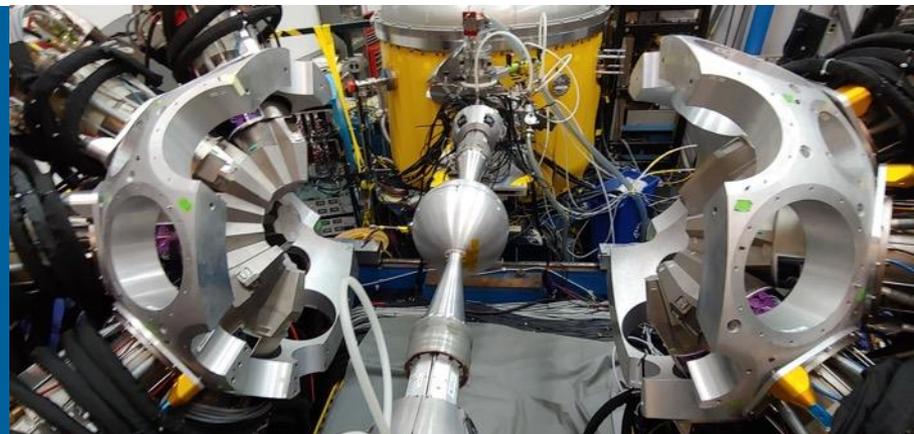


PRESENTATION TO NUCLEAR PHYSICS AI AND DATA SCIENCE, PI EXCHANGE MEETING



DEVELOPING MACHINE- LEARNING TOOLS FOR GAMMA-RAY ANALYSIS



MICHAEL CARPENTER
Physics Division
Argonne National Laboratory

THOMAS LYNN
Mathematics and Computer
Science Division
Argonne National Laboratory

TAMAS BUDNER
Physics Division
Argonne National Laboratory

PROJECT PURPOSE AND GOALS

The purpose of this project is to develop automated decision-support tools to assist physicists in the analysis of complex experimental data taken with the large gamma-ray spectrometers such as Gammasphere, GRETINA and AGATA. Specifically, we are working on three closely related areas in which modern optimization models and tools together with machine-learning approaches will be deployed to provide an automated data-analysis workflow for these types of experiments, namely:

- Develop data preparation and workflow tools to quickly extract the required information from the gamma-ray data collected by the devices.
- Develop machine-learning tools to improve γ -ray tracking
- Develop machine-learning tools to assist in the construction of complicated level schemes using γ - γ and γ - γ - γ coincidence data.

PROJECT OUTLINE

Machine-Learning (ML) tools for Gamma-Ray Analysis

Gamma-ray Tracking

- Develop new methods to improve on current gamma-ray tracking algorithms to increase both photopeak intensity and background rejection.
- Develop machine learning tools to improve on these methods.
- Extend these methods to include pair production events.
- Incorporate these tools into tracking codes used by the community.

Level Scheme Construction

- Develop tools to automatically extract intensity information from gamma-ray coincidence data.
- Using known level schemes, develop a mathematical toolkit to build levels schemes from the inputted data for both 2-fold and 3-fold coincidence information.
- Apply toolkit to both simulated data and experimental data taken with Gammasphere and GRETINA.

PROJECT PARTICIPANTS

Joint project between two ANL divisions: Physics (PHY) and Math and Computer Science (MCS)

PHY

- Tamas Budner (FOA funded Pdoc)*
- Mike Carpenter (ANL Staff)*
- Filip Kondev (ANL Staff)
- Amel Korichi (Orsay Staff)**
- Torben Lauritsen (ANL Staff)
- Marco Siciliano (ANL Staff)

MCS

- Hanqui Guo (ANL/OSU)***
- David Lenz (ANL Pdoc, 25% FOA)
- Sven Leyffer (ANL Staff)
- Thomas Lynn (FOA funded Pdoc)*
- Dominic Yang (UCLA Student)

* Today's Presenters

** On Sabbatical at ANL starting January 2023

*** Transferred to OSU summer of 2022

ML TOOLS FOR GAMMA-RAY TRACKING



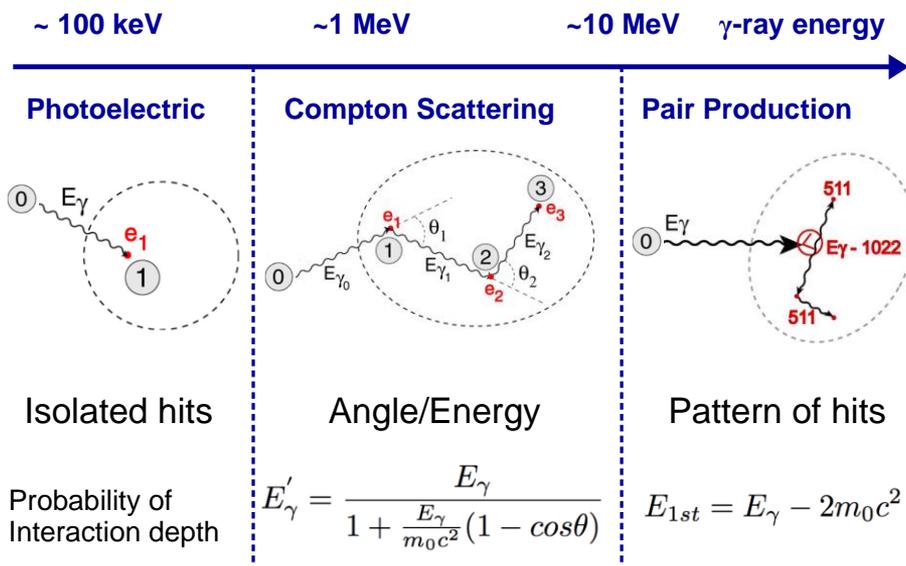
Argonne National Laboratory is a
U.S. Department of Energy laboratory
managed by UChicago Argonne, LLC.



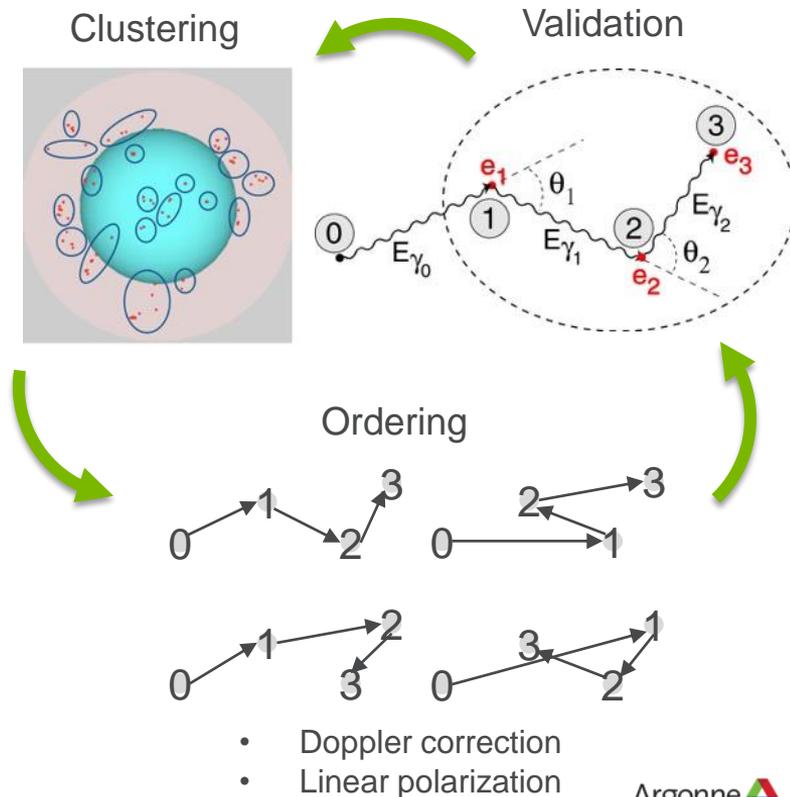
γ-RAY TRACKING PROBLEM

Overview of the problem

Three interaction types of interest



Three operations



TRACKING PROBLEM: GOALS & CHALLENGES

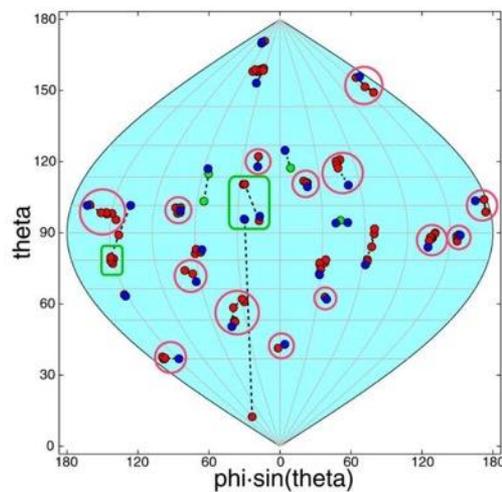
Using detector information to reconstruct and categorize γ -rays

Goals:

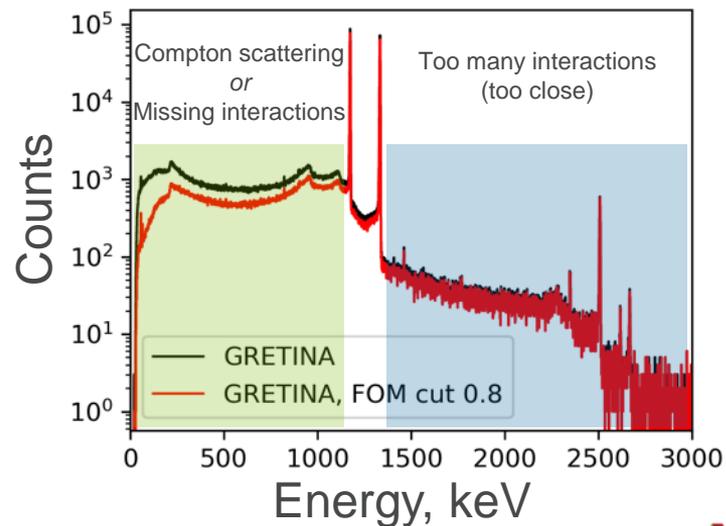
1. Find distinct γ -rays (cluster)
2. Recreate Compton suppression using FOM

Challenges:

1. γ -rays too close
2. γ -ray escape
3. γ -rays crossing the detector
4. Suppress environmental γ -rays



^{60}Co Spectrum



ML TOOLS FOR GAMMA-RAY TRACKING

Where ML and data science techniques apply to this problem

Cluster interactions into separate γ -rays

- Energy clustering
- ML clustering
- **GNN clustering**

Order interactions for individual γ -rays

- Choice of FOM
- Combined clustering/ordering

Suppress γ -rays scattering out of the detector

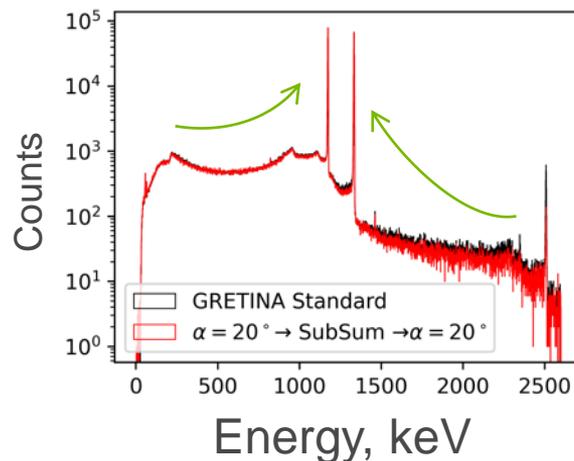
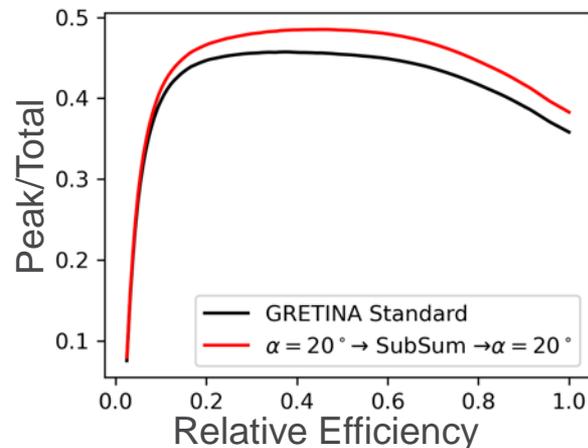
- Choice of FOM
- **ML classification**
- **Recover γ -ray energies**

(red text indicates future plans)

ENERGY BASED CLUSTERING

Energy information separates close clusters

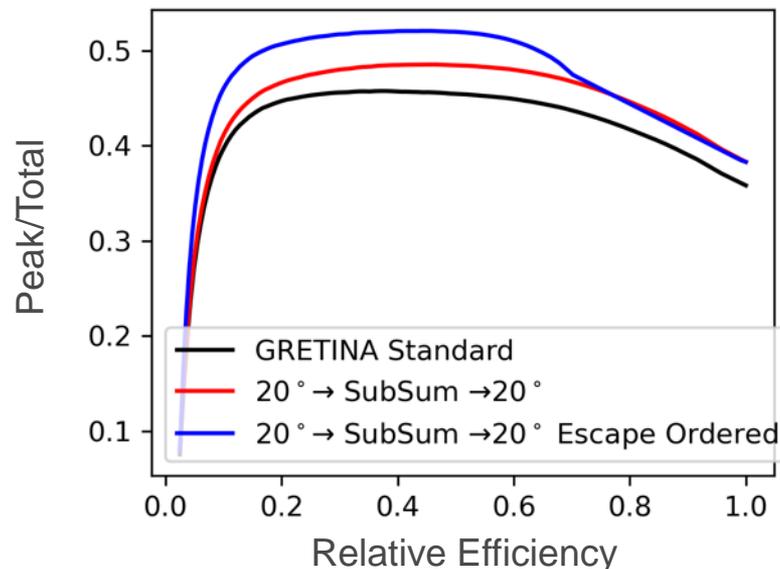
- Use spectrum to guide clustering
 - Avoids confusing geometries
- Find interactions with total energy in peaks using a fast MILP solver
- Solve “too big” / “too small” clusters
- Slightly increases P/T and efficiency by capturing more peak energy γ -rays
- Does not create any additional Compton suppression



RECREATING COMPTON SUPPRESSION

Correctly ordering escaped γ -rays improves suppression

- Previously done with BGO absorber
- FOM correctly orders < 50% of escapes
 - Wrong order favorable over truth
 - Suppression suffers
- Using escape energy estimate improves suppression (Tashenov & Gerl 2010)
 - Order for escapes is essential for suppression
- ML can further improve ordering & suppression



IMPROVING WITH ML

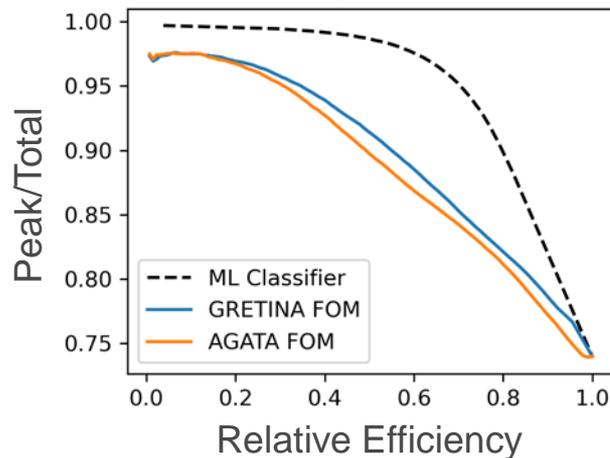
ML tools for ordering & classifying

- Use simulated data:
 - True order is known
 - Escapes are known
- Ordering considerations:
 - Speed, up to $\mathcal{O}(n!)$
 - Absolute FOM value is not important, only relative
- ML Escape classification
 - Assume clustered
- Challenging to transfer model to experimental data

Ordering Consistency

Multiplicity 30 data	GRETINA FOM	GRETINA Escape	AGATA FOM	ML FOM
Complete γ	73.8%	73.4%	87.0%	81.4%
Escape γ	46.7%	58.0%	76.2%	77.5%
Total	67.0%	69.5%	85.2%	80.4%

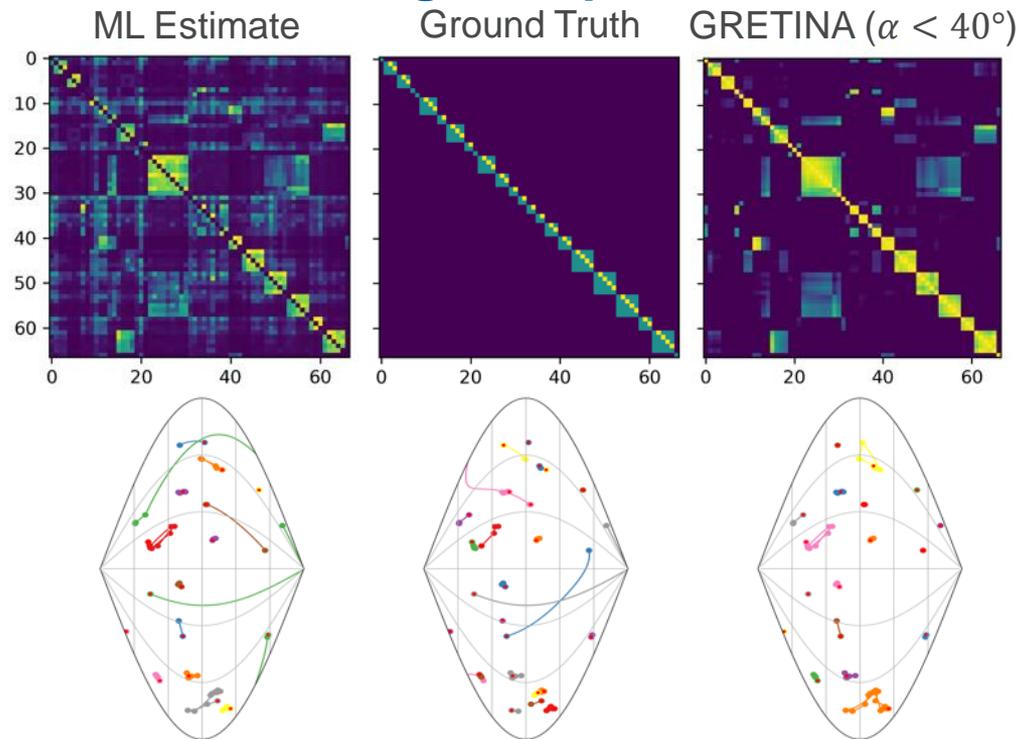
Without single interactions



ML CLUSTERING

Clustering beyond GRETINA without knowledge of spectrum

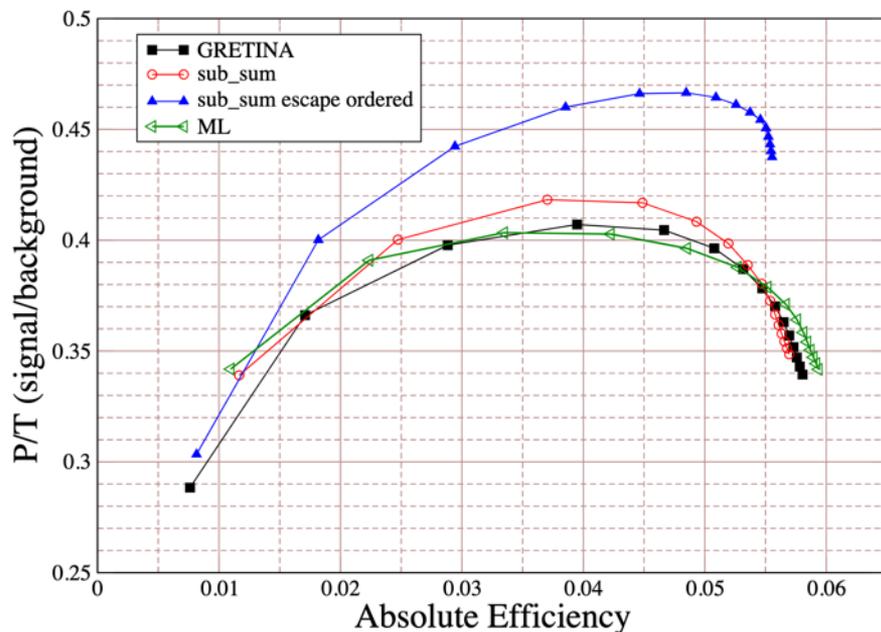
- GRETINA clustering is done spatially with respect to cluster spread (scattering forward)
- Use ML to create an alternate distance metric by which to cluster
 - Learned from data
 - Include additional clustering steps beyond singles
 - Include cluster order



FUTURE WORK AND EXTENSIONS

Improving the resolving power of GRETINA for further analysis

- Improved recovery of escape energies instead of suppression
- ML tools for fast tracking
- ML training using experimental data from sources
- ML tools for on-line learning
- Optimization based approaches for better clustering
- Apply techniques to the problem of pair production



ML TOOLS FOR LEVEL-SCHEME DESIGN



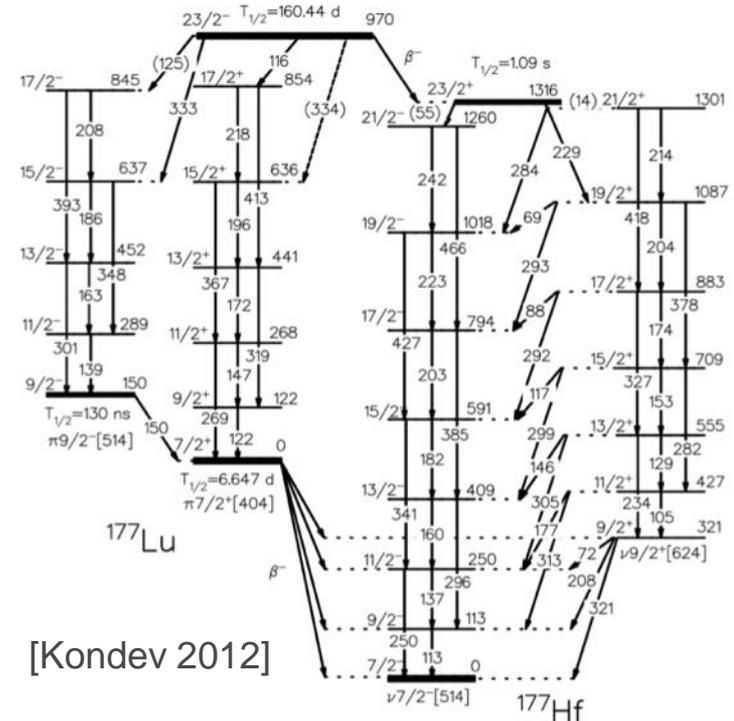
Argonne National Laboratory is a
U.S. Department of Energy laboratory
managed by UChicago Argonne, LLC.



MAPPING OF EXCITED STATES IN NUCLEI

Building level schemes from data collected from the large gamma-ray arrays

- A major deliverable from large γ -ray arrays is the mapping of excited nuclear states.
- Accomplished by analysis of γ -ray coincidence data e.g. 2-fold, 3-fold, ...
- Level schemes can be complicated, and analysis times can take many months.
- Can we develop tools to speed up analysis and quantify accuracy?



ML TOOLS FOR LEVEL-SCHEME DESIGN

Overview of Inverse Optimization Approach

Single,
Doublet, or
Triplet Data

- Data preparation
- Extraction tools for coincidence data

Optimize
Transitions

- Inverse optimization to determine transitions
- ML-based optimizers

Represent as
Level-Scheme

- Graph-based level-scheme generation
- ML-based extensions

MATHEMATICAL FORMULATION

Writing Level Scheme Construction as Matrix Equations

- Start with **data** from Gamma-Sphere experiment:
 - **S**: γ -ray transitions & intensities (as diagonal matrix)
 - **C**: γ - γ coincidence data
- Determine the **outputs**:
 - **A**: the matrix of branching ratios
 - **D**: the directed coincidence data
- Following Demand (2013), we try to satisfy two equations simultaneously:

$$D = S((I - A)^{-1} - I) \quad \text{and} \quad C = D + D^T$$

ML TOOLS FOR LEVEL-SCHEME DESIGN

Inverse Optimization to Determine Transitions

- Goal: Given S , C , find A , D such that

$$D = S((I - A)^{-1} - I) \quad \text{and} \quad C = D + D^T$$

- Formulate nonlinear constrained optimization problem:

$$\text{minimize}_{A,D} \|D - S((I - A)^{-1} - I)\|_{\Gamma^{-1}}^2 + \text{prior}(A)$$

$$\text{subject to } A \geq 0, \sum_j A_{ij} \leq 1, C = D + D^T$$

$$\text{minimize}_{A,D,T} \|D - ST\|_{\Gamma^{-1}}^2 + \text{prior}(A)$$

$$\text{subject to } (I - A)(T + I) = I \\ A \geq 0, \sum_j A_{ij} \leq 1, C = D + D^T.$$

Enforce constraints such as conservation of energy, nonnegative decay intensities etc

ML TOOLS FOR LEVEL-SCHEME DESIGN

Optimization Techniques

- Inverse optimization for transitions A
- Use nonlinear optimization methods
... solves within minutes on laptop
- Extends to γ - γ - γ -interactions (tensors)

$$\begin{aligned} & \underset{A, D, T}{\text{minimize}} && \|D - ST\|_{\Gamma^{-1}}^2 + \text{prior}(A) \\ & \text{subject to} && (I - A)(T + I) = I \\ & && A \geq 0, \sum_j A_{ij} \leq 1, C = D + D^T. \end{aligned}$$

▪ Progress so Far:

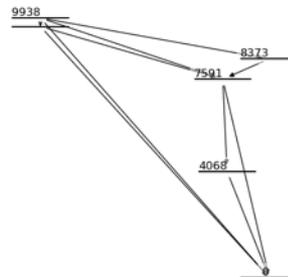
- Implemented inverse optimization in AMPL & solve model using IPOPT
- Successful proof-of-concept:
 - (1) Generate data (S, C) from given level-scheme (python code)
 - (2) Solve inverse optimization for A (AMPL/IPOPT)
 - (3) Create level-scheme & compare to original scheme

LEVEL SCHEME RECONSTRUCTION

Actionable Physics from Output Matrices

- Inverse optimization results in two matrices:
 - A : the matrix of branching ratios between subsequent γ -rays
 - D : the directed coincidence data
- Final Step: Create energy level scheme from matrix output

```
[ [ 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. ]  
 [4068. 0. 0. 0. 0. 0. 0. 0. 0. 0. ]  
 [ 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. ]  
 [3563.05 3563.05 4809.95 0. 0. 0. 0. 0. 0. 0. ]  
 [ 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. ]  
 [4229.02 4229.02 5708.98 0. 0. 0. 0. 0. 0. 0. ]  
 [ 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. ]  
 [1731.1 1731.1 2336.9 4068. 0. 0. 0. 0. 0. 0. ]  
 [1486.44 1486.44 2006.62 0. 4097.94 3493.06 0. 0. 0. 0. ]  
 [ 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. ] ]
```



ML TOOLS FOR LEVEL-SCHEME DESIGN

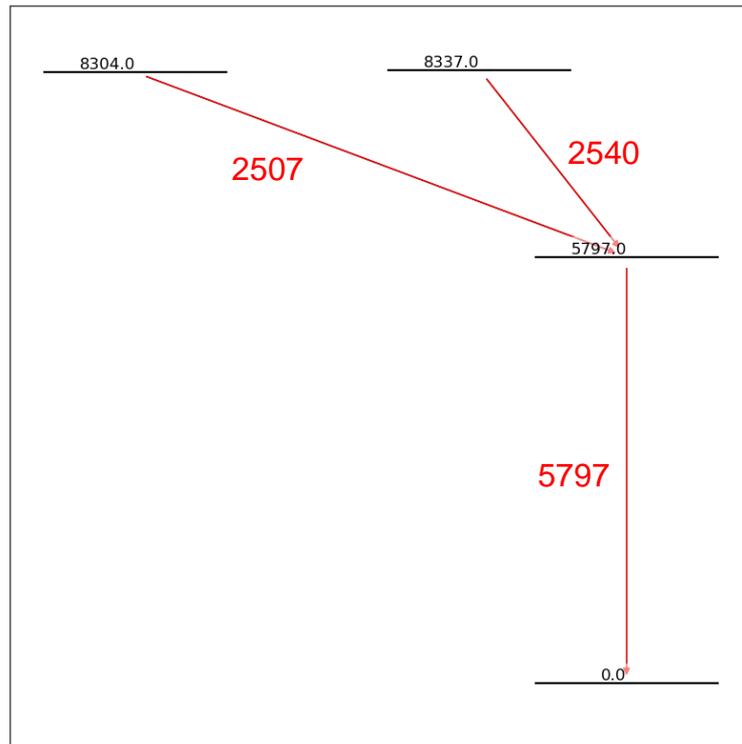
Level-Scheme Representation from Transition Matrix

Outgoing gamma energy
→

Incoming gamma energy
↓

Weighted Adjacency =

	2507	2540	4117	4150	4187	4945	5797	8337	9094	13282
2507	0	0	0	0	0	0	228	0	0	0
2540	0	0	0	0	0	0	1767	0	0	0
4117	0	0	0	0	546	0	0	0	0	0
4150	0	0	0	0	565	0	0	0	0	0
4187	0	0	0	0	0	0	0	0	0	0
4945	0	134	0	43	0	0	0	14	0	0
5797	0	0	0	0	0	0	0	0	0	0
8337	0	0	0	0	0	0	0	0	0	0
9094	0	0	0	0	298	0	0	0	0	0
13282	0	0	0	0	0	0	0	0	0	0



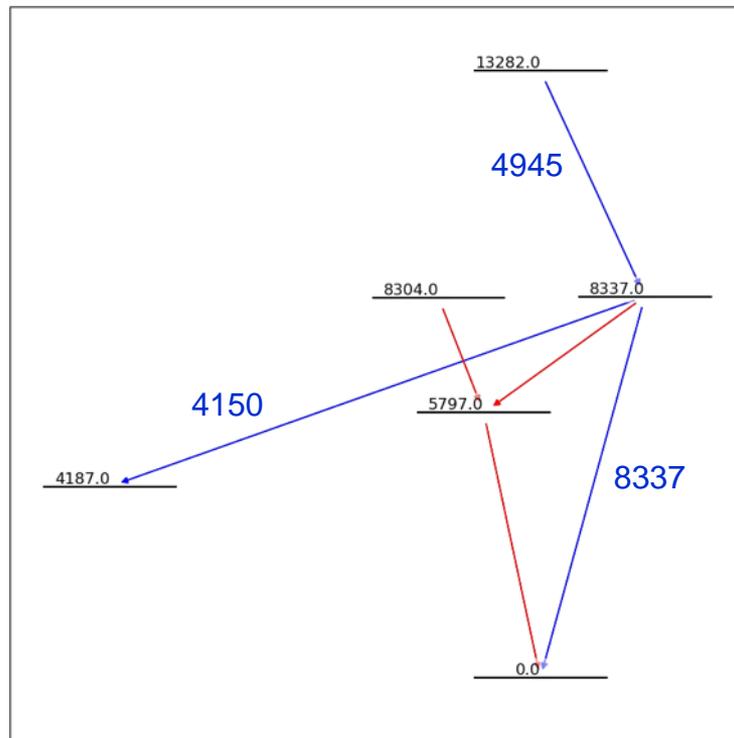
ML TOOLS FOR LEVEL-SCHEME DESIGN

Level-Scheme Representation from Transition Matrix

Weighted Adjacency =

	2507	2540	4117	4150	4187	4945	5797	8337	9094	13282
2507	0	0	0	0	0	0	228	0	0	0
2540	0	0	0	0	0	0	1767	0	0	0
4117	0	0	0	0	546	0	0	0	0	0
4150	0	0	0	0	565	0	0	0	0	0
4187	0	0	0	0	0	0	0	0	0	0
4945	0	134	0	43	0	0	0	14	0	0
5797	0	0	0	0	0	0	0	0	0	0
8337	0	0	0	0	0	0	0	0	0	0
9094	0	0	0	0	298	0	0	0	0	0
13282	0	0	0	0	0	0	0	0	0	0

*Adjacent transition



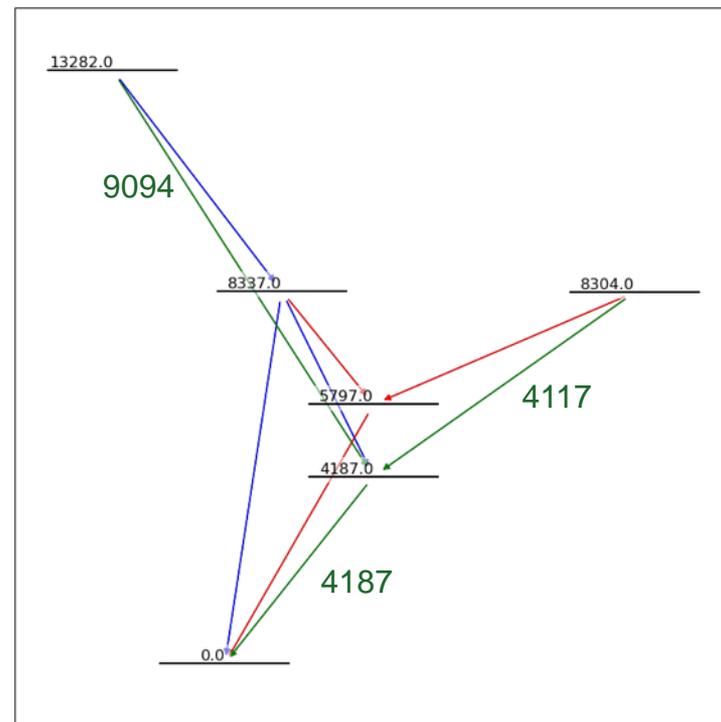
ML TOOLS FOR LEVEL-SCHEME DESIGN

Level-Scheme Representation from Transition Matrix

Weighted Adjacency =

	2507	2540	4117	4150	4187	4945	5797	8337	9094	13282
2507	0	0	0	0	0	0	228	0	0	0
2540	0	0	0	0	0	0	1767	0	0	0
4117	0	0	0	0	546	0	0	0	0	0
4150	0	0	0	0	565	0	0	0	0	0
4187	0	0	0	0	0	0	0	0	0	0
4945	0	134	0	43	0	0	0	14	0	0
5797	0	0	0	0	0	0	0	0	0	0
8337	0	0	0	0	0	0	0	0	0	0
9094	0	0	0	0	298	0	0	0	0	0
13282	0	0	0	0	0	0	0	0	0	0

*Adjacent transition



FUTURE WORK AND EXTENSIONS

- Develop tools to automatically extract γ -ray intensity information for 2- and 3-fold coincidence data.
- Handling of uncertainty/noise with level-scheme construction for robust results
- Level scheme from γ - γ - γ interactions
- Fast ML-inspired algorithms (ADMM) for level-scheme construction
- Apply algorithms to both simulated data and experimental data where gamma-ray intensities have been extracted with developed tools.

BUDGET TABLE AND TABLE OF DELIVERABLES AND SCHEDULE



Argonne National Laboratory is a
U.S. Department of Energy laboratory
managed by UChicago Argonne, LLC.



BUDGET TABLE

Summary of expenditures by fiscal year (FY):

	FY21 (\$k)	FY22 (\$k)	Total (\$k)
a) Funds allocated	500	500	1000
b) Actual costs to date	310 (FY22)	40 (FY23)	350

MAJOR DELIVERABLES AND SCHEDULE

ML Tools for Gamma-Ray Tracing and Level-Scheme Construction

Area	Project	Deliverable	Timeline
γ -Ray-Tracking	ML for Tracking	Python code	Mar 23
Level-Scheme (2D)	Inverse Optimal Design	Python code	May 23
γ -Ray-Tracking	ML for Tracking	Journal paper	Feb 23
Level-Scheme (2D)	Optimal Level-Scheme	Journal paper	Apr 23
γ -Ray-Tracking	Pair Production	Python code	Oct 23
Level-Scheme (3D)	ML Solver & Construction	Python code	Oct 23

MODERN ML & OPTIMIZATION TOOLS FOR TRACKING AND LEVEL-SCHEME DESIGN

