Astroparticle Physics

- 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

- 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
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
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

George, Huerta, Shen, Zhao – ArXiv 1711.09919
Segmentation - MicroBooNE

- 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

Adams et al. ArXiv: 1808.07269
Unsupervised Learning

- Generative Models
- Simulation Refinement

Learn to generate new samples
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 \( \sim 10^3 \text{ – } 10^5 \)
- 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**
- 70% electromagnetic
- 30% muonic

**‘Data’**
- 30% electromagnetic
- 70% muonic
  - + Increased noise

Neural network can not handle modified traces
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

![Graph showing original simulation results]

Trained on refined simulation

![Graph showing refined simulation results]

- Training on refined simulations is able to improve reconstruction

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

Deep Learning in Astroparticle Physics
Glombitza | RWTH Aachen | 03/14/19 | ACAT 2019, Saas-Fee
Visualization of Deep Networks

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

Sensitivity to energy reconstruction

muons

electromagnetic

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

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

III. Physikalisches Institut A, RWTH Aachen
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

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