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### Abstract

A novel ultra-high-energy cosmic rays energy and arrival direction reconstruction method for Telescope Array surface detector is presented. The analysis is based on a deep convolutional neural network using detector signal time series as the input and the network is trained on a large Monte-Carlo dataset. This method is compared in terms of statistical and systematic energy and arrival direction determination errors with the standard Telescope Array surface detector event reconstruction procedure.

### Motivation

Modern experiments record the full time-resolved signal of each SD station (in the case of the Telescope Array in each of the two layers of the scintillator). One may benefit from the enhanced analysis based on the full signal compared to the traditional methods based mostly on the values that could be measured by the detectors of the previous generation: the arrival time of the first particle and the integral signal of each detector.

### Method Summary

- Use full SD detector Monte Carlo to obtain raw signal (readings on SD stations) as function of primary particle properties:  $\tau_i = F(\vec{p})$
- Train neural network (NN) with Monte Carlo dataset to obtain inverse function:  $\{\vec{p}\} = F^{-1}(\tau_i)$
- Make training easier by constructing  $F^{-1}(\tau_i)$  as a correction to the standard reconstruction

# TA SD Energy and Arrival Direction Estimation Using Deep Learning



- waveform encoder extracts useful features from readings of the two SD station layers
- the extracted features are passed to 2D-convolutional network along with detector properties (coordinates, state)
- event features extracted by convolutional network are analyzed along with 14 composition sensitive variables in the dense layer part of the model
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- [2] R. U. Abbasi et al. *Phys. Rev.*, D99(2):022002, 2019.

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Distribution of the difference between the reconstructed and true values of an event's zenith angle for the standard (red histogram) and CNN-enhanced (blue histogram) reconstructions of the proton Monte Carlo event set simulated using QGSJETII-03 hadronic model for the reconstructed energy higher than 10 EeV (left figure) or 57 EeV (right figure).



Angular distance  $\omega$  distribution between the true and reconstructed arrival directions for the standard (red histogram) and CNN-enhanced (blue histogram) reconstructions of the proton Monte Carlo event set simulated using QGSJETII-03 hadronic model for the reconstructed energy higher than 10 EeV (left figure) or 57 EeV (right figure). Vertical lines denote the positions of 68% percentile of the distributions, i.e. the angular resolution values.



- improved

Acknowledgements The work is supported by the Russian Science Foundation grant 17-72-20291.

### Angular resolution



(right plots) hadronic interaction models.

### Conclusions

## • Both energy and geometry reconstruction can be

• Energy reconstruction may have bias due to uncertainty in hadronic interaction model • Hadronic interaction model choice has little effect on geometry reconstruction