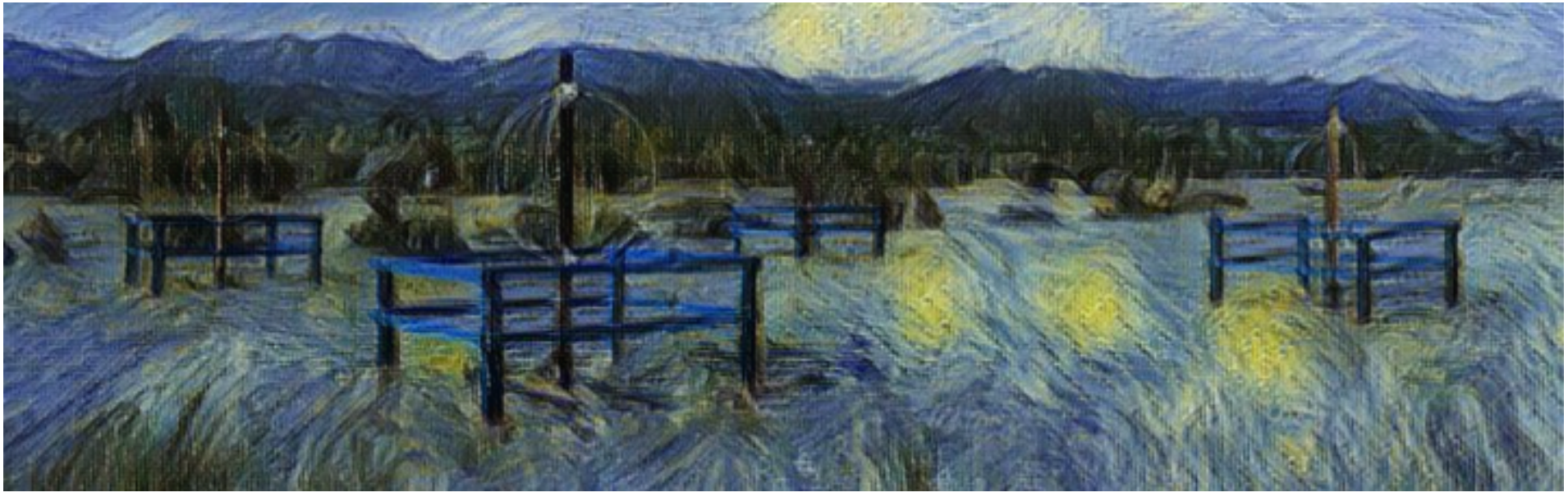
Autoencoder for denoising of radio pulses from air-showers.



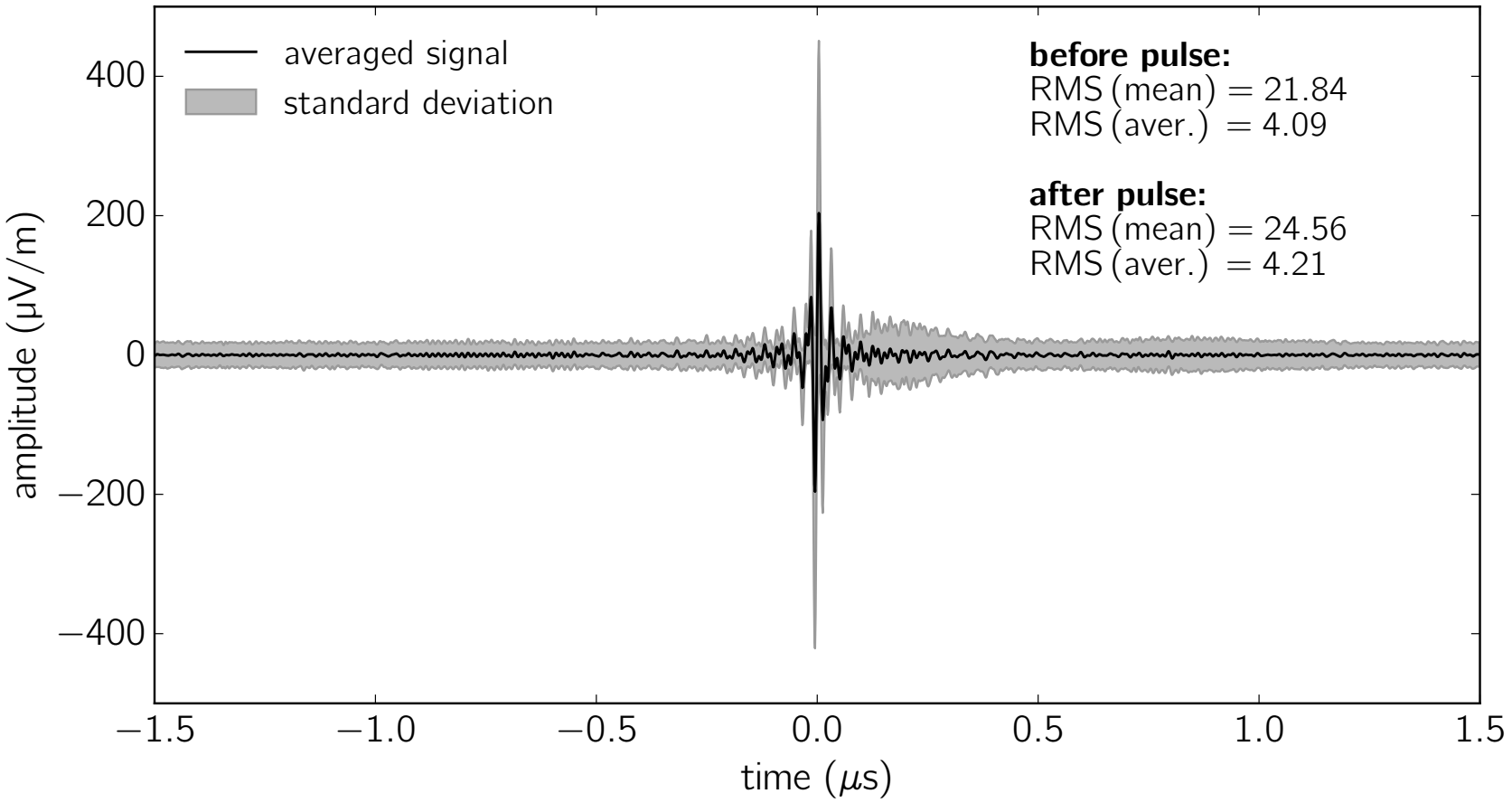
D. Kostunin for the Tunka-Rex collaboration

Big Data Science in Astroparticle Research, Aachen 2020

HELMHOLTZ GEMEINSCHAFT

DESY.

Deep learning: motivation



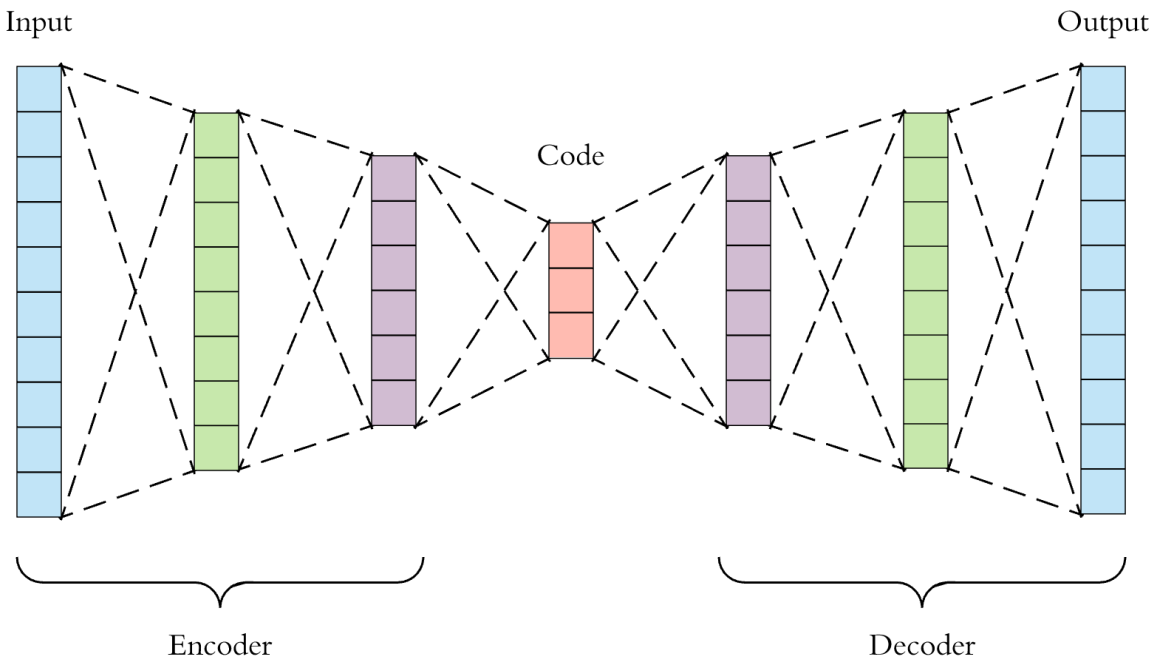
Average of 400 events, expected noise reduction with factor $\sqrt{400} = 20$

$\Rightarrow$ Noise is not white/contain features

$\Rightarrow$ Train autoencoder to learn these features

Chosen architecture (autoencoder)

- Unsupervised neural network with compressed representation
- Use Keras and Tensorflow with GPU support
- Based of 1D convolution layers
- ReLu ($\max(0, x)$) activation function
- Max pooling (and upsampling) after convolutional layers
- Binary crossentopy loss function and RMSprop optimizer
- Train networks via uDocker on SCC ForHLR II cluster



Learning strategy and training pipeline

Datasets:

- 25k upsampled ($\times 16$) traces with real background + low-amplitude simulations ($< 100\,\mu$V/m) with randomly located pulse

Training and evaluation:

- Depth (D) and number of filters per layer as free parameters
- Primary evaluate by loss metrics
- Blind test with full-pipeline Offline reconstruction

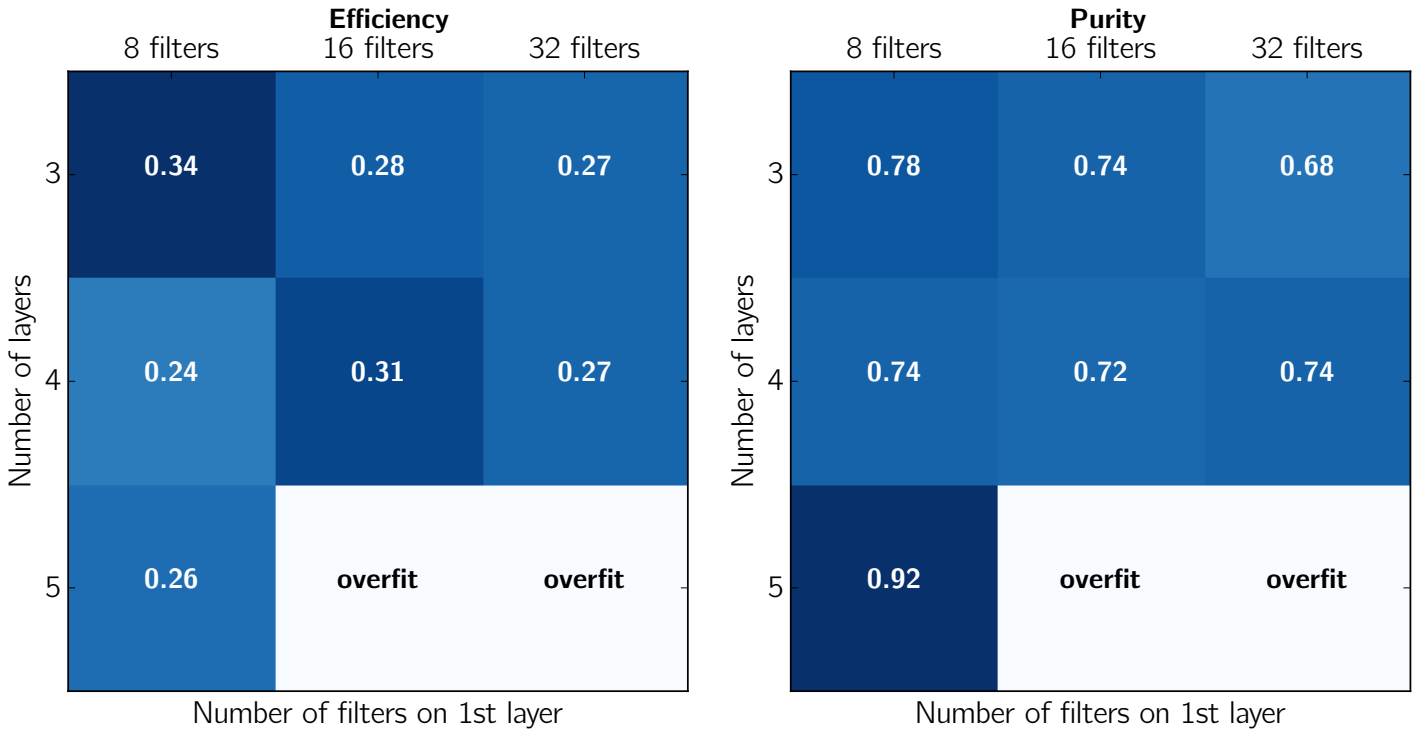
i-th encoding layer is described by the following ($i = 1, ..., D$):

$$S_i = S_{\min} \times 2^{D-i}, \quad n_i = 2^{i+N-1}, \tag{1}$$

where S_i is a size of the i-th filter, n_i is a number of filters per layer
D and N are free parameters; $S_{\min} = 16$ is minimal size of layer
Size of input/output array: 4096 (1280 ns) – 25% of original trace

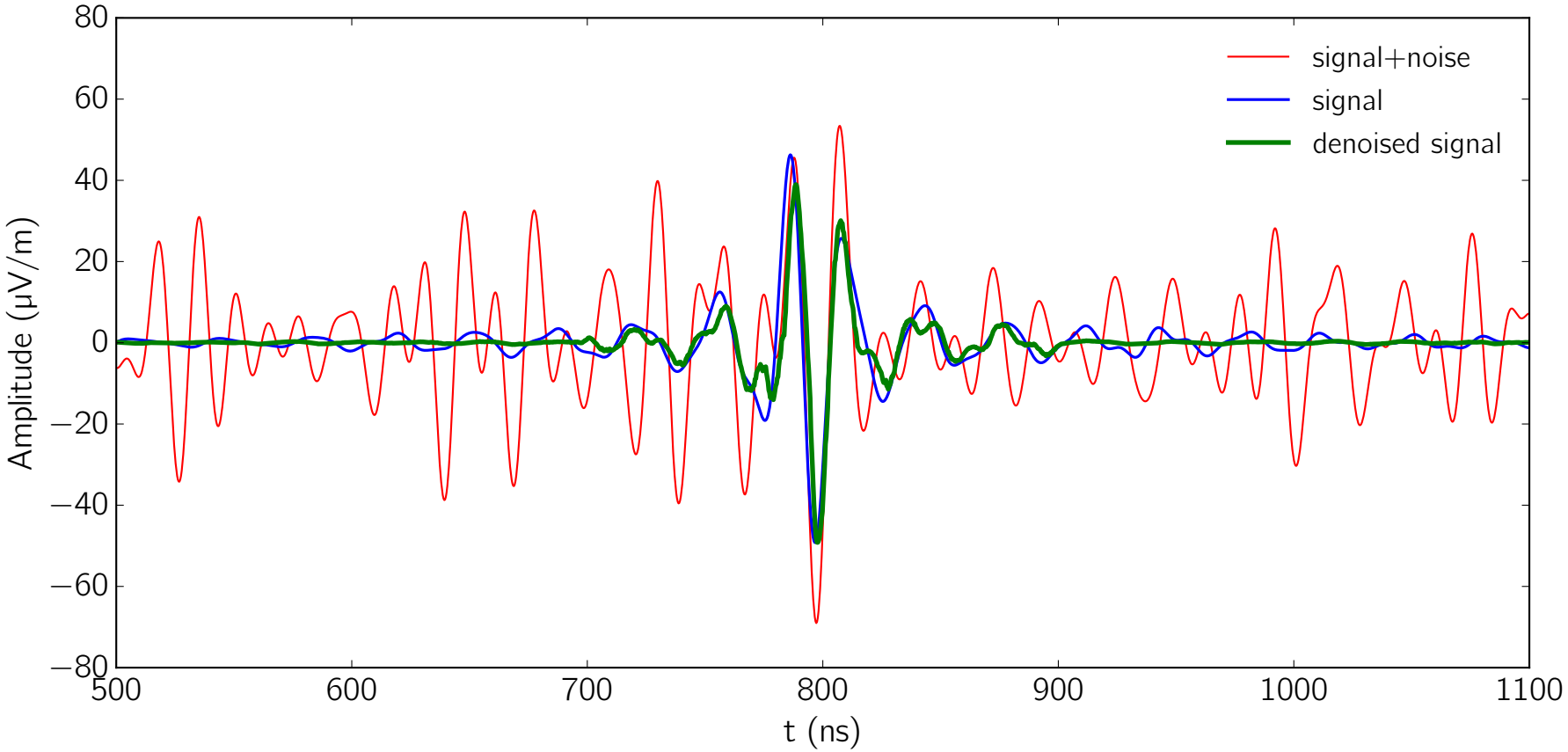
Threshold and metrics

- Threshold amplitude $\Leftrightarrow$ 5% tolerance to false positives
- Efficiency: $N_{\mathrm{rec.}}/N_{\mathrm{tot.}}$, fraction of events passed the threshold
- Purity: $N_{\mathrm{hit}}/N_{\mathrm{rec.}}$, fraction of events with reconstructed position of the peak: $|t_{\mathrm{rec.}} - t_{\mathrm{true}}| < 5$ ns



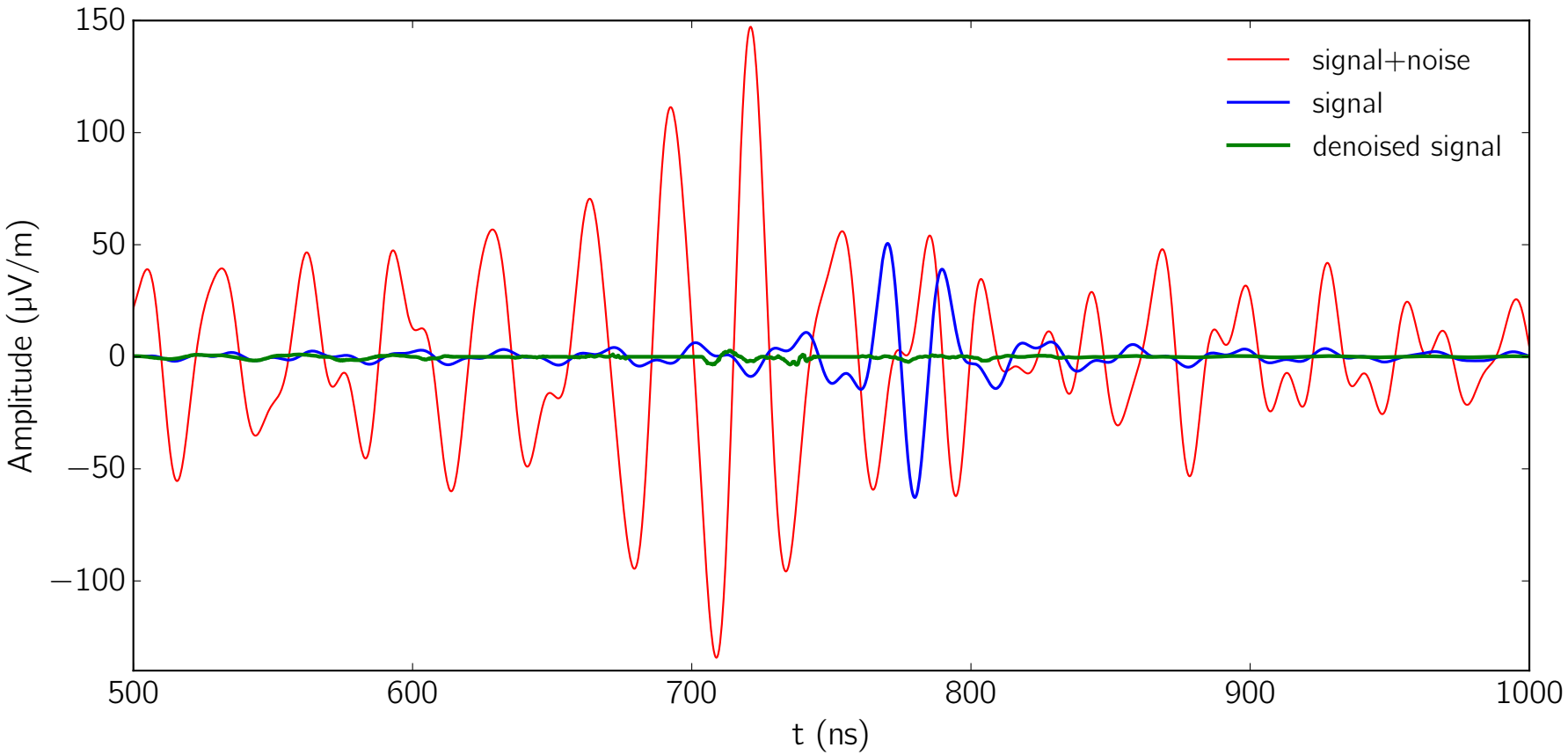
Best architecture contains $N_{\mathrm{dof}} = 10240$

Example: correct identification



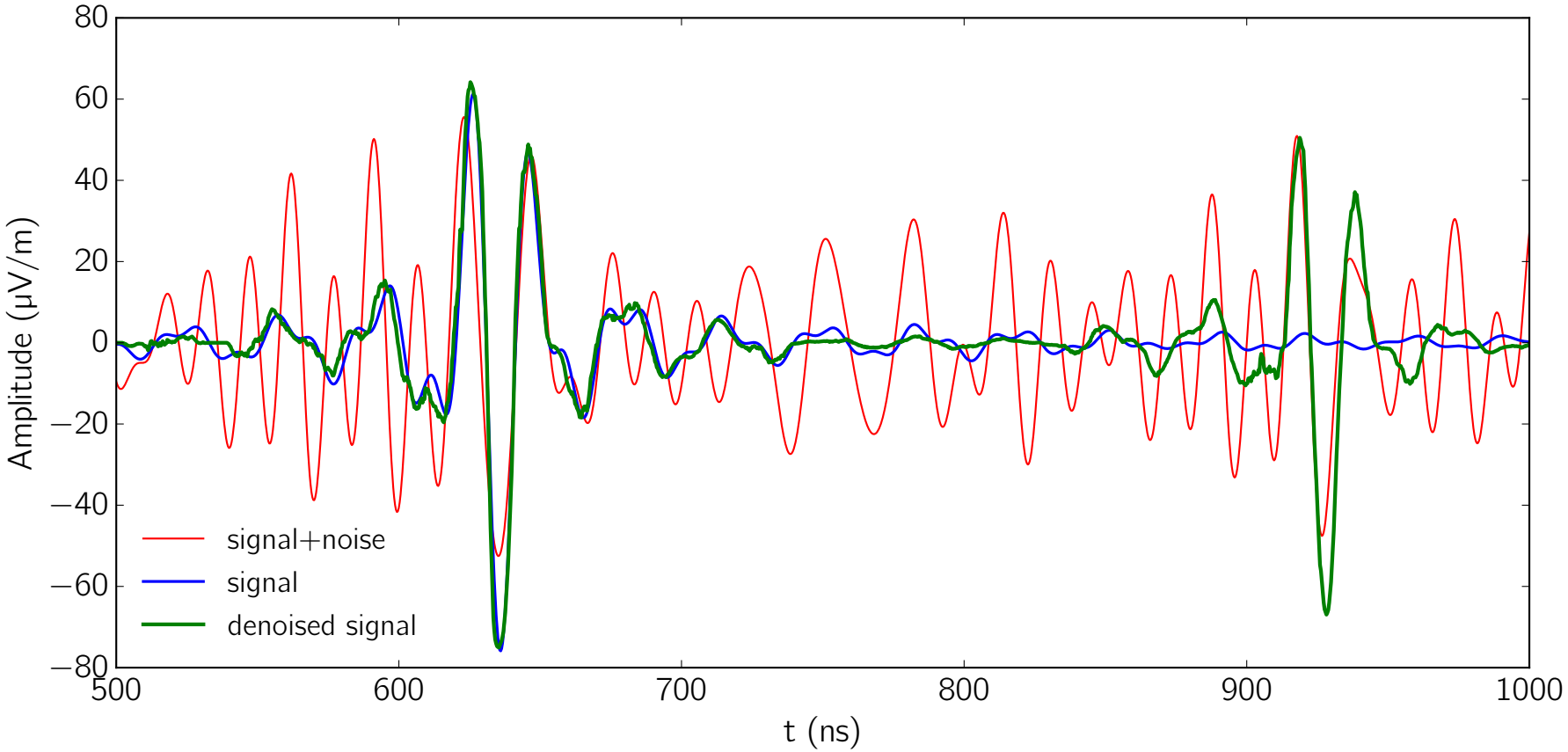
True signal and noise are identified correctly, noise is removed

Example: no identification



True signal is heavily distorted by noise, and removed as background

Example: double identification

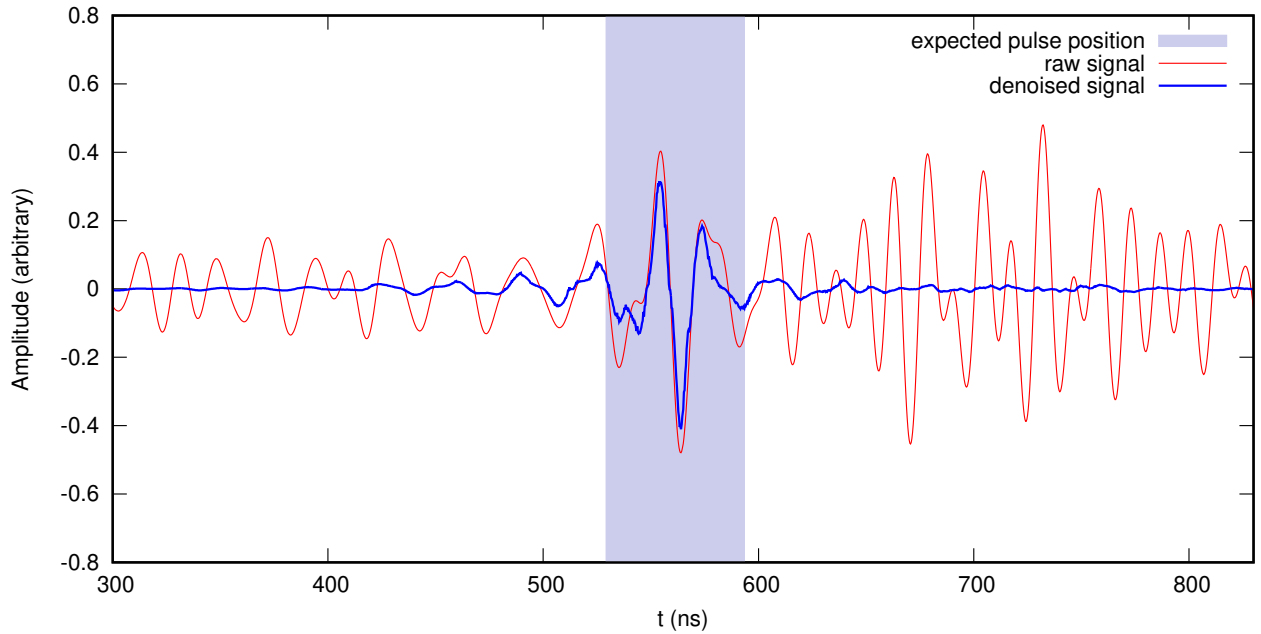


Signal-like RFI is identified as signal

Preliminary conclusion

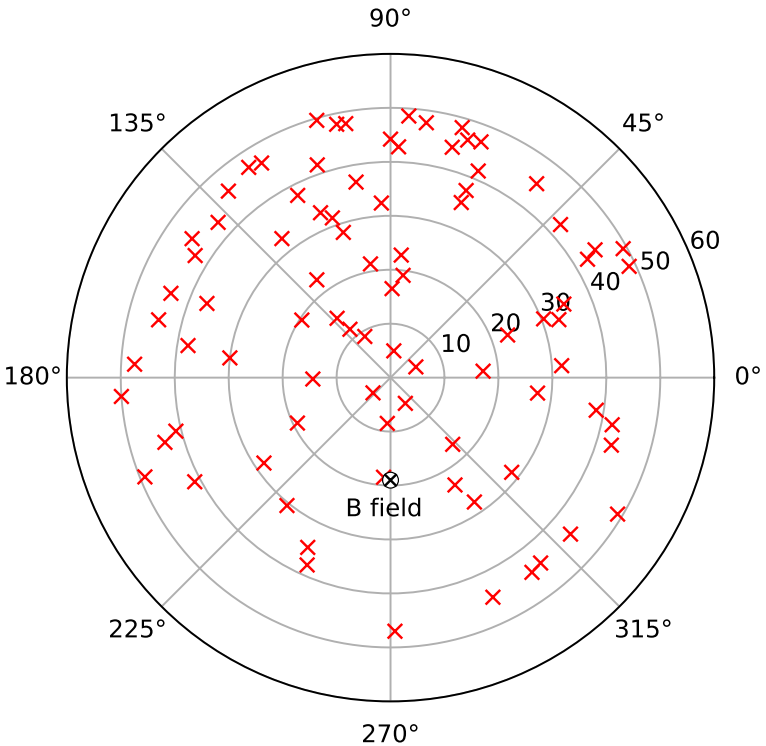
- Monte-Carlo tests show performance comparable to standard method and matched filtering
- "Stack more layers" works, but requires larger training sets
- Amplitude reconstruction degenerates when $\mathrm{SNR} < 1$ trace is normalized to $[0; 1] \Rightarrow$ peak is hidden in noise

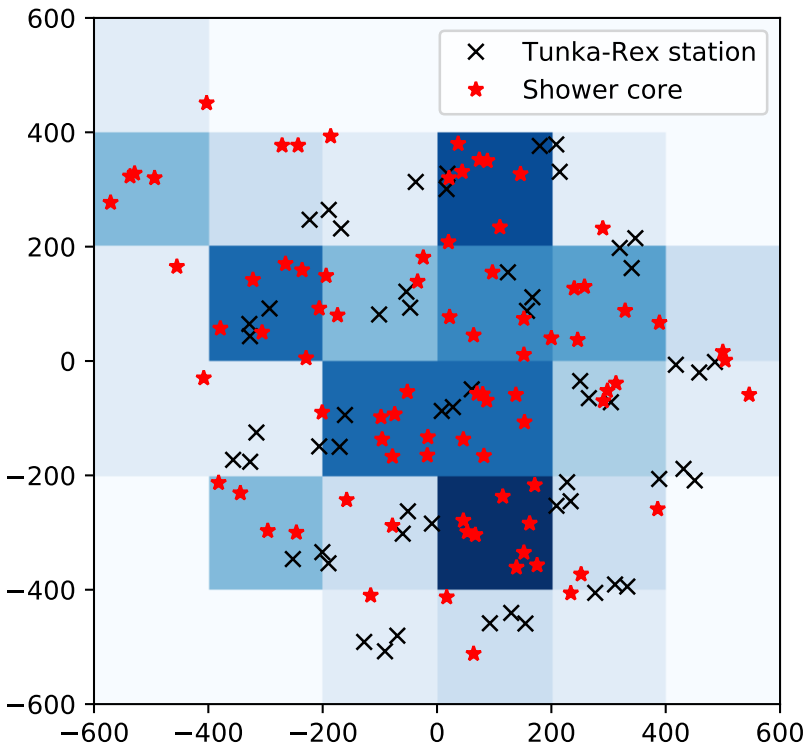
How to convince ourselves that the reconstruction is valid when the signal is not visible?



Data-driven benchmark

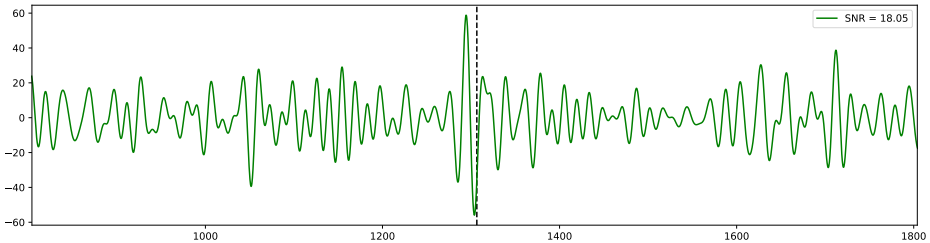
- Tunka-133/Tunka-Rex events with $E \in [10^{16} - 10^{17}]$ eV
- Almost zero events in this energy band by standard method
- Decreasing autoencoder threshold $0.395/0.500 \rightarrow 0.200/0.500$
- Cross-check cuts: direction reconstruction $\Delta\Omega < 5^\circ$, clustering events

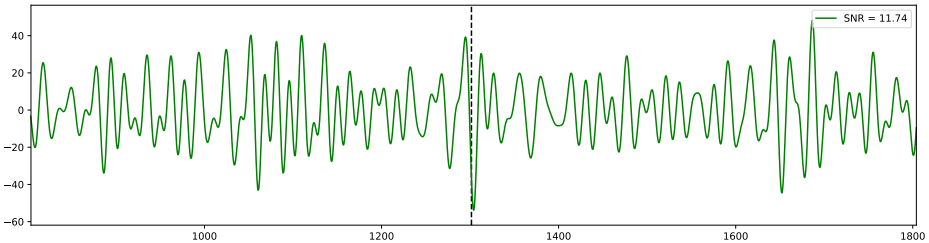


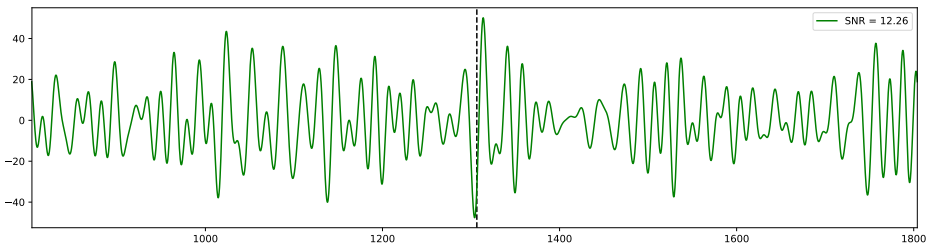


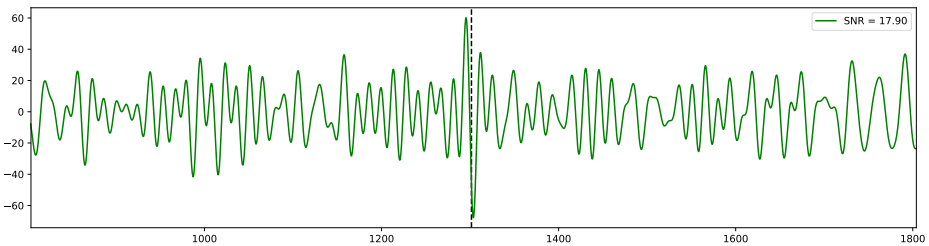
Example reconstruction

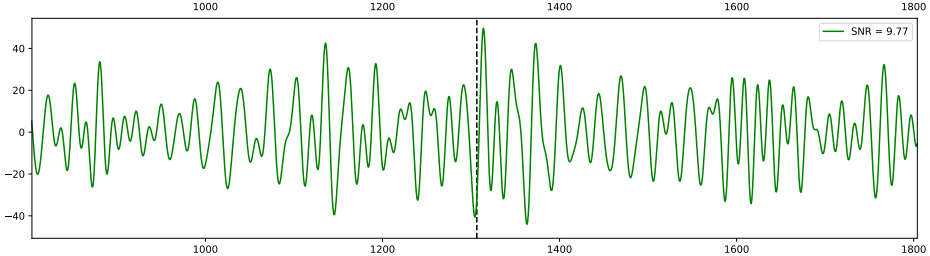
Two example events with $E = 30$ PeV

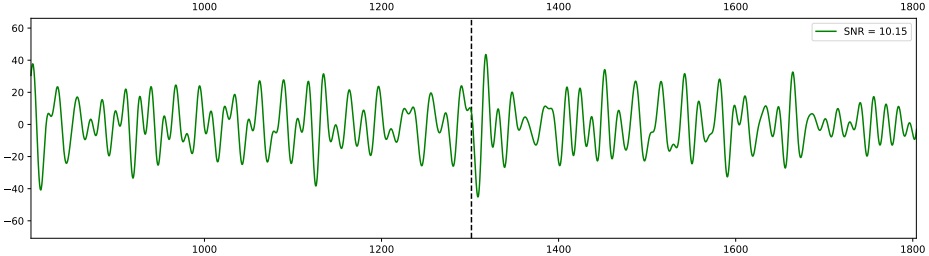




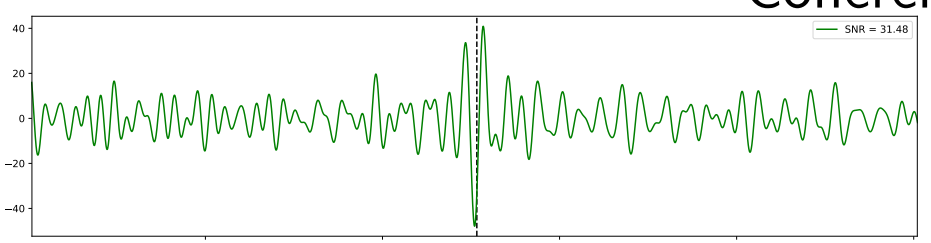


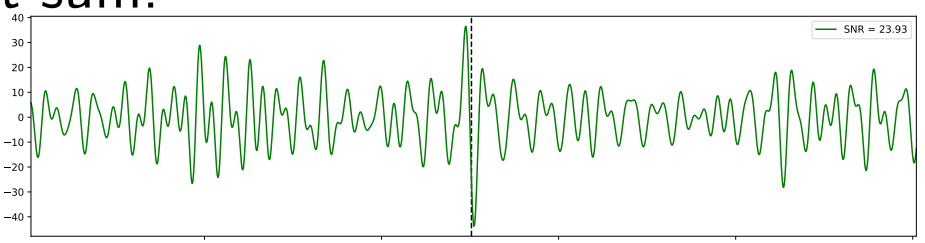






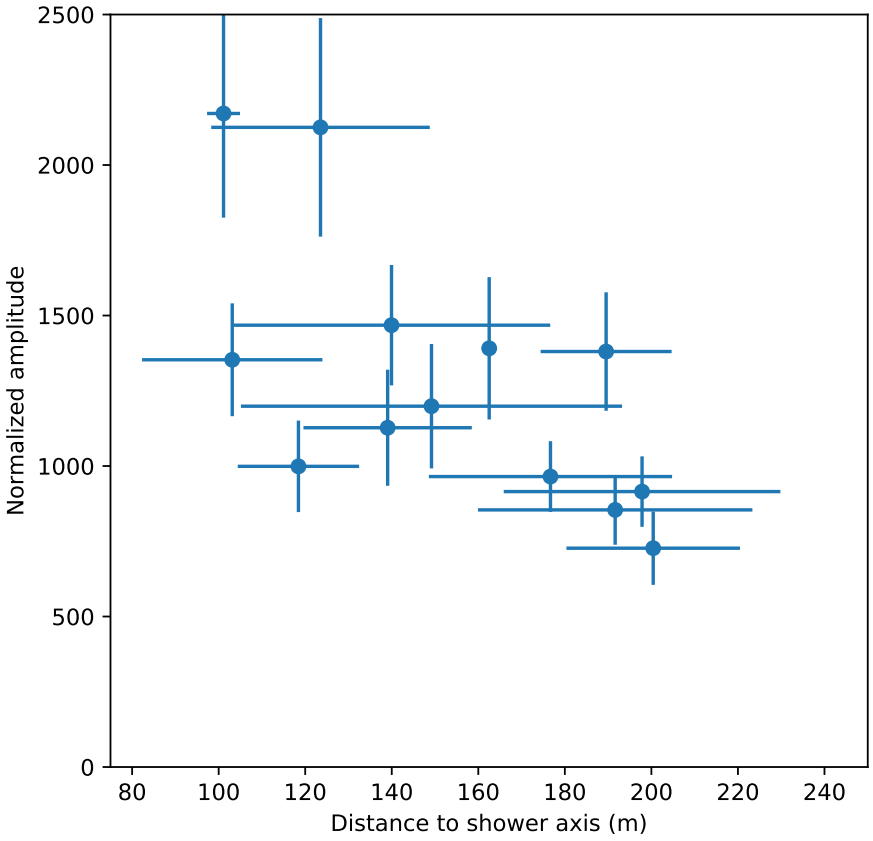
Coherent sum:

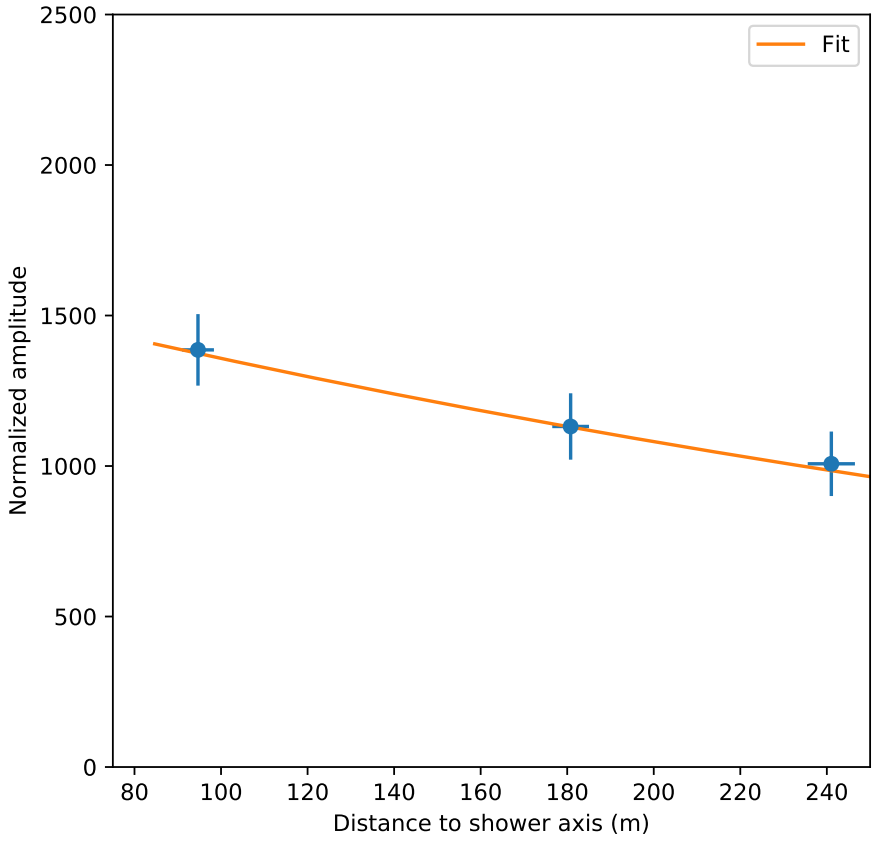




Adaptive LDF (after cuts)

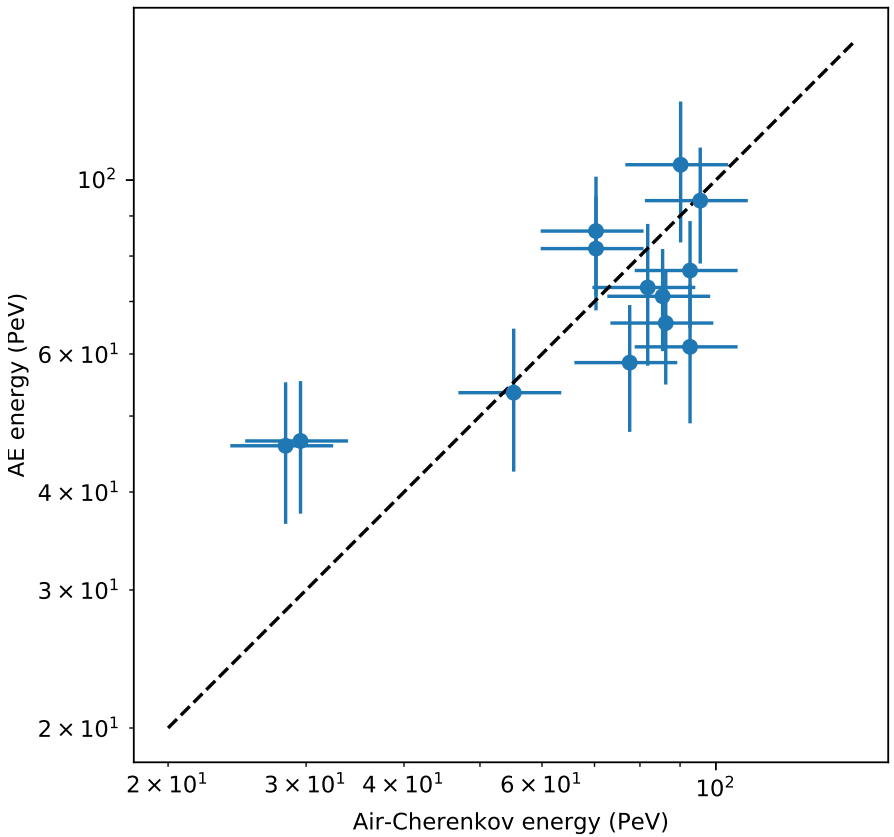
Few antennas are synthesized into single one in order to increase SNR
The slope of averaged LDF is used for energy reconstruction

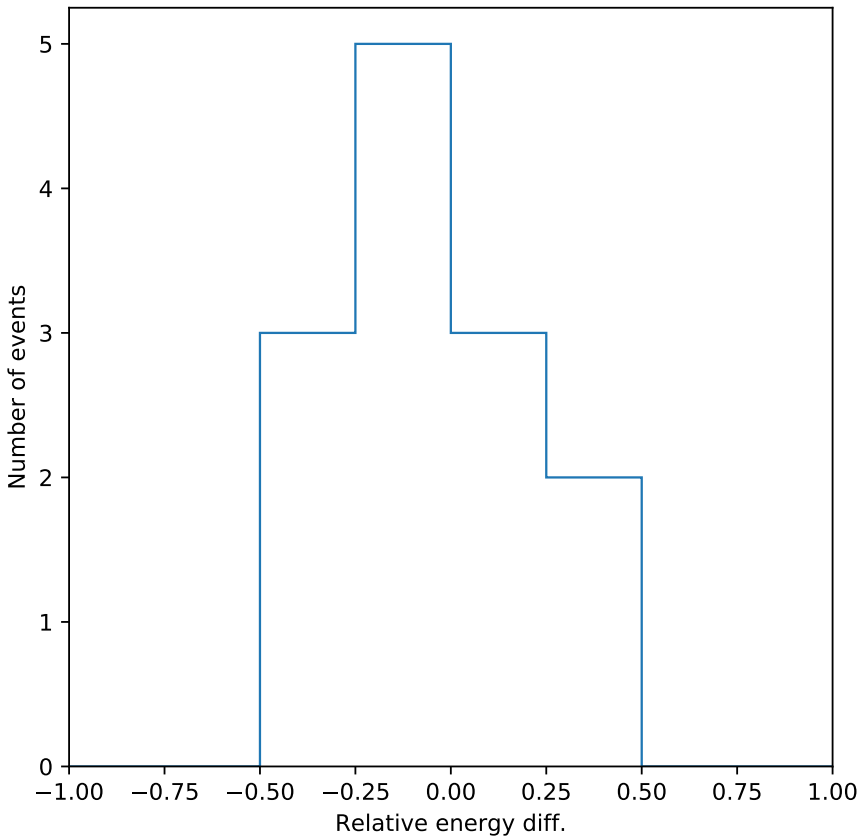




Energy reconstruction (after cuts)

Reconstruction based on single antenna method, $E = \kappa A_d e^{-\eta(d-d_0)}$
Normalization factor from standard reconstruction; $\mu = 0\%$, $\sigma = 26\%$





Conclusion

- The performance of Tunka-Rex autoencoder has been tested on real data
- Numbers of both true and false positives are increased when loosing cuts
- We can reconstruct arrival direction but struggling with energy reconstruction

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- Radio autoencoder can be used as self-trigger technique
- Need more sophisticated cuts to lower the threshold
- Need better training

Tunka-Rex Virtual Observatory: Structure

Data Layers (DL)

- DL0: raw traces recorded by the ADCs
- DL1: traces containing voltages at the antenna stations
- DL2: traces containing values of electrical field at the antenna stations
  $\Rightarrow$ `DL2-AIRSHOWER`, `DL2-ASTRONOMY`, `DL2-OTHER`
- DL3+ will contain high-level reconstruction of radio data

Antenna station data

- `Trace ID`
- `Antenna ID`
- `Timestamp`
- `Version`
- `Traces`
- `Flags`

Calibration data

- `Commission`
- `Decommission`
- `Antenna ID`
- `LNA ID`
- `Filter ID`
- `X, Y, Z`
- `Alignment`

Air-shower data

- `UUID`
- `Timestamp`
- `Theta, Phi`
- `X, Y, Z`
- `Energy`
- `Xmax`
- `Particle`

Tunka-Rex Virtual Observatory: Status

Application

- Studies of the radio background in the frequency band of 30-80 MHz
- Searching for radio transients
- Training of neural networks for RFI tagging
- Outreach and education

Implementation & performance

- 3 TB MySQL database with 100M events (DL1) deployed at IKP KIT
- Processing of 1k events/s
- Almarac (Tien-Shan radio array) DB is deployed at API ISU
- Integration with GRADLCI services