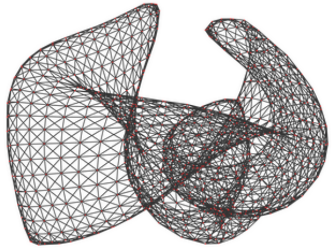
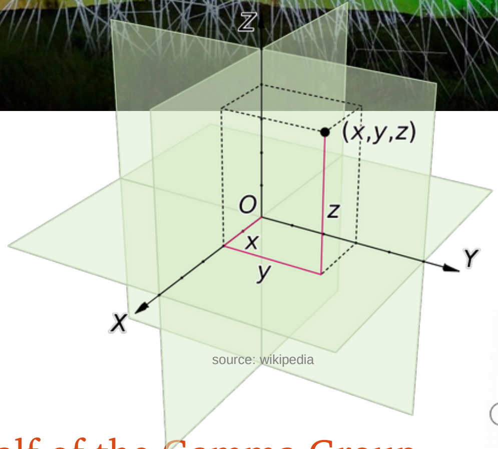
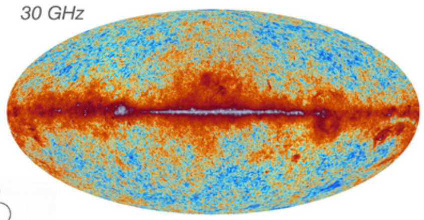
Friedrich-Alexander-Universität
Erlangen-Nürnberg

Machine Learning for Astroparticle Physics

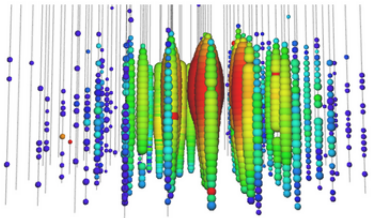




source: wikipedia



Astronomy and Astrophysics 641, p. 1 (2018)


https://arxiv.org/abs/1309.7003

Jonas Glombitza on behalf of the Gamma Group

August 1, 2022

ERLANGEN CENTRE FOR ASTROPARTICLE PHYSICS

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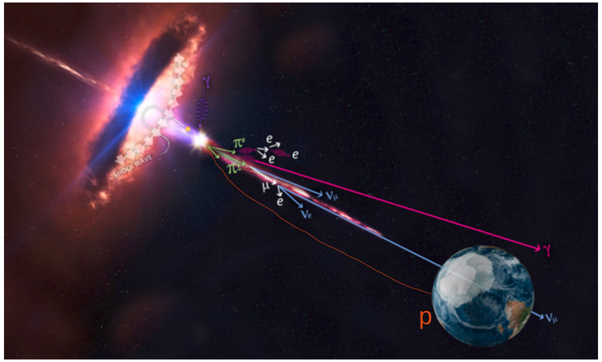
Astroparticle Physics: Reconstructions

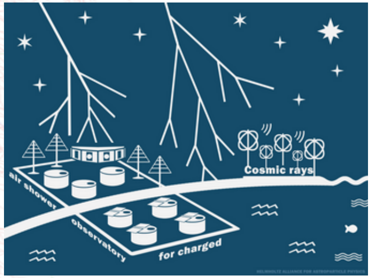


Study of particles with astronomical origin

- arrival direction, energy, particle type (high level)

Reconstruction

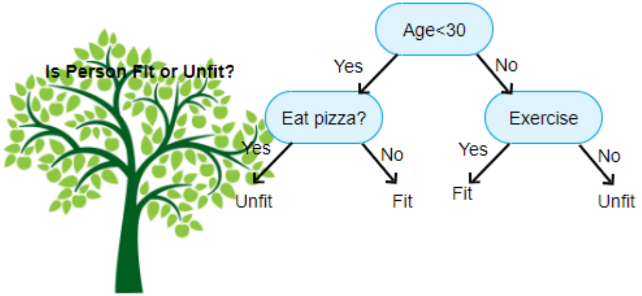
- low energies → direct reconstruction
- high energies → indirect (challenging)
  - *traditional:* fits, parameterization, physics observables
  - *more recent:* template methods, ML using physics observables
  - ***NEW:*** exploit low-level data using machine learning → Deep Learning



Machine Learning and Deep Learning

Machine Learning

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

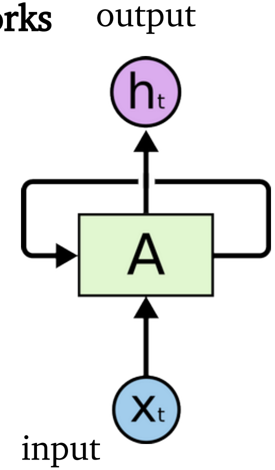


https://www.aitimejournal.com/@akshay.chavan/a-comprehensive-guide-to-decision-tree-learning

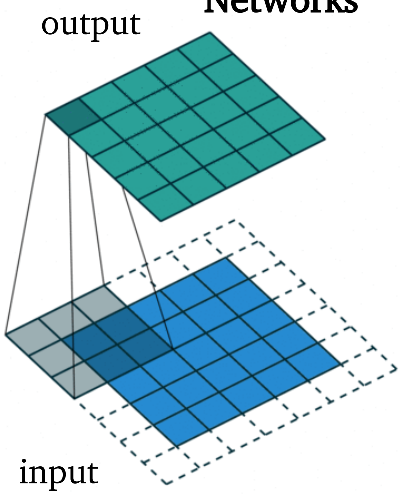
Deep Learning

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

Recurrent Networks

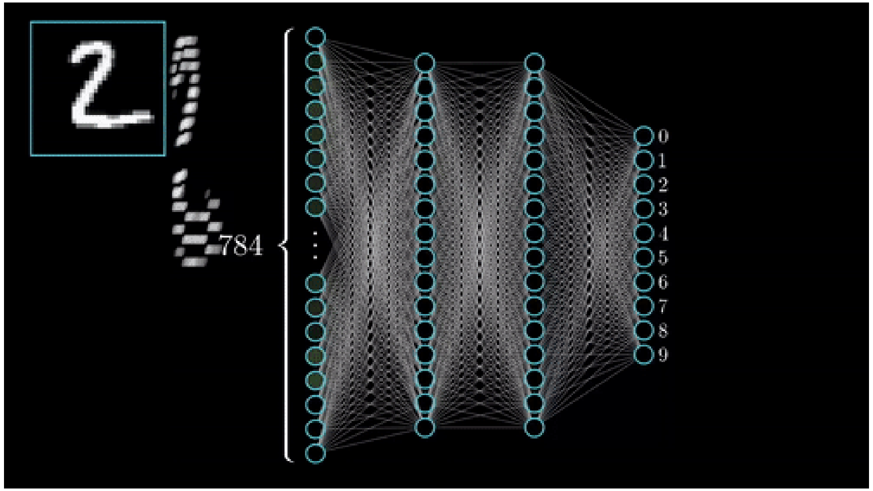


Convolutional Networks

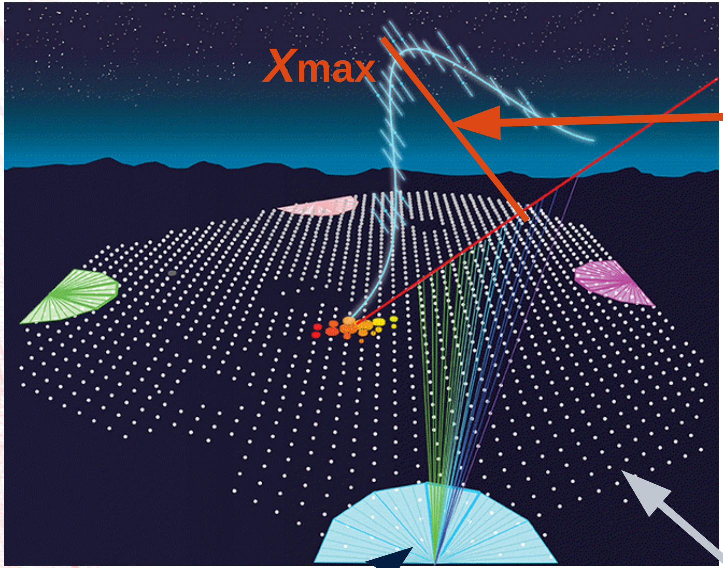


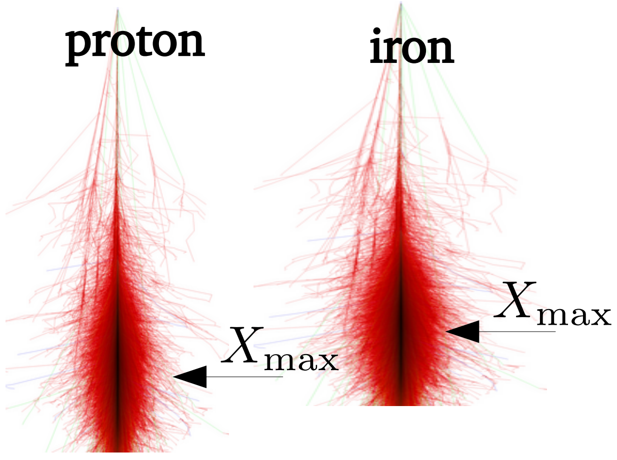
Supervised Learning

- Convolutional Neural Networks
- Recurrent Networks
- Classification, Regression, Denoising
- Segmentation

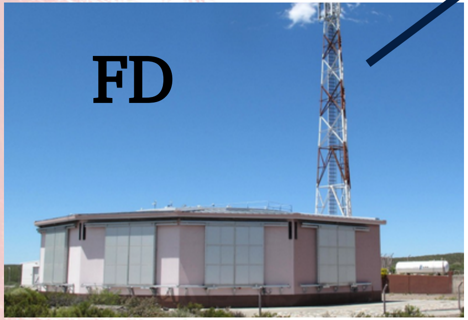


Pierre Auger Observatory

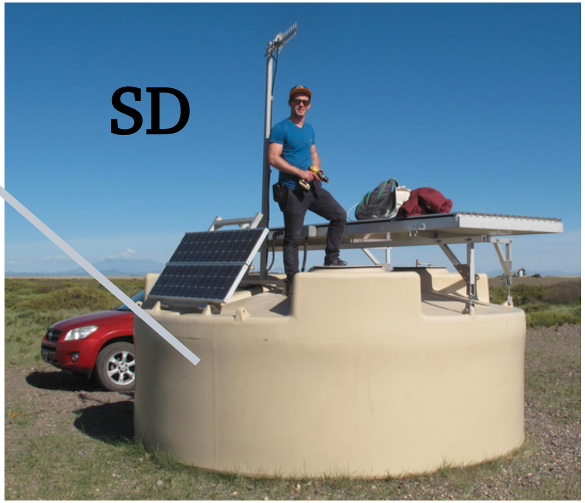




shower maximum sensitive to mass



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



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

→ use Deep Learning

Air Shower Reconstruction

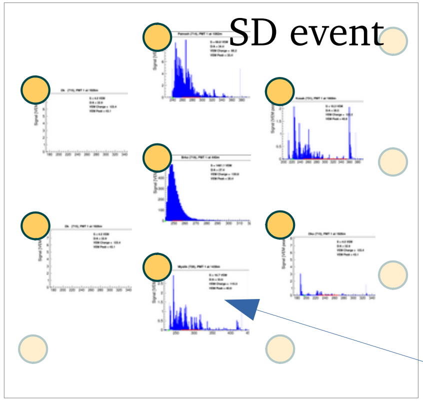
- Train neural network on simulated detector signals

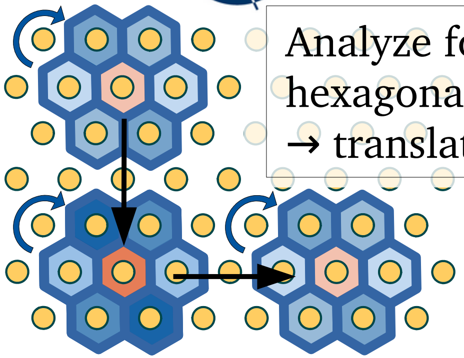
- Verify reconstruction using hybrid events

→ precise observations of maximum using FD

- ML approach outperforms physics-inspired observable

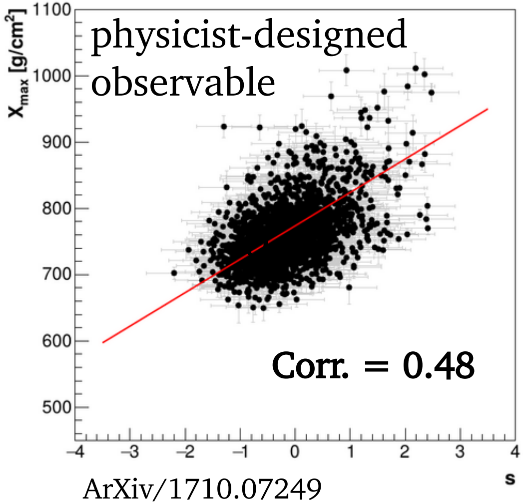
→ potential for new insights into UHECR composition



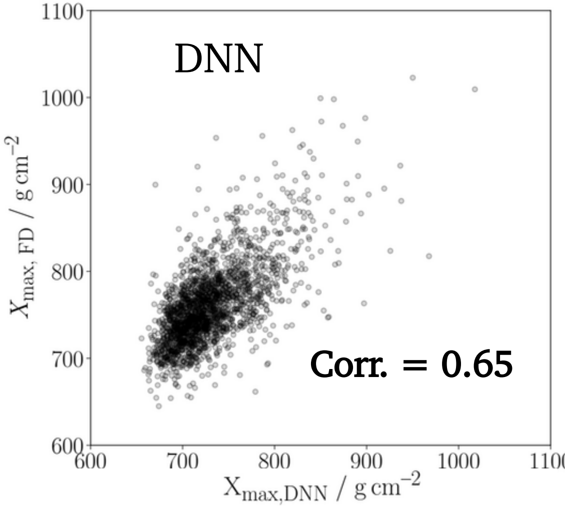


Analyze footprint with hexagonal convolution
→ translation + rotation

analyze traces with RNNs

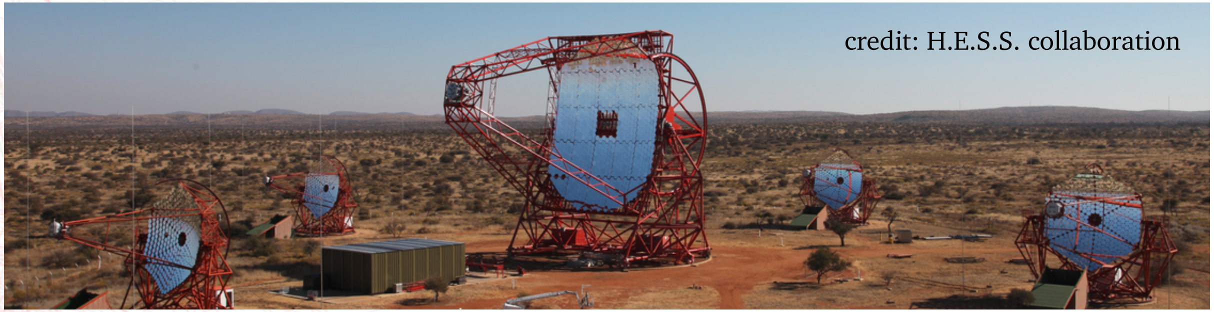


ArXiv/1710.07249

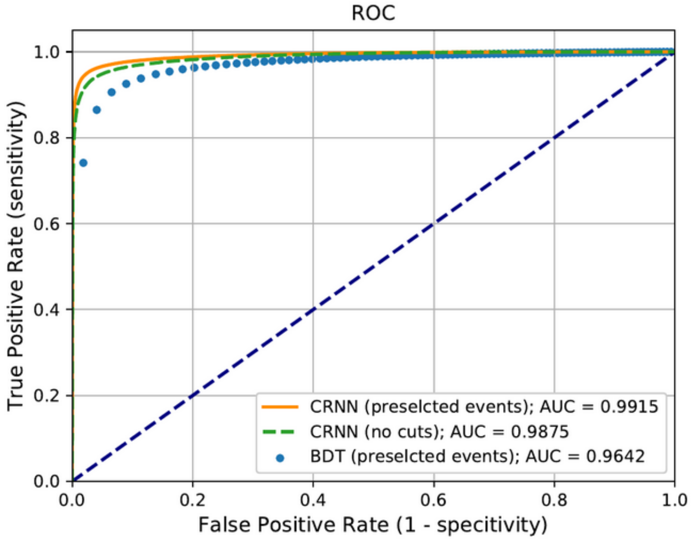


The Pierre Auger Collaboration, JINST 16 P07019 (2021)

Background Rejection



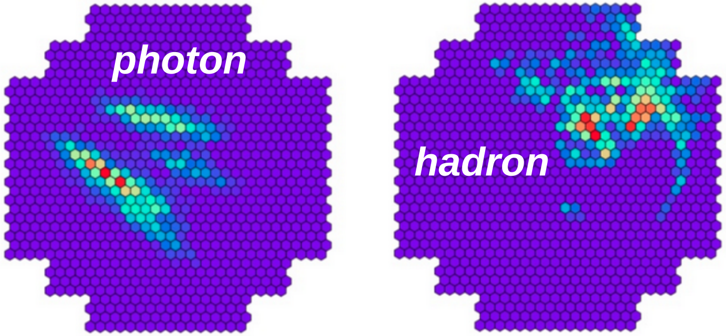
- Gamma ray telescopes in Namibia
  - background rejection (hadrons / photons)
- First promising results on simulations
  - Neural networks outperforms BDT

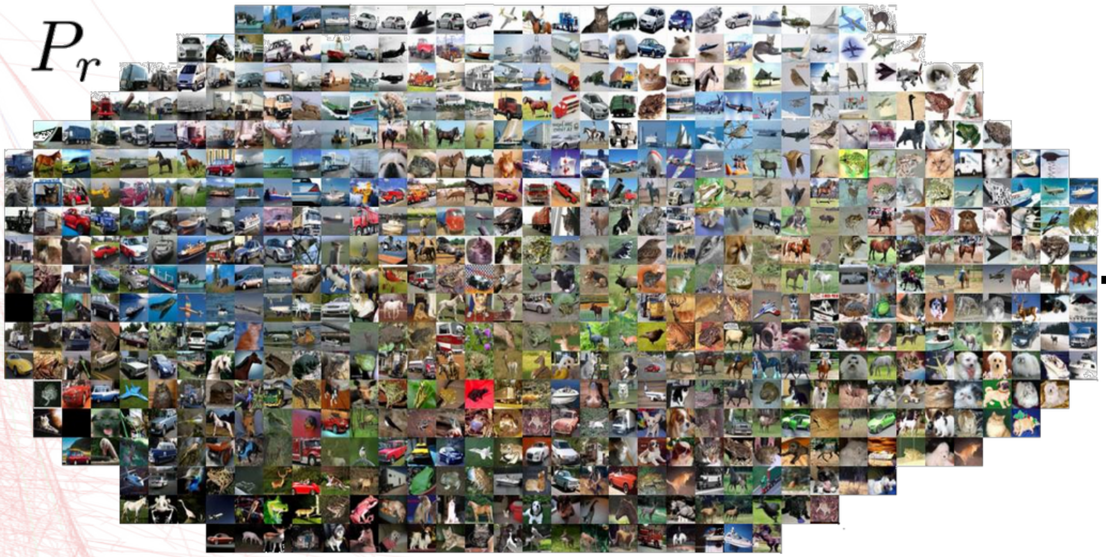


Shilon et al. - 10.1016/j.astropartphys.2018.10.003

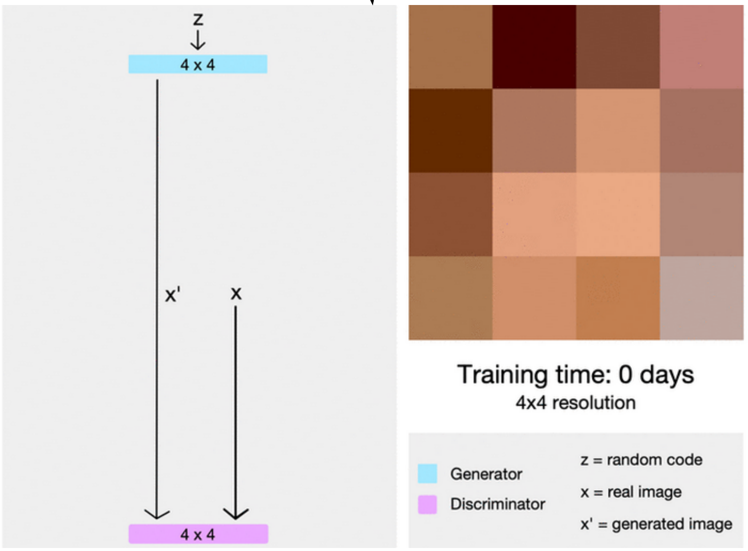
Future plans at ECAP

- develop sophisticated network architectures
- full reconstruction (stereoscopic observations)
- mitigate data simulation / mismatches





learn to generate
new samples



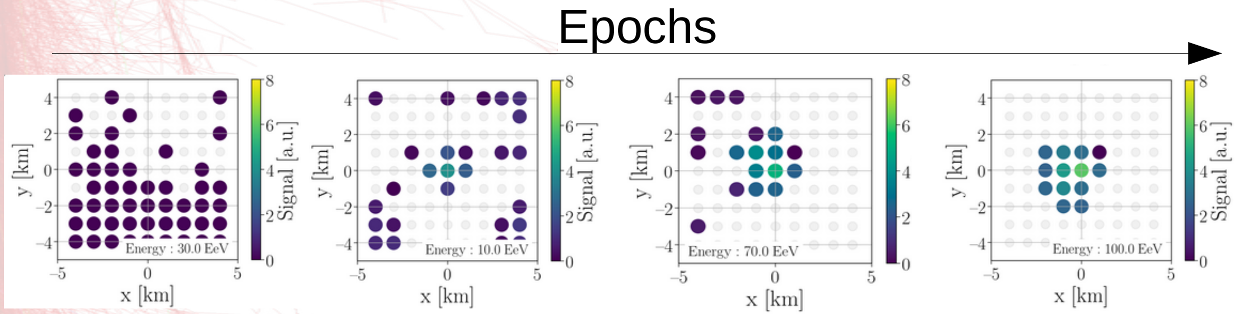
Unsupervised Learning

- Generative Models
- Simulation Refinement

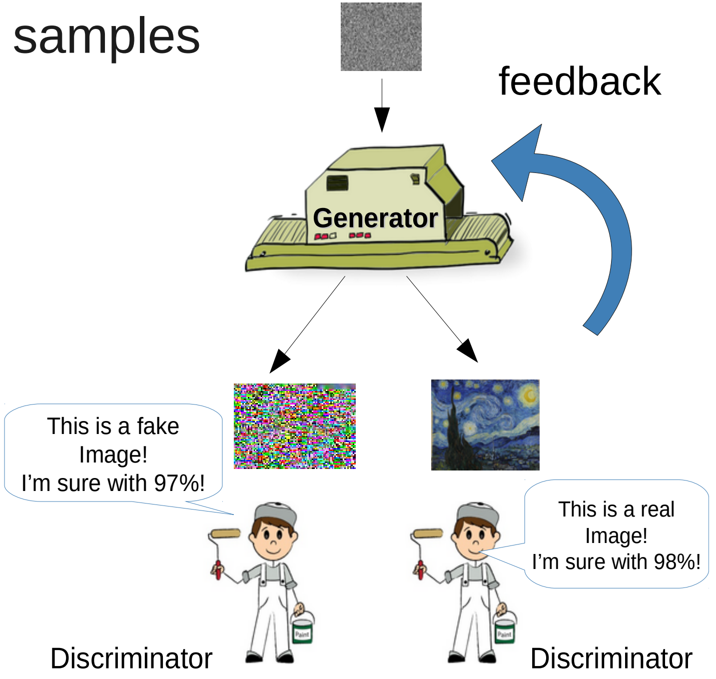
Generative Models

Unsupervised learning for approximating high-dimensional distributions

- Most powerful: adversarial frameworks (2 opponent networks)
  - train generator to generate fake samples
  - train discriminator to separate between real and fake samples
- ➔ approximate real distribution
  - ➔ fast generation of new samples



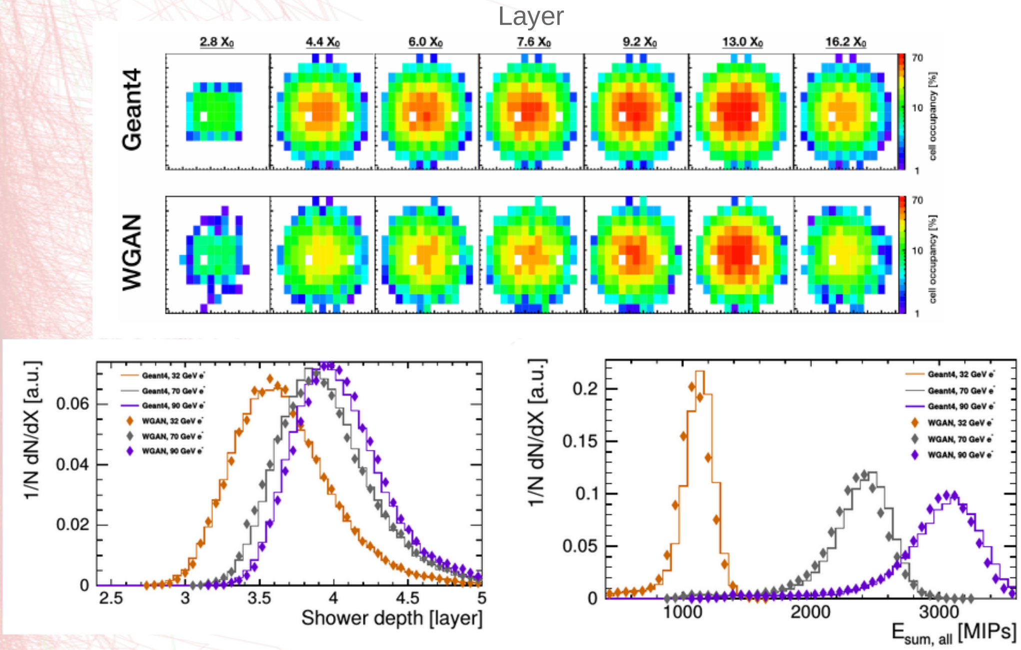
Erdmann, Geiger, Glombitza, Schmidt - 10.1007/s41781-018-0008-x



Generation of Calorimeter Images

Application at LHC

- high-luminosity phase → large MC library needed
- accelerate simulations, e.g., of calorimeter images → speed up factor $10^4 – 10^5$



Erdmann, Glombitza, Quast - 10.1007/s41781-018-0019-7

Future plans at ECAP

- continue progress
- adapt techniques:
  - generate IACT images
  - accelerate air-shower simulations
  - generate detector backgrounds

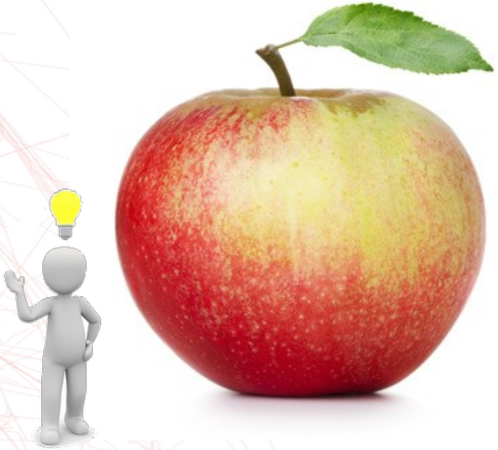
Summary

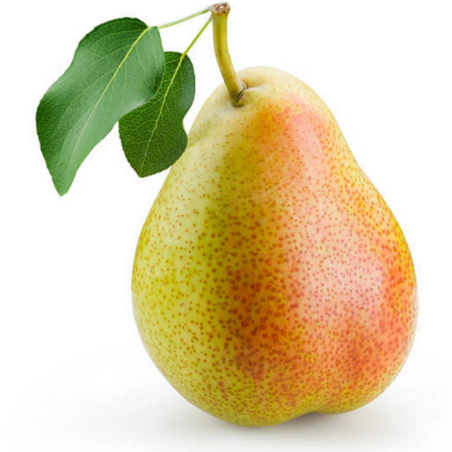
The advent of deep learning offers new tools for astroparticle physics

- supervised object reconstruction
  - event classification
  - event reconstruction
- unsupervised learning models
  - acceleration of computational-intensive simulations (generative models)
  - ‘refinement’ of simulated data (domain adaption)

- studies at ECAP:
  - event reconstruction: IACTs, (UHECR) WCD-based observatories
  - domain adaption (more realistic simulations / training data)
  - acceleration of physics simulations

Backup

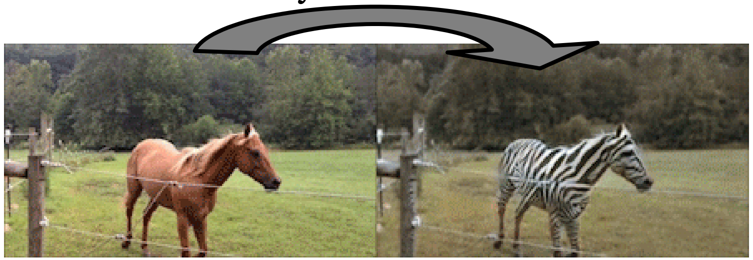




Generalization Capacities on Data

DNNs and Domain Adaption

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



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

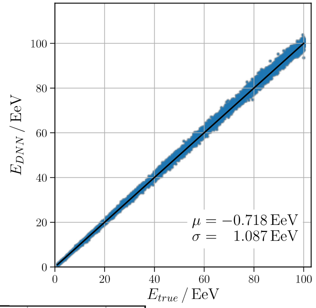
Simulation Refinement

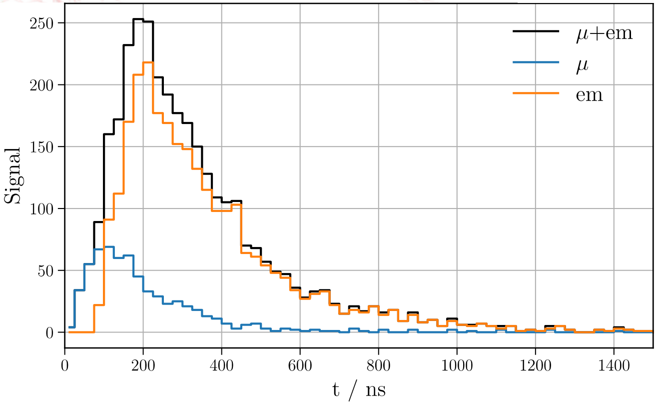
Erdmann et al.
Comput Softw Big Sci (2018) 2: 4

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

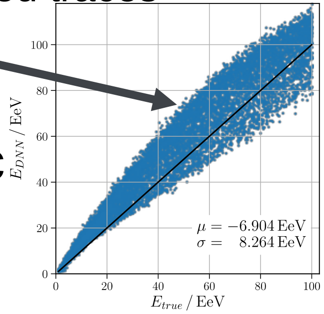
Neural network can not handle modified traces

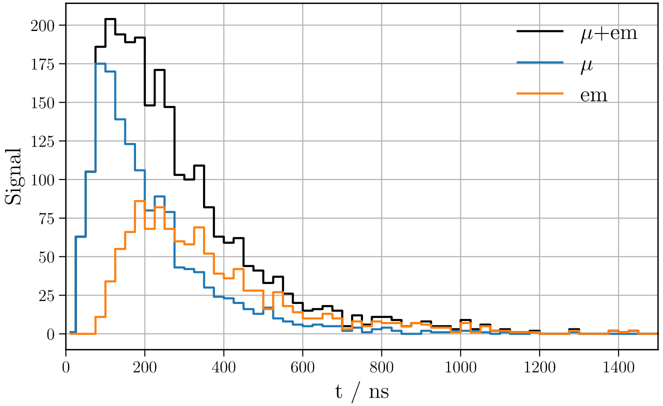
Simulation
70% electromagnetic
30% muonic





Data
30% electromagnetic
70% muonic
+ Increased noise



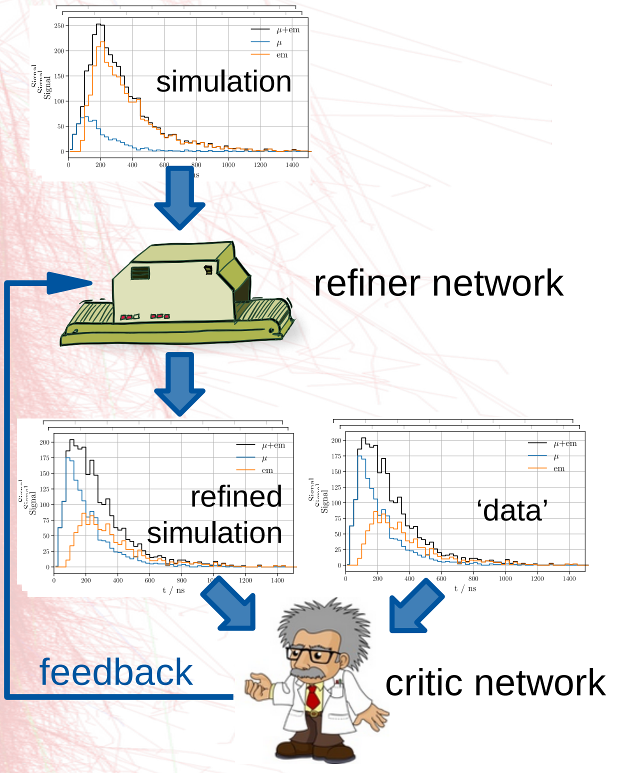


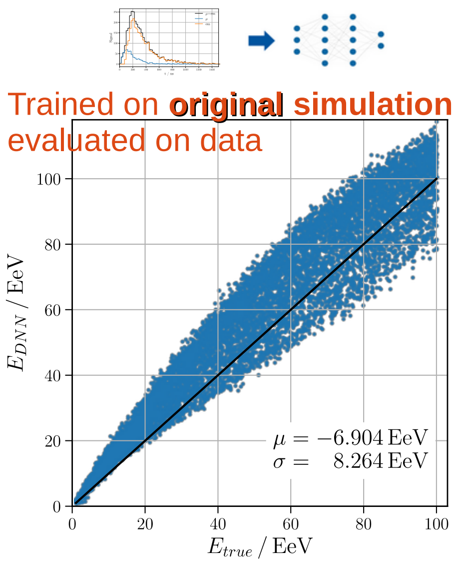
Simulation Refinement

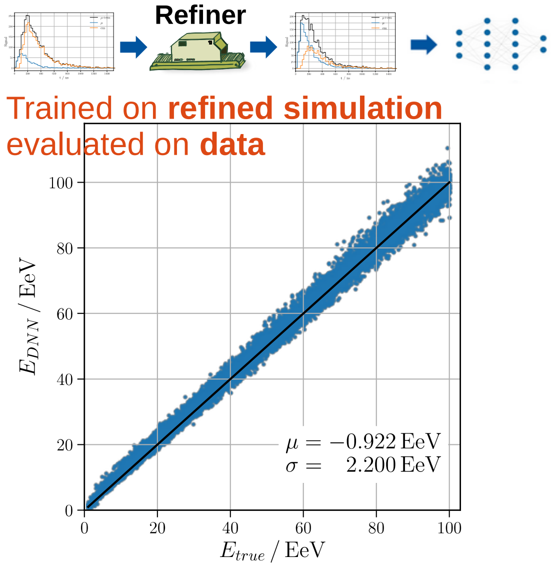
Erdmann et al.
Comput Softw Big Sci (2018) 2: 4

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

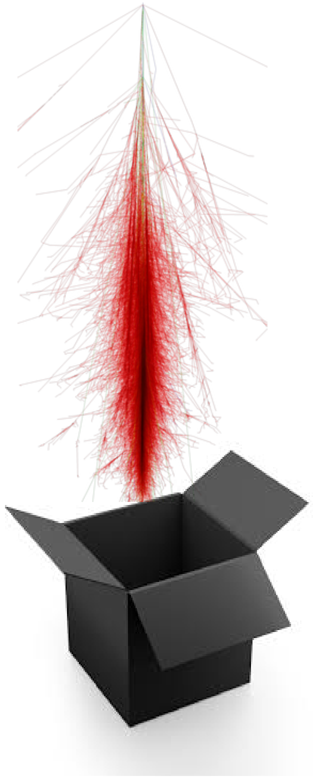






Visualization of Deep Networks

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



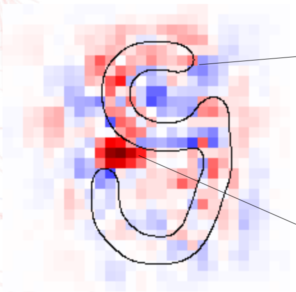
Saliency Maps

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’