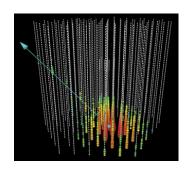


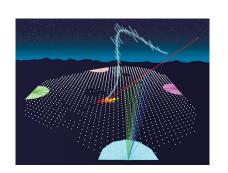


Deep Learning based Algorithms in Astroparticle Physics

Martin Erdmann, Michael Dohmen, **Jonas Glombitza**, Maximilian Vieweg, Marcus Wirtz

III. Physikalisches Institut A, RWTH Aachen







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Astroparticle Physics

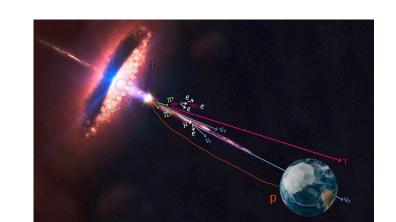
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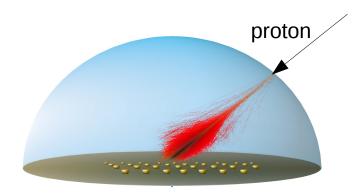
- Observation of particles with astronomical origin
- Measuring energy spectrum and composition
- Find, identify and understand sources
 - Multi-messenger astronomy
- Feature very large detector volumes
 - Ice, water, atmosphere → indirect detection
 - Relatively sparse read out
 - Limited computational resources at site

Example

Cosmic Ray Observatory

Atmosphere = calorimeter detector = single readout layer



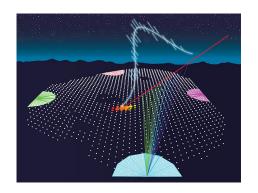


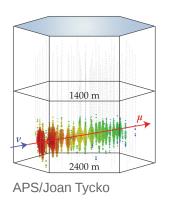
Measured Data

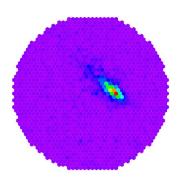


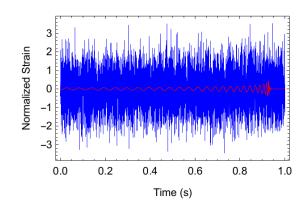


- Widely distributed sensors / telescopes
- Most experiments feature Hexagonal or Cartesian sensor grids
 - 2 and 3 dimensional structured footprints / signal patterns
- Many sensors provide time trace of signals
- Structured multi-dimensional data
- Motivates convolutional and recurrent architectures







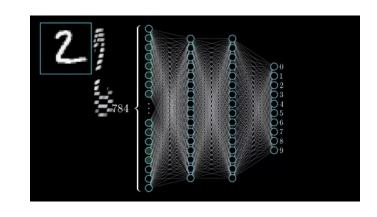






Supervised Learning

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



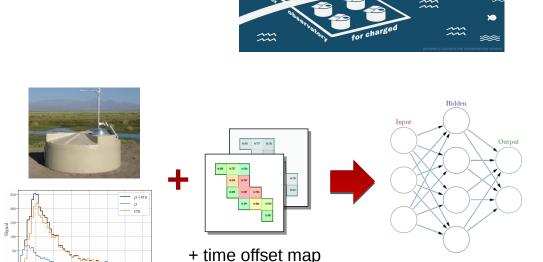
Cosmic Ray Observatory

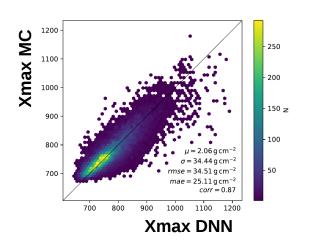
- III. Physikalisches Institut A
- RWTHAACHEN UNIVERSITY

Deep Convolutional

Neural Network

- Measurement of Ultra-high energy cosmic rays
- Reconstruction of Air Showers
 - Geometry (shower axis, shower core)
 - Inferring primary mass very challenging
- Use Deep Convolutional Network
- Results are very promising





Erdmann, Glombitza, Walz - 10.1016/j.astropartphys.2017.10.006

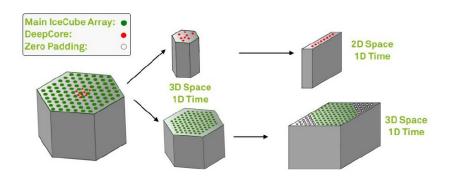
time / ns

Ice Cube: Neutrino Reconstruction

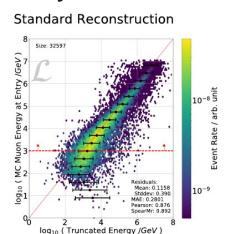


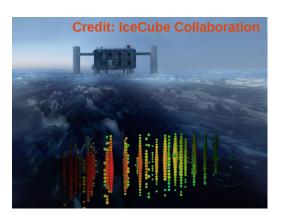


- Neutrino Observatory placed at the south pole Use 3D Convolutional Neural Network
 - Reconstruction of muon neutrino: energy, direction
- DNN shows improved runtime and performance
- On-site reconstruction: Deep Learning close to sensors
 - Real-time alerts → Multi-messenger astronomy

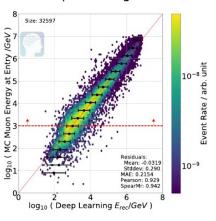


Hünnefeld, ICRC17 - 10.22323/1.301.1057









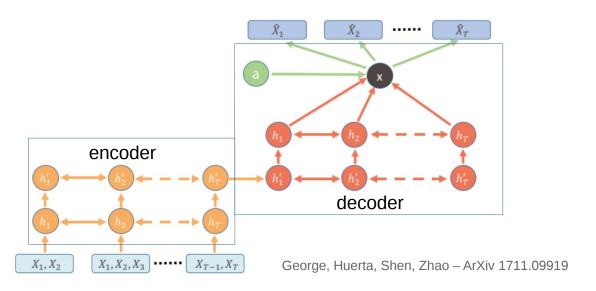
Recurrent Autoencoders

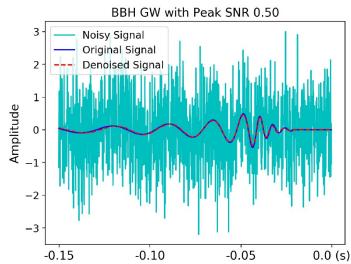




- Measured data of binary black hole mergers contain noise
- Denoising Autoencoder: remove noise and reconstruct signal
- Use Recurrent LSTM layers
- Excellent recovery of original signal







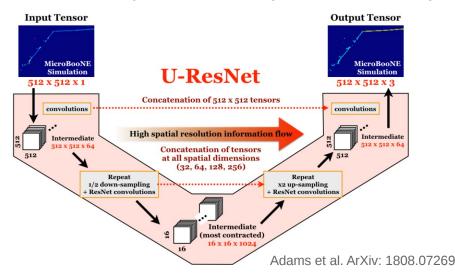
Segmentation - MircroBooNE

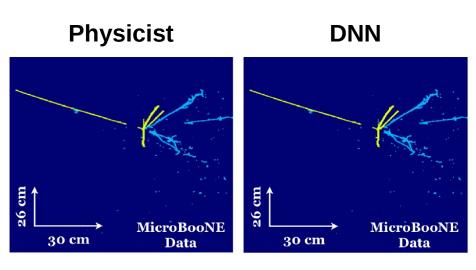
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track

10 cm

- Liquid Argon TPC for neutrino detection
- Pixel-wise segmentation into tracks and EM-showers
 - Architecture: Combination of ResNet and U-Net
- Evaluation on simulations and data (vs. physicist)
- Incorrectly classified pixel fraction per image ~ few percent









Unsupervised Learning

- Generative Models
- Simulation Refinement













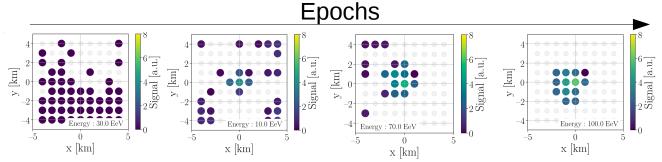
Generative Adversarial Networks

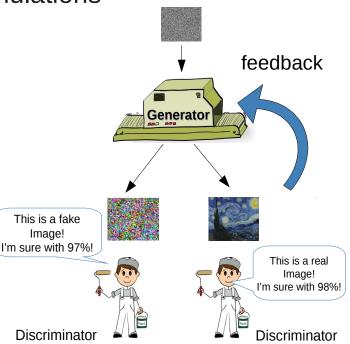




Use Generative Adversarial Networks (GANs) for simulations

- 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 $\sim 10^3 10^5$
- First application shows promising results





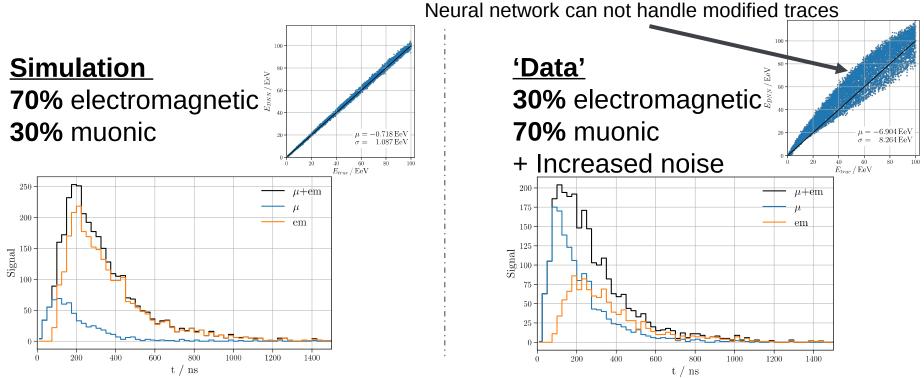
Erdmann, Geiger, Glombitza, Schmidt - 10.1007/s41781-018-0008-x

Simulation Refinement





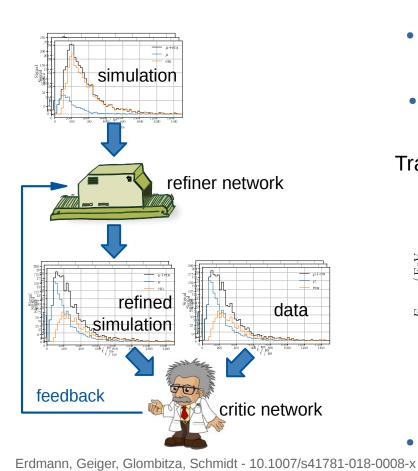
- Models trained on simulations but application on 'data' (simulated)
 - Model can be sensitive to artifacts / mismatches existing in simulation



Simulation Refinement

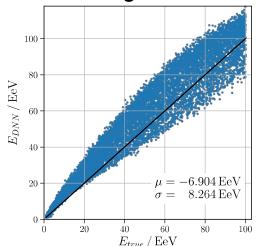




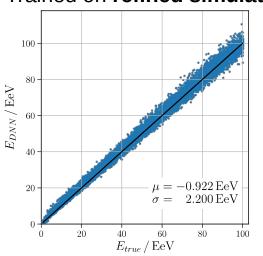


- Refiner network 'refine' simulation using feedback of critic network
- Evaluate network performance on data (simulation, with different component scalings)

Trained on **original simulation**



Trained on **refined simulation**



Training on refined simulations is able to improve reconstruction

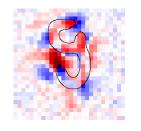
Visualization of Deep Networks





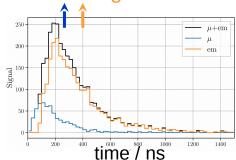
Erdmann, Eich, Glombitza

What makes a "9" a "9" for DNNs?

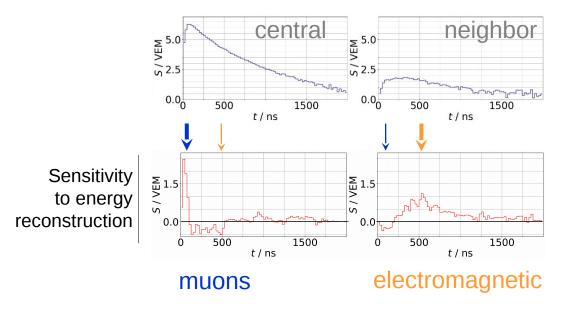




- Find patterns important for the reconstruction
 - 1. Muons arrive first, then
 - 2. Electromagnetic shower particles



1 event: raw signal traces of 2 detectors



Network learns physics aspects from data in 3h

Summary





Deep Learning arrived in all fields of astroparticle physics!

Supervised Applications

- Segmentation and Denoising
- Improved object reconstruction
- Deep Learning close to sensors
 - online reconstruction → real-time analysis
- First steps towards understanding physics networks









Unsupervised Applications

- Generative models for simulation acceleration
- Promising results on simulation refinement







Backup

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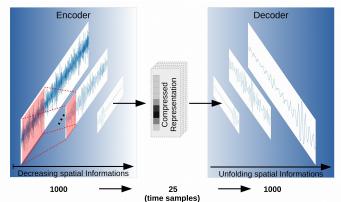
Denoising of Air Shower Radio Signals

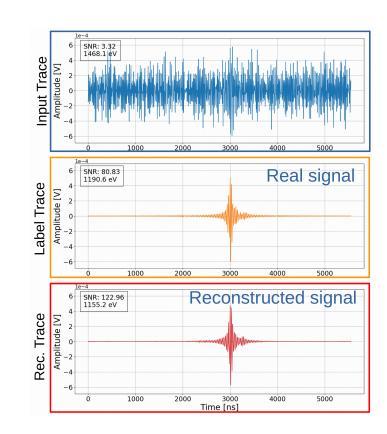




- Supervised trained Autoencoder
 - Network encodes only relevant information
- Remove noise of radio signals from cosmic ray induced air showers
- Signal energy and frequency spectrum approx. conserved







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

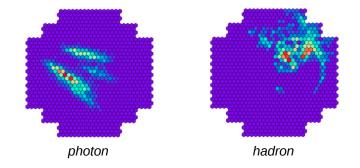
Classification: H.E.S.S.

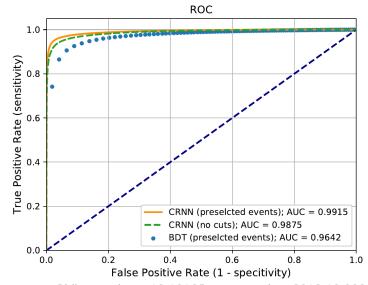
- Imaging Atmospheric Cherenkov Telescopes
- Background rejection using Convolutional Neural Network
- Classification between:
 - Hadronic showers
 - Photon showers
- Network outperforms BDT









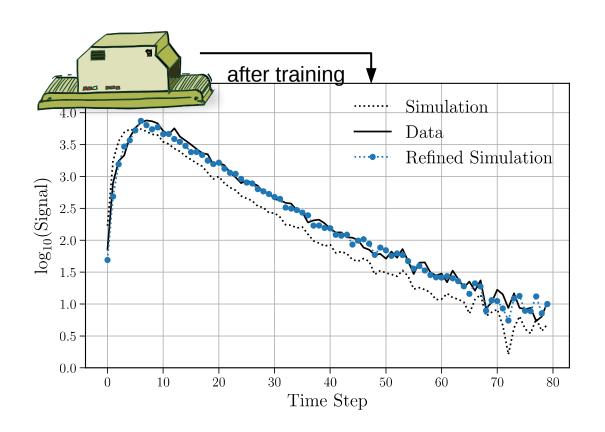


Shilon et al. - 10.1016/j.astropartphys.2018.10.003

Simulation Refinement







- ResNet like architecture
- WGAN-GP loss
- Refined trace more data like