

Development of Machine Learning Based Triggering for ICEBERG Liquid Argon Time Projection Chamber

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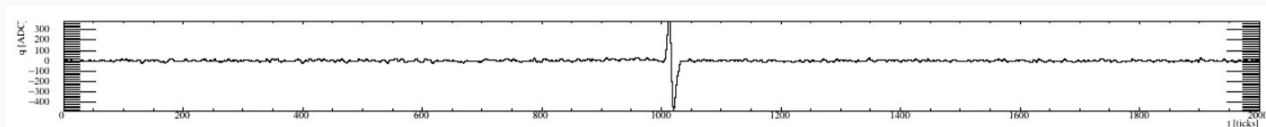
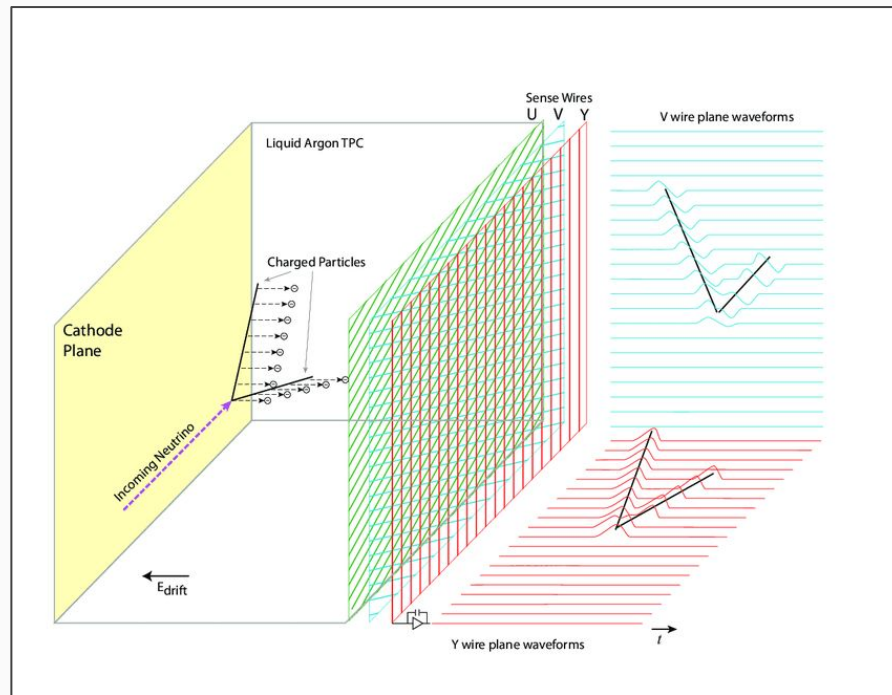
Neutrinos & Rare Events Group, 2023 NSF REU at Nevis Laboratories at Columbia University



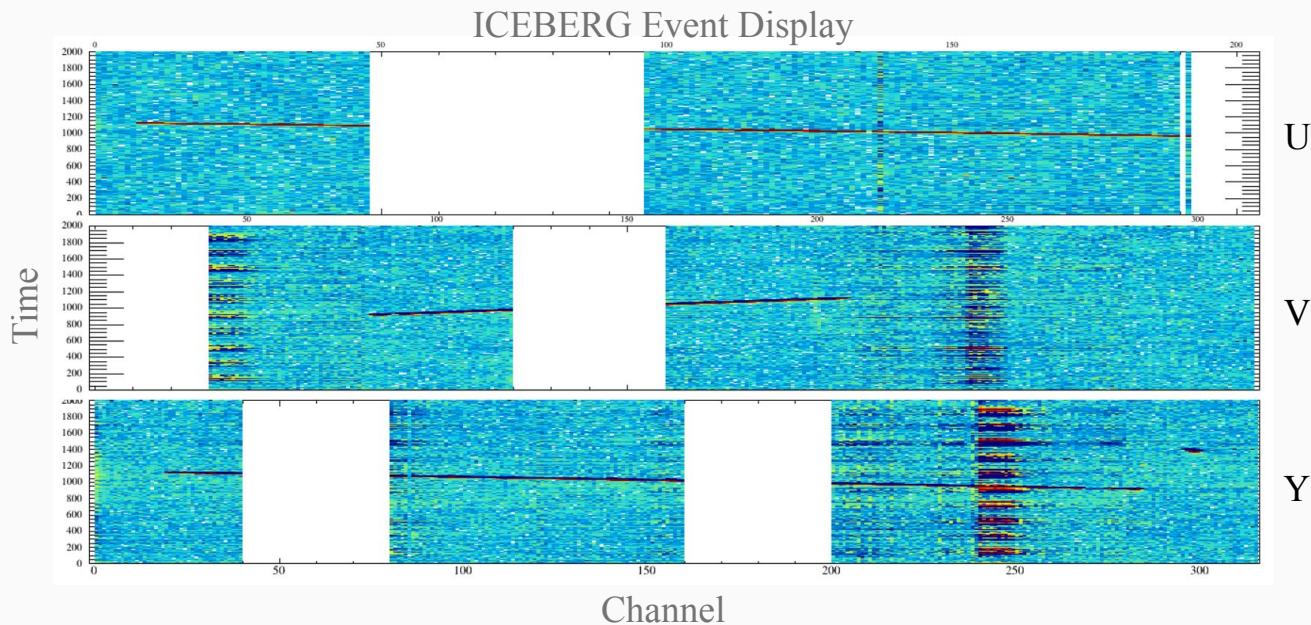
- Background & Motivation
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Background & Motivation

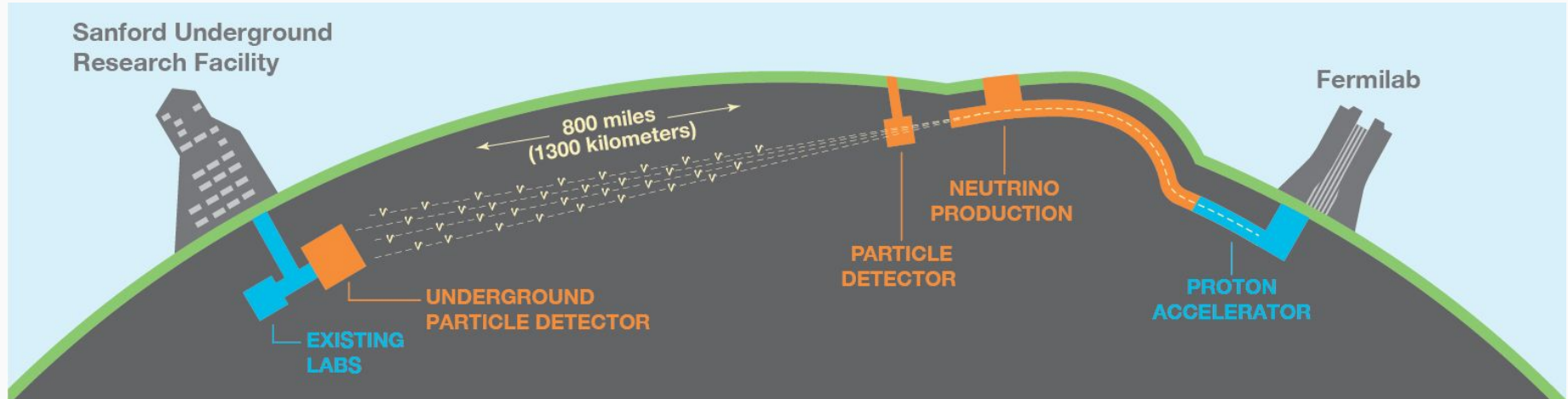
- Detection of charged particles
 - Ionization Electrons
 - Scintillation Light
- Constructs 3D particle path using spatial (channel) information and timing information
- Components:
 - Liquid Argon
 - Electric Field
 - Induction Planes
 - Collection Plane
 - PMTs



- Signals are read as ADC waveforms on the wires
- A 2D event display can be constructed to visualize the particle's path:
 - Channel vs Time vs ADC count



- LArTPC deep underground to decrease background
- Major Objectives:
 - Neutrino Mass hierarchy
 - CP Violation in neutrinos
 - Observation of proton decay
 - Supernova neutrino detection



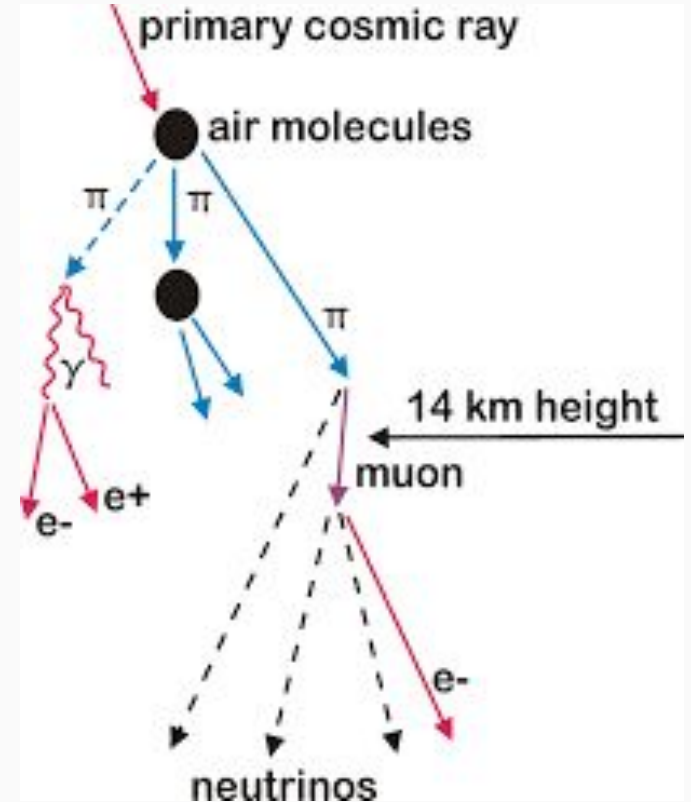
- DUNE is very large and very expensive
- Prototypes must be used to test the hardware/software
- ICEBERG
 - “Integrated Cryostat and Electronics Built for Experimental Research Goals”



- Contains ~4.5 tons of liquid argon
 - Dune will have a total of 70 kilotons
- Not underground!

- Cosmic rays
 - Atomic nuclei traversing space at relativistic speeds
- Upon entering Earth's atmosphere, they decay into pions (mesons)
- Pions decay quickly into muons (heavy leptons)
- Muons most common mode of decay (Michel Decay) is:

$$\mu \rightarrow \nu_{\mu} + \bar{\nu}_e + e$$



- Muons are unstable and decay within microseconds at rest
 - This is slower from our reference frame because they move at relativistic speeds
- DUNE will be strongly shielded from cosmic ray muons, but ICEBERG isn't
 - Michel decay is well understood and can be used for electronics calibration and testing software

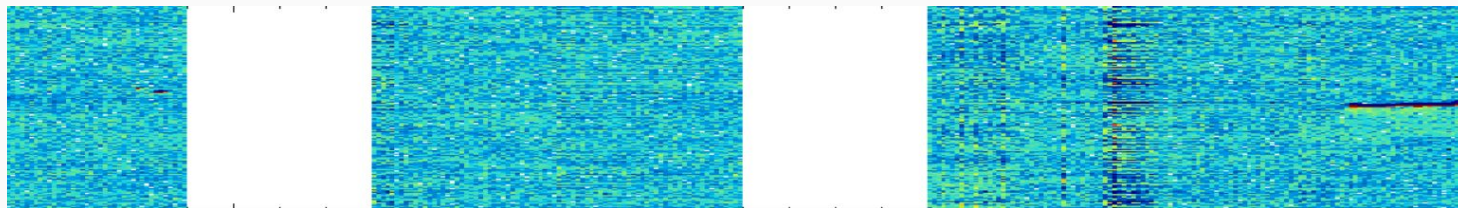


- I am creating an algorithm for detecting Michel decay against background
- DUNE will generate several terabytes of data every second
 - Most of this cannot be stored
 - Must be reduced by an order of 10,000 to meet hardware limitations

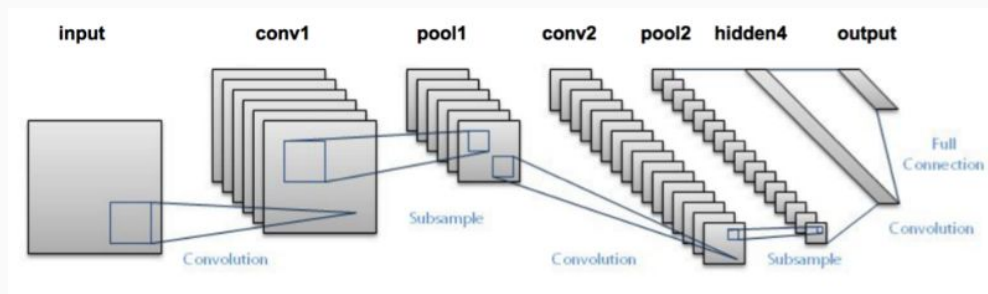
An algorithm that decides what data to store must be developed:

- Must be fast
 - DUNE will collect data in real time
- Must be accurate
 - DUNE aims to observe very rare events; we can't afford to miss them
 - ~99.5% of noise signals must be discarded
- Must not be highly computationally complex
 - Hardware resources are constrained

- Machine Learning has proven to be an effective method for event triggering
- Two-Dimensional Convolutional Neural Networks (2D CNNs) perform excellently in image classification
 - LArTPC event displays are simply images

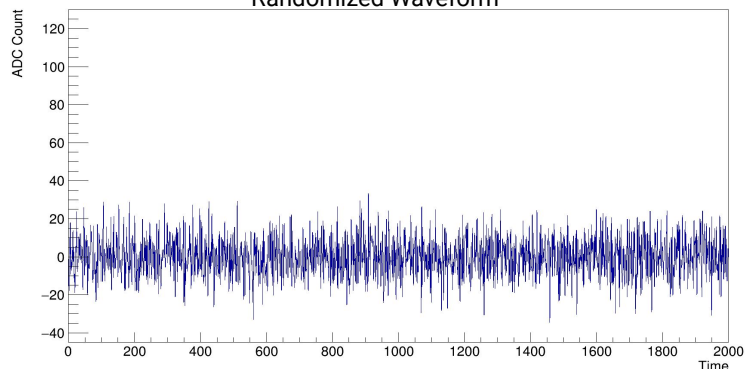


- **Input layer**
 - Tensor with dimensions: Length $\times$ Width $\times$ Color Channel
- **Zero Padding Layer**
 - Changes dimensions of tensor by adding entries with 0 value
 - May be necessary for operations in later layers
- **Pooling Layer**
 - Groups together nearby entries to reduce parameter count and computational load
- **Convolutional Layer**
 - Performs mathematical convolution between input tensor and a convolution matrix predetermined from training
- **Fully Connected Layer**
 - Every neuron applies a preset activation function to the input tensor

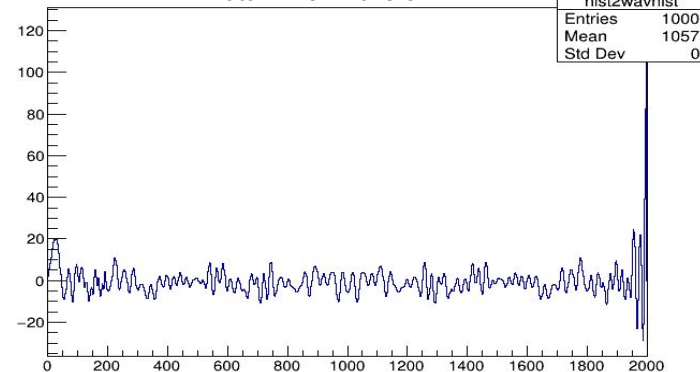


- A neural network must be trained on a very large, labelled dataset
 - This can effectively be produced via simulation
- Stopping muons can be simulated, but a data-driven noise model for ICEBERG does not yet exist
 - A method for generating noise must be generated using real noise data (because we can't simulate from first principles) to ensure accuracy to real events

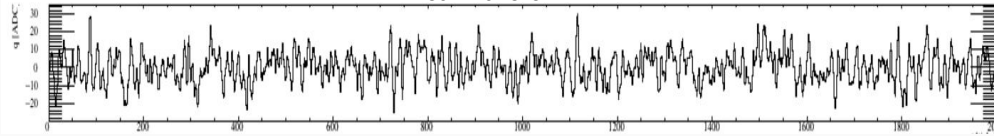
Randomized Waveform



Data-Driven Waveform



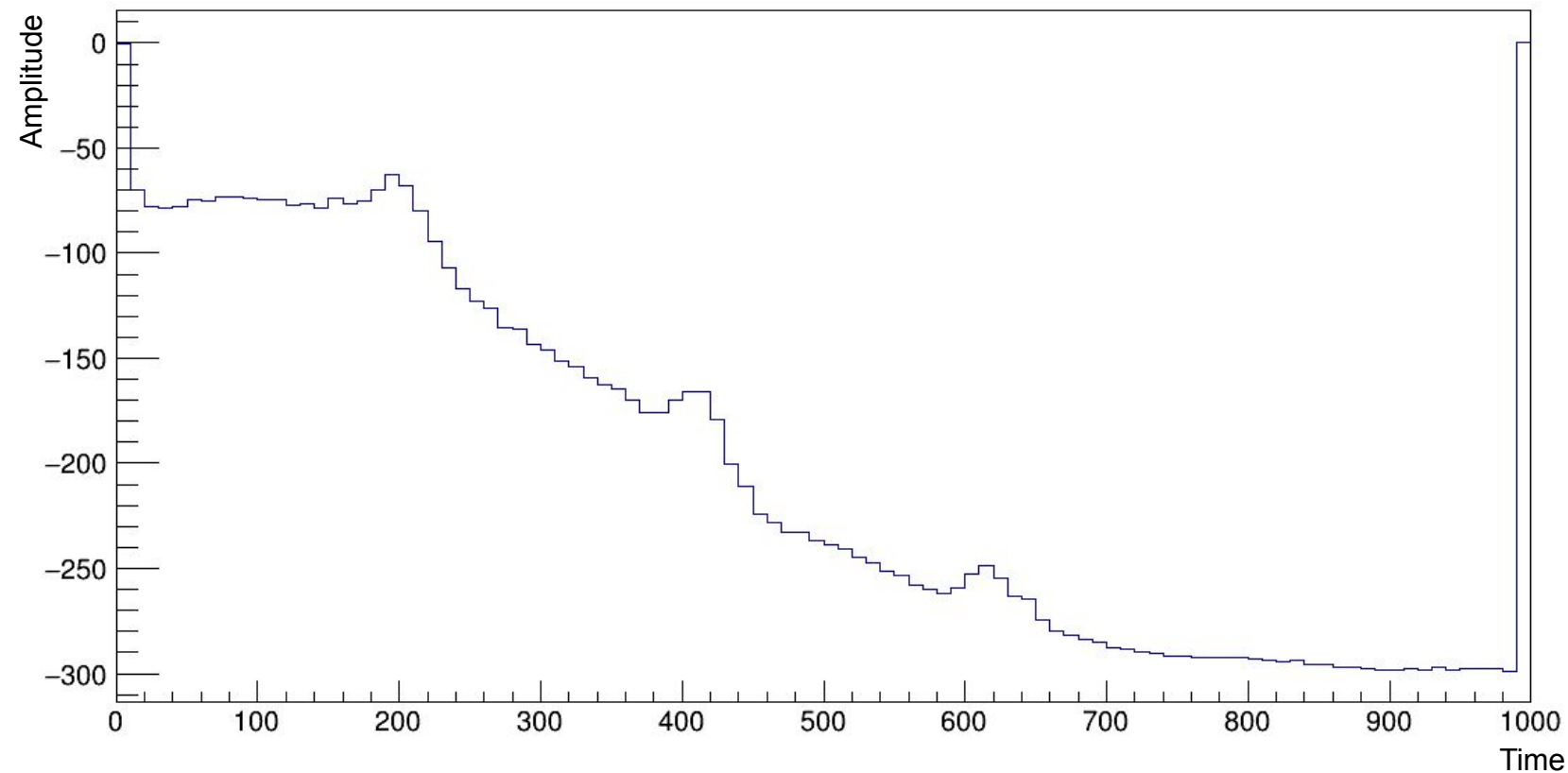
Real Waveform

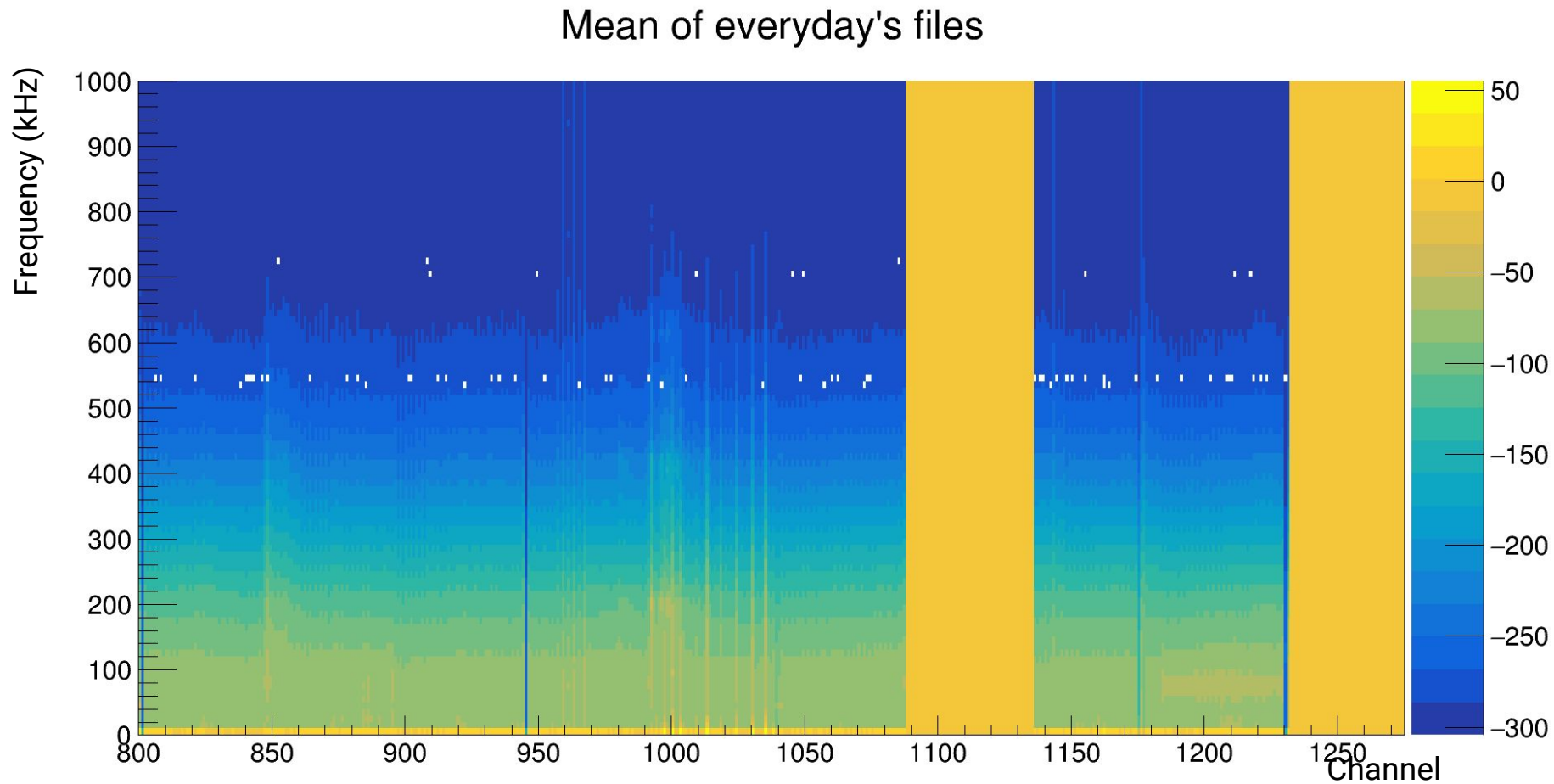


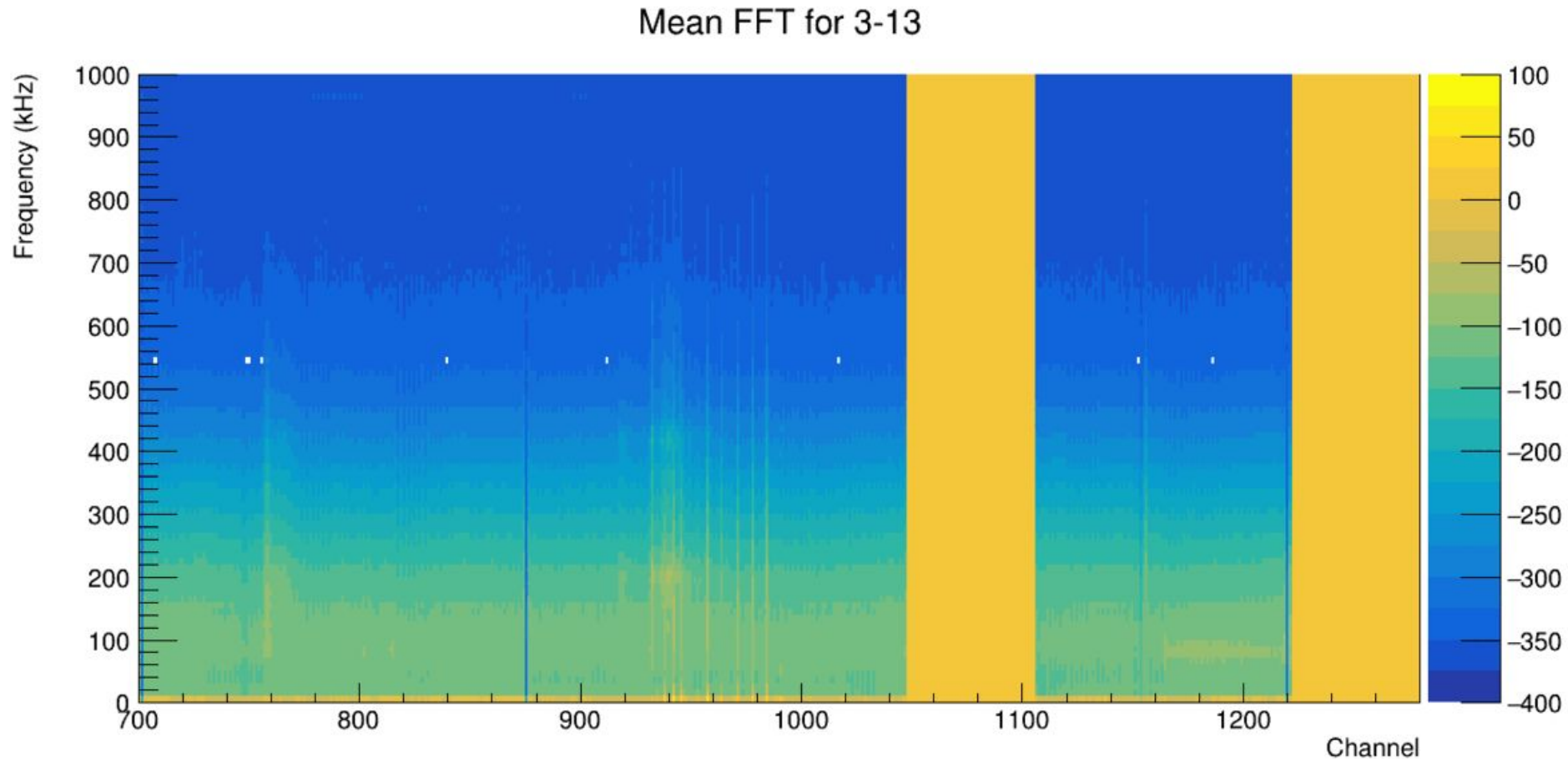
Data-Driven Noise Model

- A Fast Fourier Transform (FFT) can be used to calculate the frequencies and associated amplitudes of a given waveform
 - This information is critical for generating a simulated waveform
- Each channel experiences noise slightly different
 - Different lengths and positions within the detector
 - We must therefore analyze the frequencies associated with each channel independent of the others
- Noise varies over time
 - Files containing data collected between 3/13/21 and 4/4/21 were analyzed to avoid overfitting to a single time
 - FFT's for each day were compared to look for trends relating to time

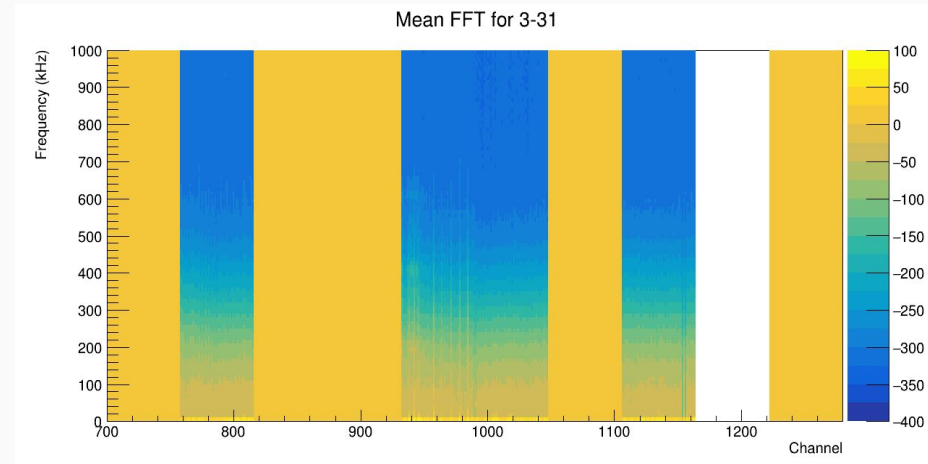
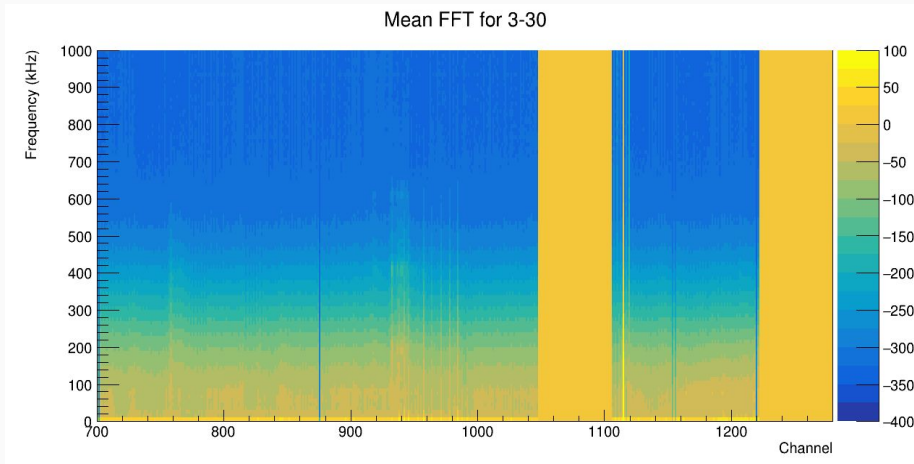
FFT of Channel 1000



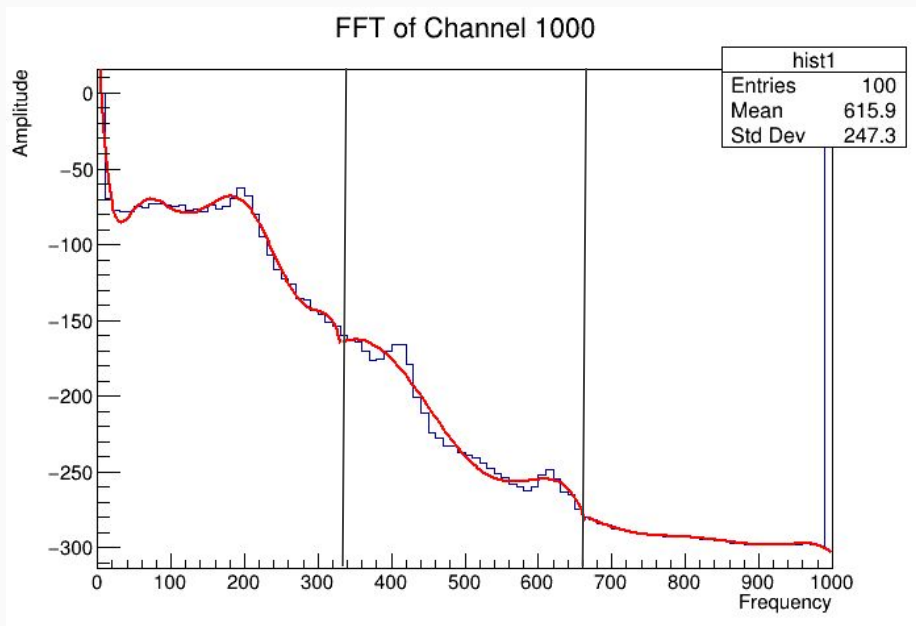




- No trends were noticeable as time passes, but variance is still present
- The same channels tend to consistently be the noisiest
- Some days have different Data Acquisition (DAQ) configurations, causing them to have different dead channels

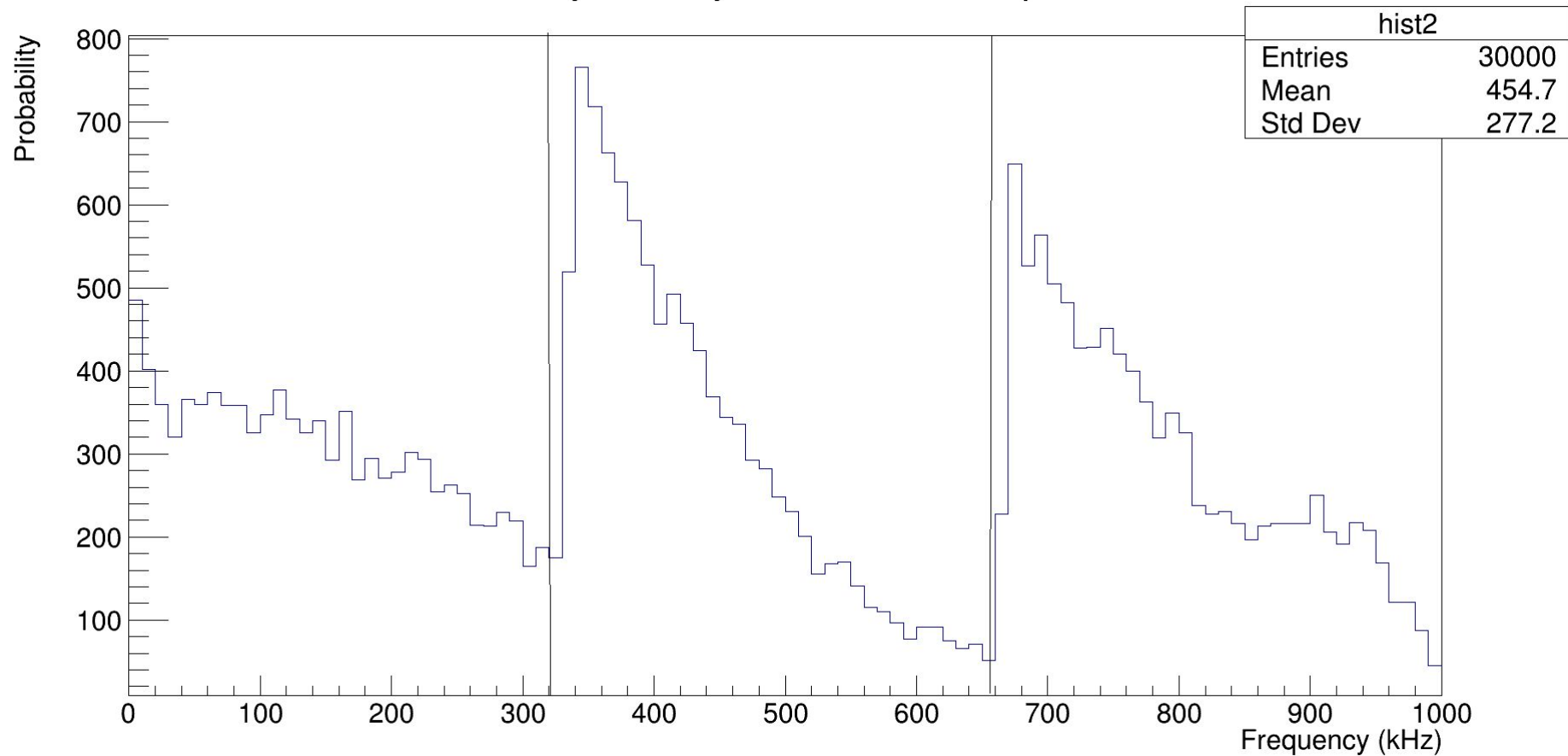


- The average FFT is divided into three regions: low frequency, middle frequency, and high frequency
- A function is fitted to each region using polynomial interpolation
 - This function behaves as a probability density function

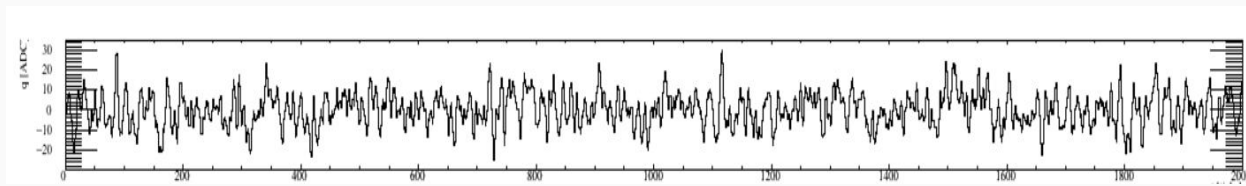
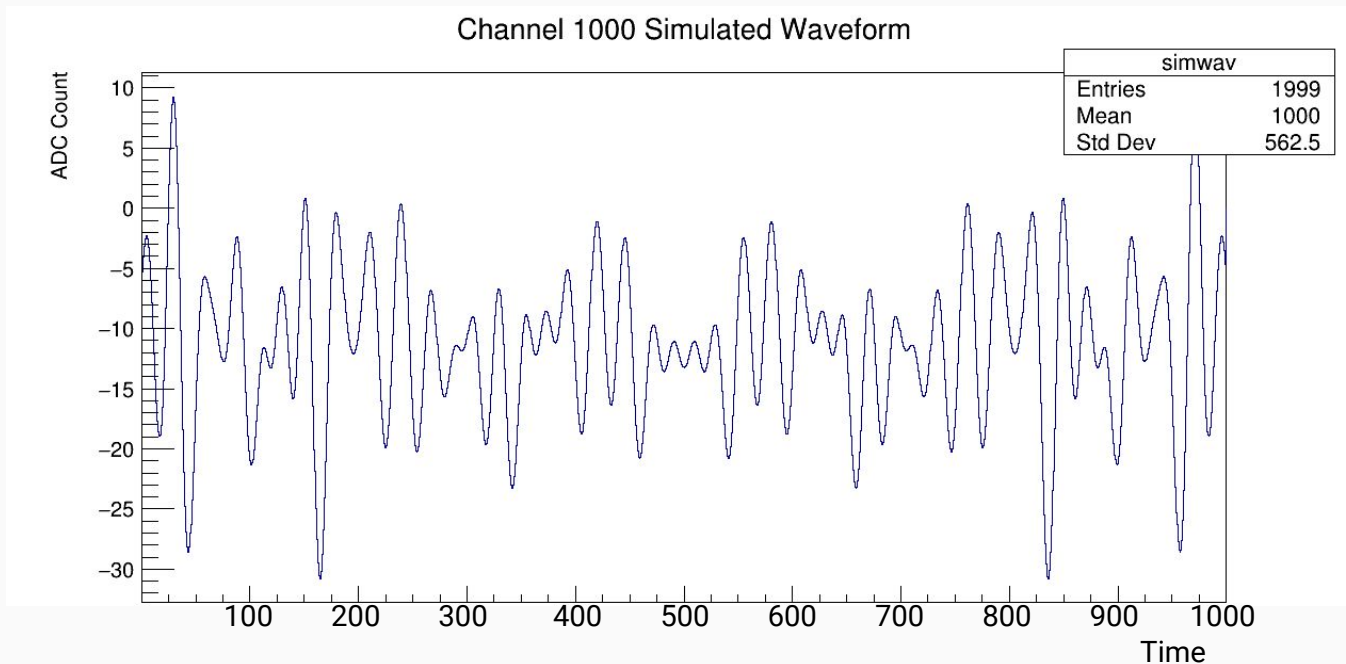


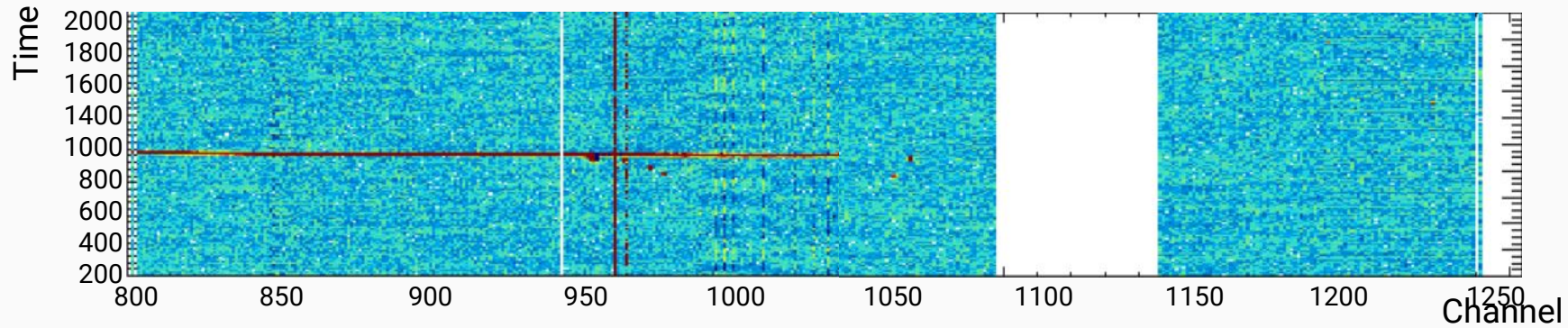
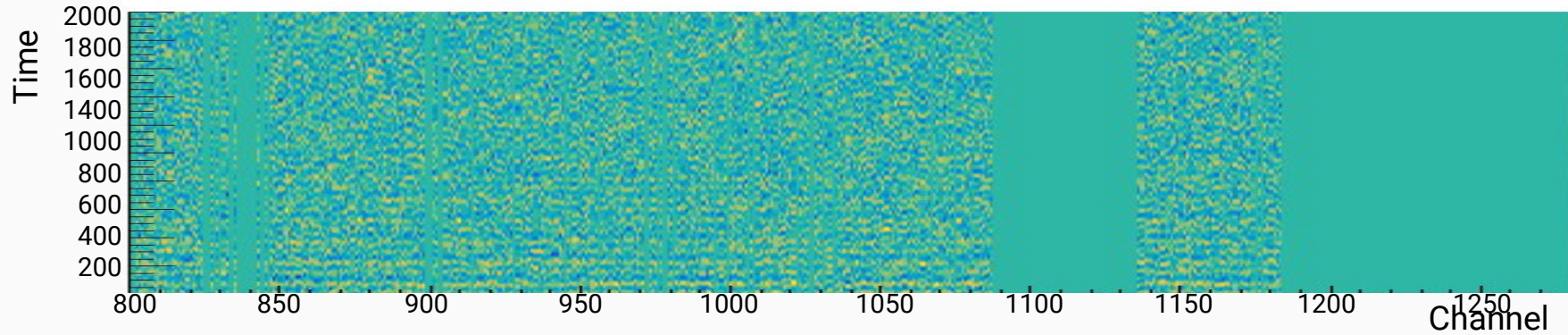
- One frequency is randomly selected from each region based on the probability density function
- An inverse FFT is performed to generate a waveform with these three frequencies

Probability Density Function of Frequencies



Low: 70 kHz
Mid: 430 kHz
High: 700 kHz



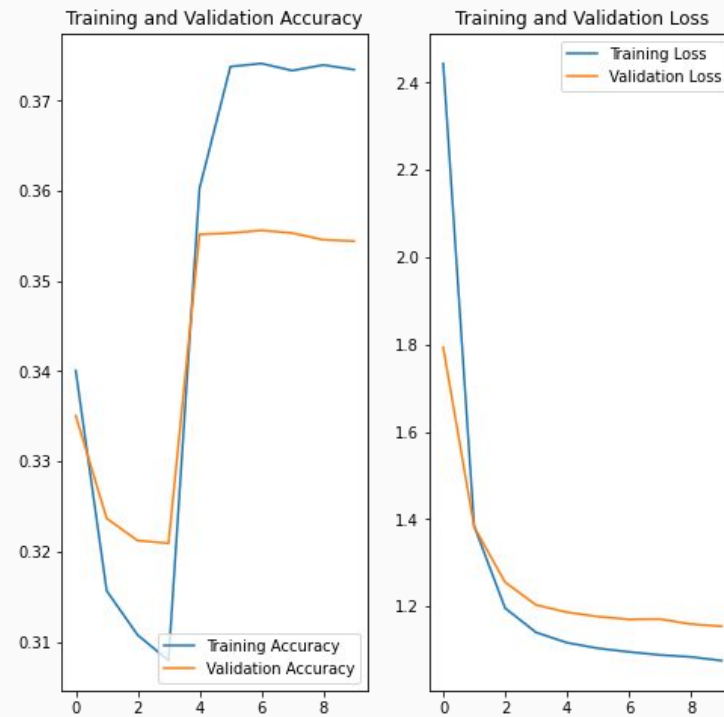


Convolutional Neural Network

- Two Dimensional Convolutional Neural Network (2D CNN)
- Based on a network previously developed to detect low energy neutrino events in DUNE
 - Low parameter count, and high accuracy

Layer (type)	Output Shape	Param #
resizing_28 (Resizing)	(None, 64, 480, 3)	0
zero_padding2d_73 (ZeroPadding2D)	(None, 64, 512, 3)	0
max_pooling2d_92 (MaxPooling2D)	(None, 32, 64, 3)	0
zero_padding2d_74 (ZeroPadding2D)	(None, 34, 66, 3)	0
conv2d_70 (Conv2D)	(None, 32, 64, 2)	56
re_lu_60 (ReLU)	(None, 32, 64, 2)	0
max_pooling2d_93 (MaxPooling2D)	(None, 16, 16, 2)	0
zero_padding2d_75 (ZeroPadding2D)	(None, 18, 18, 2)	0
conv2d_71 (Conv2D)	(None, 16, 16, 2)	38
re_lu_61 (ReLU)	(None, 16, 16, 2)	0
max_pooling2d_94 (MaxPooling2D)	(None, 4, 4, 2)	0
reshape_13 (Reshape)	(None, 1, 1, 32)	0
dense_46 (Dense)	(None, 1, 1, 12)	396
re_lu_62 (ReLU)	(None, 1, 1, 12)	0
dense_47 (Dense)	(None, 1, 1, 3)	39
Total params: 529		
Trainable params: 529		
Non-trainable params: 0		

- Training set contains simulated stopping muons and through-going muons
 - These simulations are only recently accessible, and further formatting is necessary to prepare them for training
- Network was tested on publicly accessible neural network datasets
 - Performance was poor because architecture was not optimized for this data



Summary & Conclusions

- A data-driven noise model has been developed for ICEBERG
 - A similar method will likely be used for DUNE
- A 2D CNN is promising for Michel Decay triggering, but it has not yet been trained and tested on the simulated data

- Improve accuracy of noise simulation
 - Truncate edge effects
 - Use larger dataset
- Improve speed of noise simulation
 - A simulated event display currently takes ~30 minutes to generate
- Train/optimize the Neural Network
 - Modify architecture to find ideal balance between complexity and performance
 - Compare if using all three detection planes improves performance
- Use CNN for detection of other interactions
 - Ar-39

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