# Deep Learning for Classification and Denoising of Cosmic-Ray Radio Signals

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Workshop on Machine Learning for Cosmic-Ray Air Showers, Delaware USA.



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### Outline

- □ Introduction:
  - **CR** Air showers.
  - **Q** Radio emission from air showers.
  - **Use of Deep Learning for Classification and Denoising.**
- □ Preparation of DataSet for model training.
- **CNN Network architecture**
- **Gamma** Results of trained models.
- Other network that we have tried.
- □ Work in progress and Outlook.



### Cosmic-Ray Air Showers

- Primary CRs produce Air Showers when they enter the atmosphere.
- Number of secondary particles first grows, then reach a maximum at X\_max and then declines as the shower dies out.





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BARTOL RESEARCH F.G. Schroder, Prog. Part. Nucl. Phys. 93 (2017), 1,: arXiv: 1607.08781



### Radio Emission from Air Showers



- **Geomagnetic emission**: Due to time-variation of the transverse current
- Askaryan emission: Due to time-varying charge excess in the shower front

Radio competes in precision of X\_max, arrival direction and energy, with other established techniques like fluorescence detector.

100% duty cycle.

Combining radio with particle detection will significantly increase the total accuracy of Air shower measurements.



#### Introduction

- **Q** Radio detection, like other techniques, has to deal with the continuous background.
- Because of the noise contaminating the radio signals, radio detection threshold is very high.
- U We are using ML (Convolutional Neural Networks) to try to mitigate the effects of background.
- **D** To train networks we used simulated radio signals and background.
- **D** Example Traces are shown in the bottom plots.







### Classifier and Denoiser

- Using Keras/Tensorflow to construct 1D Convolutional Neural Networks.
- **Classifier:** Identify radio signals and backgrounds.
- **Denoiser:** Recover the underlying signals from the Noisy traces.





### **Data Preparation**

#### ► Dataset:

 $\circ$  CORSIKA → Simulation of air-showers.

(IceTop atmosphere)

 $\circ$  CoREAS → Radio emission from air-showers.

(Sibyll 2.3d as a high-energy hadronic interaction model.)

- $\circ$  Zenith angles → [0, 65]deg in steps of 5 deg, random azimuth angles.
- $\circ$  For background: Modeled (Cane) Noise  $\rightarrow$  Average Galactic + Thermal background

( Dana kullgren will show results using measured background from prototype station at the South Pole)
• After adding antenna and electronic responses the signal and background are combined to produces Noisy traces.

- Filtered band [50-350] MHz.
- $\circ\,$  Traces are also normalized before inputting them to the network.



# Training and Testing Sets

- $\circ\,$  Signal to Noise ratio (SNR) is used to quantify the signal strength.
- $\circ\,$  Signals are scaled before adding noise.
- $\circ~103k$  Signal + 135k noise traces.

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- $\,\circ\,$  80% for training, 20% for testing.
  - Mean SNR of Noise ~ 7







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### Network Architecture

- Networks are based on Autoencoder technique.
- 1D convolutional layers are used with Max-pooling and Up-sampling layers to create encoding and decoding layers respectively.
- Classifier also includes Flattening and Dense layers.
- ReLu activation function is used in all except the last layer which uses Sigmoid.





## Learning Curve

- Mean squared error (MSE) is used as a loss function.
- Early stopping is used:
  - Stop training If test loss is not decreasing after 20 epochs.
- Not much difference in the training and testing loss, which means that the network is not overfitting.





### **Classifier Results**

- > Validation set: 11k signal + 15K background traces. Similar SNR distribution as training and testing set.
- > Threshold for signal trace: output value  $\geq$  **0.6**.

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> TP and FP rates (in percent), shown in the right plot.



### **Denoiser Results**

- Classified Signal traces are passed to the Denoiser for cleaning.  $\succ$
- Two examples shown in bottom left.  $\succ$
- 1st row  $\rightarrow$  best case scenario.  $\succ$
- 2nd row  $\rightarrow$  worse case.  $\succ$









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### **Accuracy Metrics**

> Left Plot 
$$\longrightarrow$$
 Power Ratio =  $\frac{[P_S - P_N]_{\text{Measured}}}{[P_S - P_N]_{\text{True}}}$ .

 $P_{s}$ ,  $P_{n}$  = power in the signal and noise window, respectively.

> Right Plot  $\longrightarrow \Delta t = T_{\text{measured}} - T_{\text{true}}$ .



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Other Networks tried



- RNNs process inputs in a **sequential manner**, where the information from the previous input is considered when computing the output of the current step.
- We have used the type of RNN called LSTM.
- LSTM's have the ability to preserve the long-term memory.







• We have also tried combining the two networks.



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#### Using the Frequency spectrum

- FFT of time series gives us complex frequency spectrum.
- We can either use the Real and Imaginary part of the spectrum.
- Or we can use Frequency Amplitude and Phases.
- So far this does not improve the results. Question: How to deal with the Phases?







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### Summary and Outlook

- □ We are using Convolution networks to study radio signal from cosmic-ray air showers.
- CoREAS simulations are used to produce radio signals.
- **G** For background we used modeled noise.
- Other networks like LSTM are also tried but they did not perform better than the CNNs.
- We have used time series information for networks training, Currently working on using the frequency spectrum as well.

