Identifying Materials in Nuclear Waste Drums using Muon Scattering Tomography and Machine Learning

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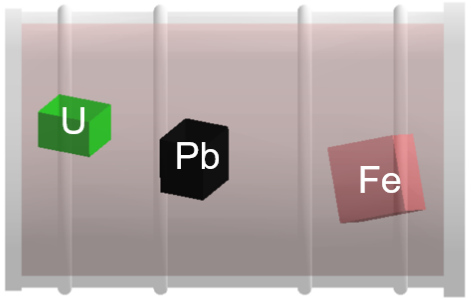
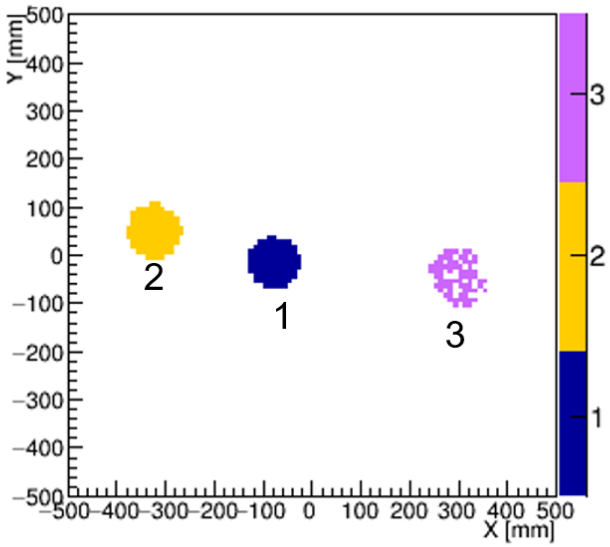
Simulated geometry



Identified clusters, z=0.0 mm



Material decisions

The University Of Sheffield.

University of BRISTOL

Warsaw University of Technology

iCHANCE
Characterization of Conditioned Nuclear Waste for its Safe Disposal in Europe

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Muon Scattering Tomography: background

- The EU H2020 CHANCE project [1] aims to develop Non-Destructive Assay (NDA) techniques for the characterisation of nuclear waste packages.
- Muon Scattering Tomography (MST) is an NDA imaging technique that makes use of cosmic ray muons.
- The sea level muon flux is around 1 cm^{-2} min^{-1} [2].
- MST exploits the muons' scatterings inside matter, which are highly sensitive to the atomic number Z of the material.

Muon Scattering Tomography: background

- Within matter muons undergo multiple elastic Coulomb scatterings.

- The width of the distribution of the resulting scattering angles is approximately given by [3]

$$\sigma \approx \frac{13.6\ \mathrm{MeV}}{\beta c p}\sqrt{X/X_0}$$

where β is the ratio of muon speed to the speed of light in a vacuum, c; p is the muon momentum, X is the material thickness and X_0 is the radiation length of the material.

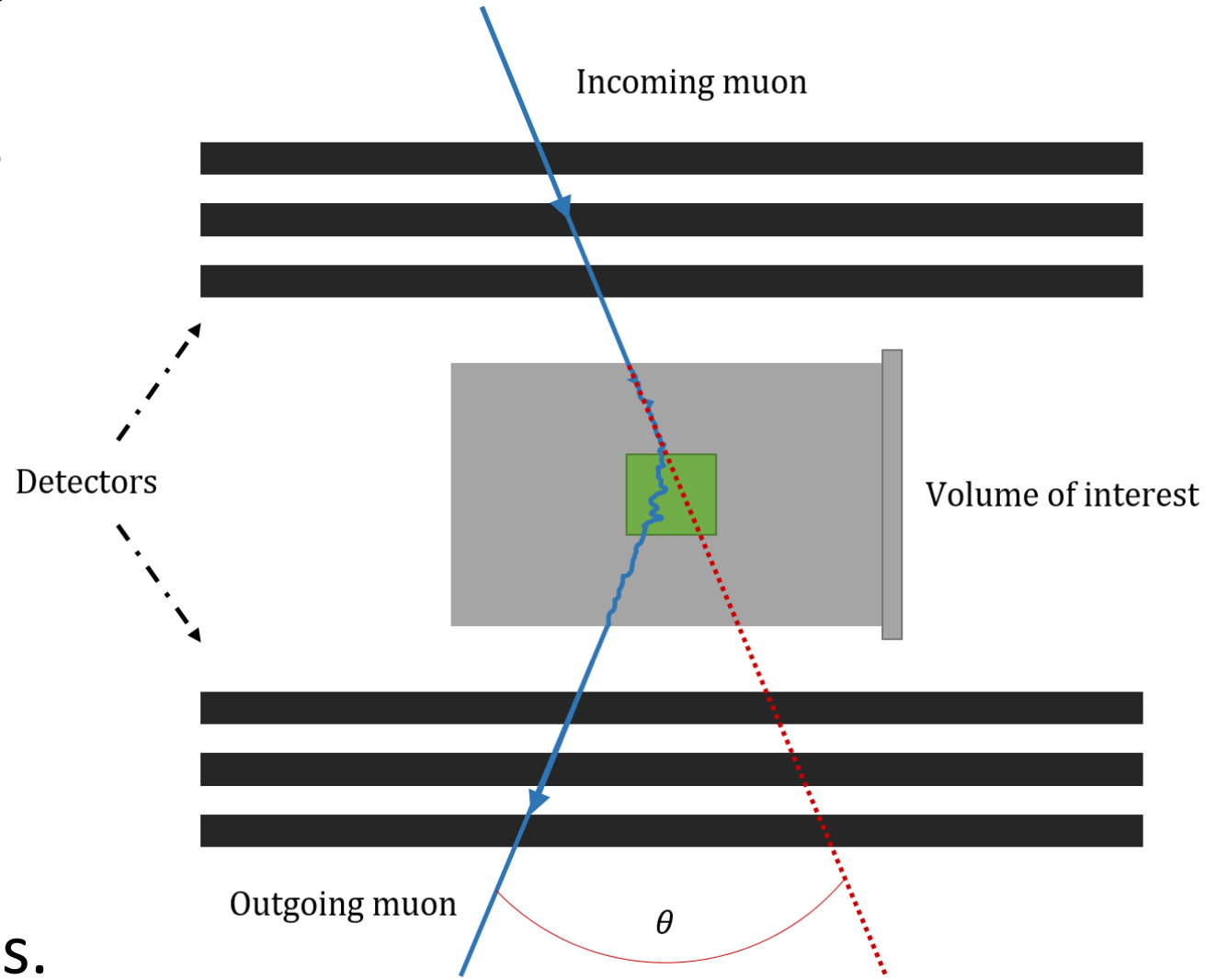
- The radiation length X_0 is approximately given by

$$X_0 \approx \frac{716.4A}{Z(Z+1)\log\left(287/\sqrt{Z}\right)}\,[\mathrm{g\ cm^{-2}}]$$

where A is atomic mass.

Principle of an MST system

- An MST experiment consists of two detector modules with some volume of interest, such as a waste drum, in between.
- Multiple detector layers allow the incident and outgoing tracks of a muon to be constructed.
- Features of the scattering, such as the scattering angle θ, can be calculated from the two trajectories.

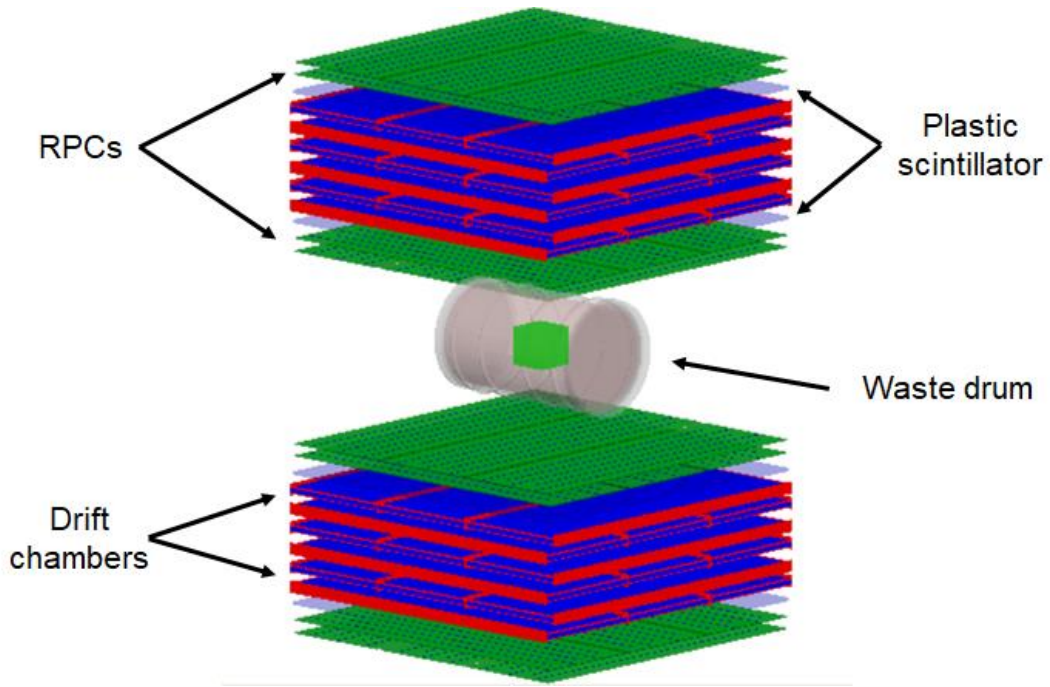


Simulation setup

- Our simulations used CRESTA, a muon simulation platform built on the Geant4 [4] particle transport toolkit and the CRY [5] cosmic ray shower generator.

- The simulated MST system consists of 2m x 2m resistive plate chambers, drift chambers and scintillator trigger panels. The waste drum is approximately 1m long and is filled with concrete.

- The measured muon momentum is obtained by applying a 50% Gaussian smear to the Monte Carlo truth momentum.



MST binned clustering algorithm

- We make use of the MST binned clustering algorithm [6], which exploits the greater density of muon scatterings in high-Z material:

  1. Divide the volume of interest into 1cm cubic voxels.
  2. Extrapolate each muon's incoming and outgoing tracks and find the point of closest approach, called the 'scattering vertex'.
  3. For each pair of scattering vertices in a voxel, calculate metric values:

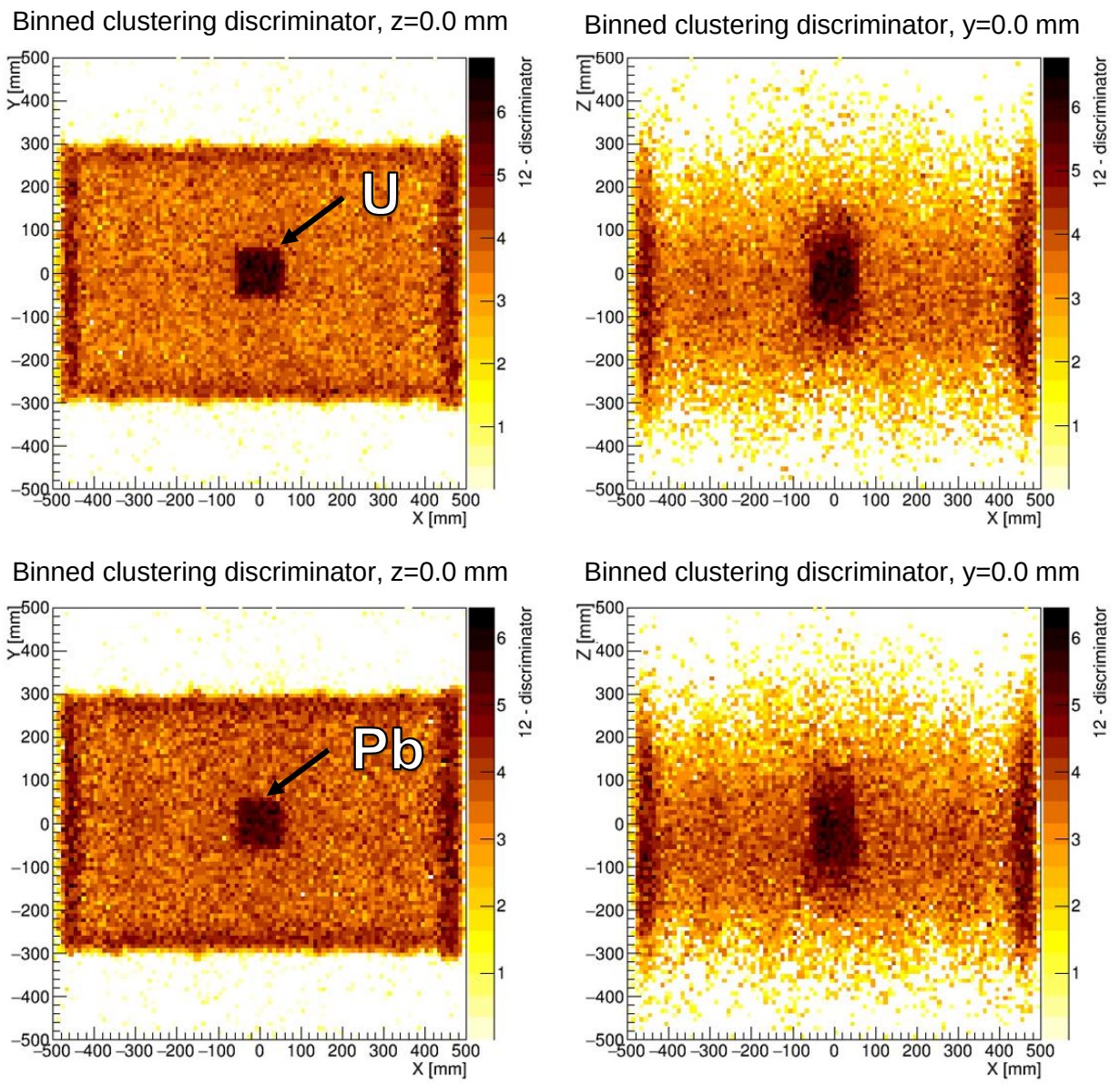
$$m_{i,j} = \frac{|\mathbf{v}_i - \mathbf{v}_j|}{(\theta_i p_i)(\theta_j p_j)}$$

where $\mathbf{v}_i$, θ_i and p_i are, respectively, the scattering vertex position, scattering angle, and momentum of muon i.

- The median of the distribution of metric values is used as the discriminator for that voxel.

MST binned clustering algorithm

- The full 3D image is a map of the discriminator values.
- High-Z objects are clearly visible against the concrete background when the image is viewed in 2D slices.
- It is difficult to distinguish between different materials in these images.



Multivariate Analysis

- Multi-Variate Analysis (MVA) classifiers allow for deeper analysis of MST data. Our MVA classifiers are built using the TMVA machine learning platform [7].

- We use a set of variables calculated from the binned clustering algorithm. The algorithm's metric values are binned, and a set of 28 bin counts are used as the MVA variables.

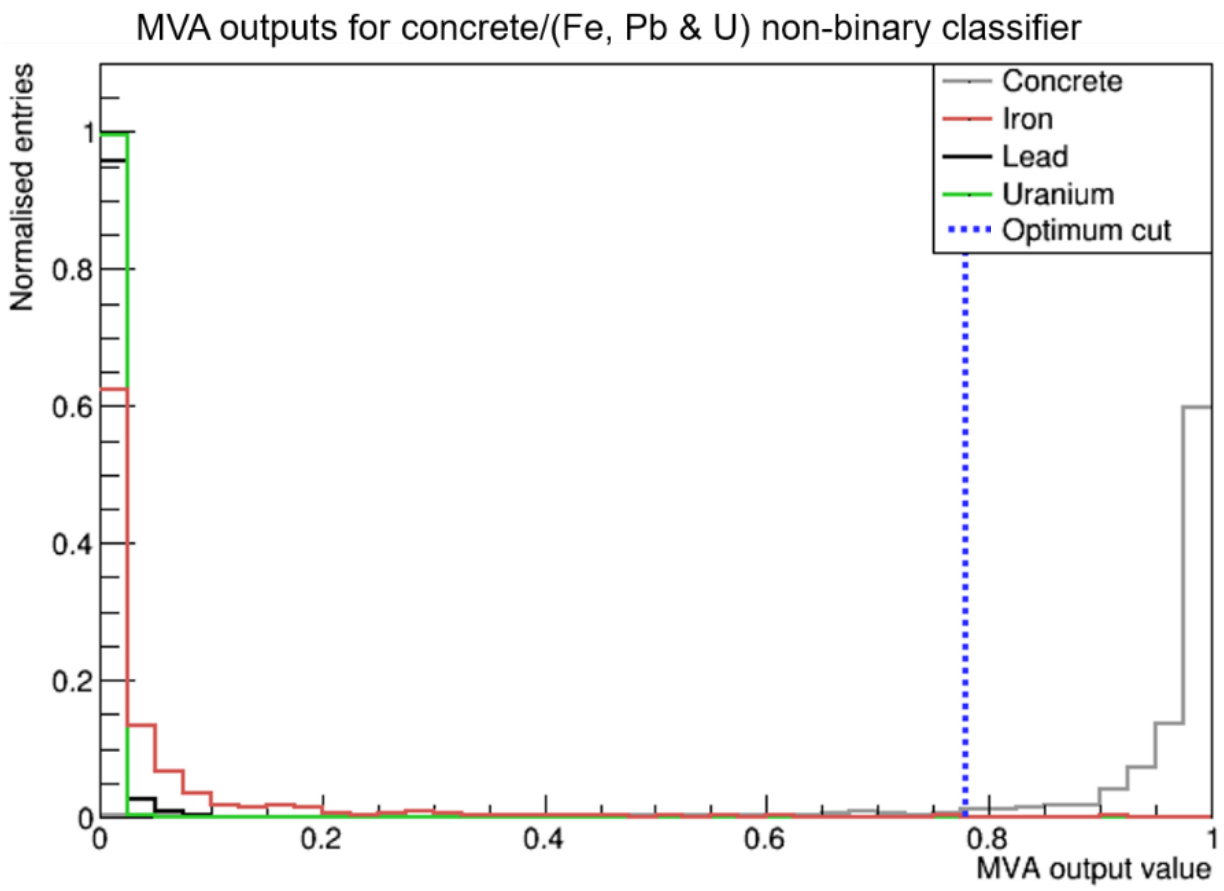
- The training data is from 10 day exposures of 20cm cubes of uranium, lead, iron and concrete.

Filtering object voxels

- One classifier is trained to discriminate concrete from the other materials, allowing the stored objects to be separated from the background.

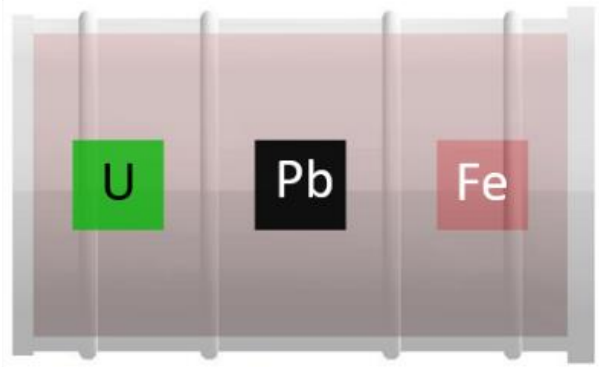
- Each voxel is classified as being concrete or not, depending on whether its MVA response value is above or below the optimum cut determined in the training stage.

- The separated voxels are then grouped into clusters with the k-means++ algorithm.

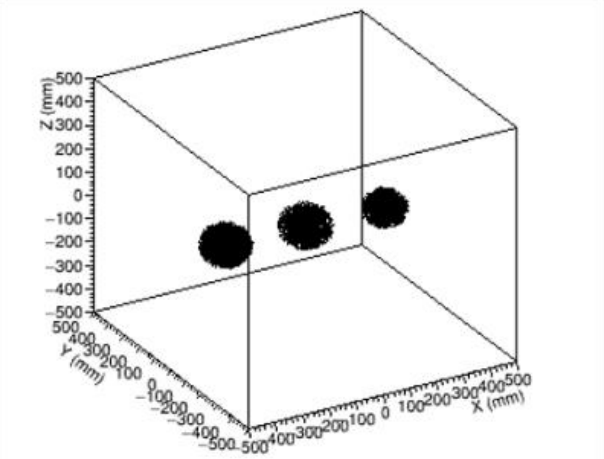


Clustering example: 15cm cubes

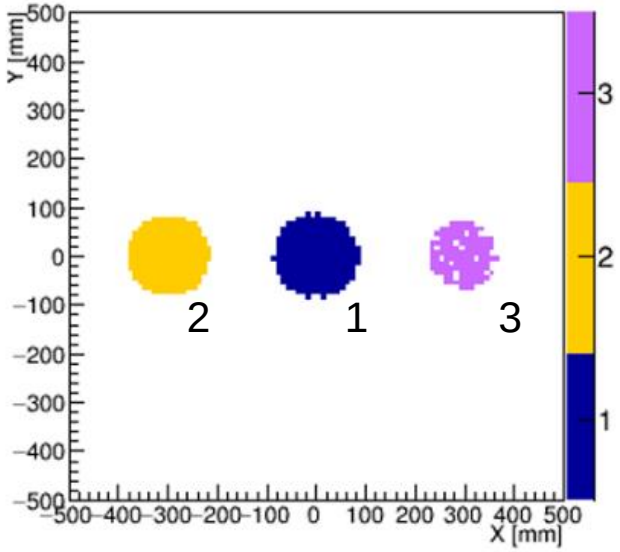
Simulated geometry, 15 cm cubes



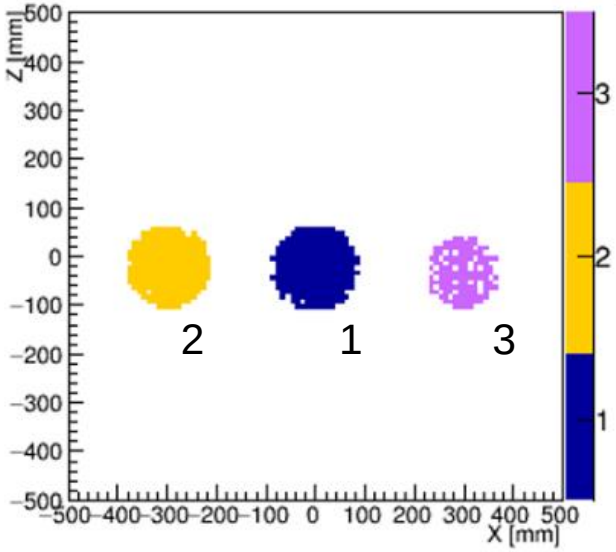
Identified clusters



Identified clusters, z=0.0 mm



Identified clusters, y=0.0 mm



Material scores

- Two further MVA classifiers are now applied to the voxels in each cluster to attempt to determine the object's material.

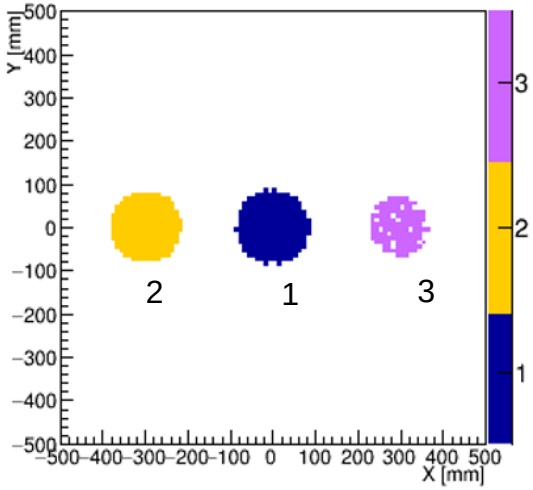
- One classifier is trained to recognise iron from the high-Z materials, and the other to distinguish between lead and uranium.

- Each classifier will return a response value for each voxel in each cluster; the proportion of response values that fall above the optimum cut is a useful 'material score' for the corresponding object.

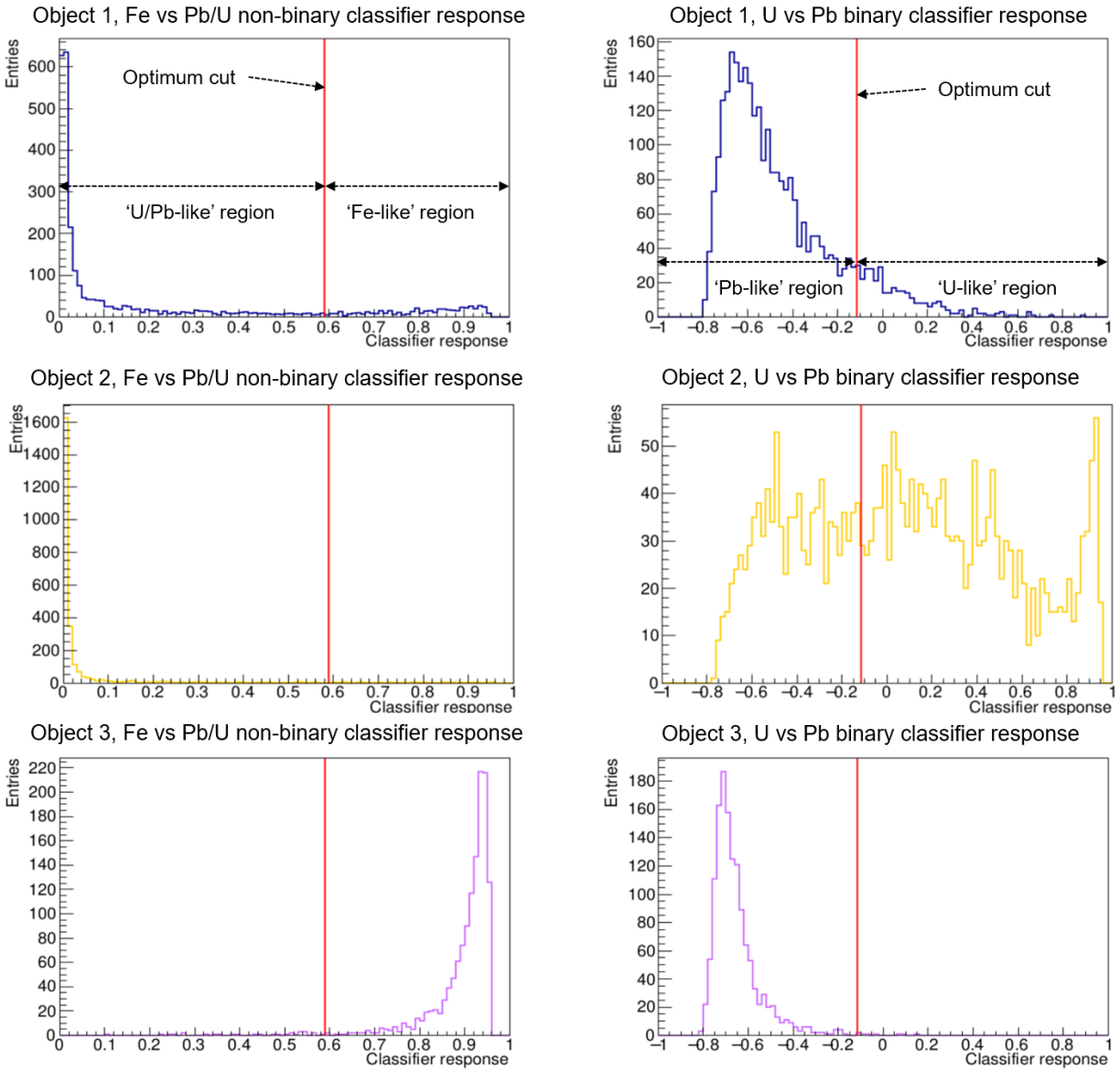
Material scores example: 15cm cubes

Simulated geometry, 15 cm cubes

Identified clusters, z=0.0 mm



- The voxels in each cluster are passed to the MVA classifiers.
- The proportion of MVA response values that fall above the optimum cuts comprise characteristic ‘material scores’ that encode information about the original object’s material.

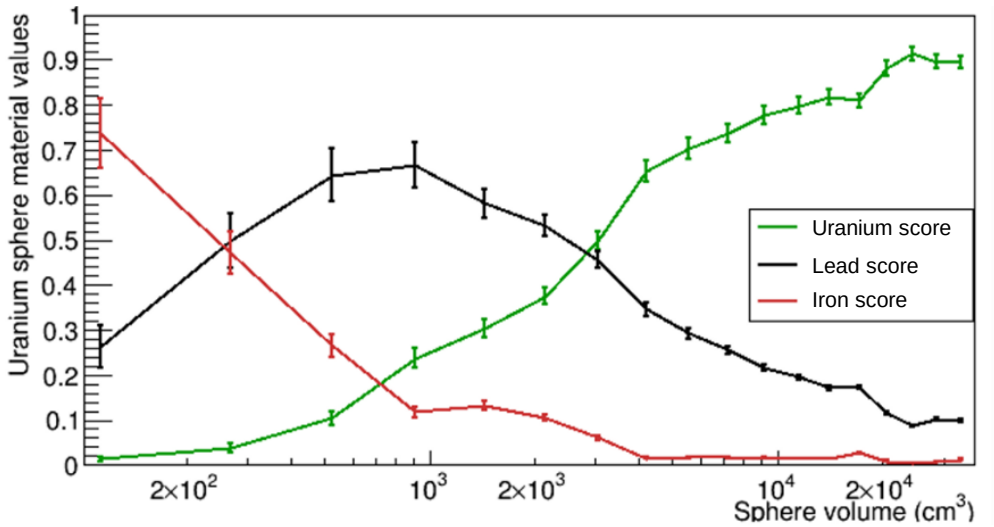


Size calibration

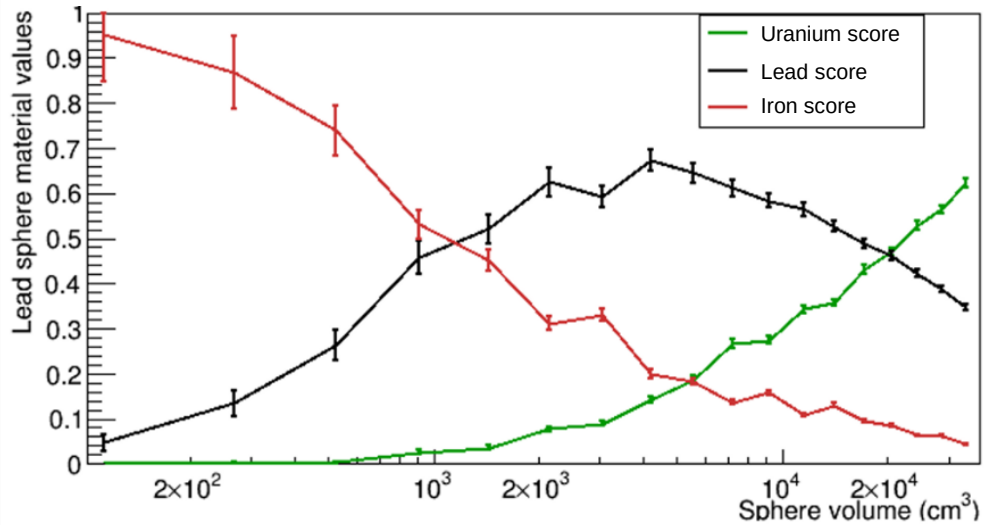
- To produce accurate material decisions it is necessary to calibrate by object volume.
- This is achieved through calibration curves of the calculated material scores for objects of a wide range of volumes.
- When applied to a new geometry, each identified object's material scores are compared to the expected values from the curves, and the material with the best match (minimum Euclidean distance) is the material decision.

Object volume calibration curves

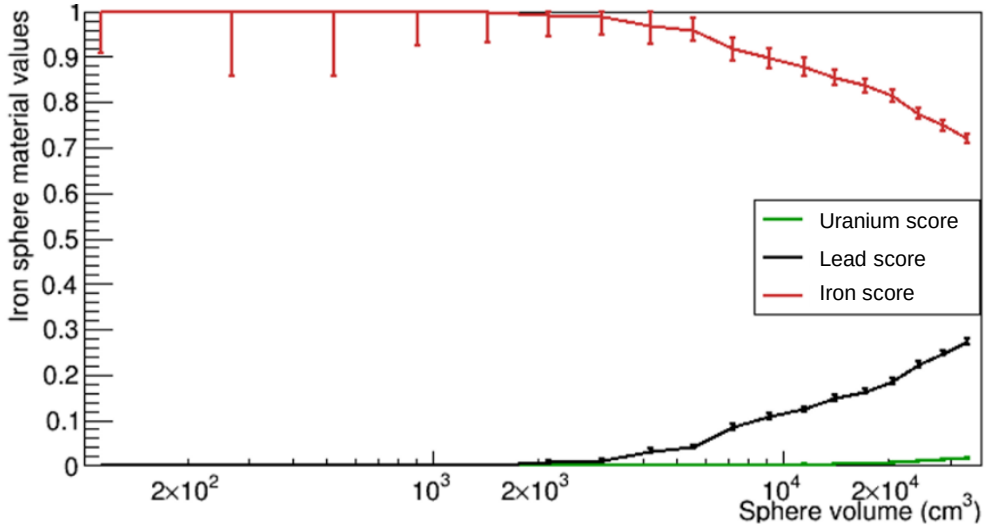
Material scores vs object volume: uranium spheres



Material scores vs object volume: lead spheres



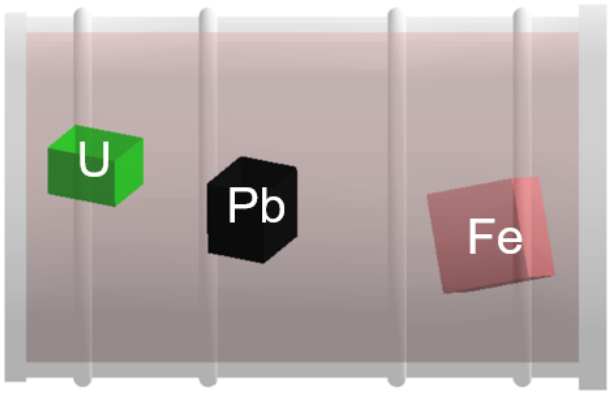
Material scores vs object volume: iron spheres



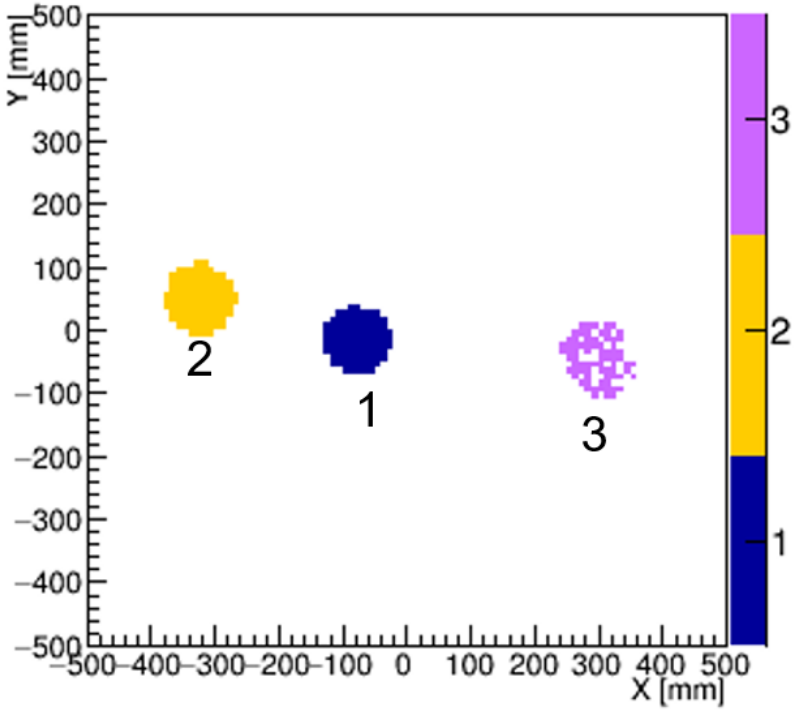
These calibration curves show the relationships between the three calculated material scores and object volume for series of spheres of different materials: uranium (top left), lead (top right), and iron (bottom middle).

Results: rotated objects

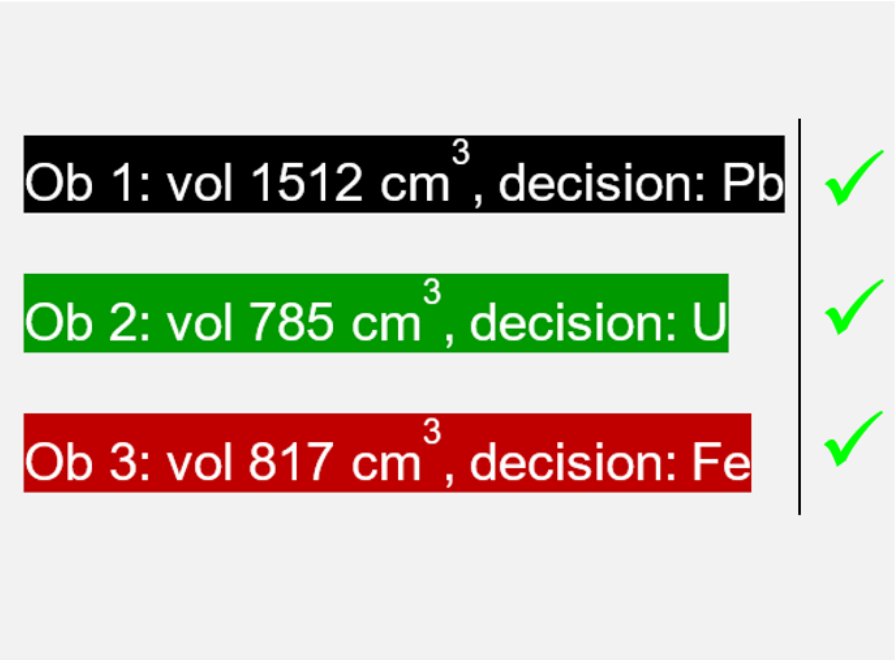
Simulated geometry



Identified clusters, z=0.0 mm



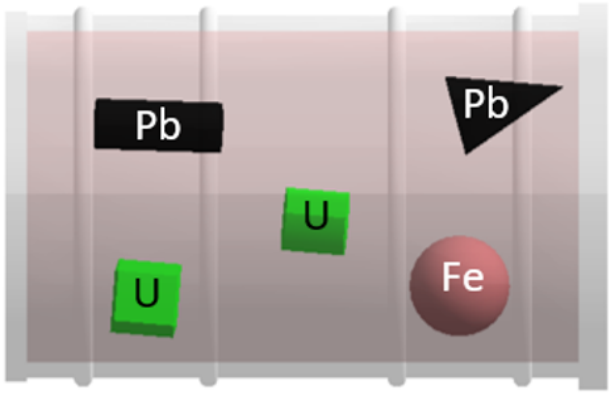
Material decisions



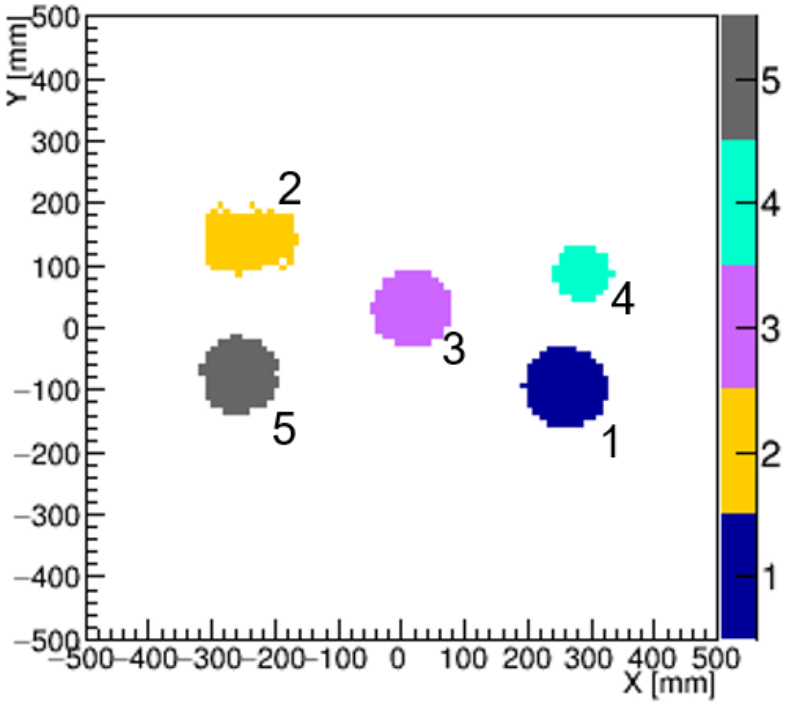
In this example, each object is correctly identified and assigned the correct material despite their difference in volume from the training geometries, and their irregular placement and rotation in the drum.

Results: varied drum contents

Simulated geometry



Found clusters (bird's eye view)



Material decisions

In this example, four of the five objects have been assigned the correct material. One lead object has been incorrectly classified as iron.

Conclusions

- Machine learning techniques greatly enhance MST's power to analyse waste drum contents in terms of stored object materials.
- Variables adapted from the MST binned clustering algorithm are suitable for building MVA classifiers.
- A system of such classifiers is effective at identifying objects of a few cm scale stored in waste drums and determining their materials.

References

[1] https://www.chance-h2020.eu/
[2] Schultz et al. 2007. Statistical reconstruction for cosmic ray muon tomography. IEEE transactions on Image Processing, 16(8), pp.1985-1993.
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[5] Hagmann et al. 2007, October. Cosmic-ray shower generator (CRY) for Monte Carlo transport codes. In 2007 IEEE Nuclear Science Symposium Conference Record (Vol. 2, pp. 1143-1146). IEEE.
[6] Thomay et al. 2013. A binned clustering algorithm to detect high-Z material using cosmic muons. Journal of Instrumentation, 8(10), p.P10013.
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