Boosting the performance of the neural network using symmetry properties for the prediction of the shower maximum using the water-Cherenkov Detectors of the Pierre Auger Observatory as an example

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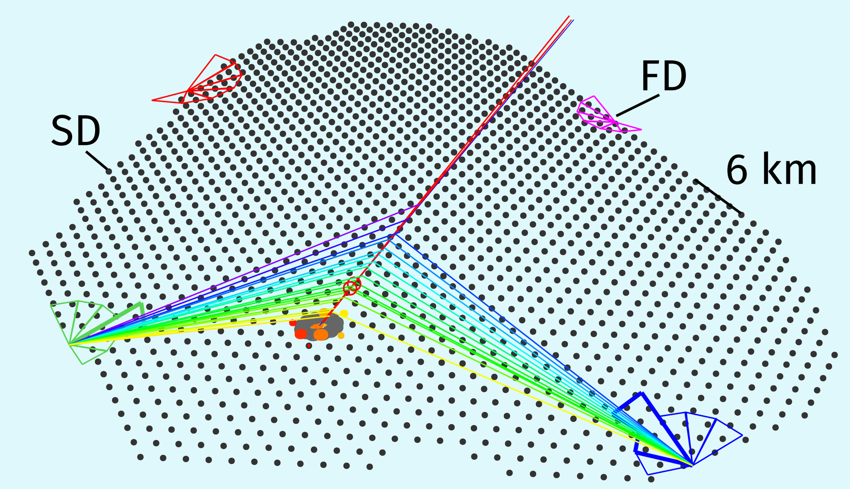
The Pierre Auger Observatory 1

The Pierre Auger Observatory is the Earth's largest (3000 km^2) detector of extensive air showers caused by ultra-high energy cosmic rays (> $10^{18.5}$ eV). It offers insights into particle physics beyond human-made accelerators and galactic sources from which these particles emerge.

To obtain physical insights, we need a good estimate of the mass of cosmic rays. One way to get this is to determine the shower maximum X_{max} – the point in shower development where the shower emits maximum fluorescence light. We can easily observe this with help of the FDs. However, these have only an uptime of ~ 15%. Therefore, we need a way to estimate X_{max} with the SD.

detection principle



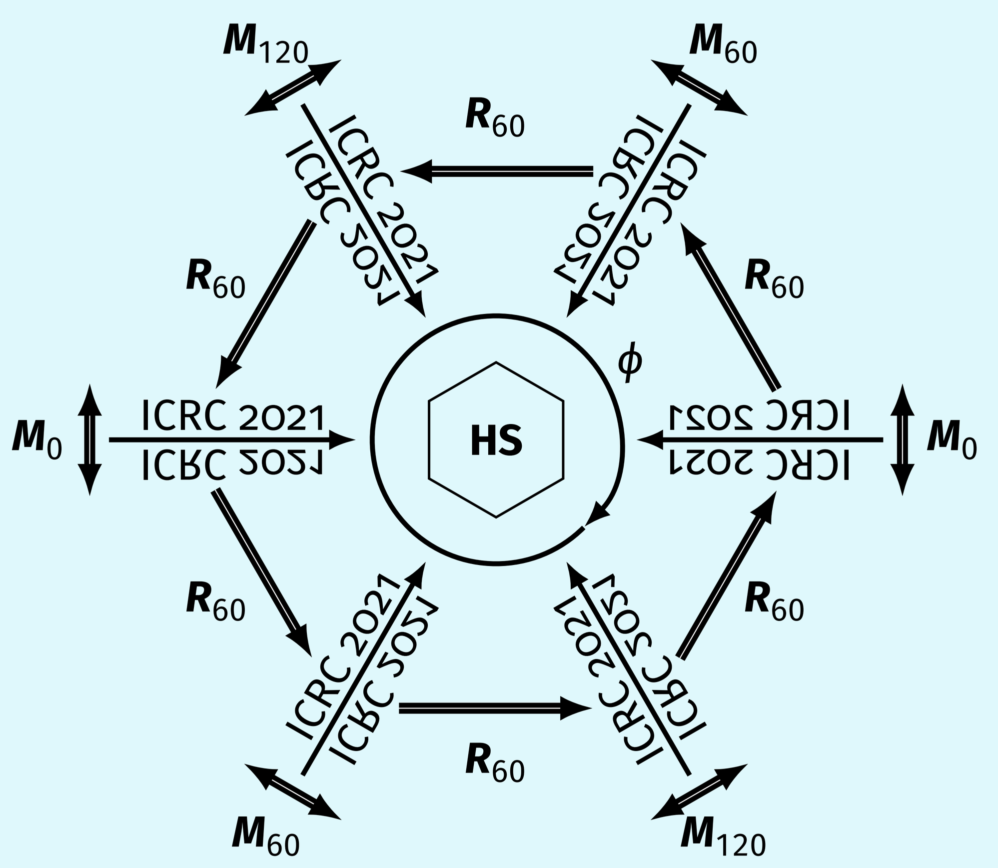
Fluorescence Detector(s) (FD)

- energy calibration of observatory
- measure longitudinal profile of showers

Surface Detector (SD)

- 1660 water-Cherenkov tanks
- measures footprint of showers

Intrinsic Symmetries of the SD 2

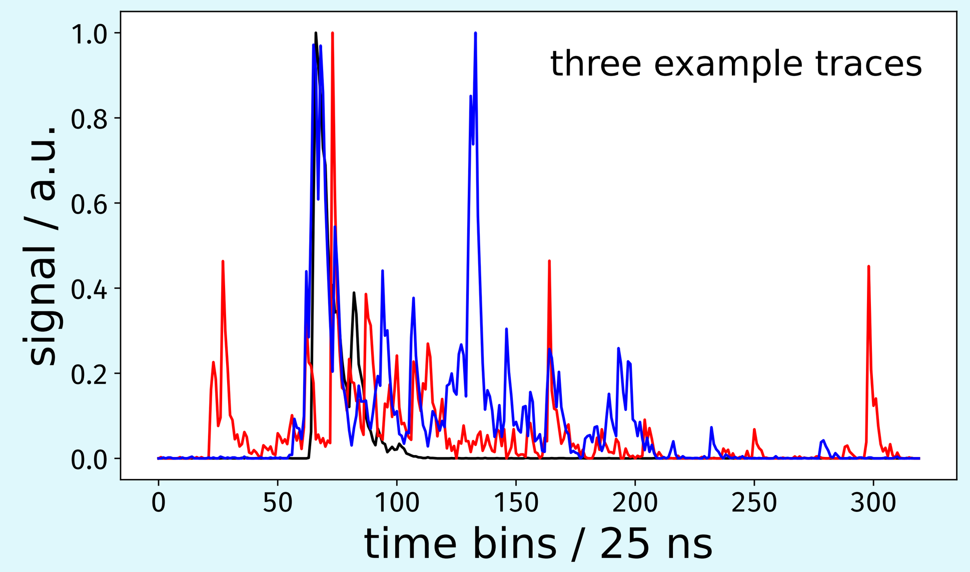


The SD is a nearly perfect triangular lattice. Assuming (to first order) that all showers are uniformly distributed in the azimutal direction (ϕ), we can find twelve unique transformations of the shower footprint that correspond to symmetries around the station (HS) closest to the shower core. Hence, we are able to rotate (***R***) and mirror (***M***) all shower footprints into a 30° interval reducing the phase space effectively by factor of twelve.

Potential problems

- wrong ϕ reconstruction
- irregularities of the grid

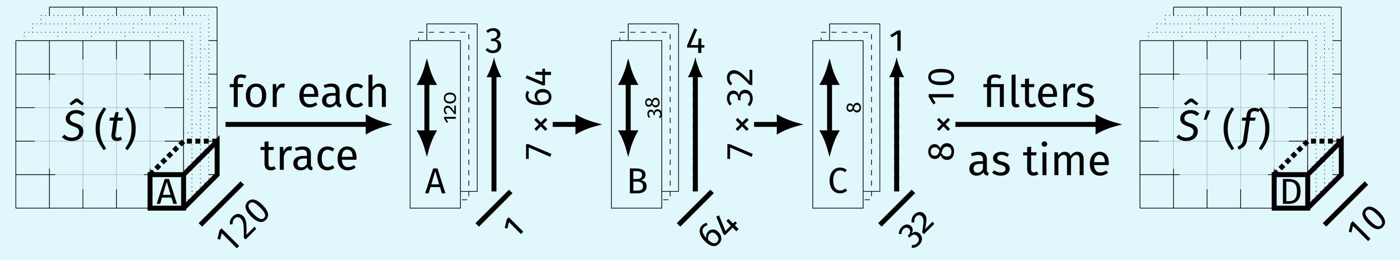
SD Traces 3



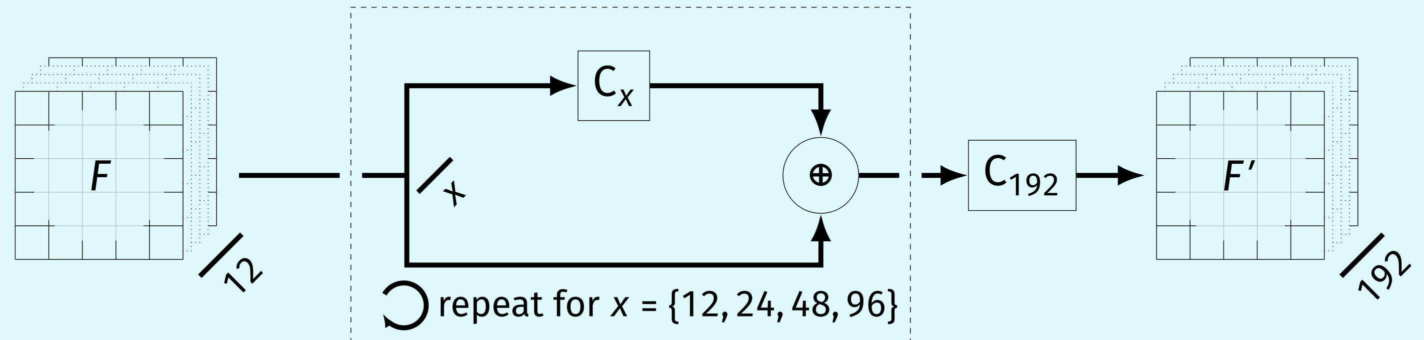
The time signal measured by the SD detector stations is quite complicated due to the complex shower process. Therefore, those signals may contain hidden/difficult-to-extract information that could be used for improved prediction of X_{max}. Because of this, Neural Networks are a valid option for the analysis the shower footprint.

Neural Network approach 4

After encoding the shower footprint in a rectangular grid we are able to apply standard neural network algorithms. First, we need to compress the traces to a subsample of features that can be used to predict X_{max}. We use a feed-forward, convolutional subnetwork for this task. This subnetwork uses the same weights for each detector station. It has the following architecture:

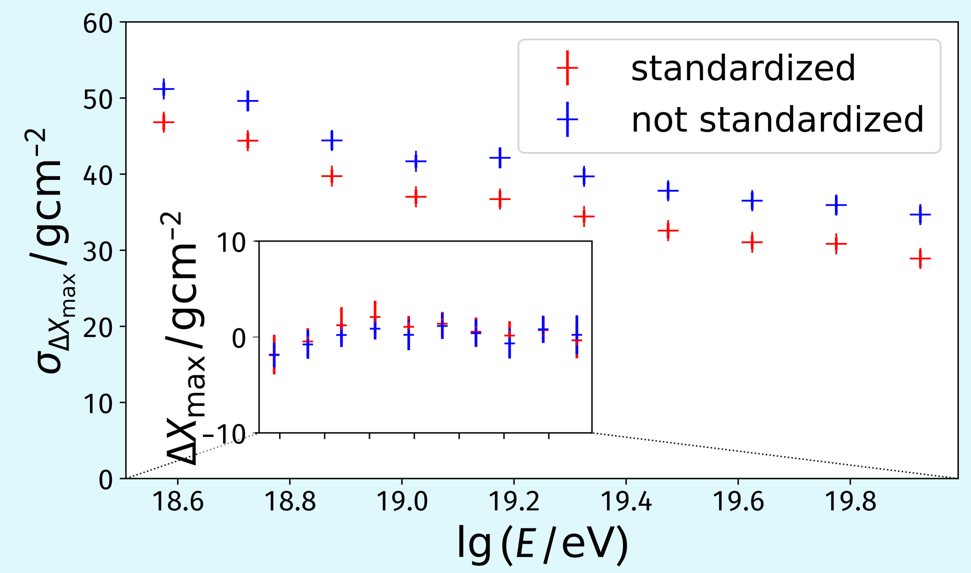


Afterwards, the trace features are concatenated to a map of the trigger times and trigger maps (10 → 12). In the second part of the network we want to correlate the spatial information contained in the shower footprint. To do this, we use "dense convolutions". In each step, a convolution of the same filter size as the input is applied and concatenated to the input from the last step.



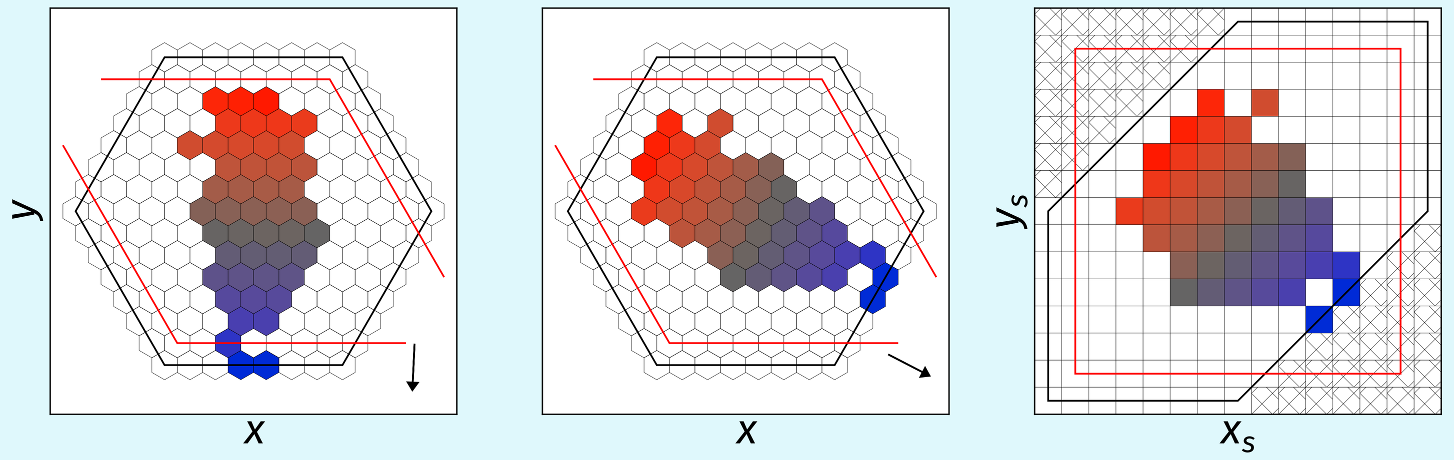
Flattening the output of the spatial analyzer, we use a fully connected final layer as predictor for X_{max}. In the entire network we use ReLu activation functions to introduce non-linearity.

Results from Simulations 5



To analyze the effect of exploiting the symmetries of the grid, we train the same network architecture on the same base dataset and compare the deviation $\sigma_{\Delta X_{max}}$ of the difference between prediction and real values of X_{max}. We use only proton primaries for this test to keep the phase space simple. Over the complete energy range of our dataset the prediction improves visibly.

Since shower footprints are elongated along the shower axis there is another advantage of using the symmetry operations. We are able to maximize the amount of information used in our rectangular map by rotating all showers in such a way to fill up the corners of incomplete rings around the hottest station.



Outlook 6

The method and network are not specifically tied to predicting X_{max}. After initial testing, it can be used for any observable. Thus, it is a multi-purpose approach which we can extent to all possible quantities. Furthermore, this approach can be applied to any complex problem exhibiting symmetries.

References

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