Anomaly Detection using Autoencoders on Fundamental LZ Signals

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OUTLINE

- LZ basics and motivation
- Anomaly detection on all waveforms
- Anomaly detection on quality S2 waveforms
  - Using basic autoencoders
  - Using variational autoencoders
- Anomaly detection on quality S1 waveforms
  - Using variational autoencoders

LUX-ZEPLIN (LZ) BASICS

The LZ detector is located ~1 mile underground in Lead, South Dakota. We hunt for dark matter.

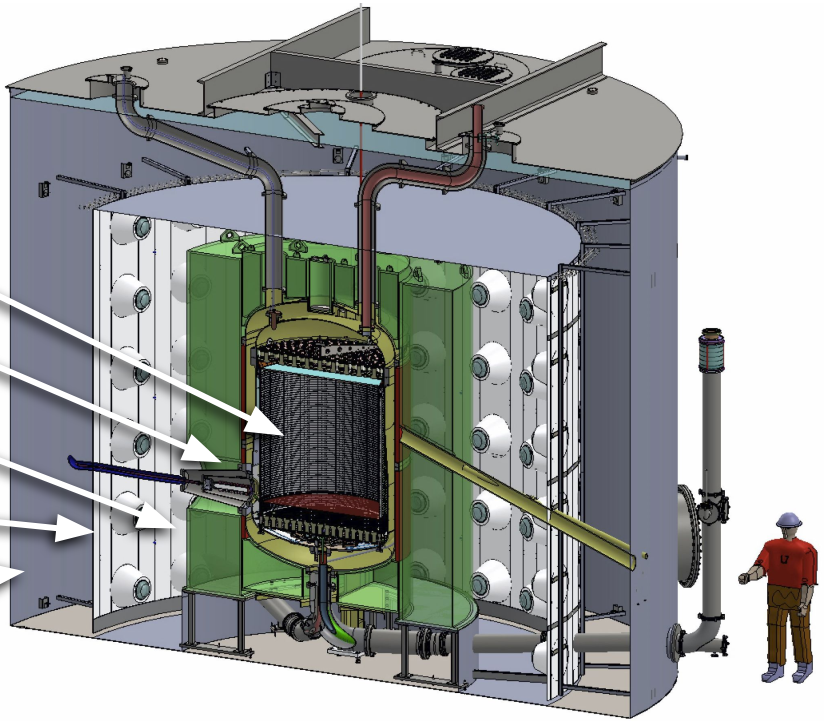
Xe-filled Time Projection Chamber (TPC)

Skin (veto)

Outer detector liquid-scintillator (veto)

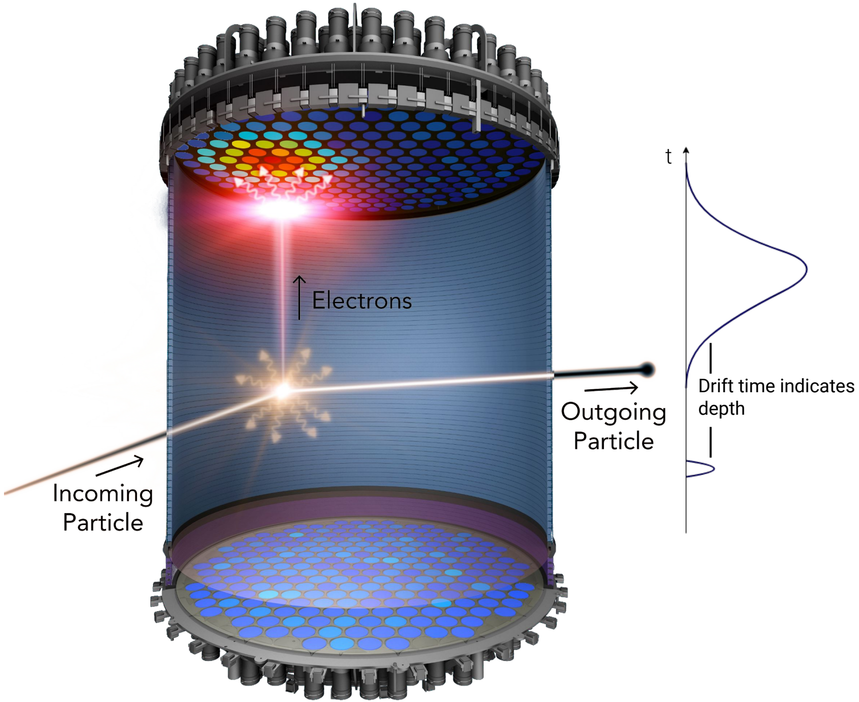
Outer detector PMTs

Water tank



LZ PHYSICS

- Photomultiplier tubes (PMTs) detect light within the TPC
- Recoils generate two light signals:
  - S1 light: proportional to Xe excitations **(photons)**
  - S2 light: proportional to Xe ionizations **(electrons)**
- 3D position reconstruction of recoils:
  - XY comes from the S2 light pattern
  - Z comes from the time between S1 and S2 as electrons drift up in the electric field
- S1 and S2 size and shape help separate non-WIMP recoils from WIMP-like recoils



WAVEFORM ANOMALY DETECTION

We use data quality cuts to exclude clearly non-WIMP recoils

- ➢ Are there any pathological backgrounds we aren't cutting?

Reconstruction potentially washes out features that help identify detector pathologies

- ➢ Search for anomalous PMT waveforms, independent of reconstruction

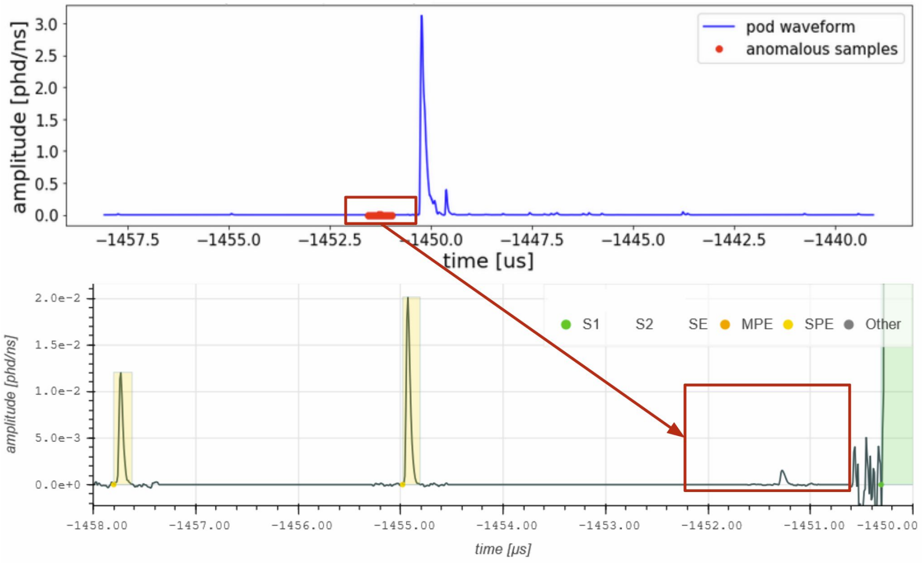
TIME SERIES ON ALL WAVEFORMS

Idea: scan over waveforms and label anomalous portions of any waveforms

Implementation: scan a dense autoencoder over waveform segments & label high reconstruction losses as anomalous

- This yields some interesting findings (e.g. undersized photons, right)

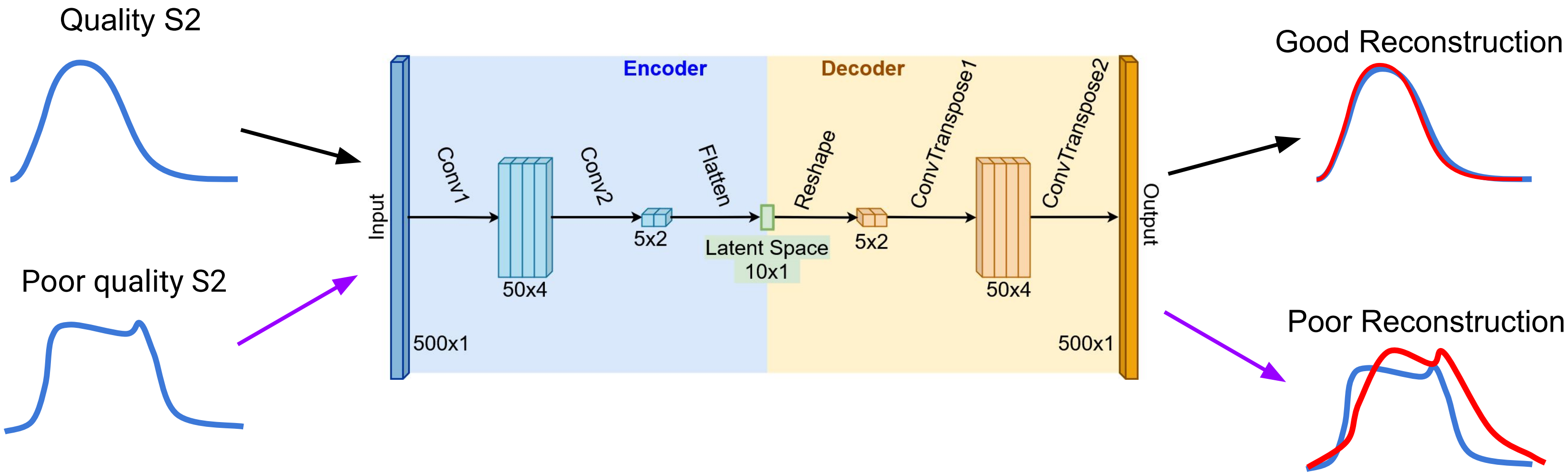
- However, by training on mostly junk (single photons, electron light), all S1s and S2s naturally emerge as "anomalies"



S2 - BASIC AUTOENCODER

Idea: train only on S2s passing our 2022 WIMP search's S2-based quality cuts in order to detect poor-quality S2s as anomalous

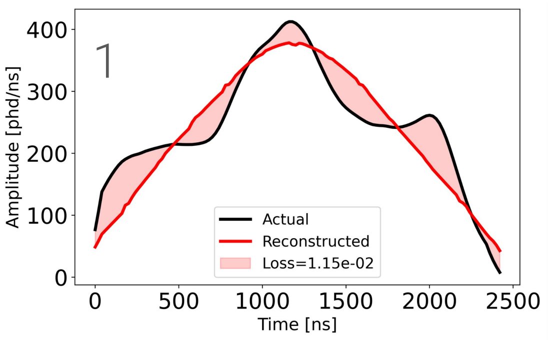
Implementation: use a basic 1D CNN autoencoder

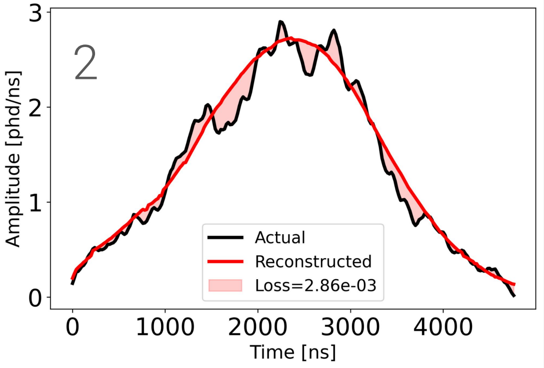


S2 - AUTOENCODER ANOMALIES

Found two notable forms of anomaly *among quality S2s*:

1. Unresolved multiple scatters at higher energies (above the WIMP search ROI)
2. Noisy low-energy S2s (uninteresting limitation)



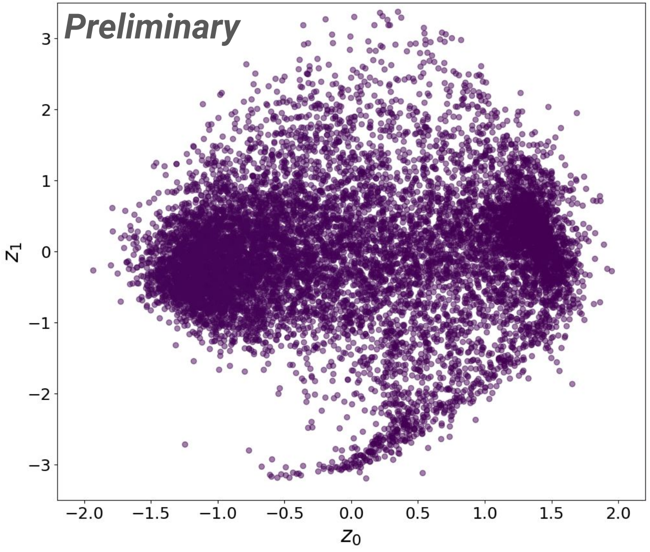


S2 - VARIATIONAL AUTOENCODER (VAE)

Idea: latent space is easier to interpret with VAEs, and provide clusters to investigate

Implementation: add the typical VAE layers and loss with a 2-dimensional latent space

Testing data, quality S2s:



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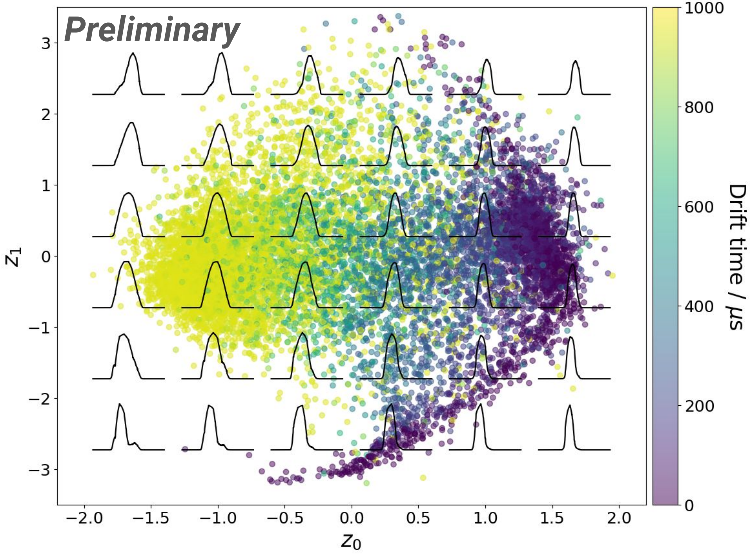
Plot a grid of decoded latent space vectors *z*.

Results:

- Latent component z_0 encodes a width-like property, correlating with drift time
- Latent component z_1 encodes a skew-like property



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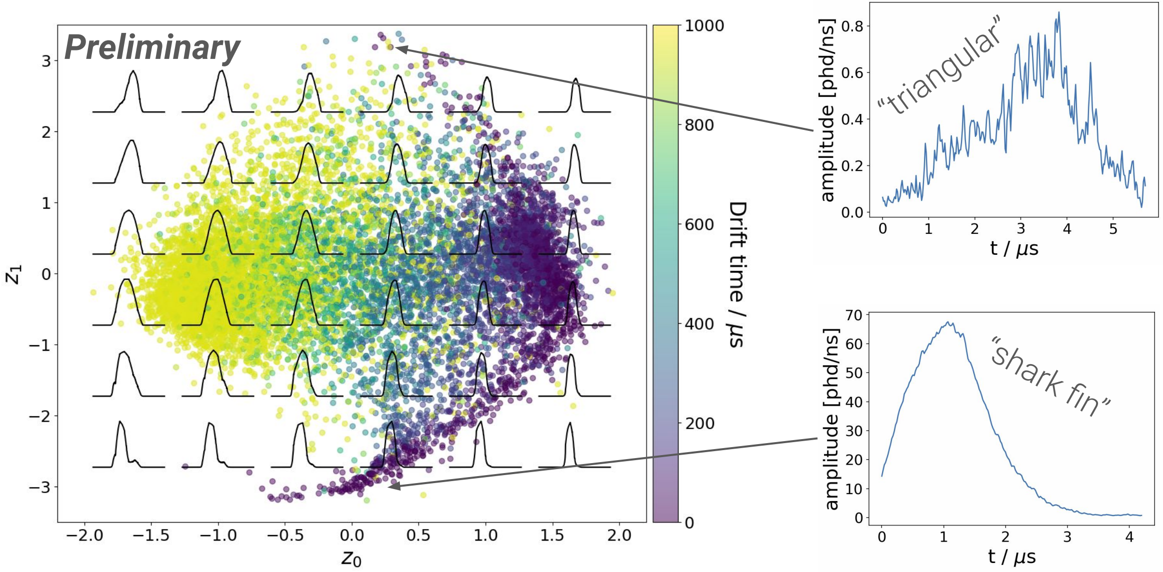
Implementation: add the typical VAE layers and loss with a 2-dimensional latent space

Outliers include similar anomalies as before, and waveforms on the right. These are not a concern for WIMP searches but useful to know about when tuning waveform-based cuts.



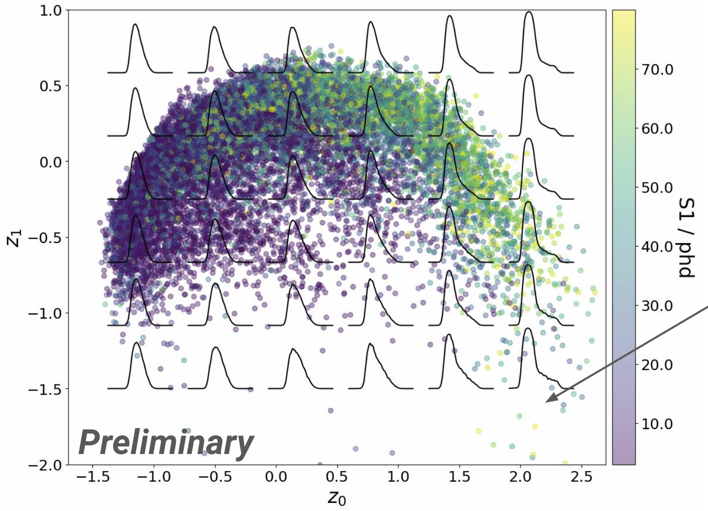
S1 - VARIATIONAL AUTOENCODER (VAE)

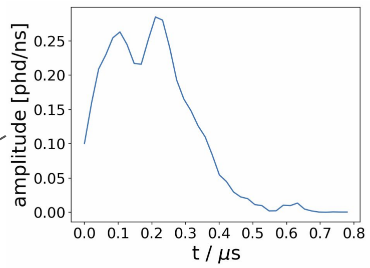
Idea: train VAEs on S1 waveforms that pass S1-based quality cuts, although S1 waveforms are generally thought to encode less physical information

Implementation: same as for S2, but with dense layers as inputs are much shorter

Results:

- z_0 roughly encodes the S1 size, even though waveform amplitudes are scaled to [0, 1]
- Some outliers at low z_1 have strange tails, but aren't *too* strange





CONCLUSIONS

- AEs provide an additional method for identifying unresolved multiple scatters
- VAEs can learn basic interpretable features of waveforms
- VAEs can help identify normal or abnormal waveforms when tuning waveform-based cuts
- Next steps:
  - Use with more recent data
  - Better understand the VAE encodings, try increasing the latent space dimension

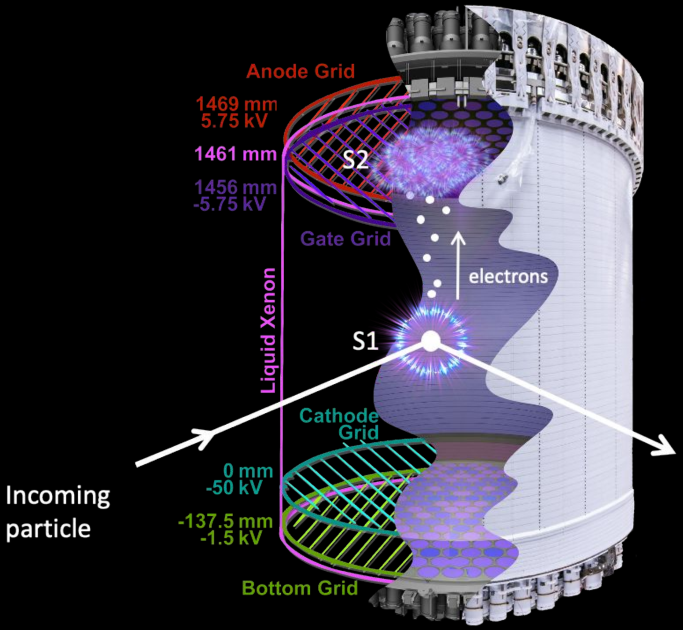


Image by Nicolas A. (Imperial College London)

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