

Classifying low-Z materials with muon scattering tomography for border security

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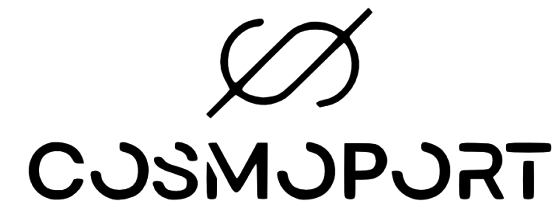
03/06/2026



Horizon 2020
European Union funding
for Research & Innovation

IMPERIAL

CosmoPort



EU-funded project aiming to improve scanning at borders
(postal centres)

Technical

GSCAN



FONDAZIONE
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CENTRE FOR SECURITY STUDIES

Customs/law enforcement



REPUBLIC OF ESTONIA
ESTONIAN TAX AND CUSTOMS BOARD



TULLI



ΑΑΔΕ

Independent Authority
for Public Revenue (IAPR)



State Revenue Service
Republic of Latvia



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Commission

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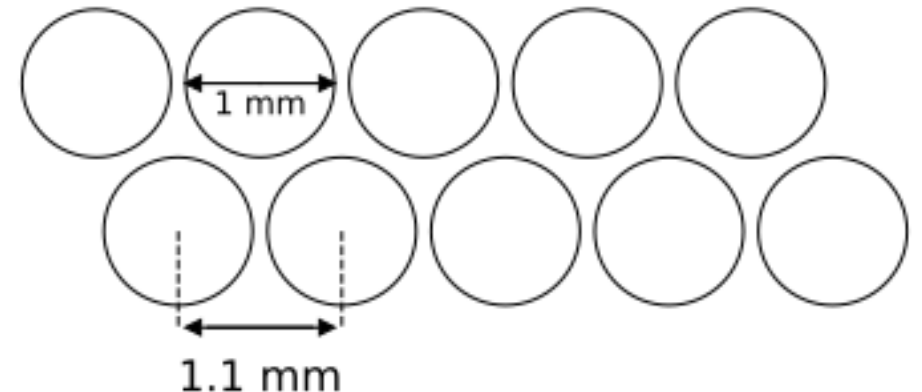
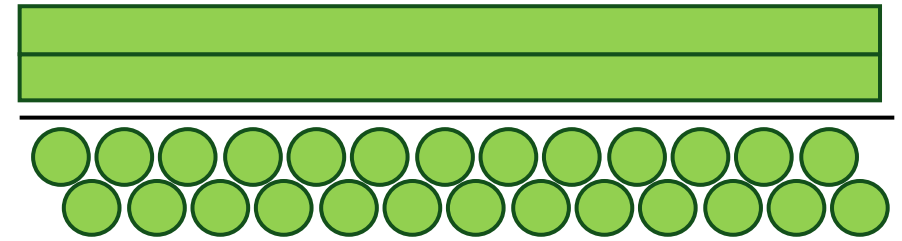
Material classification exercise

- Aimed to demonstrate separation of low-Z materials by combining MST and machine learning
- Real measurements were made using a prototype detector and used to train classification algorithms to discriminate materials

Further details available in existing publication^[1]

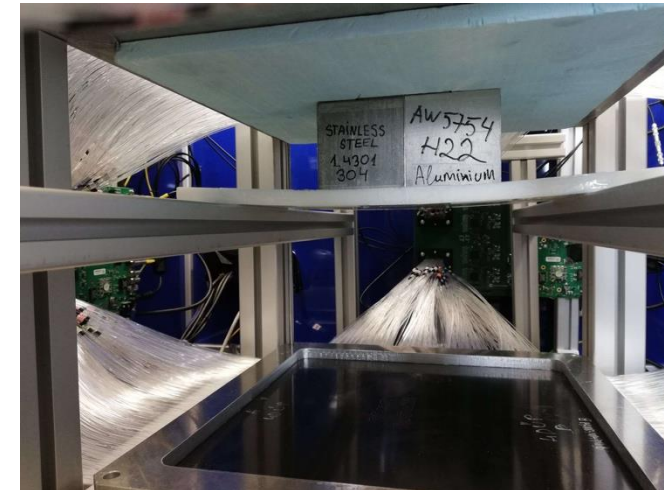
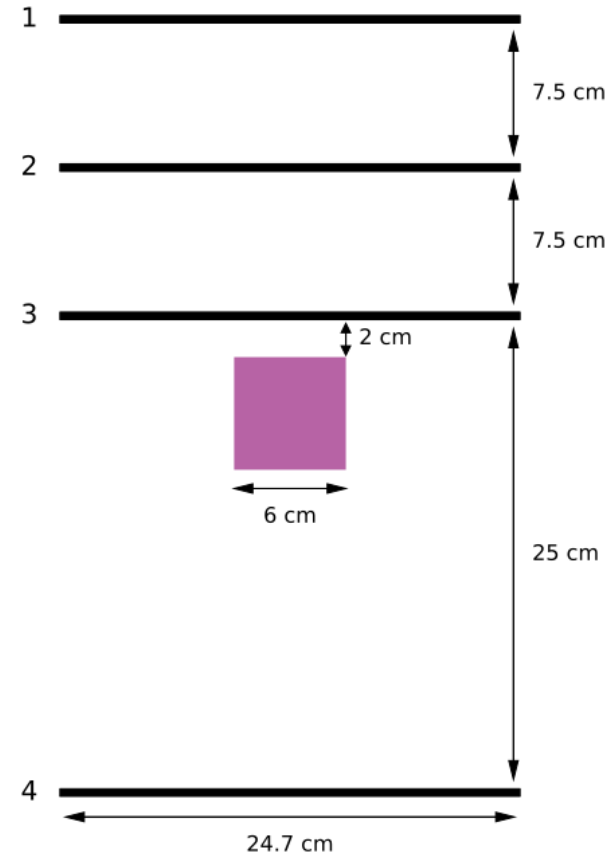
Prototype detector design

- Prototype scintillating fibre detector by GScan OU (in 2021)
- Basic hodoscope design: 3 detector plates, with two double-layered fibre mats each
- From sim study^[2]: average reconstruction error is ~ 0.1 mm, corresponding angular resolution ~ 1 mrad



Experimental setup

- Prototype detector consists of 3 detector planes above volume of interest (VOI) and 1 below
- Position measurement samples 2 cm below top hodoscope



Measurement samples

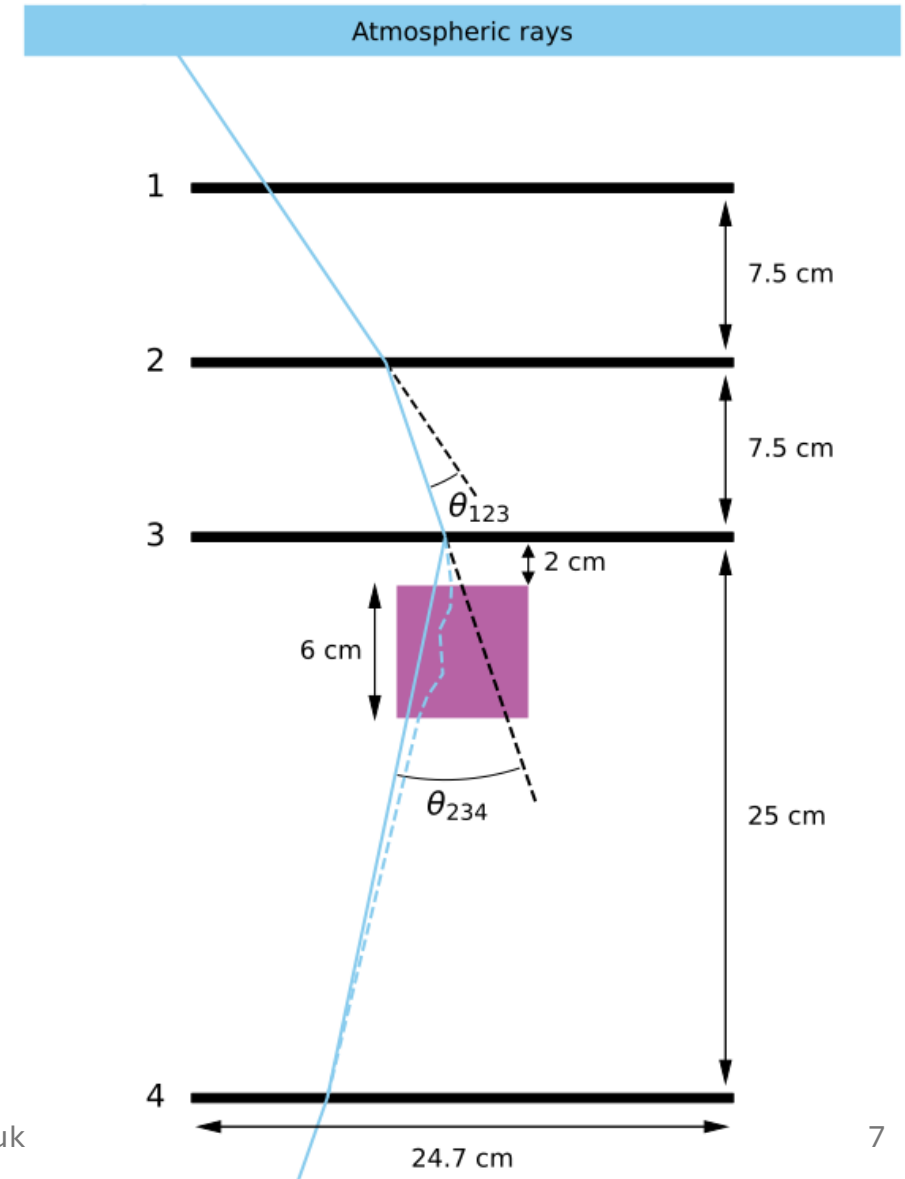
- 6 cm side length cubes of material
- Measure each material for 8 hours in 30 minute segments for 16 samples per material

Material	Weight / g
Air	-
AW5754 Aluminium	574.2
C30/37 Concrete	512.0
Glass	514.8
Water	256.9
Ammonium nitrate with sulphur pellets (NH ₄ NO ₃)	199.6
PENO plastic explosive	342.0
Plexiglass	251.6
15 mm FF Birch Plywood	147.6
S355MC Steel	1684.9



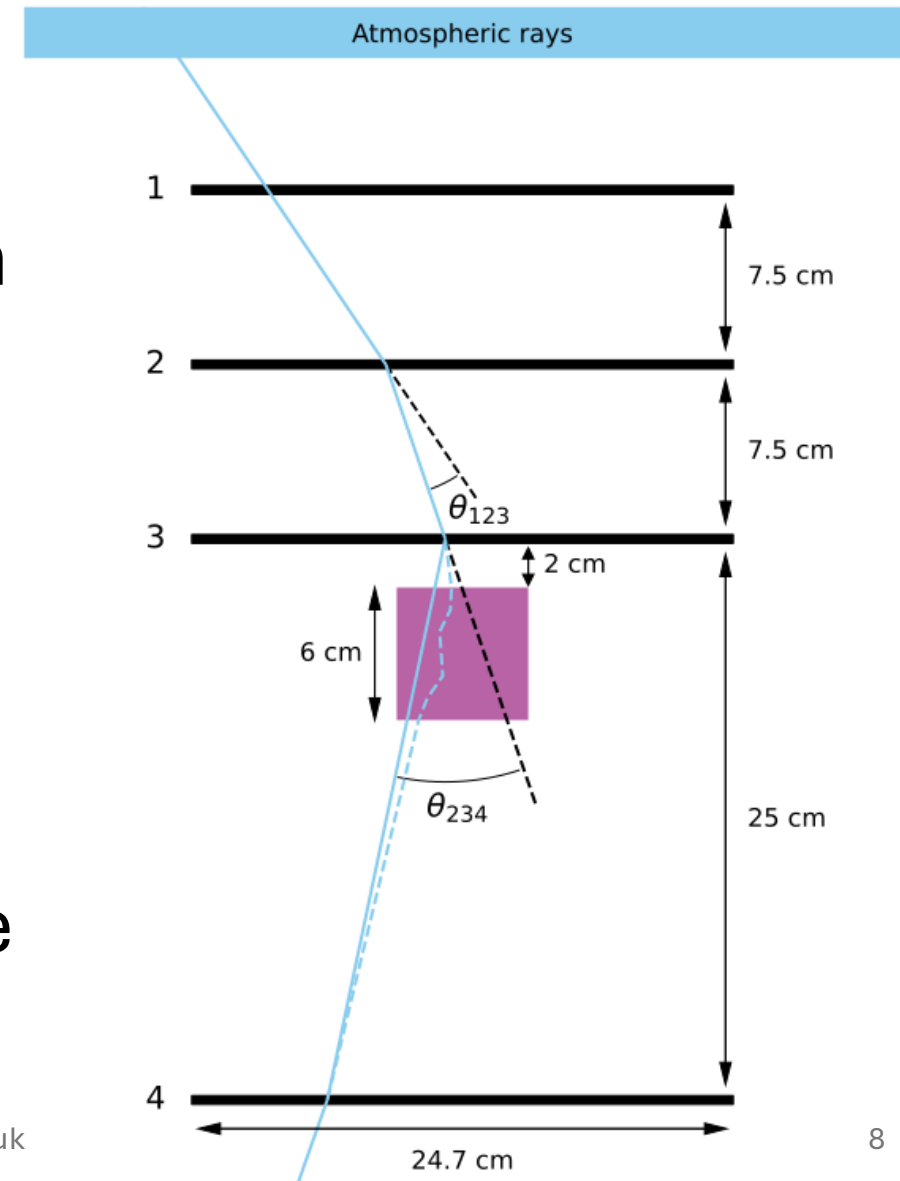
Data processing

- Approximate muon track through volume by straight line through VOI
- Use 3 filter groups based on θ_{123} to group electrons, electron/muon mixture, and muons
- Find events traversing each voxel in VOI (using 0.5 cm voxels)



Data processing

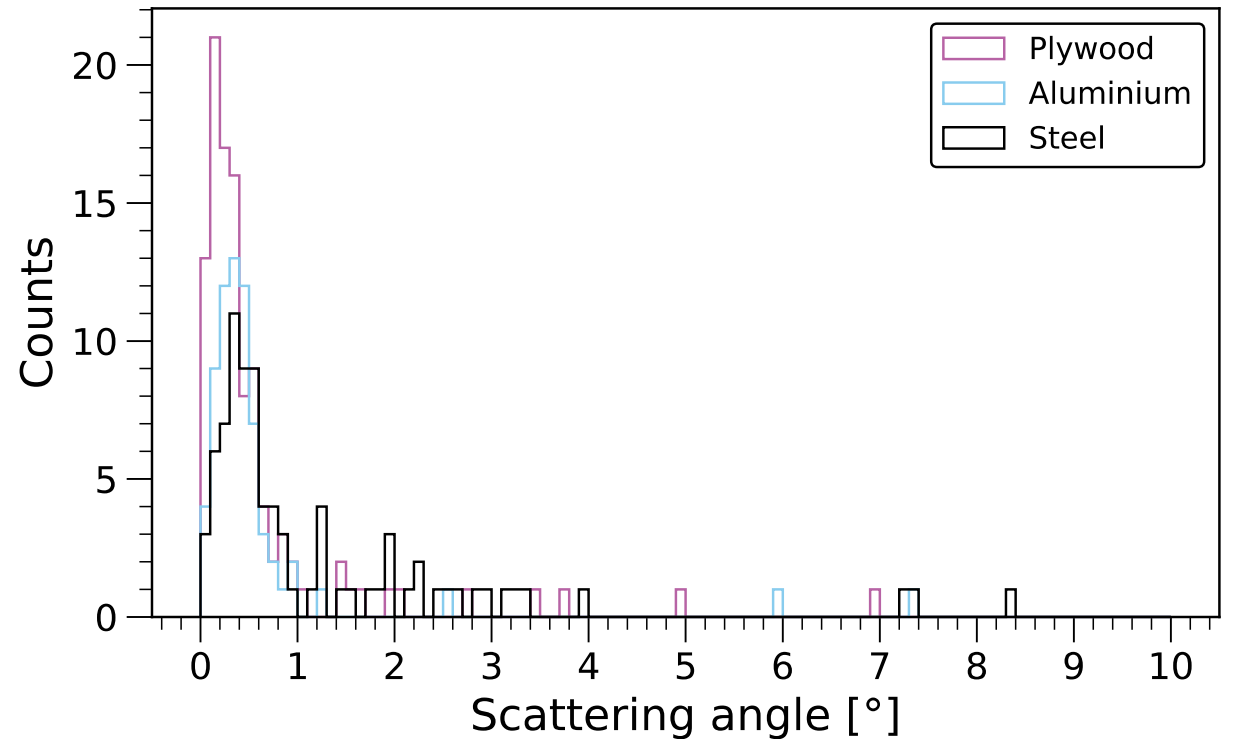
- For each voxel intersecting the known object position, compute quantities including (but not limited to):
 - Average scattering angle
 - Average track length in voxel
 - Average scattering angle per unit track length
- Repeat for each filter group and plane combination (123 and 234)



Object histograms

- Aggregate quantities across all voxels in object
- ML algorithm inputs are normalised histograms
- Separate in 15-fold cross-validation, so per material in each fold:
 - 10 training samples
 - 1 validation sample
 - 1 test sample

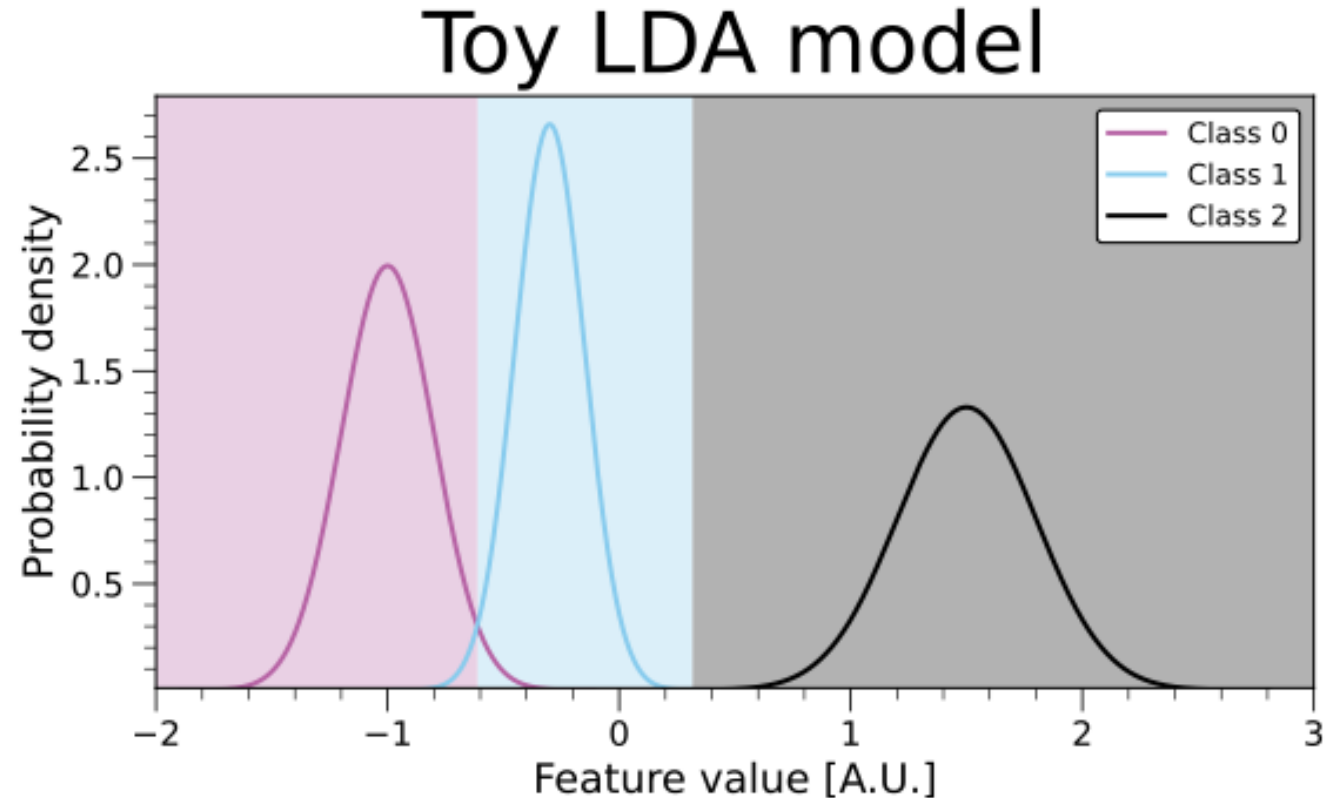
Example unnormalised $\overline{\theta}_{234}$ histograms



Material classification methods

For this exercise, use **linear discriminant analysis (LDA)**:

- Model each class with multivariate Gaussian, **minimise** in-class variance and **maximise** class separation
- At prediction, select class with highest likelihood for the sample
- Try both multiclass and 1 vs 1 LDA methods

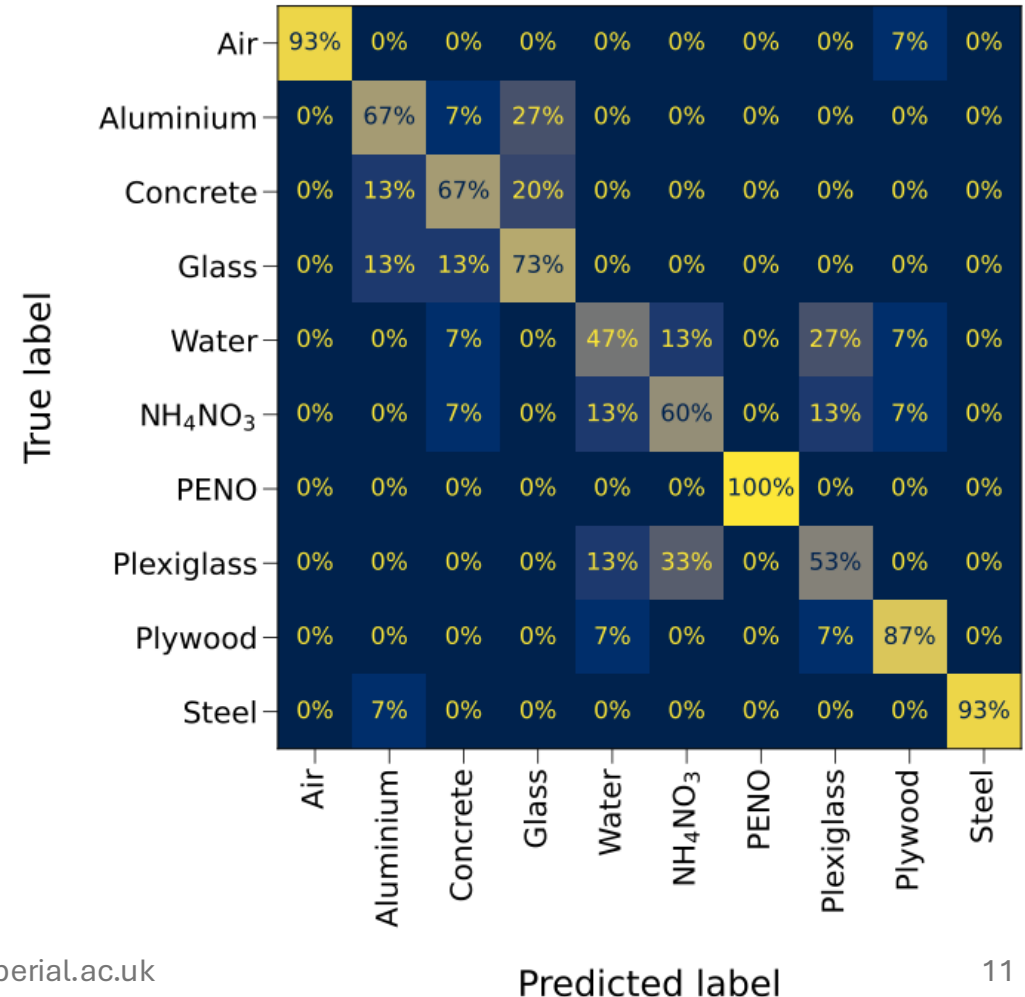


Shaded regions show what class would be predicted

Multiclass LDA

- Multiclass training scheme: simultaneously fit all class Gaussian models
- Optimise number of features based on feature importance scoring (see paper for details^[1])
- Average test set accuracy across all folds is **74.0%**

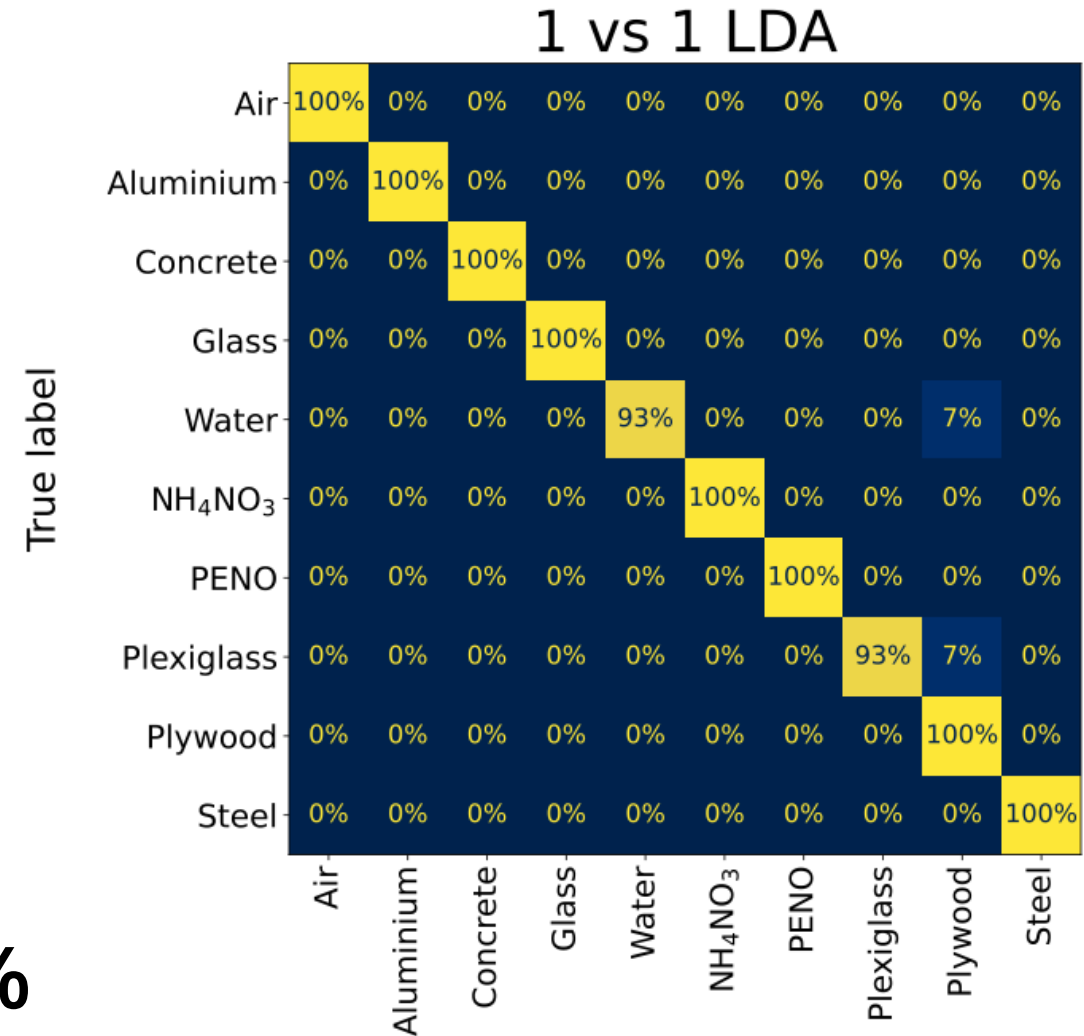
Multiclass LDA, 870 highest-ranked features



1 vs 1 LDA

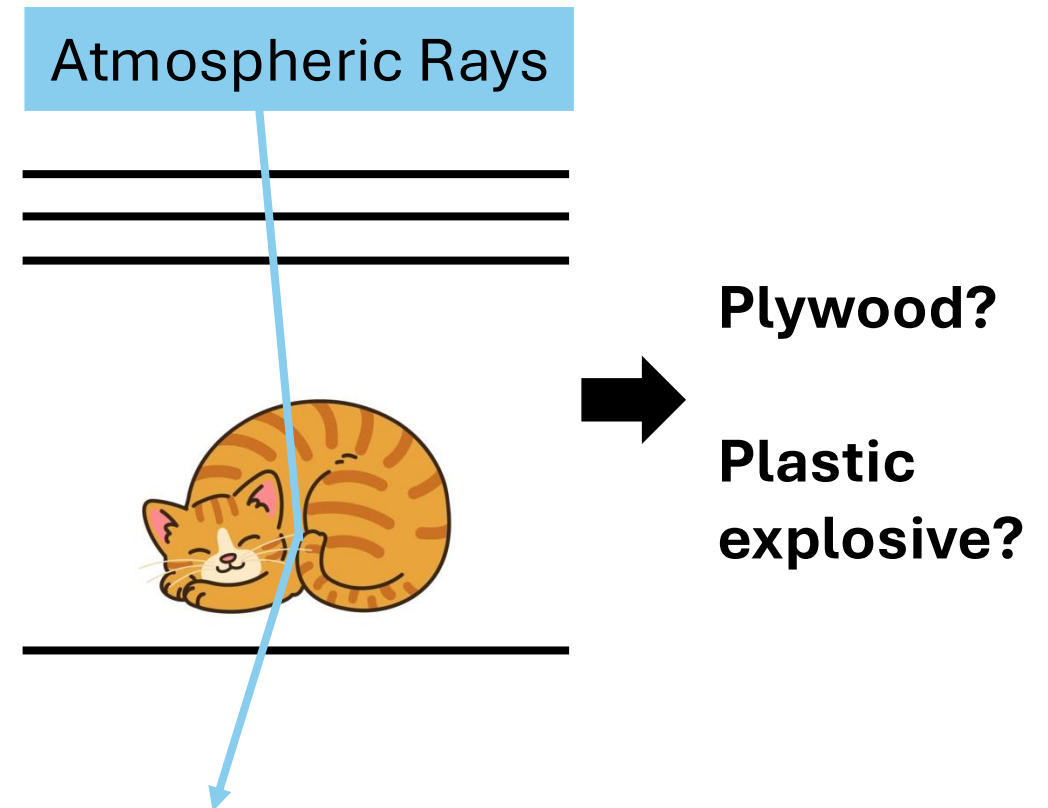
- 1 vs 1 training scheme: train an LDA classifier for each pair of classes
- Final prediction is most voted class among all classifiers
- Optimise feature count per classifier
- Same CV scheme as multiclass

Average test accuracy = 98.7%



Limitations of this exercise

- Limited tomography device, so needed ground truth to identify object voxels
- Simple experimental scenario, not realistic
- Reliance on seen materials for classification, difficult to generalise



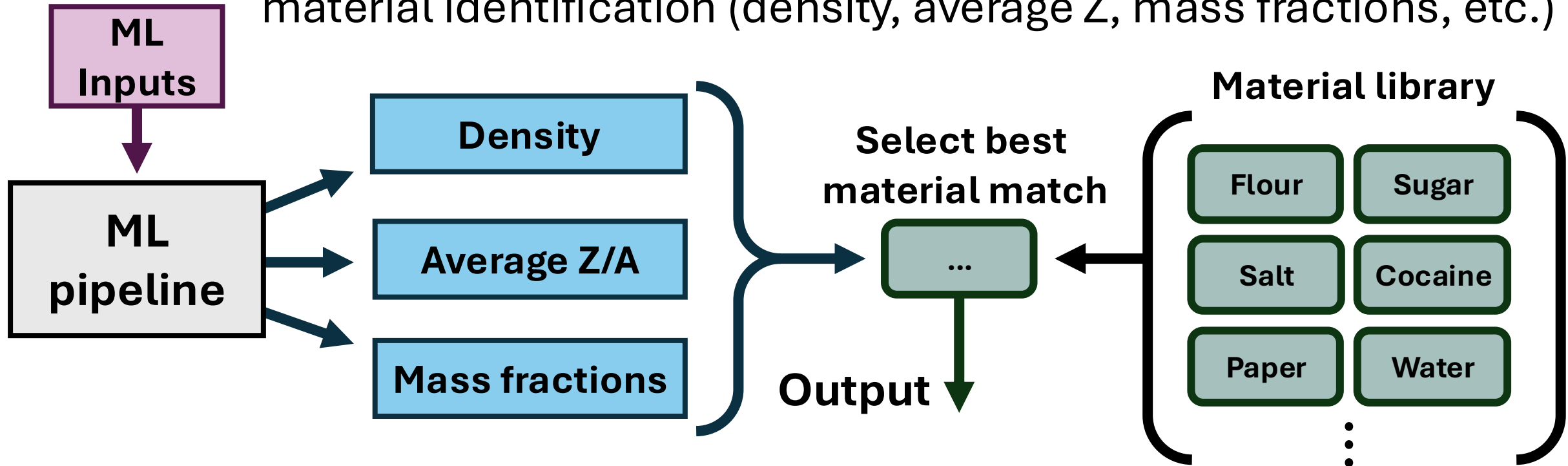
Subsequent developments

- Dedicated CosmoPort scanner in a trailer (two full hodoscopes), sized for postal roll cages
- Piloting measurement campaigns with customs partners
- Extensive simulation validation and generation of synthetic datasets



Next steps

Development of ML methods to improve **generalisation** of material identification (density, average Z, mass fractions, etc.)



Example processing pipeline

Summary

- A prototype scintillating fibre detector was built with position reconstruction error ~ 0.1 mm, corresponding angular resolution ~ 1 mrad
- ML models were trained using 30 minute scans of low-Z material cubes, achieving **98.7%** average accuracy
- Improvements to detector & methods are ongoing, with the (eventual) aim of generalised material identification

Thank you!

[1] N. Reed *et al* 2025 *JINST* **20** P07032

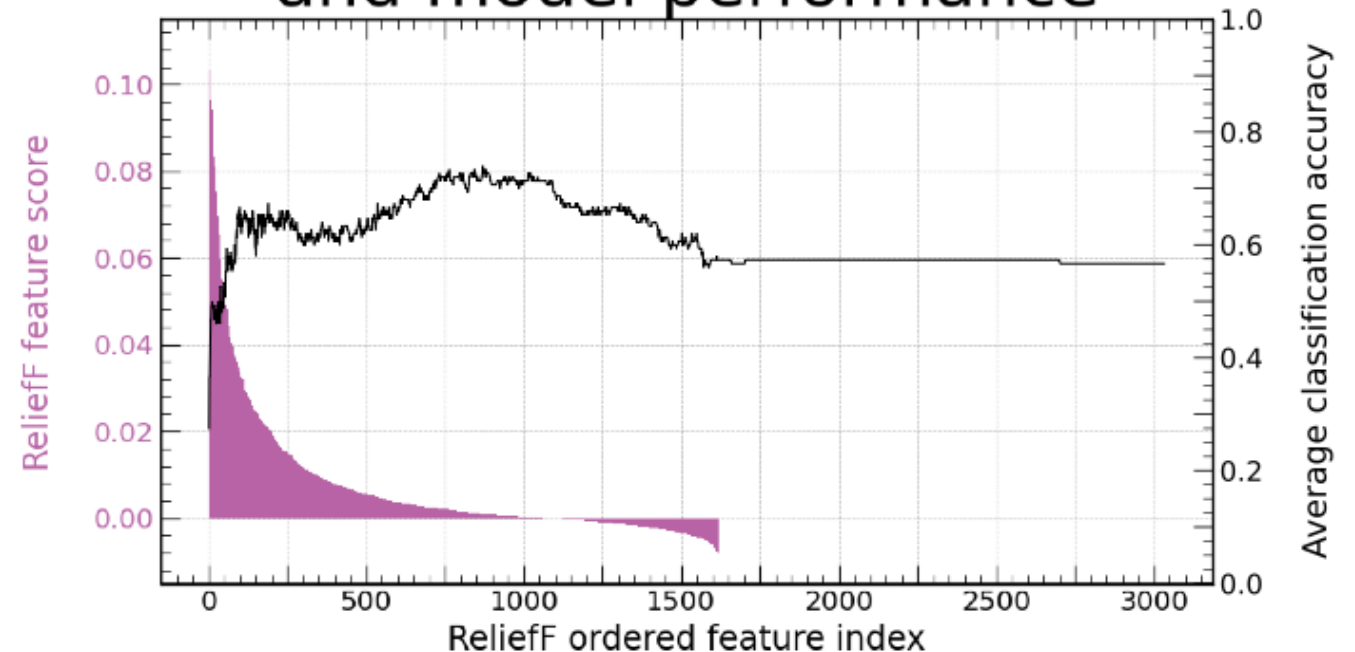
[2] G. Anbarjafari *et al* 2021 arXiv:2102.12542 [**physics.ins-det**]

Bonus Slides

Feature importance

- Use ReliefF feature importance algorithm to calculate score per feature quantifying discrimination power
- Use top N ReliefF-ordered features to train, optimise N for best validation accuracy

Comparison of ReliefF scores and model performance



Multiclass LDA feature count optimisation