The potential for

CROSS-DETECTOR FOUNDATION MODELS IN NUCLEAR PHYSICS

A CASE STUDY USING TPCS

Michelle P. Kuchera
Davidson College, Davidson, NC

IBS CONFERENCE ON EXOTIC NUCLEI
DAEJEON, SOUTH KOREA
JULY 24, 2026

ALPhA DAVIDSON COLLEGE

FRIB

NSCL

The potential for

CROSS-DETECTOR FOUNDATION MODELS IN NUCLEAR PHYSICS

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OUTLINE

- MOTIVATION
- CROSS-EXPERIMENT
- CROSS-DETECTOR
- TAKEAWAYS

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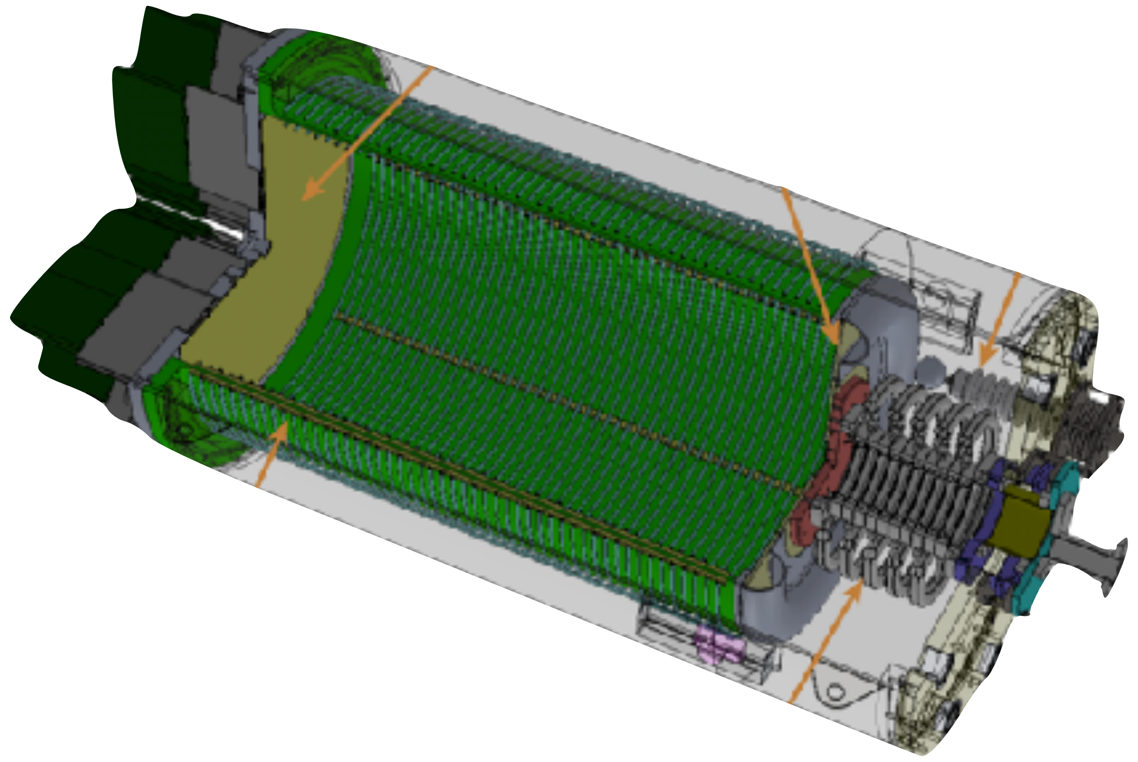
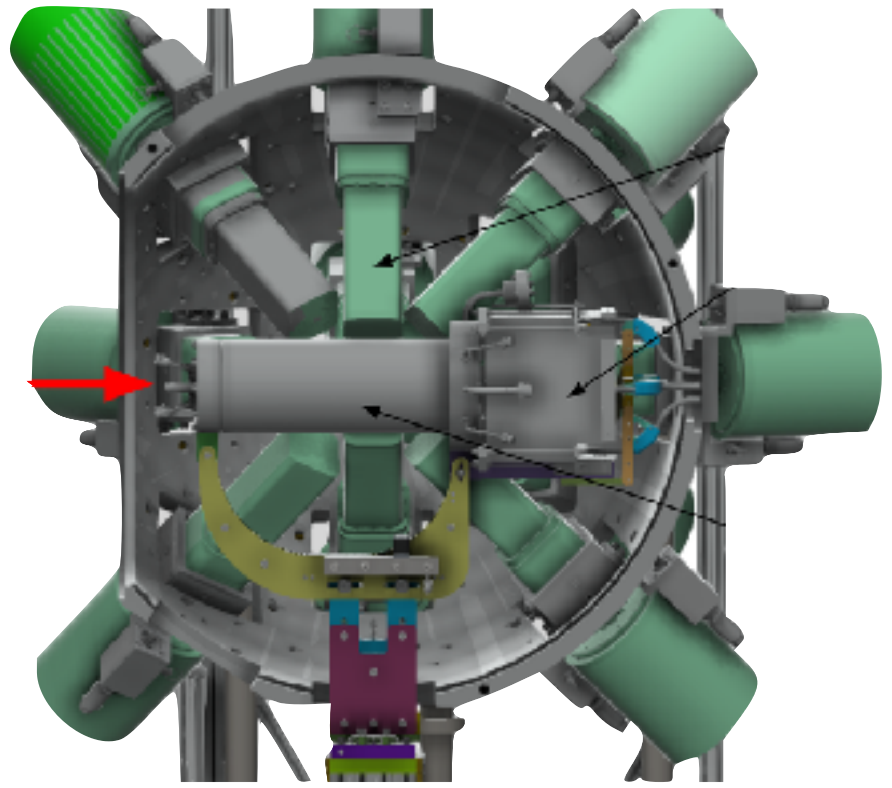
JULY 24, 2026

TIME PROJECTION CHAMBERS IN NUCLEAR PHYSICS





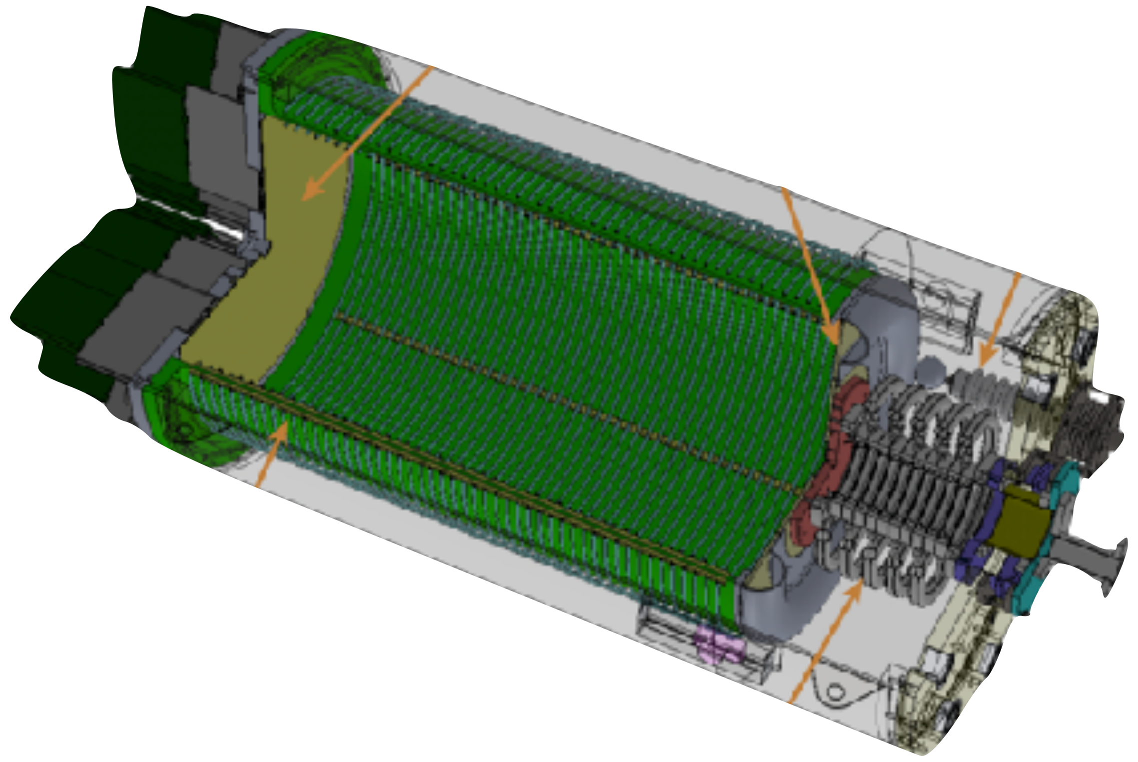
Active-Target Time Projection Chamber

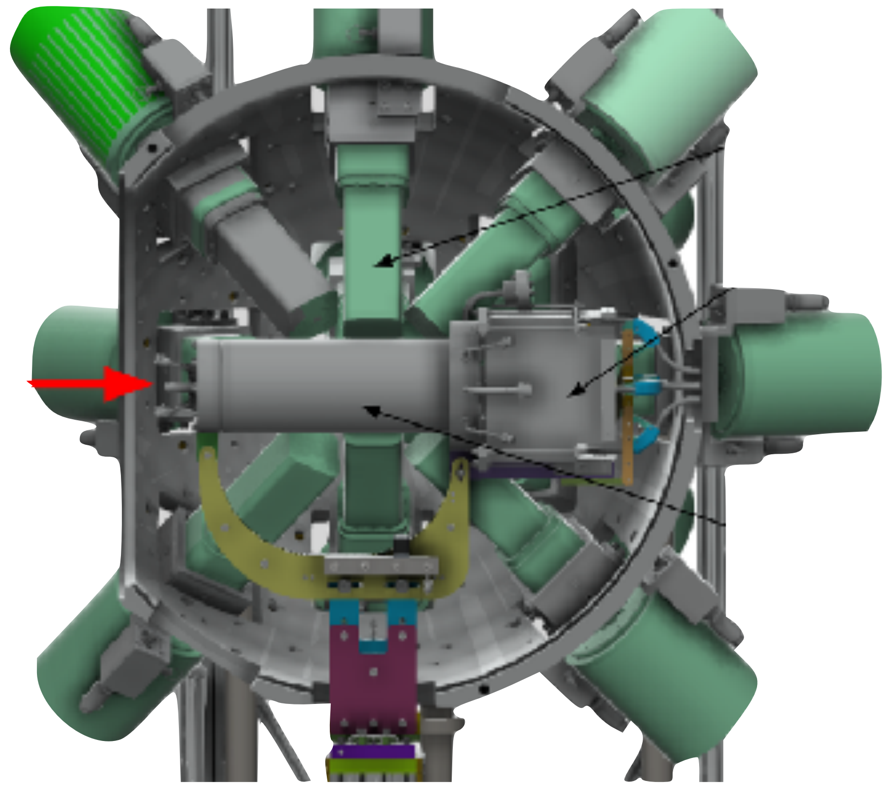
> 10k pads

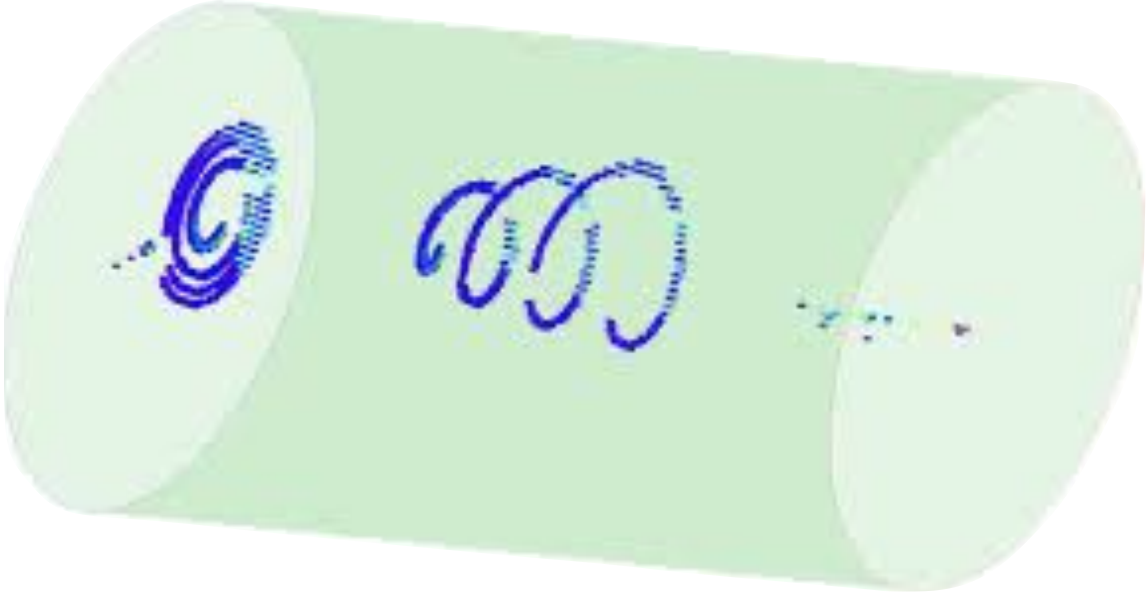
GADGET II

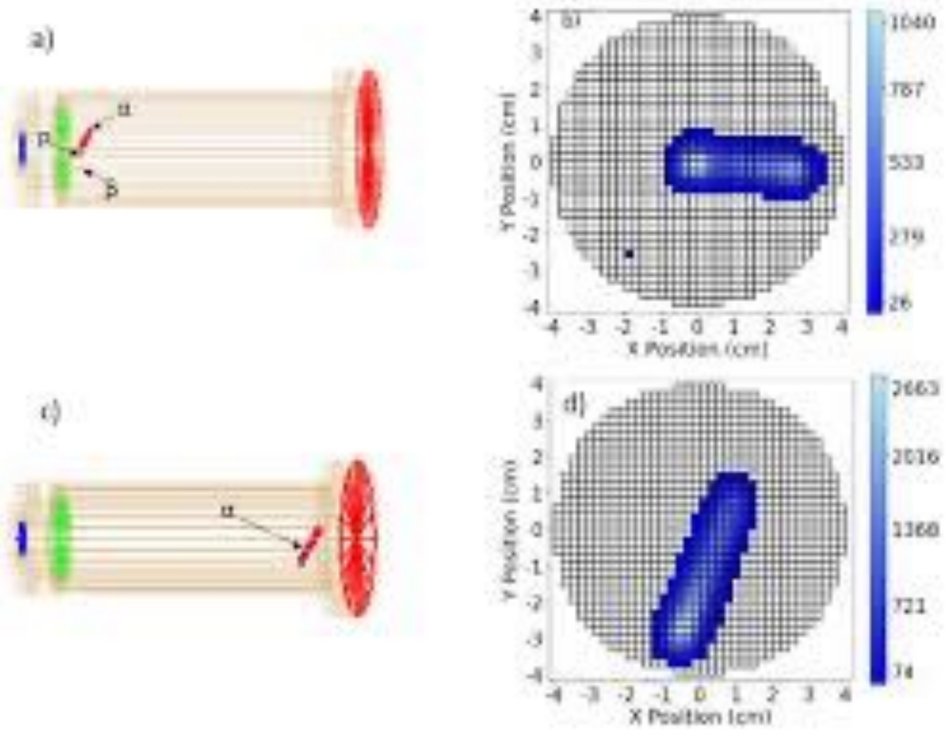
> 1k pads

TIME PROJECTION CHAMBERS IN NUCLEAR PHYSICS









MOTIVATION

MACHINE LEARNING FOR TPCS

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment
Volume 1072, March 2025, 170002

Full Length Article

Point-cloud based machine learning for classifying rare events in the Active-Target Time Projection Chamber

Poulomi Dey [a b], Adam K. Anthony [a c d], Curtis Hunt [a], Michelle P. Kuchera [e f], Raghuram Ramanujan [f], William G. Lynch [a c], ManYee Betty Tsang [a c], Joseph M. Wieske [a c], Jessica W. Ajongbah [a b], Saul Beceiro-Novo [a], Kyle W. Brown [a h], Zbigniew Chajecki [g], Kaitlin J. Cook [a h], Skyler Gangestad [d], Tom Ginter [a], Bergen Kendziorski [a], Fanurs Chi Eh Teh [a], HoTing Wong [i g]

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment
Volume 1010, 11 September 2021, 165461

Unsupervised learning for identifying events in active target experiments

R. Solli [a b], D. Bazin [c], M. Hjorth-Jensen [c d], M.P. Kuchera [e], R.R. Strauss [f g]

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment
Volume 940, 1 October 2019, Pages 156-167

Machine learning methods for track classification in the AT-TPC

M.P. Kuchera [a], R. Ramanujan [b], J.Z. Taylor [a], R.R. Strauss [b], D. Bazin [c], J. Bradt [c], Ruiming Chen [a]

Unpaired Translation of Point Clouds for Modeling Detector Response

Mingyang Li[1] Michelle Kuchera[1] Raghuram Ramanujan[1]
Adam Anthony[2] Curtis Hunt[3] Yassid Ayyad[4]
[1] Davidson College [2] High Point University
[3] Michigan State University [4] University of Santiago de Compostela
{mili, mikuchera, raramanujan}@davidson.edu
{aanthon2}@highpoint.edu
{huntc}@frib.msu.edu
{yassid.ayyad}@usc.es

Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment
Volume 1080, November 2025, 170659

Full Length Article

Object detection with deep learning for rare event search in the GADGET II TPC

Tyler Wheeler [a b c], S. Ravishankar [c d], C. Wrede [b a], A. Andalib [b a], A. Anthony [b a s], Y. Ayyad [a e], B. Jain [b a], A. Jaros [b a], R. Mahajan [a], L. Schaedig [b a], A. Adams [b a], S. Ahn [f], J.M. Allmond [m], D. Bardayan [g], D. Bazin [a], K. Bosmpotinis [b a], T. Budner [h], S.R. Carmichael [g], S.M. Cha [f], A. Chen [i]...L.E. Weghorn [b a]

FOUNDATION MODELS

Approach: Build a general-purpose deep learning model for nuclear physics time projection chamber data

Evaluate: Can we quickly tune a model for tasks (classification, regression, generation) with small amounts of labeled data?

FOUNDATION MODELS

foundation model

Approach: Build a ~~general-purpose deep learning model~~ for nuclear physics time projection chamber data

Evaluate: Can we quickly tune a model for tasks (classification, regression, generation) with small amounts of labeled data?

FOUNDATION MODELS

foundation model

What: A model trained on large amounts of diverse data that can be adapted for many different "downstream" tasks

How:

1. **Build a backbone model using a large, diverse dataset on a pretext task: pretraining task**
2. **Tune the model for a variety of desired tasks: downstream tasks**

FOUNDATION MODELS

foundation model

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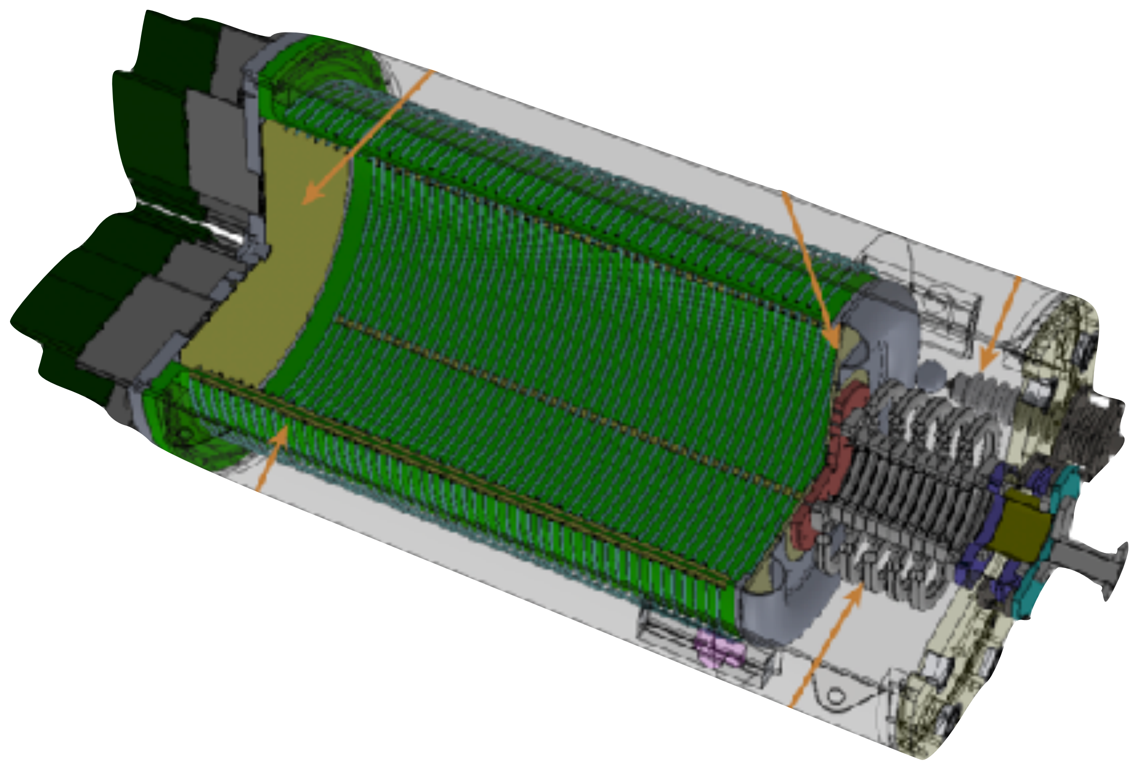
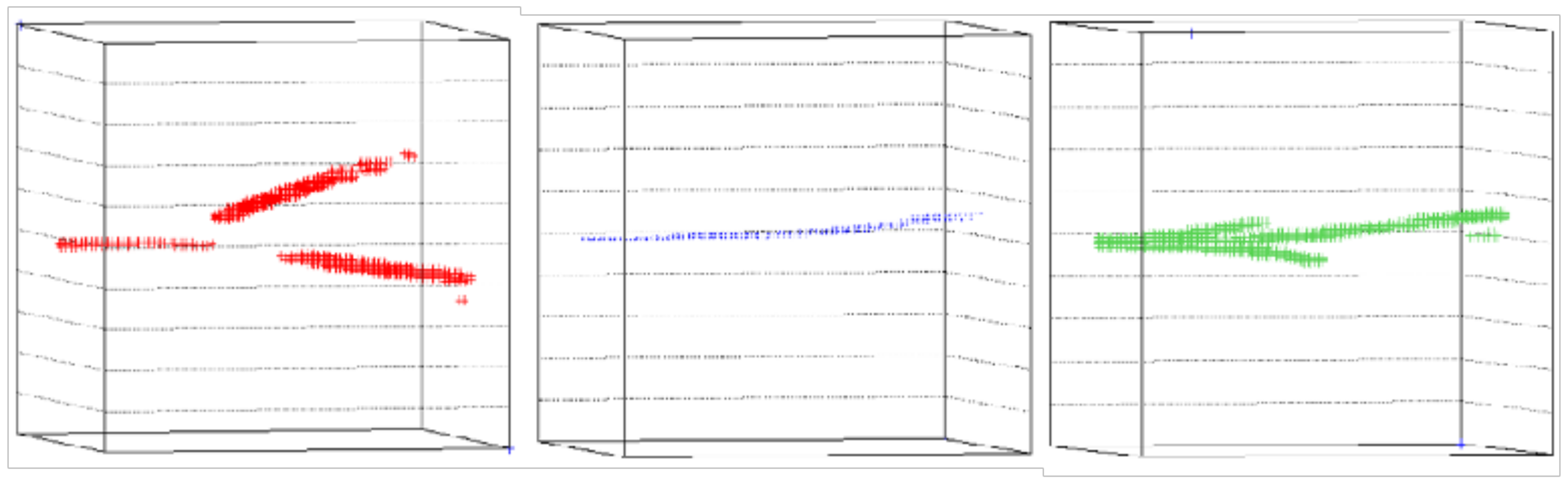
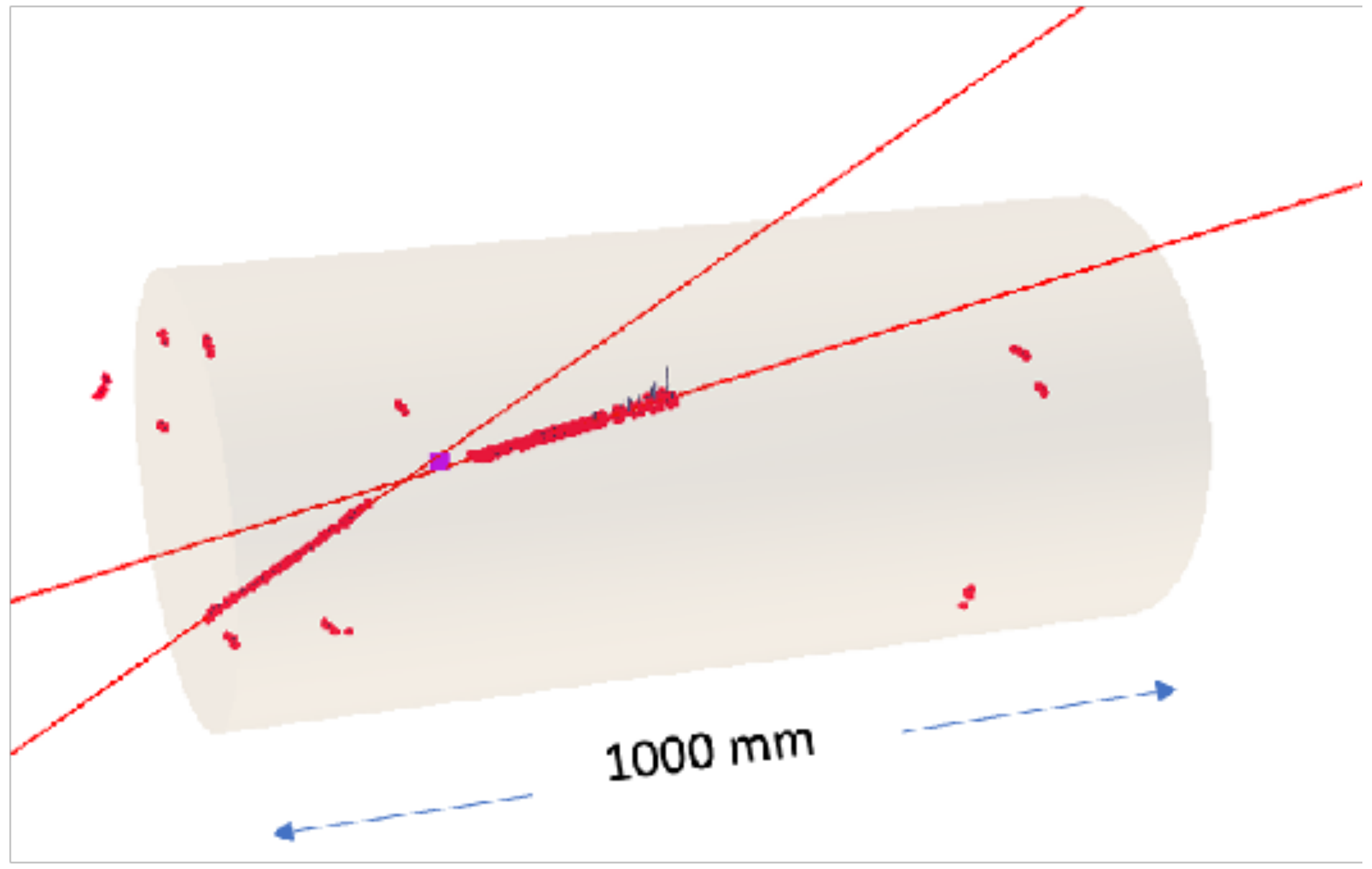
Can foundation models help with analyzing upcoming experiments?

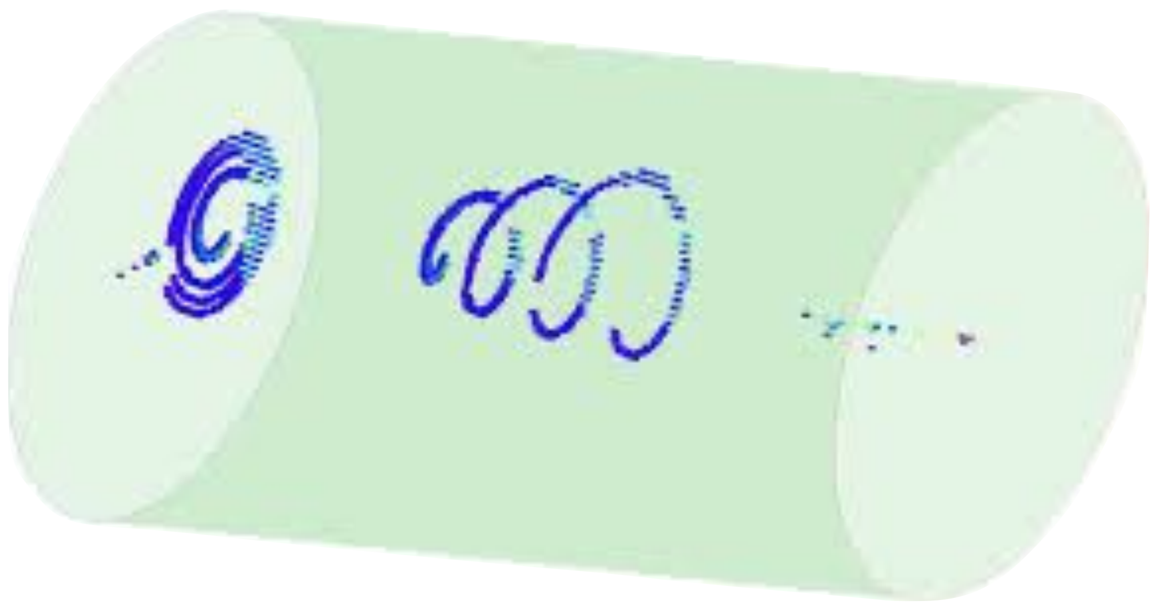
CROSS-EXPERIMENT

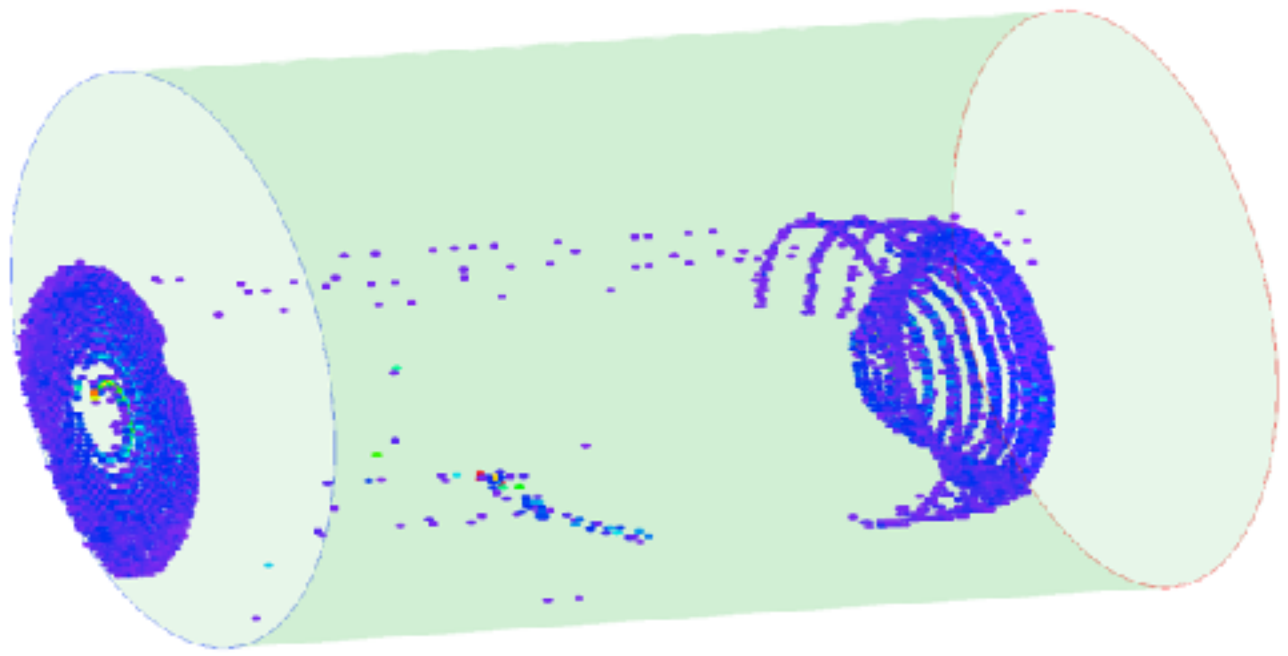
CASE STUDY: THE ACTIVE TARGET TIME PROJECTION CHAMBER (AT-TPC)

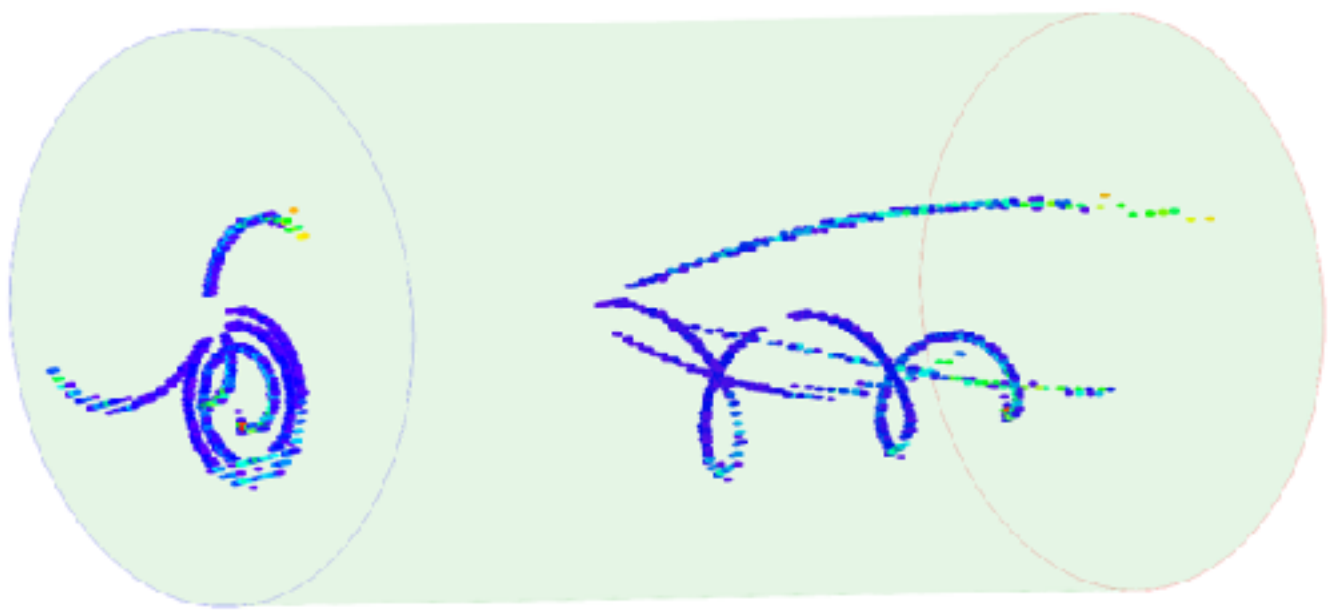










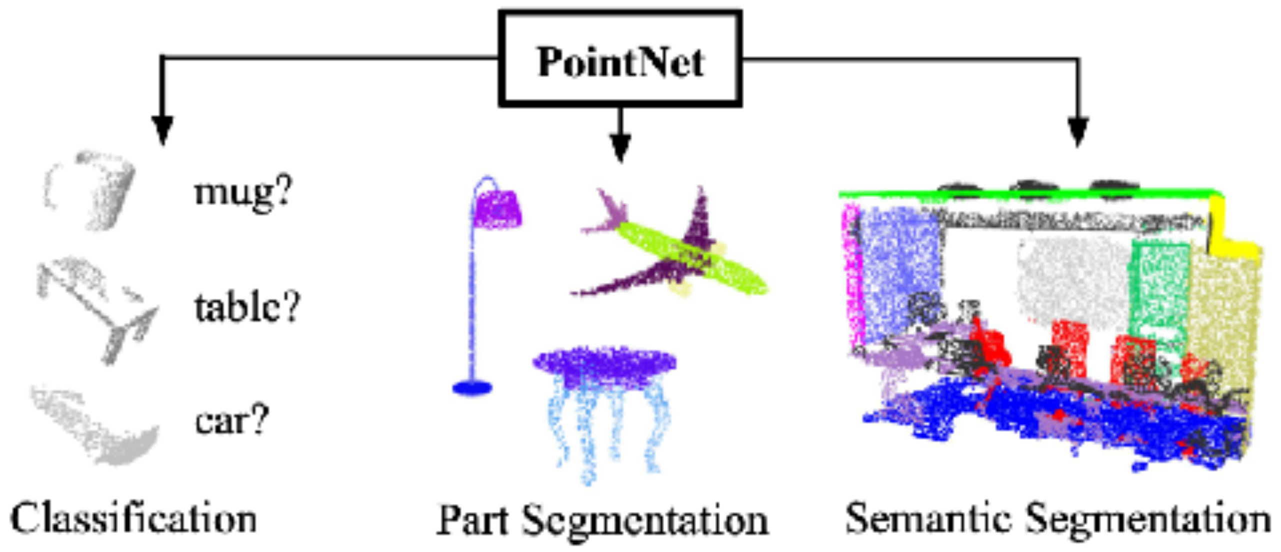


CROSS-EXPERIMENT

CASE STUDY: THE ACTIVE TARGET TIME PROJECTION CHAMBER (AT-TPC)

PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation

Charles R. Qi* Hao Su* Kaichun Mo Leonidas J. Guibas
Stanford University



Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment
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Point-cloud based machine learning for classifying rare events in the Active-Target Time Projection Chamber

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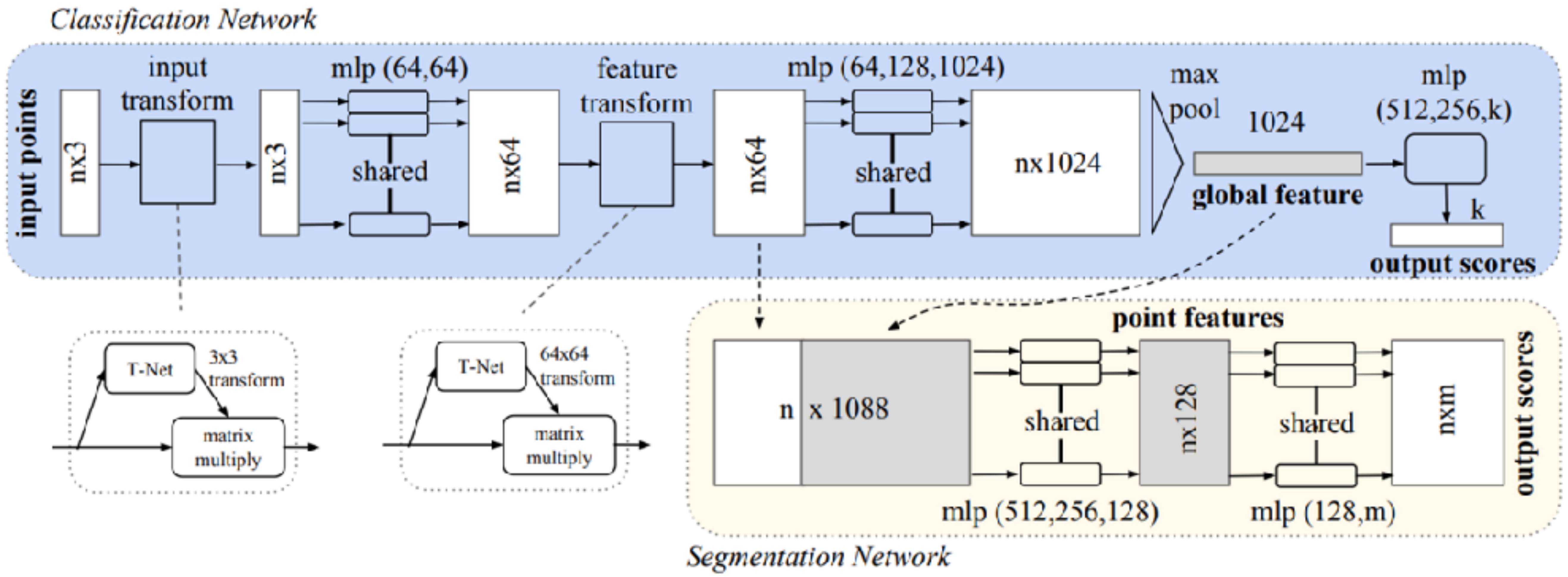


Also: $^{16}O + \alpha$ paper in preparation by MSU grad student Pranjal Singh

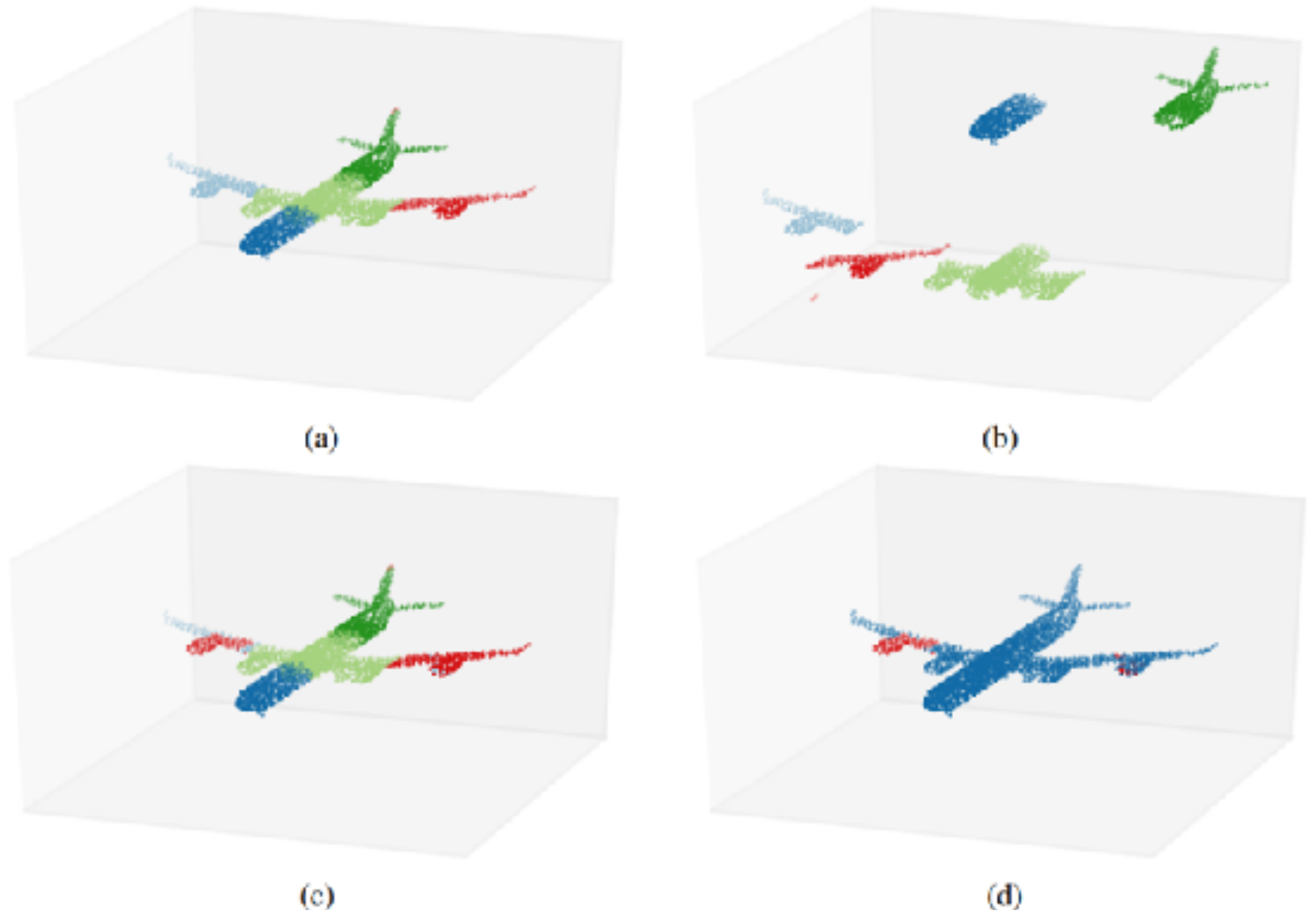
ALPhA

CROSS-EXPERIMENT

PRETRAINING: SHUFFLING TASK

1. Build a backbone model using a large, diverse dataset on a pretext task: pre-training task

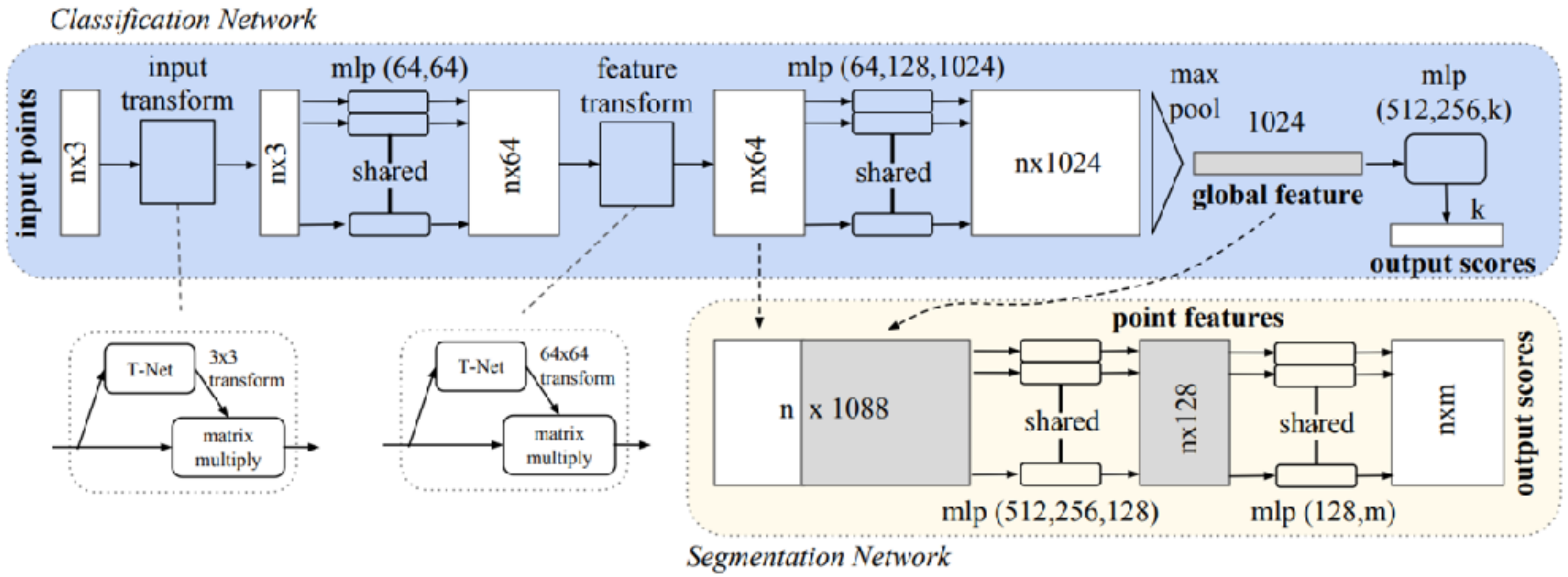
2. Fine-tune the model for a variety of desired tasks: downstream tasks

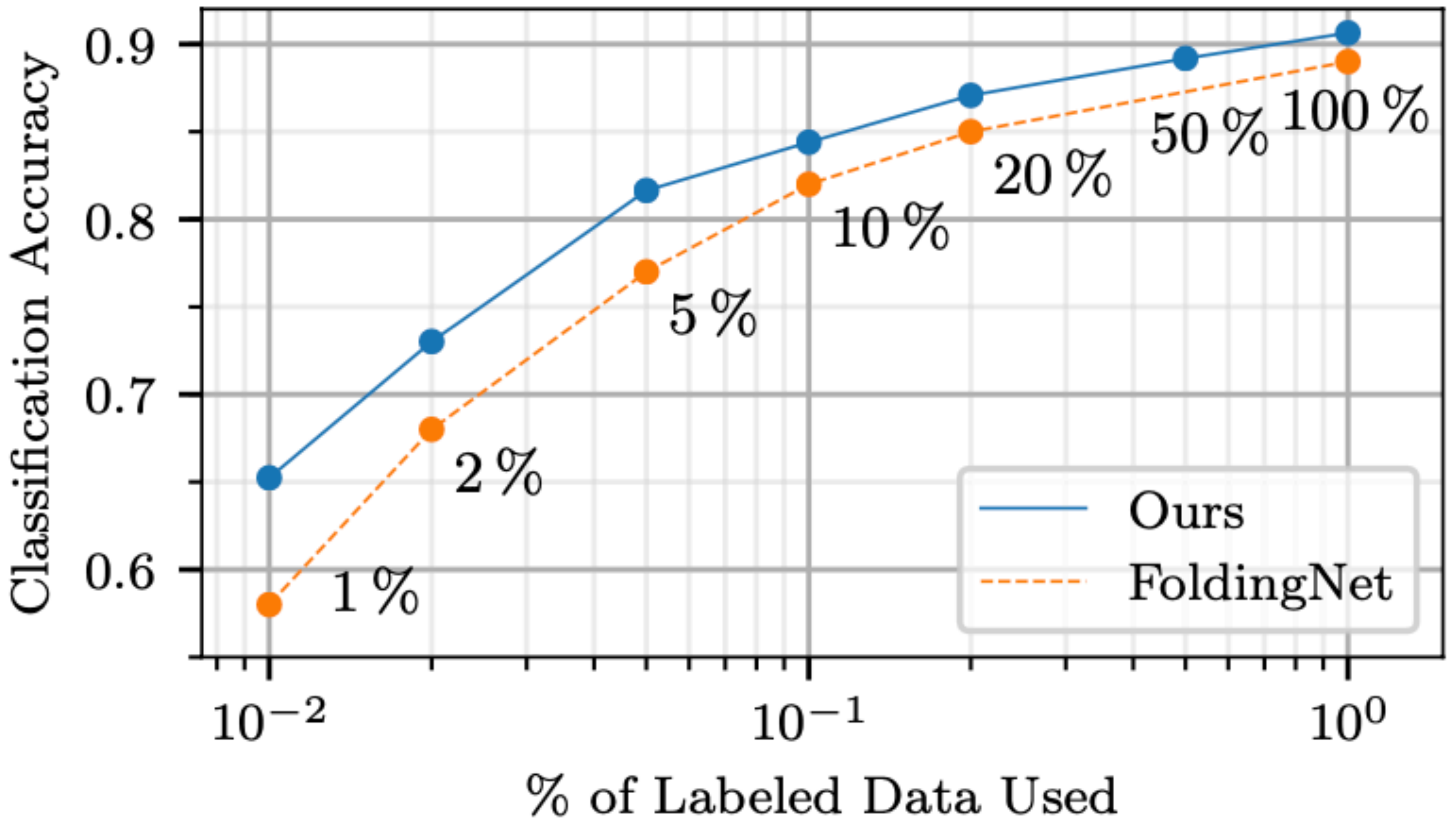


Self-Supervised Deep Learning on Point Clouds by Reconstructing Space

Jonathan Sauder
Hasso Plattner Institute
Potsdam, Germany
jonathan.sauder@student.hpi.de

Bjarne Sievers
Hasso Plattner Institute
Potsdam, Germany
bjarne.sievers@student.hpi.de





PRETRAINING: SHUFFLING TASK

1. Build a backbone model using a large, diverse dataset on a pretext task: pre-training task
2. Fine-tune the model for a variety of desired tasks: downstream tasks

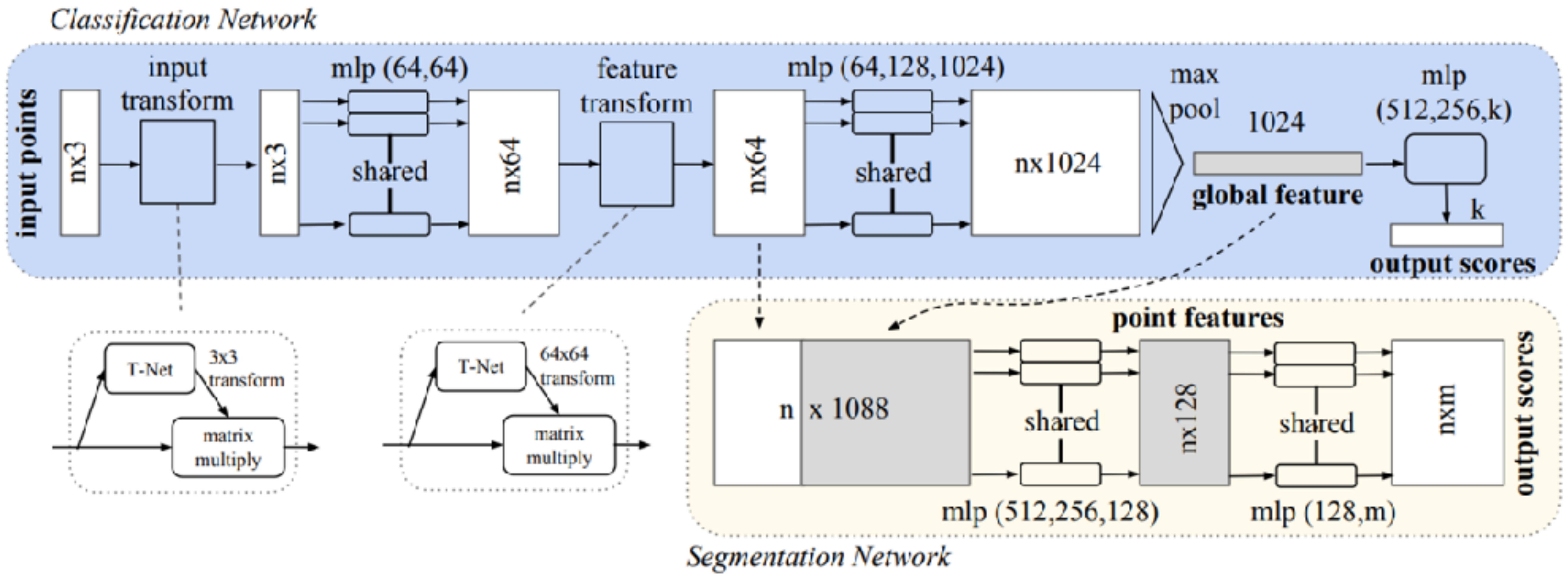
Training data: Unlabeled 4D point clouds:

Experimental data:

$$^{16}\mathrm{O} + \alpha, ^{22}\mathrm{Mg} + \alpha, ^{16}\mathrm{C} + d, ^{46}\mathrm{Ar} + p$$

Simulated data:

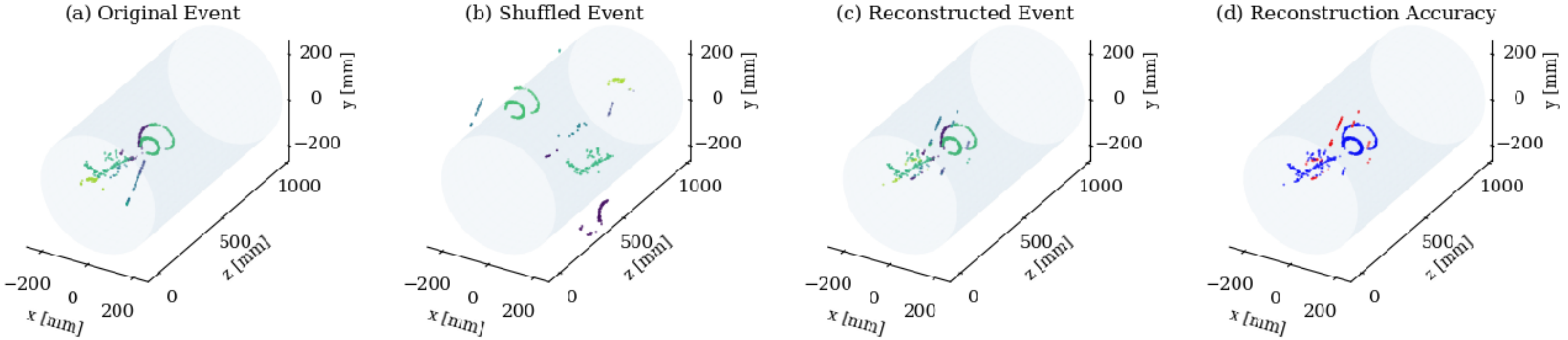
$$^{16}\mathrm{O} + \alpha, ^{22}\mathrm{Mg} + \alpha$$

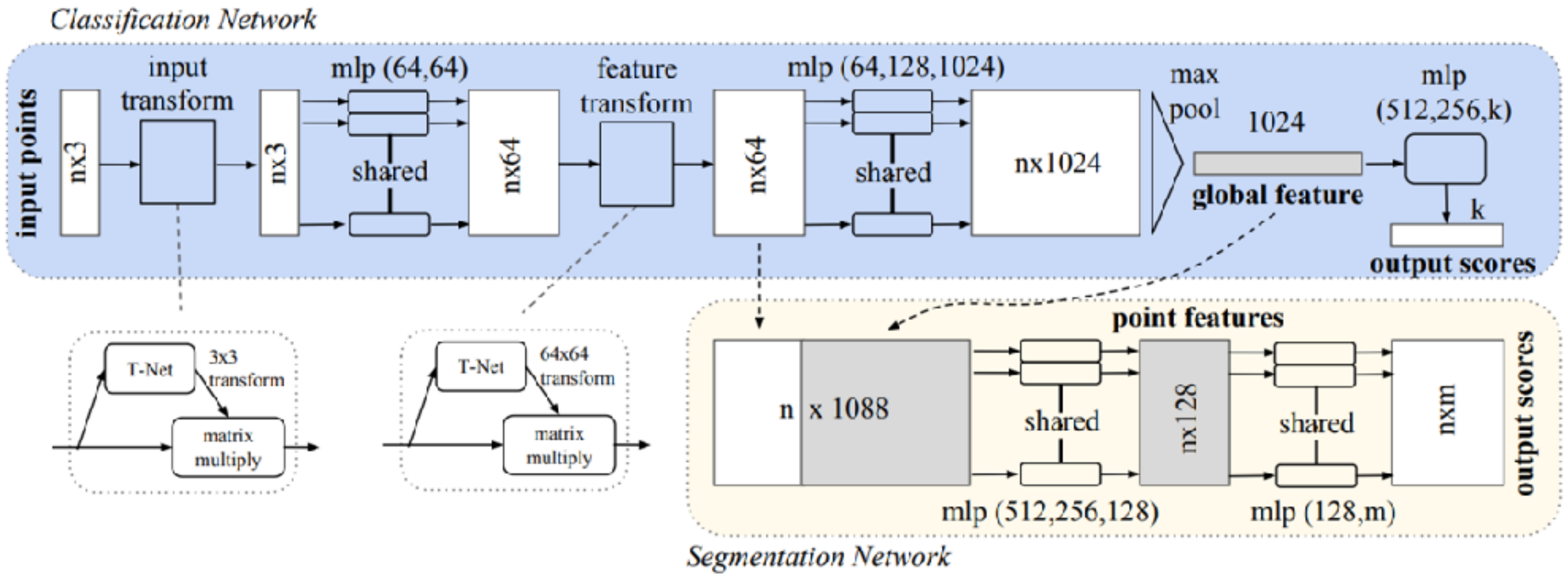


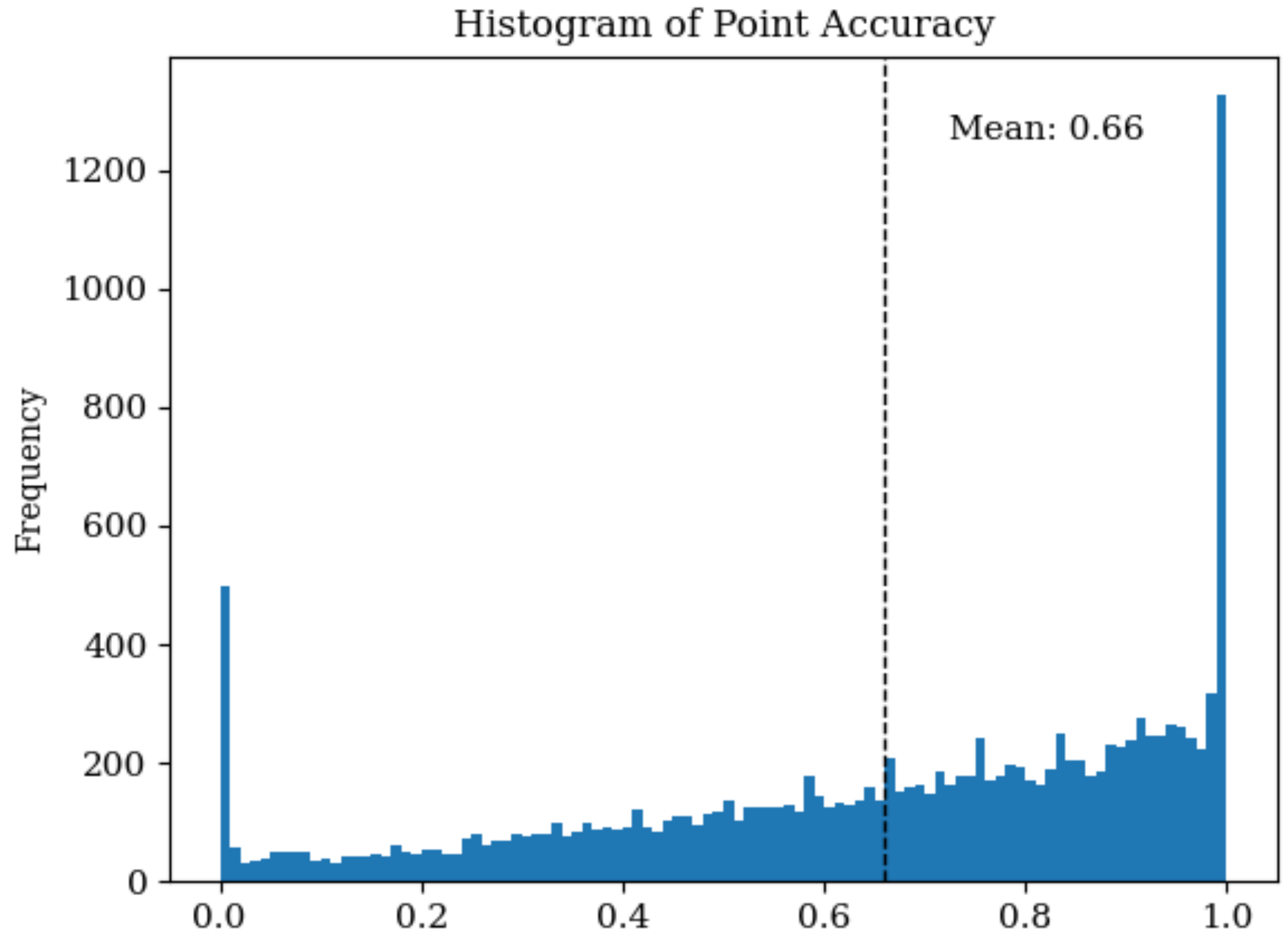
PRETRAINING: SHUFFLING TASK

1. Build a backbone model using a large, diverse dataset on a pretext task: **pre-training task**

2. Fine-tune the model for a variety of desired tasks: **downstream tasks**

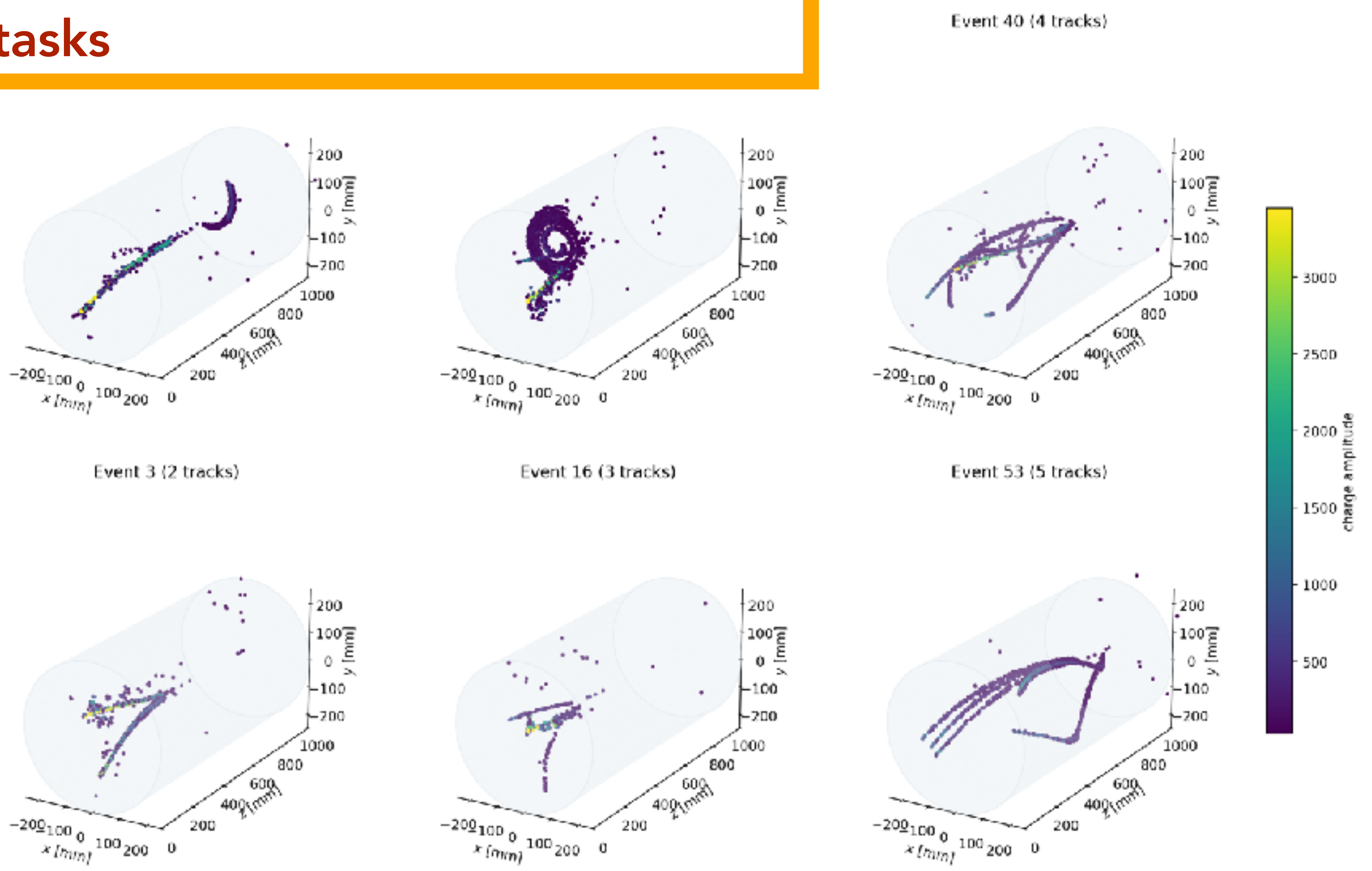


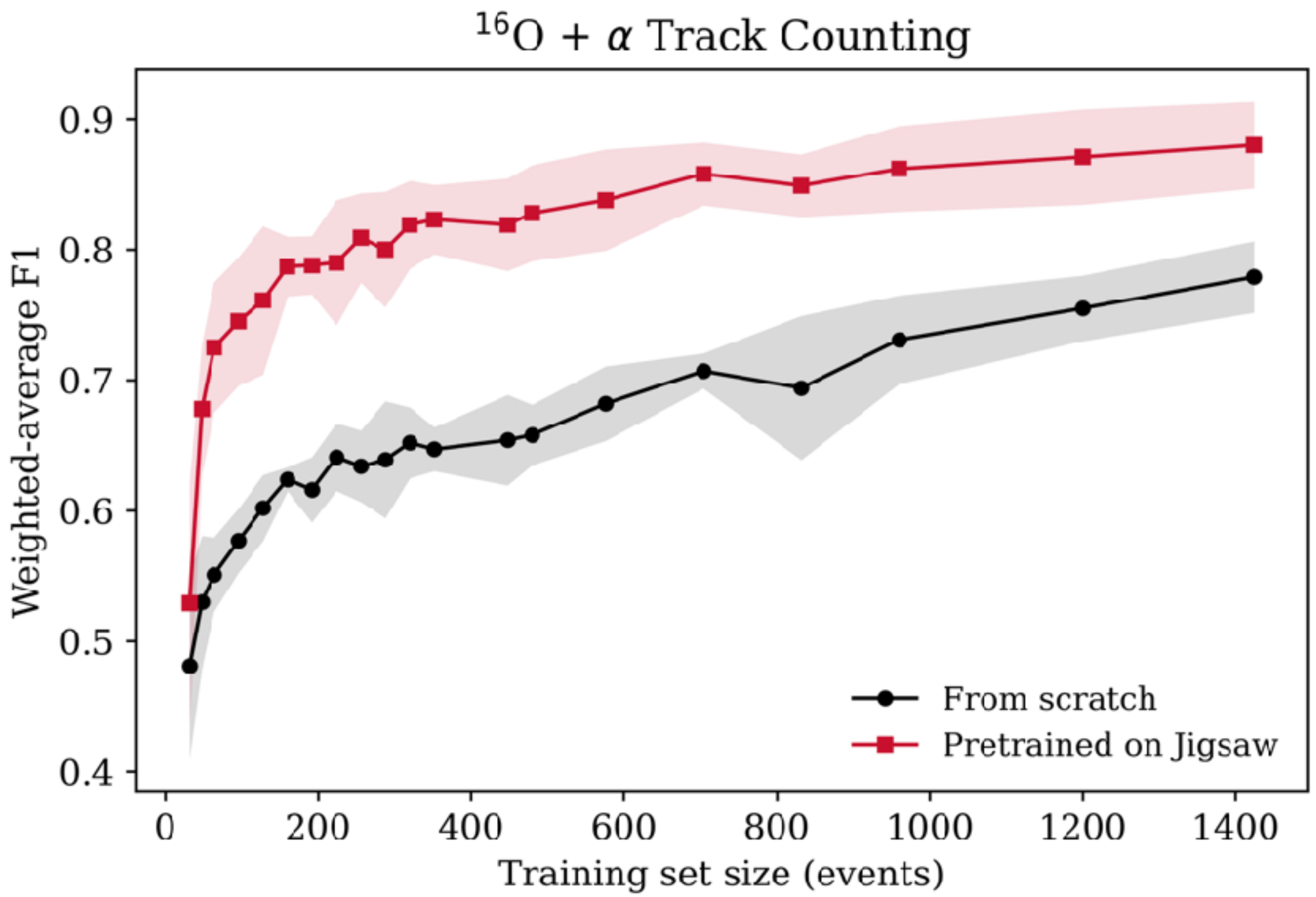




DOWNSTREAM TASK: MULTIPLICITY

1. **Build a backbone model using a large, diverse dataset on a pretext task: pre-training task**
2. **Fine-tune the model for a variety of desired tasks: downstream tasks**

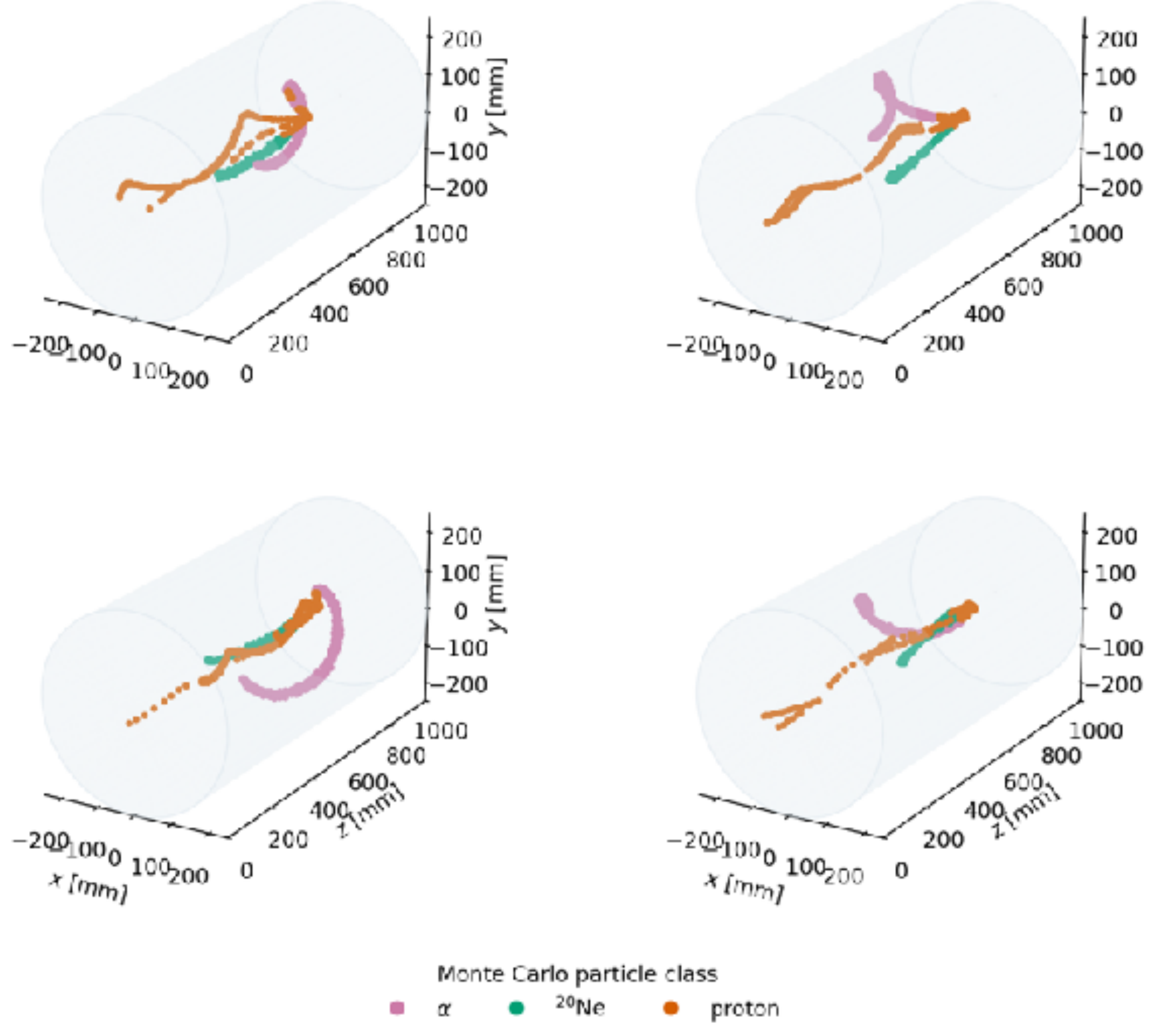


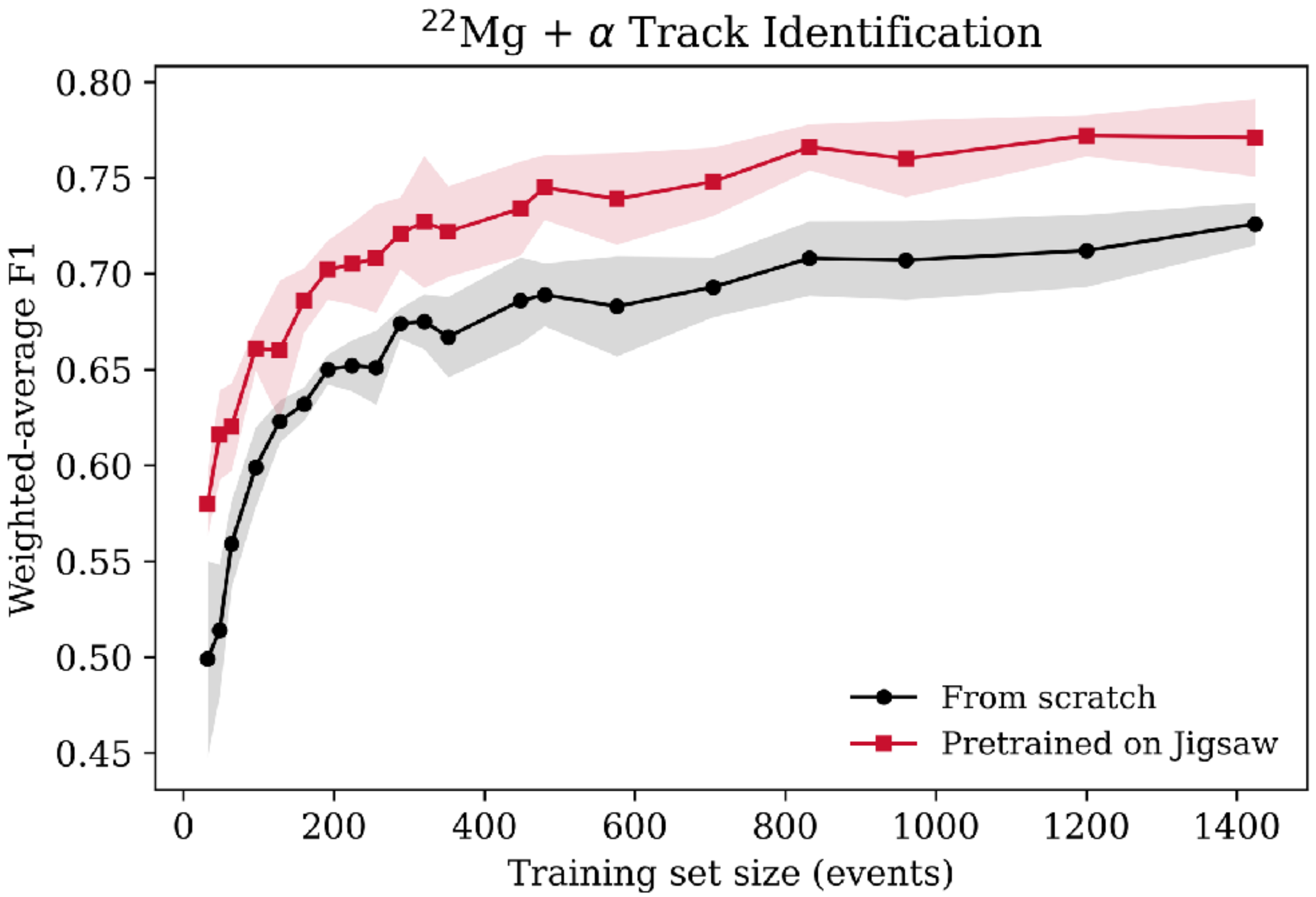


Results from Hakan Bora Yavuzkara

DOWNSTREAM TASK: TRACK IDENTIFICATION

1. Build a backbone model using a large, diverse dataset on a pretext task: pre-training task
2. Fine-tune the model for a variety of desired tasks: downstream tasks





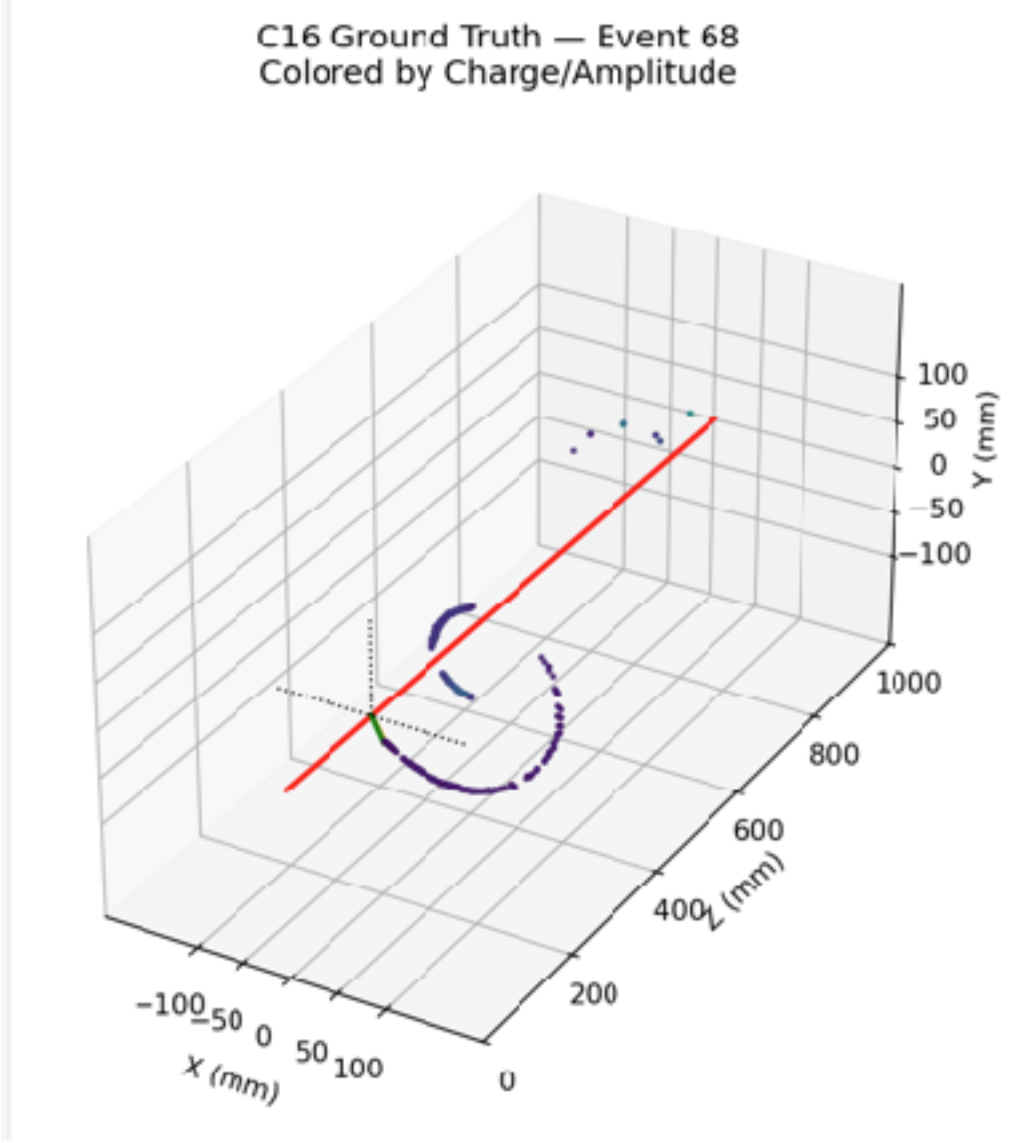
Results from Hakan Bora Yavuzkara

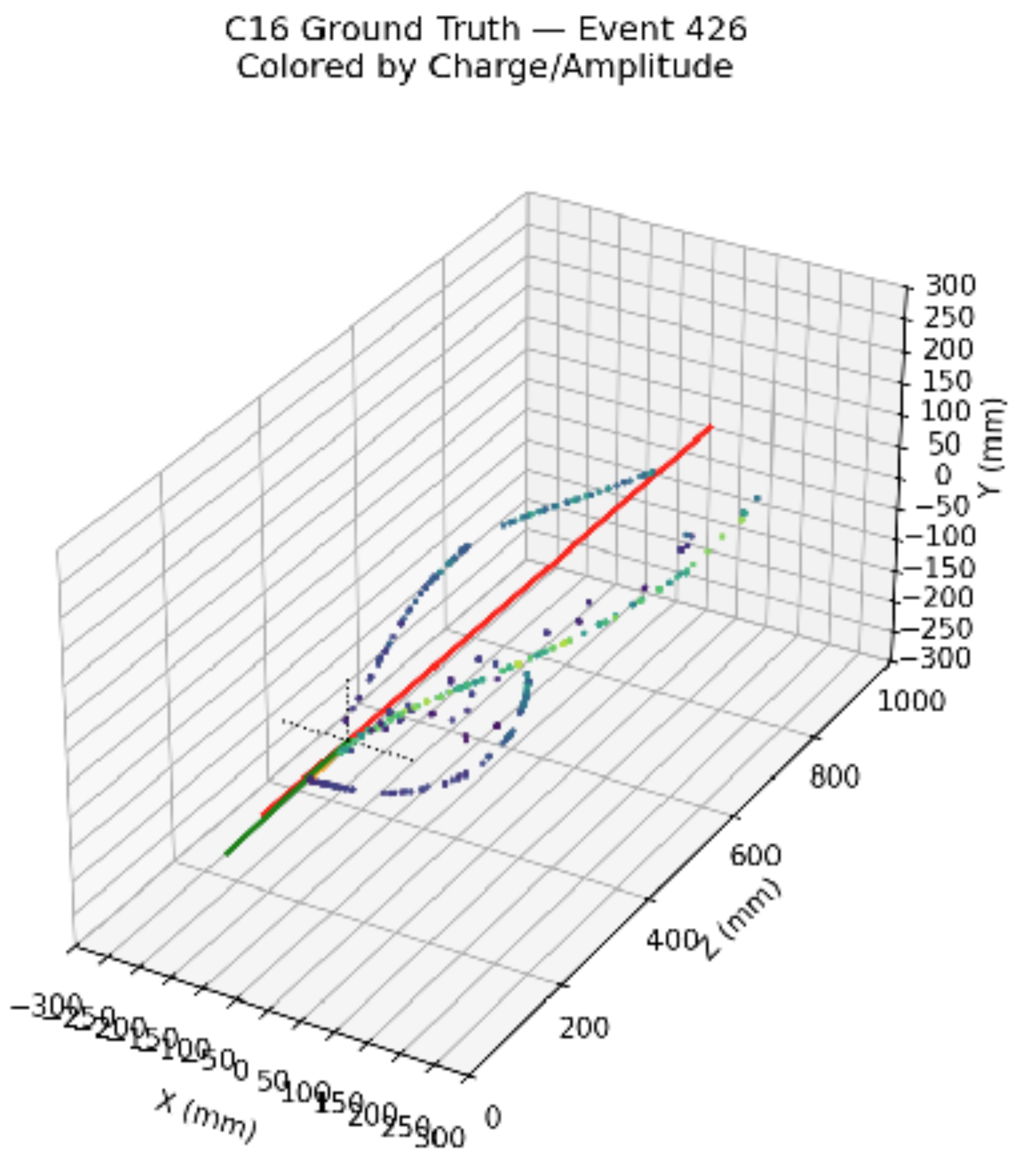
DOWNSTREAM TASK: KINEMATICS

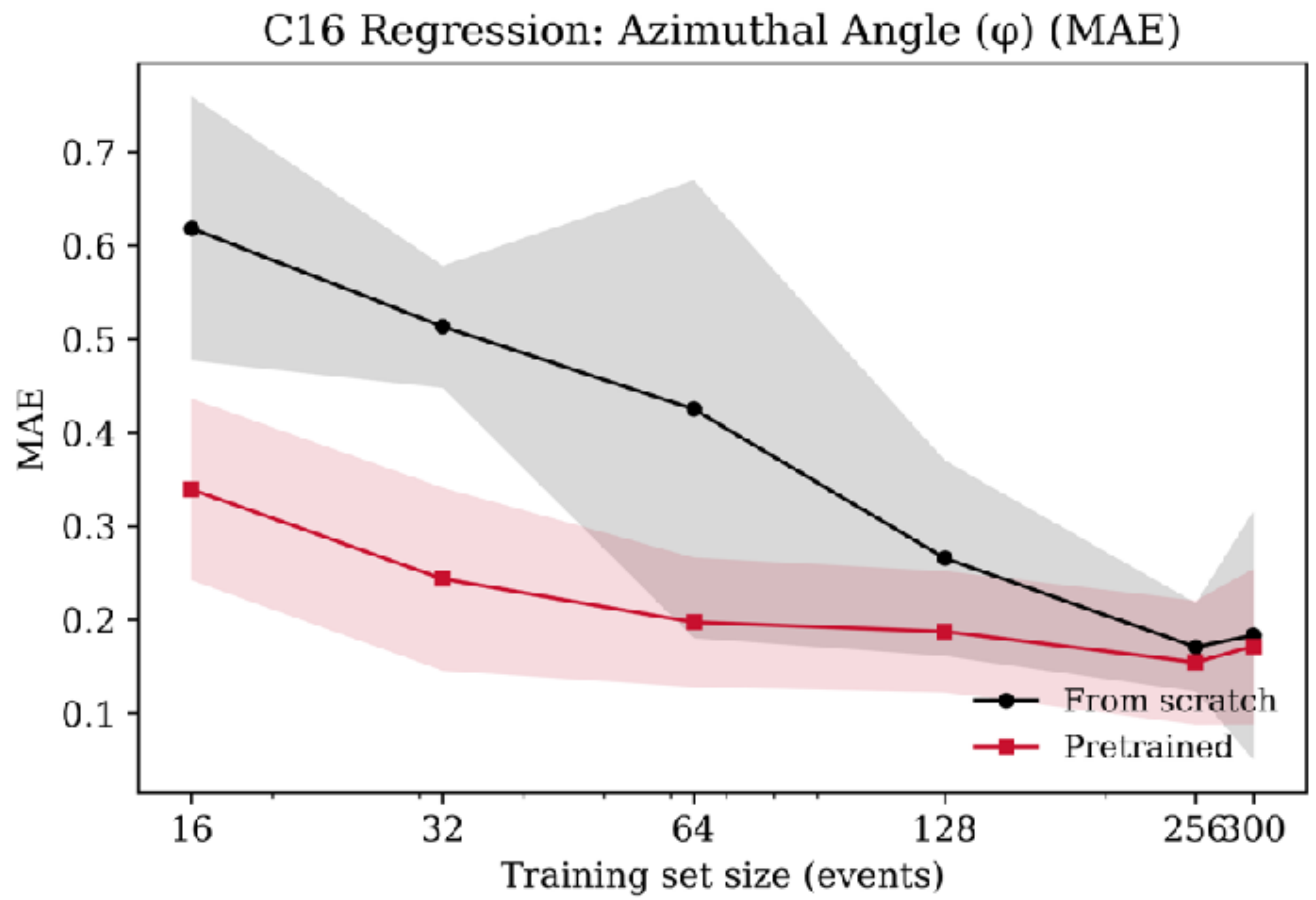
Results from Hakan Bora Yavuzkara

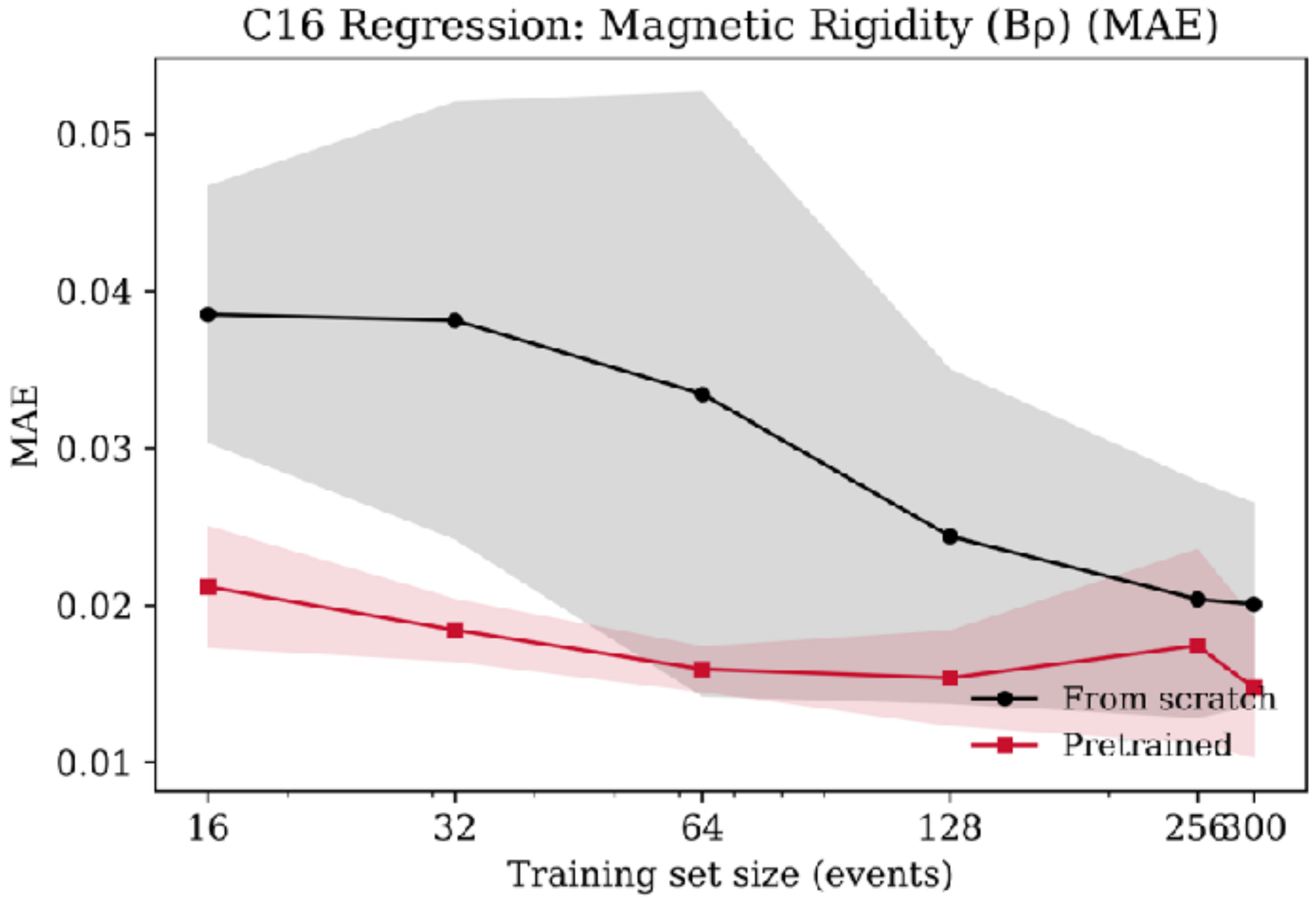
1. Build a backbone model using a large, diverse dataset on a pretext task: pre-training task

2. Fine-tune the model for a variety of desired tasks: downstream tasks









CROSS-EXPERIMENT

TAKEAWAYS

1. **Build a backbone model using a large, diverse dataset on a pretext task: pre-training task**

2. **Fine-tune the model for a variety of desired tasks: downstream tasks**

- Self-supervised pretraining consistently helps for physics tasks
- Models beginning to be used for analysis
- Results promising for future experiments not included in training data
- Large scale trainings are coming…
- But we should think more carefully about architecture choice

Paper expected on the arXiv in August.

What is the cross-detector capacity of these models?

CROSS-DETECTOR

SPARSE TENSOR APPROACHES

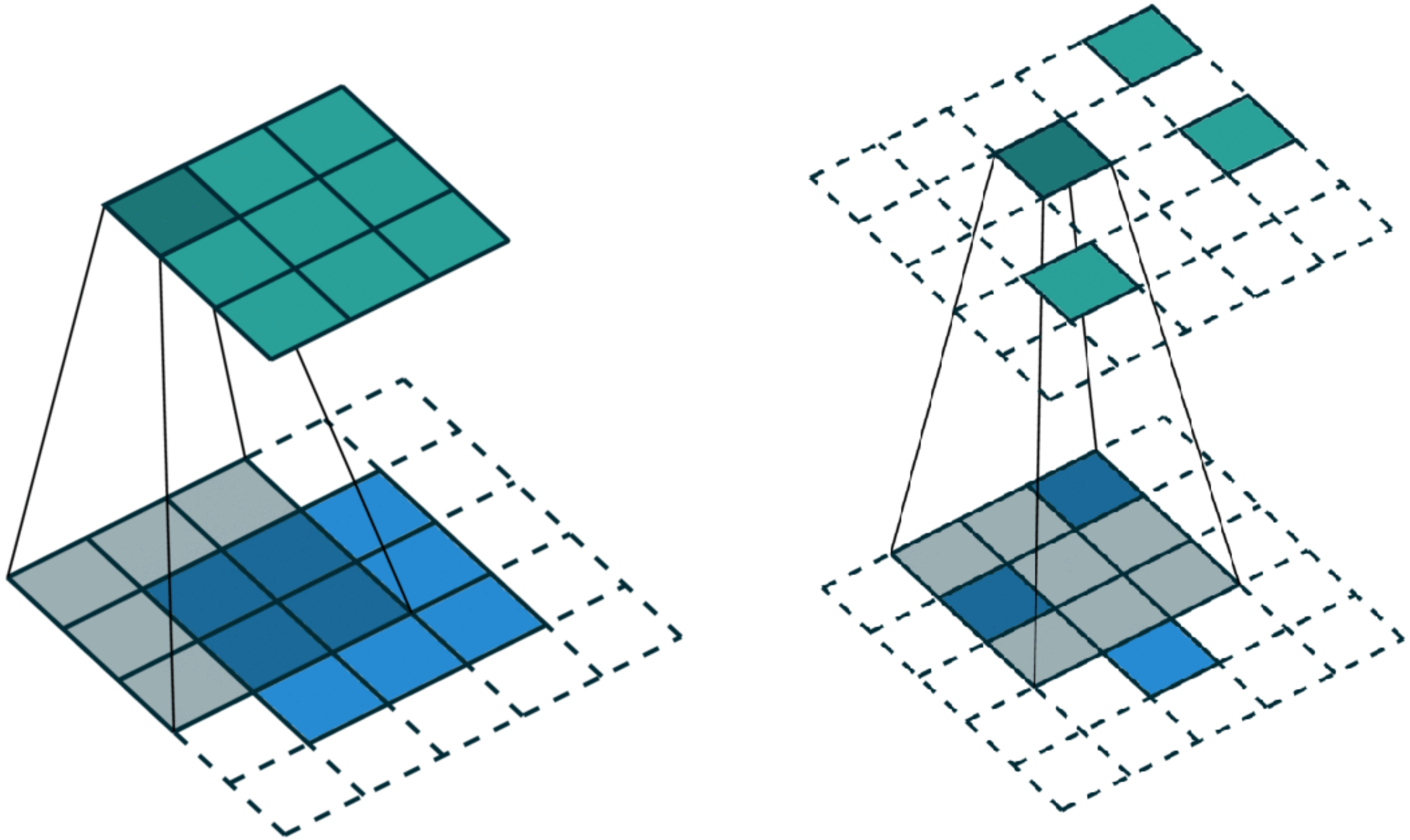
MODEL

ME POINTNET

- Random
- ^{20}Mg
- ^{21}Mg
- ^{16}O + a

ME RESNET

- Random
- ^{20}Mg
- ^{21}Mg
- ^{16}O + a

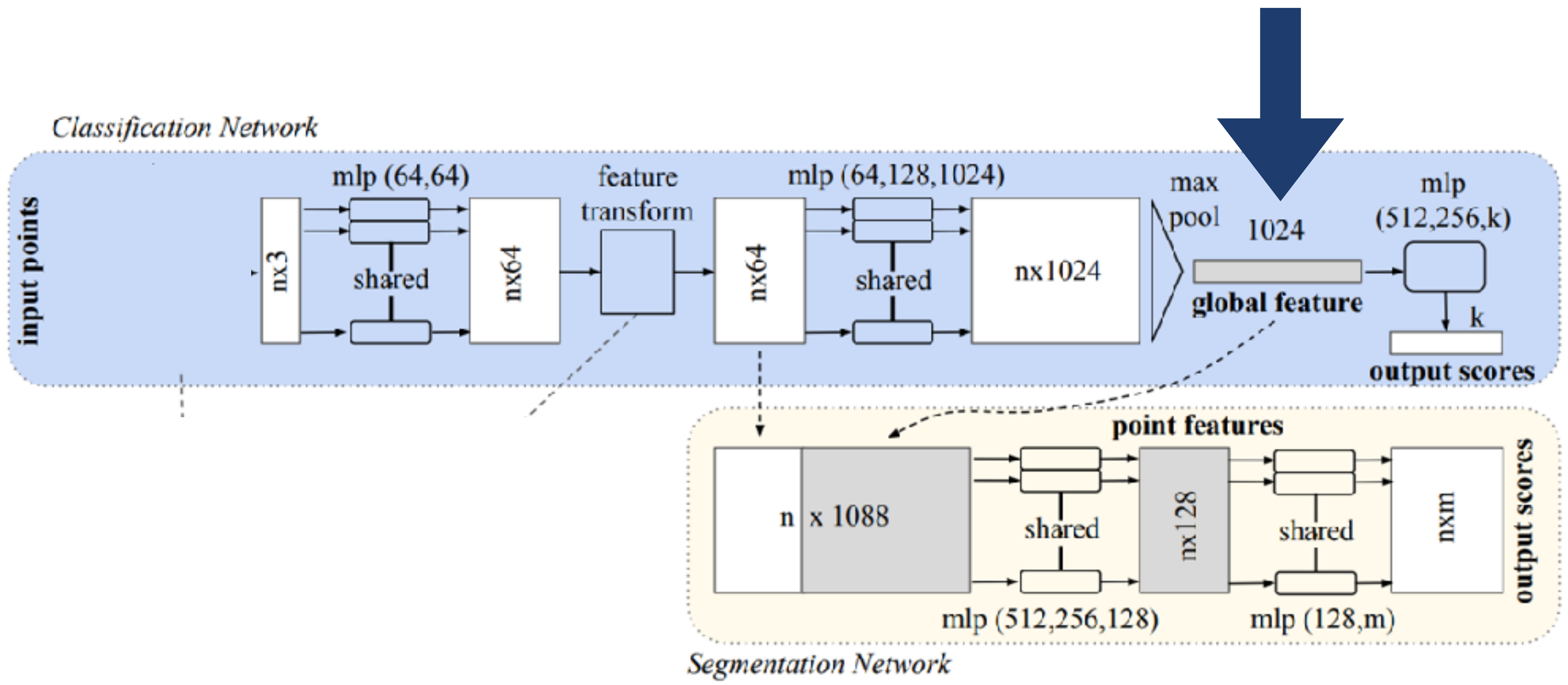


EVALUATION

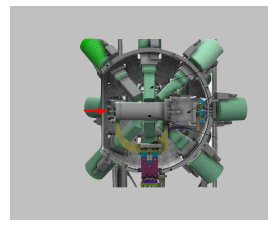
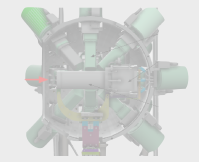
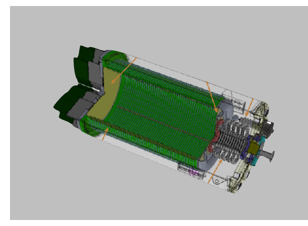
- ^{20}Mg
- ^{21}Mg
- ^{16}O + a

CAPACITY OF MODELS

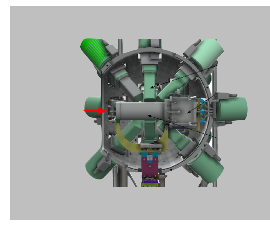
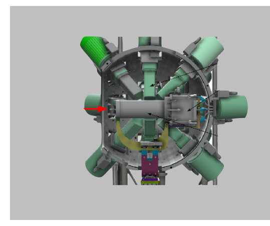
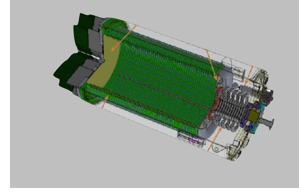
Architecture: Minkowski Engine (ME) PointNet



Training tasks:

Random	No training
 ^{20}Mg	2-class a v p
 ^{21}Mg	2-class a v p
 ^{16}O + a	3-class track counting

Evaluation tasks:

 ^{20}Mg	3-class a v p w/ energy
 ^{21}Mg	3-class a v p w/ energy
 ^{16}O + a	3-class track counting

Probe of embeddings:

PROBE	DESCRIPTION
Naive	Mode Classifier
Linear	Linear Support Vector Machine
Rbf	Svm With Radial Basis Function Kernel

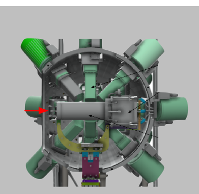
CROSS-DETECTOR

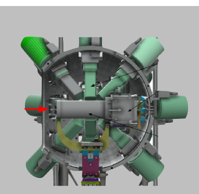
INVESTIGATING CROSS-DETECTOR CAPACITY

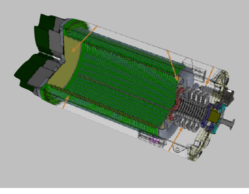
MODEL

ME POINTNET

Random

 ^{20}Mg

 ^{21}Mg

 ^{16}O + a

ME RESNET

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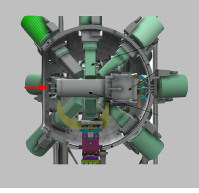
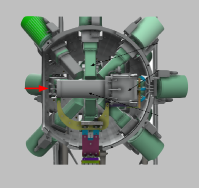
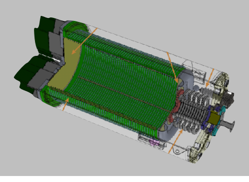
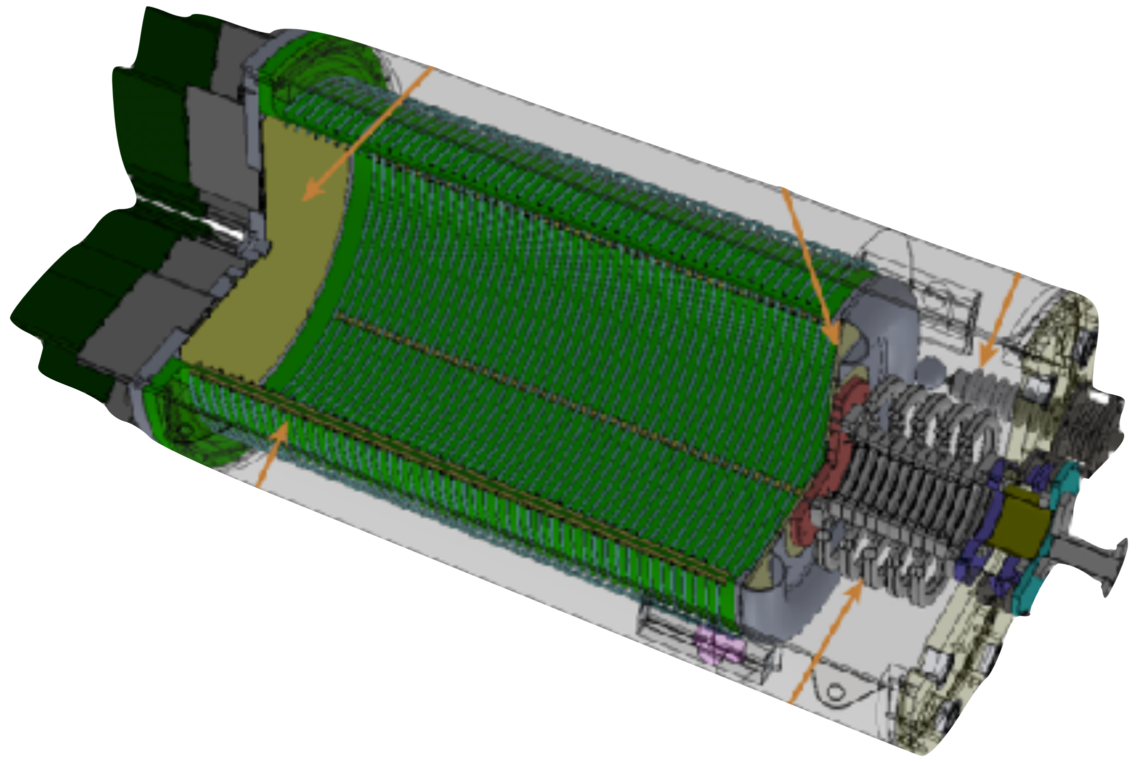
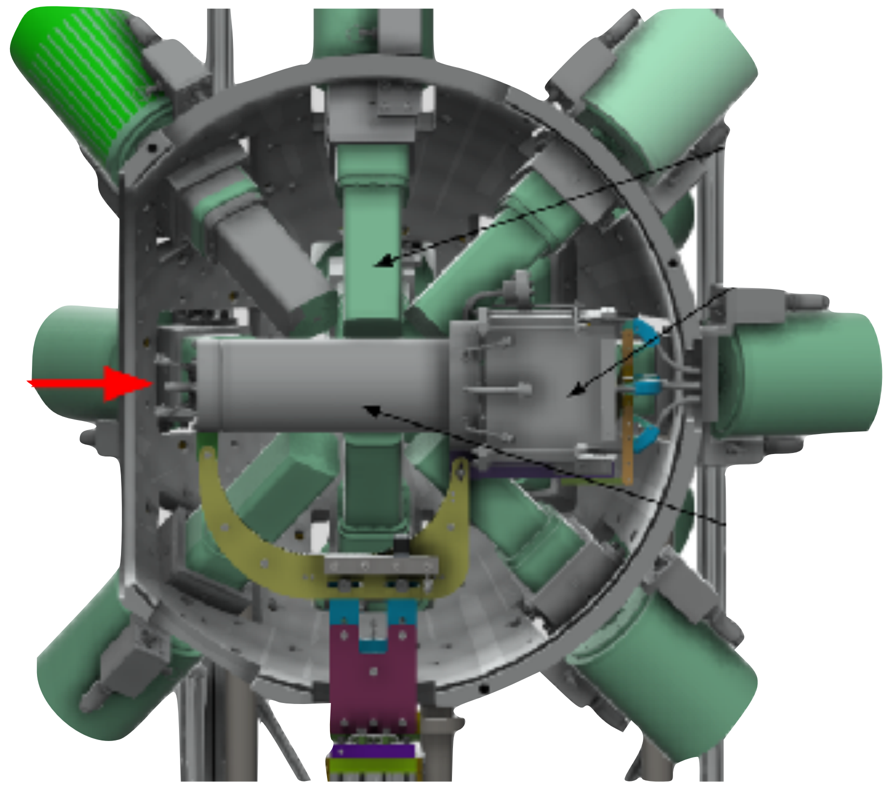
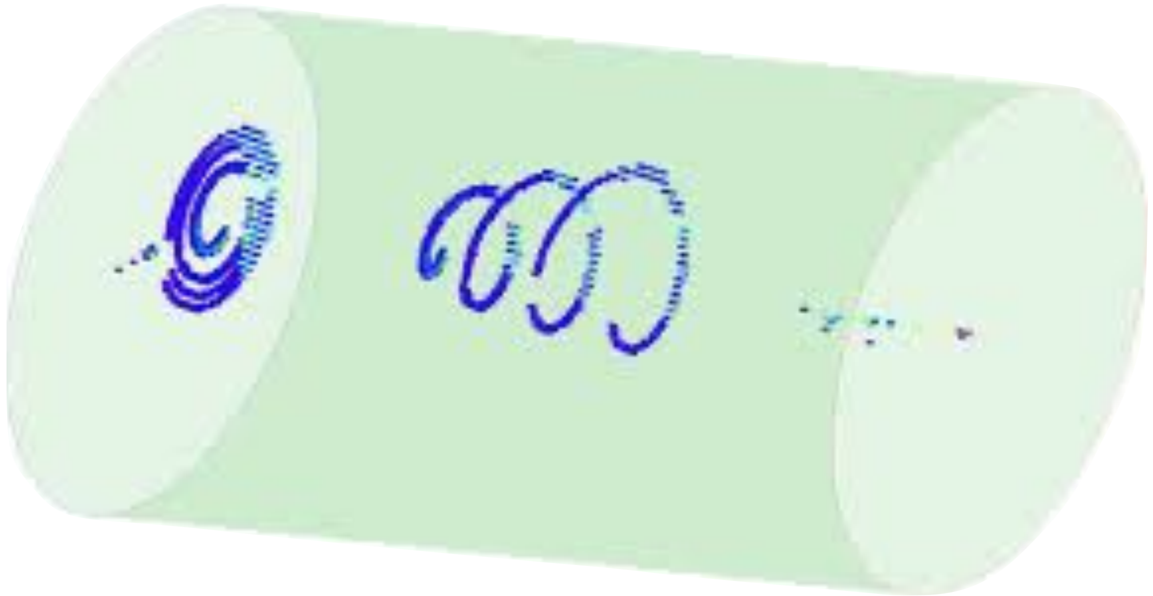
 ^{20}Mg

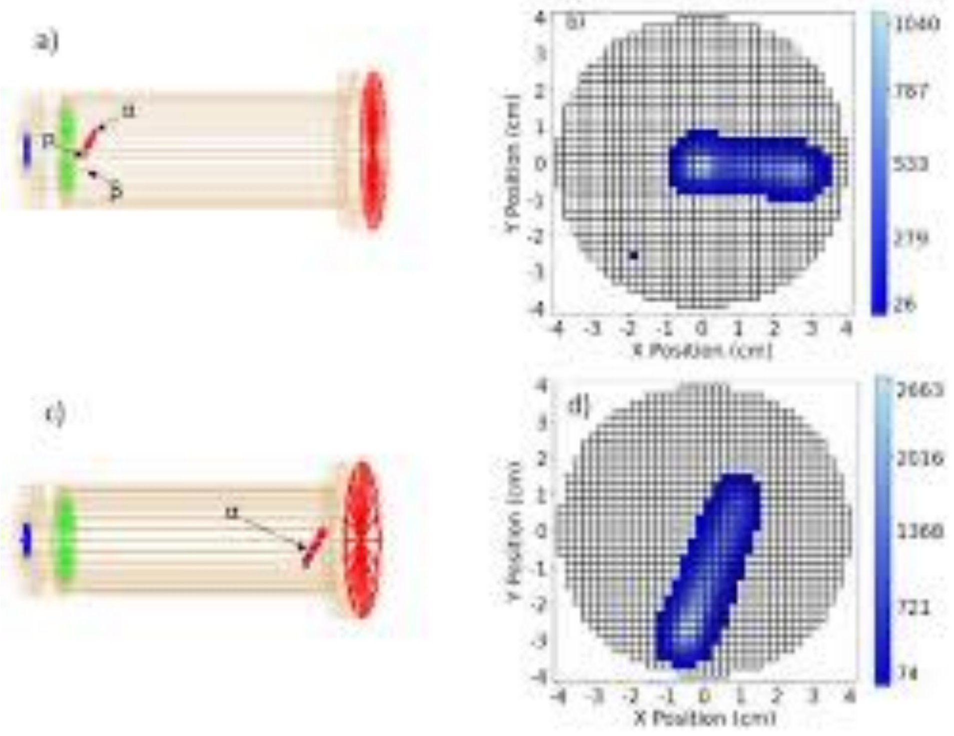
 ^{21}Mg

 ^{16}O + a

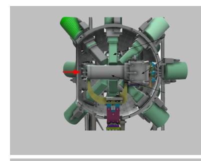


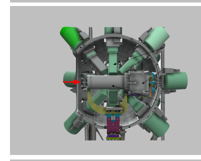


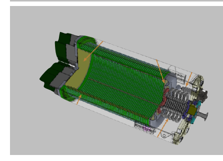




EVALUATION

 ^{20}Mg

 ^{21}Mg

 ^{16}O + a

INVESTIGATING CROSS-DETECTOR CAPACITY

CROSS-DETECTOR

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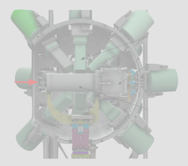
ME POINTNET

Random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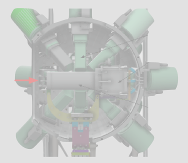
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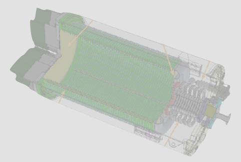
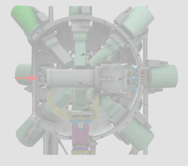

^{16}O + a

ME RESNET

Random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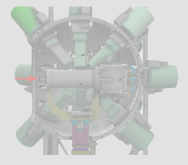
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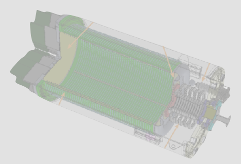
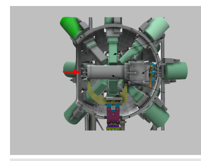

^{16}O + a

EVALUATION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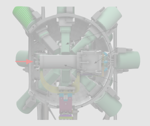
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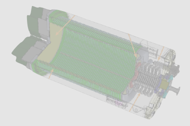

^{16}O + a

On Random Weights and Unsupervised Feature Learning

Andrew M. Saxe ASAXE@CS.STANFORD.EDU
Pang Wei Koh PANGWEI@CS.STANFORD.EDU
Zhenghao Chen ZHENGHAO@CS.STANFORD.EDU
Maneesh Bhand MBHAND@CS.STANFORD.EDU
Bipin Suresh BIPINS@CS.STANFORD.EDU
Andrew Y. Ng ANG@CS.STANFORD.EDU
Computer Science Department, Stanford University, Stanford, CA 94305, USA

How Powerful Are Randomly Initialized Pointcloud Set Functions?

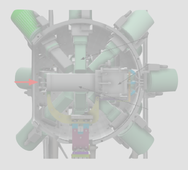
Aditya Sanghi and Pradeep Kumar Jayaraman
Autodesk Research, Toronto
{aditya.sanghi, pradeep.kumar.jayaraman}@autodesk.com

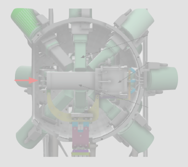
CROSS-DETECTOR

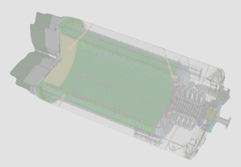
MODEL

ME POINTNET

Random

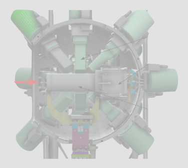
 ^{20}Mg

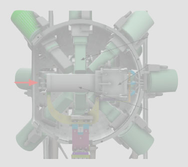
 ^{21}Mg

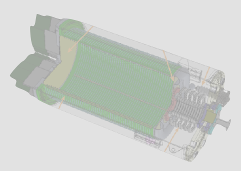
 ^{16}O + a

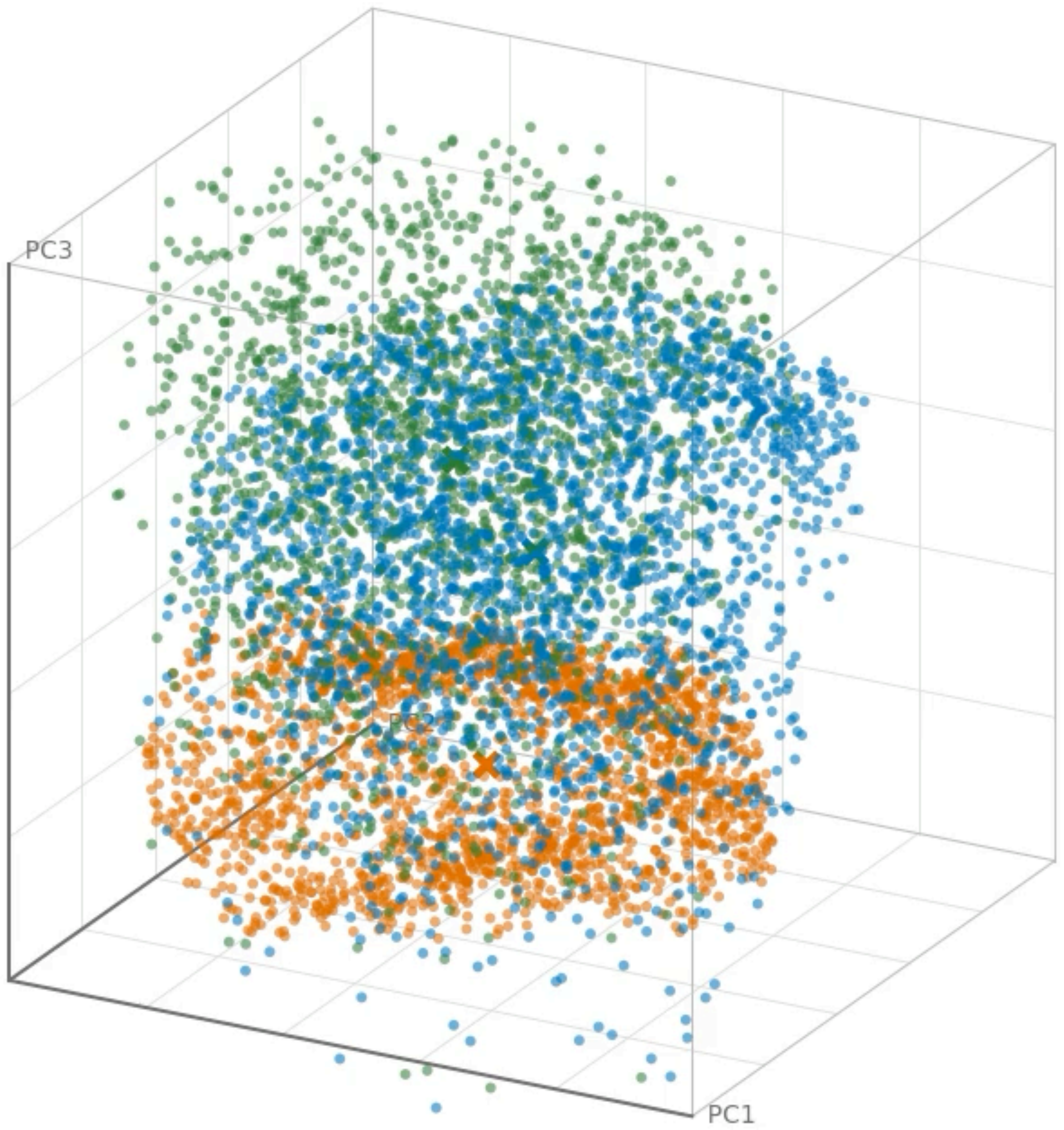
ME RESNET

Random

 ^{20}Mg

 ^{21}Mg

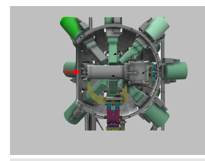
 ^{16}O + a

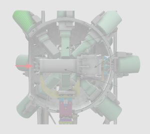


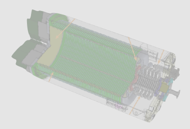
NO MODEL TRAINING

- 2200 keV alpha
- 800 keV proton
- 1600 keV proton

EVALUATION

 ^{20}Mg

 ^{21}Mg

 ^{16}O + a

Results from Liam Sieland

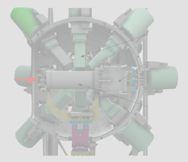
PROBE	ACCURACY	F1
Naive	0.747	0.285
Linear	0.994	0.989
Rbf	0.997	0.994

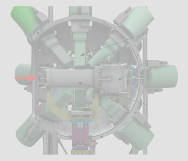
CROSS-DETECTOR

MODEL

ME POINTNET

Random


^{20}Mg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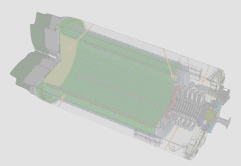
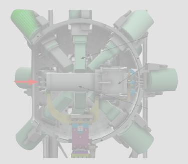

^{16}O + a

ME RESNET

Random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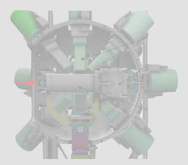
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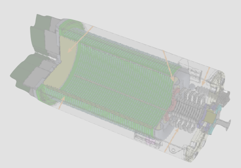
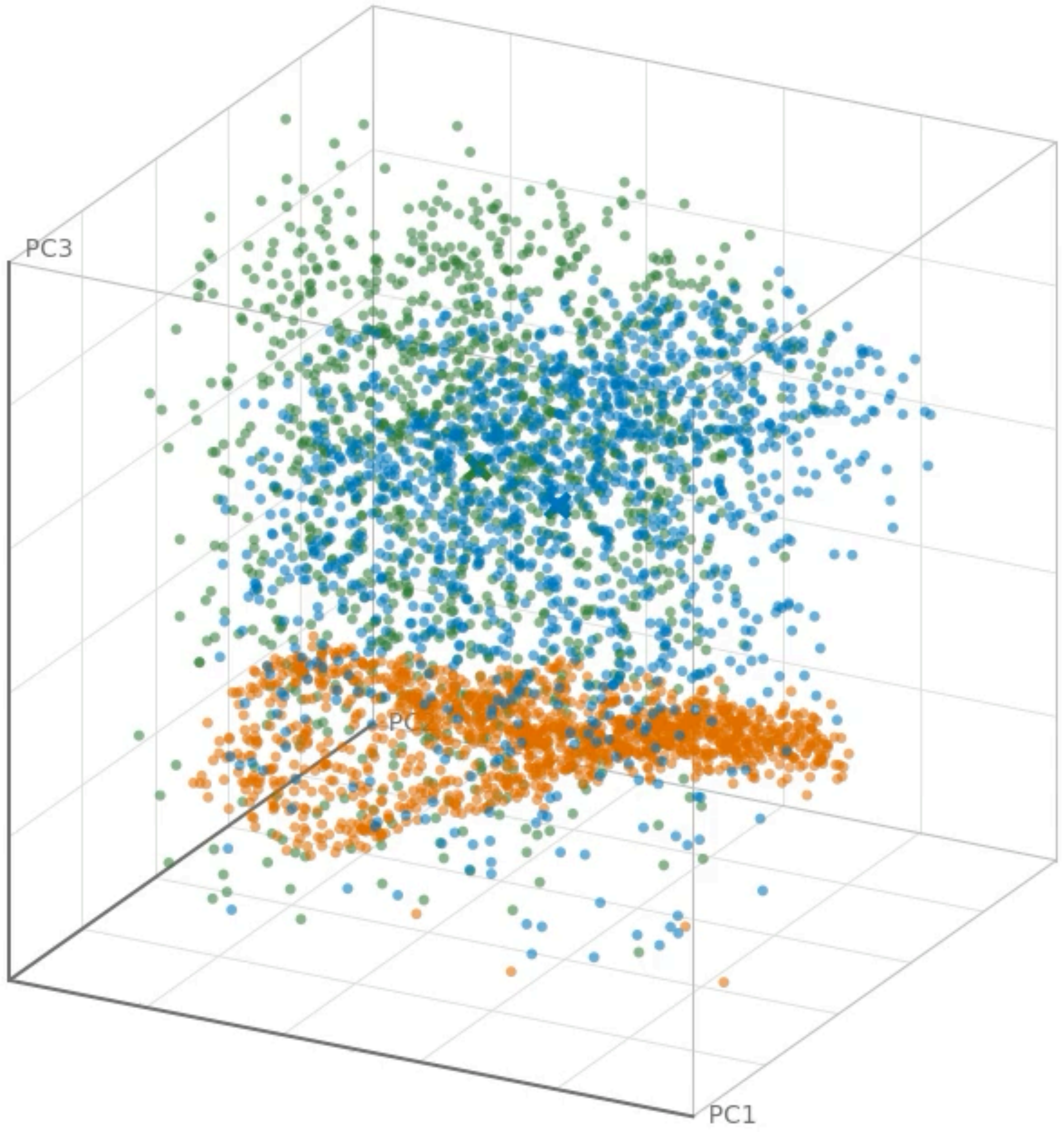

^{16}O + a



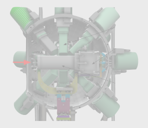
NO MODEL TRAINING

2200 keV alpha

1300keV proton

1900 keV proton

EVALUATION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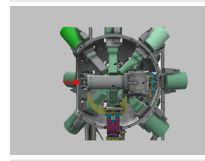
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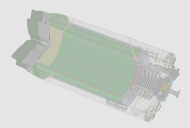

^{16}O + a

Results from Liam Sieland

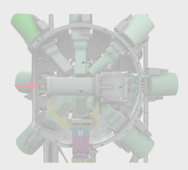
PROBE	ACCURACY	F1
Naive	0.563	0.240
Linear	0.978	0.974
Rbf	0.995	0.994

CROSS-DETECTOR

MODEL

ME POINTNET

Random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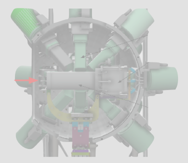
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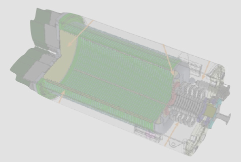
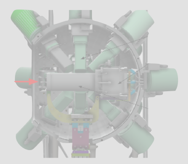

^{16}O + a

ME RESNET

Random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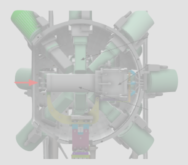
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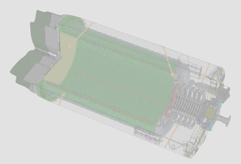
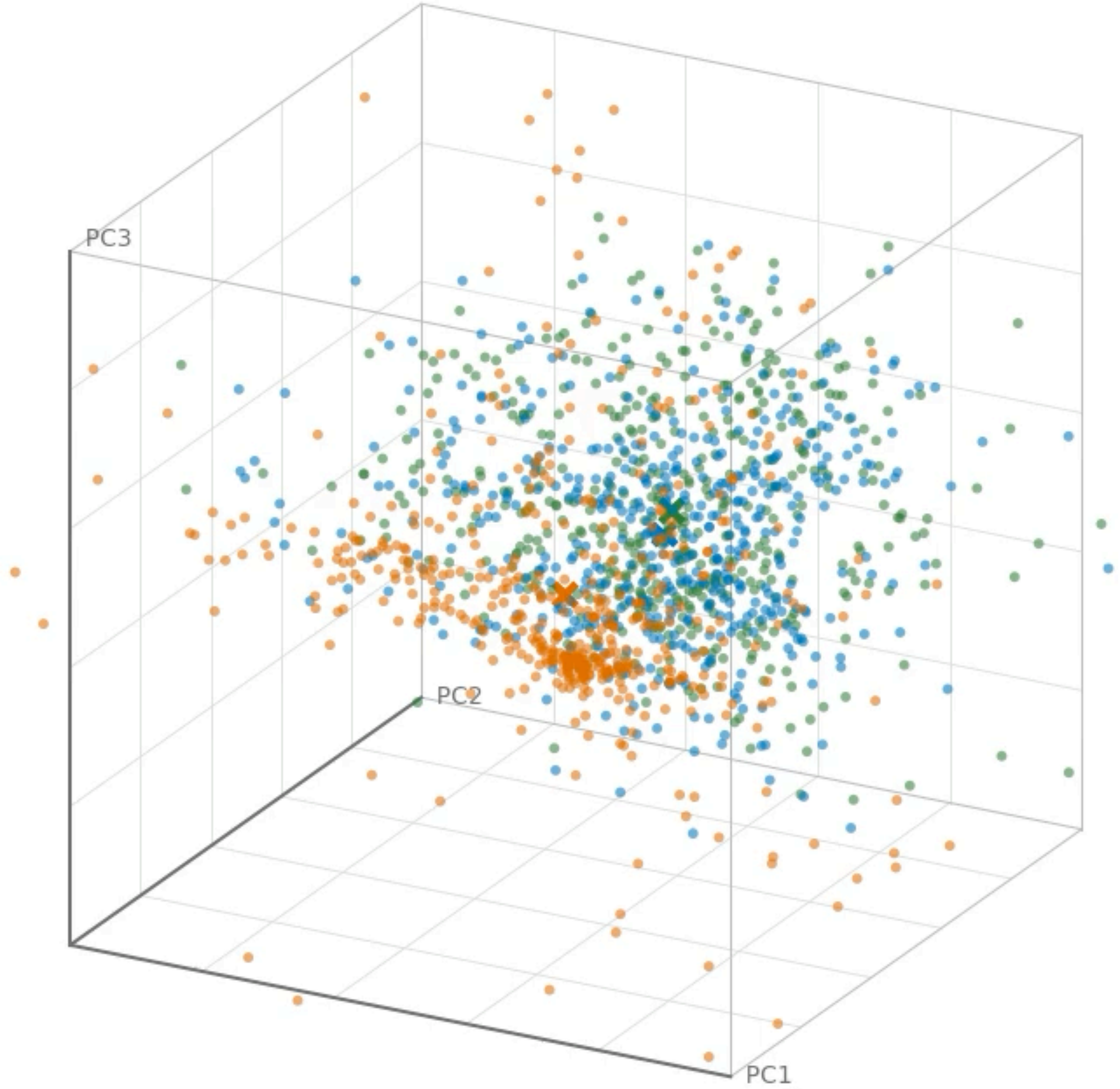
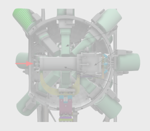

^{16}O + a



NO MODEL TRAINING

- 0,1,2 tracks
- 3 tracks
- 4,5 tracks

EVALUATION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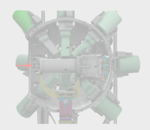
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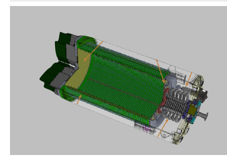

^{16}O + a

Results from Liam Sieland

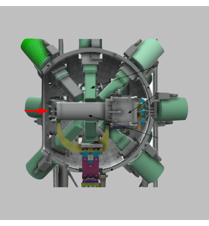
PROBE	ACCURACY	F1
Naive	0.482	0.217
Linear	0.829	0.799
Rbf	0.819	0.797

CROSS-DETECTOR

MODEL

ME POINTNET

Random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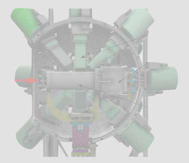
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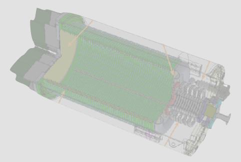
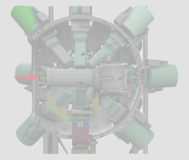

^{16}O + a

ME RESNET

Random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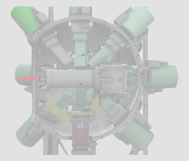
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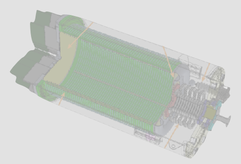
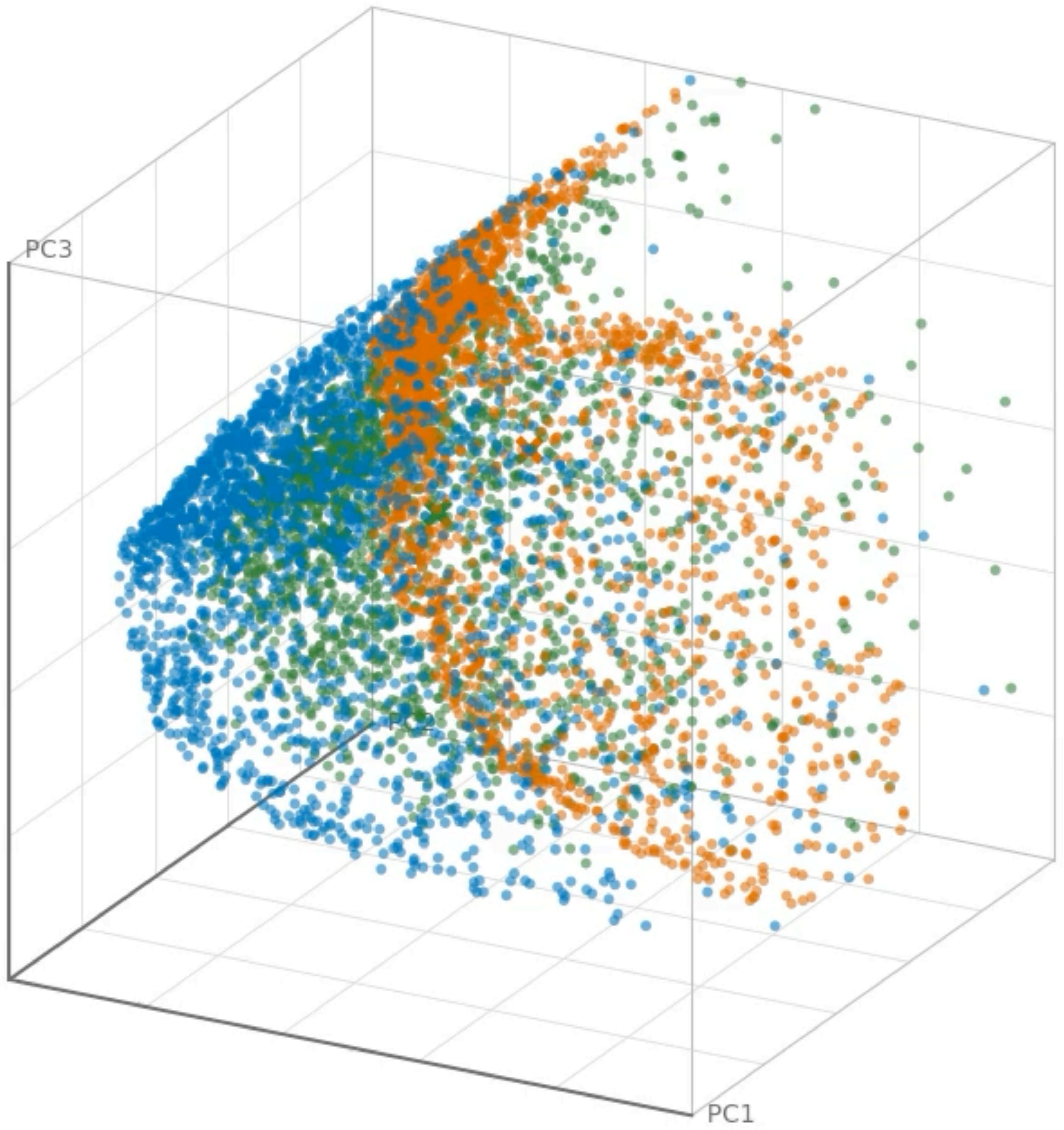
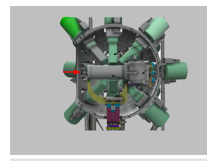

^{16}O + a



IN-DOMAIN

2200 keV alpha
800 keV proton
1600 keV proton

EVALUATION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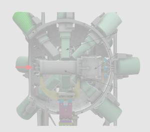
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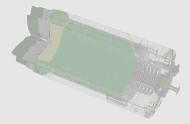

^{16}O + a

Results from Liam Sieland

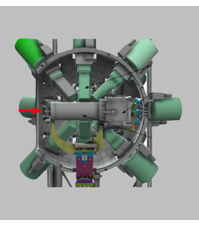
PROBE	ACCURACY	F1
Naive	0.747	0.285
Linear	1.000	1.000
Rbf	1.000	1.000

CROSS-DETECTOR

MODEL

ME POINTNET

Random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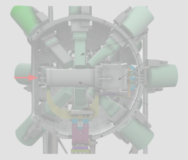
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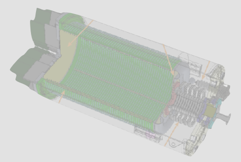
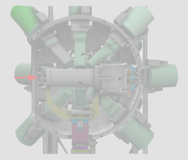

^{16}O + a

ME RESNET

Random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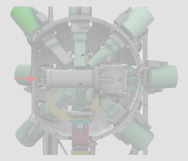
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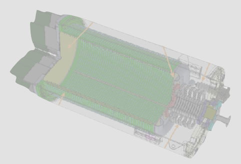
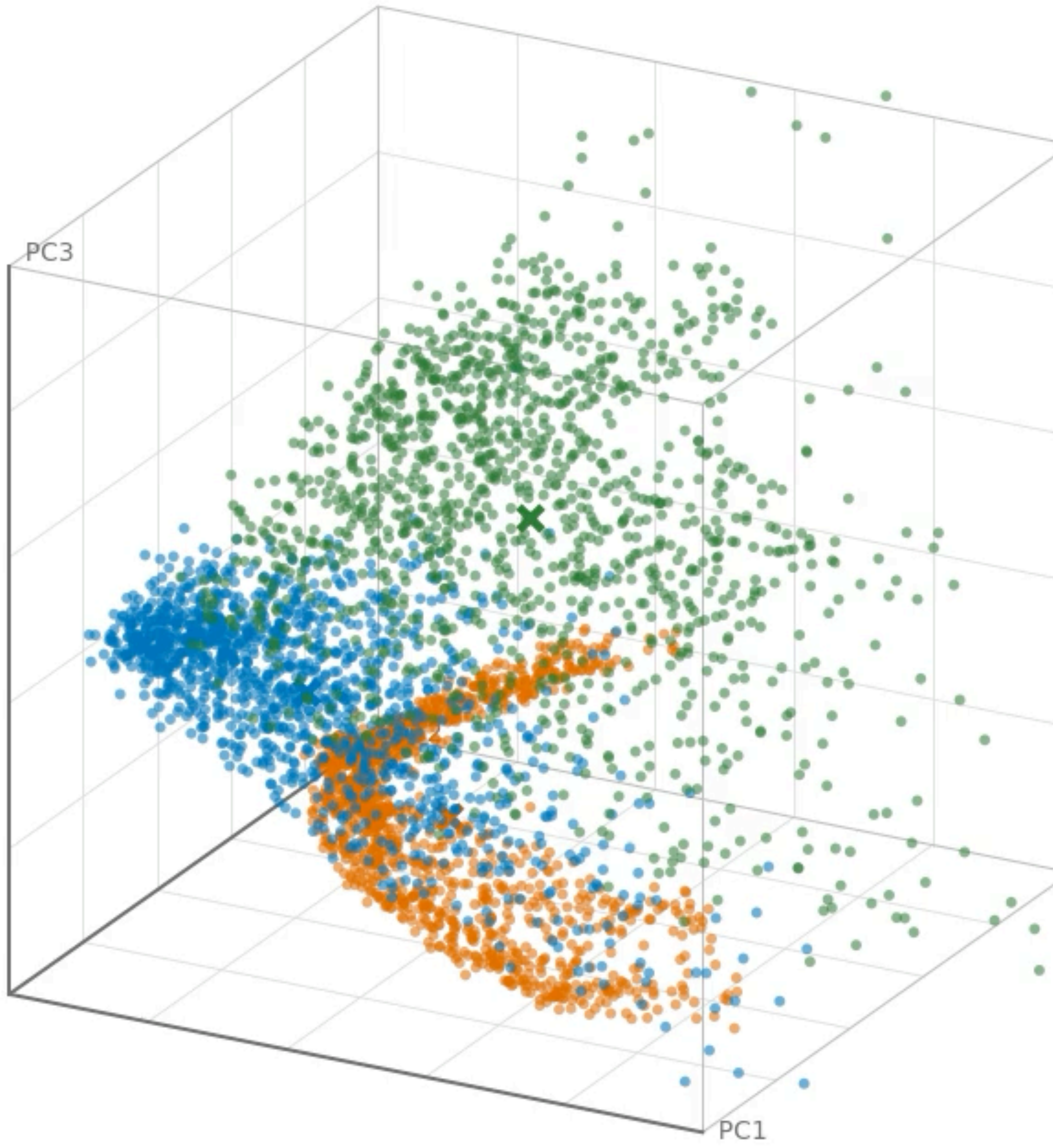
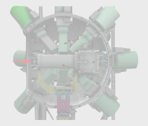

^{16}O + a



CROSS-EXPERIMENT

2200 keV alpha
1300keV proton
1900 keV proton

EVALUATION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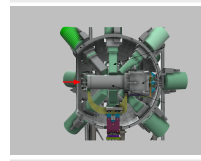
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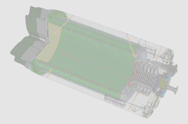

^{16}O + a

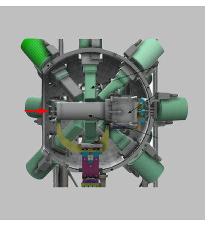
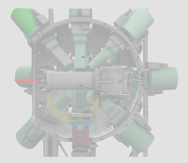
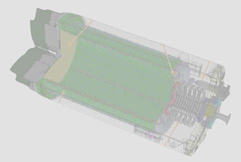
Results from Liam Sieland

PROBE	ACCURACY	F1
Naive	0.563	0.240
Linear	0.994	0.993
Rbf	0.999	0.999

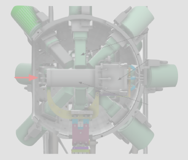
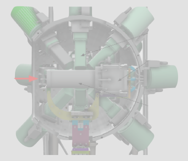
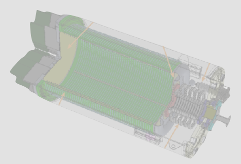
CROSS-DETECTOR

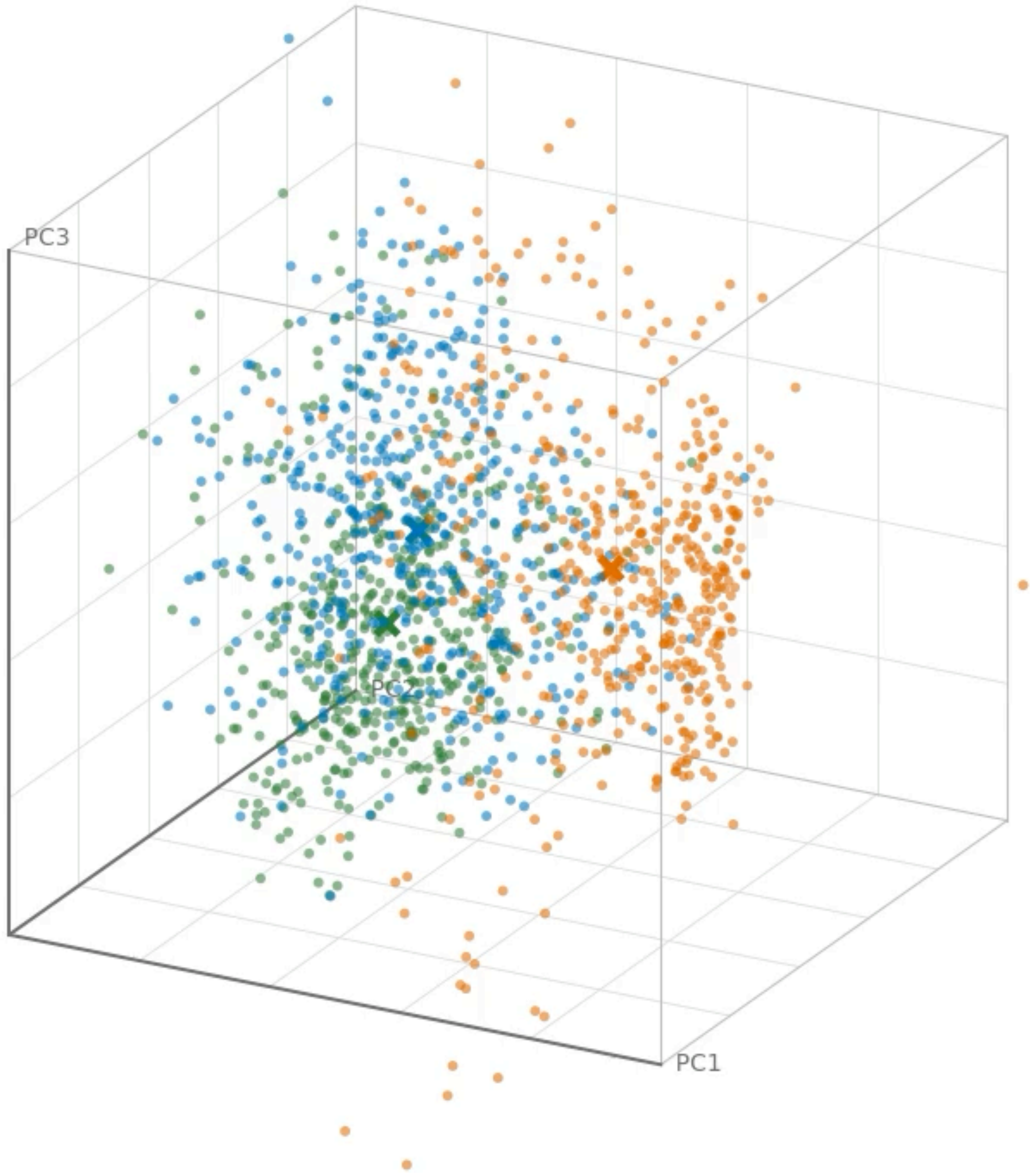
MODEL

ME POINTNET

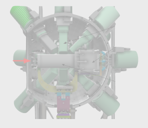
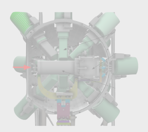
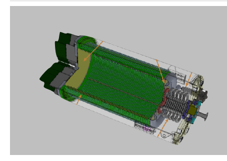
- Random
-  ^{20}Mg
-  ^{21}Mg
-  ^{16}O + a

ME RESNET

- Random
-  ^{20}Mg
-  ^{21}Mg
-  ^{16}O + a



EVALUATION

-  ^{20}Mg
-  ^{21}Mg
-  ^{16}O + a

CROSS-DETECTOR

- 0,1,2 tracks
- 3 tracks
- 4,5 tracks

Results from Liam Sieland

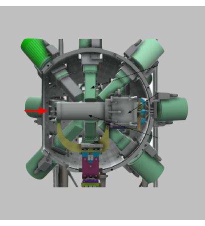
PROBE	ACCURACY	F1
Naive	0.482	0.217
Linear	0.867	0.845
Rbf	0.871	0.854

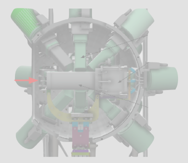
CROSS-DETECTOR

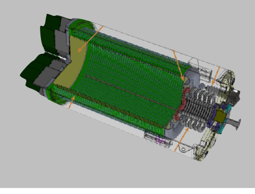
MODEL

ME POINTNET

Random

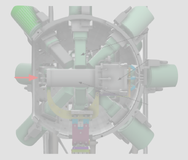

^{20}Mg

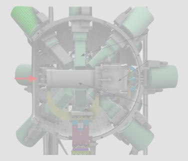

^{21}Mg

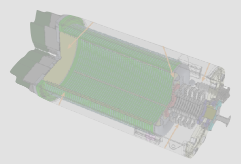

^{16}O + a

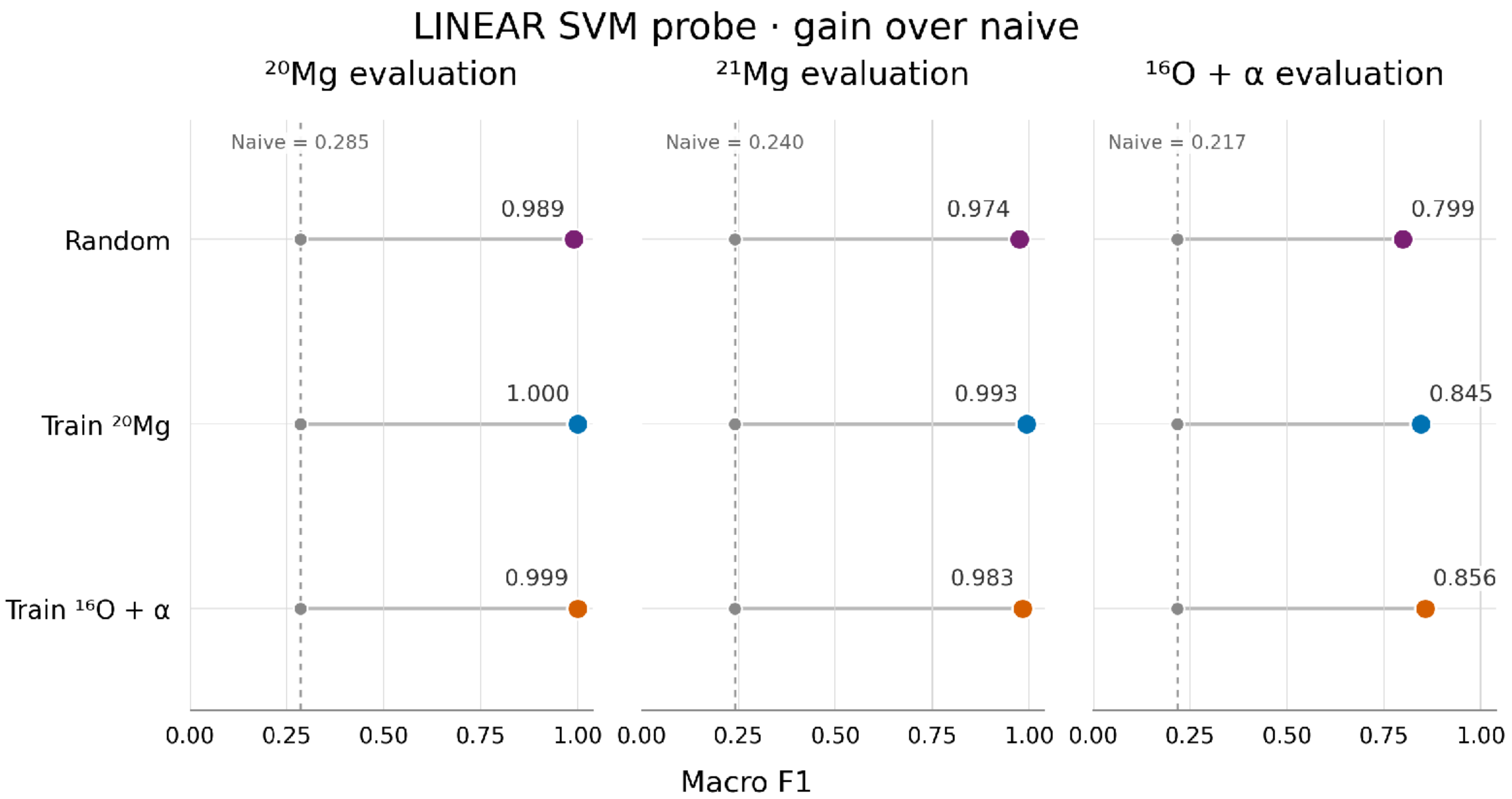
ME RESNET

Random


^{20}Mg

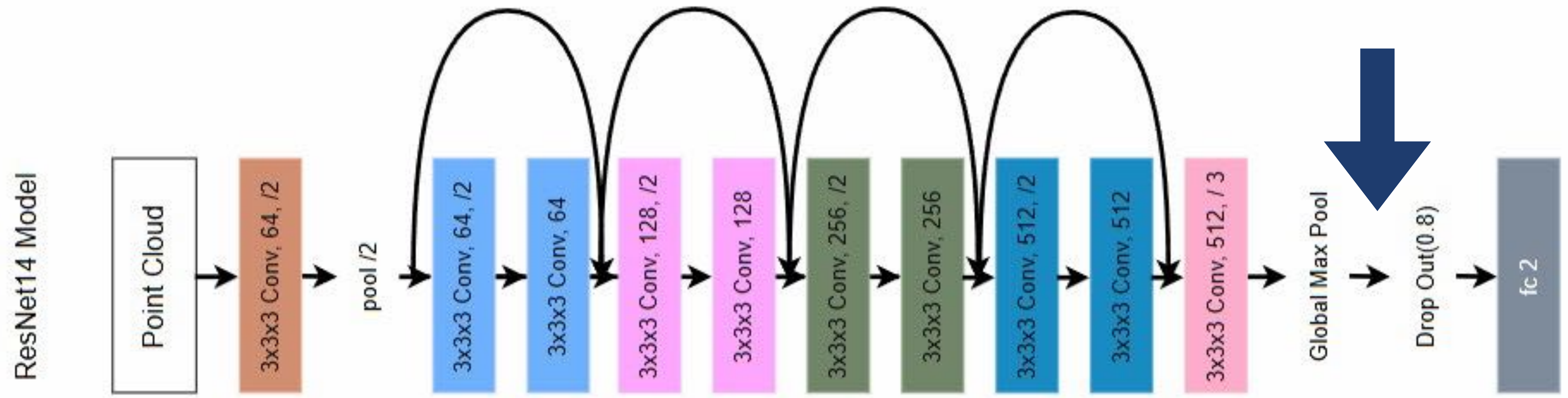

^{21}Mg


^{16}O + a

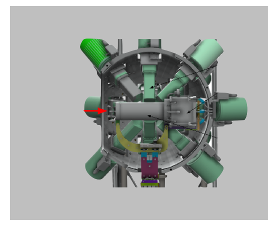
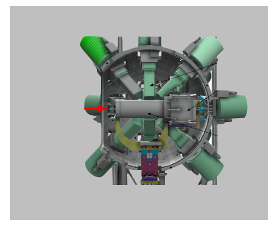
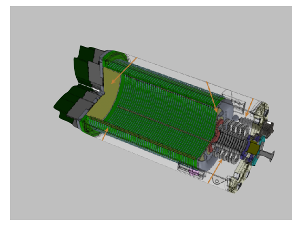


CAPACITY OF MODELS

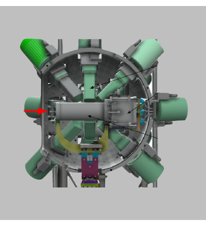
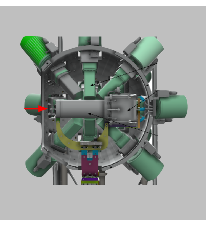
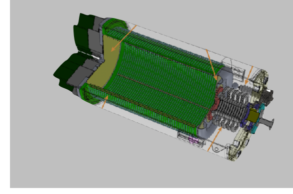
Architecture: Minkowski ResNet14



Training tasks:

Random	No training
 ^{20}Mg	2-class a v p
 ^{21}Mg	2-class a v p
 ^{16}O + a	3-class track counting

Evaluation tasks:

 ^{20}Mg	3-class a v p w/ energy
 ^{21}Mg	3-class a v p w/ energy
 ^{16}O + a	3-class track counting

Probe of embeddings:

PROBE	DESCRIPTION
Naive	**Mode Classifier**
Linear	**Linear Support Vector Machine**
Rbf	**Svm With Radial Basis Function Kernel**

CROSS-DETECTOR

MODEL

ME POINTNET

Random

^{20}Mg

^{21}Mg

^{16}O + a

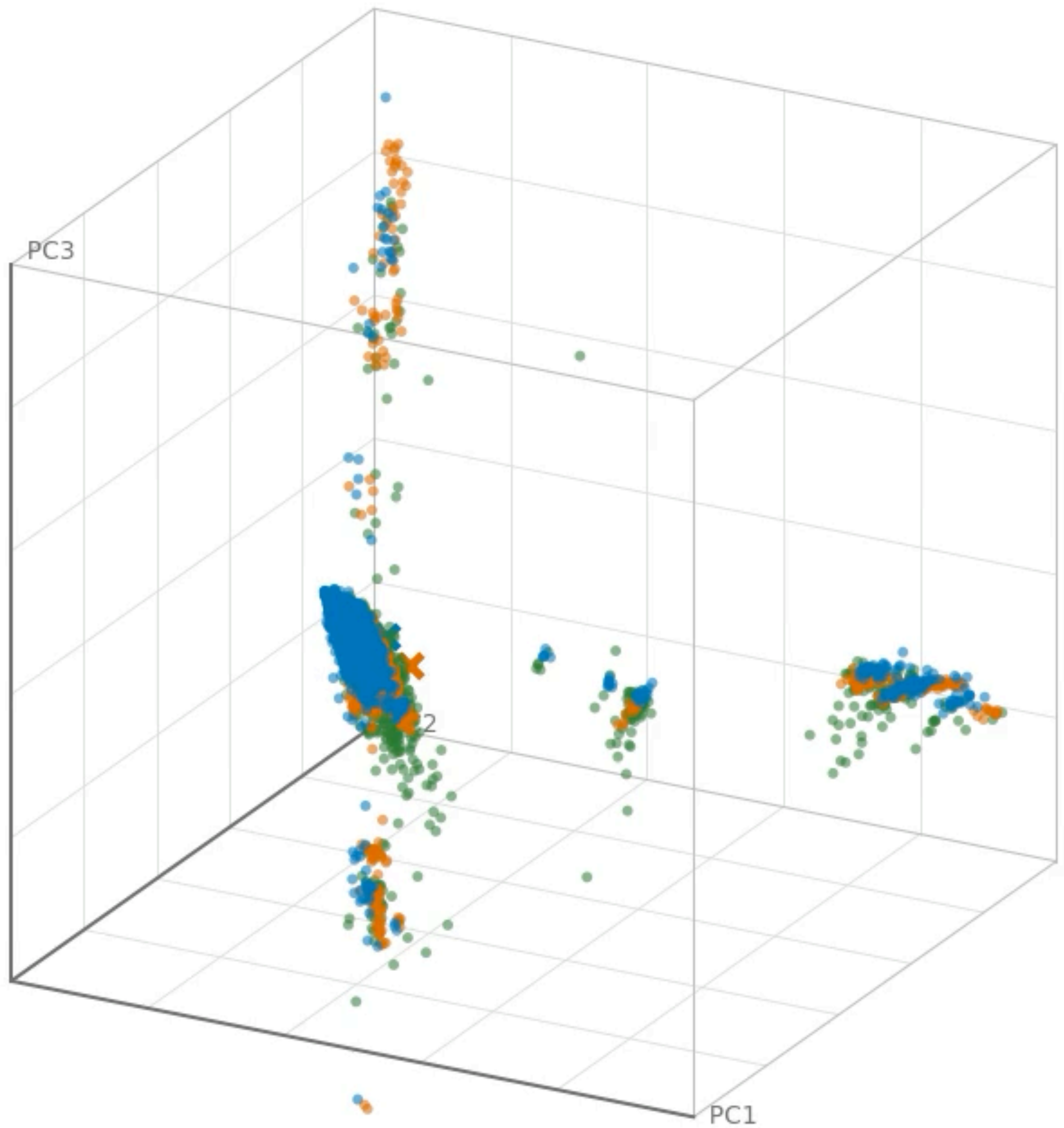
ME RESNET

Random

^{20}Mg

^{21}Mg

^{16}O + a



NO MODEL TRAINING

2200 keV alpha
800 keV proton
1600 keV proton

EVALUATION

^{20}Mg

^{21}Mg

^{16}O + a

Results from Liam Sieland

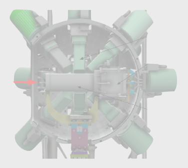
PROBE	ACCURACY	F1
Naive	0.747	0.285
Linear	0.927	0.880
Rbf	0.968	0.952

CROSS-DETECTOR

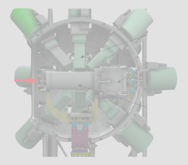
MODEL

ME POINTNET

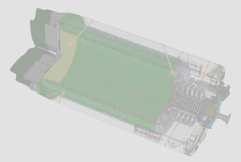
Random



^{20}Mg



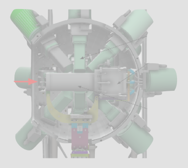
^{21}Mg



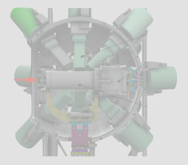
^{16}O + a

ME RESNET

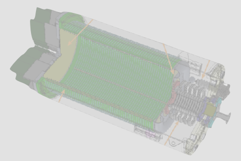
Random



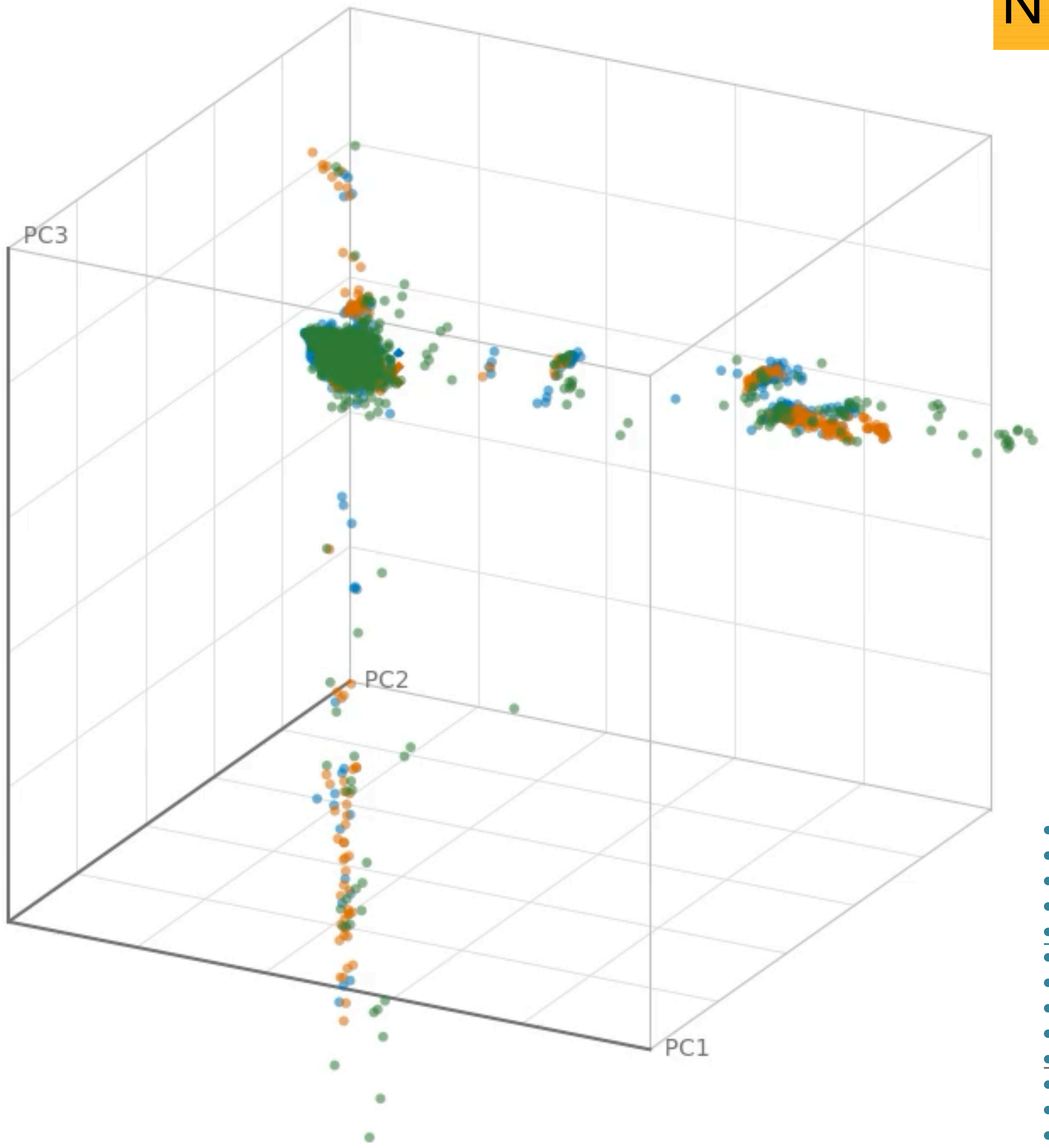
^{20}Mg



^{21}Mg



^{16}O + a



NO MODEL TRAINING

2200 keV alpha

1300keV proton

1900 keV proton

EVALUATION

^{20}Mg

^{21}Mg

^{16}O + a

Results from Liam Sieland

PROBE	ACCURACY	F1
Naive	0.563	0.240
Linear	0.842	0.785
Rbf	0.841	0.794

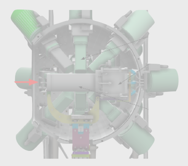
CROSS-DETECTOR

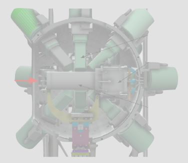
TING CROSS-DETECTOR EMBEDDINGS

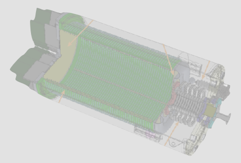
MODEL

ME POINTNET

Random

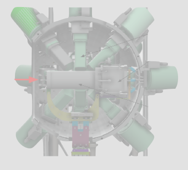

^{20}Mg

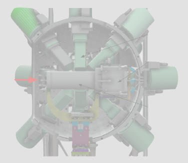

^{21}Mg

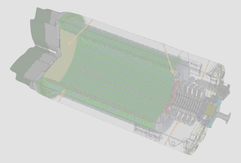

^{16}O + a

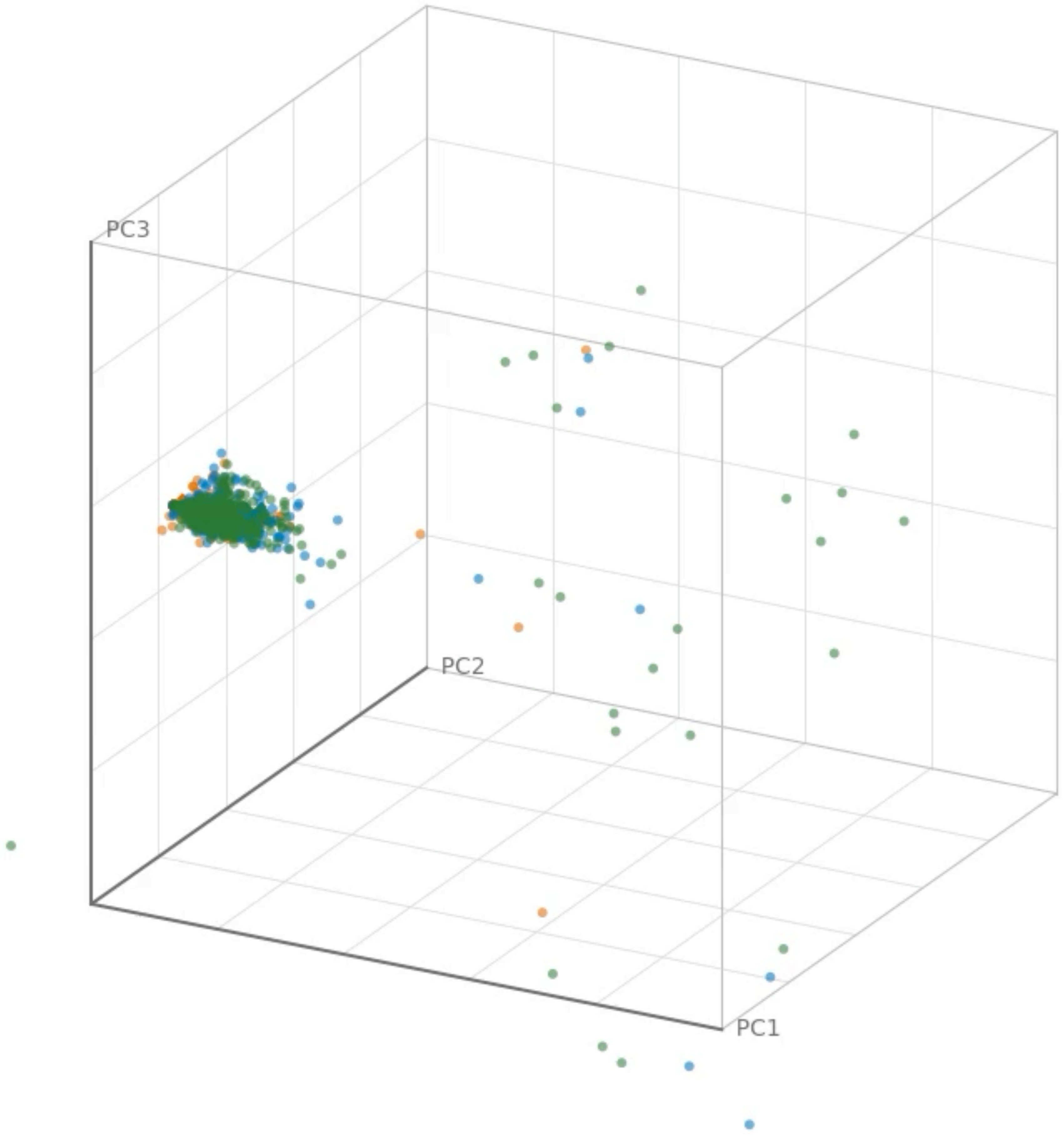
ME RESNET

Random


^{20}Mg


^{21}Mg


^{16}O + a



NO MODEL TRAINING

0,1,2 tracks

3 tracks

4,5 tracks

EVALUATION

^{20}Mg

^{21}Mg

^{16}O + a

Results from Liam Sieland

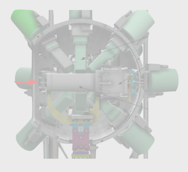
PROBE	ACCURACY	F1
Naive	0.482	0.217
Linear	0.639	0.481
Rbf	0.648	0.556

CROSS-DETECTOR

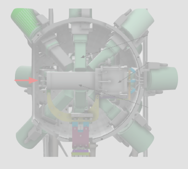
MODEL

ME POINTNET

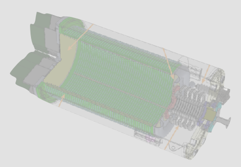
Random



^{20}Mg



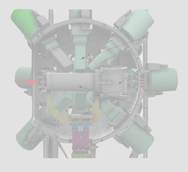
^{21}Mg



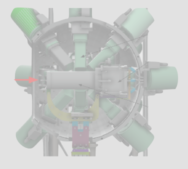
^{16}O + a

ME RESNET

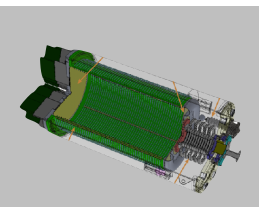
Random



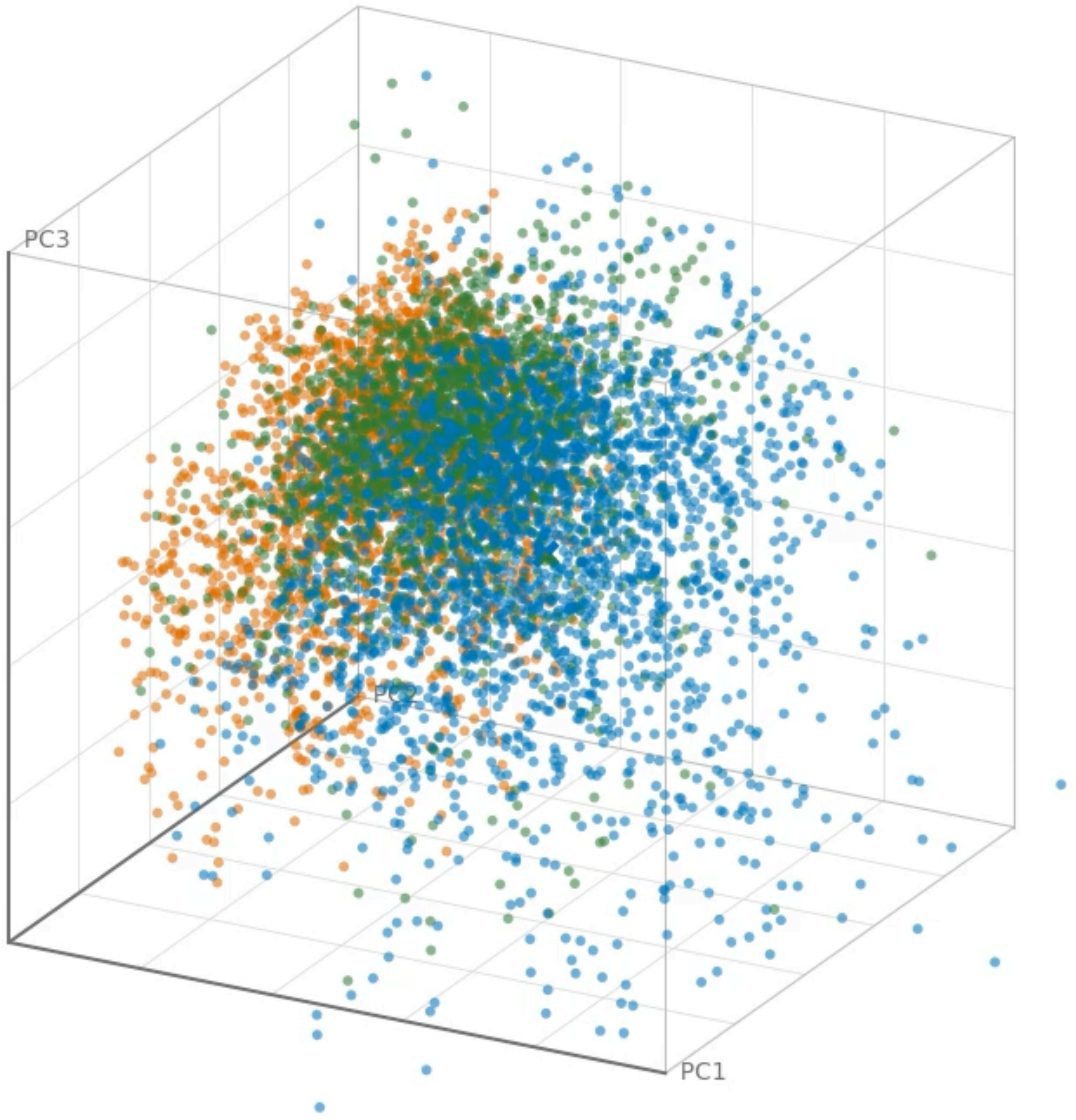
^{20}Mg



^{21}Mg



^{16}O + a



2200 keV alpha

800 keV proton

1600 keV proton

EVALUATION

^{20}Mg

^{21}Mg

^{16}O + a

Results from Liam Sieland

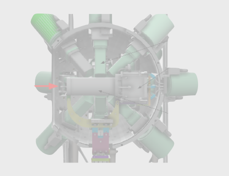
PROBE	ACCURACY	F1
Naive	0.747	0.285
Linear	0.989	0.984
Rbf	0.995	0.993

CROSS-DETECTOR

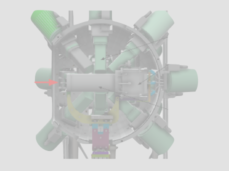
MODEL

ME POINTNET

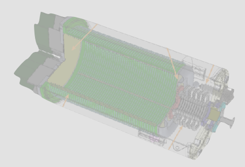
Random



^{20}Mg



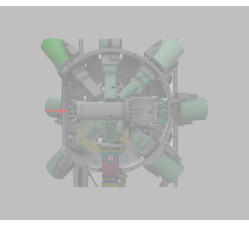
^{21}Mg



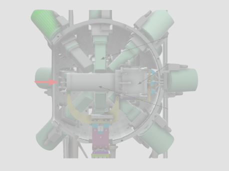
^{16}O + a

ME RESNET

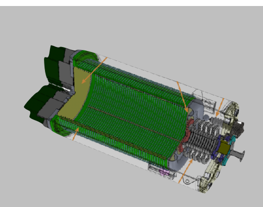
Random



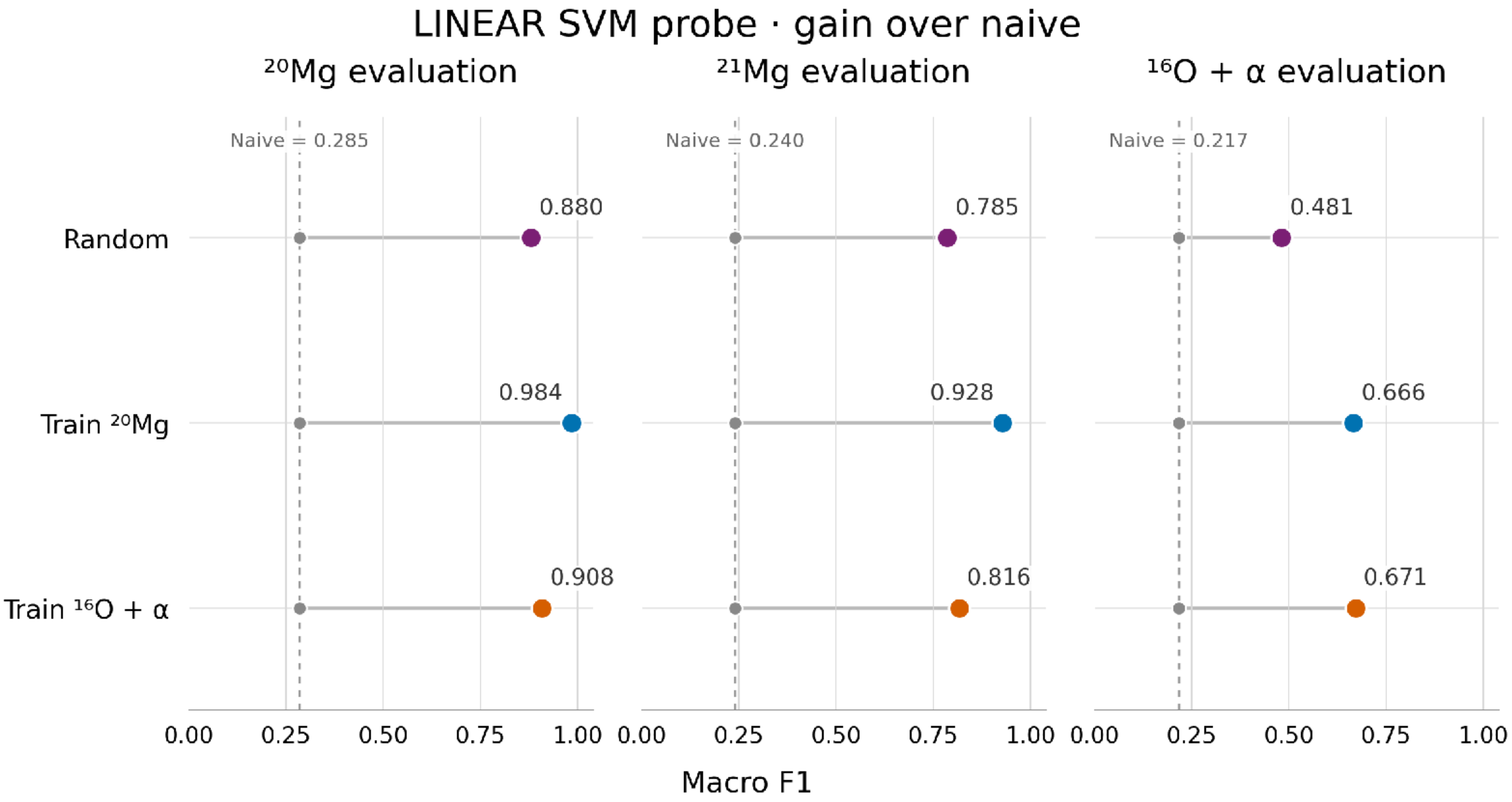
^{20}Mg



^{21}Mg



^{16}O + a



CROSS-DETECTOR

TAKEAWAYS

MODEL

ME POINTNET

- Random
- ^{20}Mg
- ^{21}Mg
- ^{16}O + a

ME RESNET

- Random
- ^{20}Mg
- ^{21}Mg
- ^{16}O + a

EVALUATION

- ^{20}Mg
- ^{21}Mg
- ^{16}O + a

- Architecture does a lot of work
- Choice of architecture affects embedding structure
- Training helps, always* (in domain, out of domain)
- Results [surprisingly] promising for cross-detector foundation models

New paper expected on the arXiv in coming weeks.

Sparse Methods for Vector Embeddings of TPC Data

Tyler Wheeler[1] Michelle P. Kuchera[2] Raghuram Ramanujan[2]
Ryan Krupp[1] Chris Wrede[1] Saiprasad Ravishankar[1]
Connor L. Cross[2] Hoi Yan Ian Heung[2] Andrew J. Jones[2] Benjamin Votaw[2]
[1] Michigan State University [2] Davidson College
wheele56@msu.edu {mikuchera,raramanujan}@davidson.edu
{krupprya,wrede,ravisha3}@msu.edu
{cocross,iaheung,anjones1,bevotaw}@davidson.edu

MOTIVATION	Foundation model approaches are well suited to NP data analysis
CROSS-EXPERIMENT	Pretrained backbones can be helpful for a variety of experiments and tasks
CROSS-DETECTOR	Deep learning architectures have capacity for cross-detector foundation models
TAKEAWAYS	We can all benefit from these approaches, we plan to release the models shown here. Incorporating more diverse data helps ;)

THANK YOU!

- Raghu Ramanujan and the Davidson ALPhA crew
- The AT-TPC Group, GADGET group
- Broader TPC collaborators

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