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NUCLEAR
ENGINEERING

A Multi-Step Machine Learning Approach to Directional Gamma Ray Detection

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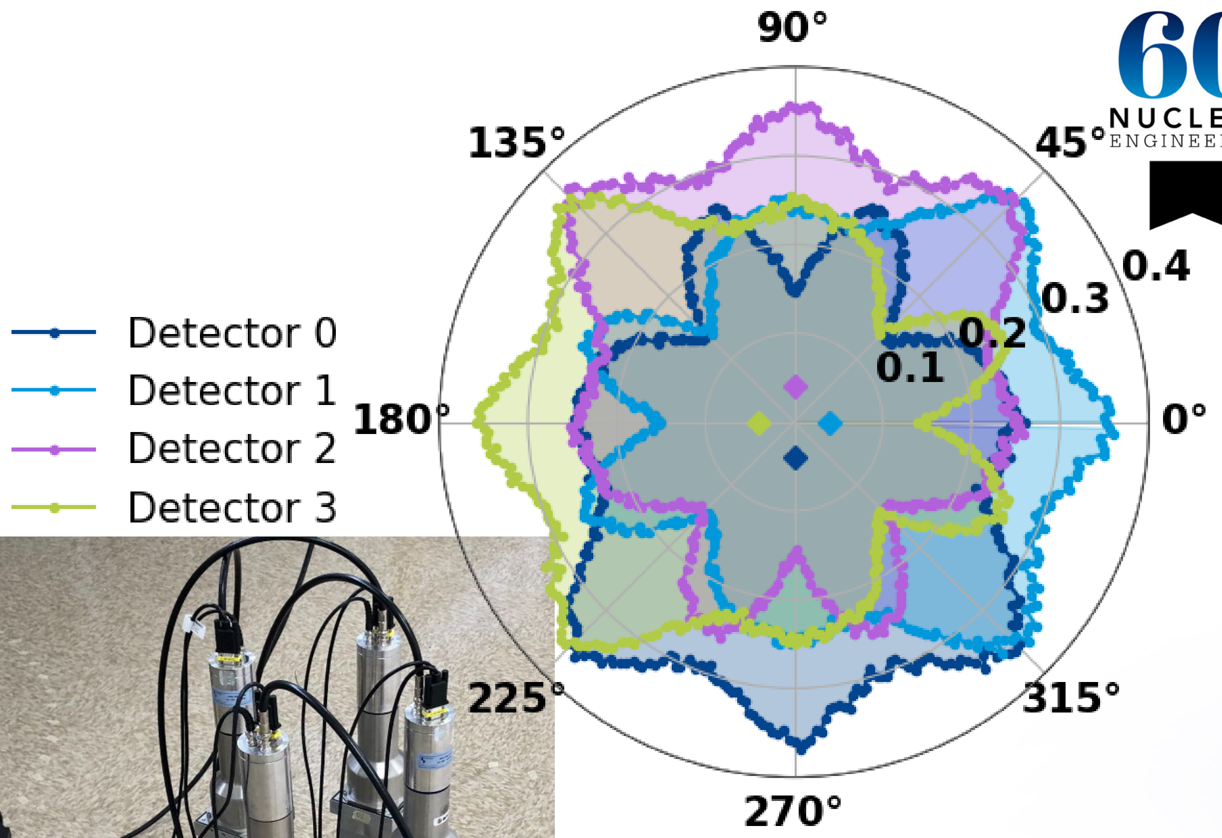
Directional Detection

- Source direction determined by analyzing the distribution of counts across an array of detectors
  - Based on differences in solid angle and self occlusion

- Applications:
  - Urban Search
  - Public Events
  - Ports/Borders

- Bounds of this work:
  - Stationary source and detector array
  - Predicting the source angle on 2D Plane
  - Four 2x4x16 inch NaI detectors



Simulated angular response to a source at 3 m

Detector Array

Minimum Least Squares/Reference Table (LSRT)

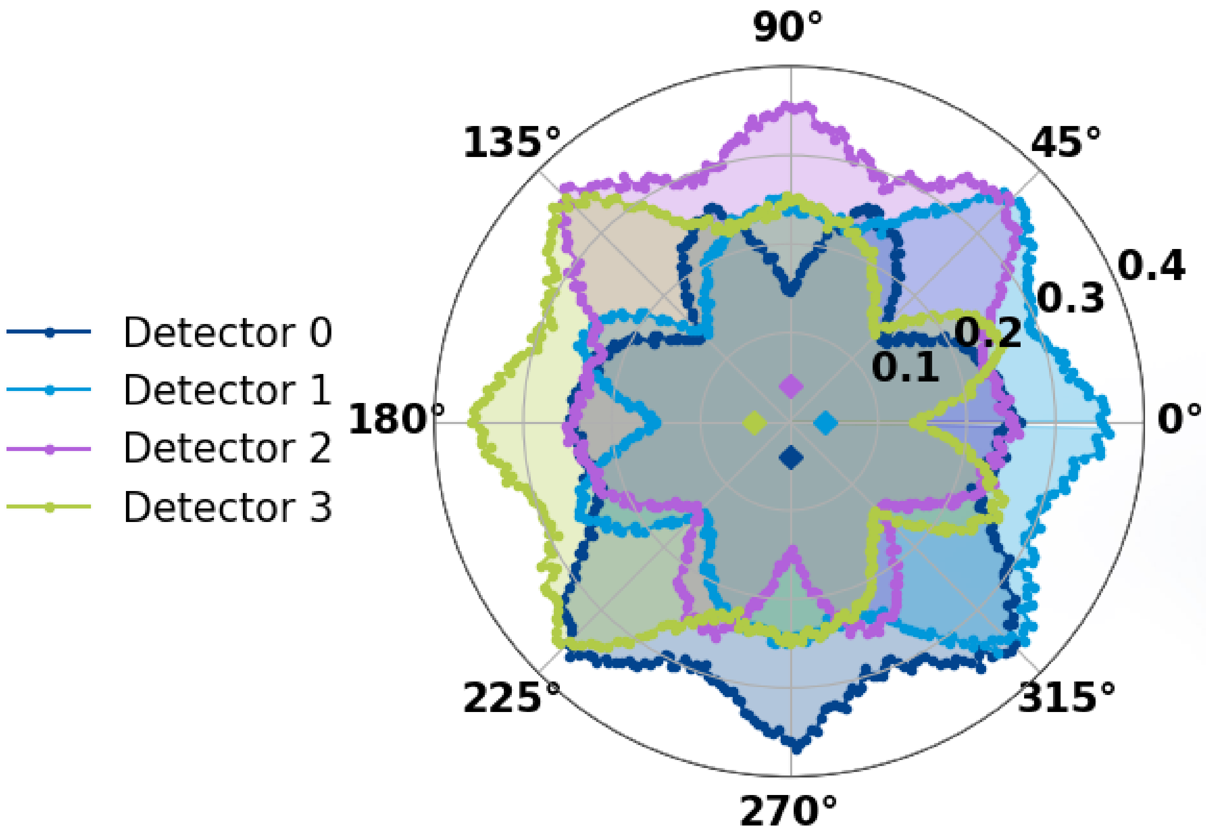
- Technique in directional detection literature
- Comparison to a prepopulated database of different angles at the same radius

Assumption:

$$R = f(\theta)$$

R: Response

Θ: Source Angle



Simulated angular response to a source at 3 m

Minimum Least Squares/Reference Table (LSRT)

- Technique in directional detection literature
- Comparison to a prepopulated database of different angles at the same radius

Reality:

$$R = f(\theta, r, E, O, N, \ldots)$$

R: Response

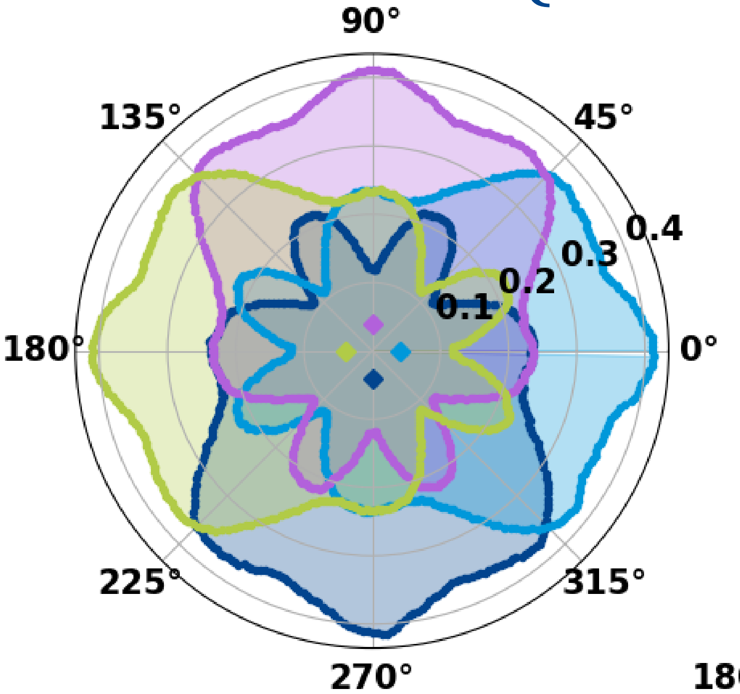
Θ: Source Angle

r: Radial distance

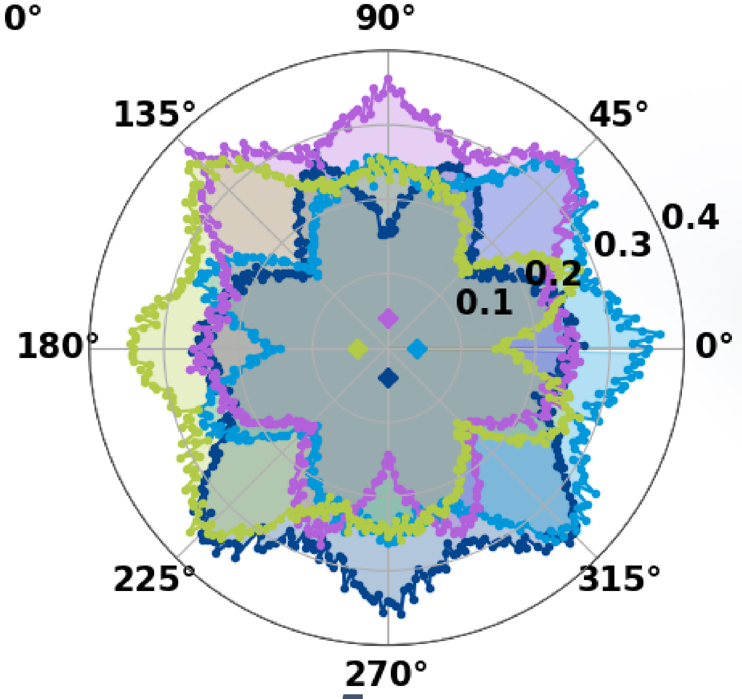
E: Energy

O: Obstructions/Environment

N: Noise



1 m



5 m

Minimum Least Squares/Reference Table (LSRT)

- Technique in directional detection literature
- Comparison to a prepopulated database of different angles at the same radius

Reality:

$$R = f(\theta, r, E, O, N, \ldots)$$

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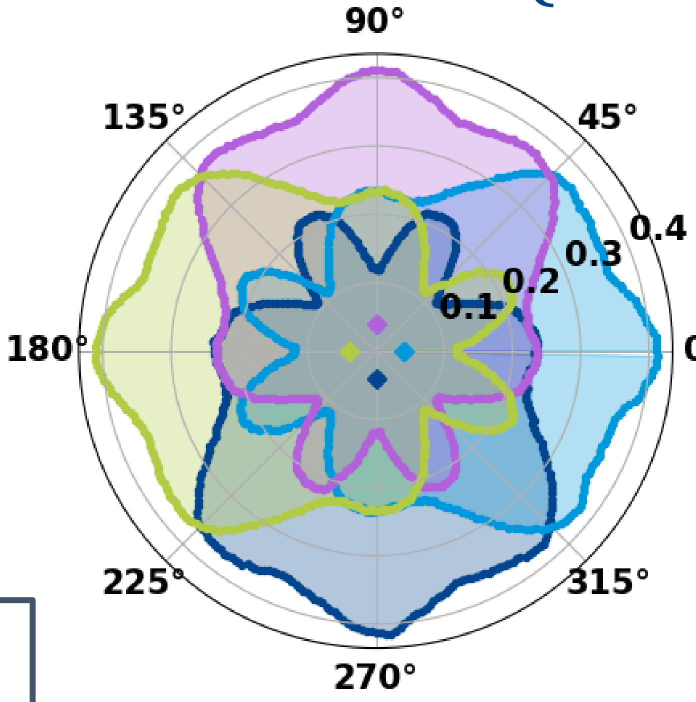
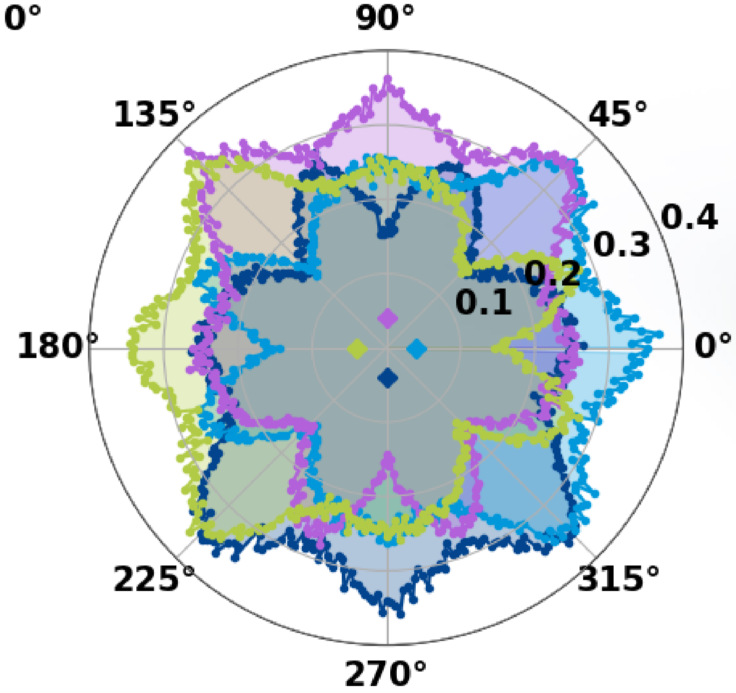
N: Noise

Can Machine Learning (ML) better capture this function?



1 m

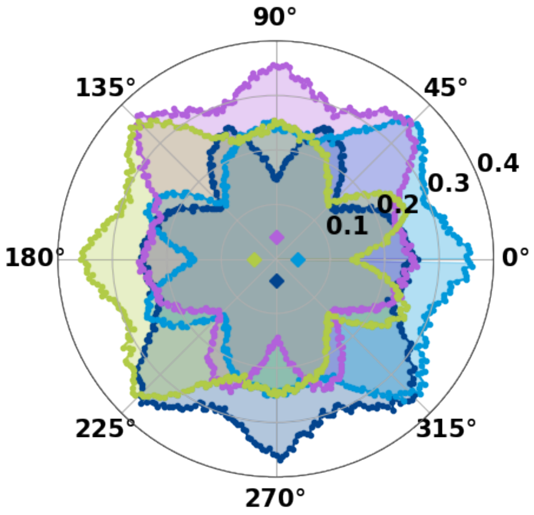


5 m

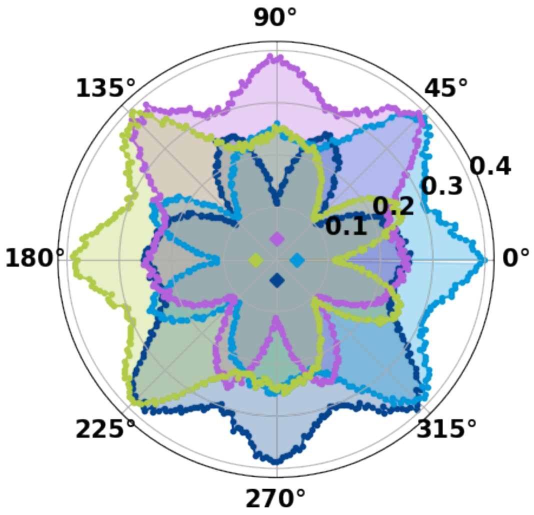
Energy Dependence

- Previous work showed that a ML can outperform the LSRT on the tested datasets
  - Better capturing of radius[1]
  - Better handling of obstructions[2]
- Energy has a notable effect on the response, and needs to be addressed

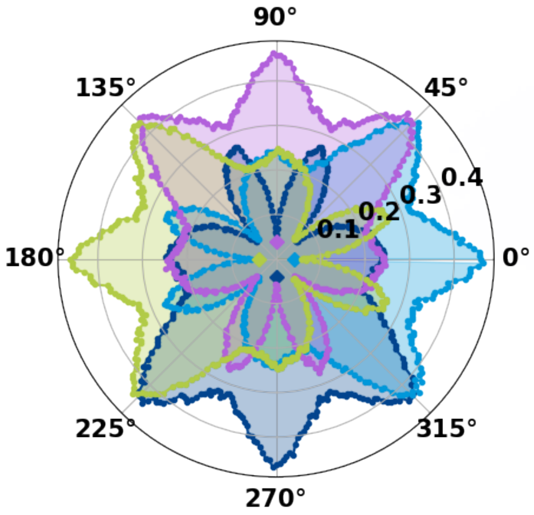
$$R = f(\theta, r, \boldsymbol{E}, O, N, \dots)$$



^{60}Co – 1.25 MeV



^{137}Cs – 0.66 MeV

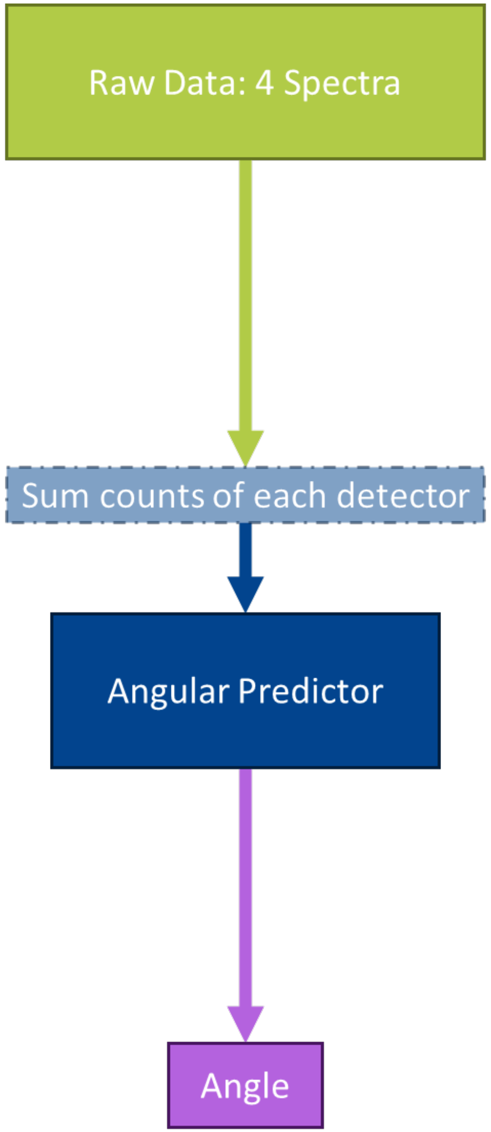


^{192}Ir – 0.32 MeV

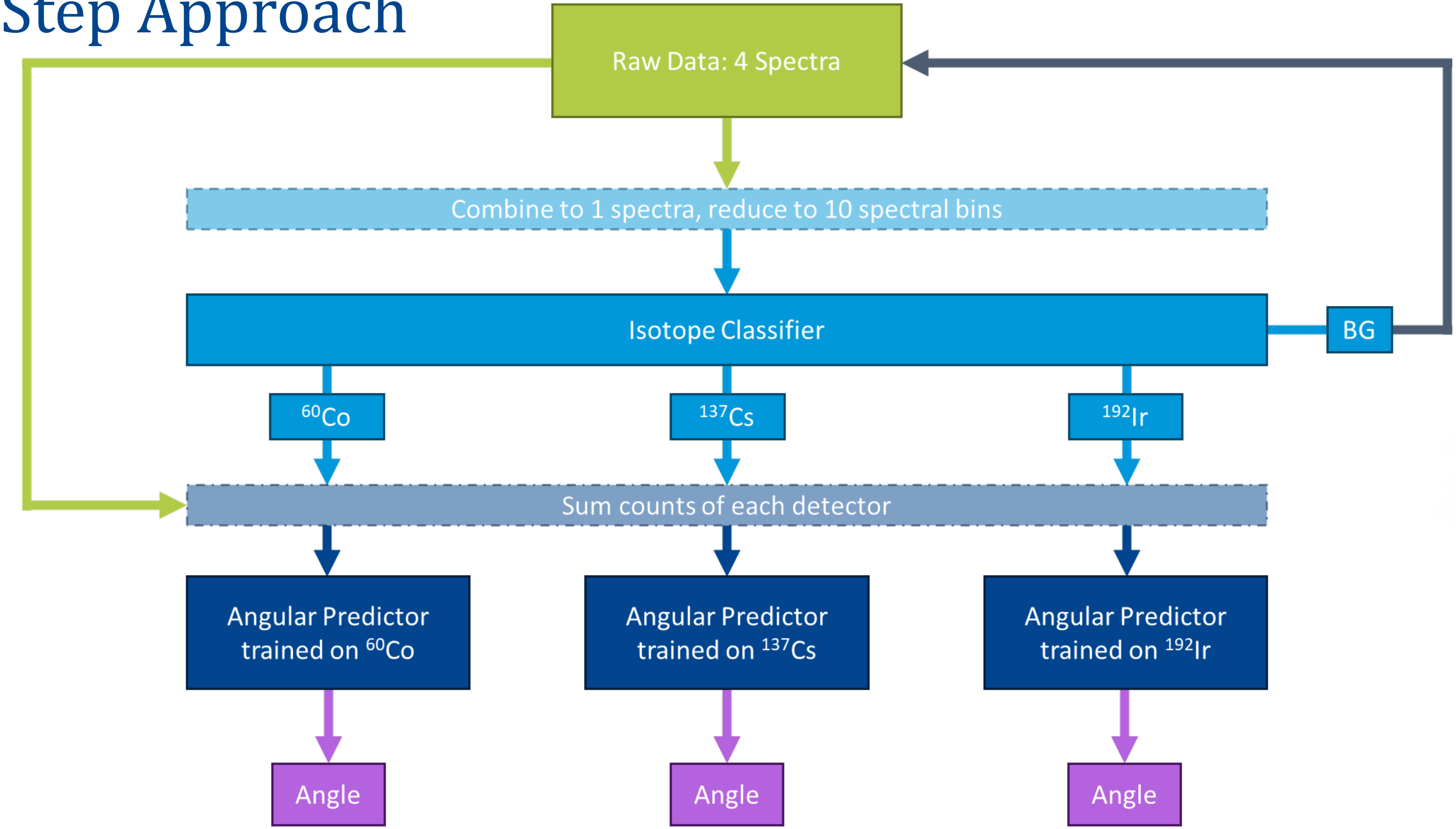
[1]*M. Durbin, et. al.*, "Development of a fully connected residual neural network for directional gamma ray detection." Int. Jrnl. Mod. Phys: Conf. Series., **50** (2020)

[2]*M. Durbin, et. al., "Development of machine learning algorithms for directional gamma ray detection." Proc. INMM Annual Meeting (2019)*

Multi-Step Approach

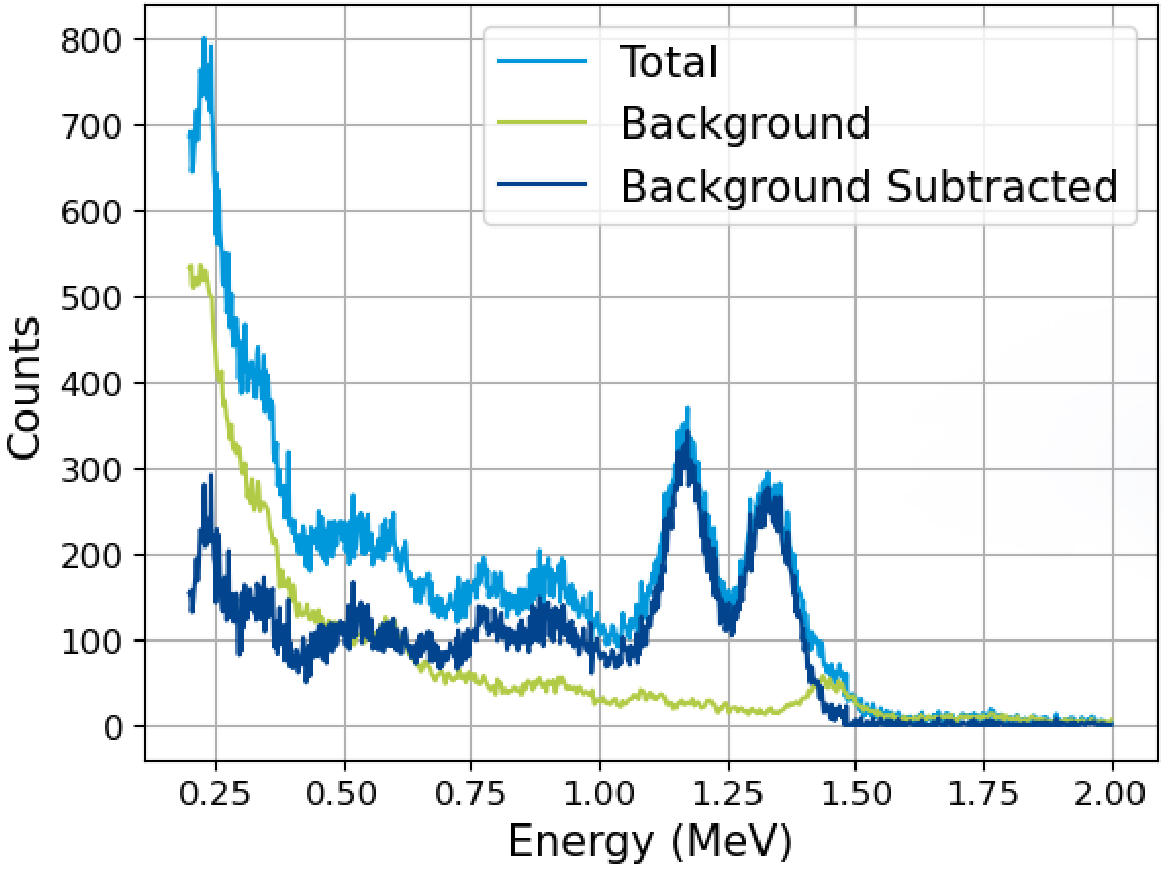


Multi-Step Approach



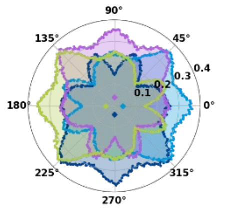
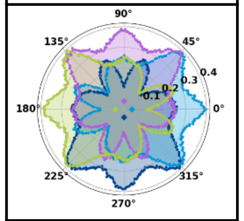
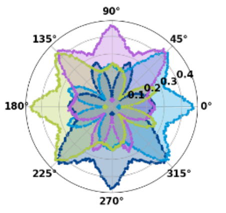
Datasets

- 3 Datasets: 10,000 MCNP simulated trials of each ^{60}Co, ^{137}Cs, and ^{192}Ir at random locations 1-5 m away from the array center
- Correlated to two-minute counts of 100 µCi sources
- Gaussian energy broadening applied, and background spectra with Poisson sampled noise injected based on laboratory measurements
- All spectra background subtracted



Investigation of Energy Dependence

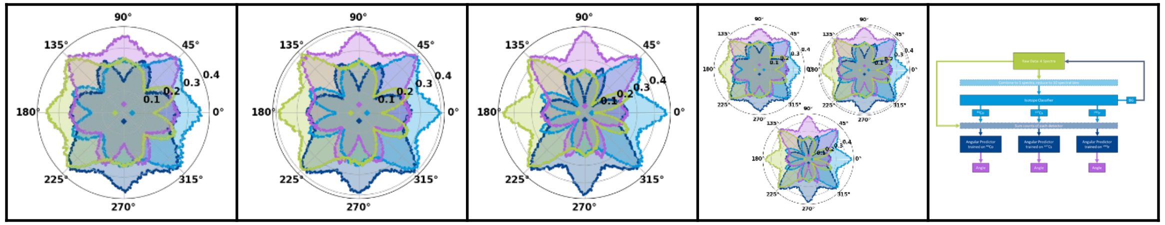
Testing Dataset

^{60}Co	
^{137}Cs	
^{192}Ir	
Overall	(average)

Investigation of Energy Dependence

Training Dataset/Approach

^{60}Co	^{137}Cs	^{192}Ir	Combined	Multi-Step



Investigation of Energy Dependence

Training Dataset/Approach

^{60}Co | ^{137}Cs | ^{192}Ir | Combined | Multi-Step

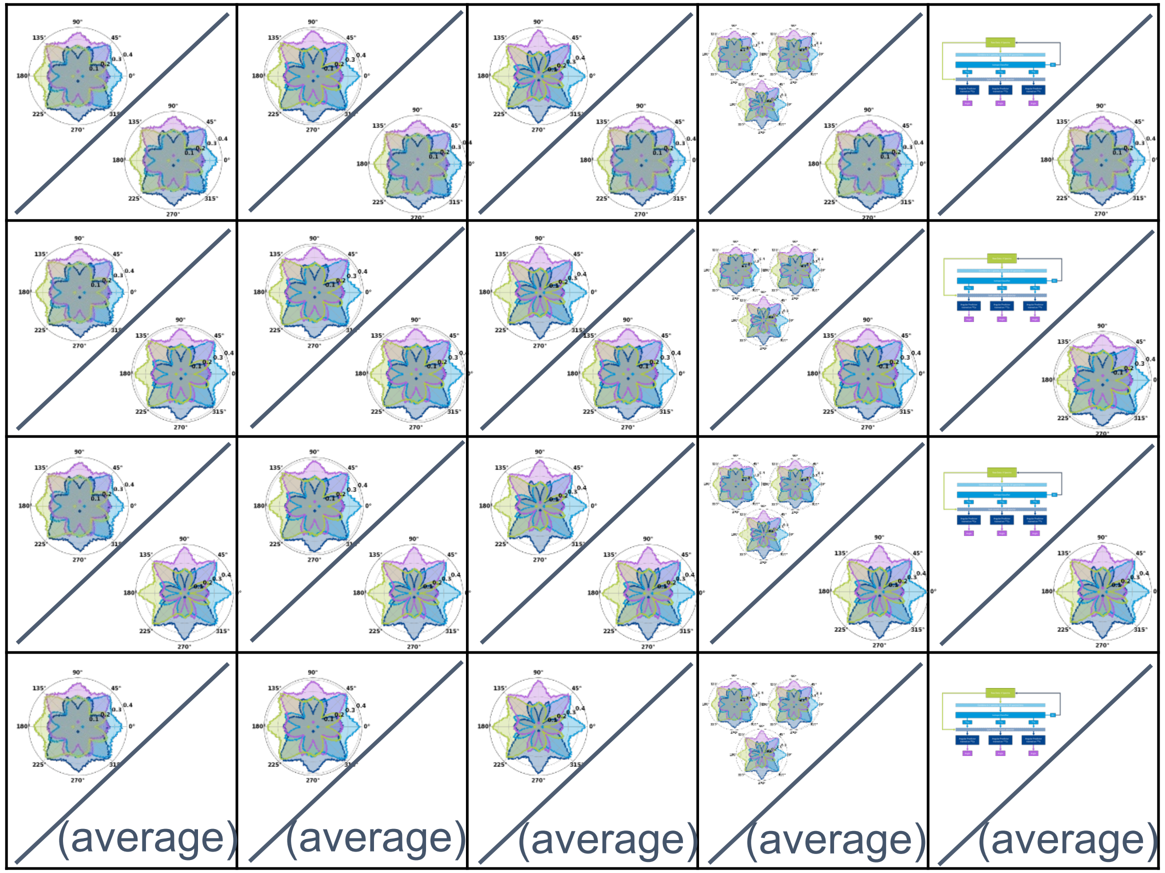
Testing Dataset

^{60}Co

^{137}Cs

^{192}Ir

Overall



Investigation of Energy Dependence

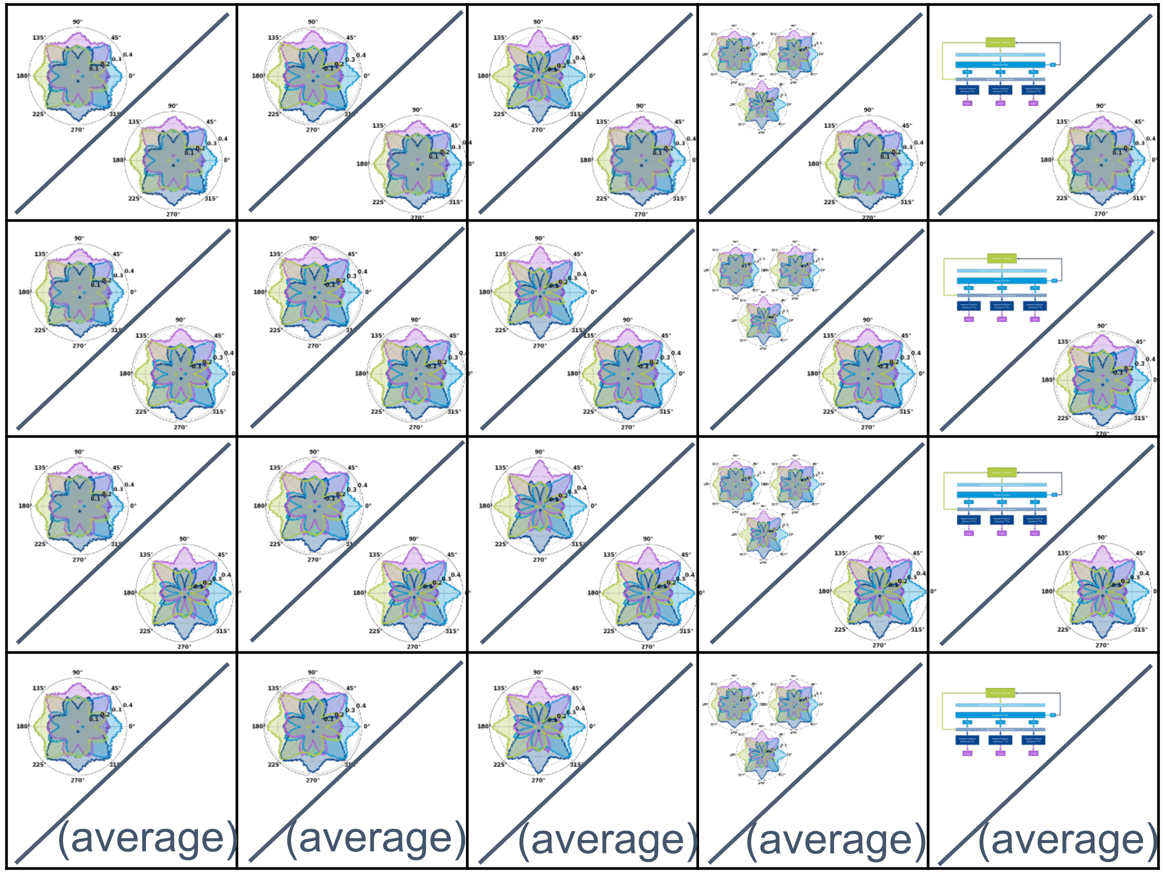
Repeat for LSRT

Training Dataset/Approach

^{60}Co | ^{137}Cs | ^{192}Ir | Combined | Multi-Step

Testing Dataset

^{60}Co
^{137}Cs
^{192}Ir
Overall



Metrics

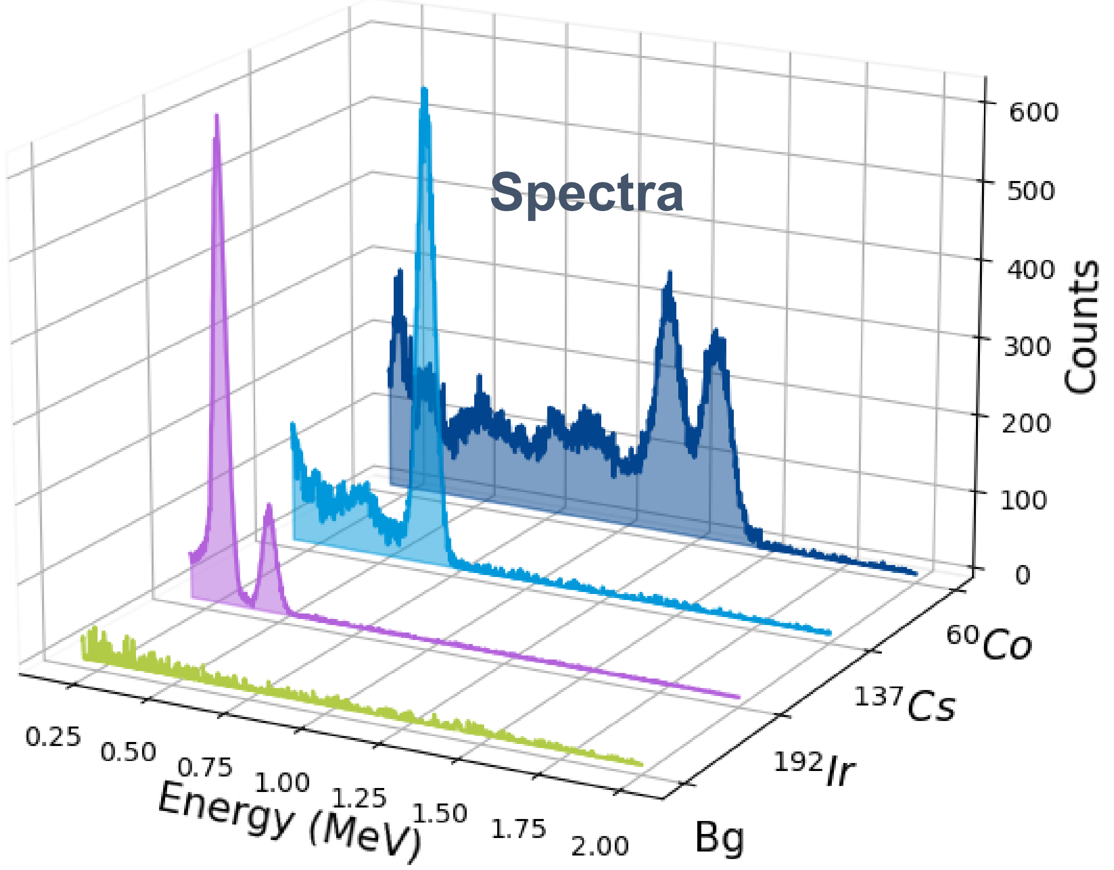
Accuracy: Percentage of correct angular predictions

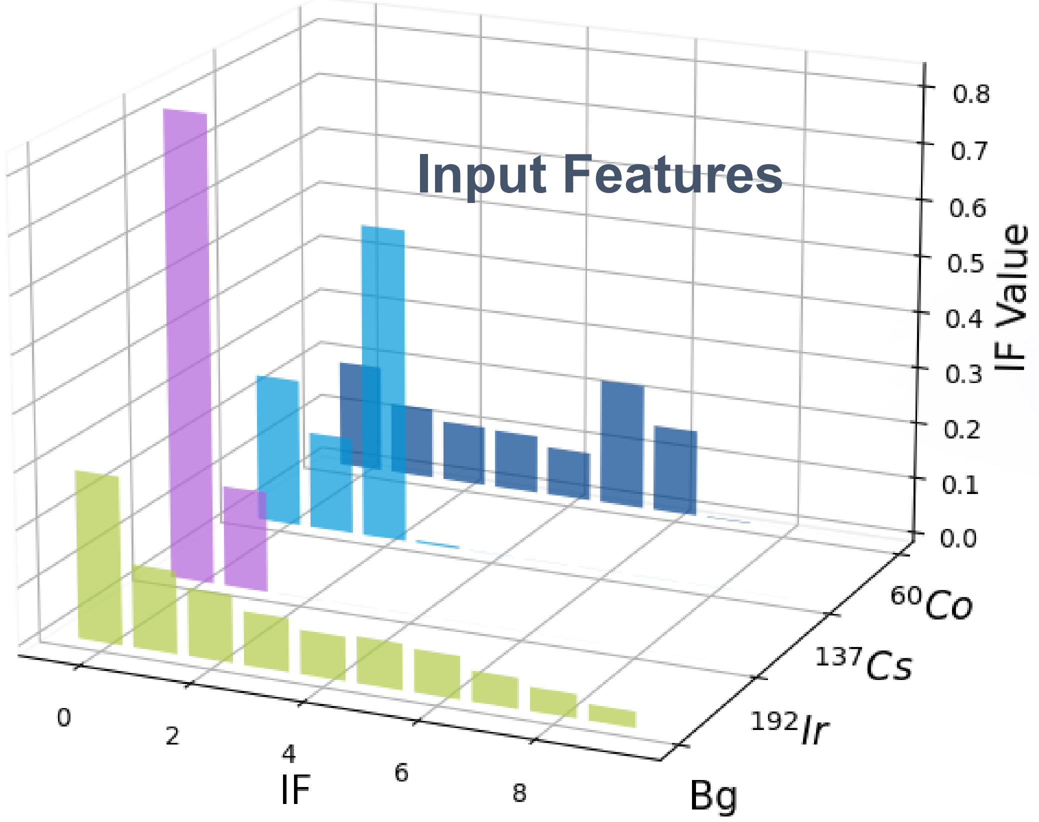
Average Angular Error: On the average, how off were the predictions

K-Fold Cross Validation: Mitigates the effects of a "lucky" shuffle/divide

Isotope Classification

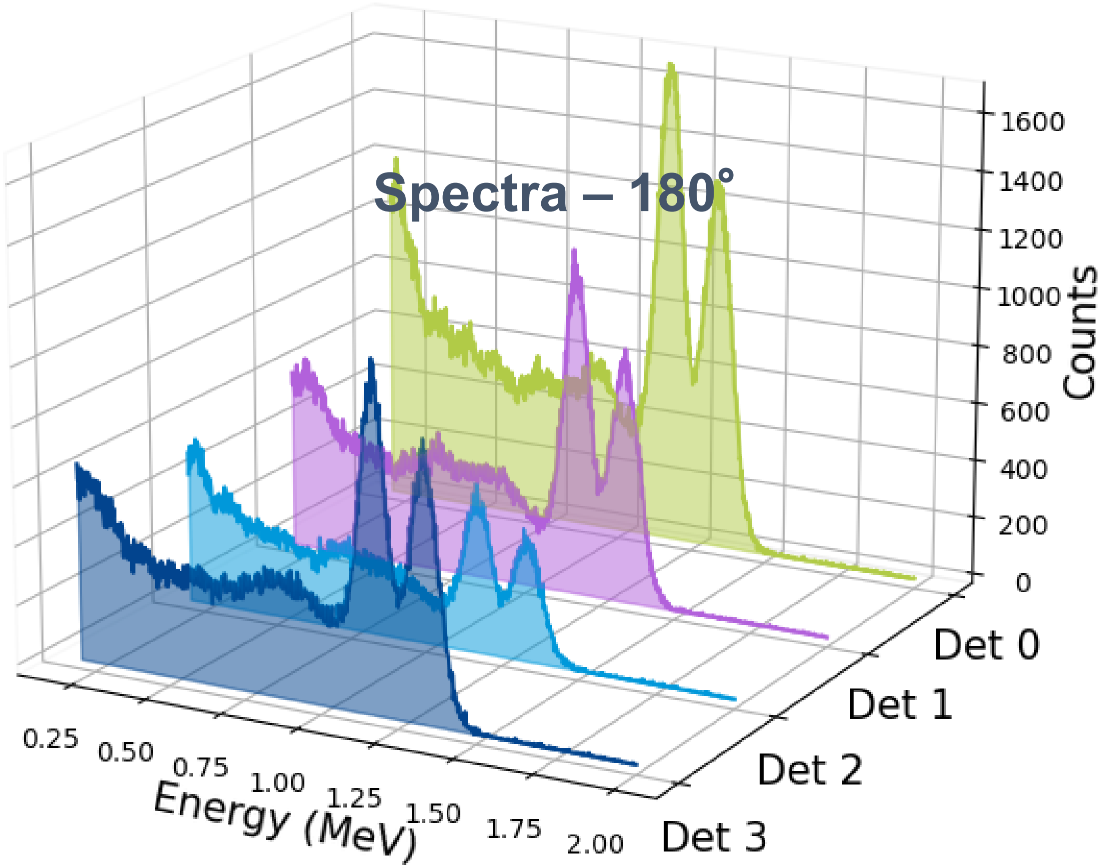
Four class KNN classifier with 10 spectral bins as input features, summed across all detectors

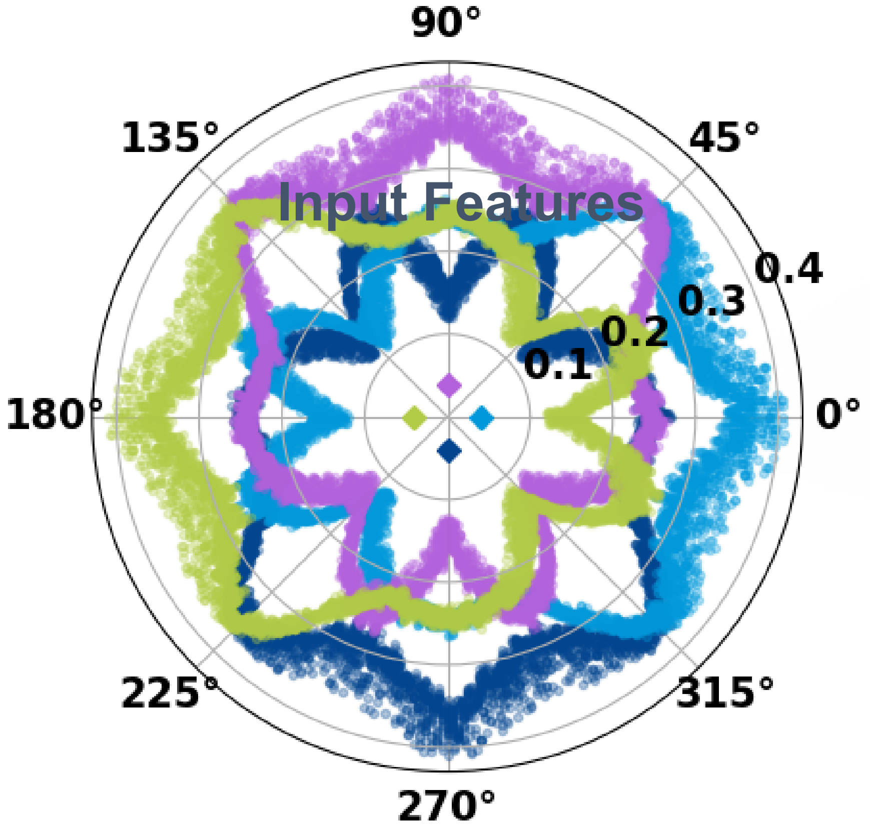




Angular Prediction

360 class KNN classifier with the sum of each detector as an input feature





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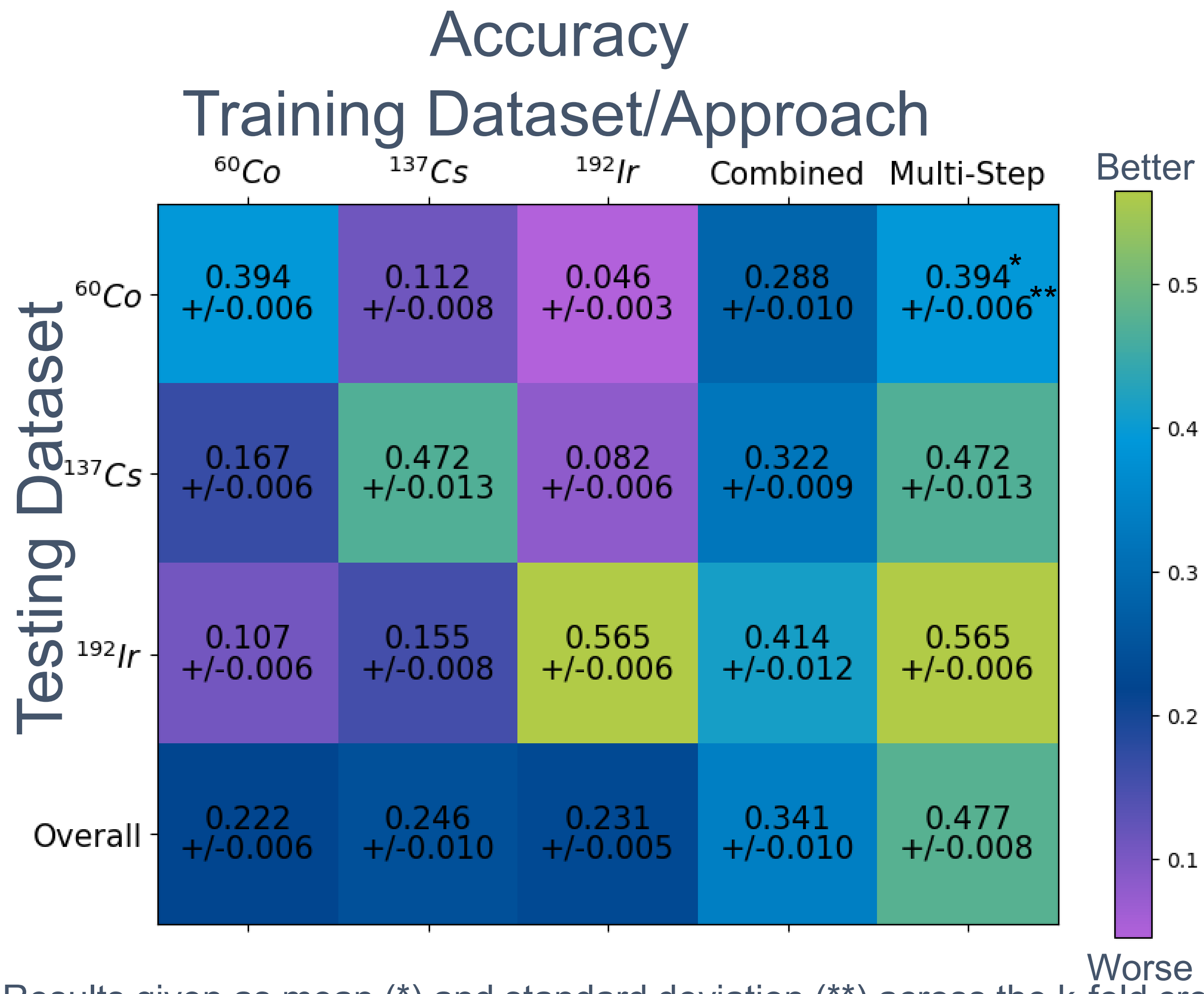
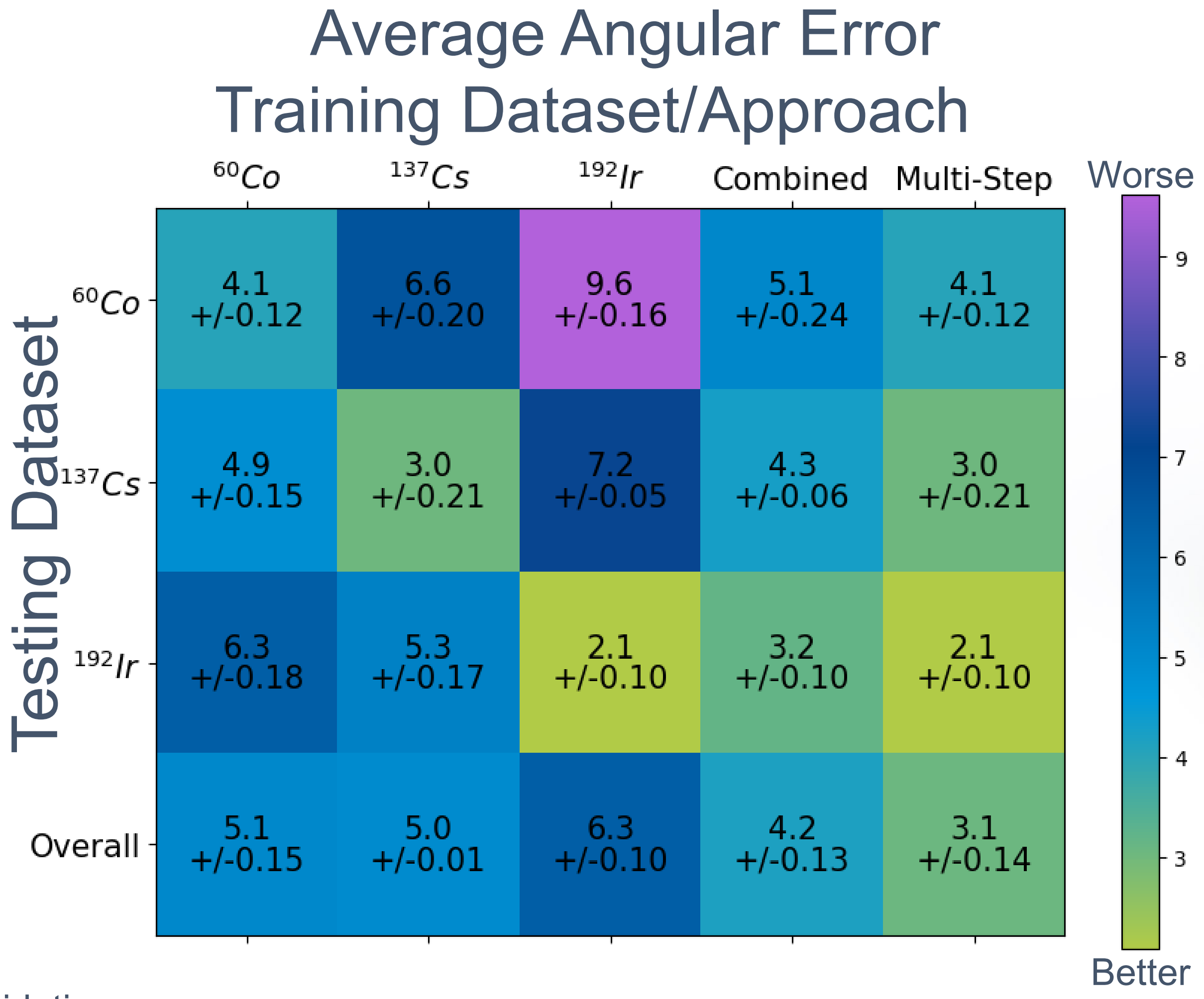
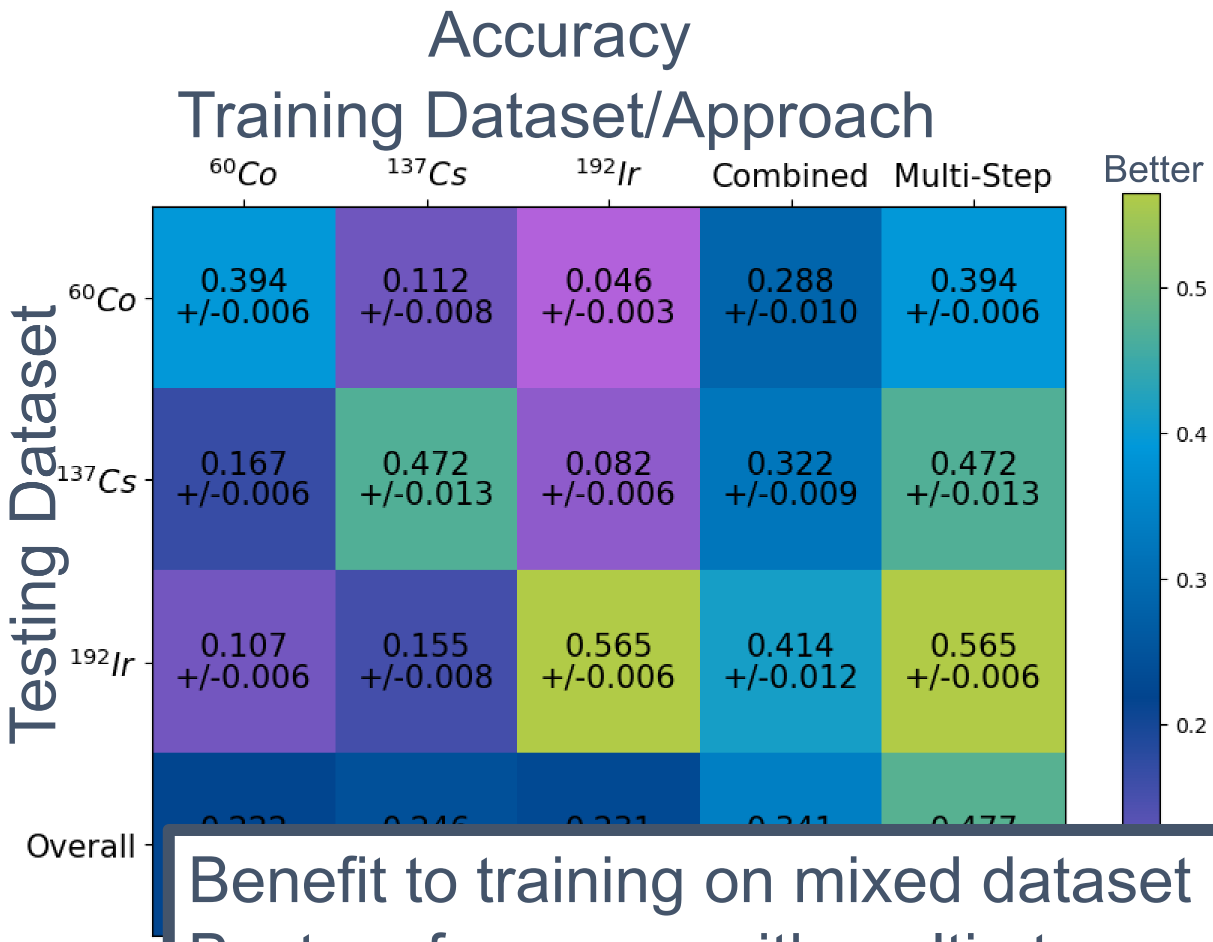
Results

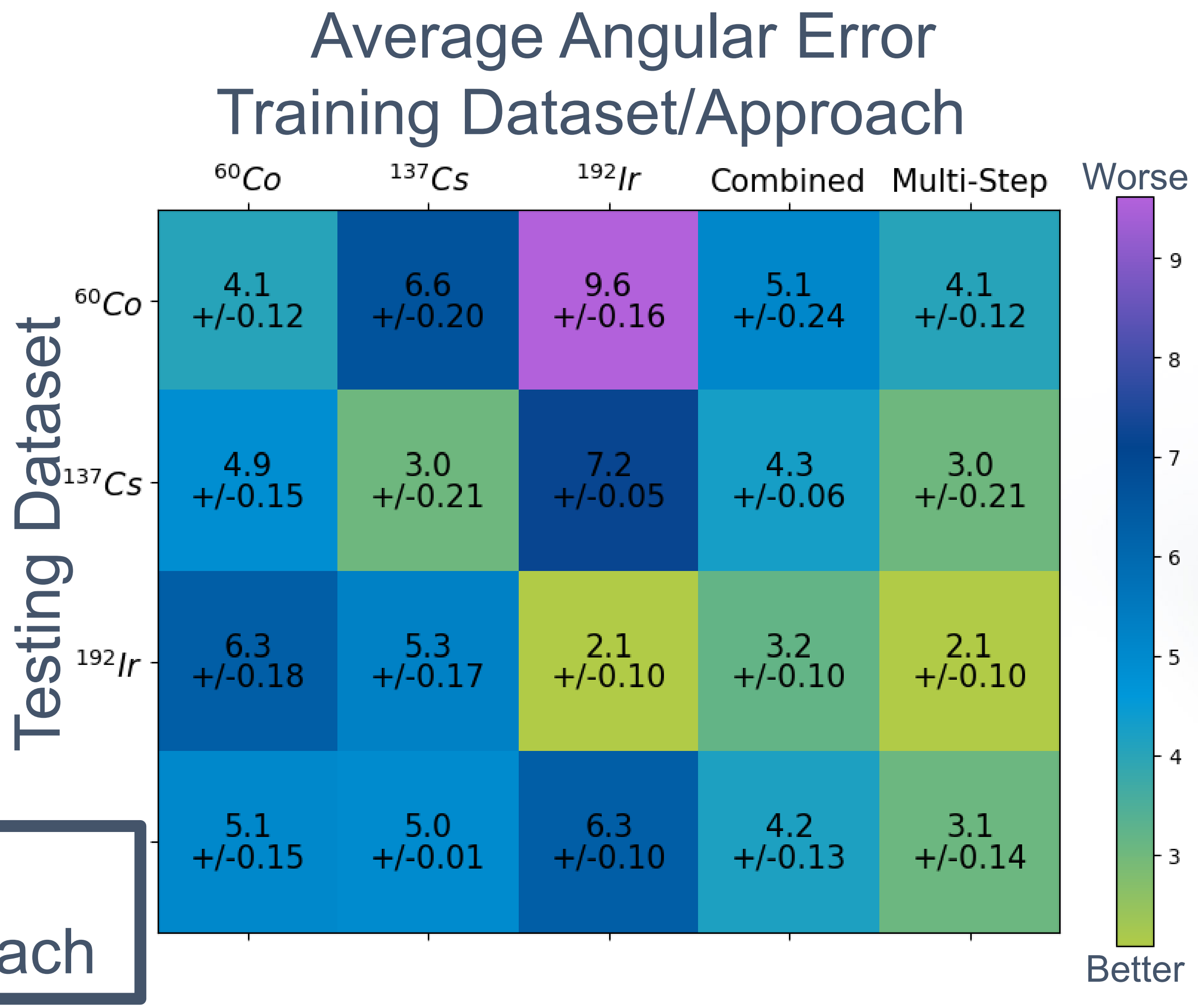




Results given as mean (*) and standard deviation (**) across the k-fold cross validation

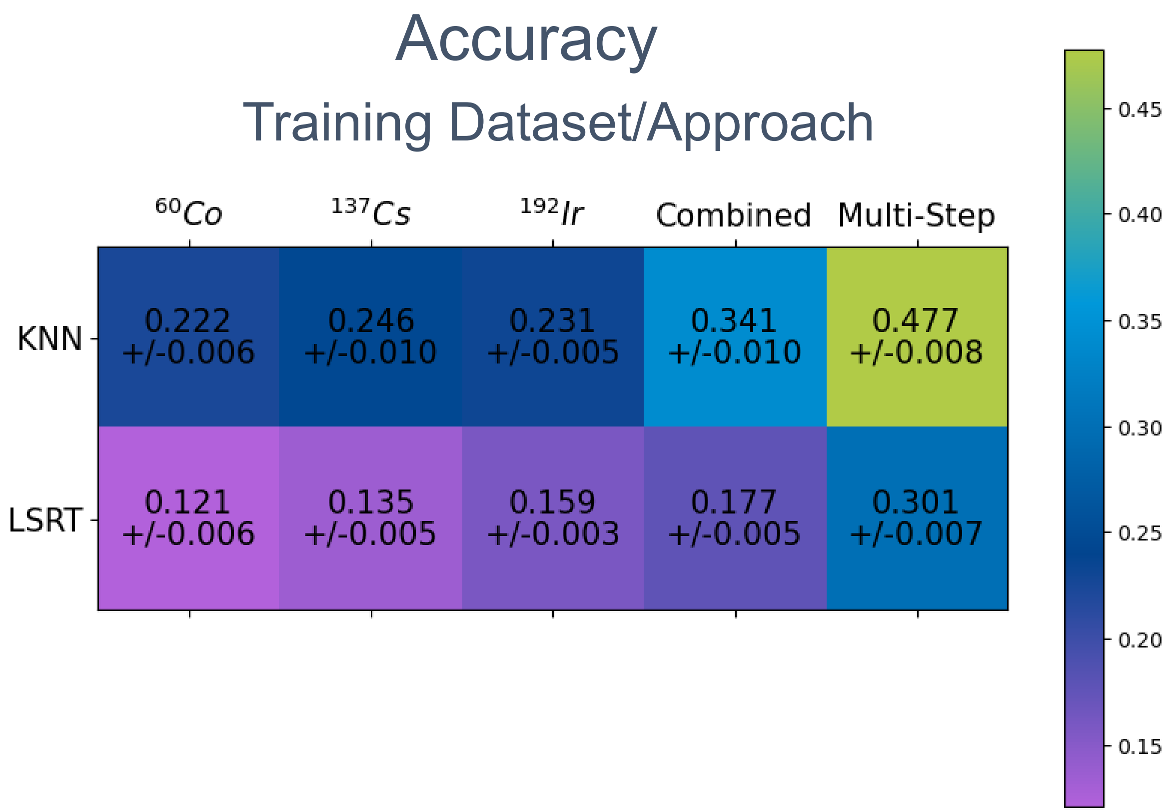
Results

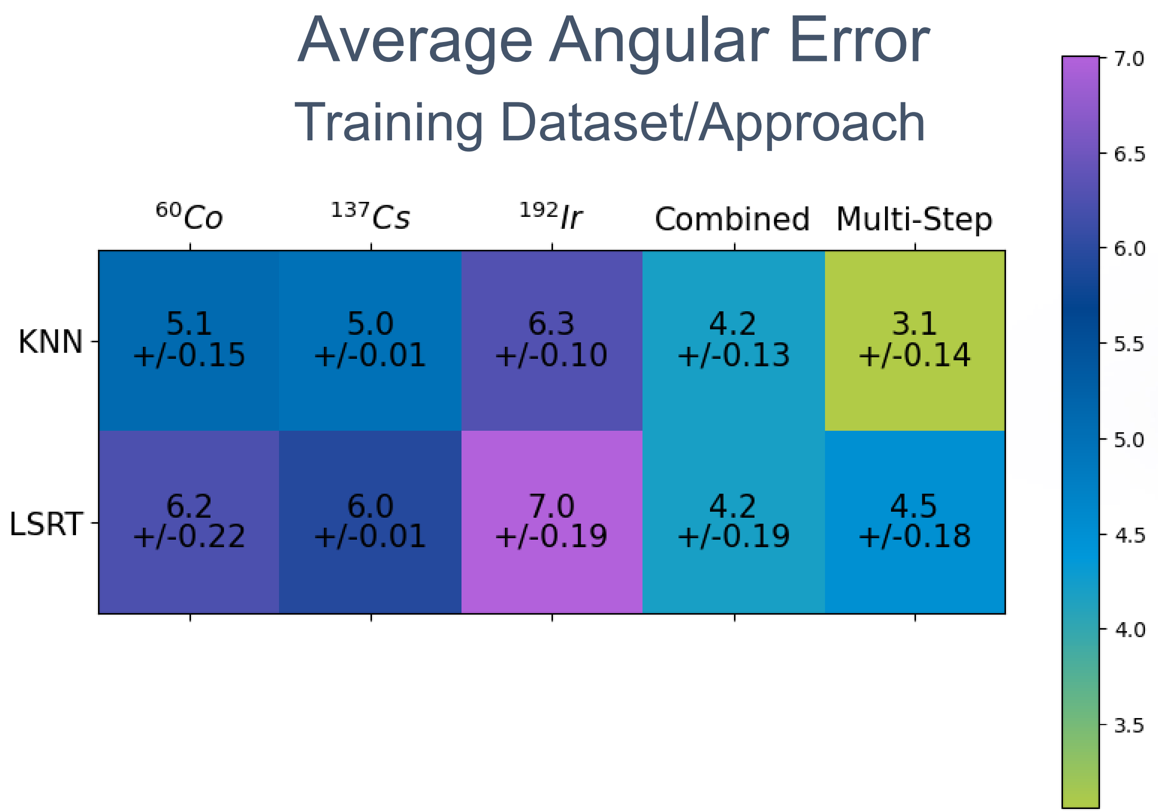




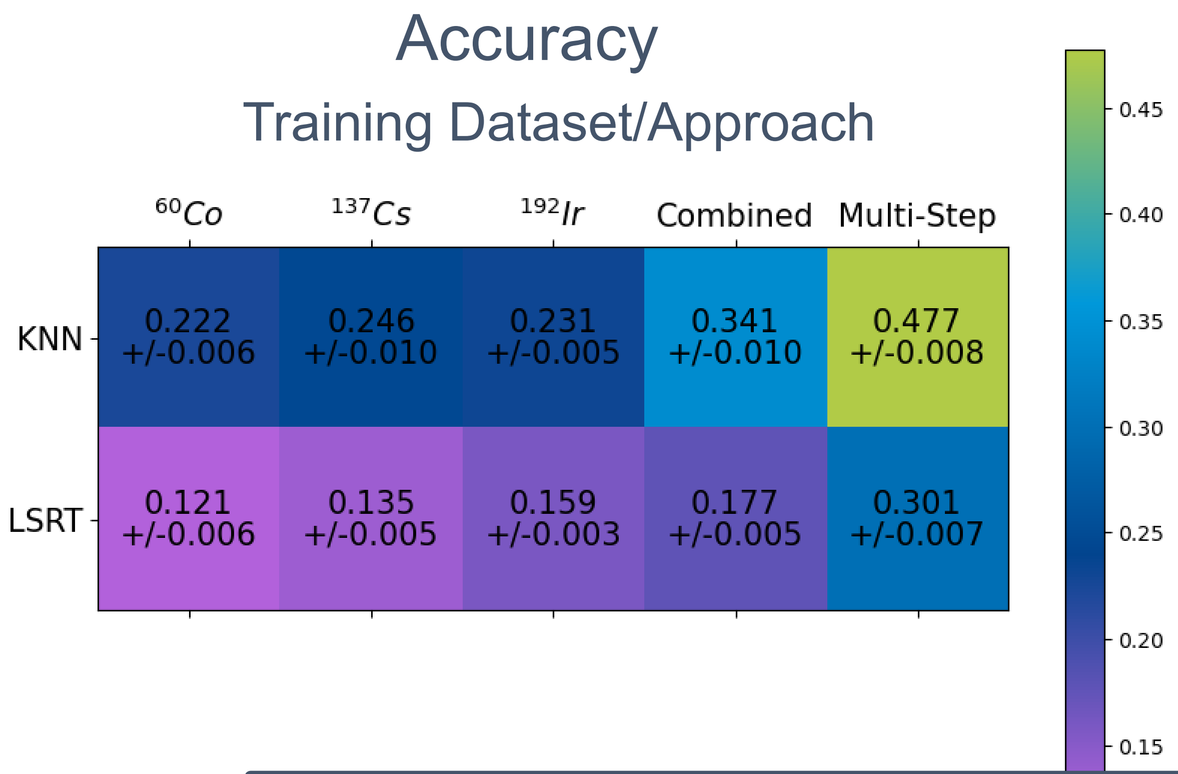
Benefit to training on mixed dataset
Best performance with multi-step approach

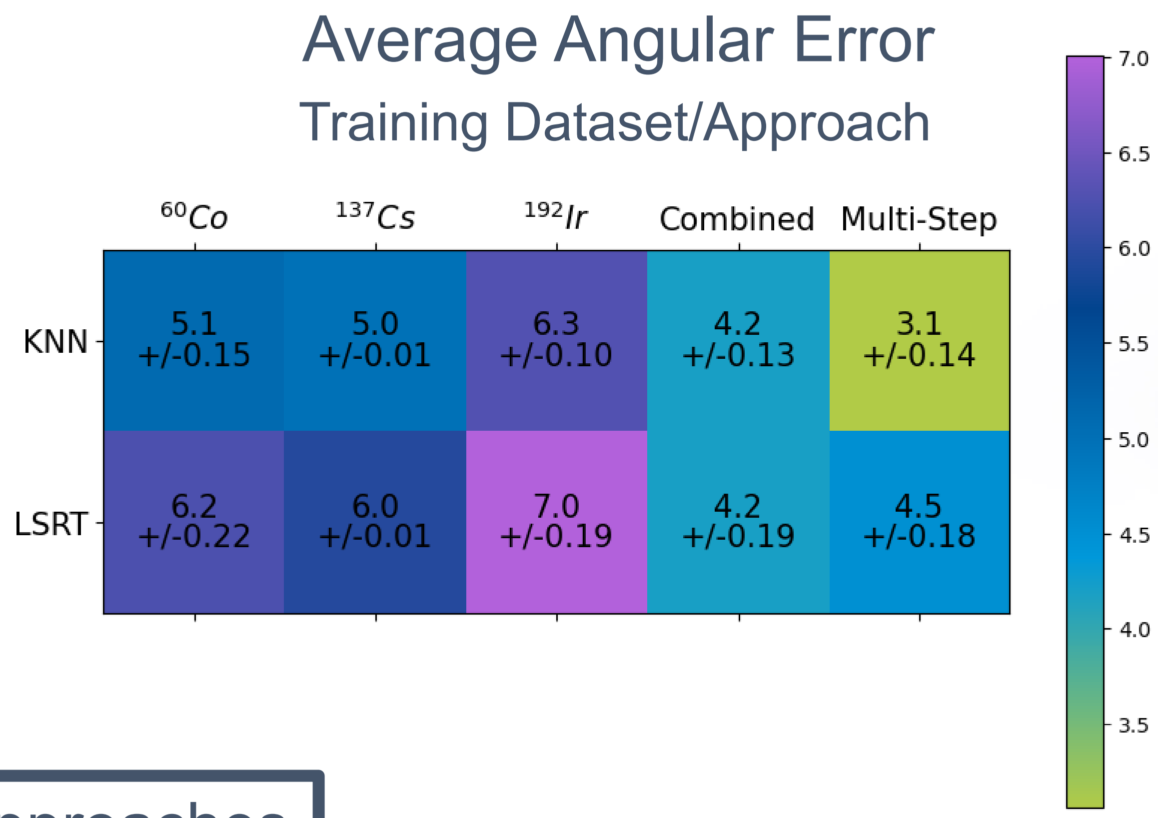
Overall Results – Comparison to LSRT





Overall Results – Comparison to LSRT

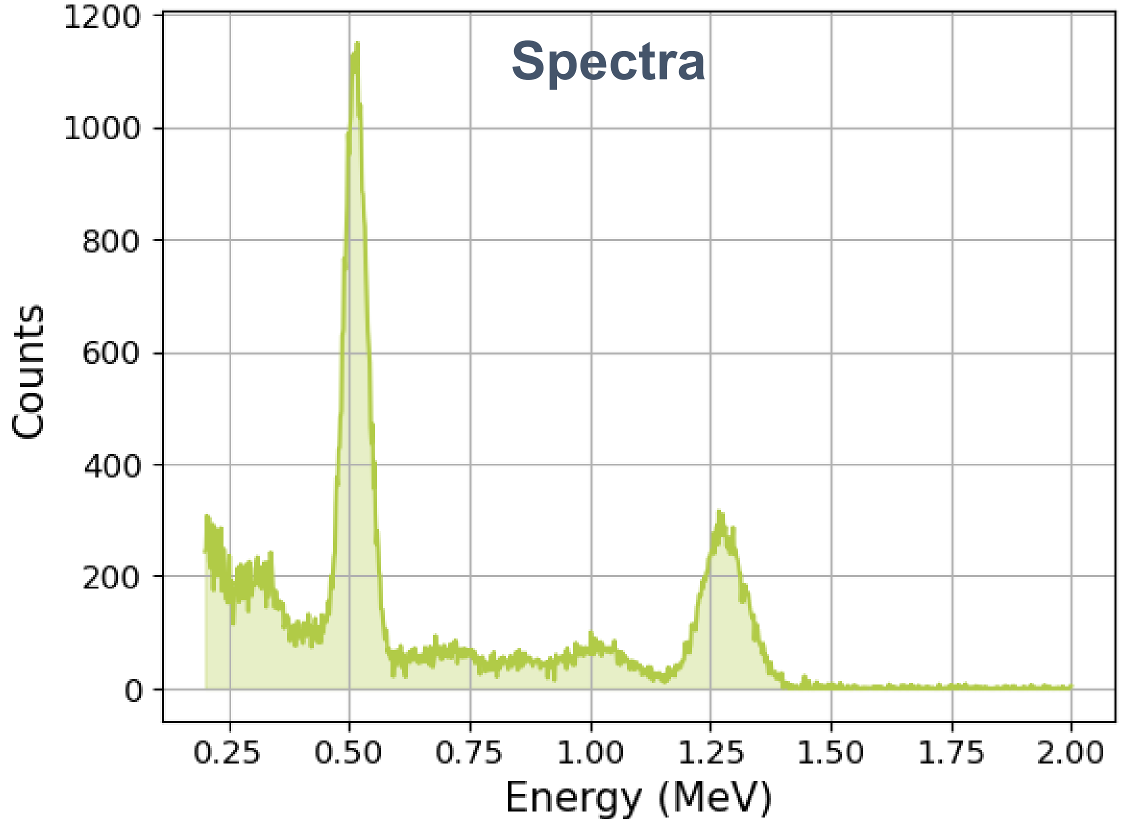


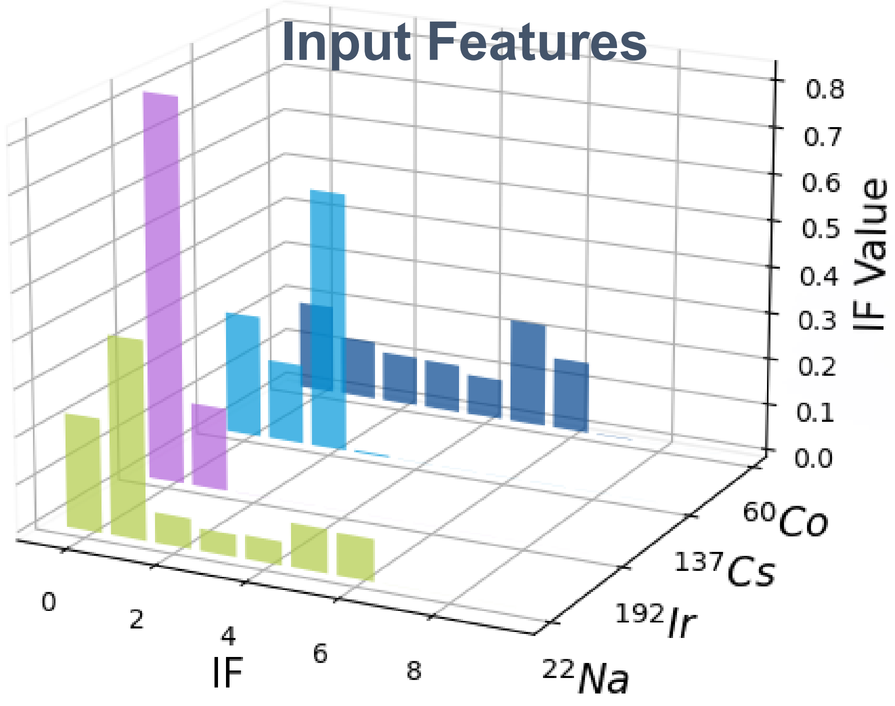


KNN outperforms LSRT across approaches

Test with Untrained Isotope – ^{22}Na

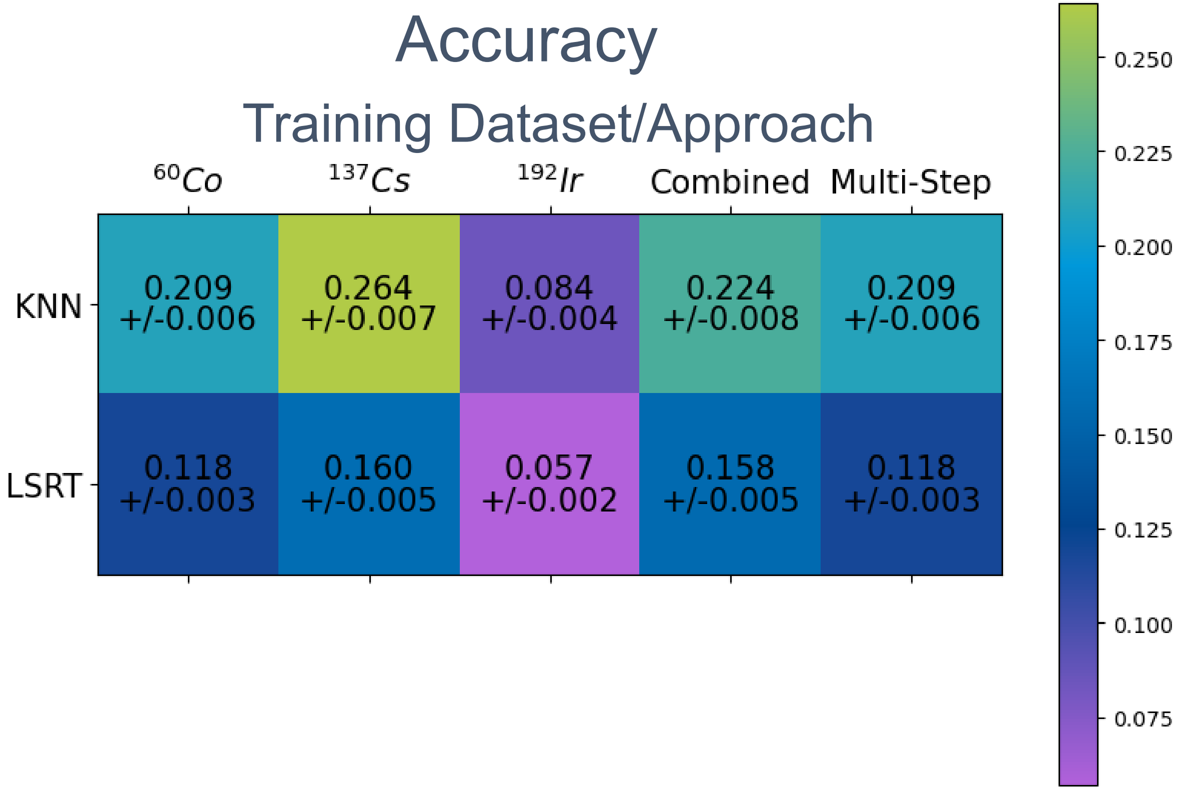
What happens when we test on an untrained Isotope?

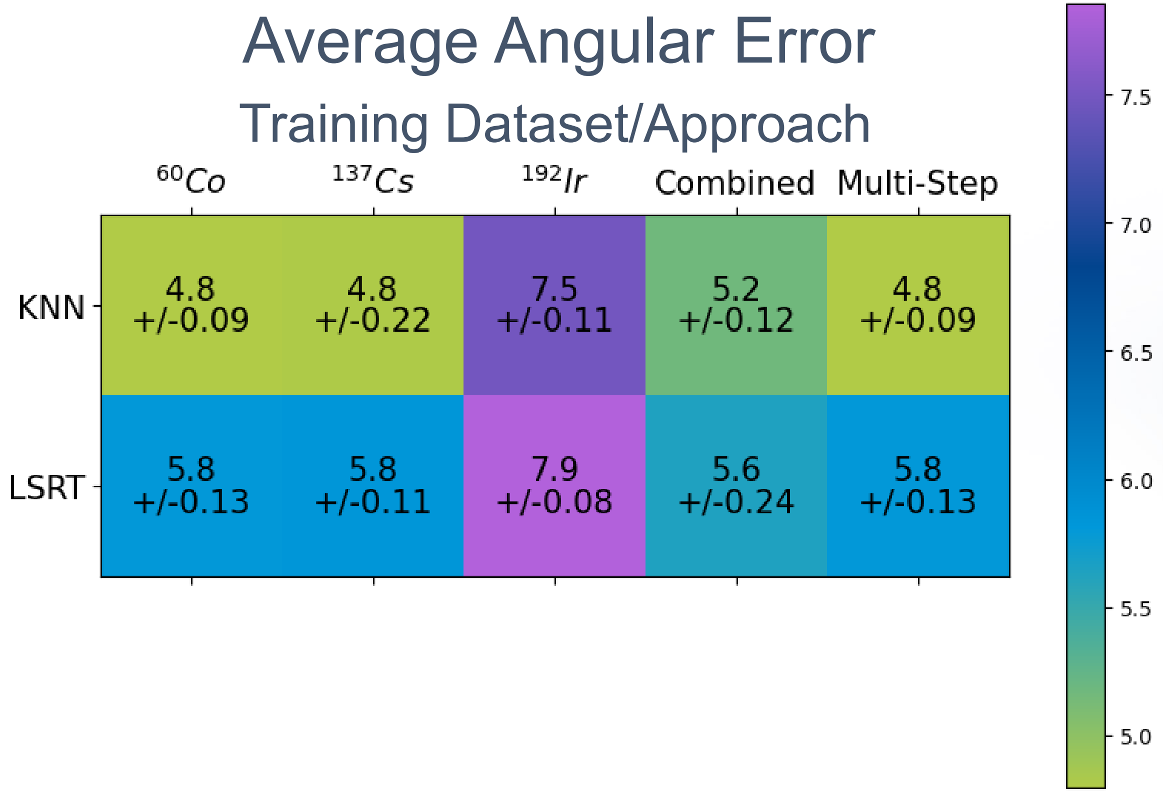




Test with Untrained Isotope – ^{22}Na

With the same input features, the Isotope classifier predicted ^{60}Co





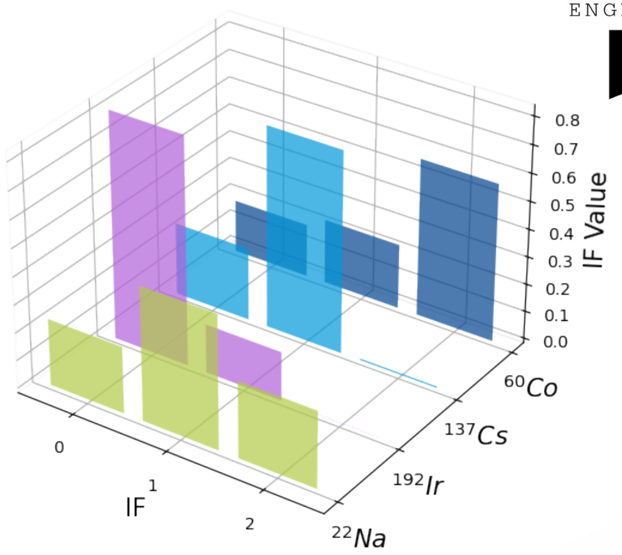
Test with Untrained Isotope – ^{22}Na

- A different or more optimized isotope classifier could lead to better results
  - With 3 input features, the classifier primarily predicted ^{137}Cs, leading to better angular predictions

- If expected isotopes are known for an application, it is beneficial to train on isotope specific datasets

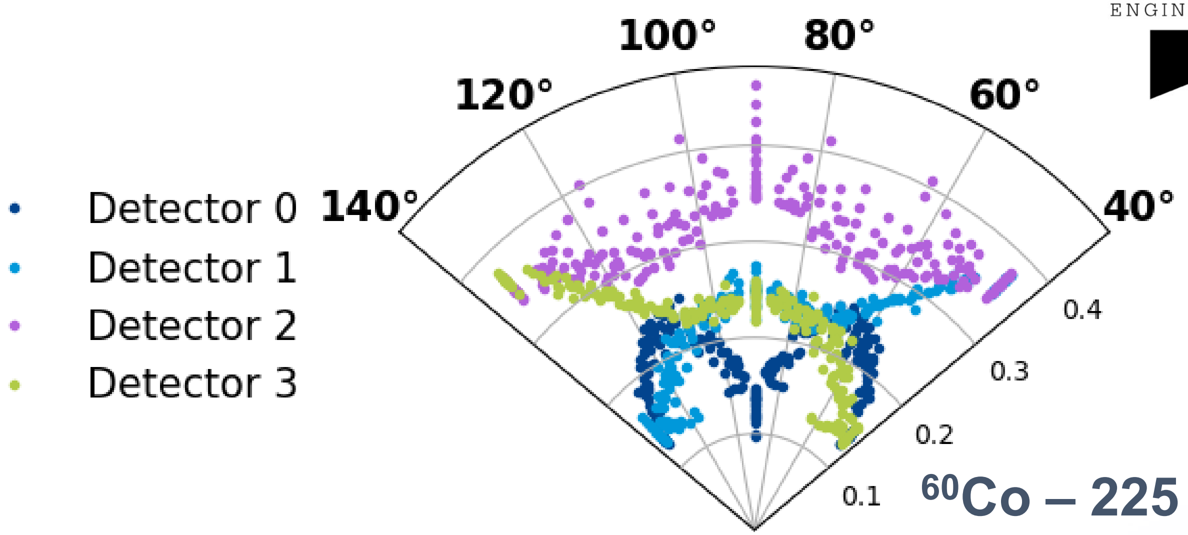
- Training on energy regions instead of specific isotopes may give comparable results

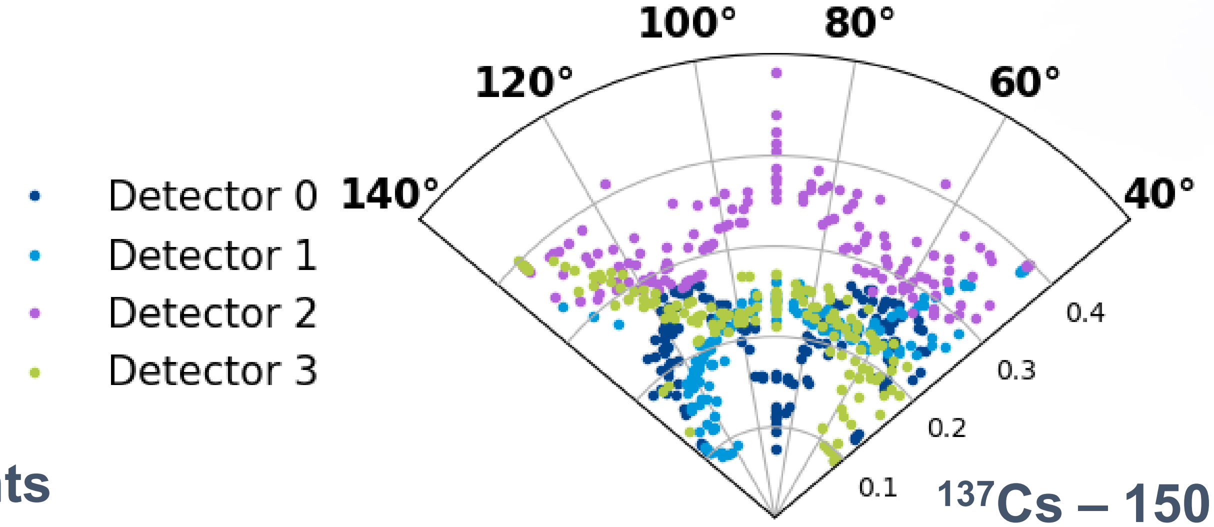
- Other ML models could use energy as an input feature



	^{60}Co	^{137}Cs	^{192}Ir	Combined	Multi-Step
KNN	0.209 +/-0.006	0.264 +/-0.007	0.084 +/-0.004	0.224 +/-0.008	0.264 +/-0.007
LSRT	0.118 +/-0.003	0.160 +/-0.005	0.057 +/-0.002	0.158 +/-0.005	0.160 +/-0.005

Preliminary Measured Tests

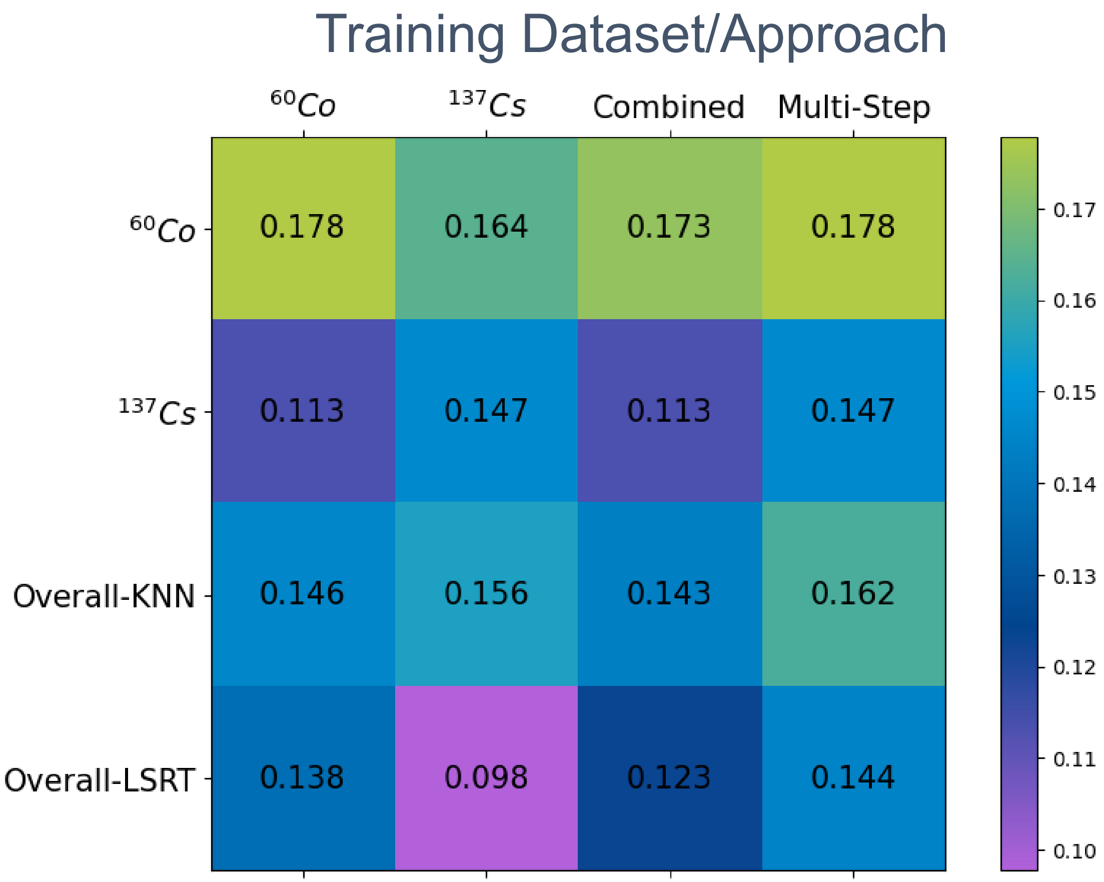




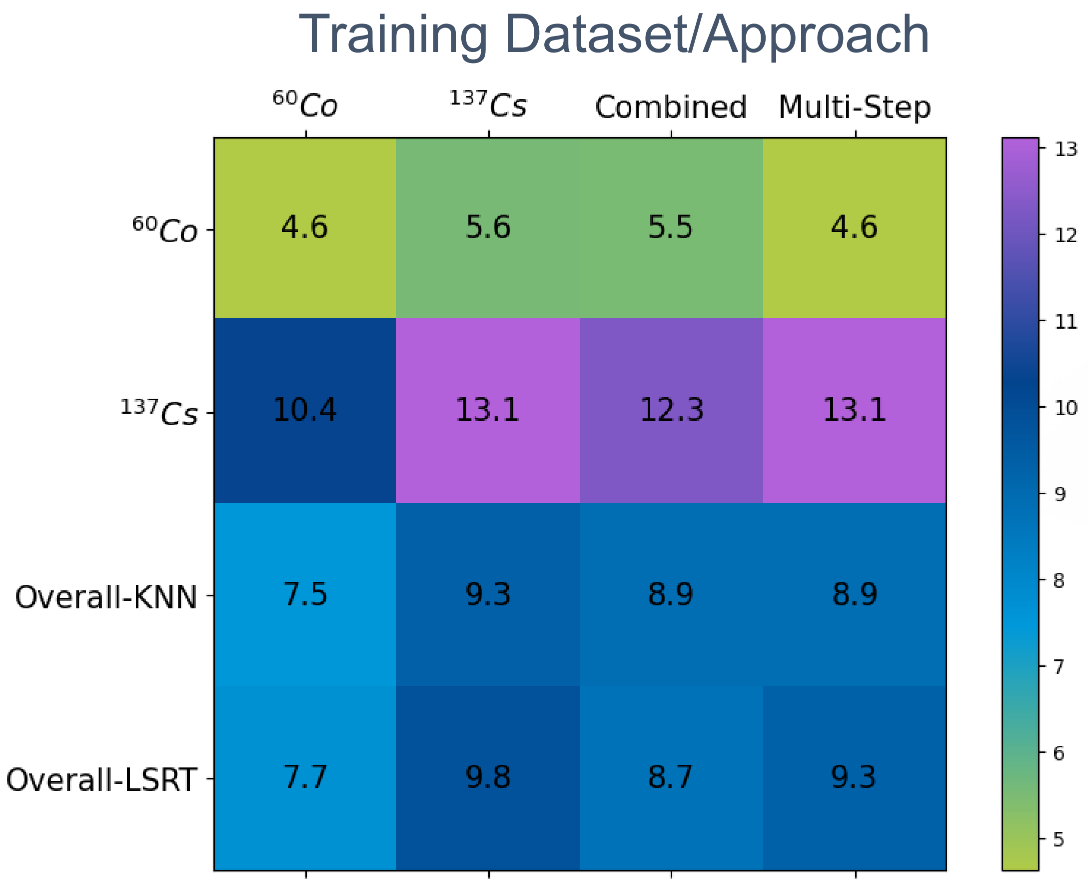
Trian on simulations, test on measurements

Preliminary Measured Tests - Results

Accuracy



Average Angular Error



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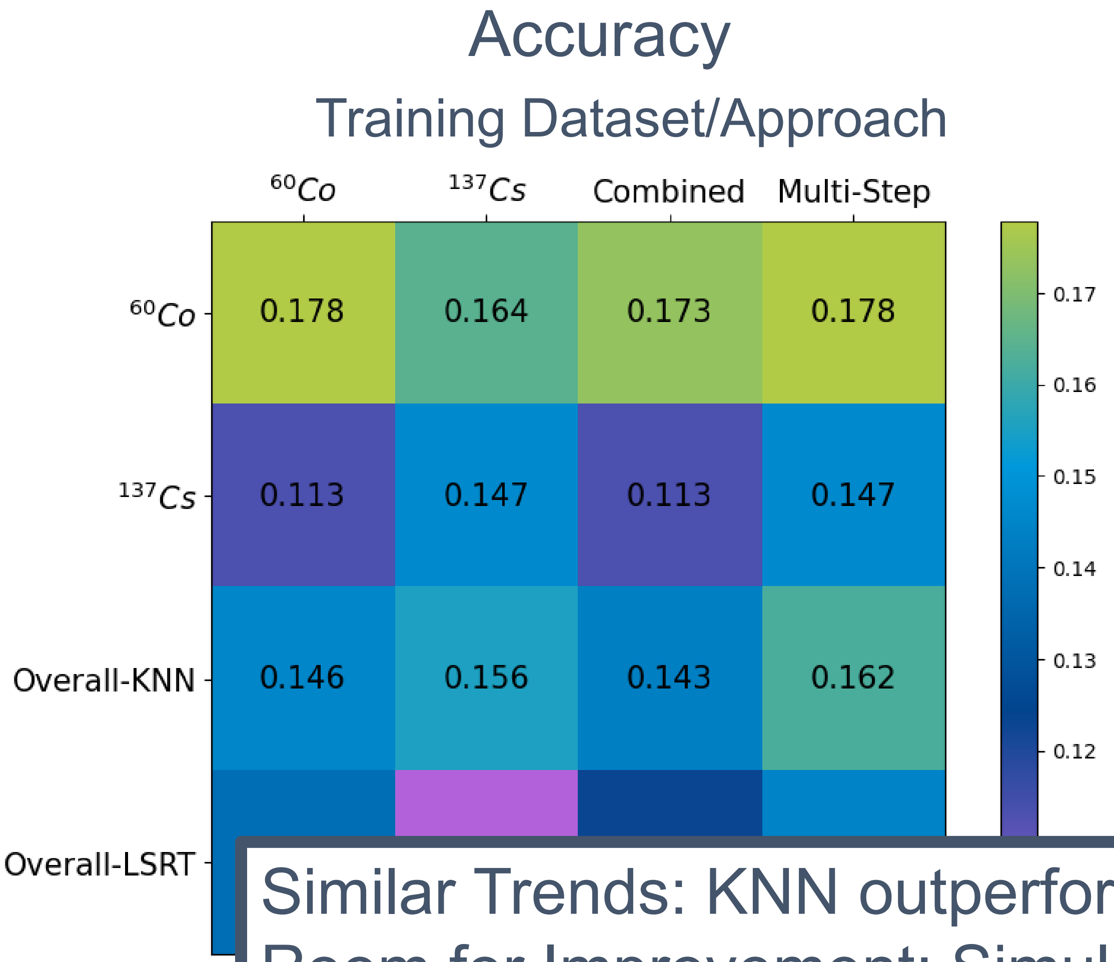
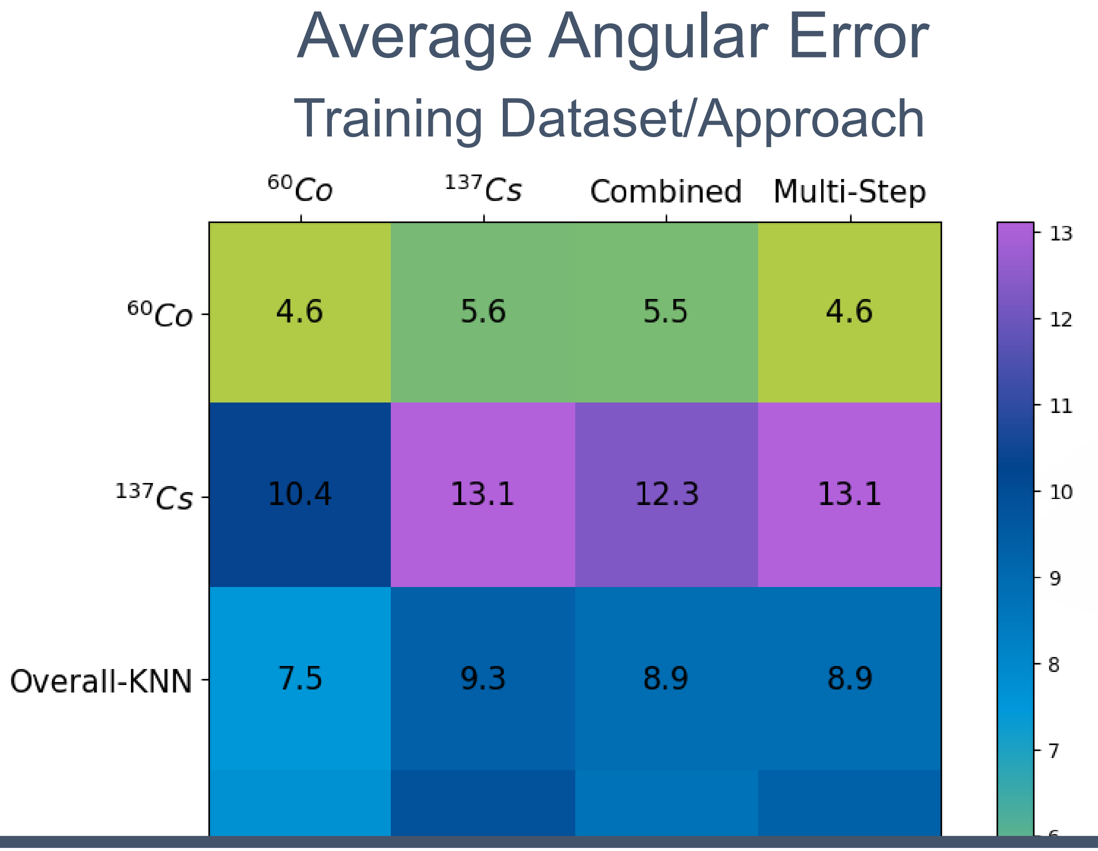
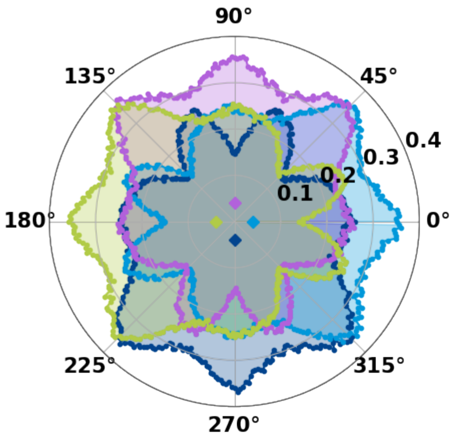




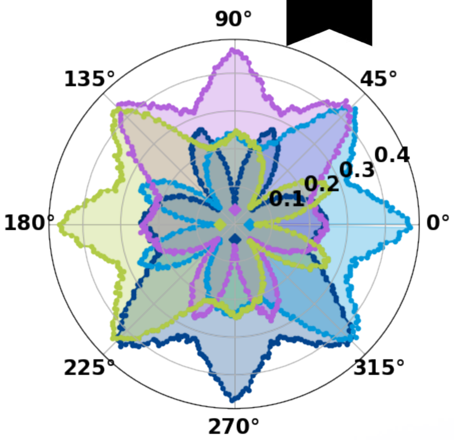
Similar Trends: KNN outperforms LSRT, Benefit of multi-step approach
Room for Improvement: Simulation/experimental agreement

Conclusions

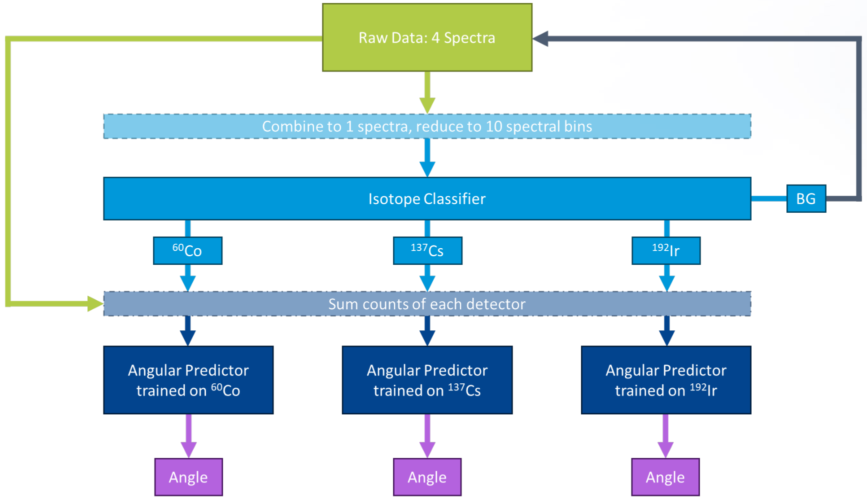
- Energy effects angular response of detector array
- A multi-step approach which trains on isotope specific data offers improvements in angular predictions
- KNN outperforms LSRT method



^{60}Co – 1.25 MeV

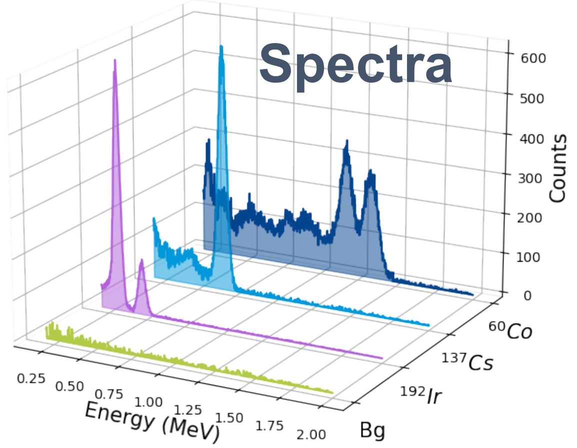


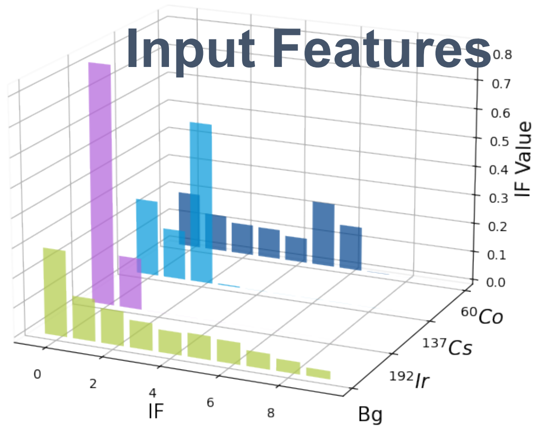
^{192}Ir – 0.32 MeV

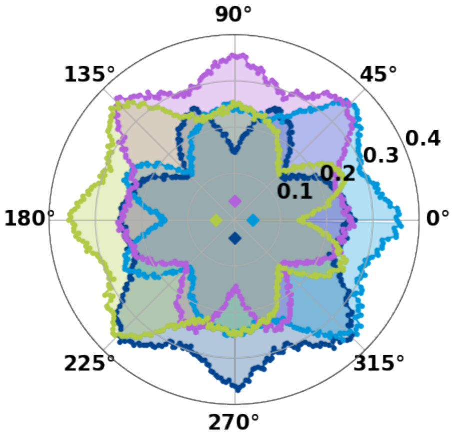


Conclusions

- Energy effects angular response of detector array
- A multi-step approach which trains on isotope specific data offers improvements in angular predictions
- KNN outperforms LSRT method
- Benefit to train on isotope specific data when expected isotopes are known, but training on energy regions may yield comparable results







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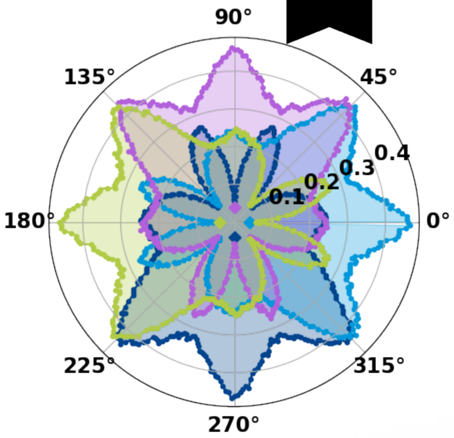

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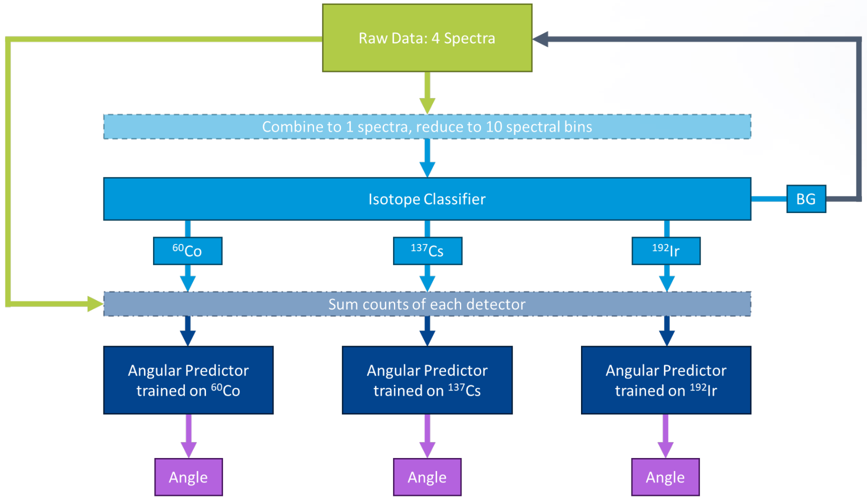
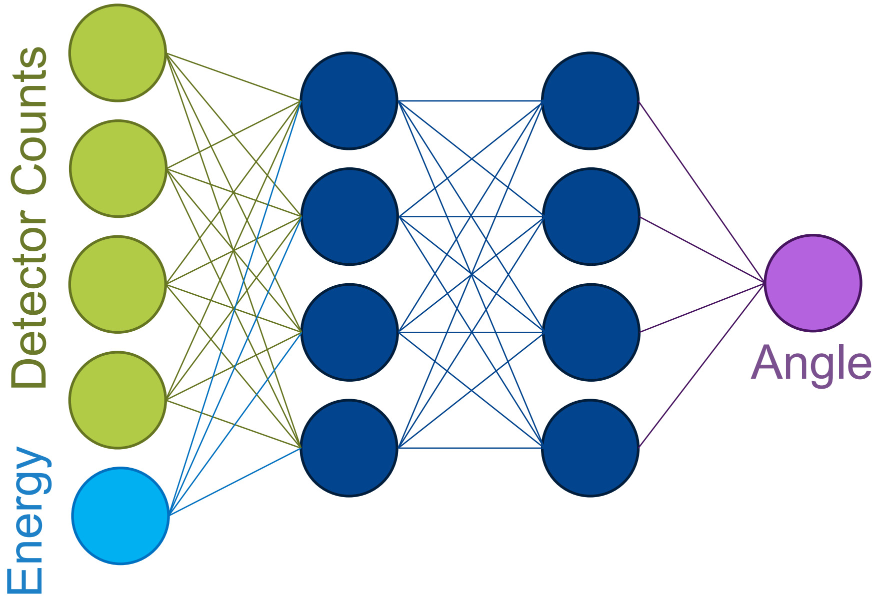
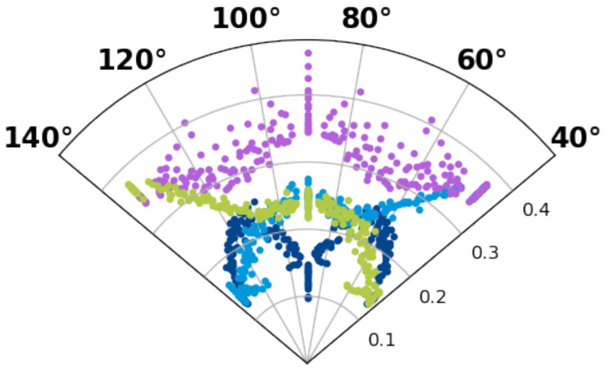
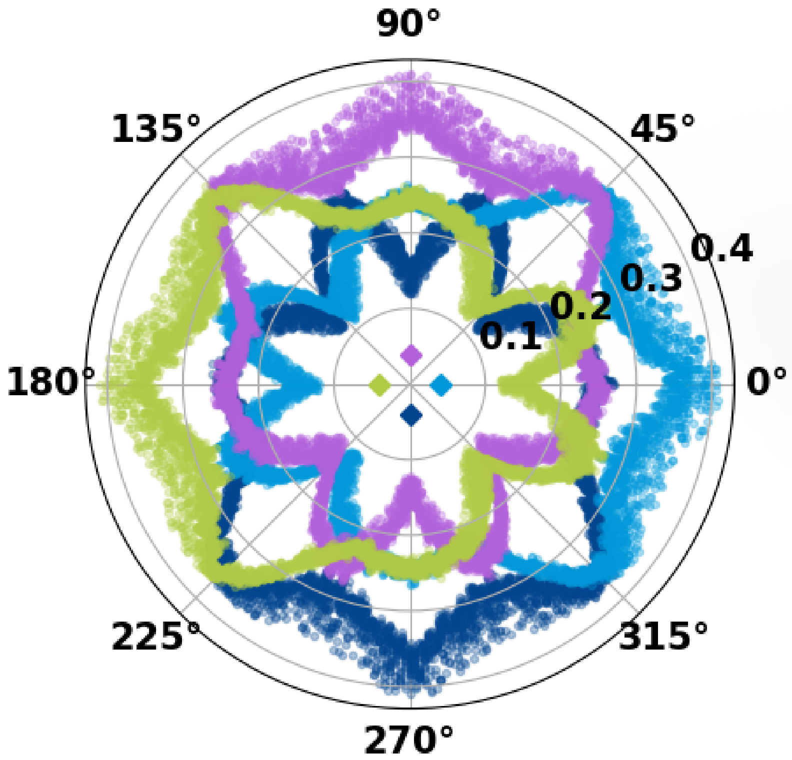


Future Works

- Investigate additional ML architectures, using energy as an input feature
- Investigating how well simulations and experimental data must agree to train ML models on the former and test on the latter







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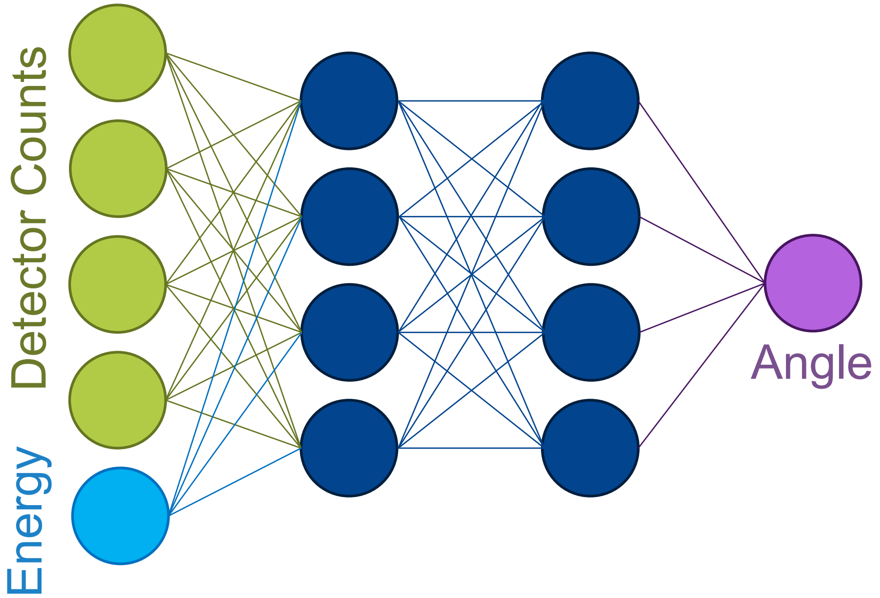

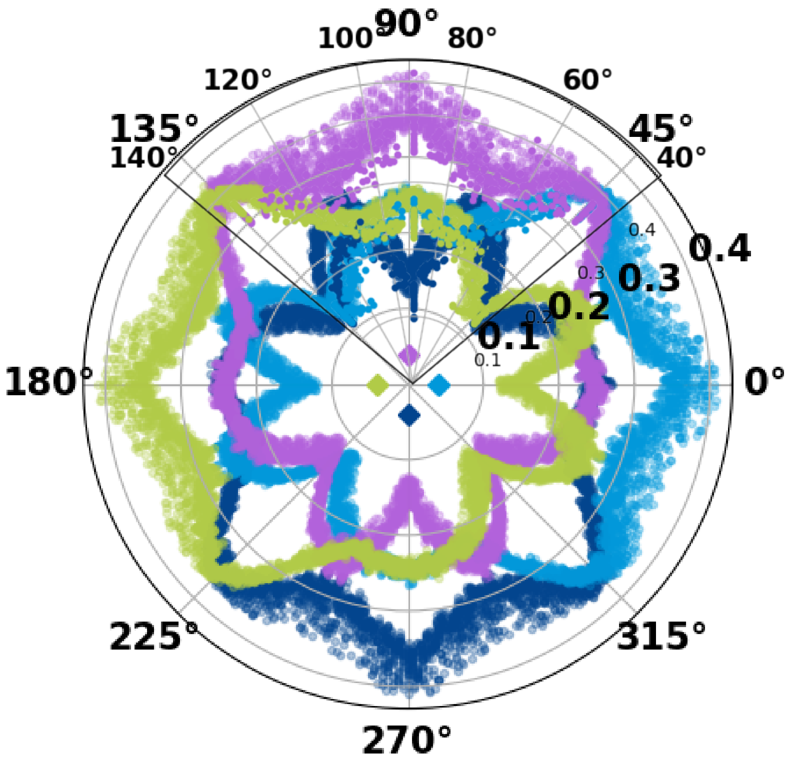

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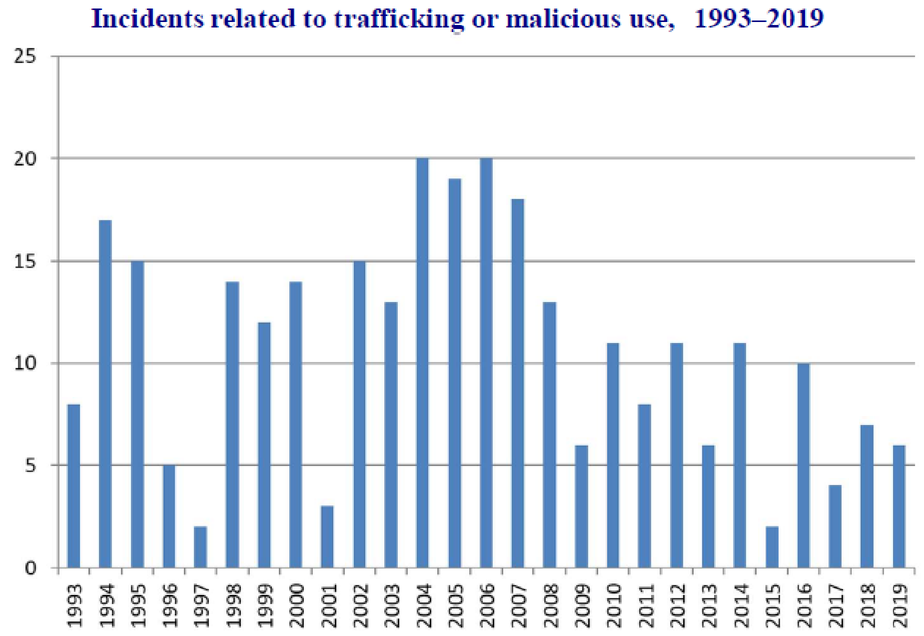
PennState College of Engineering
KEN AND MARY ALICE LINDQUIST DEPARTMENT OF NUCLEAR ENGINEERING

Background: Rogue Sources

- There is a nuclear and homeland security related motivation to be able to locate rogue sources
  - ~3700 incidents of radioactive material out of regulatory control (1993-2019)
  - ~300 related to trafficking or malicious use
- Current methods to localize sources have room to improve
  - Largely based solely on elevated count rates
- Applications:
  - Urban Search
  - Public Events
  - Ports/Borders



IAEA Incident and Trafficking Database (IRDB)

https://www.iaea.org/resources/databases/itdb

Machine Learning for Directional Detection

- Machine learning: Executing a computational task with out explicit programing
- K-Nearest Neighbors: Prediction is made by taking on the majority class of a user specified number of nearest neighbors (k) in the input feature space
  - Robust, easy to implement, computationally inexpensive
  - Natural extension of a reference table: The LSRT is equivalent to a KNN with k=1 and the reference table as the training data
- Previous work showed that a ML can outperform the LSRT on the tested datasets
  - Better capturing of radius
  - Better handling of obstructions

M. Durbin, et. al., "Development of machine learning algorithms for directional gamma ray detection." Proc. INMM Annual Meeting (2019)

M. Durbin, et. al., "Development of a fully connected residual neural network for directional gamma ray detection." Int. Jrnl. Mod. Phys: Conf. Series., **50** (2020)

Distribution Example: ^{22}Na trained on ^{137}Cs