

# Machine Learning for Time Projection Chambers at FRIB

**Award Number DE-SC0024587** 

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DOE NP AI-ML PI Exchange Meeting Zoom

19 November 2025

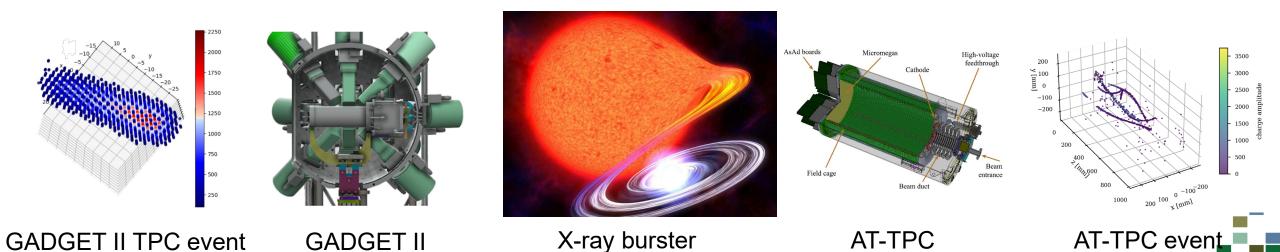




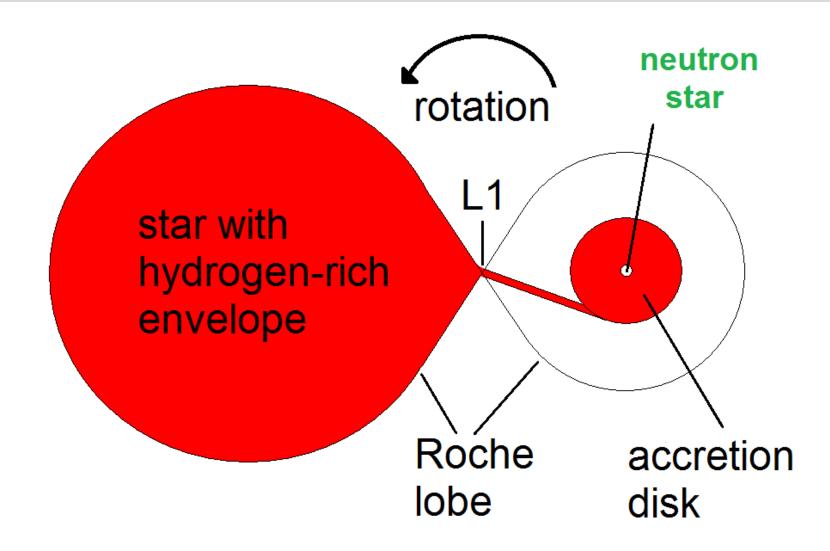


### **Outline**

- Scientific motivation: nuclear astrophysics of X-ray bursts on accreting neutron stars
- **Project Goal #1**: Machine learning to identify rare  $^{20}$ Mg( $\beta$ + $p\alpha$ ) decay events of interest in the GADGET II Time Projection Chamber (FRIB E21072 / E25058)
- **Project Goal #2**: Machine learning to improve single-particle ID in <sup>60</sup>Ga β<sup>+</sup> decay in the GADGET II Time Projection Chamber (FRIB E23035)
- Project Goal #3: Generalize machine learning methods to other TPCs at FRIB (i.e. AT-TPC)
- Administrative details of award

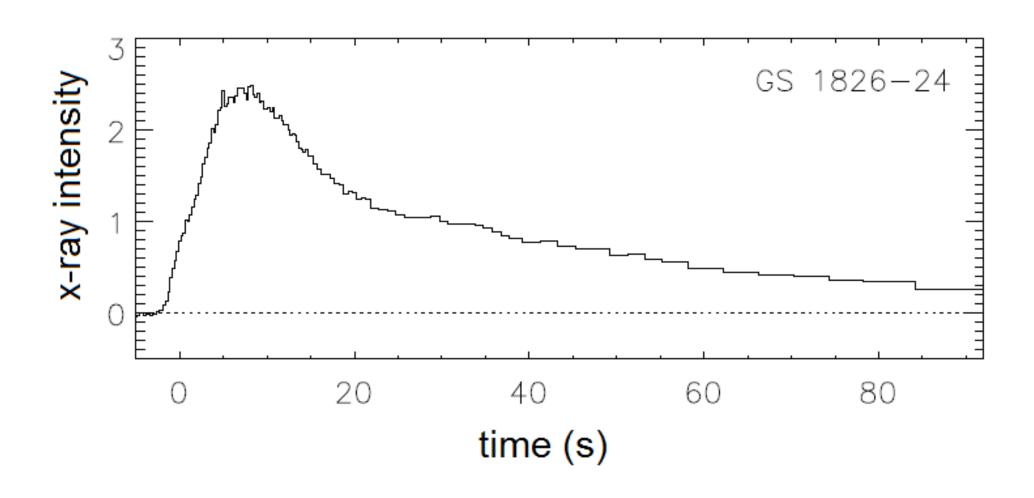


# X-ray burster





# X-ray burst light curve

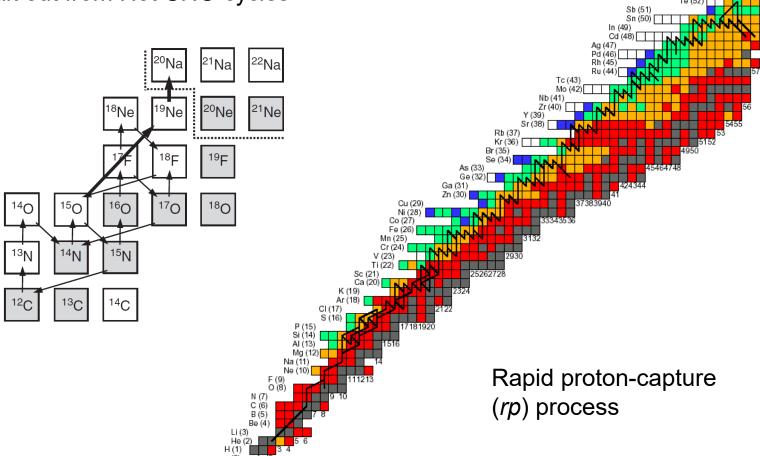




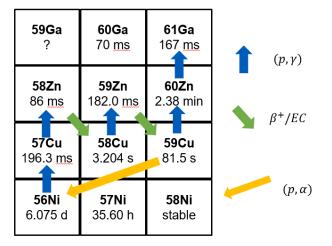
RXTE; Galloway et al., Astrophys. J. 179, 360 (2008)

# **Nucleosynthesis path in X-ray bursts**

### Break out from Hot CNO cycles



### NiCu cycle





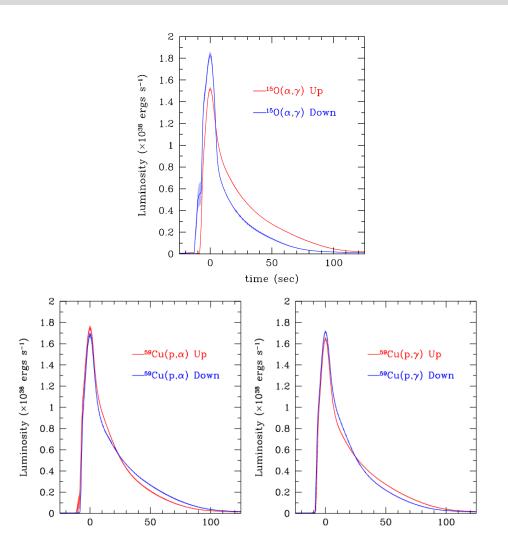




# Which reactions impact the X-ray burst light curve?

Reactions that Impact the Burst Light Curve in the Multi-zone X-ray Burst Model

Rank	Reaction
1	$^{15}\text{O}(\alpha, \gamma)^{19}\text{Ne}$
2	<sup>56</sup> Ni(α, p) <sup>59</sup> Cu
3	$^{59}$ Cu(p, $\gamma$ ) $^{60}$ Zn
4	$^{61}$ Ga(p, $\gamma$ ) $^{62}$ Ge
5	$^{22}\text{Mg}(\alpha, p)^{25}\text{Al}$
6	$^{14}O(\alpha, p)^{17}F$
7	$^{23}$ Al(p, $\gamma$ ) $^{24}$ Si
8	$^{18}\text{Ne}(\alpha, p)^{21}\text{Na}$
9	$^{63}$ Ga(p, $\gamma$ ) $^{64}$ Ge
10	$^{19}\text{F}(p, \alpha)^{16}\text{O}$
11	$^{12}\mathrm{C}(\alpha, \gamma)^{16}\mathrm{O}$
12	$^{26}\text{Si}(\alpha, p)^{29}\text{P}$
13	$^{17}\text{F}(\alpha, p)^{20}\text{Ne}$
14	$^{24}\mathrm{Mg}(\alpha, \gamma)^{28}\mathrm{Si}$
15	$^{57}$ Cu(p, $\gamma$ ) $^{58}$ Zn
16	$^{60}$ Zn( $\alpha$ , p) $^{63}$ Ga
17	$^{17}$ F(p, $\gamma$ ) $^{18}$ Ne
18	$^{40}$ Sc(p, $\gamma$ ) $^{41}$ Ti
19	$^{48}$ Cr(p, $\gamma$ ) $^{49}$ Mn



Our experimental program focuses on the top three:

- 1.  $^{15}O(\alpha,\gamma)^{19}Ne$
- 2.  $^{59}$ Cu(p, $\alpha$ ) $^{56}$ Ni
- 3.  $^{59}$ Cu(p, $\gamma$ ) $^{60}$ Zn

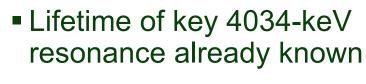
The same reactions also affect the ash composition



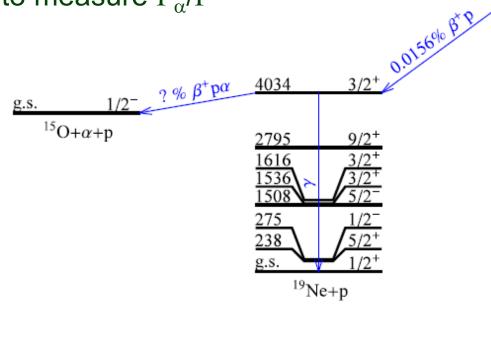
R. Cyburt et al., Astrophys. J. 830, 55 (2016)



# β decay of <sup>20</sup>Mg to probe key <sup>15</sup>O( $\alpha$ ,γ)<sup>19</sup>Ne resonance



■ Need to measure  $\Gamma_{\alpha}/\Gamma$ 



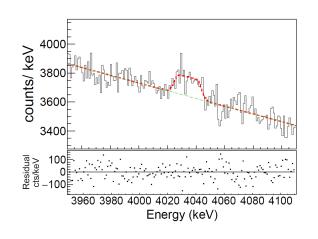
 Doppler technique yields proton energy of 1.2 ± 0.2 MeV

 $^{20}$ Mg

27.2%

72.0%

<sup>20</sup>Na



C. Wrede et al., Phys. Rev. C 96, 032801(R) (2017)

B. E. Glassman et al., Phys. Lett. B 778, 397 (2018)

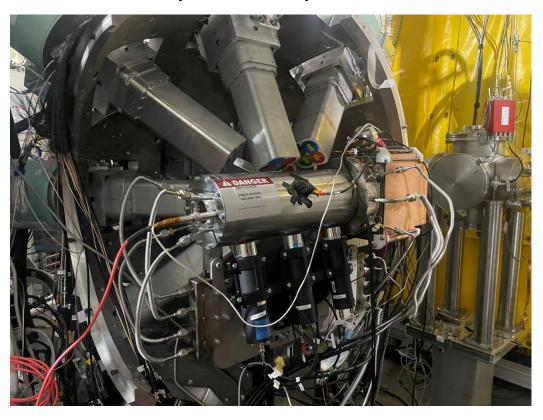
B. E. Glassman et al., Phys. Rev. C 99, 065801 (2019)

B. E. Glassman, Ph.D. thesis (MSU, 2019)



# Gaseous Detector with Germanium Tagging (GADGET II) system

GADGET II configured with TPC inside DeGAi Ge array of FRIB Decay Station initiator



- Located at Facility for Rare Isotope Beams (FRIB)
- Compact time projection chamber (TPC) surrounded by array of high purity germanium detectors such as DeGAi
- TPC produces 3D images of charged particle tracks following decays inside the gas, providing ranges, energies, particle ID, and particle multiplicity
- FRIB Decay Station initiator's DeGAi Ge array used to detect gamma rays

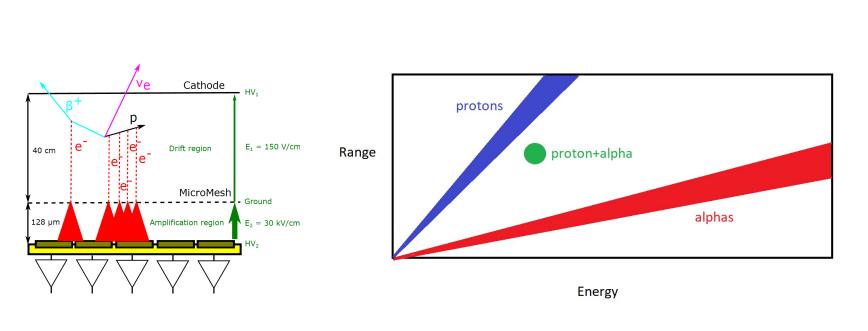


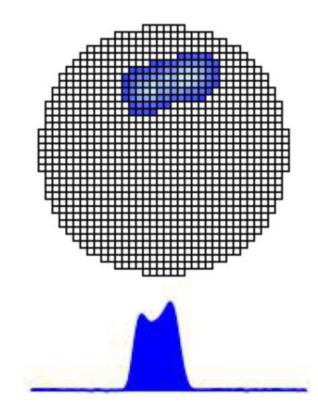
R. Mahajan, T. Wheeler et al., Phys. Rev. C 110, 035807 (2024)



# FRIB E21072 / E25058 with GADGET II Time Projection Chamber (TPC): concept

Measure  $^{20}$ Mg( $\beta$ p $\alpha$ ) $^{15}$ O through 4.03-MeV  $^{15}$ O( $\alpha$ , $\gamma$ ) $^{19}$ Ne resonance to determine  $\Gamma_{\alpha}/\Gamma$ .





Time Projection Chamber operation

Tracks have unique range vs. energy compared to protons and alphas

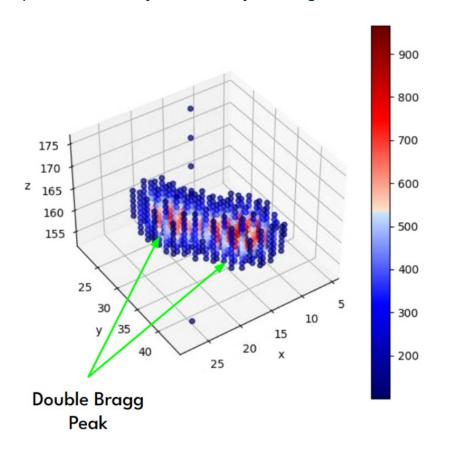
Tracks have unique topology (ATTPCROOT simulation shown)



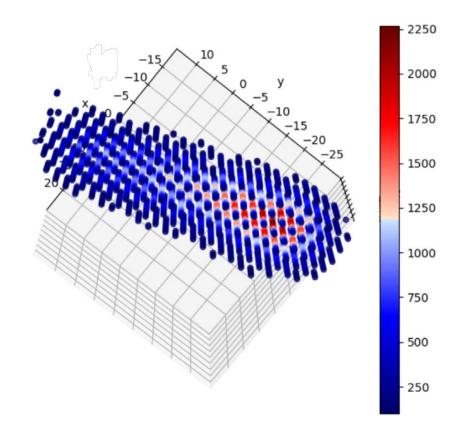
# **GADGET II analysis problem #1**

■ Find a few needles (p- $\alpha$  events, left) in a 10 $^9$  haystack (single p and  $\alpha$  events, right)

E21072 p- $\alpha$  event, likely from decay of <sup>21</sup>Mg beam contaminant

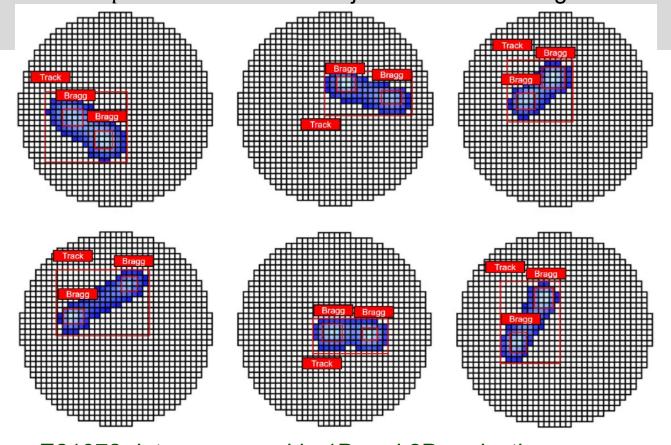


E21072 p event, likely from decay of <sup>20</sup>Mg



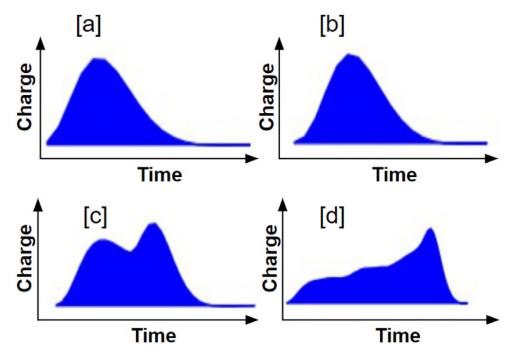


Examples of 2D parameter-varied simulations of p- $\alpha$  events used for object detector training



# GADGET II ML procedure: Object detection with CNNs

Simulated 1D time projection representations corresponding 1 and 2 particle events

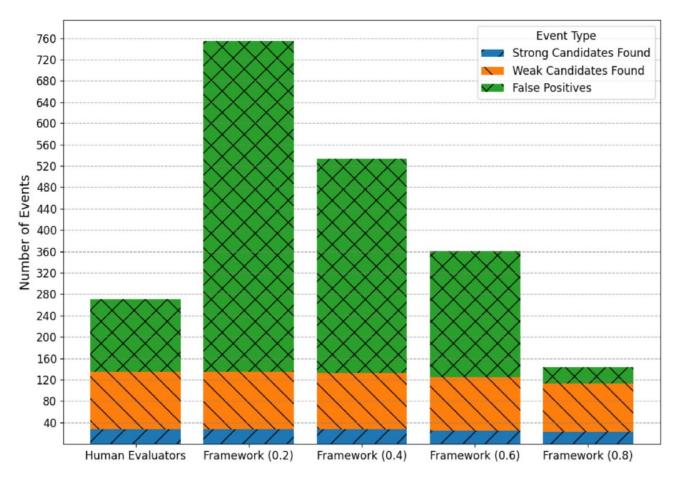


- E21072 data expressed in 1D and 2D projections
- leverages computational efficiency of 2D CNNs and benefits from the extensive availability of pre-trained models
- simulated events with parameter variations used to train 2D CNN object detectors to detect real two-particle events in 2D projections
- combine with 1D histogram peak detection algorithms for multi-modal detection framework



### **GADGET II ML results**

Comparison of  ${}^{21}\text{Mg}(\beta^+p\alpha)$  events found by human evaluators and the detection framework at various thresholds



- filters rare, two-particle  $^{21}$ Mg( $\beta^+p\alpha$ ) events of interest in data taken during E21072
- threshold on confidence score (in parentheses) affects recall and false positives
- For example, confidence score threshold of 0.4 yields 100% recall on strong candidates and identified 105 of 107 weak candidates
- Outlook: FRIB E25058 Run 2 scheduled Nov. 26-30, 2025, to provide necessary stats and purity

T. Wheeler *et al.*, Nucl. Instrum. Methods Phys. Res. A 1080, 170659 (2025)



# FRIB E23035: Is there a NiCu Cycle in X-ray bursts?

- β<sup>+</sup> decay of <sup>60</sup>Ga to <sup>60</sup>Zn
- Goals: discover resonances in the competing <sup>59</sup>Cu(p,γ)<sup>60</sup>Zn and <sup>59</sup>Cu(p,α)<sup>56</sup>Ni reactions and determine their properties (E, and p, α, γ branches)
- Evaluate NiCu cycling in X-ray bursts
- Identical setup to FRIB E21072
- Measure β-delayed protons, α particles and γ rays
- Ran successfully November 13-18, 2025

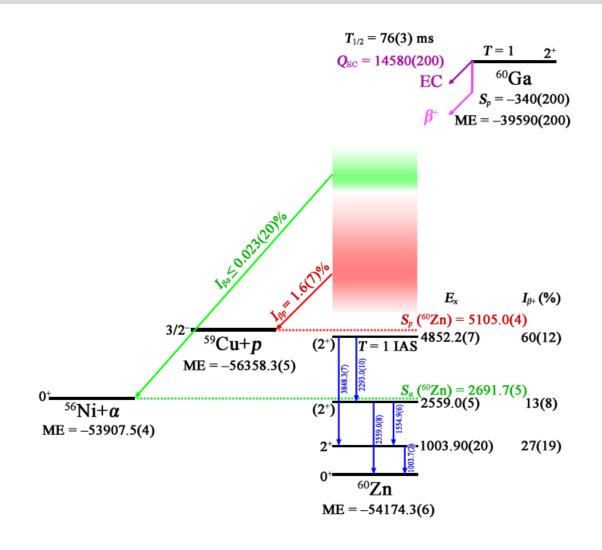
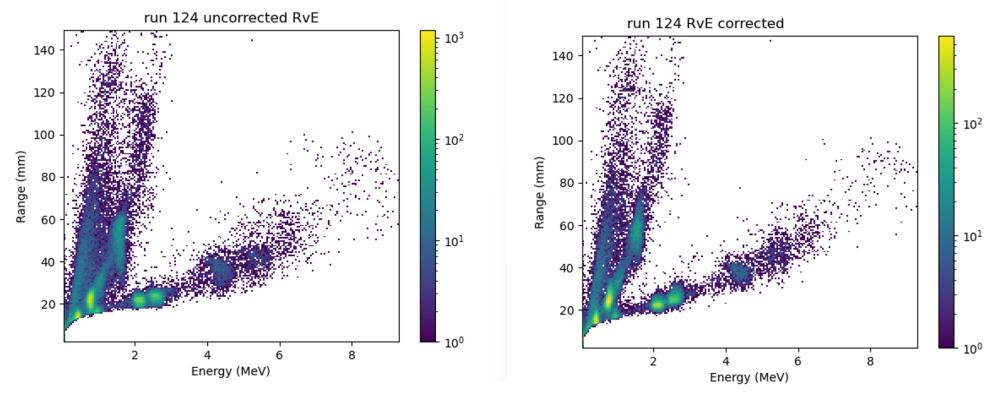


Figure: L. J. Sun et al., Phys. Rev. C 111, 055806 (2025)



# **GADGET II analysis problem #2**





- Need clean particle ID to separate protons and α particles in <sup>60</sup>Ga decay (FRIB E23035)
- Protons have low-range tails that bleed into the α-particle band below
- While working on ML techniques to solve this problem, we realized the physics solution: correct for electric field distortions from positive ions generated by beam implantation
- Parlayed ML work on the particle ID problem into advancing our third and final ML goal

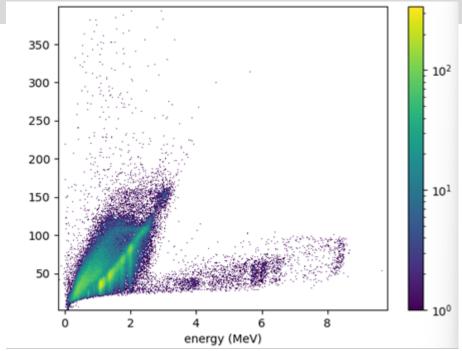




# **GADGET II analysis problem #2**

uncorrected to be corrected

Range vs. Energy for tracks measured in FRIB E23035



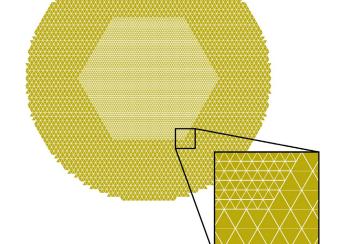
- Need clean particle ID to separate protons and α particles in <sup>60</sup>Ga decay (FRIB E23035)
- Protons have low-range tails that bleed into the  $\alpha$ -particle band below
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# AsAd boards Micromegas High-voltage feedthrough Cathode Beam Field cage entrance Beam duct

# Active Target Time Projection Chamber (AT-TPC) system & science

- Operational principle and technology similar to GADGET II TPC
- Used as an active target for reaction experiments with rare isotope beams
- Embedded in solenoidal magnetic field
- Higher-granularity pad plane with different geometry
- Investigating <sup>12</sup>C Hoyle-state  $\alpha$ -cluster analogs in light even-even N = Z nuclei (eg. <sup>20</sup>Ne)



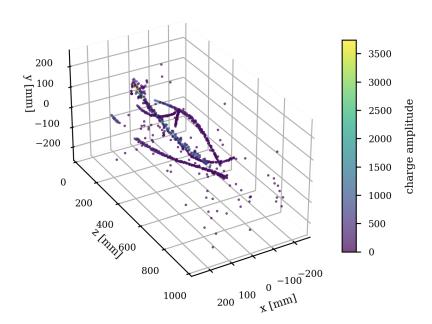


Y. Ayyad *et al.*, Nucl. Instrum. Methods Phys. Res. A 954, 161341 (2020)

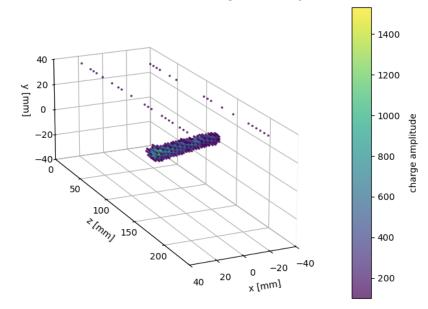
J. Bradt *et al.*, Nucl. Instrum. Methods Phys. Res. A 875, 65–79 (2017)

# AT-TPC + GADGET II analysis problem #3

Point cloud of AT-TPC 4-track event from  $^{16}\text{O}+\alpha$  reaction experiment



Point cloud of GADGET II TPC singleproton event from <sup>20</sup>Mg-decay experiment



- TPCs produce massive, high-dimensional datasets that are inherently sparse and vary significantly across detector geometries and experimental goals
- TPC data analysis often relies on detector-specific pipelines, limiting the development of generalizable tools that can be applied across experiments
- Goal: explore sparse convolutional techniques as a general tool for representation learning across TPCs

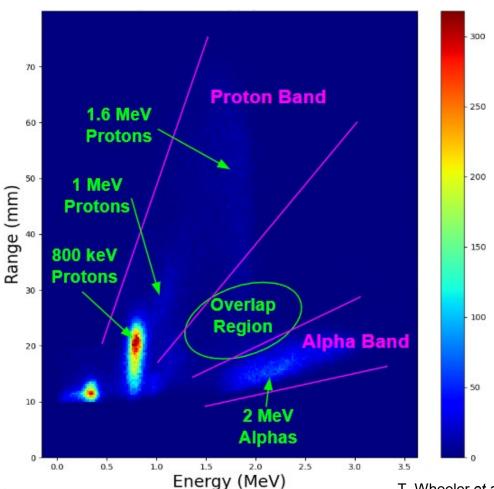
  T. Wheeler *et al.*, NeurIPS 2025 proceedings, arXiv:2511.11221; Mach. Learn.: Sci. Technol. (to be submitted)





# AT-TPC + GADGET II ML procedure

### GADGET II range vs. energy plot



- sparse convolutional neural networks implemented with the Minkowski Engine to process 4D point cloud data
- backbone is a shallow residual network (ResNet14) adapted for sparse inputs
- trained with four input channels (x, y, z, q) to perform binary proton–α classification on GADGET II data yielding ResNET<sub>train</sub> model
- Additionally, investigate the embeddings produced by a randomly initialized ResNet14 that undergoes no further training yielding ResNet<sub>rand</sub> model
- train a linear probe on various classification tasks distinct from the training task
- To visualize the structure of the embedding space, apply principal component analysis (PCA) to reduce the highdimensional latent vectors to their first two principal components

T. Wheeler et al., NeurIPS 2025 proceedings, arXiv:2511.11221; Mach. Learn.: Sci. Technol. (to be submitted)



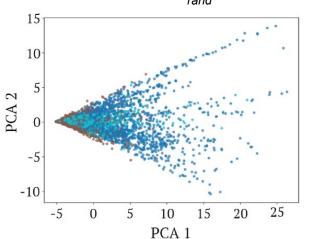
## GADGET II -> GADGET II ML results

- For GADGET data, embeddings from ResNet<sub>rand</sub> and ResNet<sub>train</sub> probed using 3-class separation task: distinguishing 800 keV protons, 1600 keV protons, and 2 MeV α's
- Even without training (ResNet<sub>rand</sub>), the architecture produces PCA projections of embeddings with some degree of ordering
- Embeddings from ResNet<sub>train</sub>, which was optimized only for binary proton–α discrimination, exhibit an even cleaner separation of all three particle classes
- Pre-training on a simple physics-driven task yields representations with richer event structure than the labels alone, producing a latent space where multi-class tasks can become linearly separable

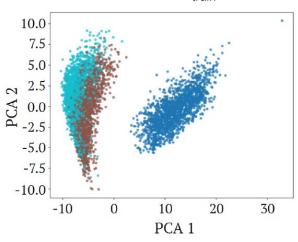
Linear probe results on GADGET II three-class particle. The untrained architecture (ResNet<sub>rand</sub>) provides non-trivial structure; pretraining on GADGET II data (ResNet<sub>train</sub>) improves in-domain transfer.

Domain	Accuracy			F1 Score		
	$\mathtt{ResNet}_{train}$	${ t ResNet}_{rand}$	Naïve	$\mathtt{ResNet}_{train}$	$\mathtt{ResNet}_{rand}$	Naïve
GADGET II	0.97	0.85	0.33	0.97	0.85	0.17

PCA of embeddings from ResNet<sub>rand</sub>



PCA of embeddings from ResNet<sub>train</sub>



Brown: 800 keV proton Light blue: 1600 keV proton

Dark Blue: 2 MeV α

T. Wheeler et al., NeurIPS 2025 proceedings, arXiv:2511.11221; Mach. Learn.: Sci. Technol. (to be submitted)



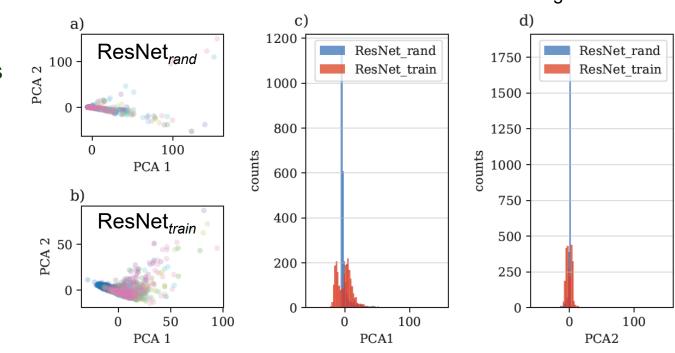
## GADGET II -> AT-TPC ML results

- For AT-TPC data, embeddings from ResNet<sub>rand</sub> and ResNet<sub>train</sub> probed using track counting task ({0, 1, 2} vs. {3} vs. {4, 5} tracks)
- For ResNet<sub>rand</sub>, projections show weak but nontrivial organization, with narrow distributions and limited separation
- Embeddings obtained by running AT-TPC events through the GADGET-trained encoder (ResNet<sub>train</sub>) show more dispersed embeddings in PCA space, allowing for more successful separation.
- Latent features learned on one detector retain their utility when transferred to a different system with vastly different geometry and physics goals!
- sparse tensor methods valuable for analyzing and processing TPC data and for building cross-domain foundation models for TPCs

Linear probe results on AT-TPC track counting tasks. The untrained architecture (ResNet<sub>rand</sub>) provides non-trivial structure; pretraining on GADGET II data (ResNet<sub>train</sub>) also improves out-of-domain transfer.

Domain	Accuracy			F1 Score		
	$\mathtt{ResNet}_{train}$	${\tt ResNet}_{rand}$	Naïve	$\mathtt{ResNet}_{train}$	$\mathtt{ResNet}_{rand}$	Naïve
AT-TPC	0.74	0.58	0.48	0.70	0.53	0.31

#### Visualization of AT-TPC ResNet embeddings



T. Wheeler et al., NeurIPS 2025 proceedings, arXiv:2511.11221; Mach. Learn.: Sci. Technol. (to be submitted)



## Hardware: "TPCGPU" GPU node





TPCGPU is installed and maintained in Division of Engineering Computing Services (DECS) at MSU

Equipped with the following hardware specifications for efficiency in ML algorithm development and deployment:

- CPU: 2 × AMD EPYC 7763 processors (128 physical cores / 256 threads total) with 512 MB total L3 cache, delivering high-throughput parallel compute performance.
- Memory: 1.0 TiB (1,024 GB) DDR4 system memory, enabling large-scale deep learning, high-resolution simulations, and memory-intensive analysis workflows.
- GPU: 4 × NVIDIA RTX A6000 GPUs, each with 48 GB GDDR6, ideal for large-batch CNN training, transformer models, computer vision, and generative workloads.
- CUDA / Driver: CUDA 12.2 with NVIDIA driver 535.183.01, optimized for modern machine learning and scientific GPU frameworks.
- Operating System: 64-bit Linux environment configured for GPU-accelerated deep learning and HPC workloads.





# Personnel: all at Michigan State University



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Senior/Key Person
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### **Dissemination**

#### Publications / theses:

Measuring the  $^{15}$ O(α,  $\gamma$ ) $^{19}$ Ne Reaction in Type I X-ray Bursts using  $^{20}$ Mg  $\beta$ -decay, T. Wheeler, Ph.D. thesis, Michigan State University (2024)

Time projection chamber for GADGET II, R. Mahajan, T. Wheeler et al., Phys. Rev. C 110, 035807 (2024)

Object detection with deep learning for rare event search in the GADGET II TPC, T. Wheeler et al., Nucl. Instrum. Methods Phys. Res. A 1080, 170659 (2025)

Sparse Methods for Vector Embeddings of TPC Data, T. Wheeler et al., NeurIPS 2025 proceedings (accepted), arXiv:2511.11221

Sparse Methods for Vector Embeddings of TPC Data, T. Wheeler et al., Mach. Learn.: Sci. Technol. (to be submitted)

Commissioning of GADGET II with <sup>21</sup>Mg decay, T. Wheeler et al., (in preparation)

#### Invited talks:

Machine Learning in Experimental Nuclear Astrophysics, C. Wrede, Fall Meeting of the American Physical Society (APS) Division of Nuclear Physics (DNP), Chicago, IL (Oct 2025)

The GADGET Program at FRIB, T. Wheeler, Fall Meeting of the American Physical Society (APS) Division of Nuclear Physics (DNP), Chicago, IL (Oct 2025)

Nuclear Astrophysics at FRIB, C. Wrede, XVIII International Symposium on Nuclei in the Cosmos (NIC XVIII), Girona, Spain (Jun 2025)

Experimental studies of key resonances for explosive of key resonances for explosive hydrogen and helium burning, C. Wrede, The 17th International Symposium on Origin of Matter and Evolution of Galaxies (OMEG2024), China (Sep 2024)

Thermonuclear runaways investigated using beta delayed charged particle emission, C. Wrede, 14th International Conference on Nucleus-Nucleus Collisions (NN2024), Whistler, BC, Canada (Aug 2024)

New Initiatives with GADGET, C. Wrede, Low Energy Community Meeting, TPC Working Group, Knoxville, TN (Aug 2024)

2D Convolutional Neural Networks with Early Data Fusion for Rare Event Search in GADGET II TPC Data, T. Wheeler, Conference on the Application of Accelerators in Research and Industry and Symposium of Northeastern Accelerator Personnel (CAARI-SNEAP), Fort Worth, TX, USA (July 2024)

Applications of machine learning at FRIB, C. Wrede, American Physical Society April Meeting, Sacramento, CA (Apr 2024)

Measuring the 15O(α, γ)19Ne Reaction Rate in Type I X-ray Bursts using 20Mg β-decay, T. Wheeler, Cyclotron Institute Seminars at Texas A&M University, College Station, TX (Jan 2024)

GADGET II: Status and Future Plans, C. Wrede, FRIB Decay Station Workshop, Atlanta, GA (Nov 2023)

FRIB Experiment 21072: Strength of the key 15O(α,γ)19Ne resonance in X-ray bursts, C. Wrede, FRIB Decay Station Workshop, Atlanta, GA (Nov 2023)



### **Deliverables & Schedule**

■ **Deliverable #1**: Machine learning to identify rare  $^{20}$ Mg( $\beta$ + $p\alpha$ ) decay events of interest in the GADGET II Time Projection Chamber (FRIB E21072 / E25058):

**Status/schedule**: Machine learning model completed, published, and ready for deployment on FRIB E25058 data set, which runs November 26-30, 2025

• **Deliverable #2**: Machine learning to improve single-particle ID in <sup>60</sup>Ga β<sup>+</sup> decay in the GADGET II Time Projection Chamber (FRIB E23035):

**Status/schedule**: Machine learning model initiated, but physics model developed in parallel solving the problem. FRIB E23035 ran successfully November 13-17, 2025, and physics model will be deployed on data set imminently

■ Deliverable #3: Generalize machine learning methods to other TPCs at FRIB (i.e. AT-TPC):

**Status/schedule**: Machine learning model developed demonstrating potential for building cross-domain foundation models for TPC. NeurIPS paper accepted and journal paper in preparation; to be submitted by end of 2025



## **Budget and Expenditures**

	Year 1 Year 2		Year 3	Totals
	9/1/2023 - 8/31/2024	9/1/2024 - 8/31/2025	9/1/2025 - 11/17/2025	
Funds allocated	205,000.00	205,000.00	-	410,000.00
Actual costs to date	104,461.11	164,185.38	20,174.98	288,821.47

Projection is that remaining funds will be spent by end of no-cost extension 8/31/2026, primarily on personnel working to meet deliverables on schedule



# Thank you for your attention!



