Application of machine learning to find anomalous events in LZ data

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Work with Scott Kravitz, Maris Arthurs, and Yi Liu
On behalf of the LZ Collaboration

UNIVERSITY OF MICHIGAN

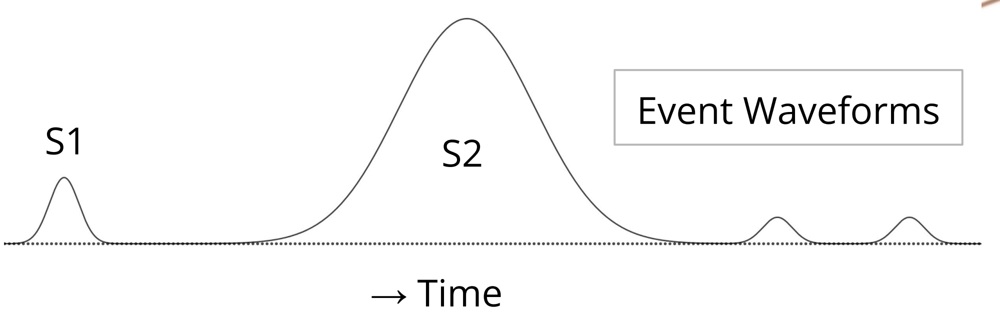
The LZ Dark Matter Experiment

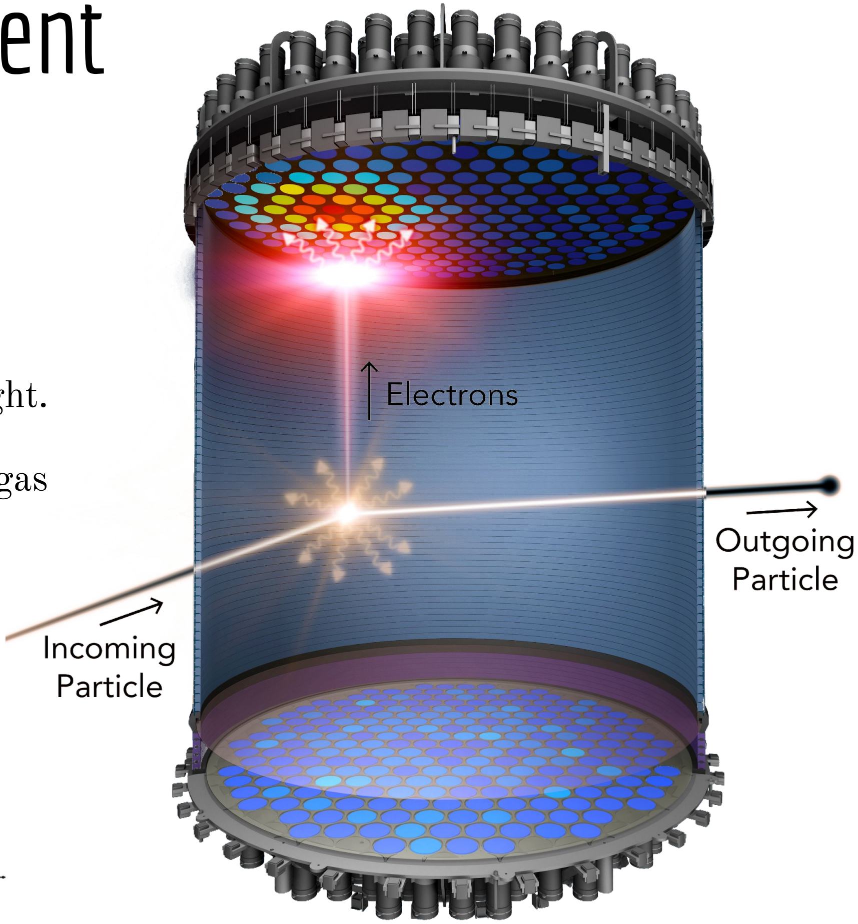
LUX-ZEPLIN (LZ) is an underground direct detection experiment at SURF.

Particle interactions with liquid xenon produce two signals:

S1 - Scintillation - Initial interaction causes LXe to emit light.

S2 - Ionization - Electrons are drifted and extracted into a gas Xe layer, which scintillates.





Anomaly Finding in LZ

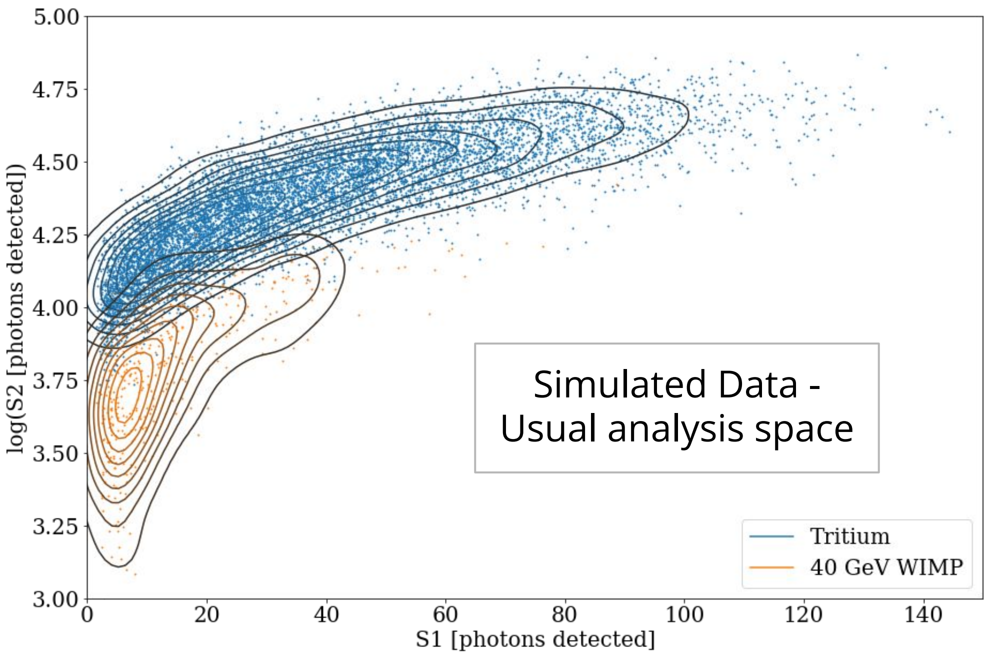
Goal - Quickly identify and interpret anomalous data in high-dimensional spaces.

Features

- Pulse shape and size.
- 3D position.
- Signal distributions.
- Number of pulses in event.

Use Cases

- Rare background discrimination.
- Tuning aid for simulations and data processing algorithms.
- Waveform handscanning aid.
- Detector anomalies in real data.



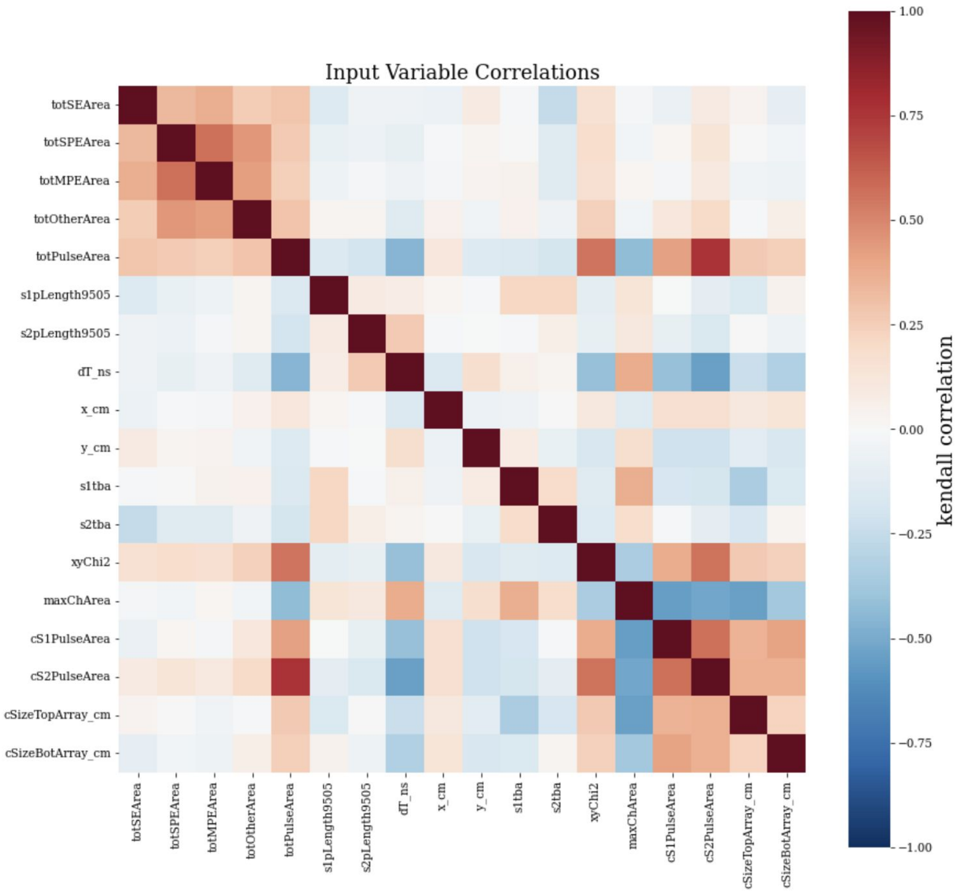
Taking advantage of the high-dimensional feature space, we have explored two unsupervised learning techniques for finding patterns in the LZ data.

1. Isolation forest
2. Dimensional reduction & clustering

LZ Data Space

Data contains both pulse and event information

- **Event level features**
  - Total area of different pulses in the event
    - Single electrons, single photoelectrons, etc.
- **S1 & S2 pulse features**
  - Pulse length
  - Pulse area
  - Summary of pulse shape
- **Other features**
  - S1 & S2 top bottom asymmetry (TBA)
  - Drift time
  - XY position
  - S1 hit pattern size



1. Isolation Forest

The isolation forest is an ensemble of random decision trees.

1. Starting at the root node, a uniformly random cut is applied to a random feature.
2. Repeated recursively to build a tree, until the datum is isolated from others.
3. Outliers take fewer cuts to isolate.

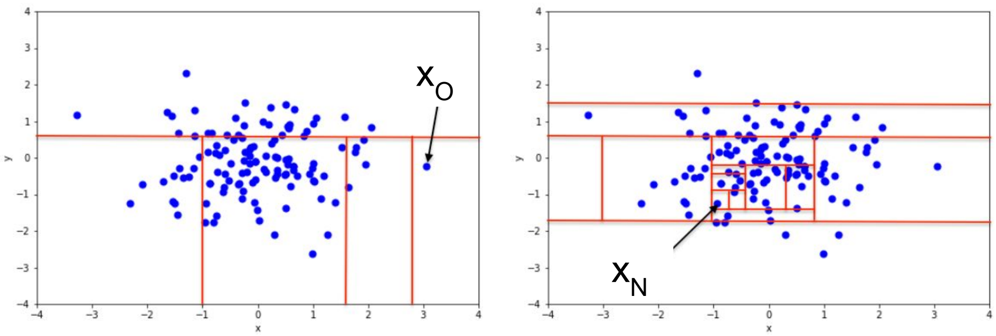
Anomaly Score - Function of the length of decision path.

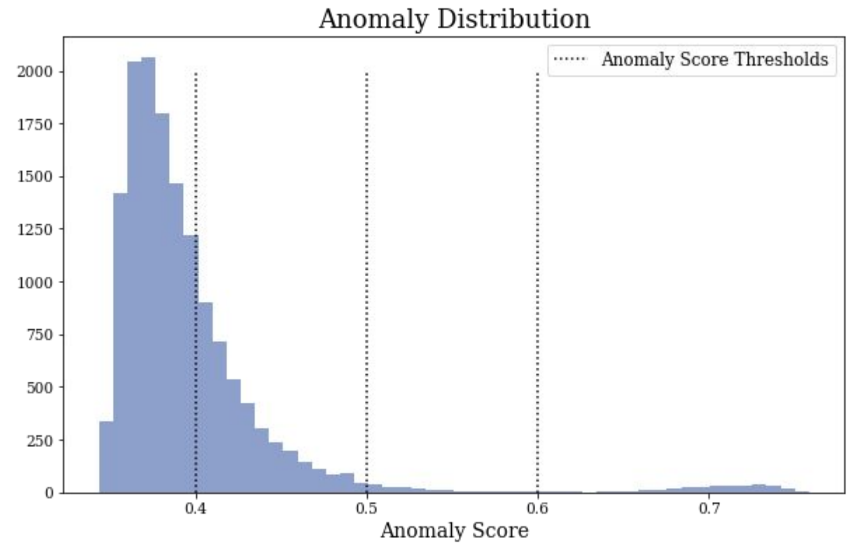
Why is a certain event anomalous?
Why is a certain set of events anomalous?

This technique is directly interpretable - Features that are cut on frequently are the cause of the outlier.

FT Liu, et. al., *Isolation forest*, ICDM 2008.

2D Example





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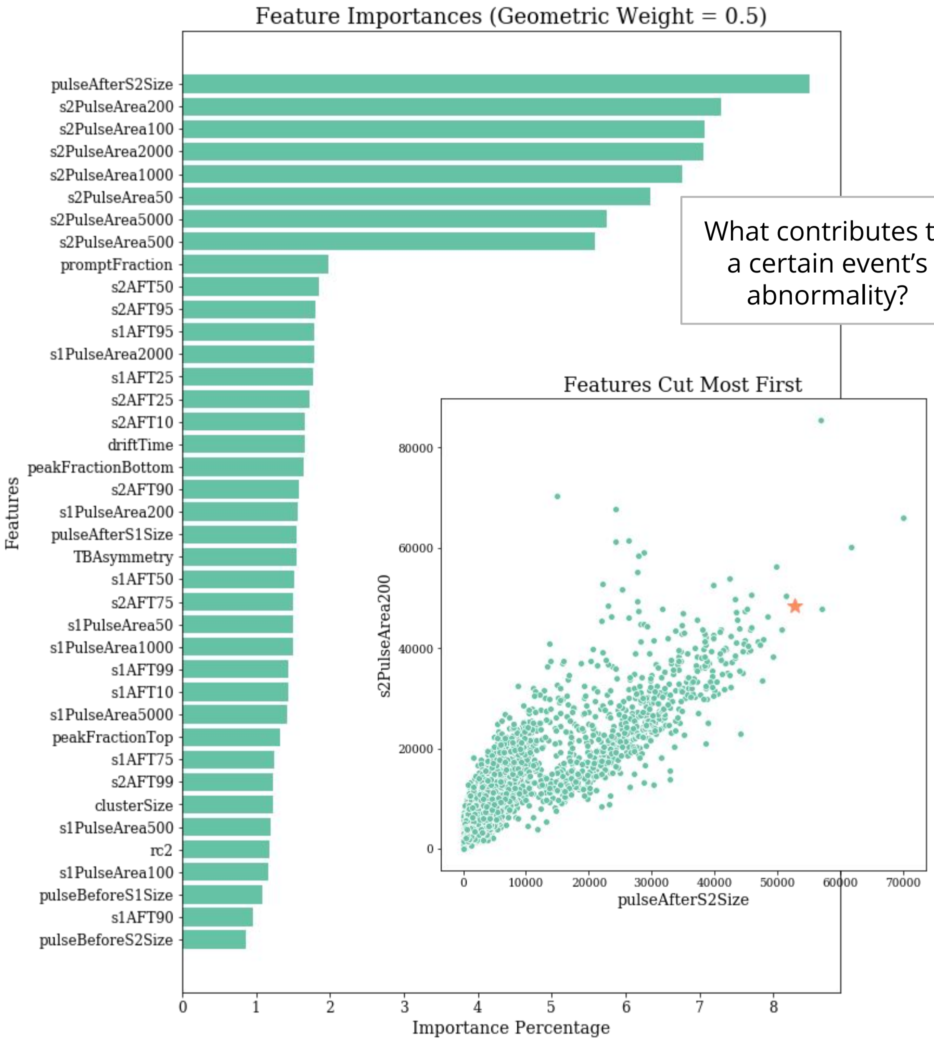


What contributes to a certain event's abnormality?

2. Dimensional Reduction

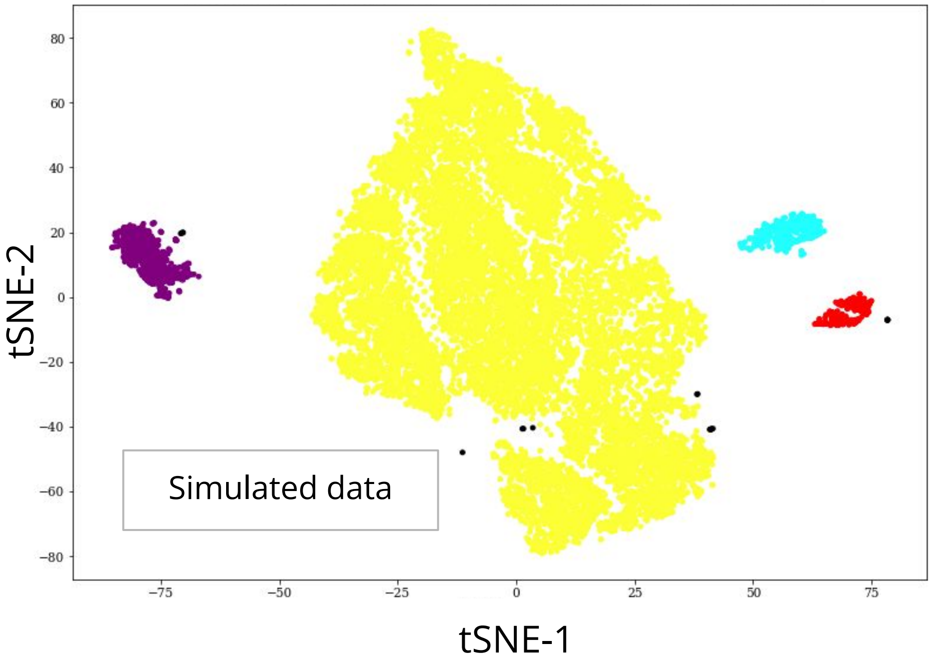
- Map N-dimensional (~30 features) data to 2D representation
    - **Why** – Outliers in multidimensional feature spaces are difficult to detect visually.
    - **Goal** – quickly identify and study (not remove) outlier events.
    - **How** – represent in 2D while **preserving structure**.

- Linear techniques preserve global structure, but lose information about local structure.
    - Example: Principal Component Analysis (PCA)
- Non-linear techniques tend to **preserve** local structure as well as global structure
    - **t-SNE**: T-distributed Stochastic Neighbor Embedding
        - L.J.P. van der Maaten and G.E. Hinton. *Visualizing High-Dimensional Data Using t-SNE*. Journal of Machine Learning Research 2579-2605, 2008.
    - **UMAP**: Uniform Manifold Approximation and Projection.
        - L McInnes, J Healy. UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction, ArXiv e-prints 1802.03426, 2018

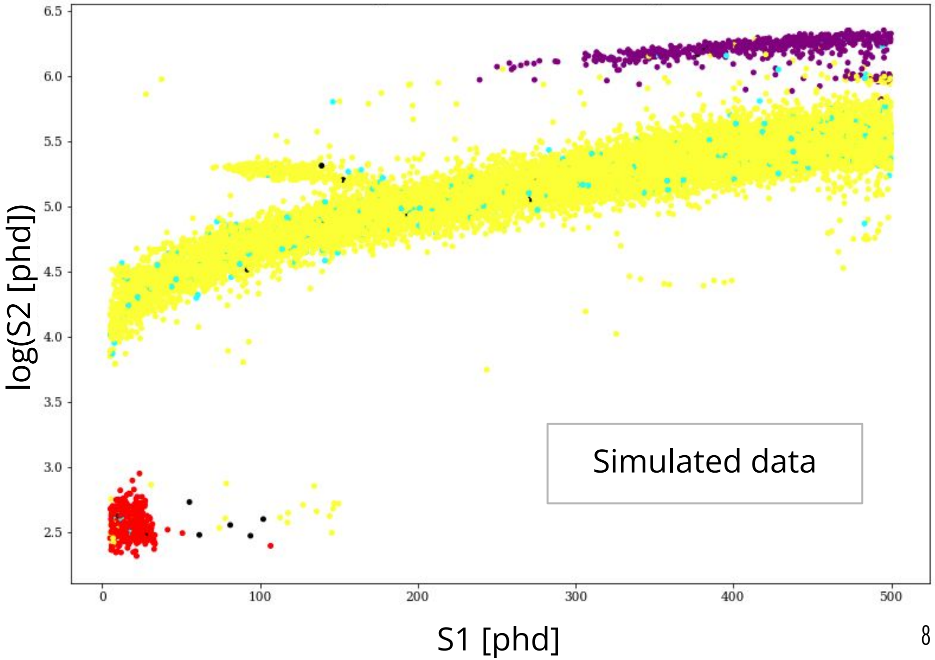
2. DR & Clustering - Simulated Data

Goal - Visualize ~30 dimensional feature space in 2D clusters and discern reasons for clusters.

tSNE-reduced data



tSNE clusters in signal space



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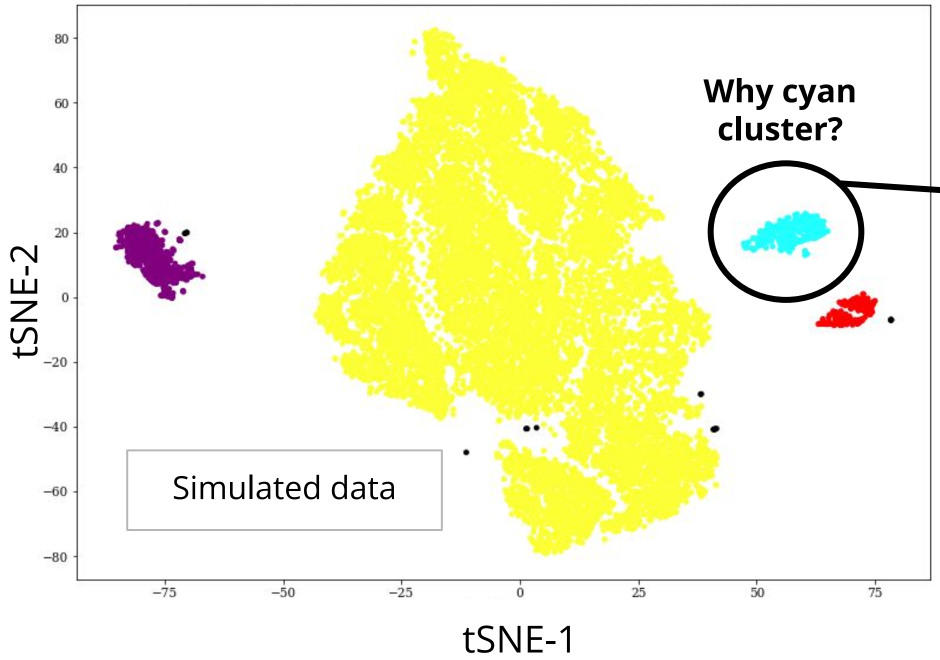

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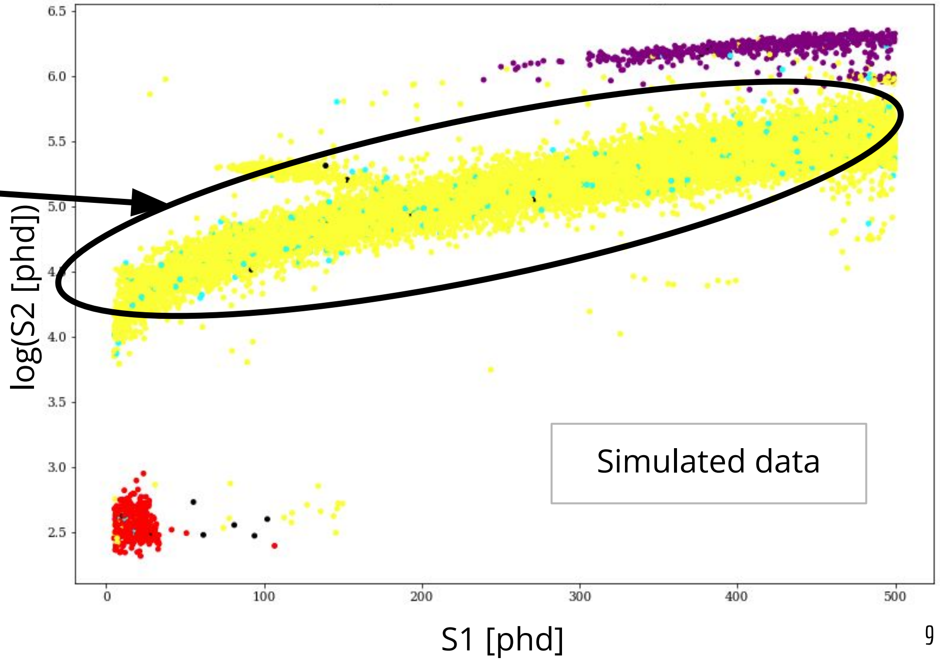
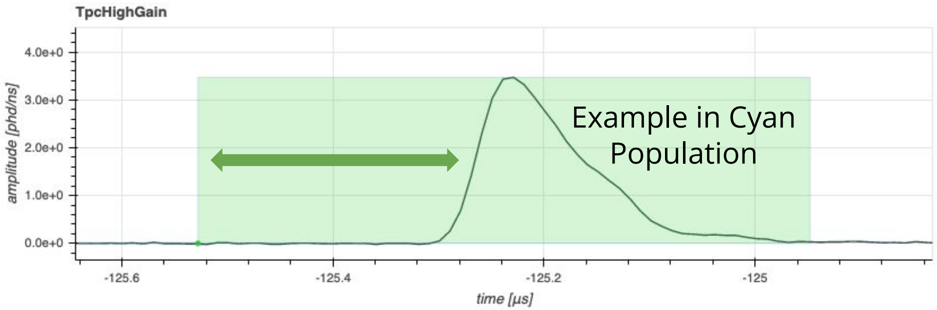
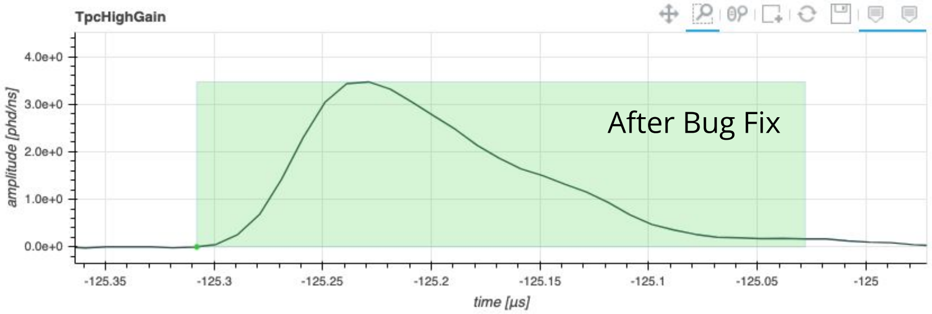


Cases in simulated data

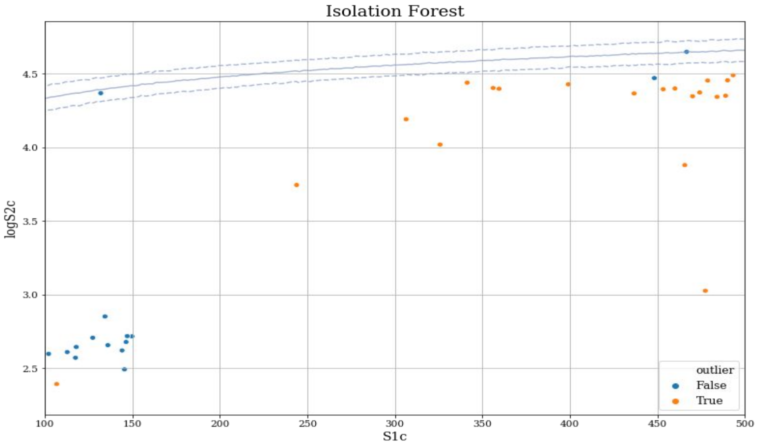
Pulse Finder Inefficiency

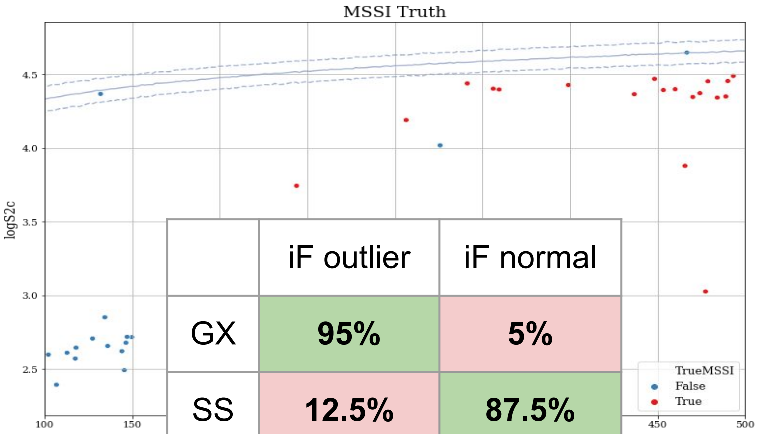
The cyan population in simulations consisted of pulses that were tagged with a long rise time.





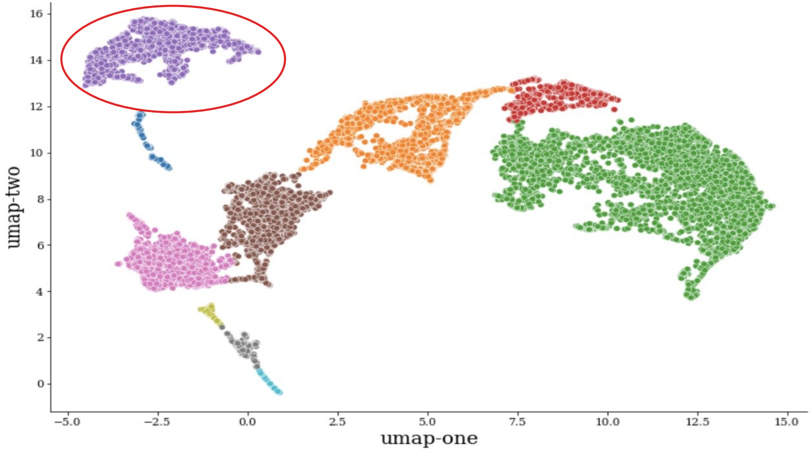
Rare Background Identification

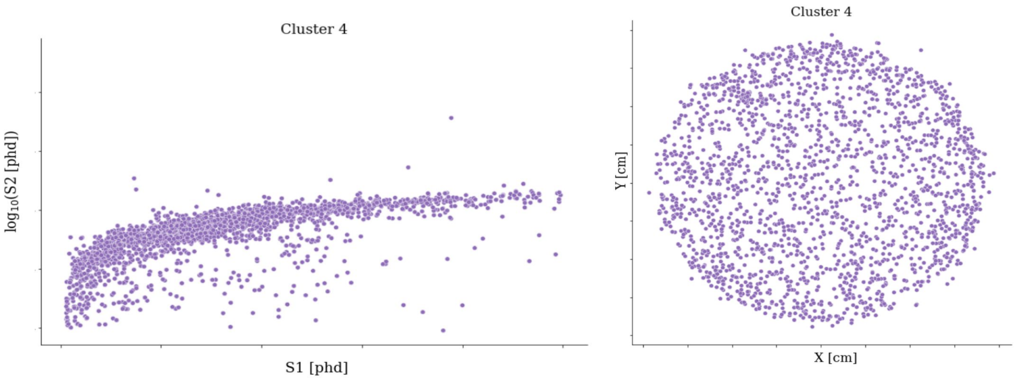


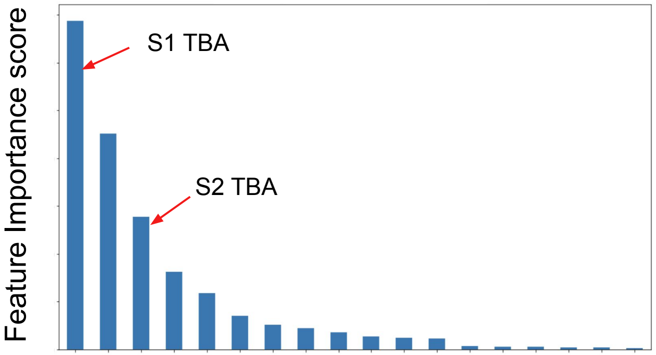


	iF outlier	iF normal
GX	**95%**	**5%**
SS	**12.5%**	**87.5%**

Clusters in Real Data - Gas Events



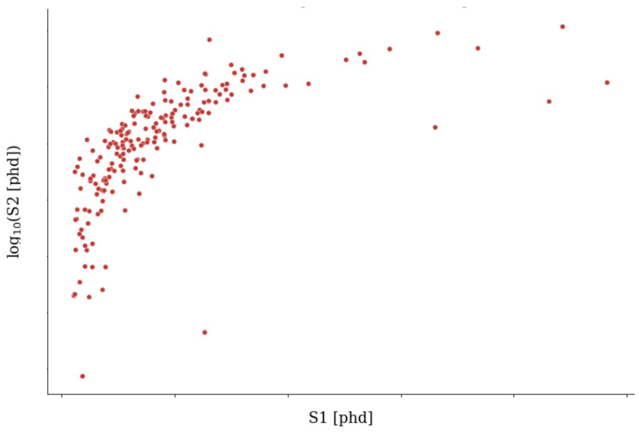


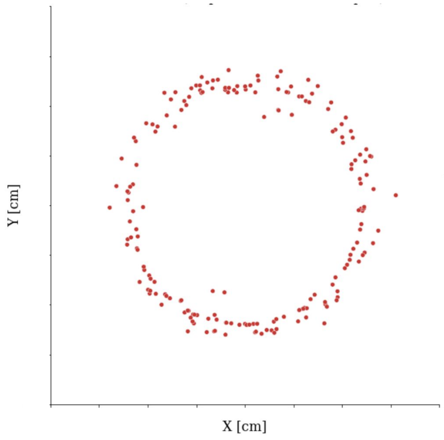


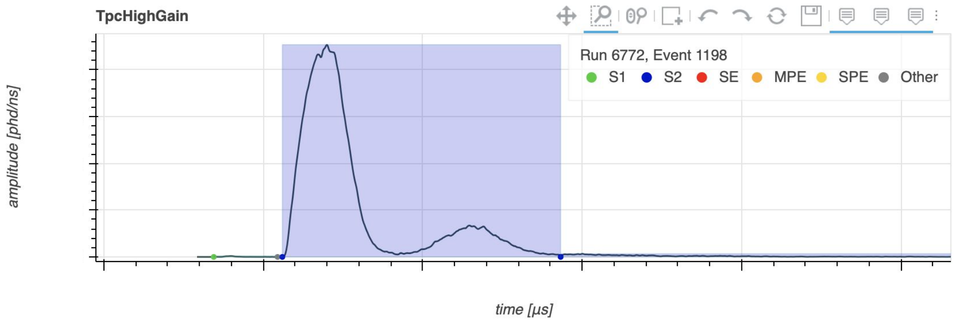
Purple cluster found to be gas events

- Found to have large S2 TBA and large S1 TBA.
- Importances allows identification of relevant RQs.

Clusters in Real Data - Photoionization







New population → after adding S2 pulse shape features

- Photoionization of the wire electrodes from S2 light
- Originates near the walls in extraction region
- Detector effect

Conclusions & Outlook

Unsupervised techniques have the potential to probe the **known unknowns** and the **unknown unknowns** in science data.

- Unknown unknowns - Use the largest representative feature set available.
- Known unknowns - Use appropriate features for the task.

Interpretability is important for studying events or groups of events. These techniques allow for a better understanding of the data.

Applications include

- Data quality,
- Anomalous backgrounds,
- Tuning data processing algorithms,
- Fixing simulation bugs.

LZ (LUX-ZEPLIN) Collaboration

35 Institutions: 250 scientists, engineers, and technical staff

https://lz.lbl.gov/ @lzdarkmatter

- Black Hills State University
- Brandeis University
- Brookhaven National Laboratory
- Brown University
- Center for Underground Physics
- Edinburgh University
- Fermi National Accelerator Lab.
- Imperial College London
- Lawrence Berkeley National Lab.
- Lawrence Livermore National Lab.
- LIP Coimbra
- Northwestern University
- Pennsylvania State University
- Royal Holloway University of London
- SLAC National Accelerator Lab.
- South Dakota School of Mines & Tech
- South Dakota Science & Technology Authority
- STFC Rutherford Appleton Lab.
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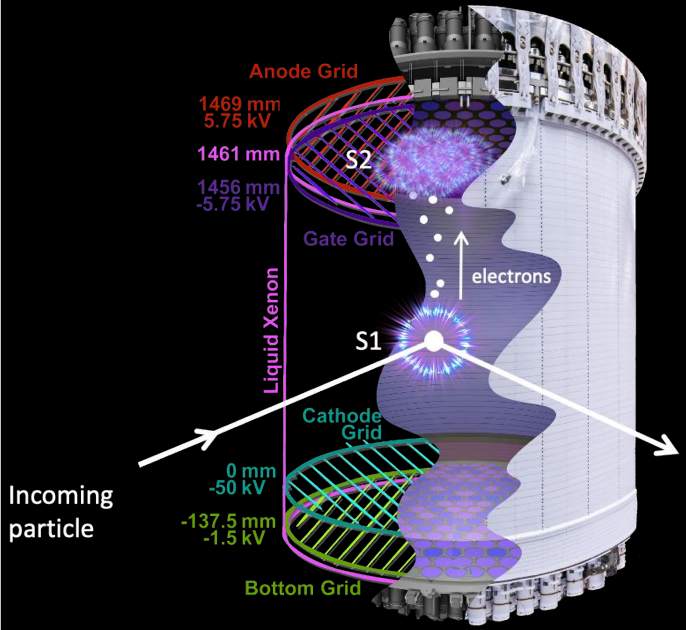

Thank you!

Thanks to our sponsors and 35 participating institutions!

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