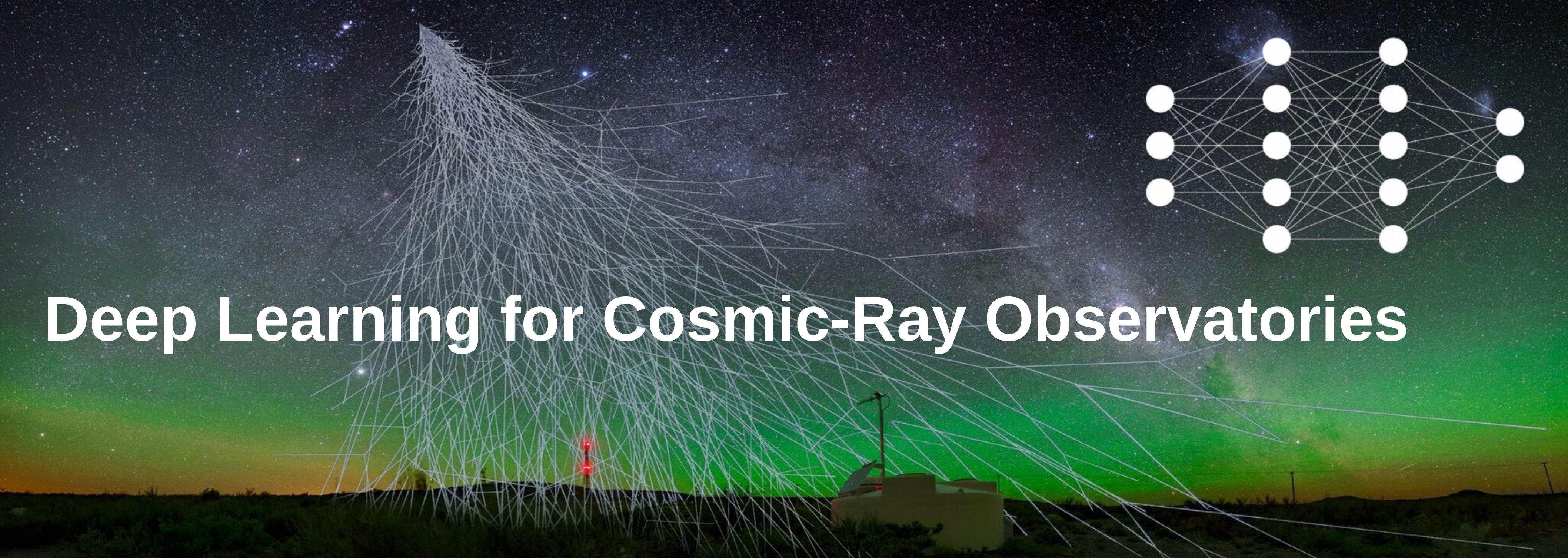

Deep Learning for Cosmic-Ray Observatories

Jonas Glombitza, *Martin Erdmann, Alexander Temme*

III. Physikalisches Institut A, RWTH Aachen

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ErUM-Data IDT

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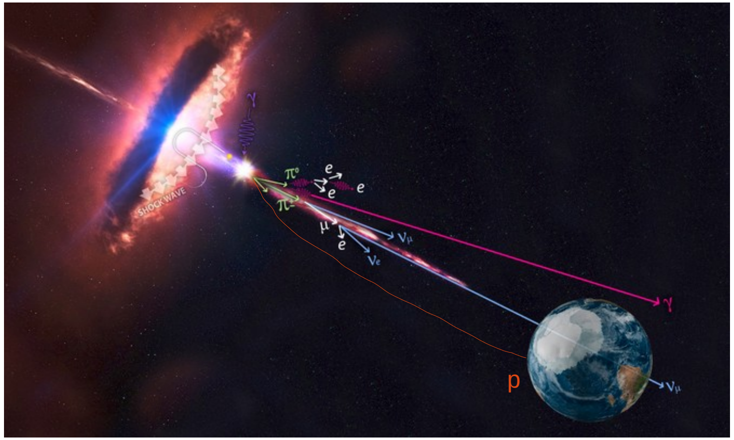
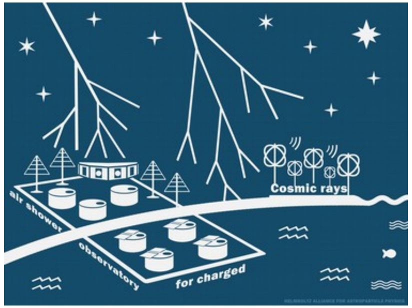
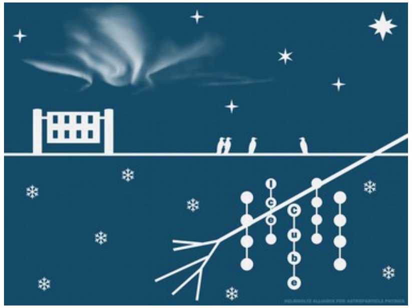
Astroparticle Physics

- Observation of particles with astronomical origin
- Search for their sources
  - Understand physics of astronomical objects
- Measure all cosmic messenger
  - Photons, neutrinos, nuclei



- Distant sources, high particle energies
  - Experiment feature **very** large detector volumes



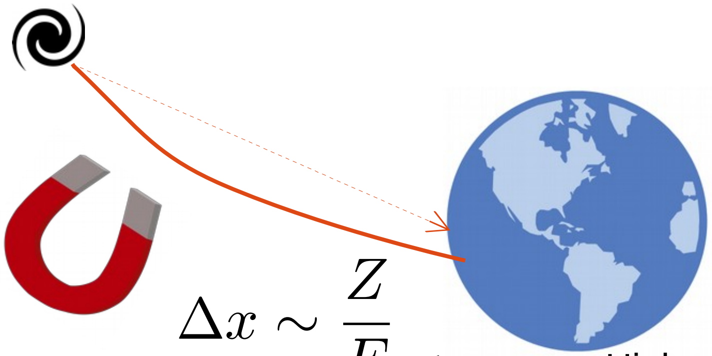


Cosmic Rays

- Charged nuclei from astronomical origins
  - **10 orders** of magnitude energy range

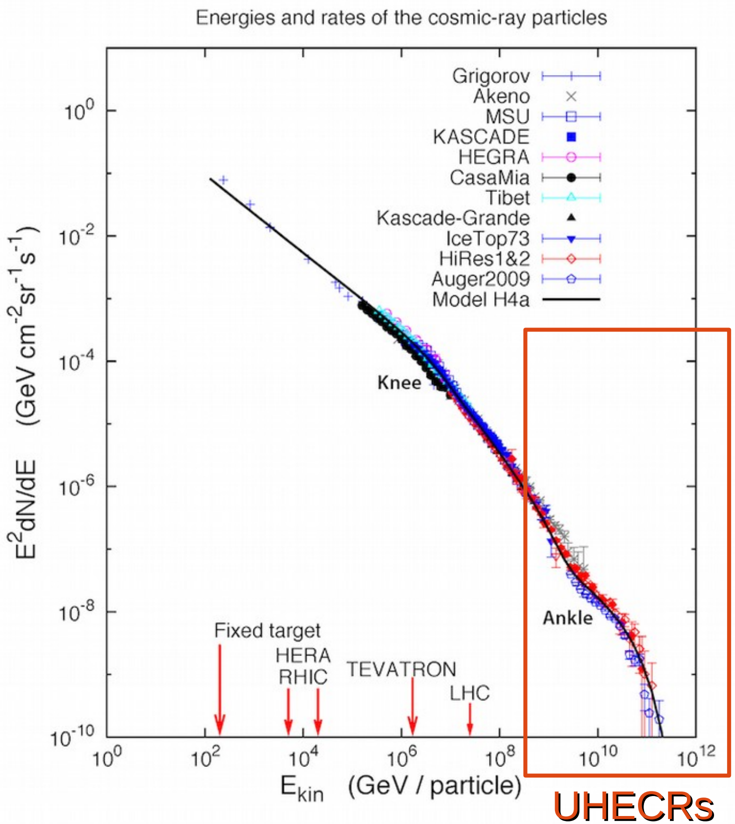
Ultra-high energy cosmic rays (UHECRs)

- Energies > 10^{18} eV
- manageable deflection by magnetic fields
  - Search for extra-galactic origins



$$\Delta x \sim \frac{Z}{E}$$

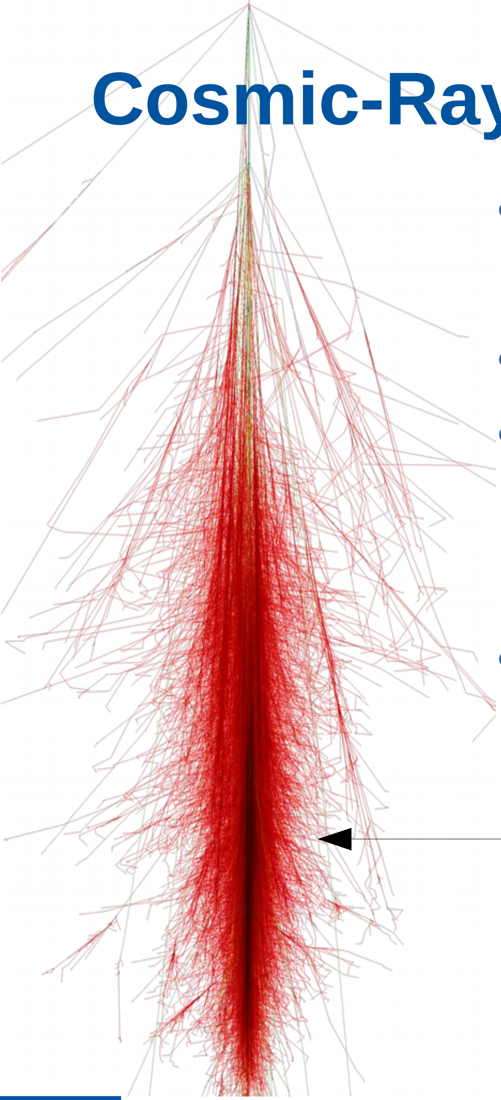
← High energies



UHECRs

10.1103/PhysRevD.88.042004

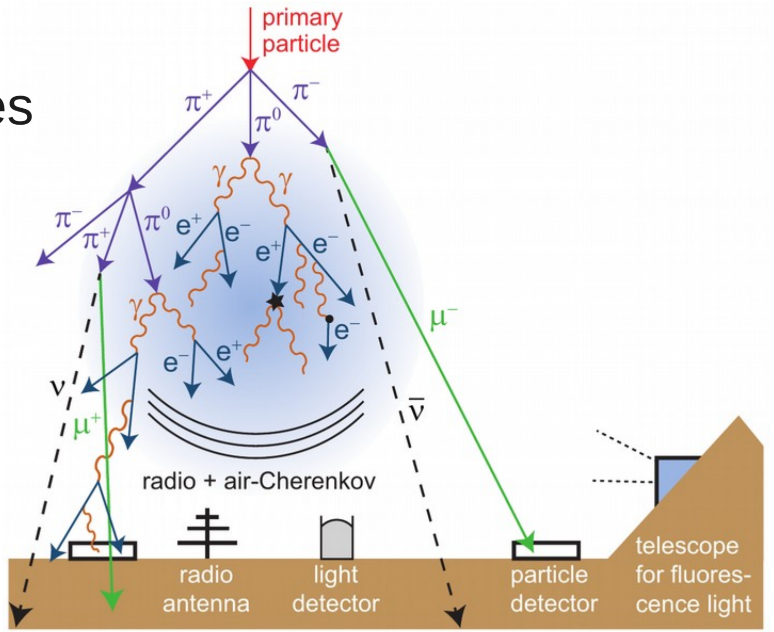
Cosmic-Ray induced Air Showers



- Cosmic rays interact with Earth's atmosphere
  - Induce extensive particle cascade
- Particle shower reach size of several km² at Earth's surface
- Particle mass determines shower structure
  - Low mass, deep penetration → late maximum
  - Heavy mass, early maximum
- Many different detection techniques

Xmax

Shower maximum
Correlates with
primary mass

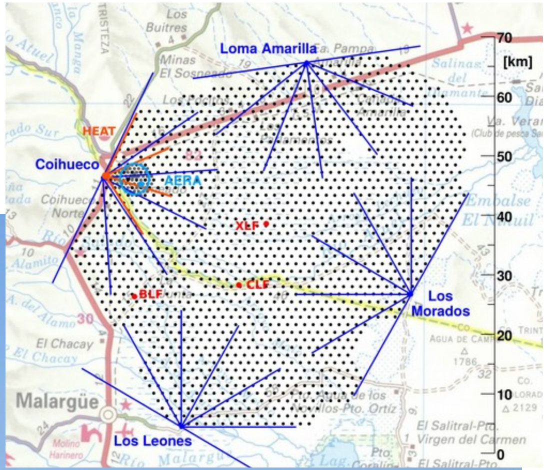


The Pierre Auger Observatory

- World largest cosmic-cay observatory
- Placed in Argentina
- Measure high-energetic particles
  - Energy > 10^{17} eV
- Study composition of cosmic rays
- Search for cosmic-ray origins

Hybrid measurements of UHECRs

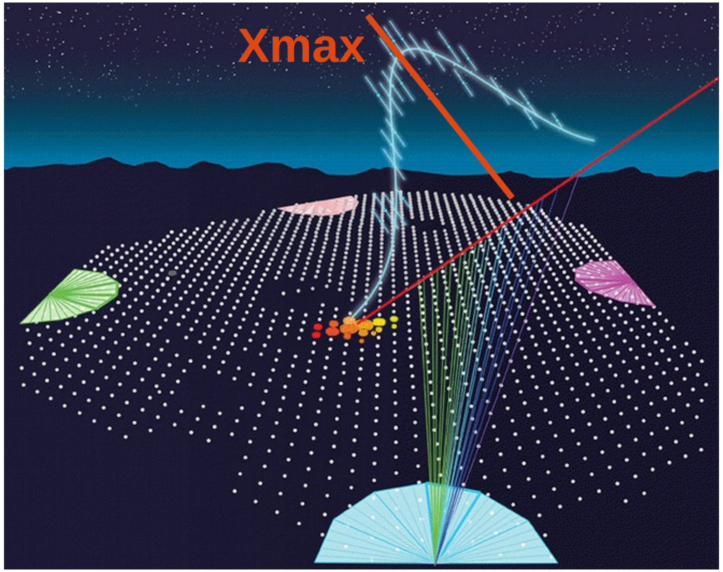
- 27 fluorescence telescopes at 4 sites
  - 15% duty cycle
- 1660 water-Cherenkov stations
  - 3000 km^2 array, ~100% duty cycle

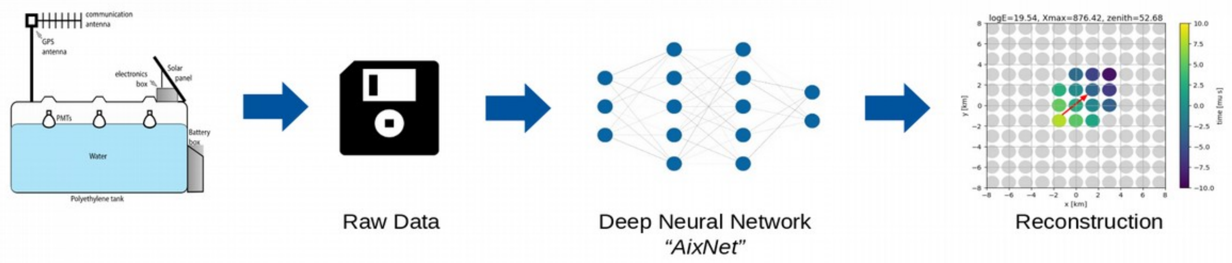


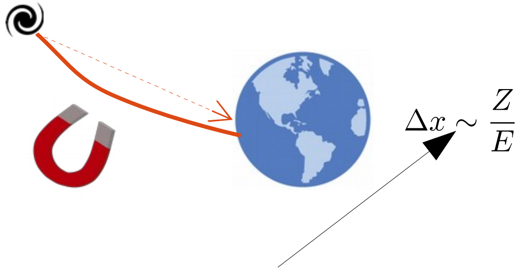
Air-Shower reconstruction using AixNet

- Shower maximum contains charge information
  - Directly observed by fluorescence telescopes
  - Challenging to measure with surface detector

- Use Deep Learning to reconstruct Xmax
  - Use data of surface detector only
  - Improve statistics (much higher duty cycle)

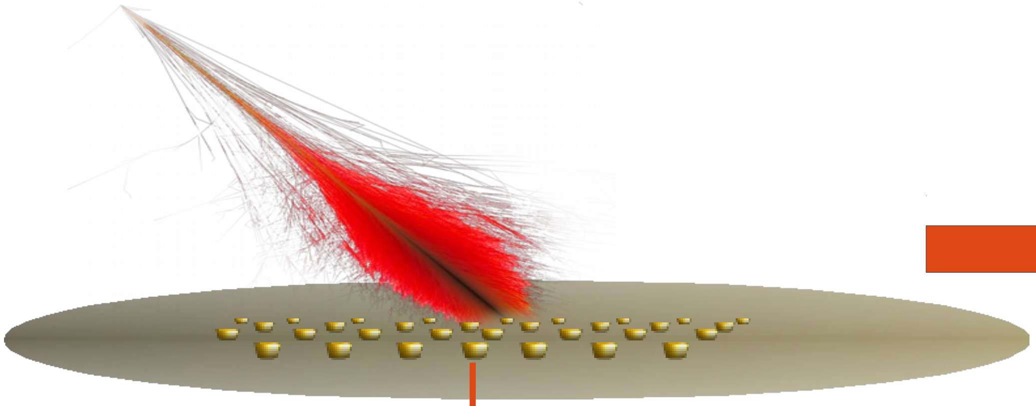


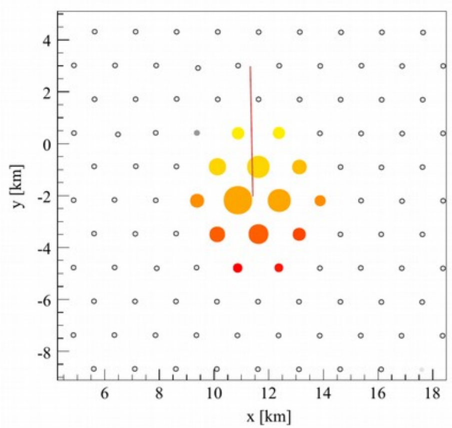




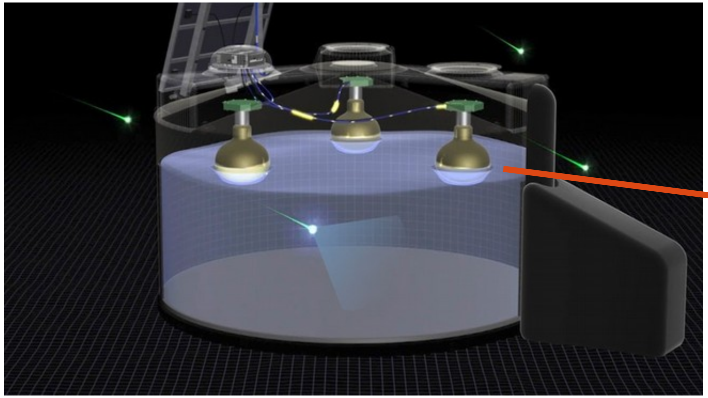
Need precise reconstruction!

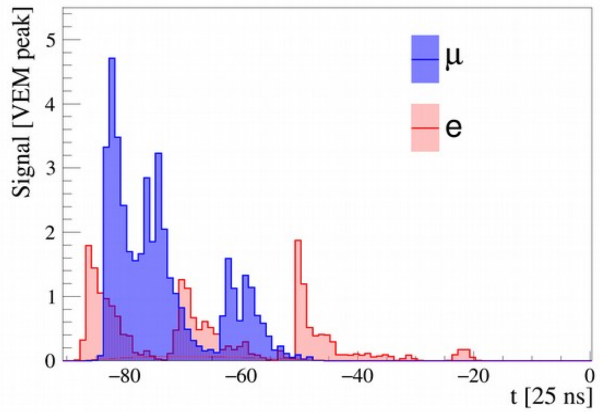
Air-Shower Detection





Air Shower footprint → images



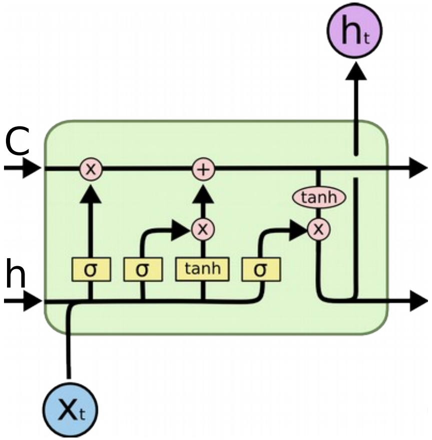


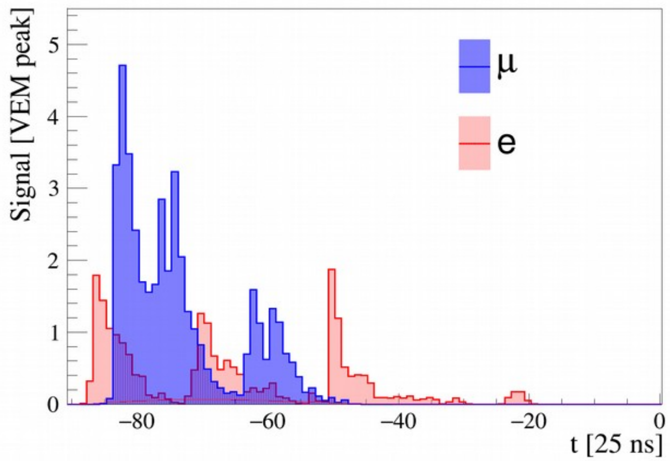
Signal Traces → Time Series (Audio)

Signal-Trace Processing

- Signal trace contains information of secondary particles
  - Different particles induce characteristic signal shapes
  - Arrival-time of particles contains information about shower development

➢ Use recurrent network (LSTM cells) to extract trace features
  - Use same network for all stations

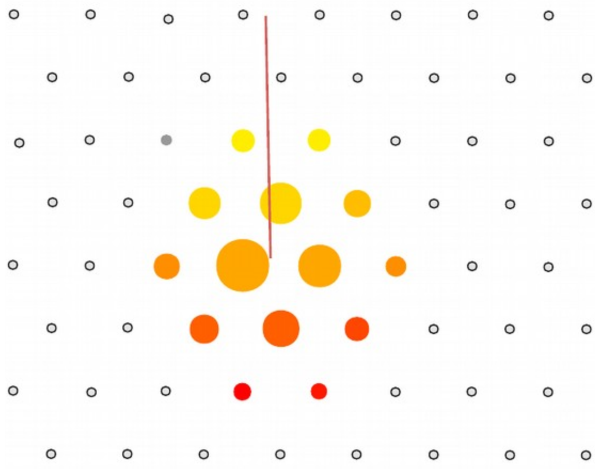


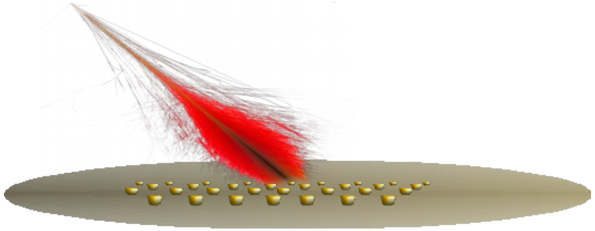


Air-Shower Footprint

- Particle footprint induces pattern of triggered stations at Earth's surface
- Clustering in time
  - Reconstruction of arrival direction
- Clustering in space
  - Shower core of footprint
  - Energy of primary particle

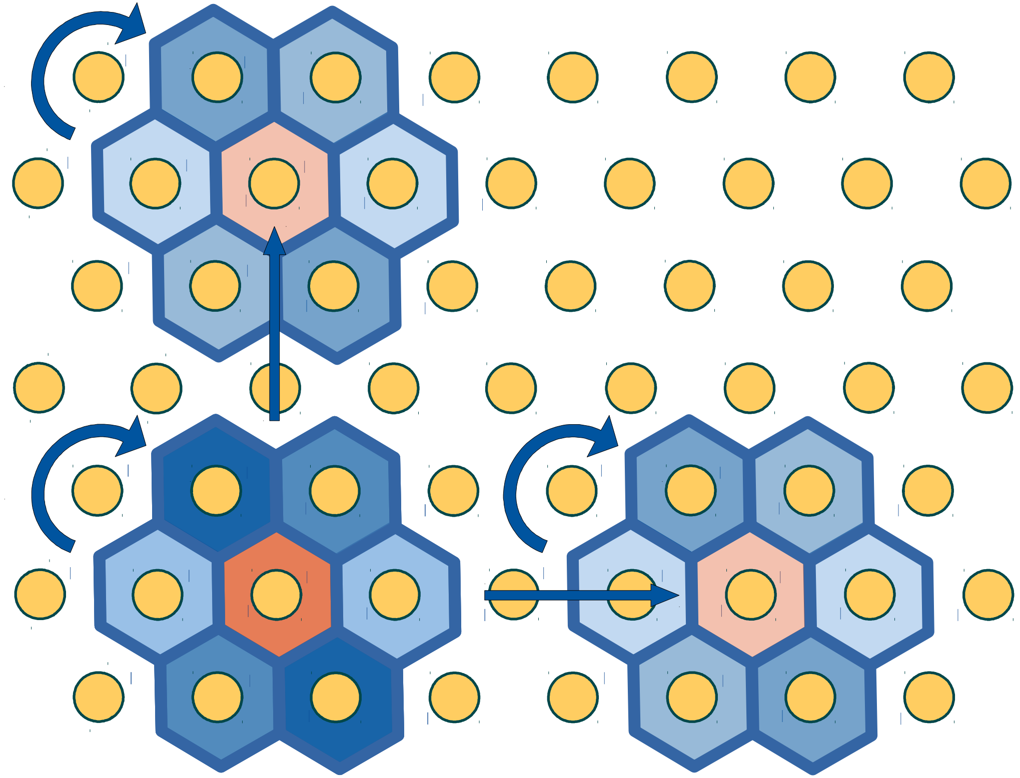
✗ **Image → Cartesian | SD → Hexagonal**





Hexagonal Convolutions

Measured footprint differs from image
➔ Cartesian vs. Hexagonal grid



Use symmetry of hexagonal grid

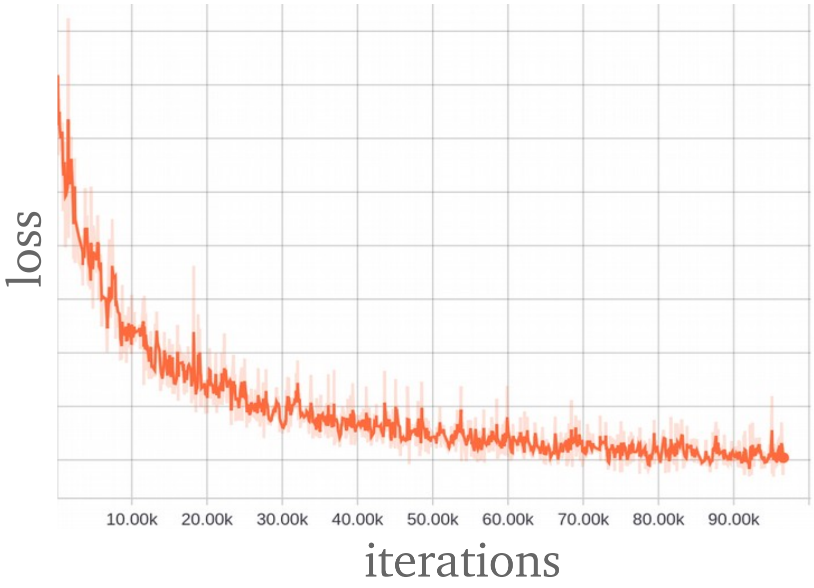
- Find hexagonal clusters
- Use of translational invariance
  - similar patterns at different grid positions
- Use of rotational invariance
- similar patterns for showers from different arrival directions

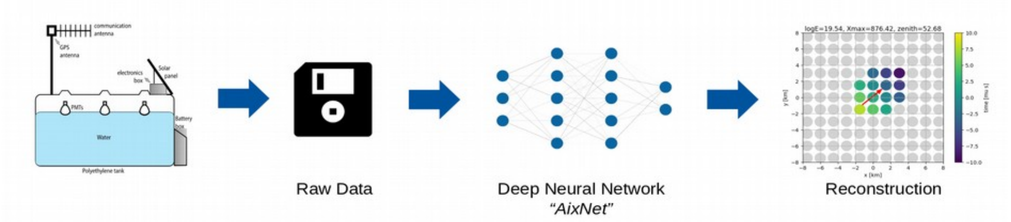
Hoogeboom, Peters, Cohen, Welling
ArXiv/1803.02108

AixNet

- ~ 1.5 million parameters
- Implemented in Keras / TensorFlow
- Training on Nvidia 1080 GTX ~ 1-2 days

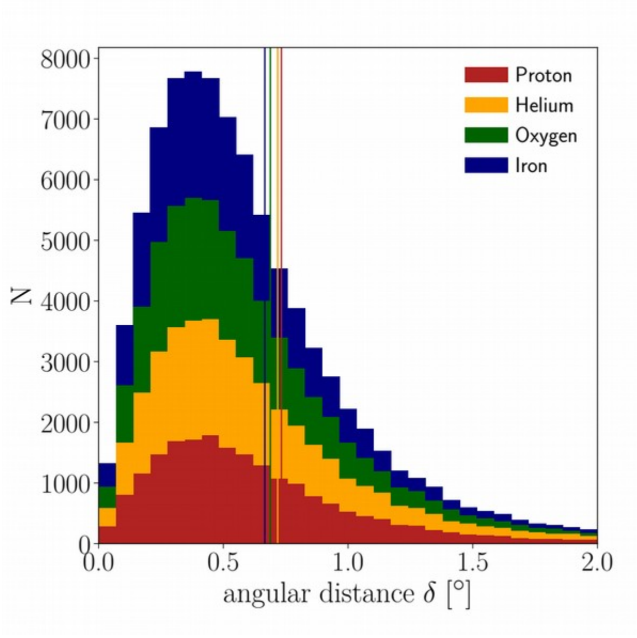
Simulated shower data	**Epos LHC**
# Showers	800,000
Training	700,000
Validation	10,000
Test	90,000
Energy	18.0 – 20.2
Spectrum	E^{-1}
Composition	25% proton 25% helium 25% oxygen 25% iron
Zenith	0 – 65°

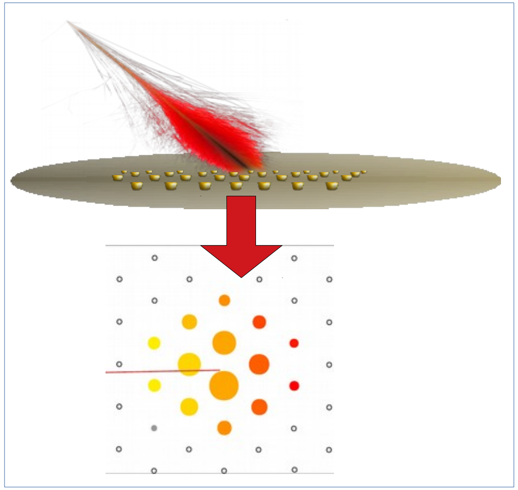


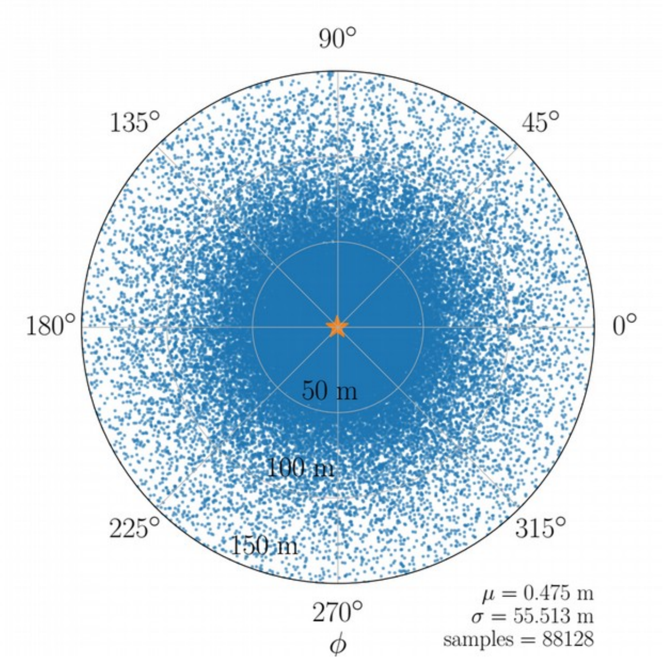


Erdmann, Glombitza, Walz
https://doi.org/10.1016/j.astropartphys.2017.10.006

Reconstruction of the Shower Geometry







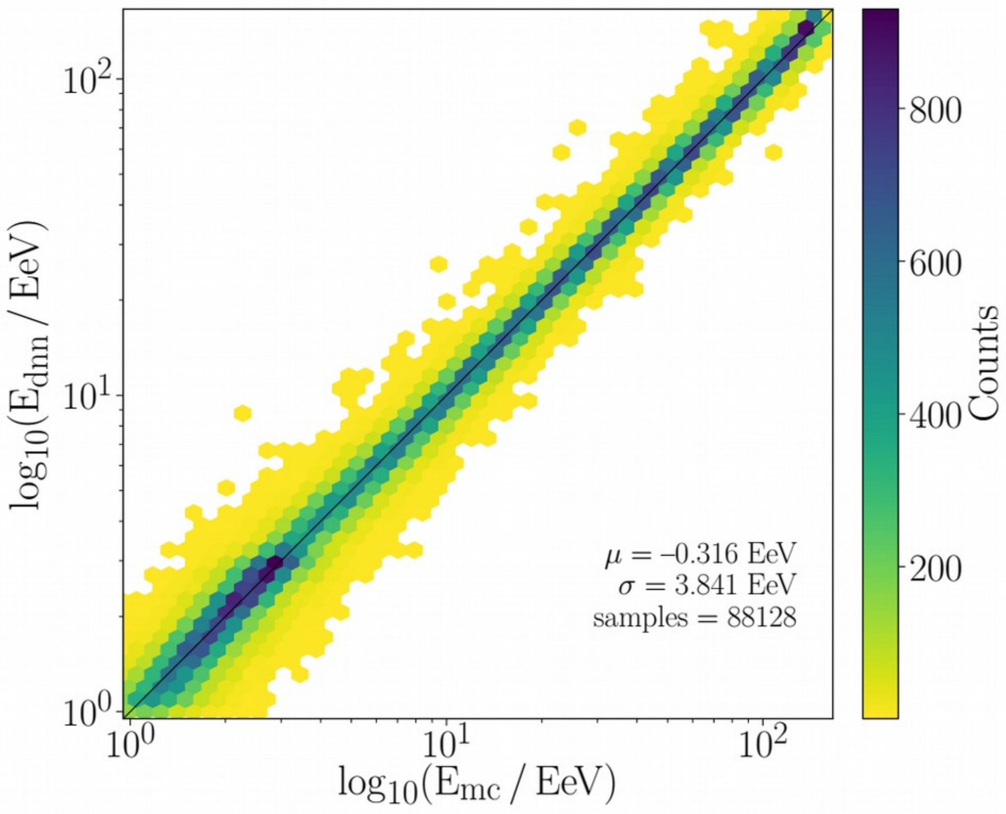
✔ Axis reconstruction

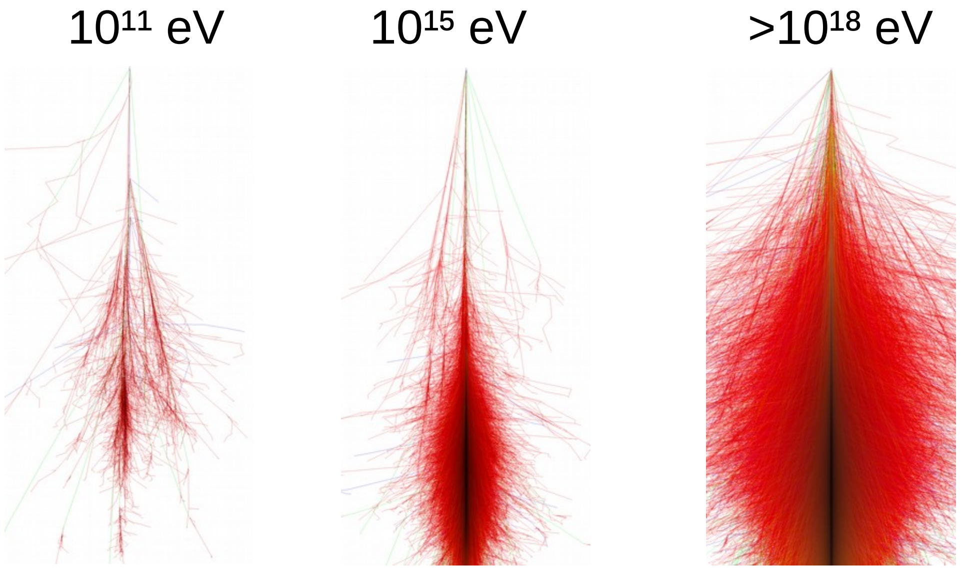
- Resolution (68% quantile) ~ 0.7°

✔ Unbiased core reconstruction

- No composition & azimuth bias
- Resolution ~ 50m

Reconstruction of Cosmic-Ray Energy

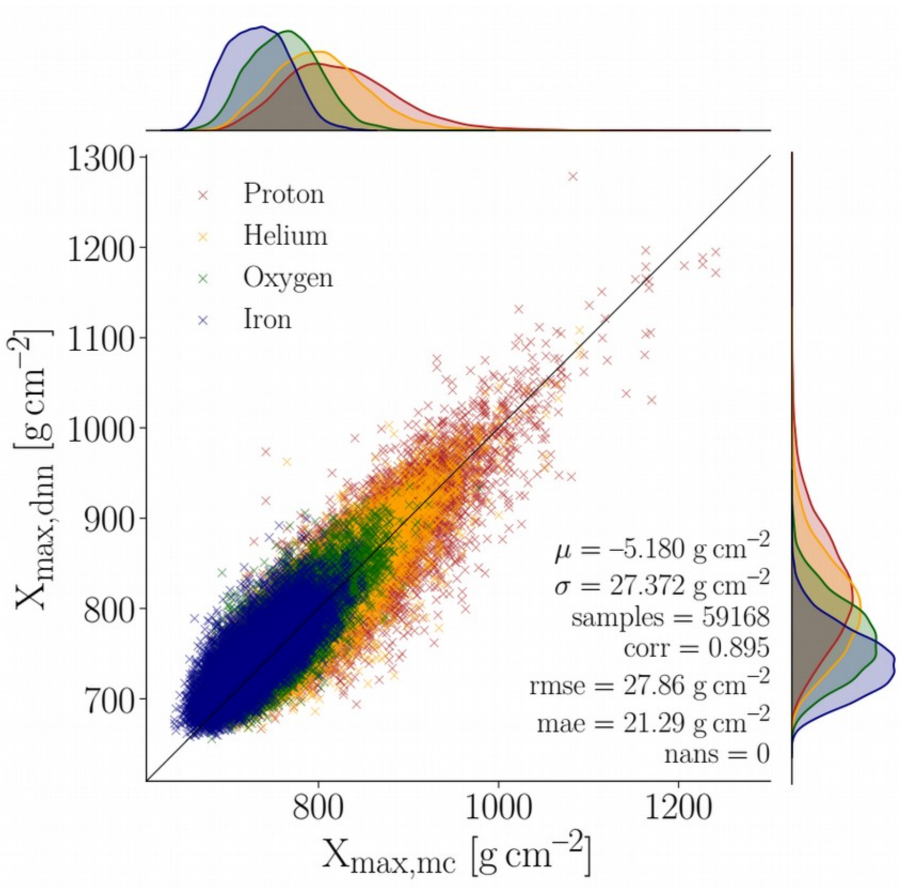


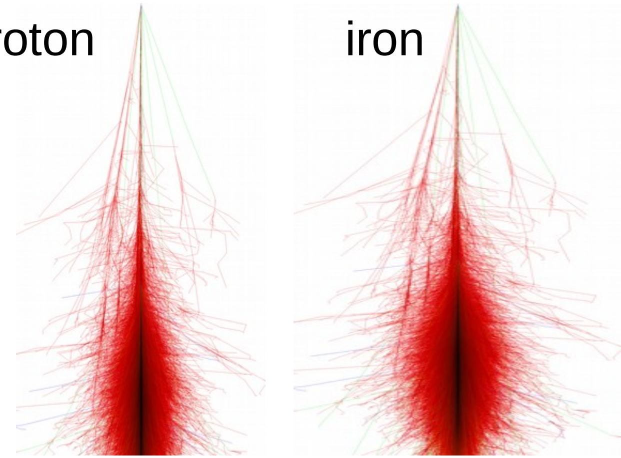


✔DNN able to reconstruct shower energy

- Overall resolution ~ 3.5 EeV
- Show negligible reconstruction bias

Reconstruction of Shower Maximum





✔ Successful shower maximum reconstruction

- Shows expected separation of elements
- Resolution < 30 g/cm²
- Absolute bias of ~ 5 g/cm²
- Significant improvement to previous methods

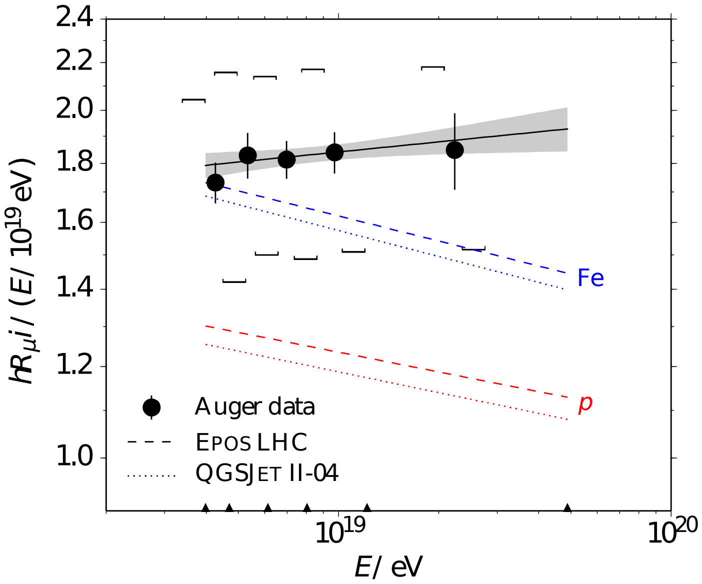
Generalization Capacities on Data

Inductive bias

- Models are trained using physics simulations
- Trained models are applied to data
  - ➔ Reconstruction bias

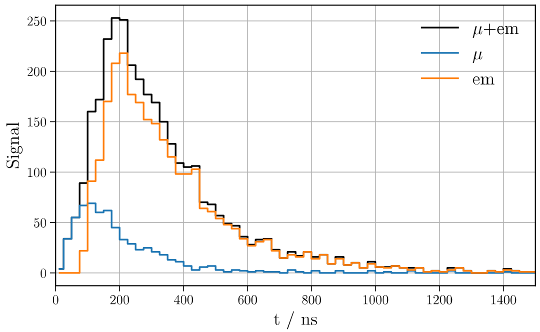
Inductive Bias

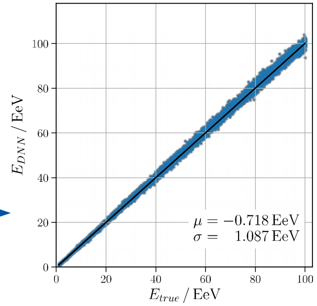
- Model trained on simulation but applied on data
- Observation of muon excess in measured air-shower data
- Can lead to reconstruction bias



Comput Softw Big Sci (2018) 2: 4

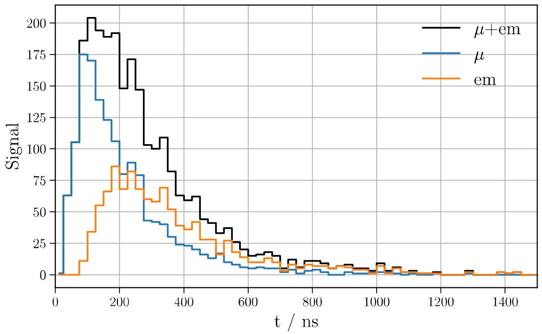
Simulation
70% electromagnetic
30% muonic

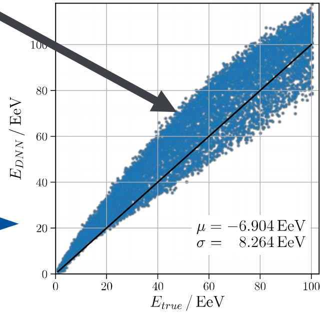




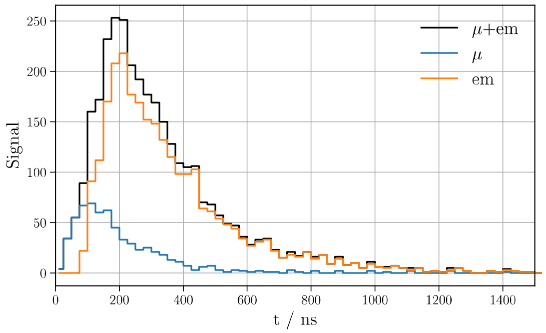
Network can not handle modified traces

'Data'
30% electromagnetic
70% muonic

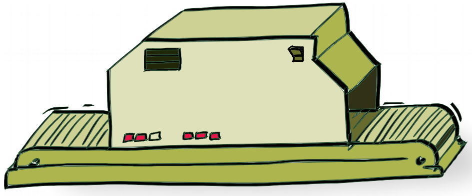


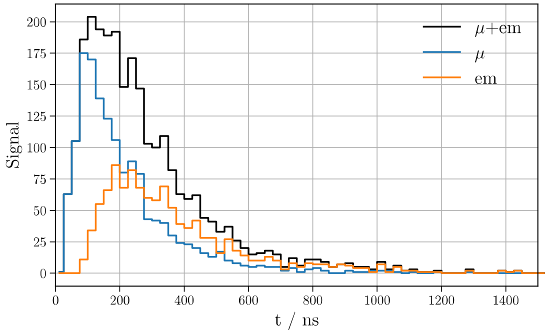


Adversarial Framework for Simulation Refinement



Refiner

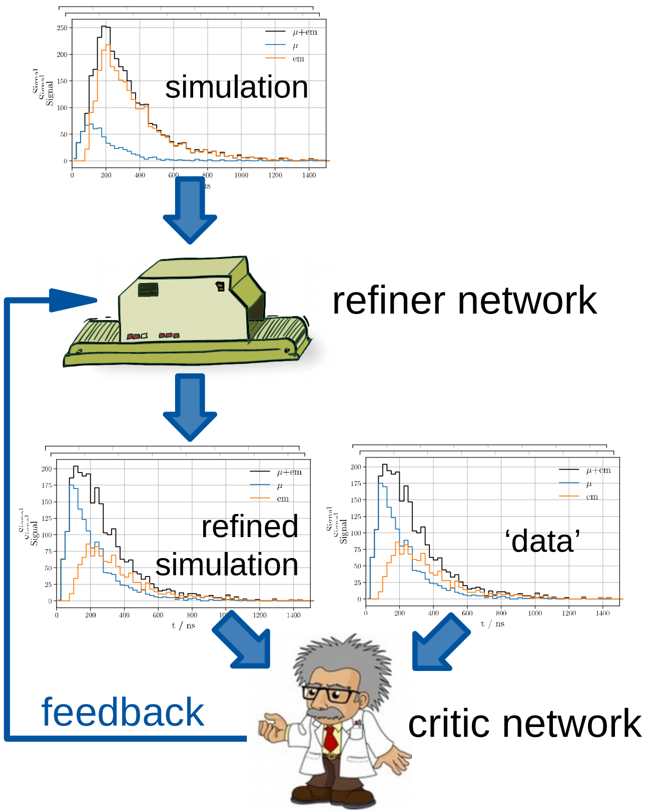




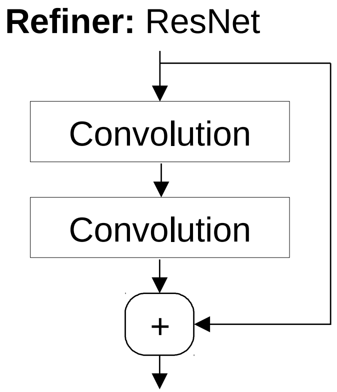
Erdmann, Glombitza, Geiger, Schmidt:
https://doi.org/10.1007/s41781-018-0008-x

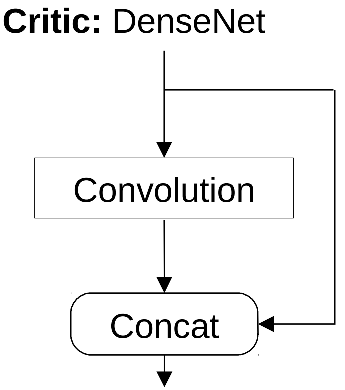
Simulation Refinement

- Mitigate data / simulation mismatches → reduce systematic reconstruction bias

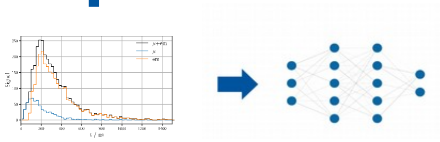


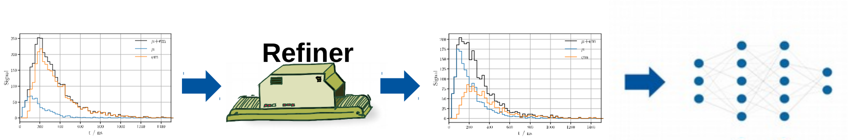
- Train *refiner* network to refine simulated data
- Feedback given by adversarial *critic* network, rating the refined simulation quality
- Refiner uses feedback to improve performance
- Constrain refinement process using residual units



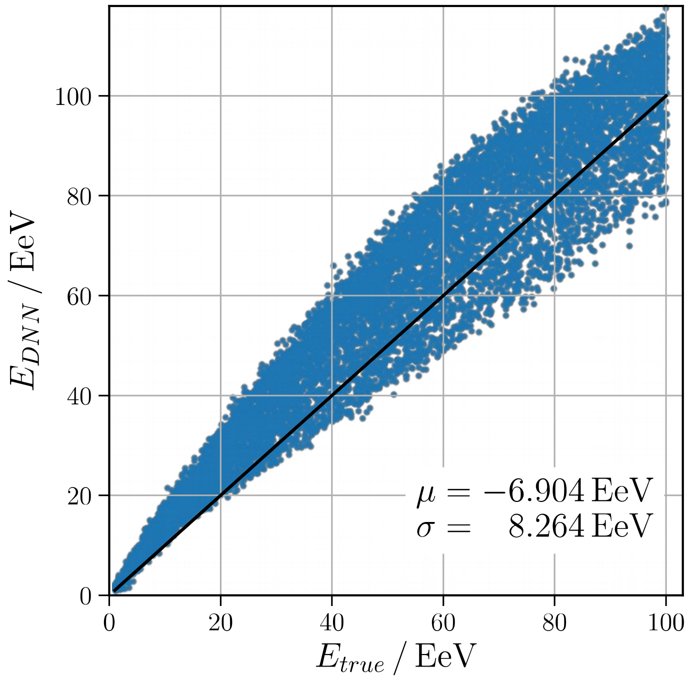


Improved Performance on Data

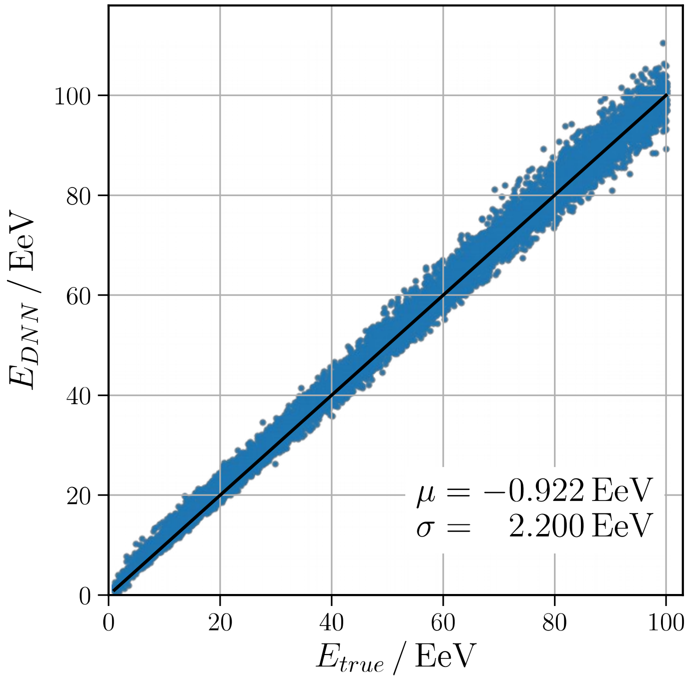




Trained on **original simulation** evaluate on data



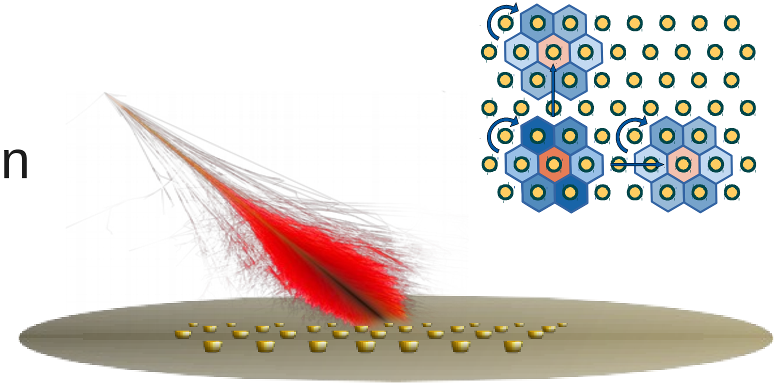
Trained on **refined simulation** evaluated on **data**



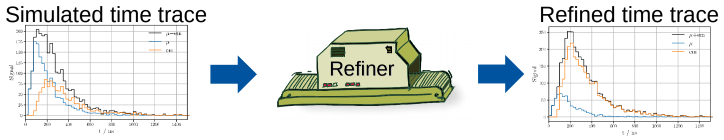
- Network shows improved performance when trained on refined simulations

Summary

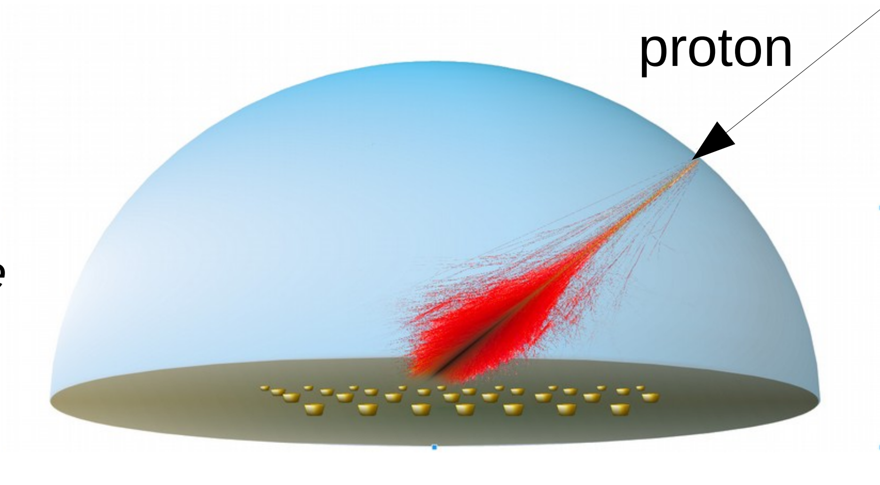
- Pierre Auger Observatory measures ultra-high energy cosmic rays
- Application of Deep Learning for air-shower reconstruction
- Reconstruct cosmic-ray properties
  - Model exploits symmetry of measured data
  - Precise extraction of mass-sensitive information
- Upcoming: Auger Prime
  - Detector upgrade will improve performance



- Inductive bias: models are trained on simulations but applied on data
- Promising results on refinement of simulations



Deep Learning for Cosmic-Ray Observatories



Martin Erdmann, ***Jonas Glombitza***, *Alexander Temme*

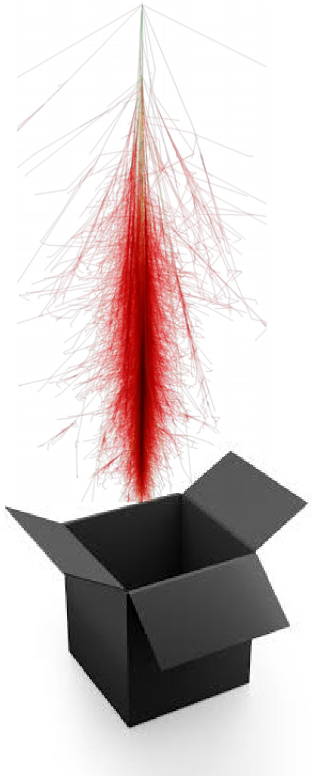
III. Physikalisches Institut A, RWTH Aachen

AISIS 2019, Mexico-City

glombitza@phyik.rwth-aachen.de

Visualization of Deep Networks

- Open black box
- Understand reasoning of network
  - Get insights of the reconstruction



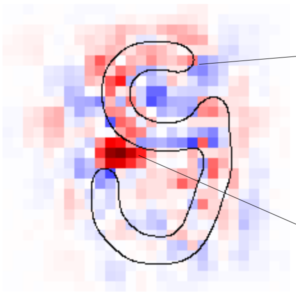
Saliency Maps

Idea:

- What influences reconstruction at most?
  - Important pixels have large gradients
- Calculate gradient of reconstruction R with respect to input pixels

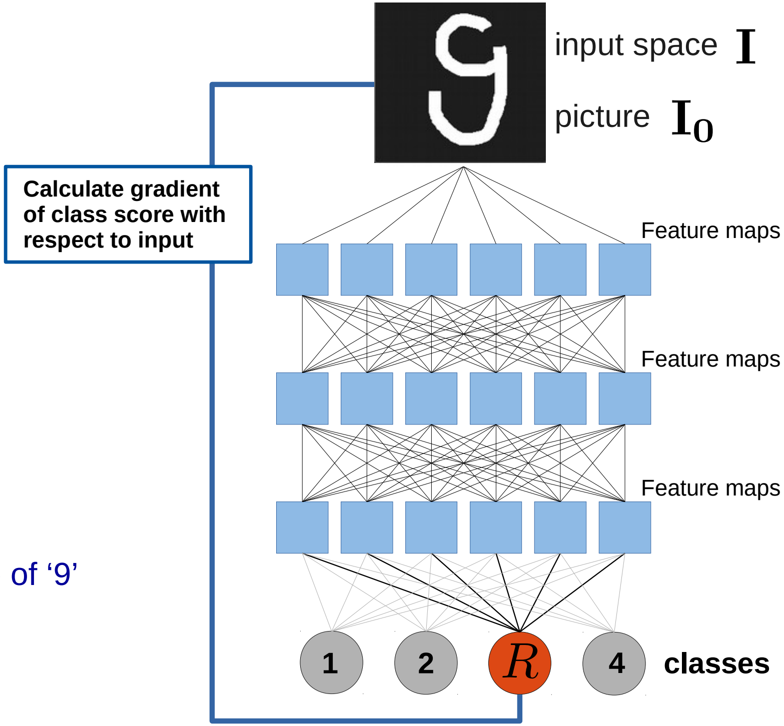
$$\mathbf{S} = \left.\frac{\partial R}{\partial \mathbf{I}}\right|_{\mathbf{I_0}}$$

Map has dimension of input image

$\mathbf{S} =$ 

Negative gradient
Missing Pixel → **reduced** reconstruction score of ‘9’

Positive gradient
Missing pixel → **raised** reconstruction score of ‘9’



Visualization of Deep Networks

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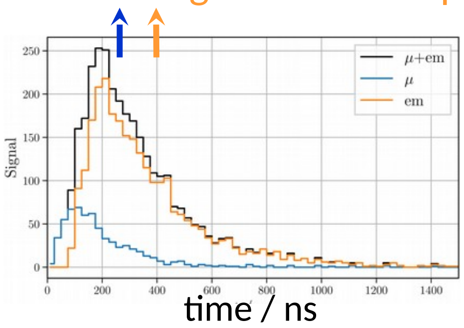
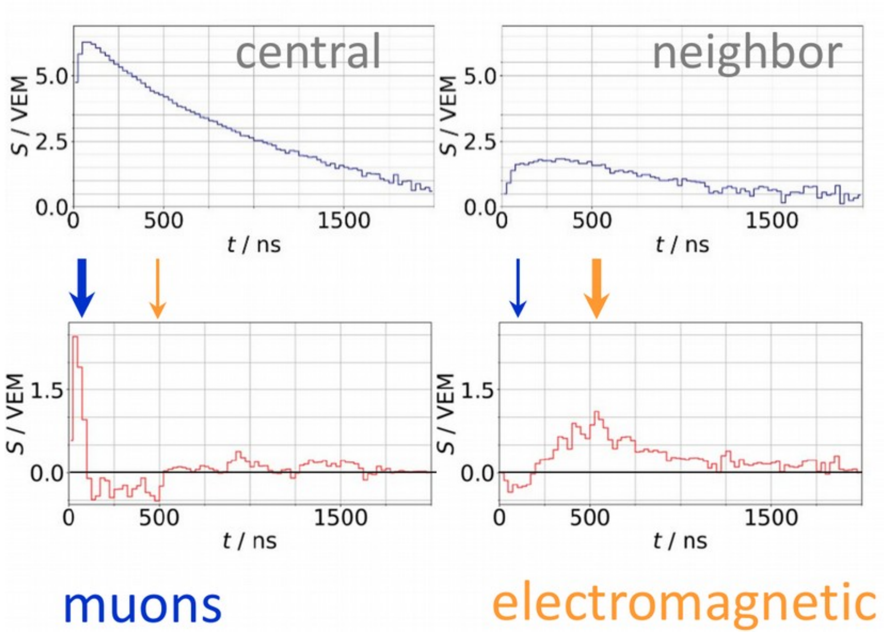
- First attempt: simplified toy simulation
- Find patterns important for energy reconstruction in signal trace

1. Muons arrive first, then
2. Electromagnetic shower particles



Sensitivity to energy reconstruction

$$\left.\frac{\partial f(\boldsymbol{x})}{\partial x_i}\right|_{\boldsymbol{x}_o}$$

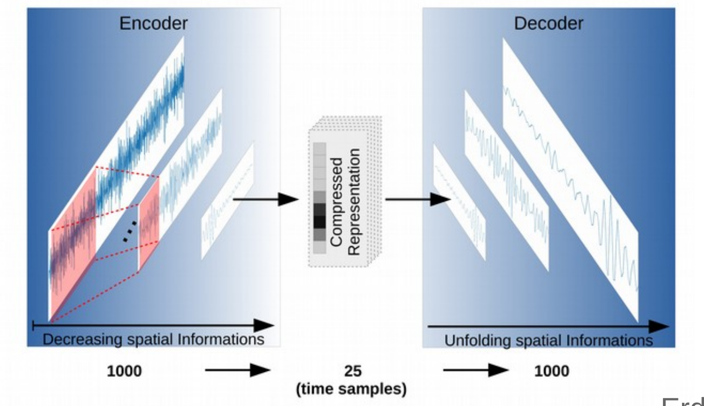


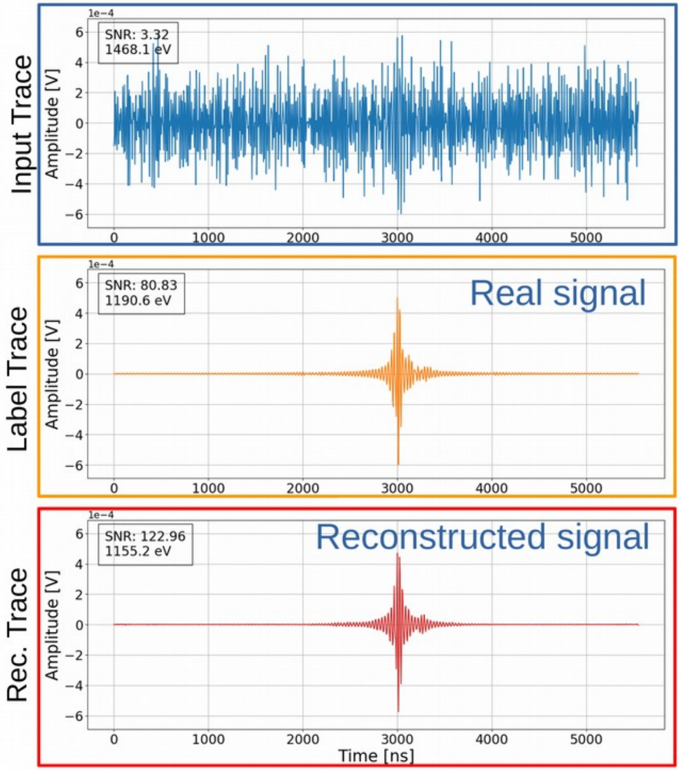
- Central stations focus on muons
- Neighbor stations focus on electromagnetic component

Erdmann, Glombitza, Walz, 10.1016/j.astropartphys.2017.10.006
Niklas Eich, Erdmann, Glombitza, RWTH Aachen 2018

Denoising of Air Shower Radio Signals

- Supervised trained Autoencoder
  - Network encodes only relevant information
- Remove noise of radio signals from cosmic ray induced air showers
- Signal energy and frequency spectrum approx. conserved

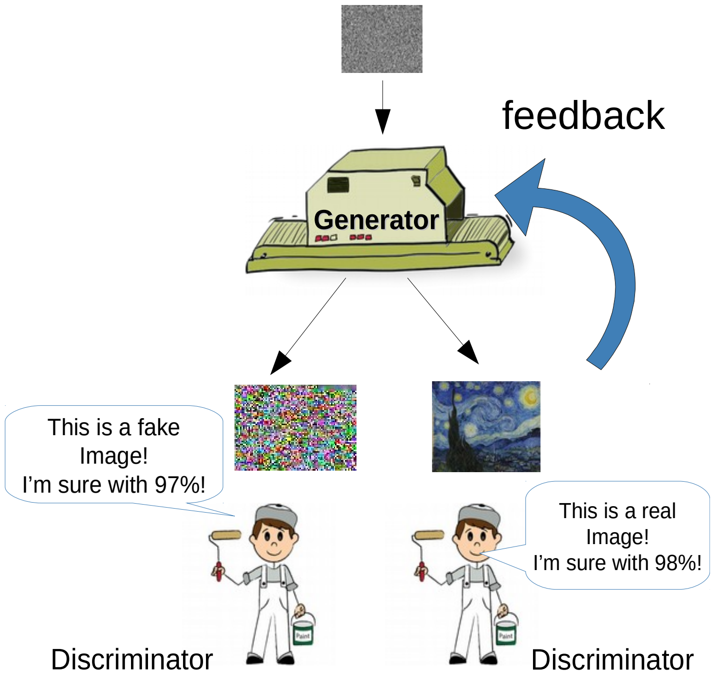


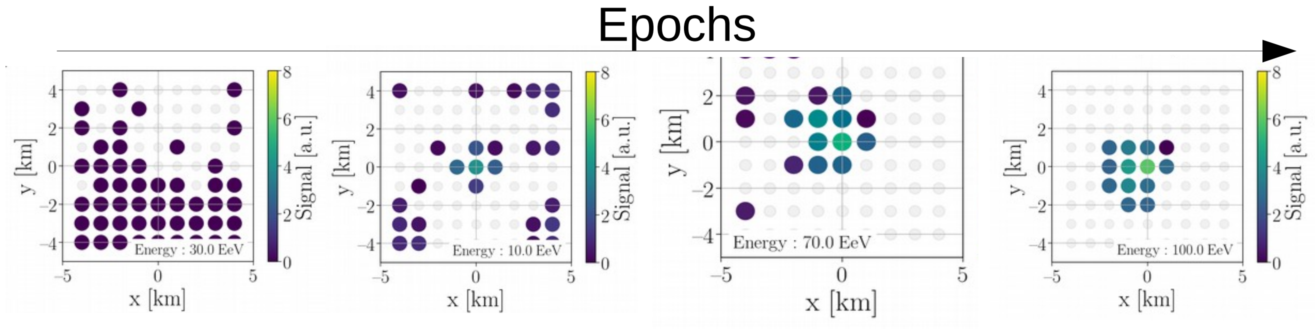


Erdmann, Schlüter, Smida - https://arxiv.org/pdf/1901.04079.pdf

Generative Adversarial Networks

- Use Generative Adversarial Networks (GANs) for simulations
- Generator network generates new events
  - Discriminator rates quality of generated events
  - Discriminator feedback is used to train generator
- Conditioning of generator to physics parameters
- Speed up physics simulations ~10^3 – 10^5
- First application shows promising results

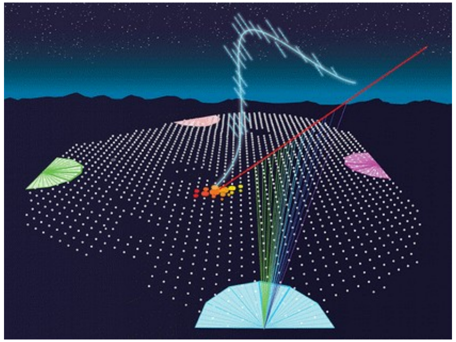


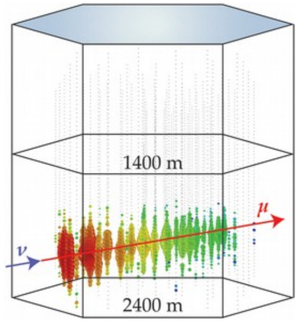


Erdmann, Geiger, Glombitza, Schmidt - 10.1007/s41781-018-0008-x

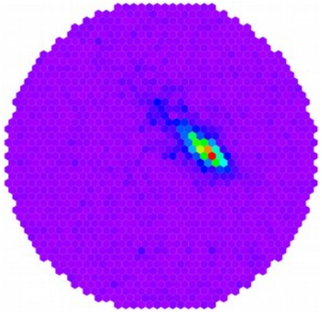
Measured Data

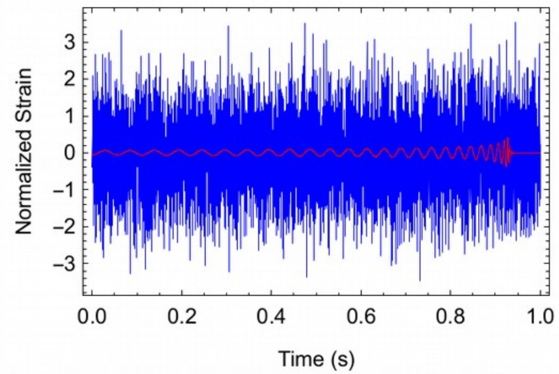
- Widely distributed sensors / telescopes
- Most experiments feature Hexagonal or Cartesian sensor grids
  - 2 and 3 dimensional **structured** footprints / signal patterns
- Many sensors provide time trace of signals
- Structured multi-dimensional data
- ➢ Motivates convolutional and recurrent architectures



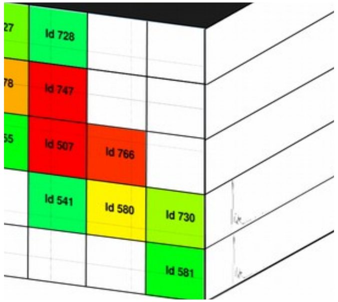


APS/Joan Tycko

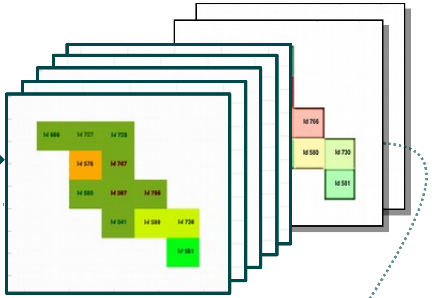




AixNet



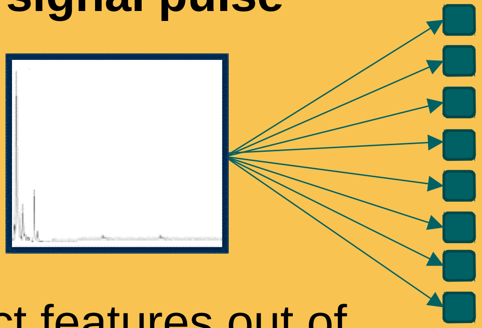
Mini network



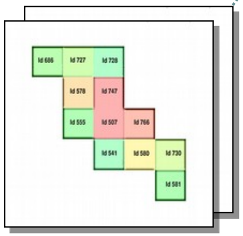
Created feature maps

Convolutional Block

Mini network works on each signal pulse



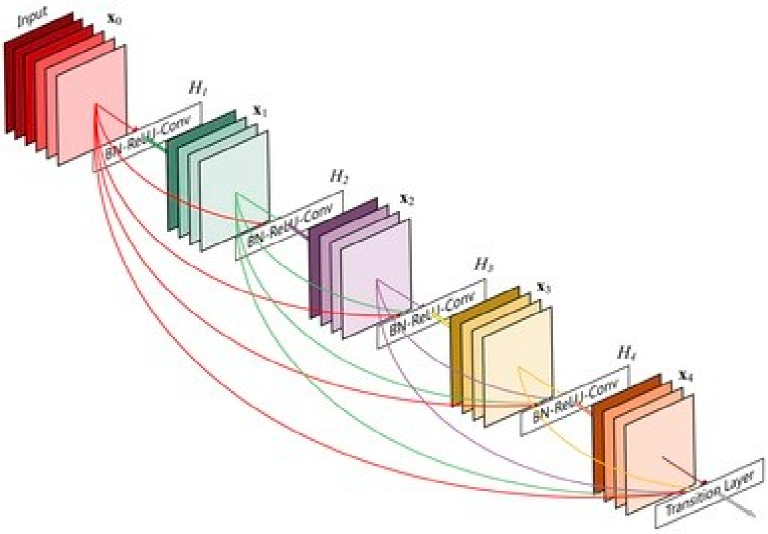
Extract features out of every signal pulse



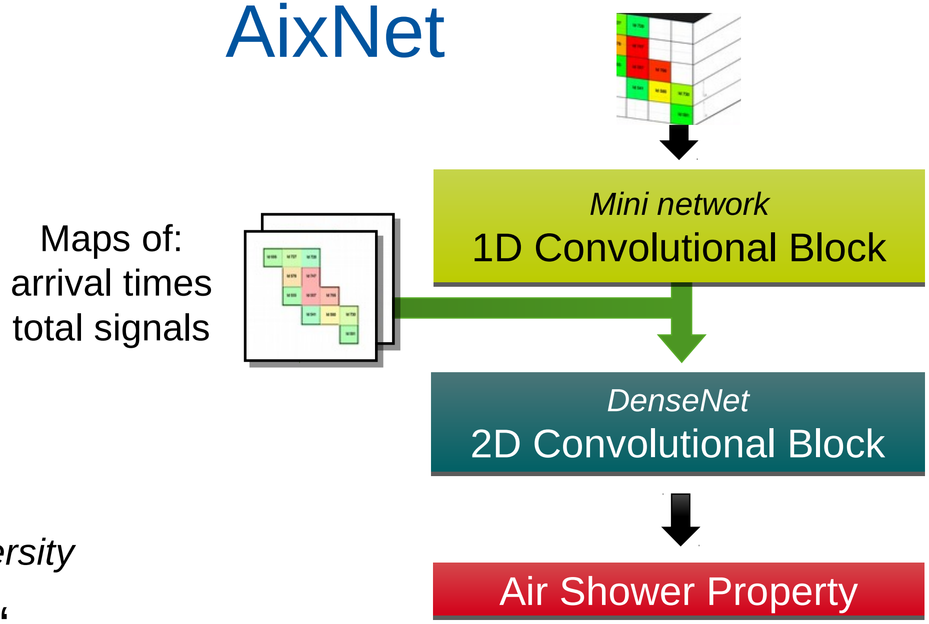
+ Add maps to stack

Maps of:
arrival times
total signals

Main Part: DenseNet Architecture



AixNet



<u>Densely Connected Convolutions (2016)</u>

Facebook AI Research, Cornell University, Tsinghua University

- Connections with all upper „feature layers“
  - Combination of high level and low level features
  - Enforces feature reusage