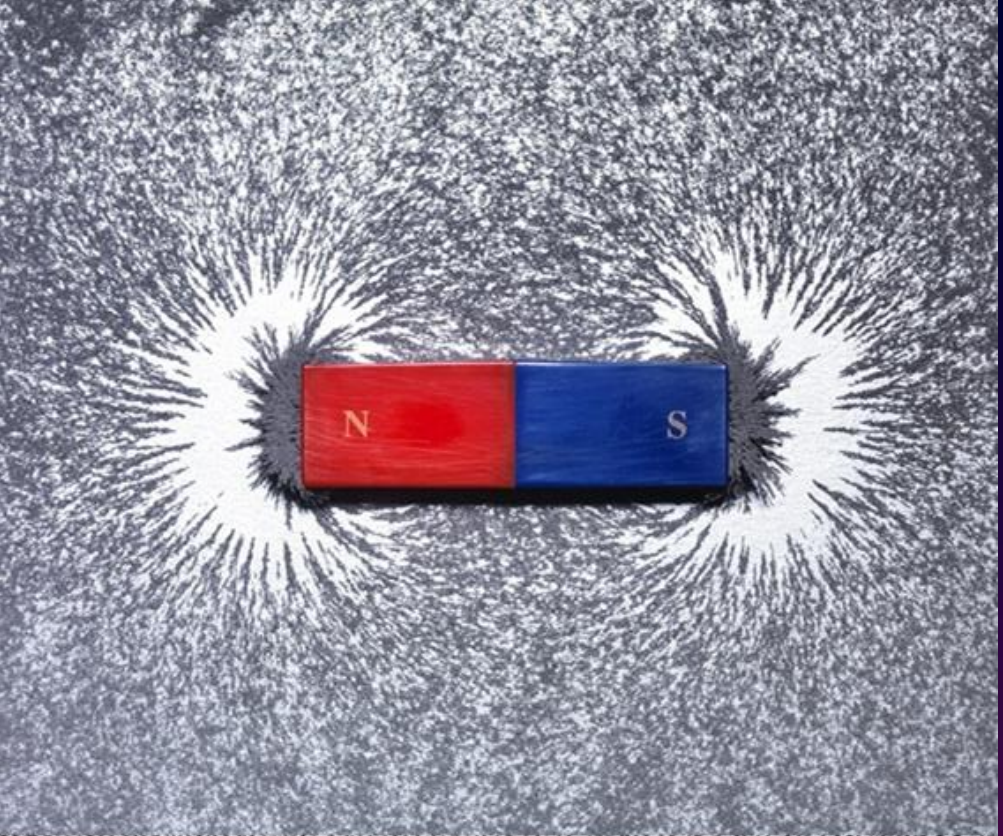

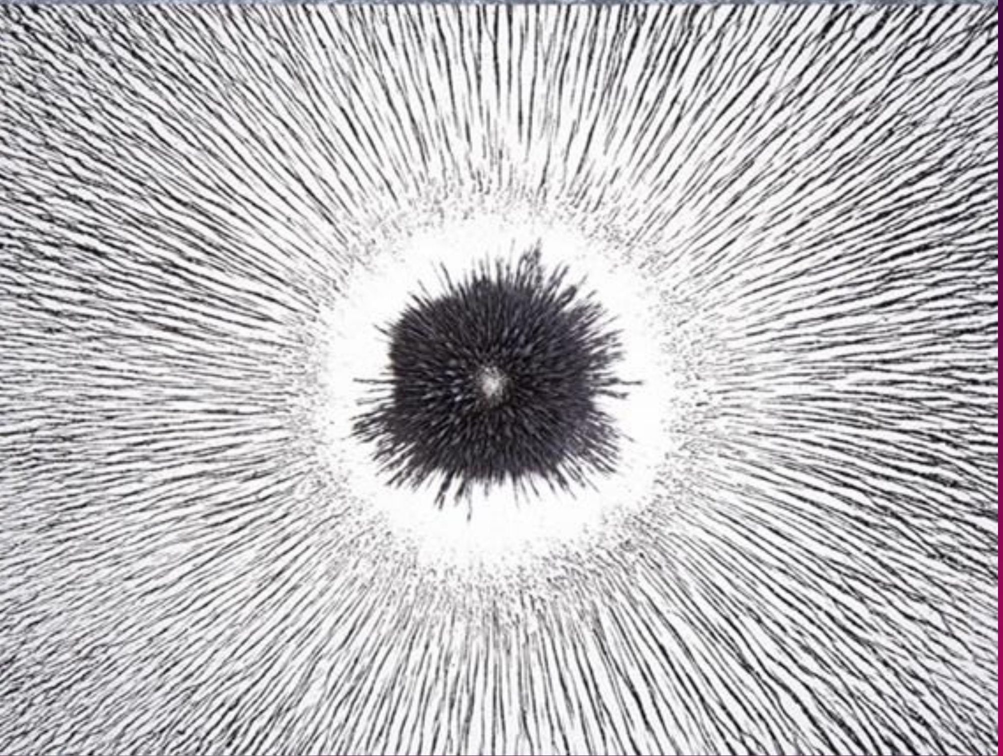

MoEDAL

Monopole and Exotics Detector at the LHC

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- MoEDAL Physics
- MoEDAL Detector
- Machine learning for MoEDAL

Magnetic Monopoles

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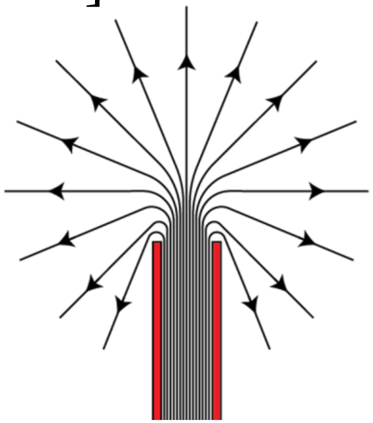
Many different predictions;

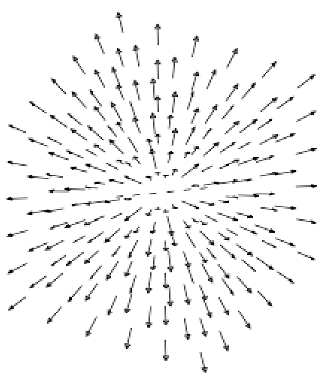
Dirac monopole [1931]

pointlike singularity
modelled as
infinitely long
solenoid
‘dirac string’



T’Hooft-Polyakov [1973] GUT

Topological soliton
in fundamental
gauge fields in
theories with
broken symmetries.



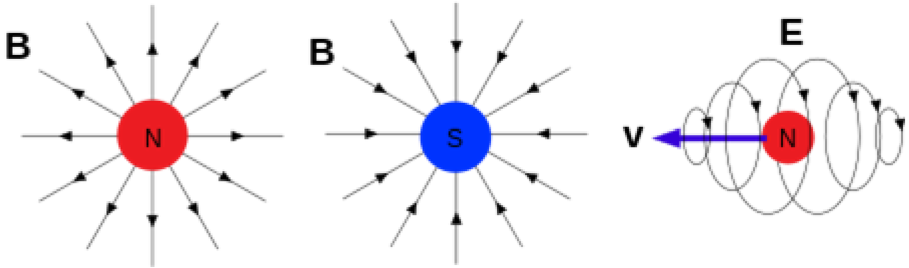
Cho, Maison [1996] EW

modifications to SU(2) x U(1) electro-weak
theory possibly allows TeV monopoles
hybrid of Dirac / T’Hooft

Dyons, magnetic and electric

Common properties;

Acts like particle with magnetic charge.
EM interaction with much stronger
coupling! $g_D \sim 68.5e$



Mass ~ varies by theory, uncertain
Unconstrained for Dirac monopoles
EW 4~10TeV, Tevatron > 600GeV

Explains charge Quantisation, possibly
baryon asymmetry, early cosmos

Stable if topological solitons

= Heavy, Stable, Highly Ionising

Exotics and HIPs

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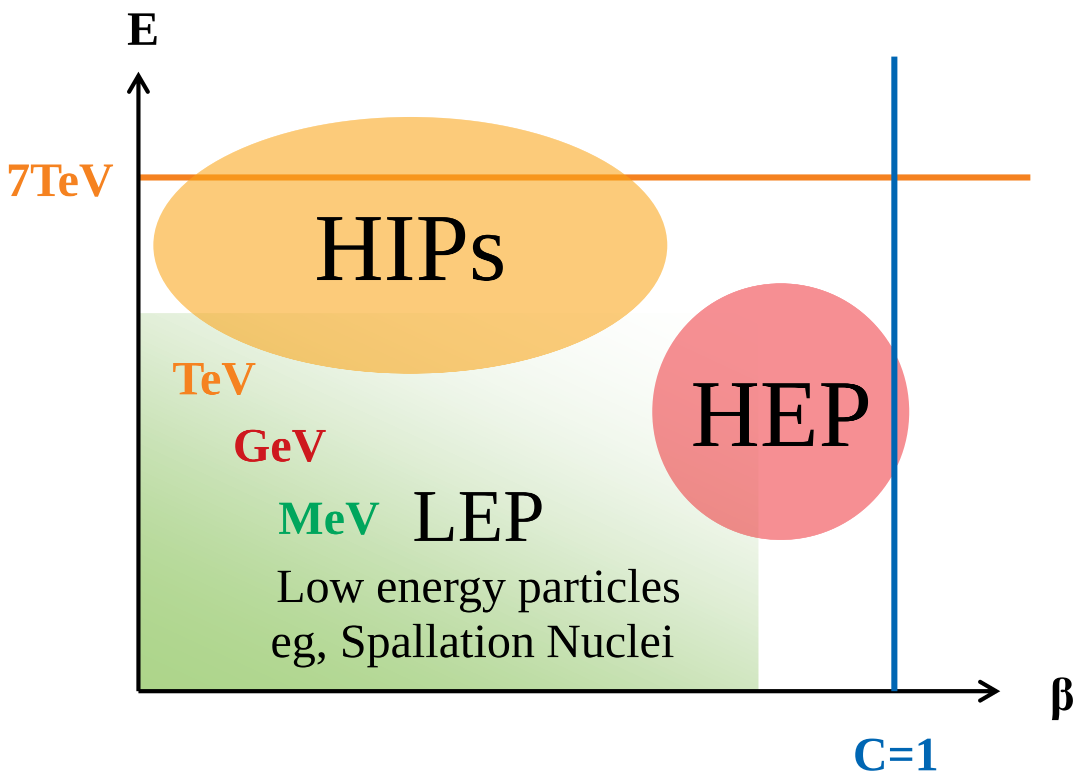
Monopole signal = Heavy, Stable, Highly Ionising particle (HIP)

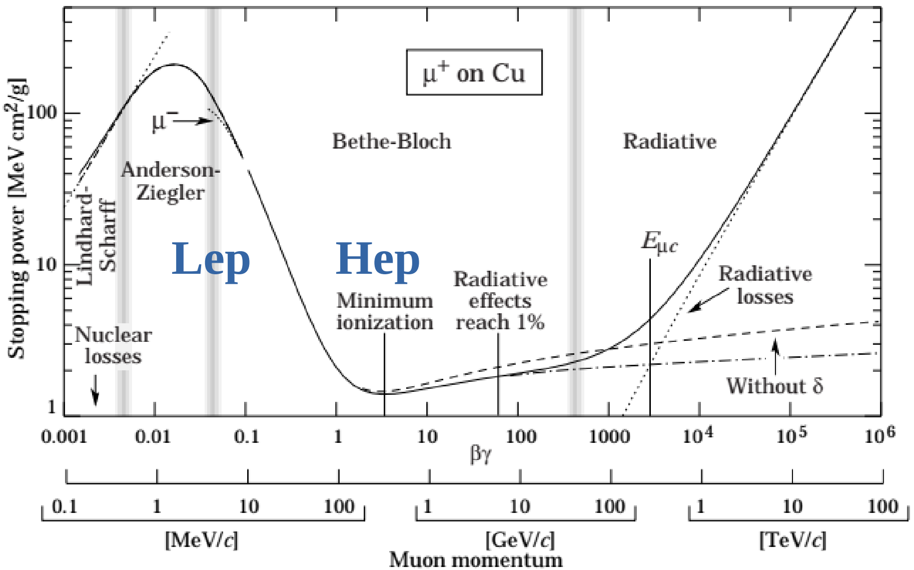
Similar BSM exotics;

Stable Massive particles
SUSY; stops, staus, gluinos
(esp. if parity conserved)

Multi-Charged particles
eg, double charged Higgs
Bilepton

No SM background for HIP signals
High momenta + low β + highly ionising



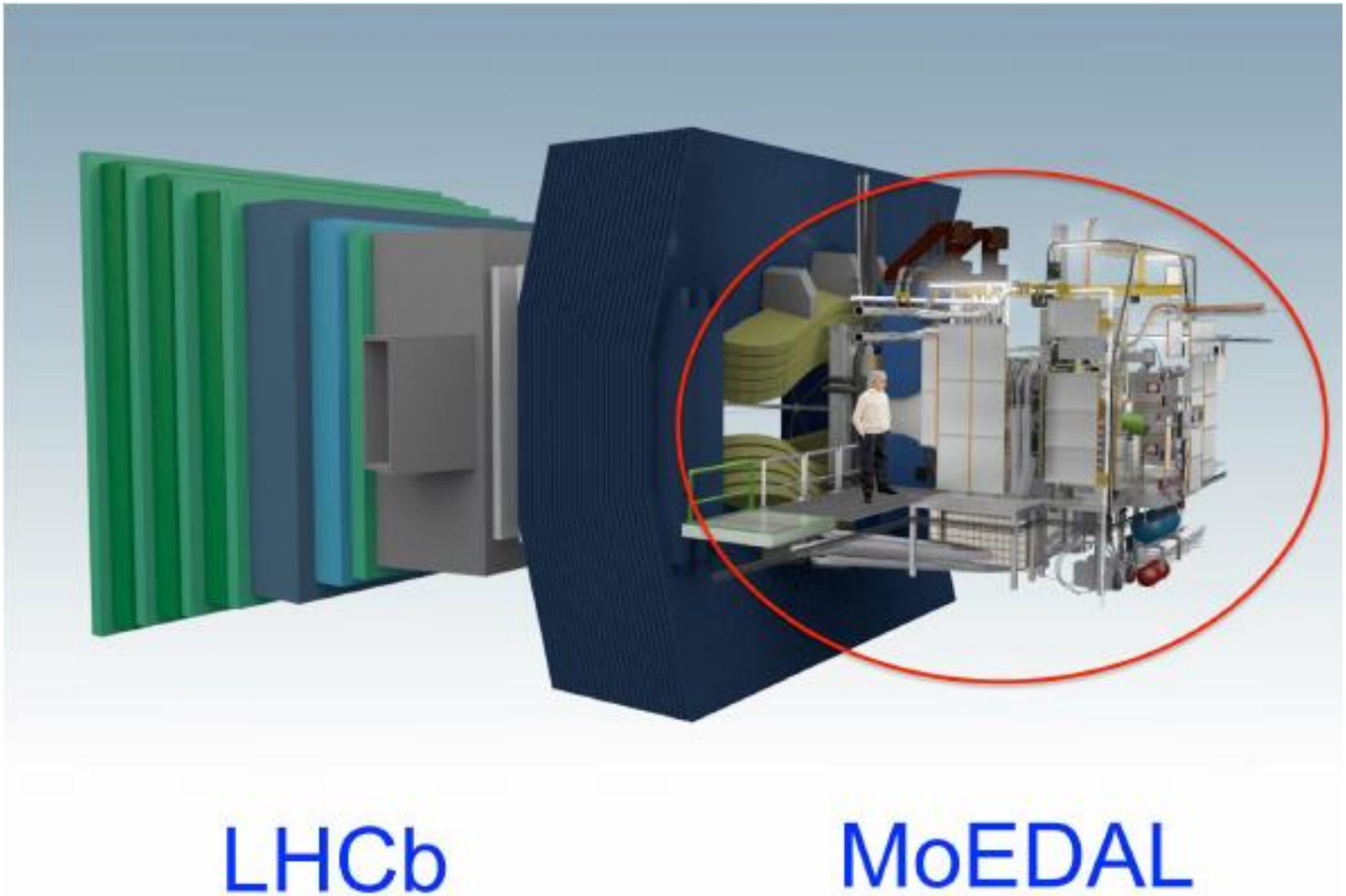


Electronic Detectors optimised to trigger on light speed particles, which are minimally ionising

High LHC bunch crossing rate, most events discarded. Rare BSM signals can be missed

MoEDAL detector

LHC IP:8



MMTs
Aluminium paramagnetic monopole trappers

NTD array + VHCC
Ionisation detectors
(rest of this talk)

Timepix
Radiation environment monitoring

MAPP
Millicharged particle detector

Moedal: NTD arrays

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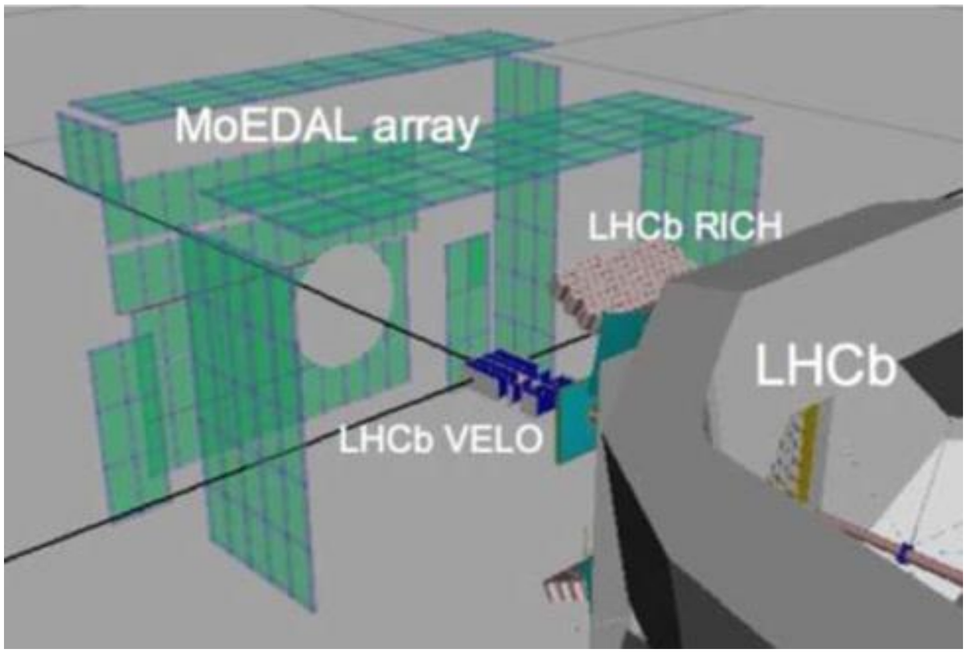
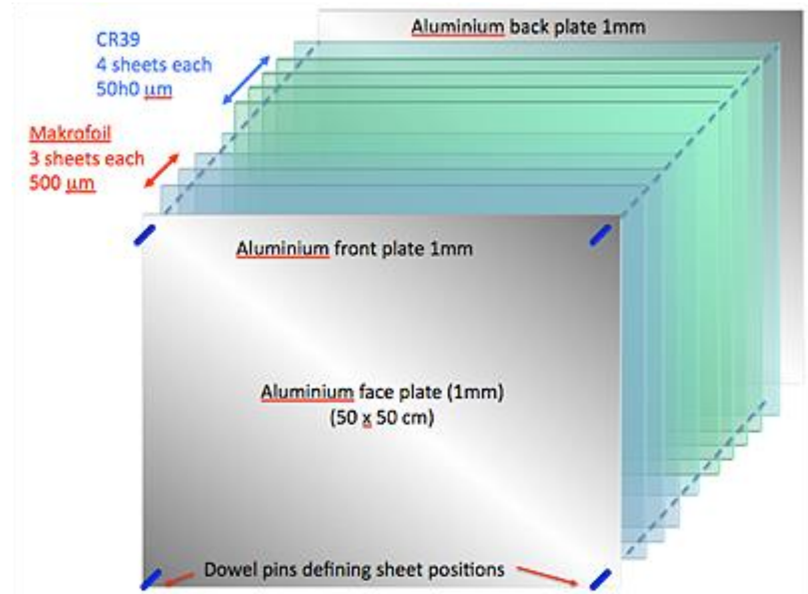
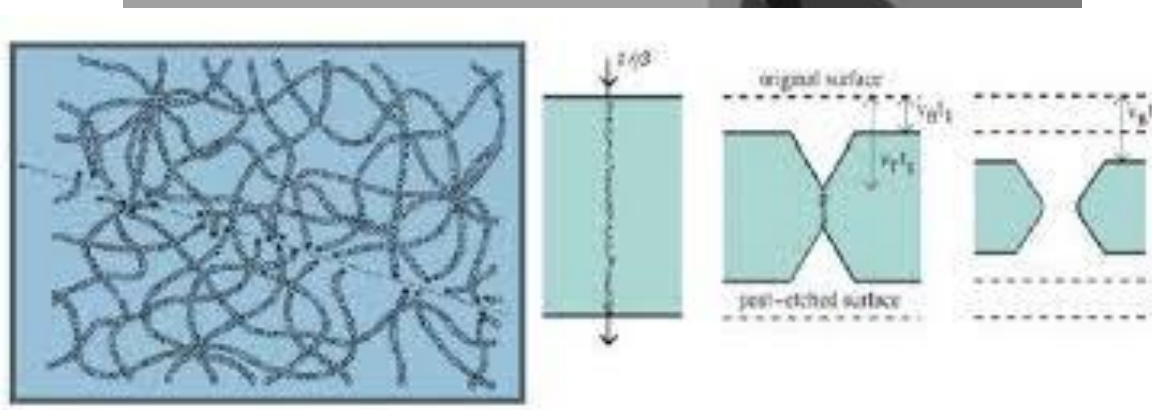
Stacked Arrays of ionisation sensitive polymer solid state nuclear track detectors (NTDs)
Sensitive to Heavily Ionising Particles, low sensitivity to standard model particles







NANOSCOPIC ⟶ MICROSCOPIC

Ionising particles break polymer chains in NTD foil in localised region

Leaves latent ‘Ion track’

Chemical etching process occurs faster along ion tracks than bulk medium

Forms ‘etch-pits’ where ionising particles entered and exited the foil

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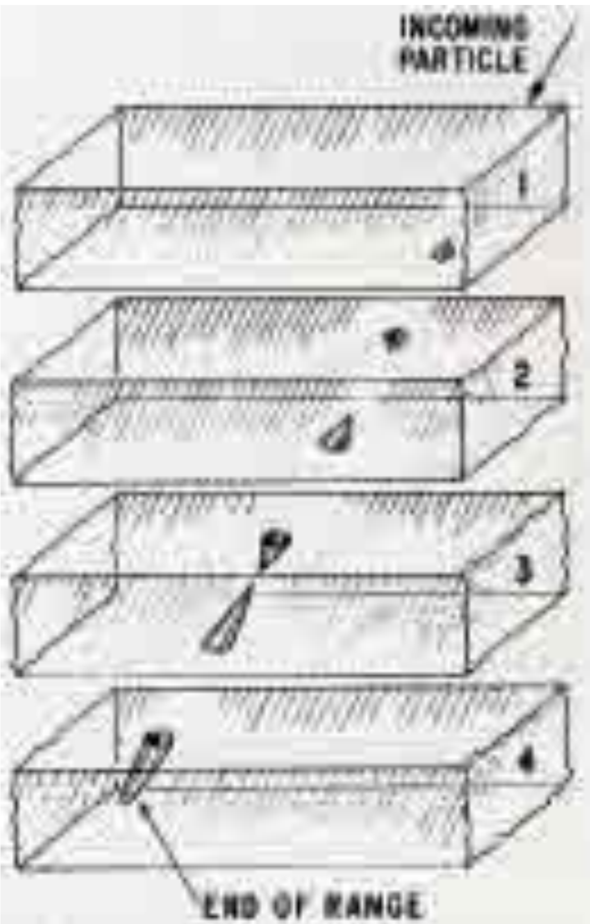
Standard Model Ionisation Behavior



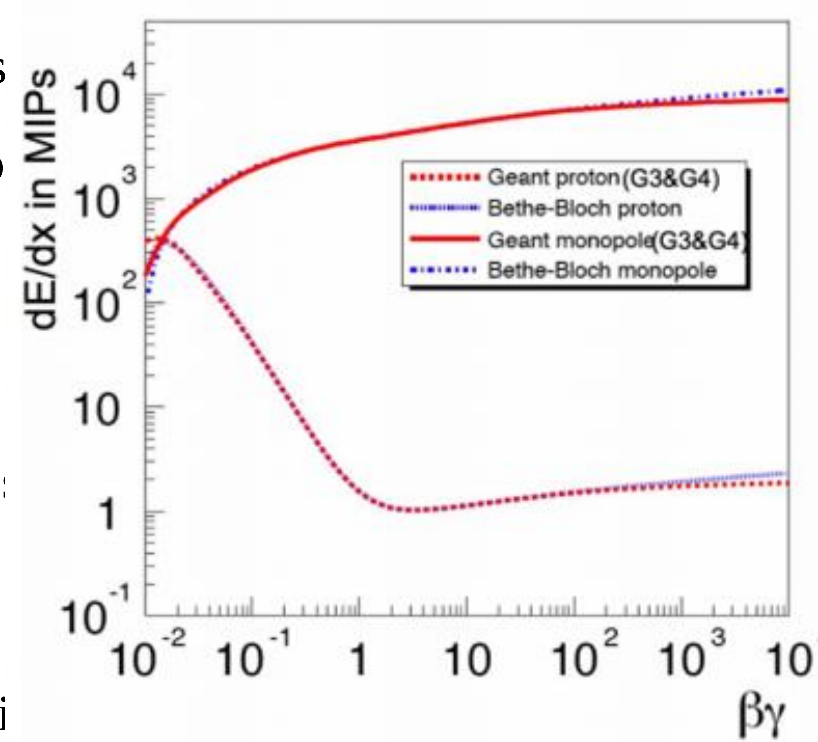
Courtesy INF Bologna

1) Initial High energy causes minimal ionisation. Doesn't show up as etch p

2) Particle loses energy, lower velocity, efficient 'electronic' ionisation. 'Ranging in'

3) Reaches peak energy los: larger etch-pits form at point of entry and exit

4) Energy loss, 'electronic' ionisation ceases, etch-pi formation stops. 'Ranging out'



In practice MoEDAL stacks designed so SM particles only appear in 1 or 2 foils
typically ranging out (4)

Particles in NTD stack

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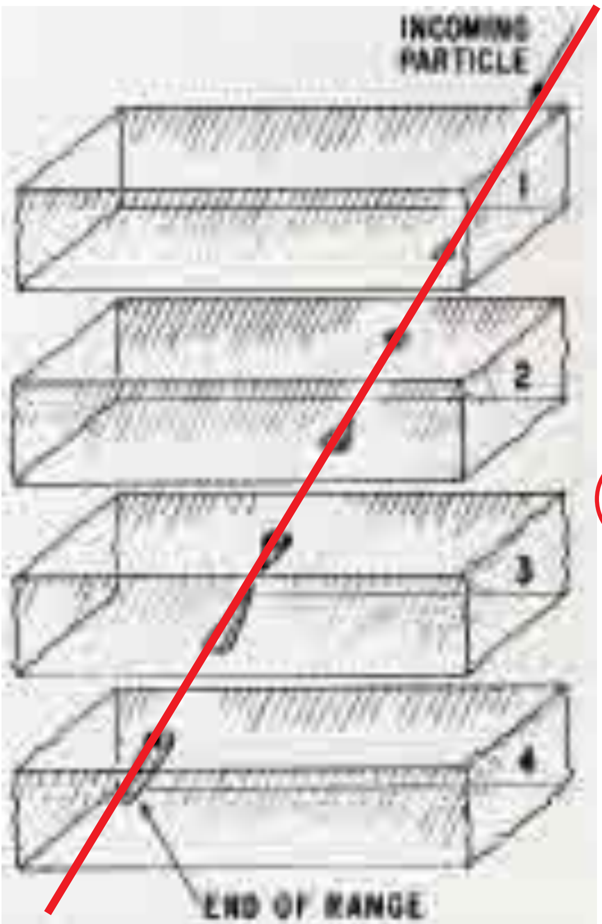
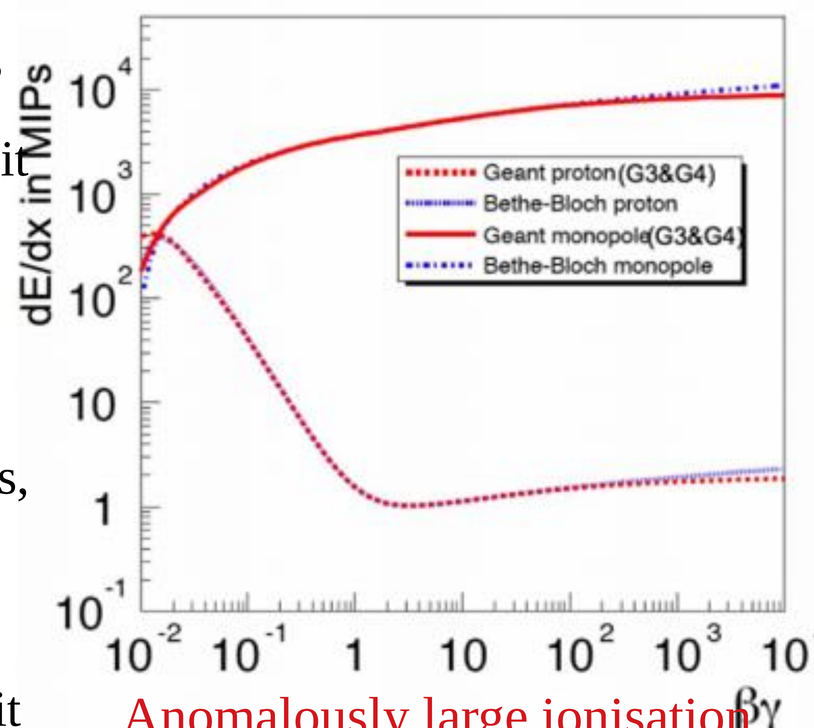
BEYOND ~~Standard Model~~ Ionisation Behavior



Courtesy INF Bologna

1) Initial High energy causes minimal ionisation. Doesn't show up as etch pit
2) Particle loses energy, lower velocity, efficient 'electronic' ionisation. 'Ranging in'
3) Reaches peak energy loss, larger etch-pits form at point of entry and exit
4) Energy loss, 'electronic' ionisation ceases, etch-pit formation stops. 'Ranging out'



Anomalously large ionisation appears in all layers
Approx no β dependance
~ TeV Energy Momentum
Primary vertex origin
Direct search
No SM background

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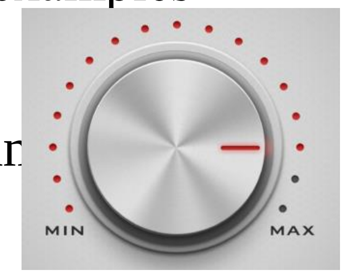
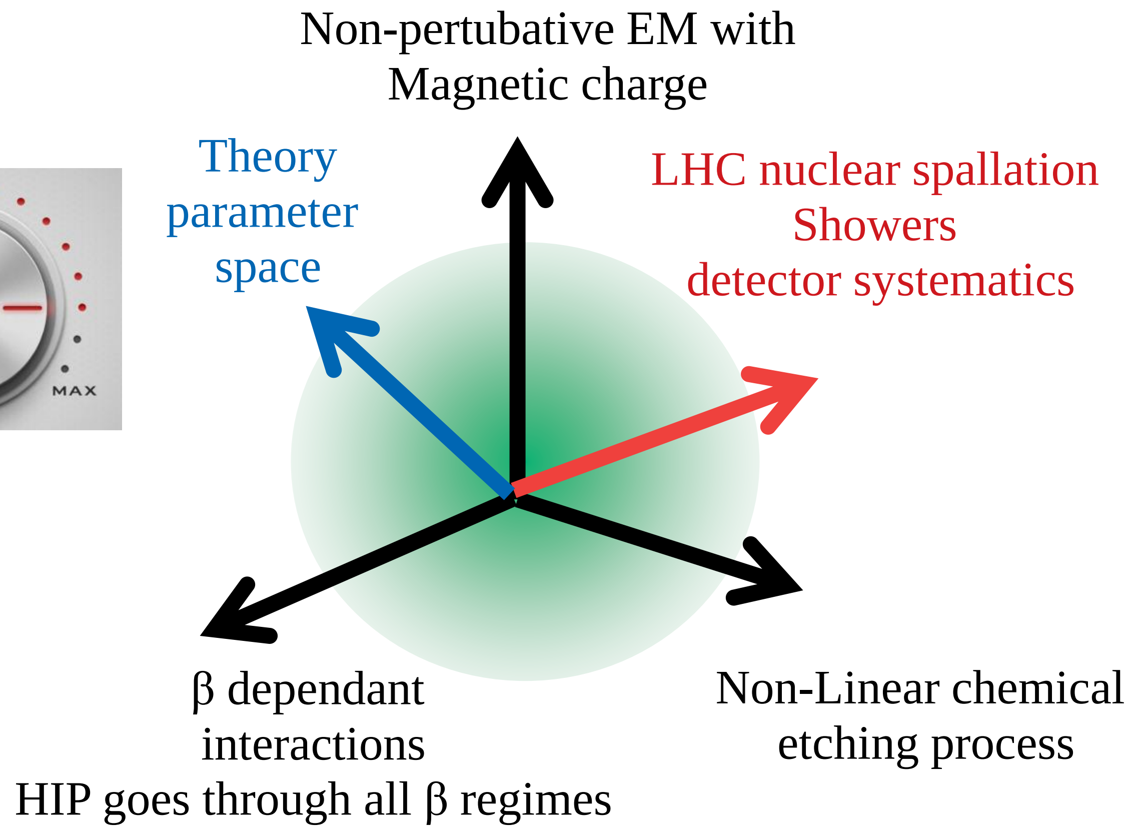
#1: Training / Modelling

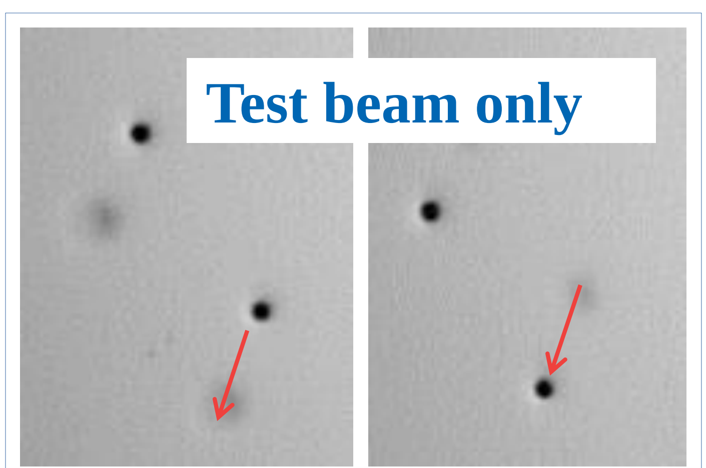
No ‘real’ magnetic monopole examples to train from

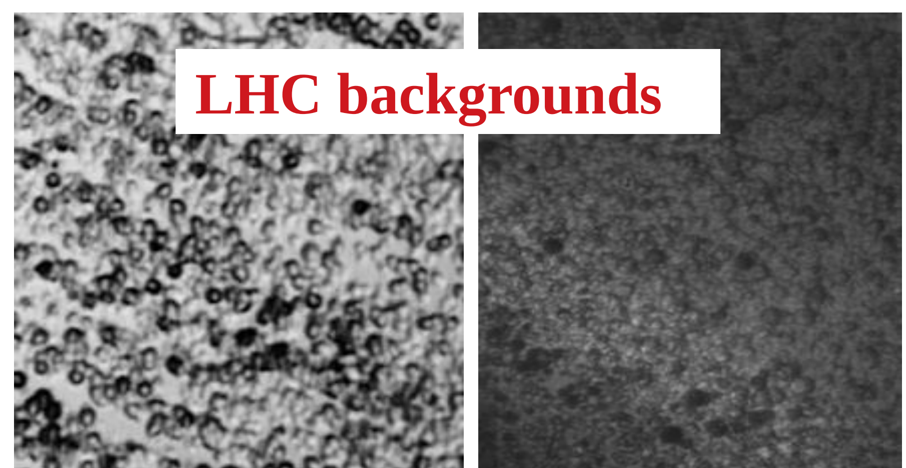


Huge uncertainties, many paran
Modelling +
Monte-Carlo impractical

Calibrated heavy ions beams & LHC produces controlled HIP signal with magnified cross-section for ML RnD







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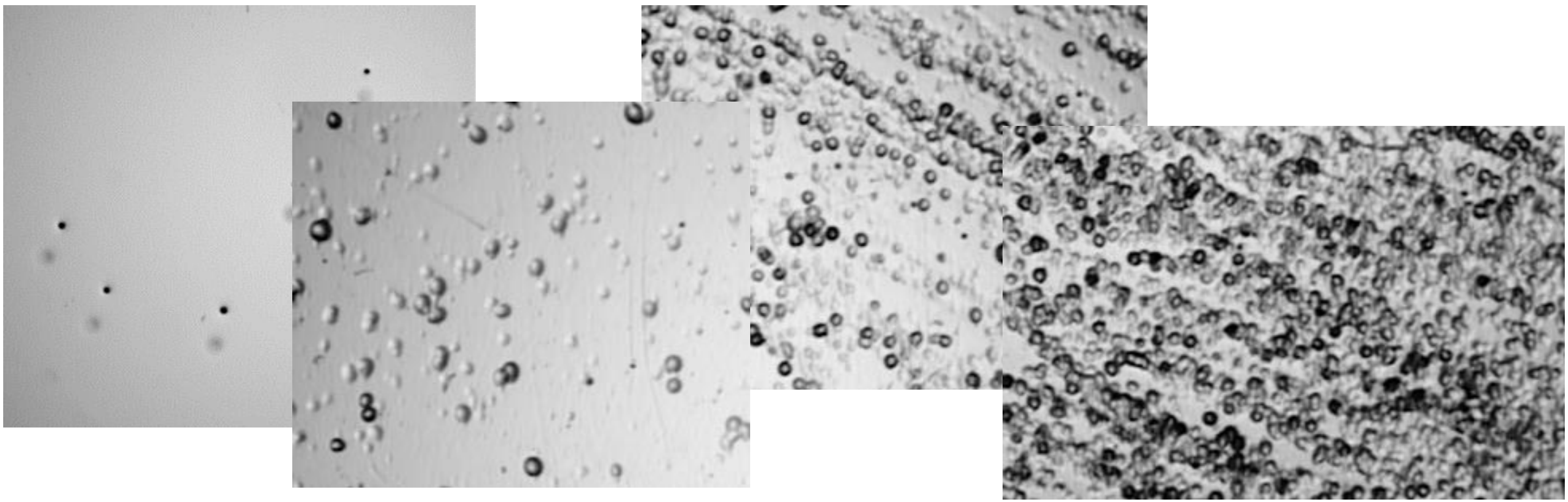
#2: Background density

CR39, Heavy ion test beam

Makrofol, heavy ion test beam
+ 8 months LHC background

LHC background
pile-up increases with Lumi

LHC Exposure



Scale

O(100) m^2 macroscopic foil area
Trillions of etch-pits total
Problem changes as density increases
Images represent ~mm^2
Millions of etch-pits in each cm^2

Complications

Foil structure altered by γ – rays changes detector response
Etch-pit clusters merge under etching
Foil thickness fluctuates

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#3: Accurate identification

Want to ID/tag peak ionisation events

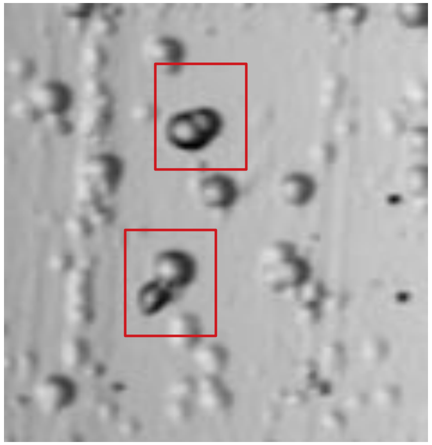
Need robust signal efficiency and background rejection. - Minimise false positive rate

LHC particle flux; all different SM ionisation behaviour happening

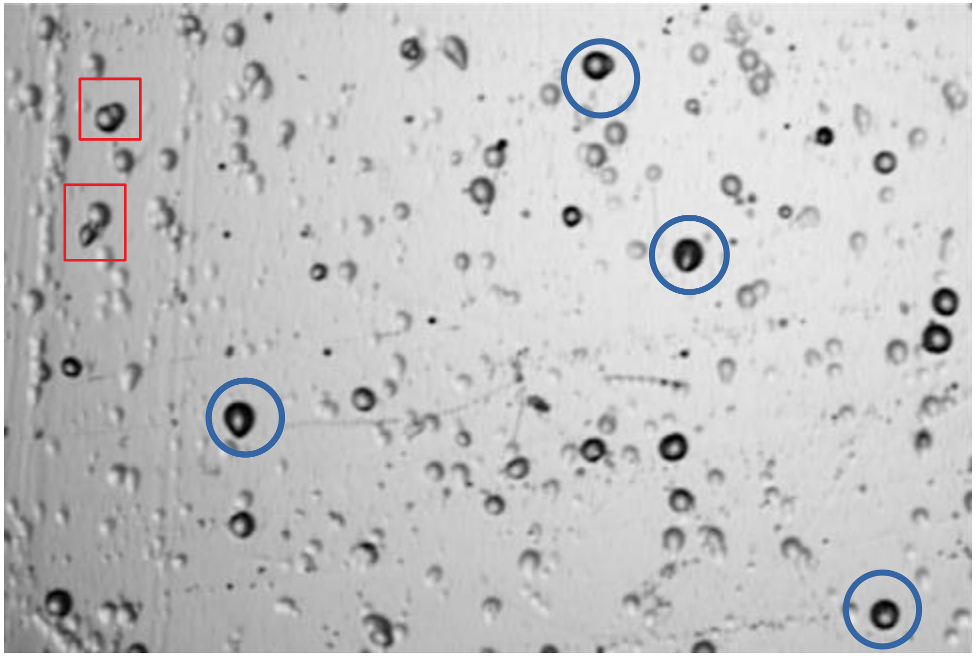
Accurate ID requires detailed 3D inspection especially when pits start to cluster and overlap

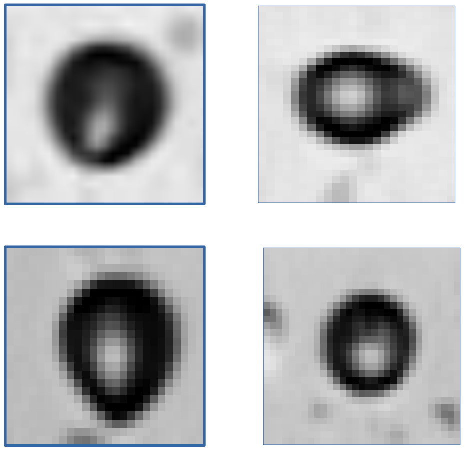
Supervised learning only as good as its label accuracy.

Example



Entry Exit pair?
Background cluster?





Strong Visual Symmetry between different physics objects / backgrounds

3D Dark-field imaging

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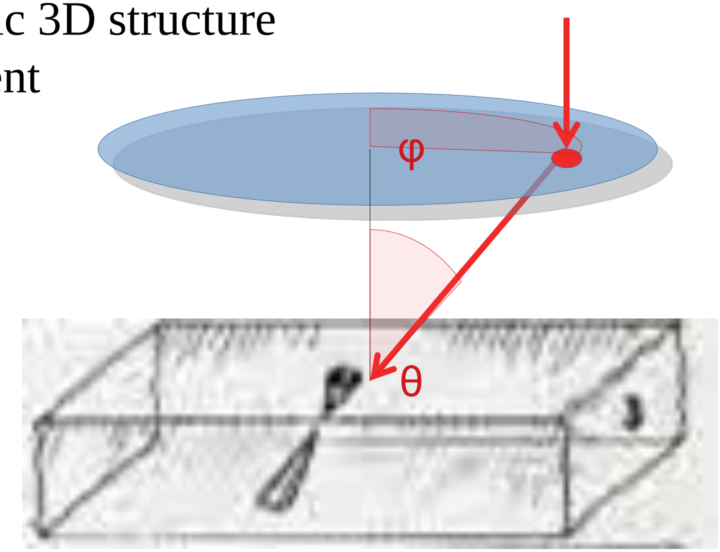
Want to probe microscopic 3D structure to understand particle event interpretation

And rapidly scan macroscopic area with minimal motion and large field of view



CAN parametrise illumination angle

LED grid, + Fresnell lens
Allows control of θ , φ

Retain microscopic alignment of focal plain over macroscopic area

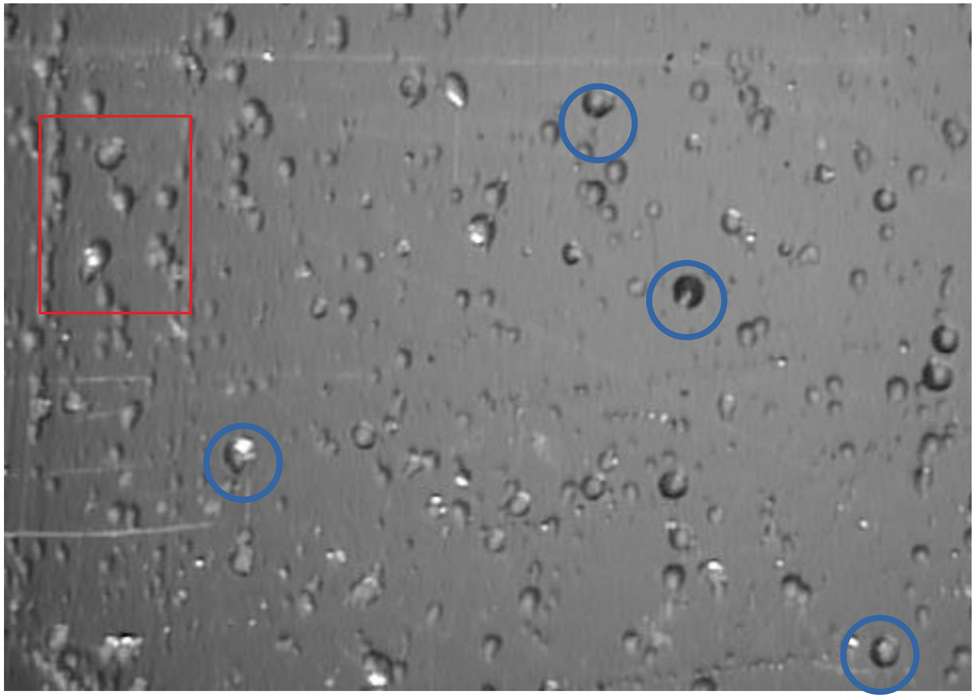
Example

X, Y, Phi becomes 3d data-space

Animation
In-phase rotation common origin

Opposite phase possible entry exit

ML / CNN sees all angles at once



Entry exit pairs look different to overlapping bkg

Resolve different 3D structures

Spot anomalies or heavy ionisations

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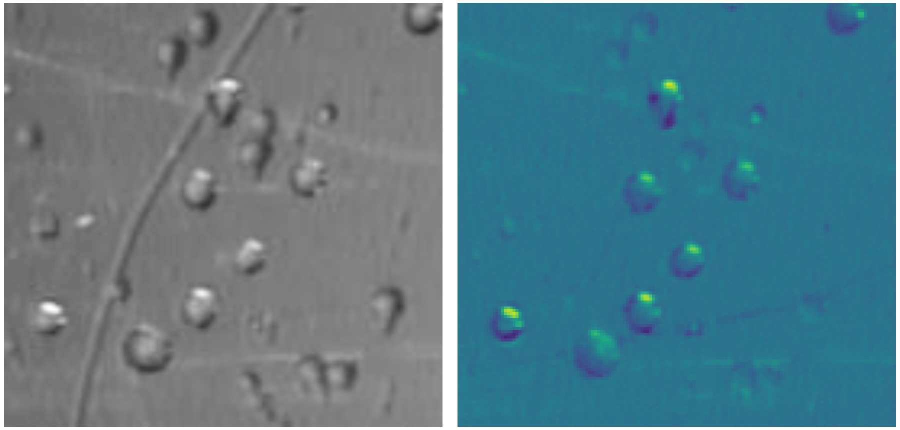
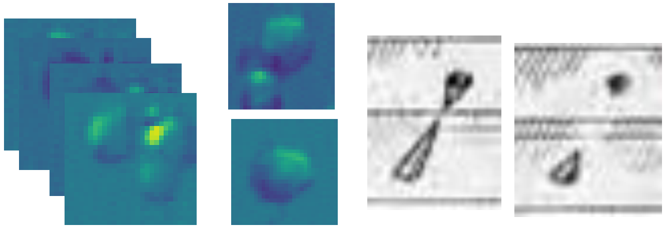
ML – Training / Analysis

1 "Normalisation" - Redefine relative to local zero, 'clean' up low ionisation pits / de-clutter. Remove systematic imaging biases + non-etch pit visual backgrounds

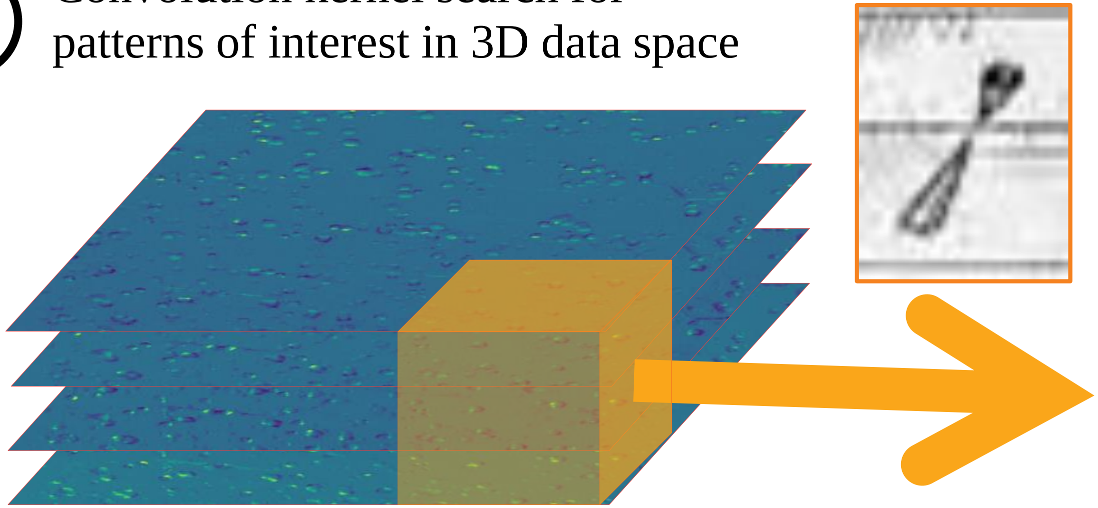


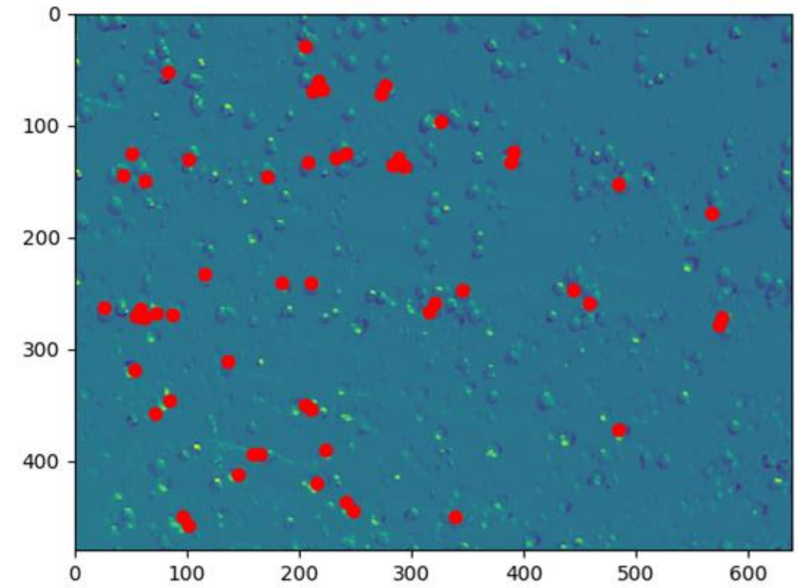
4 Build supervised ML dataset from preselection. Train sub-classifiers, eg, entry exit asymmetry ~ dE/dx
replace initial search with learnt models



3 Pre-select etch-pits
reject trivial backgrounds
reduce labelling, storage requirement ~ 1000

2 Convolution kernel search for patterns of interest in 3D data space





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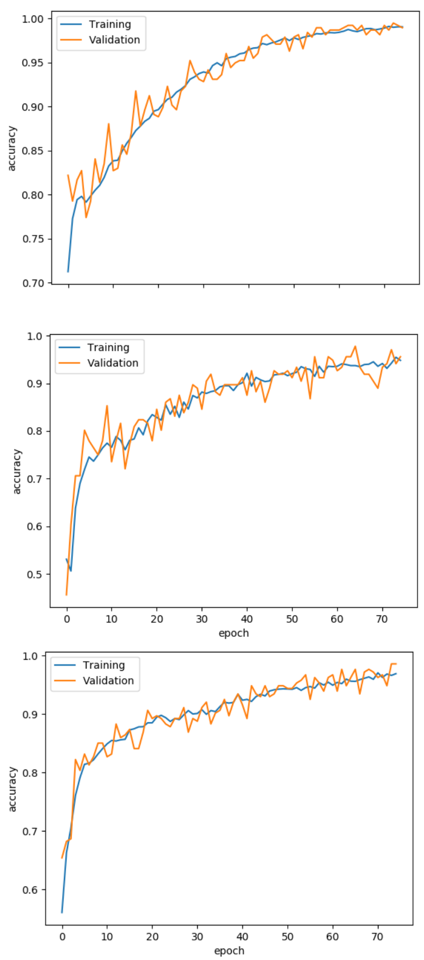
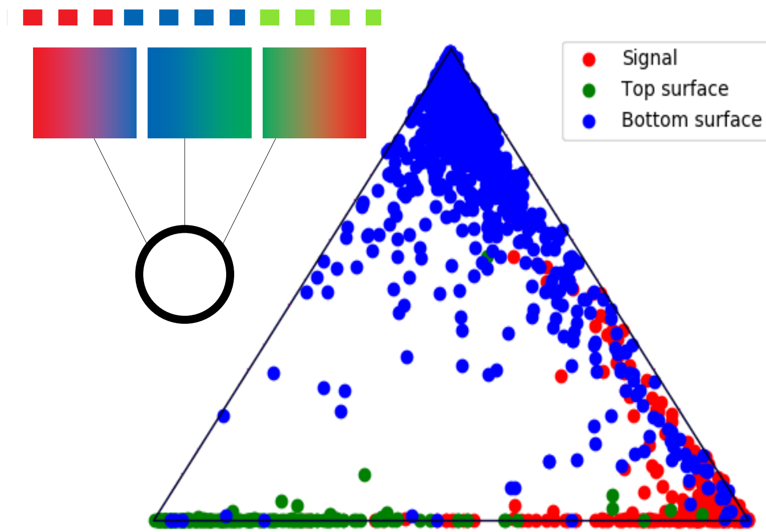
ML – Ensemble + inference

Train specialist ‘experts’ to handle sub-classifications within set of ‘signal like’ etch pits

Eg, top / bottom surface biased ionisation indicating SM range in/out





Expert Classifiers combined in ensemble to output overall classification

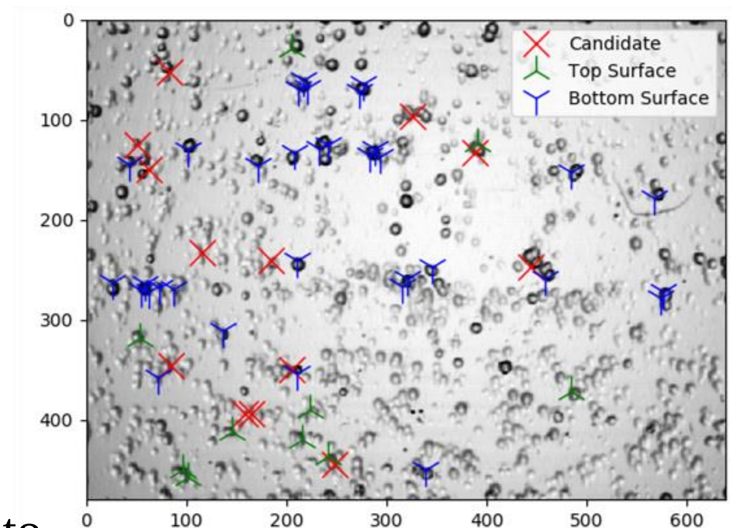
Robust + needs less training data

Geometric combination

$$C' = C_1 * C_2$$

vs arithmetic

$$C' = aC_1 + bC_2$$



Can use in inference to ID etch-pits in new areas of foil

Can use stacked neural network, replace ensemble

Summary

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- Moedal looks for Highly ionising - high energy physics signitures
- No standard model background for HIP track
- Can use ML to automate + accelerate NTD analysis
- Subtle 3d info can help find interesting ionisation events
- Ensemble methods learn quicker with less data + more robust, easy to add new signals
- Push to higher bkg densities / lumi