Neural network classifiers for analyzing measurements of fast neutrons for invariant mass spectroscopy

Jaylen Rasberry[1]
Juan Lois-Fuentes[2]
Justin Brown[1]
Thomas Redpath[1]
[1]Virginia State University
[2]Facility for Rare Isotope Beams, Michigan State University

U.S. DEPARTMENT OF ENERGY | Office of Science

The MoNA Collaboration
Quam difficile esse potest.

VIRGINIA STATE

Outline

- Background
  - Science beyond the neutron dripline
  - Multi-neutron unbound systems
  - Invariant mass spectroscopy
- Machine learning for event classification
  - Project status
  - Deliverables
  - Budget summary

Neutron dripline science

- 

  - "A powerful way to develop a predictive understanding of the
    changes in nu ... driplines is to
    track how nu ... utron number
    increases, fr ... e."

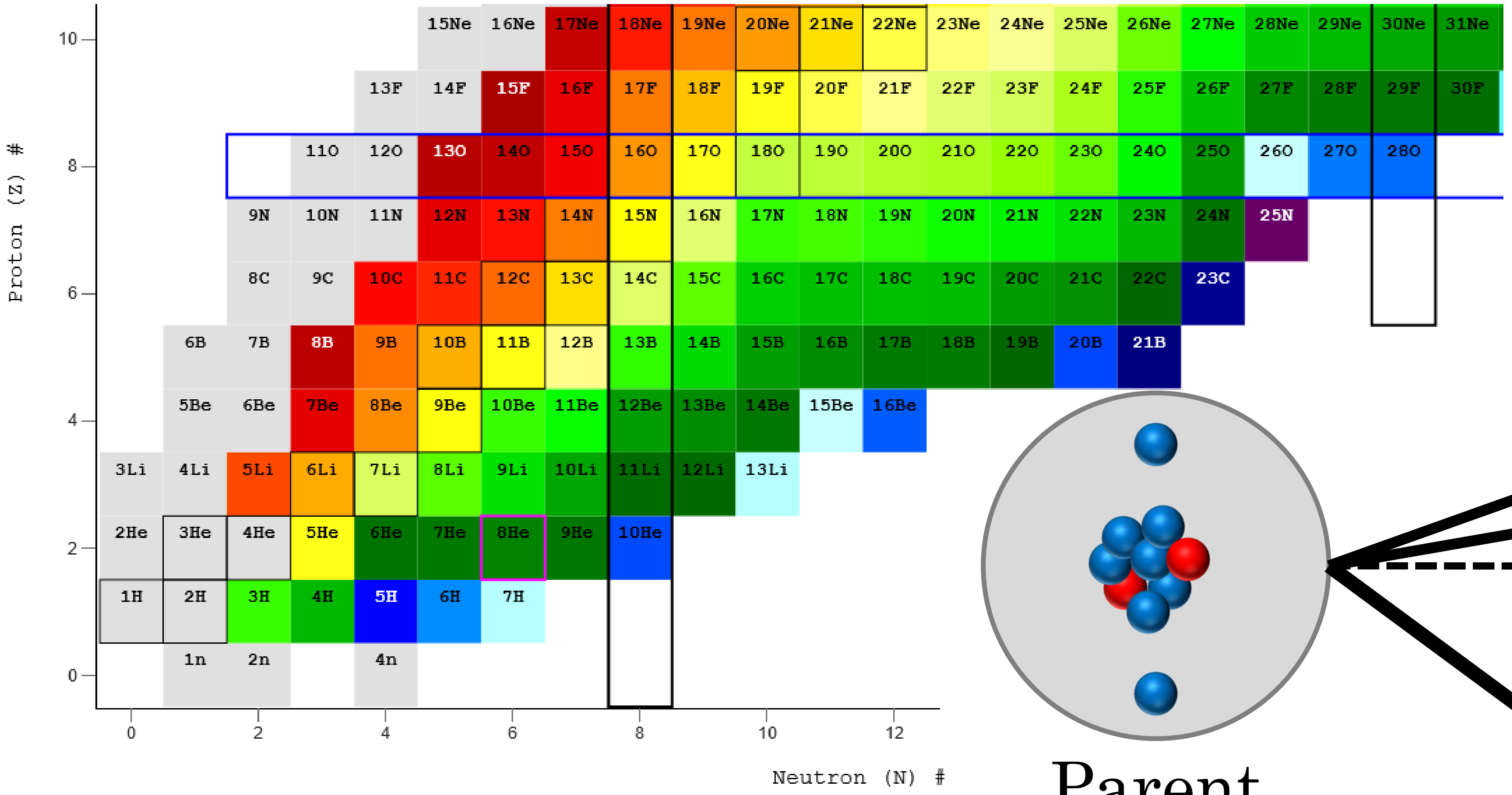
Understanding involves an interplay between
- Single particle motion
- Many-body correlations
- Neutron continuum

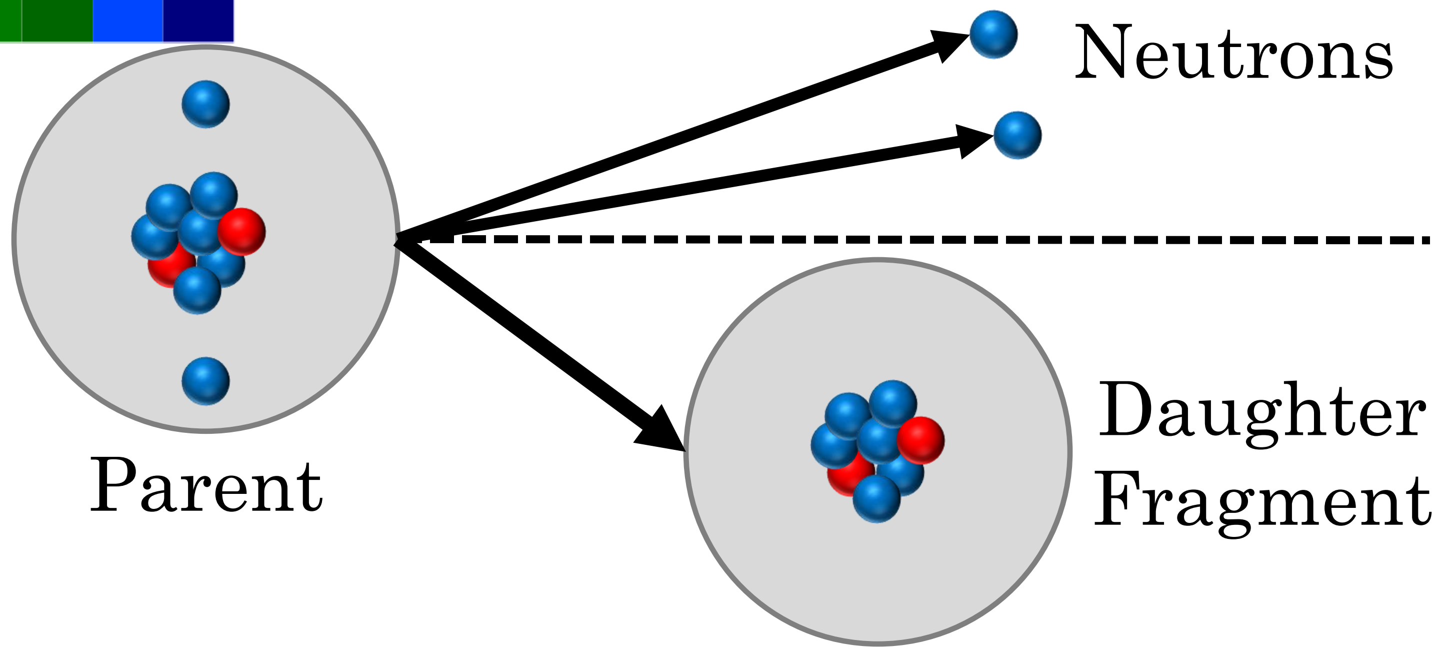
- 

  ... clei is the most
  ... clear structure."
  - "The unique data on bound and unbound states of oxygen isotopes have been used to benchmark ab-initio modes of nuclei … resulting in the development of a vastly improved theoretical formalism."

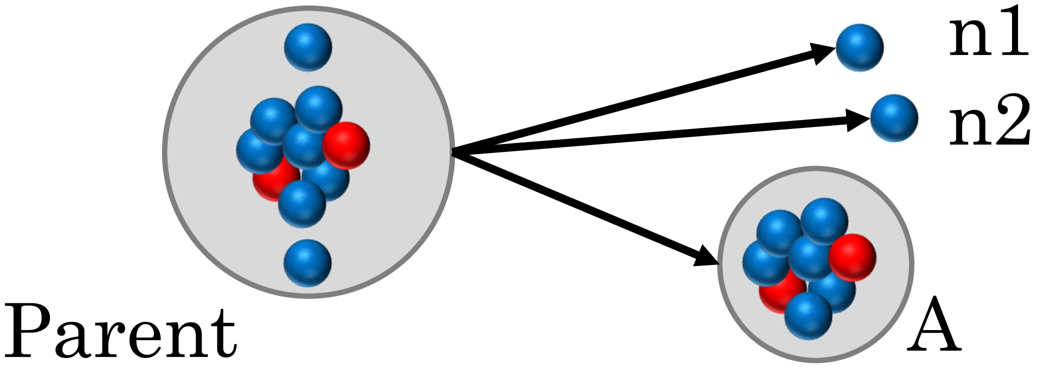
Neutron-unbound systems

NuDat 3.0, S_{2n}
nndc.bnl.gov





Extracting information

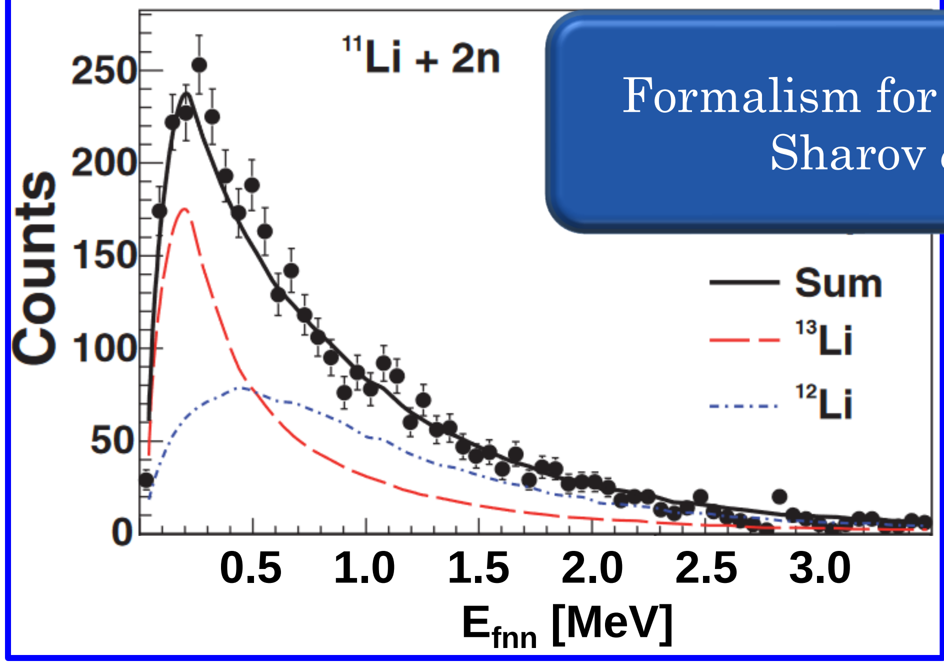


$$E_{fnn} = \sqrt{m_A{}^2 + 2m_n{}^2 + 2\left(E_3{}^2 - \vec{p}_3{}^2\right)} - m_A - 2m_n$$

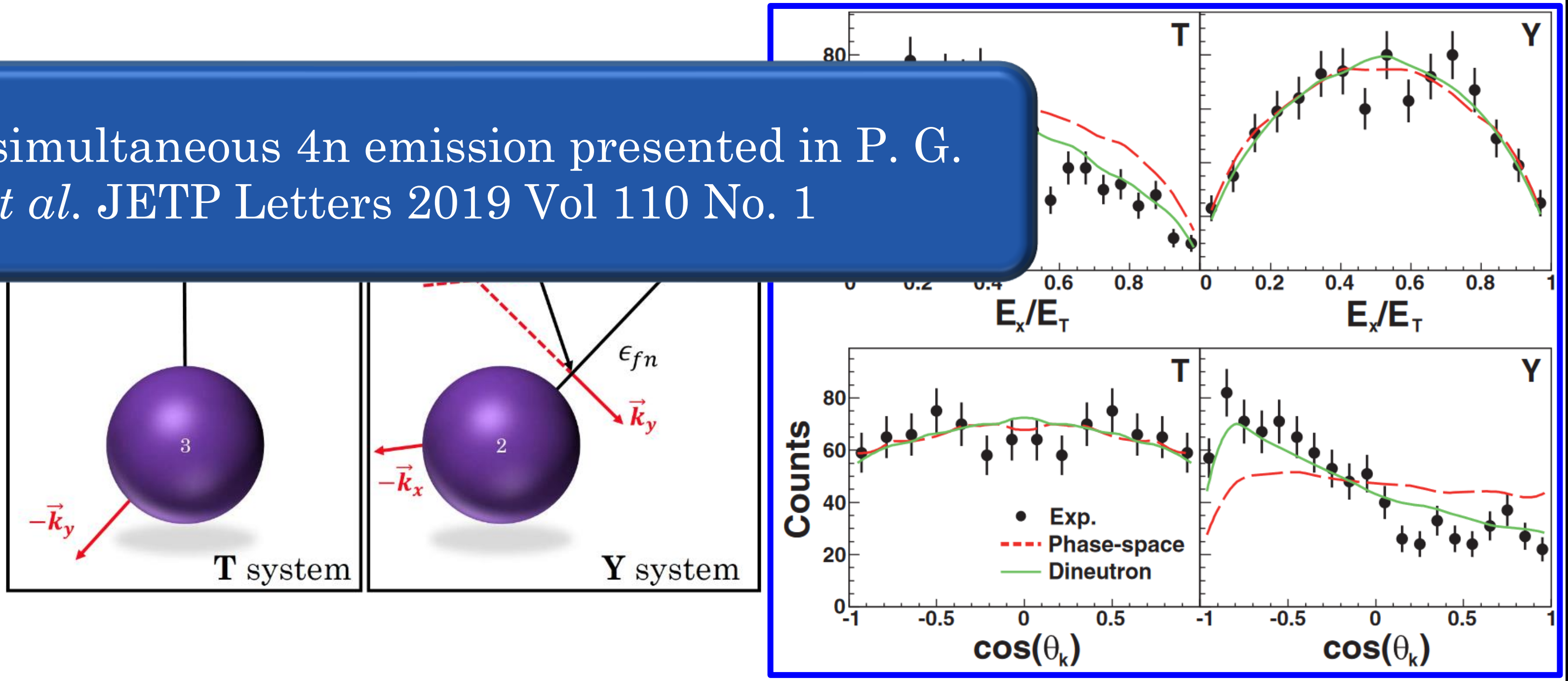
$$E_3{}^2 = E_A E_{n1} + E_A E_{n2} + E_{n1} E_{n2}$$

$$\vec{p}_3{}^2 = \vec{p}_A \cdot \vec{p}_{n1} + \vec{p}_A \cdot \vec{p}_{n2} + \vec{p}_{n1} \cdot \vec{p}_{n2}$$

Relative energy spectra



Three-body correlations



Formalism for simultaneous 4n emission presented in P. G. Sharov *et al.* JETP Letters 2019 Vol 110 No. 1

Left and right figures are from Z. Kohley *et al.*, PRC 87 011204(R) 2013 (2015)

Invariant mass spectroscopy with MoNA-LISA

$$E_{fnn} = \sqrt{{m_A}^2 + 2{m_n}^2 + 2\left({E_3}^2 - {\vec{p}_3}^{\,2}\right)} - m_A - 2m_n$$

$${E_3}^2 = E_A E_{n1} + E_A E_{n2} + E_{n1} E_{n2}$$

$${\vec{p}_3}^{\,2} = \vec{p}_A \cdot \vec{p}_{n1} + \vec{p}_A \cdot \vec{p}_{n2} + \vec{p}_{n1} \cdot \vec{p}_{n2}$$

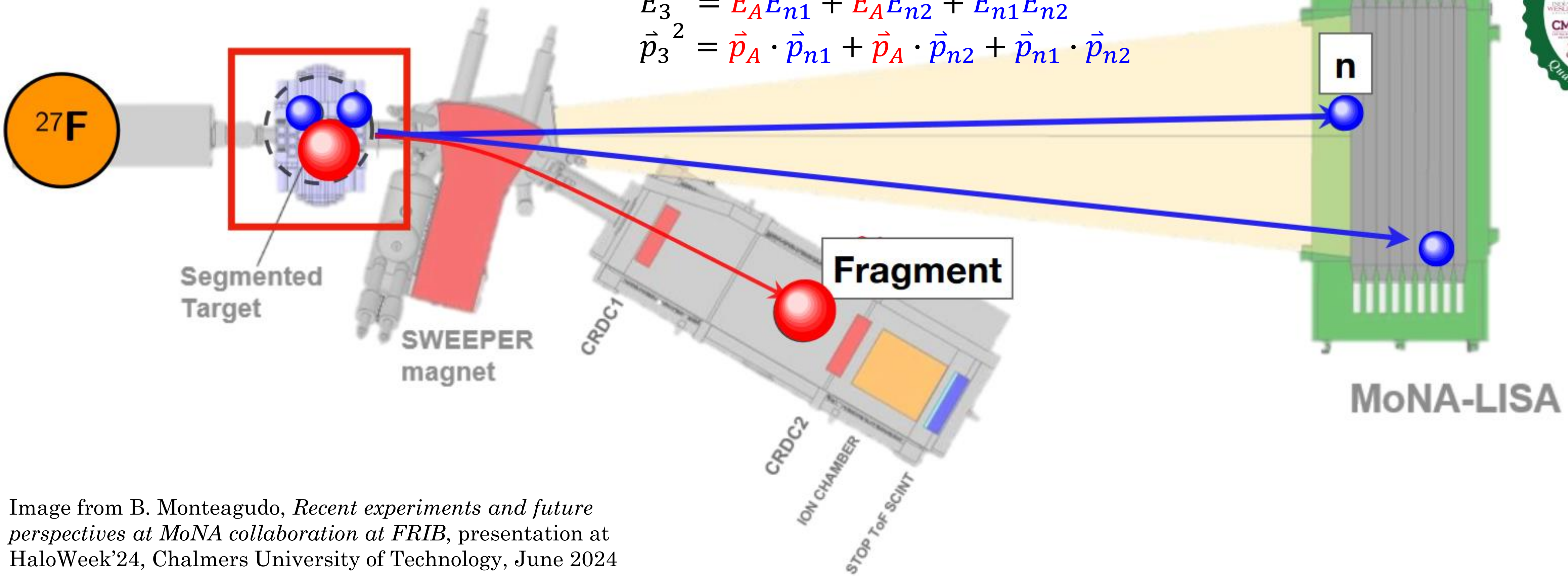
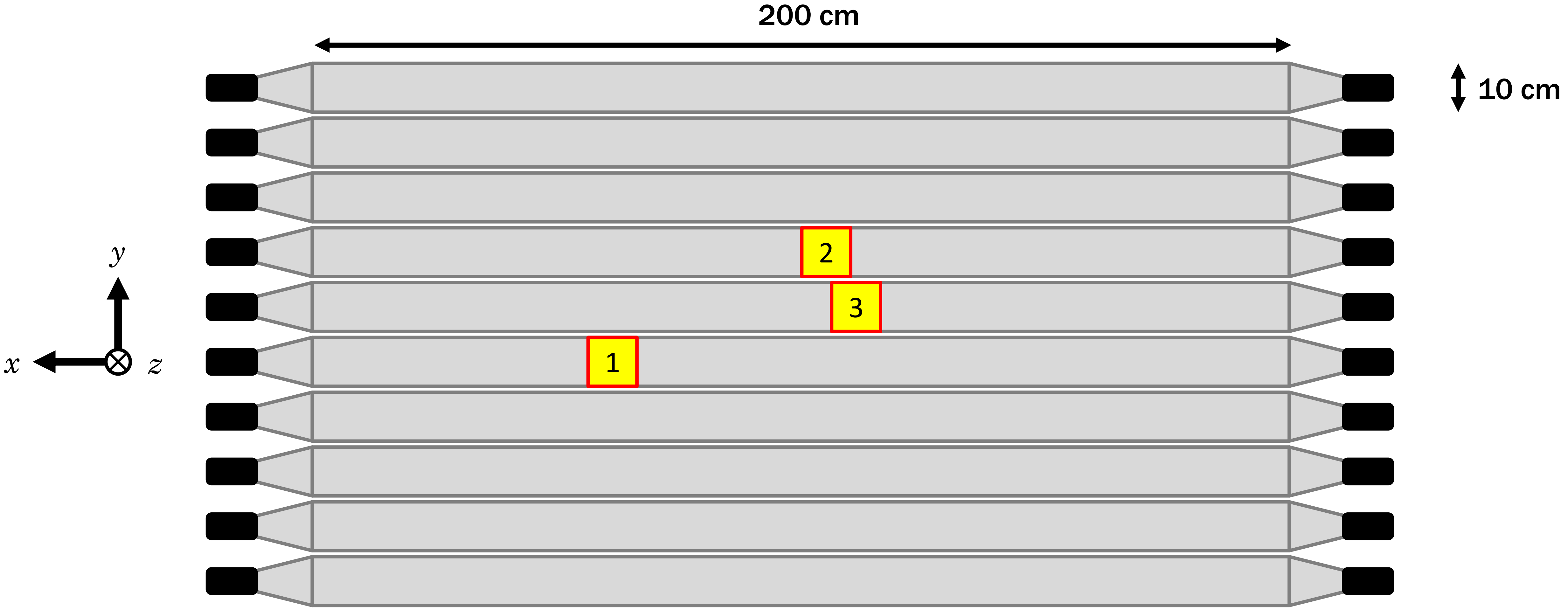


Image from B. Monteagudo, *Recent experiments and future perspectives at MoNA collaboration at FRIB*, presentation at HaloWeek'24, Chalmers University of Technology, June 2024

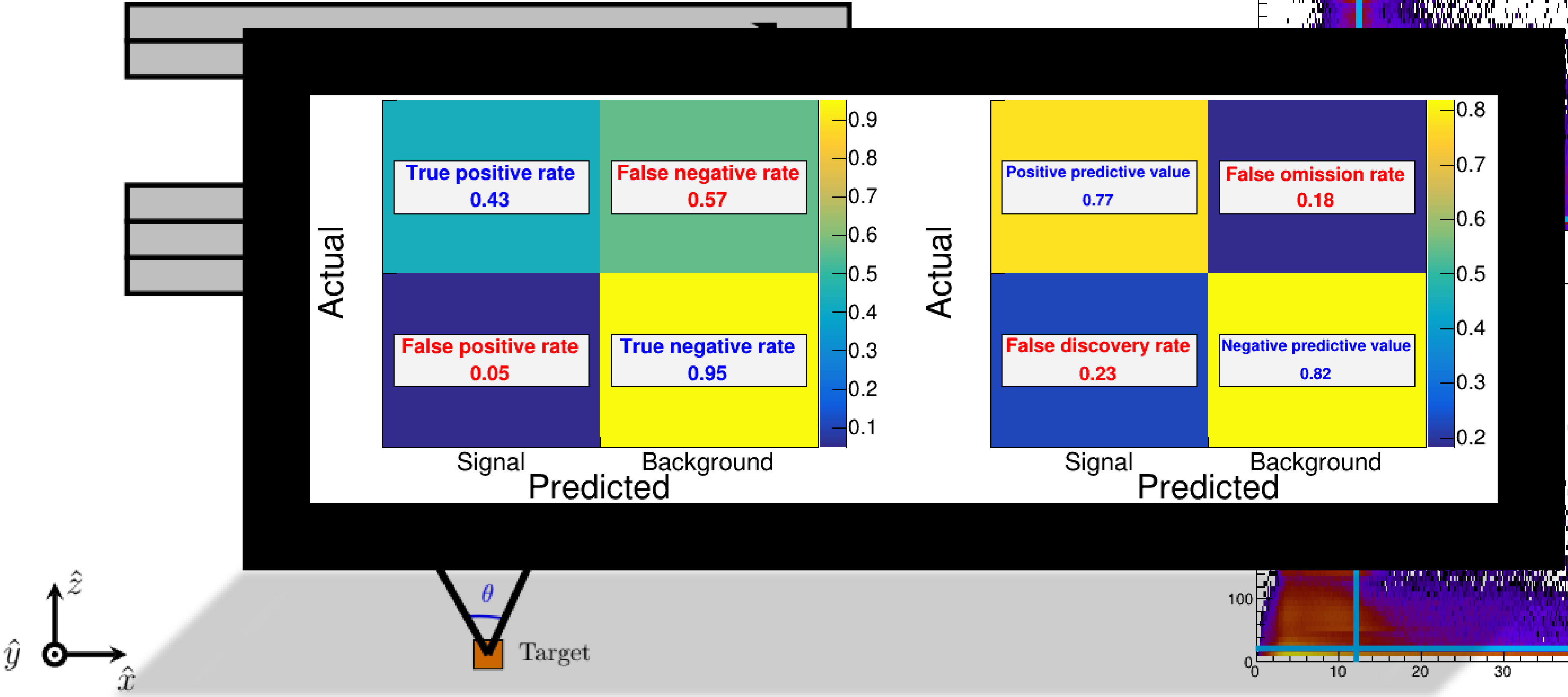
Multi-neutron detection

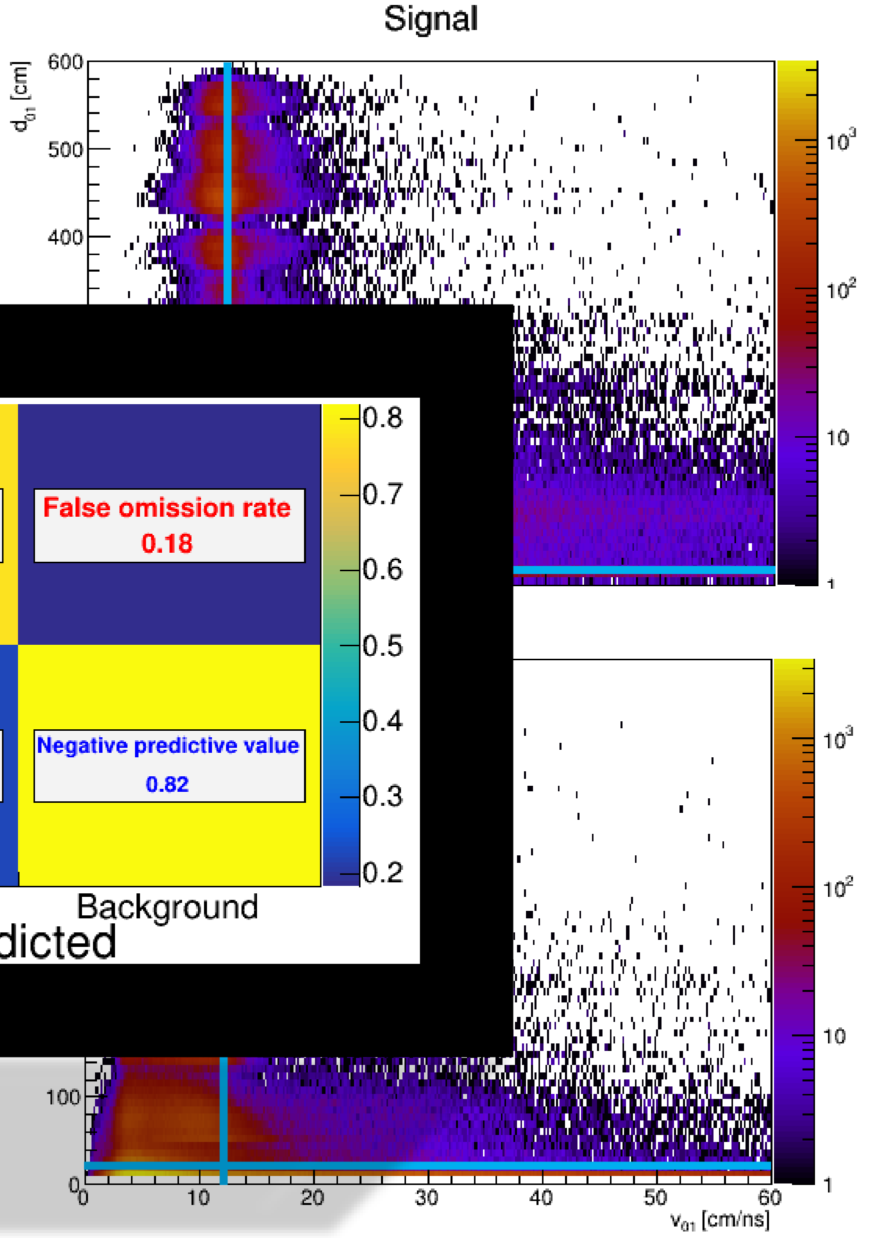
- Plastic scintillator bars
- Indirect, neutron detection via scattering
- Scintillation light detected in PMTs coupled via light guides
- (x,y,z), ToF, scintillation light recorded
- **Sparse** hits are time-sorted



Causal filters

Spatial and time separation examined for causal connections between hits





For additional causal filtering methods, see:

- Kondo *et al.* Nuclear Inst. And Methods in Physics Research B 463 (2020)
- Nakamura and Kondo, Nuclear Inst. And Methods in Physics Research B 376 (2016)

Leveraging machine learning methods

Nuclear Inst. and Methods in Physics Research, A 990 (2021) 164951

Contents lists available at ScienceDirect

Nuclear Inst. and Methods in Physics Research, A

journal homepage: www.elsevier.com/locate/nima

ELSEVIER

Development of a Deep Neural Network for the data analysis of the NeuLAND neutron detector

C.A. Douma [a,*], E. Hoemann [b], N. Kalantar-Nayestanaki [a,c,*], J. Mayer [b], for the R^{3}B Collaboration

[a] KVI-CART, University of Groningen, Groningen, The Netherlands
[b] Institut für Kernphysik, Universität zu Köln, Köln, Germany
[c] Present address: Nuclear Energy Group, ESRIG, University of Groningen, Groningen, Netherlands

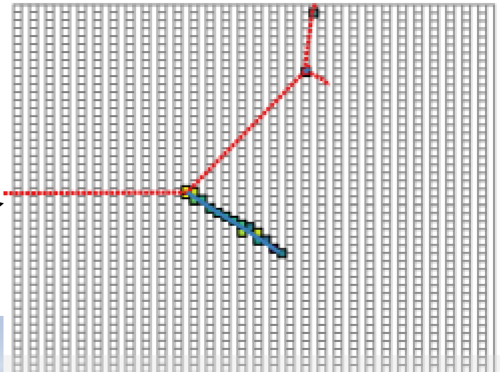
Nuclear Inst. and Methods in Physics Research, A 1013 (2021) 165666

Classical and machine learning methods for event reconstruction in NeuLAND

Jan Mayer [a,*], Konstanze Boretzky [b], Christiaan Douma [c], Elena Hoemann [a], Andreas Zilges [a], for the R^{3}B collaboration

[a] Institute for Nuclear Physics, University of Cologne, Germany
[b] GSI Helmholtzzentrum für Schwerionenforschung GmbH, Darmstadt, Germany
[c] KVI-CART, University of Groningen, Netherlands

- Applied to recover neutron multiplicity and first interaction points
- Tested a number of different ML techniques
- Found that ML methods resulted in marginal improvement for multiplicity extraction; better for determining first interaction points
- Designed for higher neutron energies (**200 – 1000 MeV**)



From Fig. 2

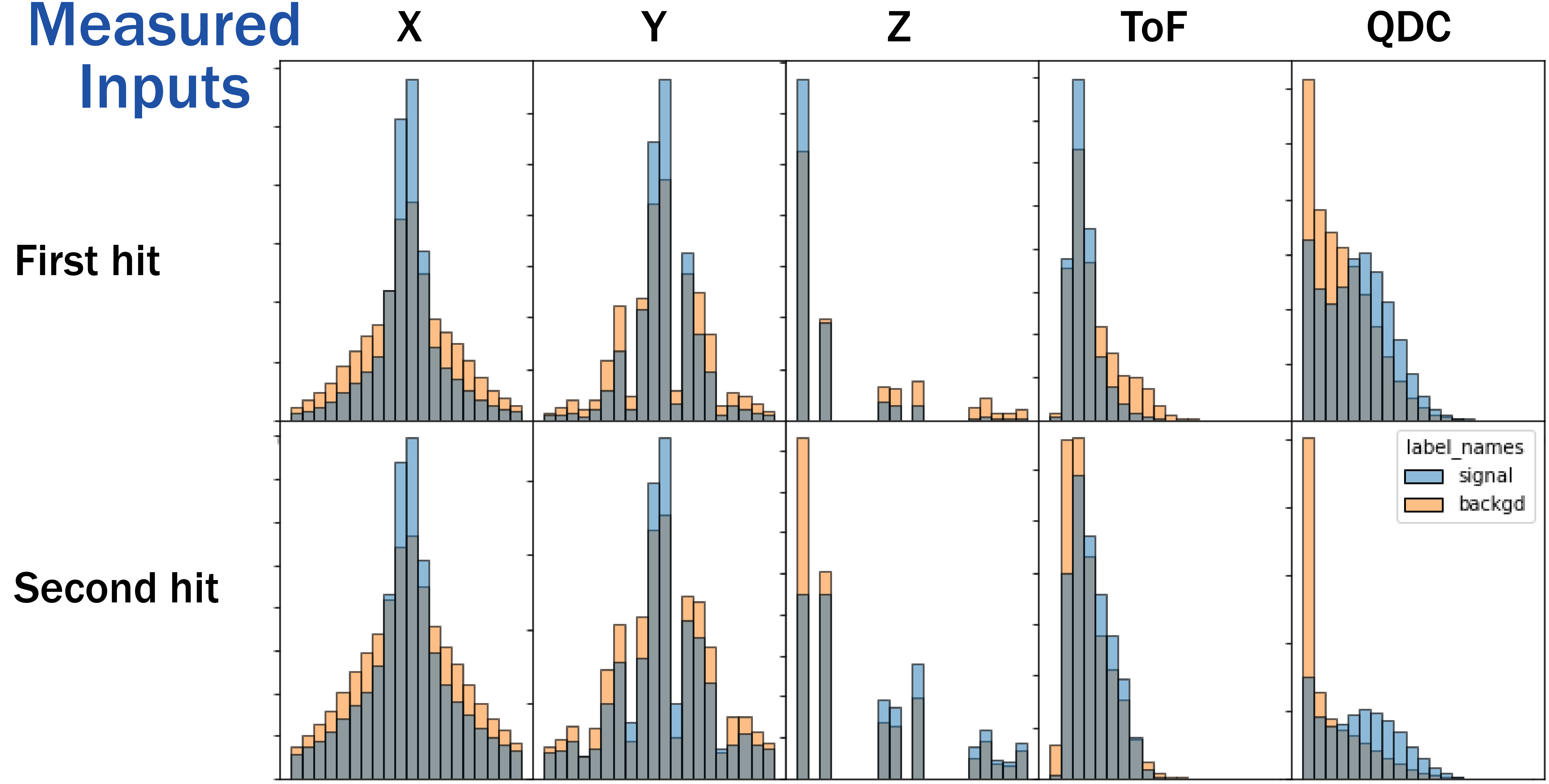
Leveraging machine learning methods

Project goals:

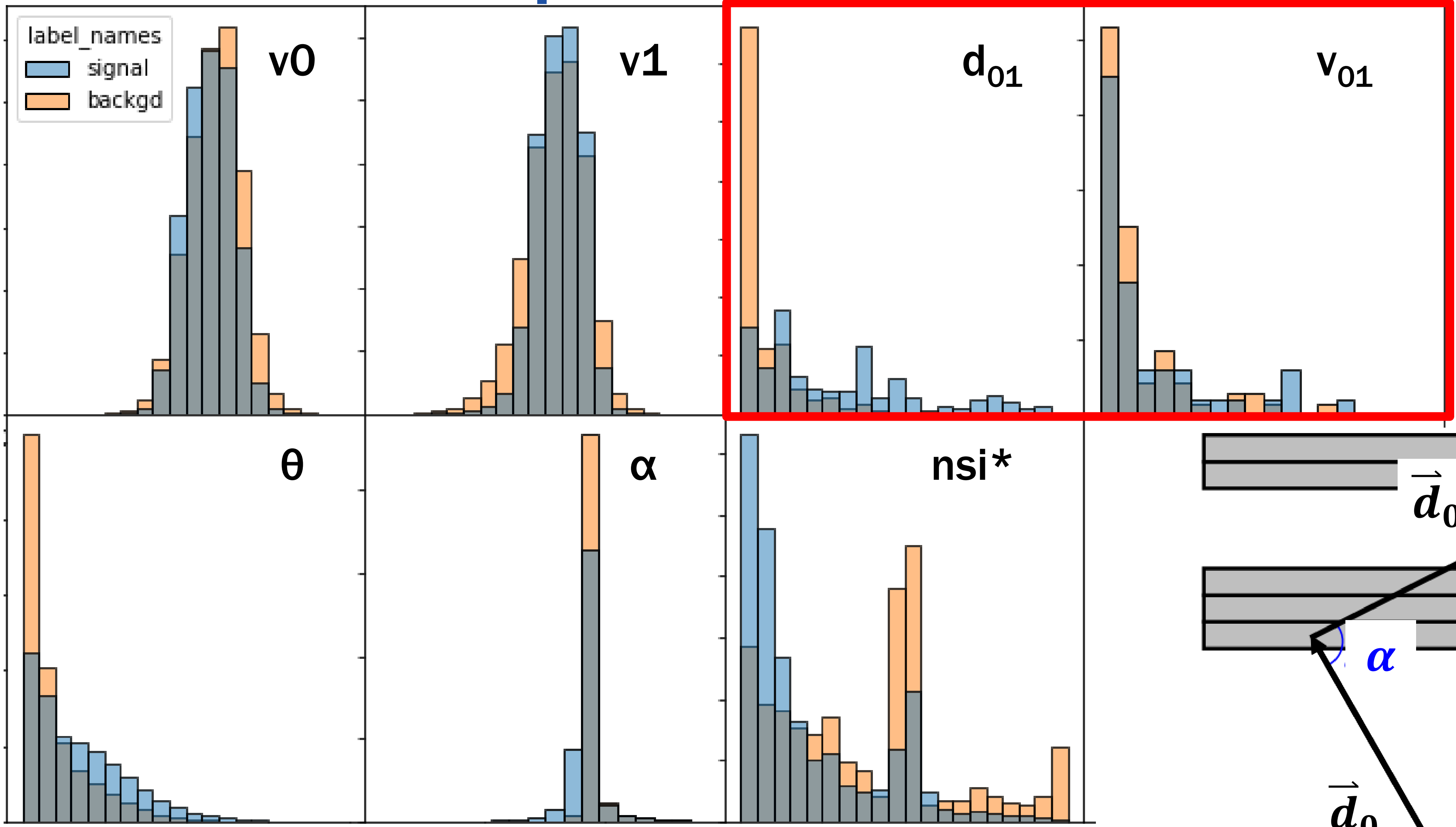
1. Investigate application of neural networks to event classification
   - Applicability across experiments
   - Extension to ‘multiplicity reduction’
2. Provide research training opportunities for VSU undergraduates

Neutron KEs range from 40 – 200 MeV

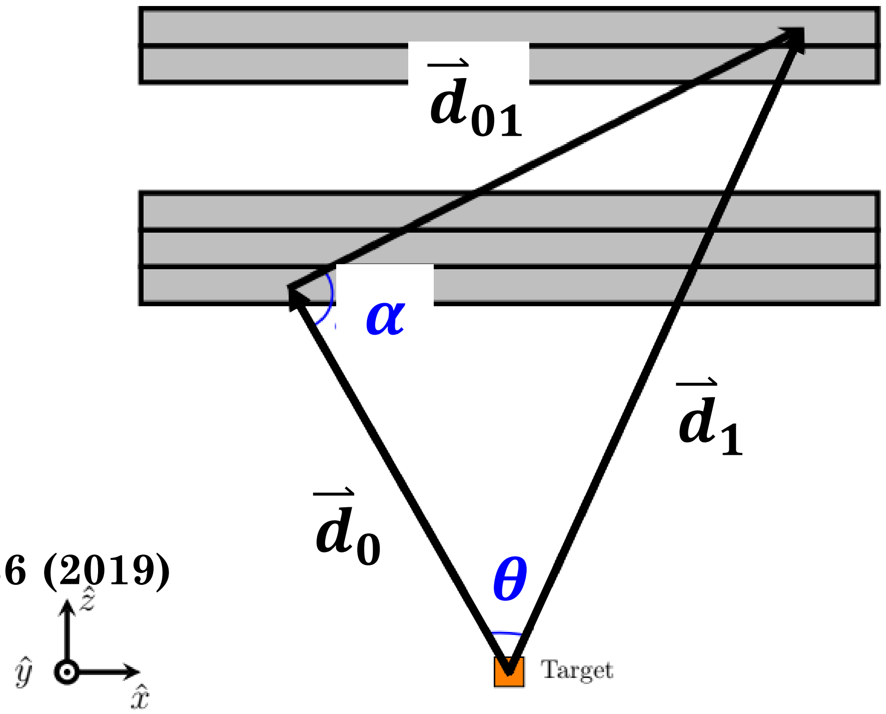
Measured Inputs



Calculated Inputs



Used in 'traditional' causality cuts



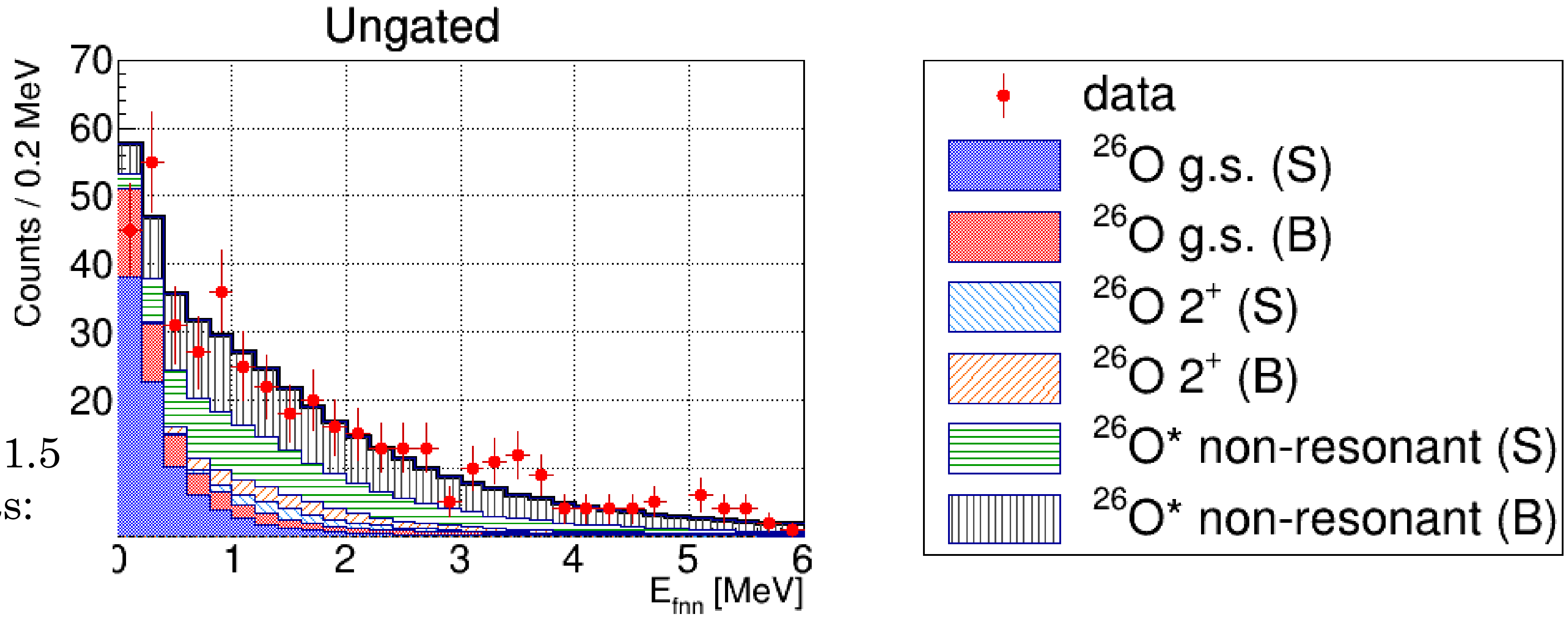
*see **W. Rogers *et al.*, NIM-A 943, 162436 (2019)**

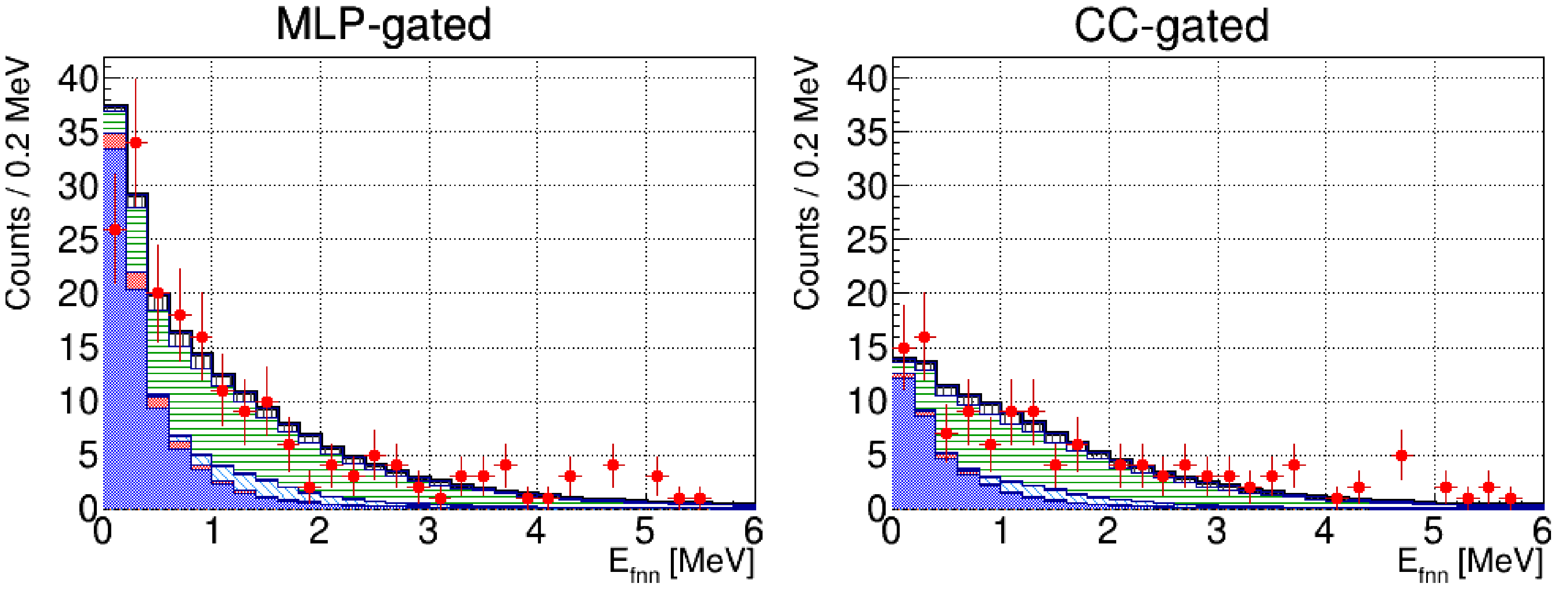
$$\text{nsi} = \left(v_{beam}^2 t_{01}^2 - d_{01}^2\right) = \left(v_{beam}^2 - v_{01}^2\right) t_{01}^2$$

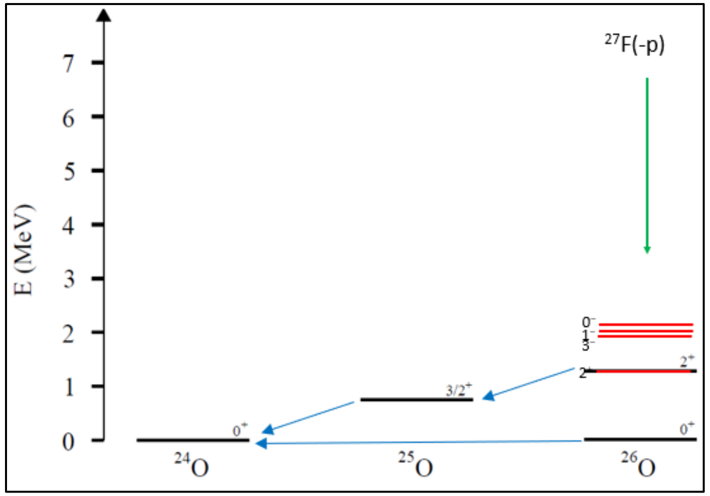
VIRGINIA STATE

Applied to data: ^{26}O

- (# CC-gated) / (# MLP-gated) = 1.5
- % difference in fitted weights:
  - G.S. (10%)
  - 2+ (10%)
  - Nonresonant (5%)



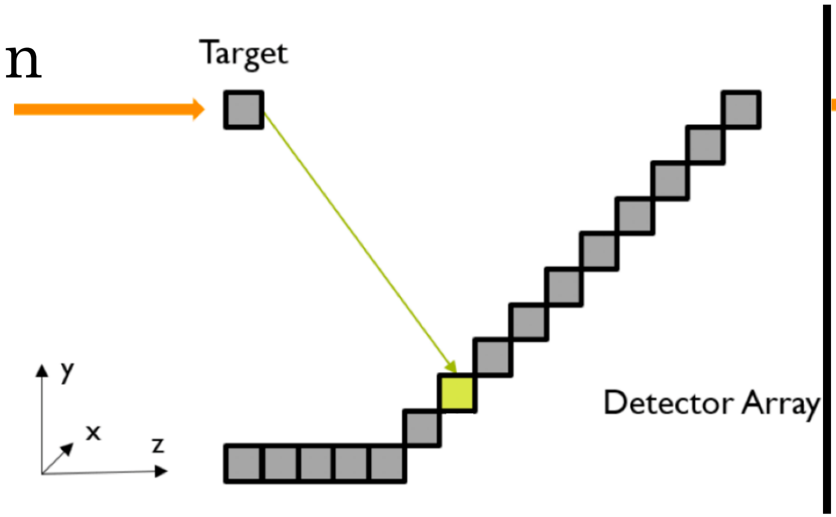


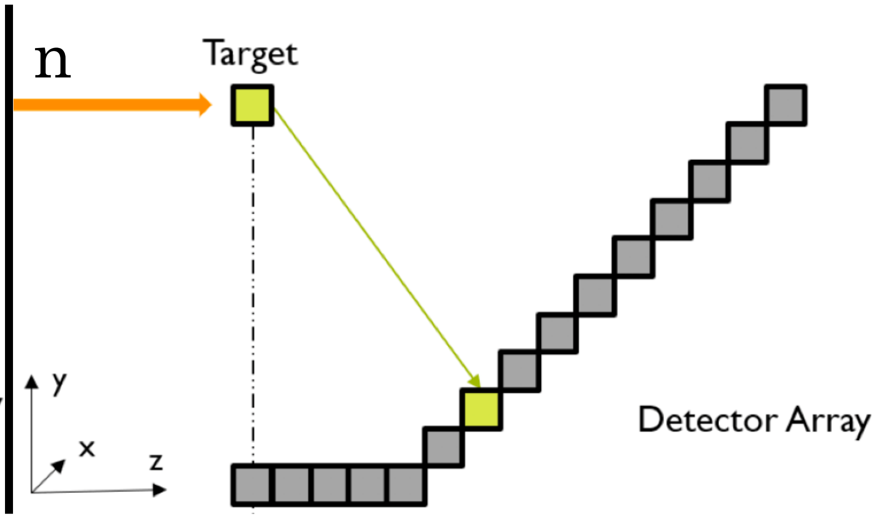


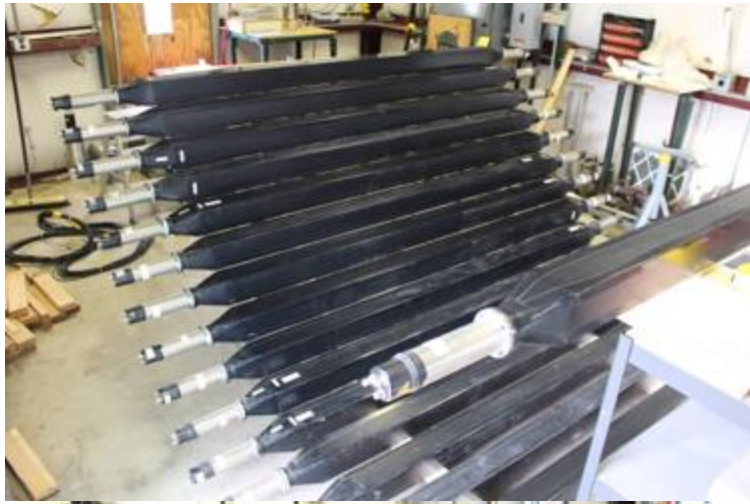
Testing with LANSCE data

PRELIMINARY

Incident neutron energy	Fraction of multiplicity 2 events predicted to be 1n scattering: > 5 MeVee	Fraction of multiplicity 2 events predicted to be 1n scattering: + gated on target bar
~20 MeV	83%	94%
~40 MeV	84%	98%
~60 MeV	86%	99%



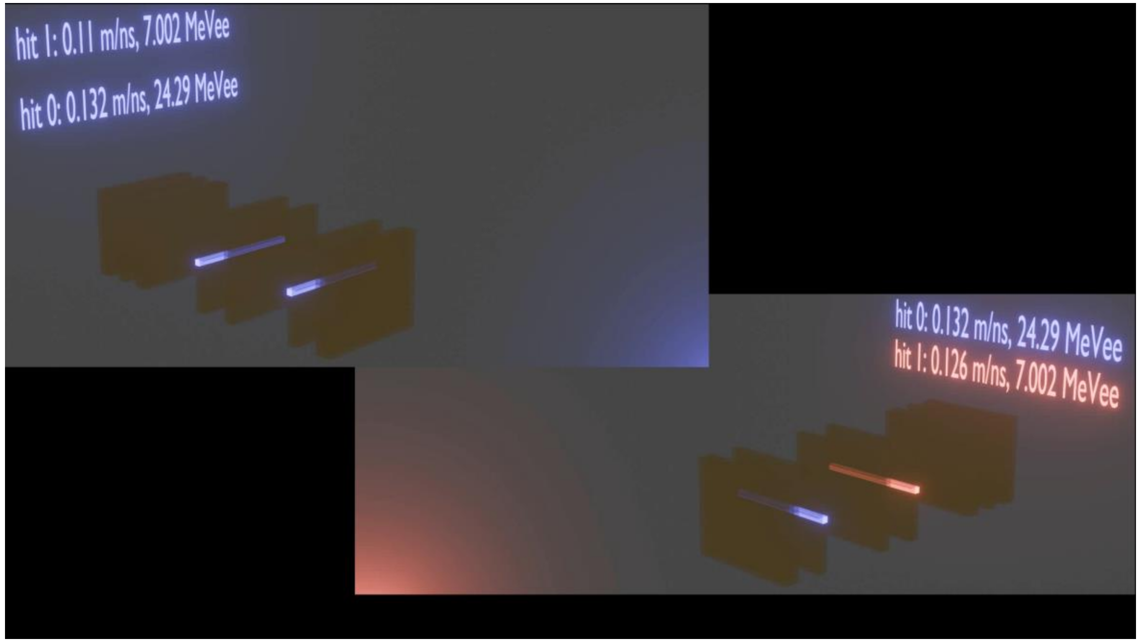




All images from A. Kuchera

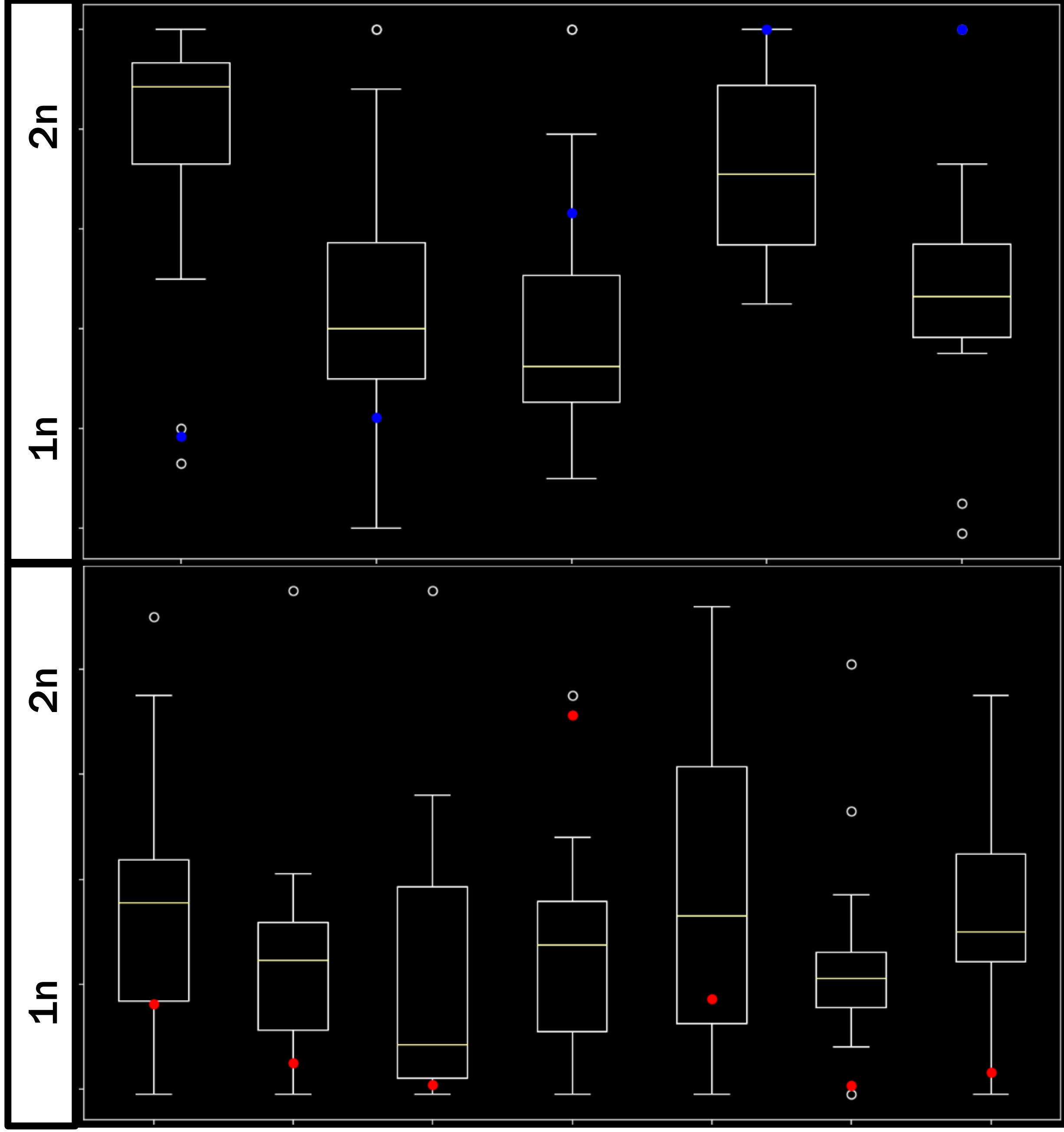
Survey for human-assigned event labels

- Provide assessment on a sliding scale 0 (1n) – 100 (2n)
- First survey deployed
  - 100 measured events
  - 12 simulated events (tracers)
  - 14 student responses so far
  - Analysis in progress
- Second survey in preparation
  - 200 measured events
  - 20 simulated events
  - Separate into 50-event chunks



Human- and machine-assigned labels

- Preliminary comparison for 'tracer events'
- Background is 'easier' to classify
  - More correct IDs
  - Better agreement



VIRGINIA STATE

Project deliverables

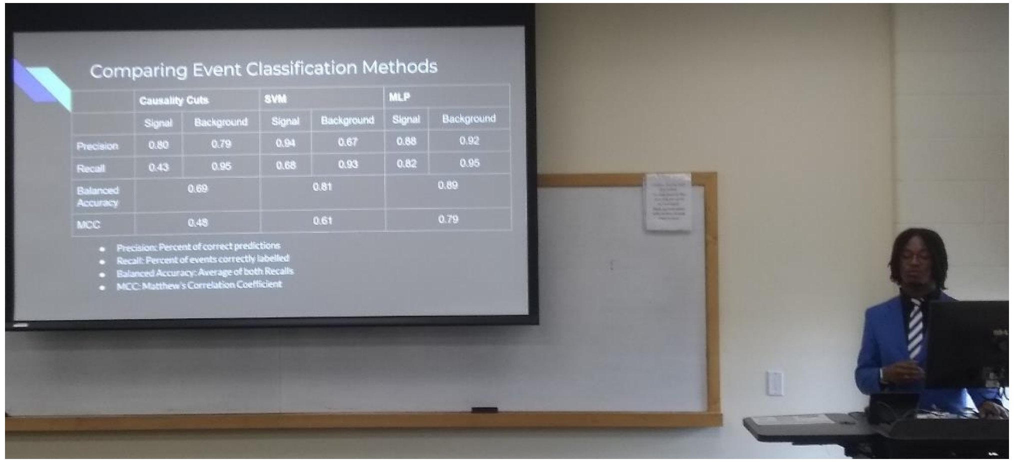
Deliverable	Projected	Status
ROOT + Python codes	May 2024	Completed
Blender animations of data events	June 2024	Completed
Survey for human-determined labels	March 2025	60% complete
Integration into analysis pipeline	August 2025	50% complete
Publication	August 2025	20% complete

Budget summary

	FY23 [k$]	FY 24 [k$]	Total [k$]
Funds allocated	256	224	480
Actual costs	160	45	205

VSU Undergraduate Researchers

- Alaura Cunningham, 2020 – 2021, DNP & NSBP 2020
- Avery Monroe, 2021, VSU Undergraduate Research Symposium 2021
- **Megan Brayton, 2021, MSU AGEP conference 2021**
- Darrius Sykes, 2021-2022, MSU AGEP conference 2021
- Kyra Rudolph, 2021 – 2022, NOBCChE regional 2022, VSU Undergraduate Research Symposium 2022
- Kayla Mills, 2021 – 2022, VSU Undergraduate Research Symposium 2022
- **Clifton Kpadehyea, 2022 – 2023, DNP 2022**
- Jeffrey Walters, 2021 – 2023, NOBCChE regional 2022, VSU Undergraduate Research Symposium 2023
- Emmanuella Kumi, 2022 – 2023, VSU Undergraduate Research Symposium 2023
- **Jaylen Rasberry, 2022 – present, DNP 2022, NOBCChE 2022, NURVa 2024**
- Isaiah Leonard, 2023 – present
- Trinity Allen, 2024 – present
- Jalen Felix, 2024 – present, MSU AGEP conference 2024
- Raven Mott, 2024 – present
- **Sarah Timothy, 2024 – present**
- **Justin Brown, 2024 – present**



Jaylen Rasberry presents at the Network for Undergraduate Research in Virginia Conference, 26 October 2024

Acknowledgements

- Anthony Kuchera, Davidson College
- Warren Rogers, Indiana Wesleyan University
- The MoNA Collaboration
- This material is based upon work supported by the U.S. Department of Energy, Office of Science, Office of Nuclear Physics, under Award Numbers DE-SC0022037 and DE-0024697.

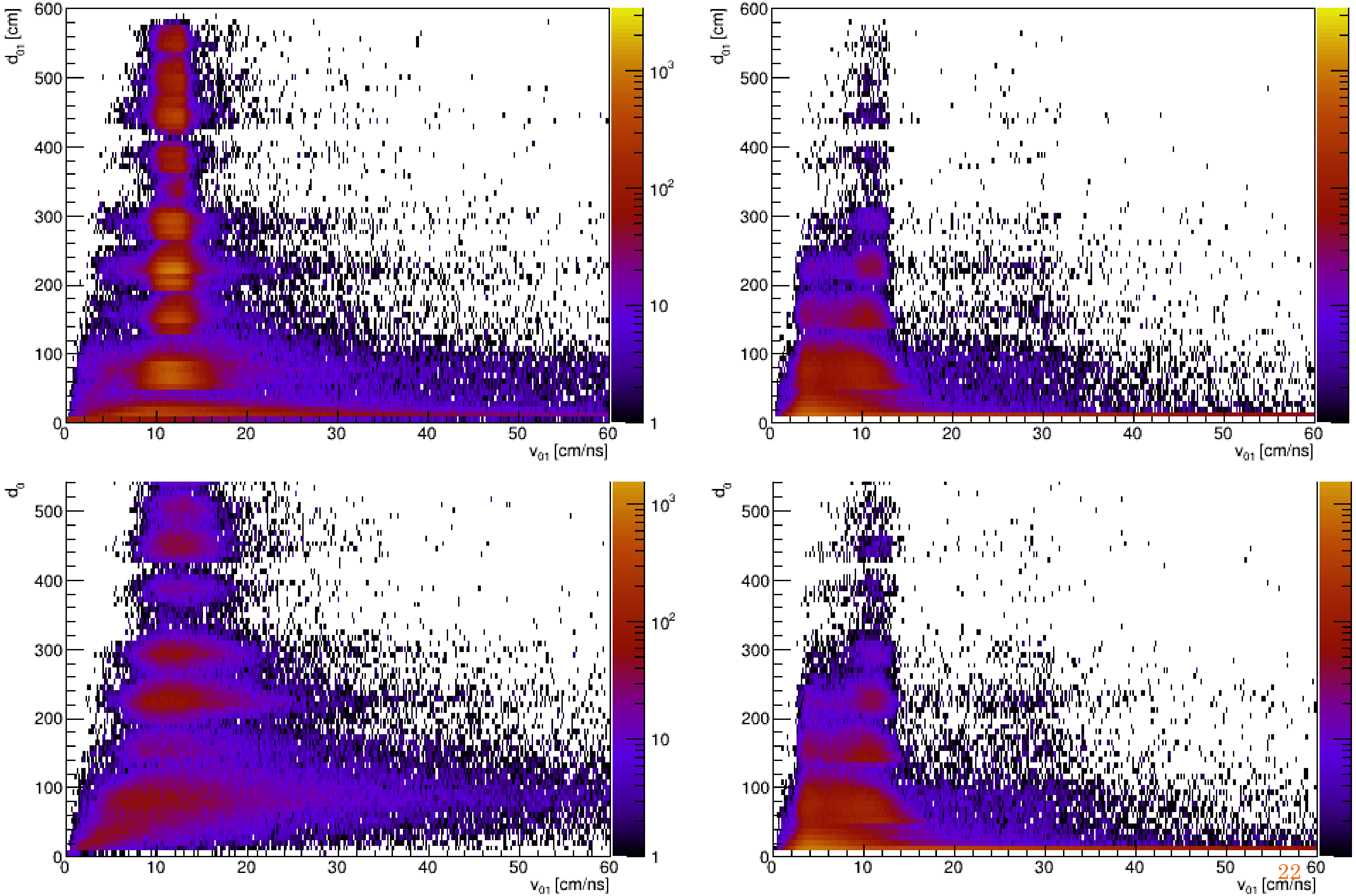
Additional slides

Signal

Background

Low decay energy

High decay energy



Confusion Matrix

Sources: [12][13] [14][15][16][17][18][19] view · talk · edit

		Predicted condition			
	Total population $= \mathrm{P} + \mathrm{N}$	**Predicted Positive (PP)**	**Predicted Negative (PN)**	Informedness, bookmaker informedness (BM) $= \mathrm{TPR} + \mathrm{TNR} - 1$	Prevalence threshold (PT) $= \frac{\sqrt{\mathrm{TPR} \times \mathrm{FPR}} - \mathrm{FPR}}{\mathrm{TPR} - \mathrm{FPR}}$
Actual condition	**Positive (P)** [a]	**True positive** (TP), hit[b]	**False negative** (FN), miss, underestimation	True positive rate (TPR), recall, sensitivity (SEN), probability of detection, hit rate, power $= \frac{\mathrm{TP}}{\mathrm{P}} = 1 - \mathrm{FNR}$	False negative rate (FNR), miss rate type II error [c] $= \frac{\mathrm{FN}}{\mathrm{P}} = 1 - \mathrm{TPR}$
	Negative (N)[d]	**False positive** (FP), false alarm, overestimation	**True negative** (TN), correct rejection[e]	False positive rate (FPR), probability of false alarm, fall-out type I error [f] $= \frac{\mathrm{FP}}{\mathrm{N}} = 1 - \mathrm{TNR}$	True negative rate (TNR), specificity (SPC), selectivity $= \frac{\mathrm{TN}}{\mathrm{N}} = 1 - \mathrm{FPR}$
	Prevalence $= \frac{\mathrm{P}}{\mathrm{P} + \mathrm{N}}$	Positive predictive value (PPV), precision $= \frac{\mathrm{TP}}{\mathrm{PP}} = 1 - \mathrm{FDR}$	False omission rate (FOR) $= \frac{\mathrm{FN}}{\mathrm{PN}} = 1 - \mathrm{NPV}$	Positive likelihood ratio (LR+) $= \frac{\mathrm{TPR}}{\mathrm{FPR}}$	Negative likelihood ratio (LR−) $= \frac{\mathrm{FNR}}{\mathrm{TNR}}$
	Accuracy (ACC) $= \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{P} + \mathrm{N}}$	False discovery rate (FDR) $= \frac{\mathrm{FP}}{\mathrm{PP}} = 1 - \mathrm{PPV}$	Negative predictive value (NPV) $= \frac{\mathrm{TN}}{\mathrm{PN}} = 1 - \mathrm{FOR}$	Markedness (MK), deltaP (Δp) $= \mathrm{PPV} + \mathrm{NPV} - 1$	Diagnostic odds ratio (DOR) $= \frac{\mathrm{LR+}}{\mathrm{LR-}}$
	Balanced accuracy (BA) $= \frac{\mathrm{TPR} + \mathrm{TNR}}{2}$	F_1 score $= \frac{2\,\mathrm{PPV} \times \mathrm{TPR}}{\mathrm{PPV} + \mathrm{TPR}} = \frac{2\,\mathrm{TP}}{2\,\mathrm{TP} + \mathrm{FP} + \mathrm{FN}}$	Fowlkes–Mallows index (FM) $= \sqrt{\mathrm{PPV} \times \mathrm{TPR}}$	Matthews correlation coefficient (MCC) $= \sqrt{\mathrm{TPR} \times \mathrm{TNR} \times \mathrm{PPV} \times \mathrm{NPV}} - \sqrt{\mathrm{FNR} \times \mathrm{FPR} \times \mathrm{FOR} \times \mathrm{FDR}}$	Threat score (TS), critical success index (CSI), Jaccard index $= \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN} + \mathrm{FP}}$