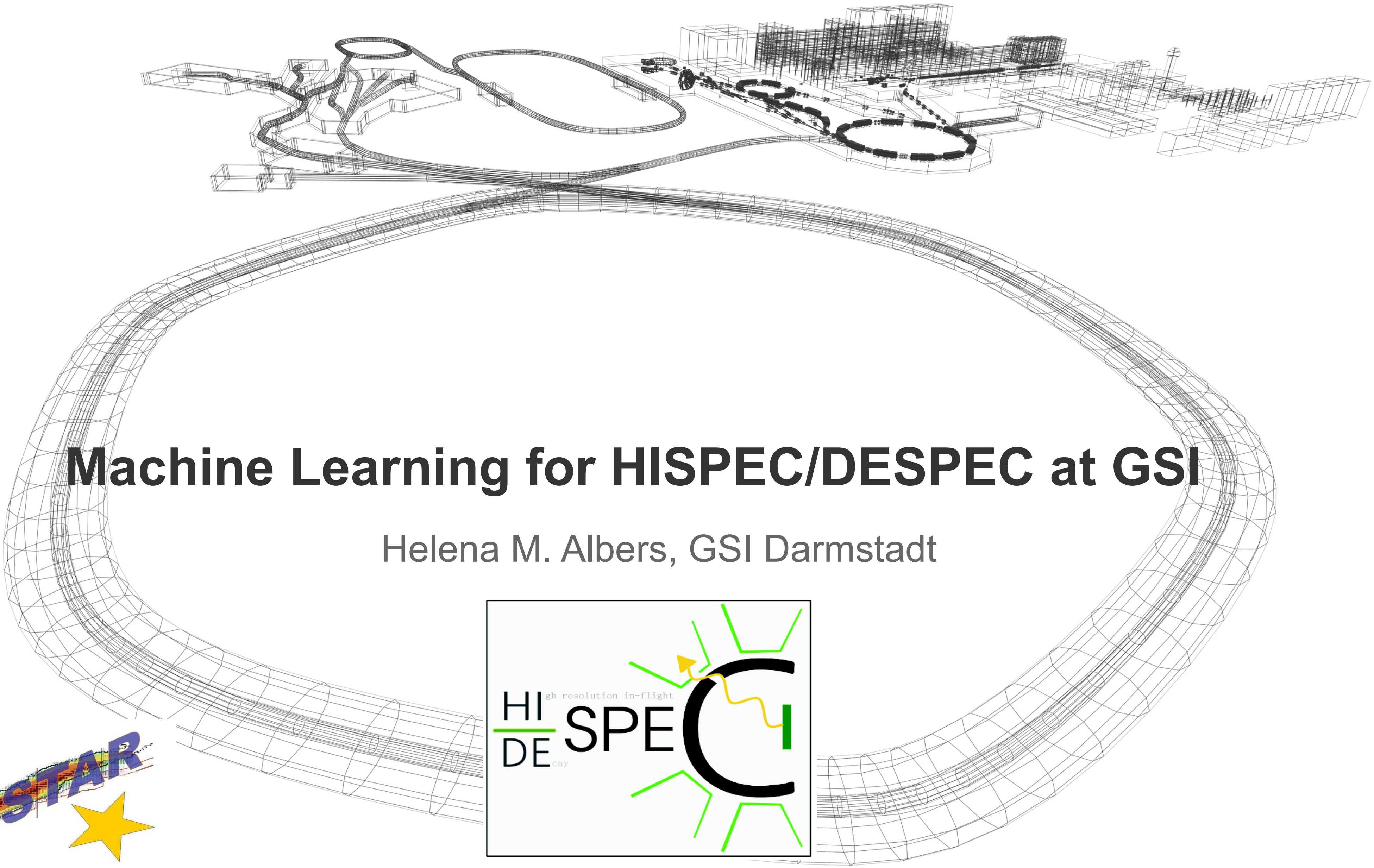


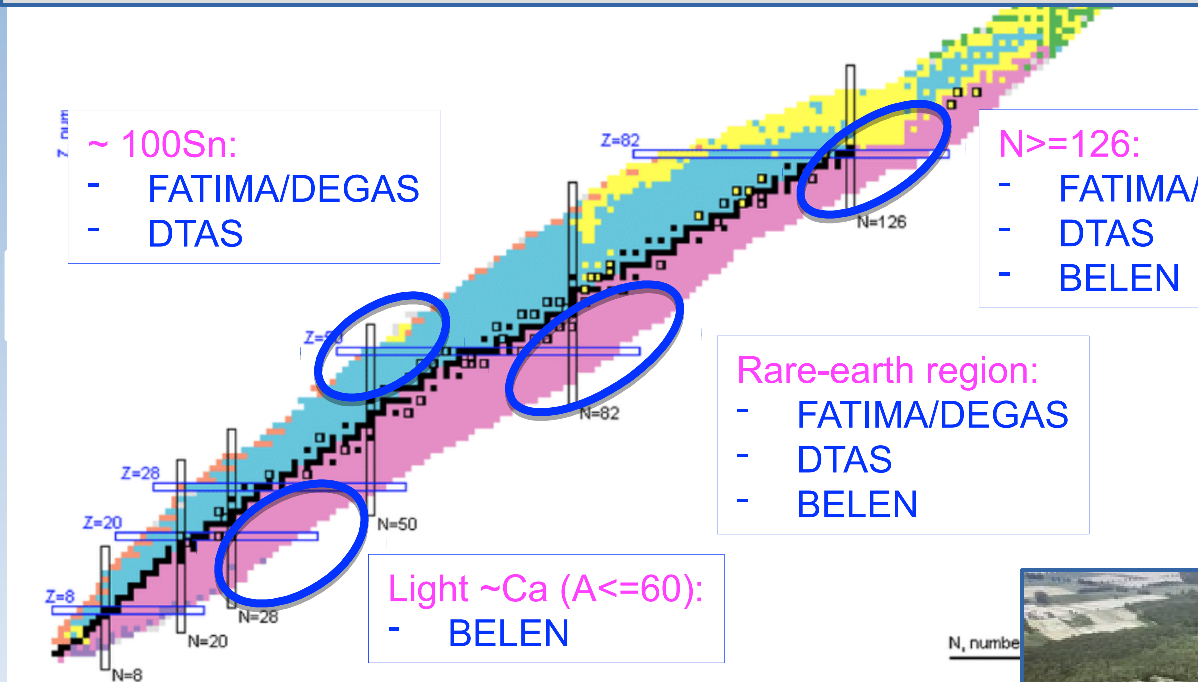
Machine Learning for HISPEC/DESPEC at GSI

Helena M. Albers, GSI Darmstadt

DEcay SPECtroscopy@FAIR

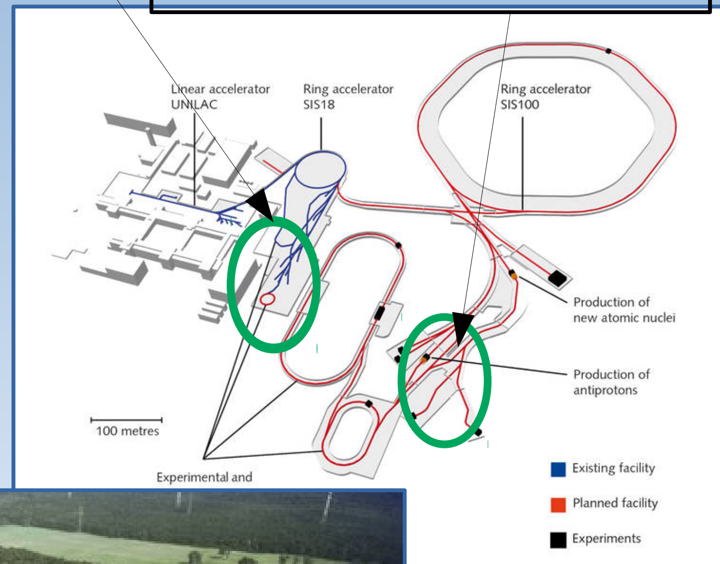
Physics goals and motivation

- Access to key r-process nuclei: towards a full picture of the beta-decay process around third **r-process peak**
- Studying **shape evolution** and accessing extreme nuclear configurations
- Nuclear structure around ^{100}**Sn and** ^{132}**Sn**



Existing GSI facility
SIS18 + FRS

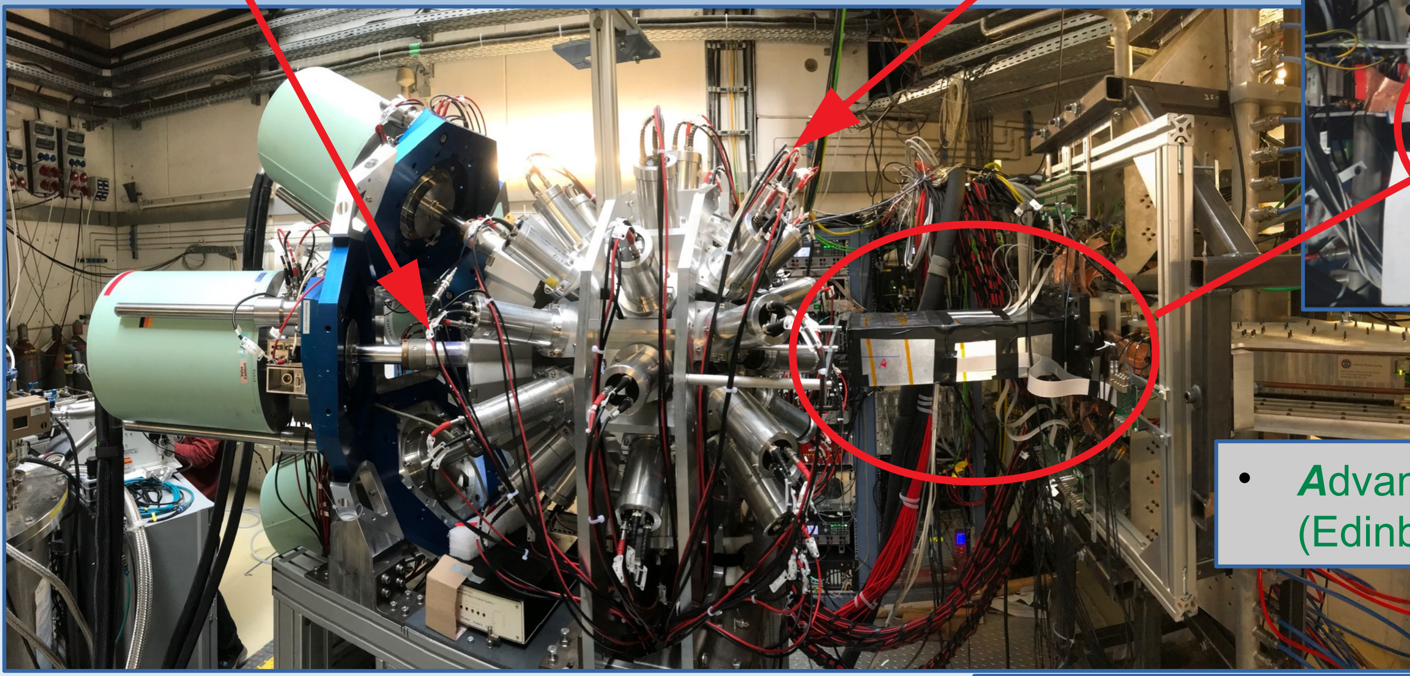
Future FAIR
SIS18/100 + S-FRS



2020-2021 Setup

- ***FA**st **TIM**ing **A**rray of $LaBr_3$(Ce) detector modules*

- Euroball (EB) gamma-ray detectors (HPGe)



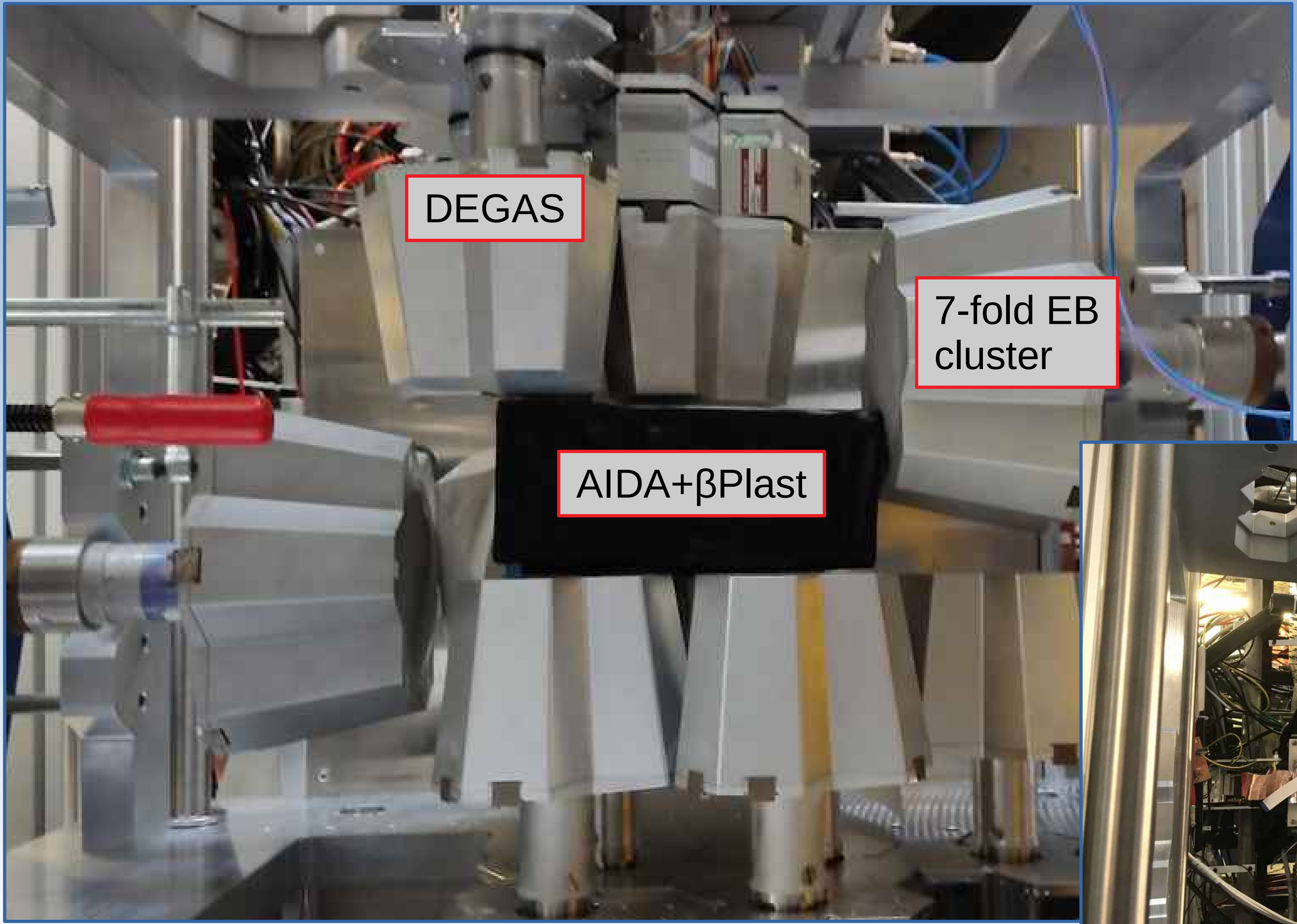
- ***A**dvanced **I**mplantation **D**etector **A**rray* (Edinburgh, Daresbury, Liverpool)

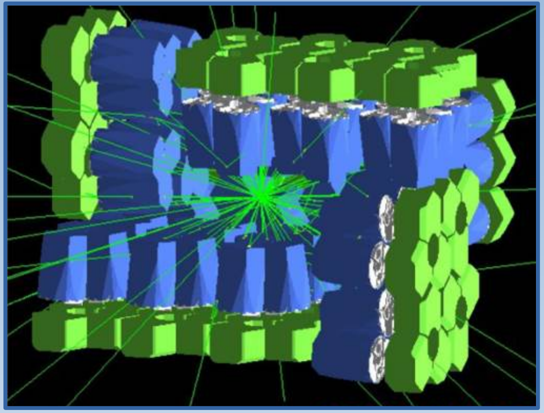
+

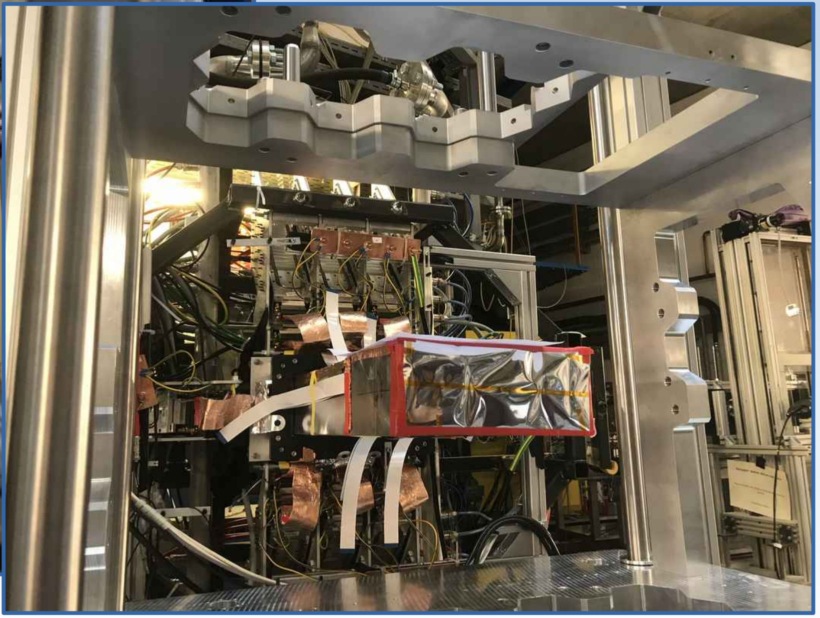
- The **βPlast** detectors: 3-mm thick plastic scintillators (UWS, GSI)

May 2022

- **DEGAS triple clusters + 2EB + wide AIDA/βPlast**

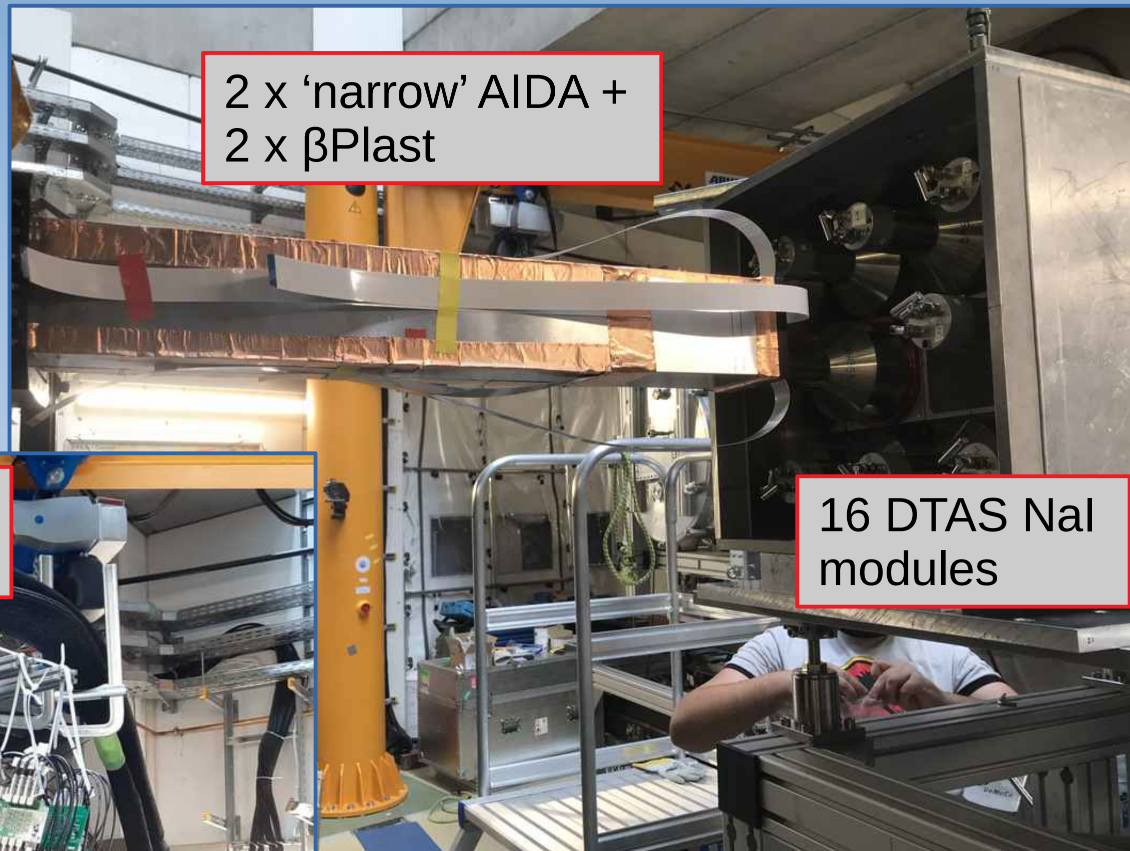


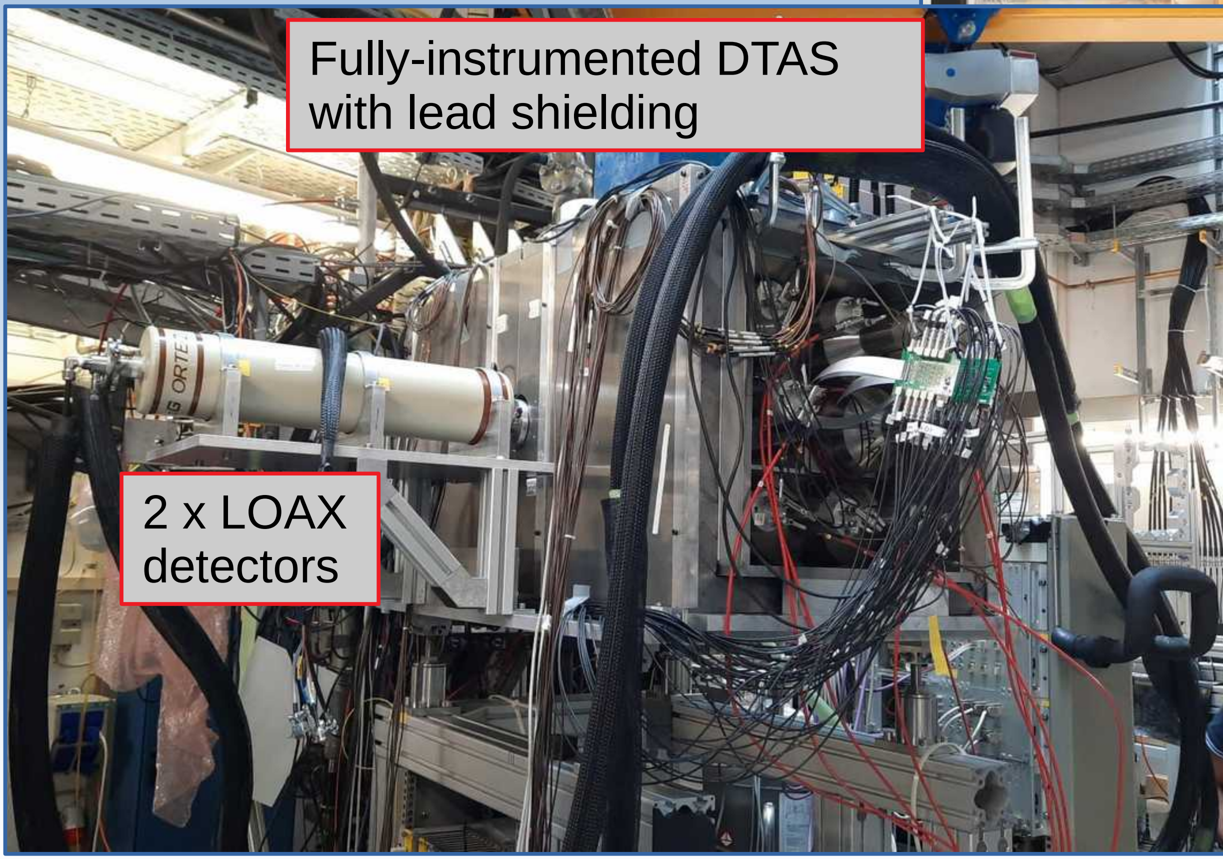


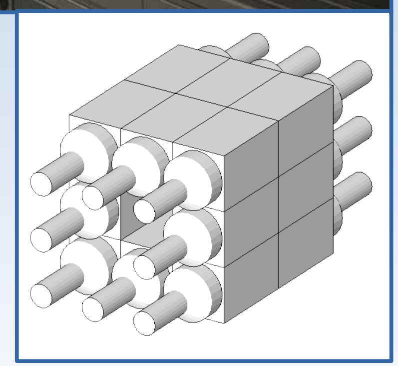


June 2022

- **DTAS Total Absorption Spectrometer + ‘narrow’ AIDA + βPlast + 2 x LOAX**

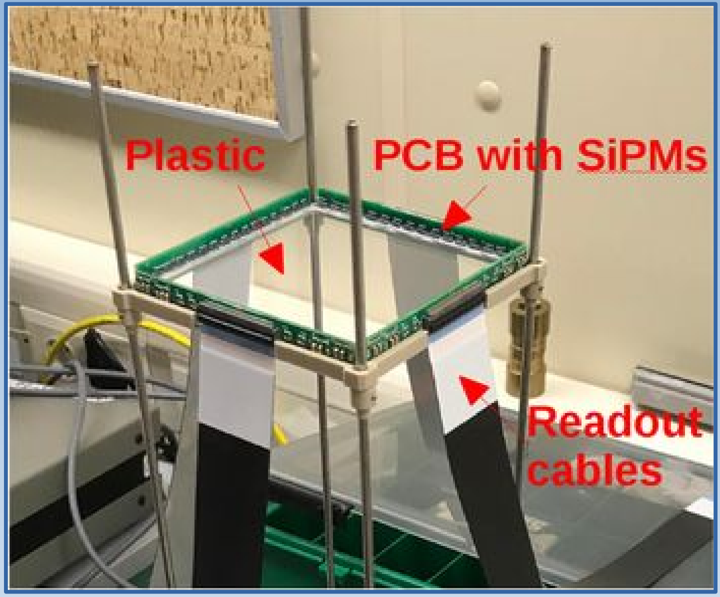






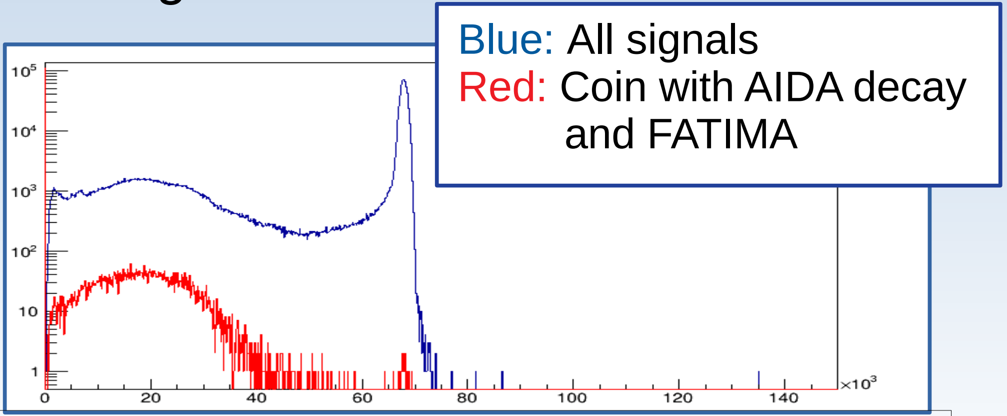
Improved position resolution of the βPlast detectors

- The βPlast detectors: 3-mm thick plastic scintillators - UWS, GSI
- Used as a veto (light ions, punchthroughs), β/α-gamma timing
- SiPMs at the edges coupled to readout channels
- Processed using in-house TAMEX electronics



- Two 8x8-cm^2 (or 24x8-cm^2) detectors sandwiching AIDA
- Excellent timing resolution (~100s ps)

- ***Students:*** Alessandro Montalbano (U Palermo) GET_INvolved program
  Güler Aggez (Uni Istanbul) PhD Student



βPlast Time-over-Threshold (ToT) distributions

Improved position resolution of the βPlast detectors, Part 1

- In the first part of the project, **heavy-ion interactions** are considered

→ These are relatively easy to deal with as large amounts of light is produced in the scintillator material

Goal: to compare *known* interaction positions to *reconstructed* positions and evaluate the achievable resolution

↓

How to generate suitable labelled data?

↓

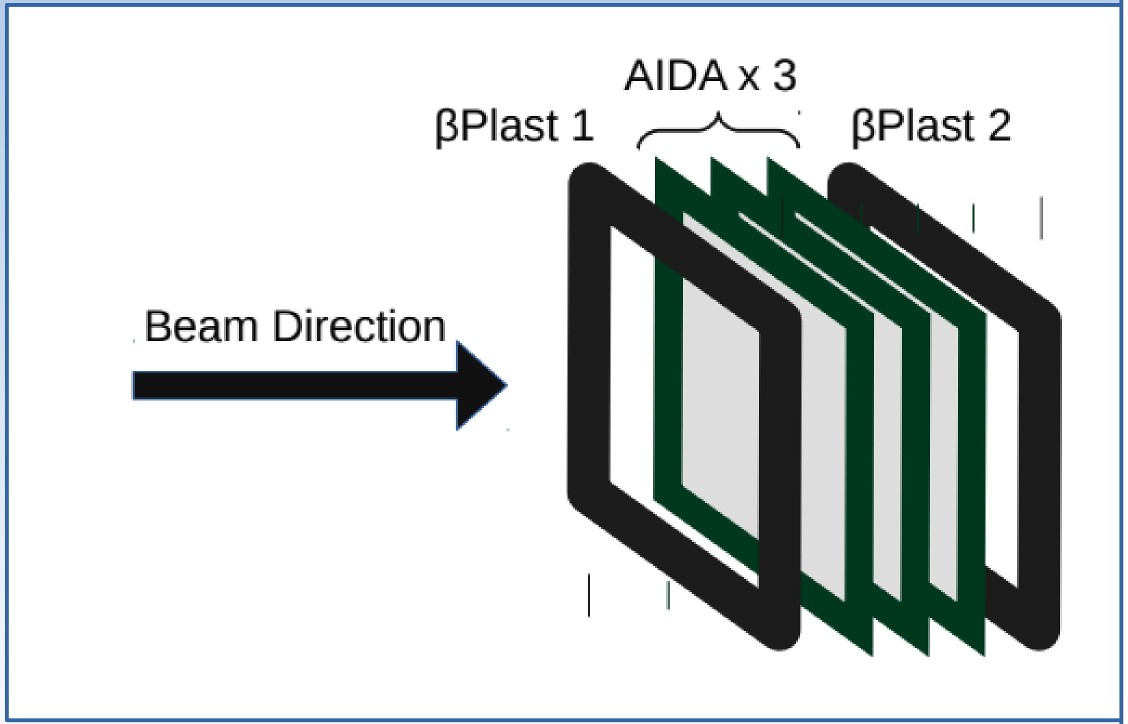
How should the data be analysed/prepared?

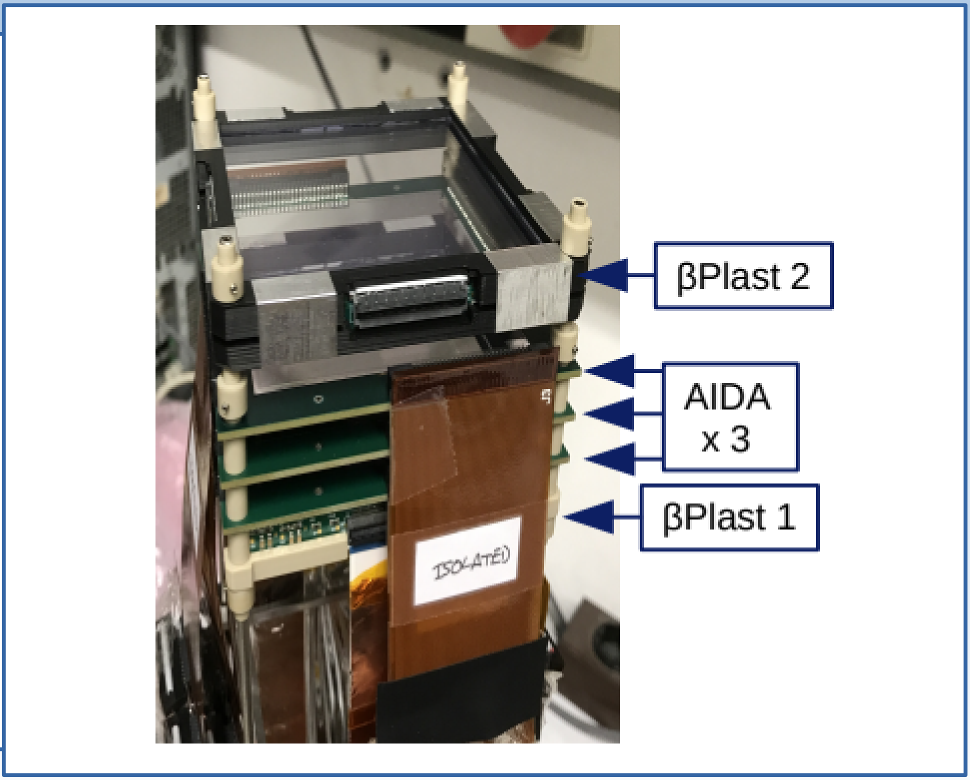
↓

How to carry out an efficient and accurate reconstruction?

Data collection and processing

- Data was generated during a DESPEC experiment in 2021
- Heavy ions with mass A∼220-230 and Z∼80-90 (Hg to Sr) were incident on a stack of detectors
- Two βPlast detectors sandwiched three ‘AIDA’ detectors
- AIDA detectors are segmented, with a pixel size ~0.5 mm and >99% efficiency

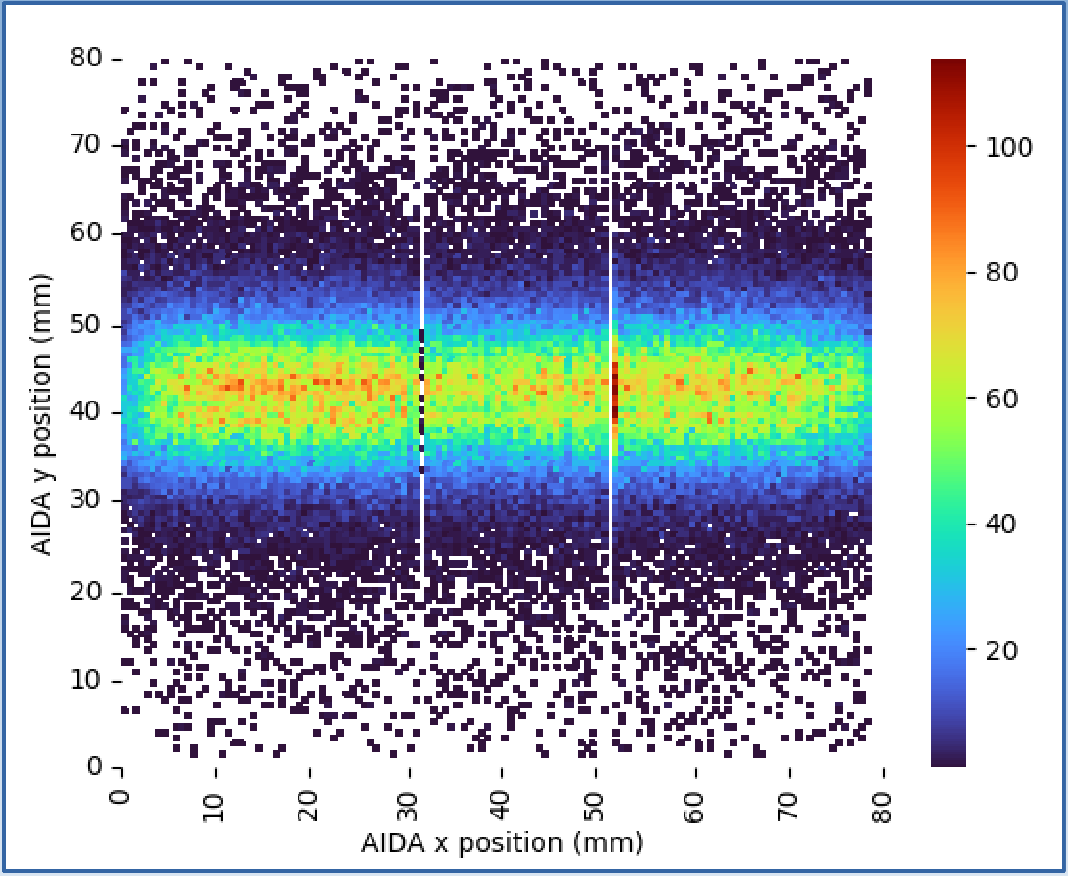


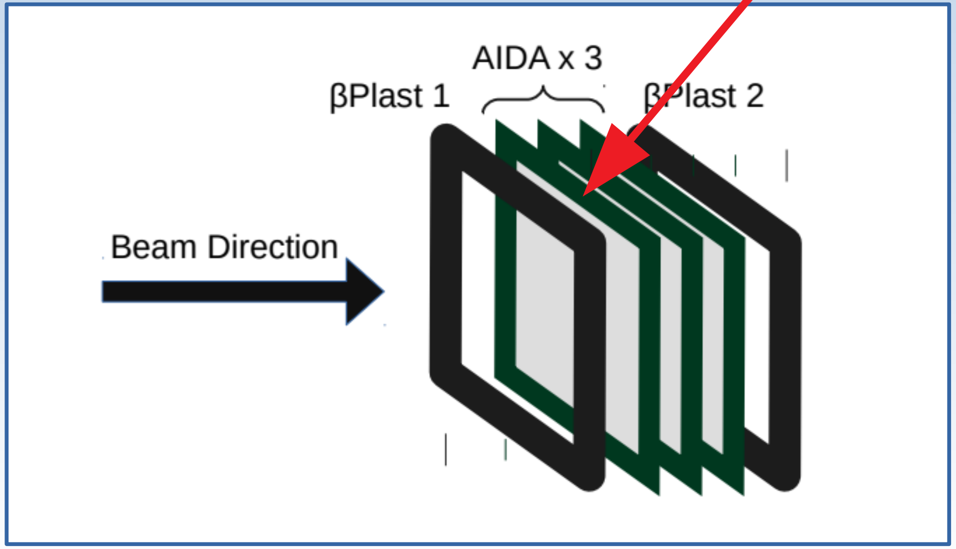


Data collection and processing

- Hit pattern on the first AIDA detector shows the position of the ions
- Beam was defocussed in x but narrow in y

- Events were selected such that:
  - AIDA 1 recorded a hit
  - Hit is unique
  - All of the βPlast channels fired

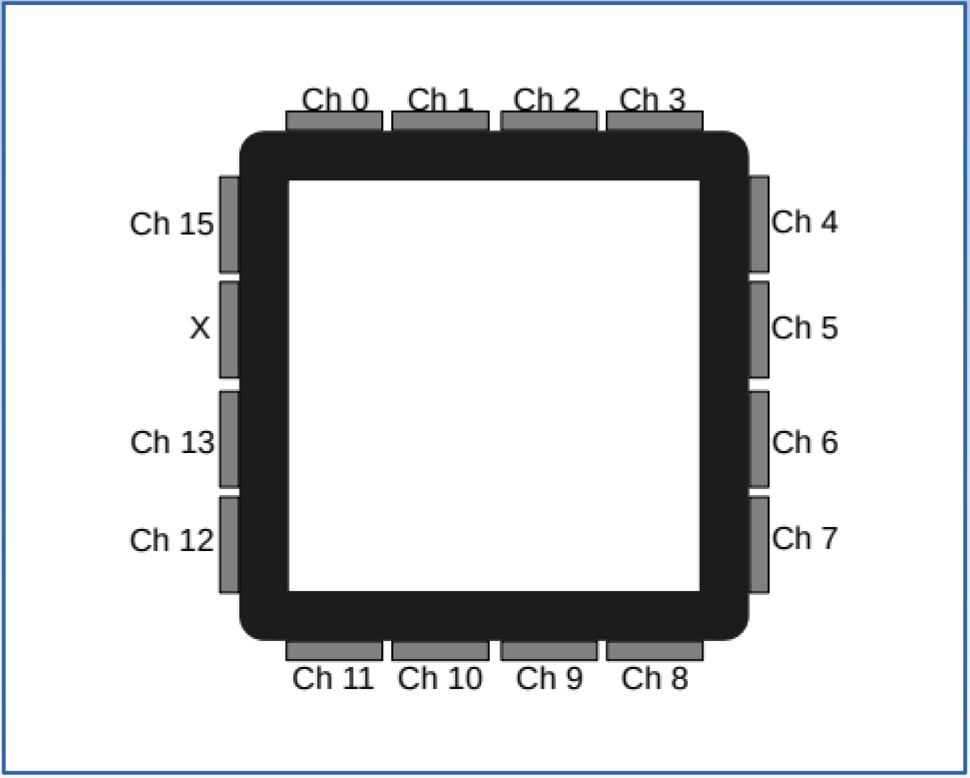




Data collection and processing

- Problem – large light output means saturated SiPMs… no usable energy information!

- Therefore ***timing*** information is used



Data collection and processing

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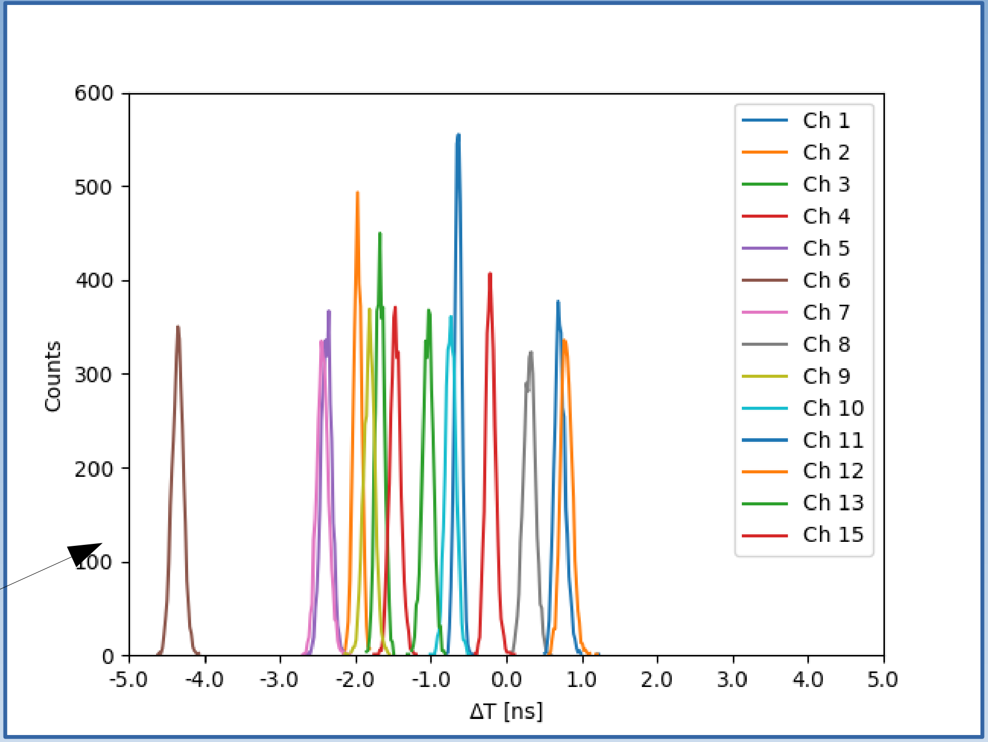
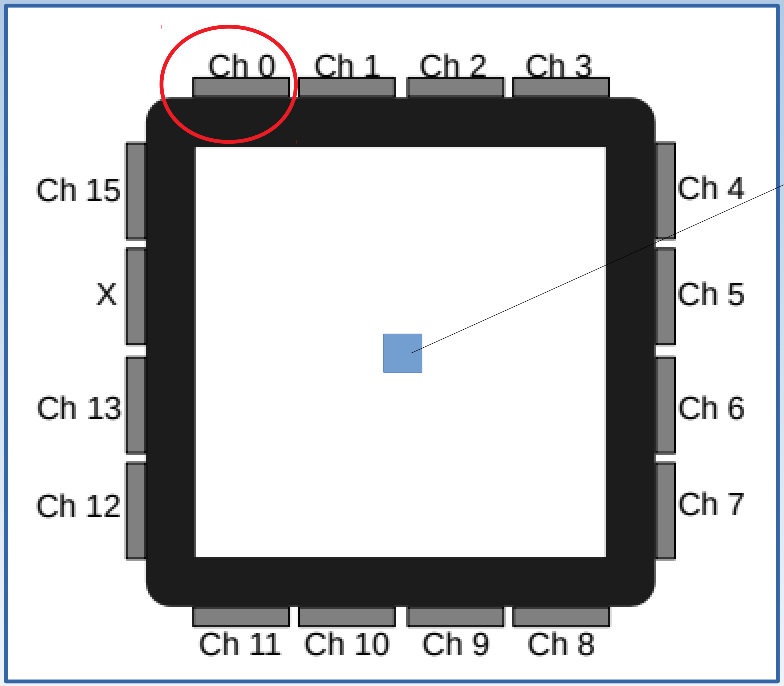
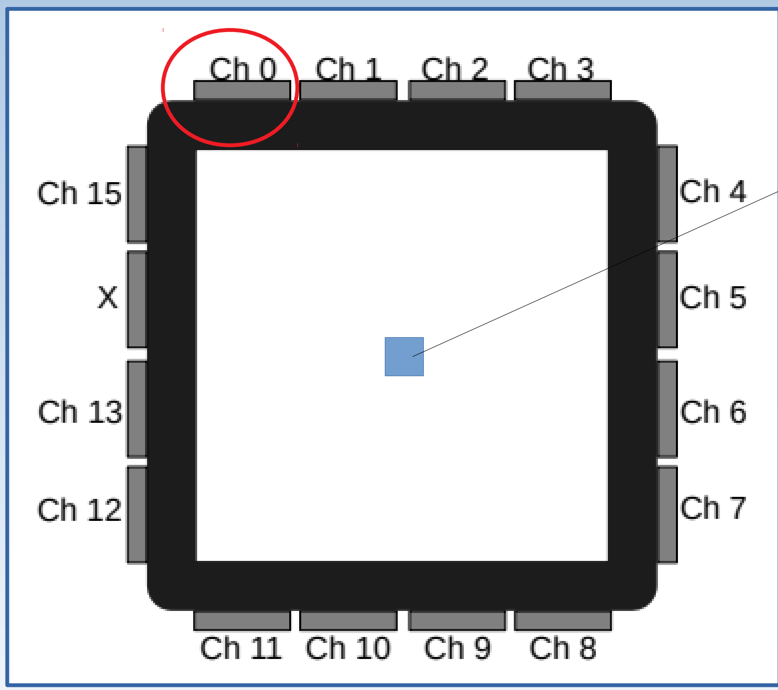
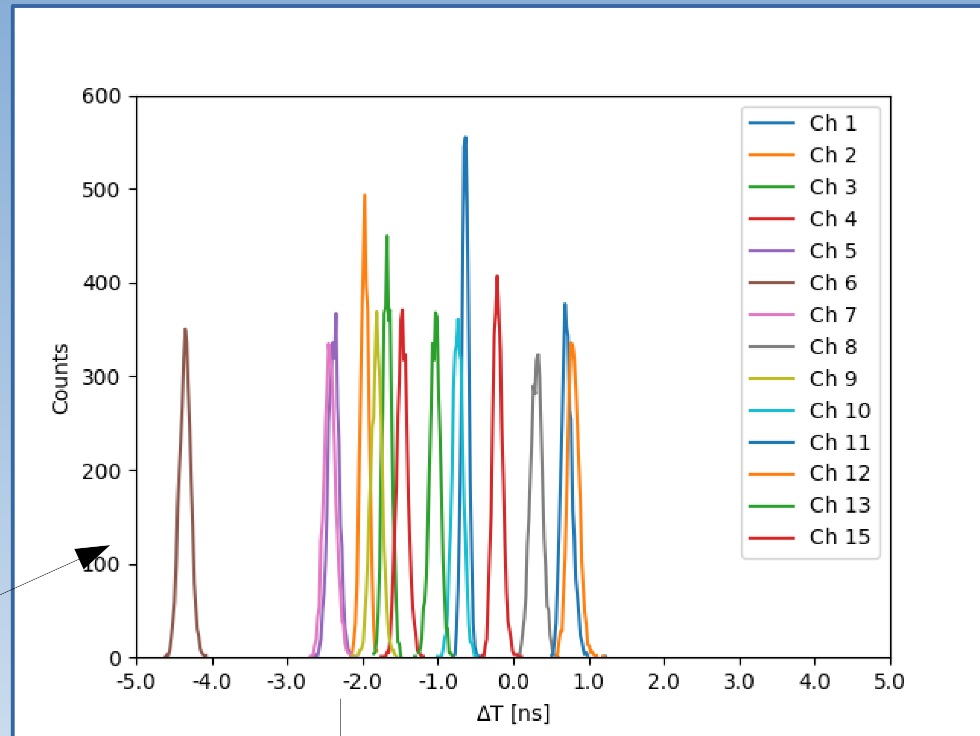


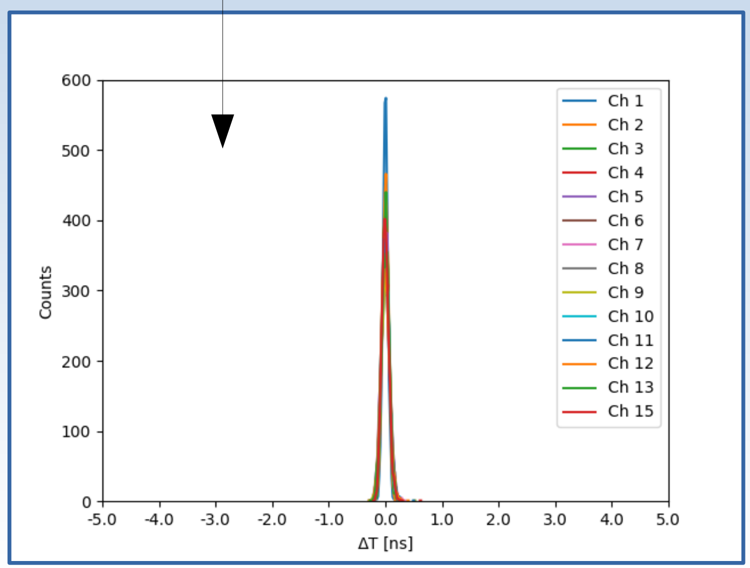


Data collection and processing

- Channels are aligned such that time difference distributions are centred at 0

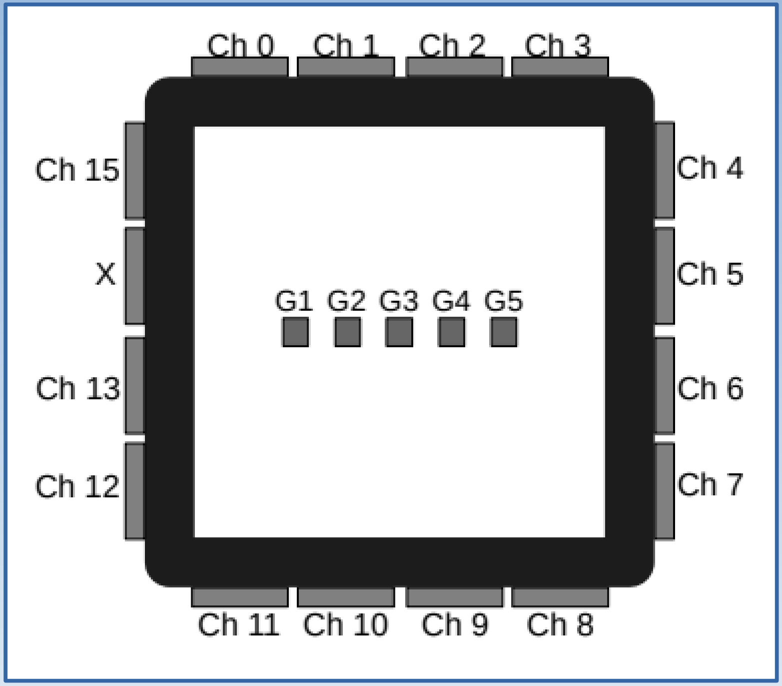


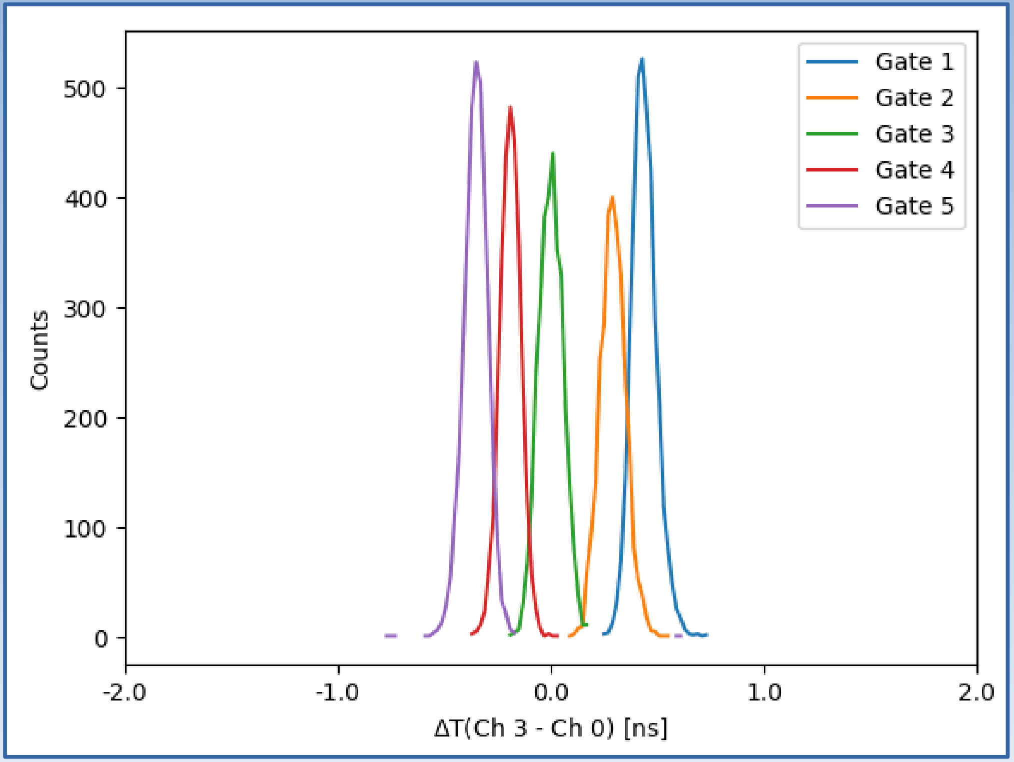




Data collection and processing

- Time difference distributions between Ch0 and Ch3 for different gates





Nearest neighbour reconstruction with KDTree

- ‘Lookup Table’ generated, with averaged time differences of all channels *for each pixel of AIDA* (i.e. 128x128 entries)
- Tables generated using 100k, 200k and 500k events

PosX (strip number X)

PosY (strip number Y)

dT# (time difference between channel # and channel 0)

PosX	PosY	dT0	dT1	dT2	dT3	dT4	dT5	dT6	dT7	dT8	dT9	dT10	dT11	dT12	dT13	dT15
91	90	0	-0.0642287	-0.109513	-0.109452	-0.108665	-0.0907854	-0.0489191	0.0202923	-0.0406718	-0.0174948	-0.00612049	0.00687765	0.00670136	-0.00197111	-0.0563917
91	91	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	92	0	-0.0793157	-0.12705	-0.134371	-0.143239	-0.117952	-0.0978655	-0.0299068	-0.0708435	-0.042535	-0.0373934	-0.0321594	-0.0295418	-0.0245802	-0.0758714
91	93	0	-0.0765231	-0.154894	-0.155575	-0.153685	-0.134458	-0.0862165	0.00163878	-0.073651	-0.0469462	-0.0368783	-0.021429	0.00015852	-0.0188813	-0.070994
91	94	0	-0.0832659	-0.153694	-0.151327	-0.157002	-0.125989	-0.0851999	-0.0187286	-0.0693139	-0.055176	-0.0339633	-0.0171839	-0.032586	-0.0394784	-0.0735781
91	95	0	-0.0857524	-0.158187	-0.153342	-0.162543	-0.125704	-0.0889414	-0.0116579	-0.0802292	-0.0486826	-0.0402342	-0.0240862	-0.0203965	-0.0318646	-0.0764803
91	96	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
91	97	0	-0.112228	-0.167083	-0.167885	-0.159266	-0.129581	-0.0975844	0.00202333	-0.0720296	-0.0487381	-0.0263663	-0.0256226	-0.0167393	-0.0264432	-0.0736081

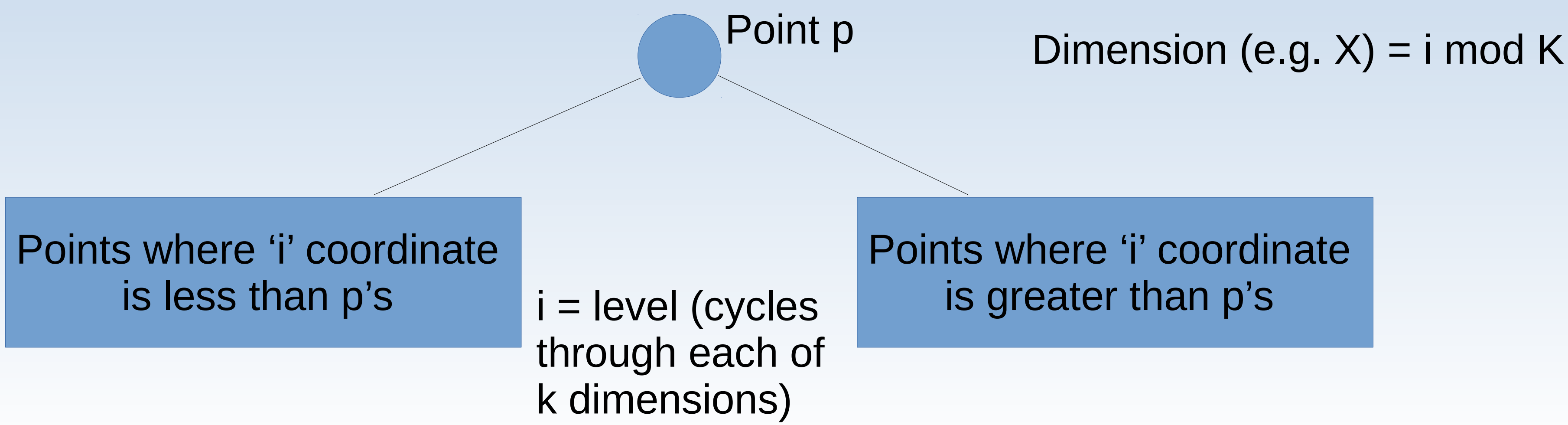
Nearest neighbour reconstruction with KDTree

- KDTrees: space-partitioning data structures, points represented in k-dimensional space
- The K-dimensional space is recursively partitioned into 2 sections
- Allows us to search for the ‘r’ nearest neighbour of a query point

- Each level has a ‘cutting dimension’
- The dimension changes as you go ‘down’ the tree

Simple example: 2D Euclidean space

Each node contains an (X,Y) coordinate
In the first level, X is the cutting dimension
Next node with (X’,Y’) is positioned either in the ‘left’ hyperspace or ‘right’ hyperspace depending on whether X’>X or X’<X

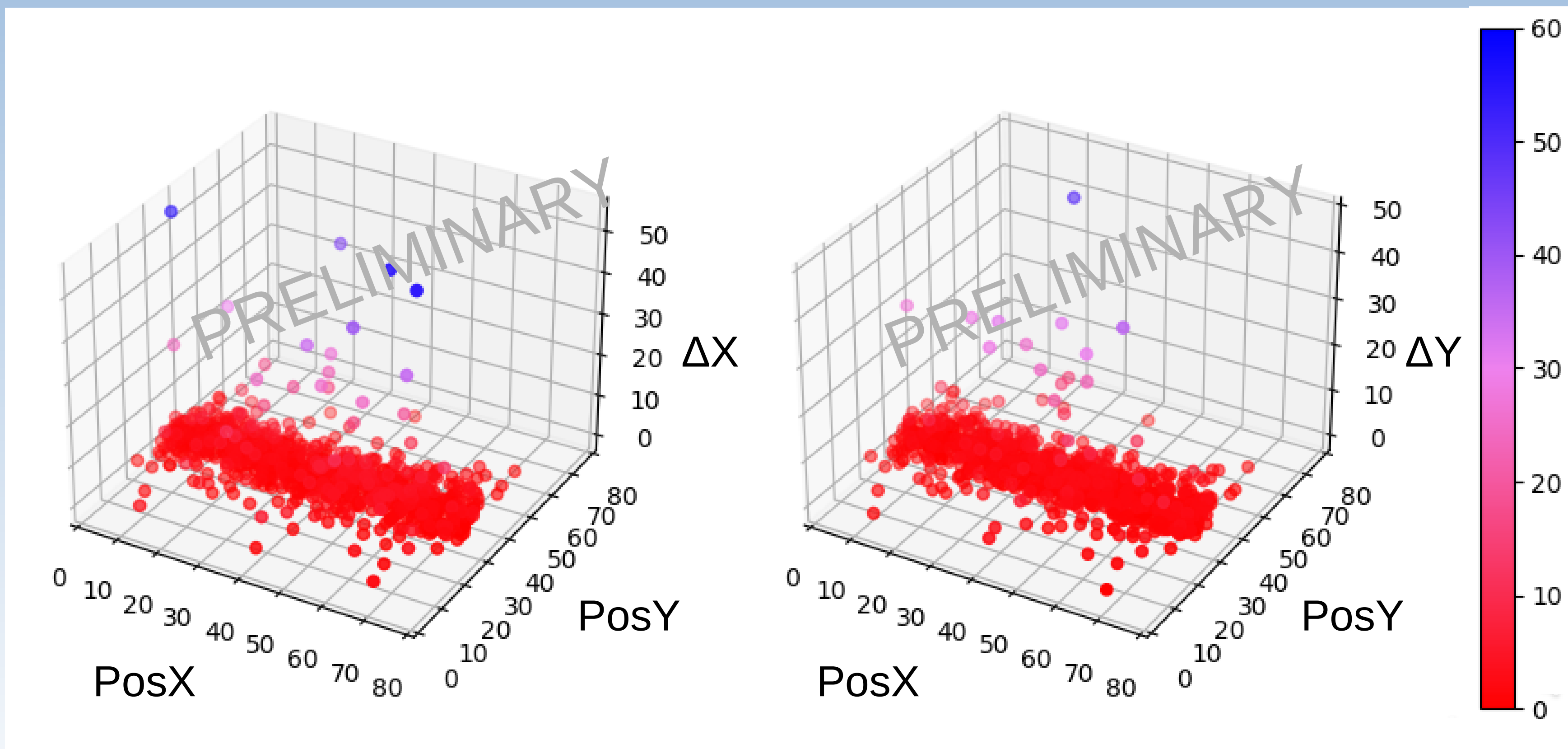


Nearest neighbour reconstruction with KDTree

- Implemented in Python using scikit learn machine learning library
- Queries for 1000 independent test events

```
class sklearn.neighbors.KDTree(X, leaf_size=40, metric='minkowski', **kwargs)
```

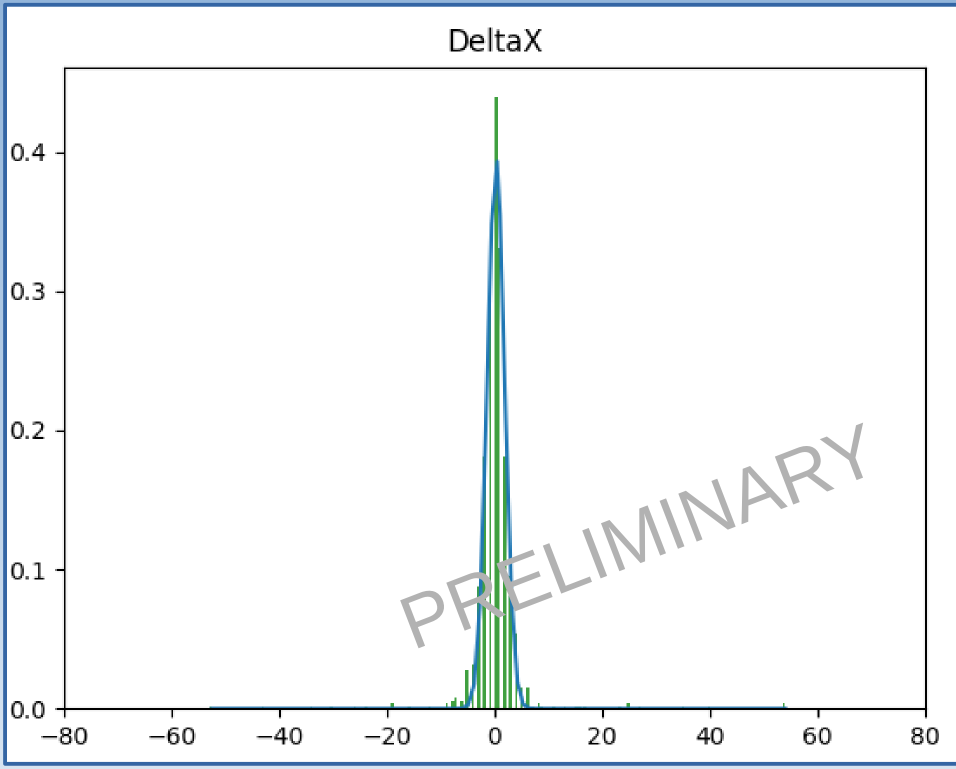
$$\Delta X = X_{label} - X$$
$$\Delta Y = Y_{label} - Y$$

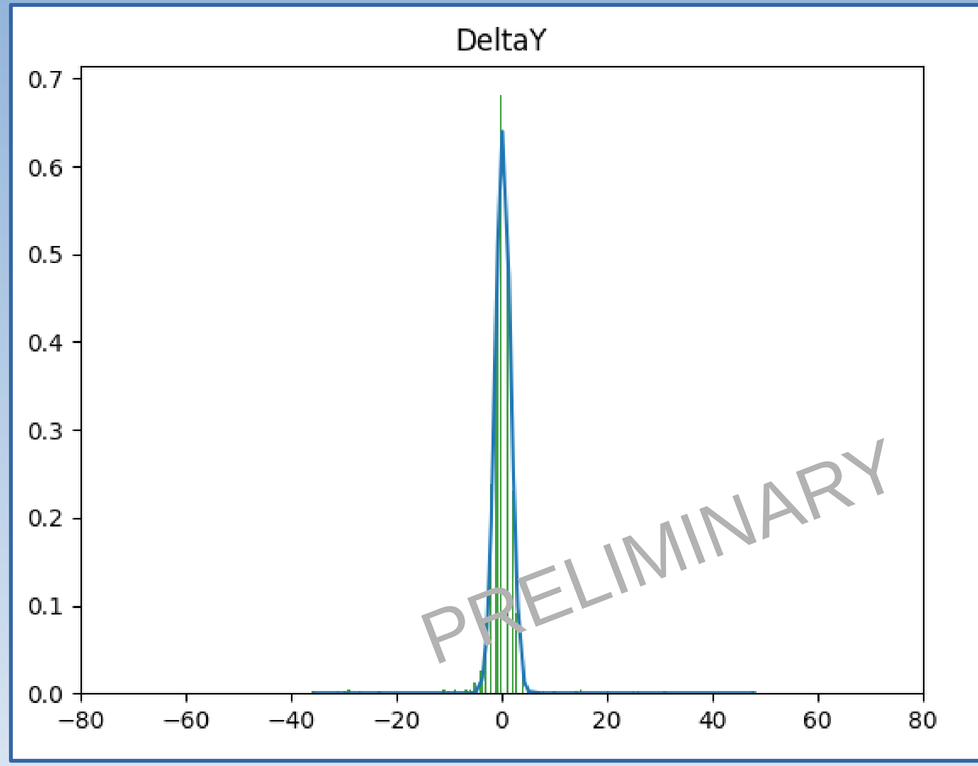


Nearest neighbour reconstruction with KDTree

$\Delta X = X_{label} - X$

$\Delta Y = Y_{label} - Y$





Remaining questions:

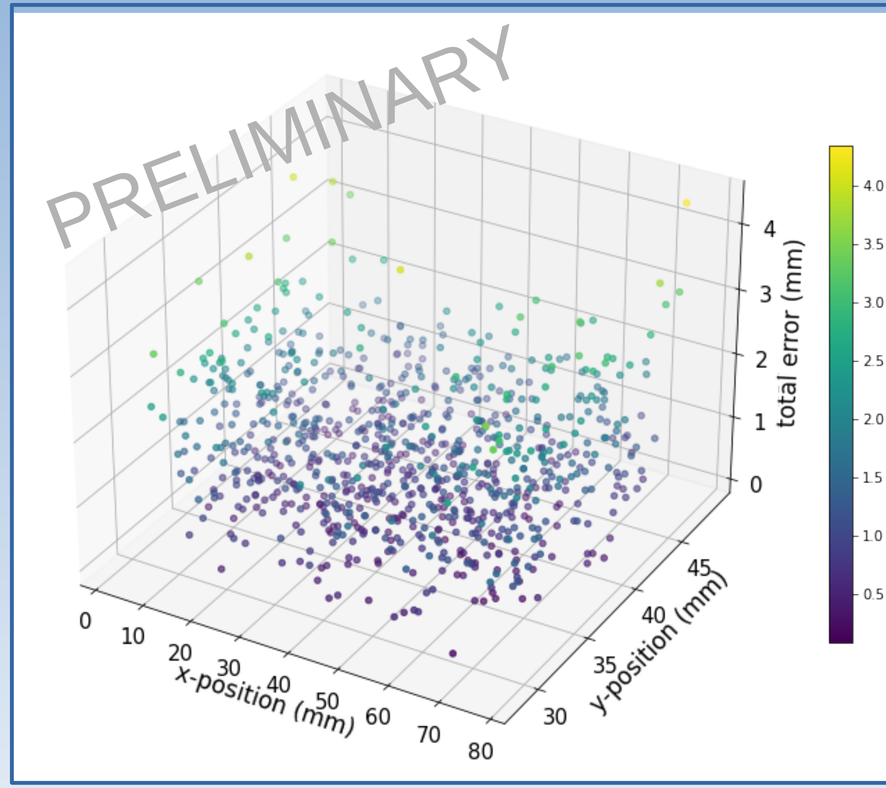
- How to reduce 'chance' matches?
- Best way to construct tree?
- How to define 'resolution' (i.e. are X and Y independent?)
- How to deal with label errors?
- Effect of dimension ordering?
- How much data is required for Lookup table generation?
- Comparison with brute force?
- ...

Reconstruction with multitarget ANN

Work of Alessandro Montalbano (Uni Palermo, GET_INvolved@GSI)

Multitarget ANN regression model:

- Python and TensorFlow ML library (+standard libraries)
- Relu activation function in hidden layer
- Bounded leaky relu activation function [1] in output layer (prediction of continuous variables in bounded range)
- Batch normalisation and dropout
- Hyperparameter tuning: epochs, learning rate, batch size, number of nodes,…
- Training data, 200k individual events
- Same event selection as for KDTree

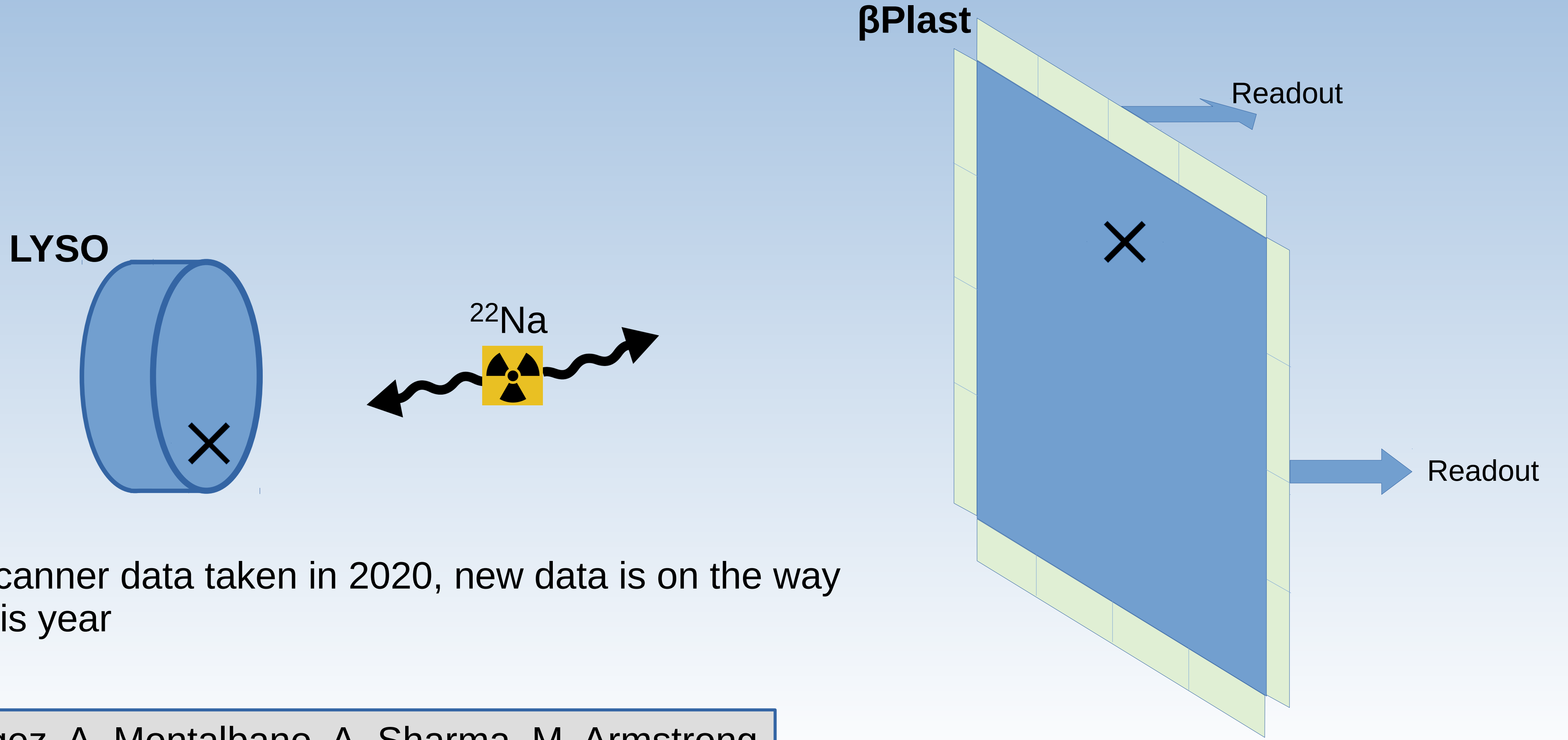


[1] S. S. Liew, M. Khalil-Hani and R. Bakhteri, Neurocomputing 216, 718 (2016)

Improved position resolution of the βPlast detectors, Part 2

- Second part of the project concerns position reconstruction for ***beta decays***
- Much more challenging!! Low photon counts, missing data, low statistics…

- Position reconstruction via ***timing*** or ***energy*** distribution
- Problem – how to generate data with labelled positions?
- Solution – GSI Scanner System



- Scanner data taken in 2020, new data is on the way this year

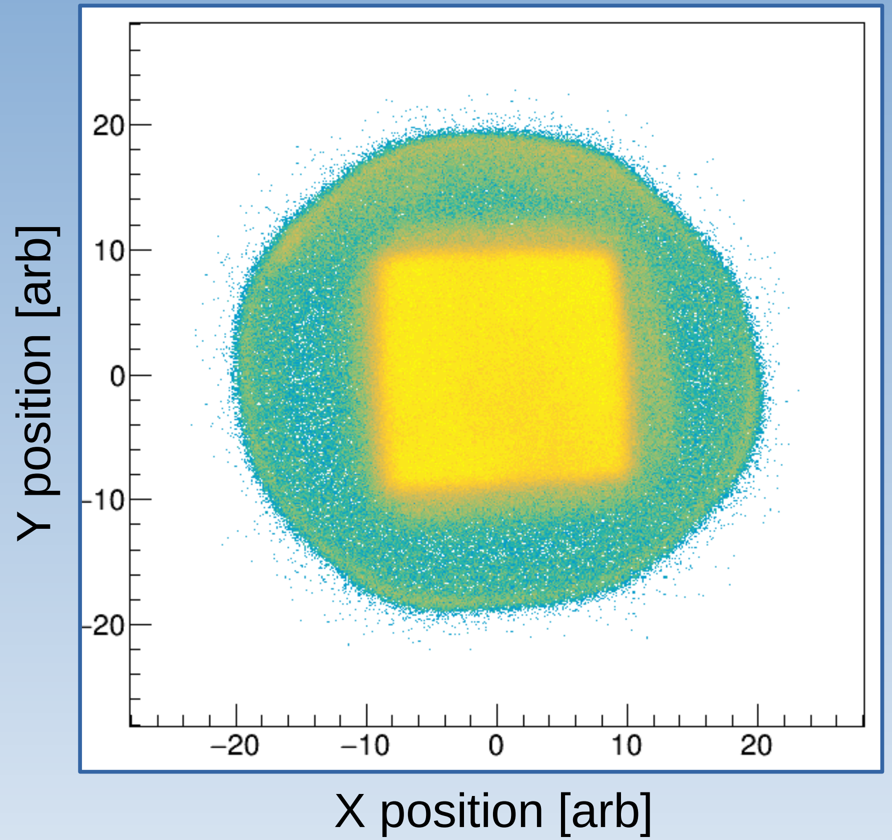
G. Aggez, A. Montalbano, A. Sharma, M. Armstrong

Improved position resolution of the βPlast detectors, Part 2

Analysis procedure and data preprocessing:

- LYSO anode gain matching
- 'Standard' gating procedure
- Standardisation: βPlast gain matching
- Event normalisation
- Handling of missing data
- Label scaling [-1,1]
- Training/validation/testing → **70/20/10**

Variable	Description
Event	The event number
Position x	x coordinate of the event of the βPlast detector
Position y	y coordinate of the event of the βPlast detector
QDC βPlast (1-14)	A measure of charge of the event



A. Montalbano (Palermo), GET_INvolved@GSI

Improved position resolution of the βPlast detectors, Part 2

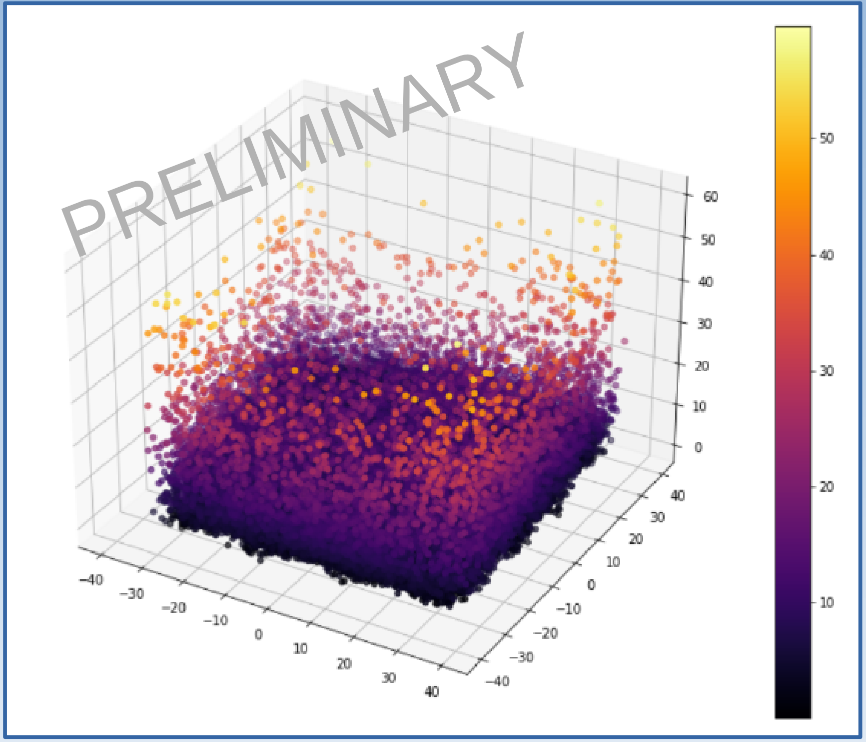
Model performance:

- Mean absolute error, LYSO error still to be determined (1-2mm)

$$\bar{\delta}_{ML} = \frac{|P - \hat{P}|}{N}$$

$$\delta_{tot} = \sqrt{\bar{\delta}^2_{ML} + \delta^2_{LYSO}}$$

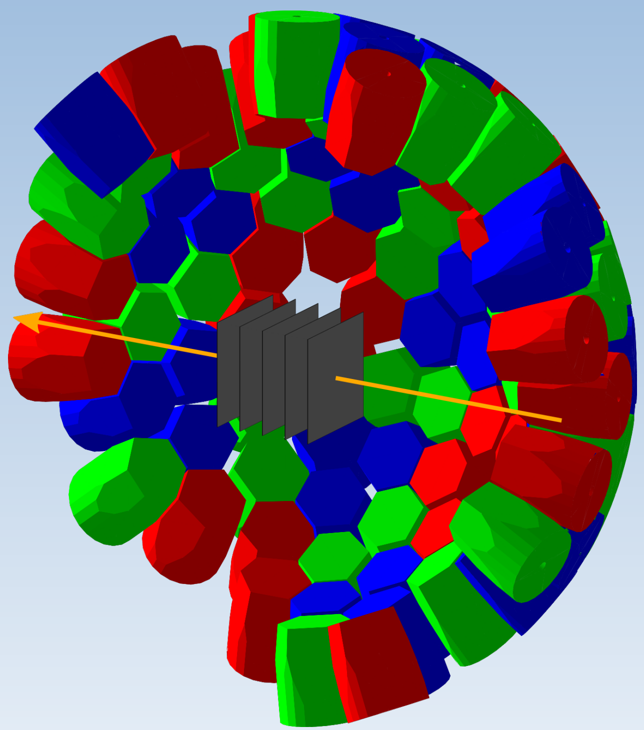
- Initial results promising...
- Could this be improved with combining energy and time information?
- Ongoing work...



3D plot of ΔP

LISA: LIfetime measurements with Solid Active targets

In nuclei, the **coexistence of single-particle and collective degrees** of freedom in atomic nuclei gives rise to various exotic phenomena.
Where and how collectivity emerges from the single-particle dynamics of protons and neutrons is an **open question in nuclear structure physics** that will be addressed with LISA in a unique way.

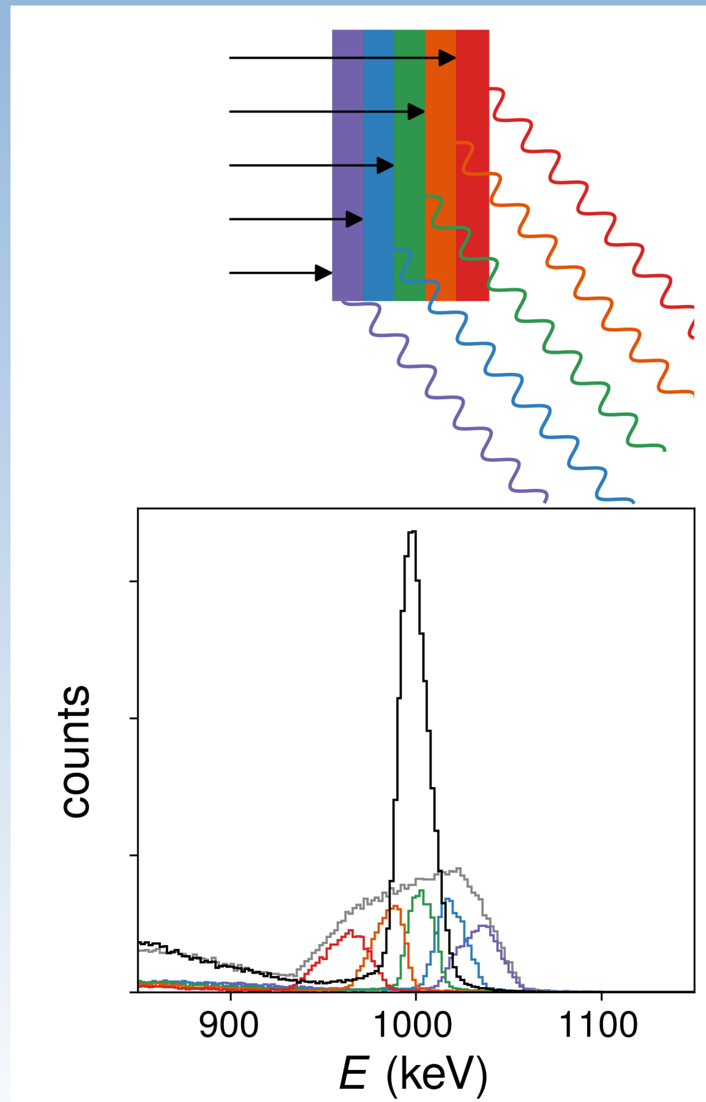


Compact array of active target detectors inside AGATA

- Energy resolution determined by unknown velocity in the target
- Several layers of active targets
- Event-by-event determination of reaction position → (β,z)

Opens new possibilities for lifetime measurements using AGATA at FAIR:

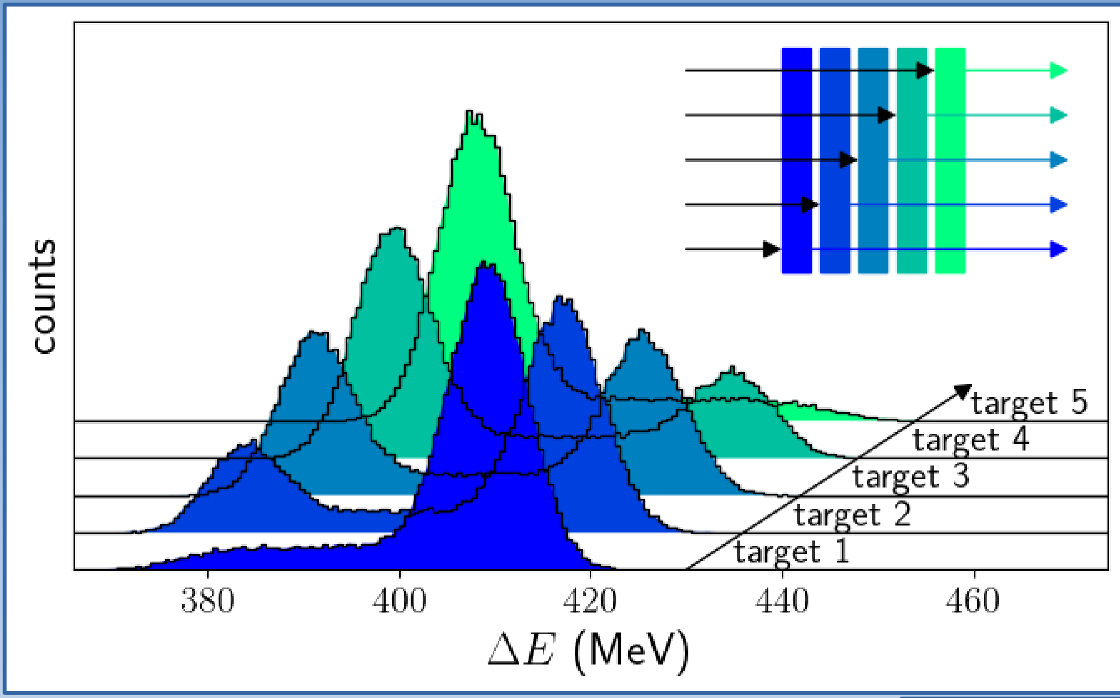
- Evolution of collectivity in Islands of Inversion
- Fate of the N=82 and 126 shell closures
- And many more



ERC-COG 101001561-LISA
PI: K. Wimmer

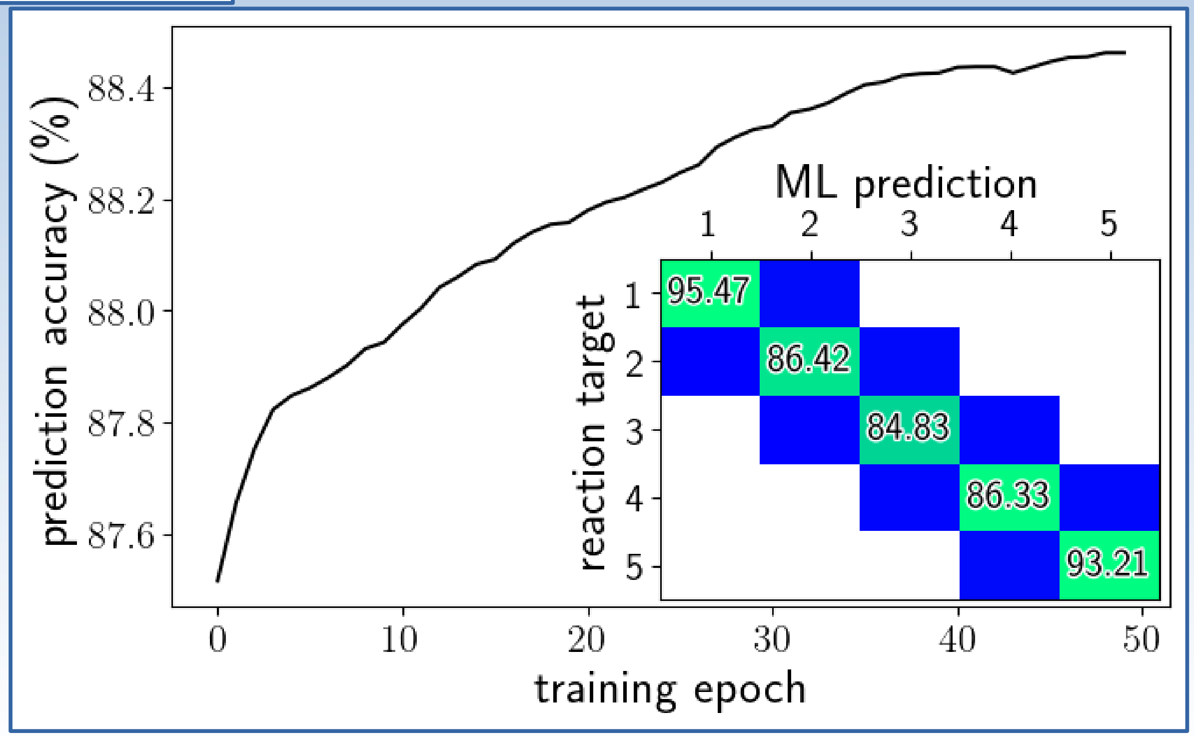
Slide courtesy of **K. Wimmer**

Layer identification by neural networks



- one-proton knockout reaction
- each layer measures the Z -dependent energy loss of the beam-like particles
- event-by-event Z identification in each layer

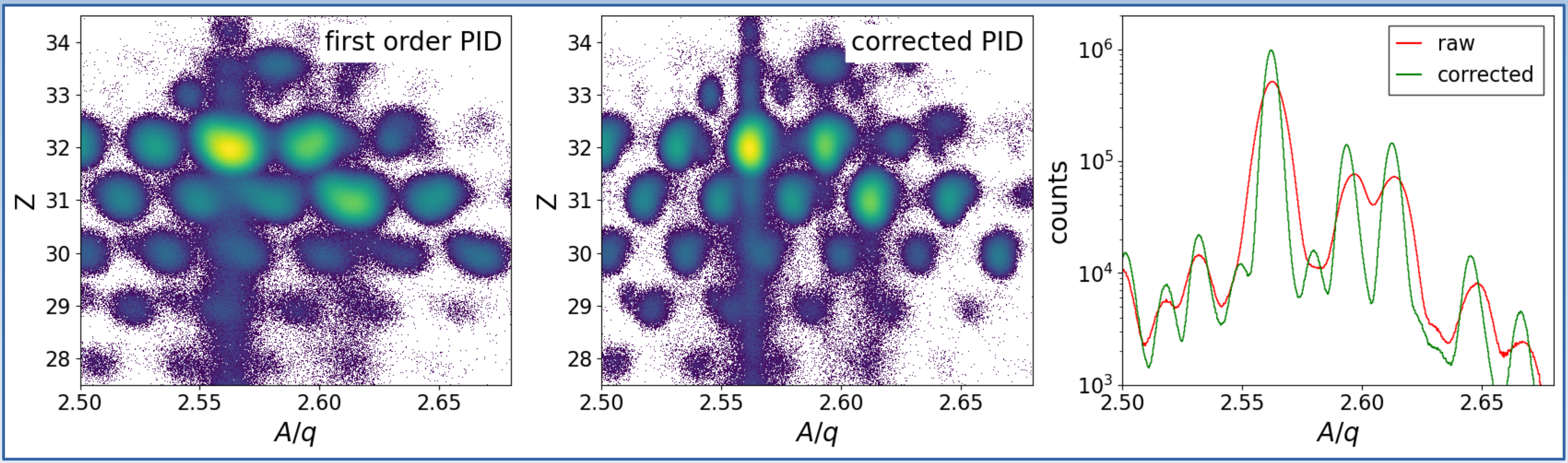
- achieved ~ 90% accuracy for identifying the correct layer
- most challenging cases are reactions at the surface of each layer
- improves accuracy for layer identification from 70 to 90% for challenging cases compared to simple gating



Slide courtesy of **K. Wimmer**

Optical corrections for particle identification

- particle identification at the BigRIPS and ZeroDegree spectrometers by ΔE-Bρ-TOF
- using first order matrix elements only
- significantly improved by (empirical) higher-order corrections
- high dimensional parameter space (7-8 dimension just for linear corrections)
- efficient stochastic batch optimization



Slide courtesy of **K. Wimmer**

What’s next?

<u>βPlast position resolution: work ongoing! Full assessment of algorithm performance</u>

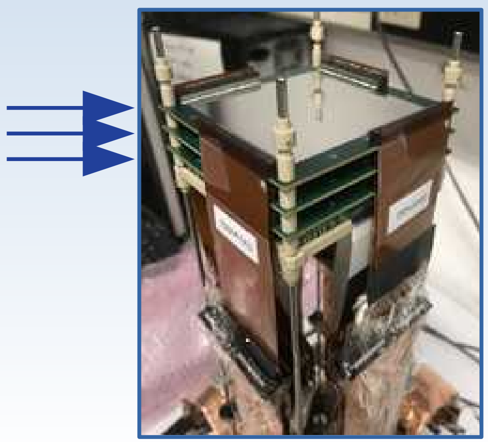
- New data being collected for ‘wide’ βPlast detector configuration in scanner setup
- Combinations of energy and timing information
- Application of algorithm to ‘real’ physics (data exists already...)!

<u>LISA: Improve and assess performance</u>

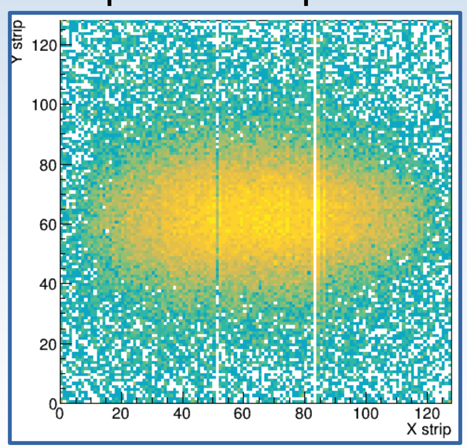
- In-beam experiment planned at GSI and HIMAC (RIKEN)
- Explore alternative algorithms

Other upcoming projects: AIDA

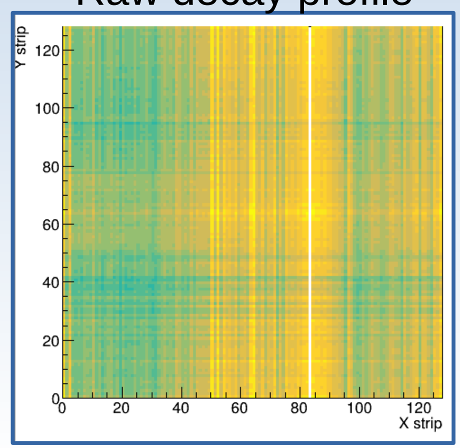
- The ***A***dvanced ***I***mplantation ***D***etector ***A***rray
- (Edinburgh, Daresbury, Liverpool)
- Triggerless DAQ and high segmentation → **large data throughput** and **noise**
- Aim to investigate **improvement of noise recognition capabilities** of current analytical techniques
- Current methods rely on subsystem coincidence, esp. for longer correlation times → reduced efficiency
- Likelihood analyses slow for large datasets - investigate use of AI filtering methods (e.g. CNNs, wavelet transforms,…)
- In collaboration with Valencia (simulations) and Uni Bologna (ML) starting in March 2023



Implantation profile



Raw decay profile



Summary and Outlook

- KDTree and MLP-ANN algorithms tested for improved βPlast position resolution
  - Data for heavy-ion and beta interactions investigated - results are promising!
- First results for improved proton-number identification with LISA promising
  - New in-beam data coming soon from GSI and HIMAC
- Further work planned!

With thanks to:

K. Wimmer, G. Aggez, T. Arici, M. Armstrong, J. Gerl,
M. Górska, I. Kojouharov, **A. Montalbano**, H. Schaffner, A. Sharma, and others

and you for your attention.