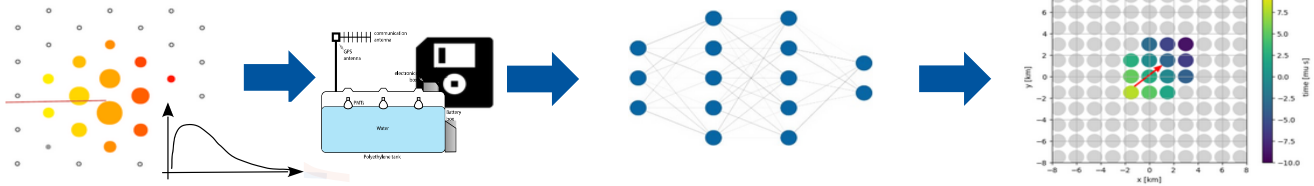
Deep Learning for Air Shower Reconstruction at the Pierre Auger Observatory

Pierre Auger Collaboration, JINST 16 P07019 (2021)



Particle footprint → Raw data → Deep neural network → Reconstruction

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Jonas Glombitza on behalf of the Pierre Auger Collaboration
III. Physics Institute A, RWTH Aachen University

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The Pierre Auger Observatory

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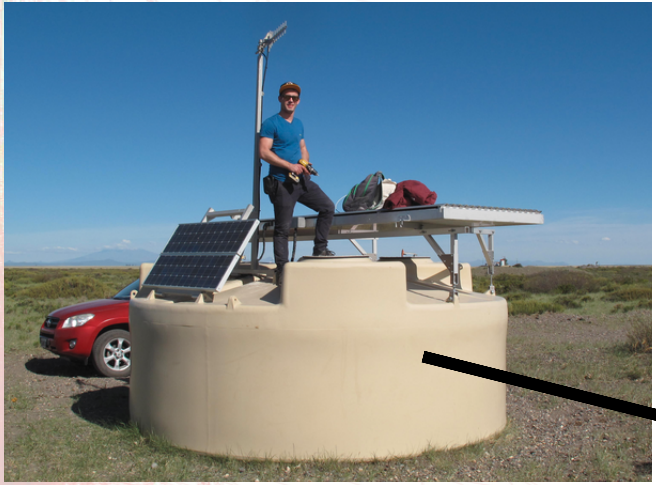
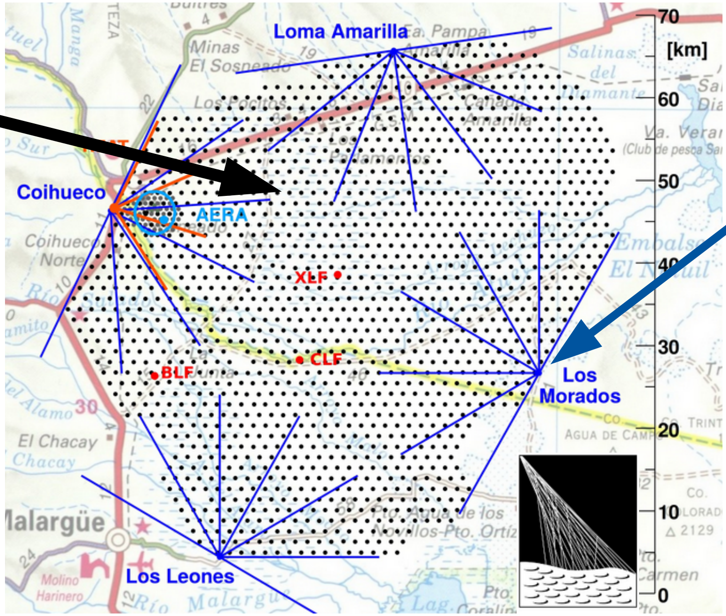


- largest cosmic-ray observatory
  - located in Argentina
- **hybrid** measurements



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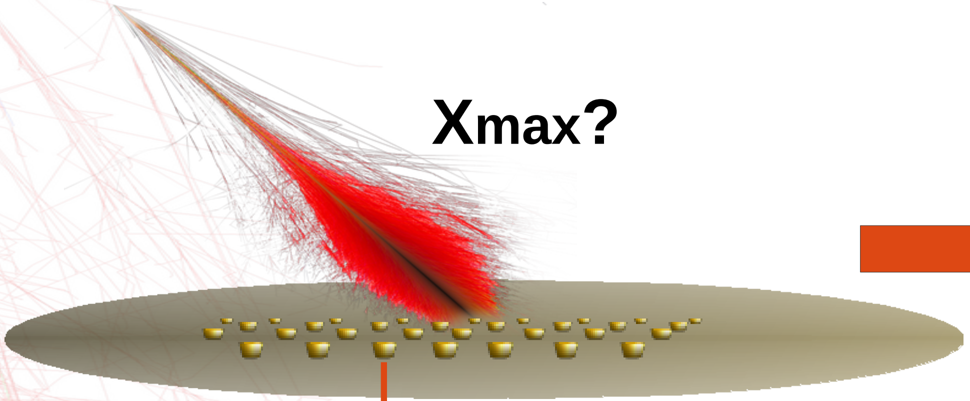
Surface Detector (SD)

- 1660 water-Cherenkov detector stations
  - 3000 km² array
  - ~100% duty cycle

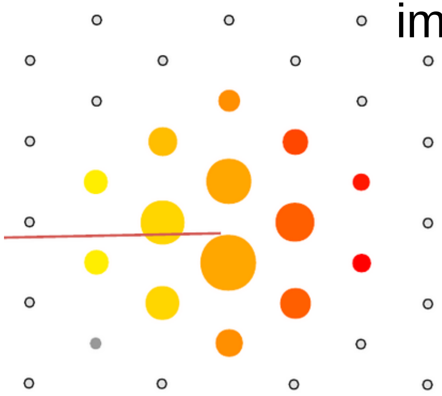
Fluorescence Detector (FD)

- 27 telescopes
  - located at 4 sites
  - ~15% duty cycle (dark, moonless nights)

Deep Learning based Xmax Reconstruction

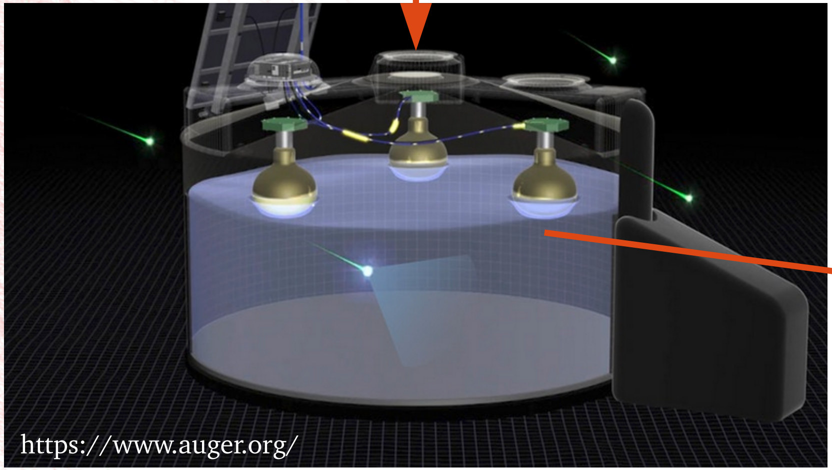


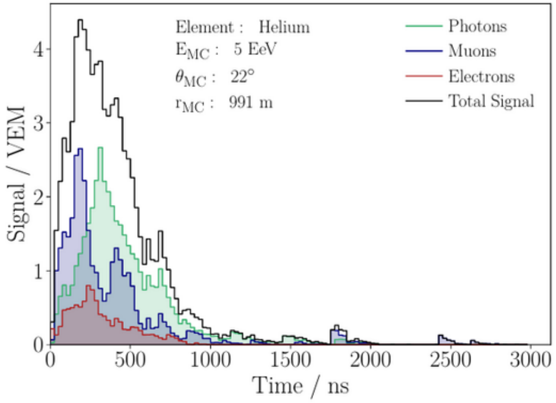
Xmax?



- image-like footprint

use convolutional network



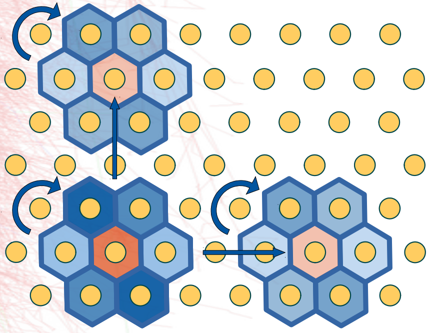


time series → use recurrent network

Network Architecture

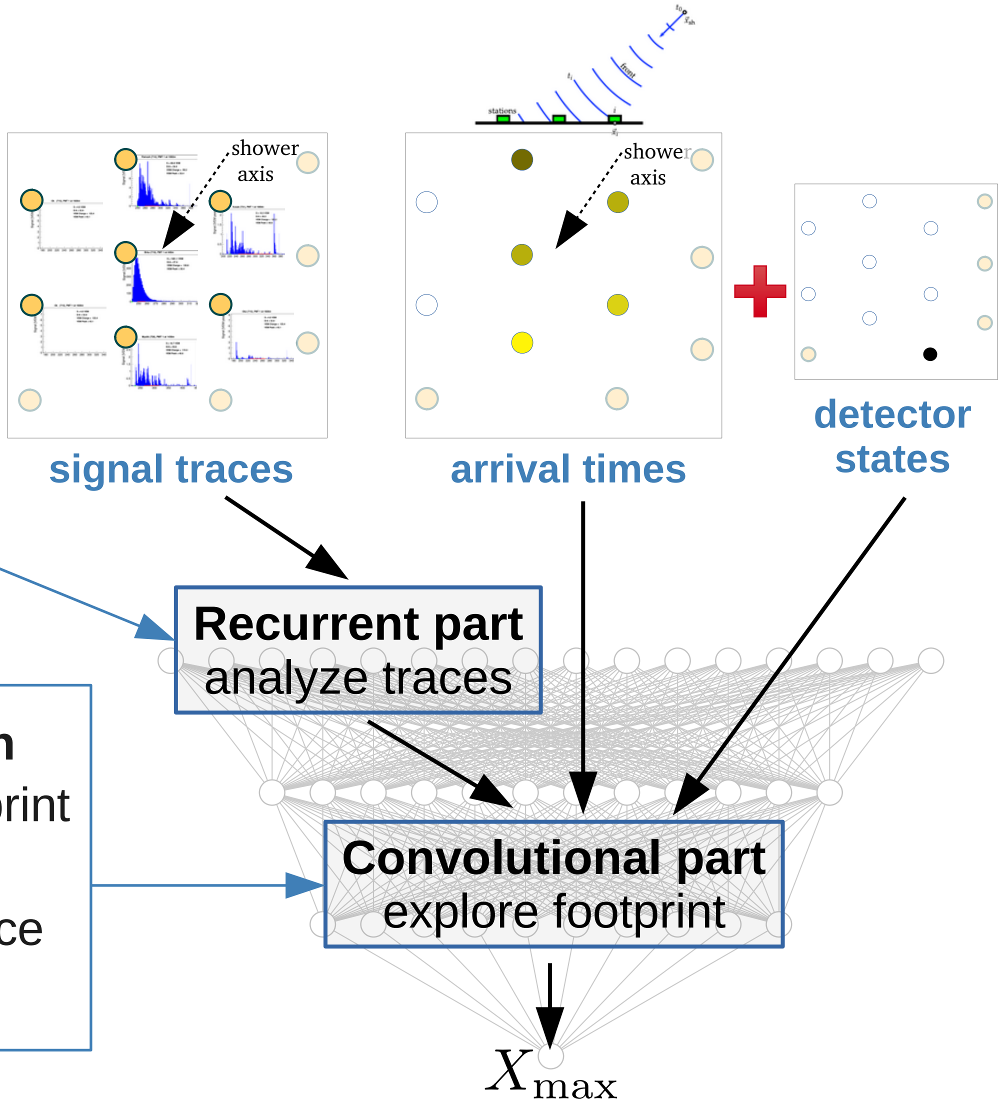
Network for X_{max} reconstruction

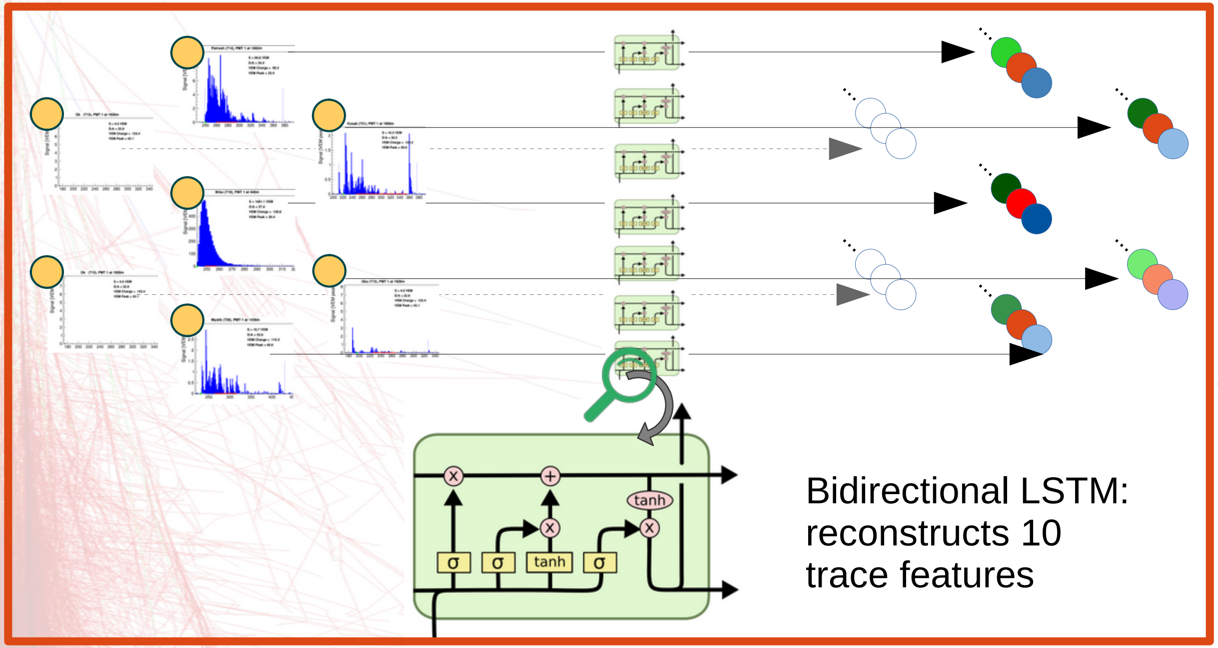
Use bidirectional LSTMs
- analyze measured signals
- network shared over stations
  - same transformation applied to each station

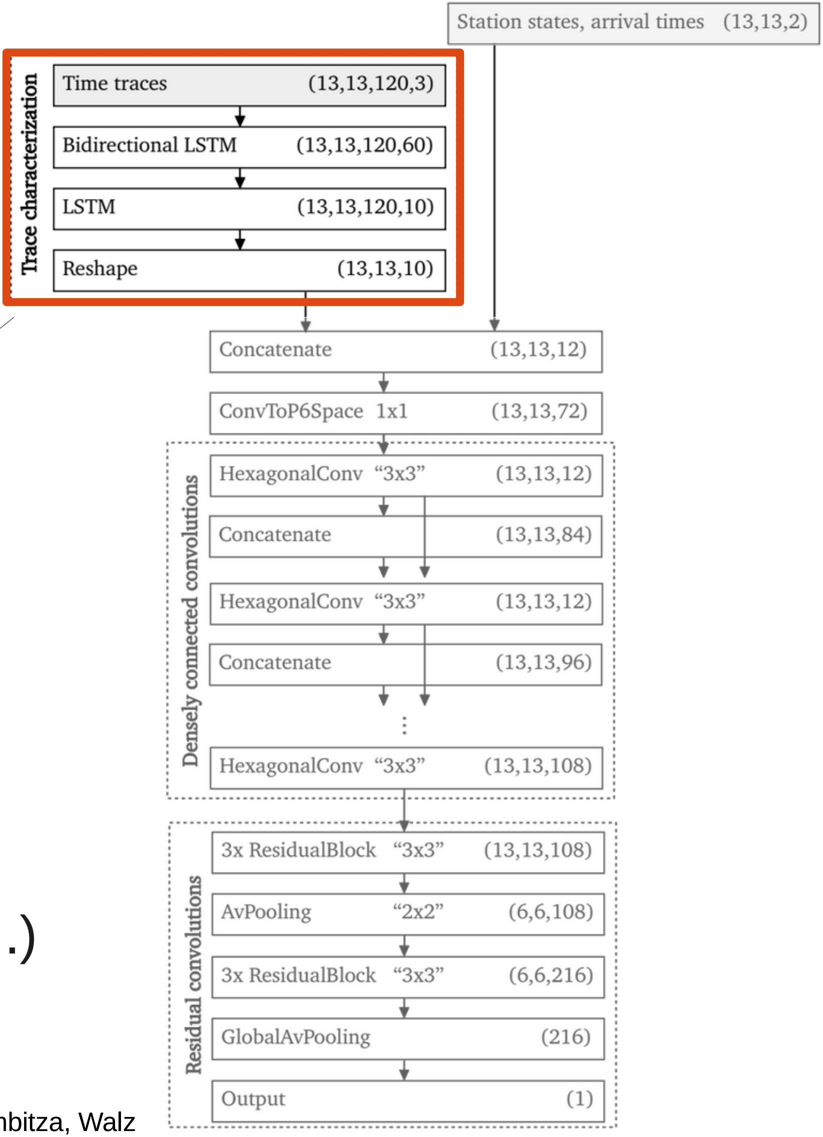


Hexagonal convolution

exploits hexagonal footprint
- hexagonal filter
- translational invariance
- rotational invariance



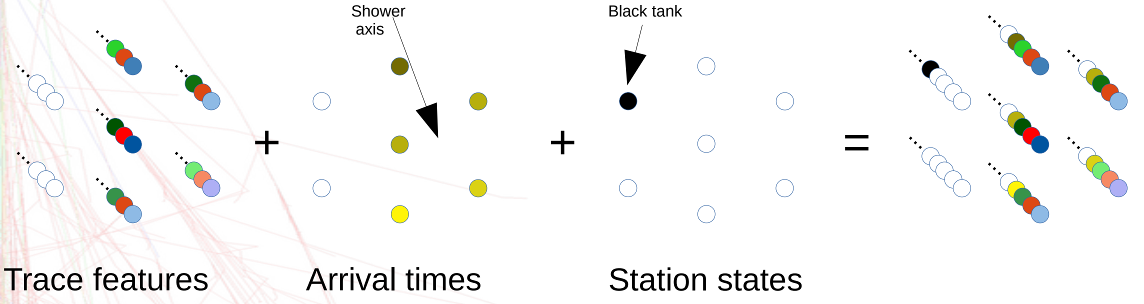




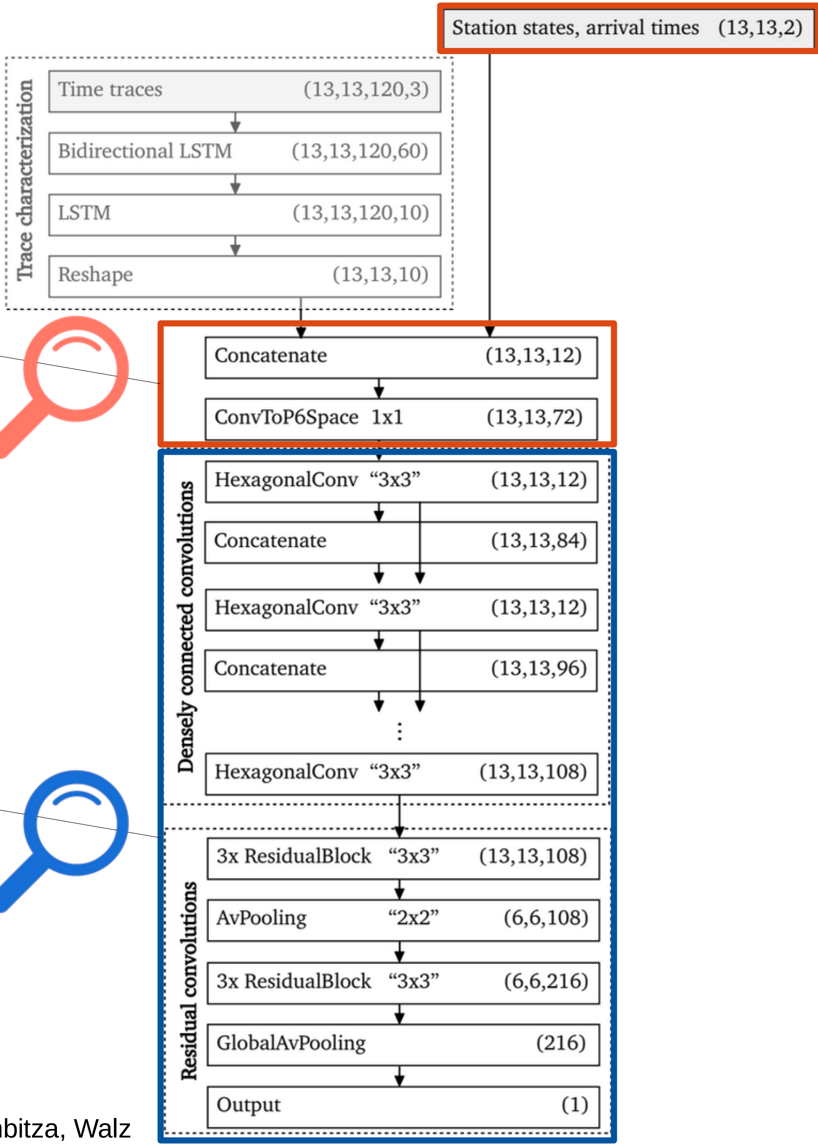
RNN part extracts trace features

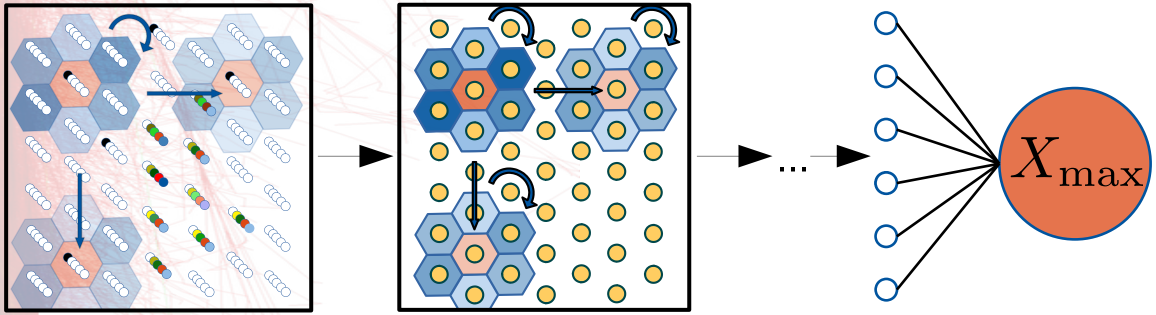
- **same network** (same weights) for each station
  - same kind of features (same color) per station (features e.g.: rising edge, falling edge, peaks ...)
  - but different characteristic → different strength

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



- add station states and arrival times to trace features



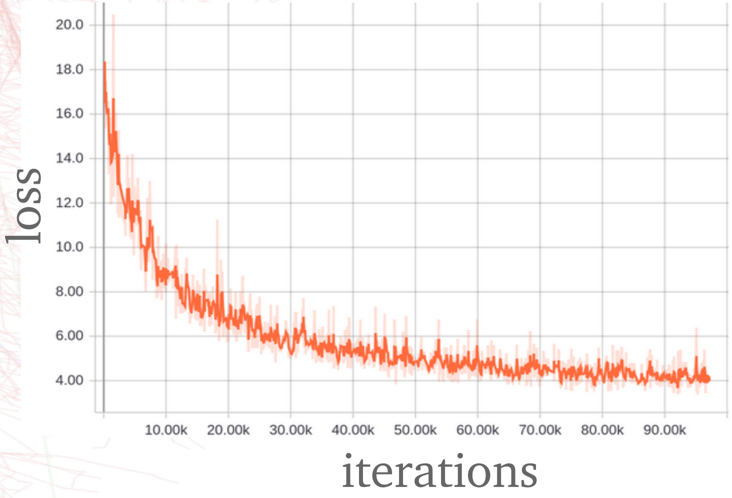


- hexagonal convolutions to combine features in space and time (DenseNet, ResNet)
- finally predict single Xmax value

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

Neural Network: AixNet

- features ~ 1.5 million parameters
- train with augmented simulation data
  - *mimic various detector states: broken stations/PMTs, saturation values*
  - *training on GPU ~ 1-2 days*

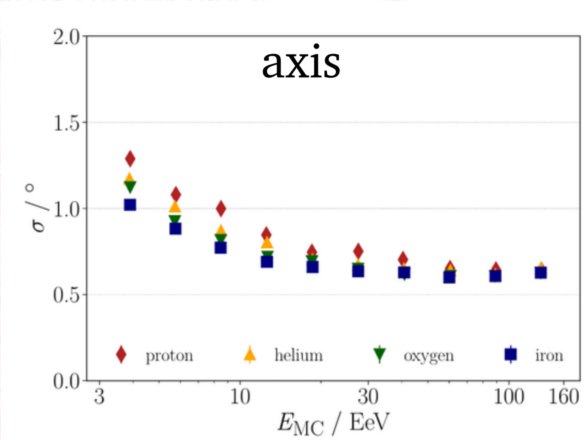


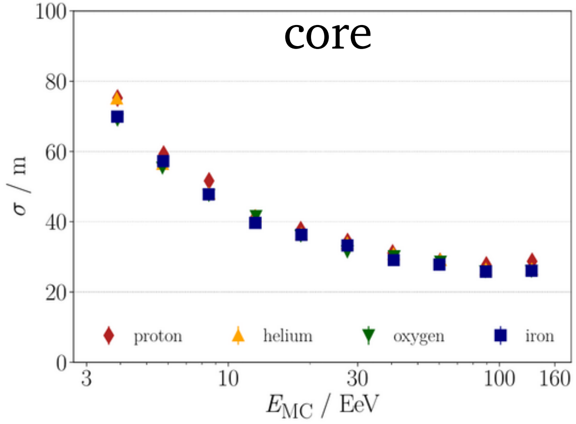
Simulated shower data	**EPOS-LHC**
# Showers	800,000
Training	700,000
Validation	10,000
Test	90,000
Energy	18.0 – 20.2 $\log_{10}(E/eV)$
Spectrum	E^{-1}
Composition	25% proton 25% helium 25% oxygen 25% iron
Zenith	0 – 65°

trained using v3p3r4 simulations

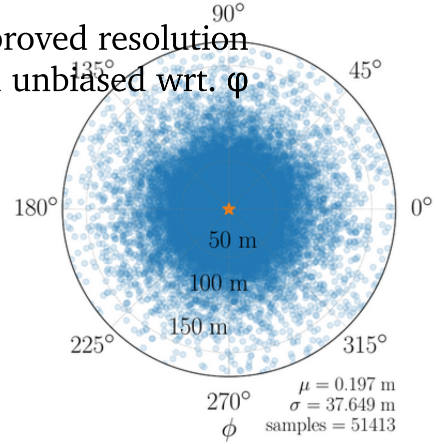
Reconstruction of geometry and energy

Shower geometry



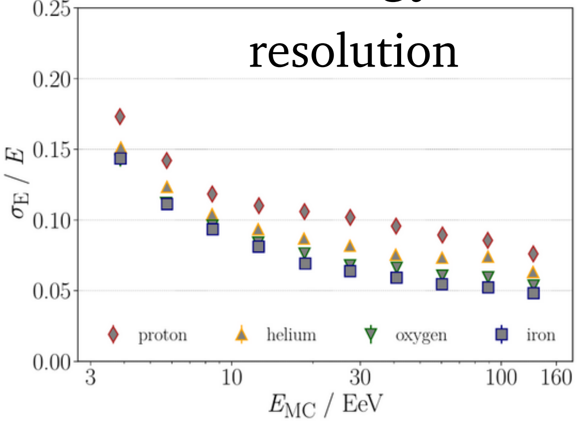


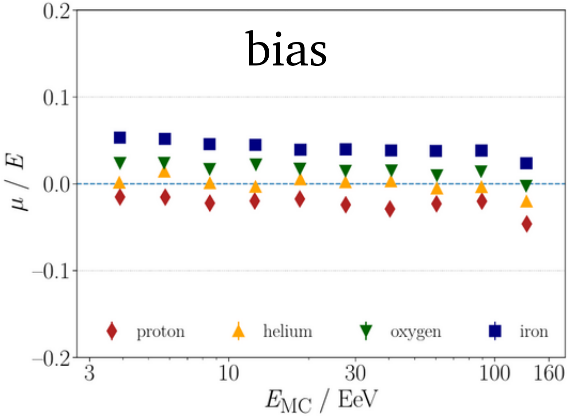
improved resolution
and unbiased wrt. φ



- slightly worse than
  standard reconstruction
- deviation from optimal grid

Energy





- half the composition bias of
  the standard reconstruction

https://pos.sissa.it/358/270/

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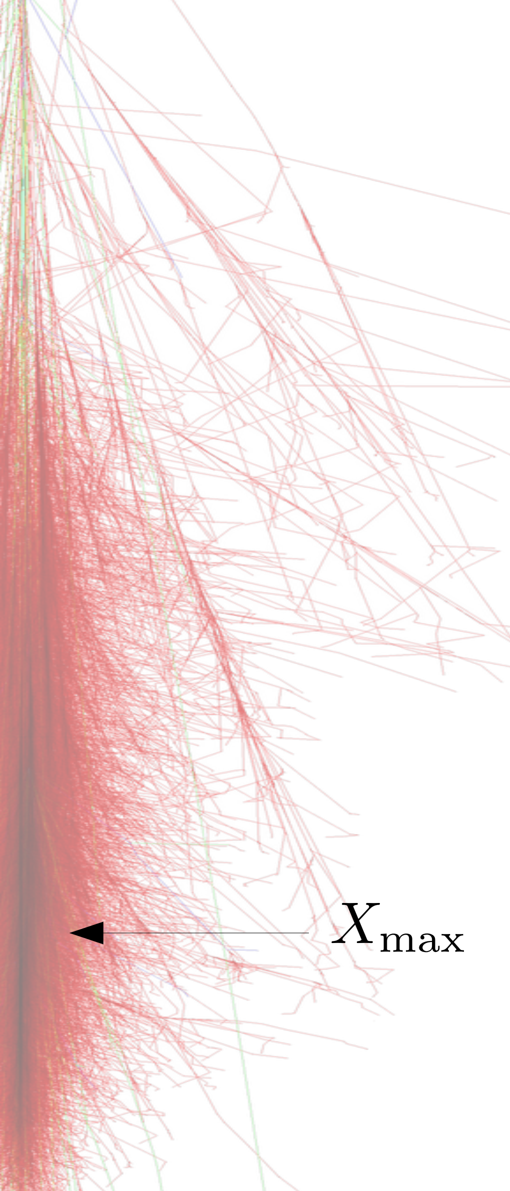
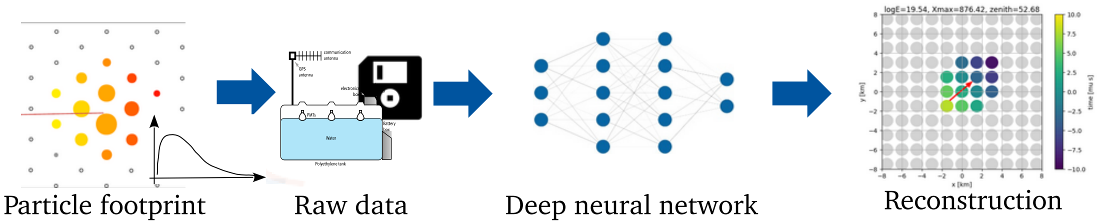
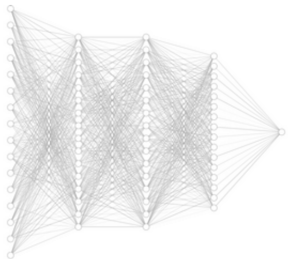
Reconstruction of Xmax using Deep Learning







UHECR Mass Composition

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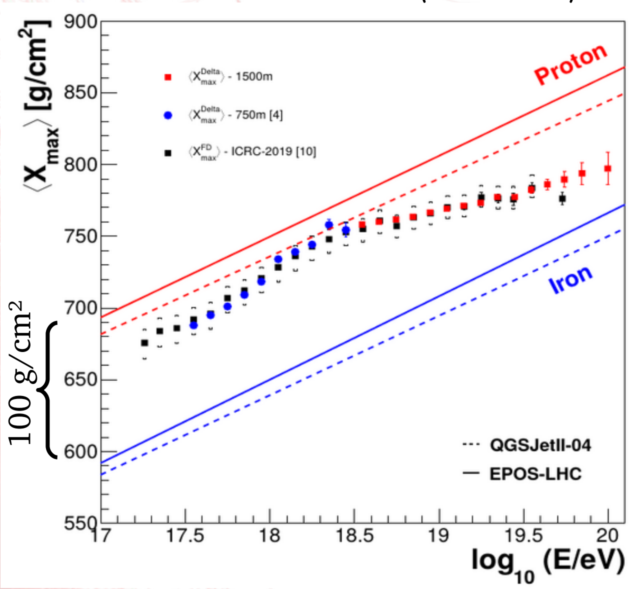
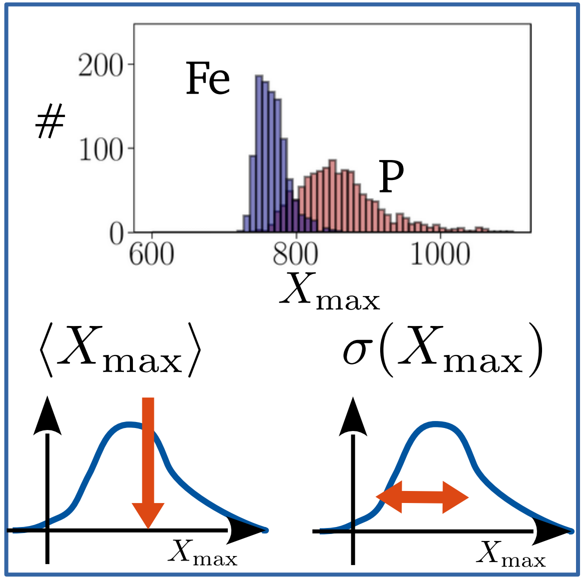
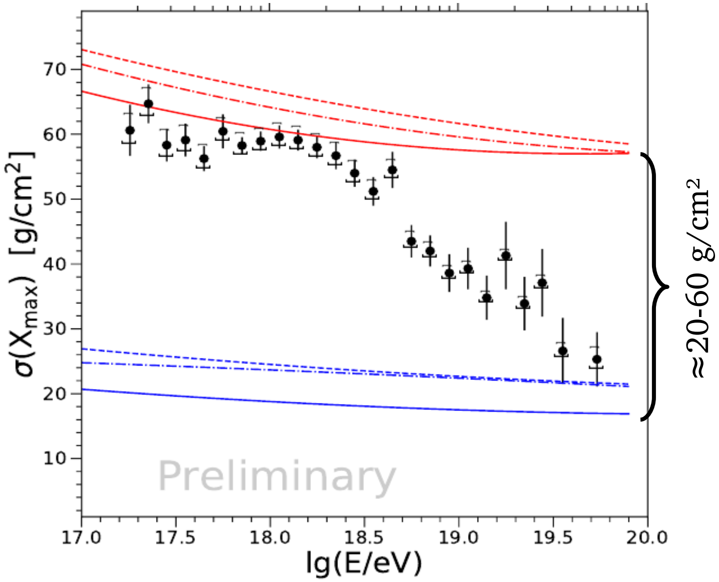
1st moment $\langle X_{\max} \rangle$



https://pos.sissa.it/358/440



2nd moment $\sigma(X_{\max})$



https://pos.sissa.it/358/482

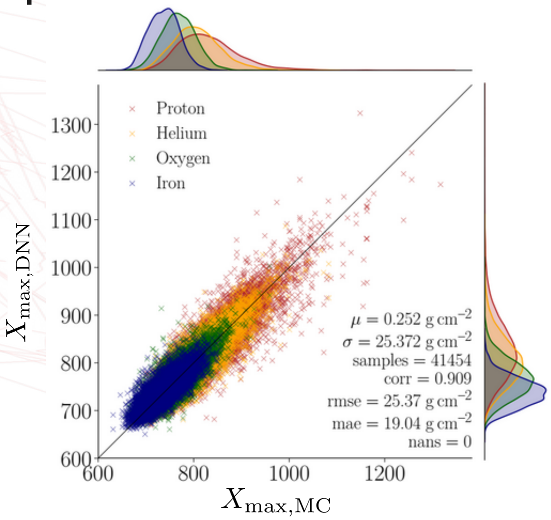
- measure **average composition**
  - reconstructed using FD, SD (signal rise times)
- uncertainties dom. by systematics

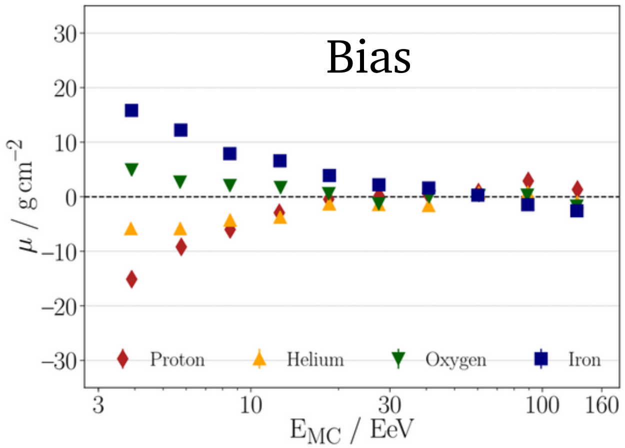
- measure **composition mix**
  - reconstructed using FD only
- statistically dom. uncertainties

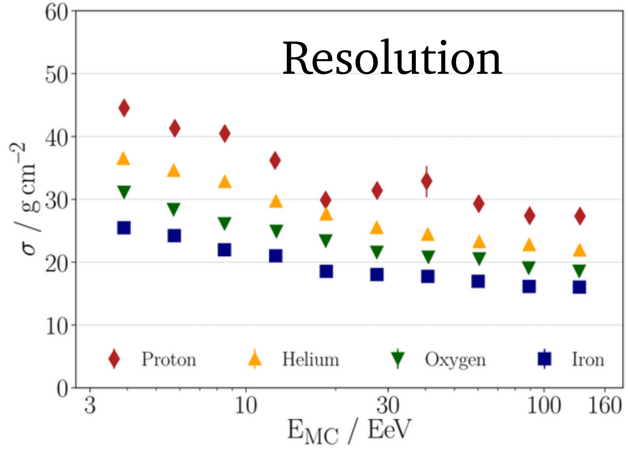
Evaluation on Simulation

Network trained on EPOS-LHC

- investigate performance on EPOS-LHC showers







- high correlation with true Xmax
- moderate dependency on primary particle

performance improves with energy

- above 10 EeV: good resolution + small bias

Evaluation - additional interaction models

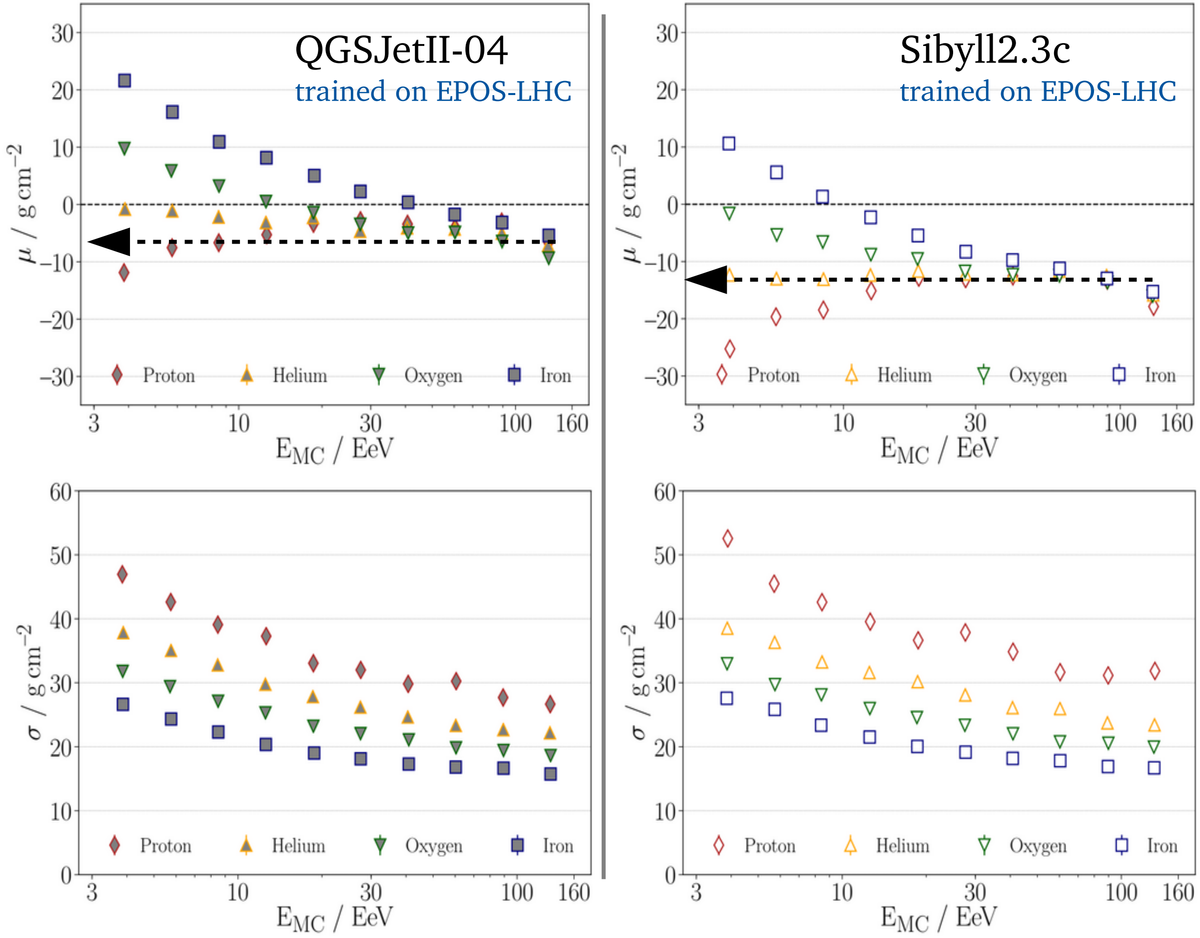
DNN trained using EPOS-LHC

Evaluate on different hadronic interaction models

- QGSJET-II.04
- SIBYLL2.3c

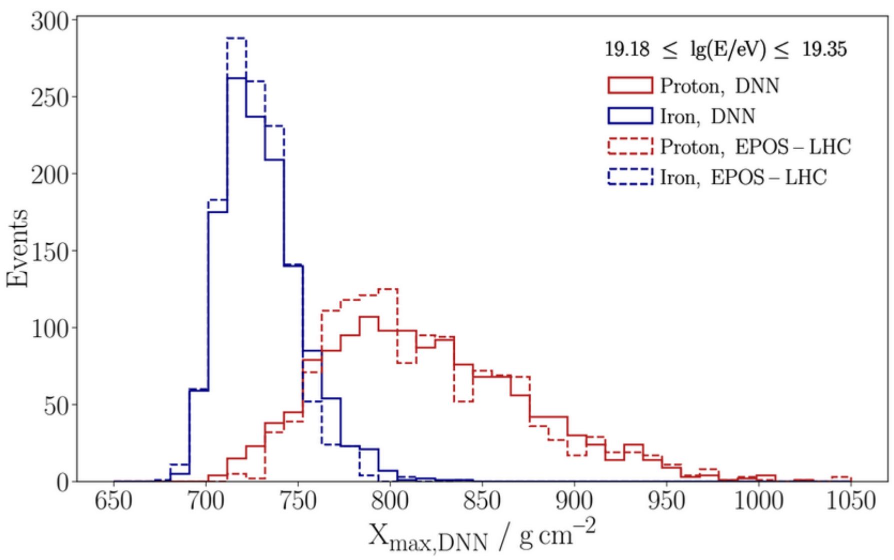
- similar resolution
  - ➔ interaction model independent

- bias different
  - absolute scale shifted (negative)
  - ➔ Xmax scale of the DNN depends on interaction model

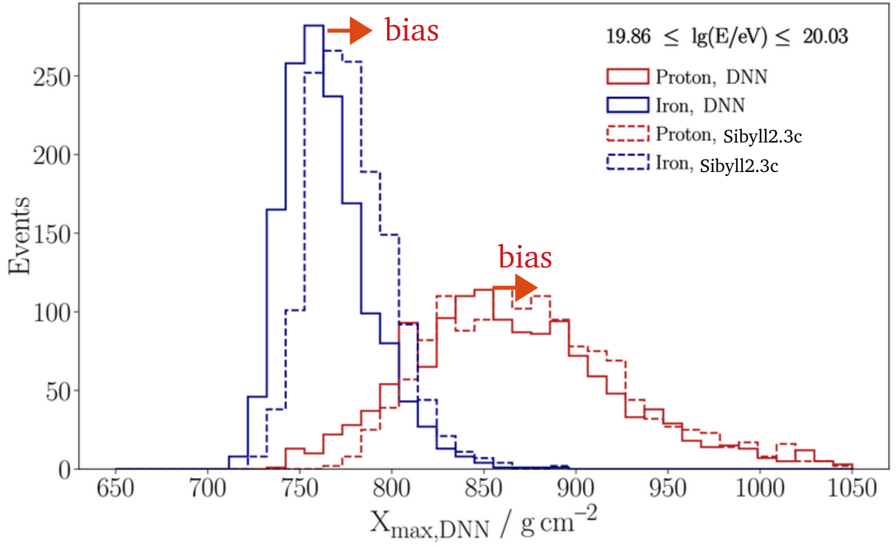


Reconstruction of Xmax distributions

EPOS-LHC



Sibyll2.3c



- overall shape reconstructed correctly
- absolute bias visible, as expected (Sibyll2.3 = -15 g/cm²)

➔ calibration to Xmax scale of the FD needed for measuring Xmax distributions

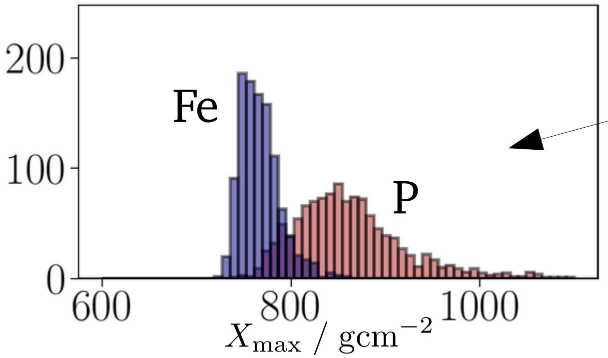
https://pos.sissa.it/395/359

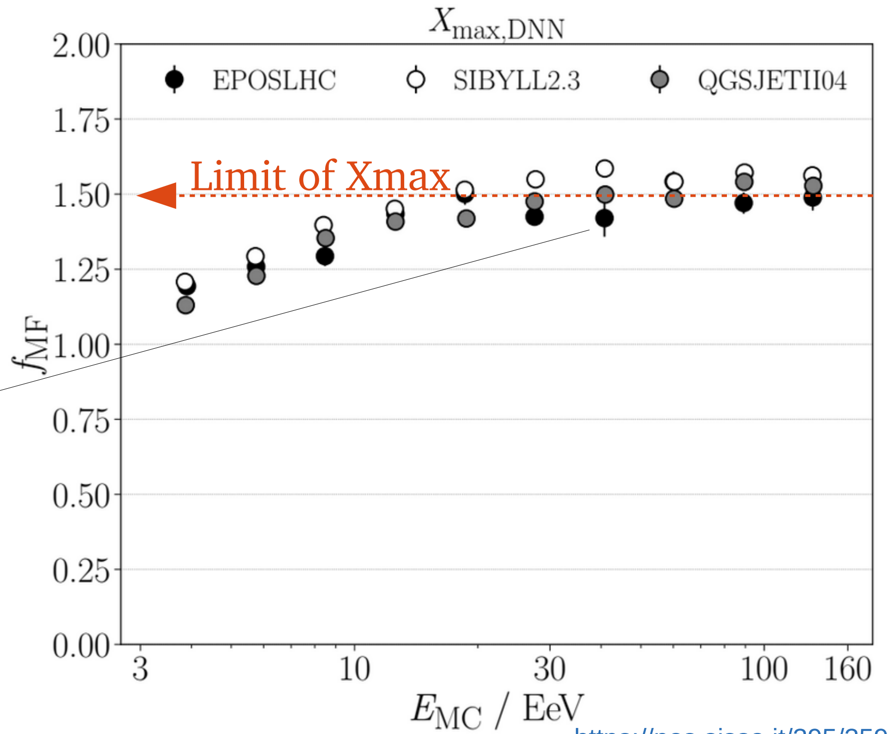
Event-wise composition measurements

Merit factor for discriminating between proton and iron

$$f_{\mathrm{MF}} = \frac{|\langle X_{\mathrm{max,P}}\rangle - \langle X_{\mathrm{max,Fe}}\rangle|}{\sqrt{\sigma^2(X_{\mathrm{max,P}}) + \sigma^2(X_{\mathrm{max,Fe}})}}$$

- merit factor of simulated $X_{\mathrm{max,MC}}$ ~ 1.5
- DNN merit factor increases with energy
  - above 10 EeV, merit factor = 1.5
  - good separation for all interaction models





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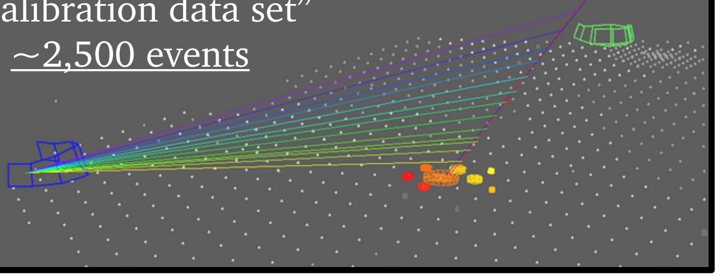
Application to hybrid data

Hybrid data

FD + SD reconstruction
fiducial FD selection
  good quality, Xmax in FoV, unbiased
fiducial SD selection
  good quality, 6T5

"calibration data set"
→ ~2,500 events



Comparison DNN vs traditional method

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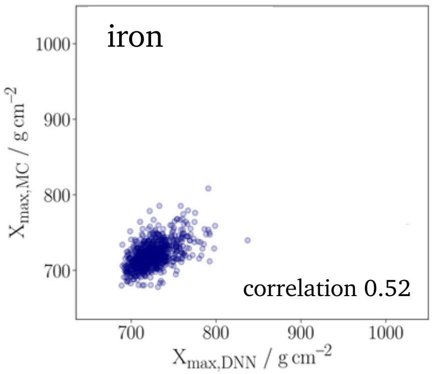
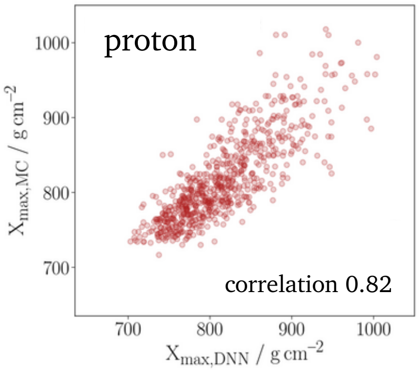
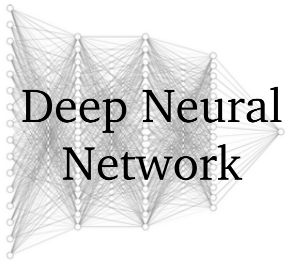
Simulations

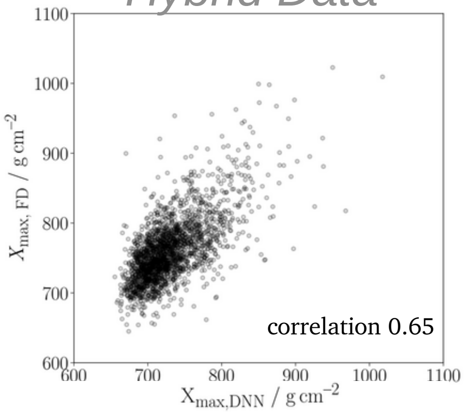




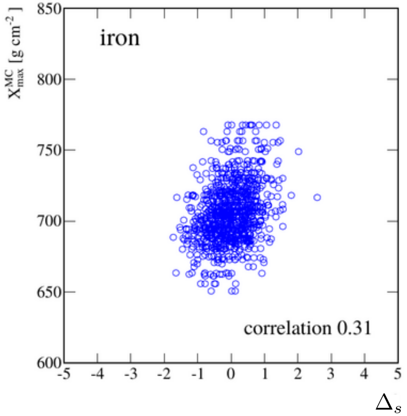


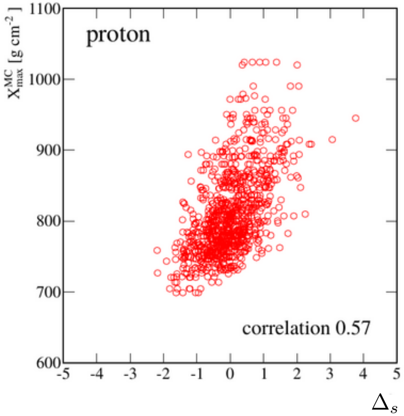
improvement of DNN
by almost 40% (correlation)

Hybrid Data



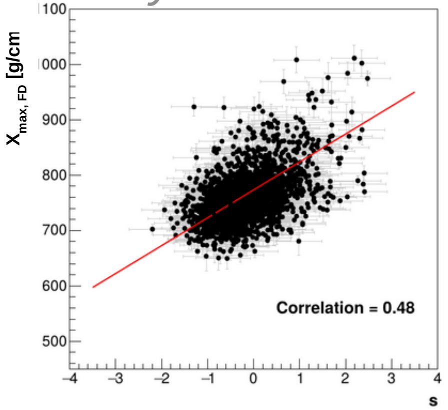
Simulations





Delta Method
determines composition
via rise time of signal

Hybrid Data

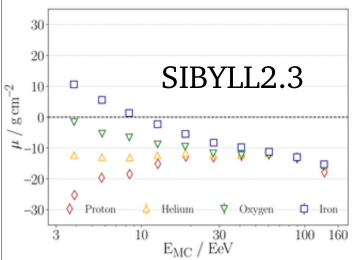


A. Aab et al. (Pierre Auger Collaboration), Phys. Rev. D 96, 122003, 2017

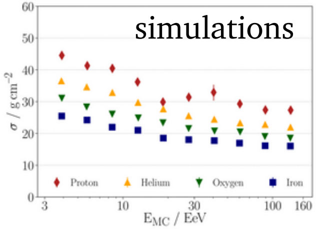
Reconstruction of the shower maximum

- Trained on simulation
  - calibrate bias using hybrid data
  - validate resolution

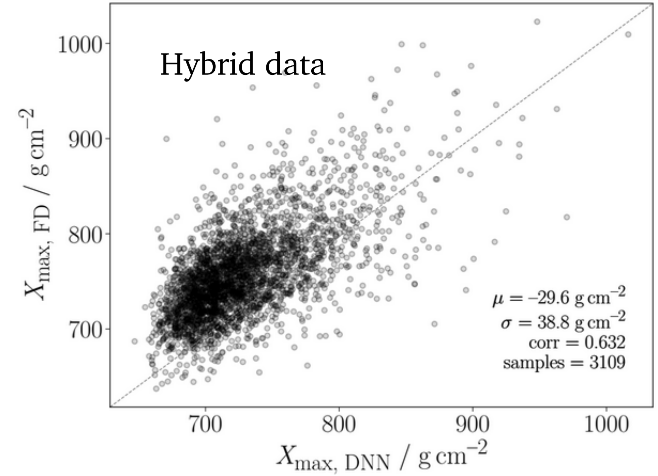
→ promising results to measure UHECR composition using SD statistics

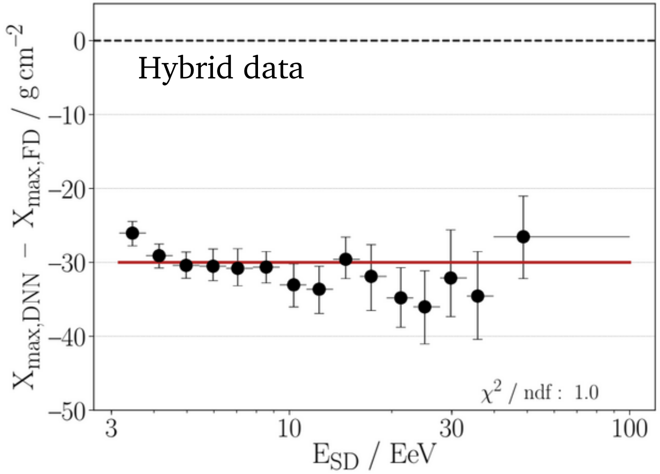


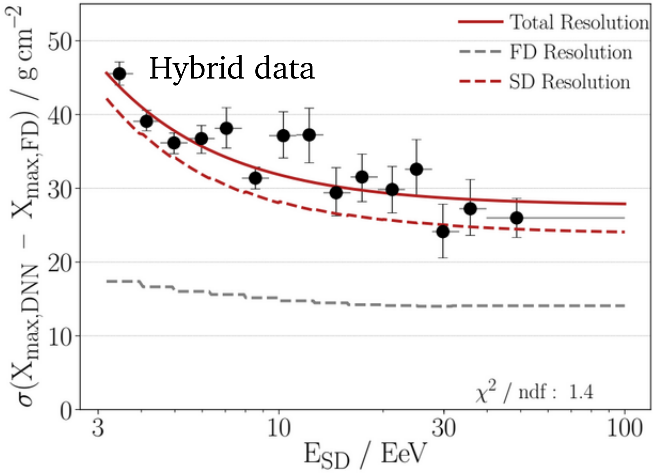
bias depends on hadr. model



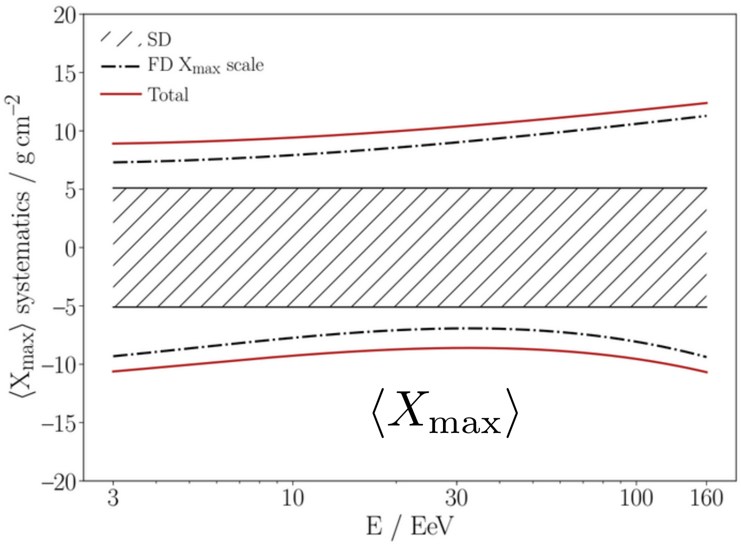
agreement with simulations

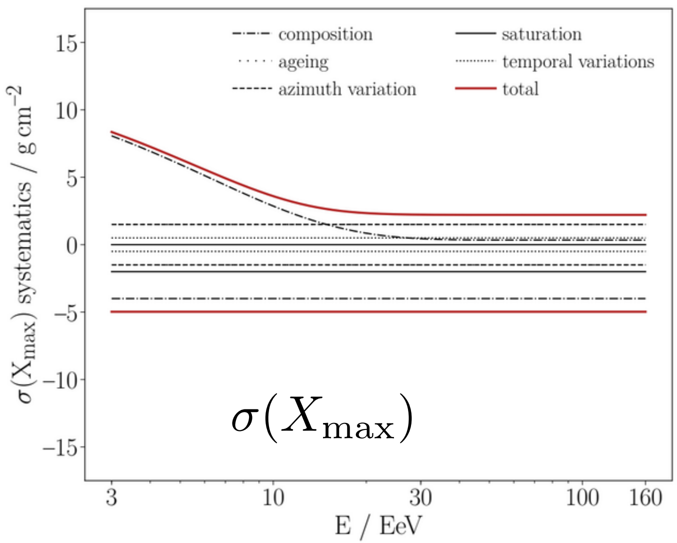






Expected Systematics





- method calibrated using the FD
  - sys. uncertainty 10 – 15 g/cm²
- uncertainty similar to delta method

- no calibration using FD
  - sys. uncertainty 5 – 10 g/cm²
  - way smaller than fluctuations
- → **1st measurement beyond 80 EeV**
- → **can provide new insights into cosmic-ray composition**

Summary

Deep Learning at the Pierre Auger Observatory:

- → extract mass-sensitive information, exploits symmetry of data (RNN + CNN)
- → geometry and energy reconstruction between competitive and improved (simulations)

event-wise **reconstruction of Xmax** Pierre Auger Collaboration, JINST 16 P07019 (2021)

- performance validated on simulations and data (hybrid events)
- expected uncertainties for $\langle X_{\mathrm{max}} \rangle$, $\sigma(X_{\mathrm{max}})$ measurements are small
  - raise in statistics of a factor 10
  - first measurement of $\sigma(X_{\mathrm{max}})$ beyond 80 EeV

AugerPrime Upgrade will enable additional insights and cross checks!

For example: reconstructing the muonic component, improved energy estimator, etc.

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