

# Detecting Neutrons in LArTPCs with Machine Learning



DUNE Collaboration Meeting (01/25/2023)

Presented by *Nicholas Carrara* on behalf of the ***BLIP ML Group*** at  
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Yashwanth Bezawada<sup>1</sup>, Junying Huang<sup>1</sup>, Will Forman<sup>3</sup>, Walker Johnson<sup>5</sup>, Ajib  
Paudel<sup>6</sup>,*



# Why are neutrons important?

To turn neutrino physics into a precision science, we need to understand complex neutrino-nucleus interactions (specifically on Ar):

- Neutrons carry away a *large fraction*<sup>1</sup> of energy.
- Neutron final states are *model dependent*.
- Neutrons are *difficult to detect* in LAr.

Neutrons are also important for low-energy physics in LAr:

- e.g., modeling **supernova** and **solar** (and now **galactic**<sup>2</sup>) neutrino physics.

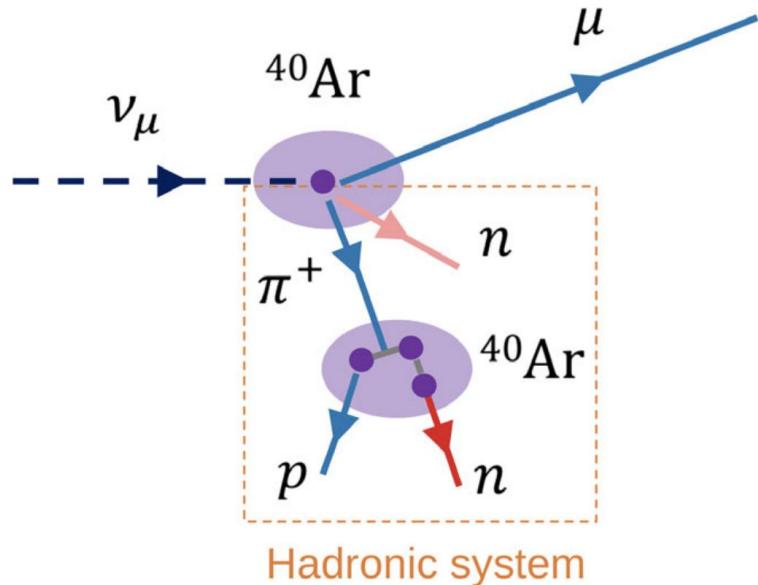


Figure from A. Friedland and W. Li (2019).

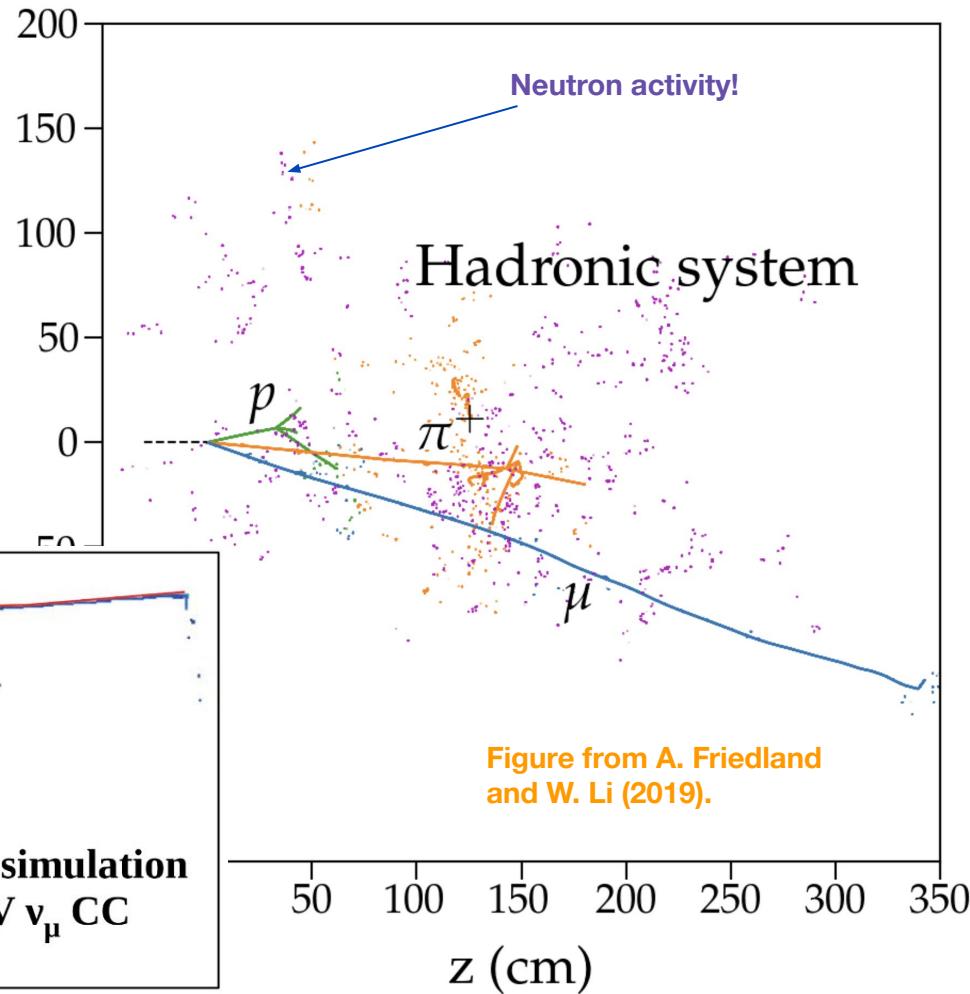
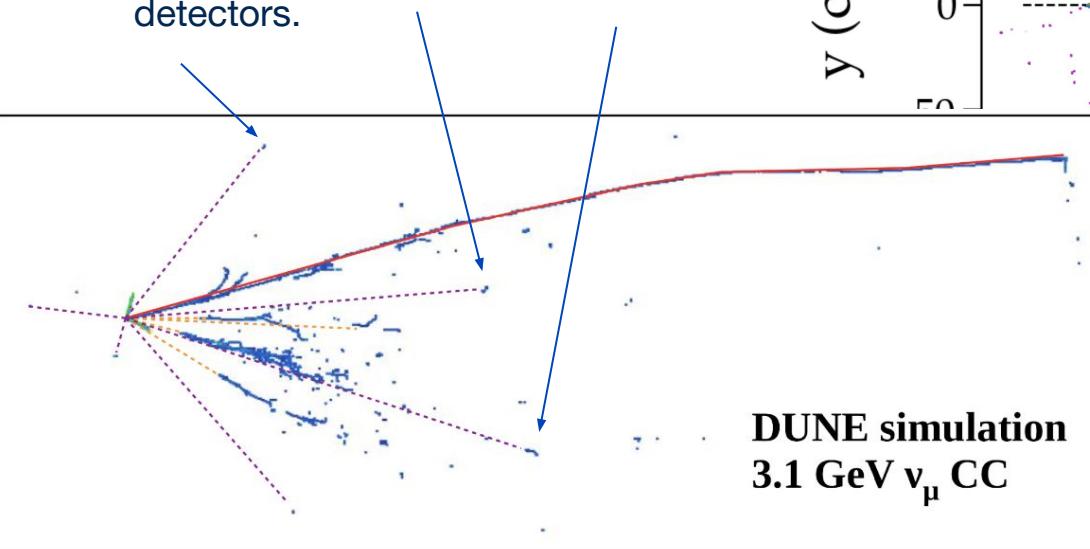
1 A. Friedland and W. Li, *Understanding the energy resolution of liquid argon neutrino detectors*, Physical Review D, **99**, 2019 (<https://arxiv.org/abs/1811.06159>)

2 ICECUBE Collaboration, *Observation of high-energy neutrinos from the Galactic plane*, Science, **380**, 2023 (<https://www.science.org/doi/10.1126/science.adc9818>)

# Difficult to detect?

It is necessary to be able to account for the neutron “missing energy” in order to make precision oscillation measurements (production and transport).

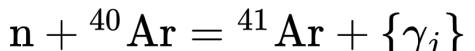
- Neutrons show up as small **blips** in LAr detectors.



# Neutron Calibration (PNS)

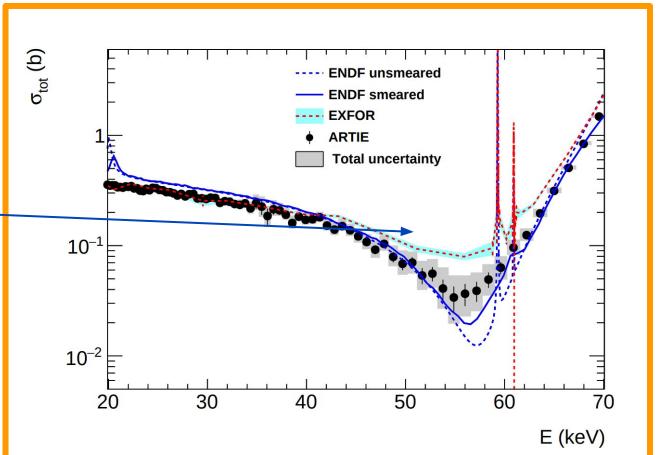
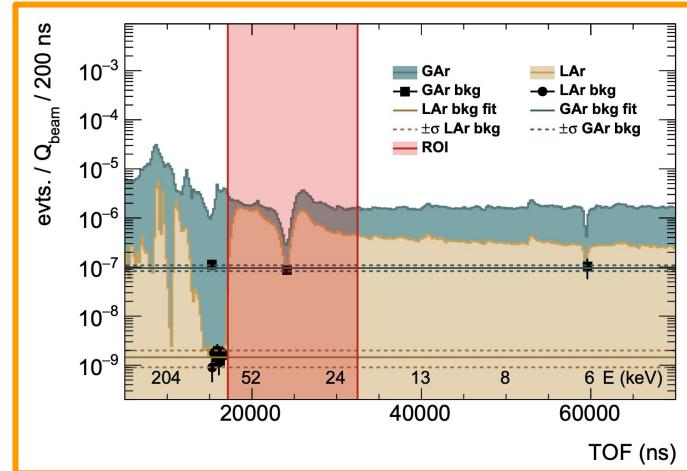
Benefits of low-energy neutrons for calibration:

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



$$\sum_j E(\gamma_j) \approx 6.1\text{MeV}$$

- **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<sup>1</sup> experiment at LANL, with a *follow-up* planned for this year (**ARTIE-II**).

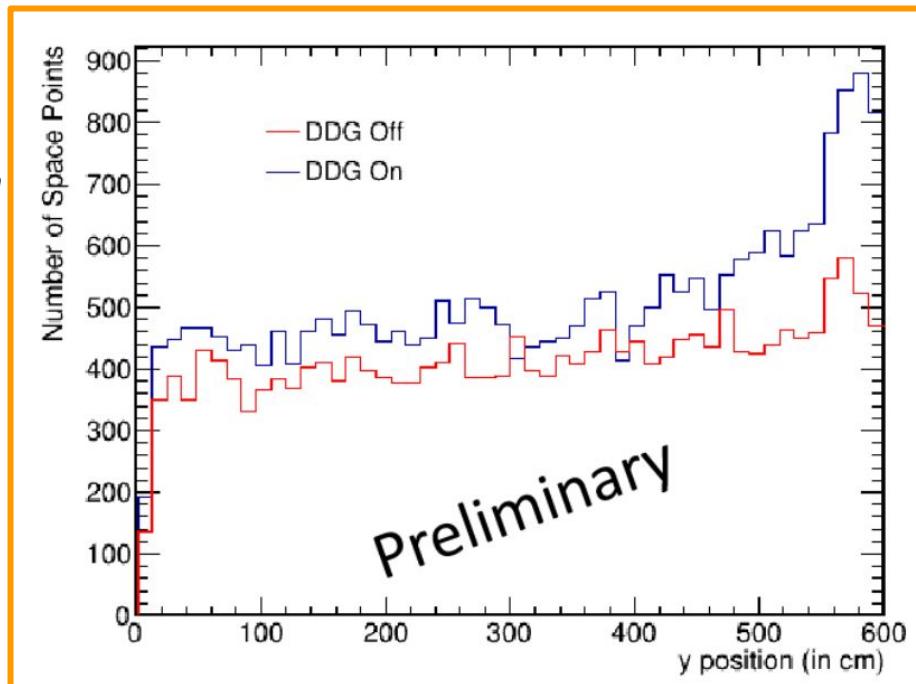
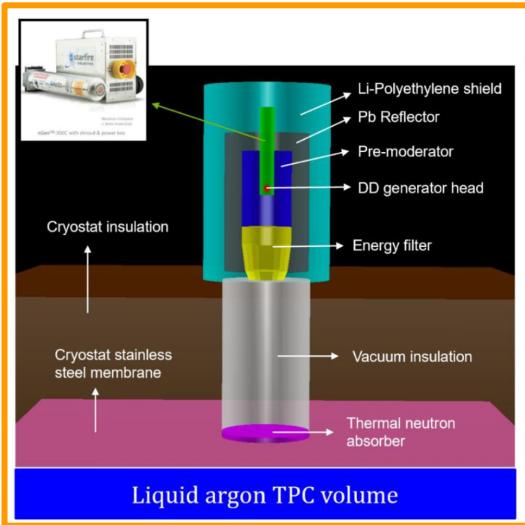


<sup>1</sup> Measurement of the total neutron cross section on argon in the 20 to 70 keV energy range, The ARTIE Collaboration, In review at PRL, 2023, (<https://arxiv.org/abs/2212.05448>).

# 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***.



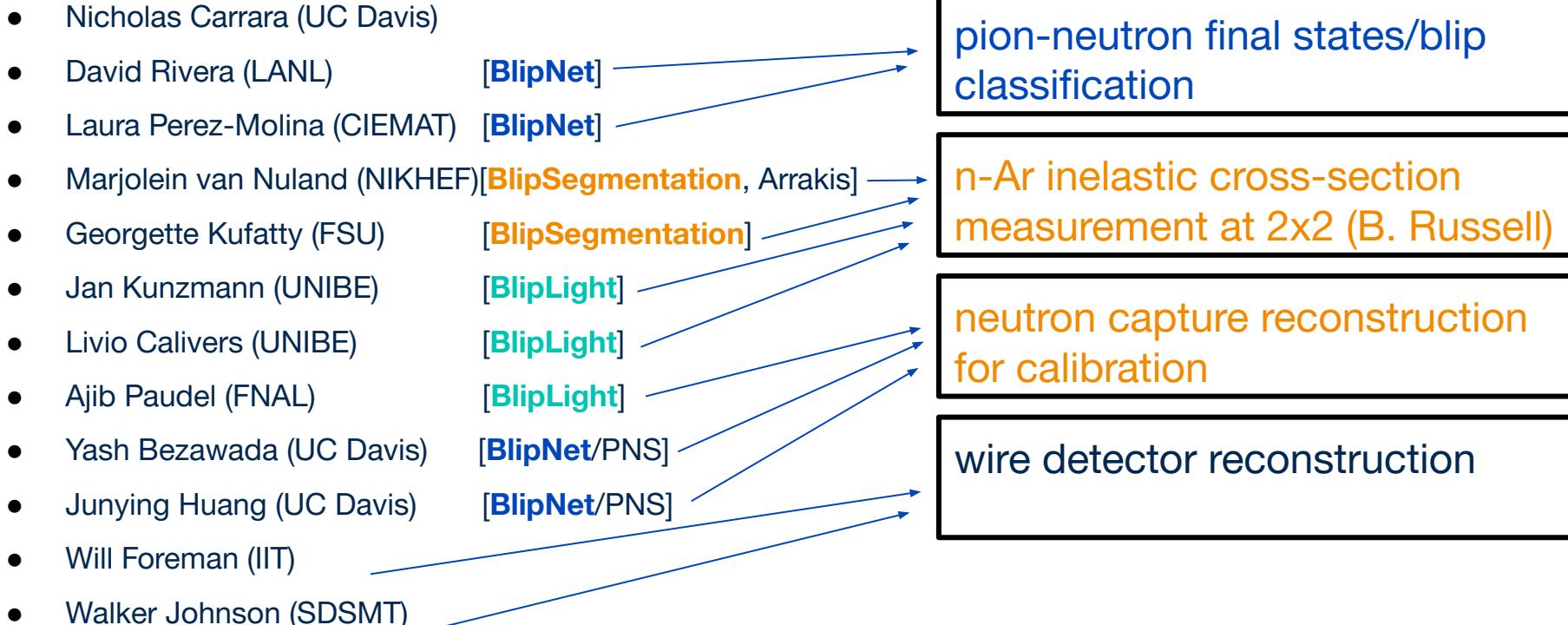
Work done by Y. Bezawada and J. Huang

UCDAVIS

# Blip

## Two neutron analyses

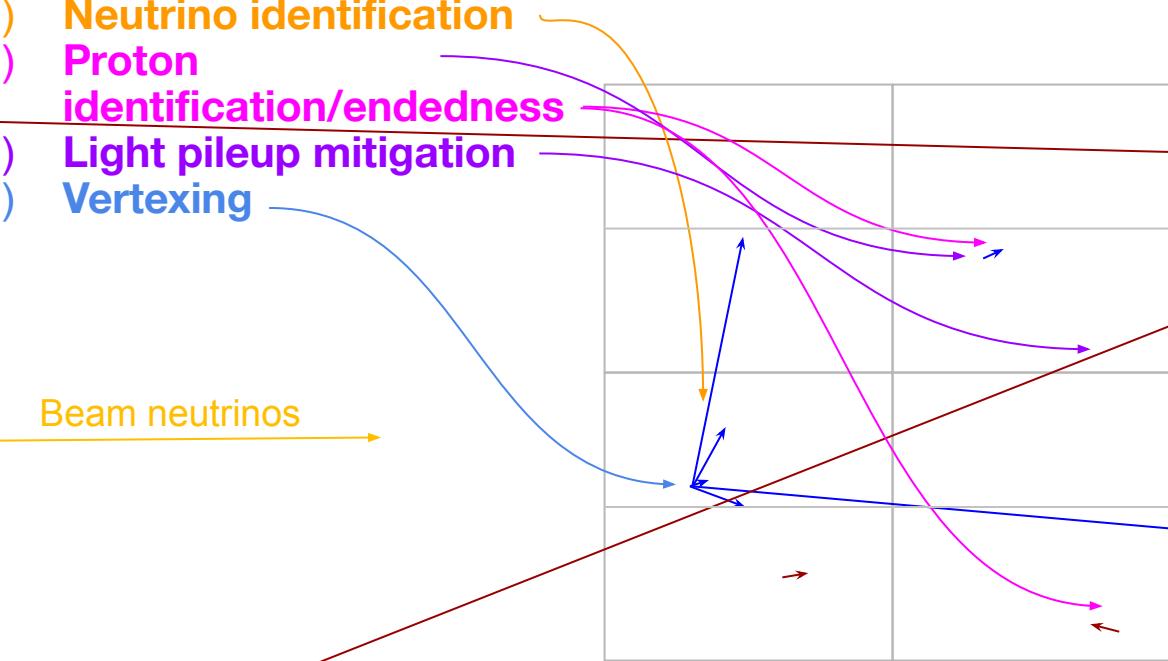
We introduce **Blip**<sup>2</sup>, a collection of ML algorithms for classifying (e.g. low energy) interactions in LArTPCs.



# n-Ar inelastic cross-section measurement at 2x2

## Key analysis elements:

- (1) Neutrino identification
- (2) Proton identification/endedness
- (3) Light pileup mitigation
- (4) Vertexing



Analysis targets:  
(1) Event-by-event Primary Neutron Kinetic Energy Spectrum  
(2) n-Ar Differential Cross Section

\*For adequate signal:background, initial truth-level studies suggest:

- (i)  $\mu^+ + n$  (primaries) + p (secondary) topology
- (ii) neutrino vertex and p reside in different TPCs/modules

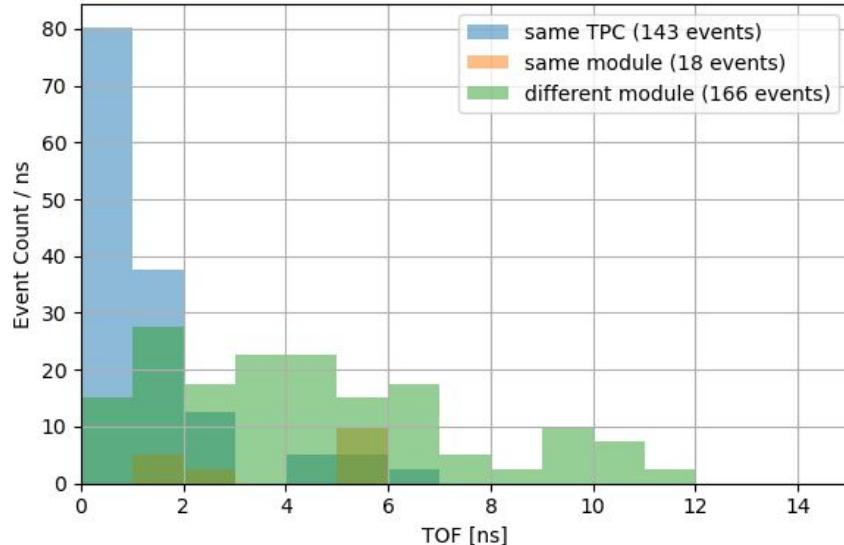
From 2x2 workshop (A. White)

# Importance of Light Readout System:

1. **Light Pileup Mitigation**: need **time of flight** of neutron from proton track
  - a. Need to have signal shape well-characterized
2. **T0** of interactions (neutrino & proton)
  - a. Tof  $\sim 5$  ns
  - b. Timing resolution  $\sim 2$  ns
3. L (lever arm)
  - a. Vertex resolution: to be investigated

$$T_n = (\gamma - 1)m_n$$

where  $\gamma = \frac{1}{\sqrt{1 - \left(\frac{l_{lever}}{ct_{tof}}\right)^2}}$



# Reconstruction

The reconstruction consists of three stages,

1. Infer **high-level variables** from low-level detector reconstruction.
2. Select **neutrino events** with **distended proton tracks**.
3. Infer **inelastic n-Ar interactions** from selection.

Goal: Identify ***distended proton tracks*** originating from a ***neutrino interaction***.



## Key analysis elements:

- (1) Neutrino identification
- (2) Proton identification/endedness
- (3) Light pileup mitigation
- (4) Vertexing

# ArrakisND [N. Carrara, M. van Nuland]

ArrakisND works with h5flow to produce ***high-level variables*** for each reconstructed charge/light hit.

Each category represents a different ***scale*** and is constructed to be ***exhaustive*** and ***mutually exclusive***; (i.e. each hit MUST be described by ONE and ONLY ONE label in each category).

The categories are chosen to capture ***ALL*** relevant physical information.



High-level features	Description
topology	topological descriptor of physics (e.g. blip, track, shower)
particle	the pdg code of the particle which caused the energy deposition
physics_micro	low-level descriptor of physics processes (e.g. mip_ionization, gamma_conversion, etc.)
physics_meso	mid-level descriptor of physics processes (e.g. hip, delta_electron, capture_gamma, etc.)
physics_macro	high-level descriptor of physics processes (e.g. cc_qe, neutron_capture, radiological, etc.)
unique_topology	unique identifier of individual topology instances
unique_particle	unique identifier of individual particle instances (i.e. track id)
unique_physics_*	unique identifier of individual physics instances

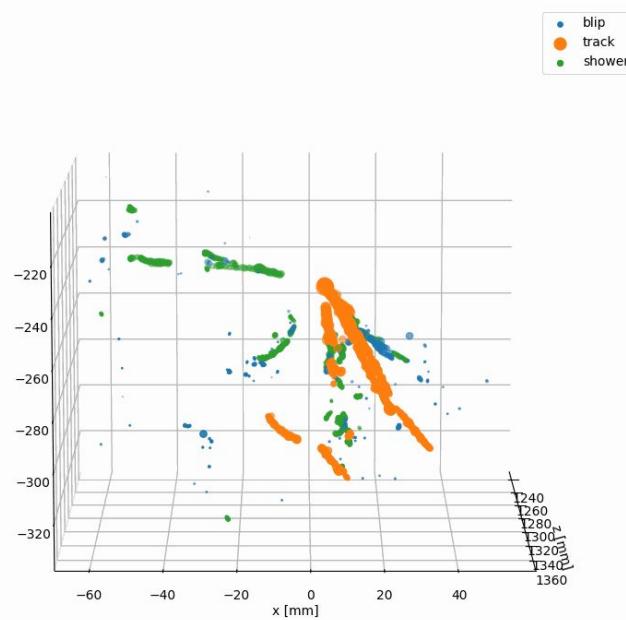
From 2x2 workshop (A. White)

[https://github.com/Neutron-Calibration-in-DUNE/ArrakisND/blob/main/arrakis\\_nd/dataset/common.py](https://github.com/Neutron-Calibration-in-DUNE/ArrakisND/blob/main/arrakis_nd/dataset/common.py)

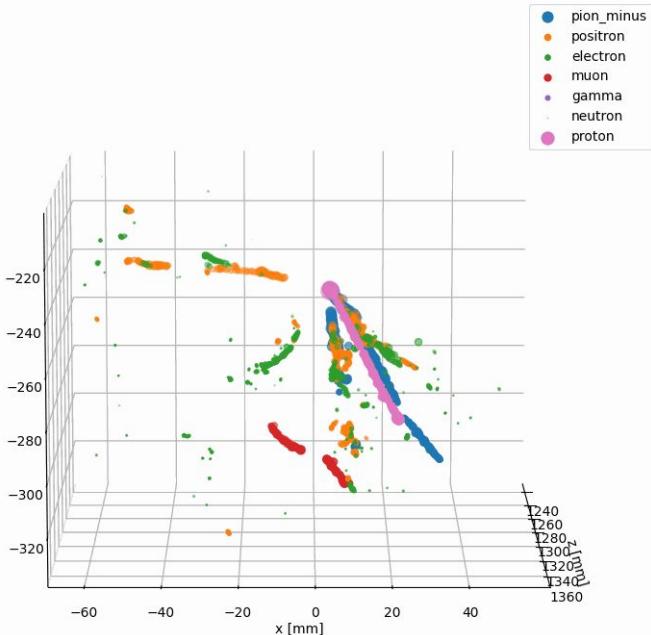
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# ArrakisND [N. Carrara, M. van Nuland]

## Topology



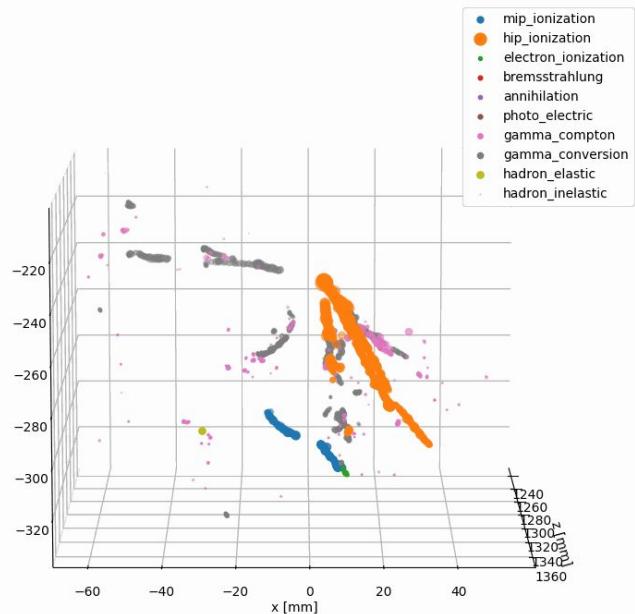
## Particle



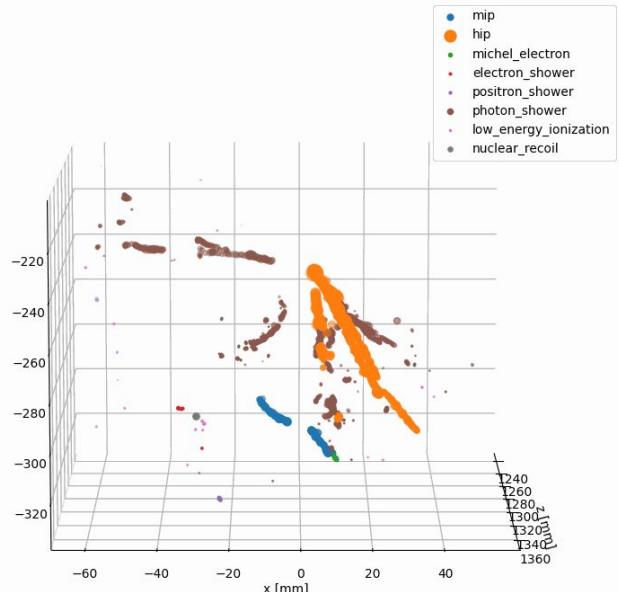
From 2x2 workshop (A. White)

# ArrakisND [N. Carrara, M. van Nuland]

## Physics Micro



## Physics Meso



From 2x2 workshop (A. White)

# ArrakisND [N. Carrara, M. van Nuland]

Work in progress:

- Add in ***track\_topology*** variables  
(vertices, track begin/end, etc.).
- Add **CAF** variables for each event  
(tracks, showers, etc.)
- Add in ***light reco truth*** and ***low level variables*** for reconstruction.
- Finish ***physics\_macro*** logic.

Arrakis is being optimized to run with the flow.

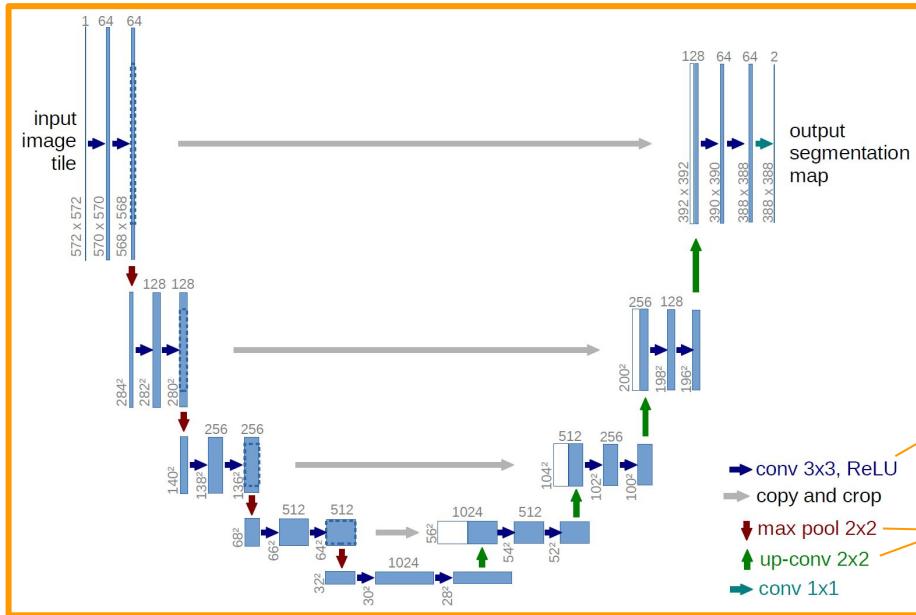
From 2x2 workshop (A. White)

```
module:  
    module_name: 'prep_data'  
    module_type: ['dataset']  
    module_mode: ['dataset_prep']  
    gpu: True  
    gpu_device: 0  
    verbose: True  
  
dataset:  
    skip_processing: false  
    transform: null  
    pre_transform: null  
    pre_filter: null  
    dataset_type: "tpc"  
    dataset_folder: "/local_data/"  
    dataset_files: [  
        "MiniRun4_1E19_RHC.flow.00000.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00001.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00002.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00003.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00004.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00005.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00006.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00007.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00008.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00009.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00010.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00011.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00012.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00013.FLOW.arrakis_nd.npz",  
        "MiniRun4_1E19_RHC.flow.00014.FLOW.arrakis_nd.npz"  
    ]  
variables:  
    positions: ['x', 'y', 'z']  
    features: []  
    classes: ['particle', 'topology', 'physics_micro', 'physics_meso']  
    labels: []  
    clusters: []  
    hits: []  
    position_normalization: []  
    features_normalization: []  
    classes_mask: []  
    labels_mask: [[[]]]  
    voxelization: [1, 1, 1]  
  
weights:  
    class_weights: []  
    sample_weights: False
```

# BlipSegmentation [G. Kuffaty]

Blip is run using a config file structure by specifying ***modules*** (such as the “ml” module).

The simplest model is a UNet structure which can be parameterized at run time.



```

module:
  module_name: 'optimize_blip_segmentation'
  module_type: ['ml']
  module_mode: ['training']
  gpu: true
  gpu_device: 0
  verbose: true
  debug: true

dataset:
  dataset_params: ""
  dataset_type: "tpc"
  skip_processing: true

loader:
  loader_type: "minkowski"
  quantization_mode: "random_subsample"
  minkowski_algorithm: "speed_optimized"
  batch_size: 16
  test_split: 0.1
  test_seed: 42
  validation_split: 0.3
  validation_seed: 42
  num_workers: 4

training:
  iterations: 1      You, 3 weeks ago + some changes
  epochs: 100
  checkpoint: 25
  progress_bar: "all" # train, validation, test, all
  rewrite_bar: false # whether to leave bars after each epoch
  save_predictions: false # whether to save network outputs in original file
  no_timing: true # whether to keep timing/memory info in callback
  skip_metrics: true # whether to skip metrics except for testing sets
  seed: 0

model:
  model_type: "single"
  BlipSegmentation:
    in_channels: 1
    out_channels: [5]
    classifications: ['particle', 'topology', 'physics_micro', 'physics_meso']
    filtrations: [64, 128, 256, 512]
    residual: true
    sparse_conv_params:
      kernel_size: 3
      stride: 1
      dilation: 1
      activation: "prelu"
      dimension: 3
      batch_norm: True
      num_of_convs: 2
      dropout: 0.1
    conv_transpose_params:
      kernel_size: 2
      stride: 2
      dilation: 1
      dimension: 3
    max_pooling_params:
      kernel_size: 2
      stride: 2
      dilation: 1
      dimension: 3

```

# Hyper-parameter Tuning [N. Carrara, G. Kuffaty]

Blip is configured through a container on NERSC.

A Blip program can generate a collection of config files with varying parameters for hyperparameter tuning.

Several models can be deployed for training simultaneously on Perlmutter. The results are then analyzed after training.



infophysics/blip ☆

By [infophysics](#) • Updated 2 days ago

Docker image for the blip package.

Image

```
setfacl -m u:nobody:x /global/cfs/cdirs/dune/users/${USER}
shifter --image=docker:infophysics/blip:latest \
--volume="${LOCAL_SCRATCH}:/local_scratch;${LOCAL_BLIP}:/local_blip;${LOCAL_DATA}:/local_data" \
./blip_segmentation_optimize.sh $hyper_parameter_config
```

You, 3 weeks ago + some changes

```
#!/bin/bash
cd /local_scratch

prep_data_config="/local_blip/BlipModels/blip_segmentation/2x2/configs/prep_data.yaml"
optimization_config="/local_blip/BlipModels/blip_segmentation/2x2/configs/optimize_blip_segmentation.yaml"

# download data to /local_data/ and process it
blip "$prep_data_config"

# generate hyper-parameter configs
create_hyper_parameter_configs "$optimization_config" -hyper_parameter_location=${LOCAL_BLIP}
```

You, 3 w

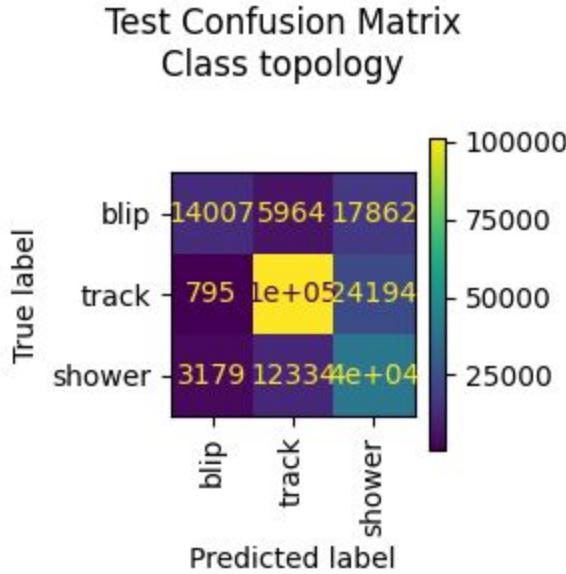
From 2x2 workshop (A. White)

# BlipSegmentation [N. Carrara, G. Kuffaty]

Very early!



Losses and metrics can also be configured at run time.



```
criterion:
  CrossEntropyLoss:
    alpha: 1.0
    target_type: "classes"
    targets: ['particle', 'topology', 'physics_micro', 'physics_meso']
    outputs: ['particle', 'topology', 'physics_micro', 'physics_meso']
    augmentations: 0

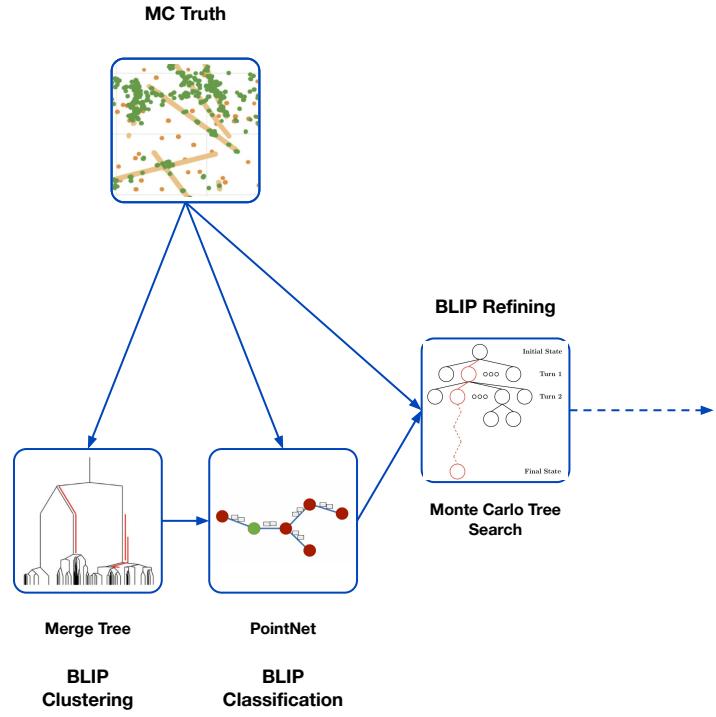
metrics:
  ConfusionMatrixMetric:
    target_type: "classes"
    when_to_compute: "test"
    targets: ['particle', 'topology', 'physics_micro', 'physics_meso']
    outputs: ['particle', 'topology', 'physics_micro', 'physics_meso']
    augmentations: 0
  AdjustedRandIndexMetric:
    target_type: "classes"
    when_to_compute: "test"
    targets: ['particle', 'topology', 'physics_micro', 'physics_meso']
    outputs: ['particle', 'topology', 'physics_micro', 'physics_meso']
    augmentations: 0
  AUROCMetric:
    target_type: "classes"
    when_to_compute: "test"
    targets: ['particle', 'topology', 'physics_micro', 'physics_meso']
    outputs: ['particle', 'topology', 'physics_micro', 'physics_meso']
    augmentations: 0
  DiceScoreMetric:
    target_type: "classes"
    when_to_compute: "test"
    targets: ['particle', 'topology', 'physics_micro', 'physics_meso']
    outputs: ['particle', 'topology', 'physics_micro', 'physics_meso']
    augmentations: 0
  JaccardIndexMetric:
    target_type: "classes"
    when_to_compute: "test"
    targets: ['particle', 'topology', 'physics_micro', 'physics_meso']
    outputs: ['particle', 'topology', 'physics_micro', 'physics_meso']
    augmentations: 0
  AveragePrecisionMetric:
    target_type: "classes"
    when_to_compute: "test"
    targets: ['particle', 'topology', 'physics_micro', 'physics_meso']
    outputs: ['particle', 'topology', 'physics_micro', 'physics_meso']
    augmentations: 0
  PrecisionMetric:
    target_type: "classes"
    when_to_compute: "test"
    targets: ['particle', 'topology', 'physics_micro', 'physics_meso']
    outputs: ['particle', 'topology', 'physics_micro', 'physics_meso']
    augmentations: 0
  RecallMetric:
    target_type: "classes"
    when_to_compute: "test"
    targets: ['particle', 'topology', 'physics_micro', 'physics_meso']
    outputs: ['particle', 'topology', 'physics_micro', 'physics_meso']
    augmentations: 0
```

# BlipNet

N. Carrara, D. Rivera, L.  
Perez-Molina

Let's compare our results with MC Truth at each stage of the reconstruction. The full chain begins with,

1. **Merge Tree** - First we construct a topological description of the event called a *decorated merge tree*.
2. **BLIP Classification** - BlipGraph is used to classify blips as different types (Ar39, Kr85, Rn222, Capture Gammas, etc.)
3. **BLIP Refining** - A Monte Carlo Tree Search algorithm is used to refine blips and construct higher-level structures.



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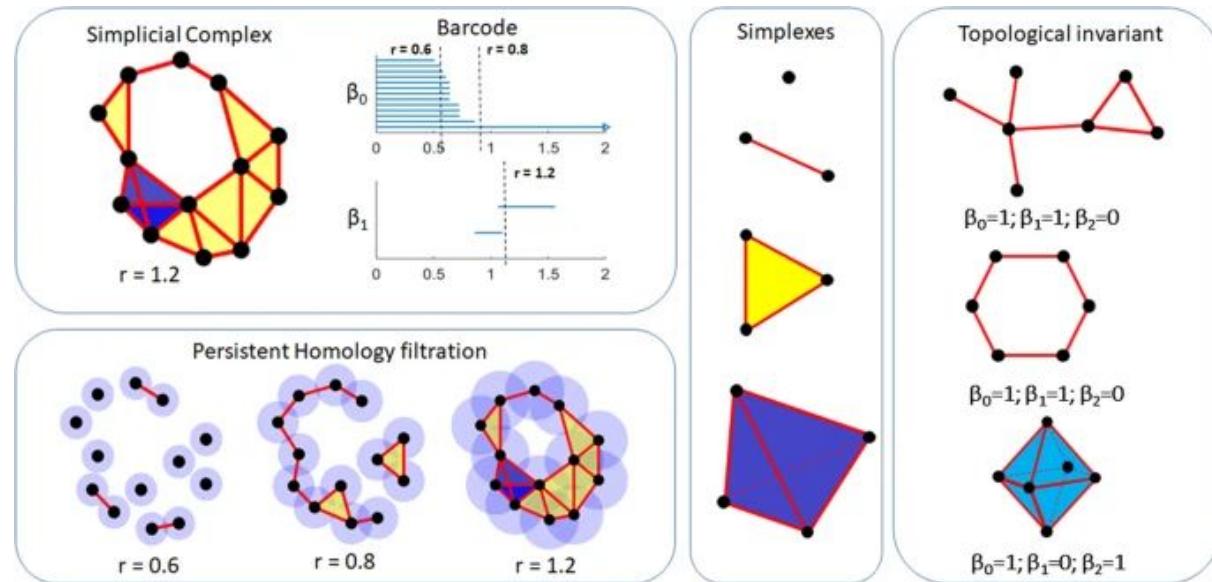
1. **Merge Tree** - First we construct a topological description of the event called a *decorated merge tree*.

5 G. Carlsson, Topology and Data,  
(<https://www.ams.org/journals/bull/2009-46-02/S0273-0979-09-01249-X/S0273-0979-09-01249-X.pdf>).

6 H. Edelsbrunner and J. Harer, Persistent Homology - A Survey,  
(<https://www.maths.ed.ac.uk/~v1ranick/papers/edelhare.pdf>).

7 H. Edelsbrunner et al., Topological Data Analysis in Information Space,  
(<https://arxiv.org/abs/1903.08510>).

**Persistent Homology** - A set of theorems and techniques in **topological data analysis** for studying topological features of point sets.



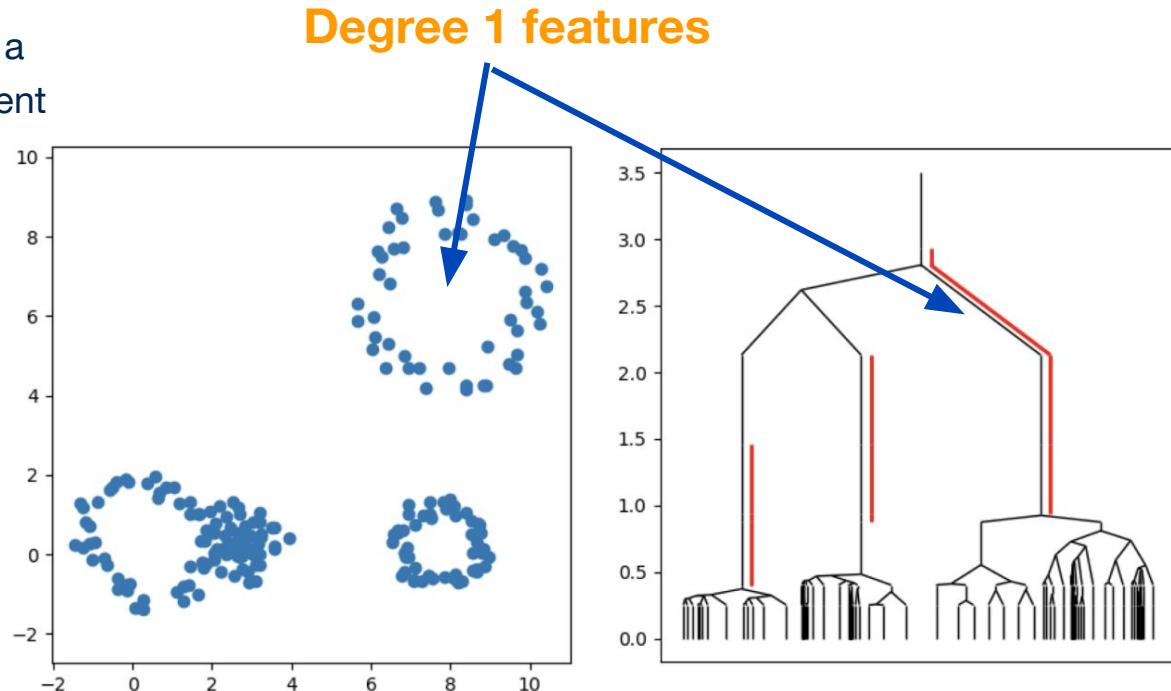
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**Decorated Merge Tree** - Topological description of a point set where a *merge tree* is decorated with degree ( $n > 0$ ) features.

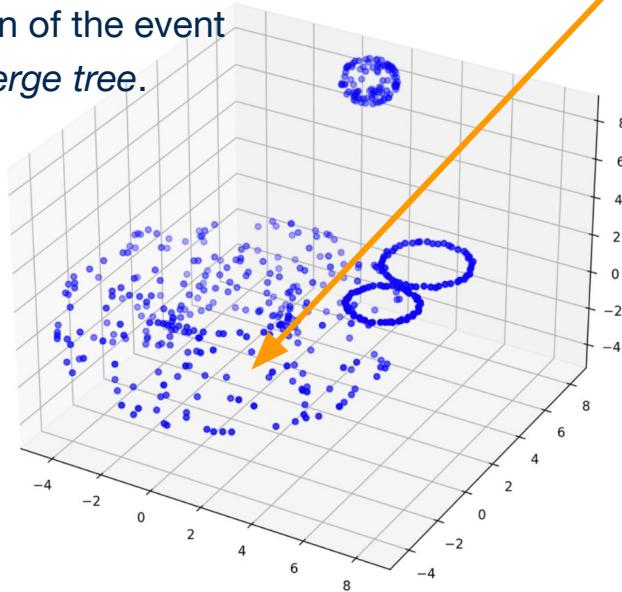


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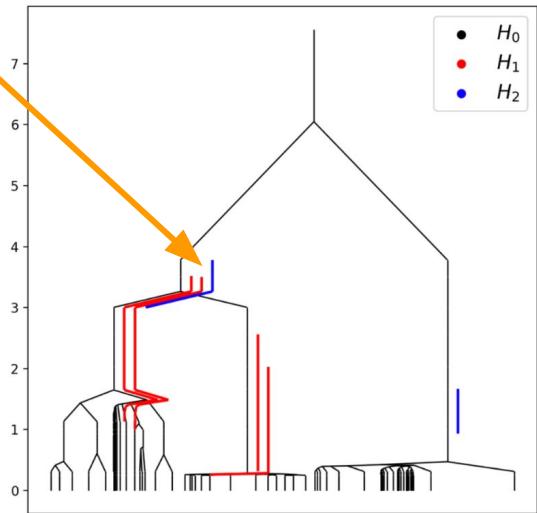
Let's compare our results with MC Truth at each stage of the reconstruction. The full chain begins with,

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**Degree 2 features**



# BlipNet

N. Carrara, D. Rivera, L.  
Perez-Molina

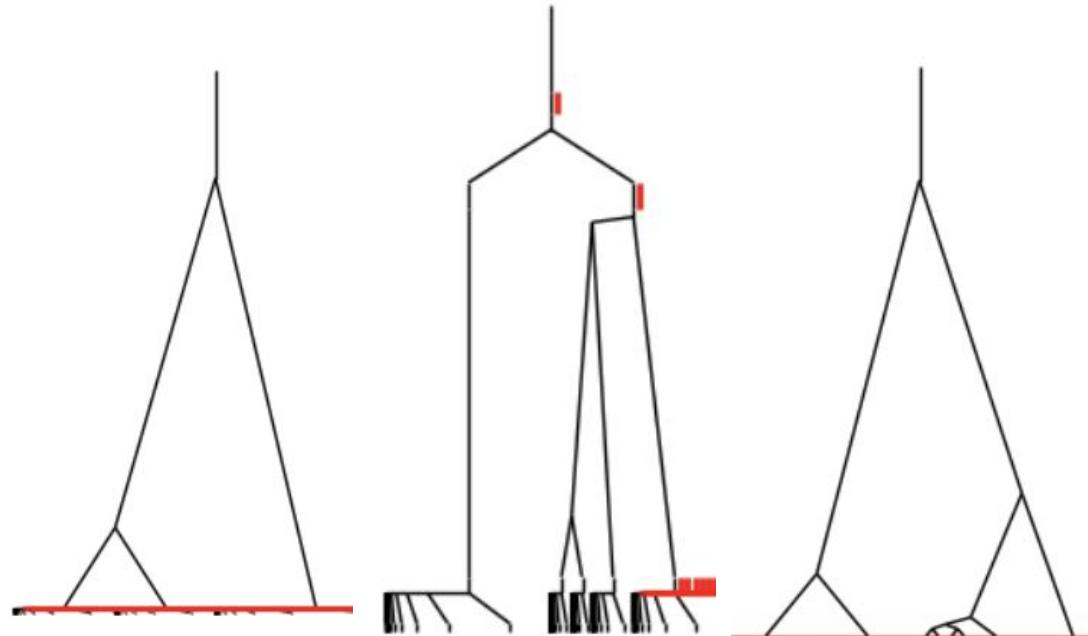
Let's compare our results with MC Truth at each stage of the reconstruction. The full chain begins with,

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**Merge Tree code  
developed by  
Laura Perez-Molina.**

**Decorated Merge Tree** - Topological description of a point set where a *merge tree* is decorated with degree ( $n > 0$ ) features.

## Merge Trees from capture gammas

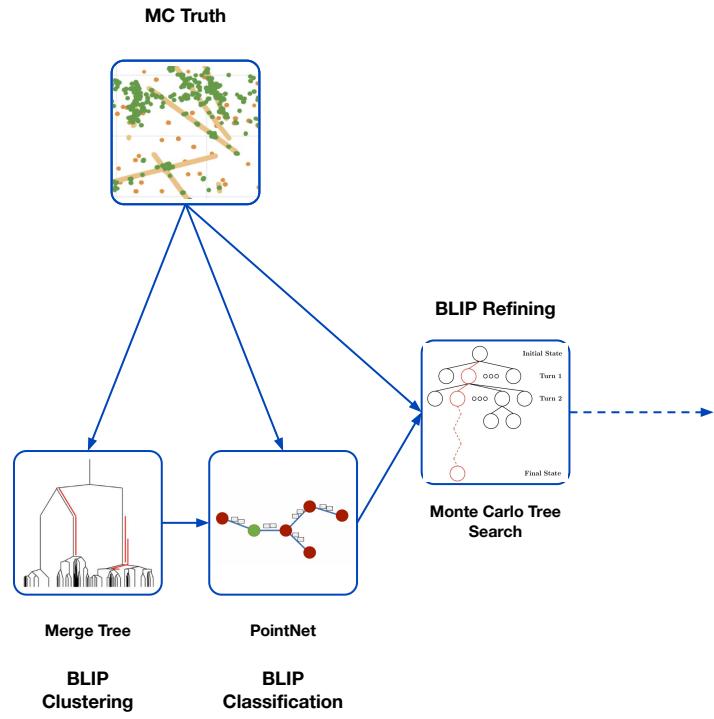


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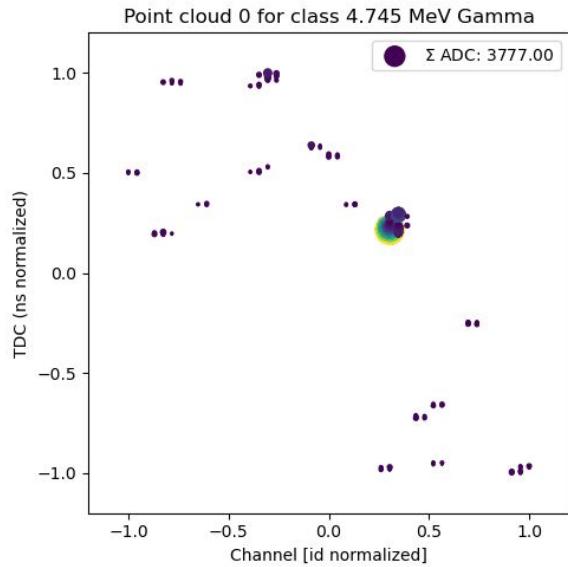
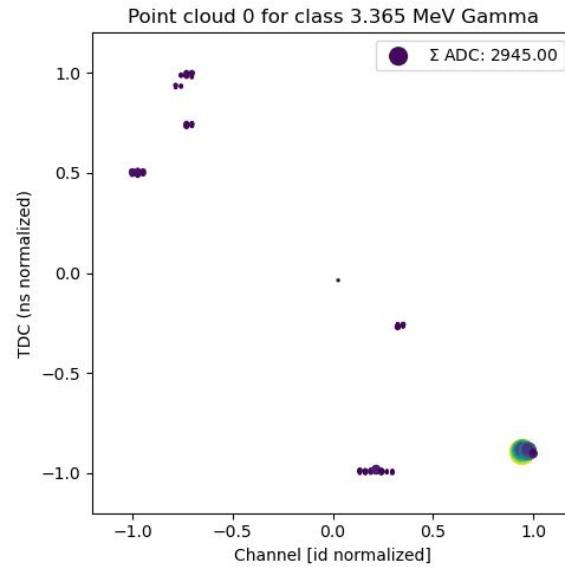
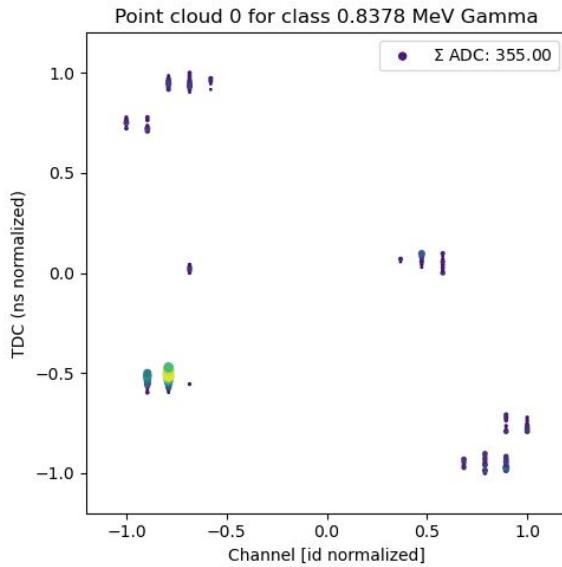
1. **Merge Tree** - First we construct a topological description of the event called a *decorated merge tree*.
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# Blip Examples

Below are examples of different neutron capture gammas simulated in LArSoft.

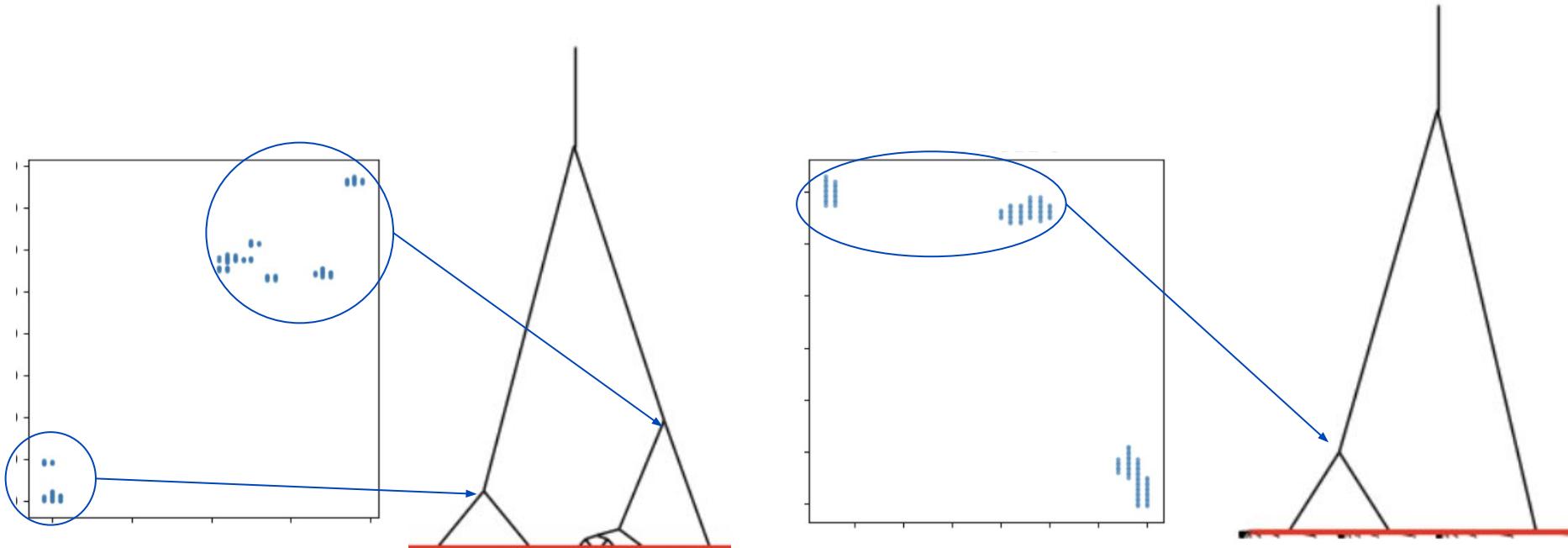
- Each cluster is normalized so that it is centered at zero and extends from [-1,1] in each variable.
- ADC is normalized over all events.



# Blip Examples

Below are examples of different neutron capture gammas simulated in LArSoft.

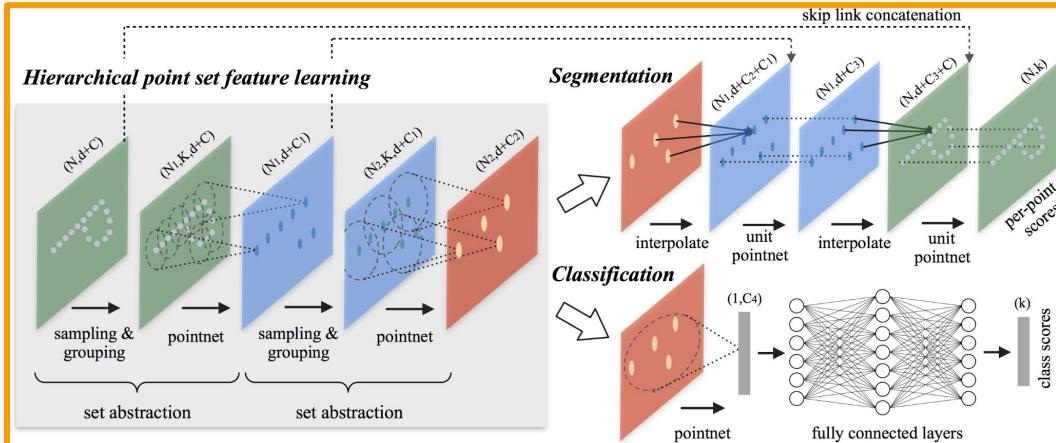
- Merge Trees for 2.5661 MeV Gammas.



# BLIP Classification

BLIP Classification will consist of at least the following two 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>).
- **BlipGraph** - The second network will learn to classify clusters at different scales (e.g. PointNet<sup>4</sup>, DynamicEdgeConv<sup>6</sup>).



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

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



**UCDAVIS**

<sup>4</sup> PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation, C. Qi et. al., CVPR 2017, (<https://arxiv.org/abs/1612.00593>).

<sup>5</sup> PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space, C. Qi et. al., (<https://arxiv.org/abs/1706.02413>)

<sup>6</sup> Dynamic Graph CNN for Learning on Point Clouds, Y. Wang et. al., 2018, (<https://arxiv.org/abs/1801.07829>)

# PointNet/DynamicEdgeConv

Point cloud neural networks take advantage of three main properties of the datasets:

1. **Unordered** - Point clouds, unlike pixel arrays, are unordered and can have a variable number of points!
2. **Distance Metric** - Our point clouds have a geometry and local interaction information.
3. **Symmetries** - Due to physics/geometry, the point clouds are invariant under certain transformations.

Figure from C. Qi et al.  
(2017).

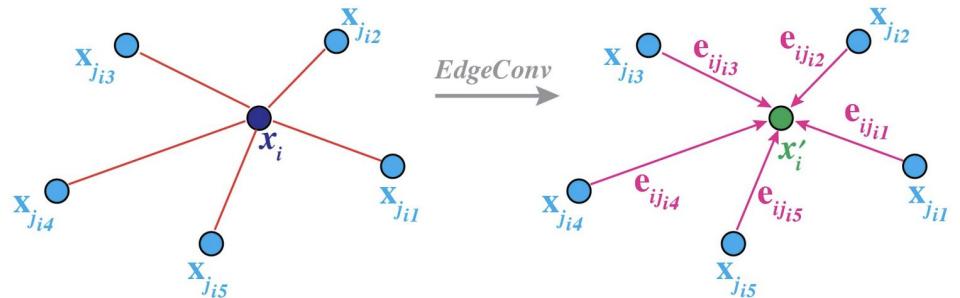
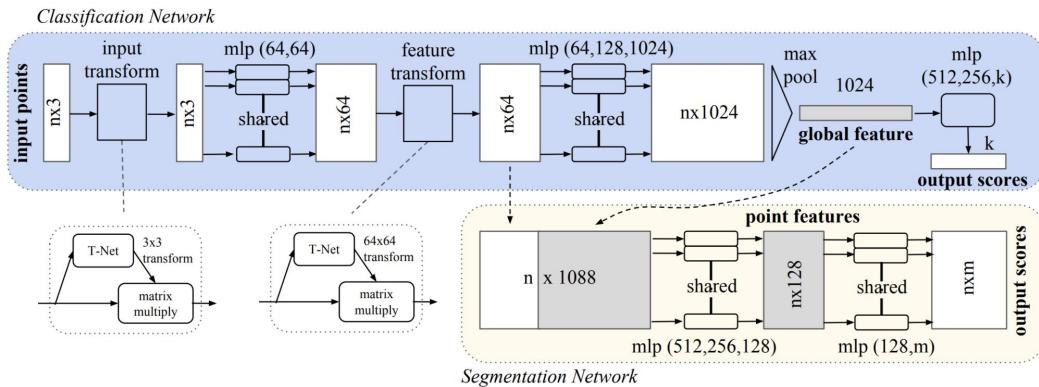


Figure from Y. Wang et al.  
(2019).

# Contrastive Learning

We can utilize symmetries in our dataset to conduct a semi-supervised learning in which point clouds are grouped together by symmetries in their representation.

Using the *Normalized Temperature-scaled Cross Entropy Loss (**NTXent**)*:

$$\ell_{i,j} = -\log \frac{\exp(\text{sim}(\mathbf{z}_i, \mathbf{z}_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\text{sim}(\mathbf{z}_i, \mathbf{z}_k)/\tau)}, \quad (1)$$

we push “like” clusters closer together in the embedding space and push all others away.

? K. Sohn, *Improved Deep Metric Learning With Multi-class N-pair Loss Objective*, NIPS (2016),  
[https://proceedings.neurips.cc/paper\\_files/paper/2016/file/6b180037abbebea991d8b1232f8a8ca9-Paper.pdf](https://proceedings.neurips.cc/paper_files/paper/2016/file/6b180037abbebea991d8b1232f8a8ca9-Paper.pdf)

Contrastive learning scheme  
<https://ai.googleblog.com/2020/04/advancing-self-supervised-and-semi.html>

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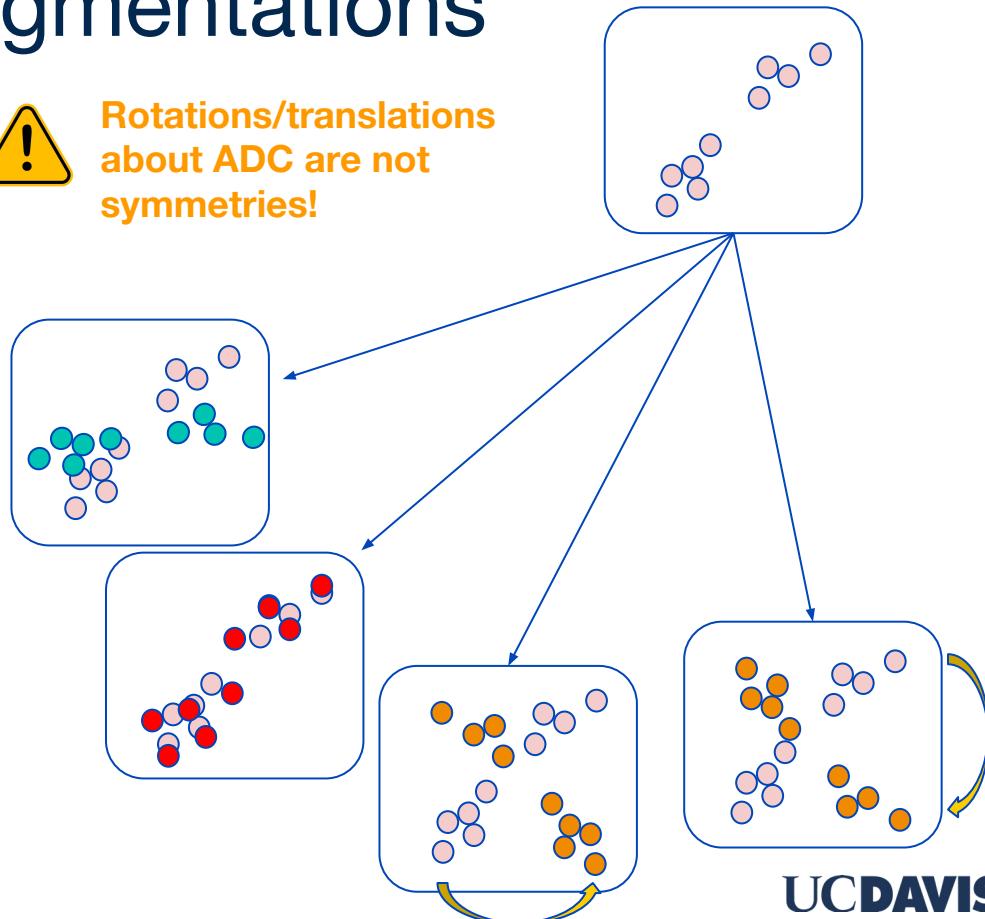
# Symmetries -> Augmentations

There are several symmetries in our dataset due to physics:

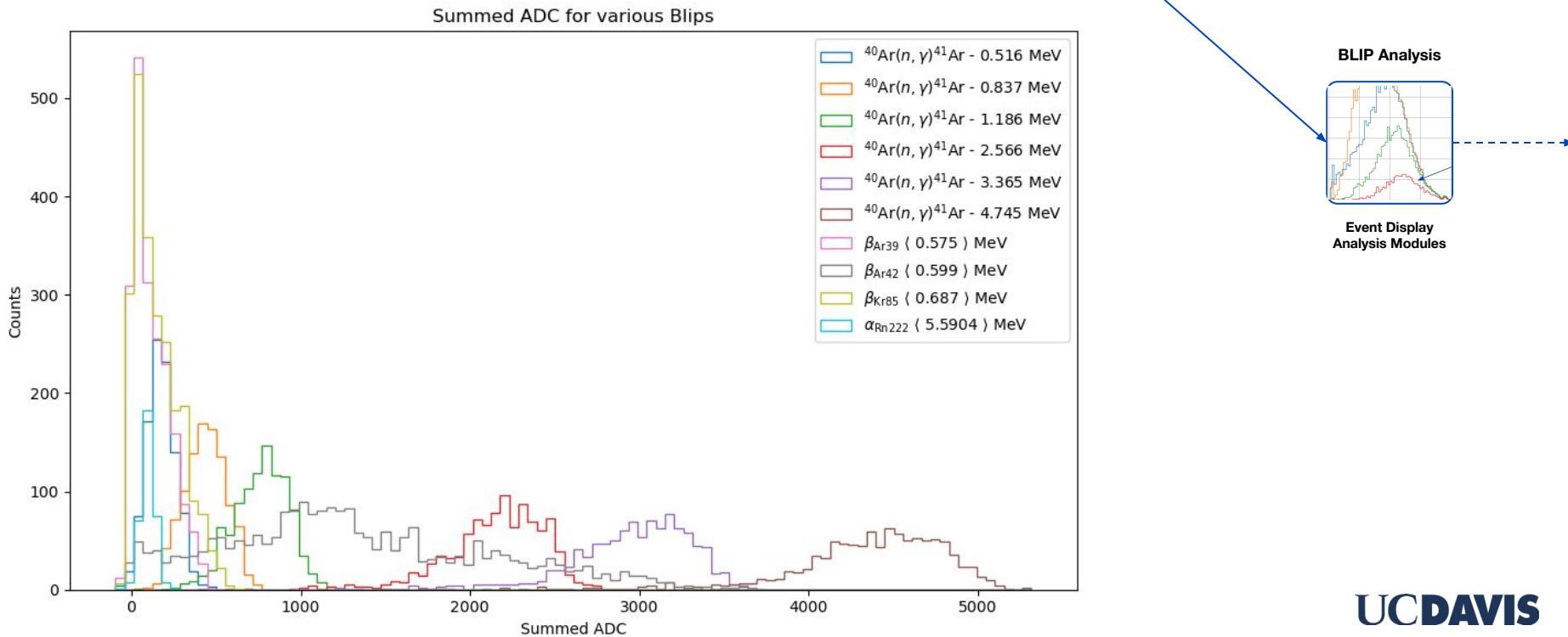


**Rotations/translations about ADC are not symmetries!**

1. **Translation** - Translations in (channel,tdc) are handled by normalizing each point cloud to the origin.
2. **Rotation** - Rotations about (channel,tdc) are implemented as part of the augmentations.
3. **Fluctuations** - Fluctuations can occur from many sources including the electron drift.
4. **Parity** - Flipping of the momentum of the particle along the (channel, tdc) directions.

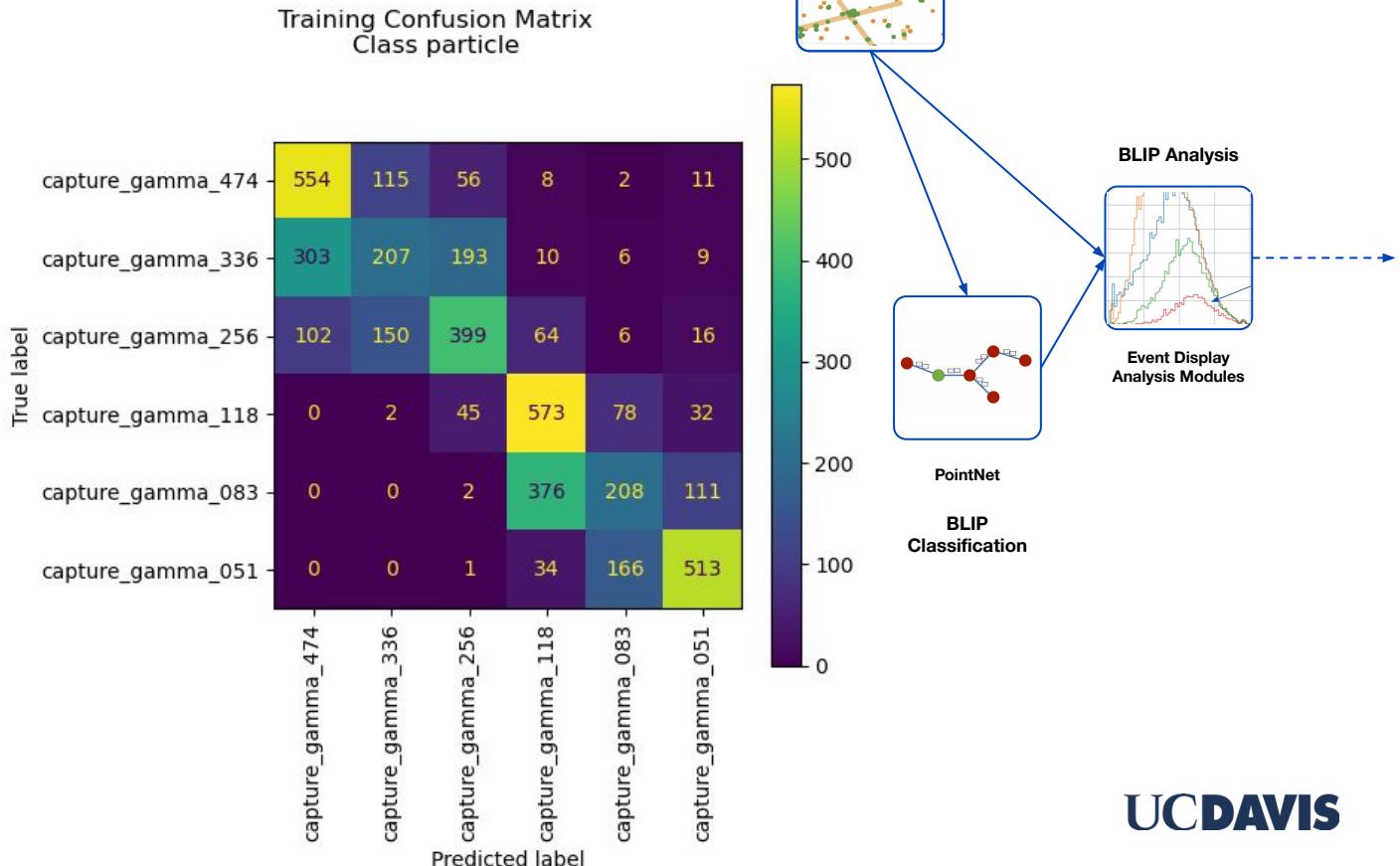


# Far Detector (channel, tdc, adc)



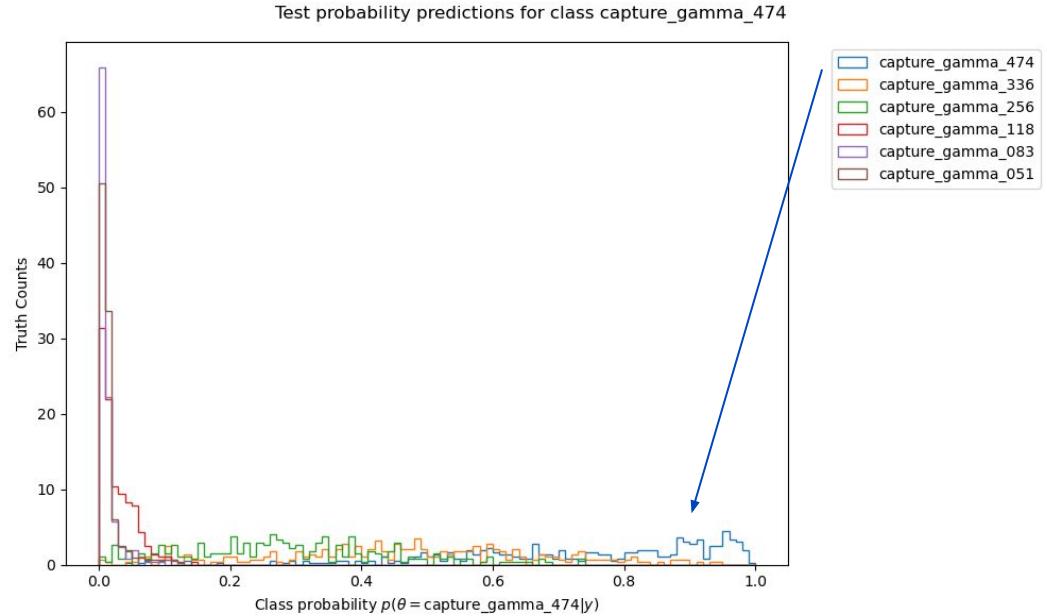
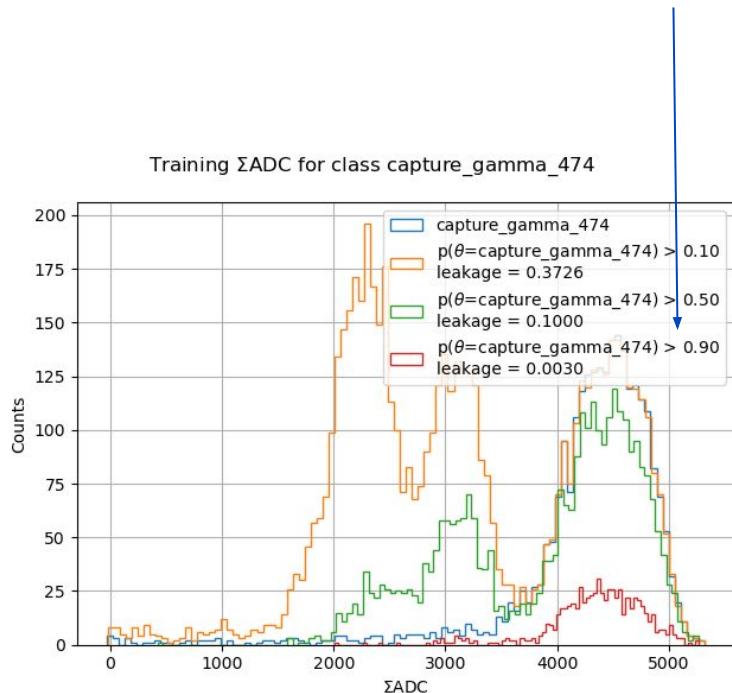
# MCTruth + BlipGraph

The model needs some tuning, but the current version seems to be learning something about the shapes of the point clouds.

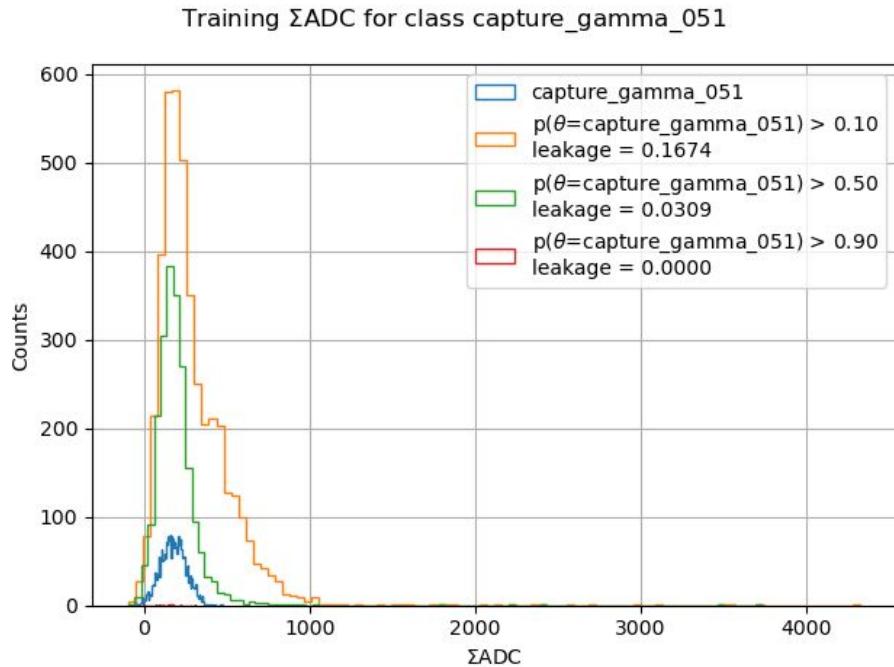
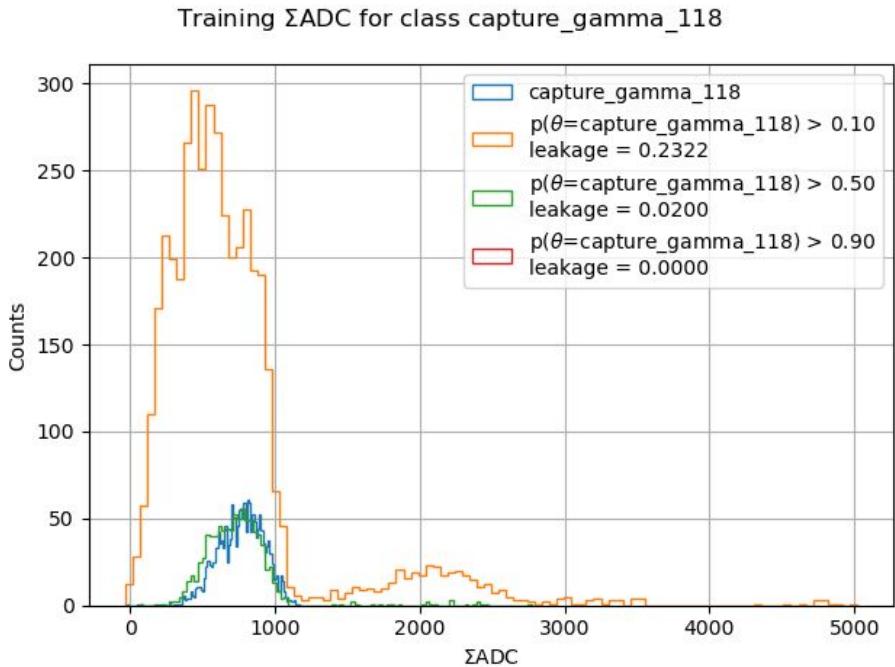


# MCTruth + BlipGraph

This early model rejects 99.7 % of all other blip types when imposing a 90% cut on the probability to being a 4.745 MeV gamma.



# MCTruth + BlipGraph

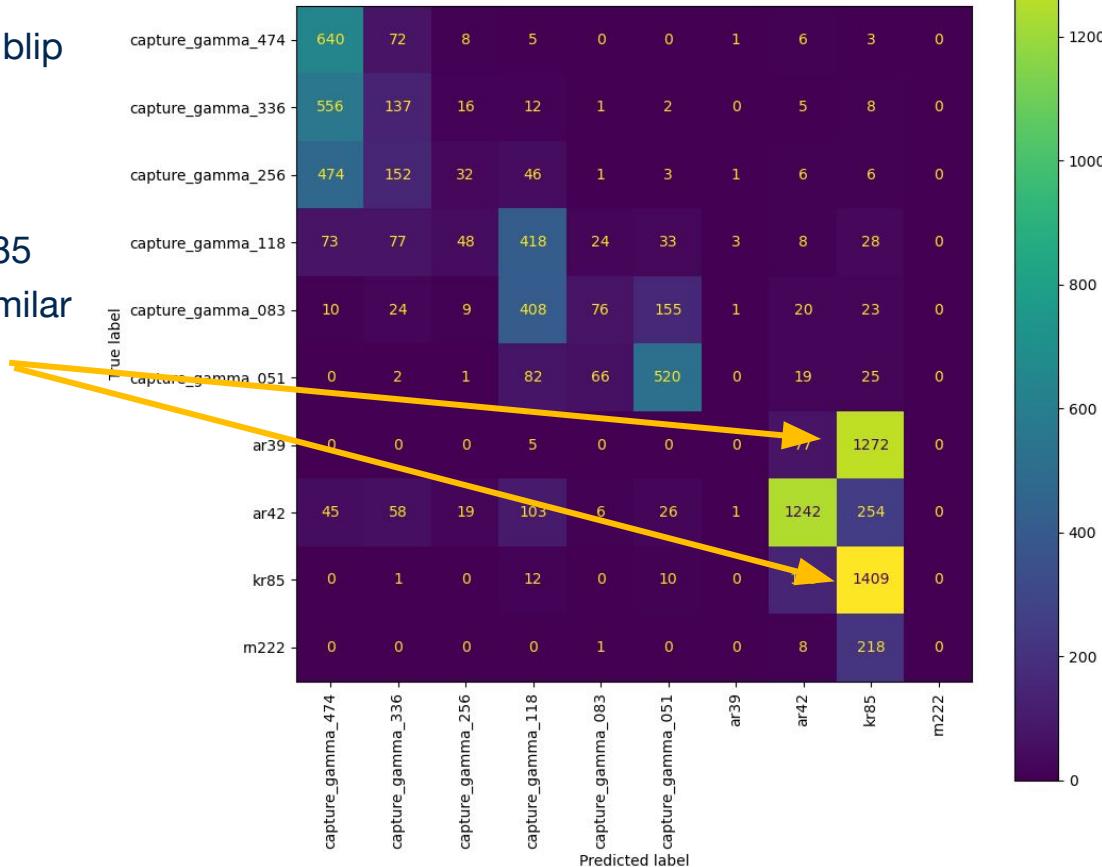


Training Confusion Matrix  
Class particle

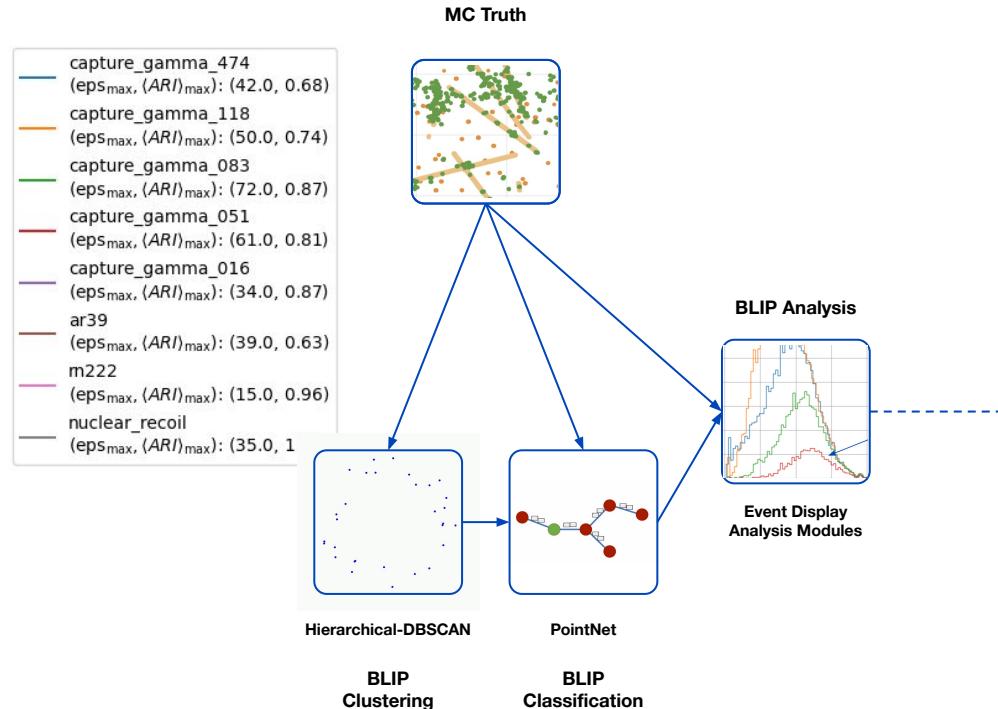
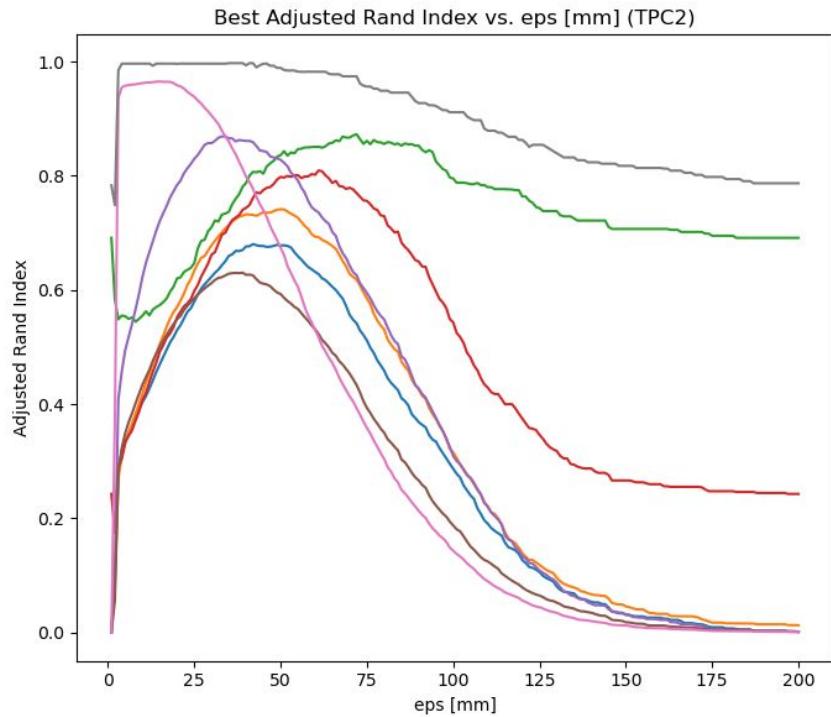
# MCTruth + BlipGraph

Some preliminary results on all current blip types.

Perhaps unsurprising that Ar39 and Kr85 are difficult to distinguish given their similar physics.



# MCTruth + Clustering + BlipGraph



# BlipNet

Let's compare our results with MC Truth at each stage of the reconstruction. The full chain begins with,

1. **Merge Tree** - First we construct a topological description of the event called a *decorated merge tree*.
2. **BLIP Classification** - PointNet is used to classify blips as different types (Ar39, Kr85, Rn222, Capture Gammas, etc.)
3. **BLIP Refining** - A Monte Carlo Tree Search algorithm is used to refine blips and construct higher-level structures.

**N. Carrara, D. Rivera, L. Perez-Molina**

Stay tuned for progress on BlipNet! See this recent publication (<https://arxiv.org/abs/2309.08516>) for some details on Monte Carlo Tree Search:

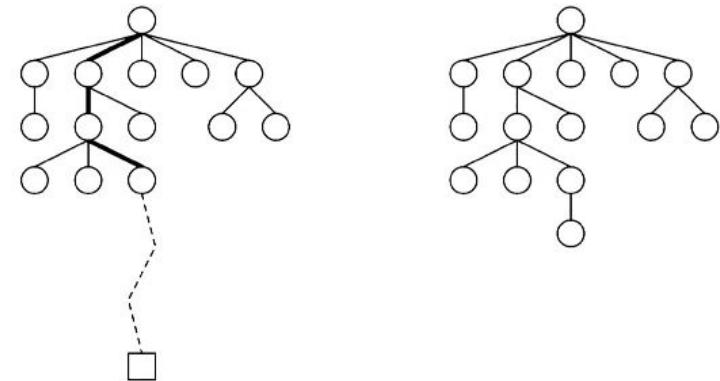
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## USING MONTE CARLO TREE SEARCH TO CALCULATE MUTUAL INFORMATION IN HIGH DIMENSIONS

---

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# Work in Progress

## Arrakis:

- ✓ 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/NERSC:

- ❑ 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.

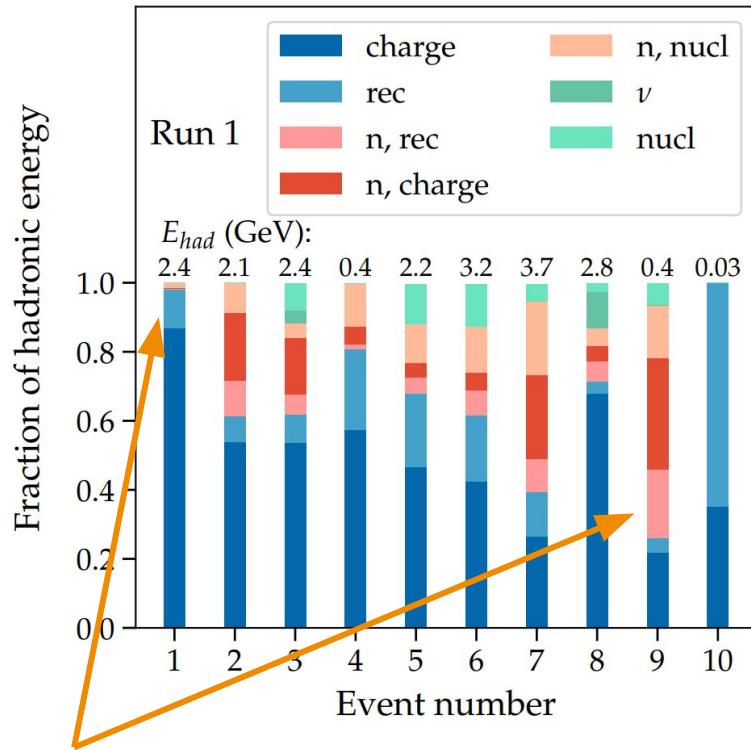
# Backup

# Energy resolution?

It is necessary to be able to account for the neutron **“missing energy”** in order to make precision oscillation measurements (production and transport).

A. Friedland and W. Li (2019) characterized the sources of missing energy in LArTPCs as,

1. Electronic shower sprays (**charge**)
2. Recombination effects (**rec**)
3. Nuclear breakup (**nucl**)
4. Outgoing neutrinos ( **$\nu$** )
5. Subthreshold particles
6. **Primary and secondary neutrons**



Contributions from neutrons vary widely from event to event!

Figure from A. Friedland and W. Li (2019).

# Energy resolution?

This pie chart from the same paper (2019) shows the average amount of missing energy over many events (~10K).

- Neutrons contribute nearly **~30%** of the missing energy on average!

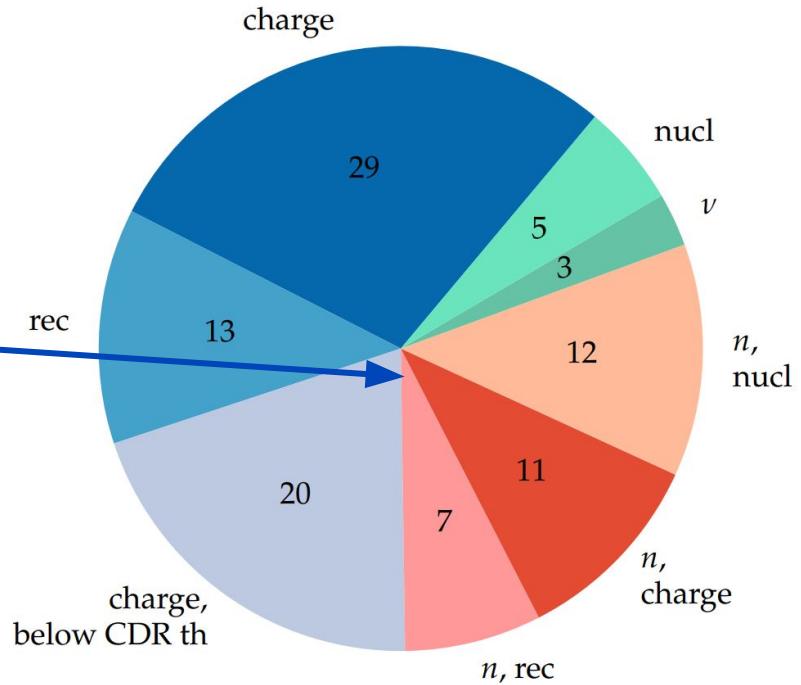
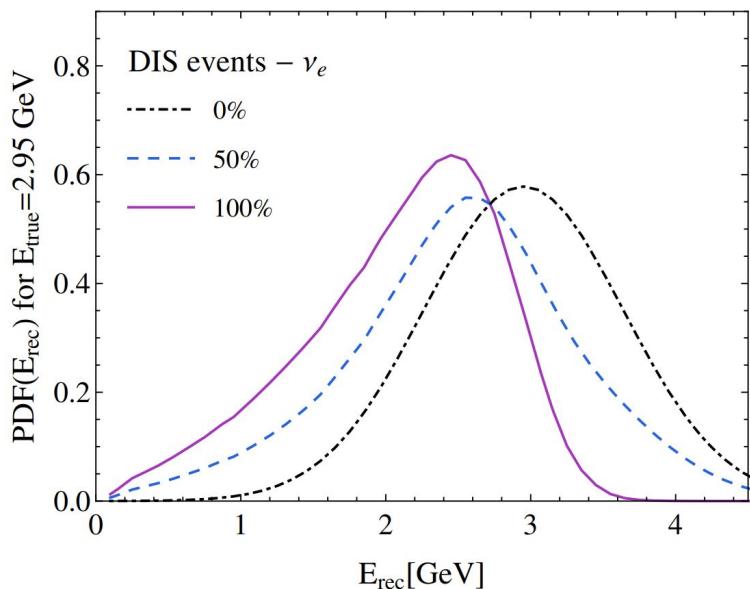
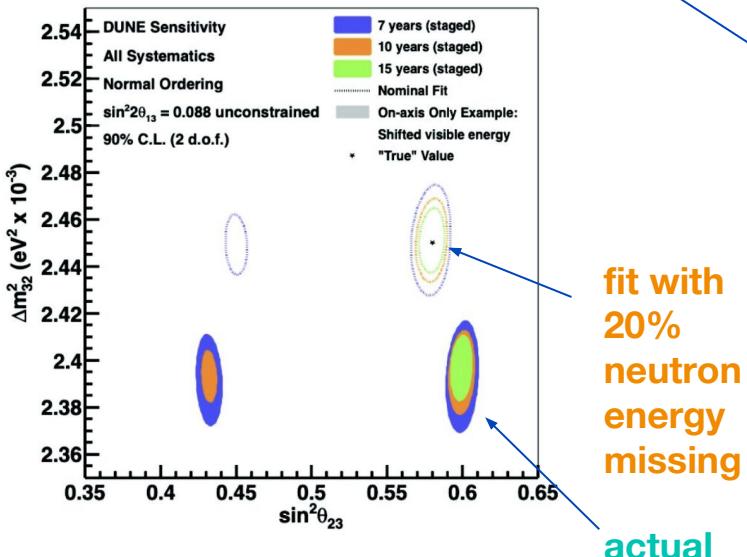


Figure from A. Ankowski et al. (2015).

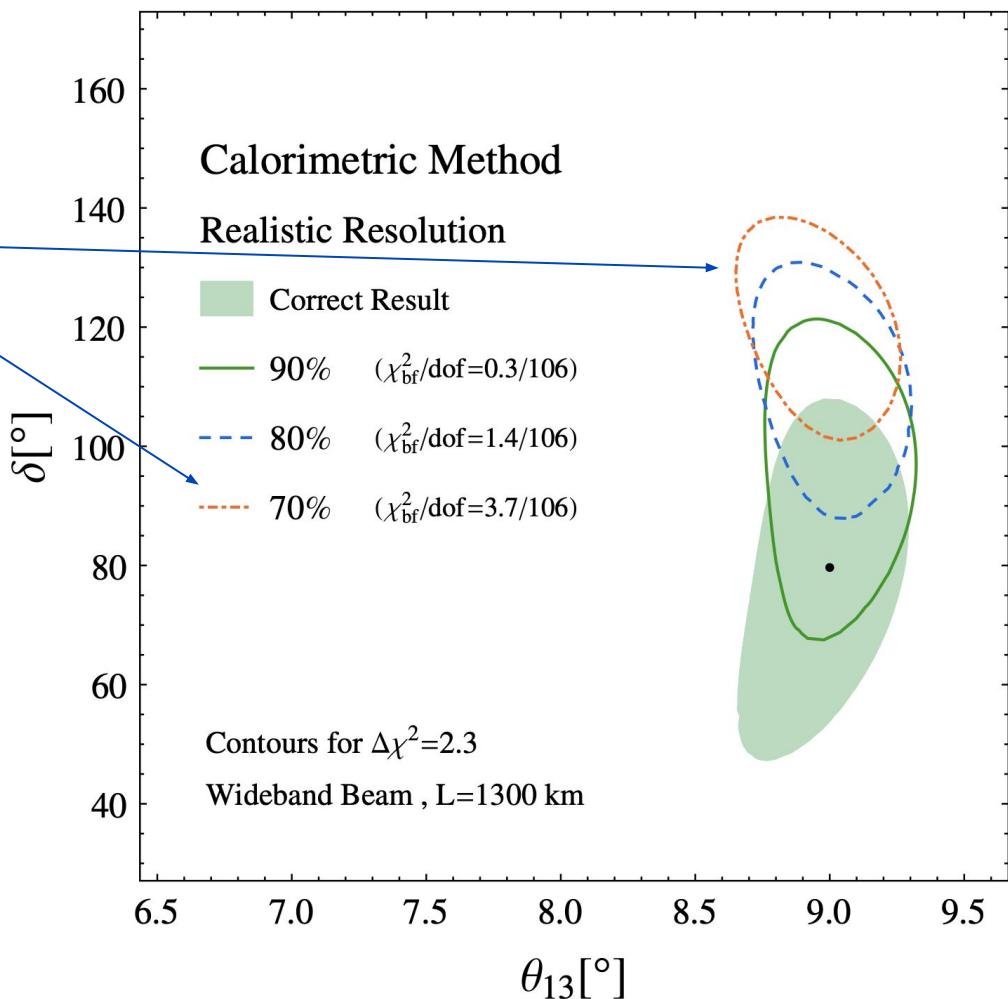
Figure from A. Friedland and W. Li (2019).

# Energy resolution?

- Measurements of the CP phase<sup>3</sup> are shifted by a large amount if neutrons are ignored!



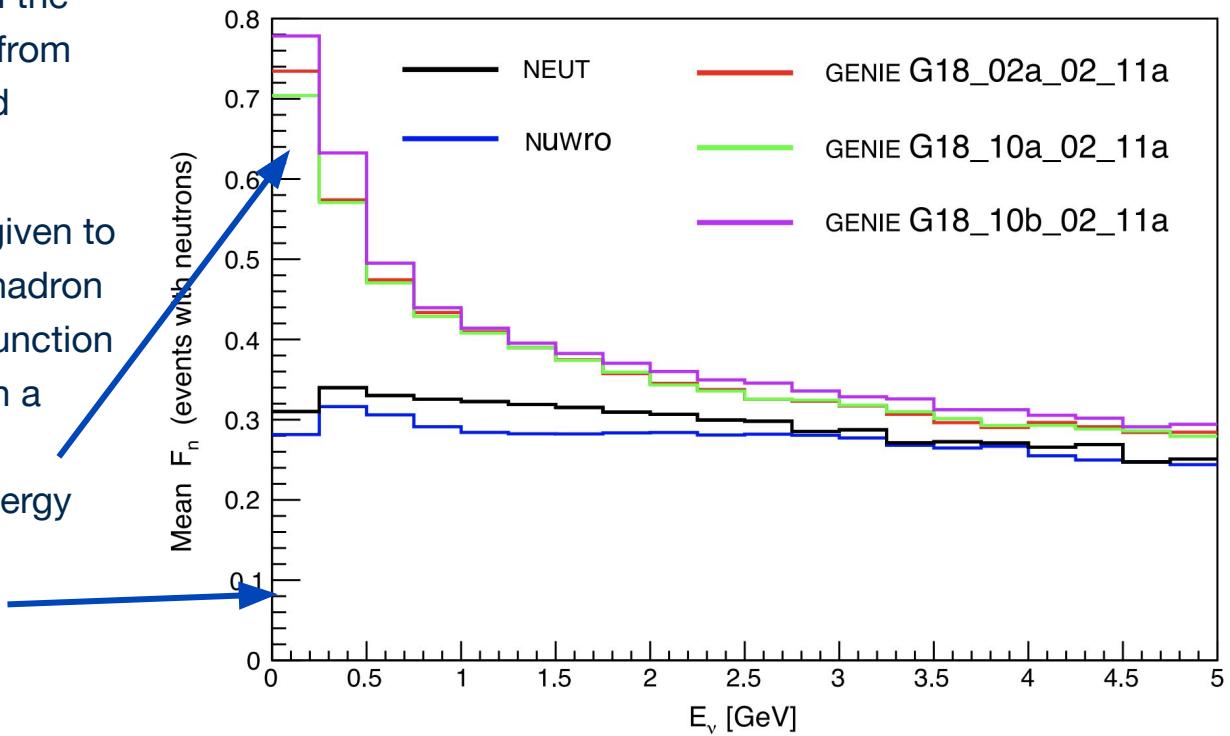
3 A. M. Ankowski et al., *Missing energy and the measurement of the cp-violating phase in neutrino oscillations*, Phys. Rev. D, **92** 2015 (<https://arxiv.org/abs/1507.08561>)



# Model dependent final-states?

M. Buizza Avanzini et al. examined the differences in neutron final-states from the generators **NEUT**, **NuWro**, and **GENIE**.

- The fraction of total energy given to hadrons (when at least one hadron is a neutron) is shown as a function of incident neutrino energy in a CC-interaction.
- GENIE varies in the lower energy regime by a factor of 2!

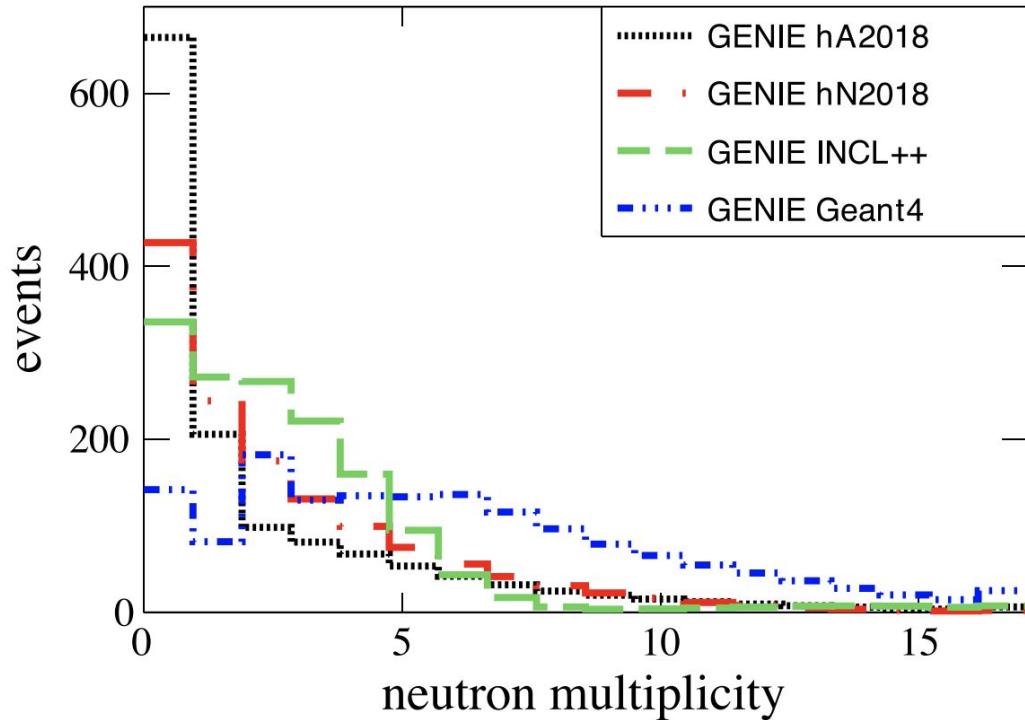


# Model dependent final-states?

The various models within GENIE<sup>5</sup> also show a discrepancy in the predictions of neutron multiplicity.

- Neutron distributions from a simulated 2GeV muon neutrino interaction on Ar40.

**Our group is working on a potential experiment to be deployed in ANNIE to measure neutron multiplicity on Ar!**

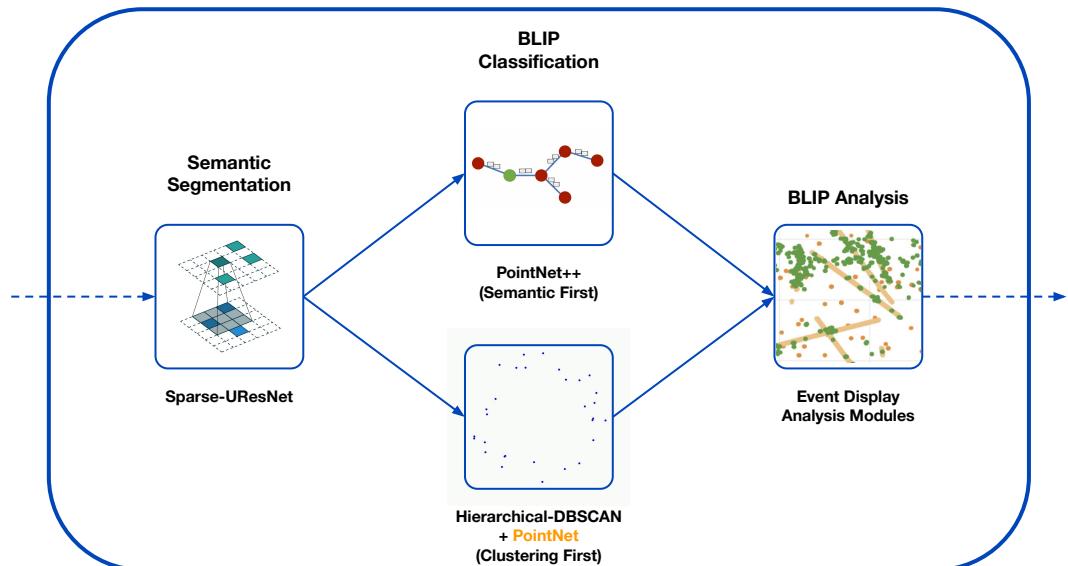


<sup>5</sup> The GENIE Collaboration, *Recent highlights from GENIE v3*, Eur. Phys. J. Spec. Top. (2021)  
(<https://link.springer.com/article/10.1140/epjs/s11734-021-00295-7>)

# BLIP

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:**
  - BlipNet 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).



<sup>2</sup> BLIP, BLIP ML Group (UC Davis), 2023,  
(<https://github.com/Neutron-Calibration-in-DUNE/Blip>).

**BLIP**

**UCDAVIS**

# 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.

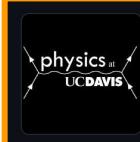
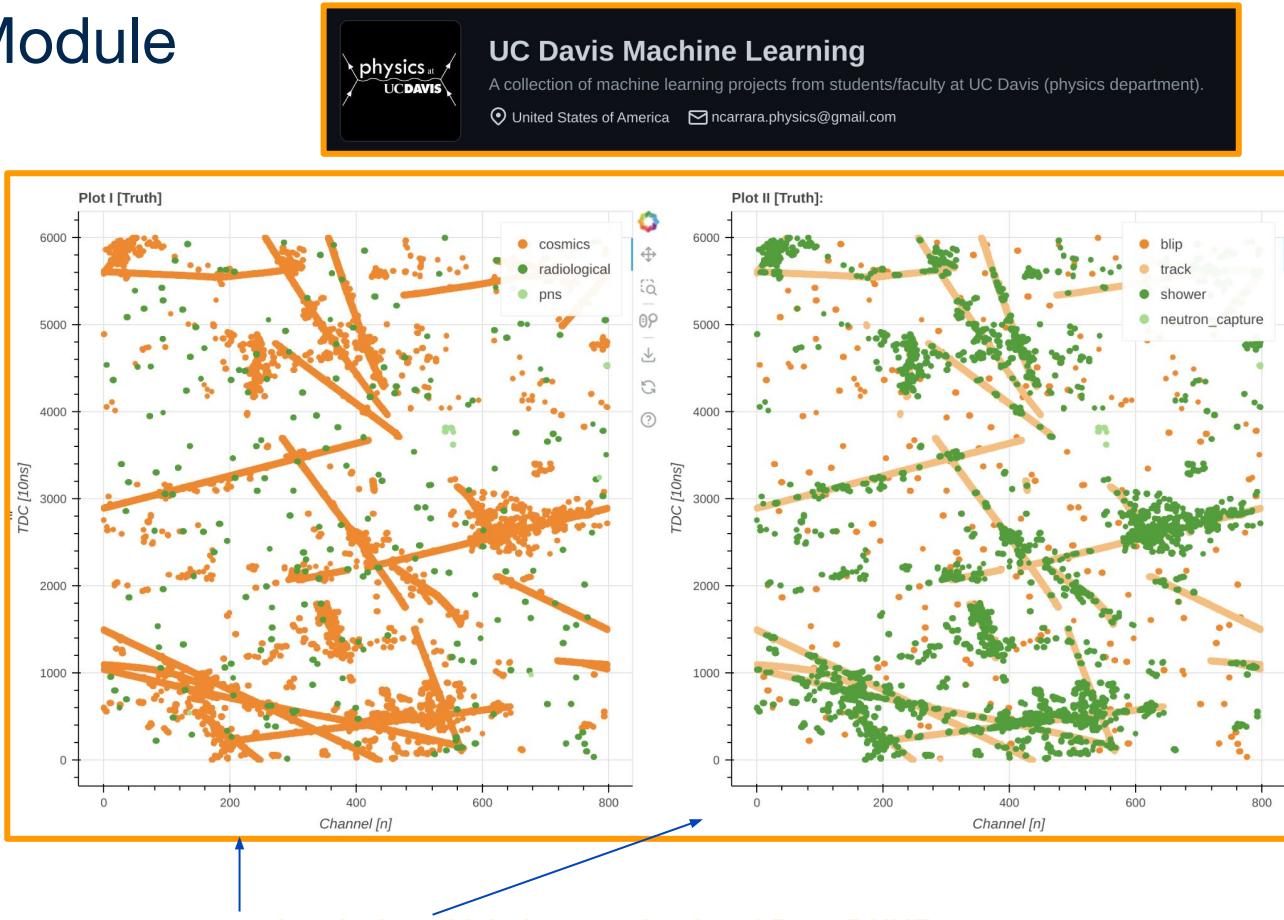
Current Labeling Schemes:

[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]

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



# 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
LArGeantProducerLabel: "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"]

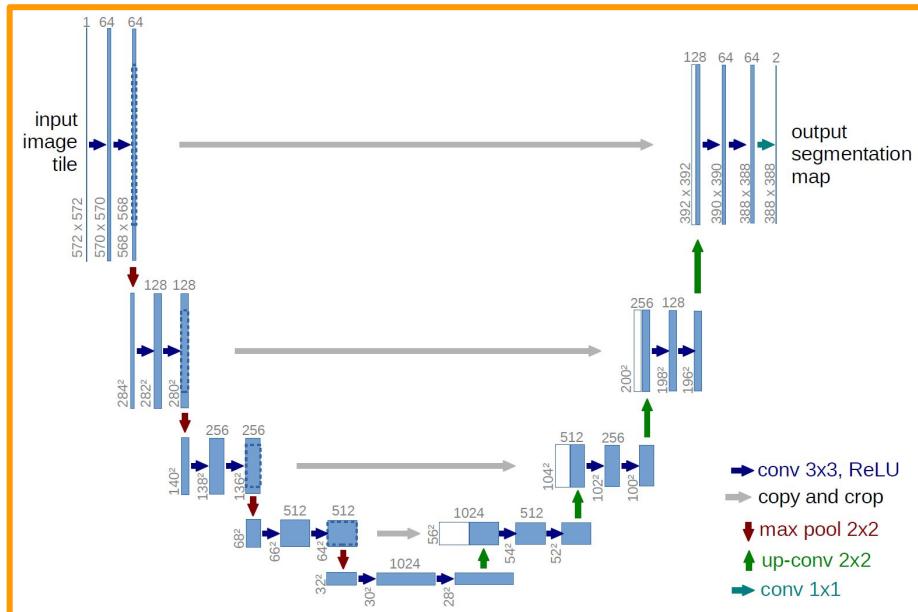
ADCThreshold: 20 # ADC threshold for saving points
InducedChannelInfluence: 10 # number of wires which are influenced by signals
InducedTDCInfluence: 200 # number of tdc ticks which are influenced by signals
```

FHiCL parameters

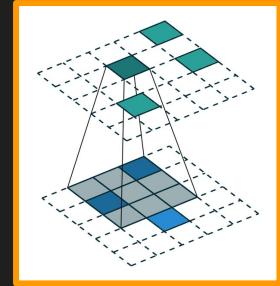
# Config file training/evaluation

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 reproducability.



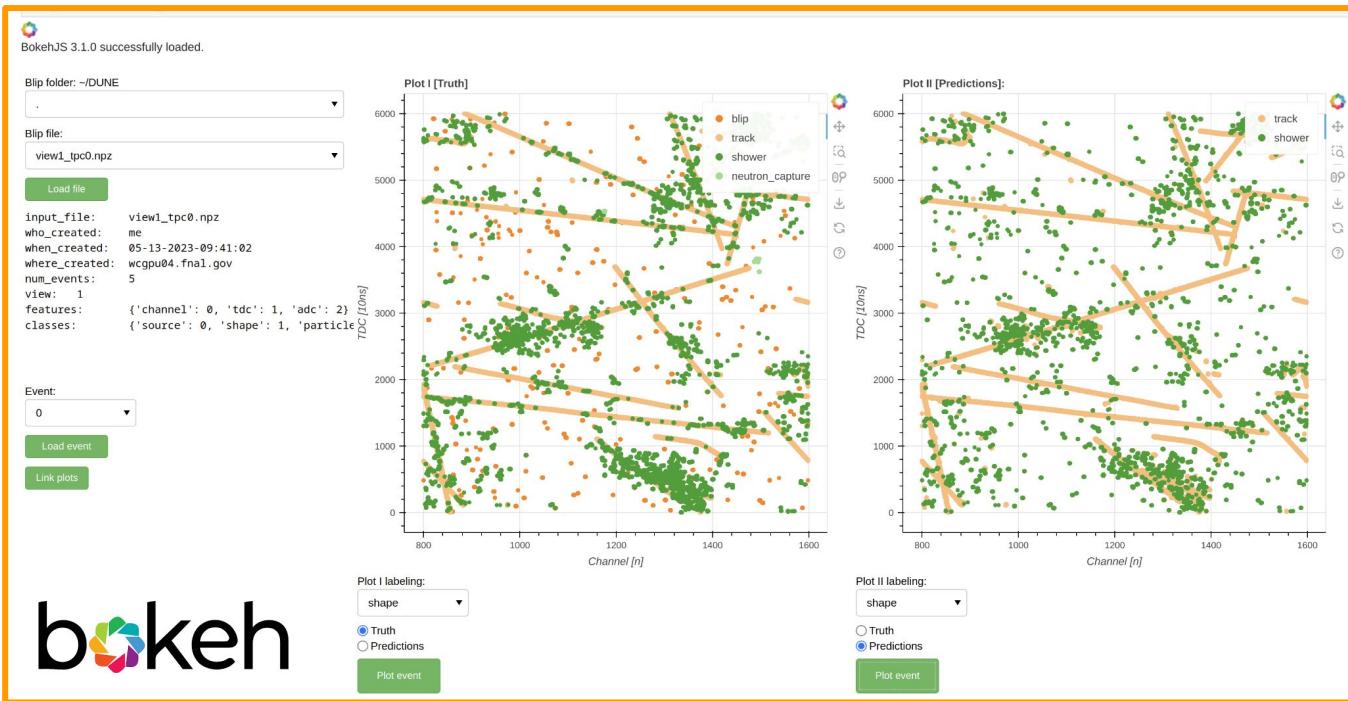
```
model:  
# uncomment the line below and specify the model to load from a checkpoint.  
# load_model: ".checkpoints/checkpoint_200.ckpt"  
  
# multiple options for model_type:  
# [ "single", "composite", ... ]  
model_type: "single"  
PointNet:  
    input_dimension: 3  
    classifications: ["particle"]  
    augmentations:  
        jitter: 0.03  
        flip:  
            positions: [0, 1]  
            probabilities: [0.5, 0.5]  
        shear: 0.2  
        rotate:  
            degrees: [15]  
            axis: [2]  
    number_of_augmentations: 5  
    embedding_type: "dynamic_edge_conv"  
    number_of_embeddings: 4  
    number_of_neighbors: [5, 10, 15, 20]  
    aggregation: ["max", "add", "mean", "max"]  
    embedding_mlp_layers: [  
        [64, 128, 64],  
        [64, 128, 64],  
        [64, 128, 64],  
        [64, 128, 64]  
    ]  
    embedding_activations: ["leru", "leru", "leru", "leru"]  
    linear_output: 512  
    mlp_output_layers: [512, 256, 128, 64, 32]  
    out_channels: [10]
```



# Event display

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

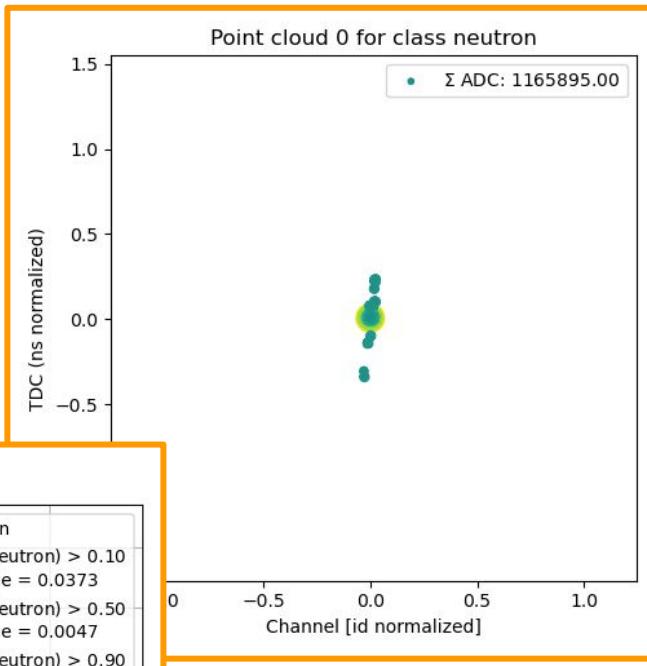
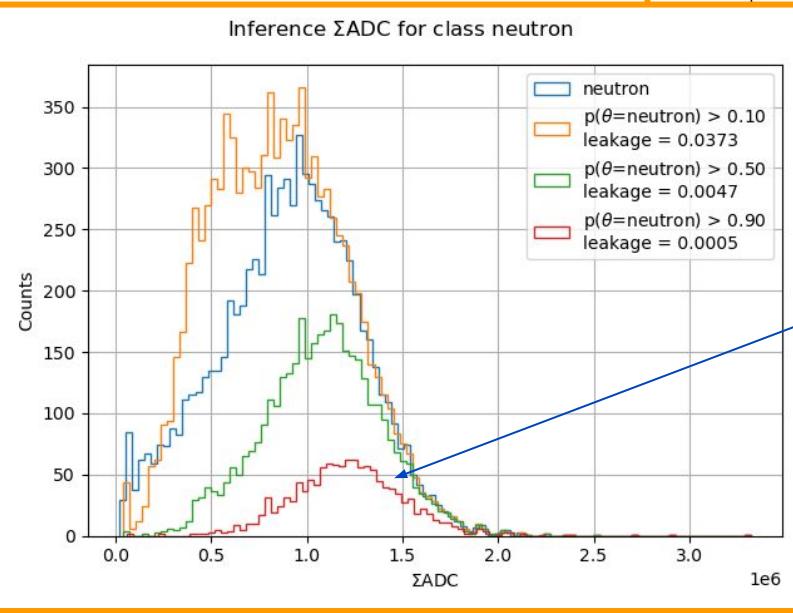
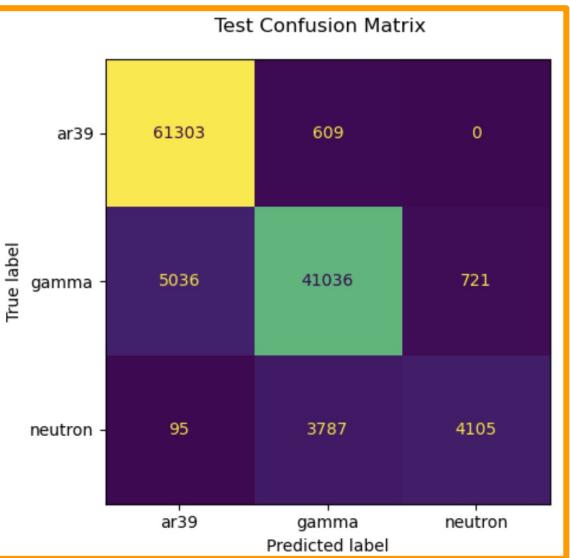
- Uses *bokeh* to create an interactive GUI.
- GUI can be run in a Jupyter notebook, or as a stand-alone html page.
- Obtain **point by point information** to quickly diagnose/access Arrakis and BLIP performance.
- Interface for analysis on network output.
- The BLIP-display could be made accessible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



# 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%)



Can calibrate against this distribution!