

“Flux + Mutability”: A Conditional Generative Approach to One-Class Classification and Anomaly Detection

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University
of Regina

Outline

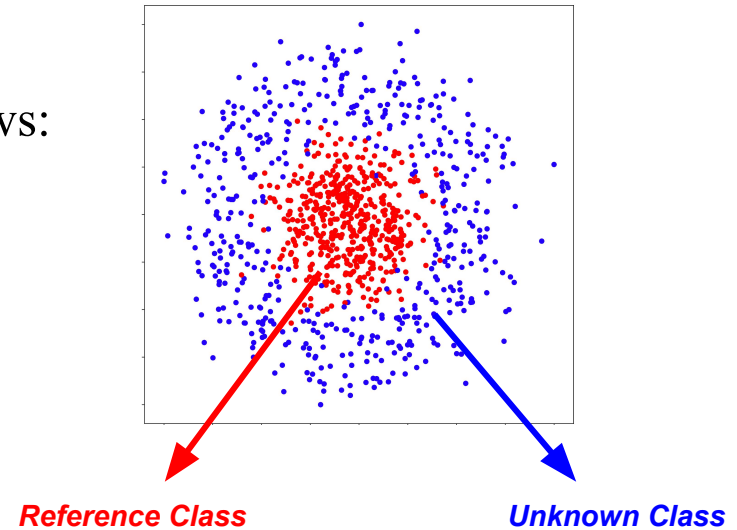
- One-Class Classification (OCC) and Anomaly Detection (AD)
- “Flux + Mutability” (F+M) - A Conditional Generative Approach
- γ/n separation at GlueX - OCC
- Standard Model(SM)/Beyond (BSM) Dijet Separation at LHC - AD
- Summary

C. Fanelli, J. Giroux, Z. Papandreou, “Flux+Mutability”: A Conditional Generative Approach to One-Class Classification and Anomaly Detection (2022).

<https://arxiv.org/abs/2204.08609>

OCC and AD

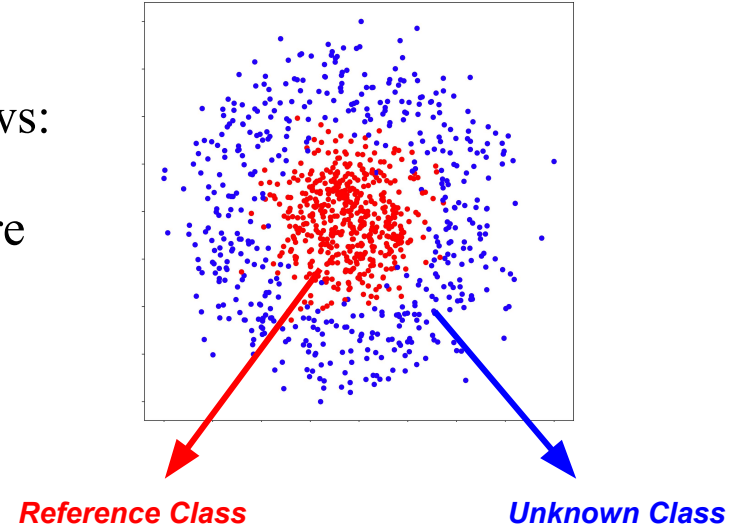
Suppose we have two classes distributed as follows:



OCC and AD

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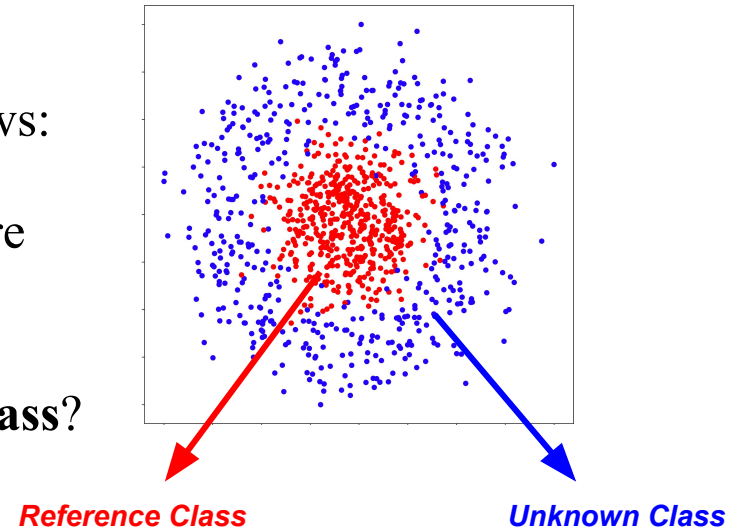
1. Can we use deep learning to separate the two more efficiently than standard rectangular cuts?



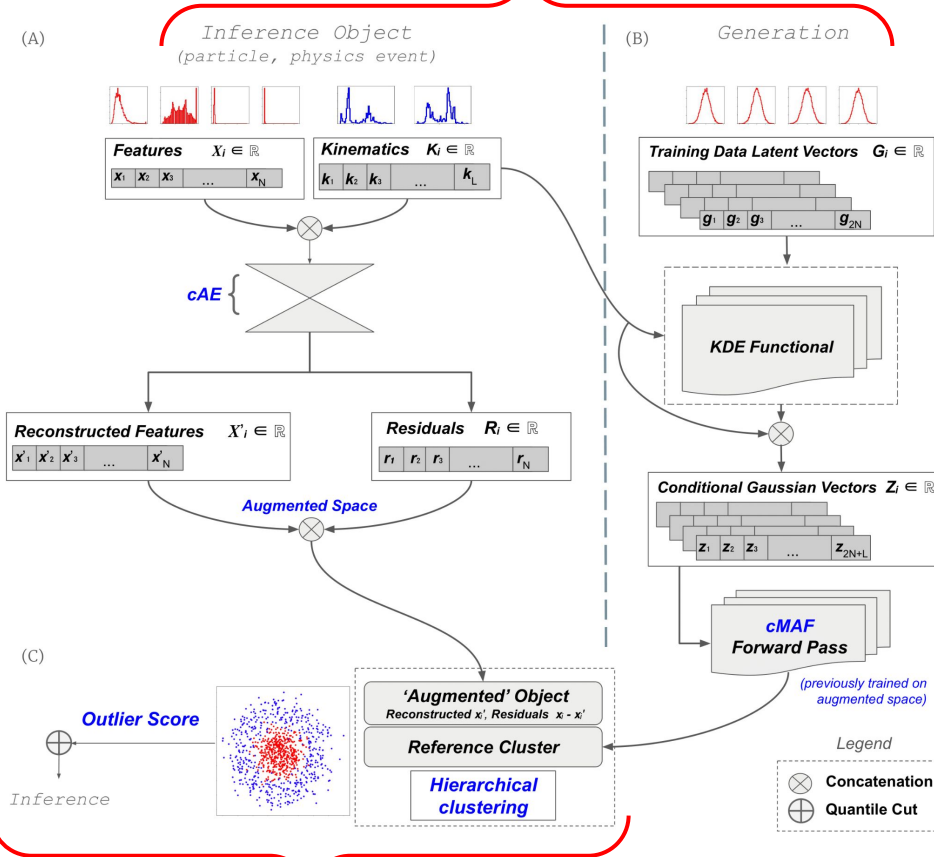
OCC and AD

Suppose we have two classes distributed as follows:

1. Can we use deep learning to separate the two more efficiently than standard rectangular cuts?
2. Can we remain agnostic towards the **unknown class**?
 - Agnostic threshold selection



“Flux

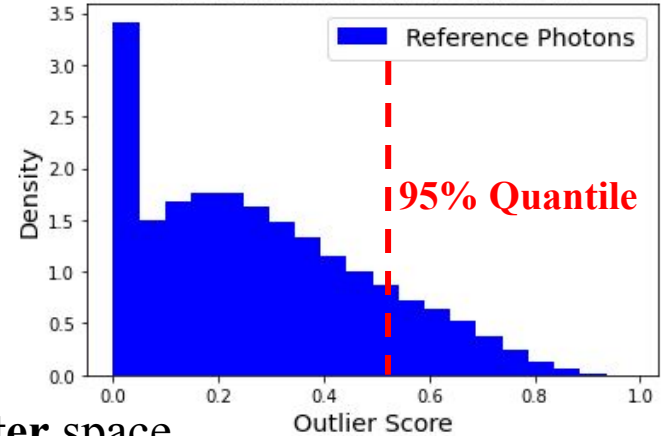
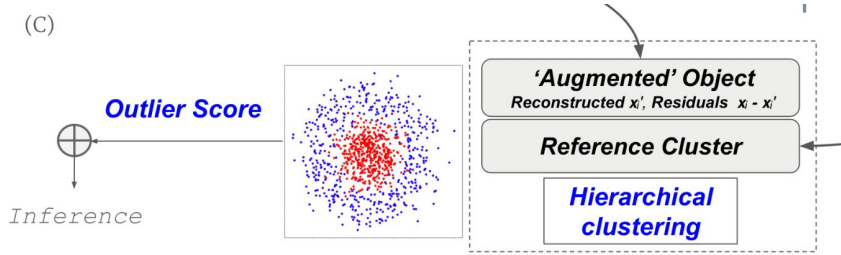


- (A) Inference Object fed through cAE
- Features ⊗ Kinematics
 - Reconstructions ⊗ Residuals ($x' - x$)
- (B) Continuous Conditional Generation
- Pre-fit KDE Objects in kinematic bins
 - Map inference kinematics to KDE object
 - Sample new Gaussian vectors from restricted domain
 - Gaussian Vectors ⊗ Inference Kinematics
 - **Conditionally generate reference population** via cMAF
- (C) Compare inference object to **reference population** via Hierarchical clustering and quantile cuts

+ Mutability”

Unsupervised OCC and AD

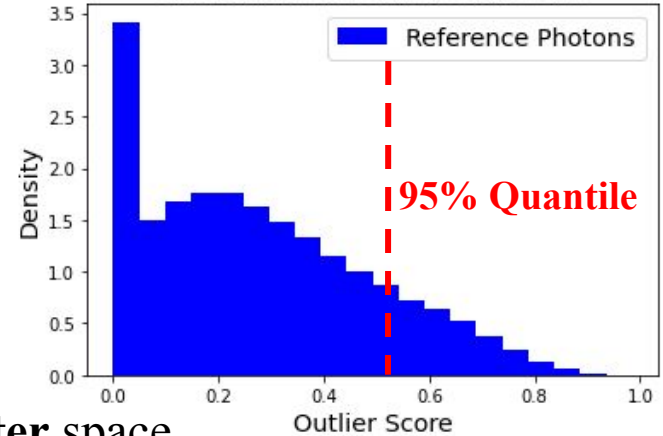
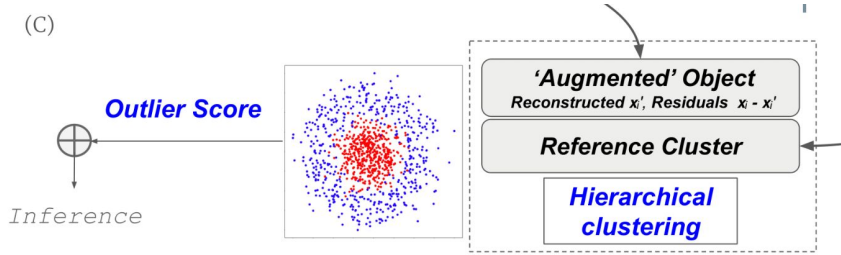
HDBScan and Quantile Cuts



- Augment the inference particle into the **reference cluster** space
 - Two notions of *membership* - density based, distance based
- Combine the two PMF's and extract a probability of membership (P_{in})
- Define *Outlier Score* as complementary probability $P_{out} = 1 - P_{in}$
- Extract **reference population** outlier score corresponding to a desired quantile

Unsupervised OCC and AD

HDBScan and Quantile Cuts

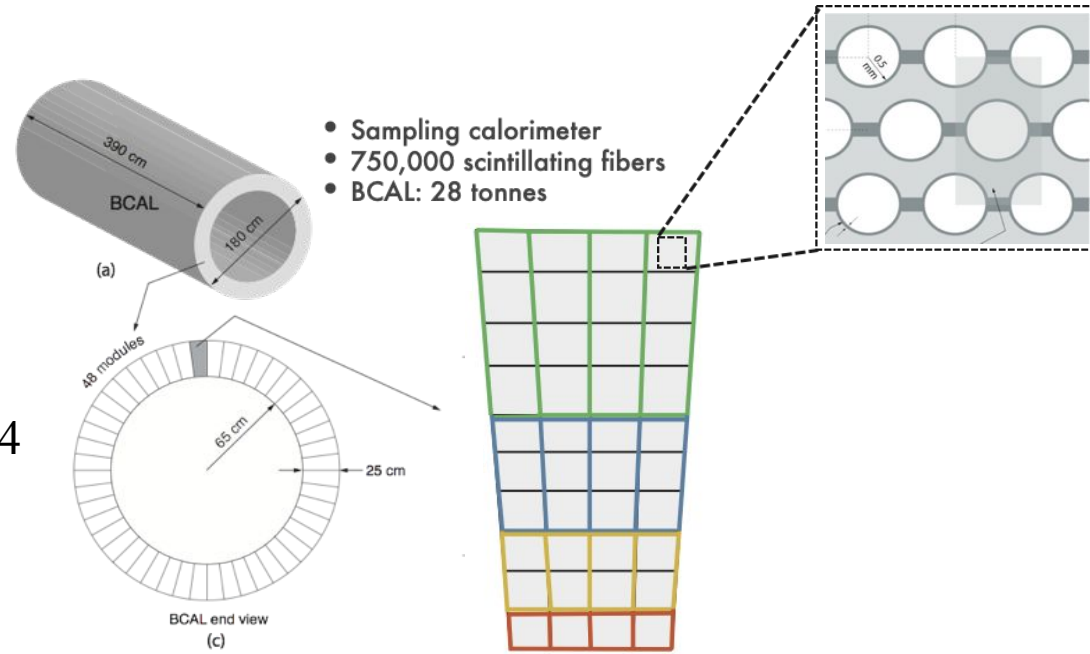


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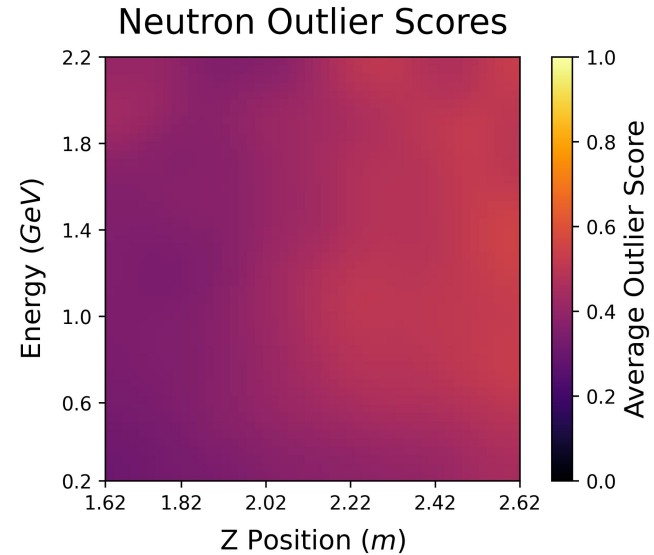
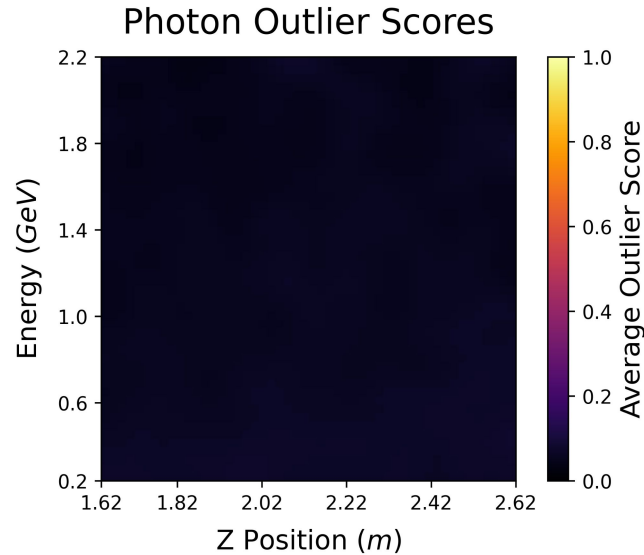
We have defined a dynamic threshold as function of the kinematics, completely agnostic towards the unknown class.

γ/n Separation at GlueX - OCC

- High confidence on **one class**
- Isolate highly active phase space within BCAL
- Reconstructed energy (E) and z position (z) as kinematic conditions
- Simulated photon (**reference**) and neutron (**unknown**) showers - Geant4
- **Strict** preselection cuts
- Deploy fiducial cuts to extract only neutron showers which highly resemble photons
- 14 input features comprising of detector response variables



γ/n Separation at GlueX - Results



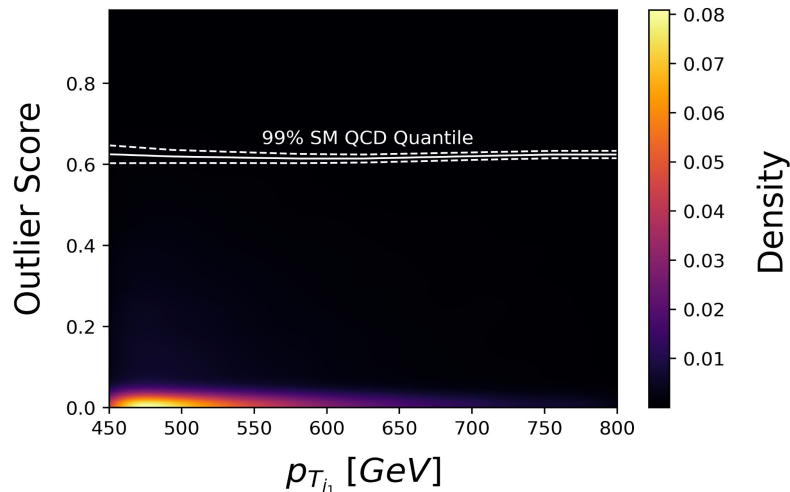
Quantile	TPR	TNR
1σ (68%)	68.28 ± 0.18 %	87.44 ± 0.13 %
2σ (95%)	95.09 ± 0.08 %	52.40 ± 0.19 %
3σ (99%)	98.97 ± 0.04 %	34.95 ± 0.18 %

BSM/SM Dijet Separation at LHC - AD

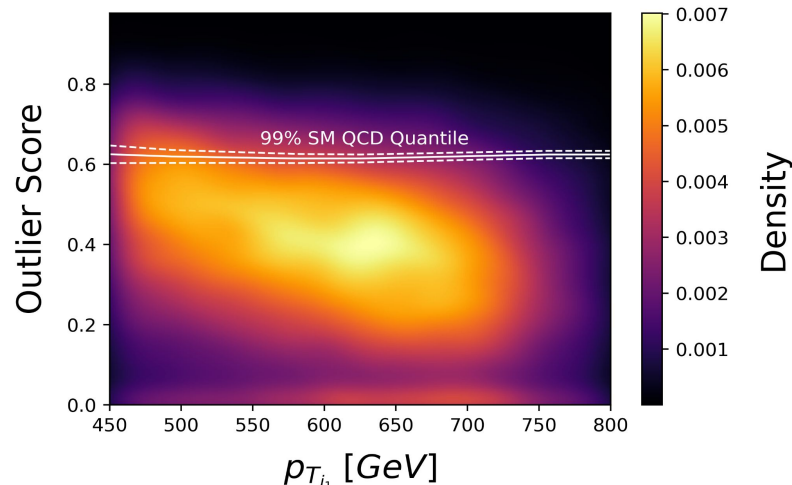
- Consider QCD dijet events as **reference**
- Isolate $Z' \rightarrow t\bar{t}$ dijets as **unknown**
- Publicly available [datasets](#) generated via *MADGRAPH* and *Pythia8* using the *DELPHES* framework for fast detector simulation
- Require leading jet transverse momenta $450 \text{ GeV} < p_T < 800 \text{ GeV}$ and sub-leading jet $p_T > 200 \text{ GeV}$
- Consider leading jet p_T as single kinematic condition
- 15 input features
 - Remaining 4 vector properties of the leading jet and n-subjettiness variables
 - Sub-leading jet 4 vector and n-subjettiness variables

BSM/SM Dijet Separation at LHC - Results

QCD Dijet Outlier Score VS Leading Jet p_T



BSM Dijet Outlier Score VS Leading Jet p_T



Quantile	TPR	TNR
1σ (68%)	68.18 ± 0.22 %	93.20 ± 0.06 %
2σ (95%)	95.15 ± 0.10 %	42.40 ± 0.22 %
3σ (99%)	99.03 ± 0.05 %	11.82 ± 0.14 %
Fiducial cuts (99%)	98.92 ± 0.05 %	2.35 ± 0.06 %

	Ours	Fraser et al.	Cheng et al.
AUC	0.885 ± 0.003	0.87	0.89

Summary

- Our architecture removes the need for semi-supervised approaches
 - Agnostic threshold selection
 - Totally unsupervised
- Highly dependable return rate (TPR = Quantile)
- Flexible - deployable on various problems
- Lends itself naturally to the role of data monitoring within detectors

GLUEX



Thank you!



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[arXiv](https://arxiv.org)

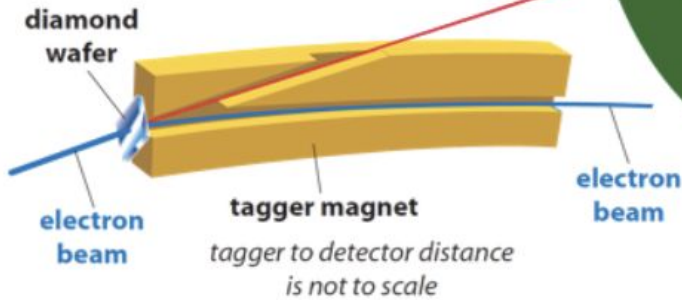
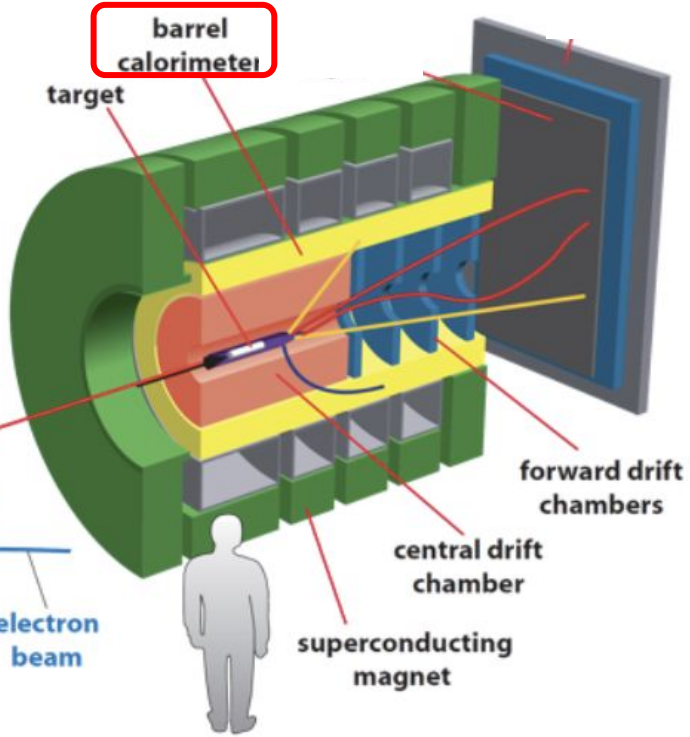
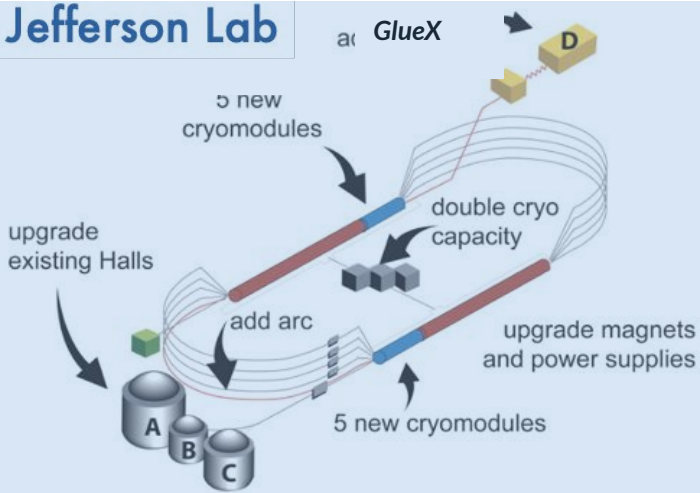


Backup Slides

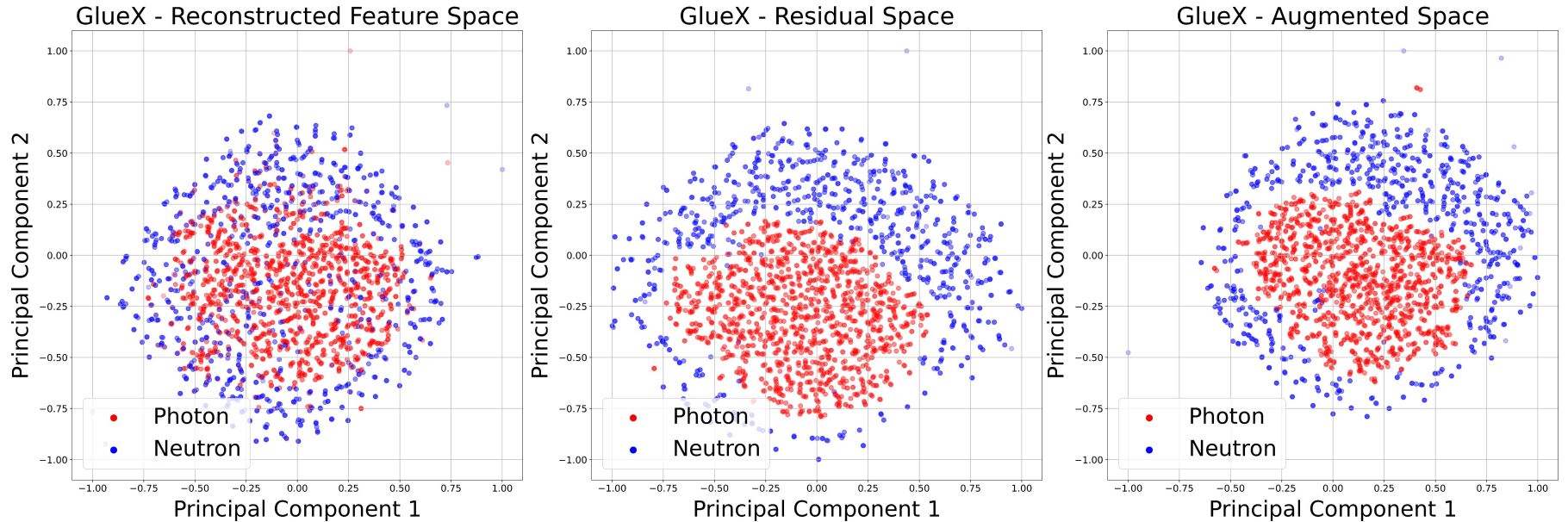
The Beamline

Jefferson Lab

at GlueX



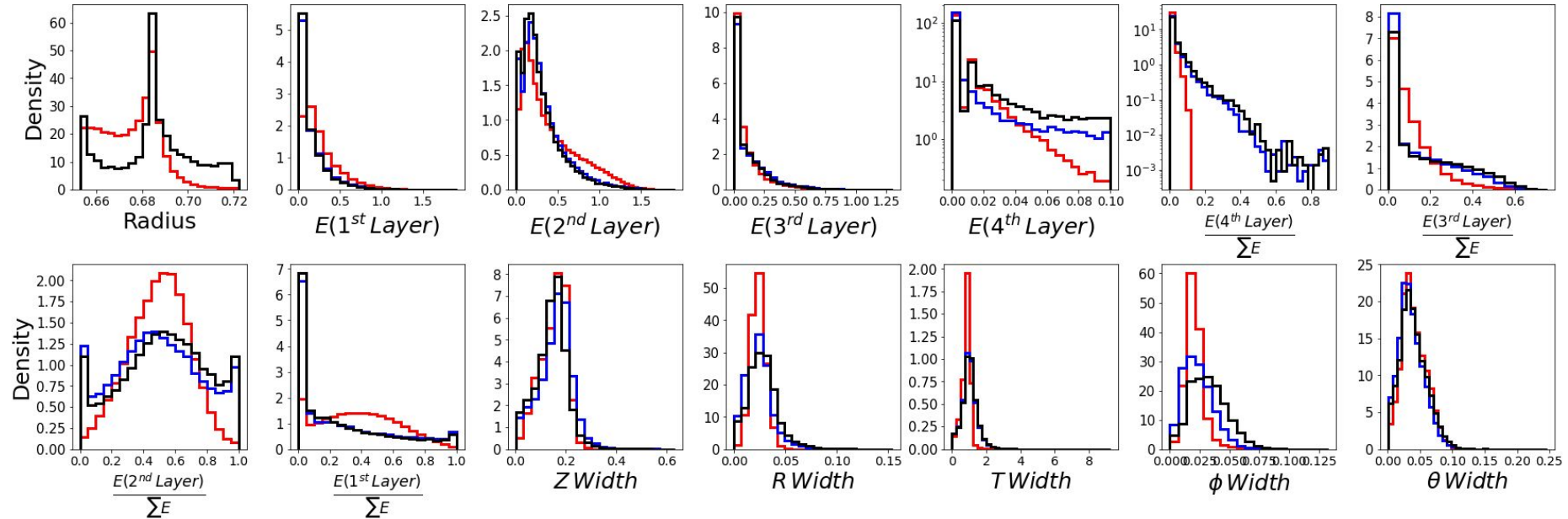
γ/n Separation at GlueX - Residuals



Features localize the space, residuals push nested clusters radially outward.

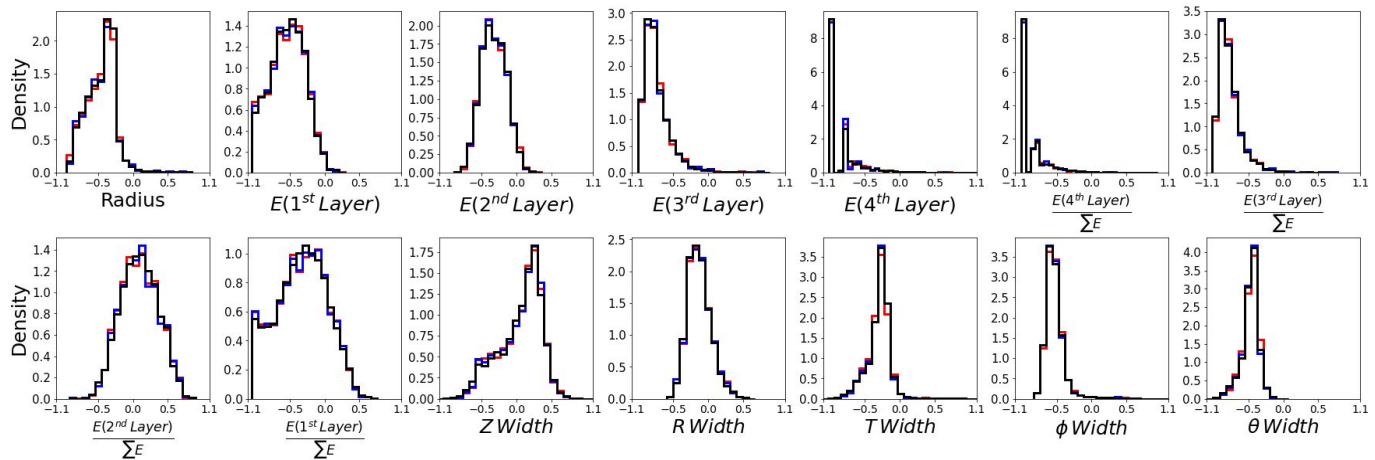
γ/n Separation at GlueX - Features

— Photons — Scaled Neutrons — Neutrons

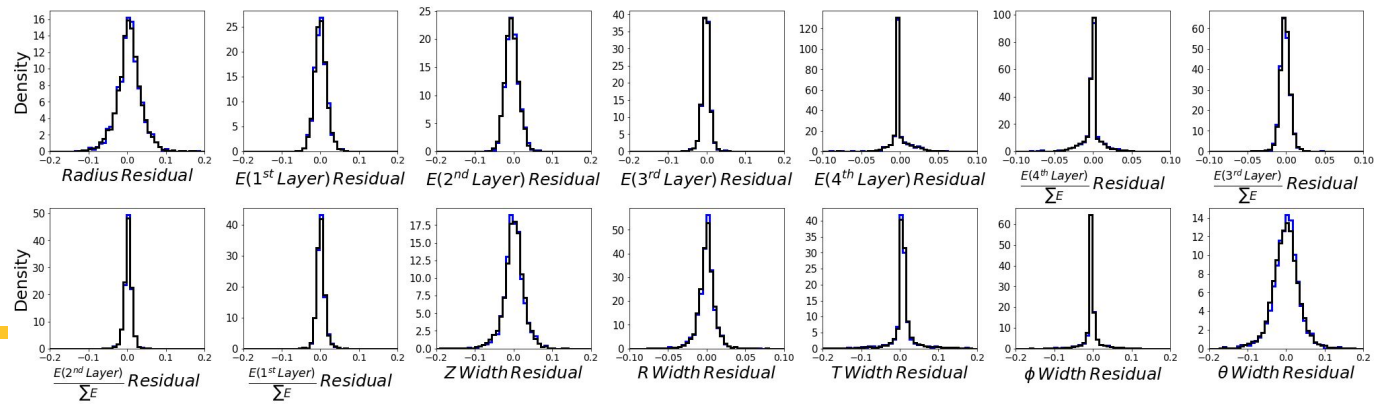


γ/n Separation at GlueX - Generations

Original Reconstructed Generated



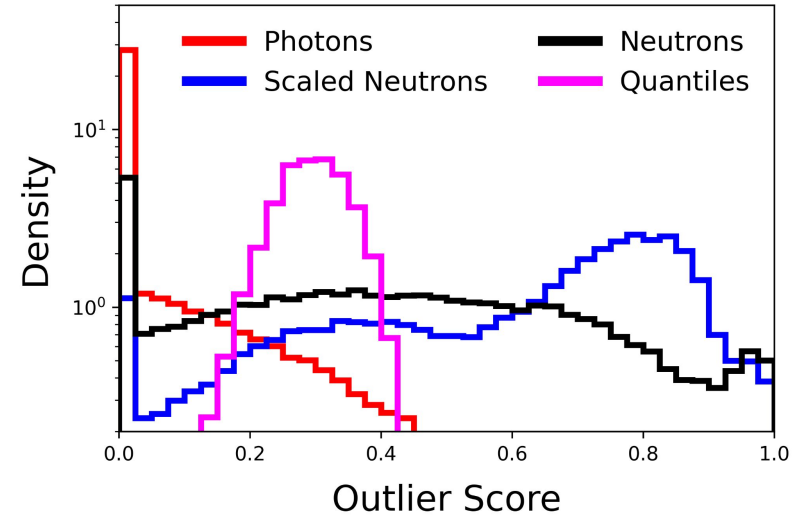
Residuals Generated



Benefits of Conditional Learning

- Perturb neutrons such that they are almost indistinguishable from photons
 - Considered “Actual” detector response
- F+M trained on only photons
- XGBoost trained on unperturbed neutron sample along with photons
- XGBoost given access to E and z as features
- Neutron kinematic correlations picked up via F+M residuals - average outlier score increased

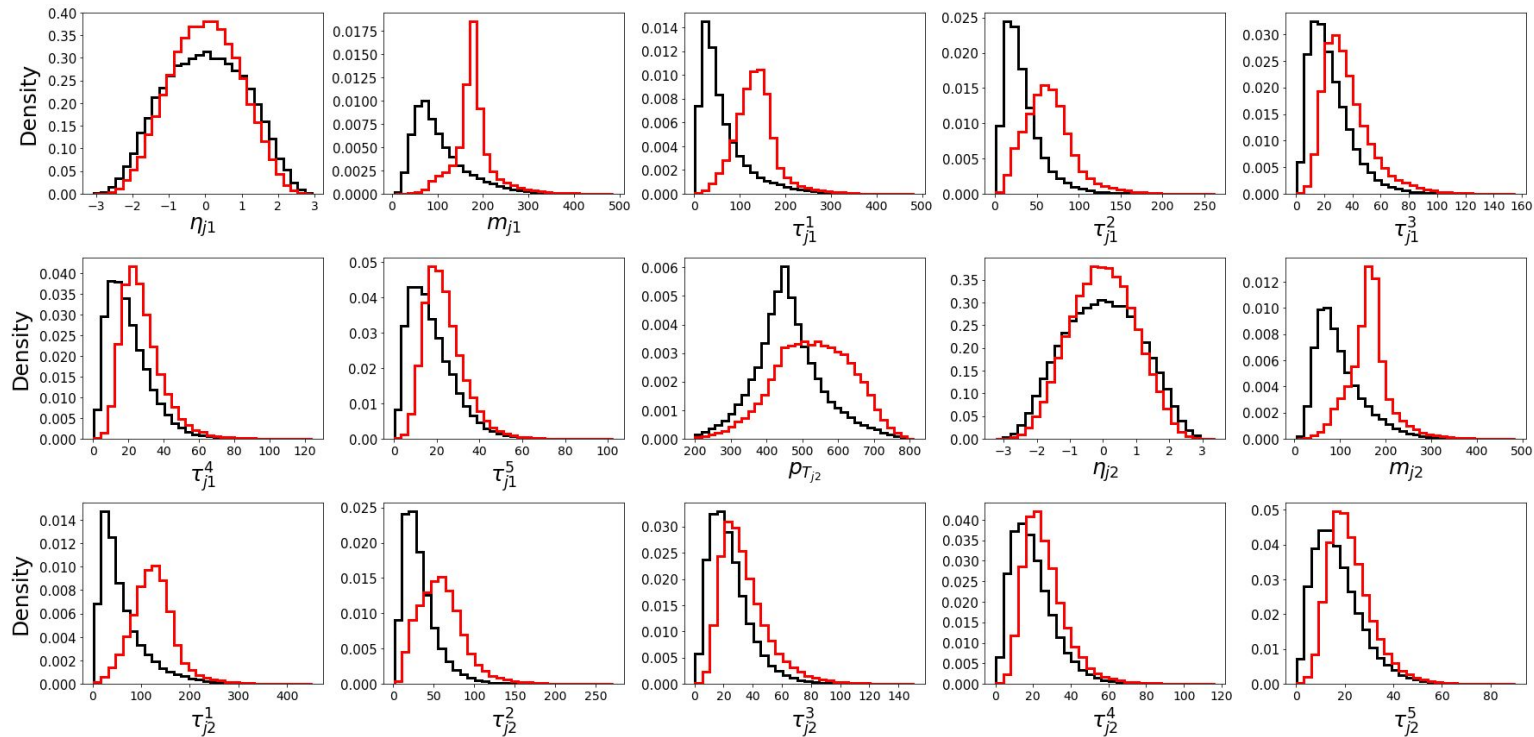
Outlier Score Distributions



Algorithm	Simulation		“Actual” Detector Response	
	TPR	TNR	TPR	TNR
XGBoost	$92.15 \pm 0.10\%$	$91.93 \pm 0.10\%$	$92.15 \pm 0.10\%$	$78.82 \pm 0.15\%$
F + M (Augmented)	$92.28 \pm 0.10\%$	$60.29 \pm 0.18\%$	$92.33 \pm 0.10\%$	$82.71 \pm 0.14\%$
F + M (Features)	$92.34 \pm 0.10\%$	$56.14 \pm 0.19\%$	$92.34 \pm 0.10\%$	$50.30 \pm 0.19\%$

BSM/SM Dijet Separation at LHC - Features

— QCD Dijets — BSM Dijets



BSM/SM Dijet Separation at LHC - Generations

