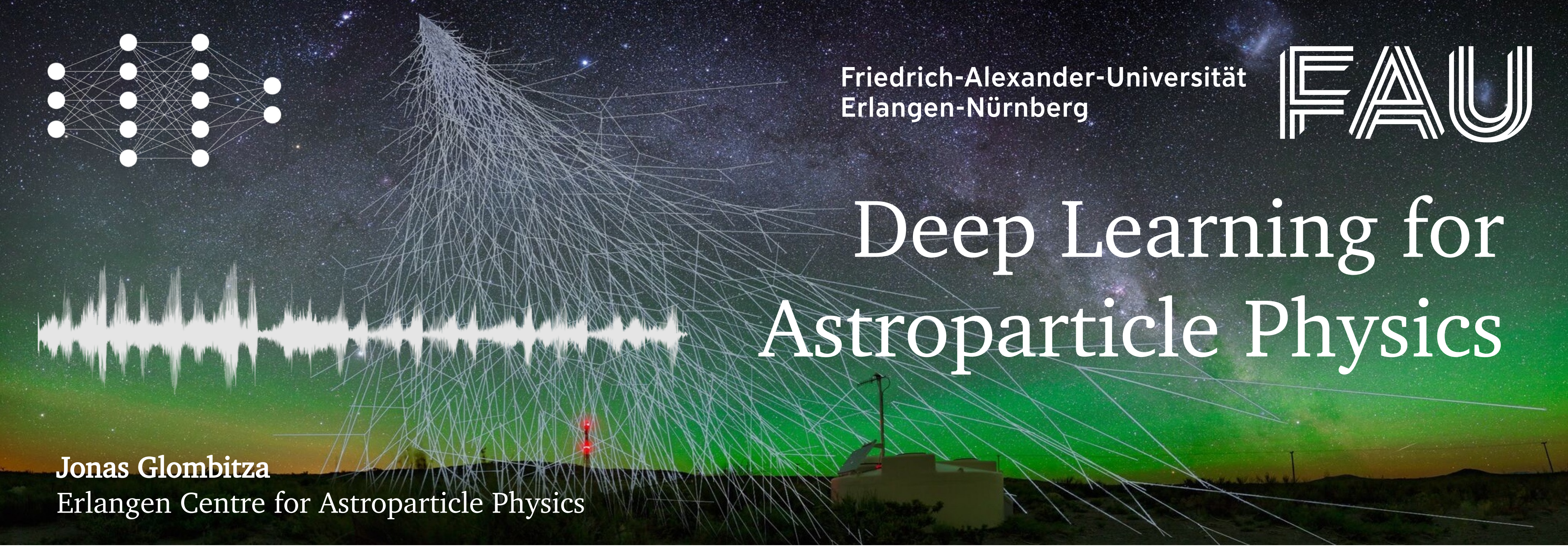
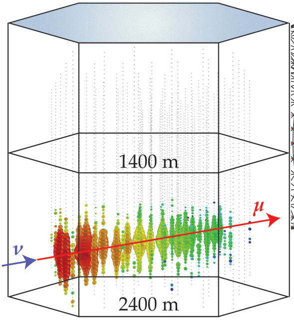
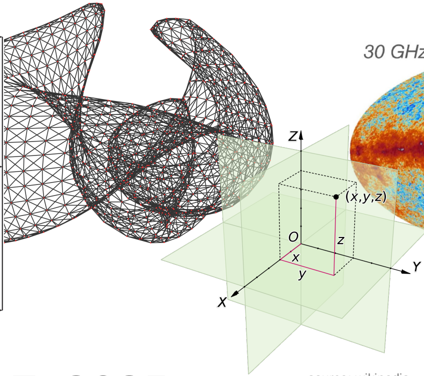


Friedrich-Alexander-Universität
Erlangen-Nürnberg

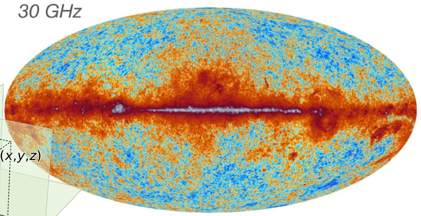
# Deep Learning for Astroparticle Physics

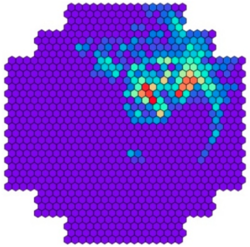
**Jonas Glombitza**
Erlangen Centre for Astroparticle Physics

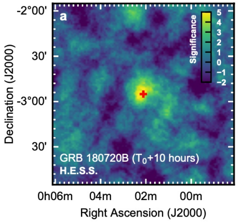



source: wikipedia






January 27, 2025

ERLANGEN CENTRE FOR ASTROPARTICLE PHYSICS

SPONSORED BY THE
Federal Ministry of Education and Research

# 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.

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

1996

Tadeusz Wibig

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

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

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

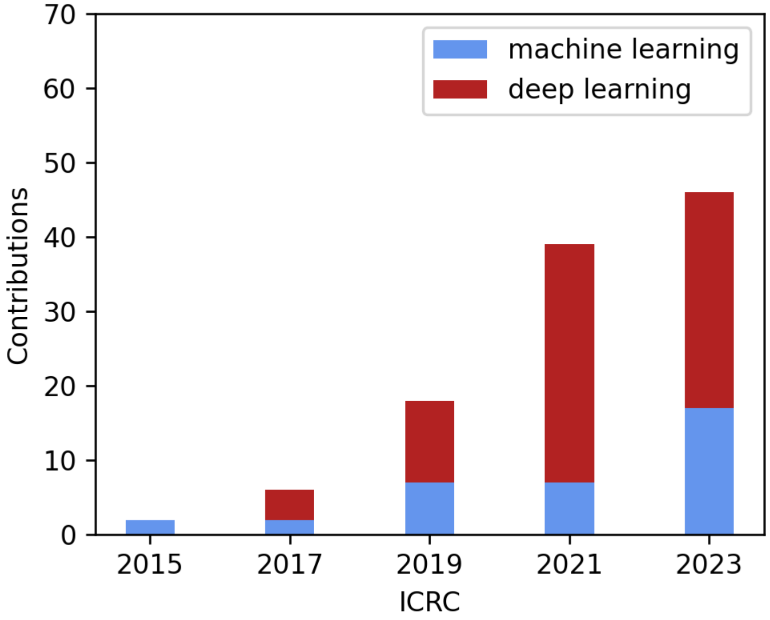
ELSEVIER

Astroparticle Physics

Volume 4, Issue 2, December 1995, Pages 119-132

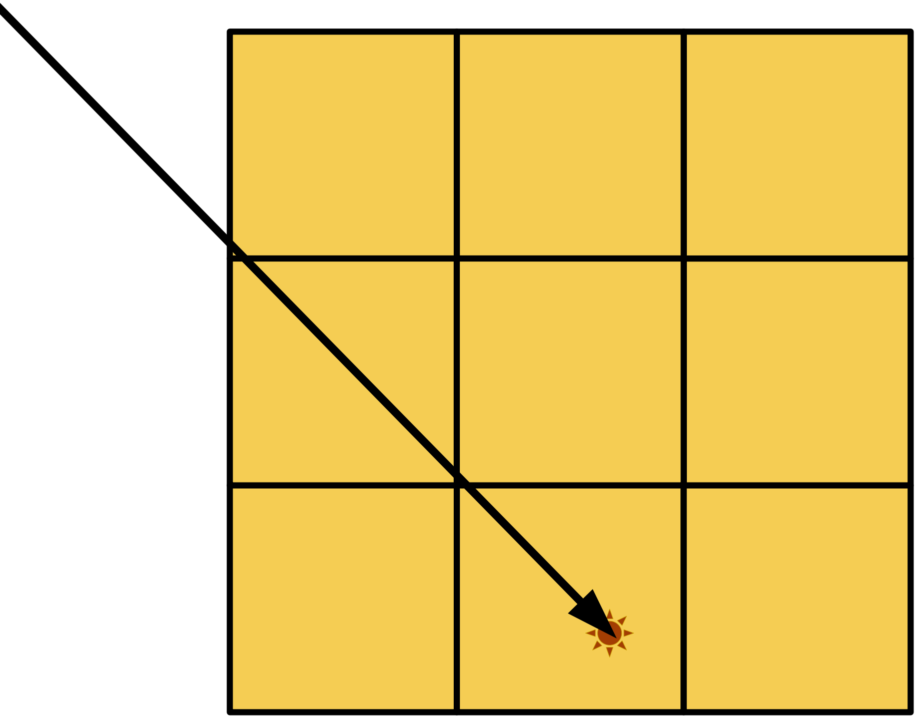
Separating γ- and hadron-induced cosmic ray air showers with feed-forward neural networks using the charged particle information ⋆

S. Westerhoff [a], B. Funk [a], A. Lindner [b], N. Magnussen [a], H. Meyer [a], H. Möller [a], W. Rhode [a], R.N. Sooth [a], B. Wiebel-Sooth [a]



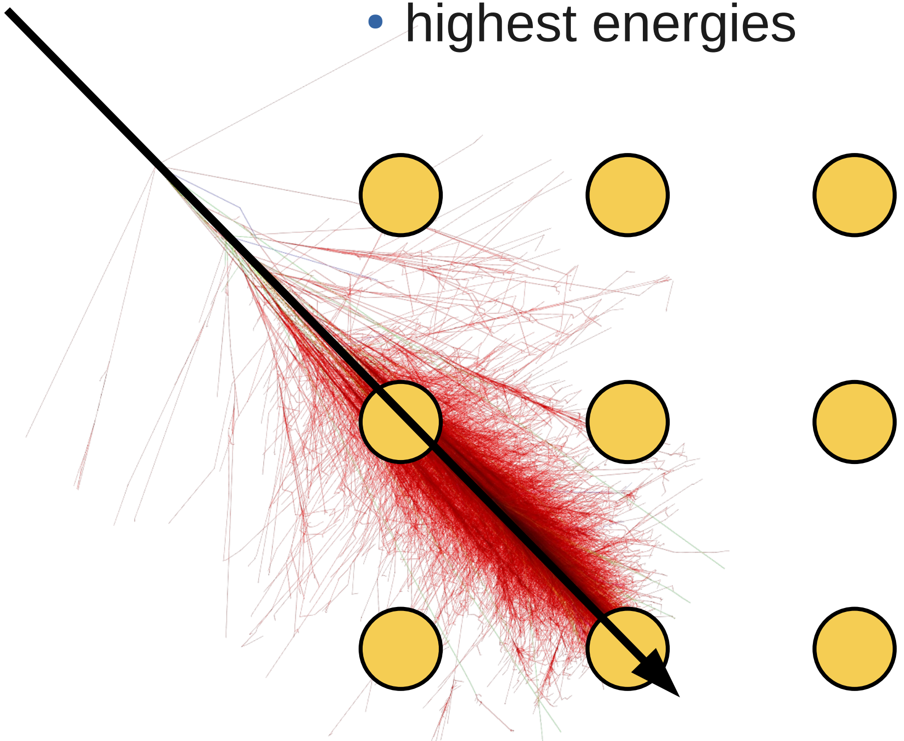
# Astronomy at the highest energies

- Lower energies



Direct
detection

- highest energies

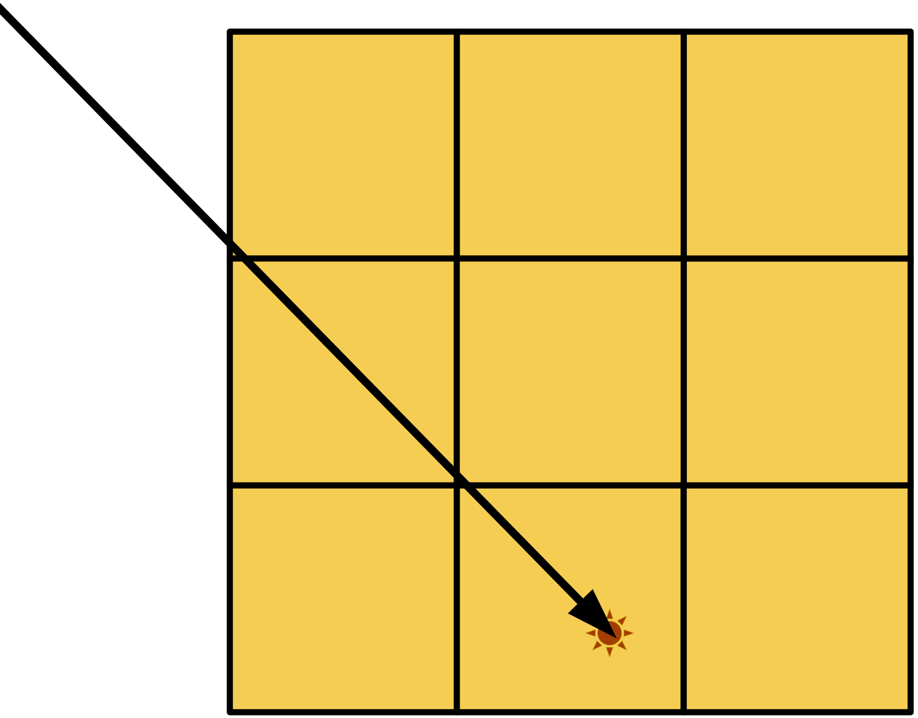


- Low flux & indirect detection
  - Sparsely instrumented detectors
- Complex reconstruction
(direction, energy, particle type)

# Astronomy at the highest energies

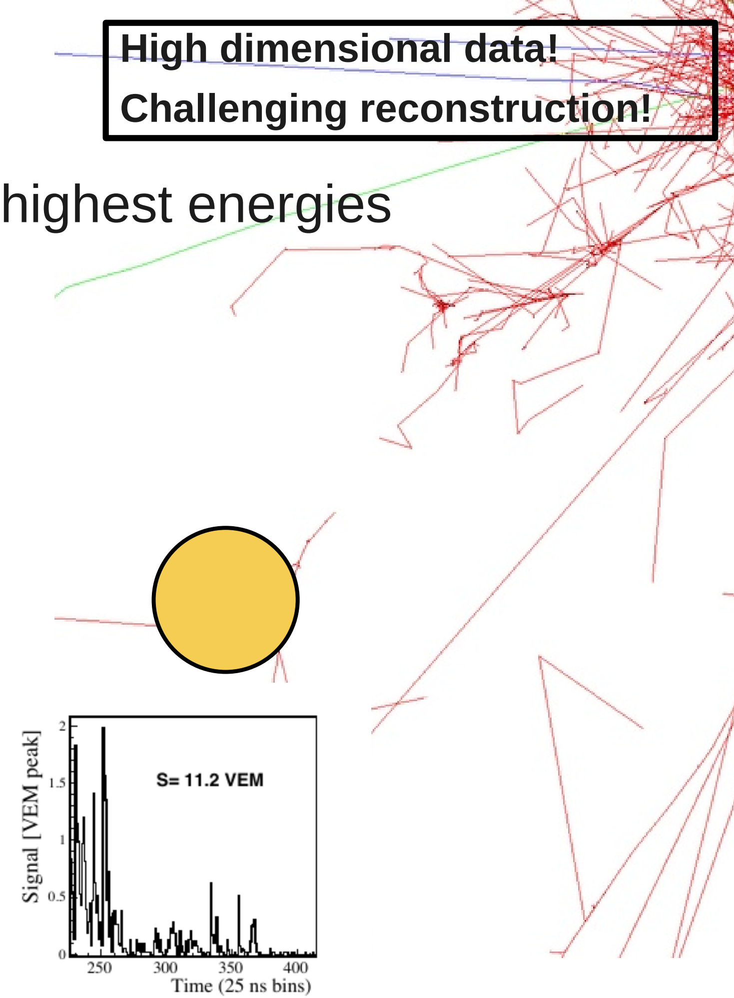
**High dimensional data!**
**Challenging reconstruction!**

- Lower energies



Direct
detection

- highest energies

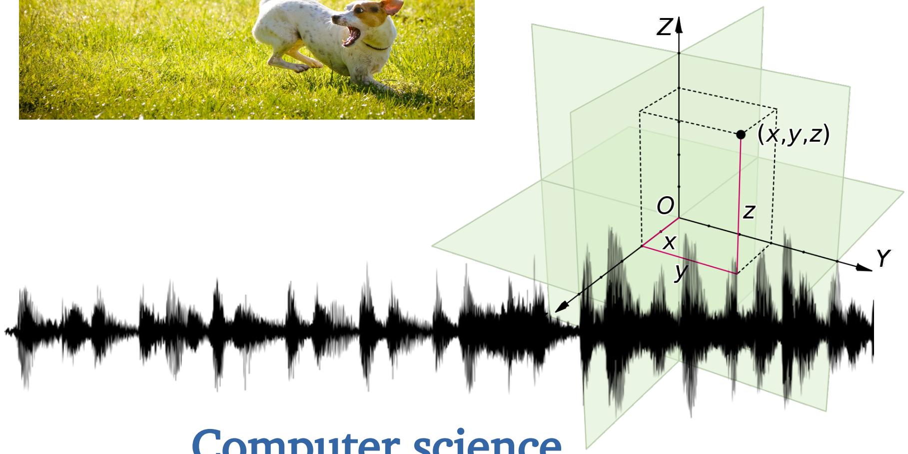



- Single sensors detect
  time resolved signals (per event)

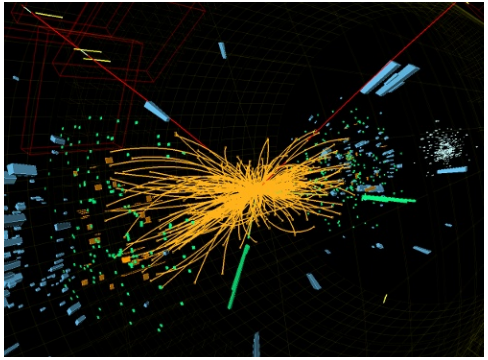
# Application in Physics

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

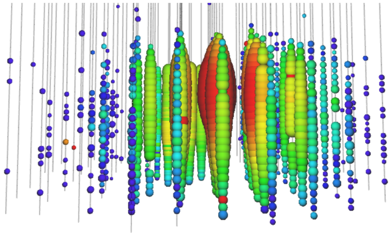
source: wikipedia



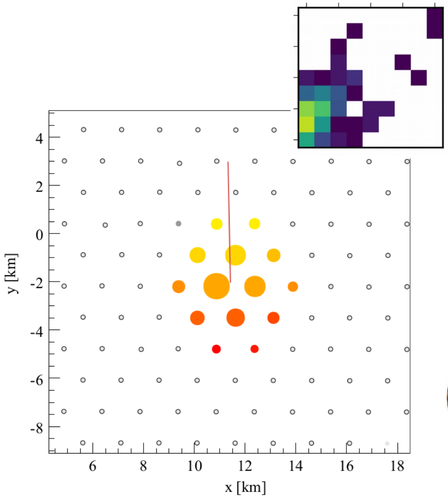

Computer science



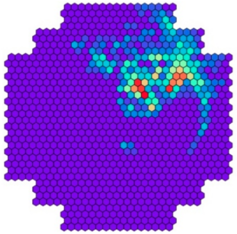
https://cds.cern.ch/record/2711418



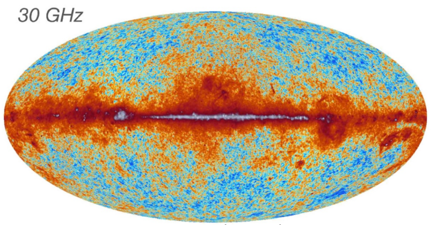
https://arxiv.org/abs/1309.7003




10.1016/j.nima.2015.06.058



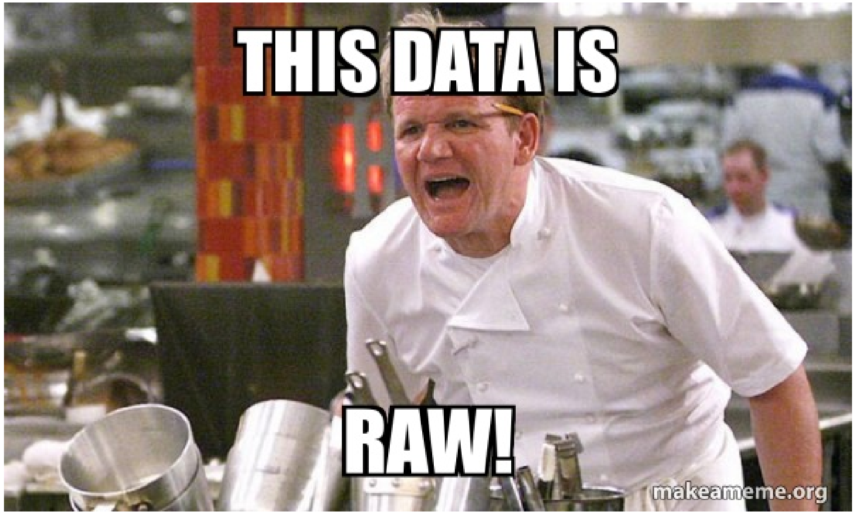
10.1016/j.astropartphys.2018.10.003




Astronomy and Astrophysics 641, p. 1 (2018)

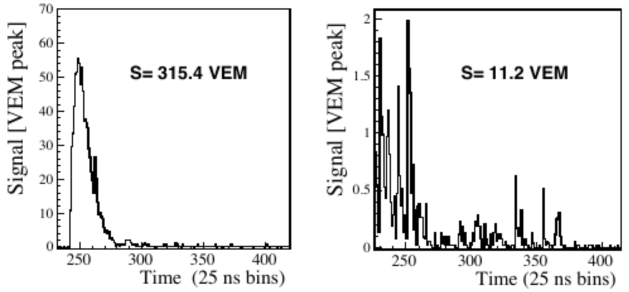
Physics

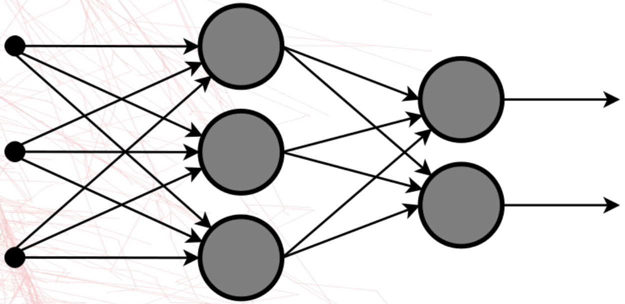
# Processing raw signals



# Machine Learning to Deep Learning

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



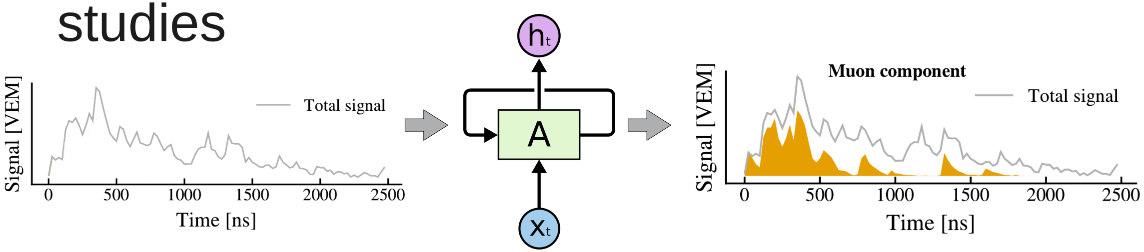
## Traditional ML approach

- Extract fraction 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 time-dependent signals induced by muons
- Promising results for mass composition studies




Pierre Auger Collaboration, JINST 16 P07016 (2021)

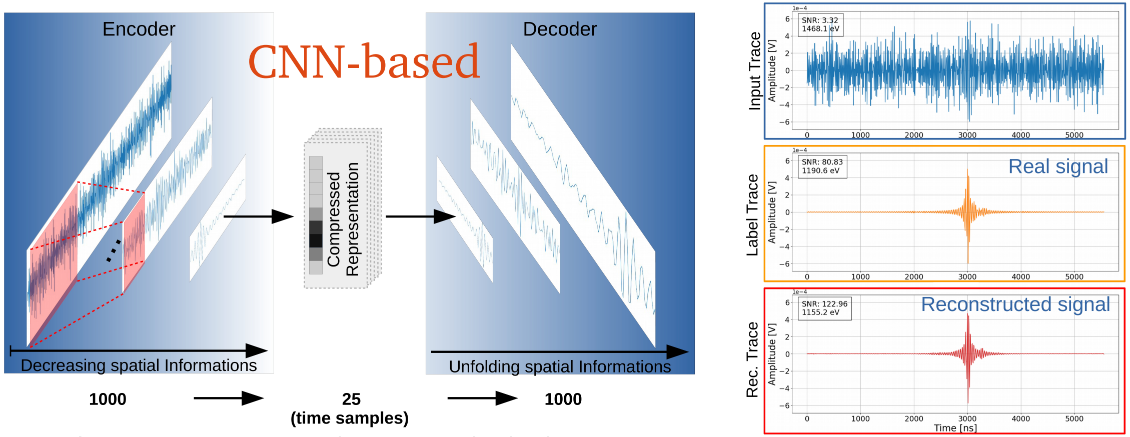
# Denoising of Signal Traces (1D)

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

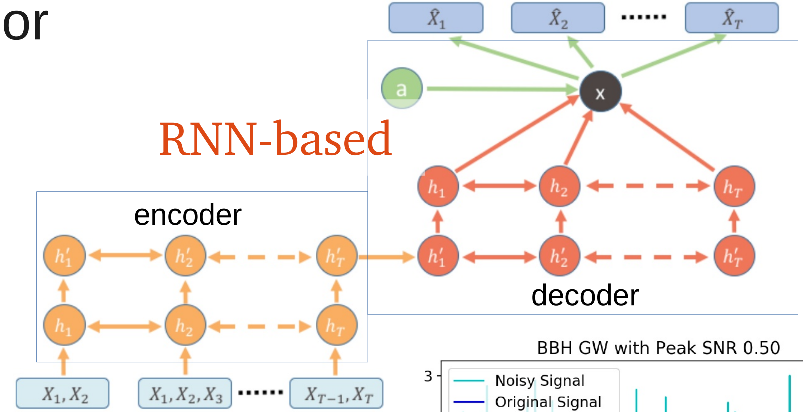
## Denoising of cosmic ray radio signals

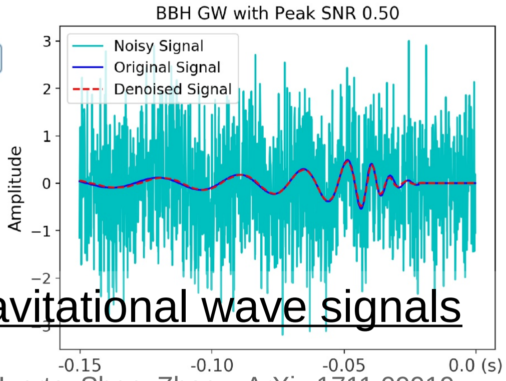



M. Erdmann et al. - 10.1088/1748-0221/14/04/P04005

A. Rehman et al., PoS ICRC2021 417

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



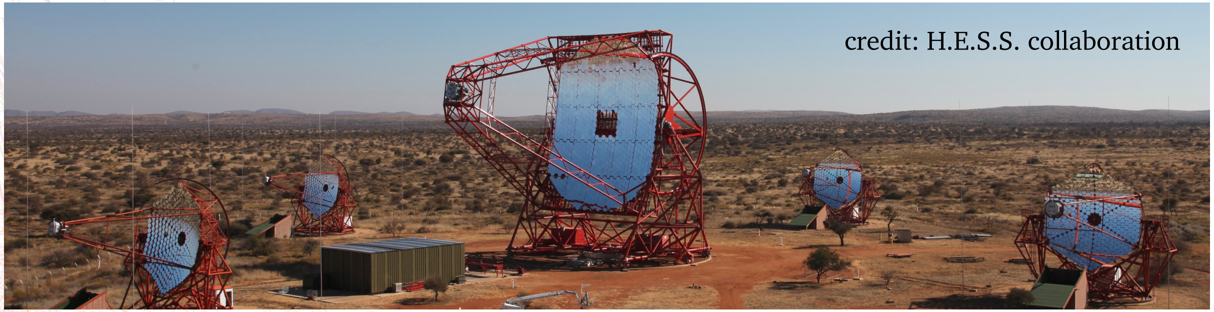

## Denoising of gravitational wave signals

George, Huerta, Shen, Zhao – ArXiv 1711.09919

**See talk on Wednesday**

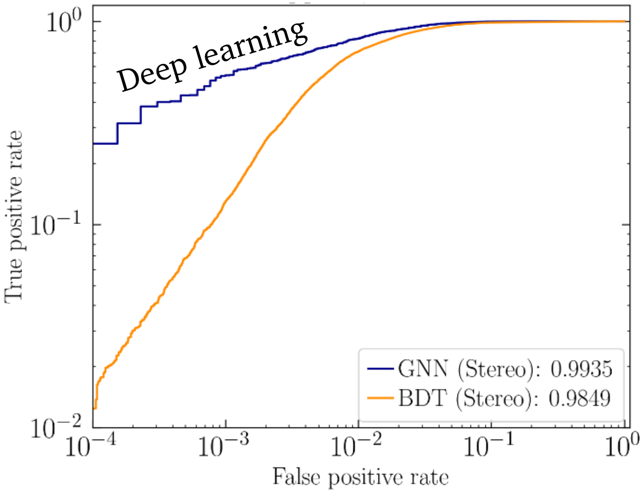
# Event reconstruction

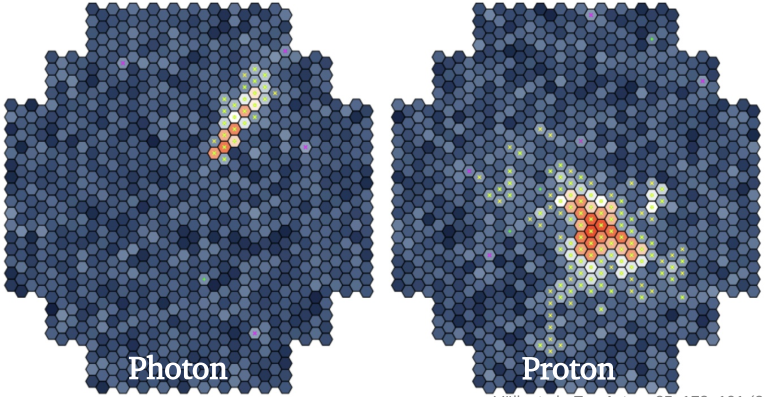
# Deep Learning for IACTs




- 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
- Challenge: application to data

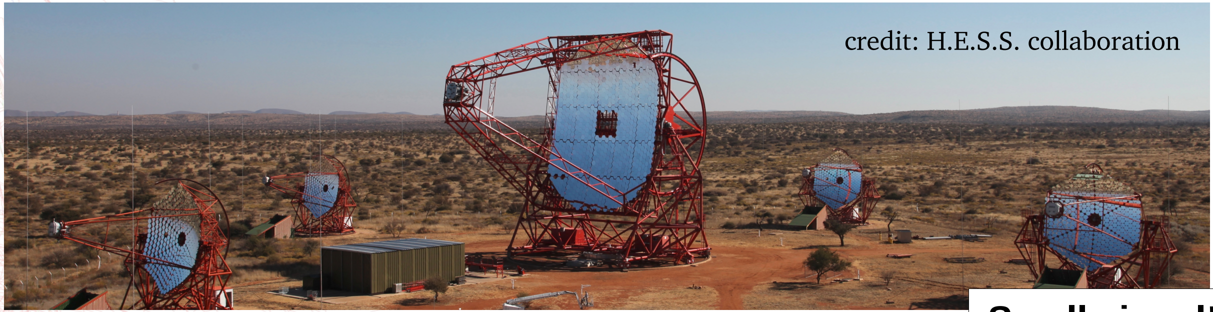


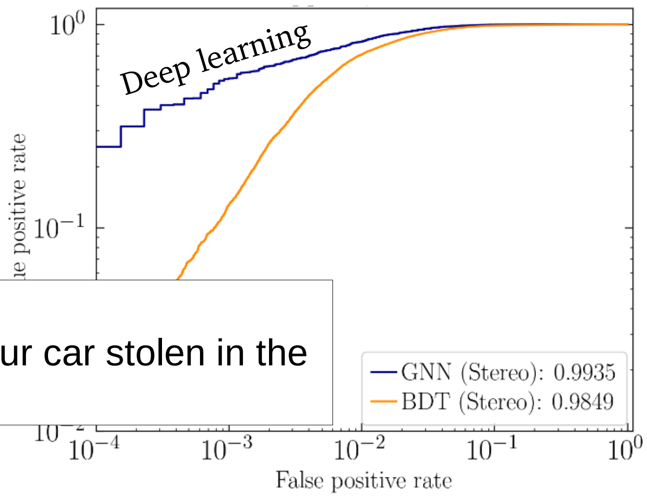




Völk et al., Exp Astron 25, 173–191 (2009)

Shilon et al., 10.1016/j.astropartphys.2018.10.003
Glombitza et al., JCAP11(2023)008, PoS(ICRC2023)715
Jacquemont et. al. arXiv:2105.14927

# Deep Learning for IACTs




**Small signal!**
Odds of getting your car stolen in the next year!

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  - Neural networks outperforms BDTs

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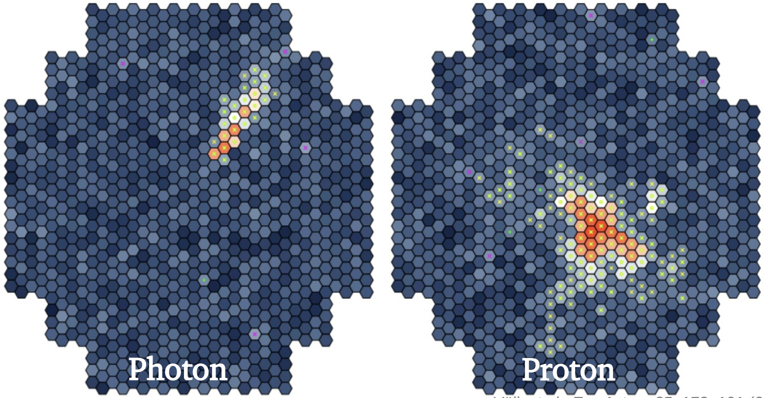
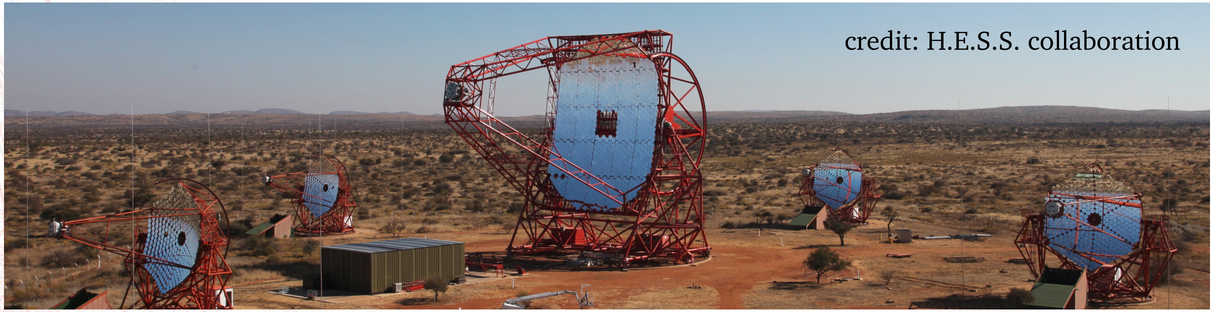
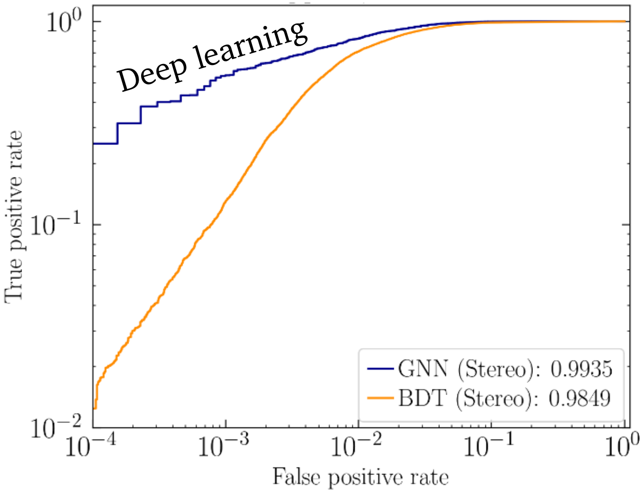


Völk et al., Exp Astron 25, 173–191 (2009)

Shilon et al., 10.1016/j.astropartphys.2018.10.003
Glombitza et al., JCAP11(2023)008, PoS(ICRC2023)715
Jacquemont et. al. arXiv:2105.14927

# Deep Learning for IACTs

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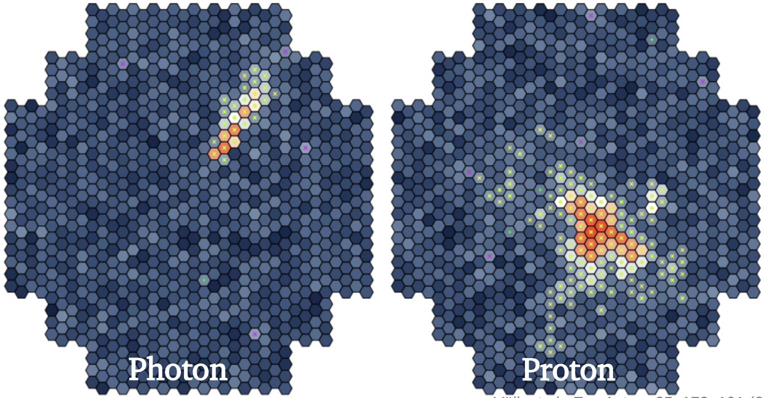
See talk today




Völk et al., Exp Astron 25, 173–191 (2009)

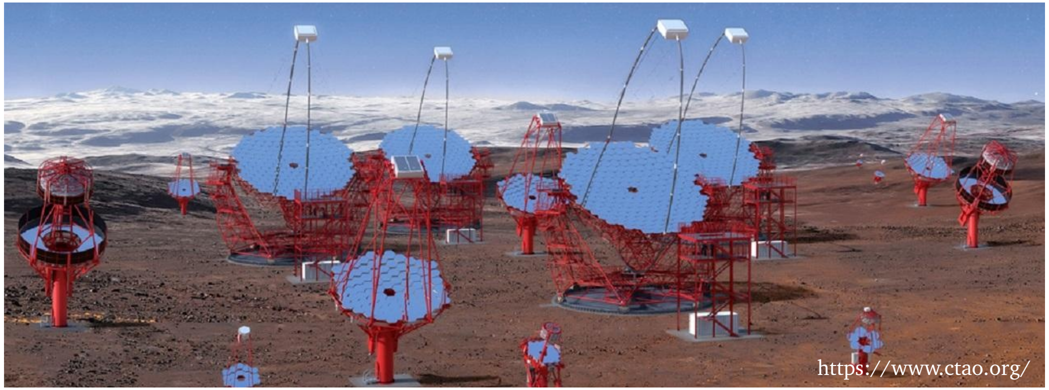
Shilon et al., 10.1016/j.astropartphys.2018.10.003
Glombitza et al., JCAP11(2023)008, PoS(ICRC2023)715
Jacquemont et. al. arXiv:2105.14927

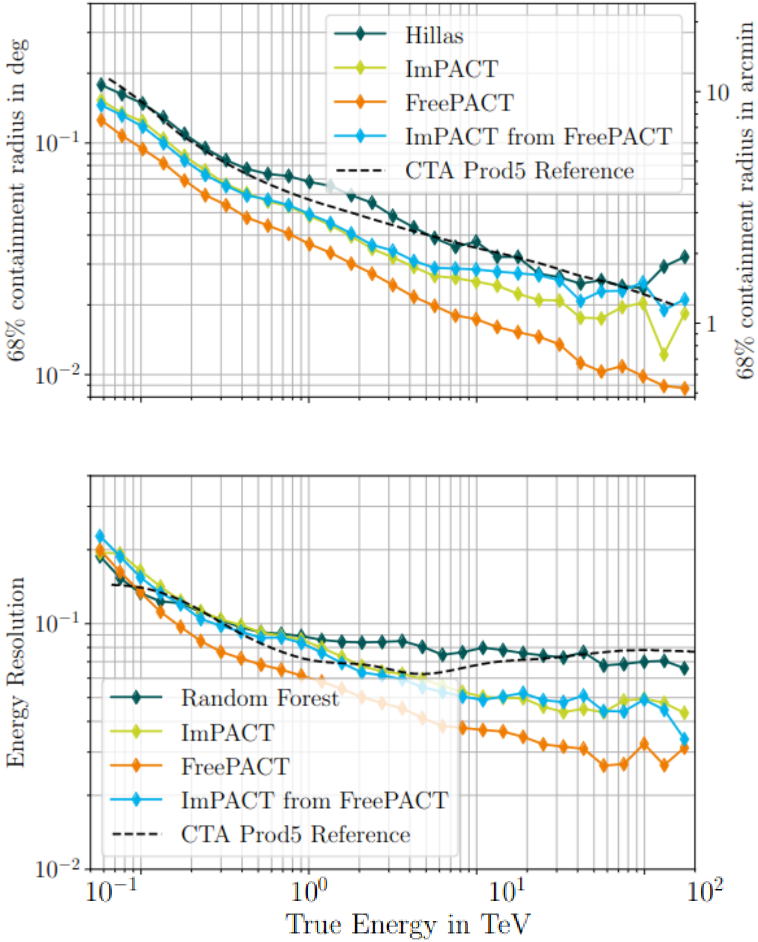
# Event reconstruction for CTA

State-of-the-art: template-based reconstruction

Hybrid approach:

- Utilize DNN to approximate charge probability density function for each pixel
- Method outperforms traditional and state-of-the-art approaches on simulations
- Previous works limited to single telescopes
  - e.g., T. Miener et al., arXiv:2109.05809, M. Jacquemont et al., arXiv:2105.14927



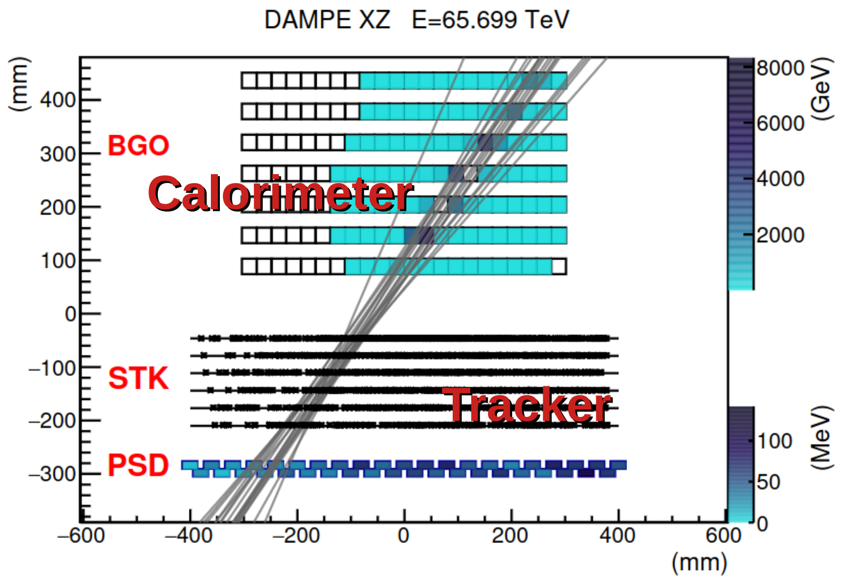




G. Schwefer, R. Parsons, J. Hinton, arXiv:2406.17502

See talk today

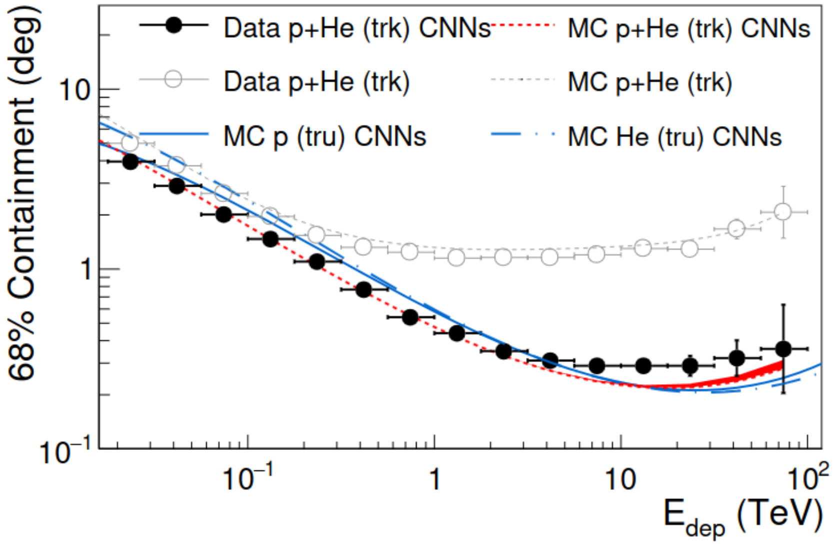
# Tracking using DNNs at DAMPE

- 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)



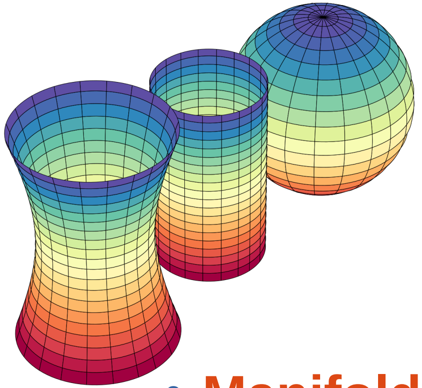

A. Tykhonov et al, Astropart. Phys. 146, 102795 (2023)

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



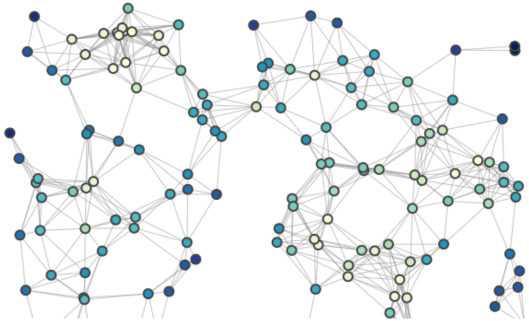
# Non-Euclidean Domains

- 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

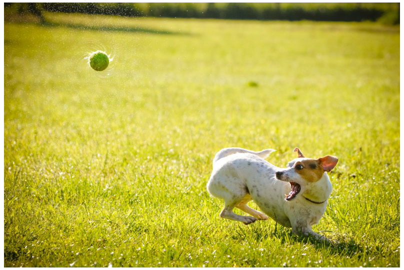


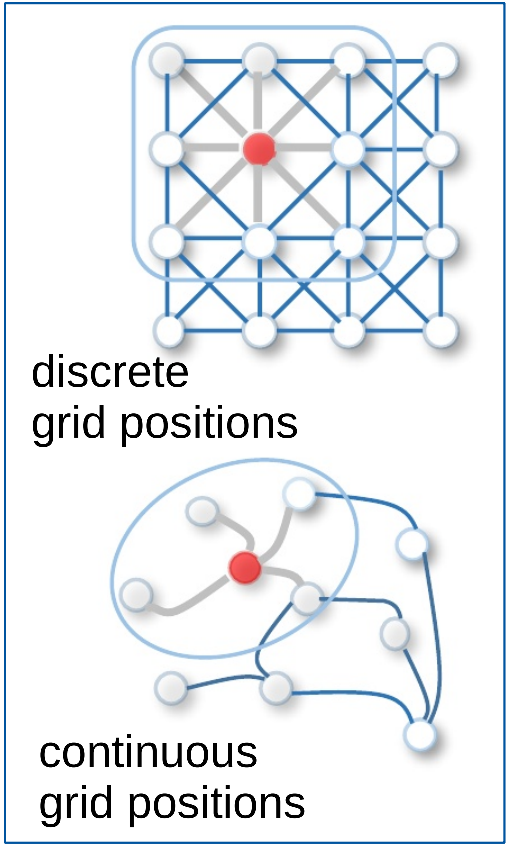
**Image-like data**

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

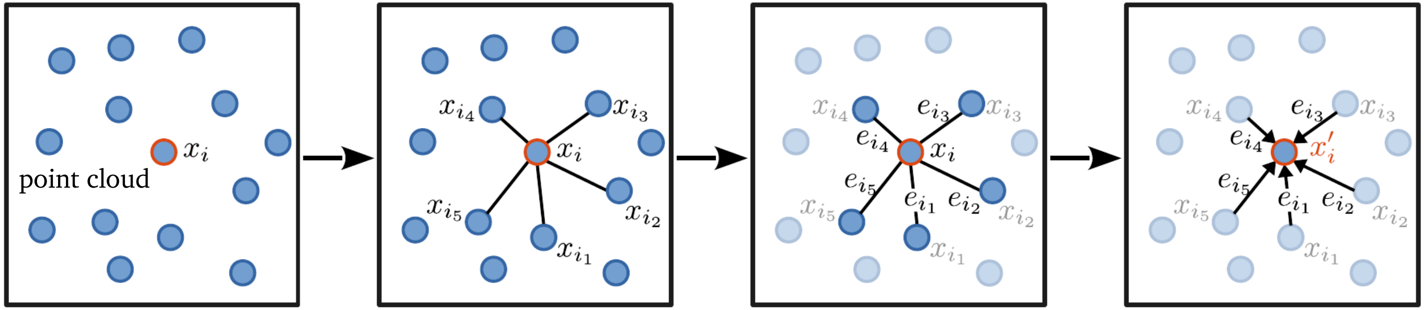
**How can we generalize convolutions?**

# 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

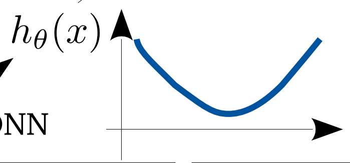
estimation of edge features

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

aggregation over neighborhood

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

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




approx. by DNN

See talk on Wednesday | See talk on Wednesday | See talk on Thursday | See talk on Thursday | See talk on Thursday

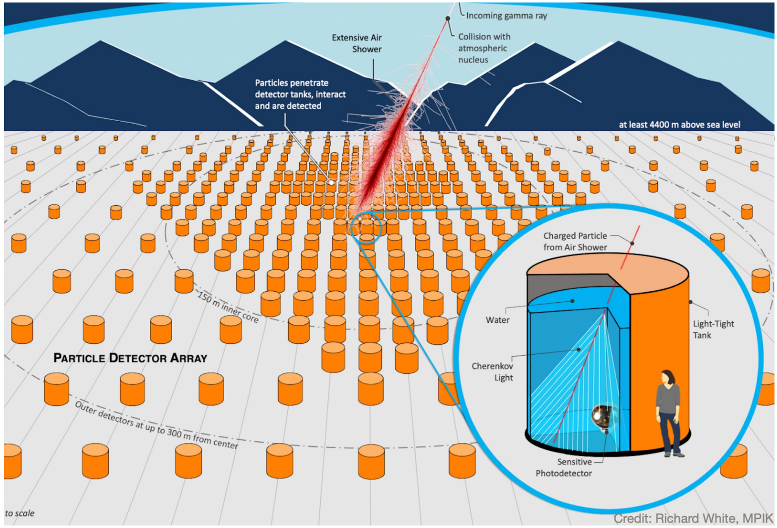
# Deep Learning at SWGO

**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

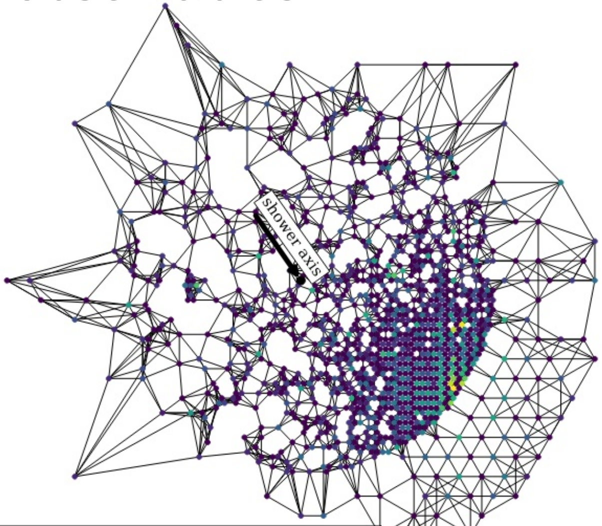
Promising results: GCNs that well handle sparsity

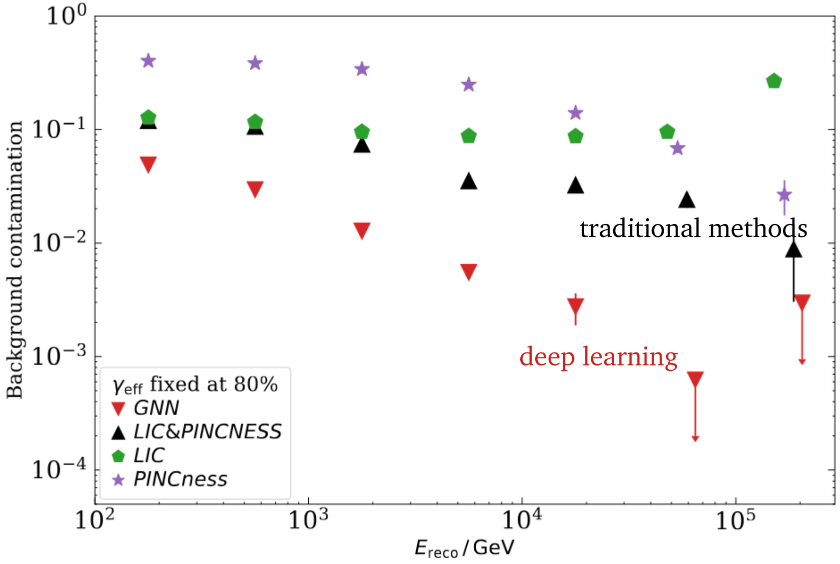
- Superior than ensemble of all previous hand-designed observables




The Southern Wide-field Gamma-ray Observatory

**Example signal graph**
Proton event
E = $10^4$ GeV
Zenith = 35°




See talk on Thursday

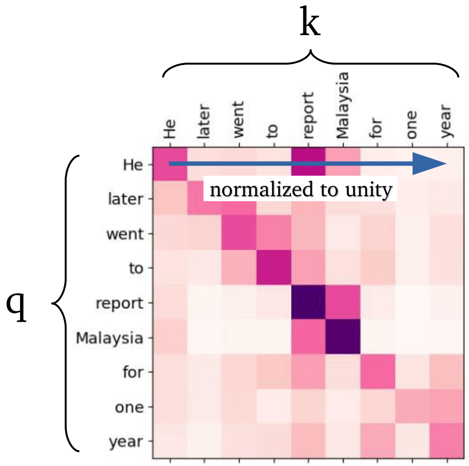
J.G., M. Schneider, F. Leitl, S. Funk, C. van Eldik, arXiv:2411.16565

# Transformers

- Transformers are **backbone of latest breakthroughs**: LLMs / Stable Diffusion
- Building blocks: DNNs with attention mechanism →noise robust
  - Which parts of sequence semantically correlated → analyze together

**Analyze *sequences* (arbitrary lengths):**

- $(x_1, x_2, x_3, x_4, x_5, \ldots, x_n)$
  - single element called *token* (e.g, word)

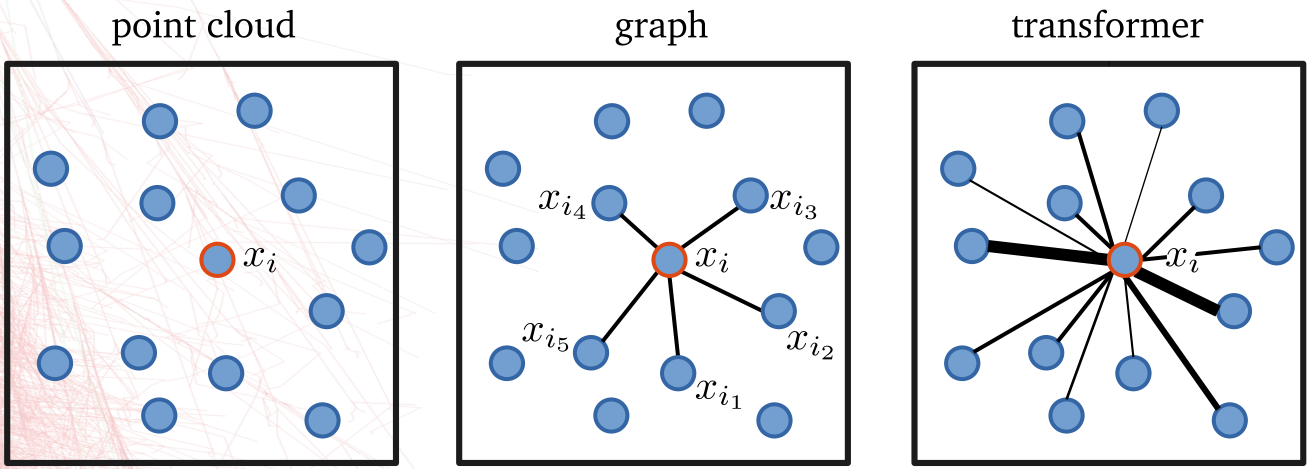


Visualized attention matrix

**Attention:** (in a nutshell) extension of fully-connected DNNs

- listen to all inputs, **focus** on most important inputs
- focus (**attention**) given by correlation in feature space
- <u>Independent</u> of sequence length

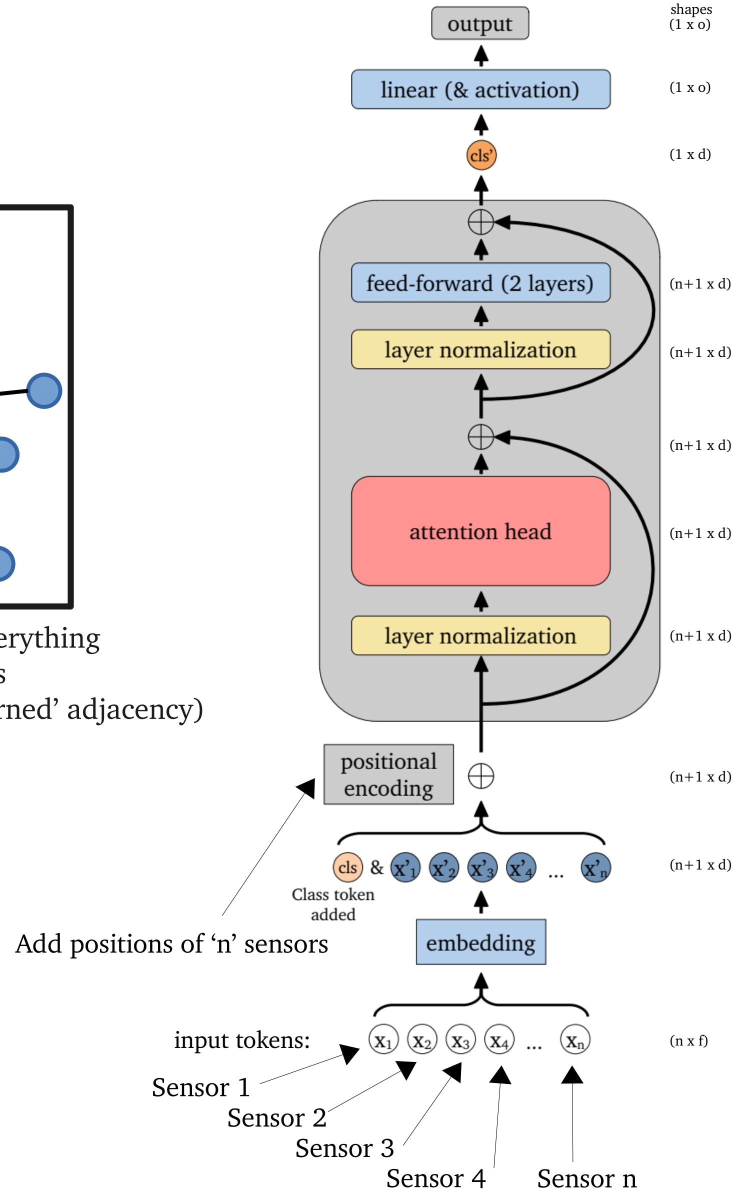
# Point cloud transformer




Prior: local correlations
- kNN clustering defines graph
→ defines **adjacency matrix**

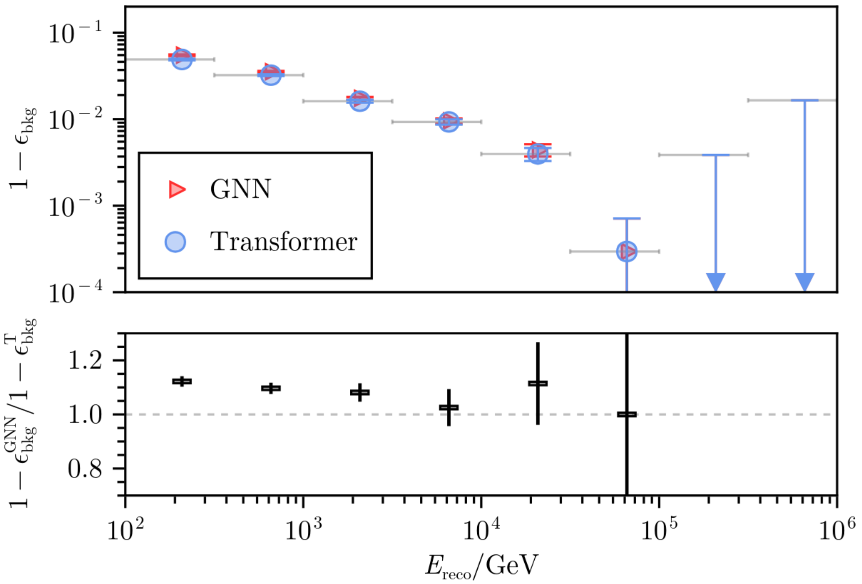
Transformers connect everything
- learns attention weights
→ **attention matrix** ('learned' adjacency)

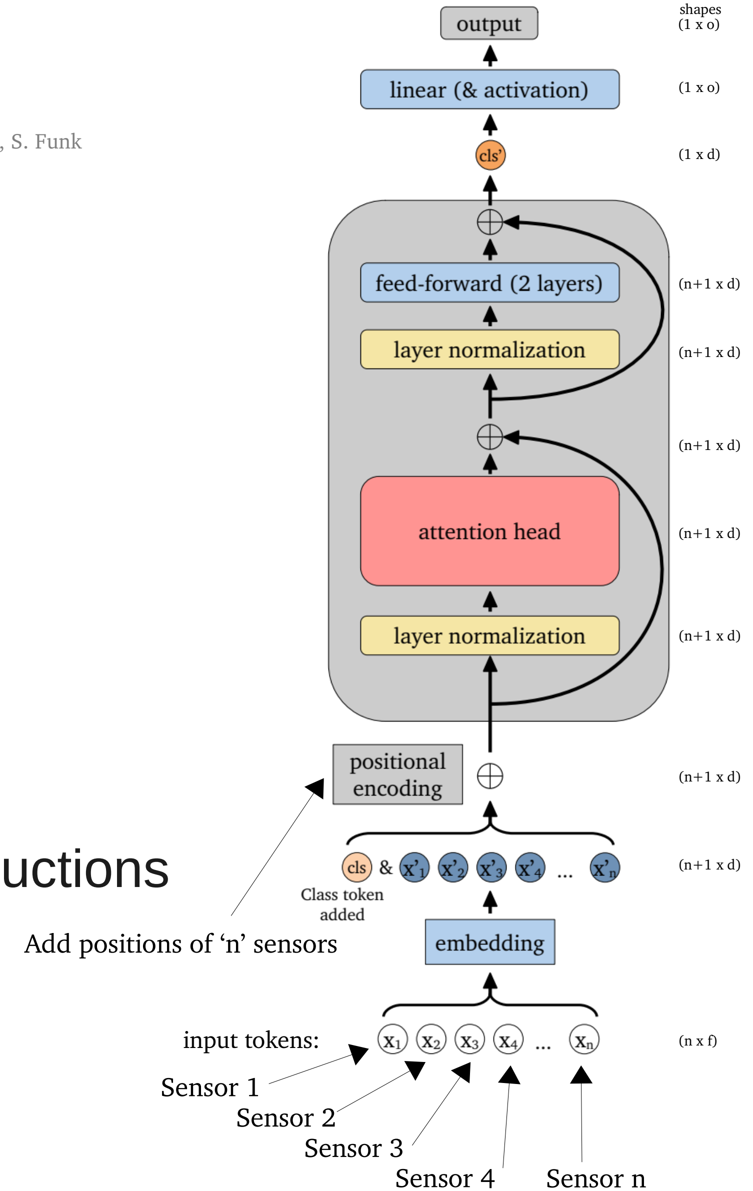
- Transformers as extensions of graph networks



# Point cloud transformer

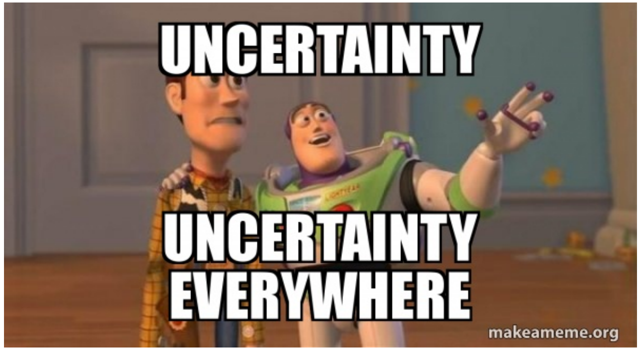
M. Pirke, J.G., F. Leitl, M. Schneider, C.van Eldik, S. Funk




- Transformers as extensions of graph networks
- Additional freedom can lead to improved reconstructions

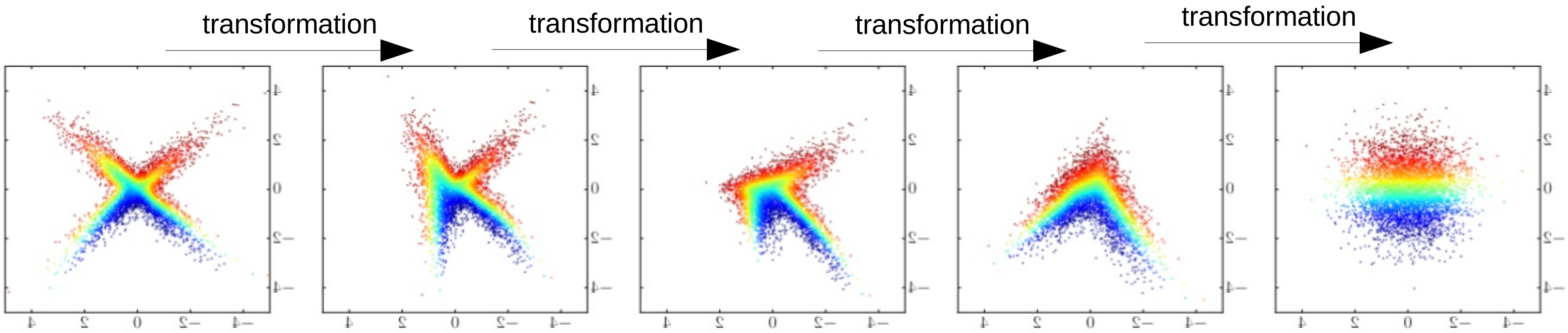
# Uncertainty estimation




See talk on Wednesday

# 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)

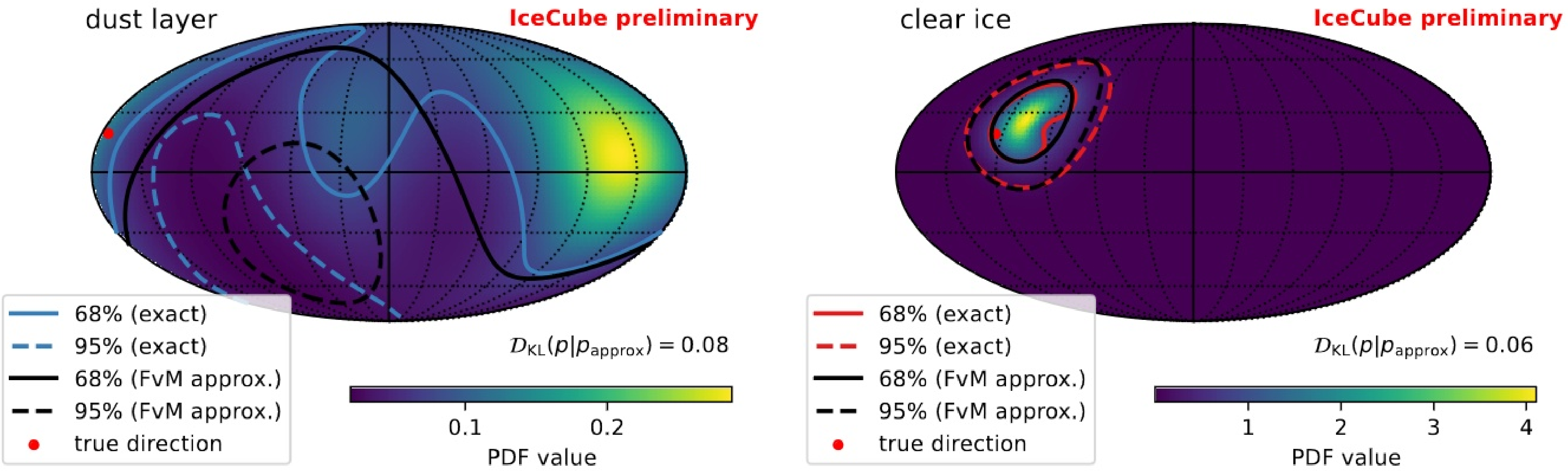
**evaluation/ inference:**

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

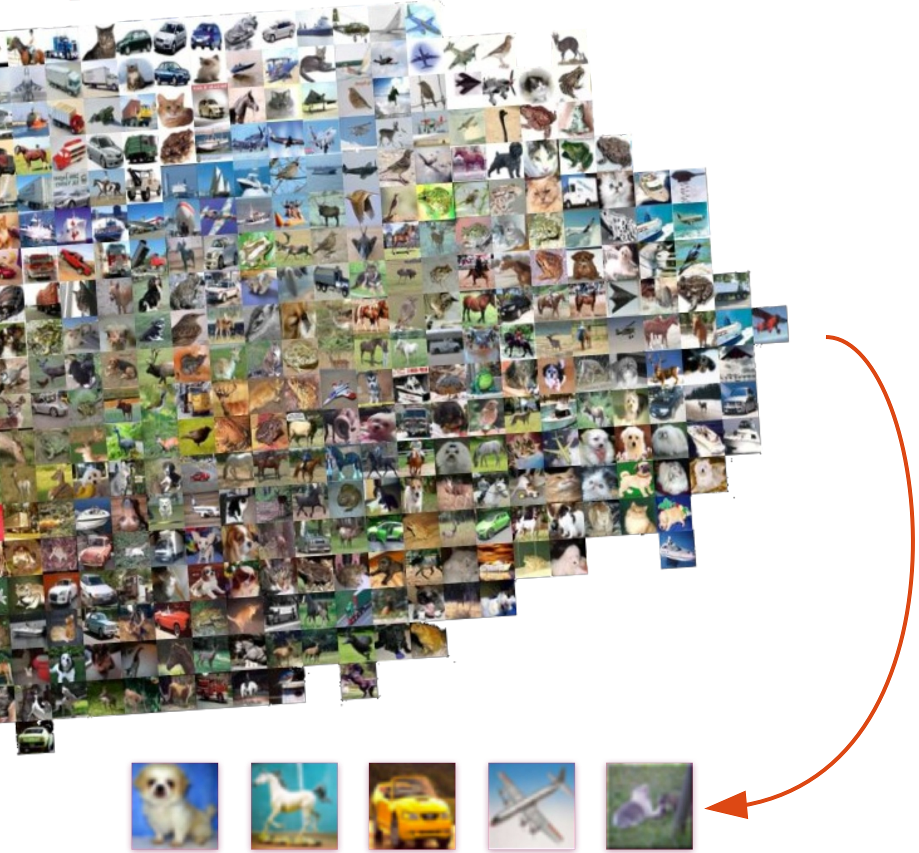



- Dust layer can affect reconstruction uncertainty → usually assumed symmetric
- Application of normalization flows: uncertainty of neutrino arrival direction
  - Reconstruction conditions flow that maps to spherical surface → asymmetric uncertainties

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

# Detector simulations

# 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?

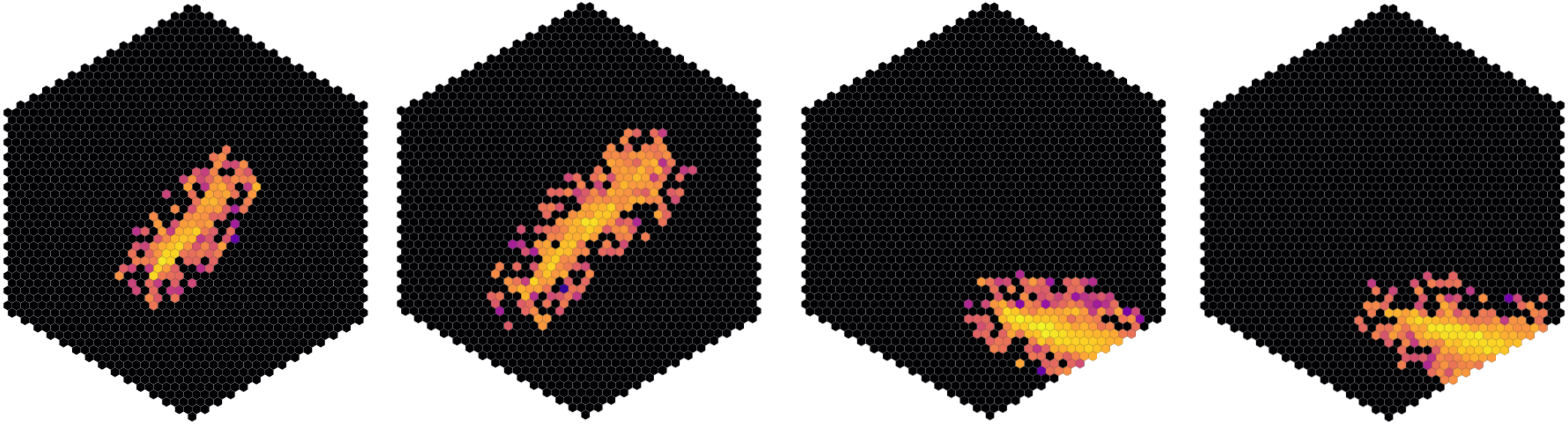


Play the game:
https://www.whichfaceisreal.com

# Which generated IACT image is real?

See talk on Thursday

See talk on Wednesday



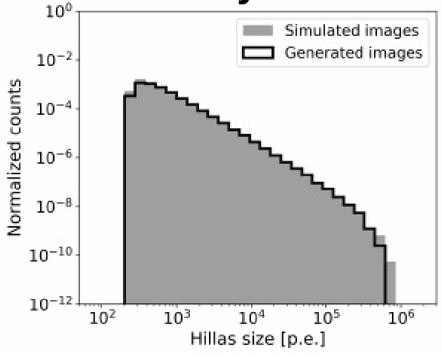
Imaging Air Cherenkov Telescope
Example simulated / generated for the CT5 telescope of the H.E.S.S. array

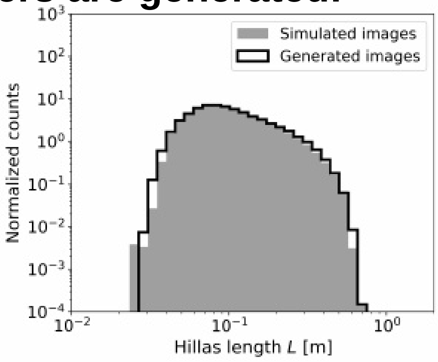


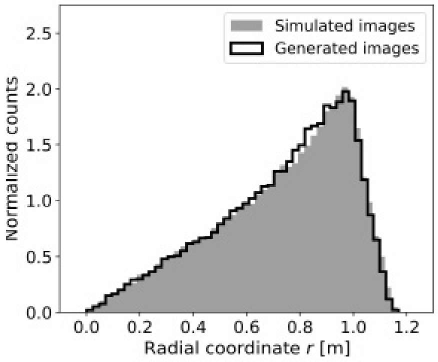
C.Elfein, S.Funk, J.G. JINST 19 P04010 (2024)

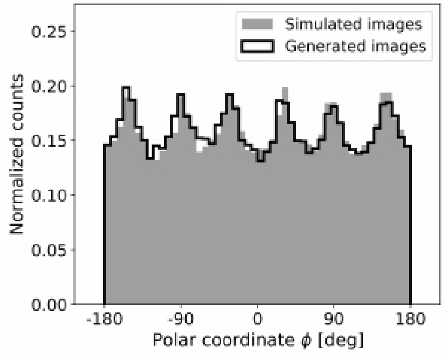
# Hillas Parameter

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



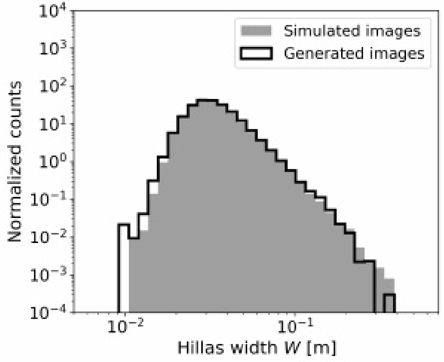
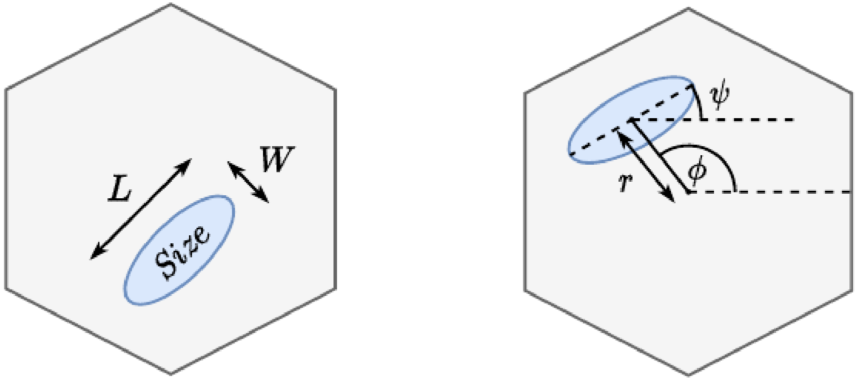
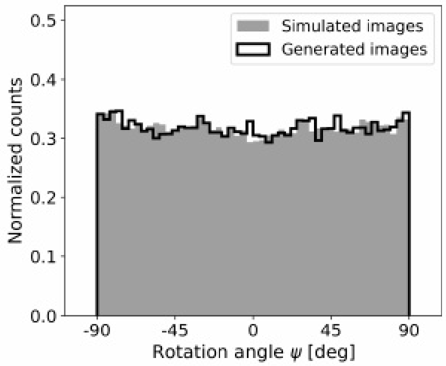




**Image shape modeled well!**




Investigate Hillas parametrization
→ traditionally used for event reconstruction




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



C.Elfein, S.Funk, J.G. JINST 19 P04010 (2024)

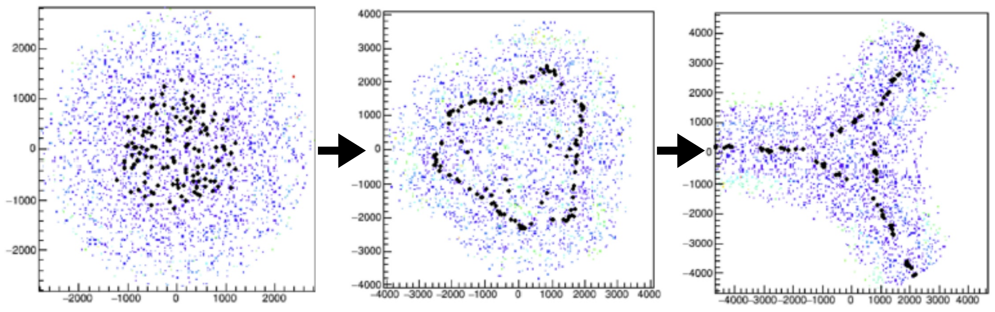
# Detector optimization
## and differentiable programming

Given science requirements → maximize utility function → optimize experiment

T. Dorigo et al, arXiv:2310.01857

Toy example: Gamma ray observatory

- Closed-from parametrization of air shower simulation
- Learn the station placing of a water-Cherenkov gamma-ray observatory

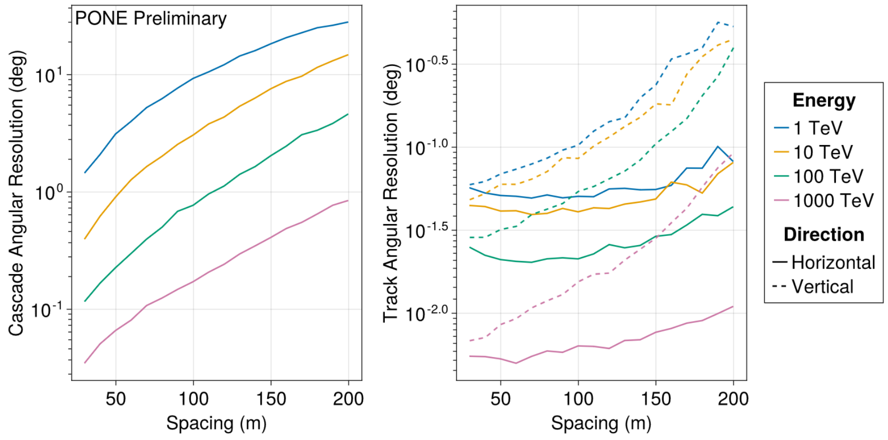


Convergence of station layout

C. Haack, L. Schumacher PoS(ICRC2023)1059

P-ONE: planned neutrino telescope

- Approximate response of single detector for various using surrogate model (NF)
- Estimate stat. limit via Fisher Information




**MODE Collaboration**

Open collaboration engaging the ML-based design of experiments

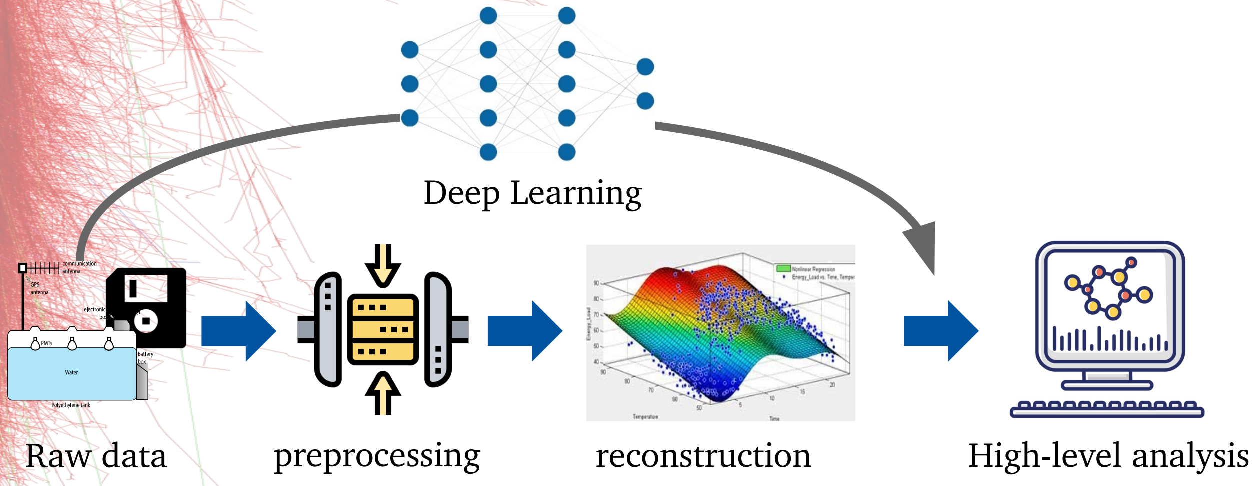
https://mode-collaboration.github.io/

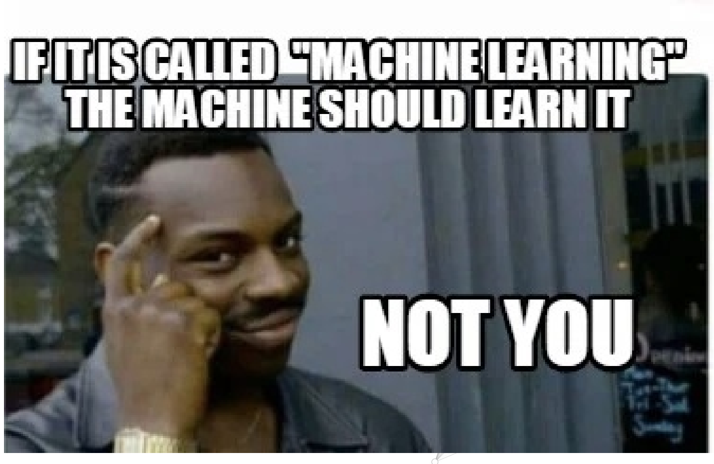
ERLANGEN CENTRE FOR ASTROPARTICLE PHYSICS

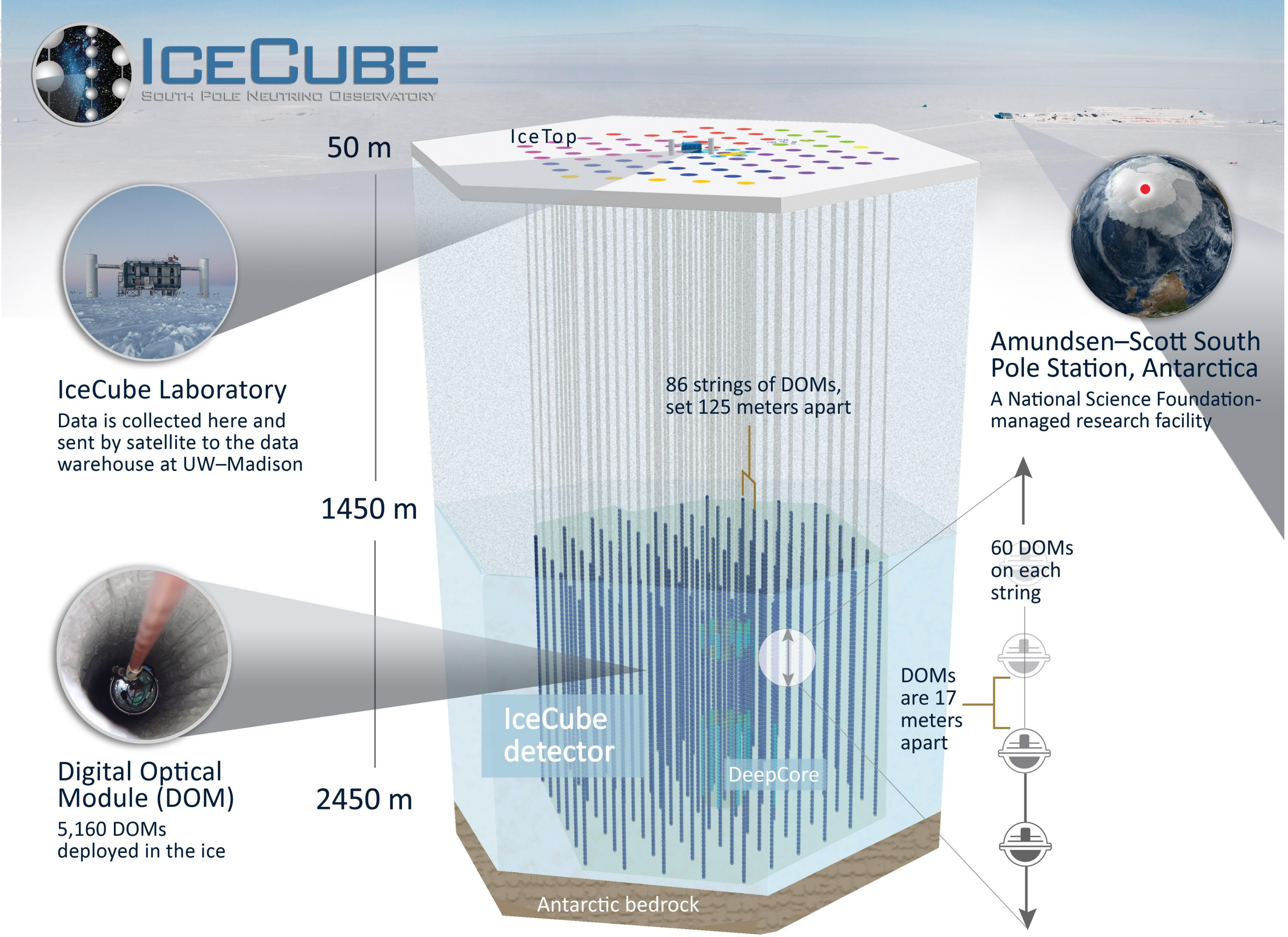
FAU

# Physics Results
# & application to measurement data

Astroparticle physics analysis → based on deep learning



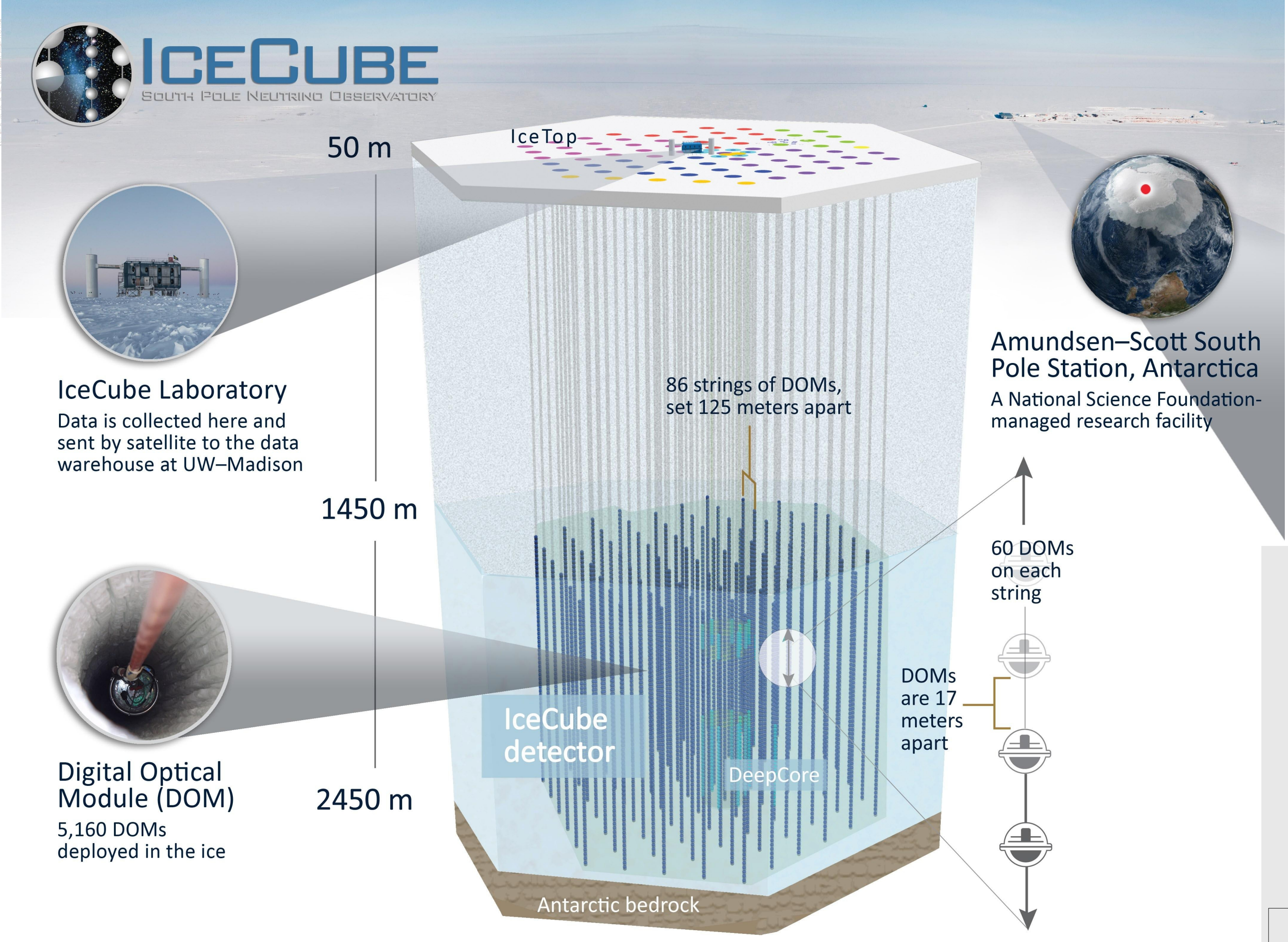



- Instrumented km³ of ice
- Detect astrophysical neutrinos (>1TeV)
- DOMs detect time resolved signals (Cherenkov light)

## Key findings

- Discovery of astrophysical neutrinos
- Evidence for neutrinos from Blazar, active galaxy, GP
- Indication for astrophysical antineutrinos (Glashow)

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



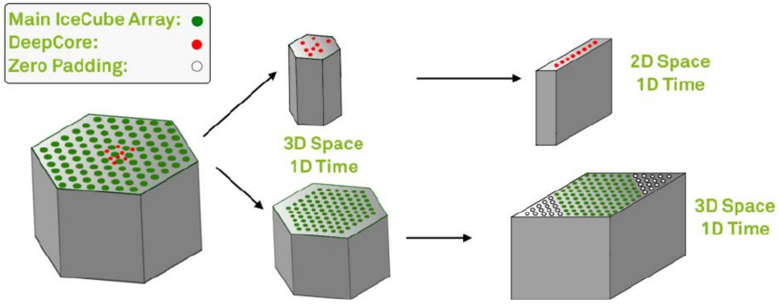

- Instrumented km³ of ice
- Detect astrophysical neutrinos (>1TeV)
- DOMs detect time resolved signals (Cherenkov light)

**Challenging background**

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

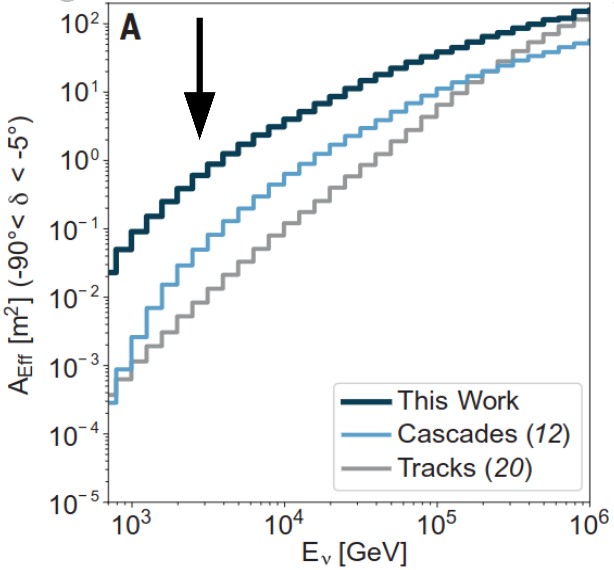
**Odds for being killed by a vending machine: 1.2 * $10^8$**

# Improvement: data-driven techniques



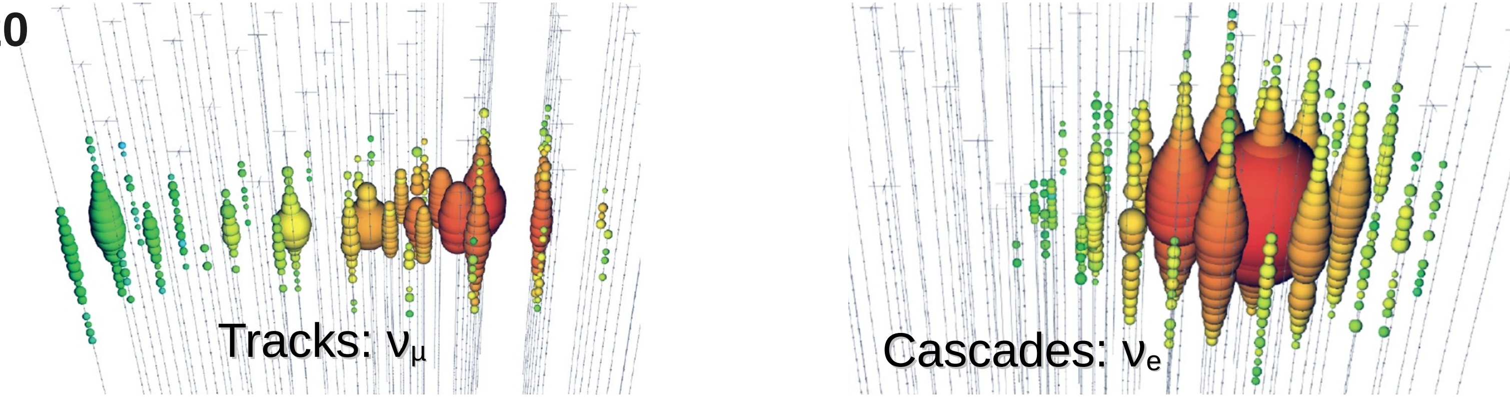

**Final sample:**
87% atmospheric neutrinos
7% astrophysical neutrinos
6% atmospheric muons

Deep learning: events x20!




## Analysis of cascade events

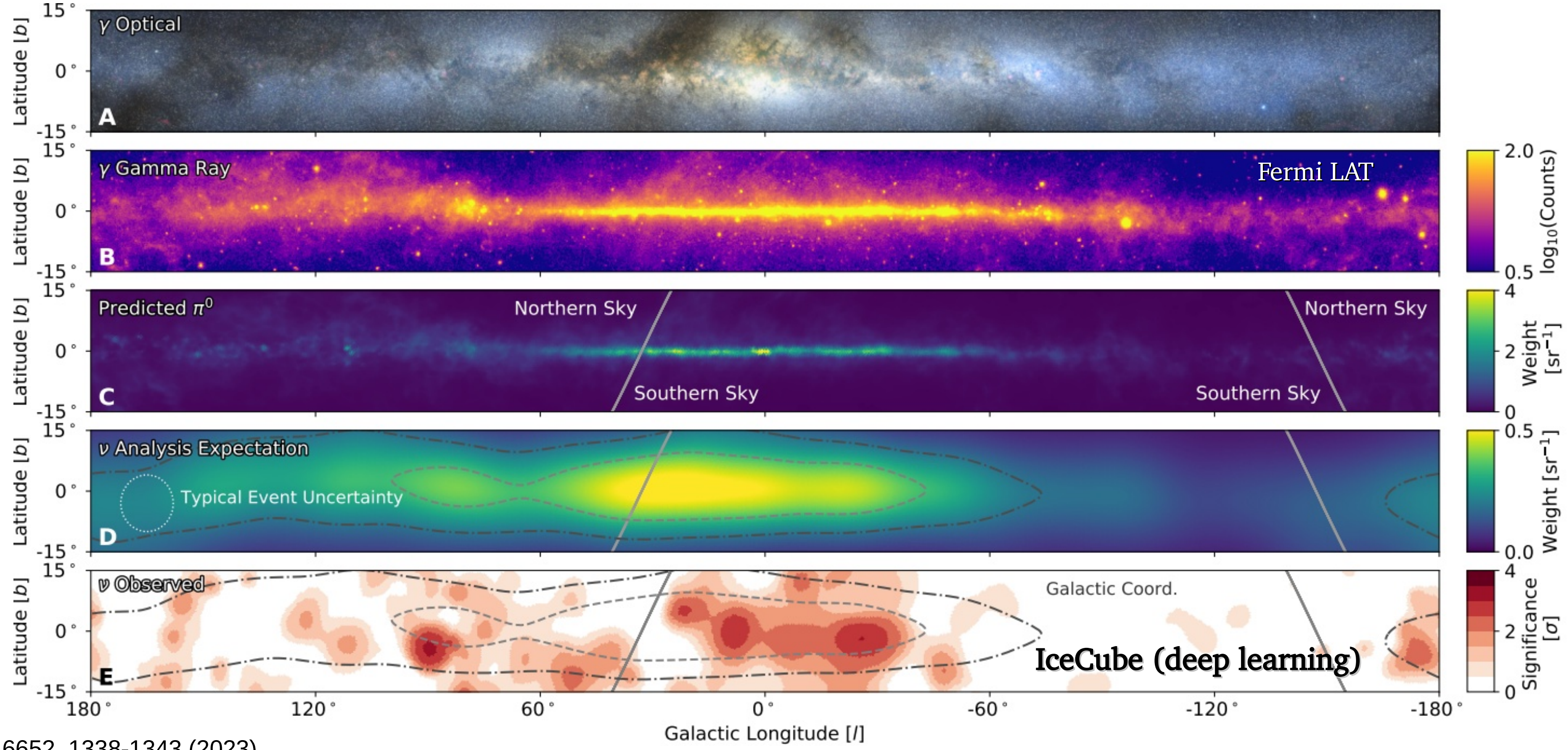
- Improved rejection of atmospheric muons (CNN based)
- Improved reconstruction of cascade events (NN + MLE)
- Reconstruct partially-contained events
- **Statistics increase x20**





[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)

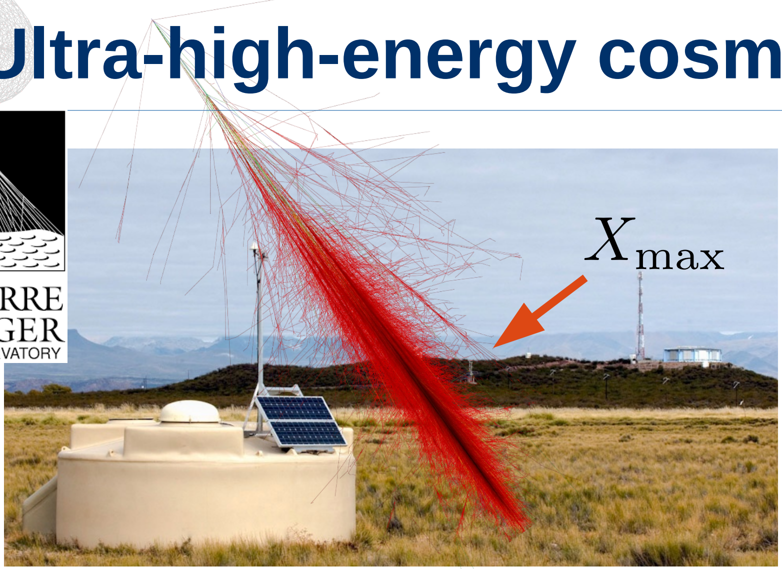
- Comparison to Gamma-ray catalog
- 4.5σ significance (scrambling w. right ascension)



**Evidence for diffuse neutrino emission from Galactic plane!**

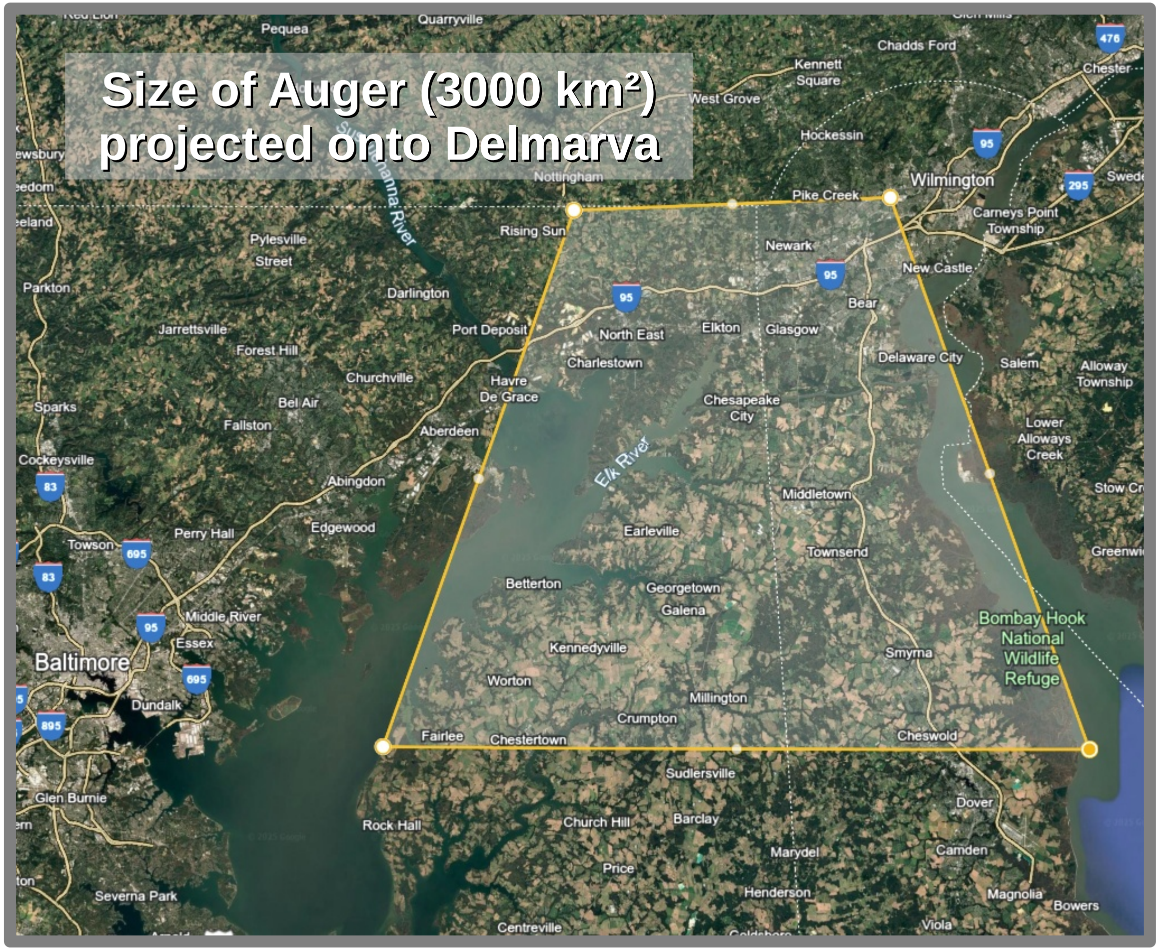
# Ultra-high-energy cosmic rays (UHECRs)

PIERRE AUGER OBSERVATORY




## The Pierre Auger Observatory

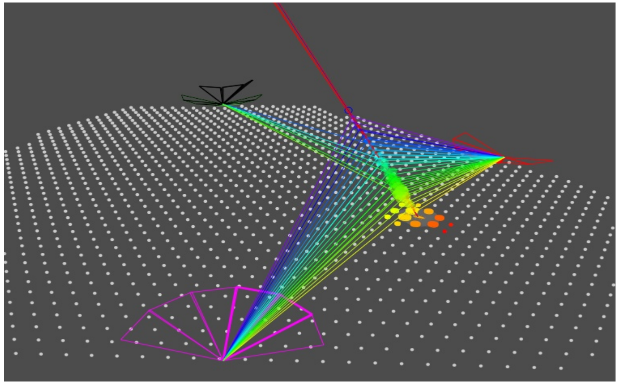
- world’s largest observatory to study ultra-high-energy cosmic rays
- hybrid detection of air showers
  - 1,660 water-Cherenkov detectors
  - 27 fluorescence telescopes
    - can precisely observe Xmax



# Air-Shower Reconstruction

The Pierre Auger Collaboration, JINST 16 P07019 (2021)

PIERRE AUGER OBSERVATORY



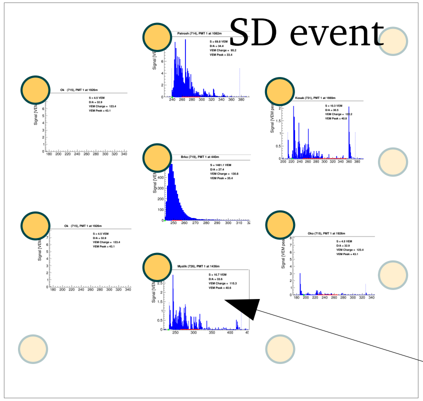
## Pierre Auger Observatory

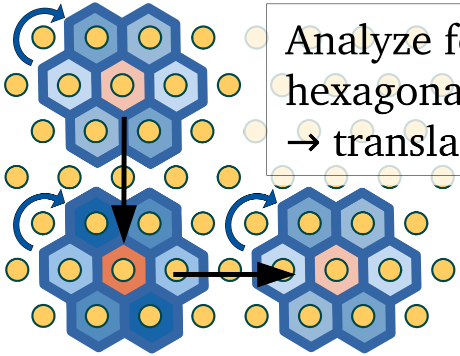
Fluorescence Detector (15% duty cycle)

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

Surface Detector (~100% duty cycle)

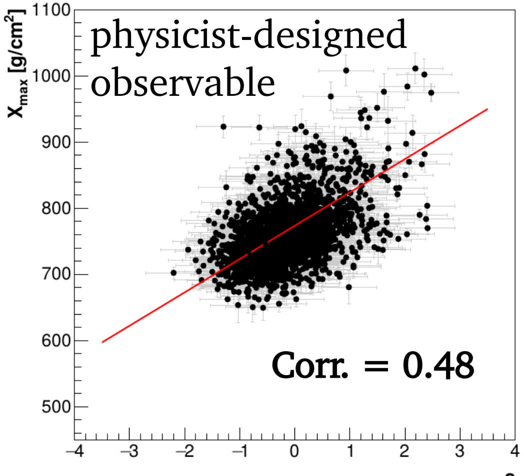
- reconstruction of shower maximum using deep learning
- verification with hybrid detection



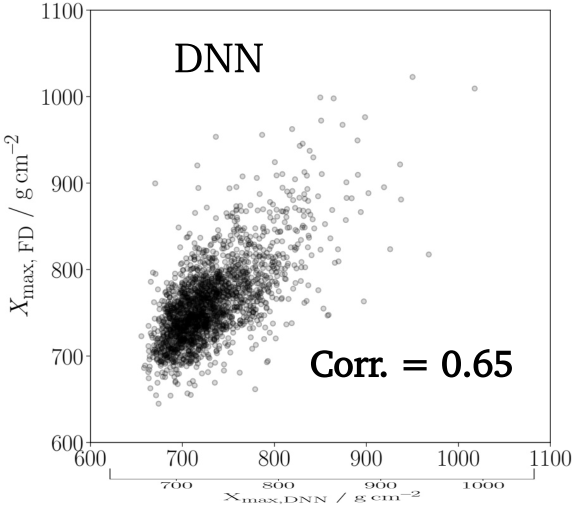



Analyze footprint with hexagonal convolution → translation + rotation

analyze traces with RNNs




ArXiv/1710.07249



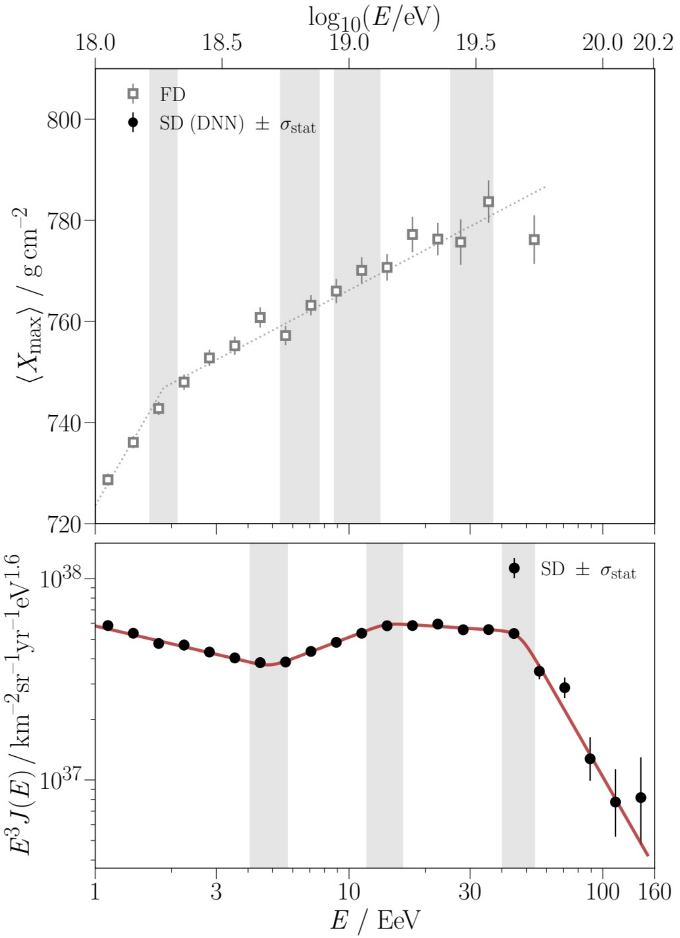
# Evidence for breaks in the elongation rate

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., Phys. Rev. Lett. 134, 021001 (2025)

A. Abdul Halim (Pierre Auger Collaboration) et al., Phys. Rev. D 111, 022003 (2025)

# 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:

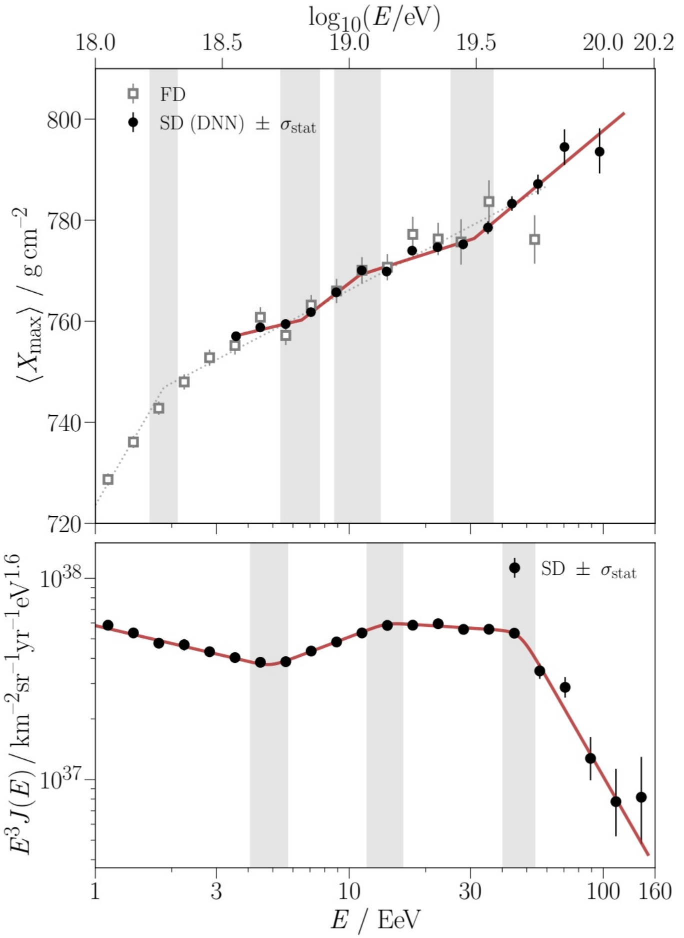
- Linear model describes transition from light to heavy

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., Phys. Rev. Lett. 134, 021001 (2025)
A. Abdul Halim (Pierre Auger Collaboration) et al., Phys. Rev. D 111, 022003 (2025)

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 (MC)

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

### IV. Exploiting symmetries
- Incorporating symmetries into architectures
- increase robustness

### V. Full Physics analyses
- Publications by Collaborations
- Application to data
- Extensive study of systematics

### DL close to sensors
On-site application of ML algorithms

### ‘Unsupervised era’
- exploiting measured data
- refinement of simulations
- AI-based detector design

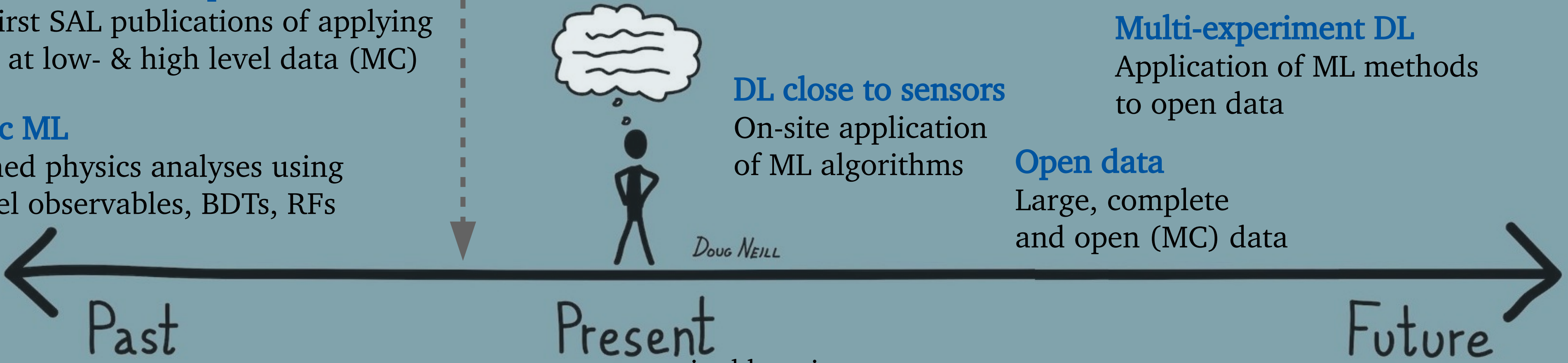
### Physics with LLMs
- use pre-trained models
- try “to teach” physics

### Interpretability
- introspection & causality
- Distilling physics laws from DNNs

### AGPI?
Artificial general Physics Intelligence

### Multi-experiment DL
Application of ML methods to open data

### Open data
Large, complete and open (MC) data

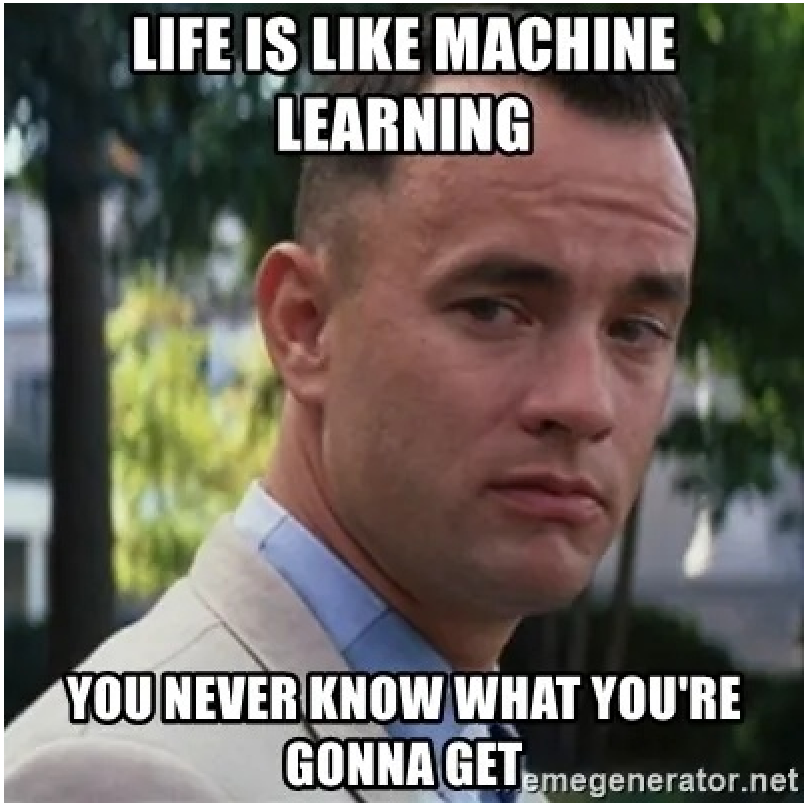



supervised learning

unsupervised learning

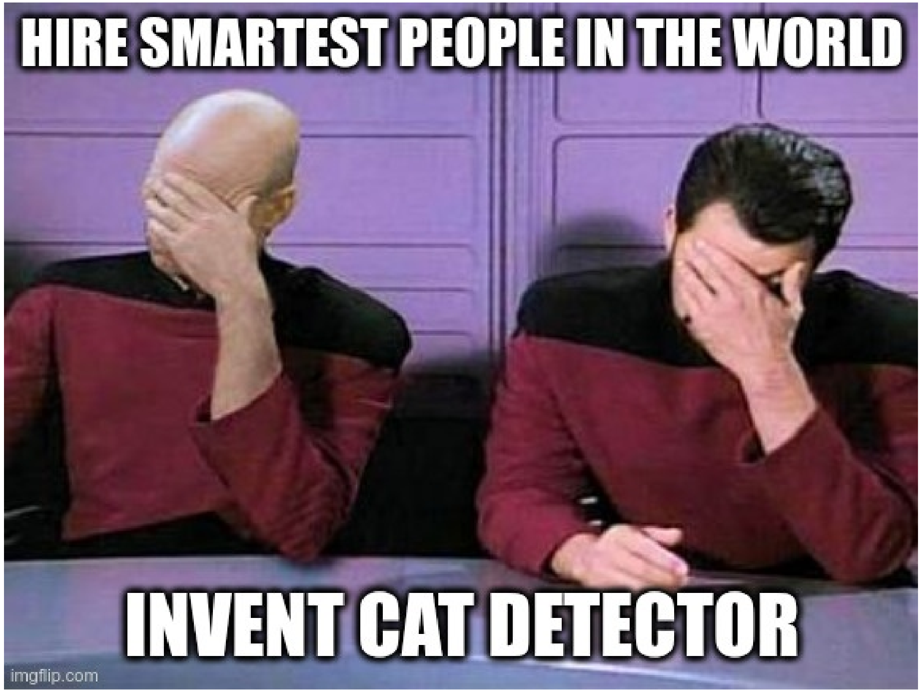
self-supervised learning

# BACKUP


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

# 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

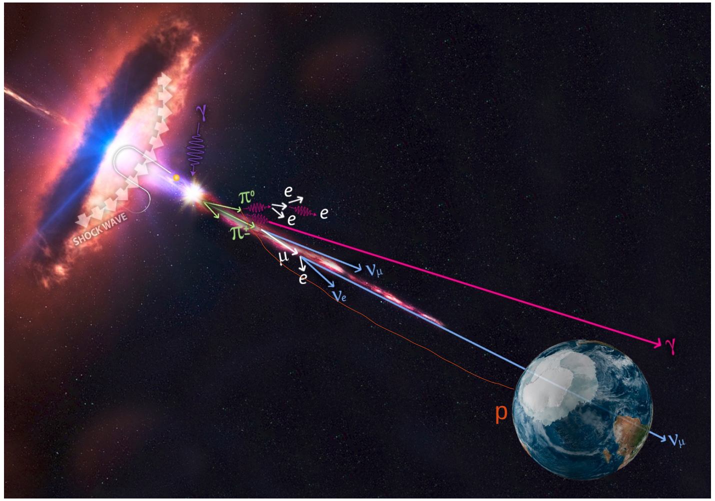


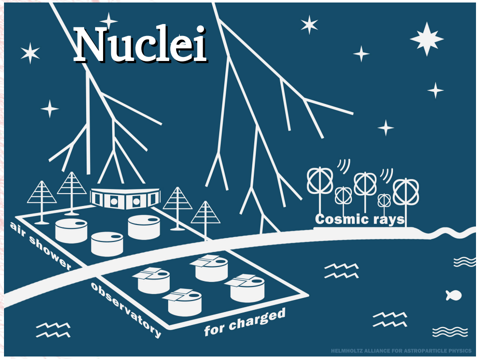

**Let’s make use of deep learning in astroparticle physics!**

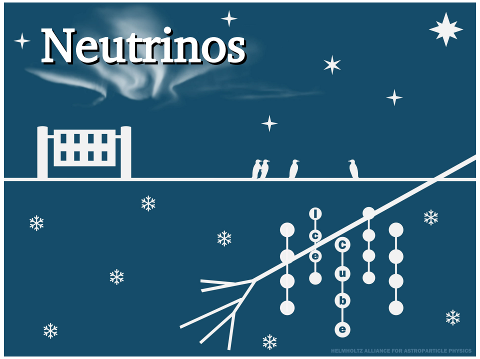
# Astroparticle Physics

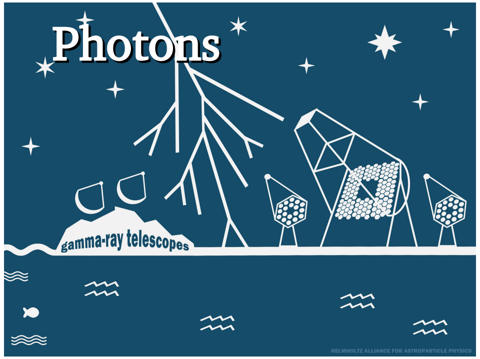
- Observation of particles with astronomical origin
- Search for their sources
  - Understand physics of astronomical objects
- Cosmic messengers: Photons, neutrinos, nuclei

- Distant sources, high particle energies
  - Experiment feature huge detector volumes



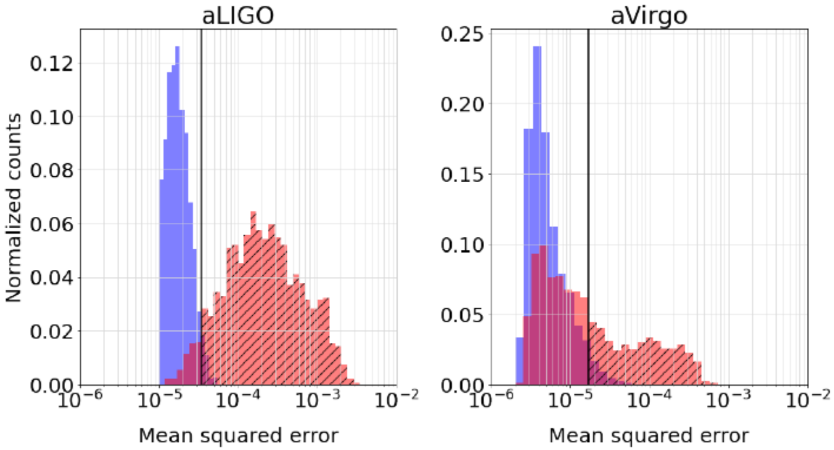



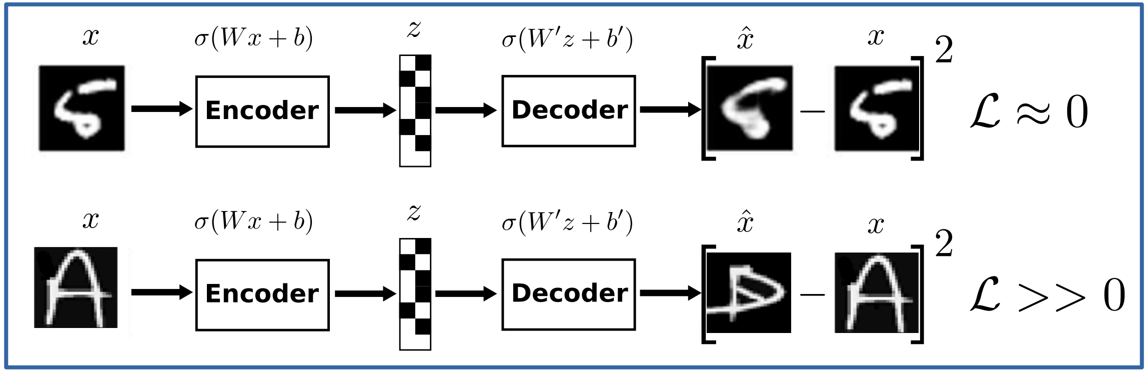




**Origin of high-energy cosmic rays not known! (since >100 yrs)**

# Anomaly Detection

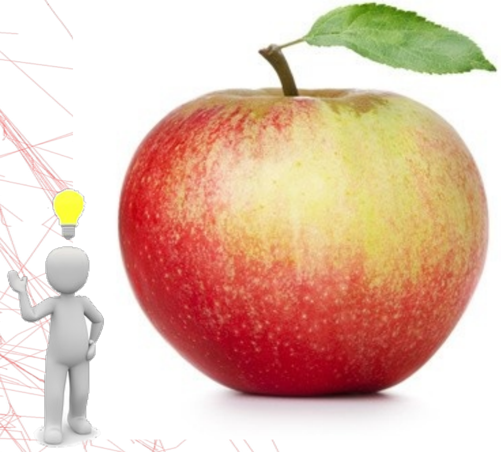
- Search for data, different than used for training, using autoencoders
- indication for new physics, proposed for BSM searches at LHC
- training without limited data (no signal labels)
  - first approaches in astroparticle physics
    - detection of gravitational waves




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

See talk on Thursday



# 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

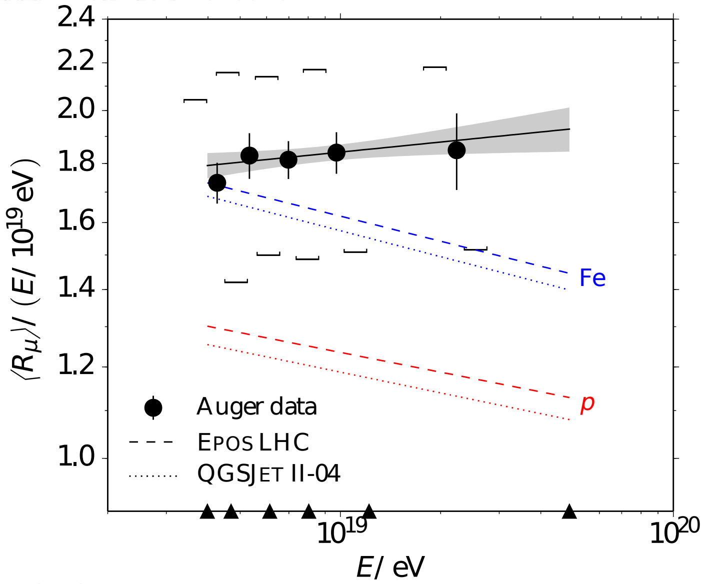
style transfer

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

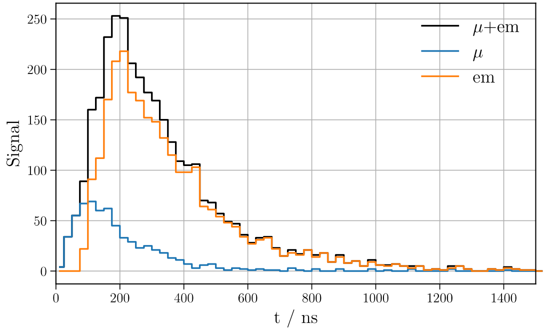
# Domain Adaption

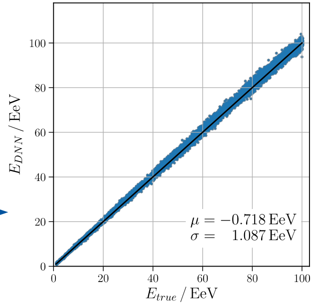
Comput Softw Big Sci (2018) 2: 4

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



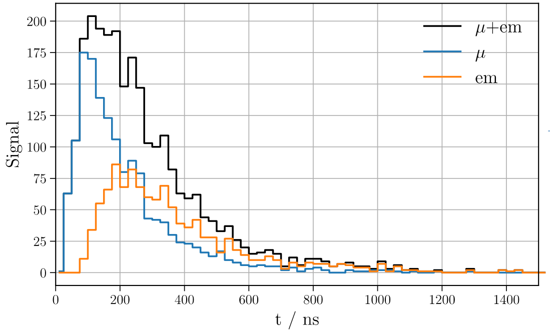

**Simulation**
**70%** electromagnetic
**30%** muonic

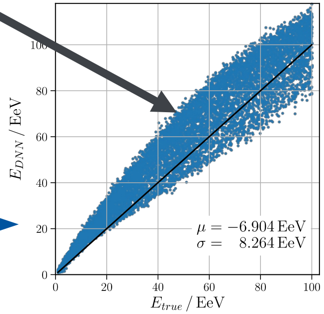



Network can not handle modified traces

**‘Data’**
**30%** electromagnetic
**70%** muonic

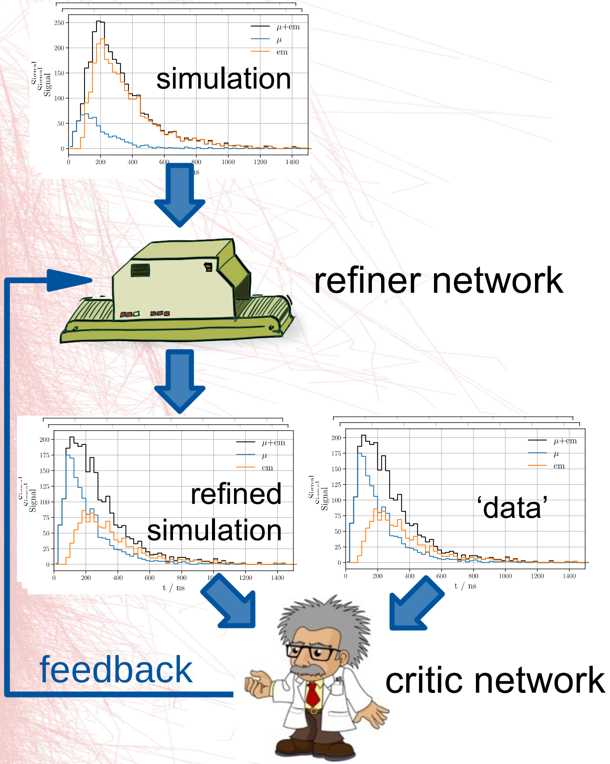


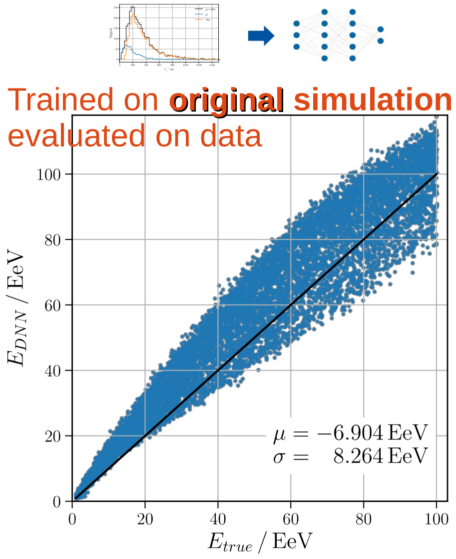
# Simulation Refinement

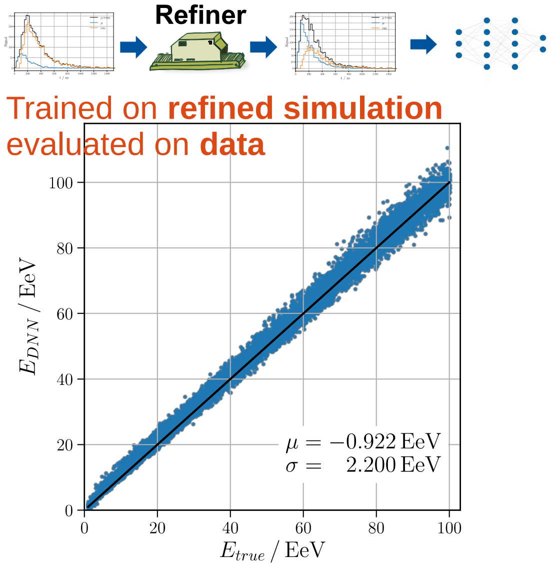
Erdmann et al.
Comput Softw Big Sci (2018) 2: 4

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

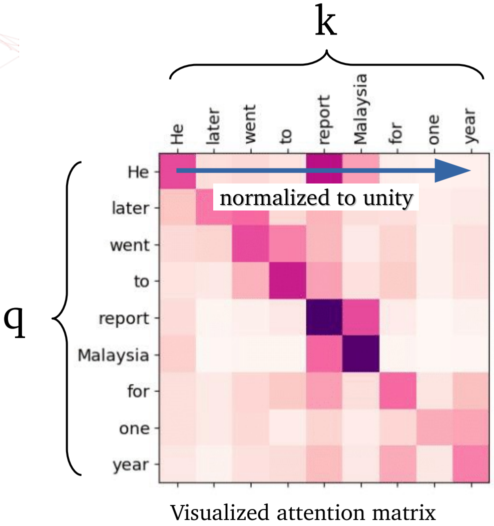


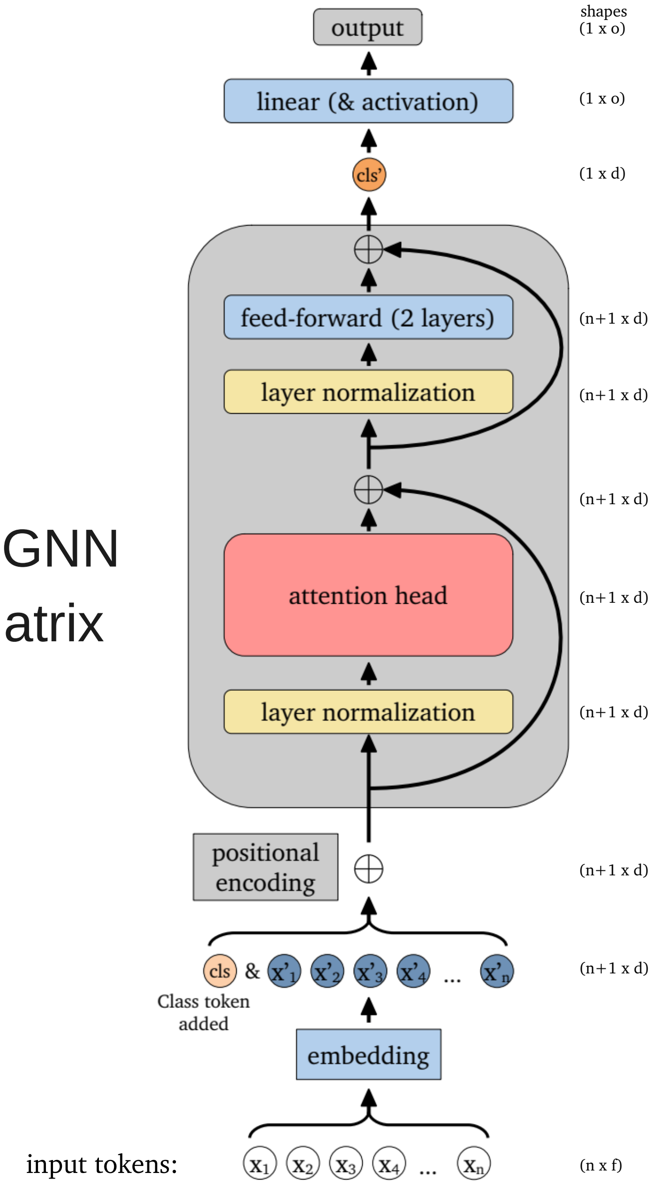
# Point cloud transformer

- Architecture designed for sequence-to-sequence tasks
  - Core of large language models (LLM)
  - Independent of sequence length

- Heavily exploits **attention** mechanism
  - Correlates everything with everything → extension of GNN
  - Clever way to tell DNN where to focus on: attention matrix



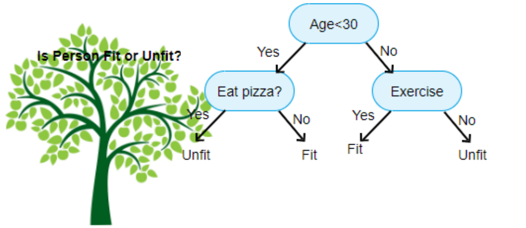
Visualized attention matrix



# 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

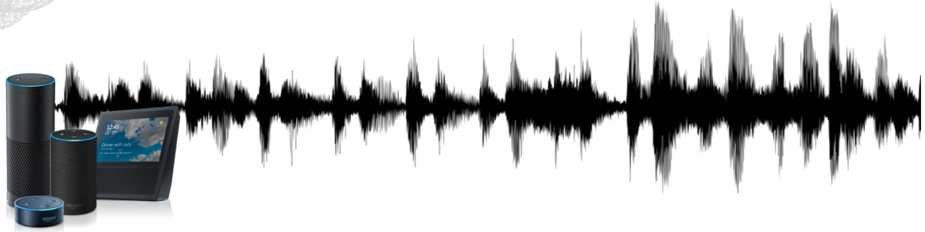
Schlau in zwei Stunden

VON ALEXANDER ARMBRUSTER - AKTUALISIERT AM 27.09.2017 -

www.faz.net


© nature

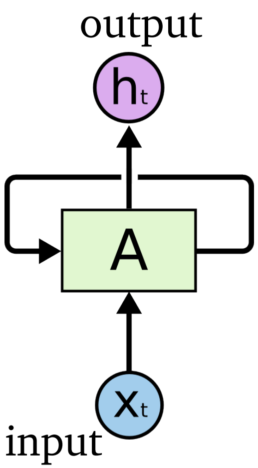
# Deep Learning: RNNs & CNNs



## Recurrent Networks (RNNs)

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

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



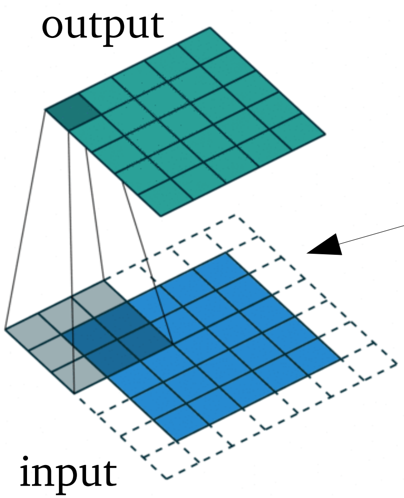

Advanced concept: LSTM

features memory

- long-rate correlations

## Convolutional Networks (CNNs)

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

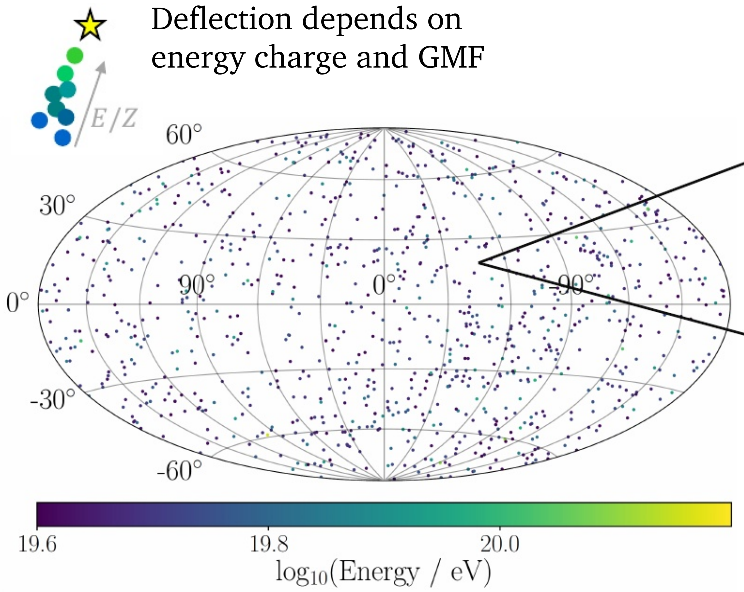



| | | |
|---|---|---|
| $w_1$ | $w_2$ | $w_3$ |
| $w_4$ | $w_5$ | $w_6$ |
| $w_7$ | $w_8$ | $w_9$ |

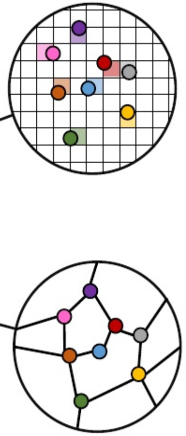
adaptive parameters of **filter**

# Search for UHECR Origins

Slide credit: Niklas Langner




Continuously distributed on **sphere**

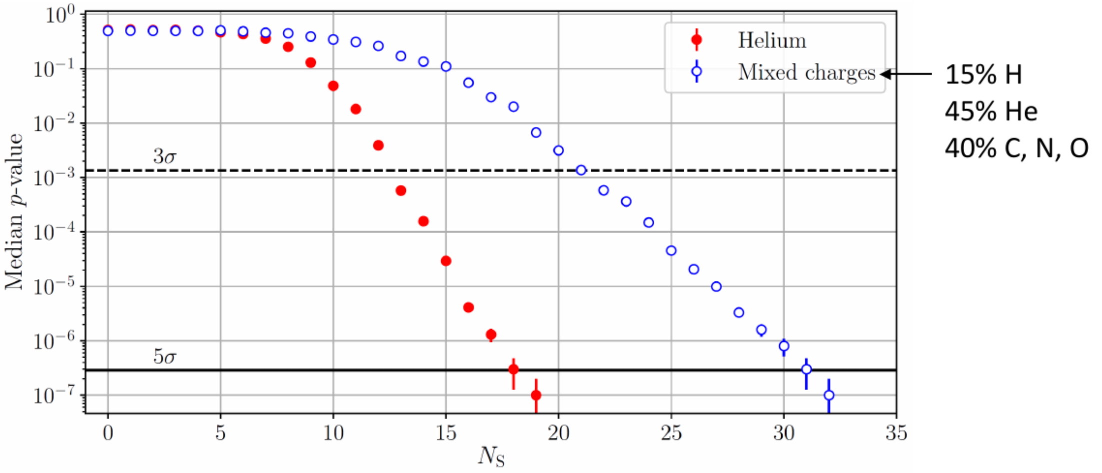



Situation:

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

Learn to classify between

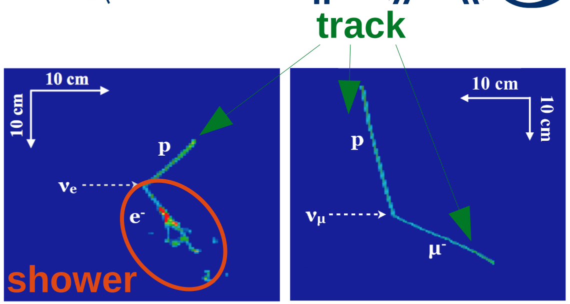
- isotropic sky / signal
- use dynamic edge convolutions

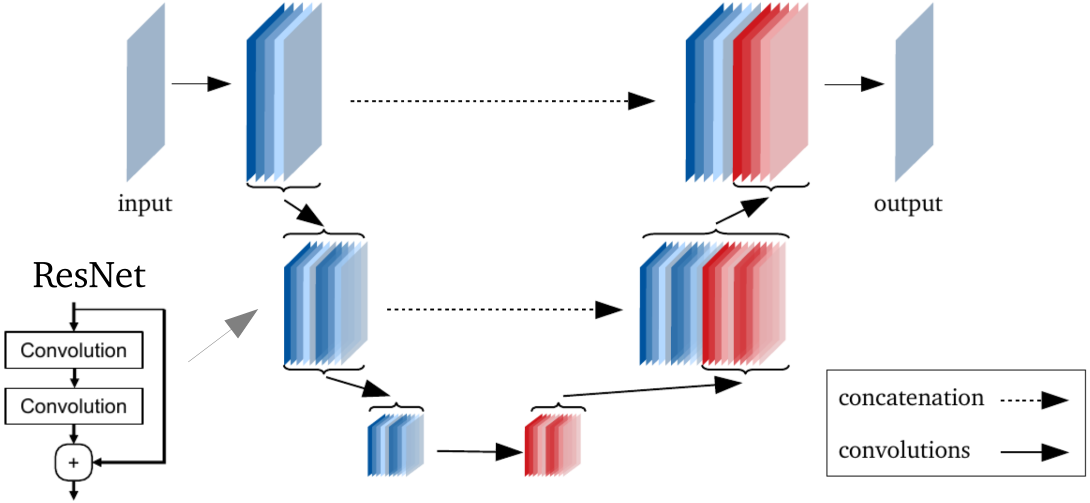


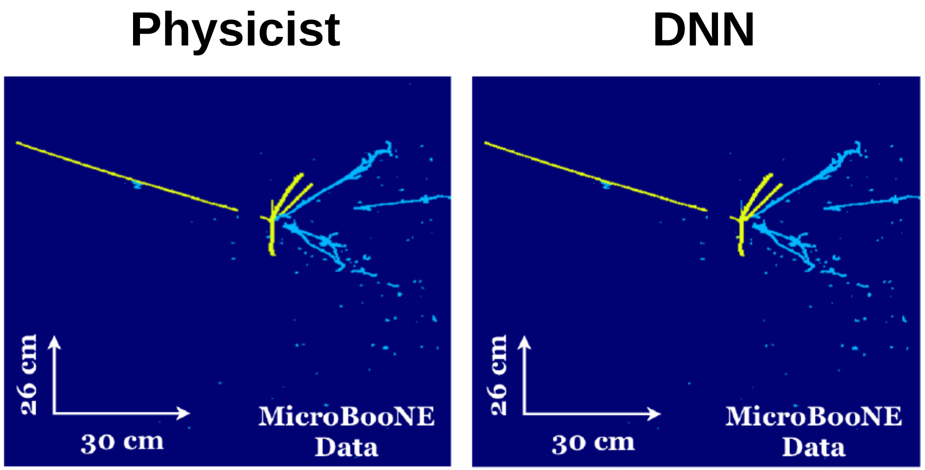

Bister et al., 10.1016/j.astropartphys.2020.102527

# 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

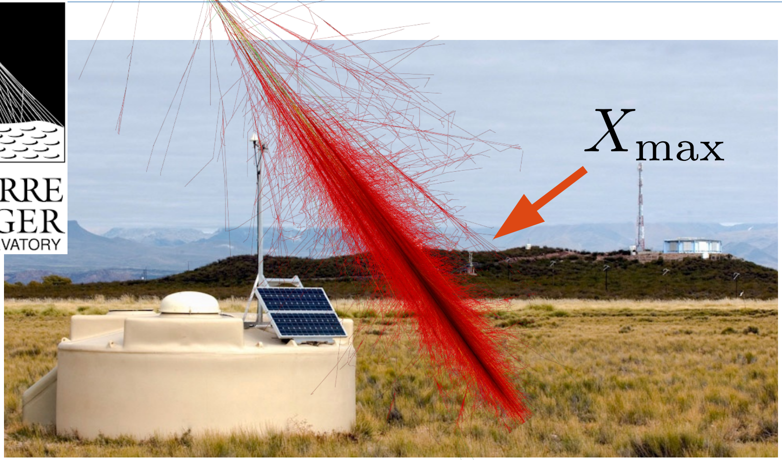



Adams et al. ArXiv: 1808.07269

# Ultra-high-energy cosmic rays (UHECRs)

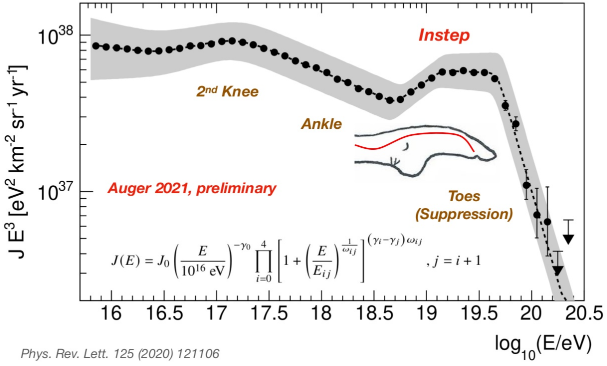



## The Pierre Auger Observatory

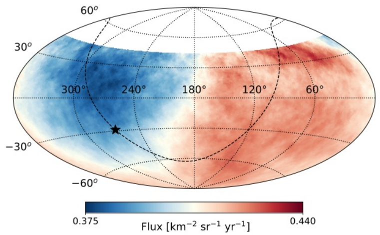
- world's largest observatory to study ultra-high-energy cosmic rays
- hybrid detection of air showers
  - 1,660 water-Cherenkov detectors
  - 27 fluorescence telescopes
    - can precisely observe Xmax

## Key findings

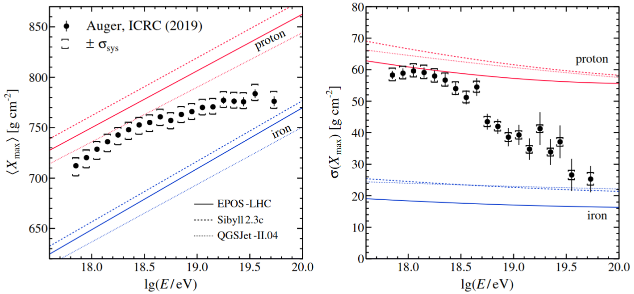
Characteristics of the <u>energy spectrum</u>



*Phys. Rev. Lett. 125 (2020) 121106*




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

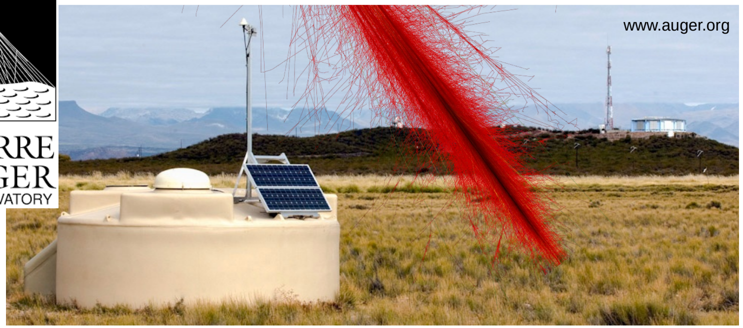



<u>Mass composition</u>
Towards heavier and purer composition

Cutoff not caused by GZK only

# Air-Shower Reconstruction

The Pierre Auger Collaboration, JINST 16 P07019 (2021)



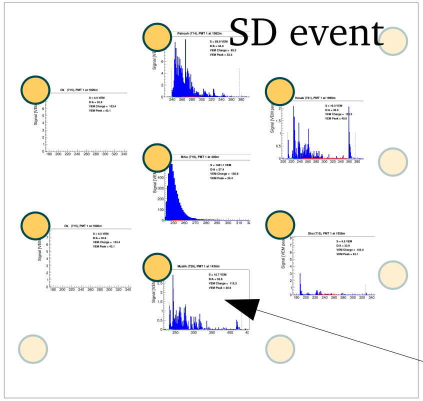

## Pierre Auger Observatory

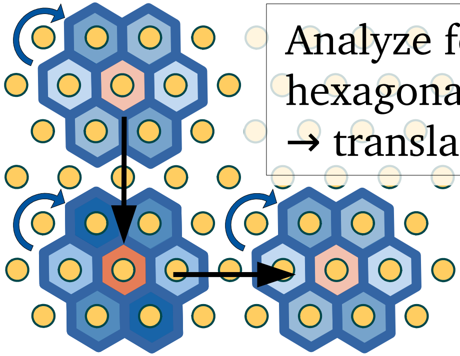
Fluorescence Detector (15% duty cycle)

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

Surface Detector (~100% duty cycle)

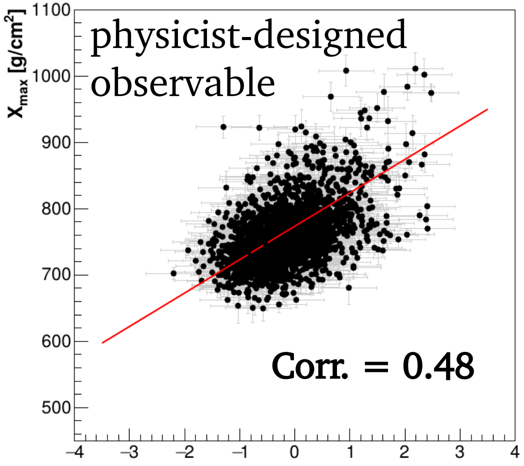
- reconstruction of shower maximum using deep learning
- verification using hybrid measurements



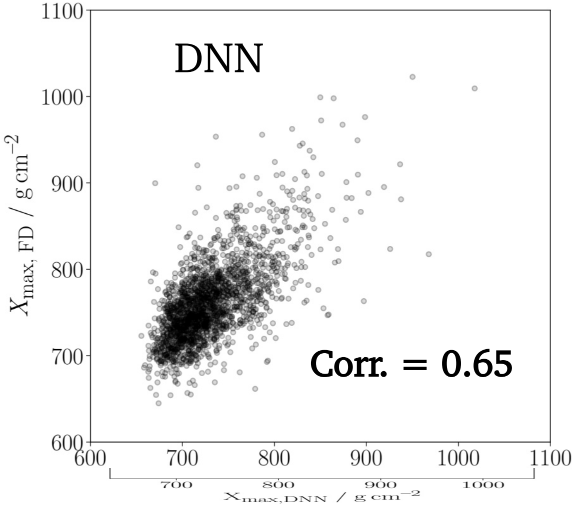



Analyze footprint with hexagonal convolution → translation + rotation

analyze traces with RNNs



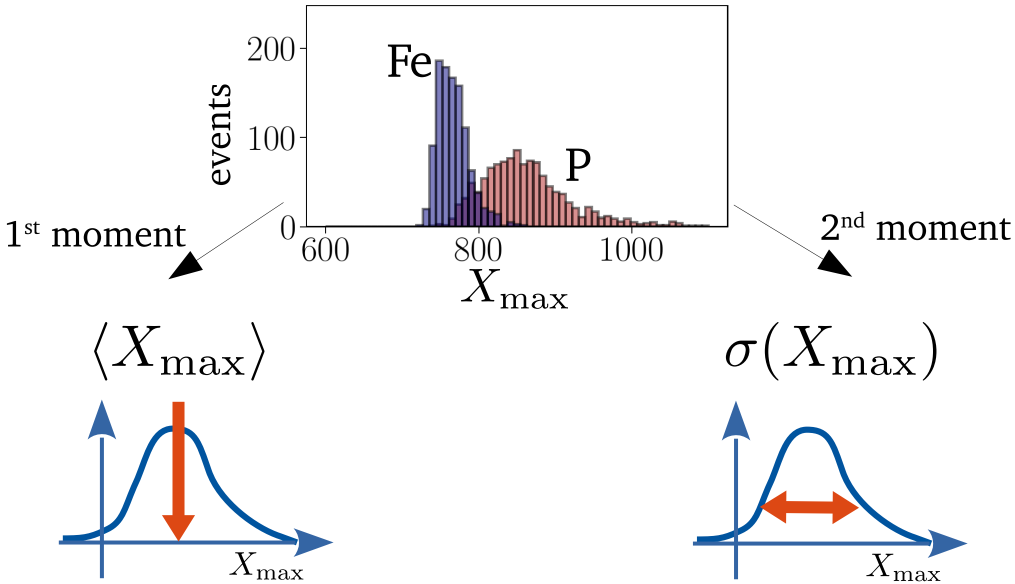

ArXiv/1710.07249

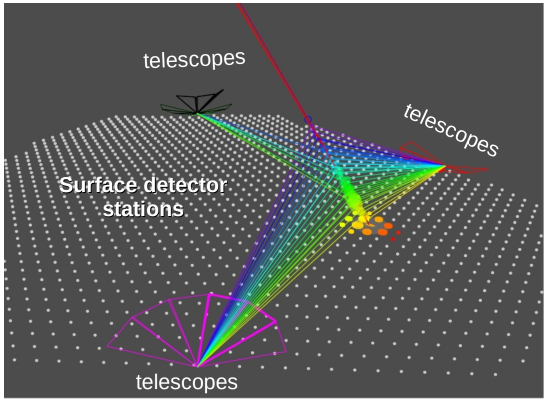


# $X_{max}$ reconstructed with SD data

## Mass composition of UHECRs

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




## Hybrid detector

Fluorescence Detector (15% duty cycle)

- direct and precise observation of $X_{max}$

Surface Detector (~100% duty cycle)

- Backbone of detector
- Cannot directly observe Xmax

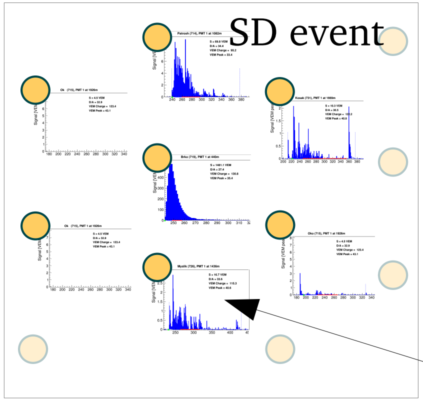
Hybrid events (events measured by both)

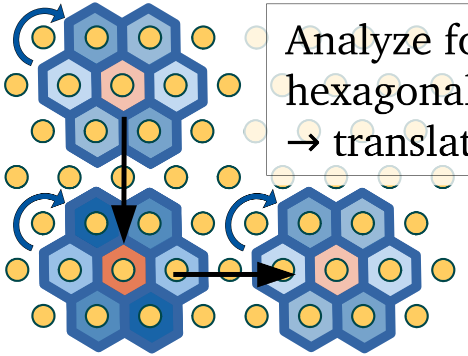
- used to calibrate surface detector

# Air-Shower Reconstruction

## DNN-based Xmax reconstruction

- Reconstruct Xmax using SD signals
- Exploit structure in signal traces (RNNs)
- Analyze footprint using convolutions



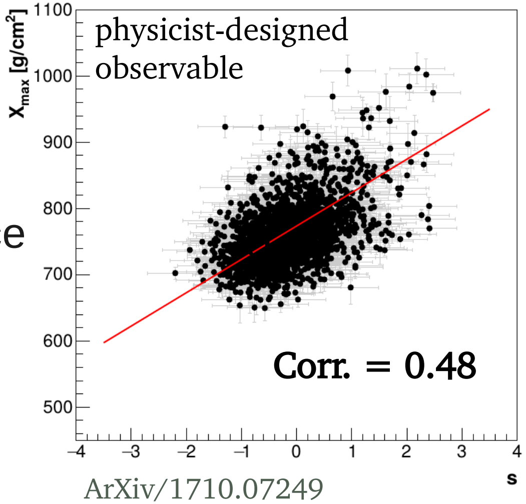



Analyze footprint with hexagonal convolution
→ translation + rotation

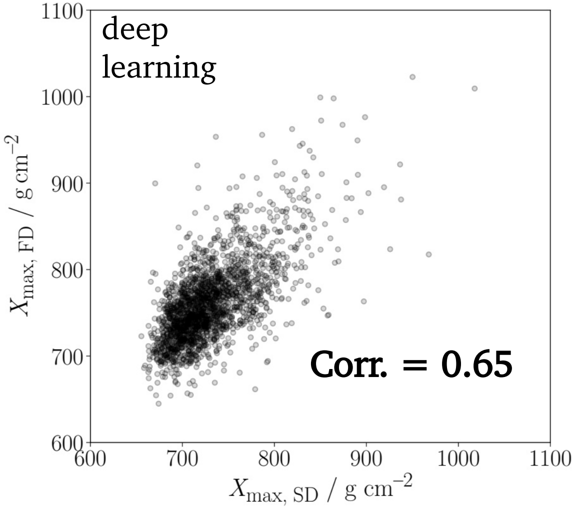
analyze traces with RNNs

## Hybrid data: Calibration & crosscheck

- Recalibrate offset: Remove MC dependence
- Deep learning outperforms traditional Method based on signal rise times




ArXiv/1710.07249

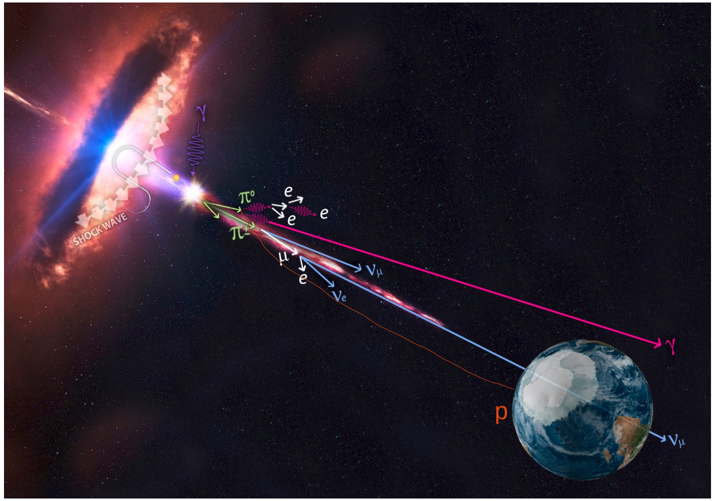


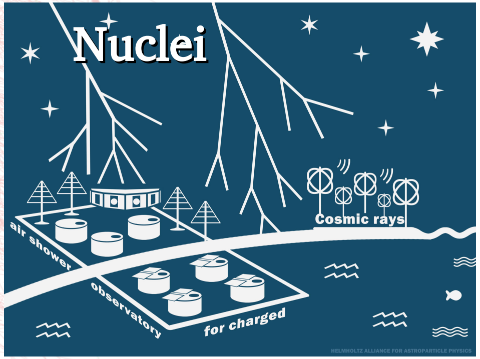

The Pierre Auger Collaboration, JINST 16 P07019 (2021)

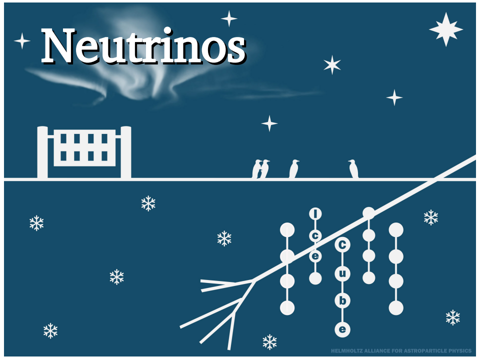
# Astroparticle Physics

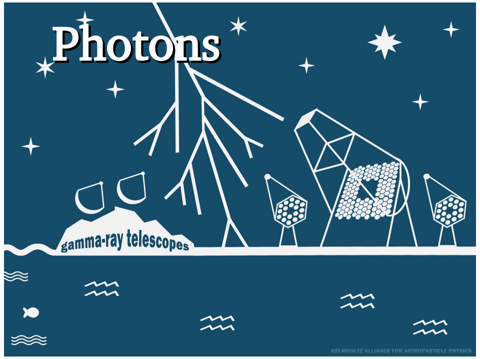
- Observation of particles with astronomical origin
- Search for their sources
  - Understand physics of astronomical objects
- Cosmic messengers: Photons, neutrinos, nuclei

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




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

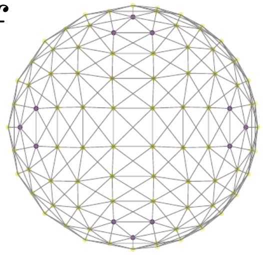
# Convolutions on Spherical Domains

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

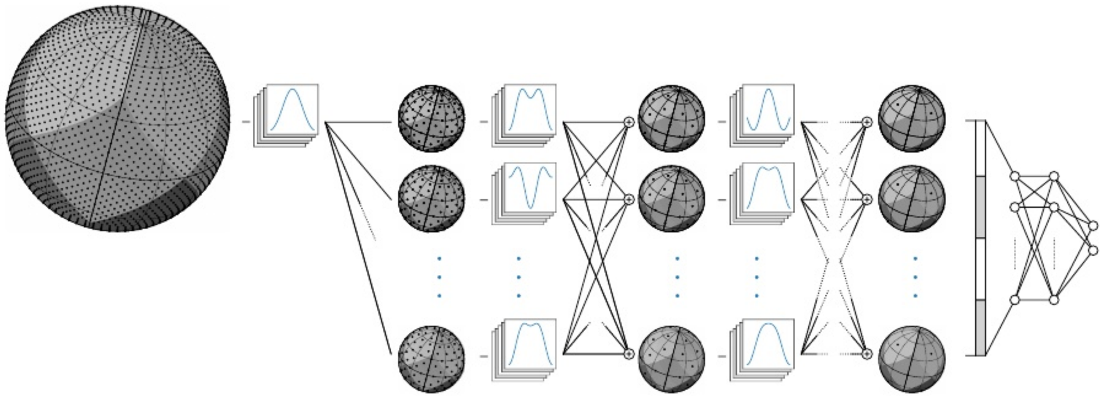
  Example: DeepSphere, for spherical data
  - HEALPix pixelization defines graph structure
- based on fixed pixels (useful for sensor configurations)

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

filter adaptive in spectral (Fourier) domain



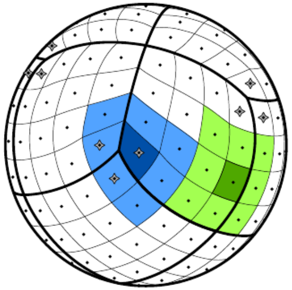
constructed graph



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

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

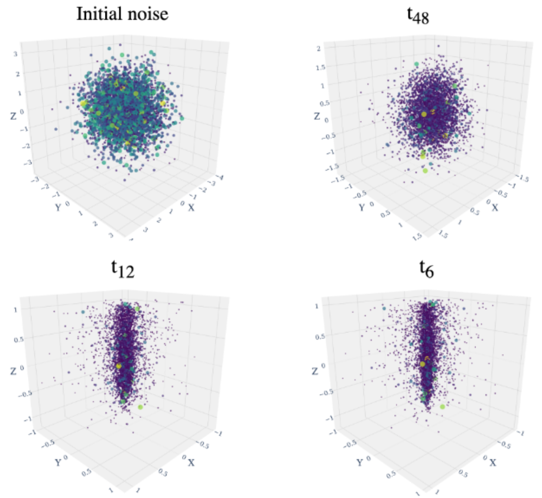
**Hybrid approach:**
'Indexed Conv'
Define 'HEALPix filters'



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

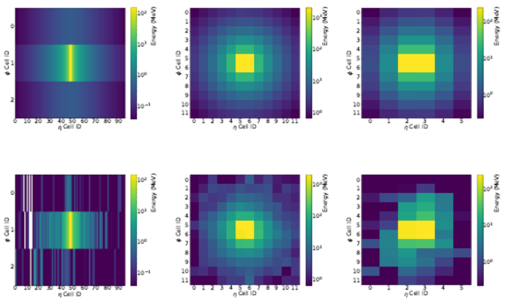



Buhmann et al., ArXiv/2305.04847

Layer

Geant4

GAN

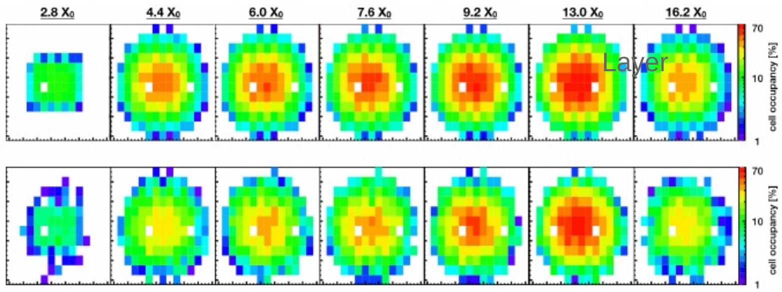


Paganini, Oliviera, Nachman - Phys. Rev. D 97, 014021 (2018)

Layer

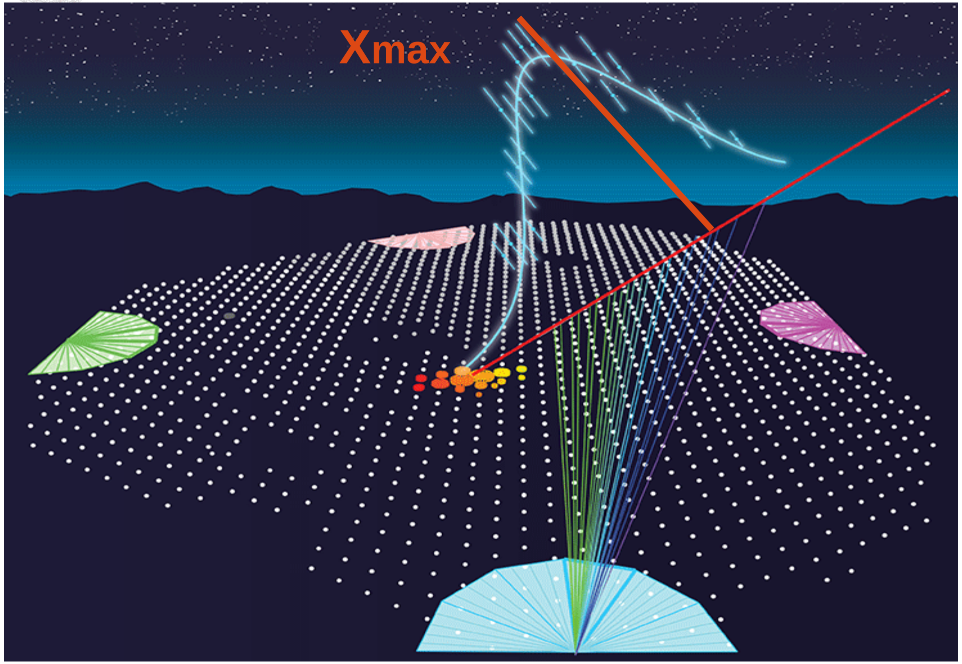
Geant4

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

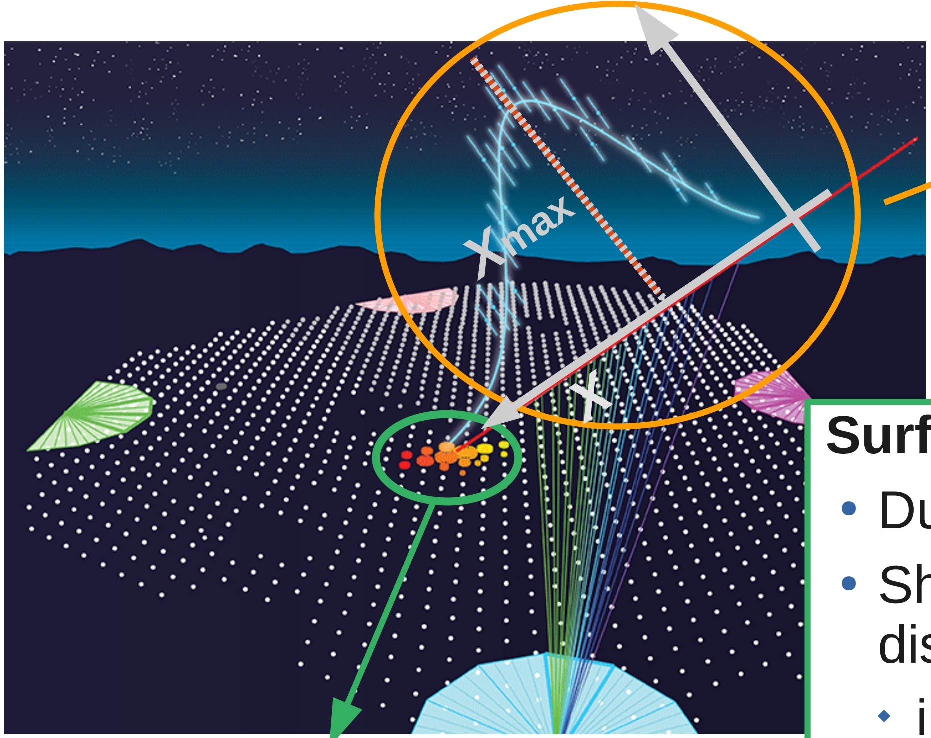

**Size of Auger projected on Sicily**

**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**

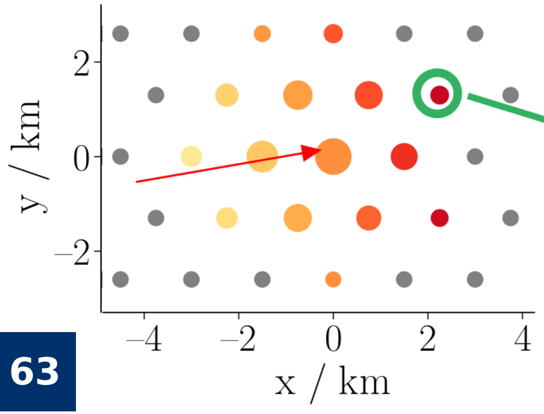


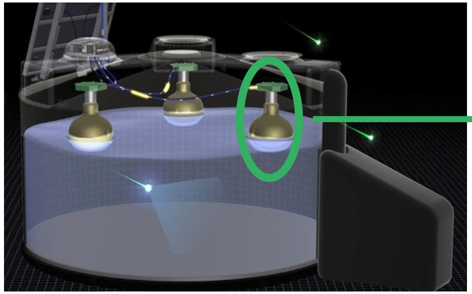

## Fluorescence Detector (FD)

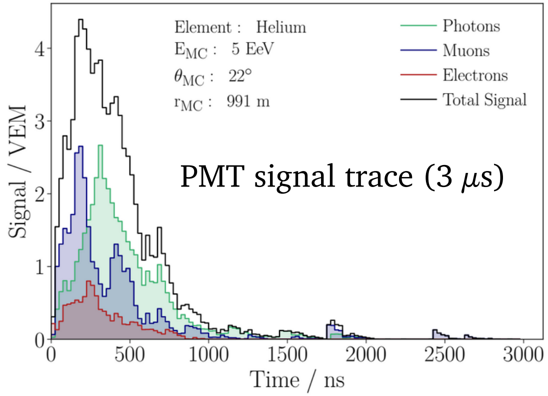
- Duty cycle ~15%
- Observe longitudinal shower profile
  - direct measurement of $X_{max}$

## Surface Detector (SD):

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



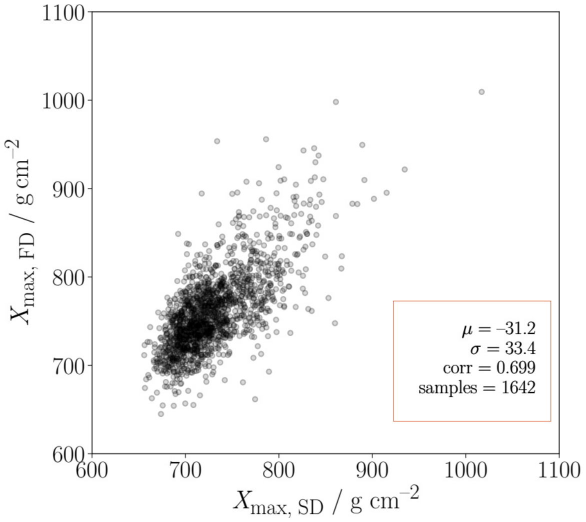


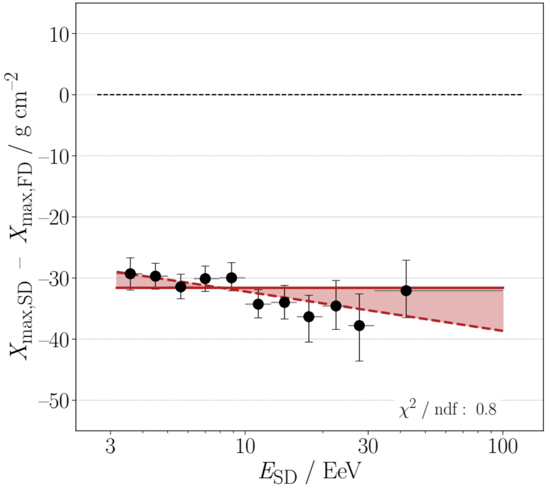
# Application to hybrid data

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 generated?**

**Which is a real image ?**


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

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

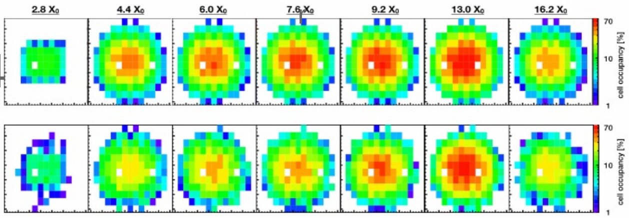
- Approximation of simulation / physics process
- Unsupervised training of *generative models*

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

Laye

Geant4

WGAN




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

# Can we generate images with distinct physical properties?

Test: “classic”

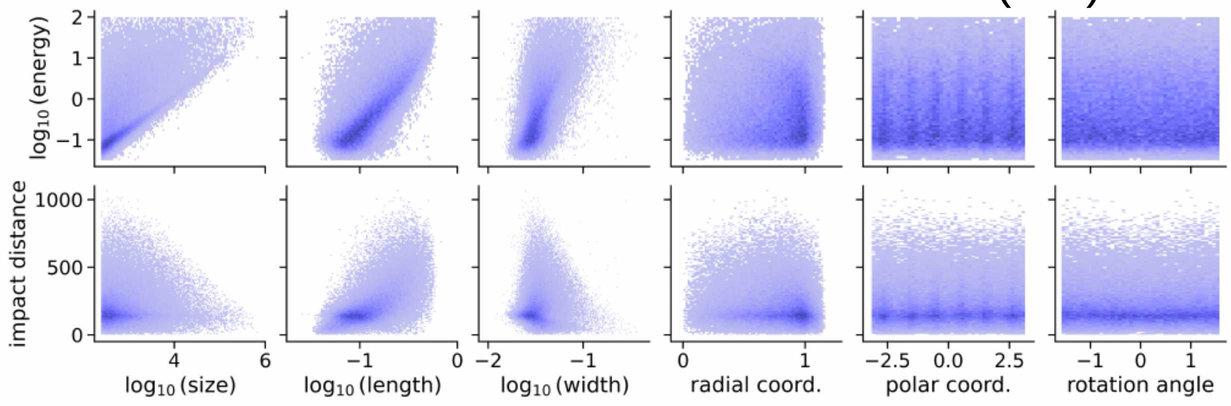
compare parameter correlation w.r.t.

- Impact distance
- Energy

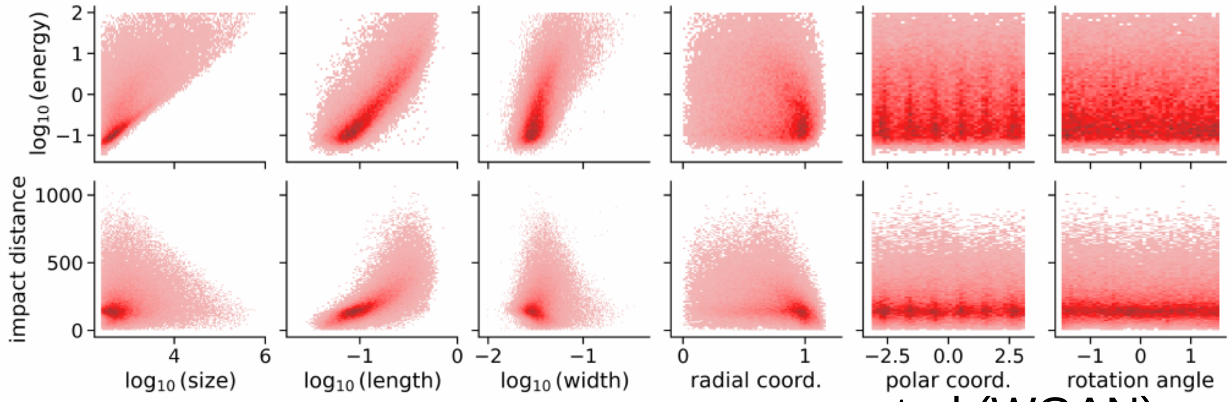
(set in CORSIKA)
(input to generator)

**Correlations are very similar!**

simulated (MC)



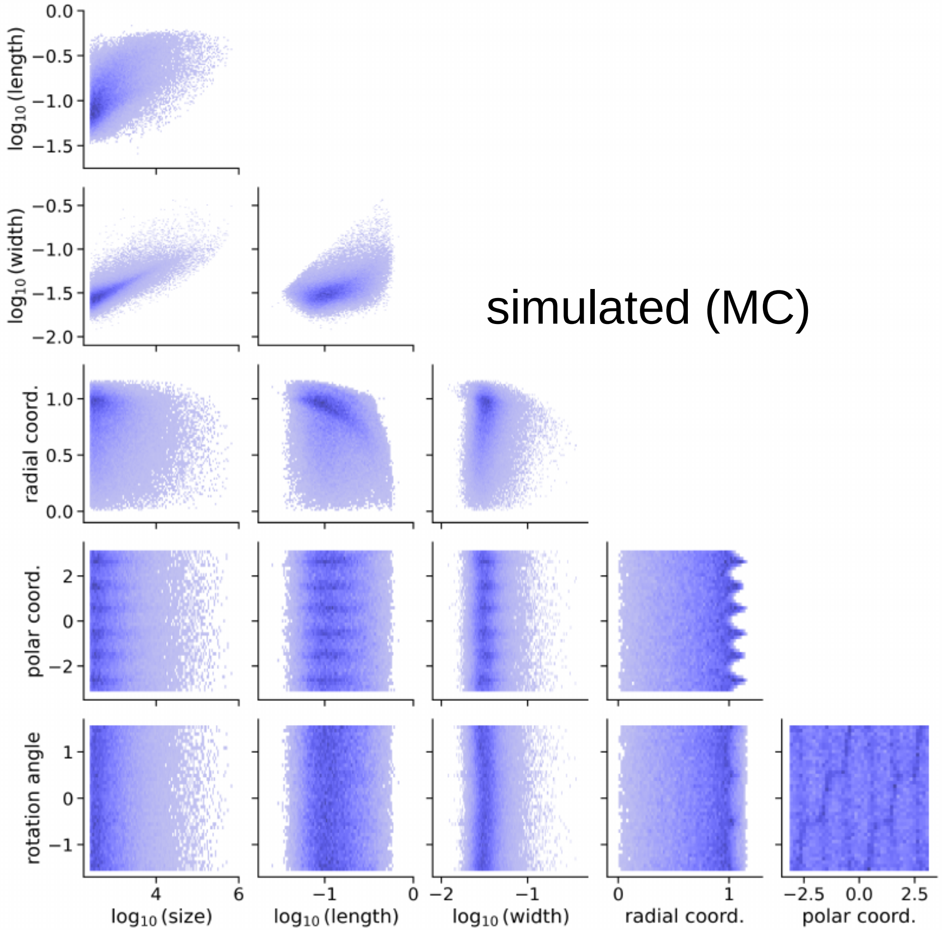

(a)



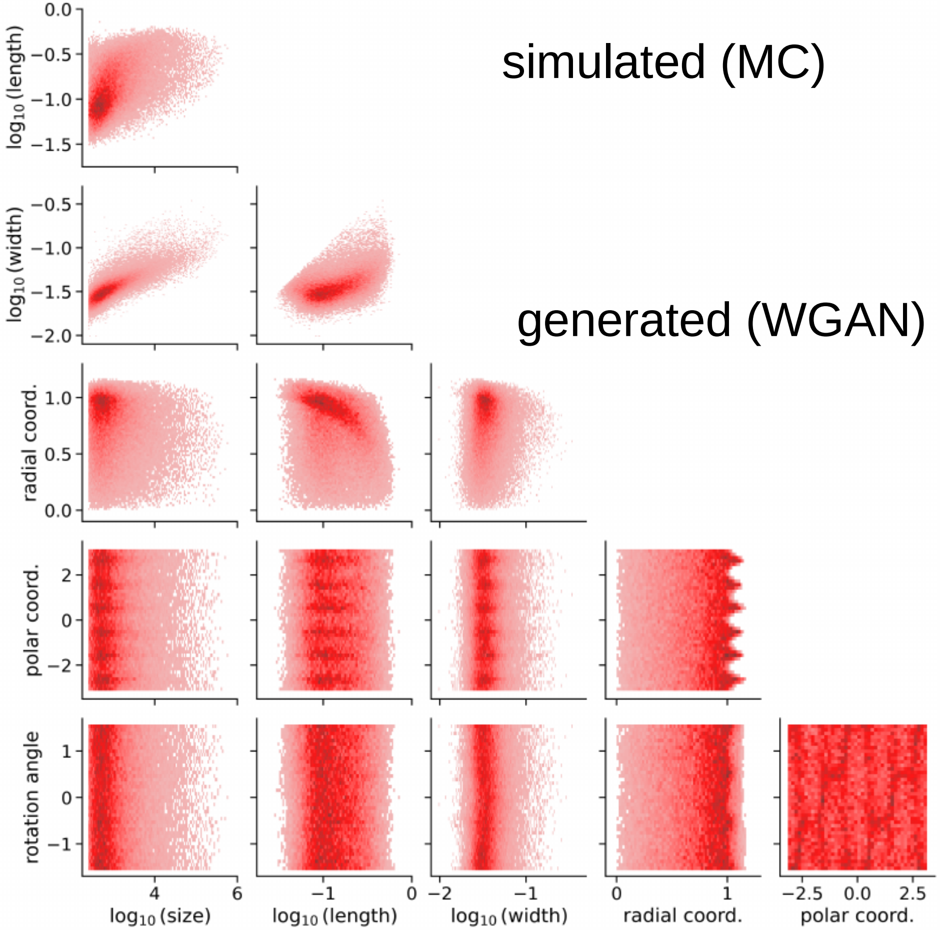

generated (WGAN)

(b)

# Correlation of Hillas parameters




simulated (MC)

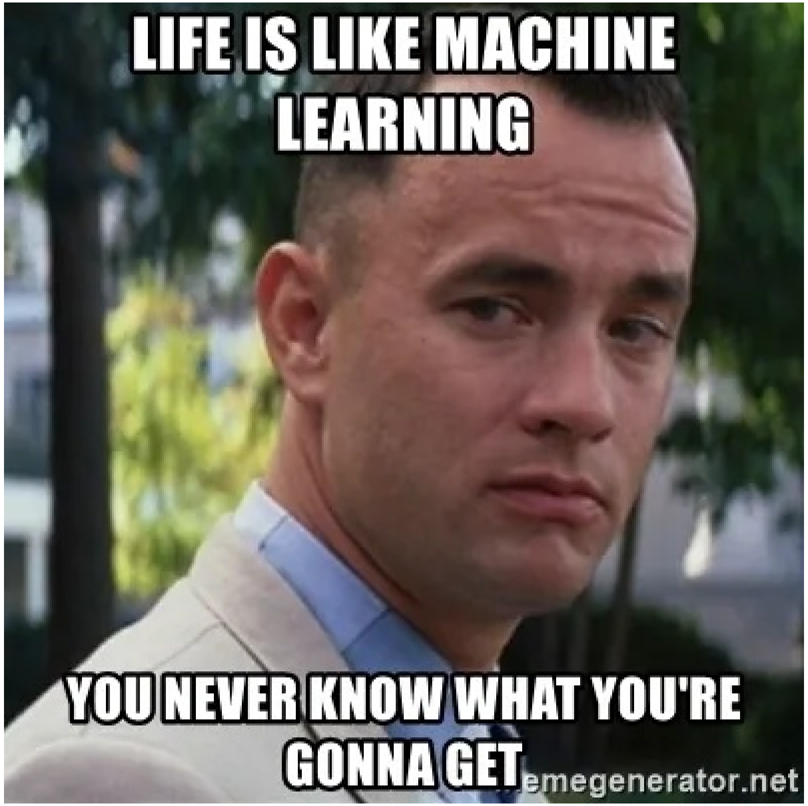



simulated (MC)

generated (WGAN)

generated (WGAN)

**Correlations are very similar!**


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

# ?