Neutron Calibration with Machine Learning

DUNE Collaboration Meeting: CERN (01/25/2023)

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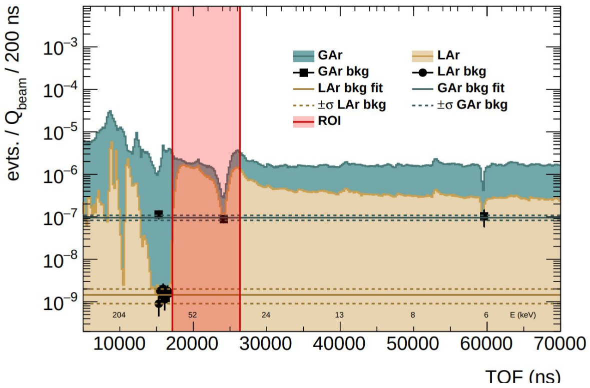
Neutron Calibration

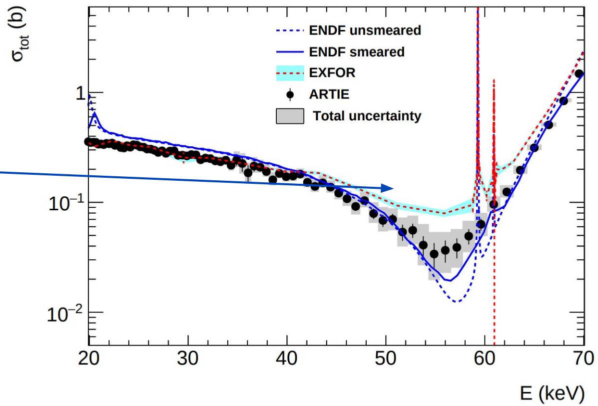
Benefits of low-energy neutrons for calibration:

- ***Standard Candle*** - Neutron captures on Ar-40 emit a 6.1 MeV gamma cascade.

$$\mathrm{n} + {}^{40}\mathrm{Ar} = {}^{41}\mathrm{Ar} + \{\gamma_j\}$$
$$\sum_j E(\gamma_j) \approx 6.1\mathrm{MeV}$$

- ***Scattering Length*** - Some percentage of neutrons above 57 keV will fall into the resonance well.
  - Average *fractional energy loss* is ~4.8%.
  - The *effective scattering length* is ~30 m.
  - The resonance well has been measured by the ARTIE[1] experiment at LANL, with a ***higher precision follow-up*** planned for this year.





1 *Measurement of the total neutron cross section on argon in the 20 to 70 keV energy range,* The ARTIE Collaboration, In review at PRL, 2023, (https://arxiv.org/abs/2212.05448).

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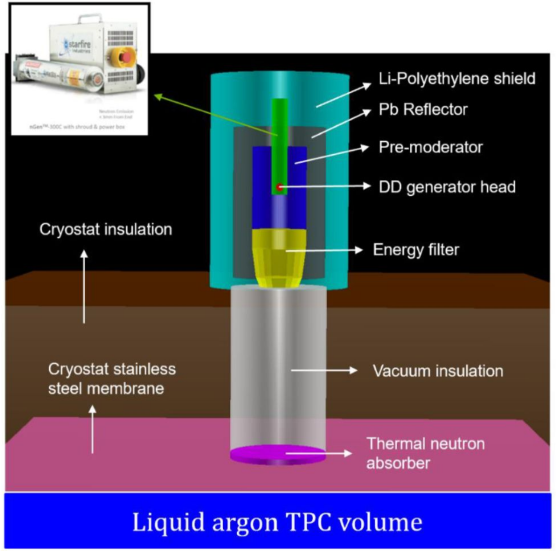
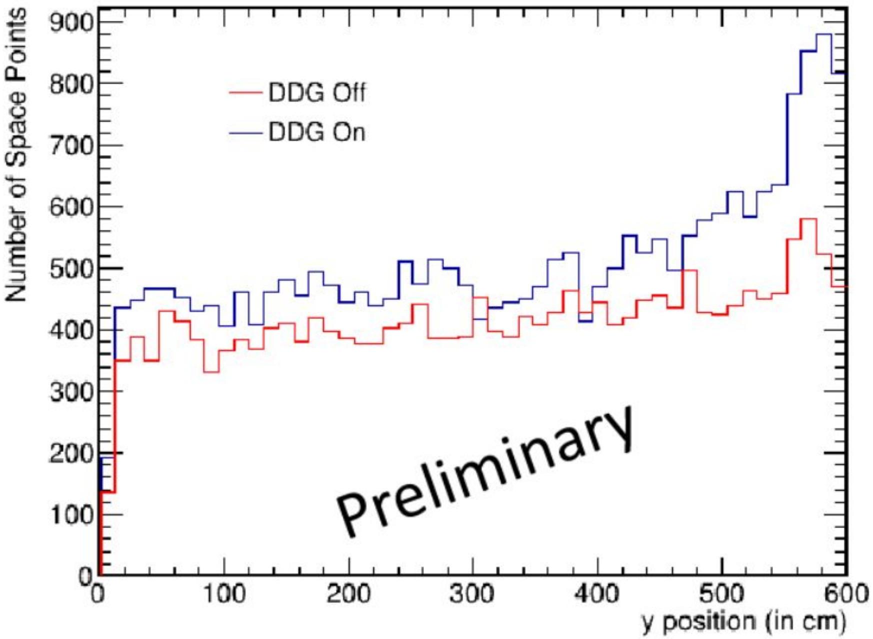
How Can We Isolate Captures?

A **pulsed neutron source**, such as a deuterium-deuterium generator (DDG), can create a *mono-energetic* spray of low-energy neutrons.

- A DDG was used in ProtoDUNE-I, from which the neutrons could be seen in the detector reconstruction.
- So far, we have not had the ability to isolate ***individual neutron captures***.





Work done by Y. Bezawada

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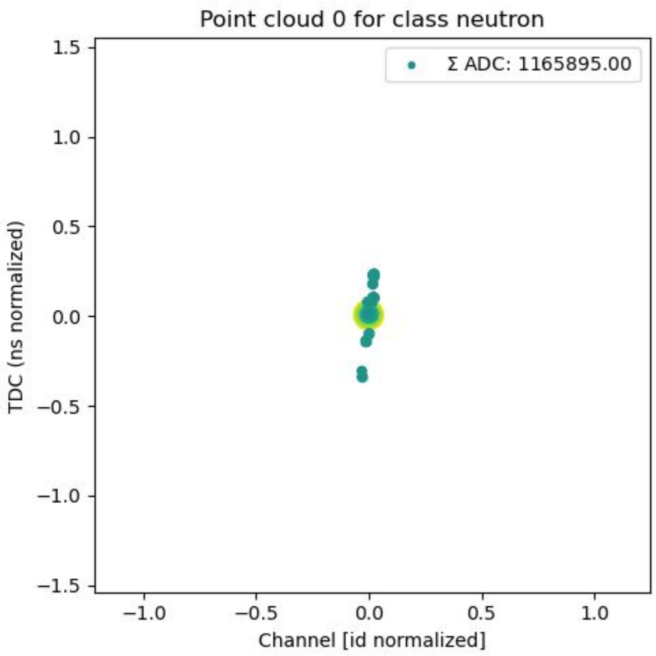
BLIP: (Blips and Low-energy Interaction PointNet)

We introduce ***BLIP***[2], a collection of ML algorithms for classifying low energy interactions in LArTPCs.

- **Input variables** - 3D point clouds (*tdc, channel, adc*) from detector readout (normalized with respect to all events).
- **Labels** - Currently trains to classify individual point clouds, but will eventually work semantically on entire detector readout.

Benefits of this approach:

- Operates on ***detector readout only*** (no reconstruction needed!)
- Generates a model for each view rather than on reconstructed space points.



2 *BLIP: Blips and Low-energy Interaction PointNet,* DUNE PNS Group (UC Davis), 2023, (https://github.com/Neutron-Calibration-in-DUNE/Blip).

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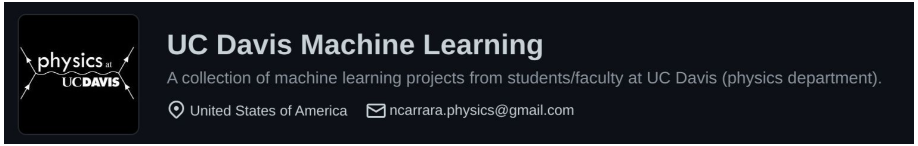
Arrakis LArSoft Module



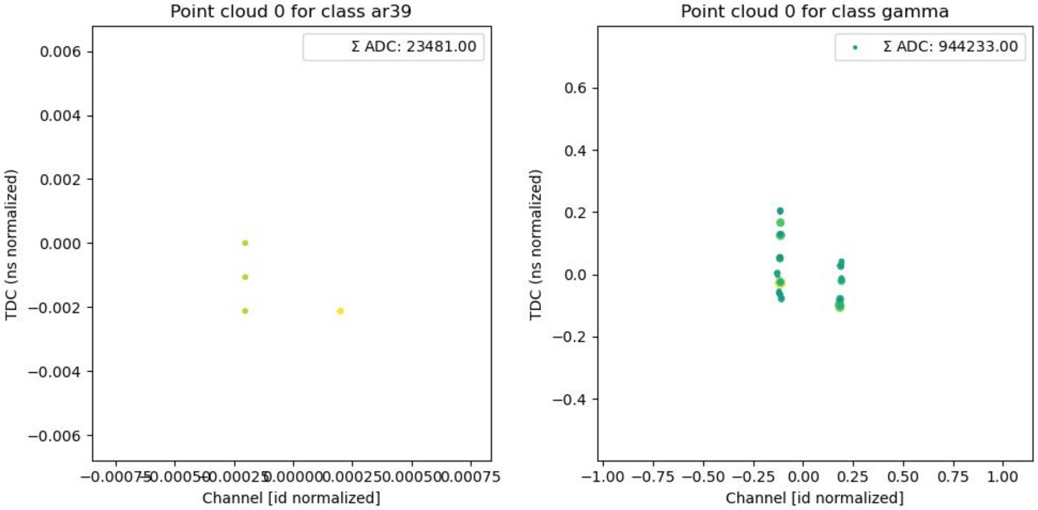
The ***Arrakis***[3] LArSoft module is responsible for collecting MC truth/detector output information and generating point clouds for training.

Current Labeling Schemes:

- **Radiologicals** - Ar39, Ar42, Kr85, Rn222, …
- **Neutron captures**:
  - Gammas: [4.75 MeV, 1.18, …]
  - Captures: [6.1 MeV]

Planned Labeling to be added:

- **Tracks**:
  - MIPS, protons, muons, etc.,
- **Showers:**
- **Deltas/Michels**
- **etc?**



3 *Arrakis (LArSoft module),* DUNE PNS Group (UC Davis), 2023, (https://github.com/UC-Davis-Machine-Learning/Arrakis).

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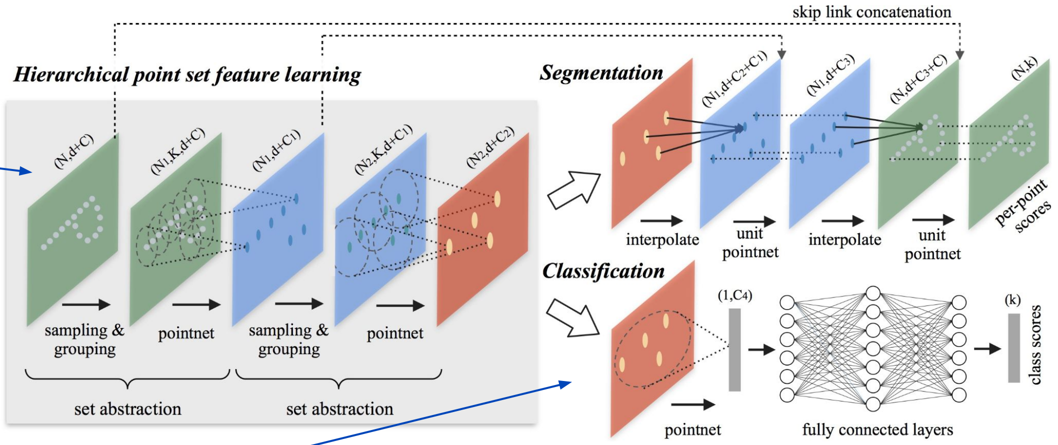
Point Cloud Classification

BLIP will consist of at least two main models:

- **Semantic Clustering** - The first network will take in an entire detector readout for an event and learn to generate clusters (e.g. PointNet++[5]).

- **Cluster Segmentation/Classification** - The second network will learn to classify these clusters into different types (e.g. PointNet[4], EdgeConv[6]).



Models are built using the ***PyTorch Geometric*** API (https://pytorch-geometric.readthedocs.io/en/latest/)

4 *PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation,* C. Qi et. al., CVPR 2017, (https://arxiv.org/abs/1612.00593).
5 *PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space*, C. Qi et. al., (https://arxiv.org/abs/1706.02413)
6 *Dynamic Graph CNN for Learning on Point Clouds,* Y. Wang et. al., 2018, (https://arxiv.org/abs/1801.07829)

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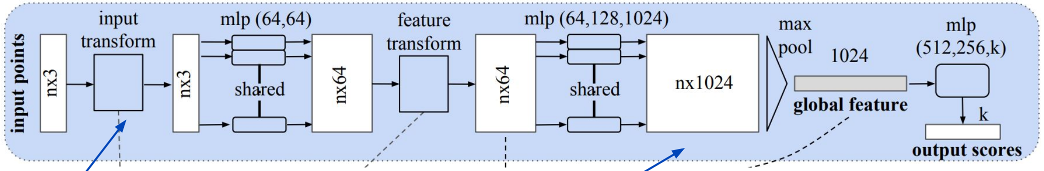
Unsupervised Learning

Our point cloud model works by combining an unsupervised and supervised approach together.



Unsupervised EdgeConv:

- Each point cloud is passed through an augmentation filter which applies random:
  - **Jittering** - a small amount of noise is applied to each coordinate.
  - **Shearing** - a small amount of stretching is applied.
  - **Rotation** - a rotation about the *adc* axis is applied.

- The point clouds are then **embedded** into a large feature space, which is then **pooled** and fed into an **MLP**.

$$\ell_{\mathrm{NTX}}(x_i, x_j) = -\log\left[\frac{\exp\left[\frac{x_i \cdot x_j}{\tau|x_i||x_j|}\right]}{\sum_{k=1}^{2N} 1_{k\neq i}\exp\left[\frac{x_i \cdot x_k}{\tau|x_i||x_k|}\right]}\right]$$

- The model then learns to cluster ***"like"*** point clouds and push away all others using the ***Normalized Temperature-scaled Cross Entropy Loss*** (NTXent).

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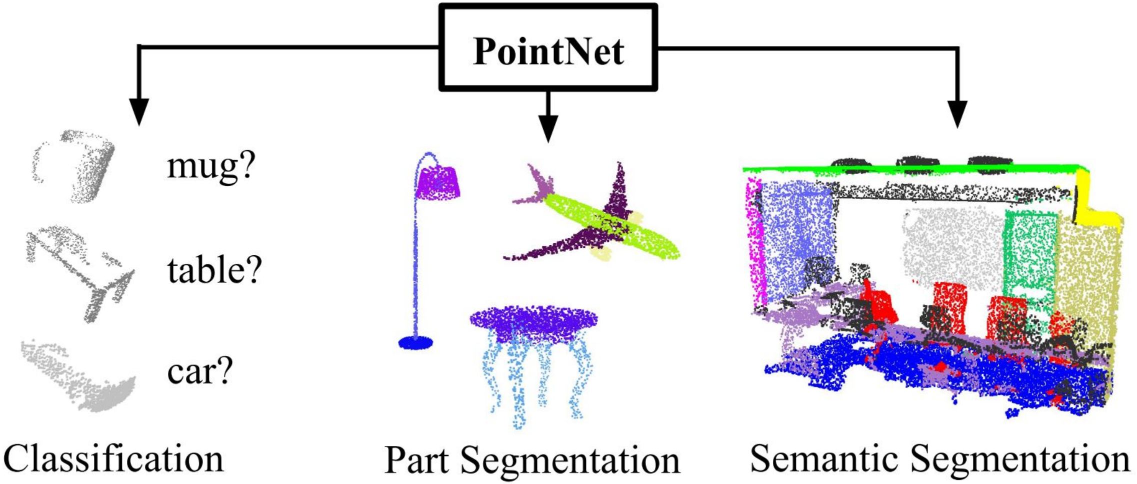
Supervised Learning

Our point cloud model works by combining an unsupervised and supervised approach together.

Supervised MLP:

- In addition we send the output of the unsupervised EdgeConv network to another MLP which learns to classify the point clouds according to an appropriate labeling scheme (e.g. [ar39, gamma, neutron]).



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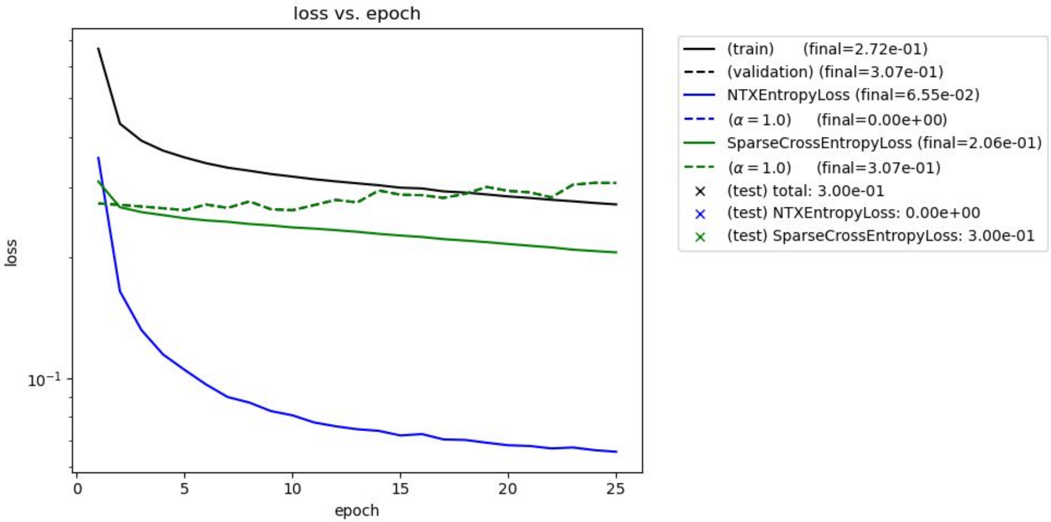
Preliminary Results

We trained a BLIP model on 116K point clouds with a 70/30 train/test split and the following classes:

- Argon-39: 61,912 events (~53%)
- Capture Gammas: 46,793 events (~40%)
- Neutron Captures: 7,987 events (~7%)



After only a few training cycles, the network learns to distinguish the point clouds with some success, although it seems to ***overtrain on classification*** quickly.

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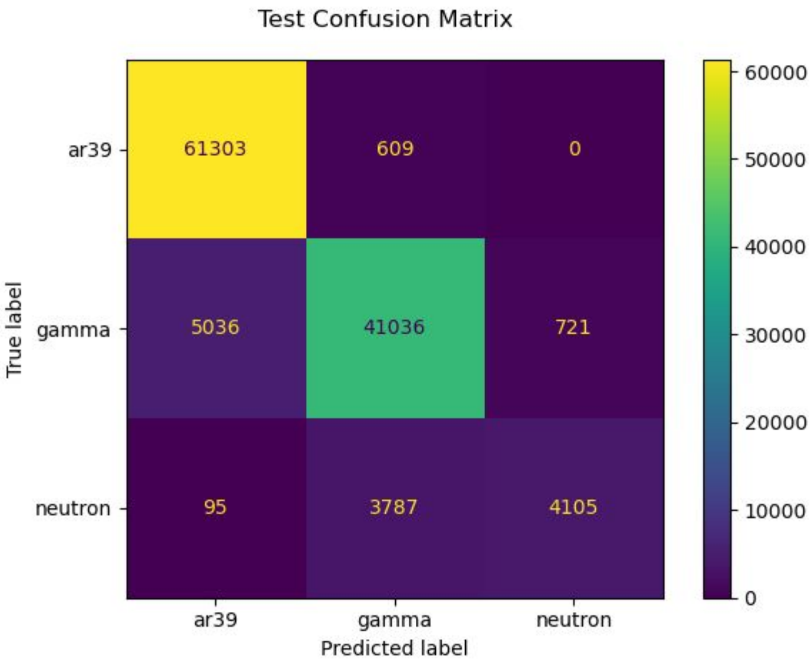
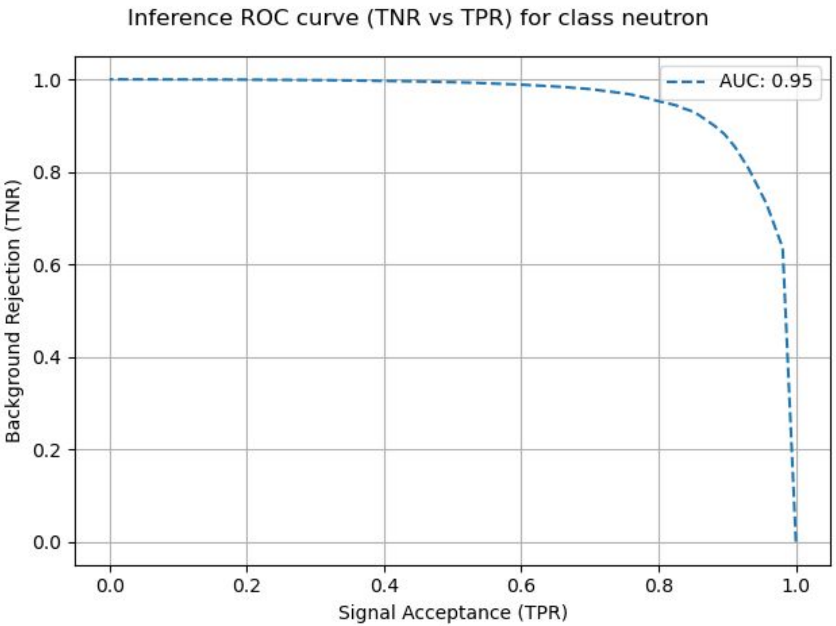
Preliminary Results Cont.





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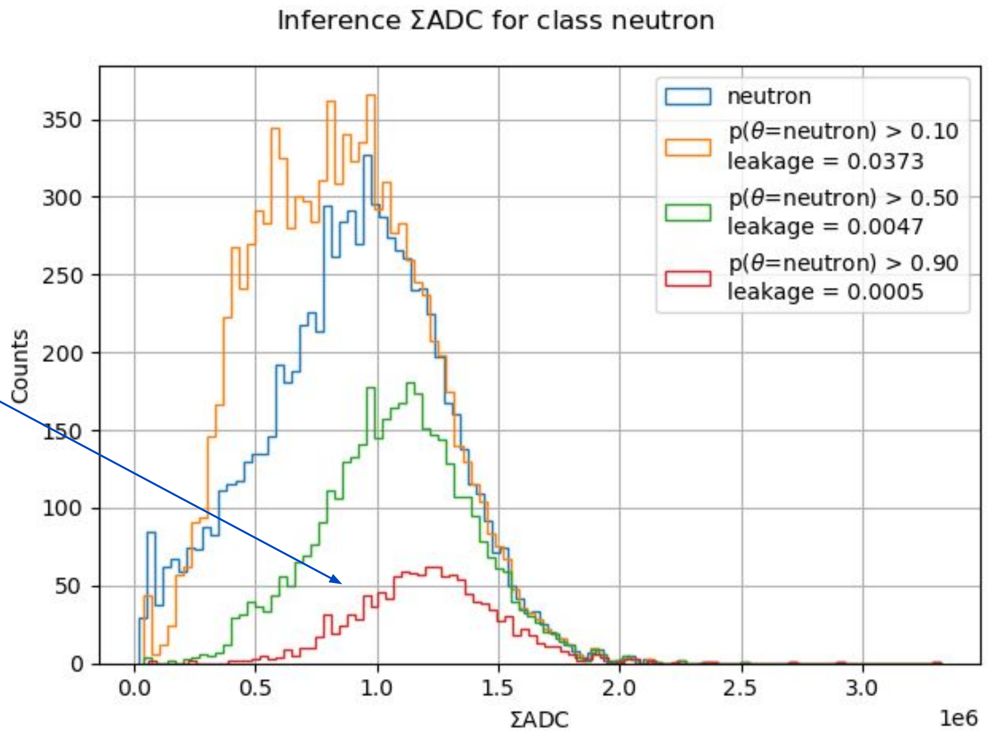
Summed ADC

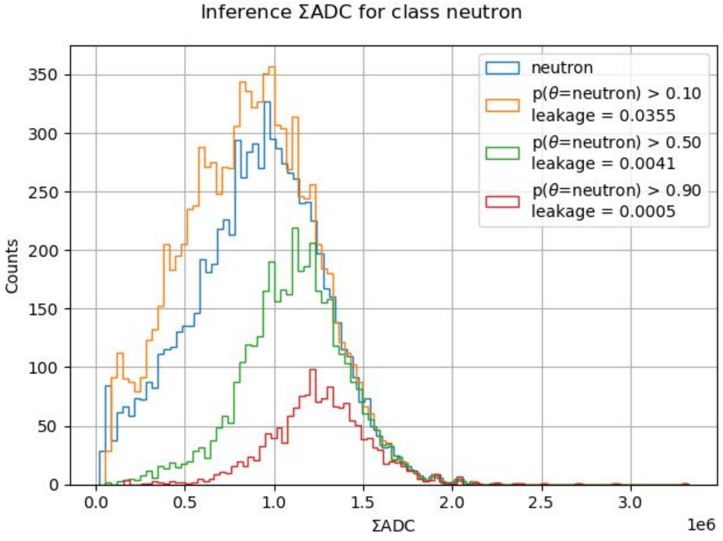
Applying cuts to the classification output, we can isolate neutron captures with only a small background leakage (~.05%).

The resulting distribution of detector output ADC values can be used for calibrating energy!

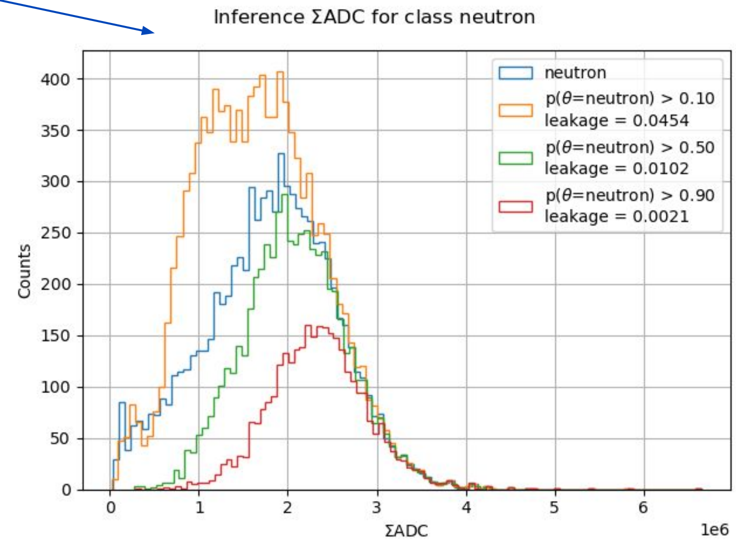


Summed ADC Test

To test wether the approach is insensitive to certain detector simulation parameters (e.g. gain), we trained two models with a **factor of 2** different in detector ADC output.



default gain



2 x gain

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Summed ADC Test

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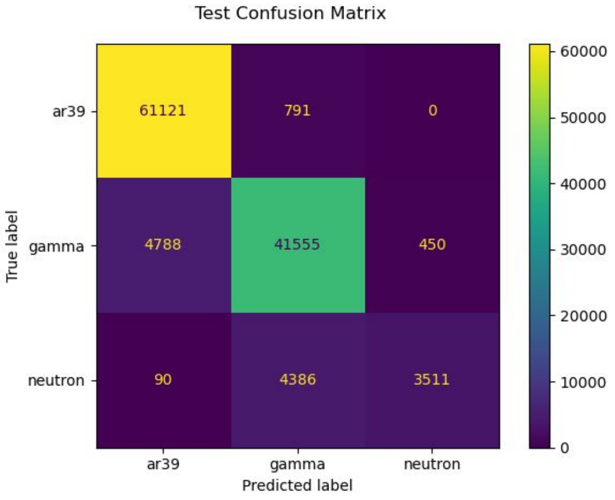
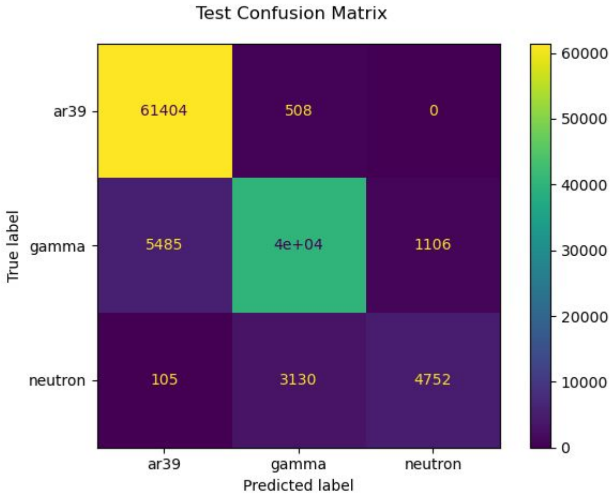


default gain



2 x gain

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Next Steps

- ❑ Construct a **hierarchical model for semantic segmentation** on the entire detector readout.
- ❑ Build a scheme for combining inference on the different detector views (induction vs. collection planes).
- ❑ Add truth labeling and point clouds for other particle types.
  - ❑ cosmics,
  - ❑ electron showers,
  - ❑ delta-rays,
  - ❑ Michel electrons,
  - ❑ pions,
  - ❑ etc.,
- ❑ Apply the model to ProtoDUNE-I data
  - ❑ Prepare for use in ProtoDUNE-II …