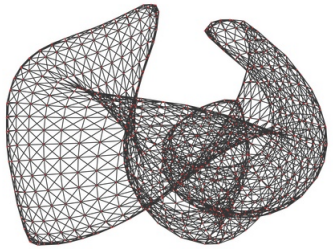
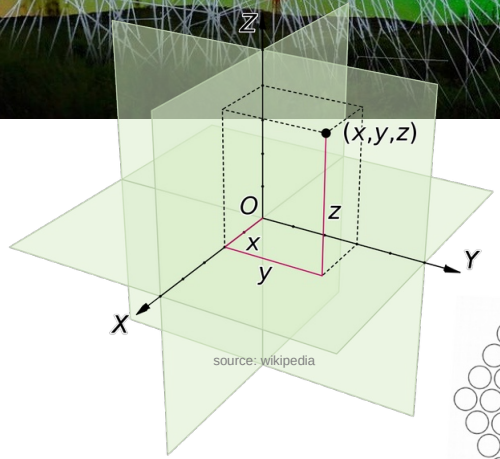
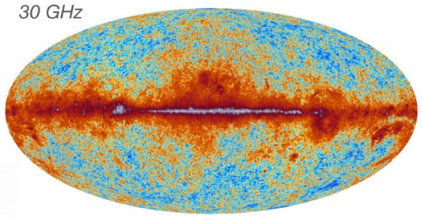
Friedrich-Alexander-Universität
Erlangen-Nürnberg

Machine Learning for Astroparticle Physics

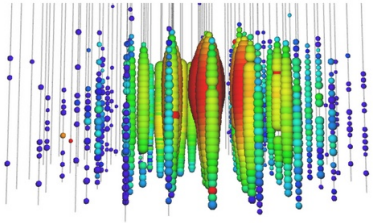




source: wikipedia



Astronomy and Astrophysics 641, p. 1 (2018)



https://arxiv.org/abs/1309.7003

Jonas Glombitza

May 9, 2023

ERLANGEN CENTRE FOR ASTROPARTICLE PHYSICS

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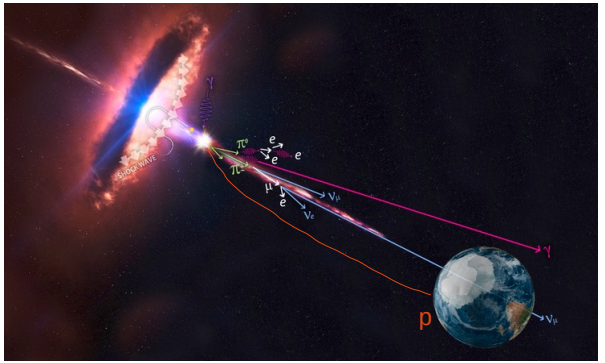
Astroparticle Physics: Reconstructions

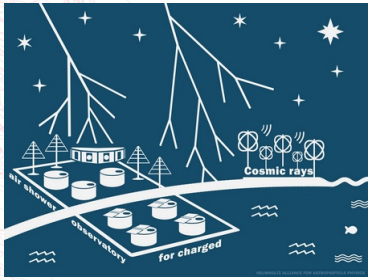


Study of particles with astronomical origin

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

Reconstruction

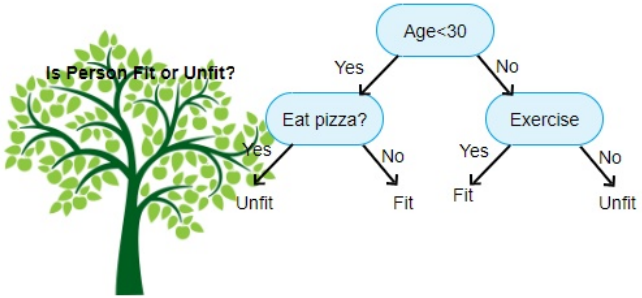
- low energies → direct reconstruction
- high energies → indirect (challenging)
  - *traditional:* fits, parameterization, physics observables
  - *more recent:* template methods, ML using physics observables
  - ***NEW:* exploit low-level data using machine learning → <u>Deep Learning</u>**



Machine Learning and Deep Learning

Machine Learning

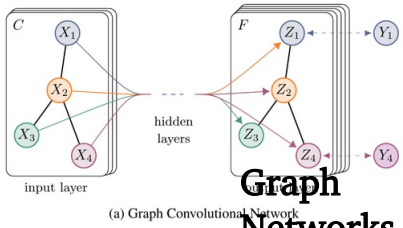
- applications across many physics domains, e.g., for (background rejection, multi-class classifications)
- BDTs, random forest, shallow NNs



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

Deep Learning

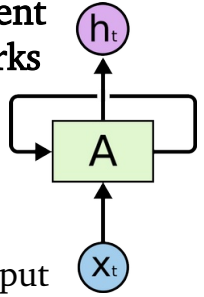
- driven by computer science (BigTechs)
- major improvements in:
  - speech recognition, NLP
  - pattern recognition, CV
- (usually) requires huge amounts of data



(a) Graph Convolutional Network

Graph Networks

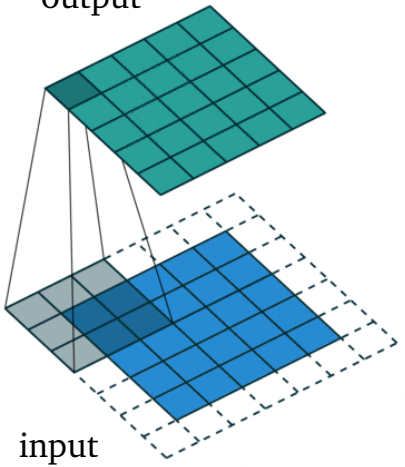
Recurrent Networks



input

Convolutional Networks

output

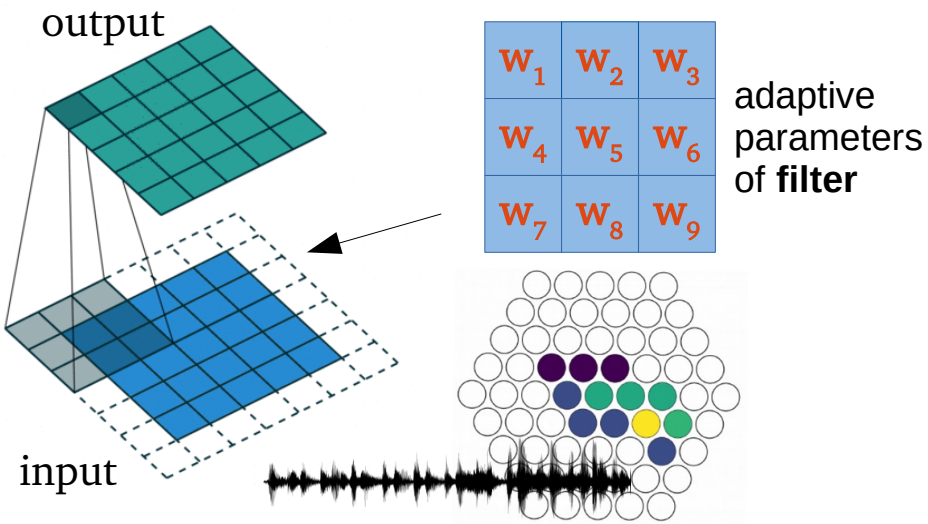


input

Deep Learning: RNNs & CNNs

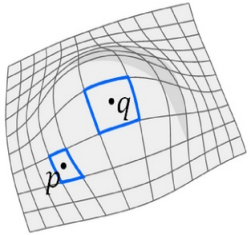
Convolutional Networks (CNNs)

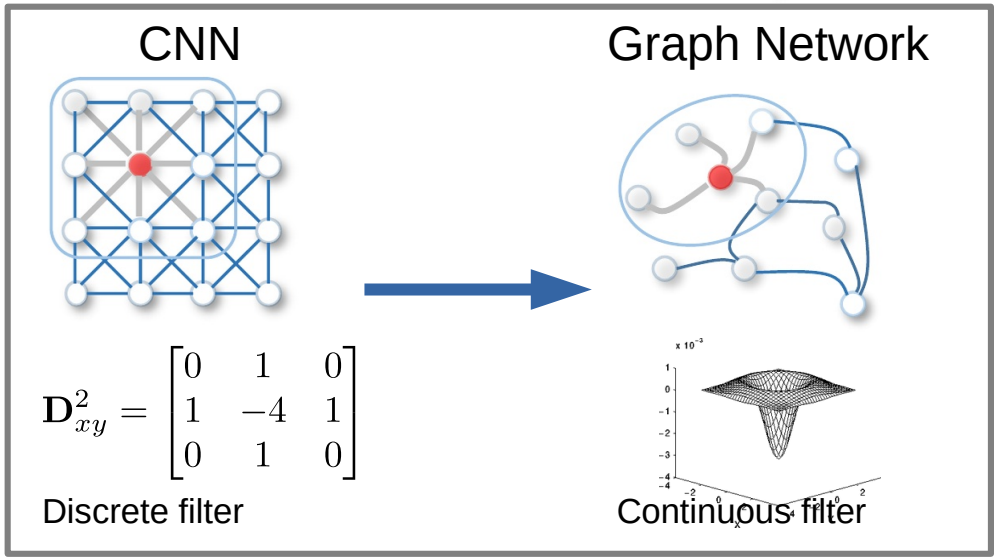
- analyze image-like data
- **filter** exploits image
  - features translational invariance
  - prior on local correlations



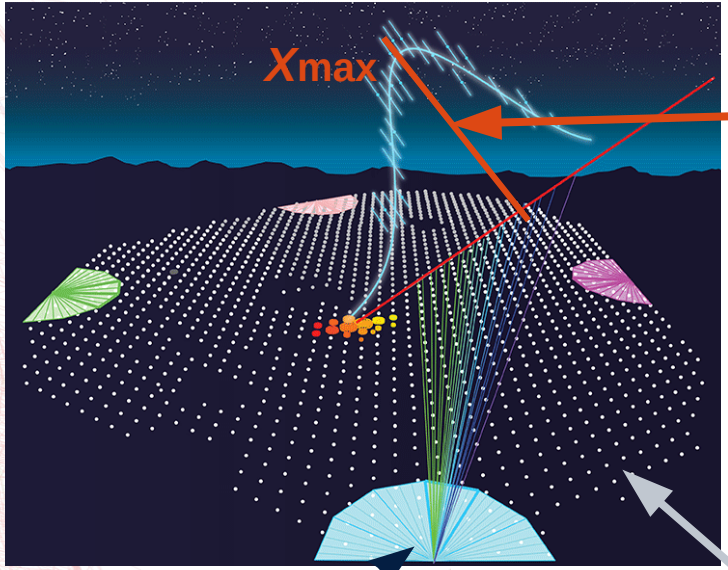
Graph Network

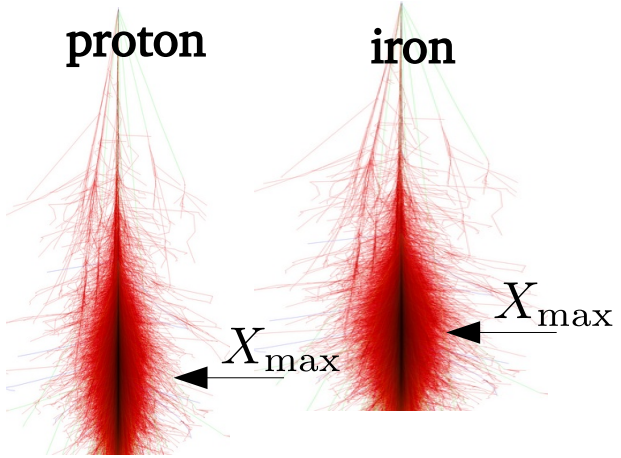
- For data with spatial correlations
  - Local proximity important prior
- Extent concept of CNNs to
  - Non-regular grids
  - Non-Euclidean Manifolds



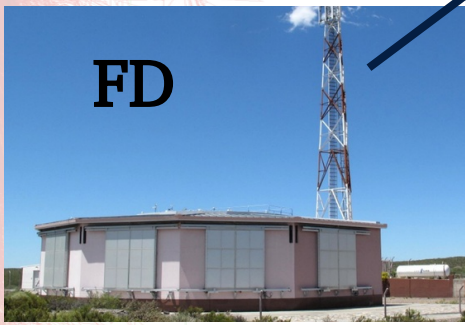


Pierre Auger Observatory

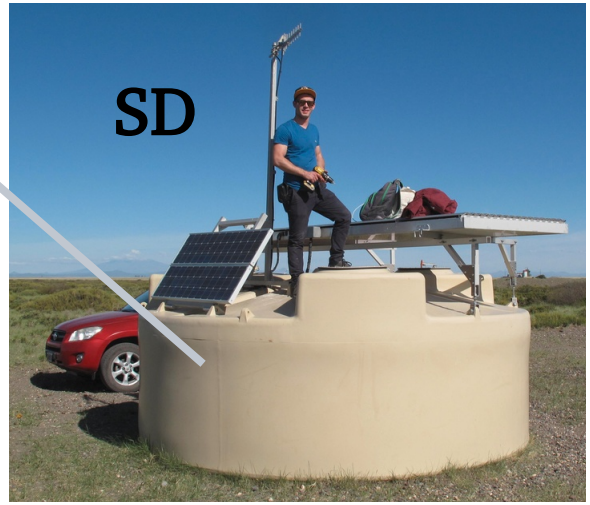




shower maximum sensitive to mass



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



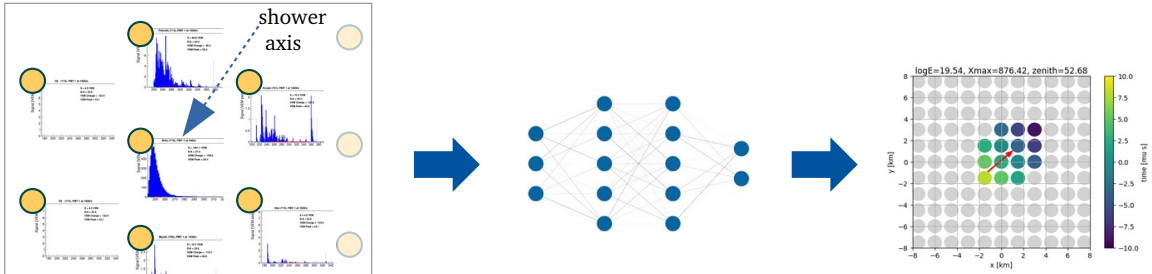
- ~1600 detectors
- 3000 km²
- cannot directly access Xmax
- 100% duty cycle

→ use Deep Learning

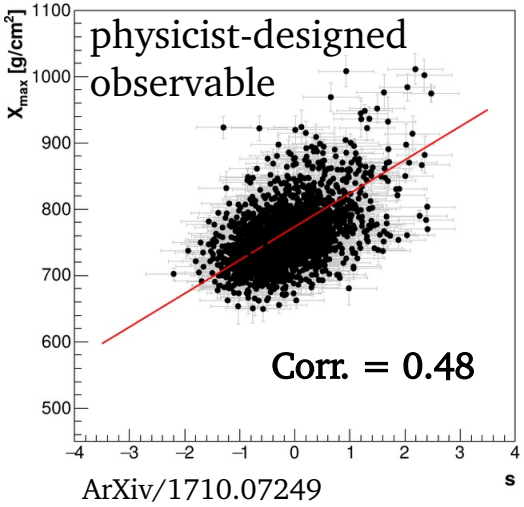
Air Shower Reconstruction

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

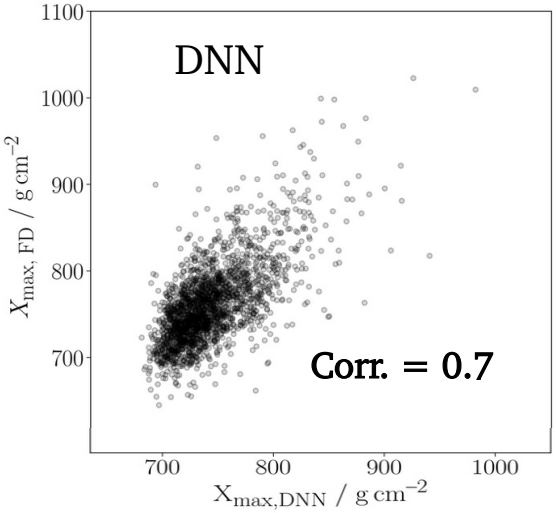
➔ potential for new insights into UHECR composition



signal traces

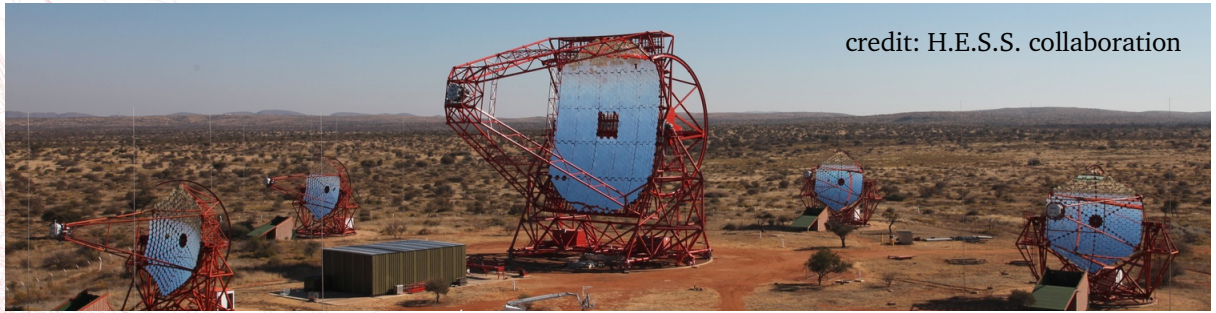


ArXiv/1710.07249

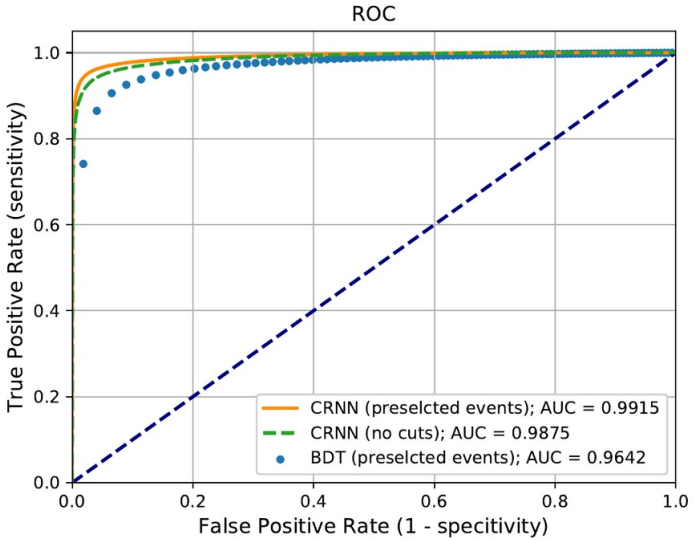


The Pierre Auger Collaboration, JINST 16 P07019 (2021)

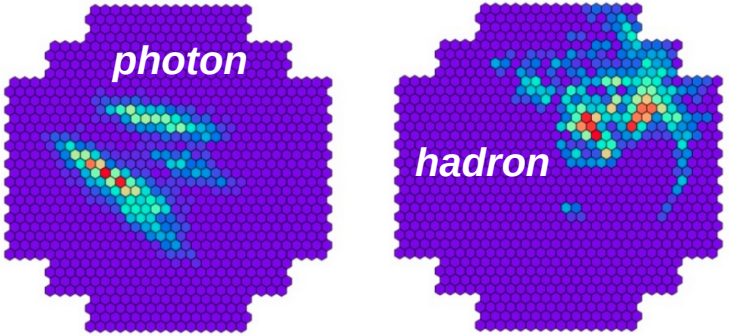
Background Rejection



- Gamma ray telescopes in Namibia
  - background rejection (hadrons / photons)
  - 1 gamma each 10^4 protons
    - Powerful discrimination needed
- First promising results on simulations
  - Neural networks outperforms BDT



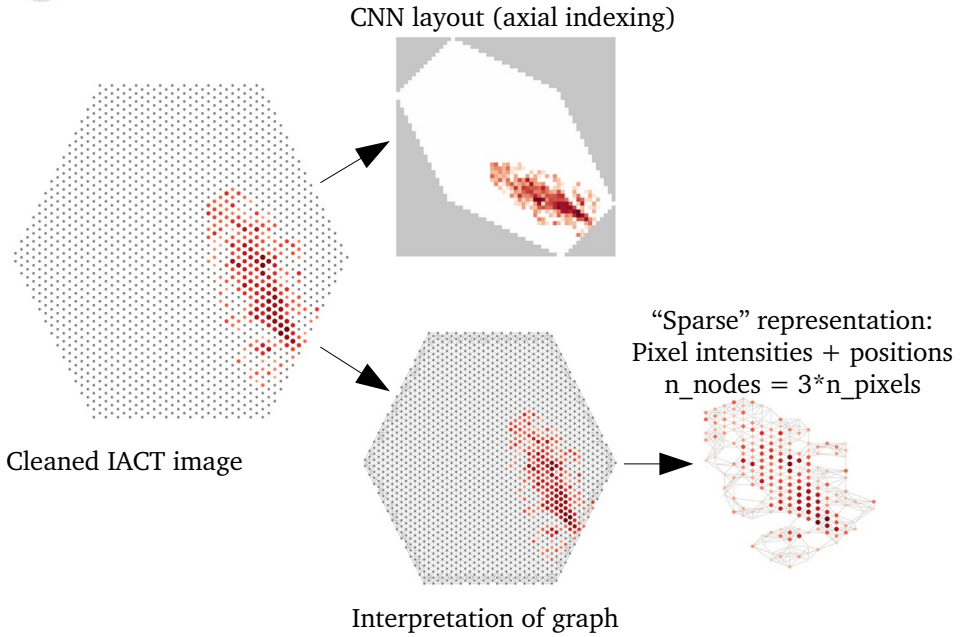
Shilon et al. - 10.1016/j.astropartphys.2018.10.003

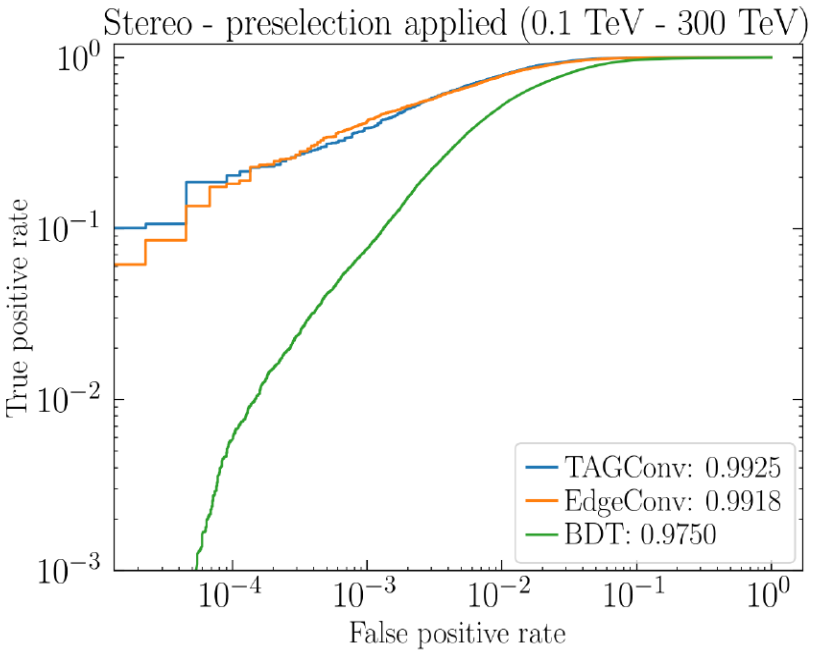


Future plans at ECAP

- full reconstruction (stereoscopic observations)

Gamma/Hadron Separation for IACTs

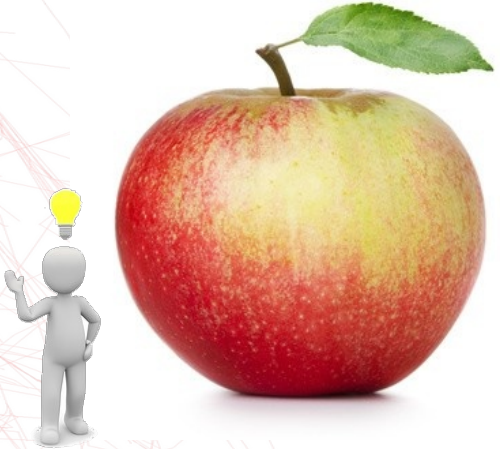




Interpret IACT images as graphs

- Consider only pixels after cleaning
  - Built graph using kNN cluster (k=6 due to hexagonal grid)

- Preselection applied (local distance cut)
- At gamma efficiency of 50%, FPR of 10^{-3}
  - background rejection improved by factor of 10 compared to BDT



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

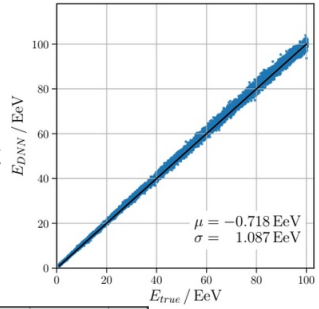
Erdmann et al.
Comput Softw Big Sci (2018) 2: 4

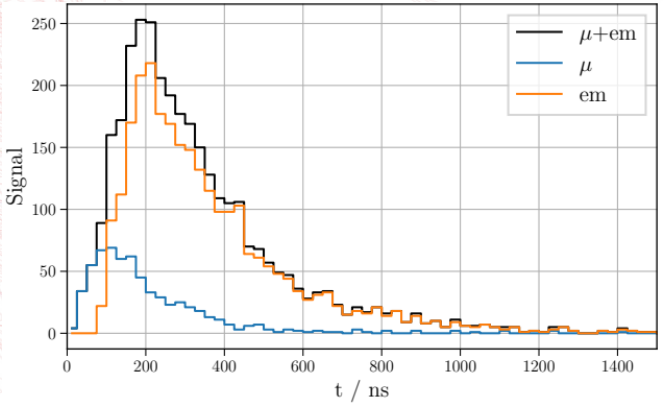
- Training on **simulations** but application on **data**
  - Model can be sensitive to artifacts / mismatches existing in simulation

Neural network can not handle modified traces

Simulation

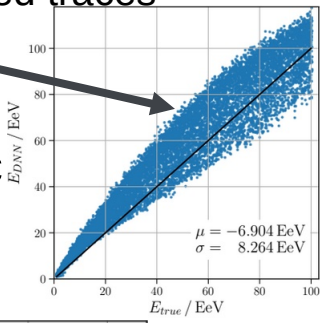
70% electromagnetic
30% muonic

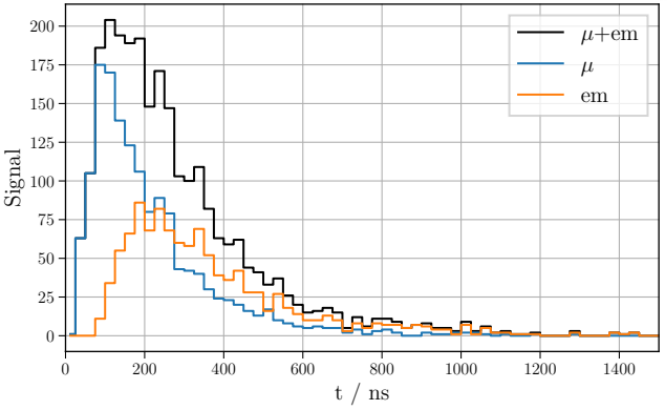




Data

30% electromagnetic
70% muonic
+ Increased noise

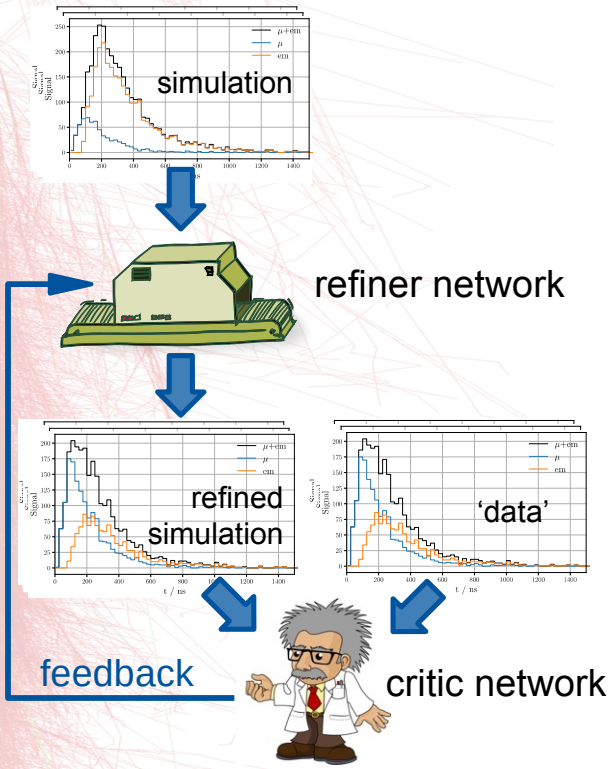




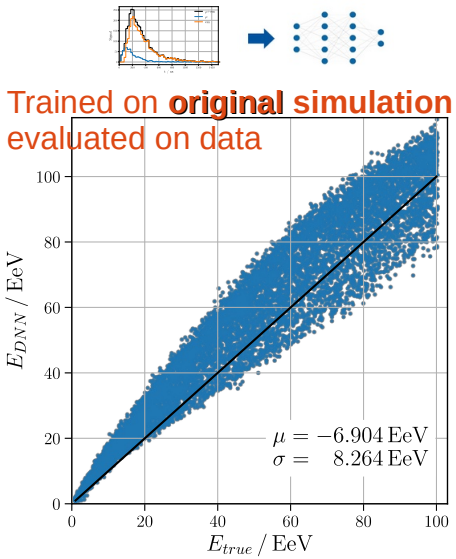
Simulation Refinement

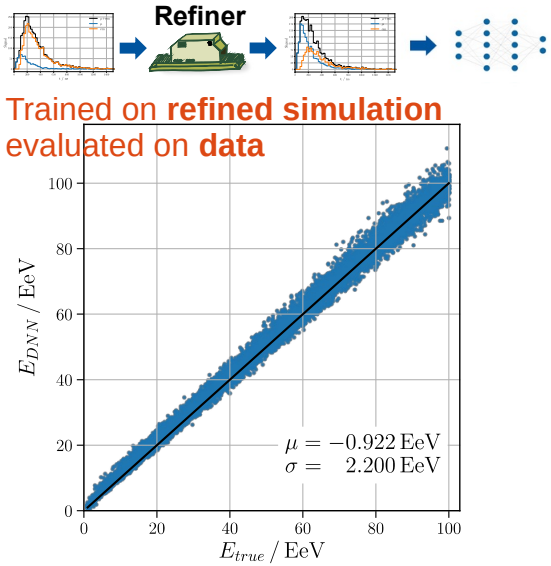
Erdmann et al.
Comput Softw Big Sci (2018) 2: 4

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





Summary

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

- Event reconstruction
- Background rejection

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

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

Will artificial intelligence replace us (physicists)?

Will artificial intelligence replace us (physicists)?

Quantitative study to assess to what extent robotics and AI abilities can replace human abilities (technology readiness level):

Safest job →

Occupation	Main Texta (low-automation- high-automation)				Sensitivity (Missing at Random)			
	Rank	Mean	low-automation	high-automation	Rank	Mean	p5	p95
Physicists	1	0.44	0.20	0.67	1	0.49	0.43	0.55
Robotics Engineers	122	0.55	0.31	0.80	78	0.64	0.59	0.69
Economists	203	0.57	0.31	0.83	207	0.68	0.61	0.74

This is the wrong question!

How can we (physicists) use the new technology to accelerate and improve our research?

Summary

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

- Event reconstruction
- Background rejection

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

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