

# Neutron Calibration with Machine Learning

**DUNE Collaboration Meeting: CERN (05/21/2023)**

Presented by *Nicholas Carrara* on behalf of the **PNS group** at  
**UC Davis** and **South Dakota School of Mines**:

*Michael Mulhearn, Emilija Pantic, Robert Svoboda, Jingbo Wang*

*Yashwanth Bezawada, Junying Huang, Walker Johnson*

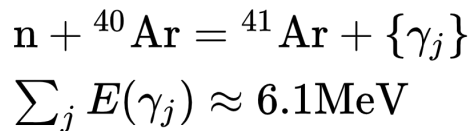
Many thanks to **Dominic Brailsford,**  
**Ken Herner, Tom Junk and Kyle**  
**Knoepfel!**



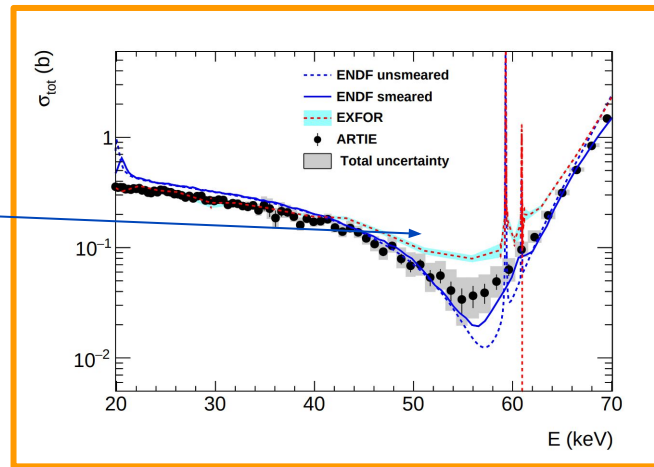
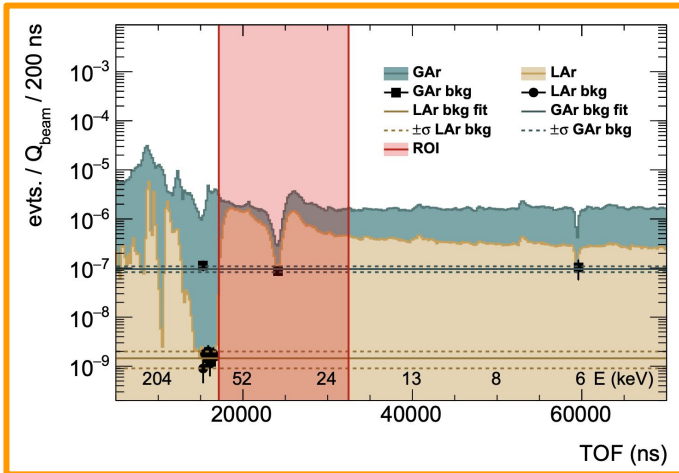
# Neutron Calibration

Benefits of low-energy neutrons for calibration:

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



- **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<sup>1</sup> experiment at LANL, with a **higher precision follow-up** planned for this year.

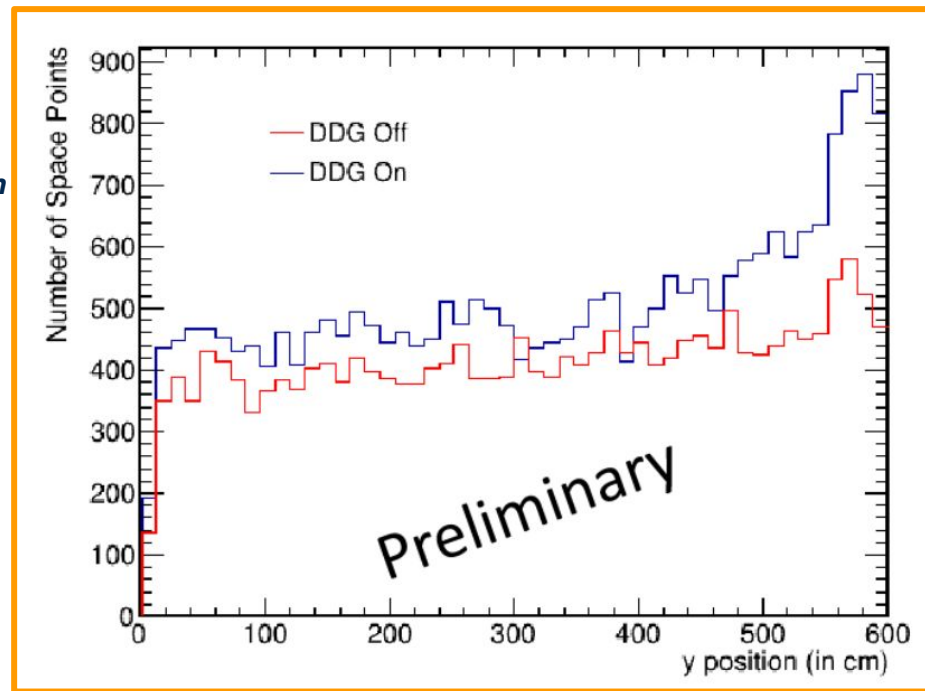
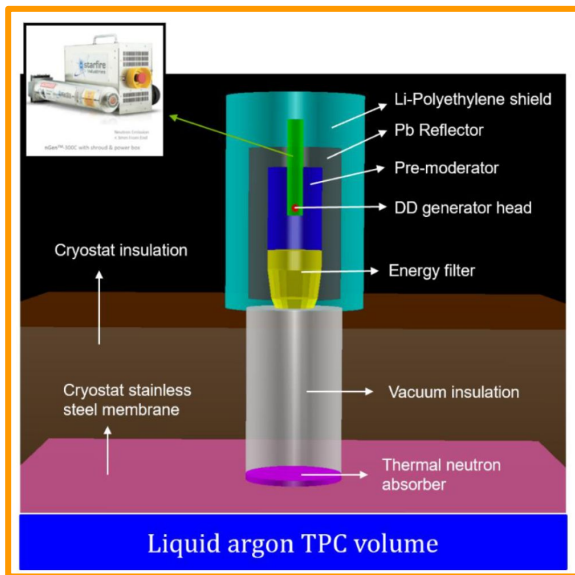


<sup>1</sup> Measurement of the total neutron cross section on argon in the 20 to 70 keV energy range, The ARTIE Collaboration, In review at PRL, 2023, (<https://arxiv.org/abs/2212.05448>).

# 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 and J. Huang

# BLIP: (Blips and Low-energy Interaction PointNet)

We introduce **BLIP**<sup>2</sup>, a collection of ML algorithms for classifying low energy interactions in LArTPCs.

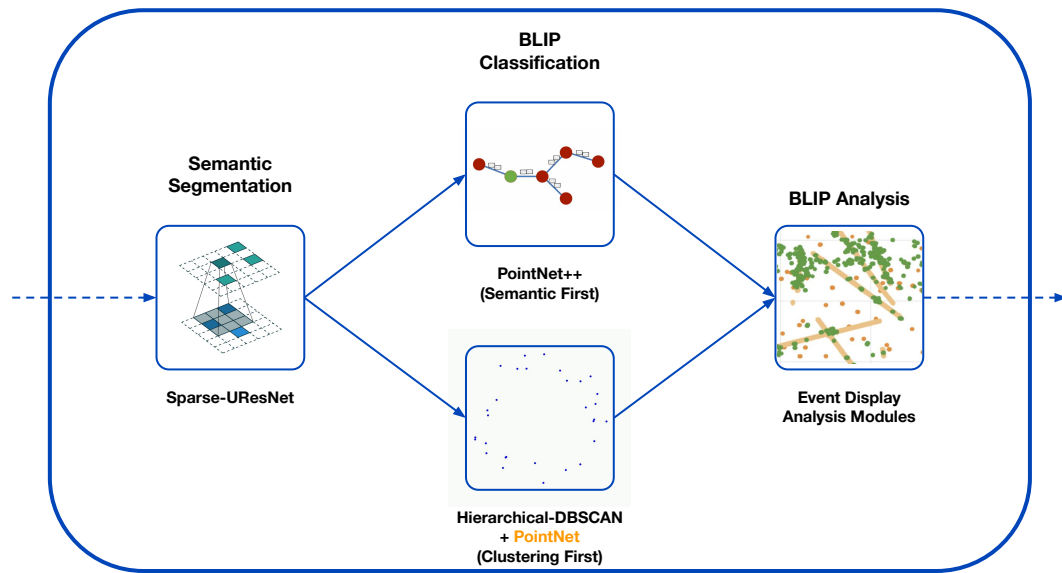
- **Semantic Segmentation:**
  - Pixel/point-cloud level classification for detector readout and/or reconstructed space points.
  - Identification of tracks/showers in order to **isolate** Blips.
- **Heirarchical Clustering:**
  - DBSCAN and Heirarchical-DBSCAN for clustering BLIPs.
- **Point-cloud Classification:**
  - PointNet++/PointNet models for classifying BLIP point clouds.
- **Topological Data Analysis (TDA):**
  - State-of-the-art algorithms for characterizing the topology of point sets (e.g. persistent homology).



## Neutron Calibration in DUNE

Source code and documentation for the neutron calibration effort in the DUNE experiment.

<http://svoboda.ucdavis.edu/> [✉ ncarrara.physics@gmail.com](mailto:ncarrara.physics@gmail.com)



# Arrakis LArSoft Module

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

Current Labeling Schemes:

[Segmentation]

- **Source** - specifies the generator.
- **Shape** - generic topological descriptor (track, shower, blip, ...)
- **Particle** - particle type responsible for the energy deposition ( $\mu^+$ -, neutron, proton, michel, delta, ...)

[Clustering]

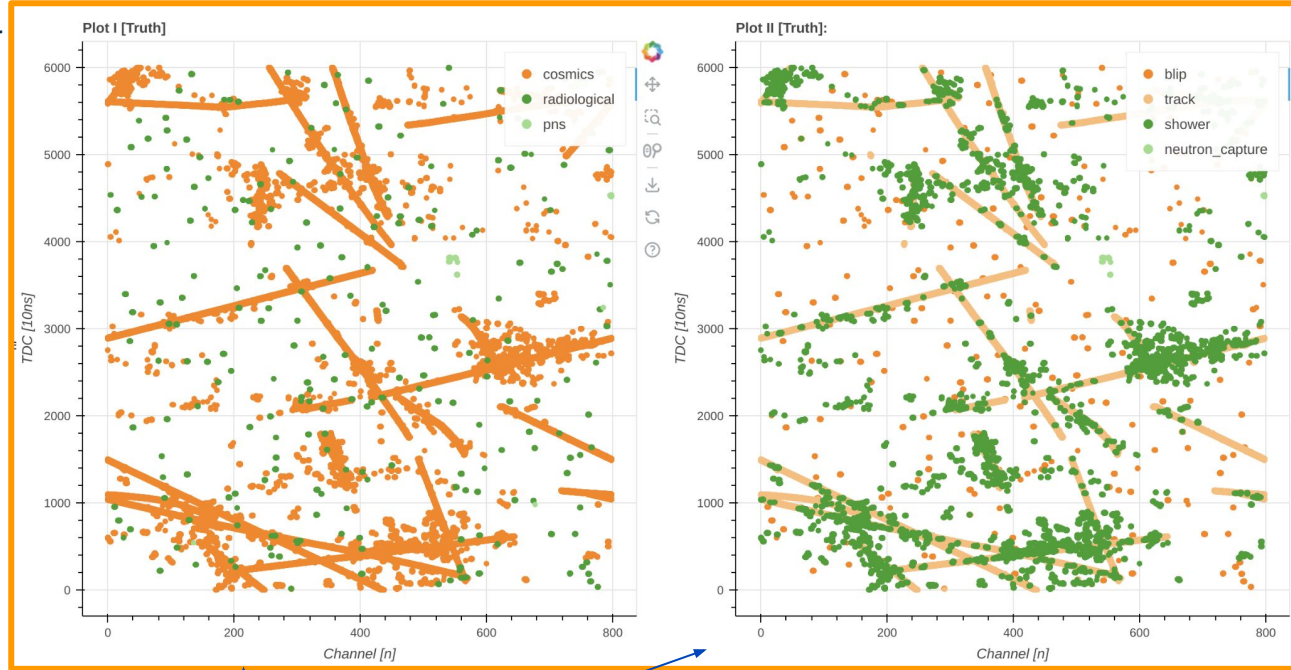
- **ShapeCluster** - individual instance of a particular shape.
- **UniqueParticle** - individual instance of a particular particle.



## UC Davis Machine Learning

A collection of machine learning projects from students/faculty at UC Davis (physics department).

United States of America ✉ [ncarrara.physics@gmail.com](mailto:ncarrara.physics@gmail.com)



↑  
‘source’ and ‘shape’ labels for a simulated ProtoDUNE event

UCDAVIS

# Arrakis LArSoft Module

To use Arrakis,

[Current setup]

- Can use the [LArSoftArrakis](#) repository to set up a local LArSoft install on an FNAL server.
- Download [Arrakis](#) into larana and compile.
- Add “arrakis” as an analyzer module and specify parameters.

```
#include "Arrakis.fcl"

physics:
{
  analyzers: {ana: @local::Arrakis}
  analysis: [ana]
  trigger_paths: [simulate]
  end_paths: [analysis]
}
```

[Future setup]

- Eventually, Arrakis will be integrated into LArSoft and will be available as an analyzer module.
- Allow the user to register custom *logic* for generating training datasets.

```
module_type: "Arrakis"

# which products for the wrangler to handle
ProcessType: "data" # simulation, data
ProcessMCTruth: true
ProcessMCParticles: true
ProcessSimEnergyDeposits: true
ProcessSimChannels: true
ProcessRawDigits: true

# module labels
LArGiantProducerLabel: "largeant"
SimEnergyDepositProducerLabel: "IonAndScint"
SimEnergyDepositInstanceLabel: "priorSCE"
SimChannelProducerLabel: "tpcrawdecoder"
SimChannelInstanceLabel: "simpleSC"
RawDigitProducerLabel: "tpcrawdecoder"
RawDigitInstanceLabel: "daq"

GeneratorLabels:
{
  Ar39Label: "Ar39"
  Ar42Label: "Ar42"
  Kr85Label: "Kr85"
  Rn222Label: "Rn222"
  BeamLabel: "Beam"
  CosmicsLabel: "Cosmics"
  HEPevtLabel: "HEPevt"
  PNSLabel: "PNS"
}

# which products to save
SaveMeta: true
SaveGeometry: true
SaveSimulationWrangler: false # save SimulationWrangler maps
SaveWirePlanePointCloud: true # save wire plane point cloud data
SaveEnergyDepositPointCloud: true # save energy deposit point cloud data

# whether to collect detector simulation by edep or
# by particle track id.
FilterDetectorSimulation: "TrackID" # ["TrackID", "EdepID"]

# labeling scheme for neutron captures,
# simple labels all gammas as "other", while medium labels
# 4.75 and 1.81 MeV gammas separately from others, and full
# labels all energies as different types.
NeutronCaptureGammaDetail: "Simple" # ["Simple", "Medium", "Full"]

ADCThreshold: 20 # ADC threshold for saving points
InducedChannelInfluence: 10 # number of wires which are influenced by signals
InducedTDCInfluence: 200 # number of tdc ticks which are influenced by signals
```

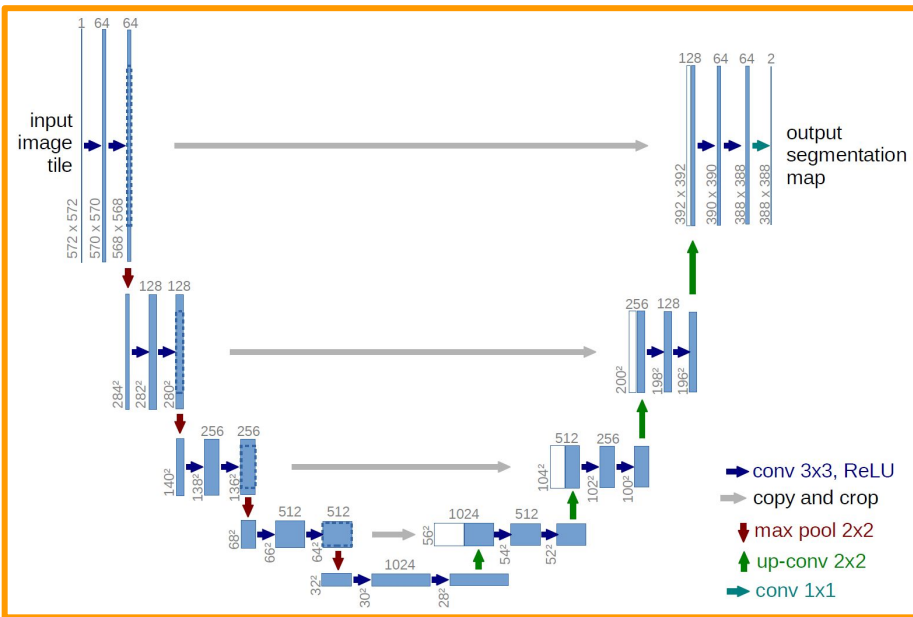
FHiCL parameters



# Config file training/evaluation

BLIP models can be constructed at run time with tunable parameters.

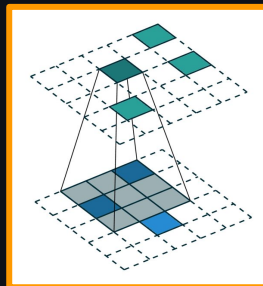
- The long term goal is to make a completely modular setup so that different models can be chained together.
- Model parameters/weights are saved in a config dictionary for reproducibility.



```
training:
  epochs:      150
  checkpoint:  10
  progress_bar: 'all' # train, validation, test, all
  rewrite_bar:  False # wether to leave bars after each epoch
  save_predictions: True # wether to save network outputs in original file
  no_timing:   False  # wether to keep timing/memory info in callback
  gpu:         True
  gpu_device:  0
  seed:        42

model:
  # uncomment the line below and specify the model
  # to load from a checkpoint.
  # load_model:  ".checkpoints/checkpoint_200.ckpt"

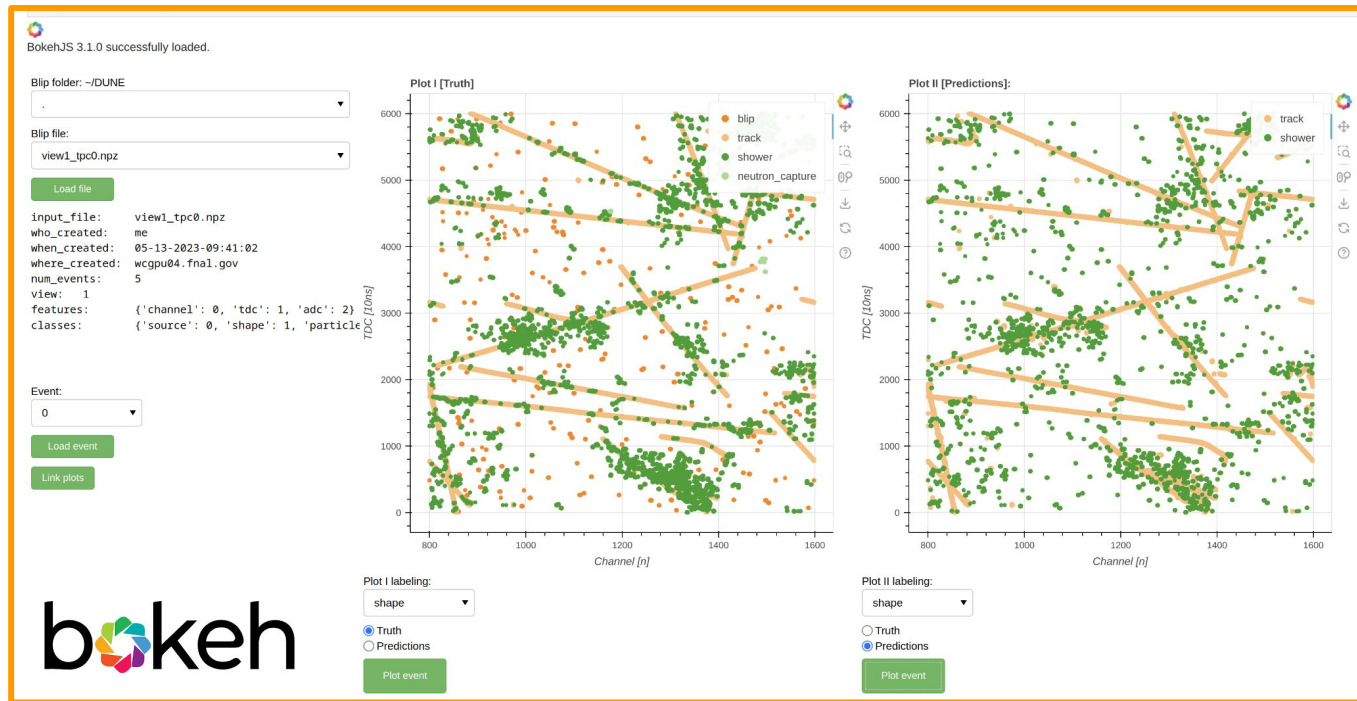
  # multiple options for model_type:
  # [ "SparseUNet", "PointNet", "UNet", ... ]
  # or a Composite.
  model_type:    "SparseUNet"
  in_channels:   1
  classifications: ["shape"] # {"source", "shape", "particle"}
  out_channels:  [7]         # {8, 7, 32}
  filtrations:   [64, 128, 256, 512] # the number of filters in each downsample
  double_conv_params:
    kernel_size: 3
    stride:      1
    dilation:    1
    activation:  "relu"
    dimension:   2
    batch_norm:  True
  conv_transpose_params:
    kernel_size: 2
    stride:      2
    dilation:    1
    dimension:   2
  max_pooling_params:
    kernel_size: 2
    stride:      2
    dilation:    1
    dimension:   2
```



# Event display

We are also working on an event display for BLIP which has the following features:

- Uses *bokeh* to create an interactive GUI.
- GUI can be run in a Jupyter notebook, or as a stand-alone html page.
- Obtain **point by point information** to quickly diagnose/access Arrakis and BLIP performance.
- Interface for analysis on network output.
- The BLIP-display could be made accessible through a **Wilson Cluster** jupyter interface.

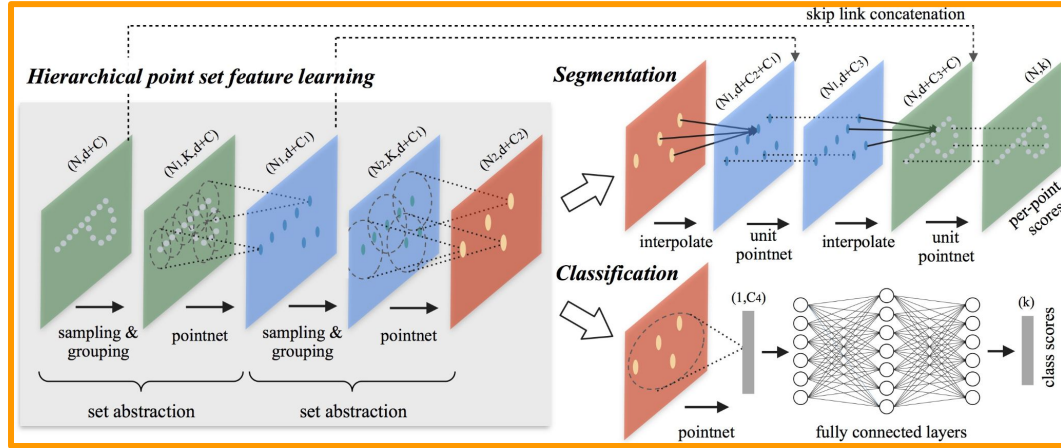




# BLIP Classification

BLIP Classification will consist of at least two main models:

- **PointNet++** - The first network will take in an entire detector readout for an event and learn to semantically label blips (e.g. PointNet++<sup>5</sup>).
- **HDBSCAN-PointNet** - The second network will learn to classify clusters at different scales (e.g. PointNet<sup>4</sup>, EdgeConv<sup>6</sup>).



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>)

Models are built using the **PyTorch Geometric** API

(<https://pytorch-geometric.readthedocs.io/en/latest/>)



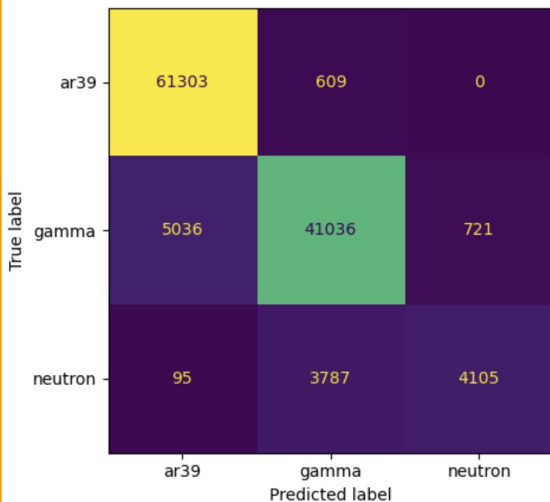
**UC DAVIS**

# Preliminary PointNet Results

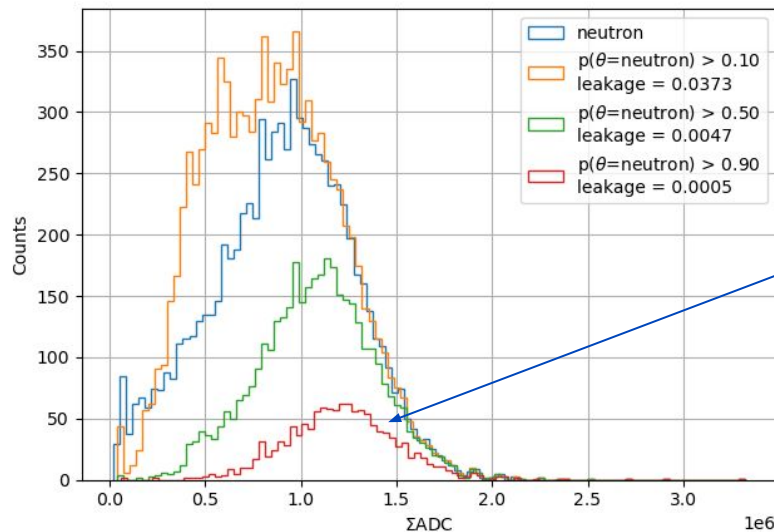
We trained a BLIP model on 116K point clouds with a 70/30 train/test split and the following classes:

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

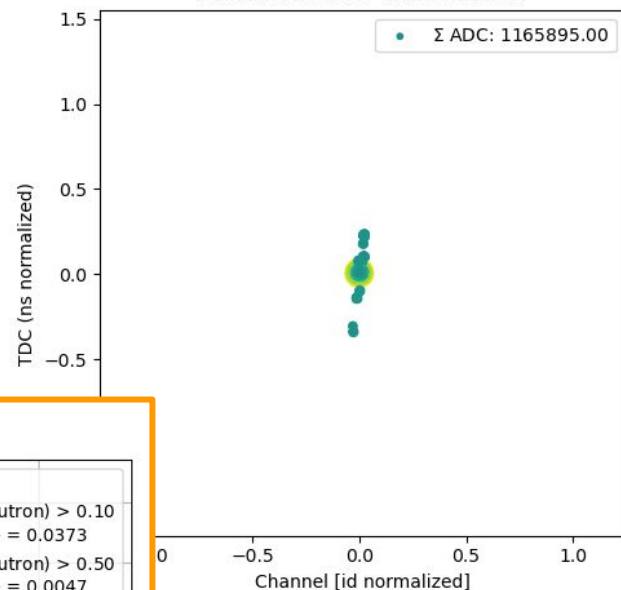
Test Confusion Matrix



Inference  $\Sigma$ ADC for class neutron



Point cloud 0 for class neutron



Can calibrate against this distribution!

# Work in Progress

## Arrakis [Need a more informative name!]:

- ✓ module for gathering simulation/data products.
  - ✓ Wire plane/Raw digit data.
  - ❑ Reconstructed 3D space point data.
- ✓ module for labeling logic.
- ❑ integrate into 'lar' repositories.
- ❑ methods for 'registering' custom labeling logic.

## Wilson Cluster:

- ❑ Implement BLIP as a module that users can easily access without having to install (e.g. 'module load blip').
- ❑ Jupyter-lab/event-display over ssh integration.

## BLIP:

- ✓ Construct infrastructure for generating training data/implementing models and training.
- ✓ Construct Semantic Segmentation model.
  - ❑ Optimize semantic segmentation.
- ✓ Construct Simple PointNet model.
  - ❑ Optimize BLIP Classification models (PointNet++ and HDBSCAN-PointNet).
- ❑ Continue adding new models/modules to extend the scope of the neural network applications.
- ❑ Implement a system to allow users to integrate their own model/analysis code.