ICEBERG as a Demonstrator for ML Integrated SN Pointing Algorithms

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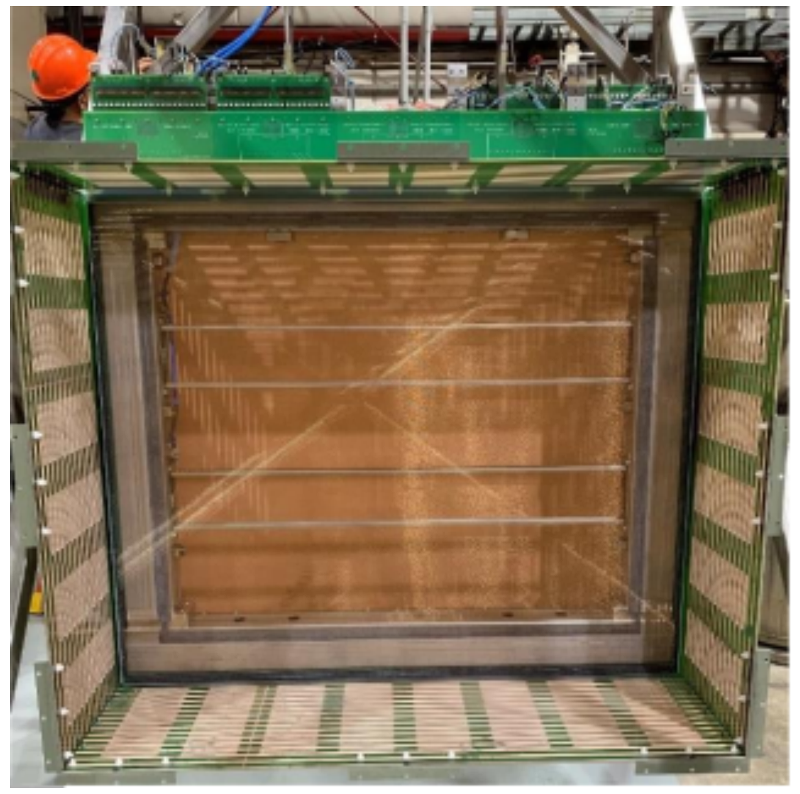
Going beyond Offline MC Studies for SN Pointing with ICEBERG

- Supernova pointing is a complex, real time problem for DUNE FD
- Offline DUNE MC simulation is a useful tool for model development, but supernova pointing is an *online* problem that will require us to model realistic detector noise conditions and backgrounds
- Since DUNE operations are a ways away, it would be ideal to have a small scale test bed to collect data, retrain offline models with real data, and eventually deploy retrained models online.
- Answer: ICEBERG!

The ICEBERG Detector

"*The Integrated Cryostat and Electronics Built for Experimental Research Goals*"

- Mini DUNE TPC primarily for cold electronics and DAQ functionality tests
- Data taking has happened from 2019-present
- Runs generated data under various gain, trigger configurations, shaping times
  - Makes for a great, diverse training dataset
  - The complete electronics DAQ integration makes ICEBERG a realistic choice for our tests as they would occur in DUNE FD

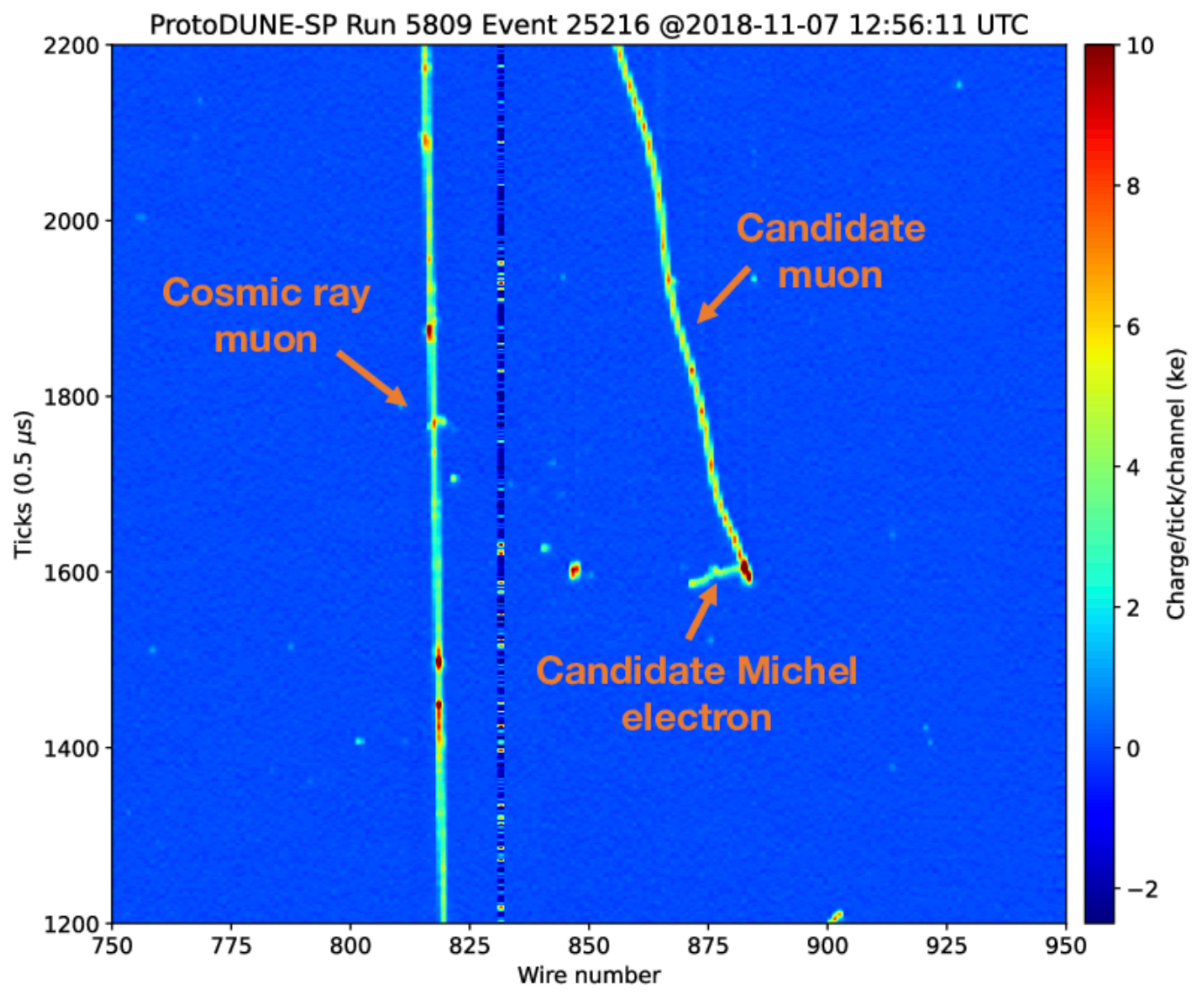


ICEBERG at Fermilab: EDMS id 2620749/1

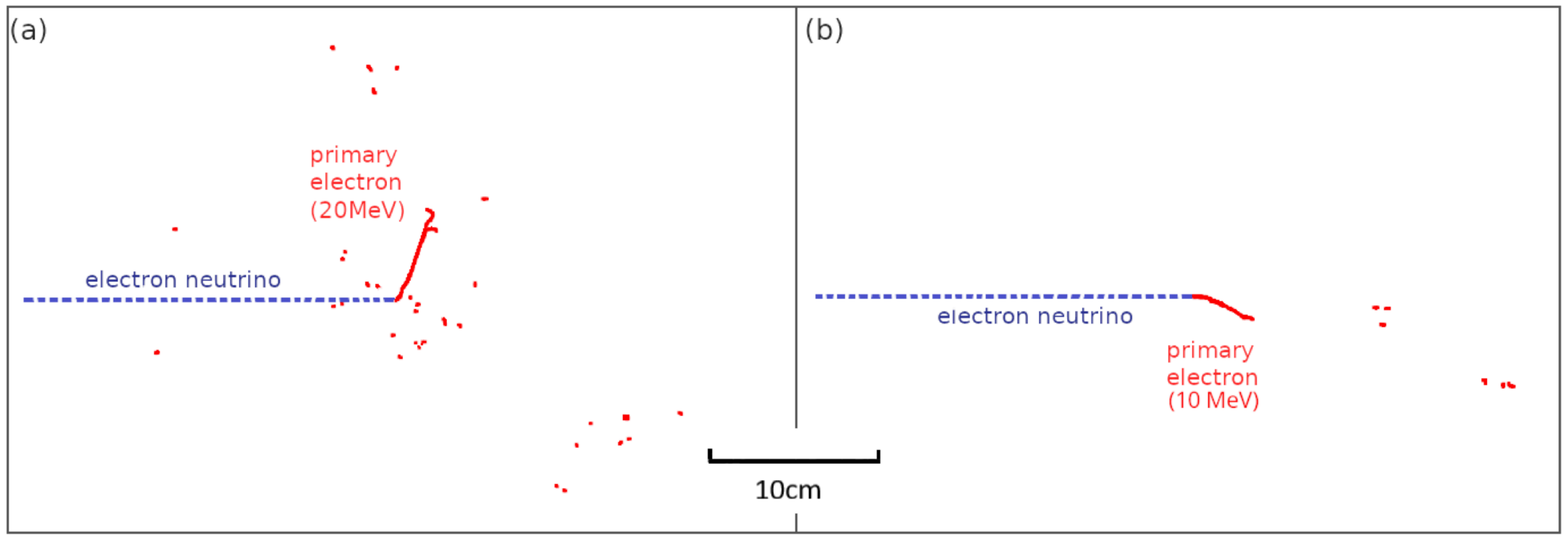
Why ICEBERG Data for a Supernova Pointing Demonstrator?

- Michel electron spectrum overlaps with Supernova electron neutrino spectrum so it can be used as a proxy for supernova tracks

- Muon tracks will exist within the ICEBERG event display while the electron neutrino will not, only the primary electron from scattering. The direction of the Michel electron is known since we can trace it back to the muon decay vertex. This allows us to test our algorithms that will determine the direction of the primary electron track from the supernova electron neutrino interaction



https://arxiv.org/pdf/2211.01166



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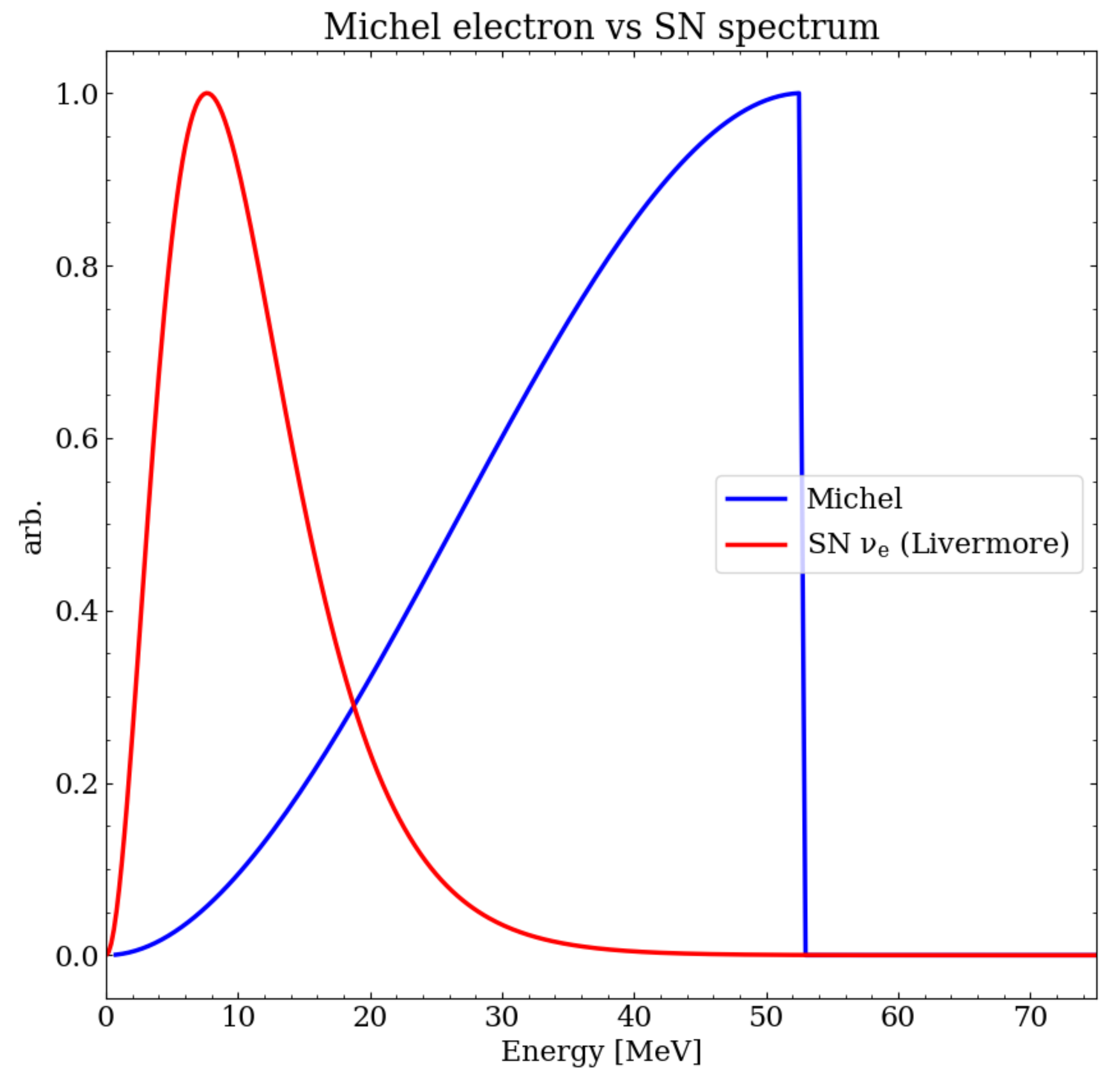


What Parts of our Current SN Pipeline can be Trained and Tested on ICEBERG Data?

DUNE FD

Ar-39 Beta vs. SN neutrino event Classifier (2D CNN)

Identifying eES vs. nuCC Hits (possibly localized) (CNN, BDT, LBP + Dense)

Electronics Denoising and LE Signal Reco (1D AE, GAN training)

Event Reconstruction and "Daughter Flipping" (Classical Algorithms, GNNs?)

Burst Likelihood

ICEBERG

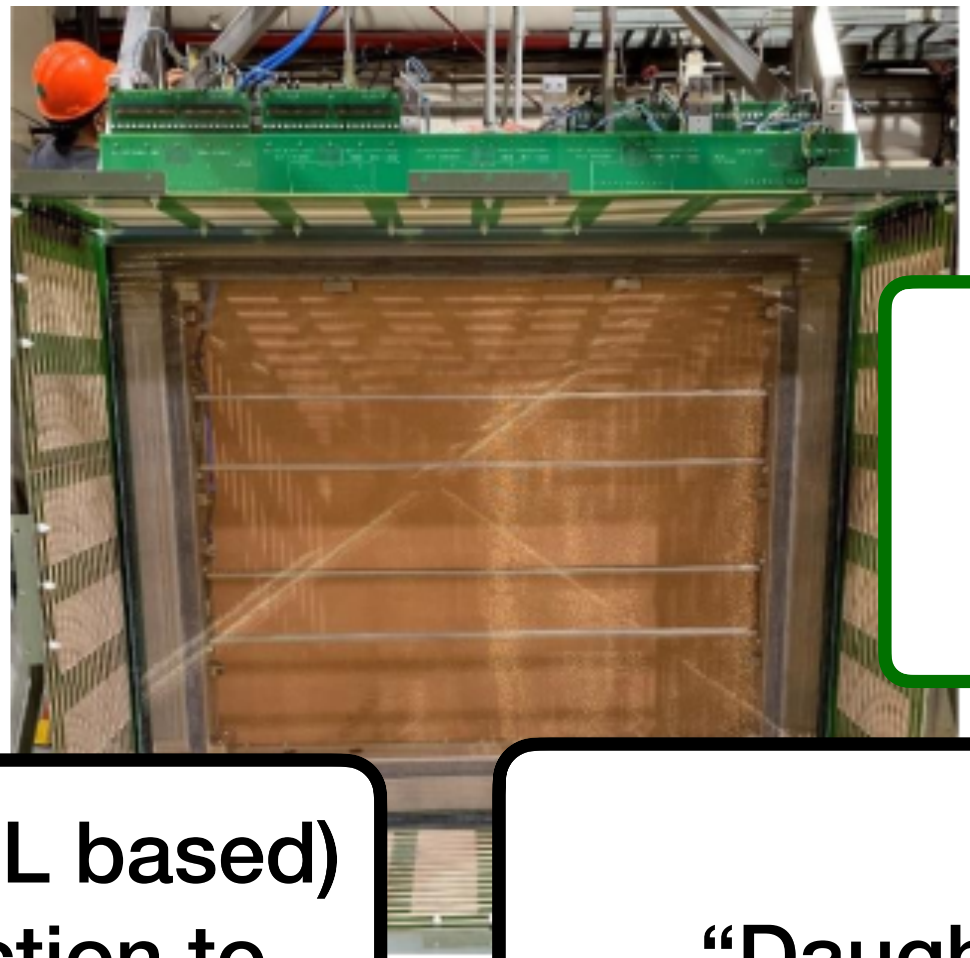
2D CNN for Ar-39 Betas vs. low energy tracks of interest

Classical (and/or ML based) Event Reconstruction to Determine Direction of Michel Track

"Daughter Flipping" Disambiguation Algorithm

(Independent of Pointing) 1D AE Based Reconstruction of Ar-39 for Calibration

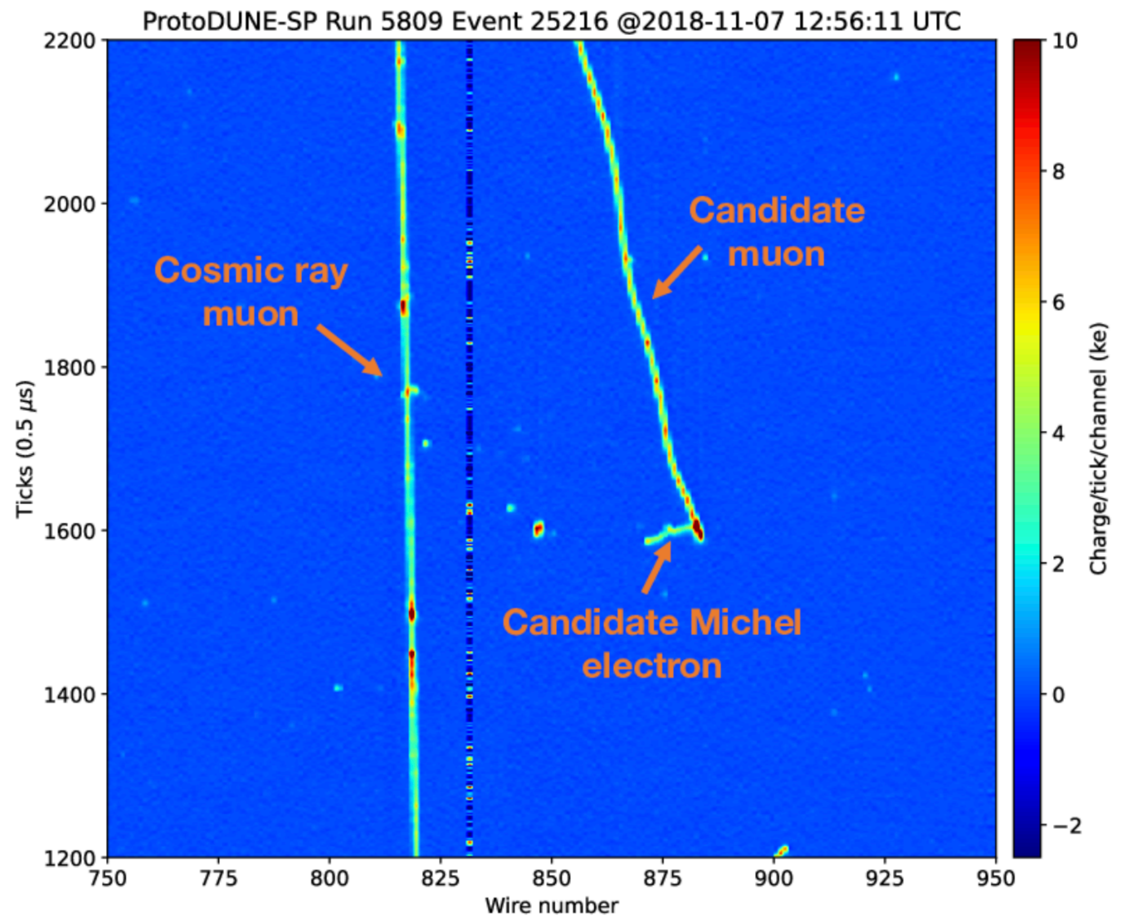
Some Motivations for Using ML in These Applications



ICEBERG

Classical (and/or ML based) Event Reconstruction to Determine Direction of Michel Track

"Daughter Flipping" Disambiguation Algorithm



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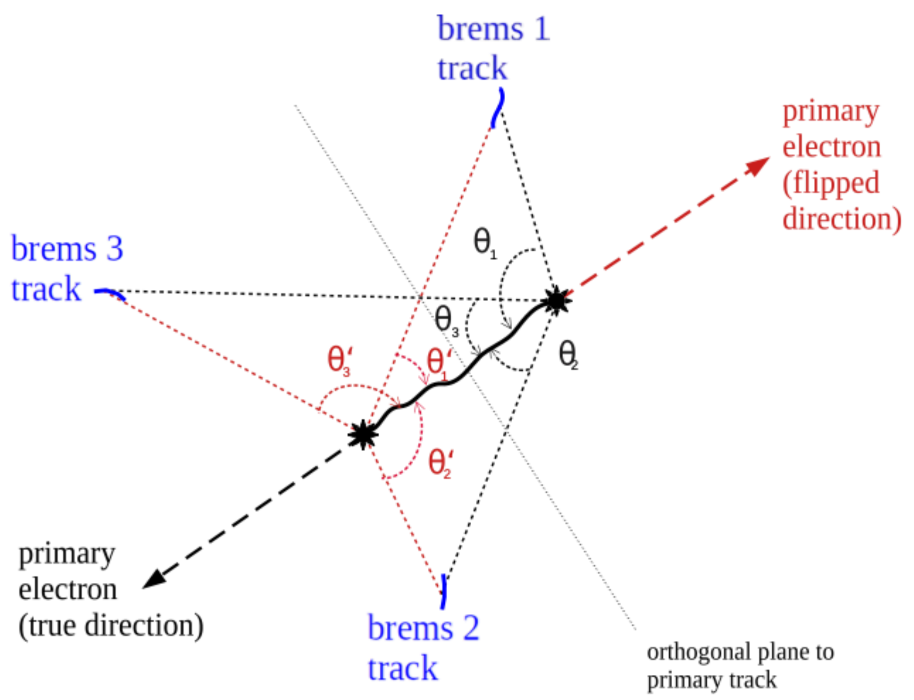

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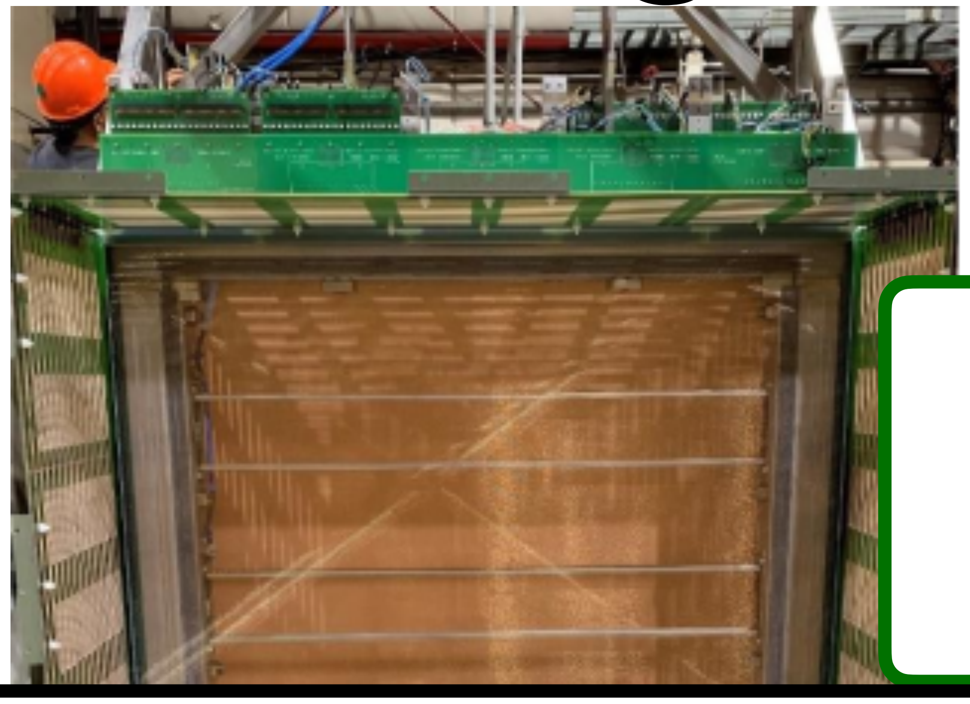
- Explicit study of how pointing resolution algorithms scale in the presence of more electronics noise *and the opportunity to train models to adapt to these noise conditions*
- Alternative clustering methods for difficult to capture small secondary hits i.e an alternative to "daughter flipping" algorithm

Some Motivations for Using ML in These Applications

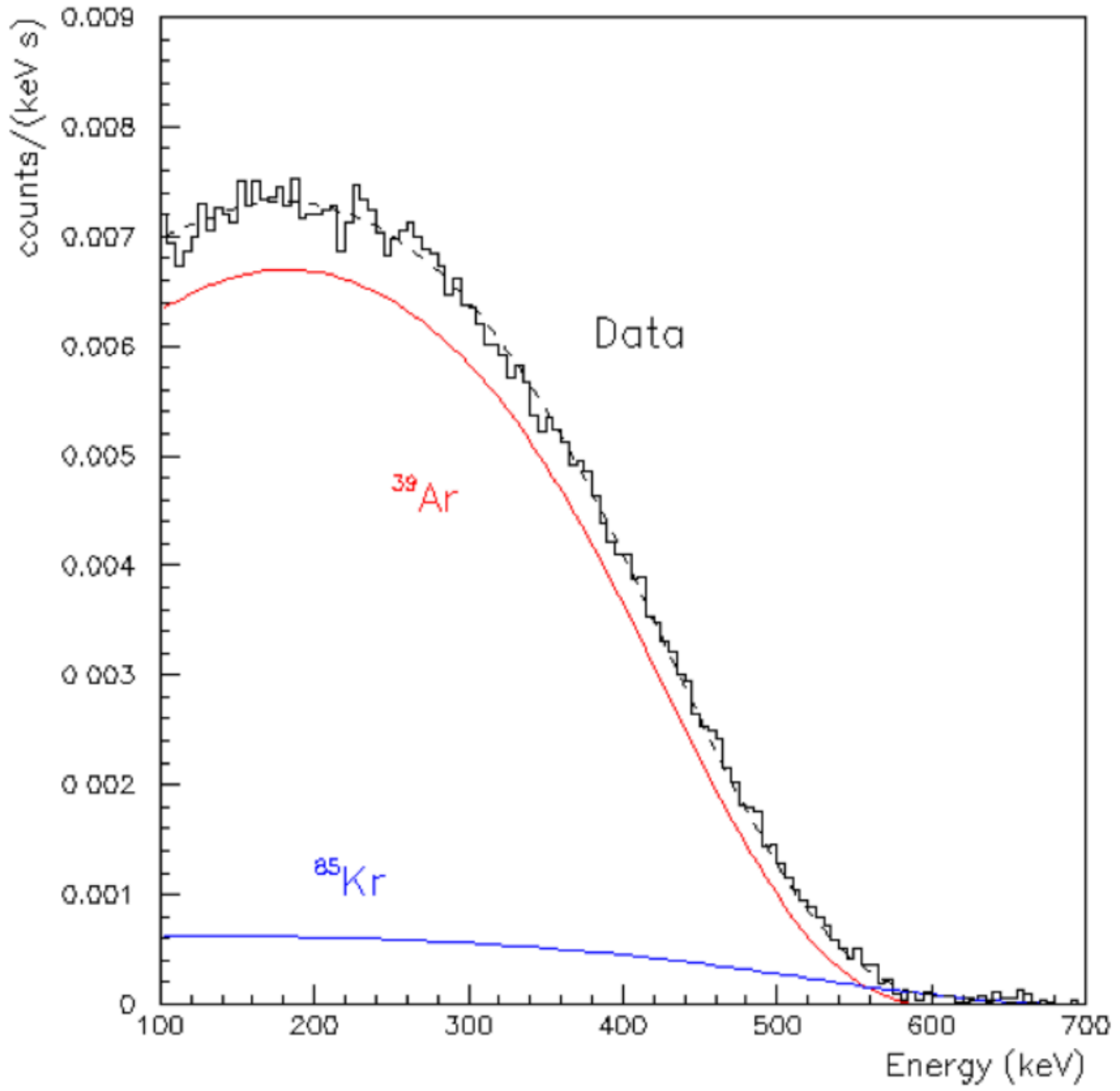


ICEBERG

(Independent of Pointing)
1D AE Based Reconstruction
of Ar-39 for Calibration

- See public note MICROBOONE-NOTE-1050-PUB for details

- Electron lifetime and recombination factors change the Ar-39 spectrum differently. We can isolate the effects of these under low noise conditions to calibrate detector measurements and potentially increase our detector resolution



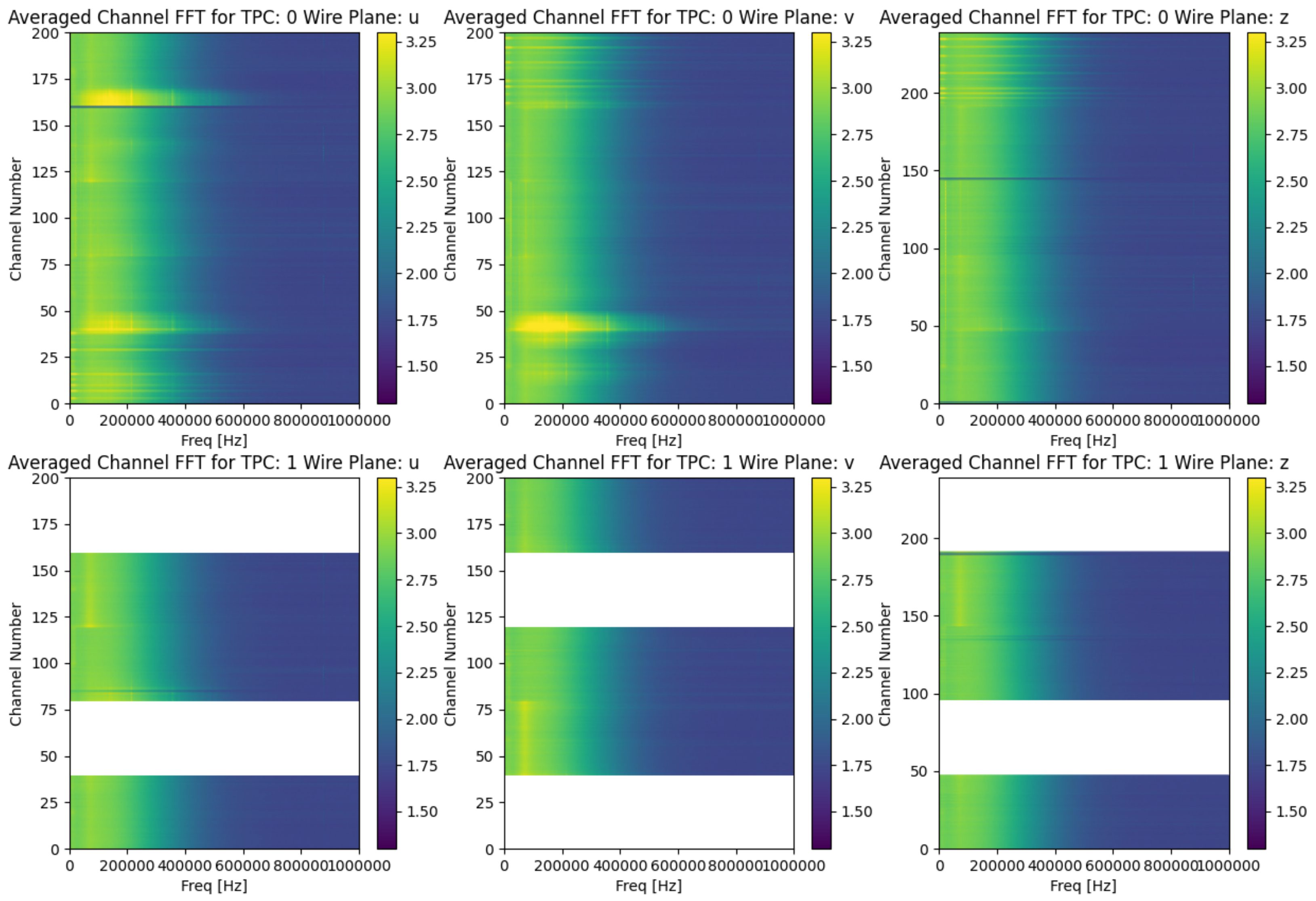
Source: MICROBOONE-NOTE-1050-PUB

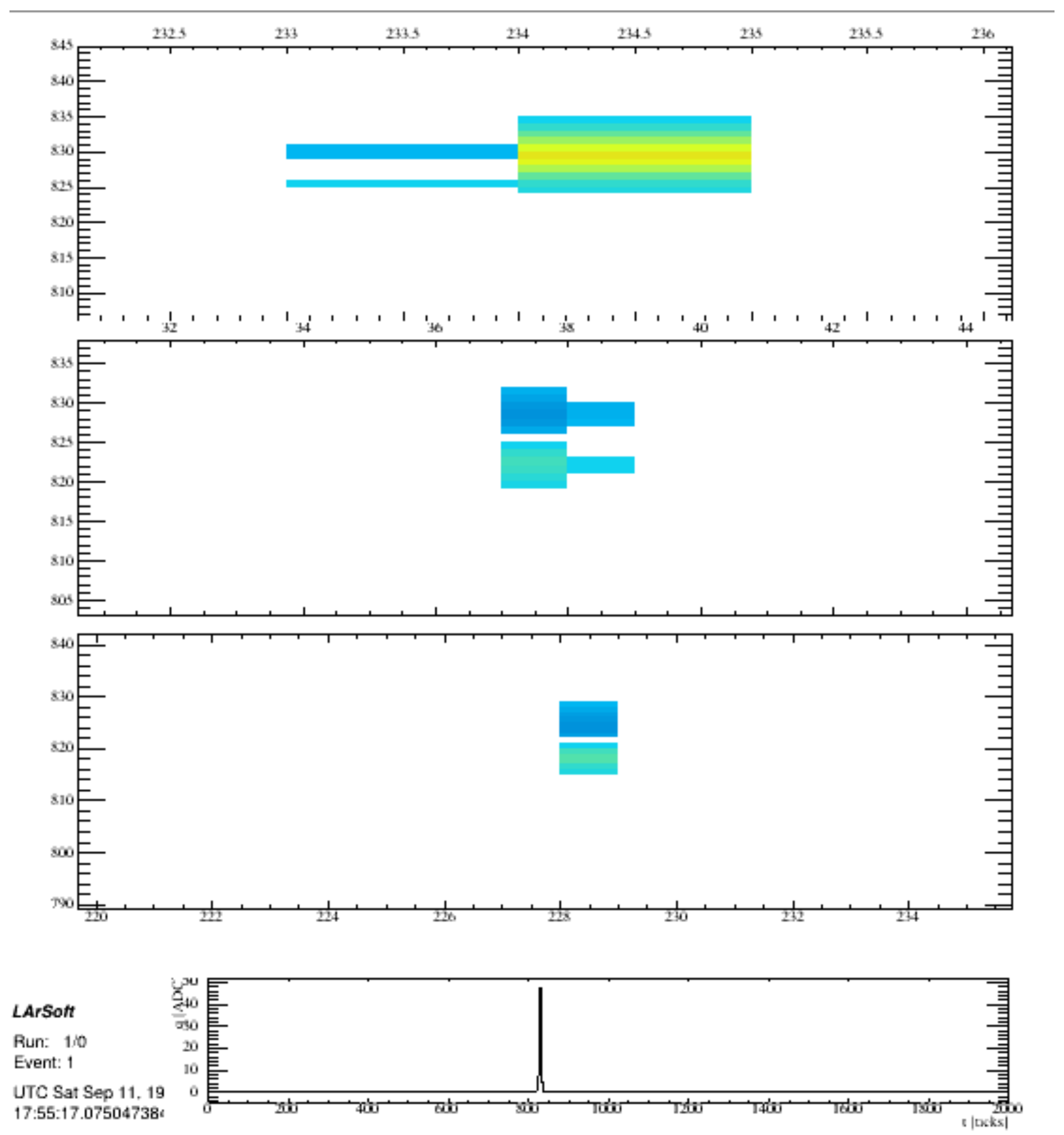
A Realistic Noise Model for Offline Training

- A data driven FFT spectrum based noise model by Matt King and Avinay Bhat (U Chicago) for independent wires has been developed and integrated in LArSoft. Refer to his talk where plots below are shown here

- Both noise and Ar-39 have been simulated in wire cell for eventual use in 1D Hit AE algorithm for Ar-39 calibration

- Still in validation stages, and coherent noise effects studies are in progress





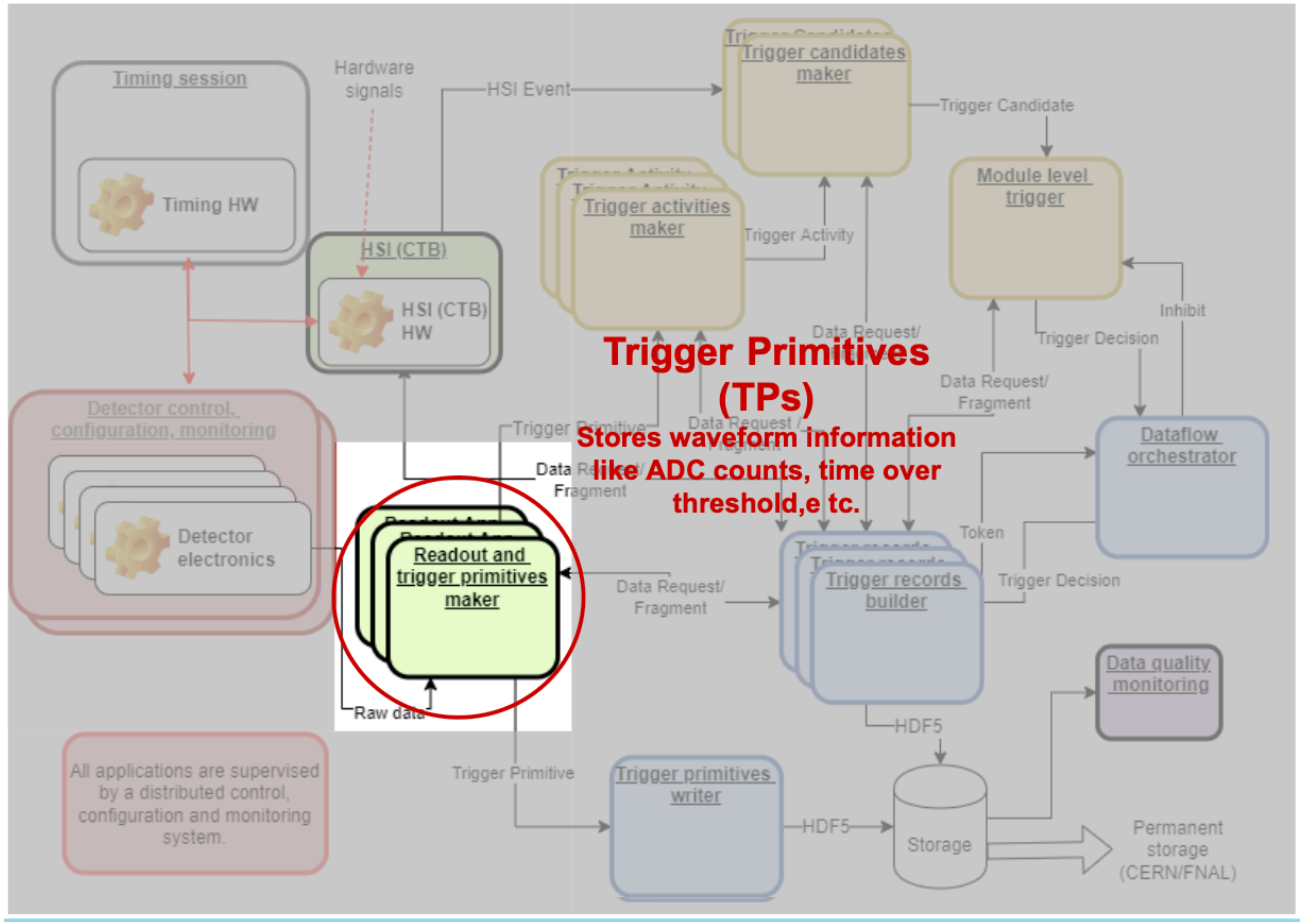
Cosmics MC for Offline Training

- Cosmics MC Sample sample generation containing Michel electron tracks from stopped muons is in progress.
- Initial `.fcl` has been produced by Josh Queen, see his previous talks here for details of event generators, and stopped muon simulation
- We can put Ar-39, Michel simulation, and noise model together to start to test the
  - Effect of electronics noise level on Ar-39 spectrum reconstruction for calibration
  - Effect of realistic noise levels on electron track reconstruction and daughter flipping algorithms
- Further "realistic" training datasets with various noise and electronics conditions are to be updated as data from runs of ICEBERG become more available

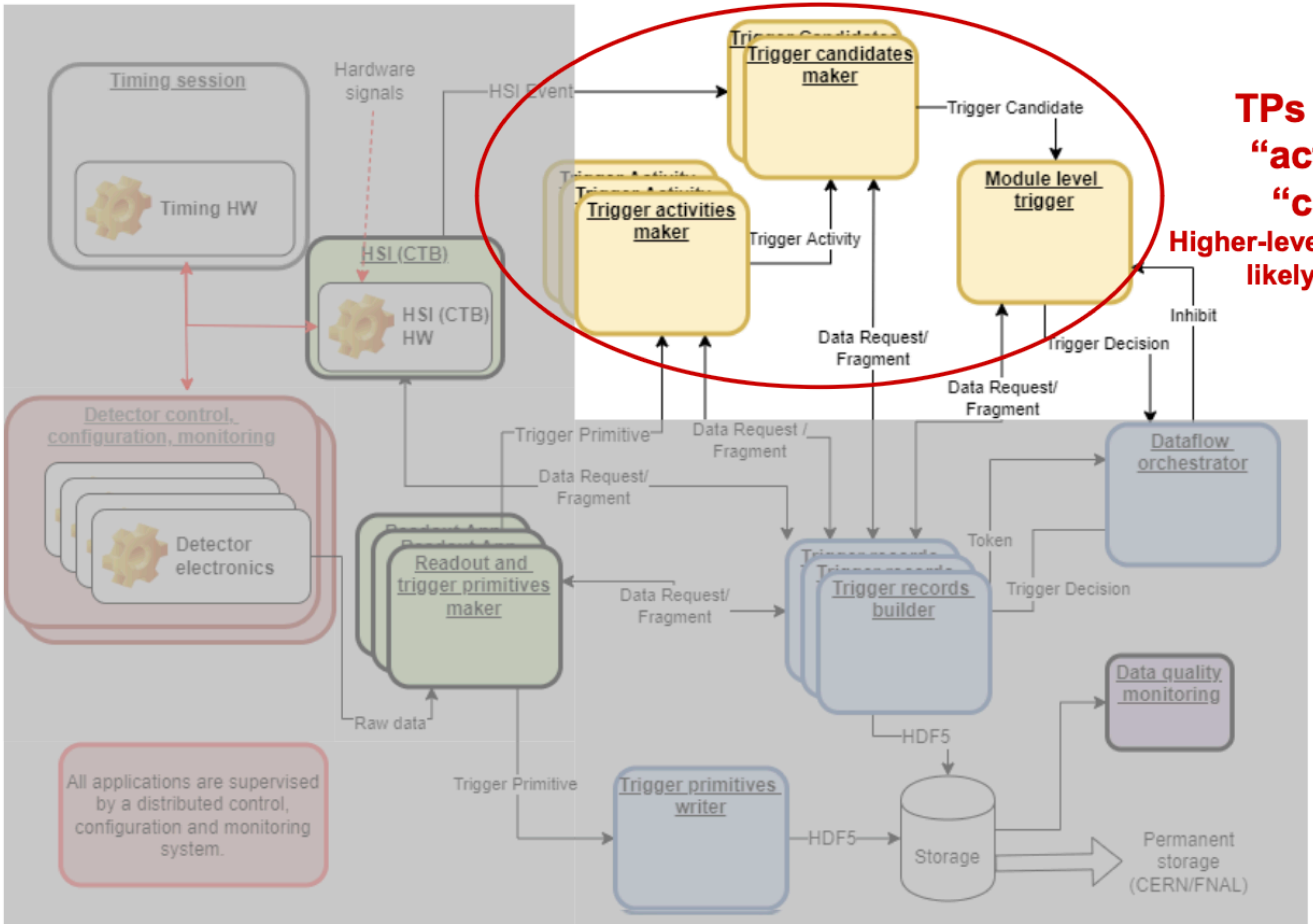
How do we actually run online?

- Current “more realistic” datasets for offline have been generated agnostic of which inputs we will use in our final model
- However, we must integrate with the current implementation of ICEBERG-DAQ software which is equivalent to DUNE-DAQ.
- So, we must use Trigger Primitives (TPs), essentially a reduced collection of information about a given hit
- To use TPs as inputs in a live time selection process, our model must take inputs that are compatible with the outputs of the DAQ TP stream writer.
- We are still building a training workflow to adapt the DUNE based raw models to TP based models as described in Meghna’s talk.

DUNE DAQ Data Flow



Current DUNE-DAQ Candidate Selection



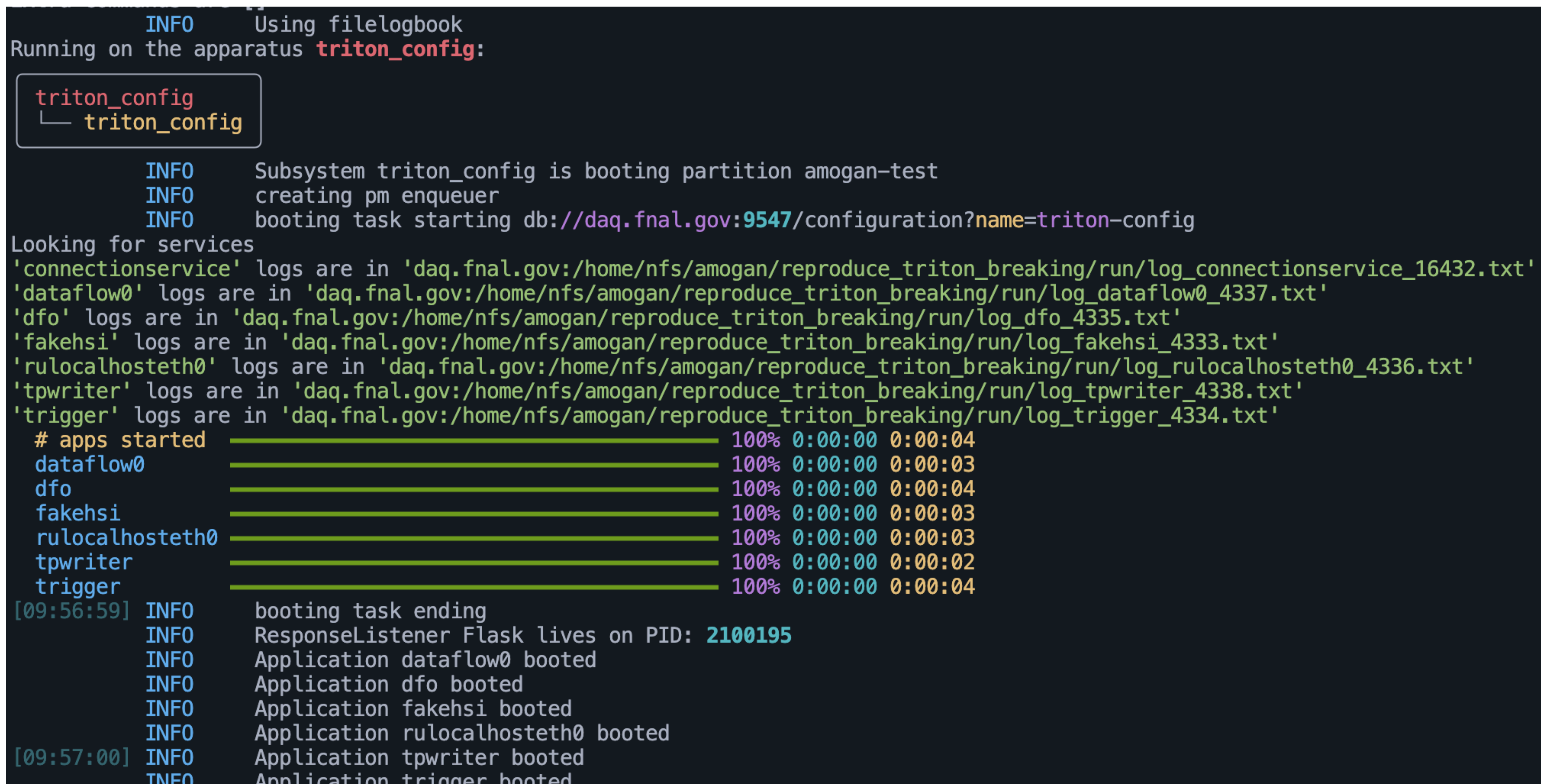
TPs bundled into "activities" and "candidates"

Higher-level objects that are more likely to be interesting

We would like an ML event level data selection alternative to above

Integrating Software in ICEBERG (DUNE)-DAQ

- Once models are trained, we would like to use and online machine learning “inference as a service” method using NVIDIA Triton client
- Thanks to work from Andrew Mogan see talk here , we can now make server calls from inside DUNE-DAQ.
- This will allow us to handle data flow from the TP stream writer *within* the DAQ and allow us to make inference requests from the DAQ server itself
- Triton has many user friendly tools to optimize workflow for varying data rates, model inference times.
- We can also be minimally invasive to the DAQ and hardware agnostic while still running an online demonstrator system



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           INFO     Using filelogbook
Running on the apparatus triton_config:

 triton_config
 └── triton_config

           INFO     Subsystem triton_config is booting partition amogan-test
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Summary of Current Status and Plan Forward

- An initial data driven simulation workflow containing electronics noise, Ar-39, and cosmics has been generated in the LArSoft `.fcl` framework
- Models from the raw supernova pipeline are still to be adapted to the TP based framework to allow for better integration into ICEBERG-DAQ
- There is a lot to gain from moving from offline MC trained models to data driven models in ICEBERG, but not without challenges:
    - Neutrino data is sparse, and low energy signals are particularly sparse! Getting models with many parameters to isolate and classify regions with limited training data will require us to use well curated loss functions, features and architectures.
    - Recovering Ar-39 from below a noise spectrum means we have to try more complex training techniques. We have tried GANs, and a few others, still in progress.
- Still, ML holds to gain: Threshold based systems can’t recover low energy hits, classify betas vs. low energy signals, and are not as easily adaptable to real time detector constraints.

Backup Slides

Current Performance of Raw SN Pipeline

Algorithm	Performance	GPU Inference Time for Optimal Batch
2D CNN for Ar-39 background rejection	99.42% signal efficiency, 99.69% background rejection	80 us per image of (wires time) as (480, 128)
1D AE for electronics noise reduction	~69% primary track efficiency ~99% background rejection	0.061 sec/nuCC event 0.031 sec/eES event
Neutrino Interaction Identification LBP + Dense Model	AUC: 0.85 83% eES->eES	Not measured