Open questions in deep learning techniques for the radio detection

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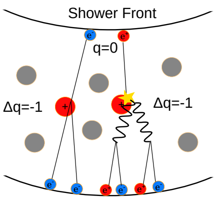
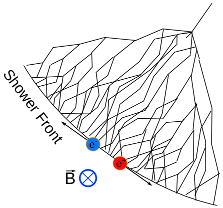
Introduction

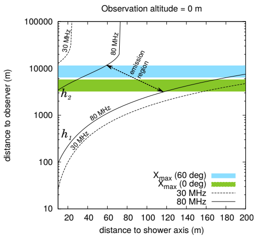
This presentation is given on the Workshop on Machine Learning for Cosmic-Ray Air Showers. I have tried to summarize the progress in radio data analysis and include comments appeared during discussion of the talk.

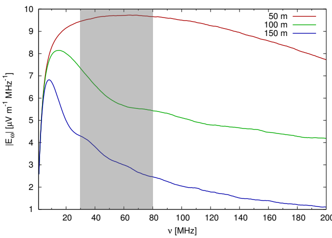
Quick introduction in radio generation

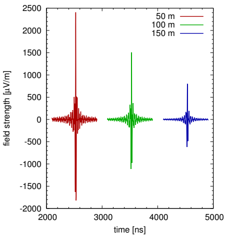


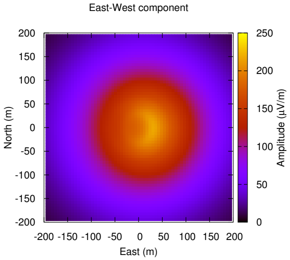


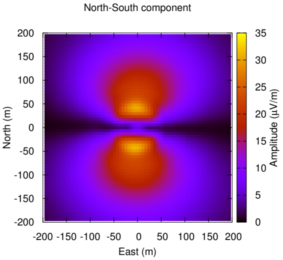
- Askaryan effect
- Geomagnetic effect

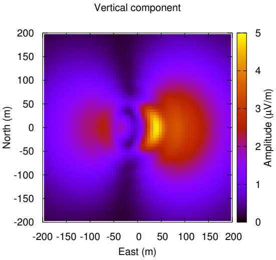




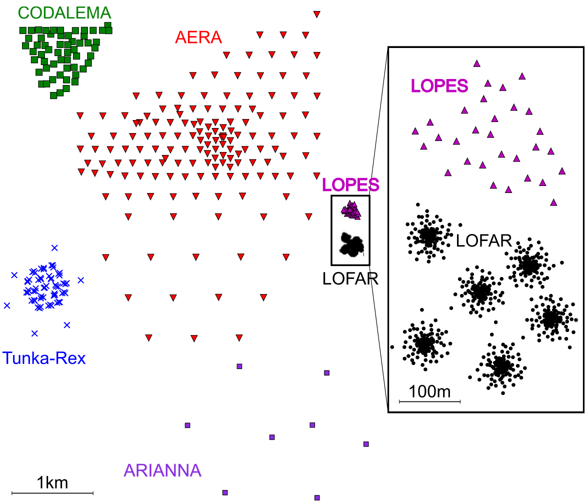


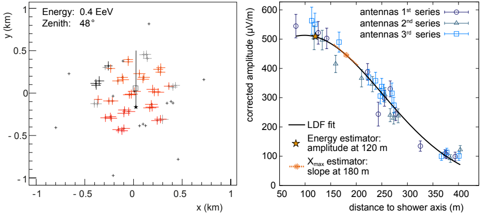


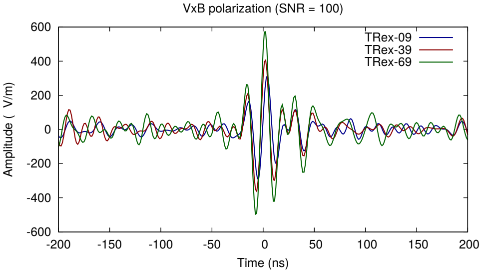




Quick introduction in radio detection

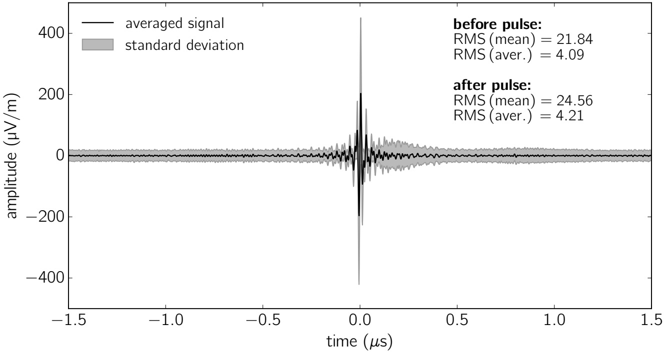


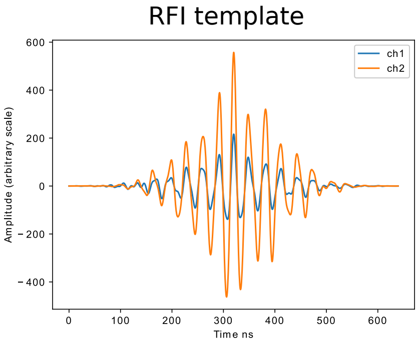




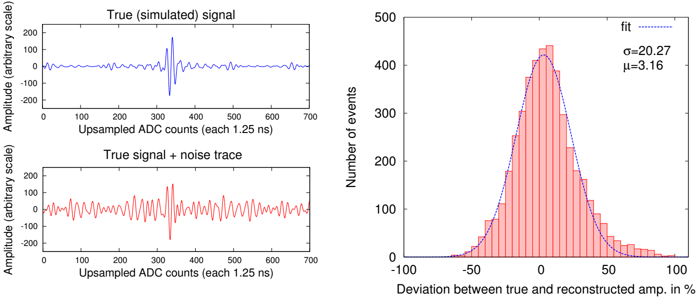
Why do we need machine learning for radio?

- Most of the detectors operate in the low signal-to-noise (SNR) environments
- Background is not completely white $\Rightarrow$ limitation to classical methods
- Radio-frequency interference (RFI) are diverse $\Rightarrow$ hard to account for all





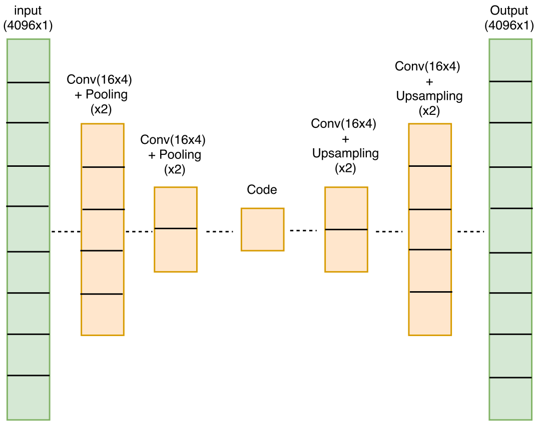
First attempts (back in 2015)



arxiv:1701.05158 (Bezyazeekov+ at ECRS2016)

- Simple perceptron (PyBrain): 200 input neurons, 3 layers $\times$ 500 each, 1 output
- Amplitudes are not normalized, no augmentation $\overset{?}{\rightarrow}$ non-invariant in (t, A)
- Was not tested on real data

Autoencoder approach



Motivation:

- Signal of interest is compact and short comparing to input waveform
- Convolutional filters effectively store signal and background features
- Can be used as denoiser

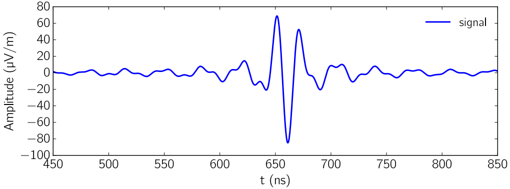
Implementation decisions:

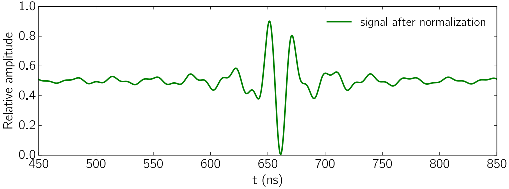
- Size of input waveforms
- Length of convolutional filters
- "Stack more layers" rule should work with large training set

Autoencoder implementation: Preprocessing of the input waveforms

(based on Shipilov+, but others are very similar)

- Nyquist upsampling
- Normalization of amplitudes: $A(t) \to \bar{A} \in [0,1]$
  $\Rightarrow$ amplitude-invariant
- Cropping input to $\mathcal{O}(1024)$ + augmentation: signal is randomly shifted
  $\Rightarrow$ translation-invariant



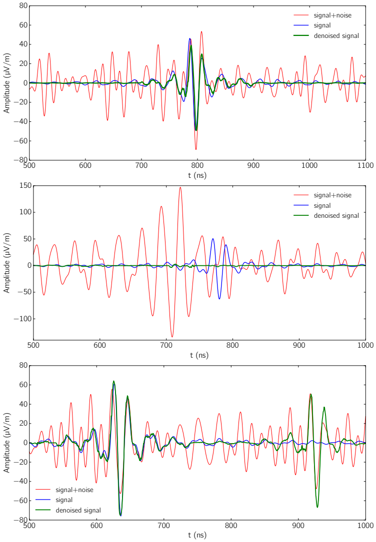


Autoencoder implementation: design and training

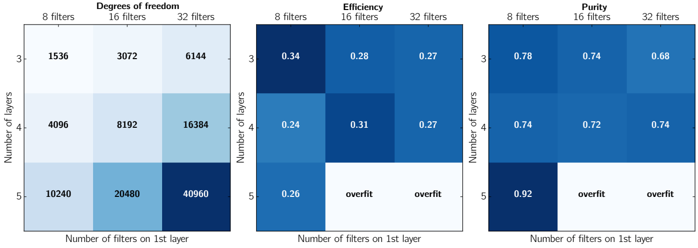
Your input is welcome!

- Filter design
  - Use physical input: air-shower pulse and RFI duration!
  - Upper and lower boundaries for kernel size?
  - Constant or variable size?
  - Upsampling might help autoencoder: optimal sampling factor
- Input waveforms
  - Median filter for preprocessing?
  - Sensitivity to narrow-band background
  - Optimal size in samples and nanoseconds
- Training strategy
  - Optimal size of dataset
  - Binning in amplitude/SNR?
  - Including pure noise in training?
  - How to properly include samples with strong pulse-like RFI

Response and metrics



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



Current state of autoencoder implementations

	Shipilov+ 1812.03347	**Schlüter+** 1901.04079	**Rehman+** PoS ICRC2021 (2021) 417
Band (MHz)	30–80	30–80	50–350
Background	Real	Simulated	Simulated*
Normalization	$[0;1]$	$[0;1]$	$[-1;1]$
Input	4096	1000	1024
Bin size (ns)	0.3125	5.6	0.25
Kernel size	$32 \to 16 \to \ldots$	fixed to 5	fixed to 256
Kernel size at 1st layer (ns)	10	28	64
Filters/layer	$16 \to 32 \to \ldots$	$16 \to 32 \to \ldots$	fixed to 8
Layers	3	5	2
Training set	$\approx$15k	$\approx$70k	$\approx$103k+50k
Tested on real data	Yes	No	No

*improved by Kullgren+ (doi:10.5281/zenodo.6011170)

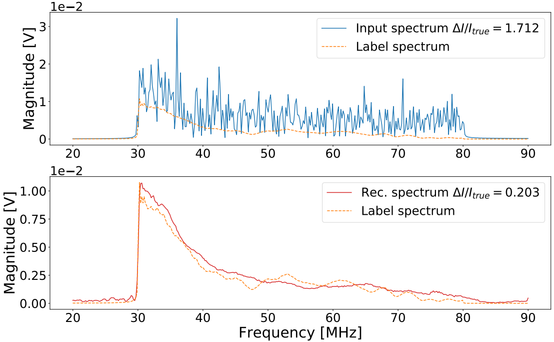
Hereafter we consider only denoisers

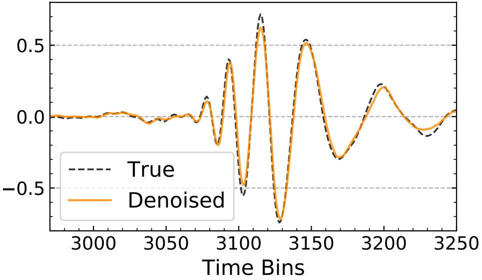
Artificial spectral noise

Artifact when high-rate upsampling is applied (Shipilov+):

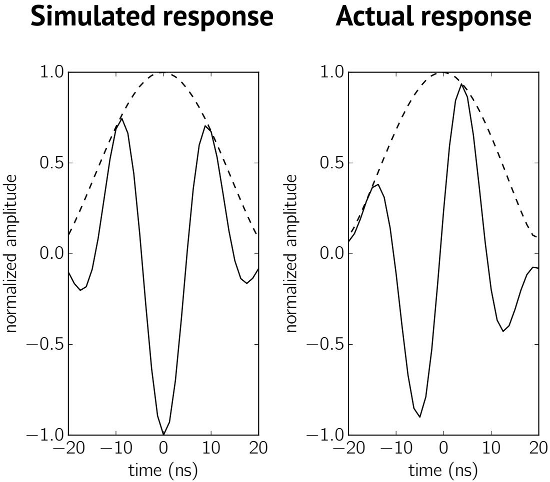
- Nyquist upsampling adds zero-amplitude higher frequencies
- Reconstruction contains noise in-between initial bins
  $\Rightarrow$ artificial noise at higher frequencies

Less impact for non-upsampled (Schlüter+) or low-rate upsampled (Rehman+) signals:





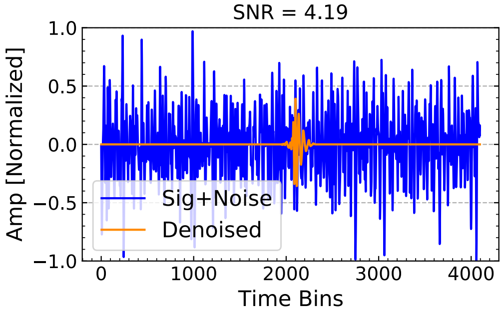
Antenna and phase response invariance

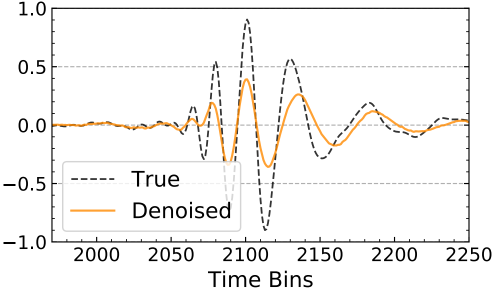


- Calibration does not describe hardware response precisely
- Autoencoder trained by Shipilov+ works surprisingly well both with and without antenna response
- Indication of phase shift invariance
- Implication of this feature?

Amplitude reconstruction

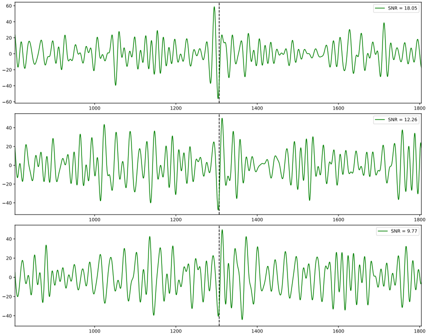
- At low SNR normalization is done w.r.t. noise peaks
- Due to normalization information about absolute amplitude is erased
- Is it fundamental problem for only this architecture or general one?



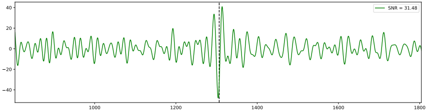


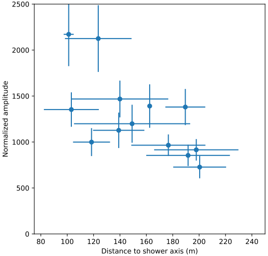
Hybrid approach: autoencoder + interferometry

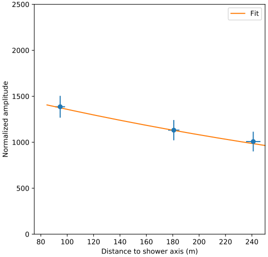
Synthesis of signals using reconstructed arrival times

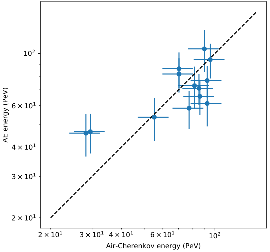


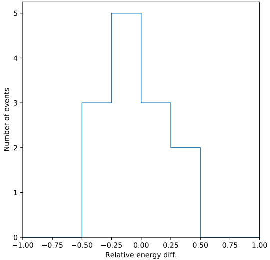
Synthesized signal:











Next steps

Improvements of the current networks

- Alternative architectures, e.g. U-Net, RNN, transformers, LIGO experience
- Adding more channels, wavelets, spectral information
- Integration of modern tools for interpretation, e.g. SHAP
- Spatial information $\Rightarrow$ combination with GNN
- Timing information $\Rightarrow$ combination with CNN encoding sky noise

Compressed neural networks for radio trigger on FPGA

- `hls4ml`: firmware implementations of machine learning algorithms using high level synthesis language (HLS)
- Intensively used in collider physics
- Successfully tested on old ARIANNA hardware (arXiv:2112.01031)
- The only solution for ultra-large scale sparse arrays featuring single antennas

Path to universal network

Search for Holy Grail (and reduce carbon footprint of CoREAS)

Start from GAN?

- High-dimension space: $A(\vec{r},t)$
- Likely more accurate than analytical models, but still not good enough
- Ideal for design studies and template production
- Can be used for RFI and air-shower pulses generation

Ultimate denoiser

- Universality in background? RFI library?
- Train in frequency domain
  - Do they adjustable to every frequency band?
  - CNN will likely not work. Architecture?
  - $F_{\mathrm{true}} = F_{\mathrm{meas}} * F_{\mathrm{IRF}}^{-1}$. How to propagate F_{IRF} to NN?

Conclusion

- Radio community has successfully learned how to use neural networks
- Several architectures are implemented, but only one tested in production
- The recipes for optimal design are not well defined
- Few unique features of radio autoencoders have already been discovered
- The killer feature of technology is FPGA trigger for stand-alone antennas

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- Training in the frequency domain is almost unexplored:
  - Representation of signals: complex numbers? phase-amplitudes?
  - Treatment of noise? CNN for dynamic spectra? LIGO approach?
  - Efficient phase unwrapping?