Improving the Sensitivity and Data Analysis Techniques of the ARIANNA Detector with Deep Learning

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SLAC Seminar

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Outline

- Introduction
  - Ultra high-energy neutrino astronomy
  - The ARIANNA experiment
  - Deep learning
- Project 1: Real-time deep learning filter implementation
- Project 2: Improving offline analysis techniques with deep learning

Multi-Messenger Astronomy

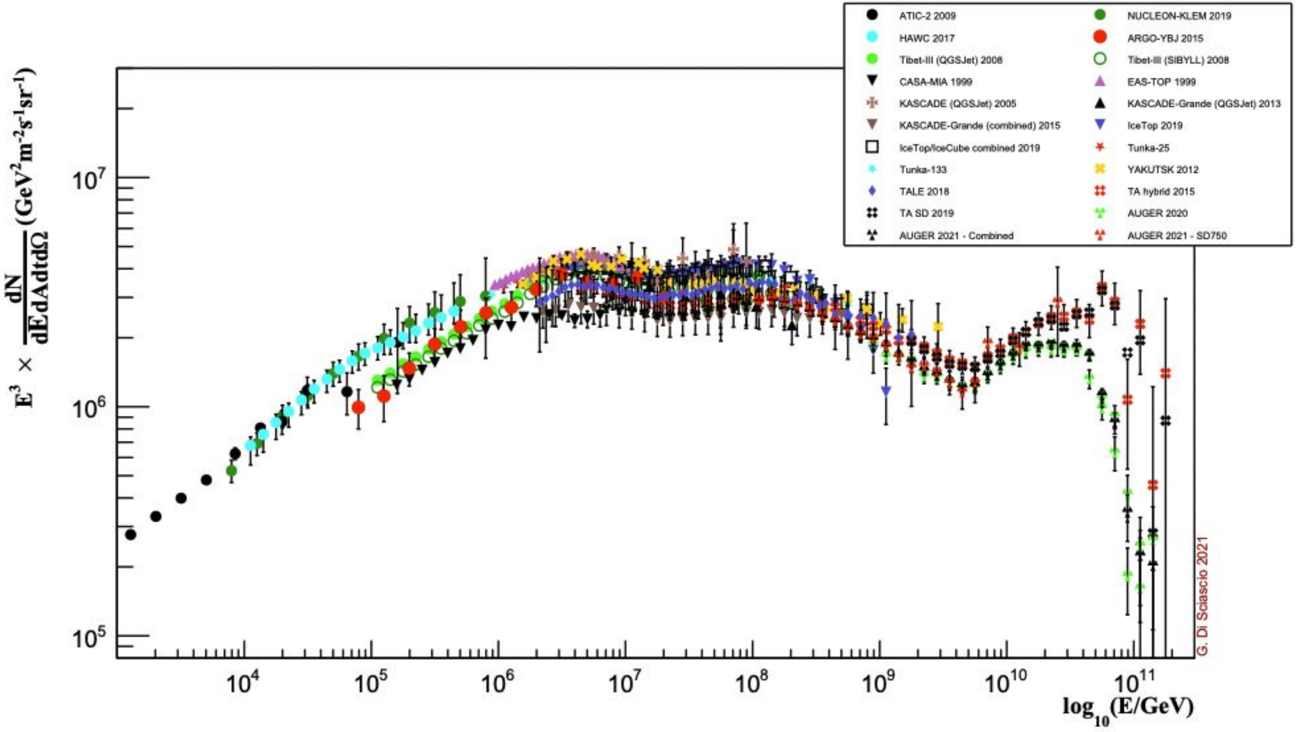
Messengers:

- EM waves
- Gravitational waves
- High-energy particles
- Neutrinos

quantamagazine.org/neutrinos-linked-with-cosmic-source-for-the-first-time-20180712/

Cosmic Ray Energy Spectrum

Ultra High Energy >= 10^{17} eV



G. Di Sciascio arXiv:2202.11618

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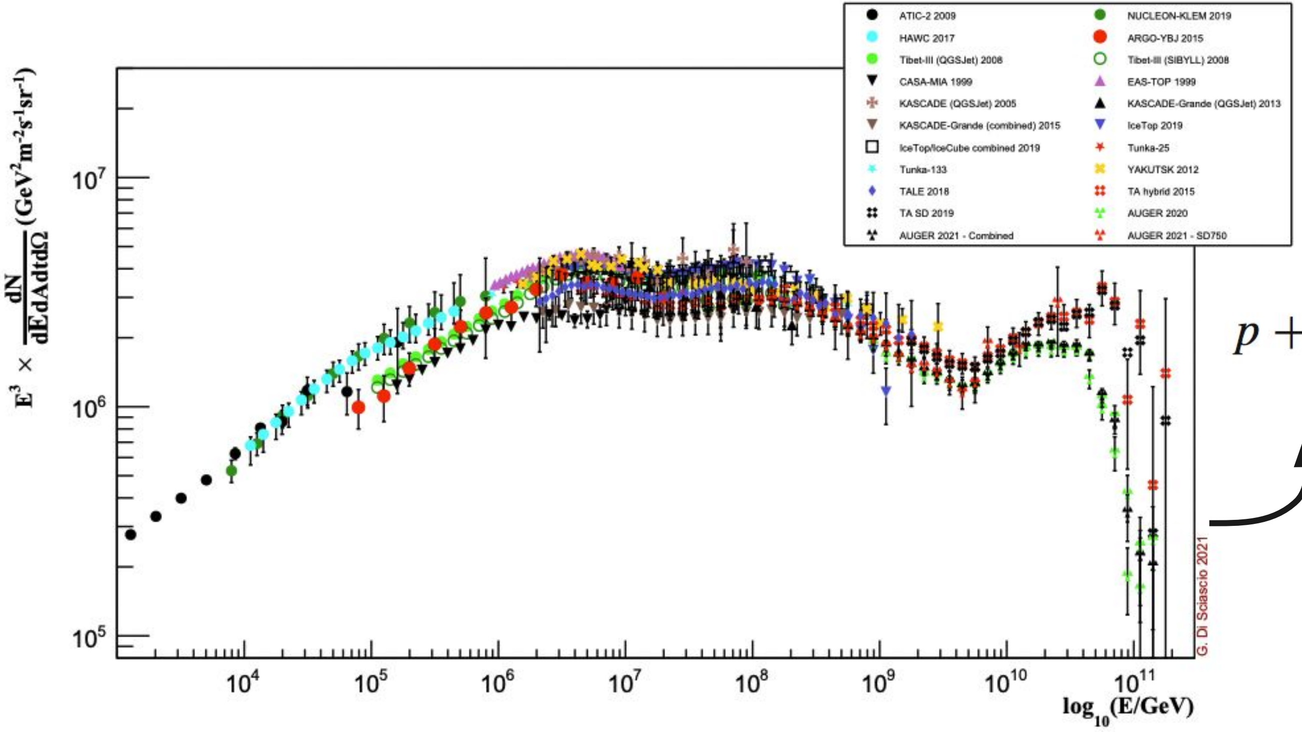
Extreme High Energy >= 10^{17} eV



GZK Mechanism

$$p + \gamma_{CMB} \rightarrow \pi^+ + n$$
$$\pi^+ \rightarrow \mu^+ + \nu_\mu$$
$$\mu^+ \rightarrow e^+ + \nu_e + \bar{\nu}_\mu$$

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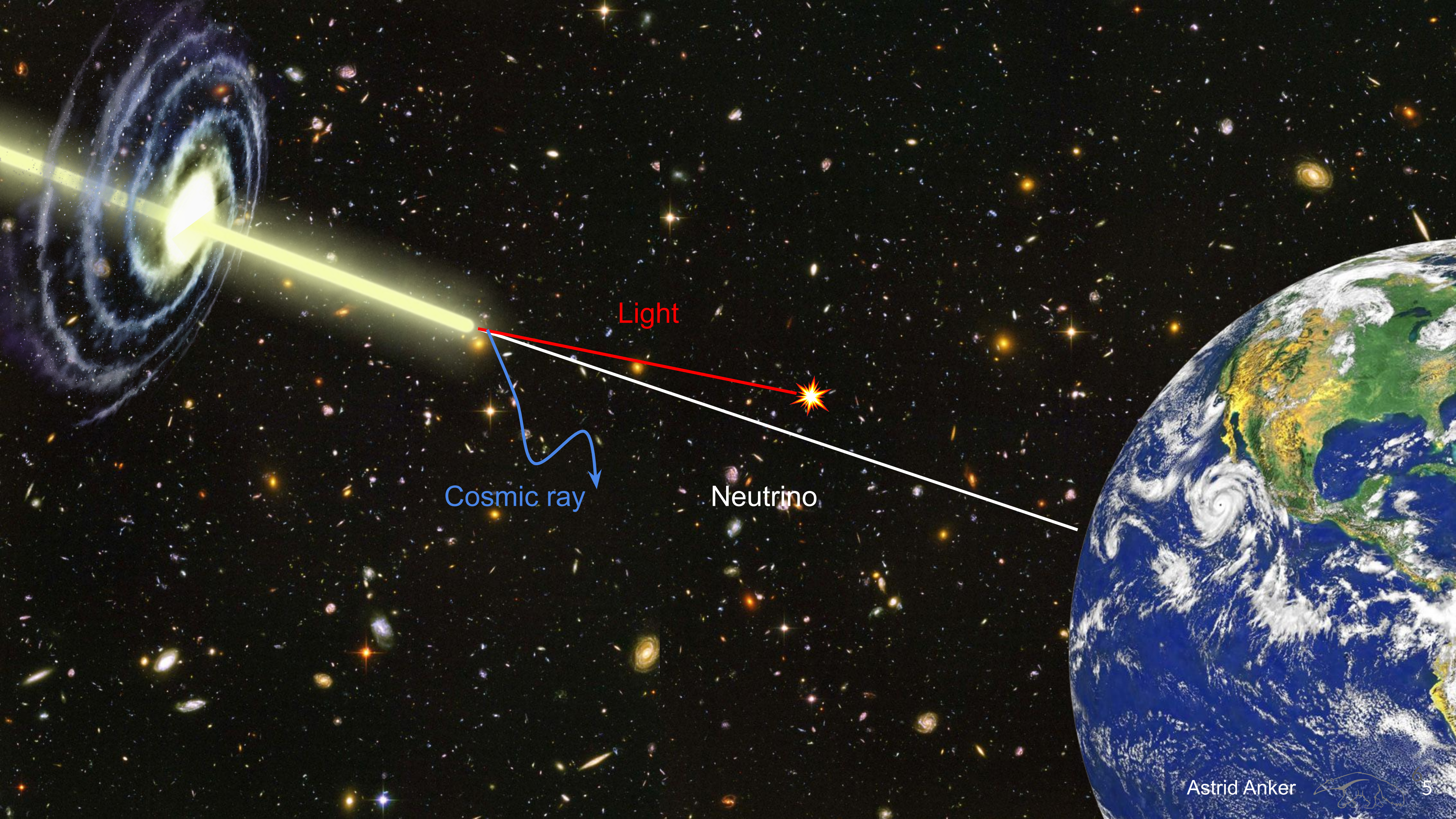
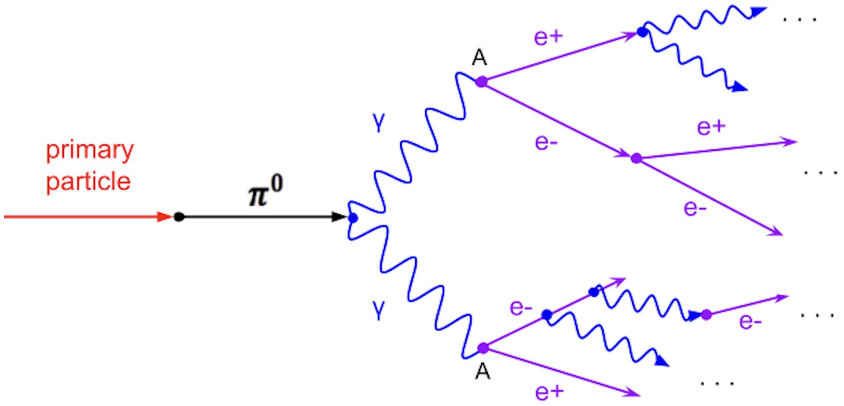

Light
Cosmic ray
Neutrino

Radio Detection of Neutrinos in Ice

The Askaryan effect

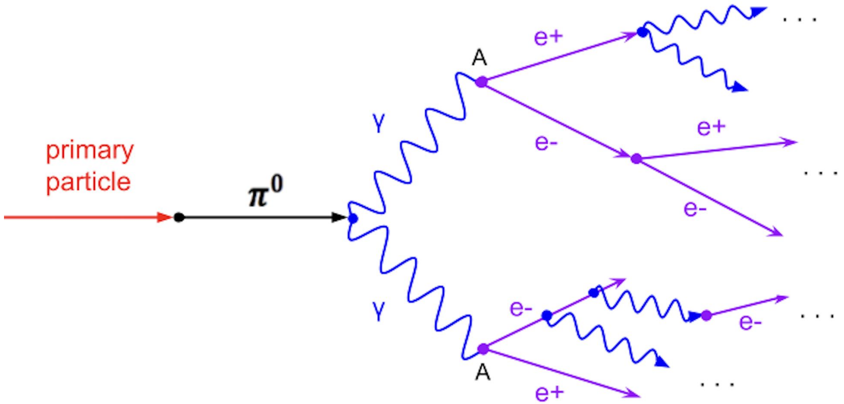
- Askaryan emission occurs in ice when excess charge builds on the shower front, producing coherent radio Cherenkov emmission

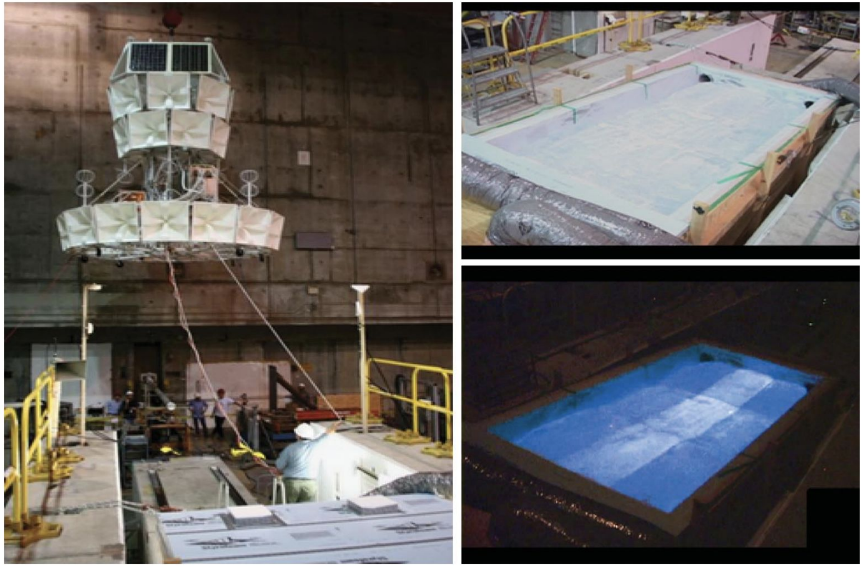


Radio Detection of Neutrinos in Ice

The Askaryan effect

- Askaryan emission occurs in ice when excess charge builds on the shower front, producing coherent radio Cherenkov emmission
- First observed in ice here at SLAC!

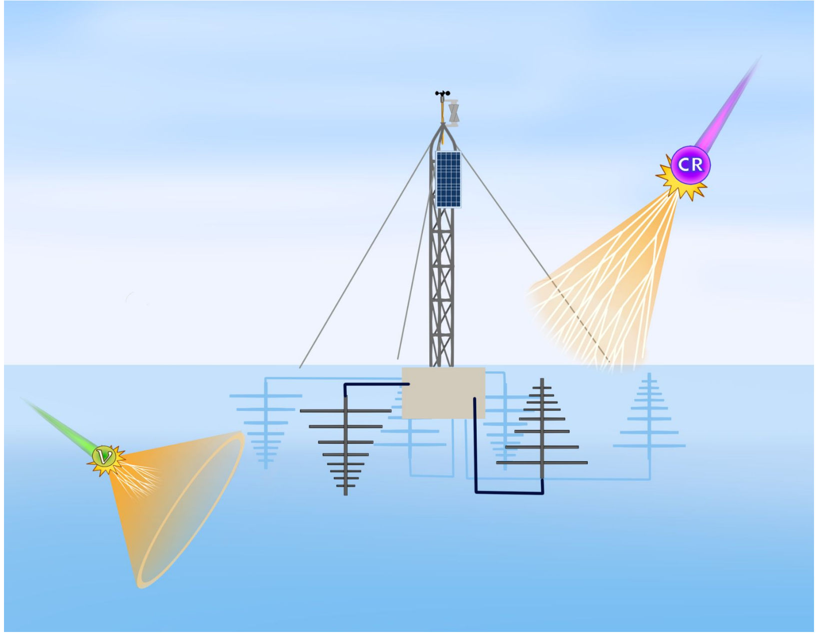




ANITA collaboration arXiv:hep-ex/0611008

ARIANNA Detector

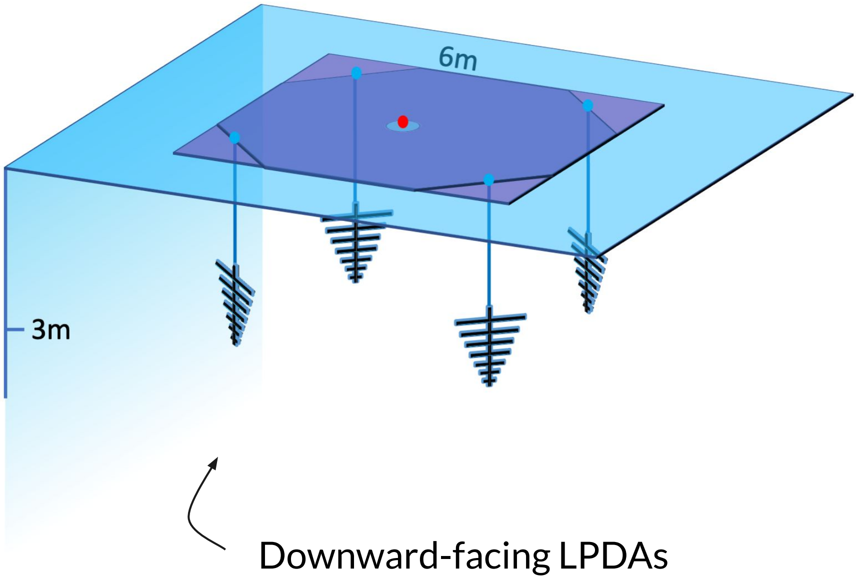
- An array of autonomous stations
- Powered by solar (5 watts)
- Detectors can be sensitive to both neutrinos and cosmic rays, depending on antenna orientation
- Collected data is transmitted to UCI over satellite
- Pilot stage has ended, and working on a large scale proposal



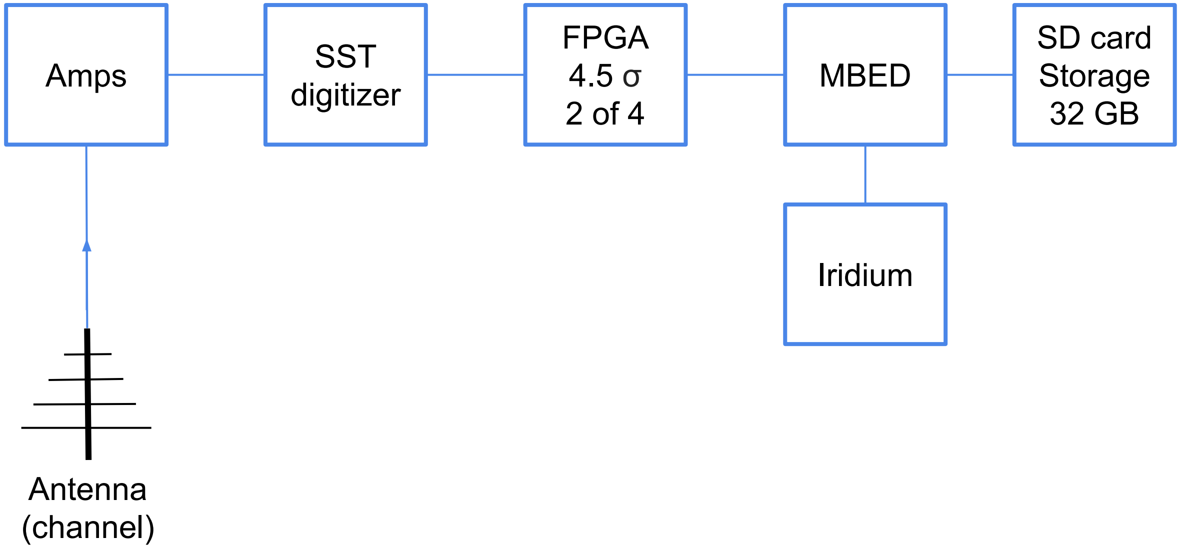
ARIANNA Detector

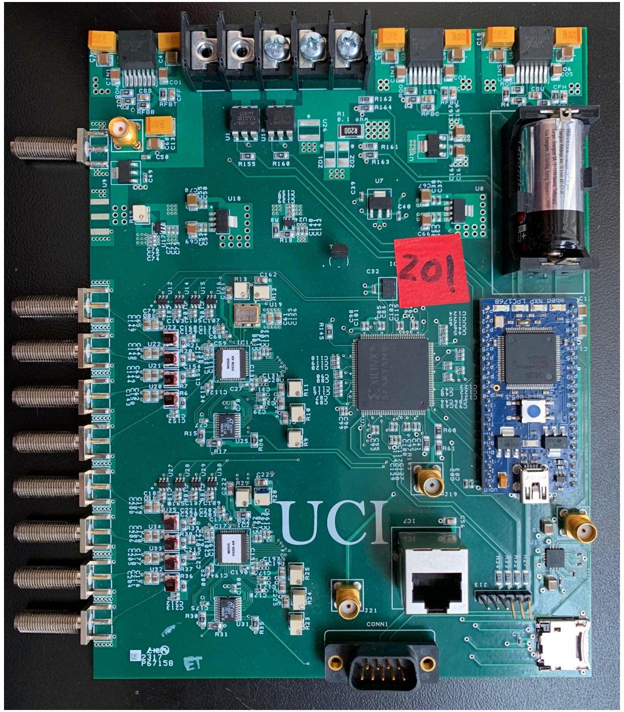
- Consists of 4 (or 8) LPDA antennas
- Buried 3m below the ice surface
- 2 sets of parallel antennas
- Uses a 2 of 4 majority triggering logic
- Thresholds set by the factor of signal-to-noise ratio (SNR), ex: 4.4 SNR is 4.4 x VRMS
- Equates to an event rate of ~ 10^-3 Hz

➔ This constraint is due to Iridium communications transmission rate



ARIANNA Detector

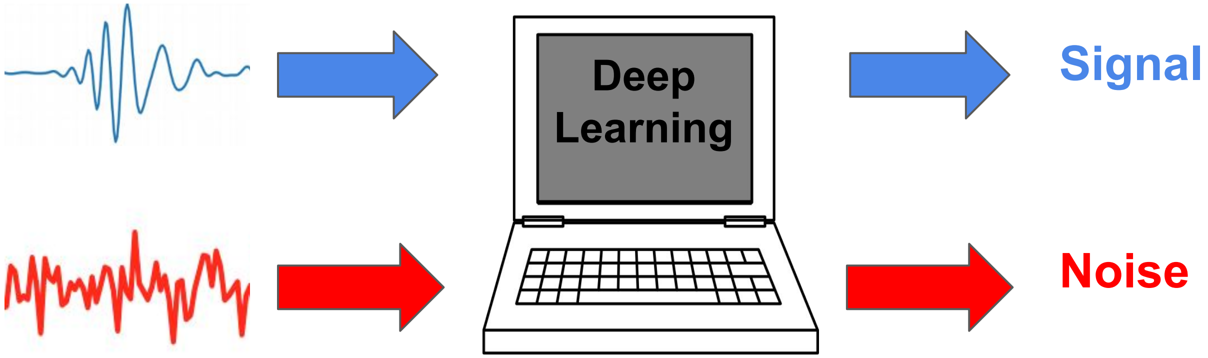




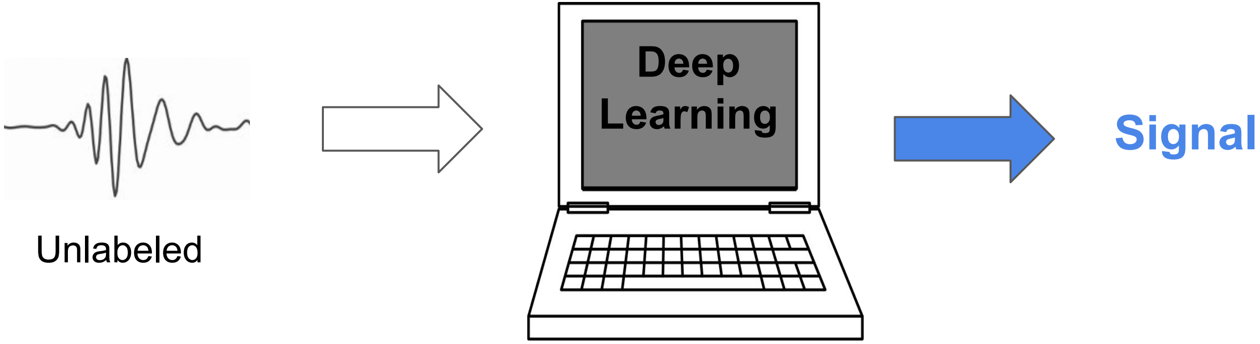
Deep Learning

(s1, s2, s3, s4,....)
(s, s, s, s,......)

(n1, n2, n3, n4,....)
(n, n, n, n,......)

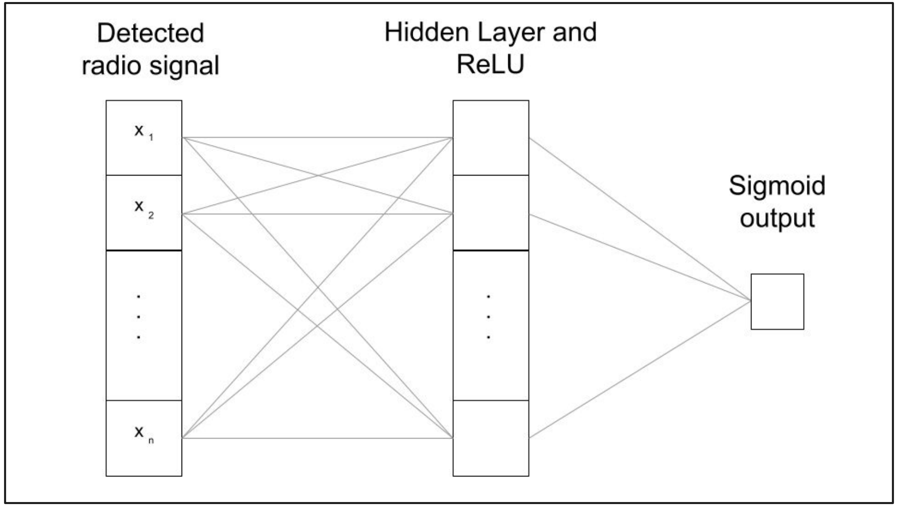


Deep Learning

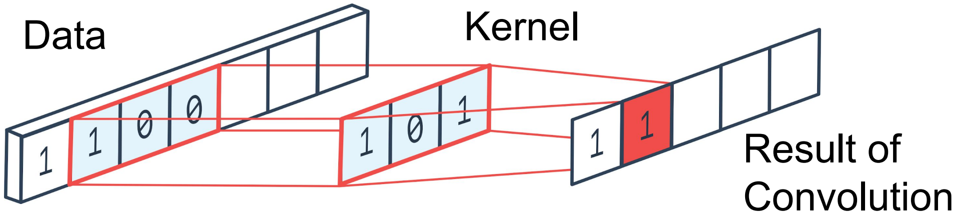


Deep Learning

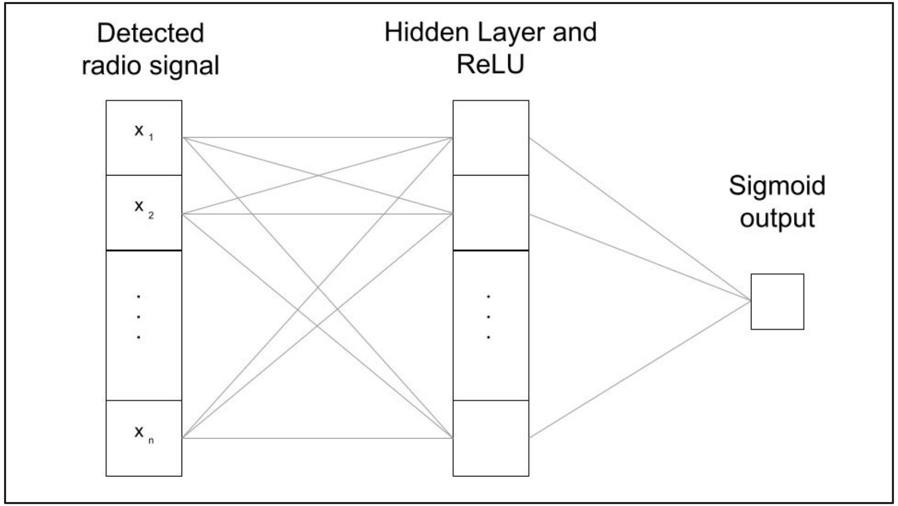
Fully connected neural network (FCNN)



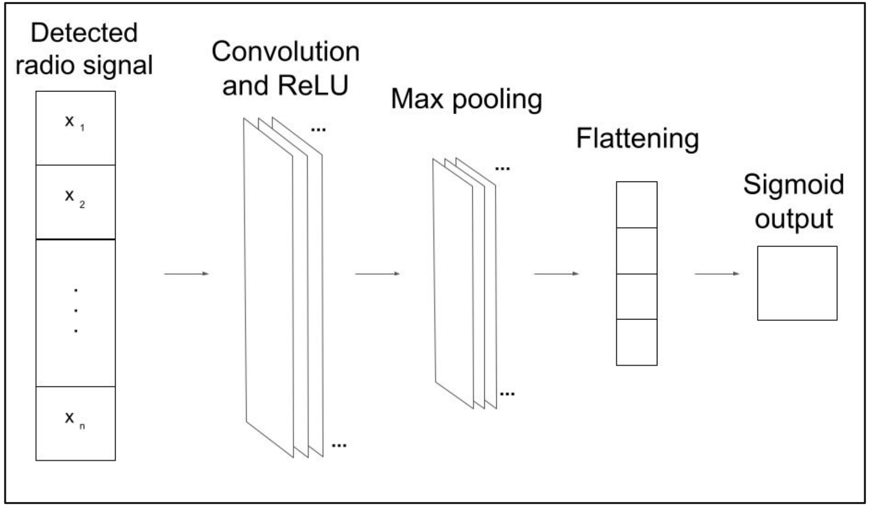
Deep Learning



Fully connected neural network (FCNN)



Convolutional neural network (CNN)



Real-time Deep Learning Filter Implementation

Goal: improve the neutrino sensitivity of the ARIANNA detector

Journal of Instrumentation, DOI: 10.1088/1748-0221/17/03/P03007

Real-time Deep Learning Filter Implementation

Goal: improve the neutrino sensitivity of the ARIANNA detector

- Current trigger threshold of 4.4 SNR gives a data rate of 10^-3 Hz
- Lowering the trigger thresholds to our target of 3.6 SNR gives a new data rate of 100 Hz
- The transmission of data is constrained to 10^-3 Hz
- To get from 100 Hz to a 10^-3 Hz, we need 5 orders-of-magnitude noise rejection and still require 95+% signal efficiency
- Need to improve the sensitivity with the given resources and constraints we have

Journal of Instrumentation, DOI: 10.1088/1748-0221/17/03/P03007

Real-time Deep Learning Filter Implementation

Goal: reduce the trigger thresholds, which increases our ability to measure neutrinos

➔ This would increase the sensitivity of the detector by almost a factor of two

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Constraints:

- ➔ Data transmission rate
  - ◆ From 4.4 to 3.6 SNR, the trigger rate increases from 10^-3 Hz to 100 Hz
  - ◆ This requires a noise reduction factor of 10^5
- ➔ Deep learning filter rate
  - ◆ Requires incoming data to be processed/classified at a rate above 1 kHz to limit deadtime

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Steps:

- ➔ Generate simulated data
- ➔ Train an efficient but small network
- ➔ Implement DL on ARIANNA hardware
- ➔ Lab test validation
- ➔ Ongoing work

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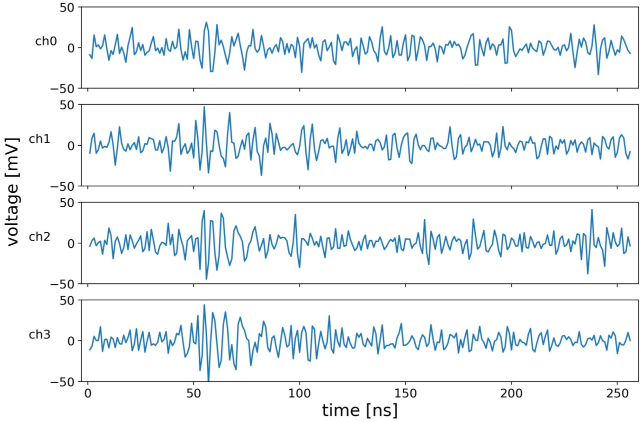
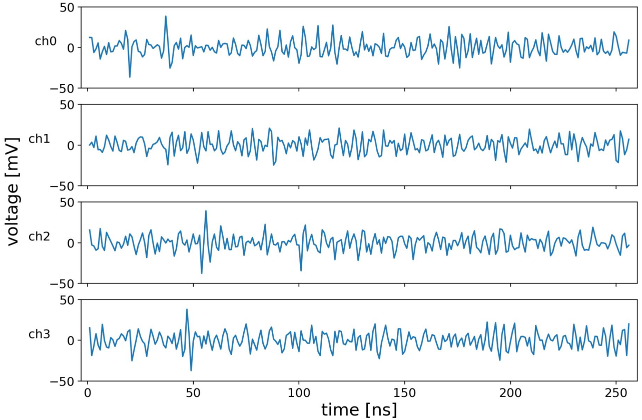
Simulations

- Generated with NuRadioMC (Monte Carlo)
    - The signal set contains a full neutrino spectrum
    - The noise set contains thermal noise events
- Trigger thresholds lowered from 4.4 SNR to 3.6 SNR (increases trigger rate by 10^5)

Neutrino signal event



Thermal noise event



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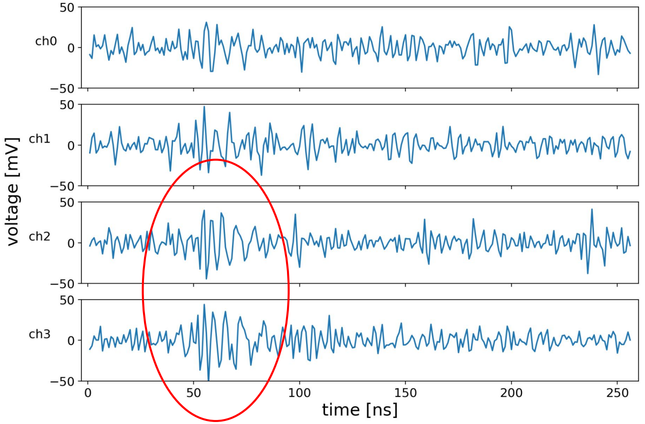
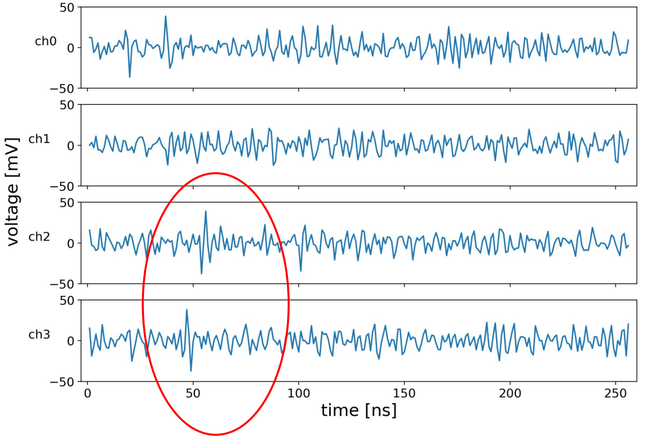
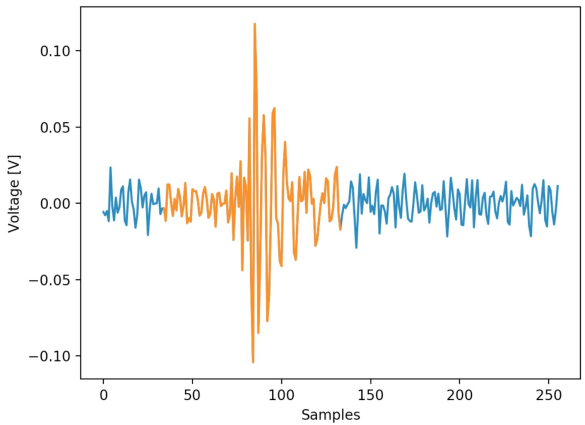


Thermal noise event

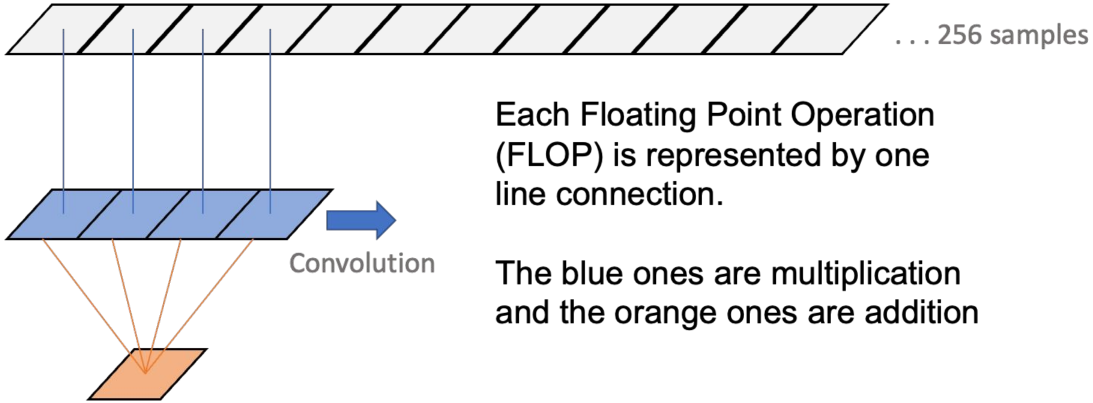


Minimizing the Network Size

- Decrease input data size



- Decrease size of the network structure



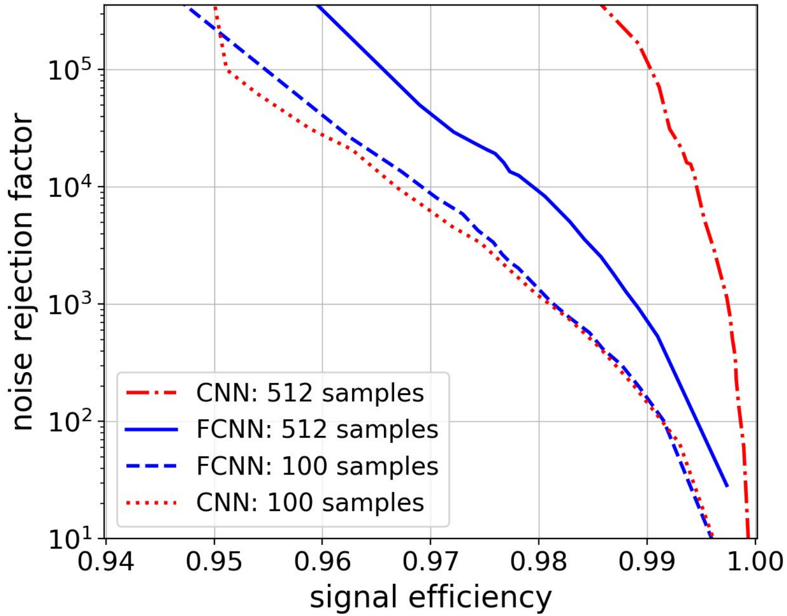
Each Floating Point Operation (FLOP) is represented by one line connection.

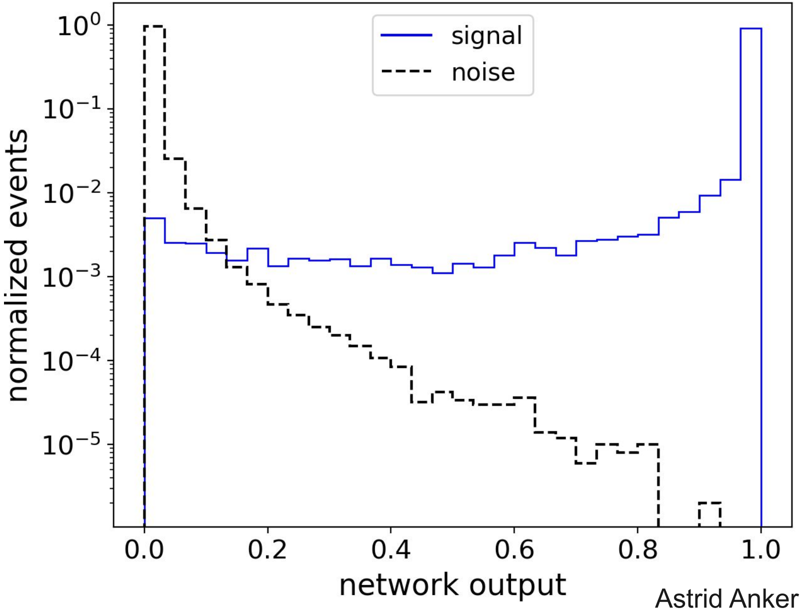
The blue ones are multiplication and the orange ones are addition

model	FLOPs	MBED
CNN 100 samples	~ 10k	3.7 ms | 270 Hz
CNN 256 samples	~ 27k	9.4 ms | 106 Hz

Network Efficiency

- Target efficiency: >95% signal efficiency for at least 10^5 noise rejection





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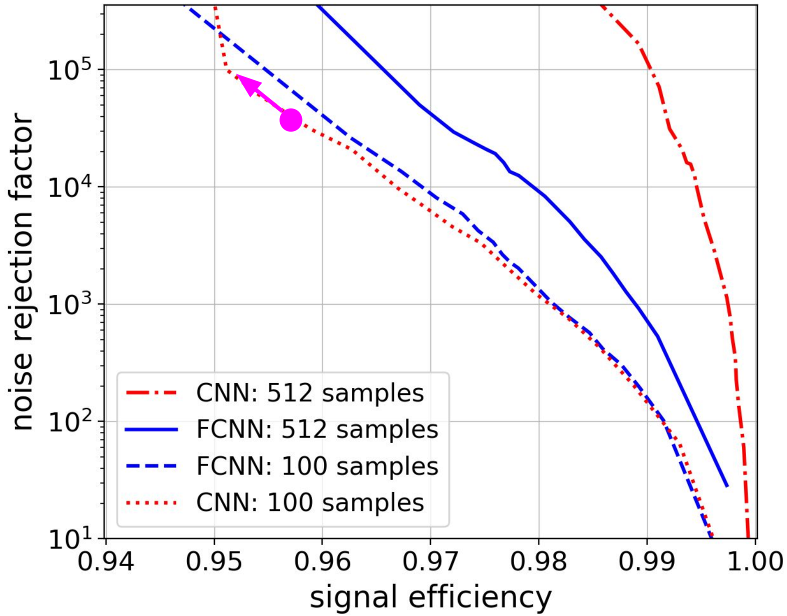
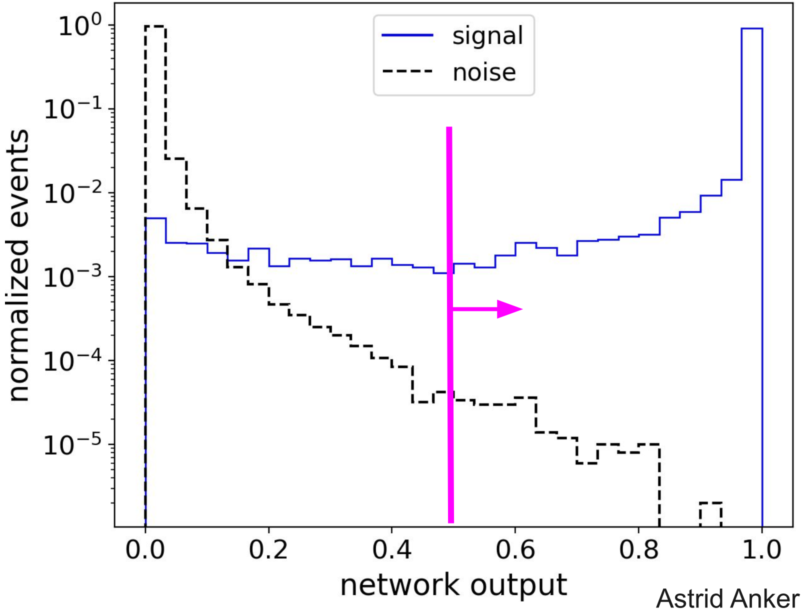
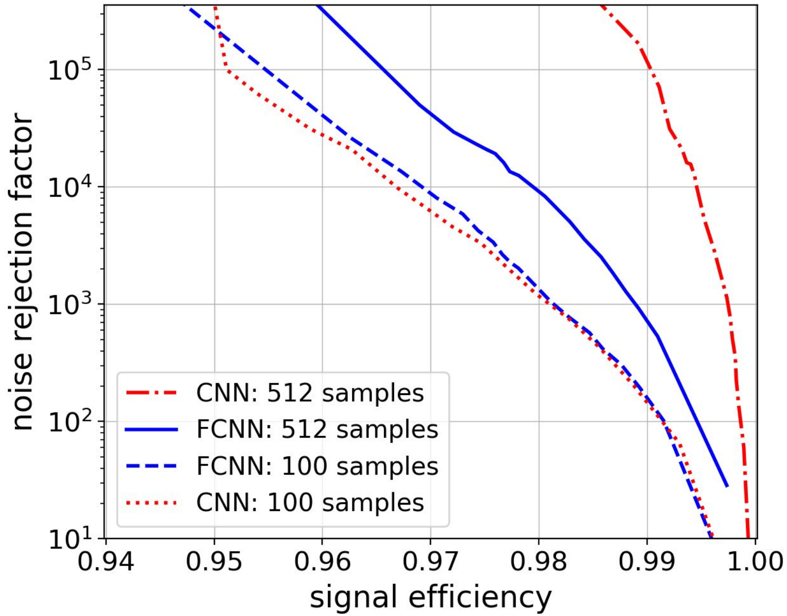




Network Efficiency

- Goal: >95% signal efficiency for at least 10^5 noise rejection
- Target processing time: below 1 ms (1 kHz)



model	Processing rate
CNN: 512 samples	50 Hz
FCNN: 512 samples	22 Hz
FCNN: 100 samples	212 Hz
CNN: 100 samples	270 Hz

Implementation of Deep Learning Filter

- Trained the CNN ahead of time and extracted trained weights and biases
- Manually wrote data formatting and matrix multiplication code within the MBED software

```
//convolution
for(int i = 0; i < n_filters; ++i)
{
    for(int j = 0; j < shifts; ++j)
    {
        float counter = 0;
        for(int k = 0; k < filt_size; ++k)
        {
            counter += indata_signal[j+k]*M[i][k];
        }
        //relu activation
        if (counter + Mb[i] >=0)
        {
            e1[j][i] = counter + Mb[i];
        }
        else
        {
            e1[j][i] = 0;
        }
    }
}
```

Lab Verification

Goal: compare network output values for simulated and experimental data

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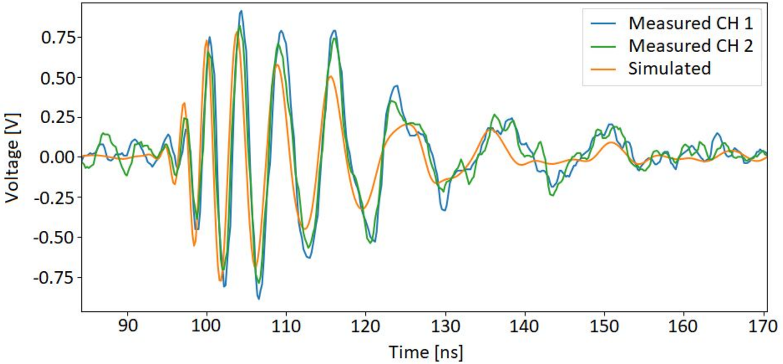
- Measured signal data:
  - Neutrino template generated and programmed into pulse generator
  - Pulse generator output fed into amplifiers and then ARIANNA hardware
- Measured noise data:
  - Produced via the amplifiers
- Simulated signal is generated with the neutrino template and simulated thermal noise is also generated

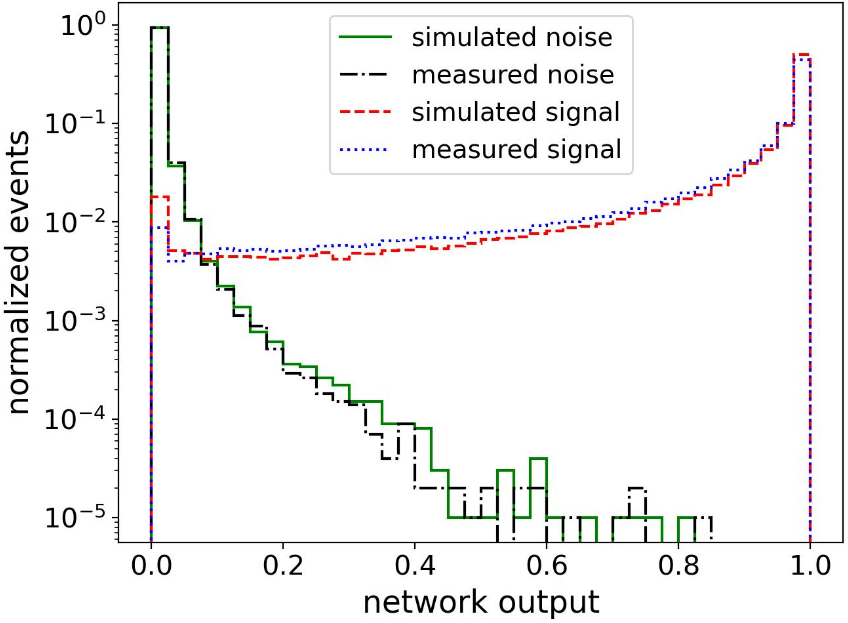


Lab Verification

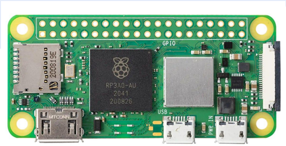
Goal: compare network output values for simulated and experimental data

- The network outputs for simulated and measured signal and noise agree well
- Simulations accurately describe experimental data
- Noise rejection factor and signal efficiency found with simulations earlier are credible

➔ Did not achieve a processing rate of 1 kHz



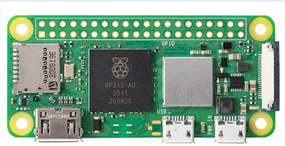
Ongoing work



A deep learning filter will be added to the next generation of ARIANNA detectors

➔ Microprocessor will be upgraded

Ongoing work



MBED	Raspberry Pi
~ 0.3 W	~ 1 W
3.7 ms | 270 Hz	0.39 ms | 2.5 kHz

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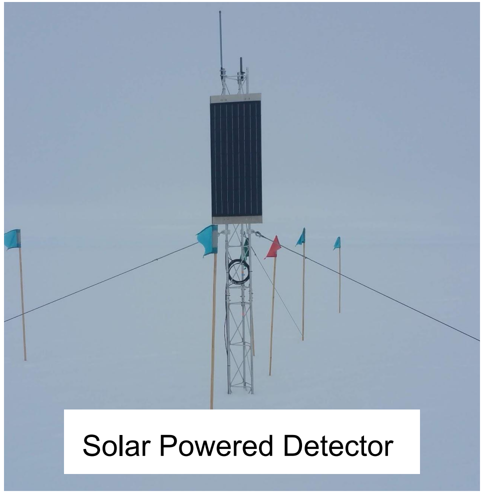
- Power consumption studies



Solar Powered Detector

Ongoing work

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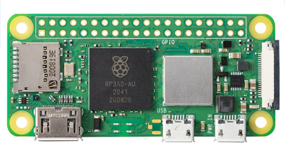
- Power consumption studies
- Cold testing



MBED	Raspberry Pi
~ 0.3 W	~ 1 W
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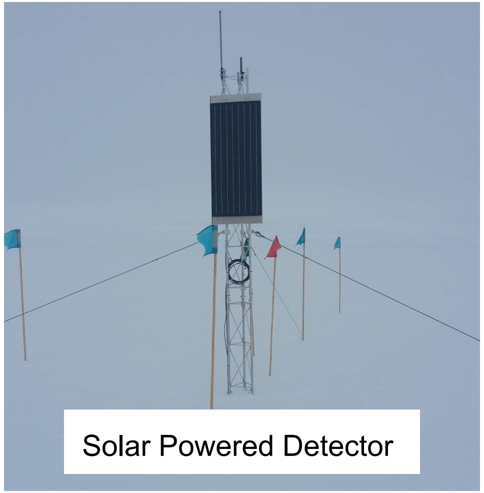
Thermal Chamber (-60c)

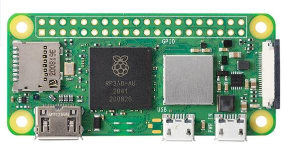


Solar Powered Detector

Ongoing work

A deep learning filter will be added to the next generation of ARIANNA detectors

- ➔ Microprocessor will be upgraded
    - ◆ Power consumption studies
    - ◆ Cold testing
    - ◆ Implementation onto ARIANNA board
    - ◆ Robustness studies



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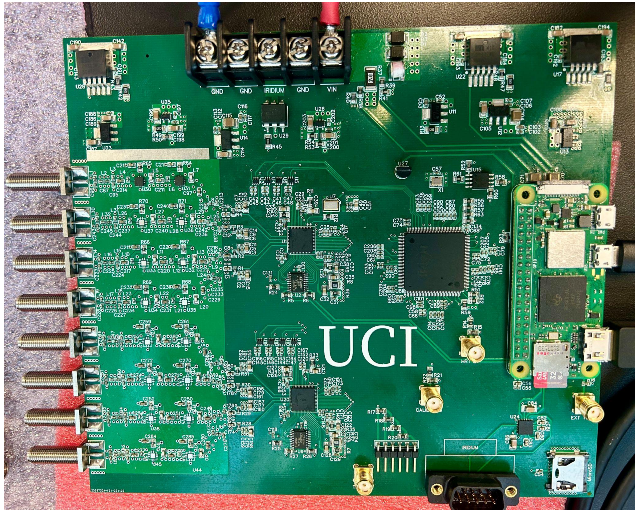

Improving Offline Analysis Techniques with Deep Learning

Goal: Improve neutrino search techniques on experimental ARIANNA data with deep learning

- ➔ Using recently acquired station 61 (neutrino configuration)
- ➔ Want to reject all experimental data since it does not contain neutrinos

Paper in preparation

Project 2

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*Not simulatable

- ➔ Experimental background consist of **wind, BMU,** and **thermal noise**
- ➔ We have no experimental neutrino signal
  - ◆ Train a network on experimental station 61 background and simulated neutrino signal

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- ➔ Potential issues include the network training on artifacts of the simulated/measured data

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- ➔ We have no experimental neutrino signal
  - ◆ Train a network on experimental station 61 background and simulated neutrino signal

- ➔ Potential issues include the network training on artifacts of the simulated/measured data
- ➔ A solution is to use experimental ARIANNA cosmic ray signal data as a check for potential artifacts
  - ◆ Using station 52 data (cosmic ray configuration)

Paper in preparation

Data sets

Neutrino station 61:

- Experimental background noise (wind, BMU, thermal)
- Simulated neutrino signal

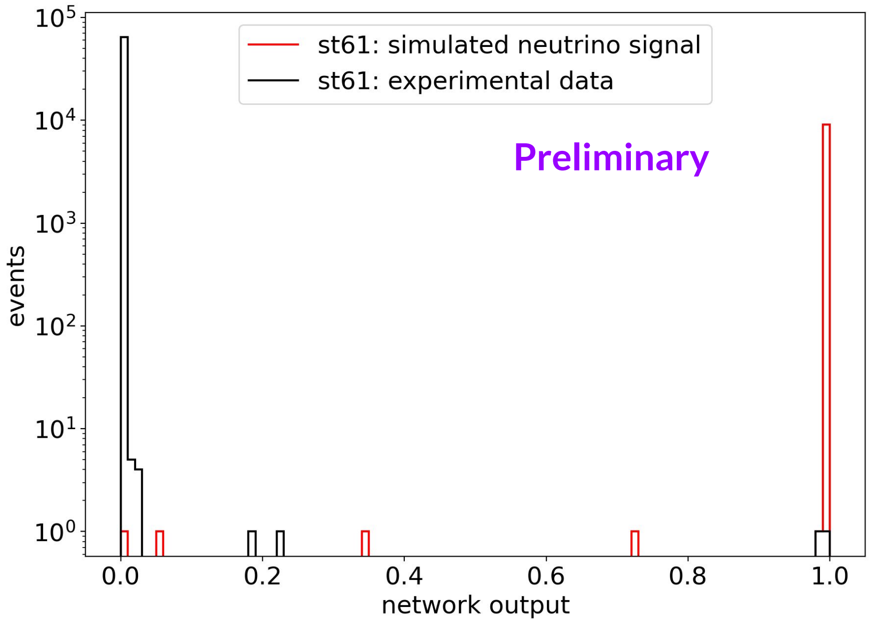
Cosmic ray station 52:

- Experimental background noise (wind, BMU, thermal)
- Simulated cosmic ray signal
- Experimental cosmic ray signal (85 events)

Classification Efficiency

Neutrino station 61:

- Experimental background noise (wind, BMU, thermal)
- Simulated neutrino signal

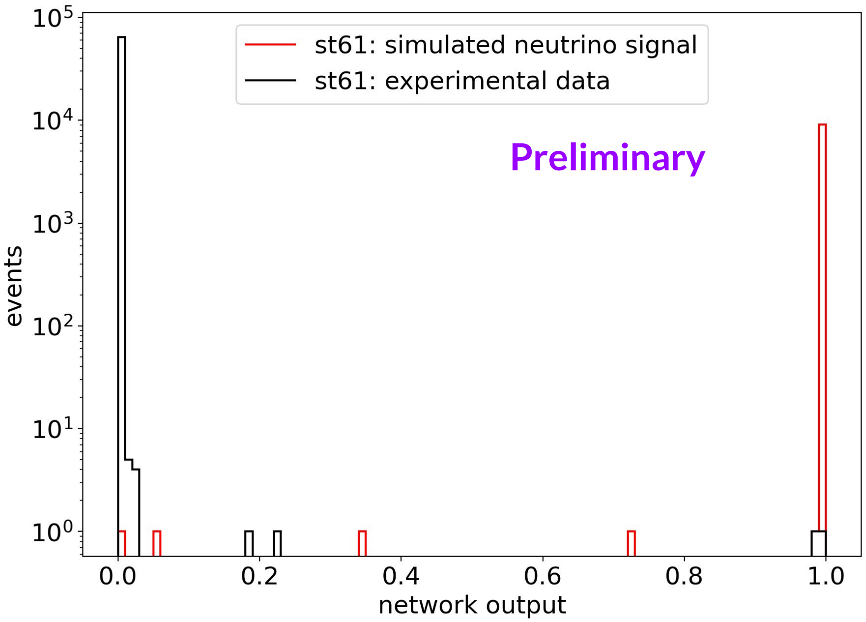


Classification Efficiency

Neutrino station 61:

- Experimental background noise (wind, BMU, thermal)
- Simulated neutrino signal

➔ Convolutional neural network trained on these data sets incorrectly classifies two noise events as signal and three neutrino signal events as noise



Classification Efficiency

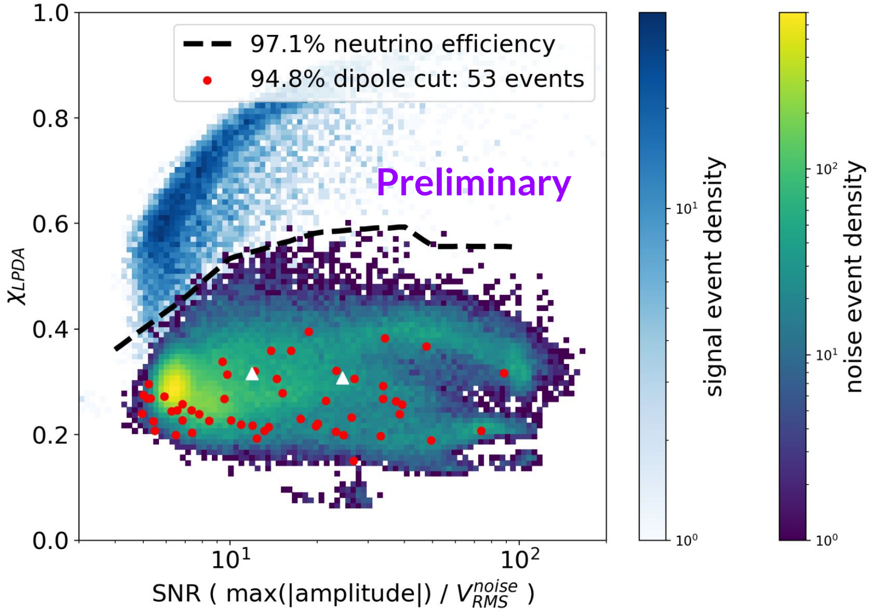
Neutrino station 61:

- Experimental background noise (wind, BMU, thermal)
- Simulated neutrino signal

➔ Convolutional neural network trained on these data sets incorrectly classifies two noise events as signal and three neutrino signal events as noise

➔ Trained network achieves 99% signal effciency with 2 remaining noise events (white triangles)

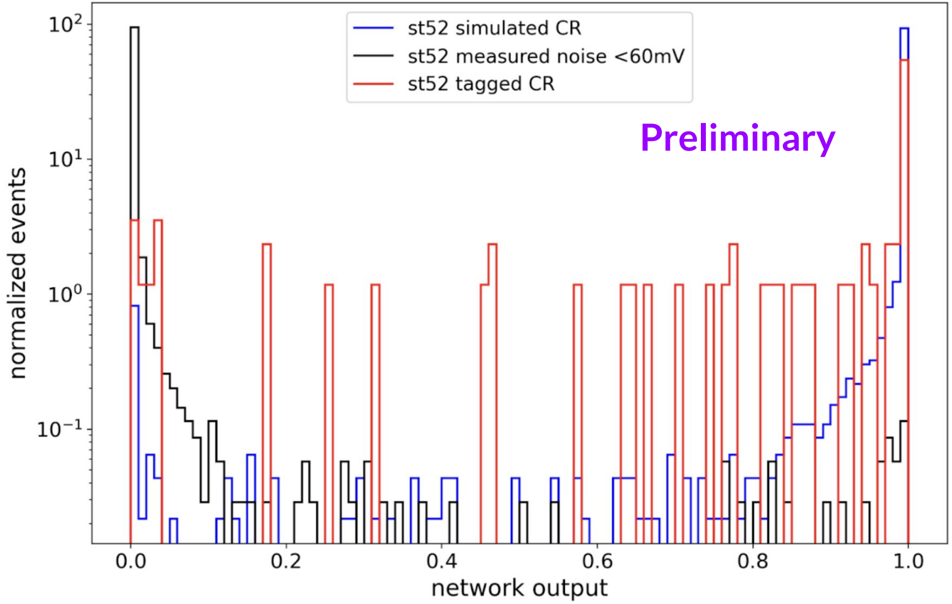
➔ Traditional methods achieve 97% signal efficiency with 53 remaining noise events (red dots)



Artifact Study

Cosmic ray station 52:

- Experimental background noise (subset)
- Simulated cosmic ray signal
- Experimental (tagged) cosmic ray signal (85 events)



Artifact Study

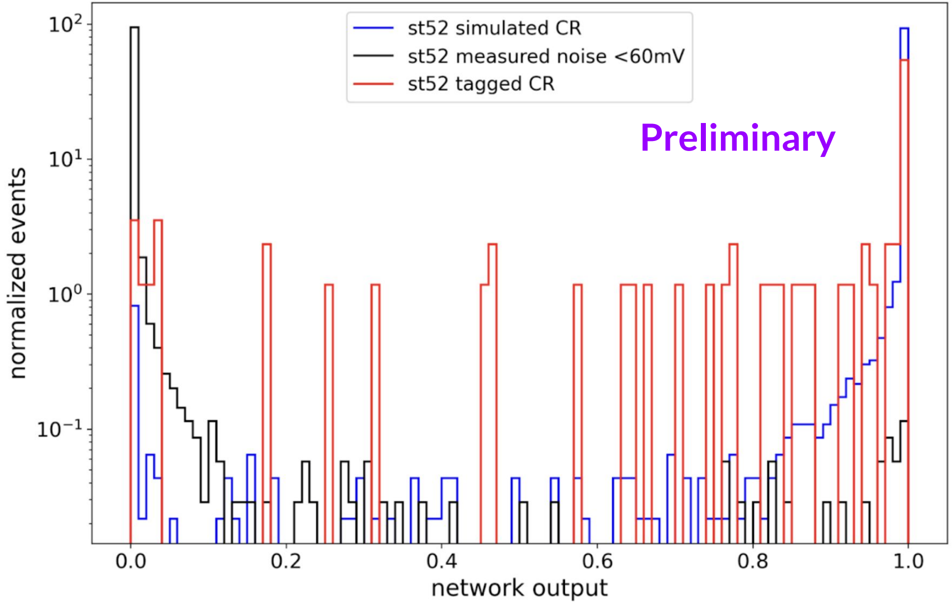
Cosmic ray station 52:

- Experimental background noise (subset)
- Simulated cosmic ray signal
- Experimental (tagged) cosmic ray signal (85 events)

➔ Low statistics in experimental tagged cosmic rays (red data)

➔ If an artifact is present, red data would match black data

➔ Vast majority of experimental cosmic rays (red data) are properly identified



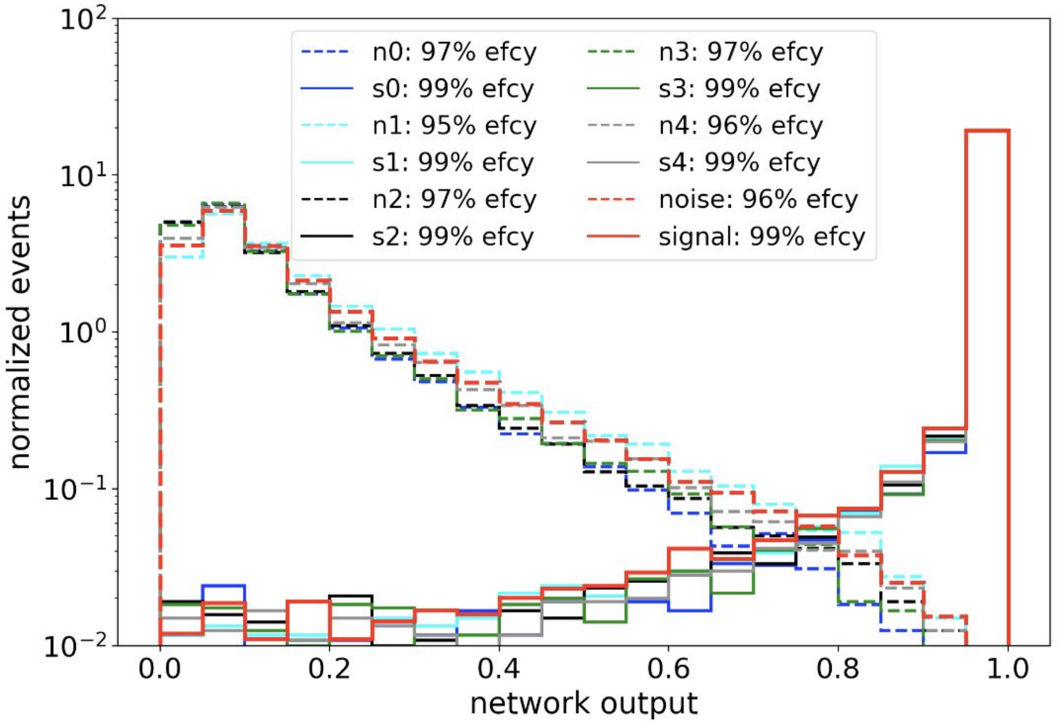
Thank you!

ARIANNA collaboration

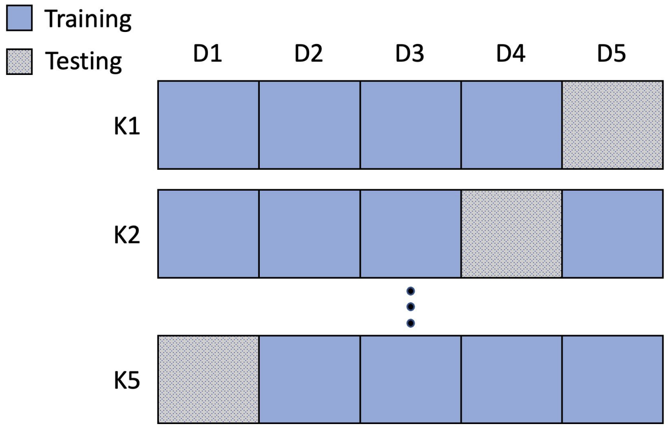
A. Anker [a,1] P. Baldi[b] S. W. Barwick[a] J. Beise[c] D. Z. Besson[d] S. Bouma[e] M. Cataldo[e] P. Chen[f] G. Gaswint[a] C. Glaser[c] A. Hallgren[c] S. Hallmann[g] J. C. Hanson[h] S. R. Klein[i] S. A. Kleinfelder[j] R. Lahmann[e] J. Liu[a] M. Magnuson[d] S. McAleer[b] Z. S. Meyers[g,e] J. Nam[f] A. Nelles[e,g] A. Novikov[d] M. P. Paul[a] C. Persichilli[a] I. Plaisier[e,g] L. Pyras[g,e] R. Rice-Smith[a] J. Tatar[k] S.-H Wang[f] C. Welling[e,g] L. Zhao[a]

Extra slides

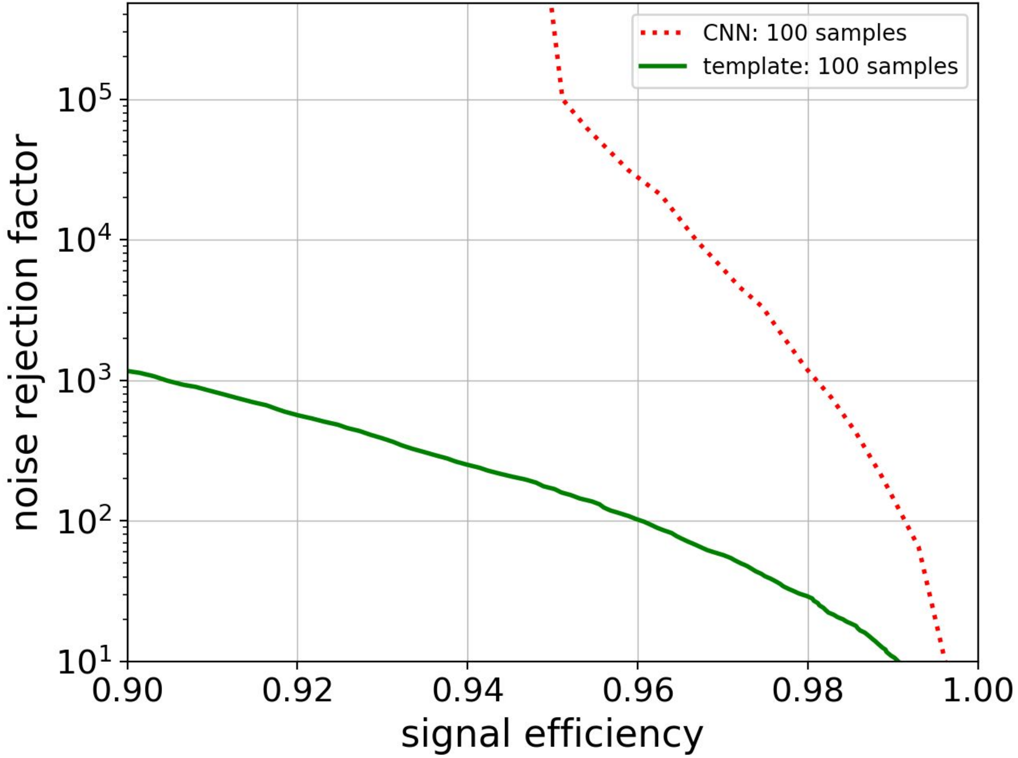
Stability in training a DL network



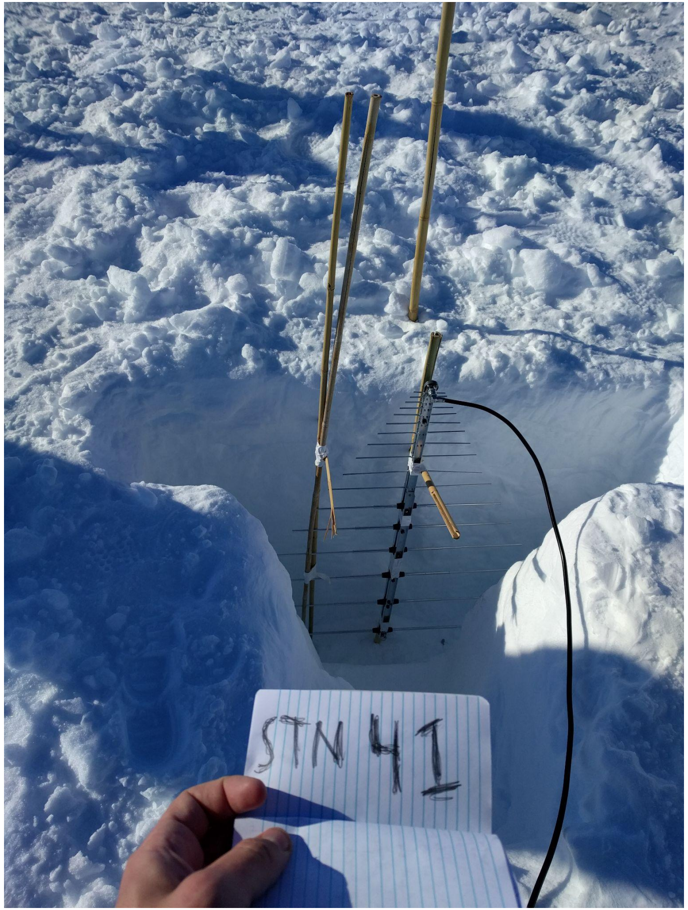
100 sample CNN
5-fold cross validation



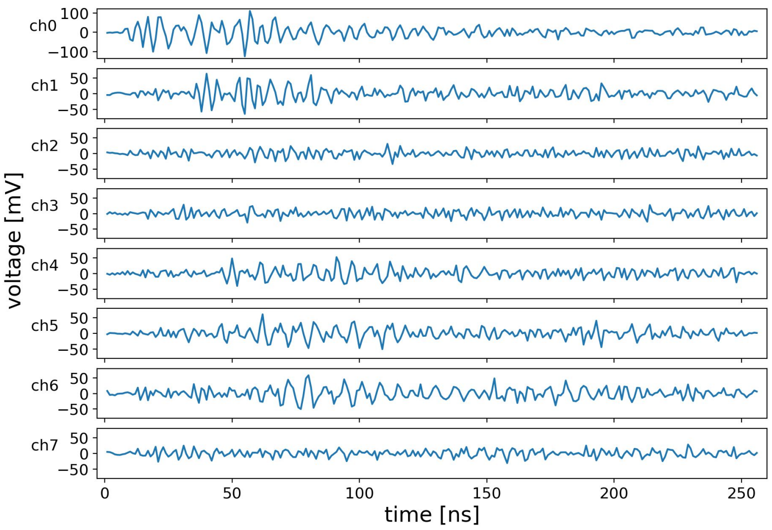
DL compared to more classical analysis methods

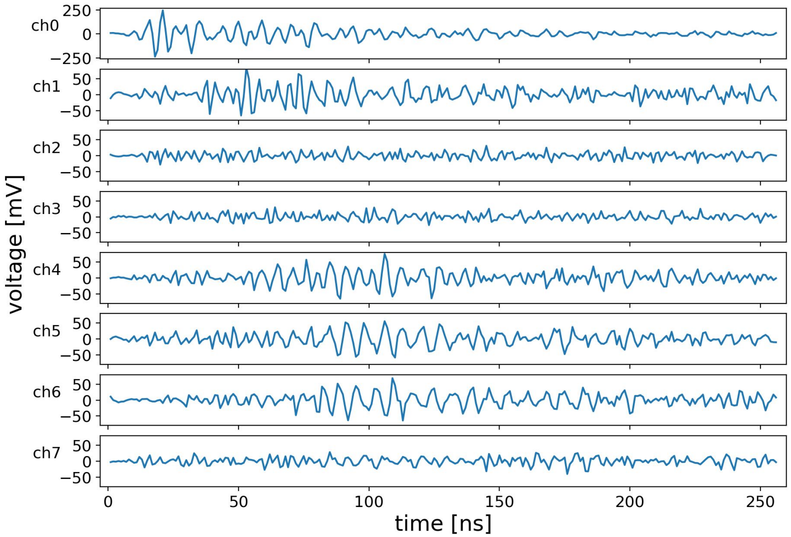


Antennas buried in the ice



Two noise waveforms for station 61 classified as signal





Training Data Sets

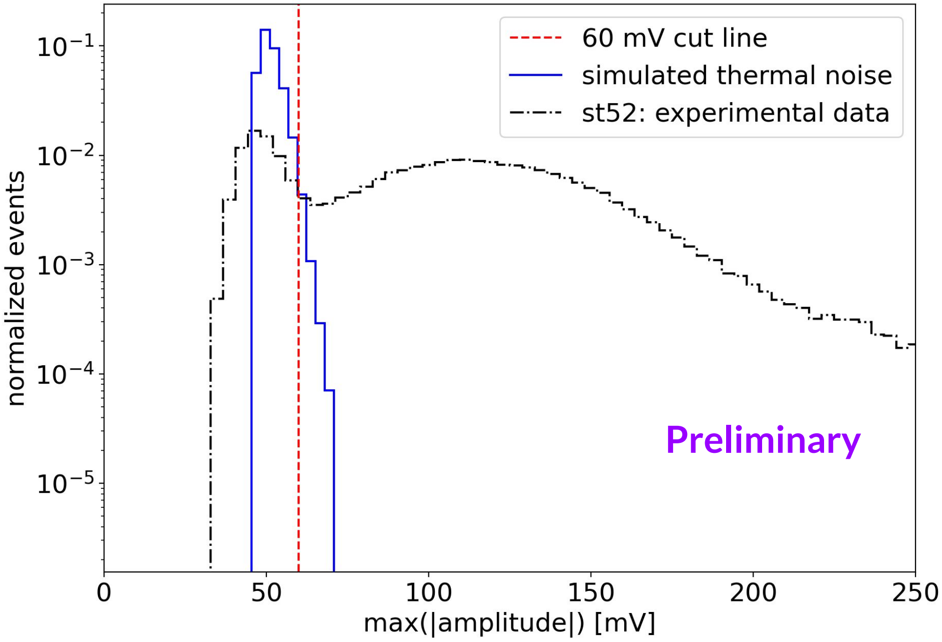
Cosmic ray station 52:

- Experimental background noise (wind, BMU, thermal)
- Simulated cosmic ray signal
- Experimental cosmic ray signal (85 events)

➔ Experimental data has separate populations of thermal noise and wind/BMU events

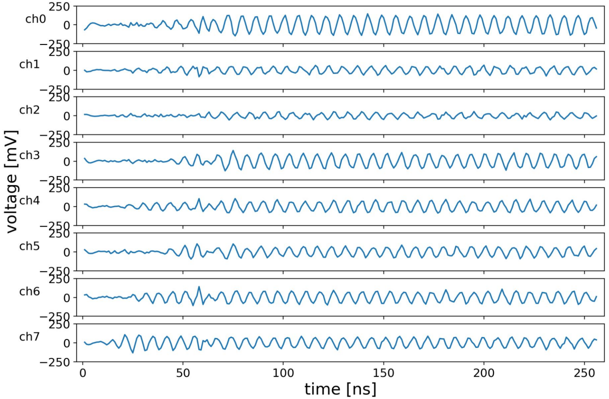
➔ Cut on experimental data above 60 mV to match the thermal noise distribution

➔ Use this data for training

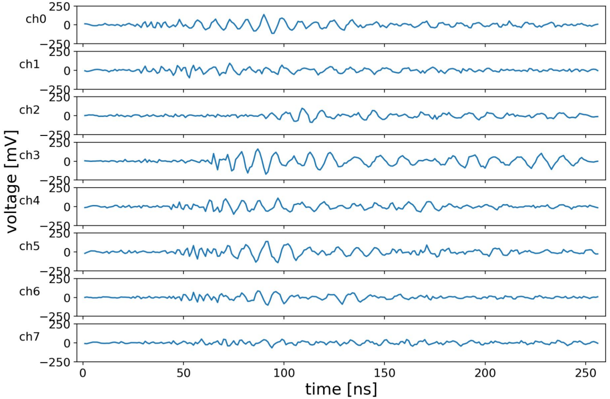


Example waveforms (BMU, wind, expCR, NU, TN)

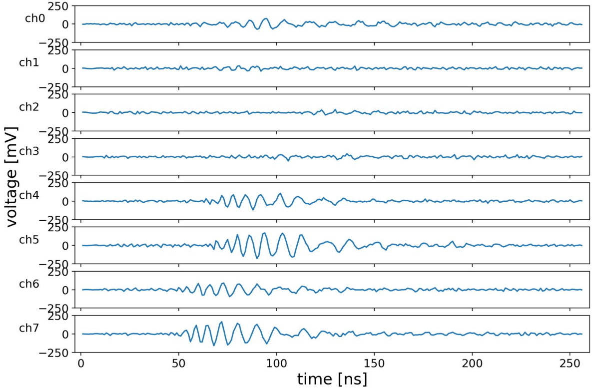
BMU



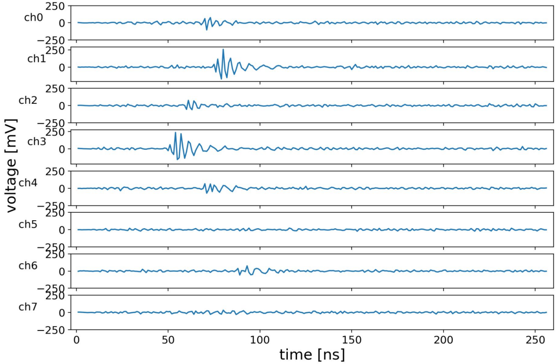
wind

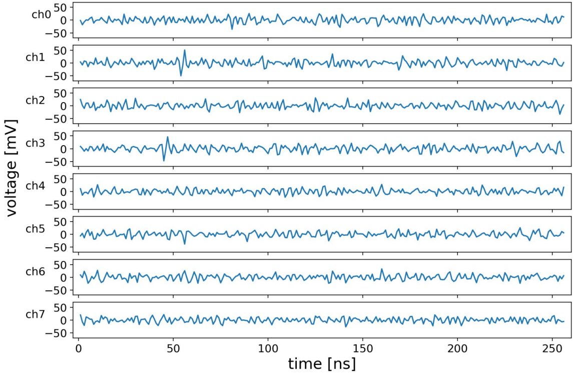


expCR



simNU





Thermal noise