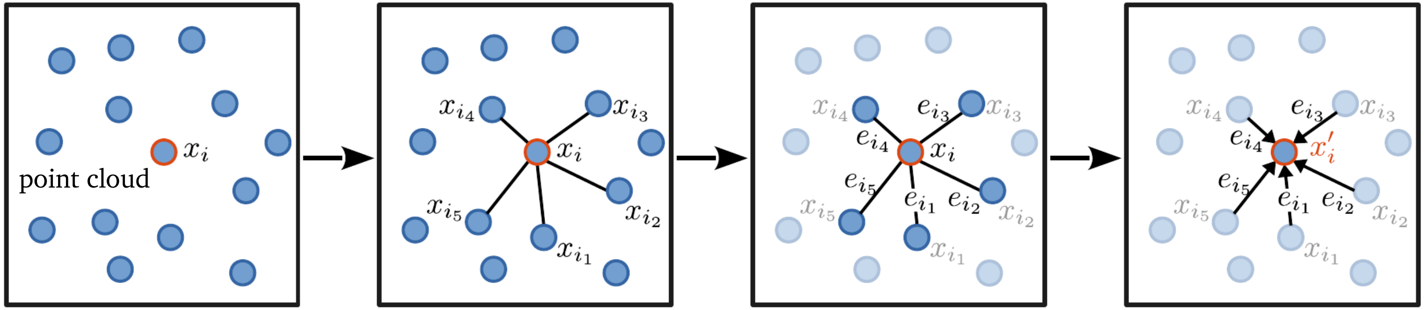
- collection of pixels (vector)
- coherent (rarely sparse)
- discrete, regular (symmetric)
- feature euclidean space

Graph Networks: Edge Convolutions

Y.Wang et al,
https://arxiv.org/abs/1801.07829



- Define graph/neighborhood → e.g., using kNN
- Apply continuous filter based on distances (filter → DNN)
  - flexible for many settings: irregular structures, point clouds



construction of directed graph

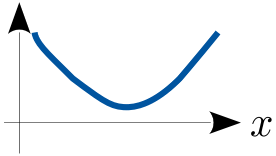
→ search k nearest neighbors

estimation of edge features

$$e_{i_j} = h_\theta(x_i, x_{i_j})$$

$h_\theta(x)$

approx. by DNN



aggregation over neighborhood

$$x_i' = \square_{j=1}^{k} e_{i_j}$$

e.g. $x_i' = \sum_{j=1}^{k} e_{i_j}$

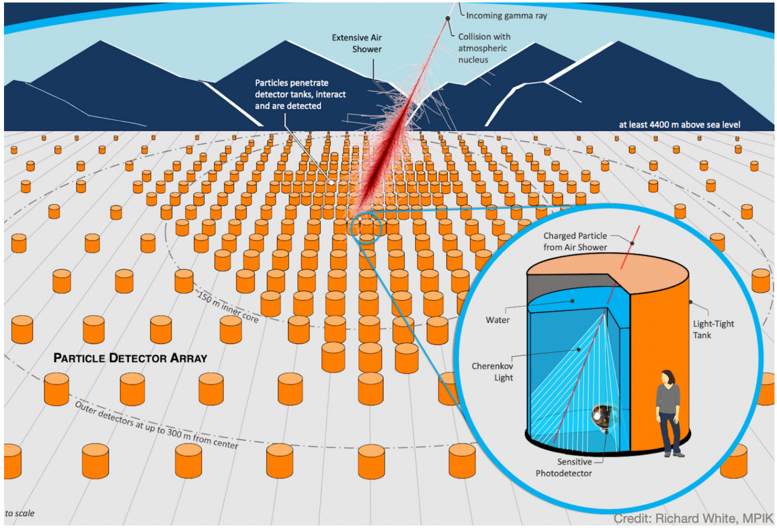
Deep Learning SWGO

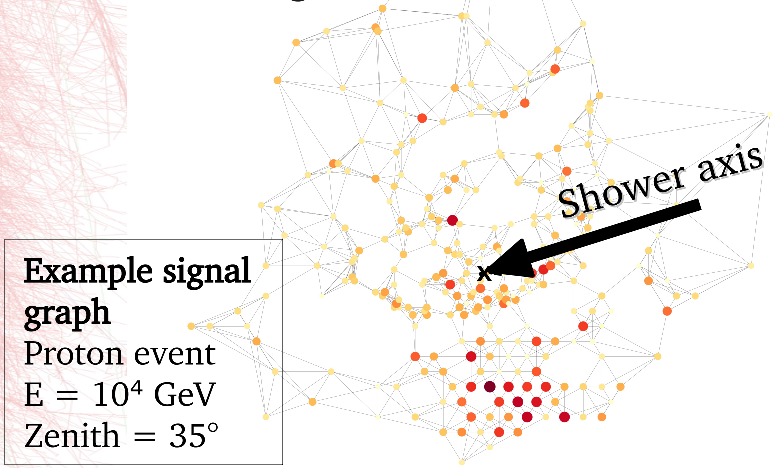
The Southern Wide-field Gamma-ray Observatory

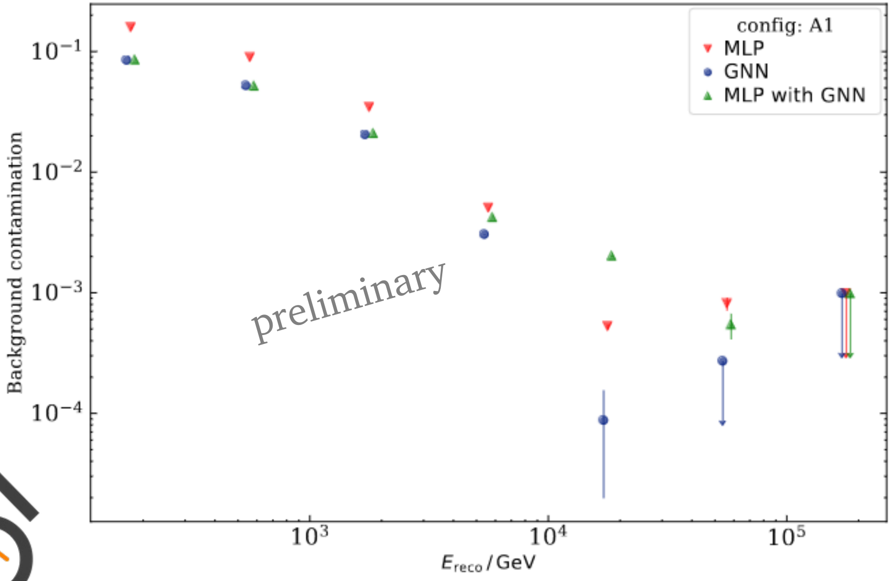
- Surface-detector-based gamma-ray observatory
  - Sensitivity: 100s GeV → PeV scale
- Feature different zones with different fill factors

Promising results: GCNs that well handle sparsity

- Superior than ensemble of all previous hand-designed observables



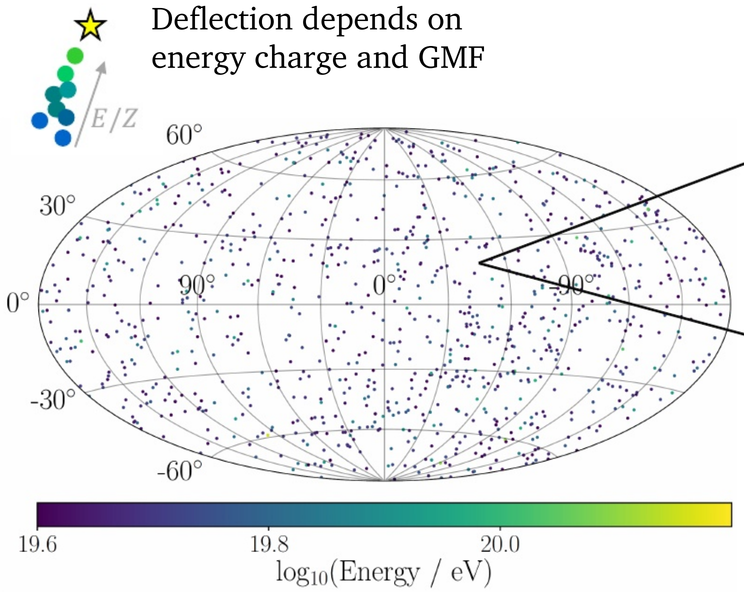




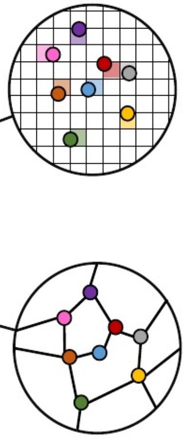
J.G., M. Schneider, F. Leitl, S. Funk, C. van Eldik

Search for UHECR Origins

Slide credit: Niklas Langner



Continuously distributed on **sphere**



sparse, spherical not suited for CNN

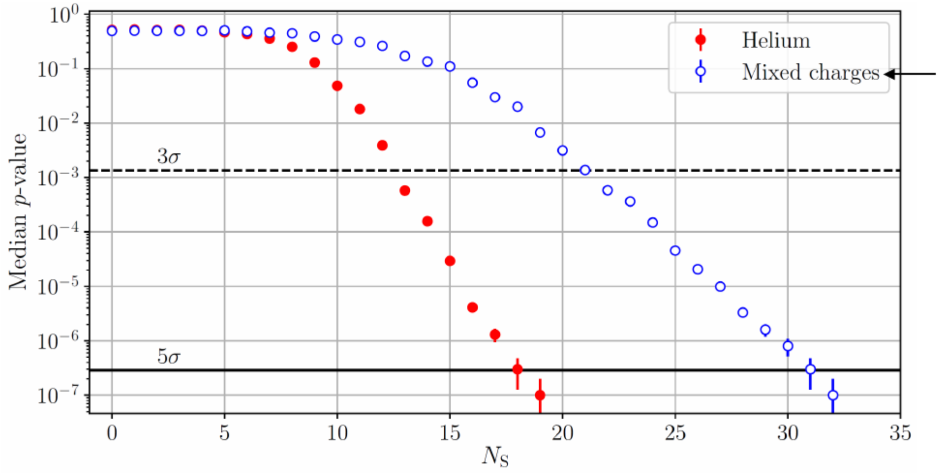
use Dynamic Graph Network

Situation:

<u>One</u> measured sky (spherical)

Learn to classify between

- isotropic sky / signal
- use dynamic edge convolutions

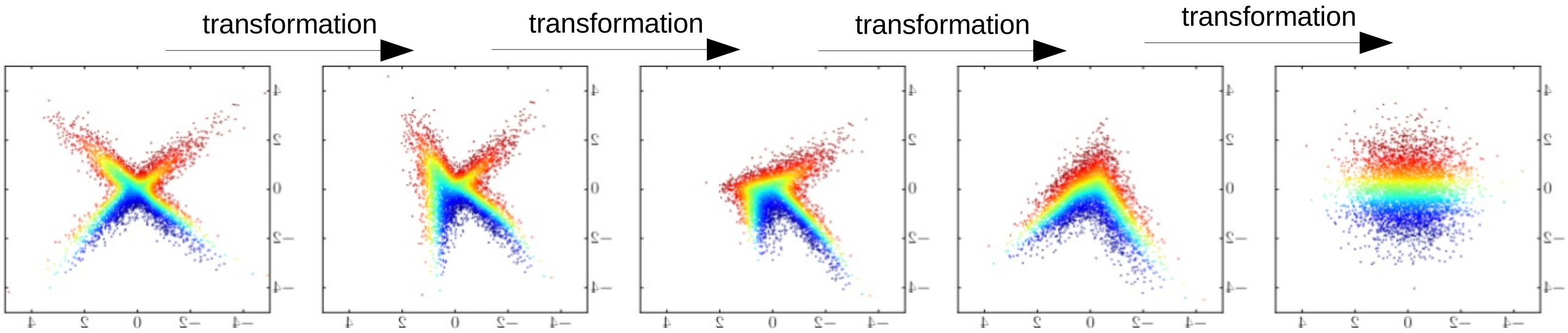


15% H
45% He
40% C, N, O

Bister et al., 10.1016/j.astropartphys.2020.102527

Normalizing Flows

Normalizing flows: stack several simple <u>invertible</u> mappings



training:

complicated distribution (e.g., natural images)

“Fit data distribution to match Gaussian”

→ Direct maximization of Likelihood!

simple distribution (e.g., Gaussian)

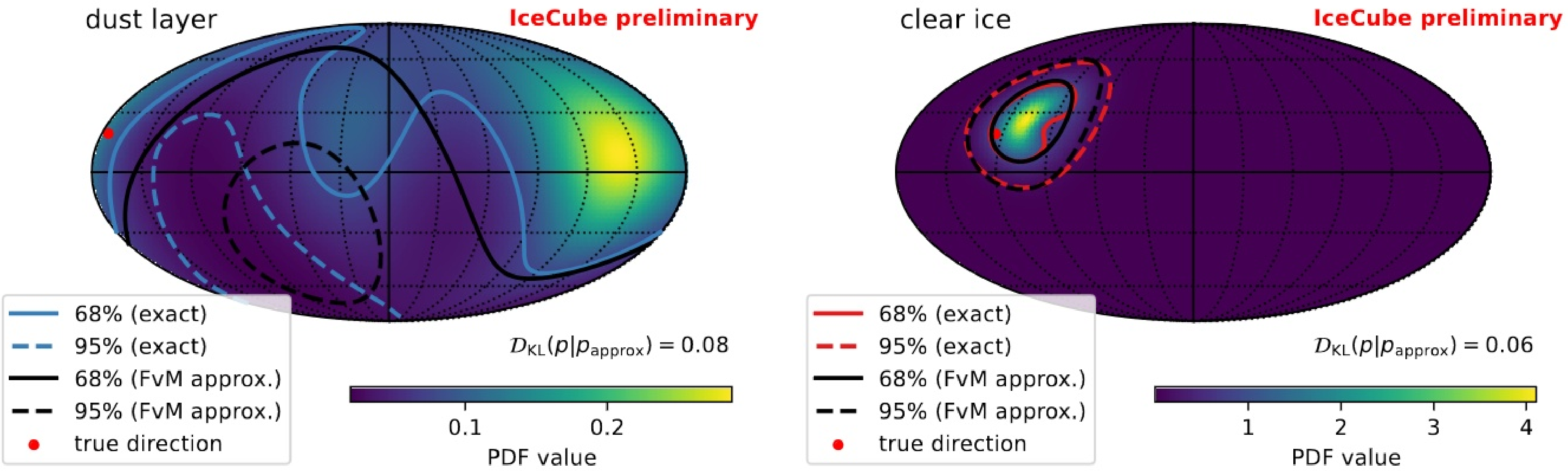
evaluation/ inference:

Since model invertible and distribution normalized

Revert direction → get samples proxy of complicated distribution

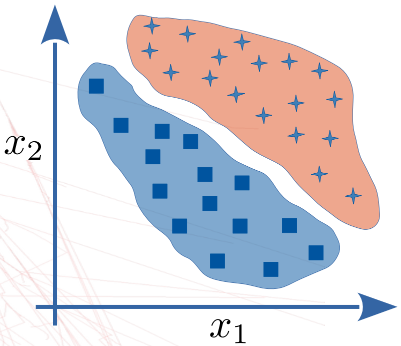
enables:
- fast generation of new samples (**direct density estimation**)
- reconstruction of objects, including uncertainty estimate

Normalizing flows at IceCube



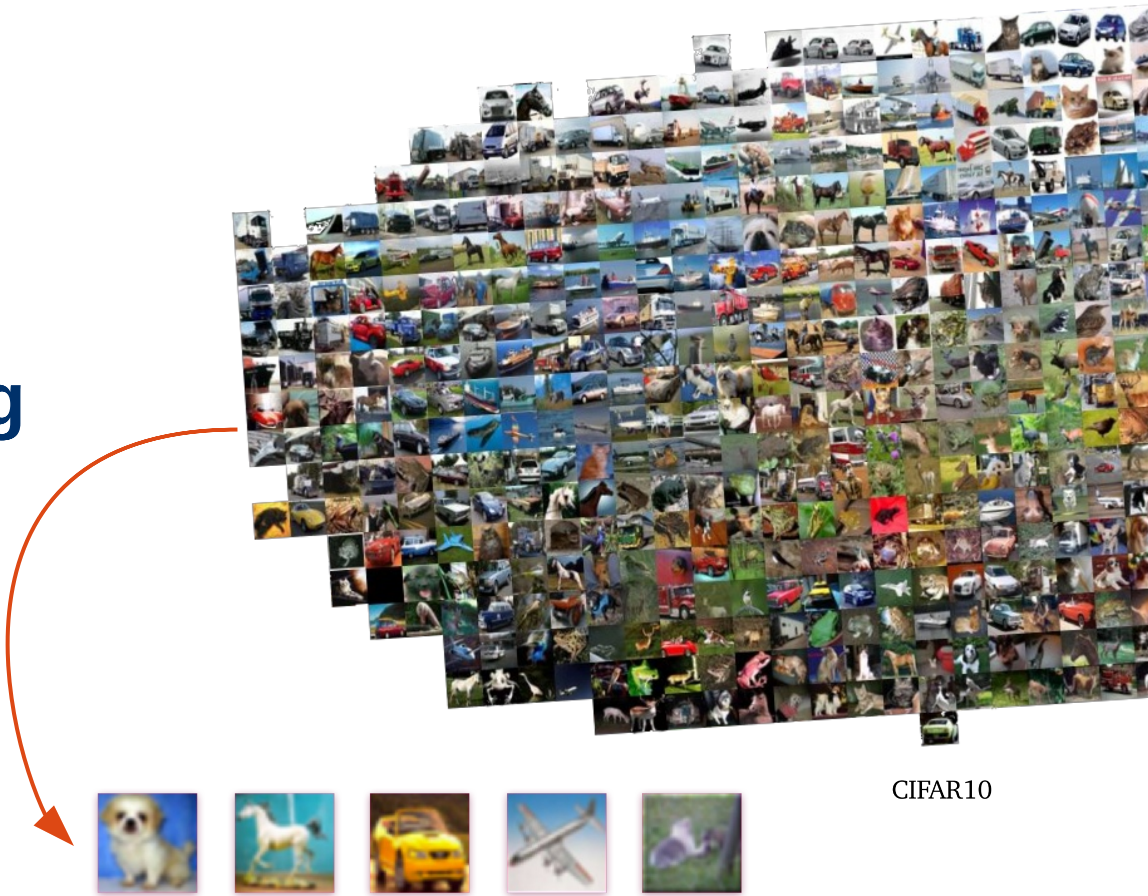
- Dust layer can affect reconstruction uncertainty → usually assumed symmetric
- Application of NF: uncertainty of neutrino arrival direction
  - Reconstruction conditions NF that maps to spherical surface → asymmetric uncertainties

PoS(ICRC2023)1003
Eur. Phys. J. C 84, 163 (2024)



Unsupervised Learning

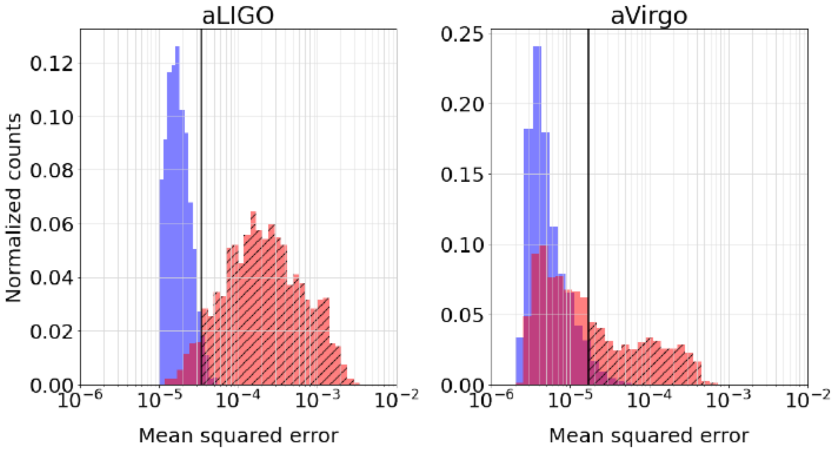
- Density estimation
- Anomaly detection
- Generative Models
- Simulation Refinement

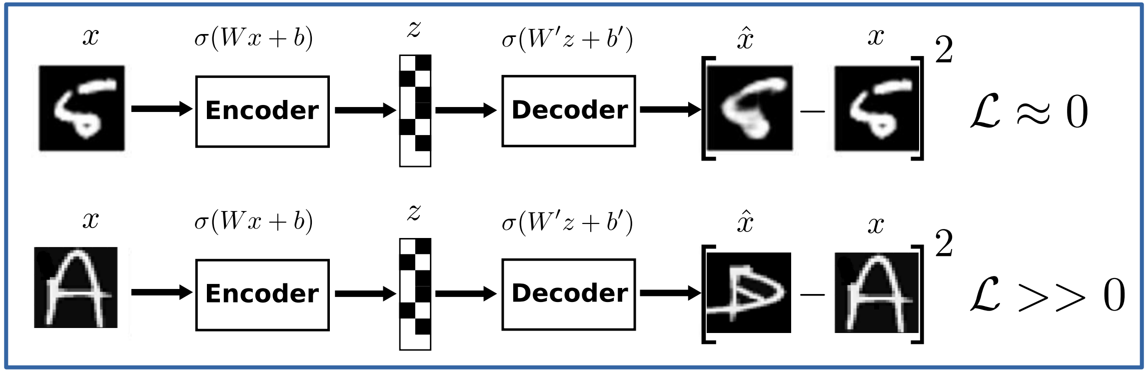


CIFAR10

Anomaly Detection

- Search for data, different than used for training, using autoencoders
- indication for new physics, proposed for BSM searches at LHC
- training without limited data (no signal labels)
  - first approaches in astroparticle physics
    - detection of gravitational waves





F. Morawski et al., Mach. Learn.: Sci. Technol. 2 045014

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

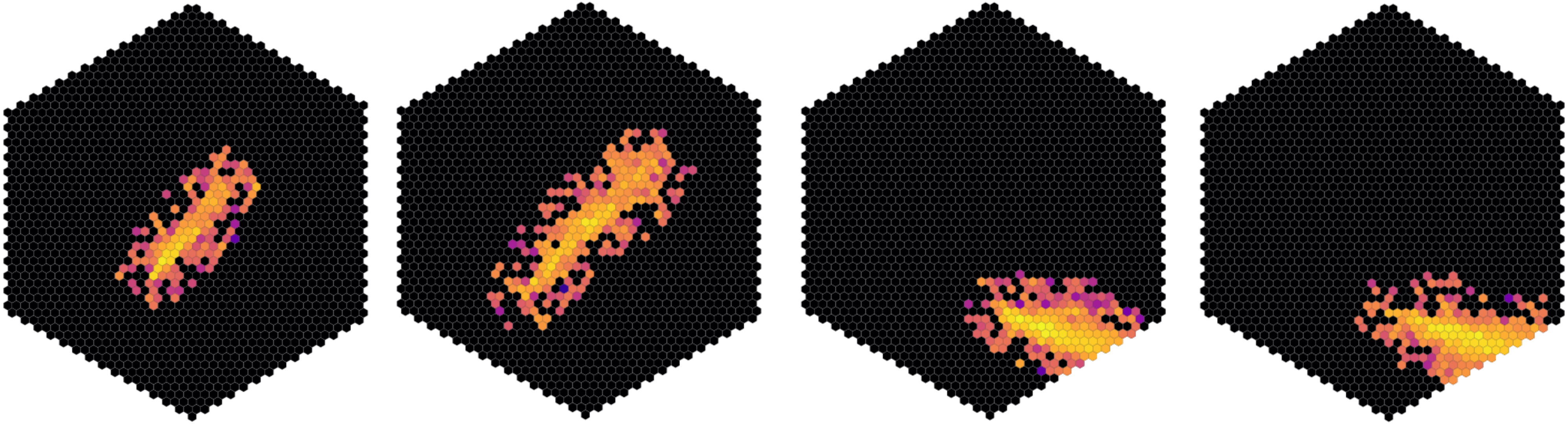
- generation of realistic images
- image feature local and global coherence
- realistic image super resolution

Which face is real?



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

Which generated IACT image is real?

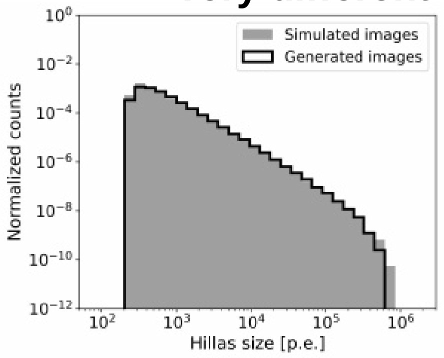


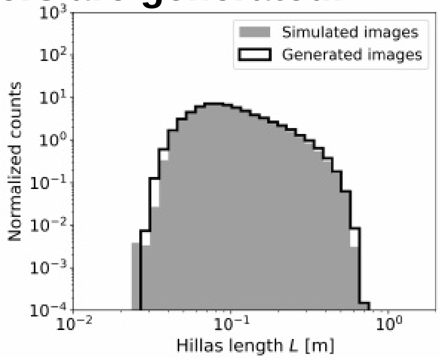
Imaging Air Cherenkov Telescope
Example simulated / generated for the CT5 telescope of the H.E.S.S. array

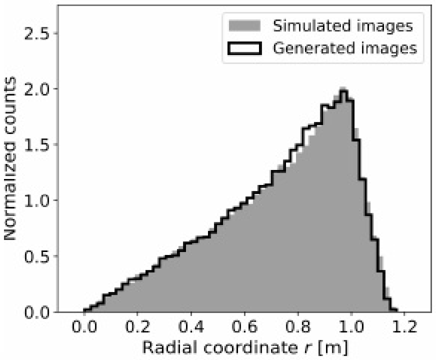
C.Elfein, S.Funk, J.G. arXiv:2311.01385

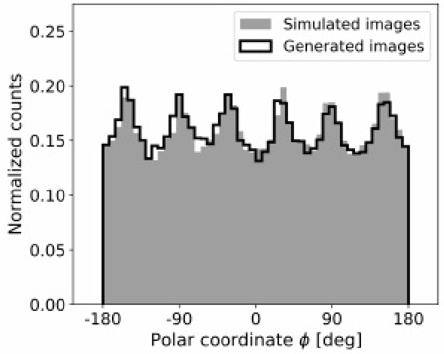
Hillas Parameter

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









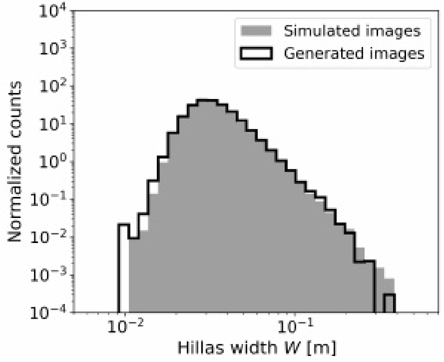
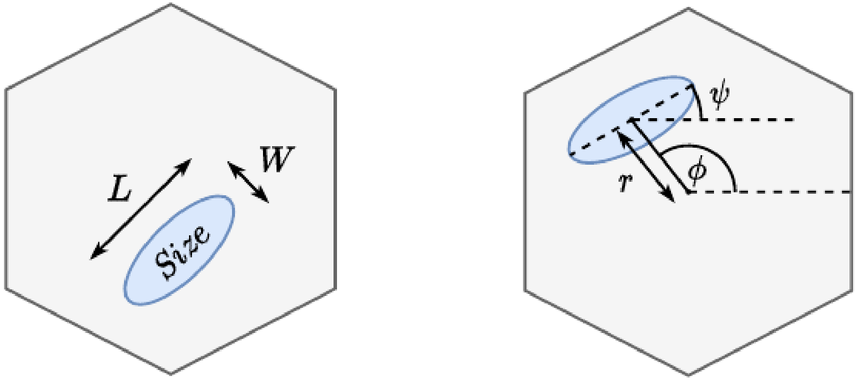
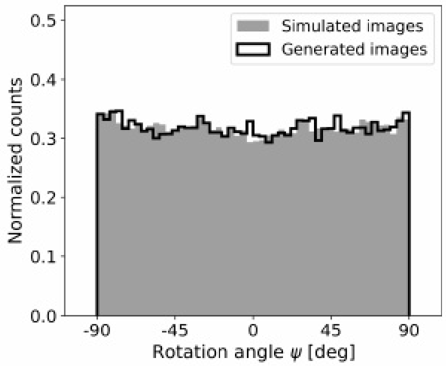


Image shape modeled well!

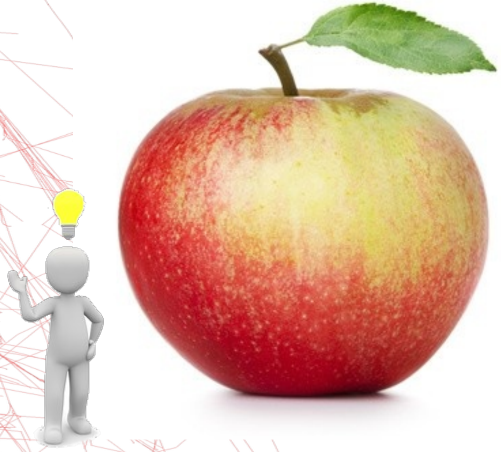


Investigate Hillas parametrization
→ traditionally used for event reconstruction



Full camera used
→ Very different geometries

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



Generalization Capacities on Data

DNNs and Domain Adaption

I. models are trained using physics simulations

II. trained models are applied to data

- ➔ can lead to reconstruction biases

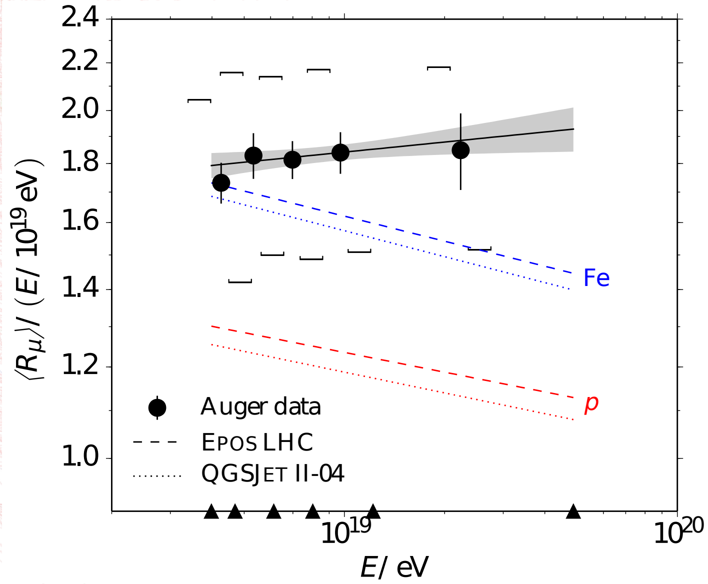
style transfer

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

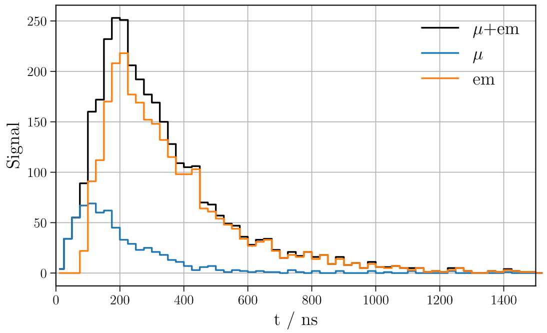
Domain Adaption

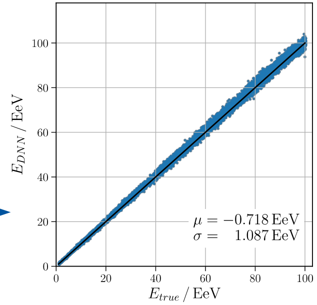
Comput Softw Big Sci (2018) 2: 4

- model trained on simulation but applied on data
- observation of muon excess in measured air-shower data
- can lead to reconstruction bias



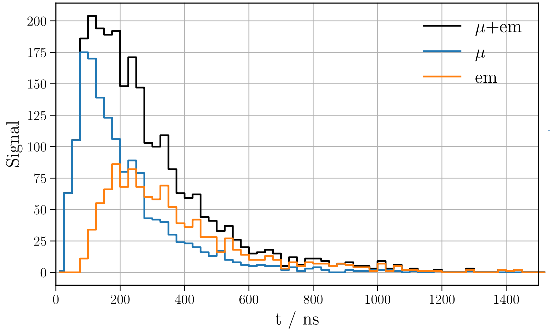
Simulation
70% electromagnetic
30% muonic

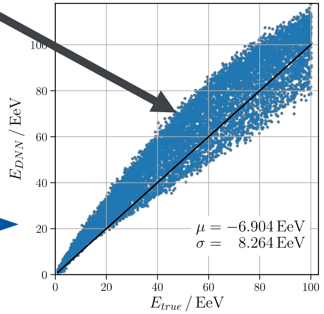




Network can not handle modified traces

'Data'
30% electromagnetic
70% muonic



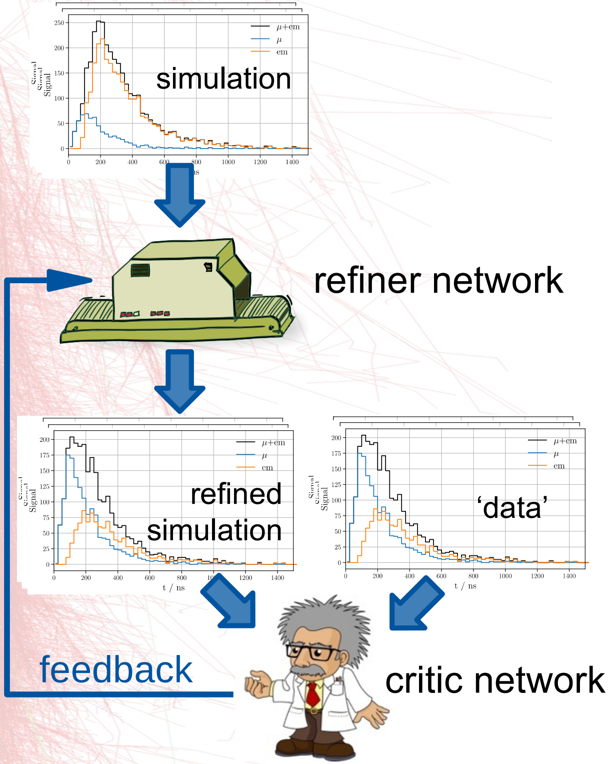


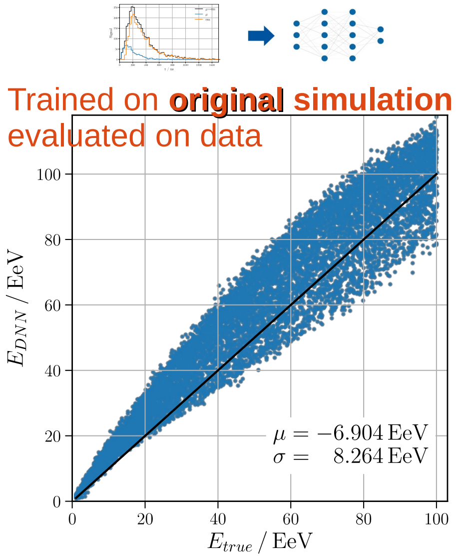
Simulation Refinement

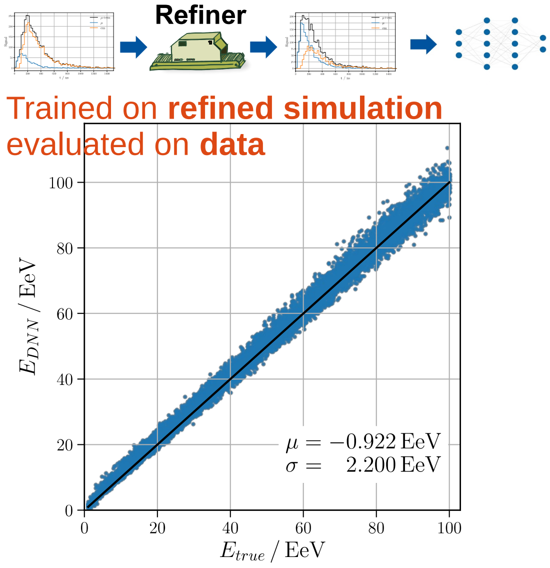
Erdmann et al.
Comput Softw Big Sci (2018) 2: 4

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

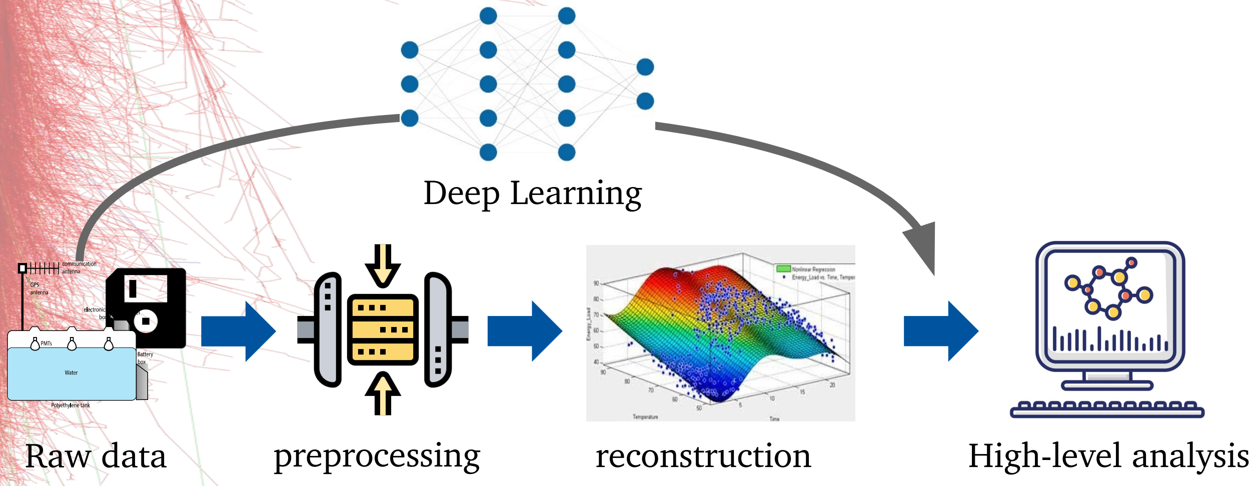


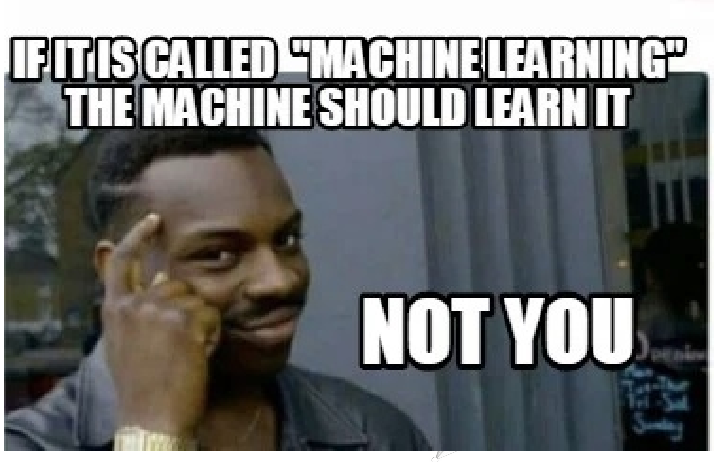


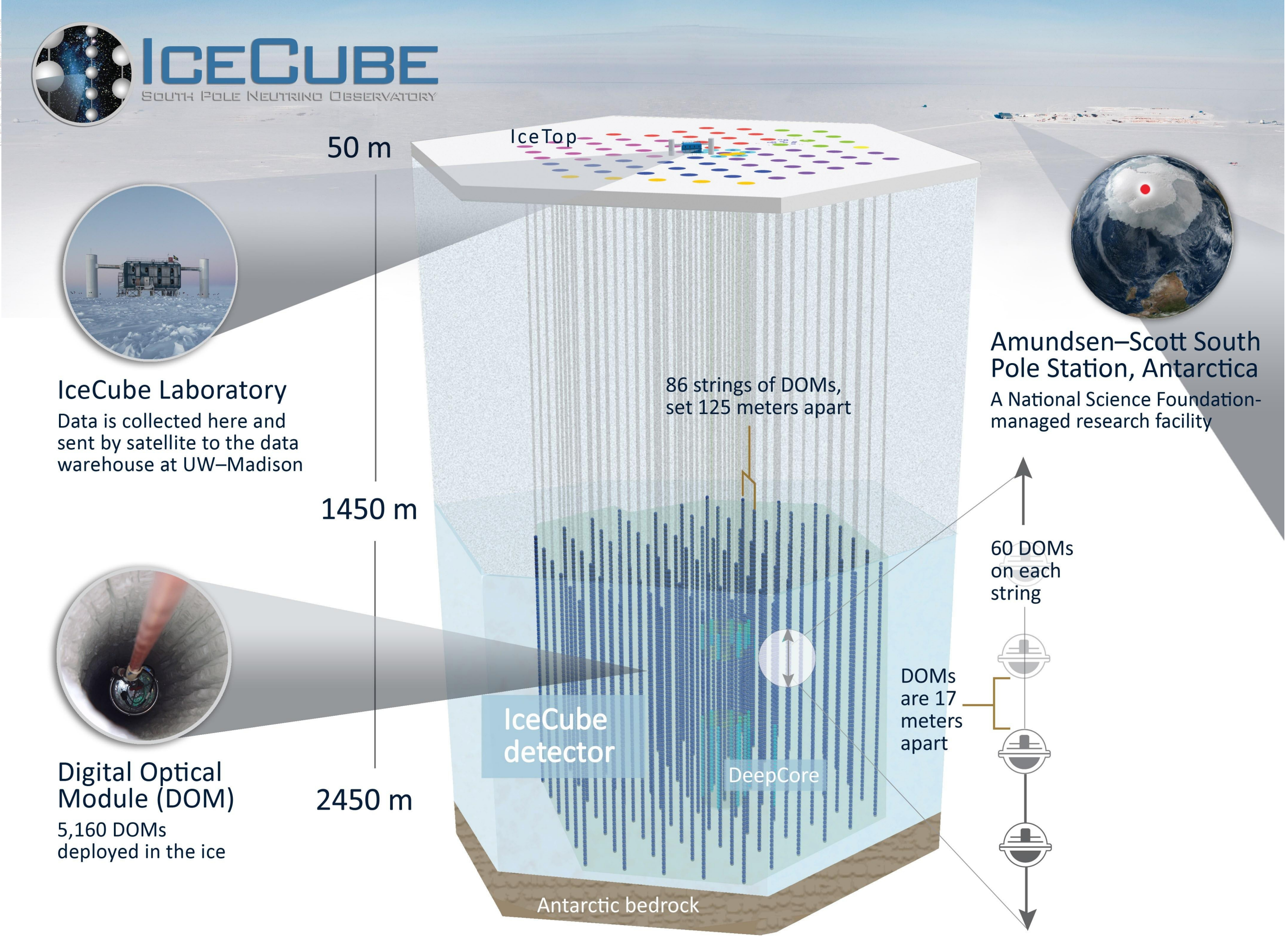


Physics Results
& application to measurement data

Astroparticle physics analysis → based on deep learning





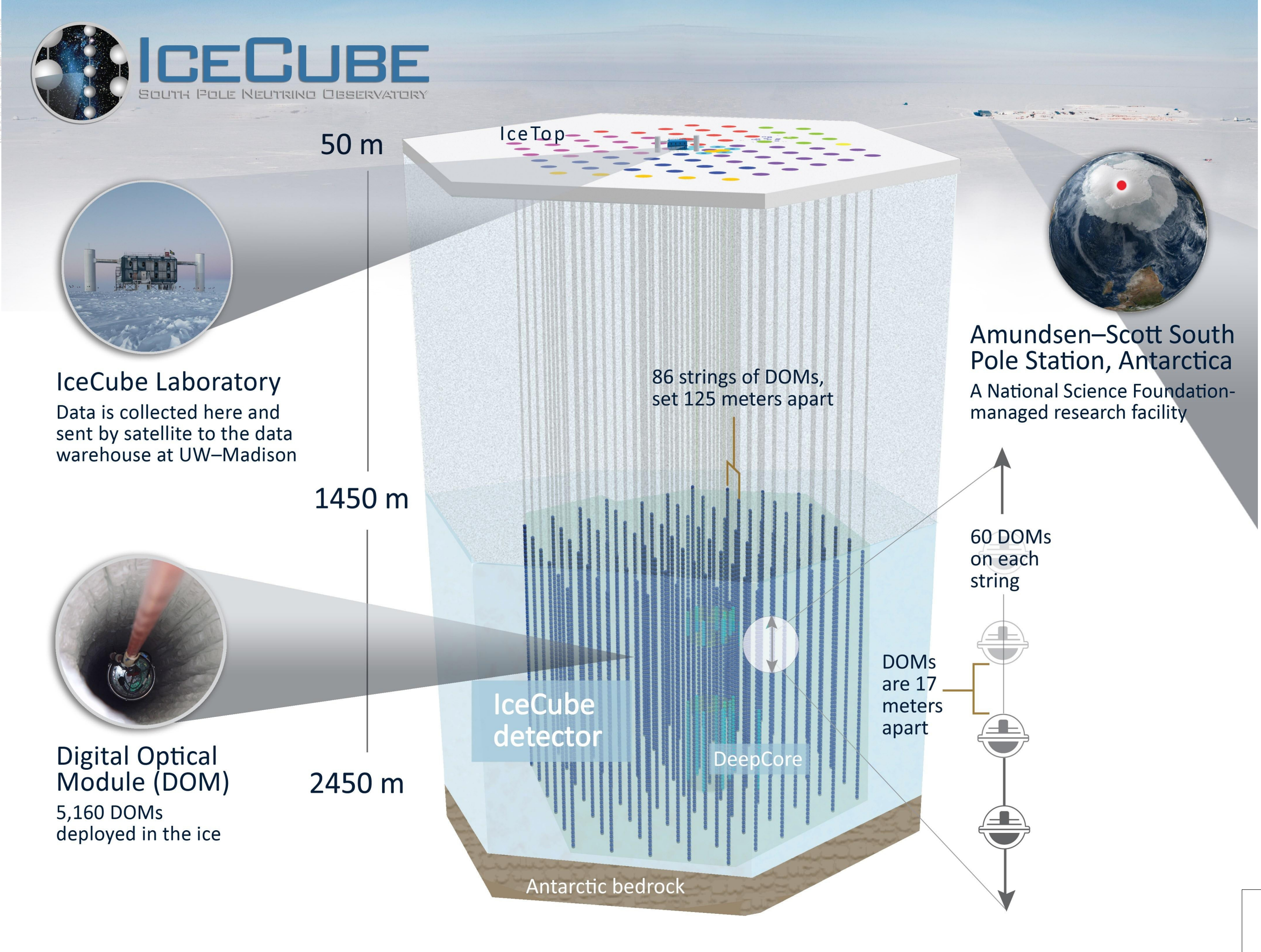


- Instrumented km³ of ice
- Detect astrophysical neutrinos (>1TeV)
- DOMs detect time resolved signals (Cherenkov light)

Challenging background

- Atmospheric muons/neutrinos
- Per single astrophysical neutrino → 10^8 bkg. events

Science 361, 147-151 (2018)
Science 378, 538-543 (2022)
Nature 591, 220-224 (2021)
Astrophys.J. 833 (2016) no.1, 3



- Instrumented km³ of ice
- Detect astrophysical neutrinos (>1TeV)
- DOMs detect time resolved signals (Cherenkov light)

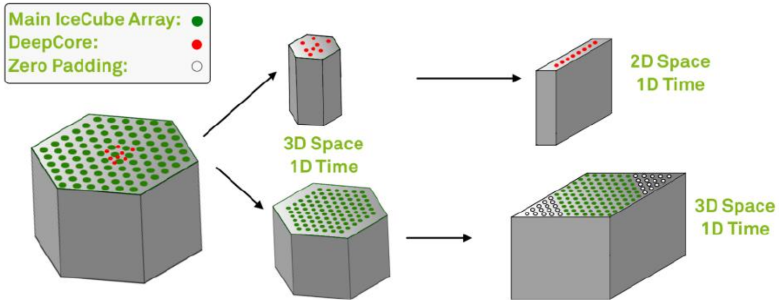
Challenging background

- Atmospheric muons/neutrinos
- Per single astrophysical neutrino → 10^8 bkg. events

Odds for being killed by a vending machine: 1.2 * 10^8

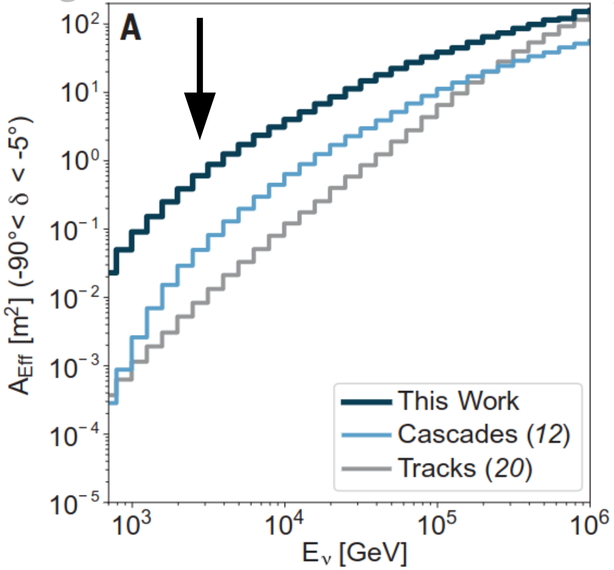
Science 361, 147-151 (2018)
Science 378, 538-543 (2022)
Nature 591, 220-224 (2021)
Astrophys.J. 833 (2016) no.1, 3

Improvement: data-driven techniques



Final sample:
87% atmospheric neutrinos
7% astrophysical neutrinos
6% atmospheric muons

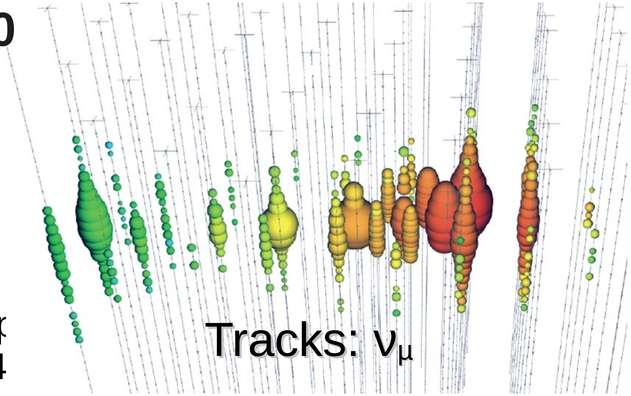
Deep learning: events x20!

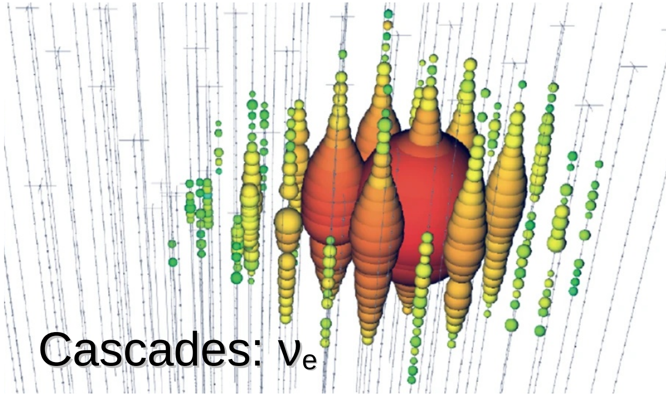


Analysis of cascade events

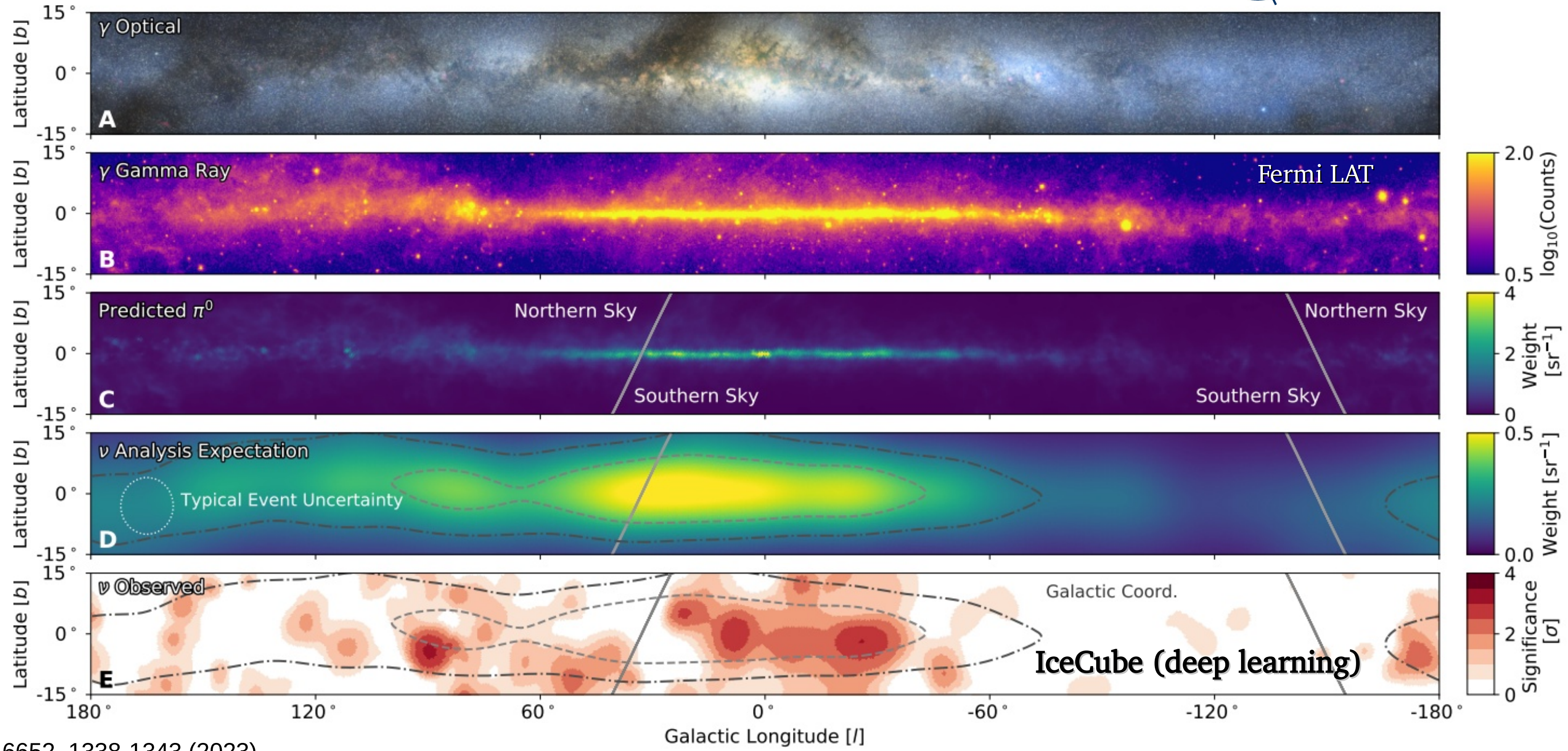
- Improved rejection of atmospheric muons (CNN based)
- Improved reconstruction of cascade events (NN + MLE)
- Reconstruct partially-contained events
- **Statistics increase x20**

[1] M. Hünnefeld et al., PoS(ICRC2017)1057
[2] A. Aiello et al., JINST 15 (2020) P10005
[3] R. Abbasi et al., JINST 16 (2021) P07041
[4] M. Hünnefeld et al., PoS(ICRC2021)1065





The Galactic Plane

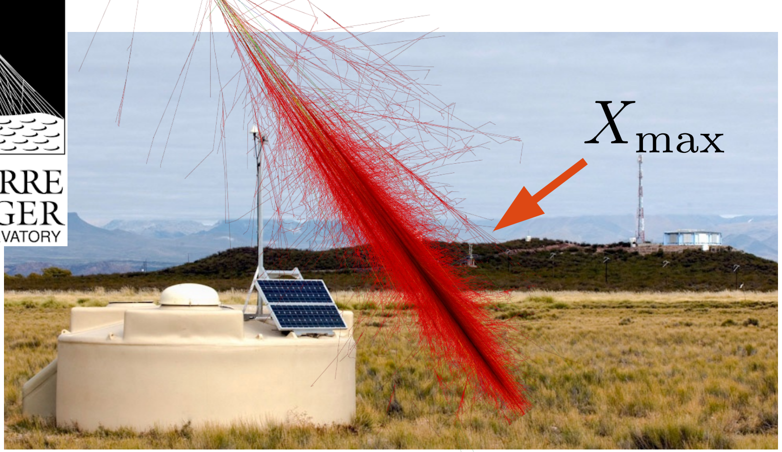


Science 380, 6652, 1338-1343 (2023)

- Comparison to Gamma-ray catalog
- 4.5σ significance (scrambling w. right ascension)

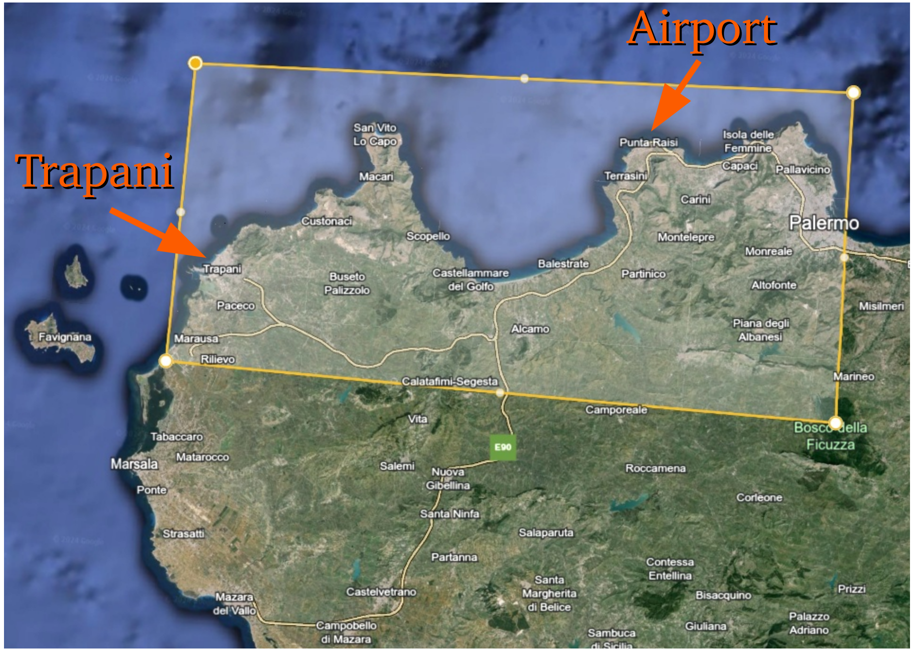
Evidence for diffuse neutrino emission from Galactic plane!

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



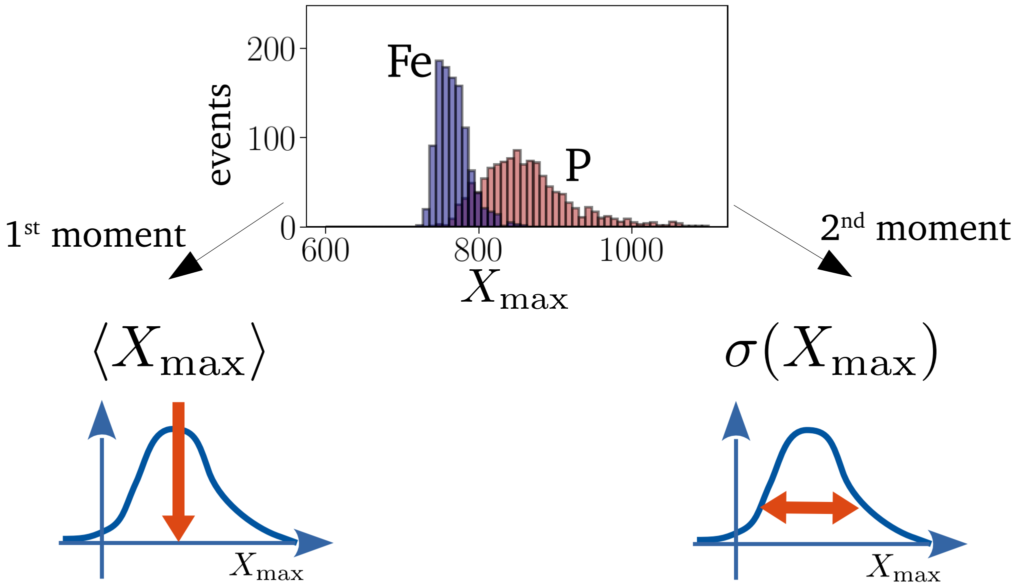
Size of Auger 3,000 km²

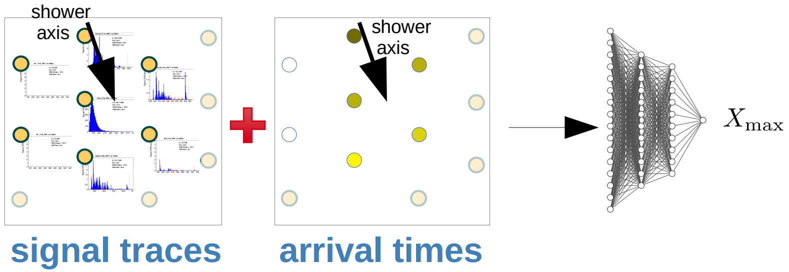
→ Projected on Trapani
Distance from Trapani to Airport ~60 km

Xmax reconstructed with SD data

Mass composition of UHECRs

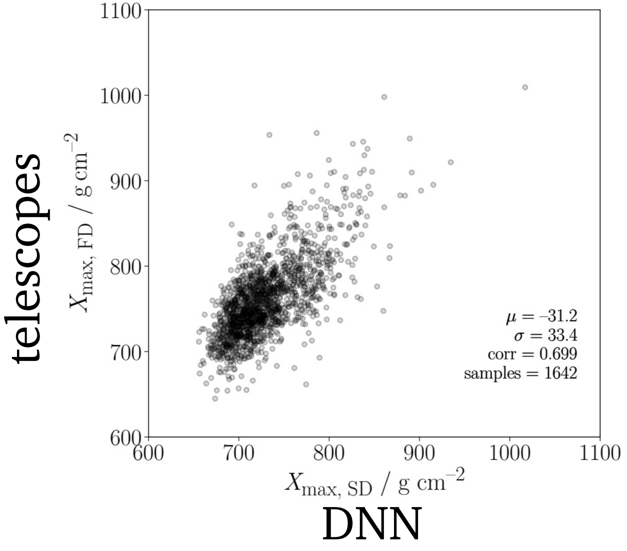
- currently: most precise mass estimator by reconstructing shower maximum *X*max
- determine composition by studying the measured *X*max distributions





DNN-based Xmax reconstruction

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



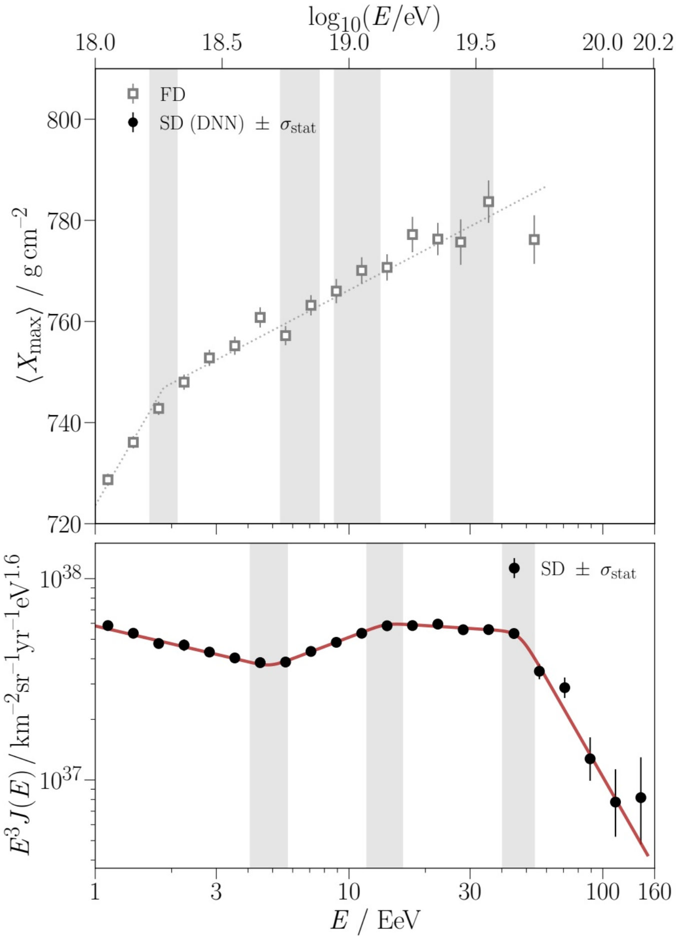
Evidence for breaks in the elongation rate

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



Current interpretation:

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

A. Abdul Halim (Pierre Auger Collaboration) et al., arXiv:2406.06315

A. Abdul Halim (Pierre Auger Collaboration) et al., arXiv:2406.06319

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:

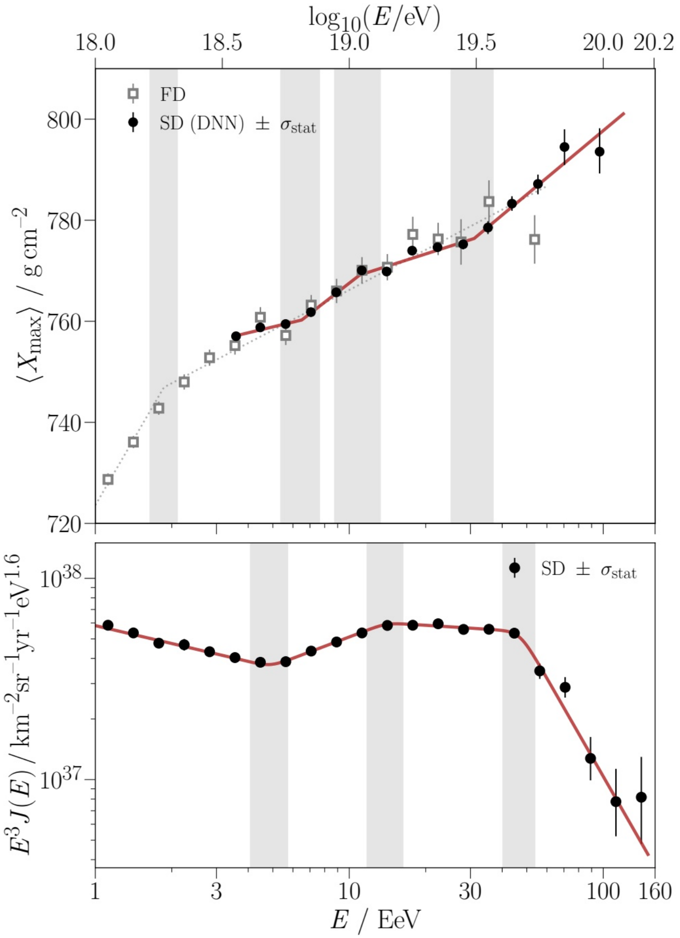
- Linear model describes transition from light to heavy

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

- Evidence for three breaks, in proximity of spectrum features
  same statistic: telescopes would need to operate for 150 years!

Current interpretation:

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



A. Abdul Halim (Pierre Auger Collaboration) et al., arXiv:2406.06315

A. Abdul Halim (Pierre Auger Collaboration) et al., arXiv:2406.06319 cartoon credit: Doug Neill

*Note: There is no free lunch → "Older algorithms" are not necessarily worse

Past, Present, and Future – Deep Learning in Astroparticle Physics

I. Classic ML
Published physics analyses using high-level observables, BDTs, RFs

II. Proof of concept
- First SAL publications of applying DL at low- & high level data
- Use of standard architectures: FCNs, RNNs, CNNs mostly on simulations and toy simulations

III. Verified reconstruction mechanisms
First publications by Collaborations, e.g., Pierre Auger, IceCube, KM3Net ...

IV. Exploiting symmetries
Incorporating symmetries into DNNs, GCNs, transformer

V. Physics analyses with DL
- Publications by Collaborations
- Application to full data sets
- Extensive study of systematic unc.

DL close to sensors
On-site application of ML algorithms

'Unsupervised era'
- exploiting measured data
- refinement of simulations
- AI-based detector design

Open data
Large, complete and open (MC) data

Multi-experiment DL
Application of ML methods to open data

Interpretability
- DNN introspection & causality studies
- Distilling physics laws from DNNs

AGPI?
Artificial general Physics Intelligence

supervised learning →

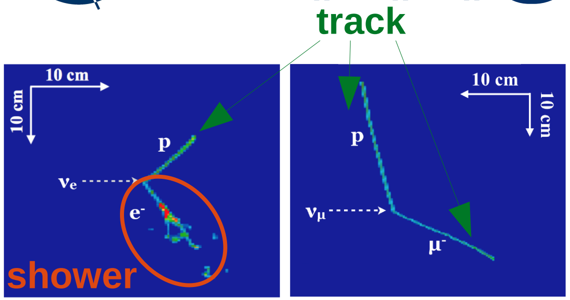
unsupervised learning →

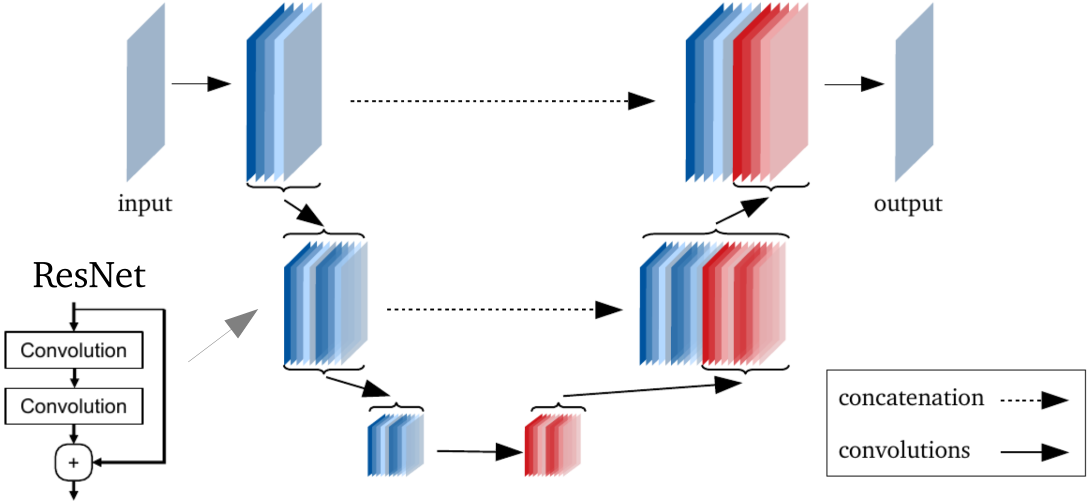
self-supervised learning →

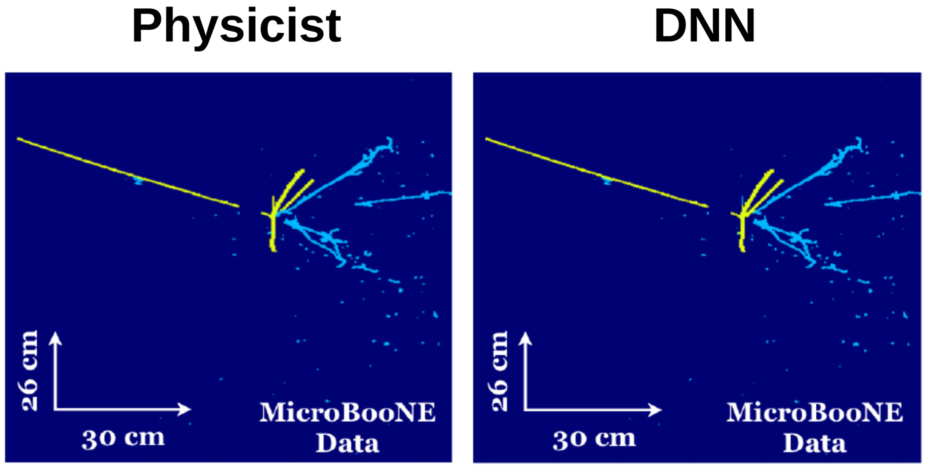
BACKUP

Segmentation - MircroBooNE

- Liquid Argon TPC for neutrino detection
- Segmentation (pixel-wise class prediction) into tracks and electromagnetic-showers
  - Architecture: combination of ResNet and U-Net
- Incorrectly classified pixel fraction per image ~ few percent

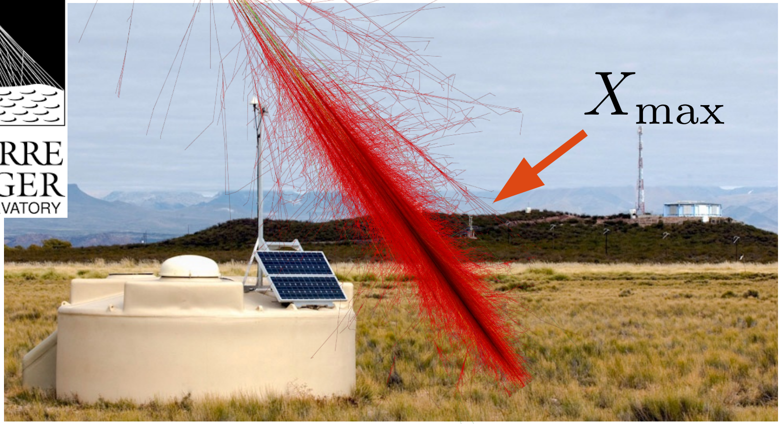






Adams et al. ArXiv: 1808.07269

Ultra-high-energy cosmic rays (UHECRs)

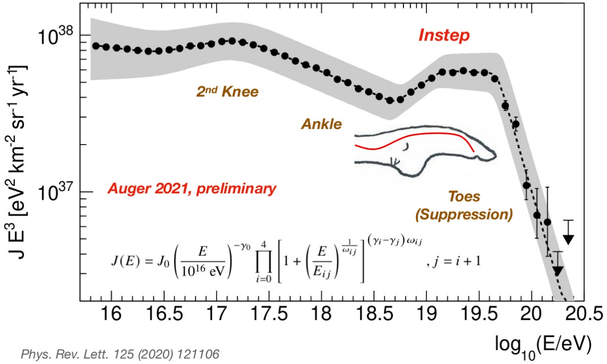


The Pierre Auger Observatory

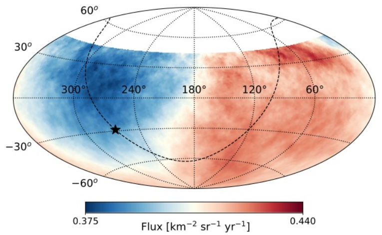
- world's largest observatory to study ultra-high-energy cosmic rays
- hybrid detection of air showers
  - 1,660 water-Cherenkov detectors
  - 27 fluorescence telescopes
    - can precisely observe Xmax

Key findings

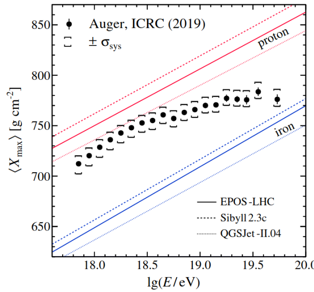
Characteristics of the energy spectrum

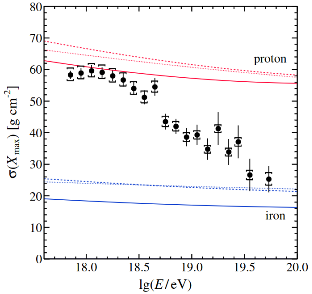


Phys. Rev. Lett. 125 (2020) 121106



Discovery: large-scale anisotropy pointing away from galactic center
Hint: UHECRs are extragalactic



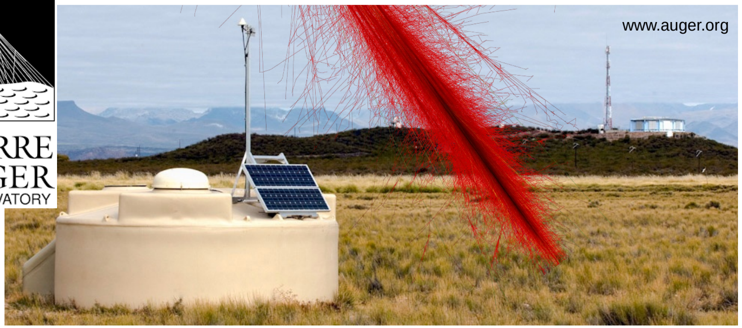


Mass composition
Towards heavier and purer composition

Cutoff not caused by GZK only

Air-Shower Reconstruction

The Pierre Auger Collaboration, JINST 16 P07019 (2021)



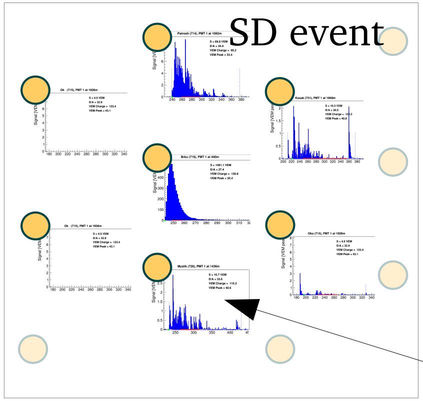
Pierre Auger Observatory

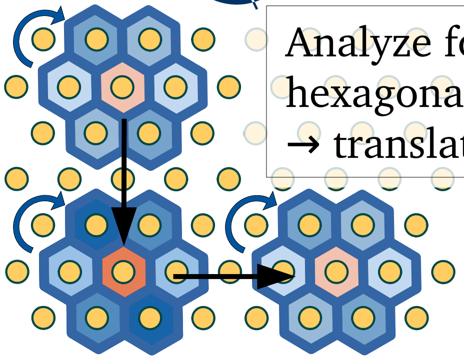
Fluorescence Detector (15% duty cycle)

- direct and precise observation of shower maximum *X*max

Surface Detector (~100% duty cycle)

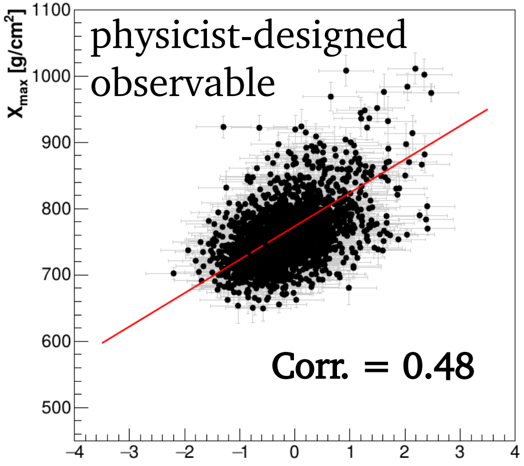
- reconstruction of shower maximum using deep learning
- verification using hybrid measurements



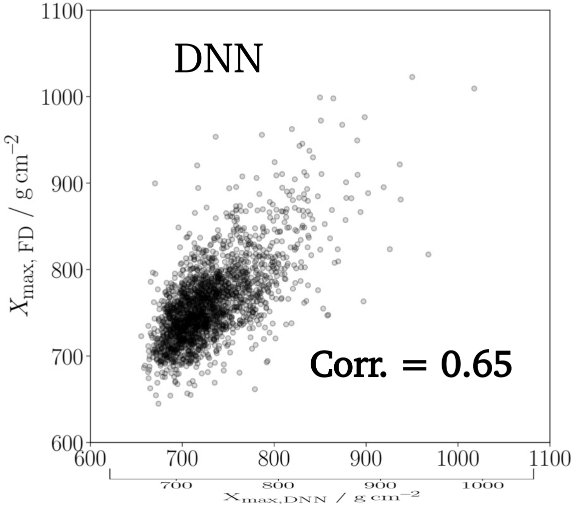


Analyze footprint with hexagonal convolution
→ translation + rotation

analyze traces with RNNs



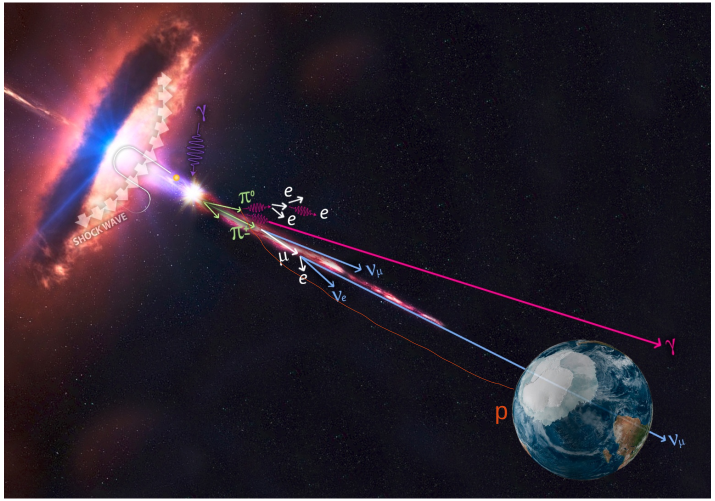
ArXiv/1710.07249

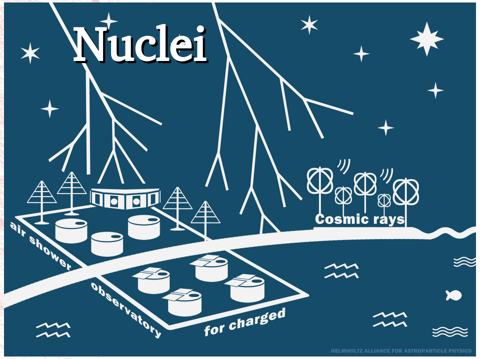


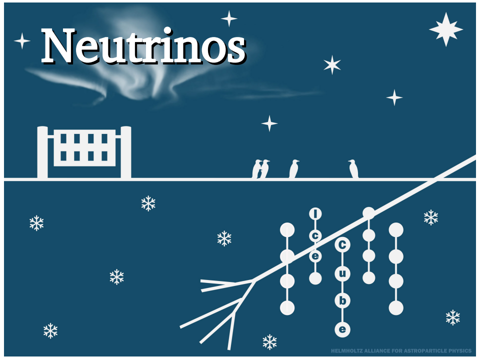
Astroparticle Physics

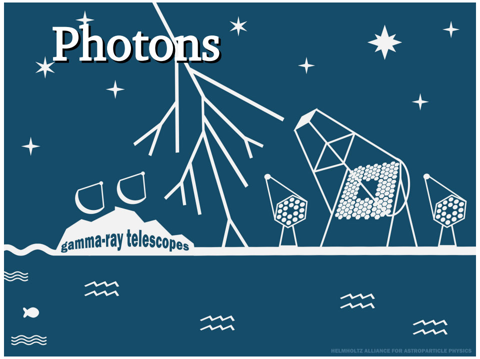
- Observation of particles with astronomical origin
- Search for their sources
  - Understand physics of astronomical objects
- Cosmic messengers: Photons, neutrinos, nuclei

- Distant sources, high particle energies
  - Experiment feature <u>huge</u> detector volumes









Origin of high-energy cosmic rays not known! (since >100 yrs)

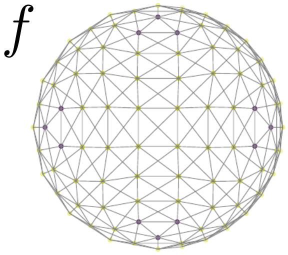
Convolutions on Spherical Domains

- (Graph) convolution in spectral domain
  smooth, localized filter → Chebychev expansion

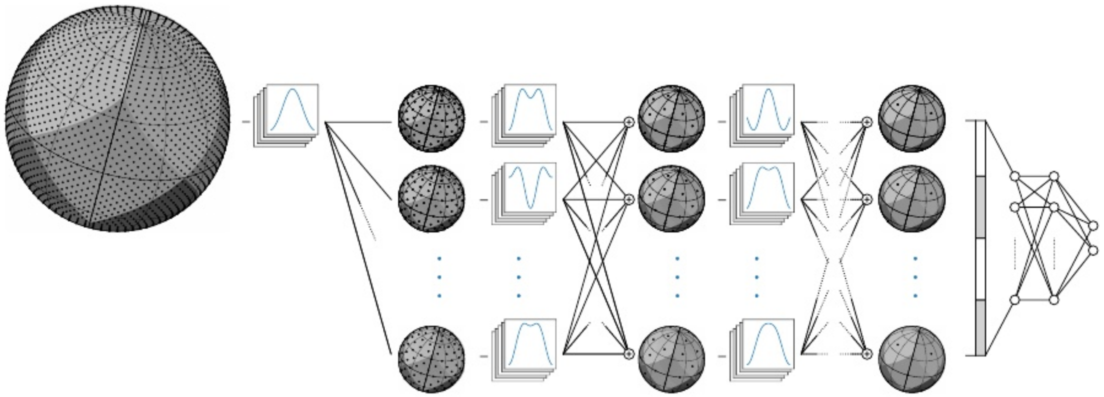
  Example: DeepSphere, for spherical data
  - HEALPix pixelization defines graph structure
- based on fixed pixels (useful for sensor configurations)

$$f * w = \Phi \hat{W} \Phi^T f$$

filter adaptive in
spectral (Fourier)
domain

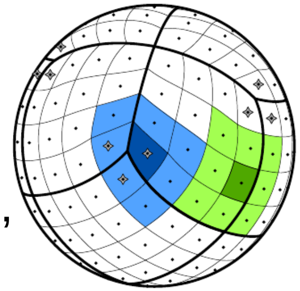


constructed graph



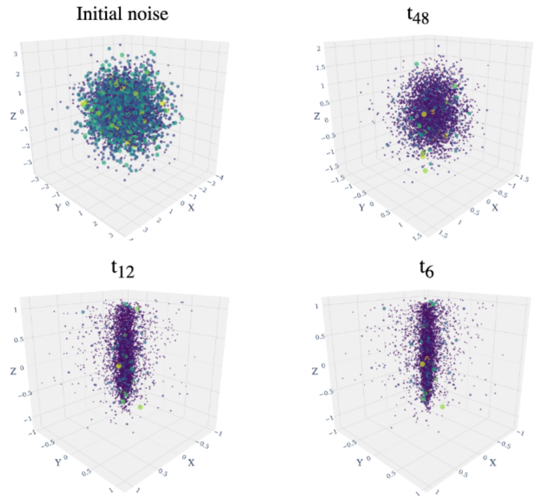
N. Perraudin el al., 10.1016/j.ascom.2019.03.004

N. Krachmalnicoff et al.,
A&A 628, A129 (2019)



Hybrid approach:
'Indexed Conv'
Define 'HEALPix filters'

Application to search for
UHECR sources:
O. Kalashev et al.,
10.1088/1475-7516/2020/11/005



Application in Particle Physics

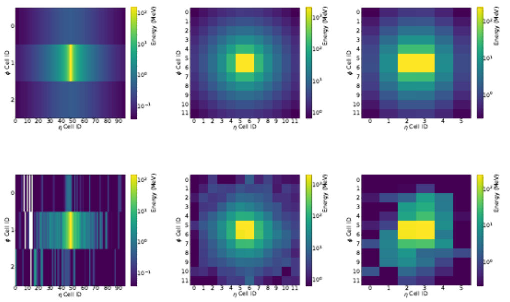
- Detector simulation are very time consuming
  - accelerated (10^3–10^5) using generative models
- Conditioned on the physics observables
  - e.g., (energy, particle type, arrival direction)
- Samples must comply with physics laws
- Samples have to follow phase space density → usually no cherry-picking

Buhmann et al., ArXiv/2305.04847

Layer

Geant4

GAN

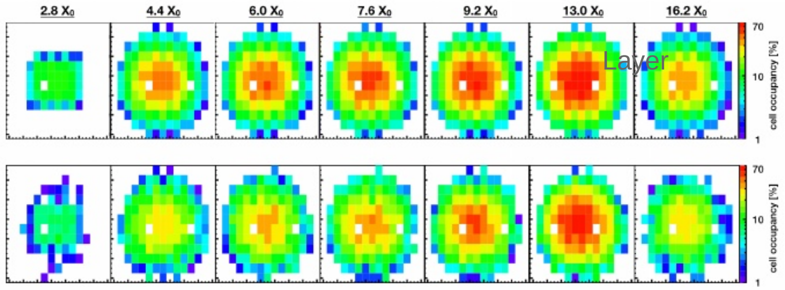


Paganini, Oliviera, Nachman - Phys. Rev. D 97, 014021 (2018)

Layer

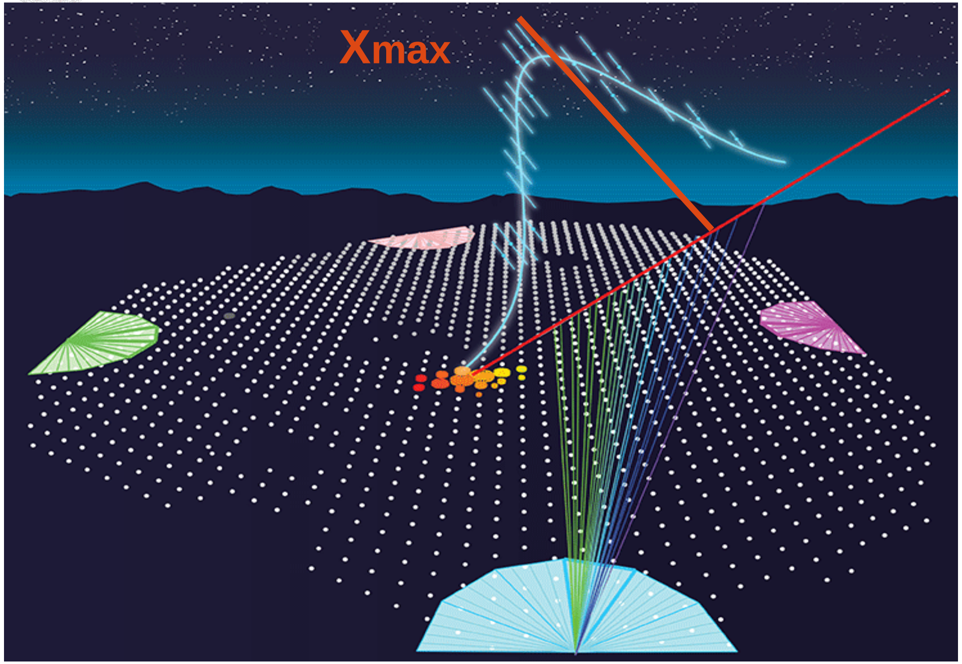
Geant4

WGAN



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

Astroparticle physics detectors



Fluorescence Detector (FD)

- 27 telescopes
  - located at 4 sites
  - ~15% duty cycle

Surface Detector (SD)

1660 water-Cherenkov detector stations

- **3000 km² array**, ~100% duty cycle
- Measure **arrival time distribution of particles**

Astroparticle physics detectors

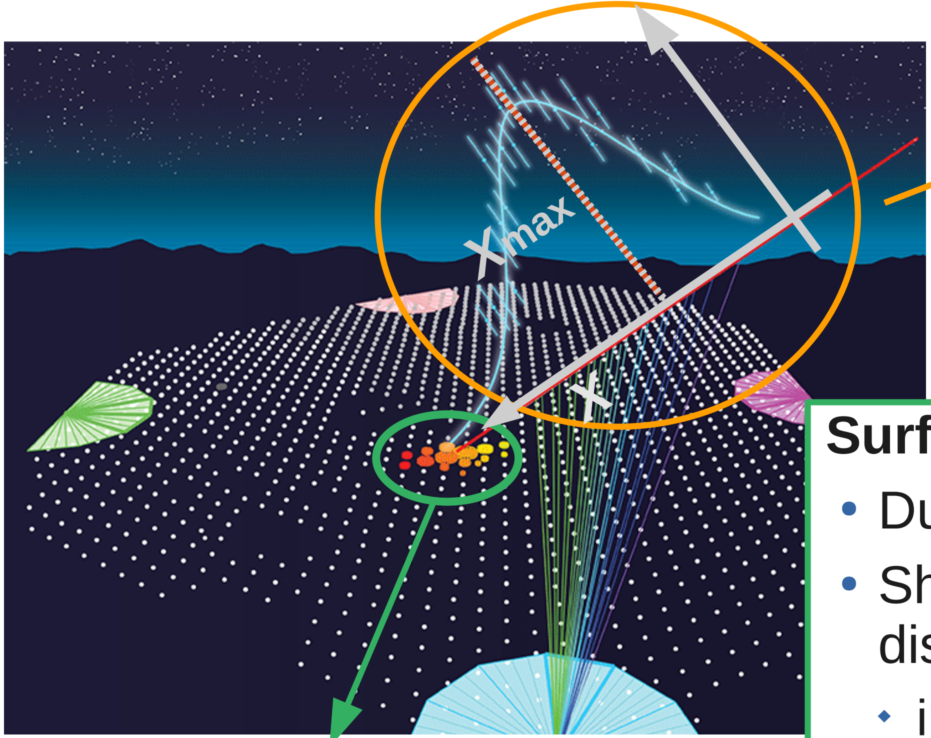
Size of Auger projected on Sicily

Distance from Trapani to Airport ~60 km

Surface Detector (SD)

1660 water-Cherenkov detector stations

- **3000 km² array**, ~100% duty cycle
- Measure **arrival time distribution of particles**

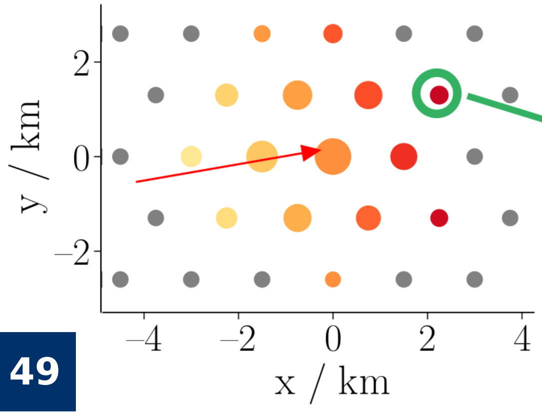


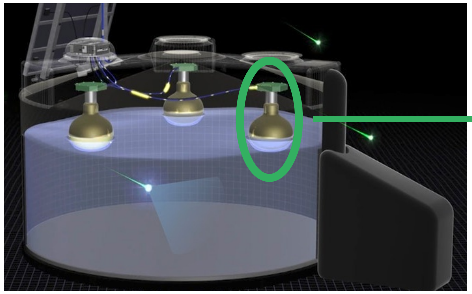
Fluorescence Detector (FD)

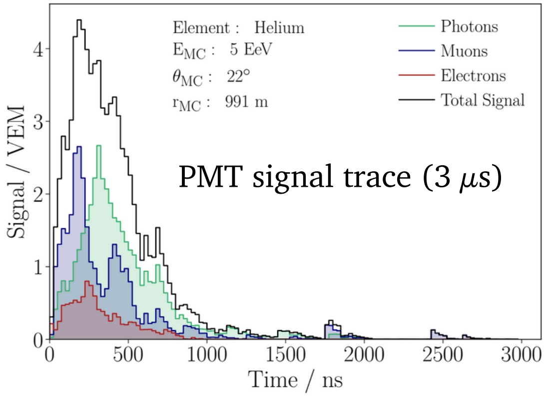
- Duty cycle ~15%
- Observe longitudinal shower profile
  - direct measurement of X_{max}

Surface Detector (SD):

- Duty cycle ~100%
- Shower development encoded in arrival time distribution of secondary particles
  - indirect observation → exploit using deep learning





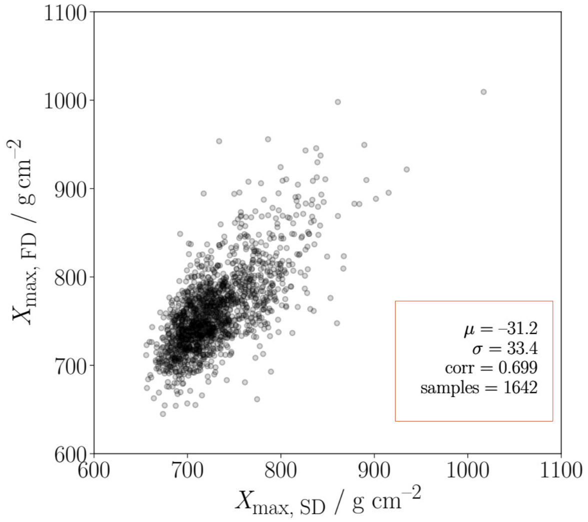


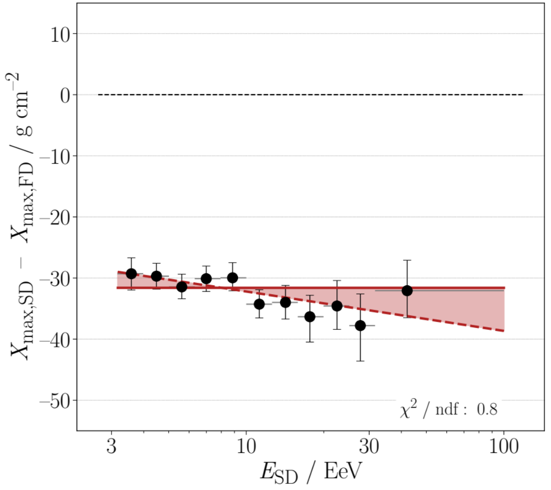
Application to hybrid data

Calibration of DNN predictions using hybrid data

- **correlation 0.7** (>0.6 when correcting for elongation rate)
- **matches** expectations from simulation (0.73)
- resolution: 40 → 20 g/cm²
- **X_{max}(SD) - X_{max} (FD): bias of -30 g/cm²**
  - larger than expected from simulation studies
  - bias can be due to 'muon puzzle' / detector simulations
  - perform energy-independent calibration

First application to hybrid data: JINST 16 P07019 (2021)





Generative Models

Which picture is <u>generated?</u>

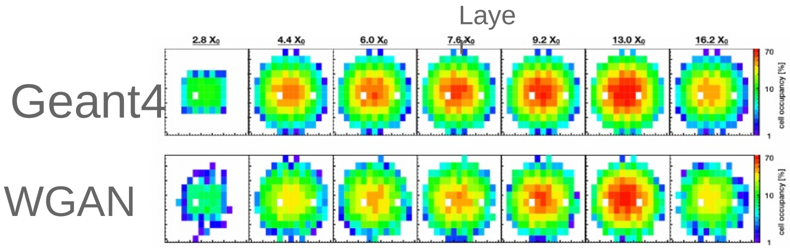
Which is a <u>real</u> image ?

T. Karras et al. - https://arxiv.org/abs/1812.04948

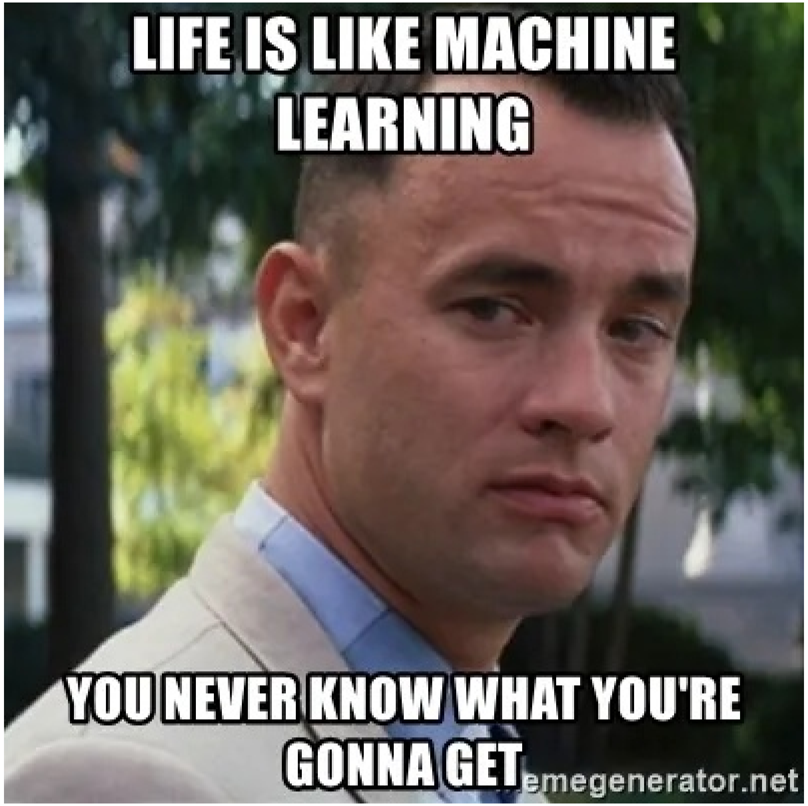
https://poloclub.github.io/ganlab/

- Approximation of simulation / physics process
- Unsupervised training of *generative models*

- New opportunities for:
  - Tractable likelihoods
  - Differential simulations
  - Fast simulations



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


LIFE IS LIKE MACHINE LEARNING
YOU NEVER KNOW WHAT YOU'RE GONNA GET
emegenerator.net

?

Can we generate images with distinct physical properties?

Test: “classic”

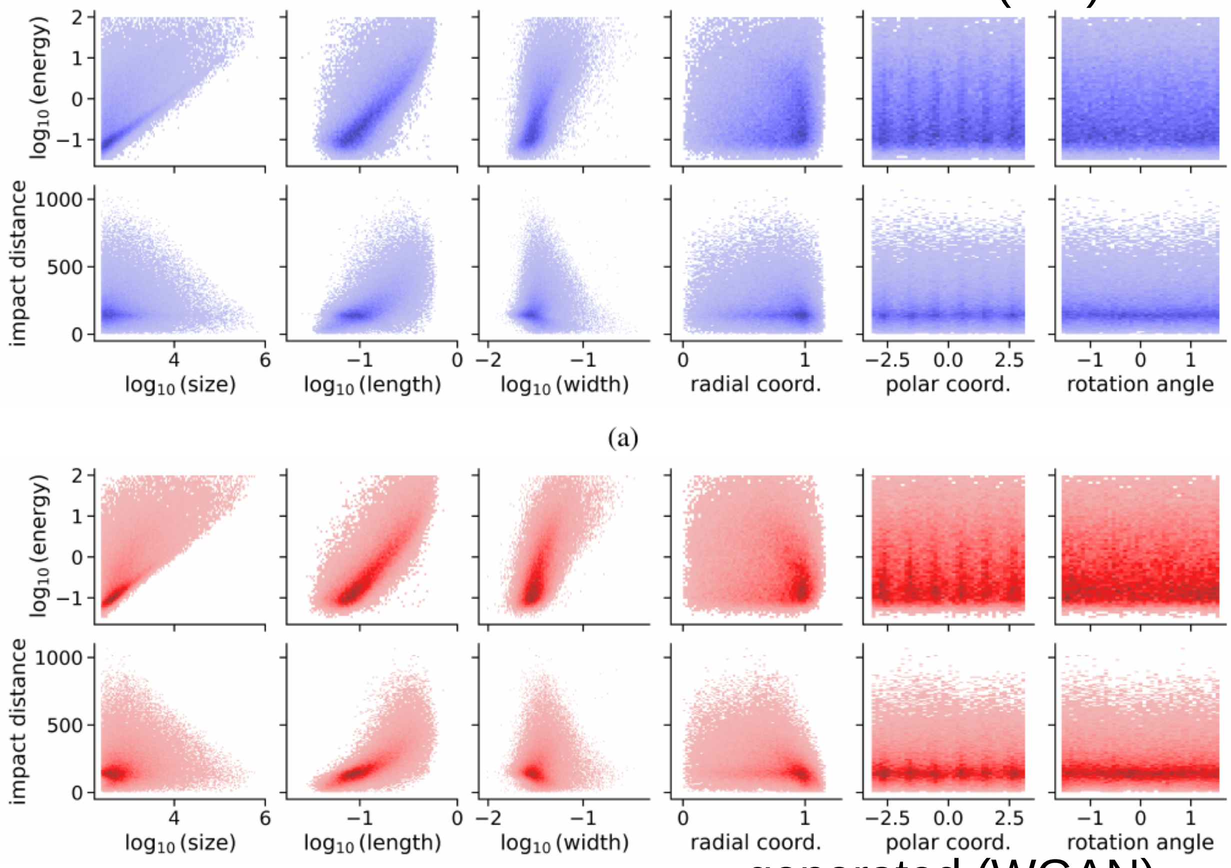
compare parameter correlation w.r.t.

- Impact distance
- Energy

(set in CORSIKA)
(input to generator)

Correlations are very similar!

simulated (MC)

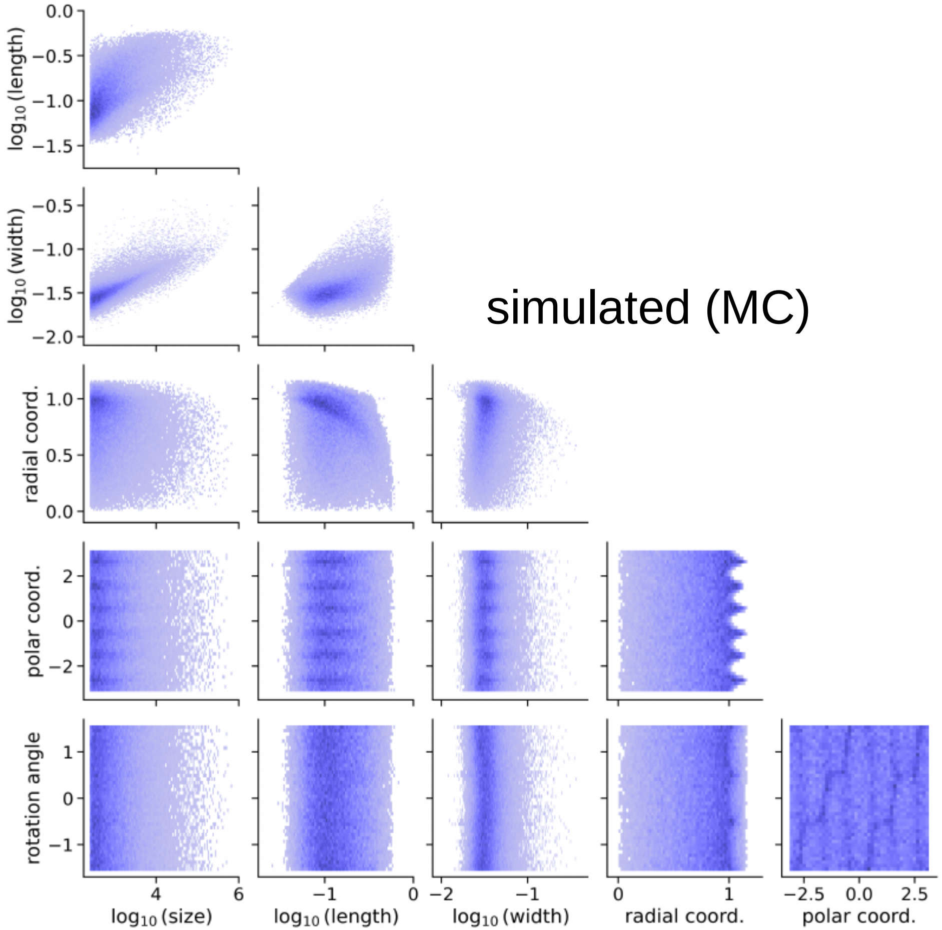


(a)

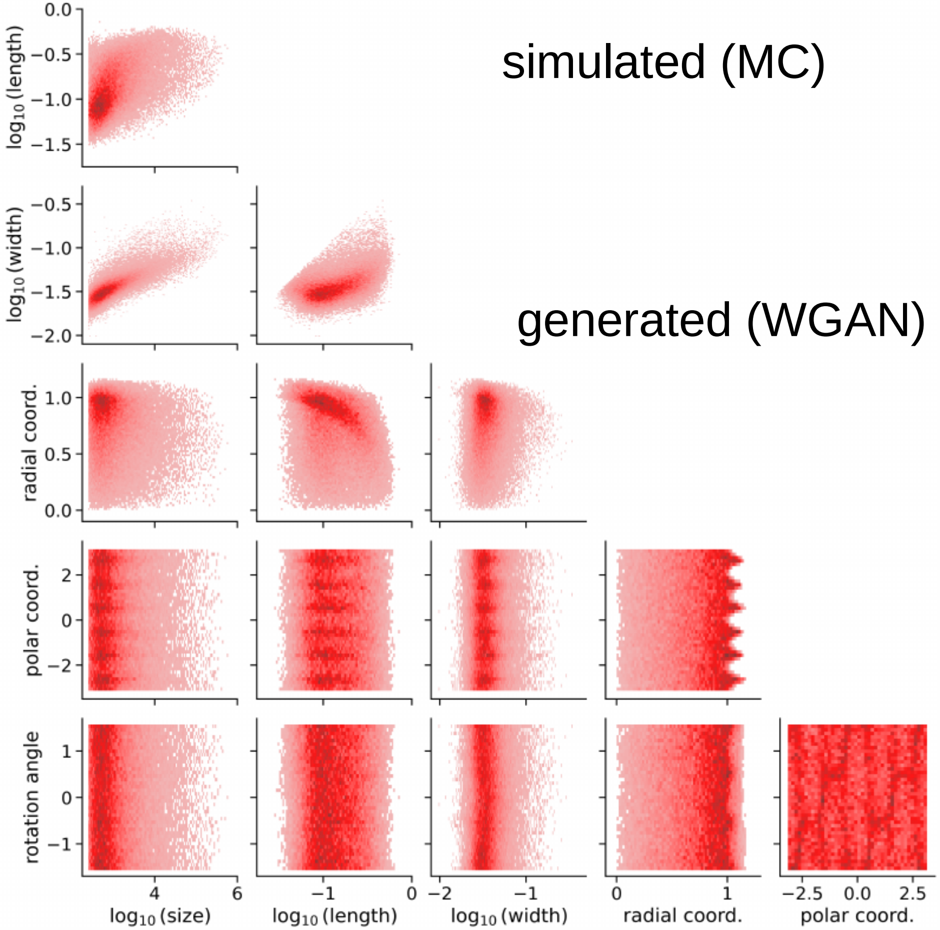
(b)

generated (WGAN)

Correlation of Hillas parameters



simulated (MC)



simulated (MC)

generated (WGAN)

generated (WGAN)

Correlations are very similar!