Calibration of scintillation cameras: machine learning approach

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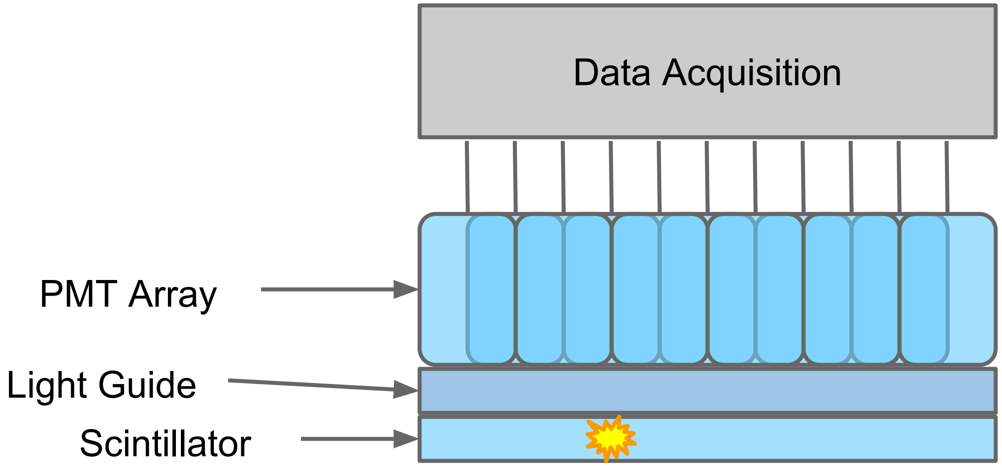
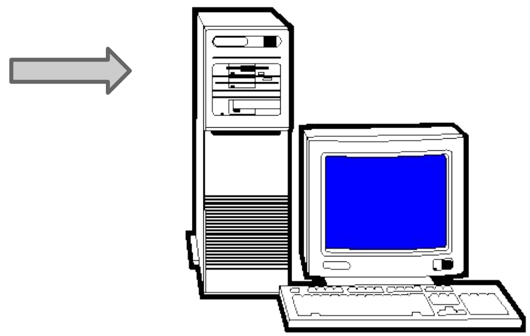
Overview

- Scintillation cameras
- Reconstruction and calibration: traditional way
- Machine learning view: manifold in signal space
- Nearest neighbour calibration
- 3D position reconstruction in thick crystals
- Channel mapping through manifold learning
- Machine learning tools in ANTS2

Scintillation cameras

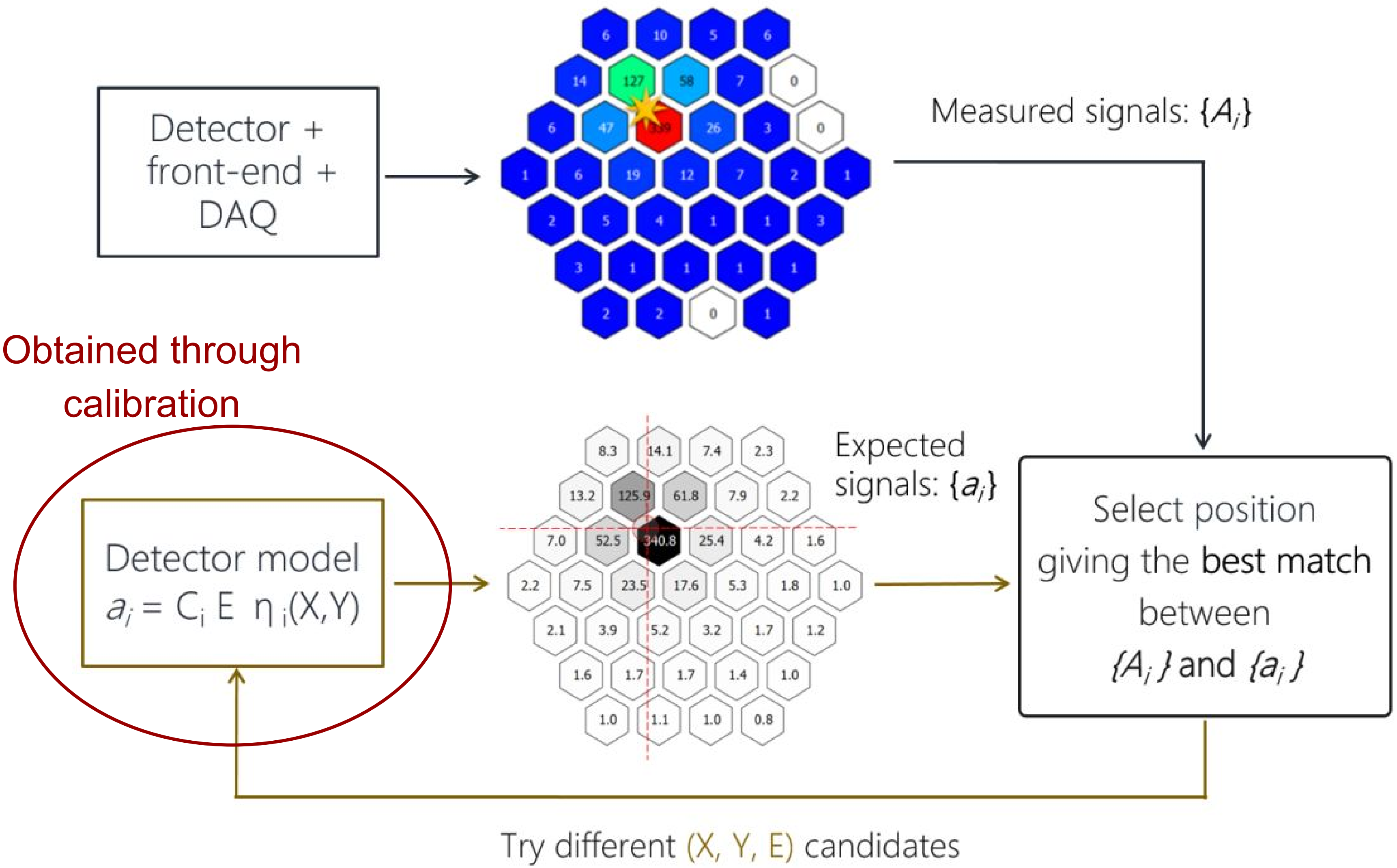




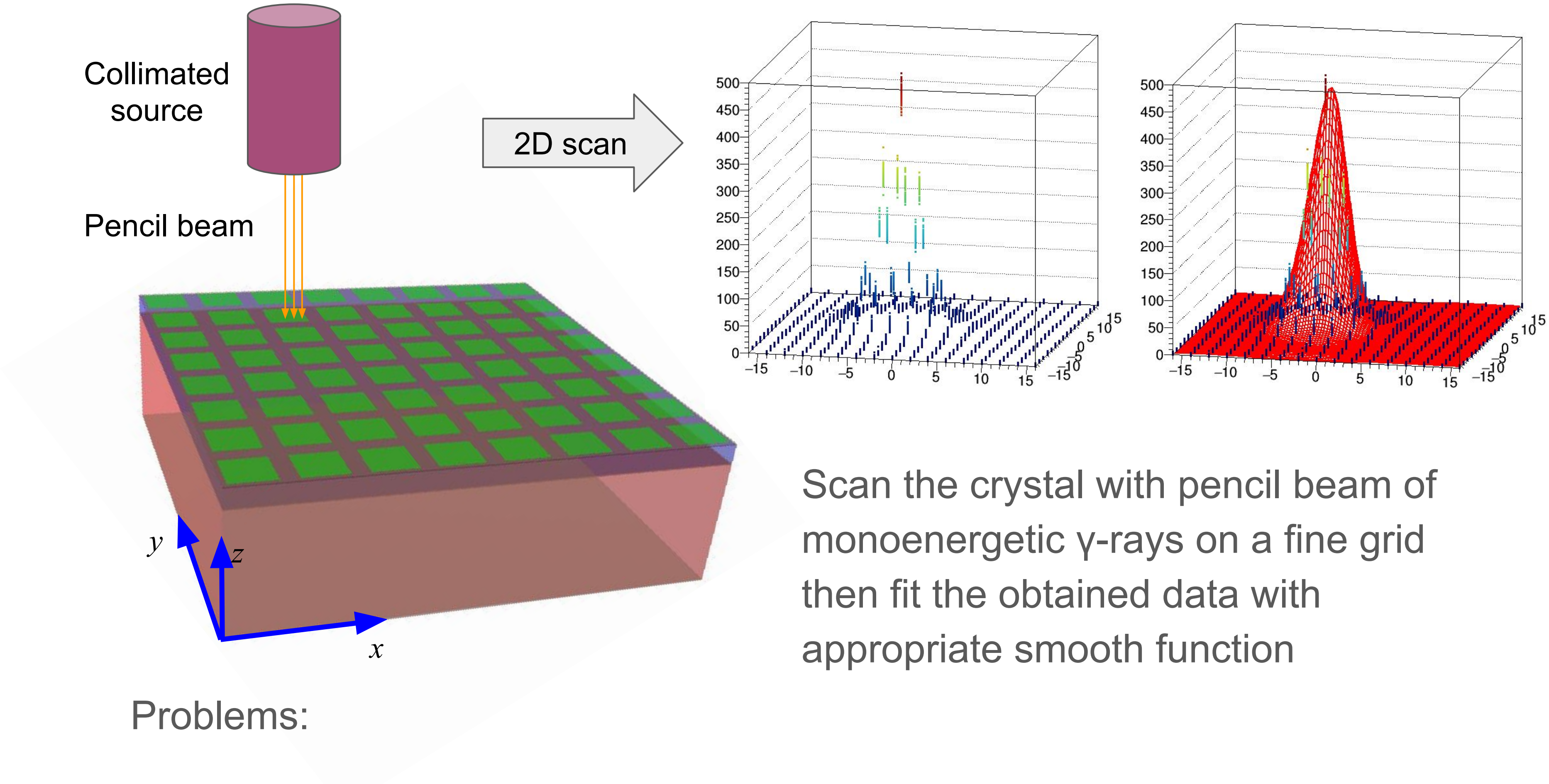
Applications:

- Medical imaging (clinical and pre-clinical)
- Quality control - defectoscopy
- Radiation monitoring - visualisation of contamination
- Neutron imaging

Statistical reconstruction



Standard calibration procedure

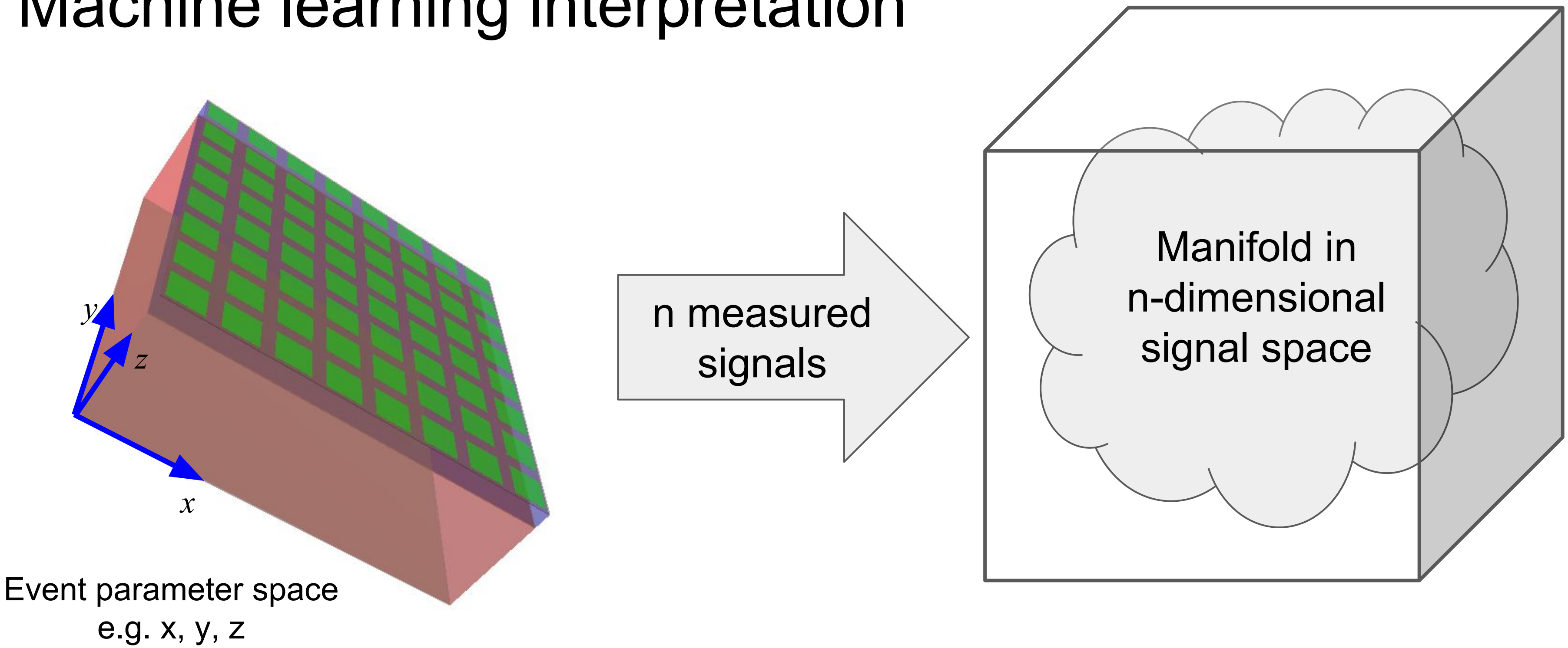


Scan the crystal with pencil beam of monoenergetic γ-rays on a fine grid then fit the obtained data with appropriate smooth function

Problems:

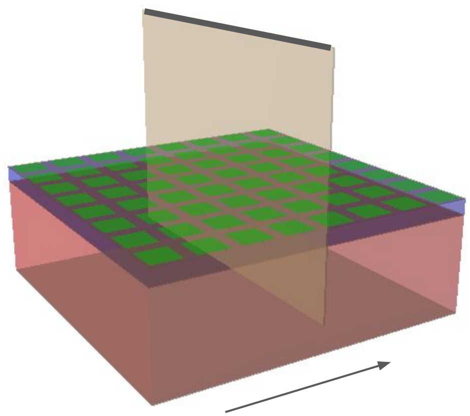
- Time consuming (N_{steps}^2)
- 3D is feasible (scan at different angles and solve a linear system) but cumbersome and even more time consuming (N_{steps}^3)

Machine learning interpretation

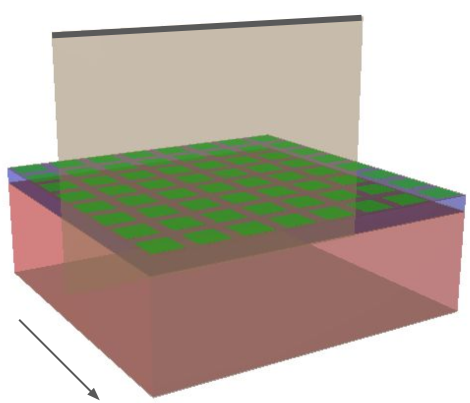


- Treat each event as a n-dimensional vector / point in n-dimensional space (signal space)
- Similar events (close position/energy) ⇔ neighbours in the signal space
- Events are mapped from (low-dimensional) parameter space to the signal space
- These mapped events lay on a low-dimensional manifold embedded into higher-dimensional signal space

Nearest neighbour (kNN) calibration



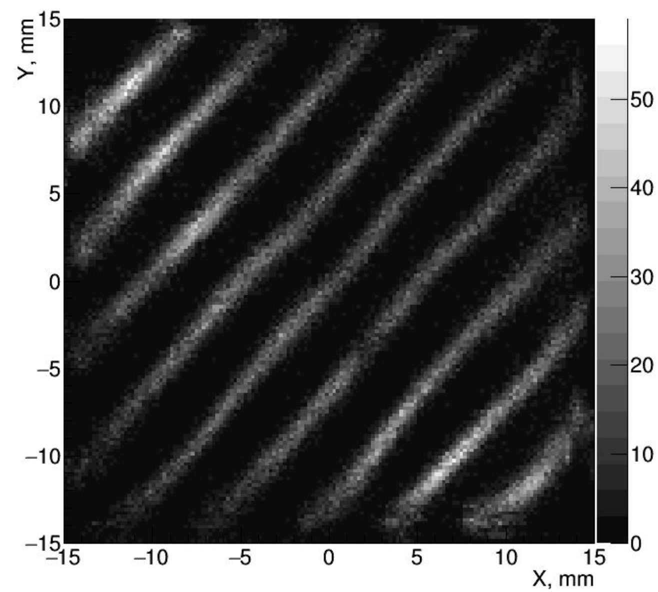
X-scan



Y-scan

- Pencil beam -> knife-edge beam
- 2D scan -> 2 x 1D scans (N_{steps}^2 -> 2 x N_{steps})
- 3D scan -> 3 x 1D scans (N_{steps}^3 -> 3 x N_{steps})
- Use kNN to find the points on the intersection between the scan lines/planes
- Then proceed as in the standard calibration

First test with small (30x30 mm^2) scintillation camera confirmed feasibility, though additional work is required to improve linearity

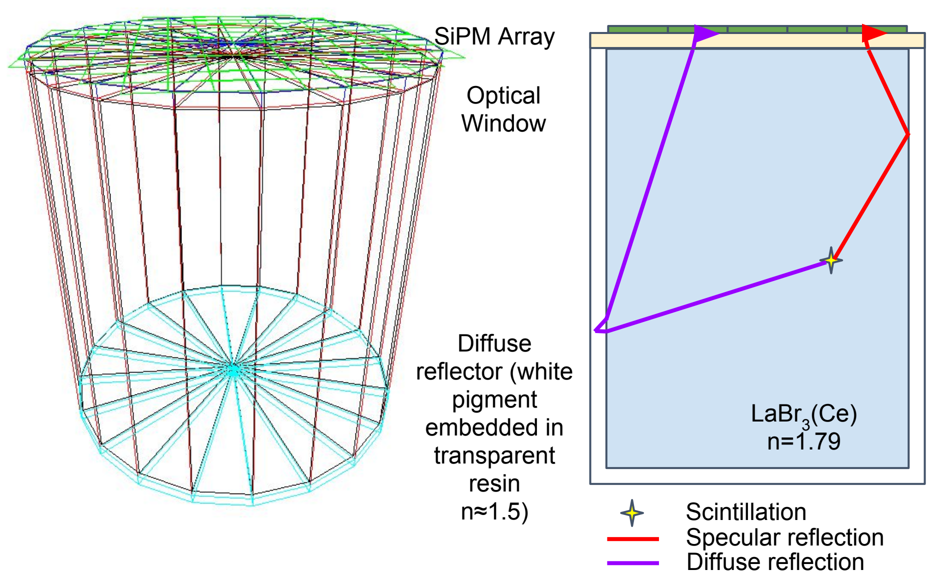


3D position sensitivity of thick LaBr3 crystals

$LaBr_3$ crystals are very popular due to their excellent energy resolution. In some applications, 3D position sensitivity is required as well:

- Study of radioisotopes at relativistic velocities
- Compton camera for radiotherapy monitoring

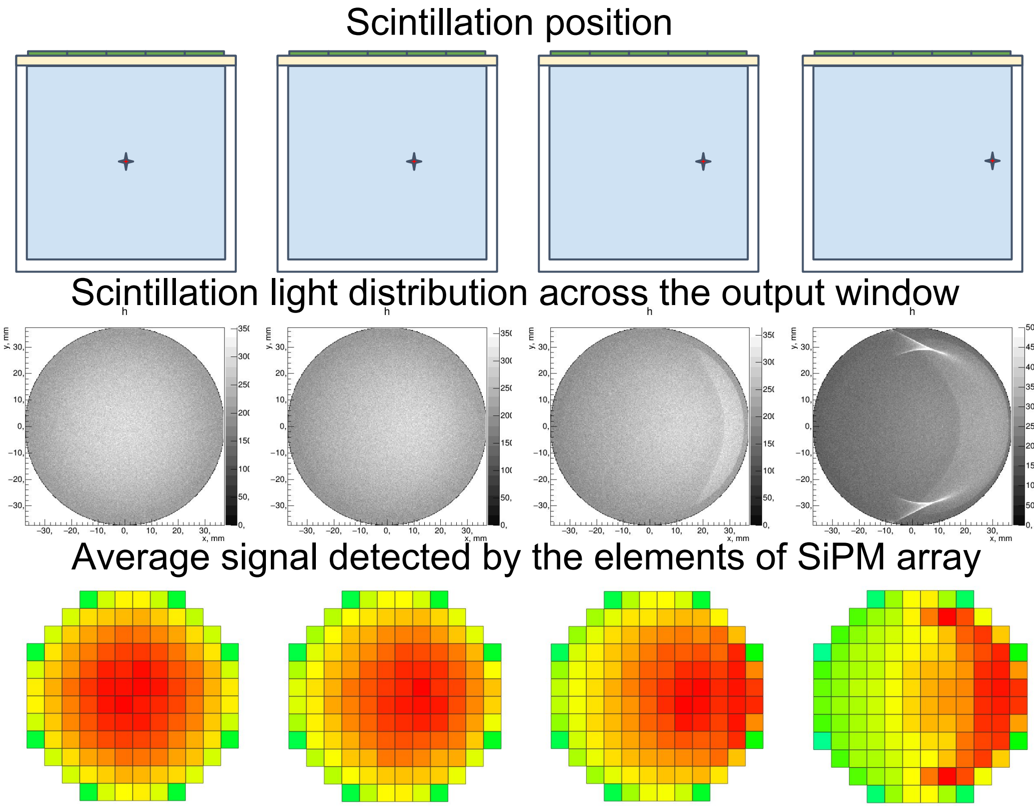
In the work carried out in collaboration with **Politecnico di Milano** we explored possibility of achieving position sensitivity in an off-the-shelf encapsulated crystal.



As a proof-of-the-concept work, we used Monte Carlo simulation in order to evaluate the position sensitivity in the full volume of a reference scintillator detector consisting of a 3” ×3” $LaBr_3$:Ce scintillator read out by a square array of 6x6 mm^2 silicon photomultipliers (SiPM)

Scintillator and coffee cup

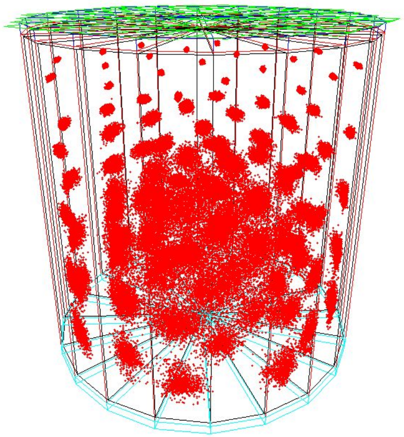
The challenge: the scintillator is designed to make light collection as uniform as possible. However, the position reconstruction depends on variation of photosensor response with coordinates. Fortunately, the crystal is polished, so part of the scintillation light undergoes specular reflection



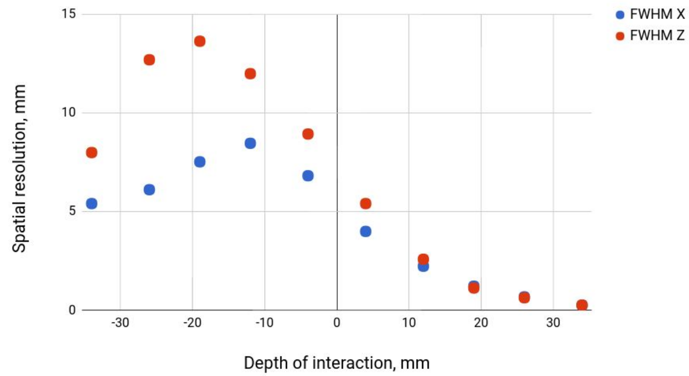
The specularly reflected light creates spatial patterns (caustics) on the output window of the detector. The shape of these light patterns depends on the source position so it can be used to train the position reconstruction algorithm.

LaBr$_3$ - Simulation results

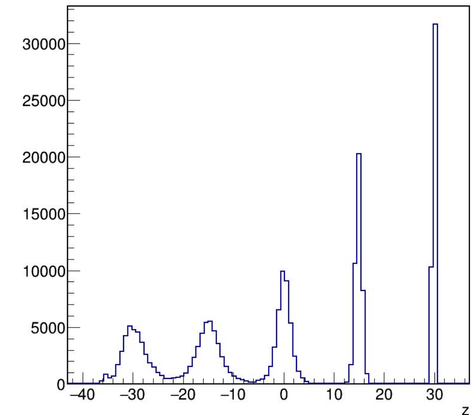
Grid (xyz): 15 x 15 x 7.5 mm^3



Spatial resolution at the crystal axis

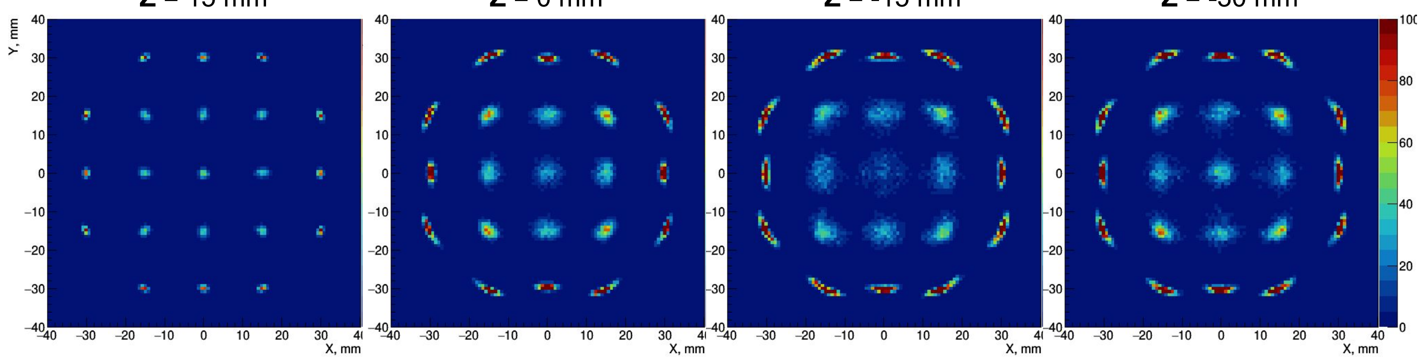


Z projection for the reconstructed grid points at Z = -30, -15, 0, 15 and 30 mm

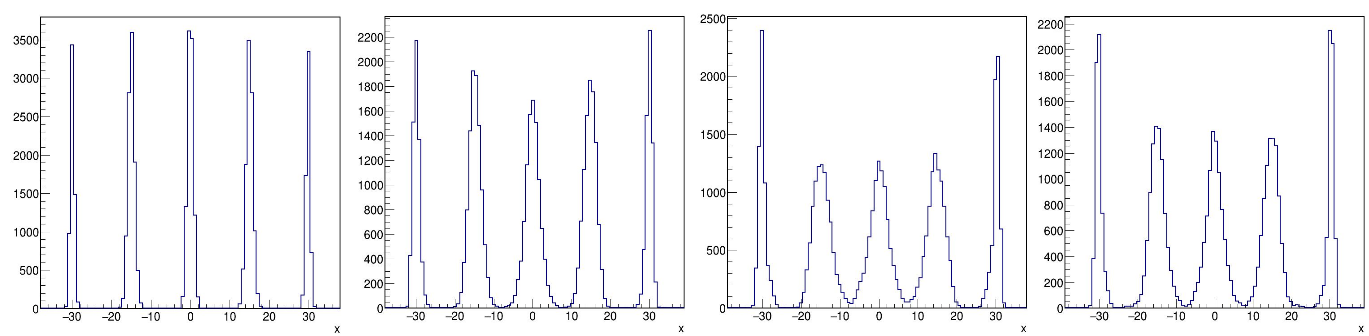


X vs **Y** scatter plot for the reconstructed grid points at given **Z**

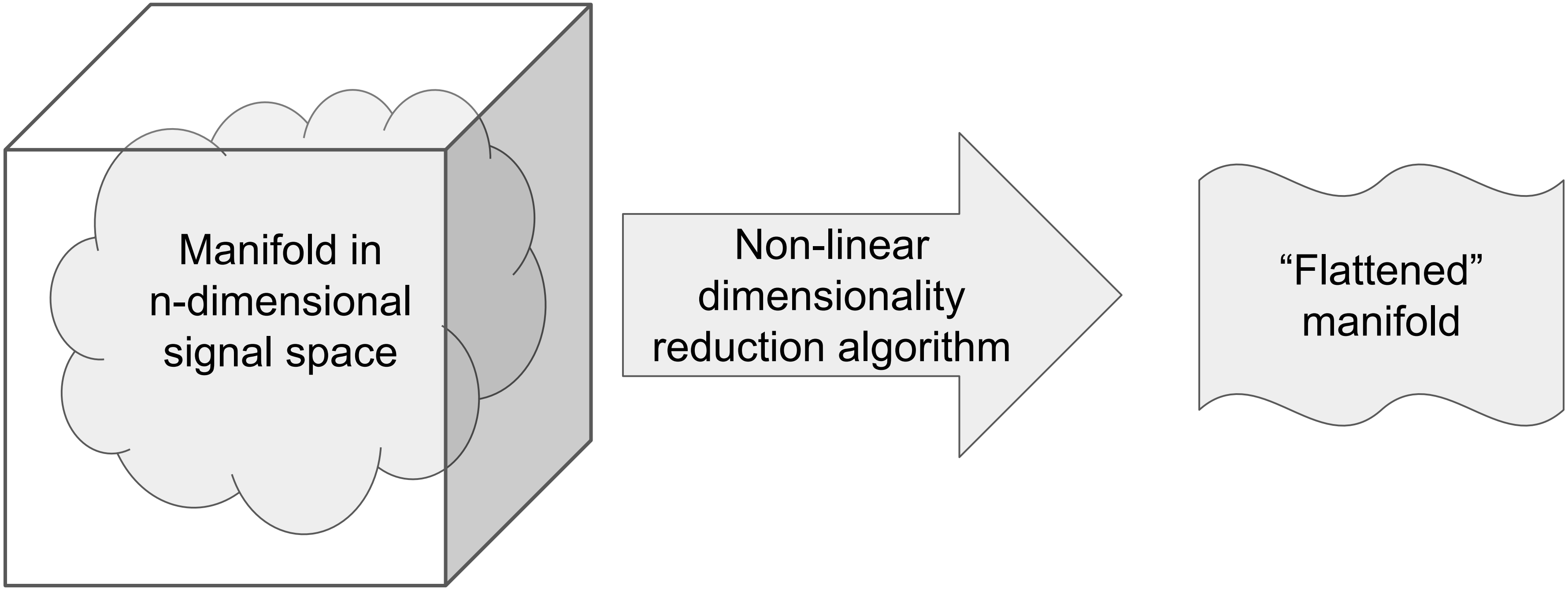
Z = 15 mm | **Z** = 0 mm | **Z** = -15 mm | **Z** = -30 mm



X projection for the reconstructed grid points at given **Z**



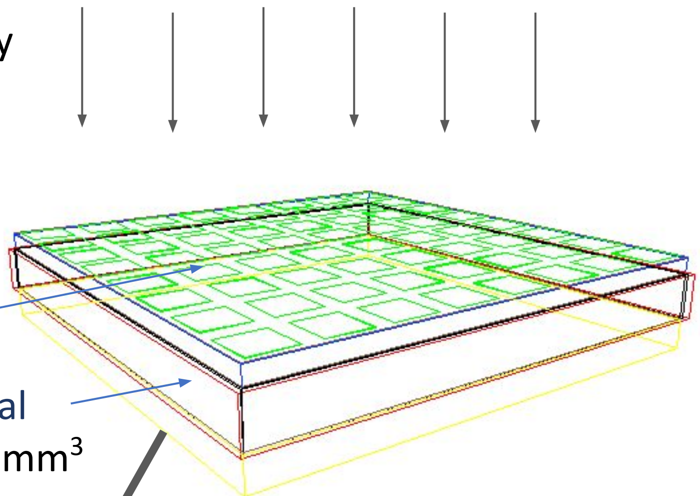
Manifold learning



- Would it work on data from a scintillation camera?
- What kind of information can be extracted?
- What is the best method?
    - Multidimensional scaling
    - Isomap
    - Locally linear embedding
    - Spectral embedding
    - ...

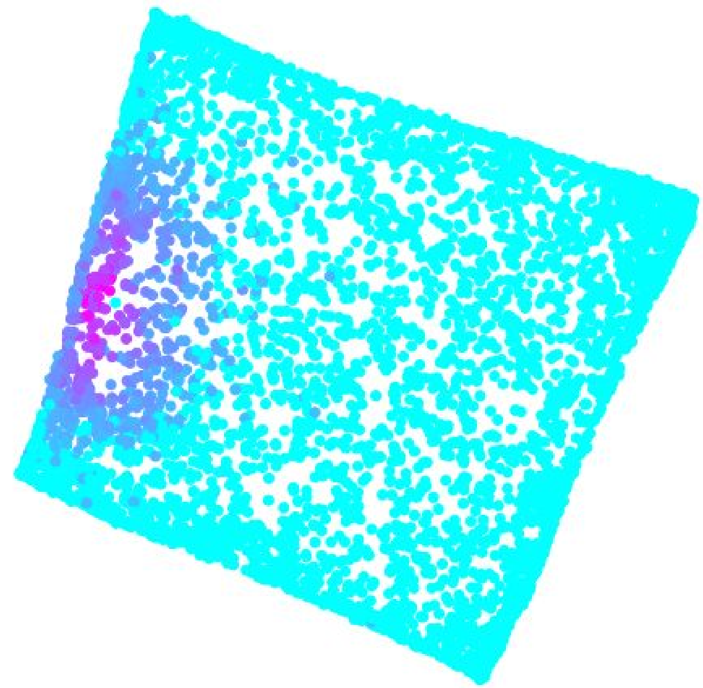
Locally linear embedding (LLE)

Flood irradiation by
511 keV from ^{22}Na



8 x 8 array of
SensL SiPMs

GAGG:Ce crystal
33.2 x 33.2 x 3 mm^3



Data acquisition

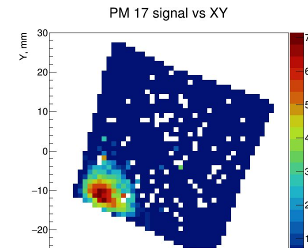
Raw data

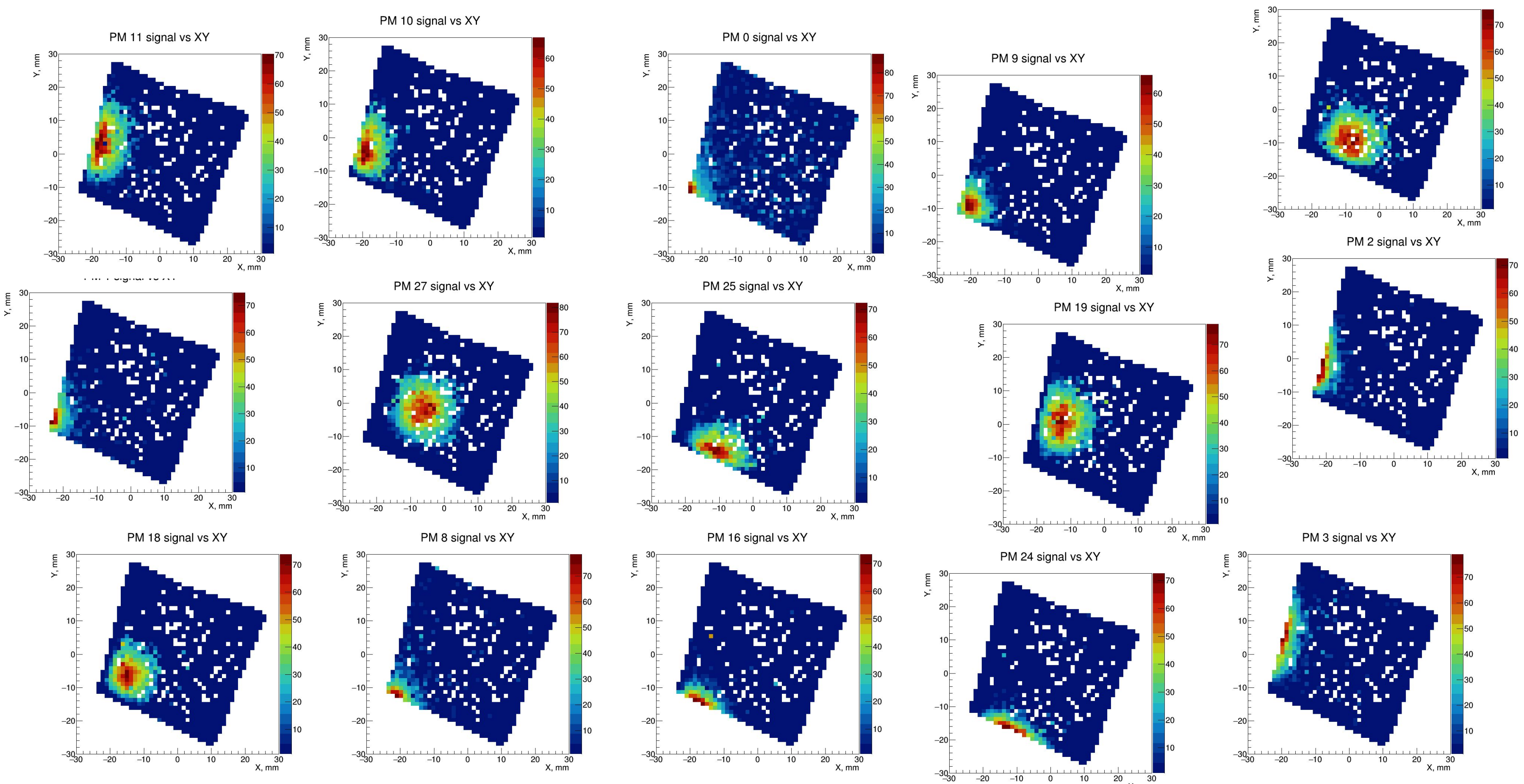
LLE
30 neighbors
64 dimensions in
2 dimensions out

Scikit-learn package was used for data processing

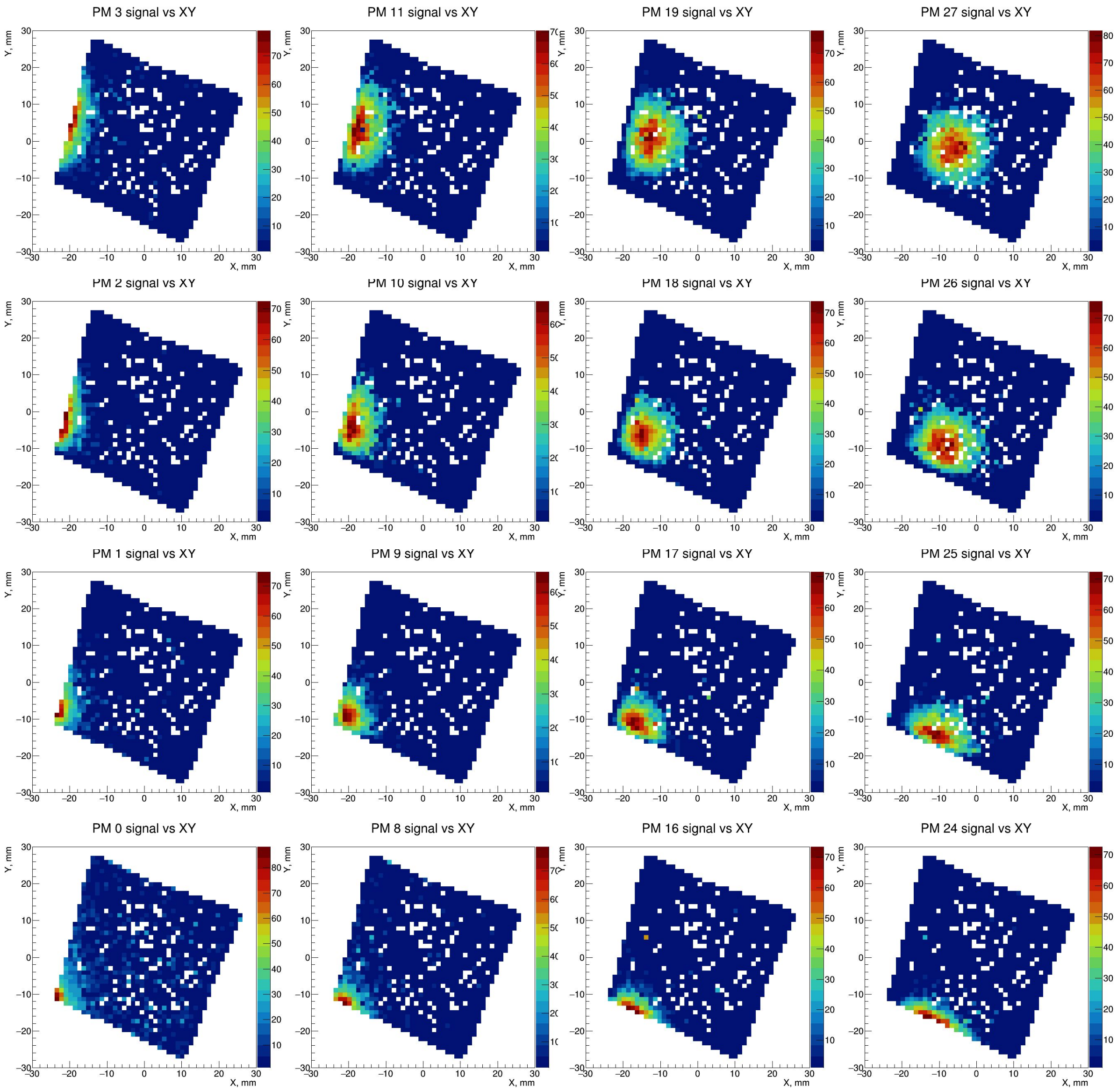
Manifold mapping

“Heat maps” of the SiPM signal amplitude vs pseudo-coordinates supplied by LLE. Arranged in right order they will indicate relative positions of the corresponding SiPM.

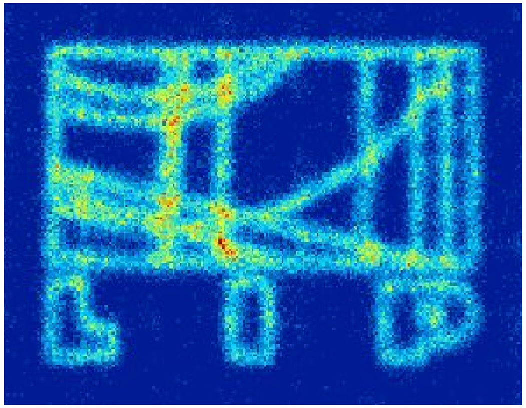




Manifold mapping



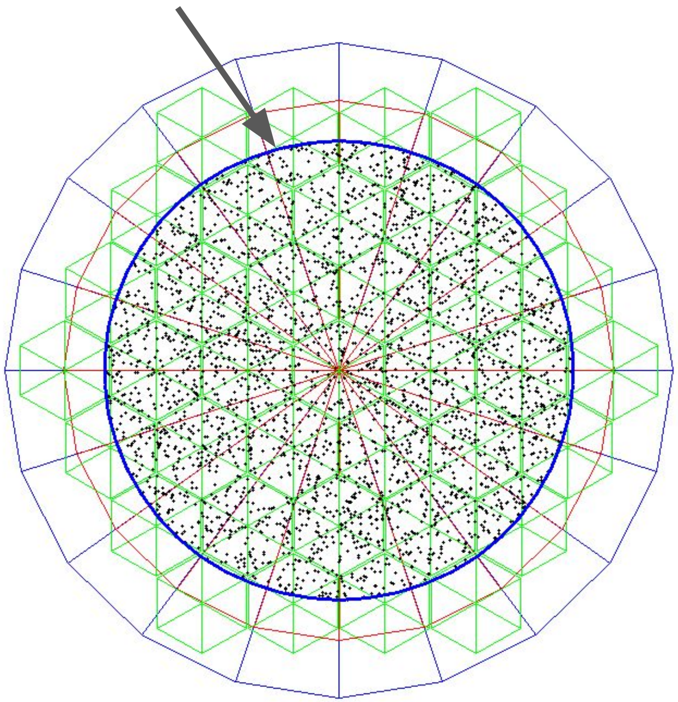
The solved "puzzle" indicates the correct channel mapping, as confirmed by the reconstructed image



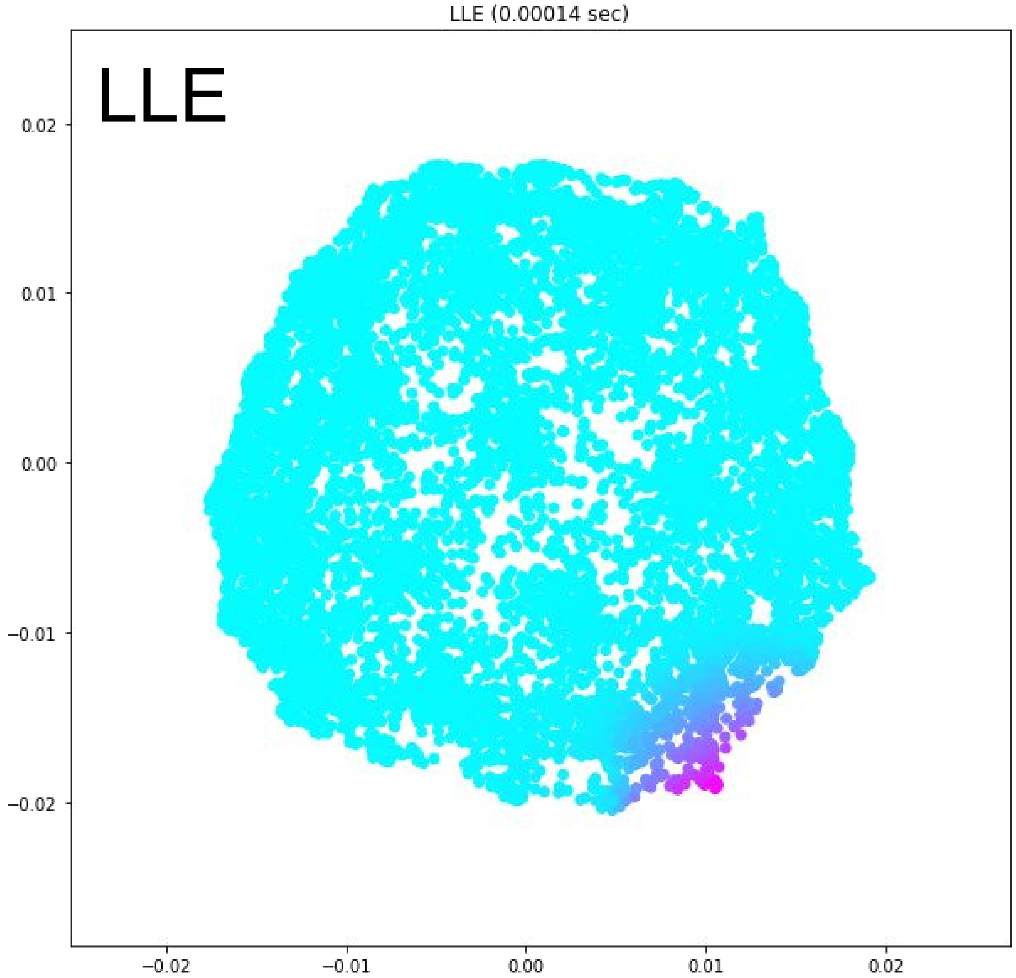
LLE for the clinical camera

The same technique works for the clinical gamma camera as well.

Flood irradiation by ^{57}Co source

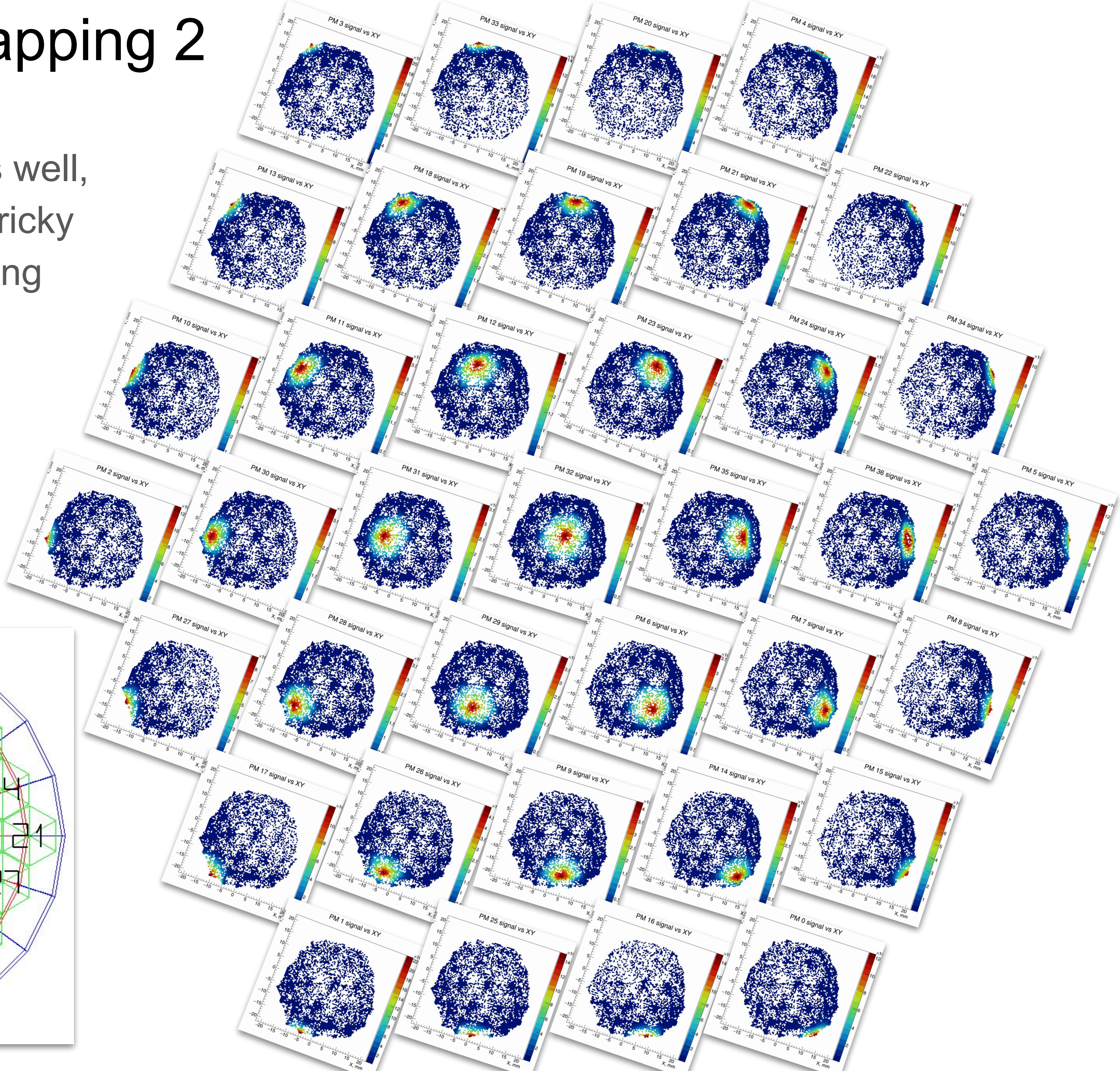


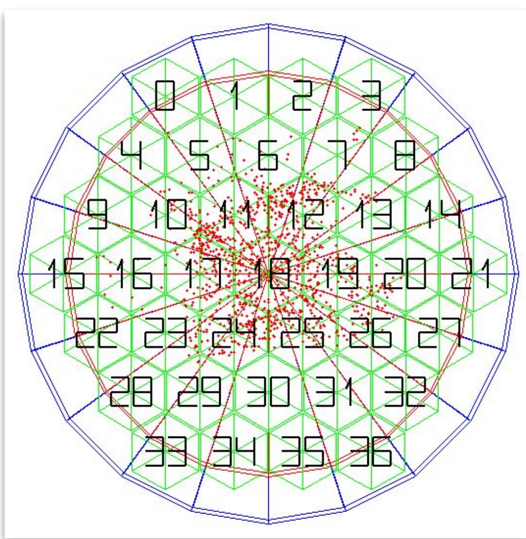
Round camera with 37 PMT



Manifold mapping 2

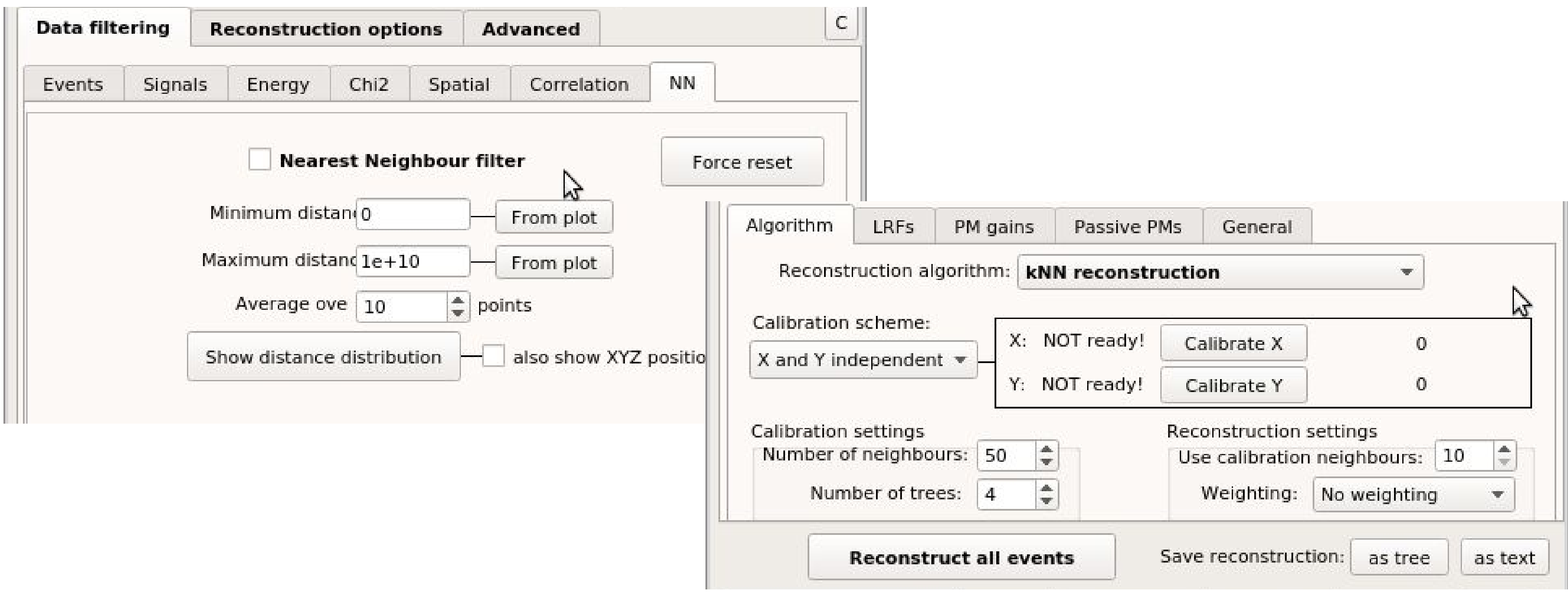
Mapping worked as well, thought was more tricky for the outer PMT ring





Machine learning in ANTS2

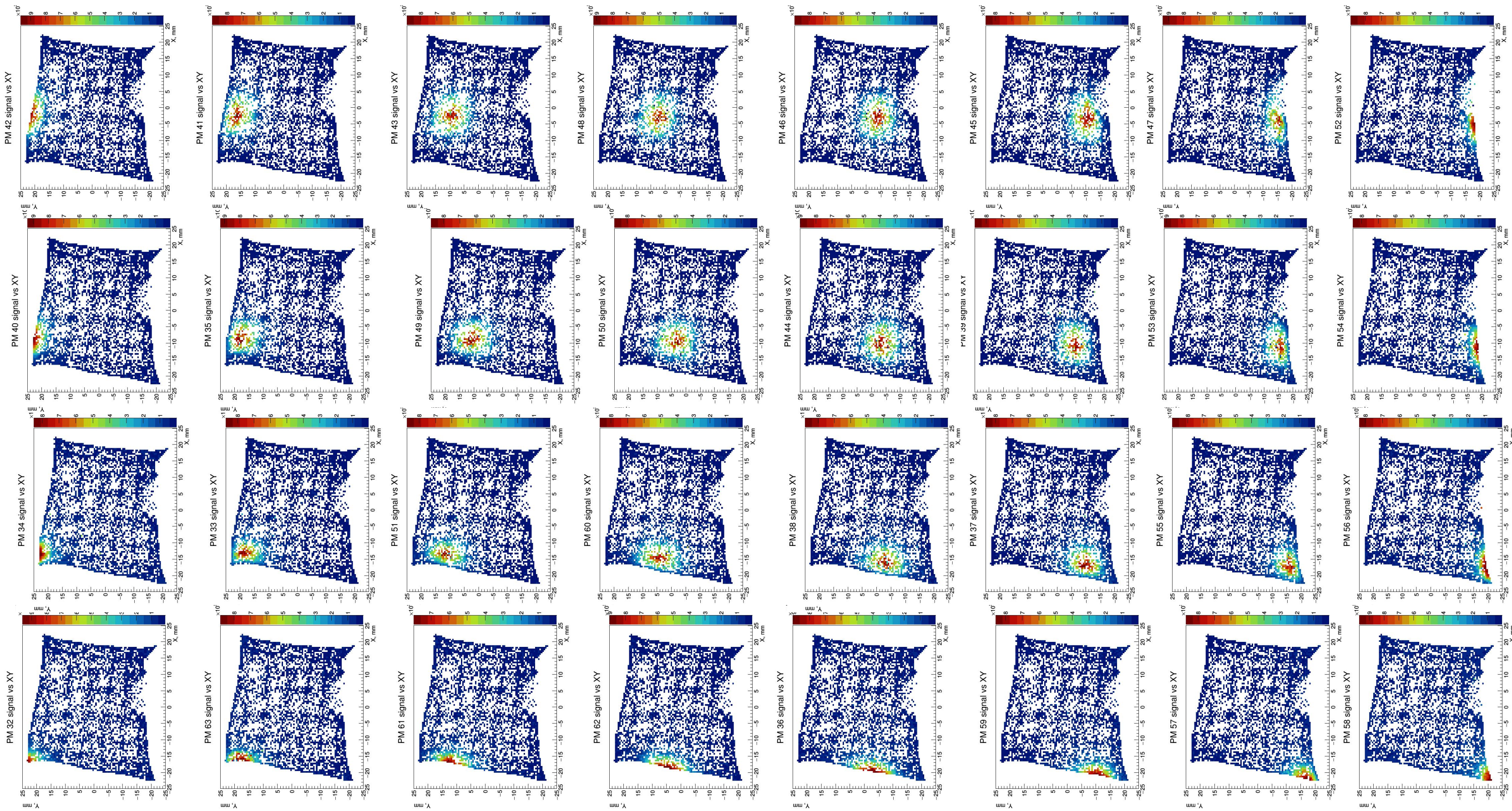
- K Nearest neighbor (kNN) reconstruction
- Nearest neighbor filtering
- Neural networks
  - Currently: FANN
  - Planned: upgrade to KERAS
- Channel gain (photoelectrons) calibration from flood irradiation
- Also planned:
  - Genetic algorithms
  - Self organizing maps



Thank you

Backup

Mapping 1a


PM 42 signal vs XY
PM 41 signal vs XY
PM 43 signal vs XY
PM 48 signal vs XY
PM 46 signal vs XY
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PM 47 signal vs XY
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PM 35 signal vs XY
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PM 33 signal vs XY
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PM 60 signal vs XY
PM 38 signal vs XY
PM 37 signal vs XY
PM 55 signal vs XY
PM 56 signal vs XY
PM 32 signal vs XY
PM 63 signal vs XY
PM 61 signal vs XY
PM 62 signal vs XY
PM 36 signal vs XY
PM 59 signal vs XY
PM 57 signal vs XY
PM 58 signal vs XY

Mapping 1