Image simulation and analysis for NEWSdm

PhD:
Artem Golovatiuk

Supervisor:
Giovanni De Lellis

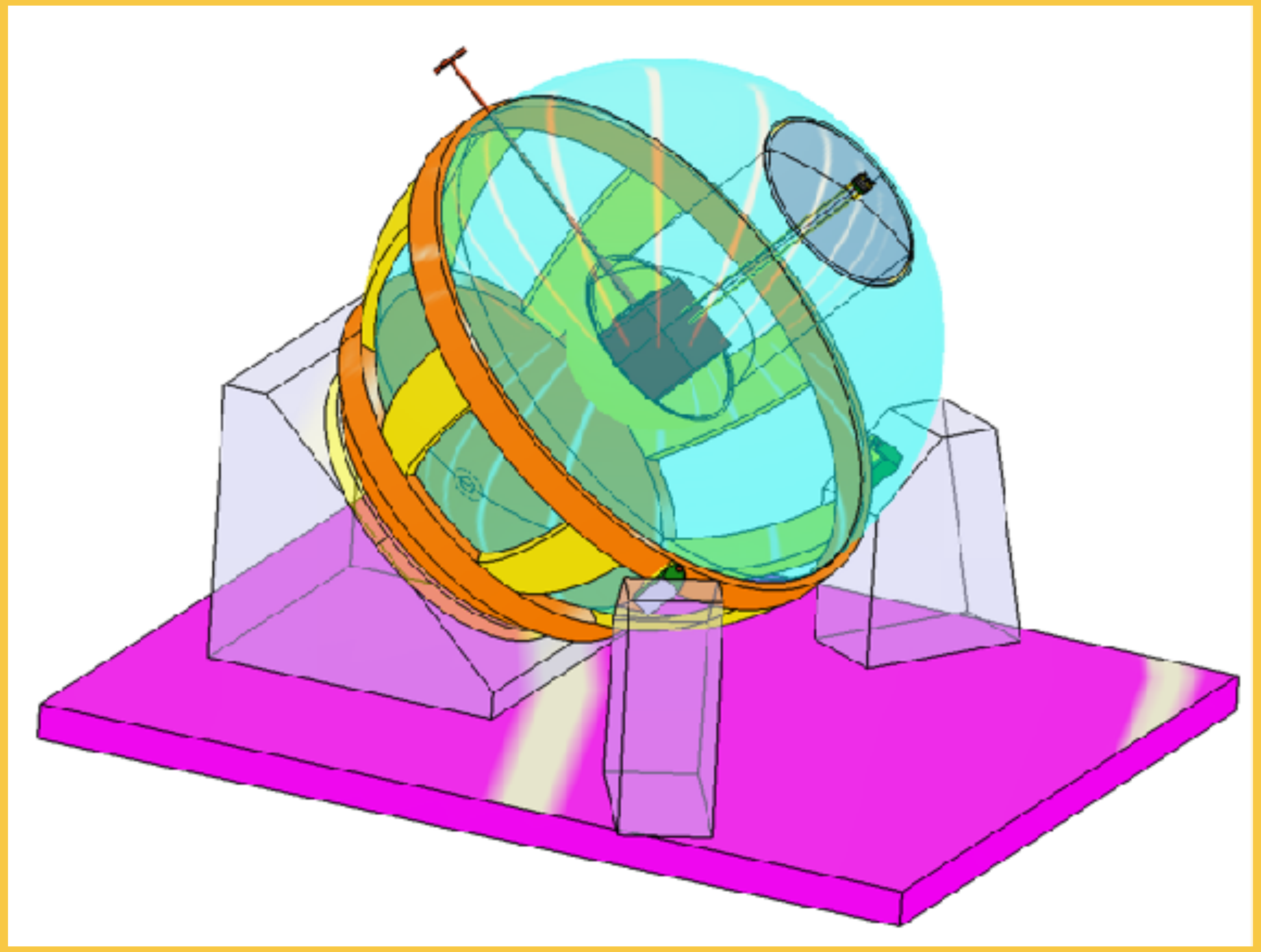
Co-supervisor:
Andrey Ustyuzhanin

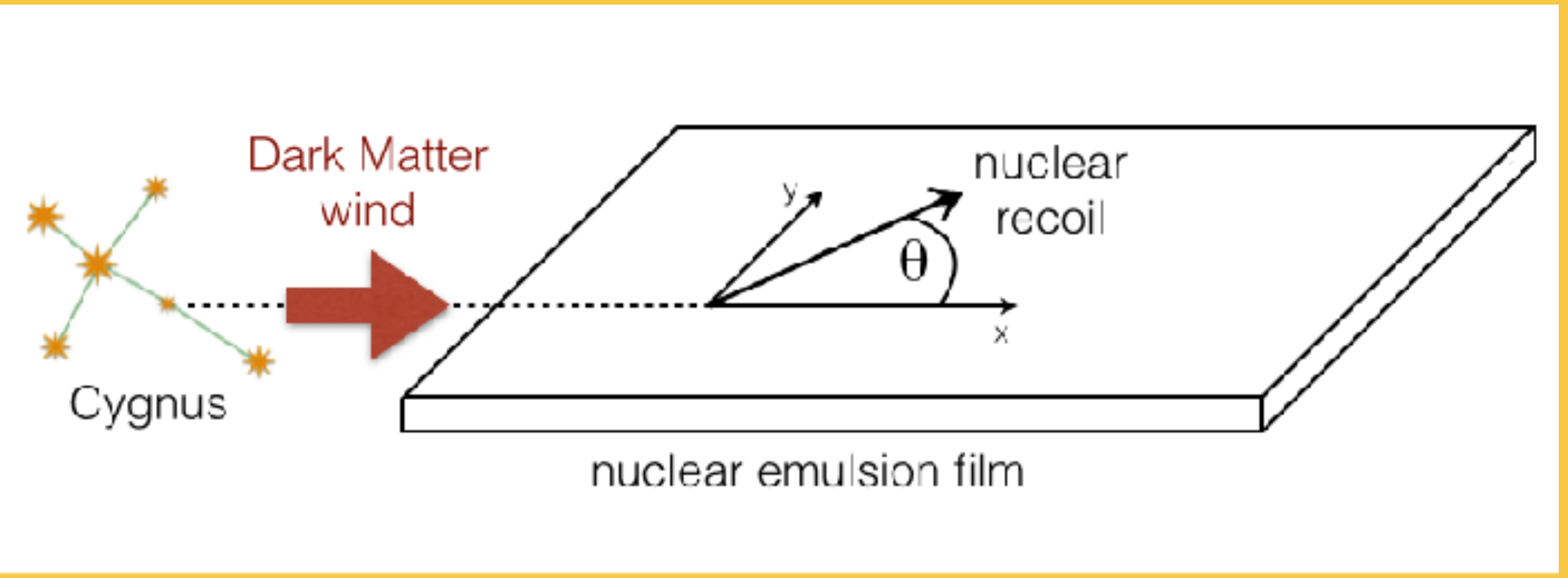
Insights is funded by the European Union’s Horizon 2020 research and innovation programme, call H2020-MSCA-ITN-2017, under Grant Agreement n. 765710

Dark Matter search with nuclear emulsions

The NEWSdm experiment

- **Aim:** detect the direction of nuclear recoils produced in WIMP interactions
- **Expected track length:** O(100 nm)
- **Target:** nuclear emulsions acting both as target and tracking detector
- **Background reduction:** neutron shied surrounding the target, purified gelatine, etc.
- **Fixed pointing:** target mounted on equatorial telescope constantly pointing to the Cygnus Constellation
- **Location:** Underground Gran Sasso Laboratory

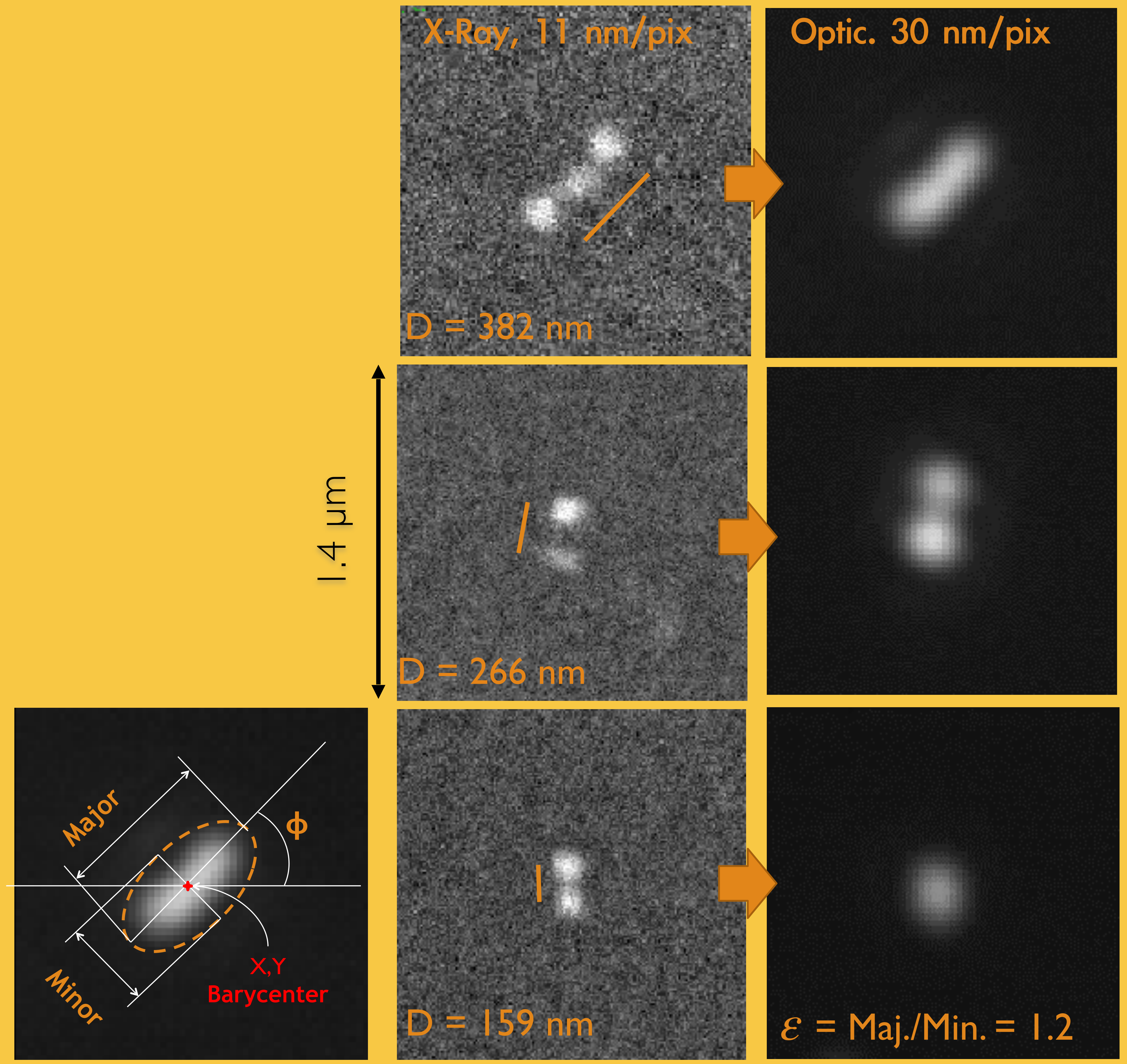




Dark Matter search with nuclear emulsions

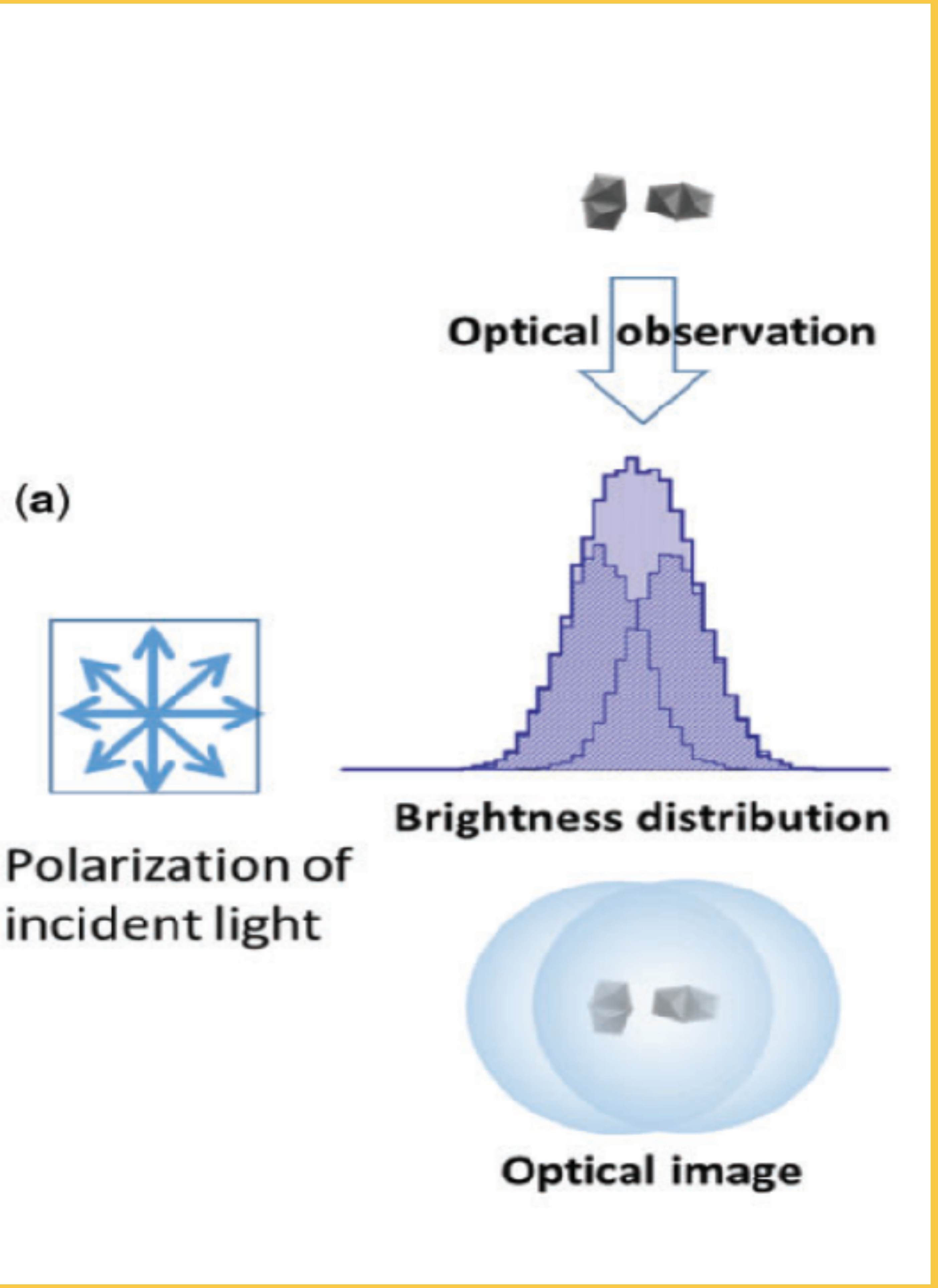
Track image analysis

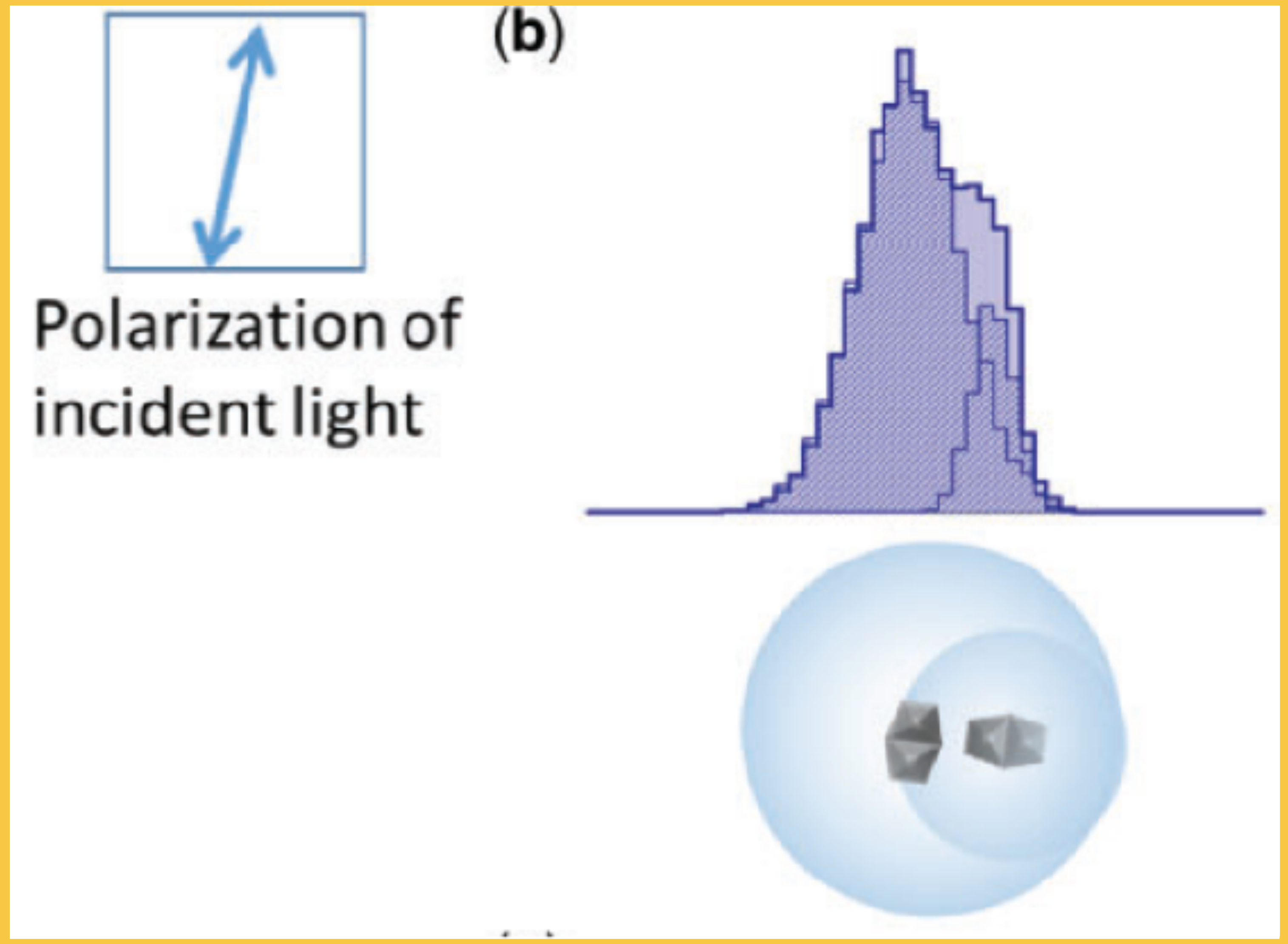
- Track is a sequence of close and aligned grains
- Resolve a track = distinguish it from a single grain
- Grains, closer than the mic. resolution = single spot
- Single grain (background) = round spot
- Important signal: $\sim 100nm$
- Plasmon resonance effect allows probing the internal structure of the cluster with polarized light
- Barycenter shift for different light polarizations can highlight tracks among background.

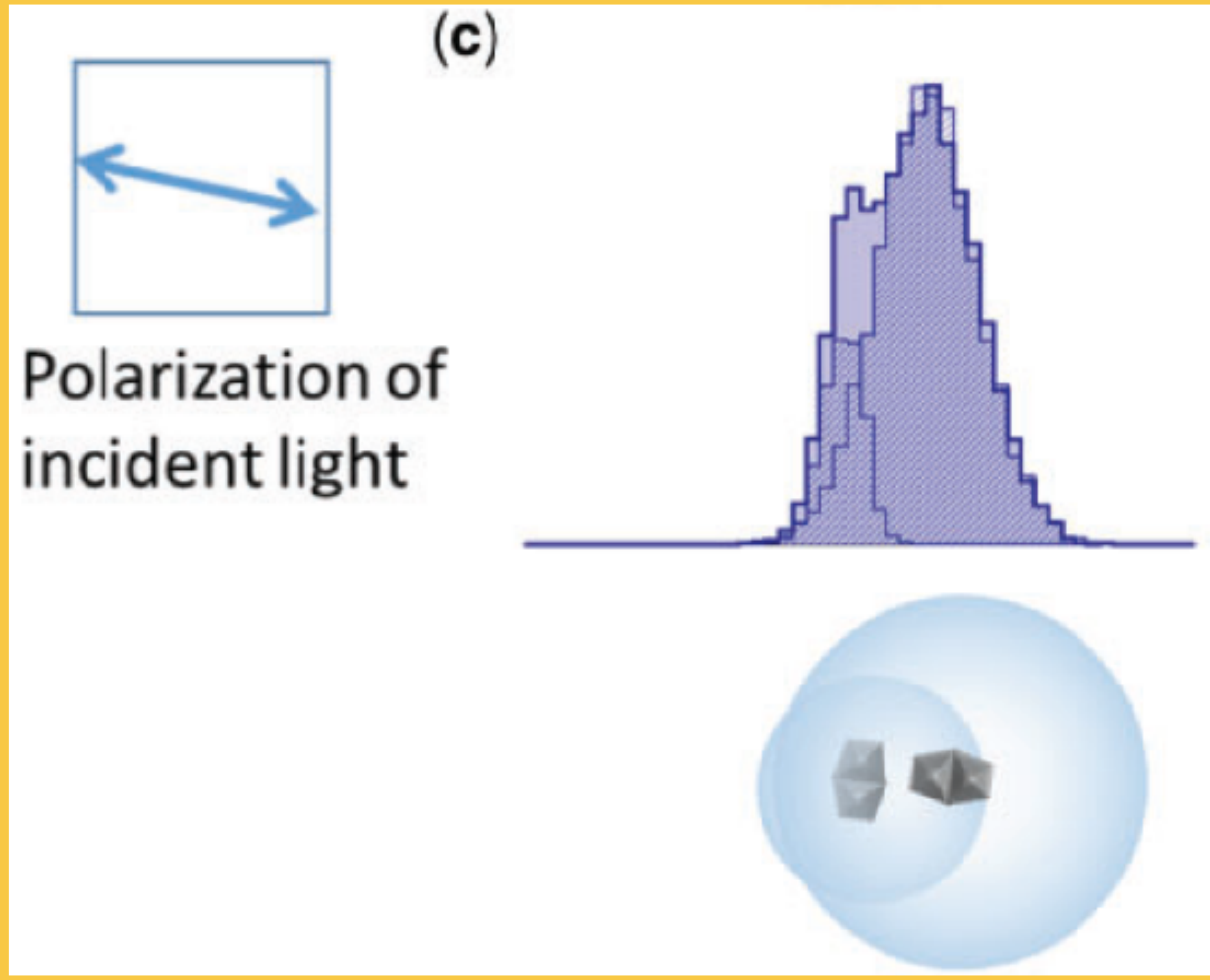


Dark Matter search with nuclear emulsions

Polarised light analysis







"Super-resolution plasmonic imaging microscopy for a submicron tracking emulsion detector", *PTEP*, 2019(6), 063H02

Presentation plan

- WIMP simulation with Carbon beam
  - Expected WIMP rate
  - Track length distributions for different WIMP masses
  - Carbon combinations to mimic expected WIMPs
- Optical images for nanometric tracks
  - Discrete dipole approximation
  - 3d models of simulated objects
  - Physical cross-checks of the simulated images
- Machine Learning analysis of the optical images
  - Pre-processing images
  - Producing optimal neural network
  - Comparing the results

Recoil rate

My derivation vs Lewin&Smith

- My derivation
- $$\frac{dR_n}{dE\ d\cos\theta} = \frac{\rho_o \sigma_p A^2}{2\mu_p^2 m_W N_{esc} \sqrt{\pi} v_0} \left(\exp\left[-\frac{(v_n - v_E \cos\theta)^2}{v_0^2} \right] - \exp\left[-\frac{v_{esc}^2}{v_0^2} \right] \right)$$
- $v_n = \sqrt{\frac{m_n E}{2\mu_n^2}}$; $\mu_i = \frac{m_i m_W}{m_i + m_W}$; $N_{esc} = \mathrm{erf}\left[\frac{v_{esc}}{v_0}\right] - \frac{2}{\sqrt{\pi}} \frac{v_{esc}}{v_0} \exp\left[-\frac{v_{esc}^2}{v_0^2} \right]$
- After integrating out $\cos\theta$:
- $$\frac{dR}{dE} = \frac{\rho_o \sigma_p A^2}{\sqrt{\pi} v_0 \mu_p^2 m_W N_{esc}} \left(\frac{\sqrt{\pi}}{4} \frac{v_0}{v_E} \left[\mathrm{erf}\left(\frac{v_n + v_E}{v_0} \right) - \mathrm{erf}\left(\frac{v_n - v_E}{v_0} \right) \right] - \exp\left[-\frac{v_{esc}^2}{v_0^2} \right] \right)$$
- Formulas are exactly the same.

- Lewin&Smith
- $$\frac{d^2 R(v_E, \infty)}{dE_R\, d(\cos\psi)} = \frac{1}{2} \frac{R_0}{E_0 r} e^{-(v_E \cos\psi - v_{min})^2 / v_0^2}. \qquad (3.16)$$
- $$\frac{dR(v_E, \infty)}{dE_R} = \frac{R_0}{E_0 r} \frac{\pi^{1/2}}{4} \frac{v_0}{v_E} \left[\mathrm{erf}\left(\frac{v_{min} + v_E}{v_0} \right) - \mathrm{erf}\left(\frac{v_{min} - v_E}{v_0} \right) \right]; \qquad (3.12)$$
  $$\frac{dR(v_E, v_{esc})}{dE_R} = \frac{k_0}{k_1} \left[\frac{dR(v_E, \infty)}{dE_R} - \frac{R_0}{E_0 r} e^{-v_{esc}^2 / v_0^2} \right]. \qquad (3.13)$$
- $$v_{min} = (2E_{min}/M_D)^{1/2} = (E_R/E_0 r)^{1/2} v_0.$$
- $R_0 = \frac{2}{\pi^{1/2}} \frac{N_0}{A} \frac{\rho_D}{M_D} \sigma_0 v_0$; $E_0 = \frac{1}{2} M_D v_0^2$; $r = 4 M_D M_T / (M_D + M_T)^2$

This A contains also m_p inside

$\sigma_0 = \sigma_p \frac{\mu_n^2}{\mu_p^2} A^2$

Recoil rate

Numerical cross-checks (Golwala, derived from Lewin&Smith)

- $R_0 = \frac{361}{M_w M_N}\left(\frac{\sigma_0}{10^{-36}\text{cm}^2}\right)\left(\frac{\rho_0}{0.3\text{GeV}c^{-2}\text{cm}^{-3}}\right)\left(\frac{v_0}{220\text{km s}^{-1}}\right)\text{kg}^{-1}\text{d}^{-1}$
- $E_0 r = \left(\frac{M_w}{100\text{GeV}c^{-2}}\right)\left(\frac{v_0}{220\text{km s}^{-1}}\right)^2 \frac{4M_w M_N}{(M_w + M_N)^2} \times 26.9keV$

target	R_0/(kg d)			$E_0 r$, keV		
	M_w, GeV			M_w, GeV		
	10	100	1000	10	100	1000
H (A=1)	3.88E-05	3.88E-06	3.88E-07	0.84	0.98	1.0
Si (A=28)	7.81E-02	5.45E-02	8.1E-03	2.16	17.65	26.66
Ge (A=73)	2.96E-01	5.44E-01	1.32E-01	1.2	25.92	64.15
I (A=127)	5.76E-01	1.7E+00	6.36E-01	0.77	26.71	101.78

	R_0 [kg^{-1} d^{-1}]			$E_0 r$ [keV]		
	M_δ [GeV c^{-2}] =			M_δ [GeV c^{-2}] =		
target	10	100	1000	10	100	1000
H ($A = 1$)	3.9×10^{-6}	3.9×10^{-5}	3.9×10^{-7}	0.8	1.0	1.0
Si ($A = 28$)	7.8×10^{-2}	5.5×10^{-2}	8.1×10^{-3}	2.2	17.6	26.6
Ge ($A = 73$)	3.0×10^{-1}	5.4×10^{-1}	1.3×10^{-1}	1.2	25.9	64.1
I ($A = 127$)	5.8×10^{-1}	1.7×10^{0}	6.4×10^{-1}	0.8	26.7	101.7

https://www.slac.stanford.edu/exp/cdms/ScienceResults/Theses/golwala.pdf

Recoil rate

Form-factor and simplified formula

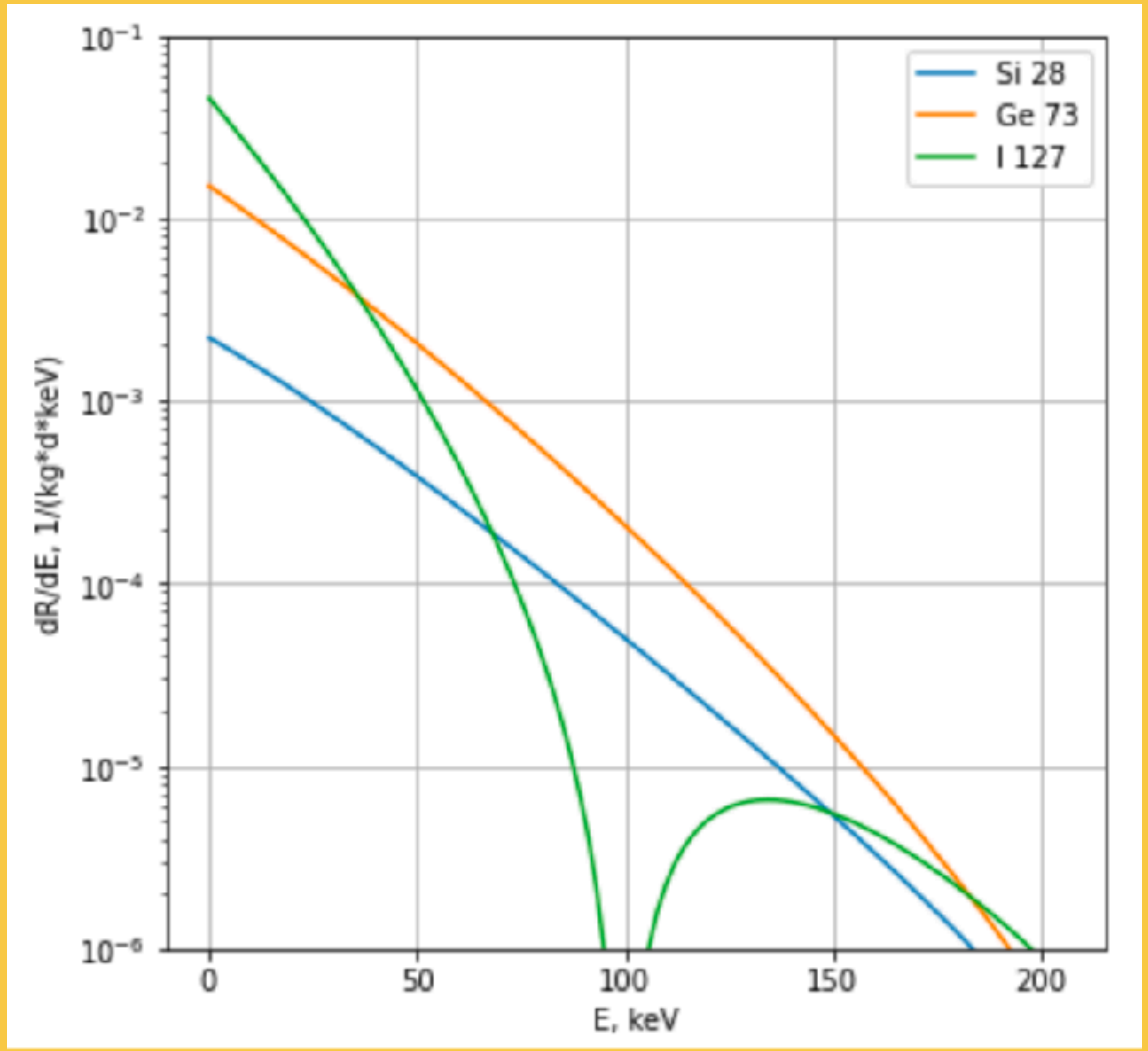
- $$\frac{d^2R}{dE\ d\cos\theta} = \frac{R_0}{2N_{esc}\ E_0 r}\left[\exp\left(\frac{(v_n - v_E\cos\theta)^2}{v_0^2}\right) - \exp\left(-\frac{v_{esc}^2}{v_0^2}\right)\right] \times F^2(qr_n)$$
- $v_n = v_0\sqrt{E/E_0 r}$
- $q = \sqrt{2M_N E};$

$$\begin{aligned} F(qr_n) &= 3\,\frac{j_1(qr_n)}{qr_n}\,e^{-(qs)^2/2} \\ &= 3\,\frac{\sin(qr_n) - qr_n\cos(qr_n)}{(qr_n)^3}\,e^{-(qs)^2/2} \end{aligned}$$

$$\begin{aligned} r_n^2 &= c^2 + \frac{7}{3}\pi^2 a^2 - 5s^2 \\ c &= 1.23A^{1/3} - 0.60\,\mathrm{fm} \\ a &= 0.52\,\mathrm{fm} \\ s &= 0.9\,\mathrm{fm} \end{aligned}$$

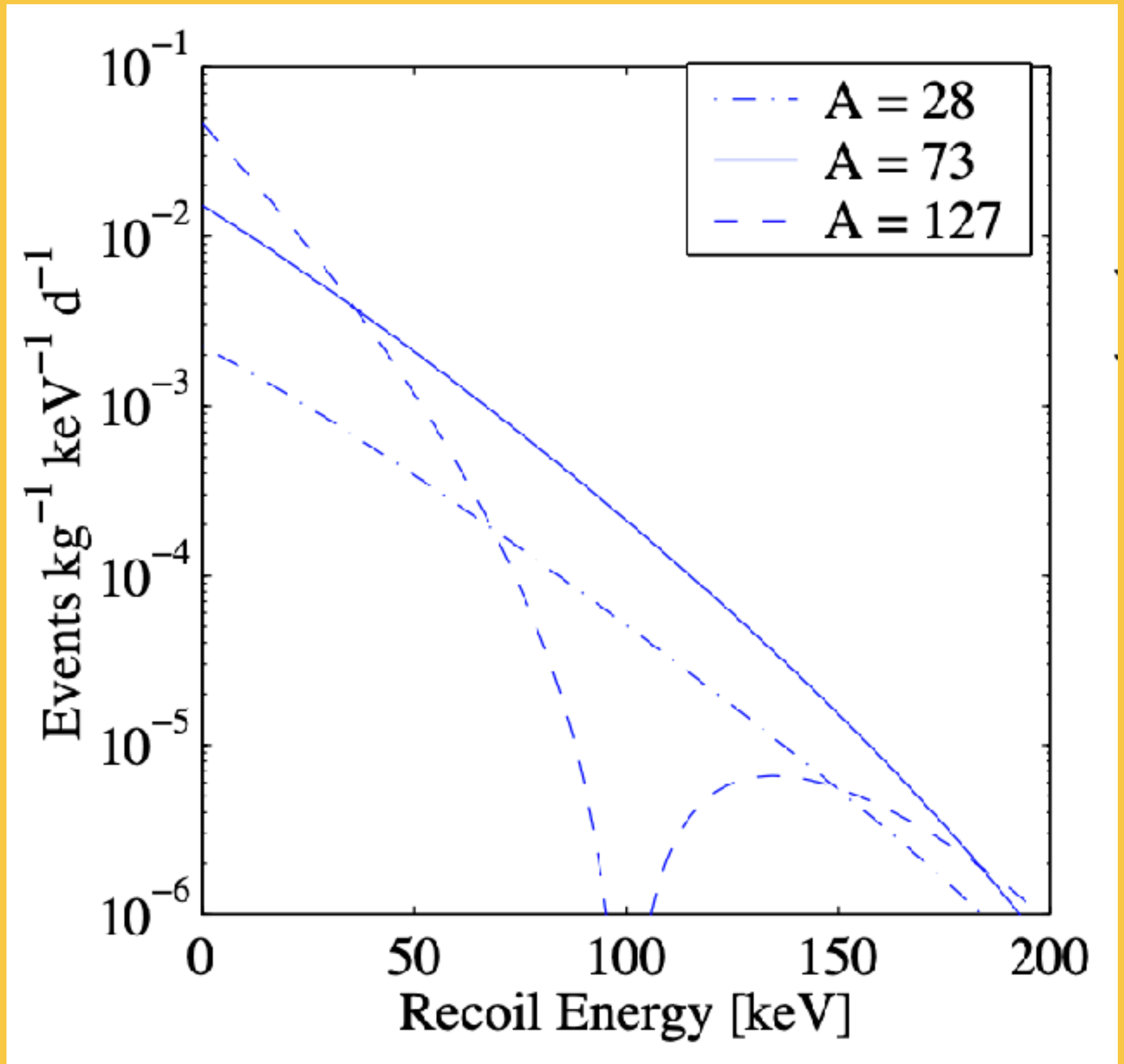
Recoil rate

Cross-check with Golwala



My simulation

$\sigma_p = 10^{-42} cm^2; v_{esc} = 650 km/s$

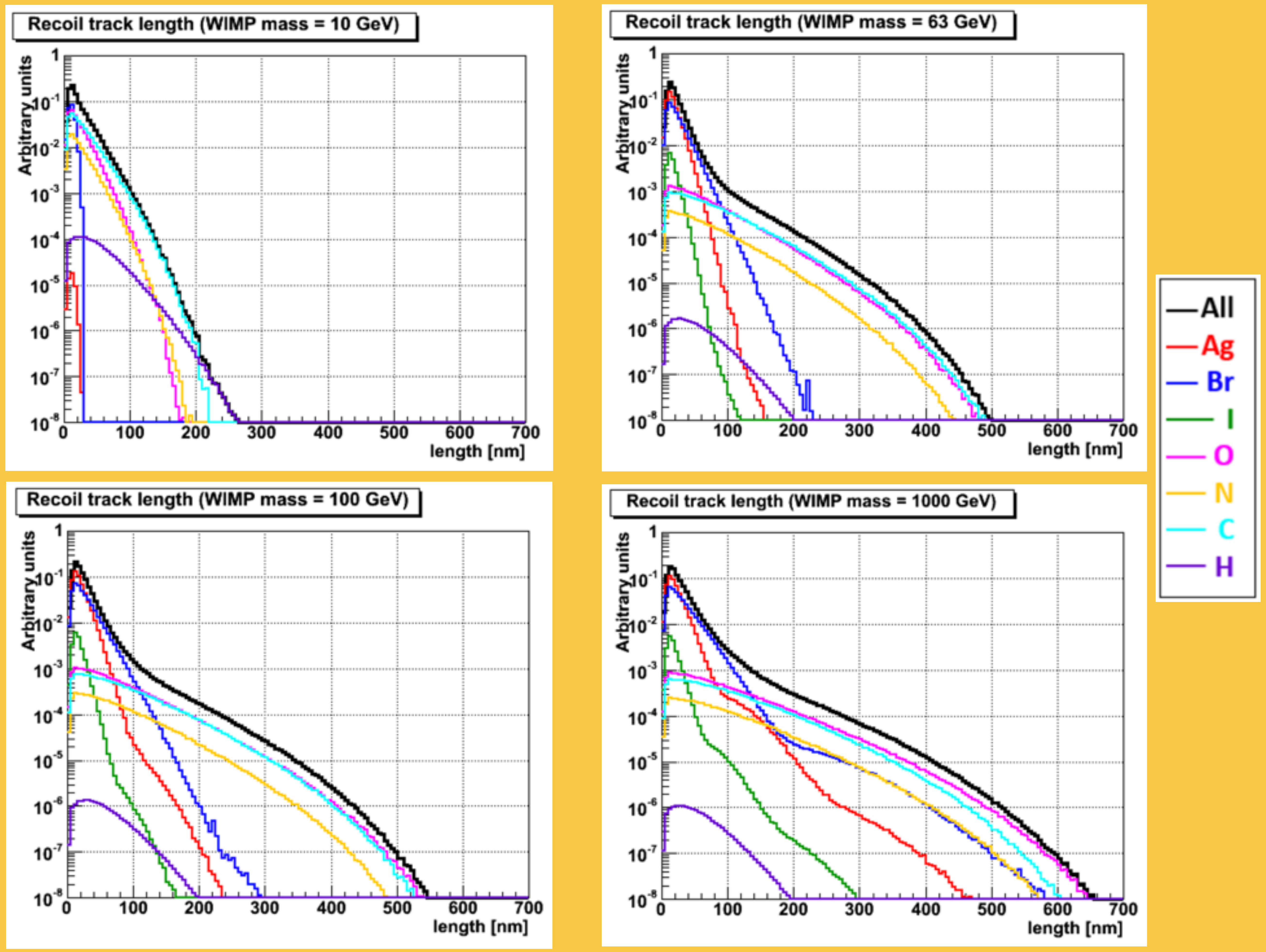


Golwala's thesis

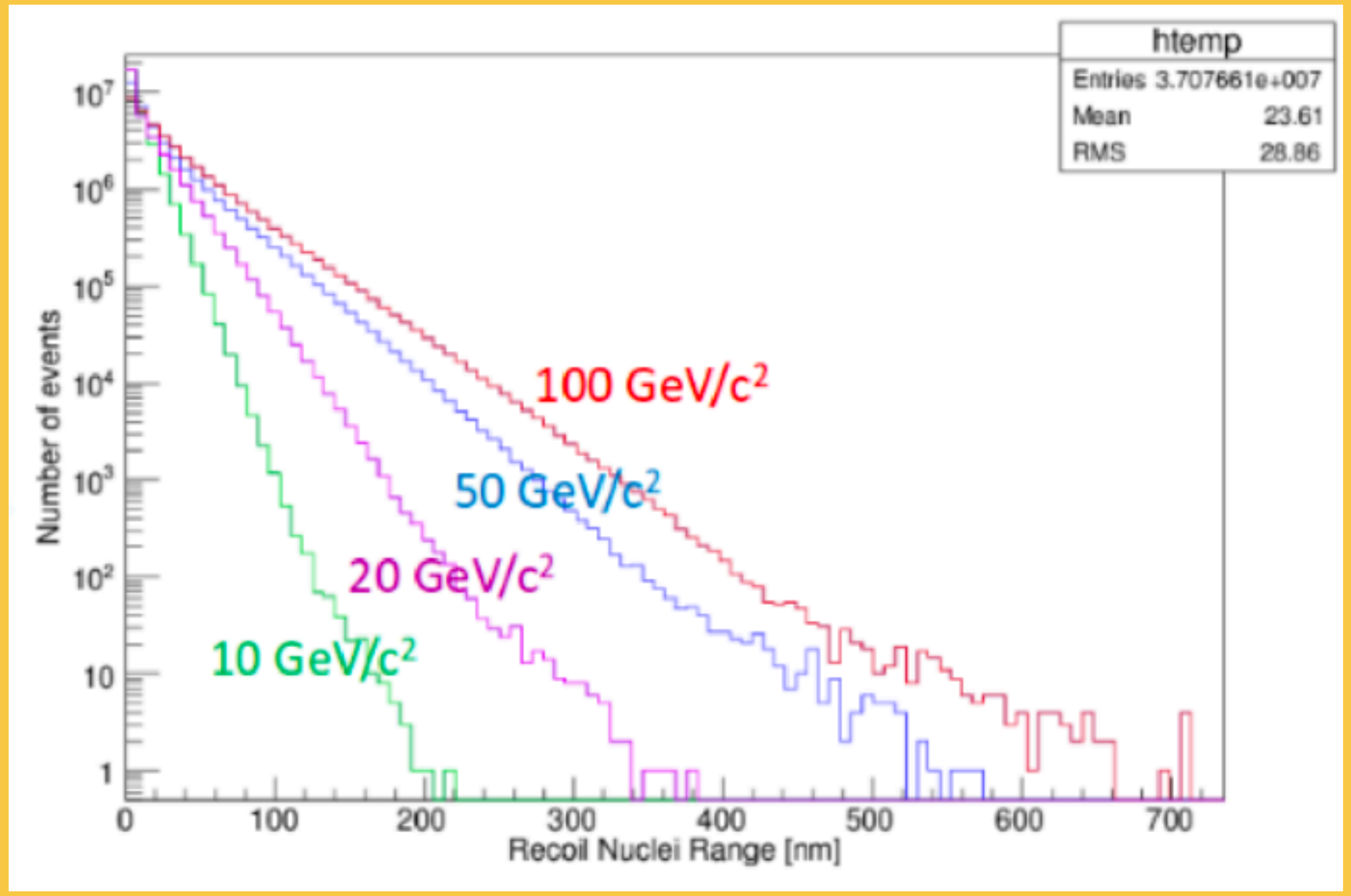
https://www.slac.stanford.edu/exp/cdms/ScienceResults/Theses/golwala.pdf

WIMP simulation with Carbon beams

Expected WIMP rate



Our simulation



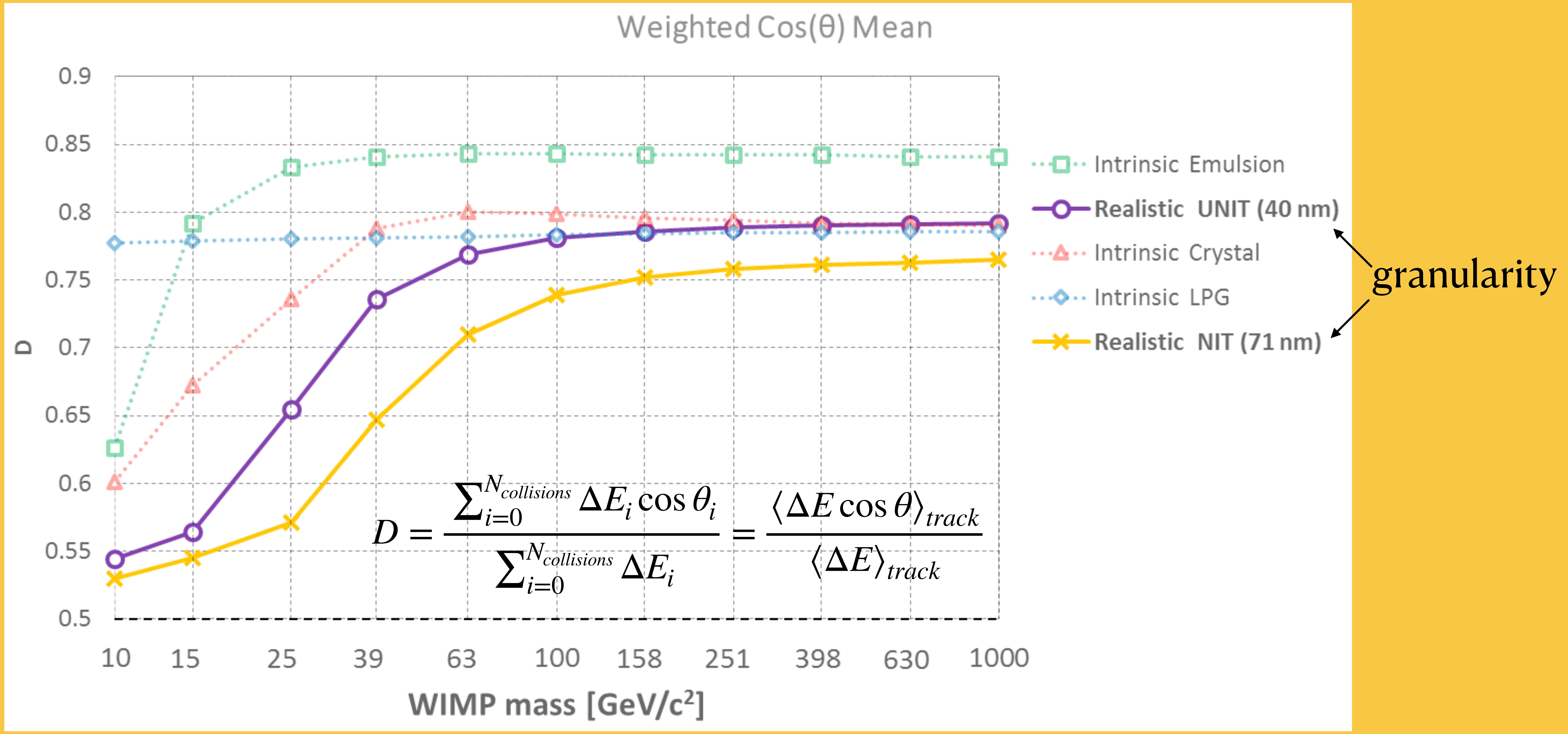
Nagoya's simulation

WIMP simulation in emulsion

WIMP simulation in emulsion

Directionality paper

https://arxiv.org/abs/2102.03125

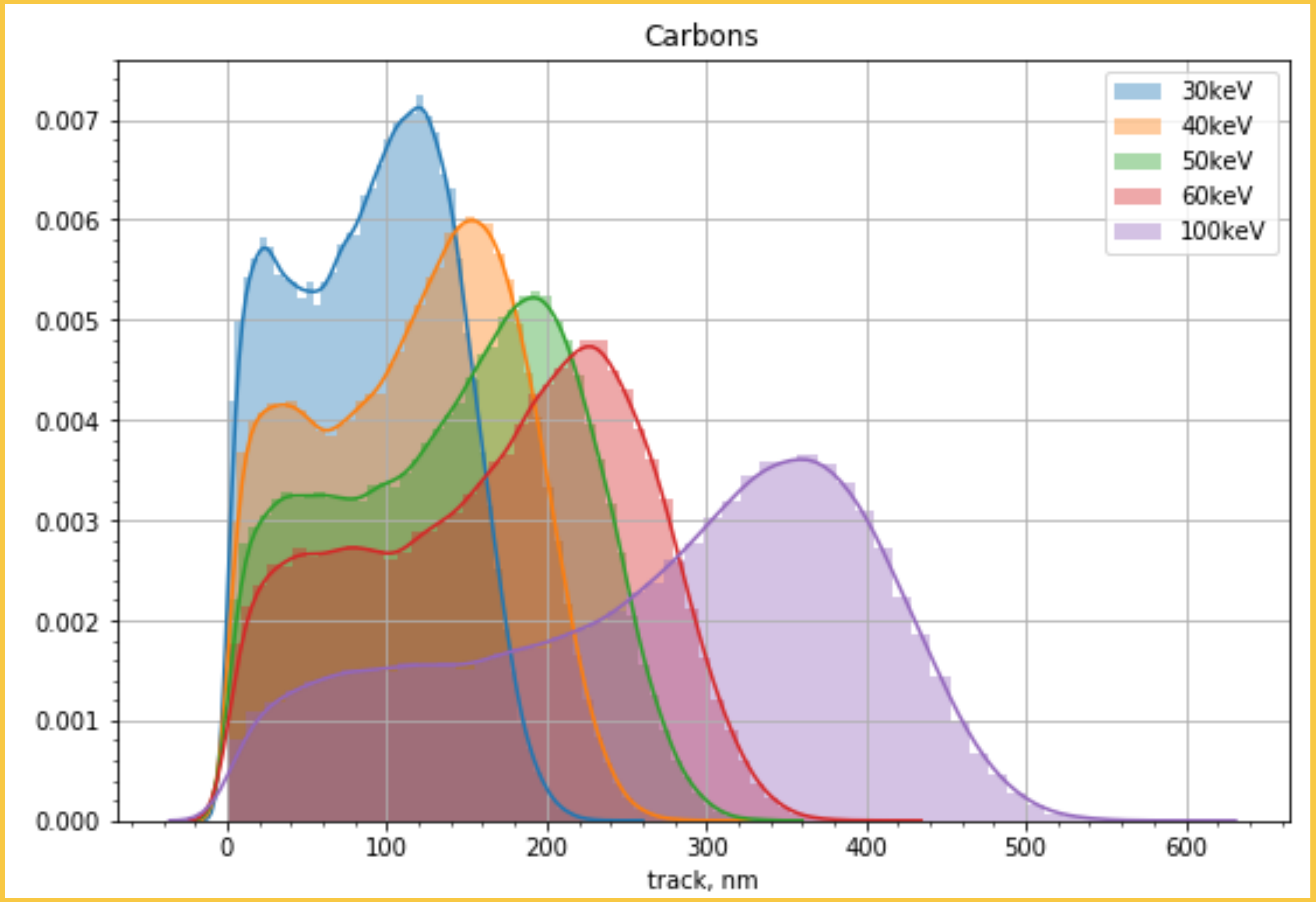


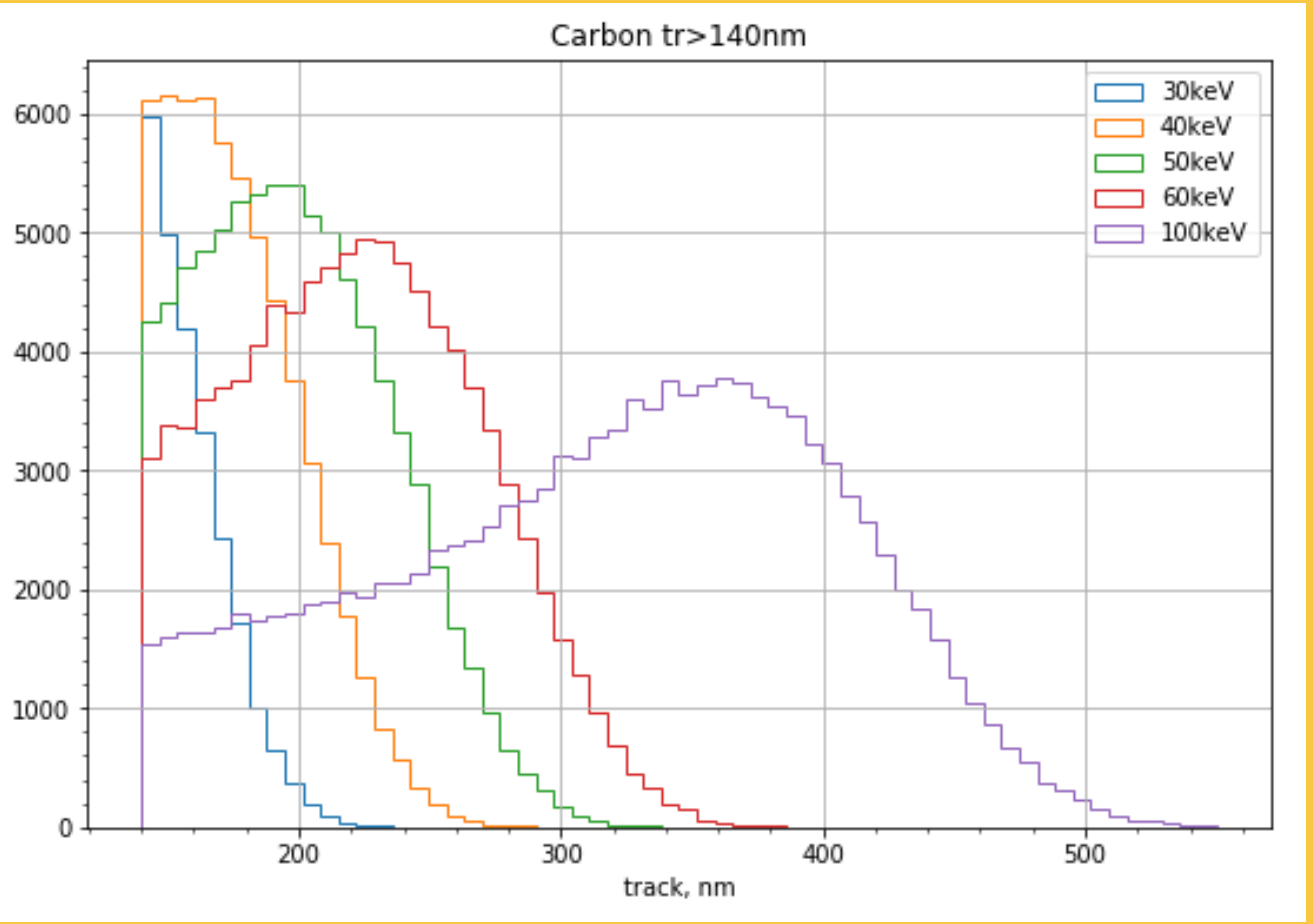
$$D = \frac{\sum_{i=0}^{N_{collisions}} \Delta E_i \cos\theta_i}{\sum_{i=0}^{N_{collisions}} \Delta E_i} = \frac{\langle \Delta E \cos\theta \rangle_{track}}{\langle \Delta E \rangle_{track}}$$

WIMP simulation with Carbon beams

Carbon tracks

Granularity effect for 70nm NIT



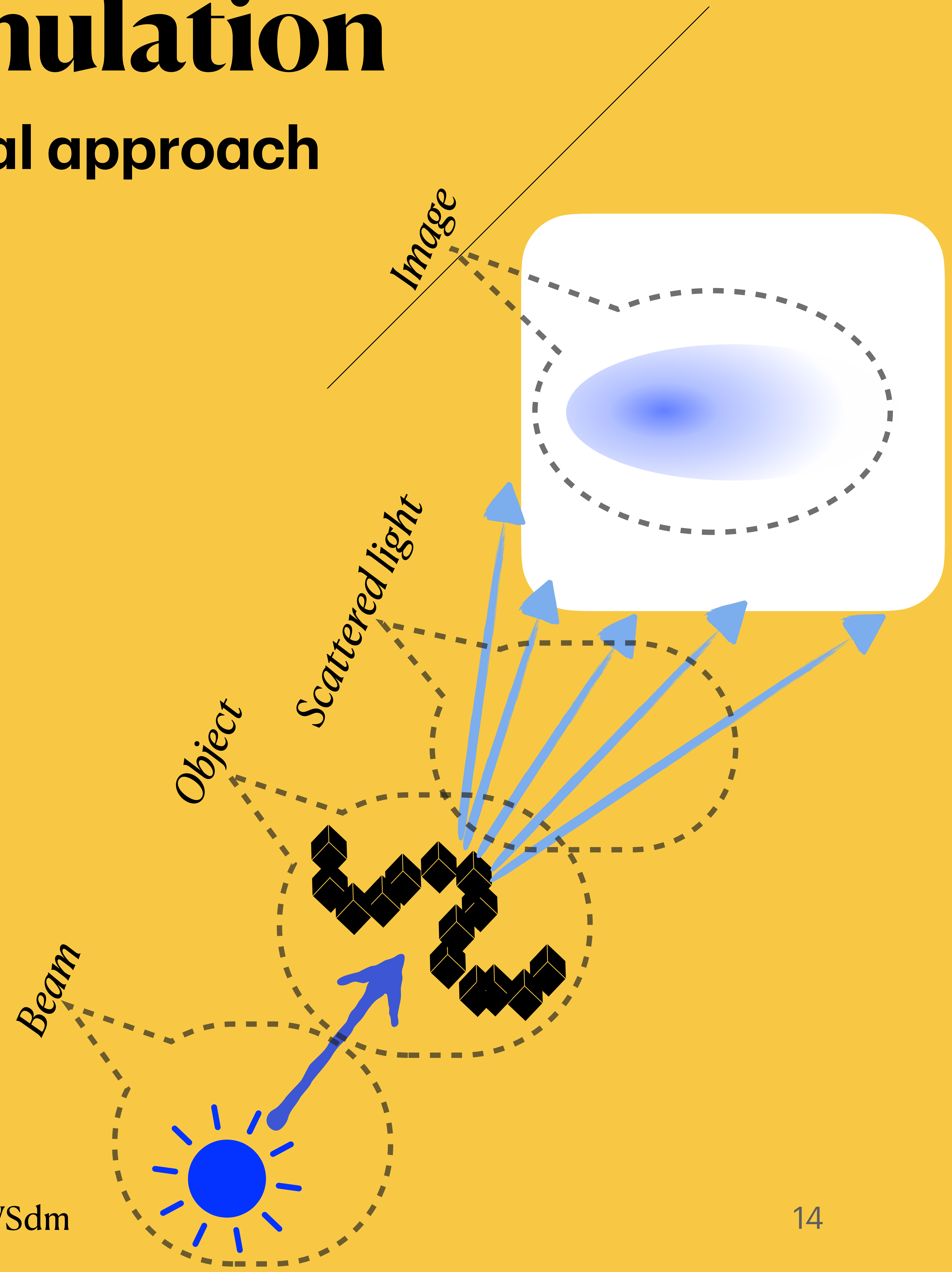


linear combinations of distributions to fit per-bin distribution corresponding to WIMP

Realistic image simulation

Discrete dipoles and numerical approach

- Why simulate?
  - Scanning large datasets is slow.
  - Optical microscope adds instrumental noise.
  - Large Dark Matter samples are not available :)
- How?
  - Generate a 3D model of the object to be simulated (filaments, nano-particles)
  - Use discrete dipole approximation to obtain optical images (ADDA, HoloPy)
  - Tune the parameters and check the simulation by comparison with real samples.



HoloPy

DDA for holography in Python

- *Open-source: https://github.com/manoharan-lab/holopy*
- *Has a user-friendly pythonic syntax*
- *Uses ADDA for scattering calculations: https://github.com/adda-team/adda*
- *Created for simulating Holograms in biophysics*
- *Can output raw fields*
- *Implements functions for propagation of the fields*
- *Supports superposition of scatterers*
- *Has a microscopic lens implementation*
- *Can pass a set of wavelength*

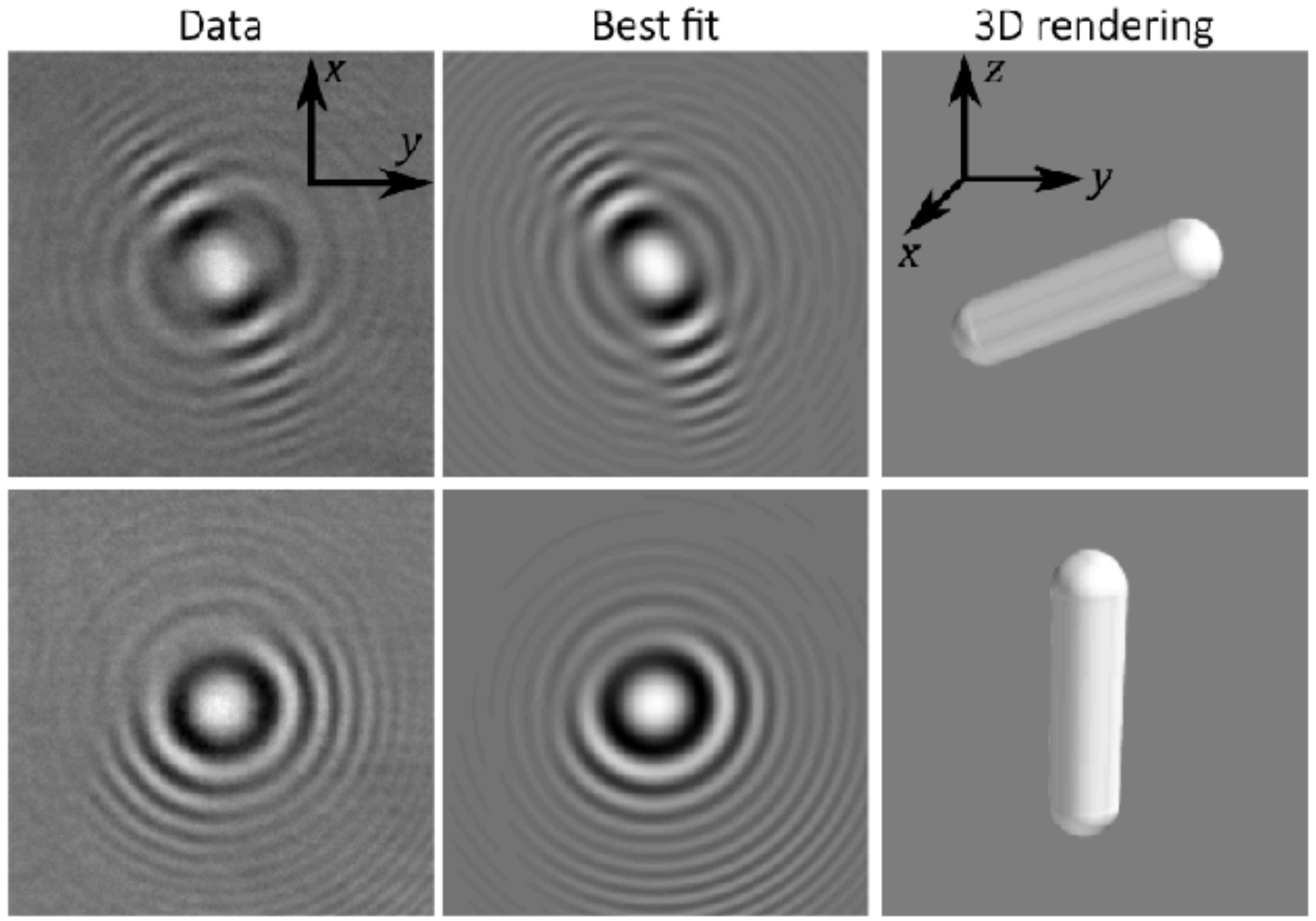


Fig. 2. We capture holograms of freely swimming *E. coli* in a time series. Two frames are shown in the left column, where the asymmetry in the fringes is noticeably different between the frames. The best-fit holograms are shown in the middle, and three-dimensional renderings from the best-fit holograms are shown on the right.

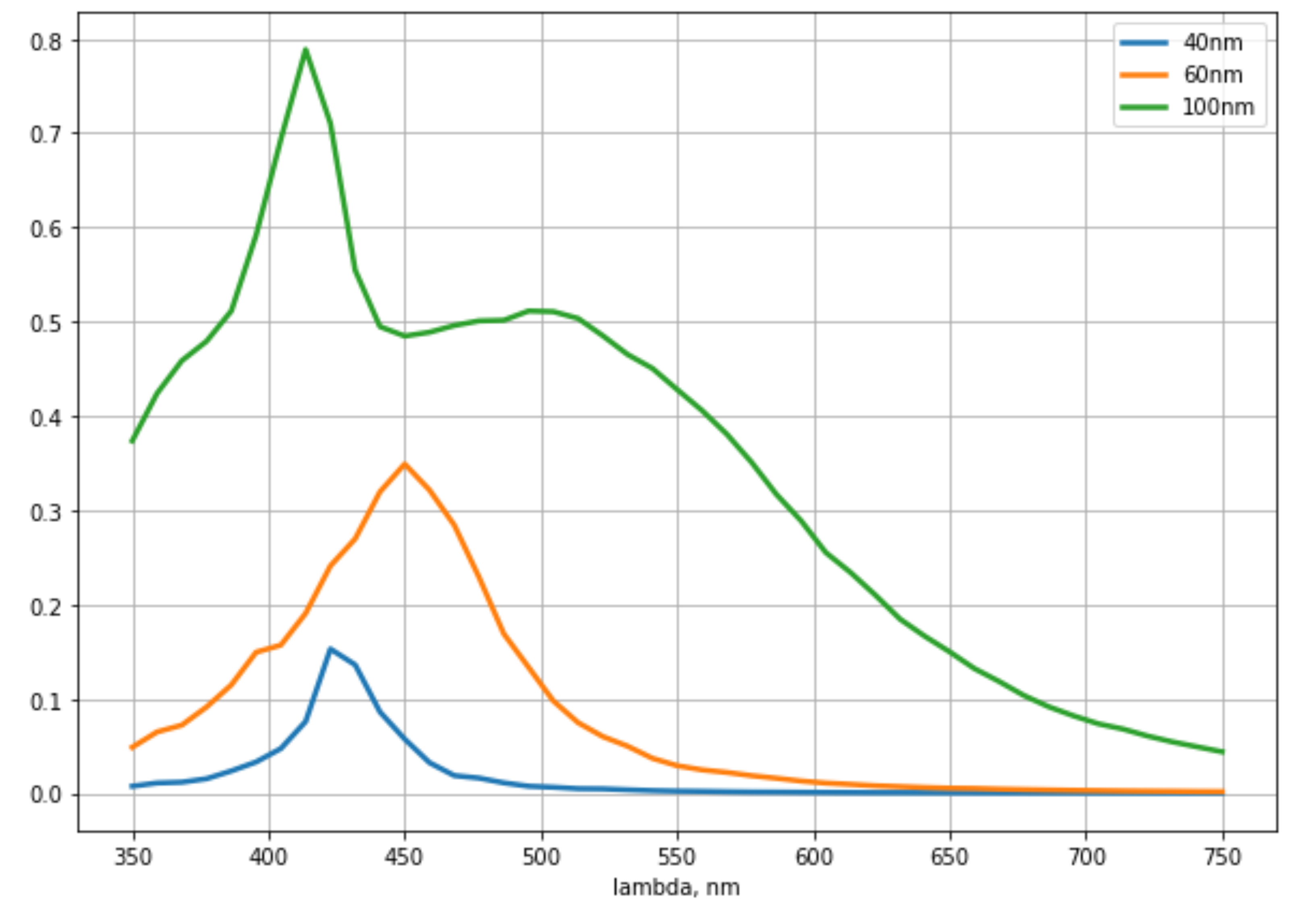
DOI: 10.1364/OE.24.023719

Plasmon effect for spheres

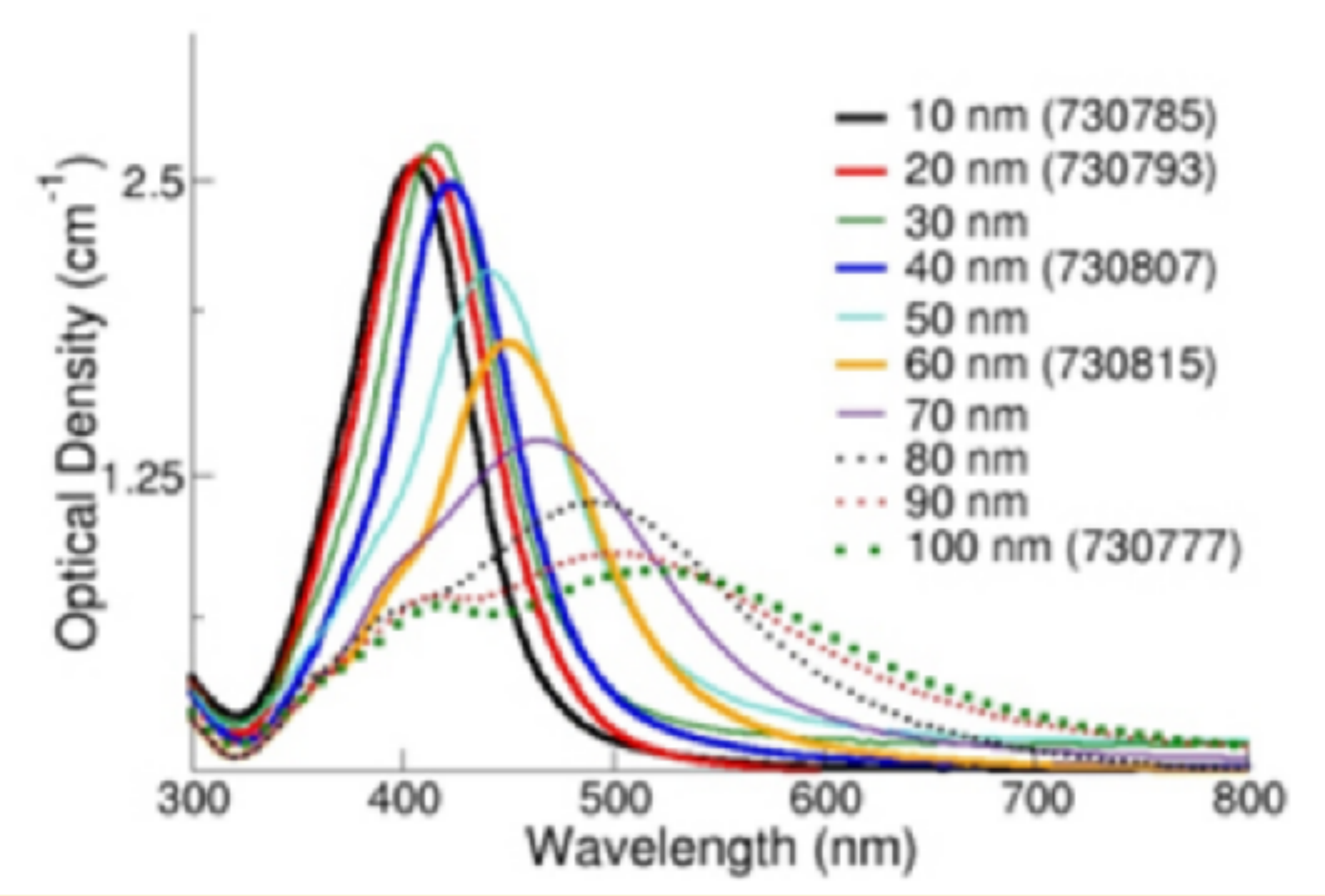
Silver vs dielectric

Silver

Peak brightness

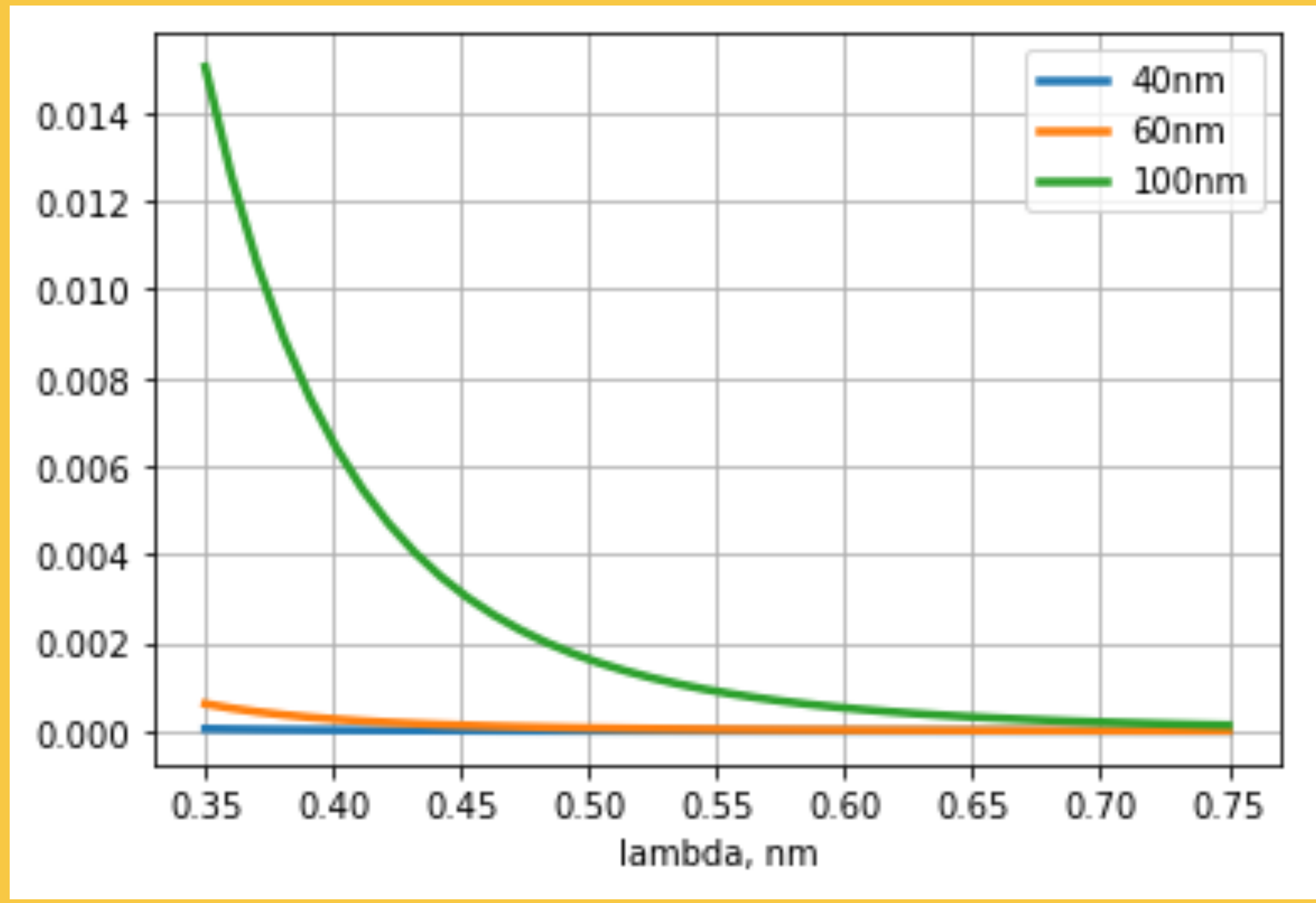


Extinction cross-section

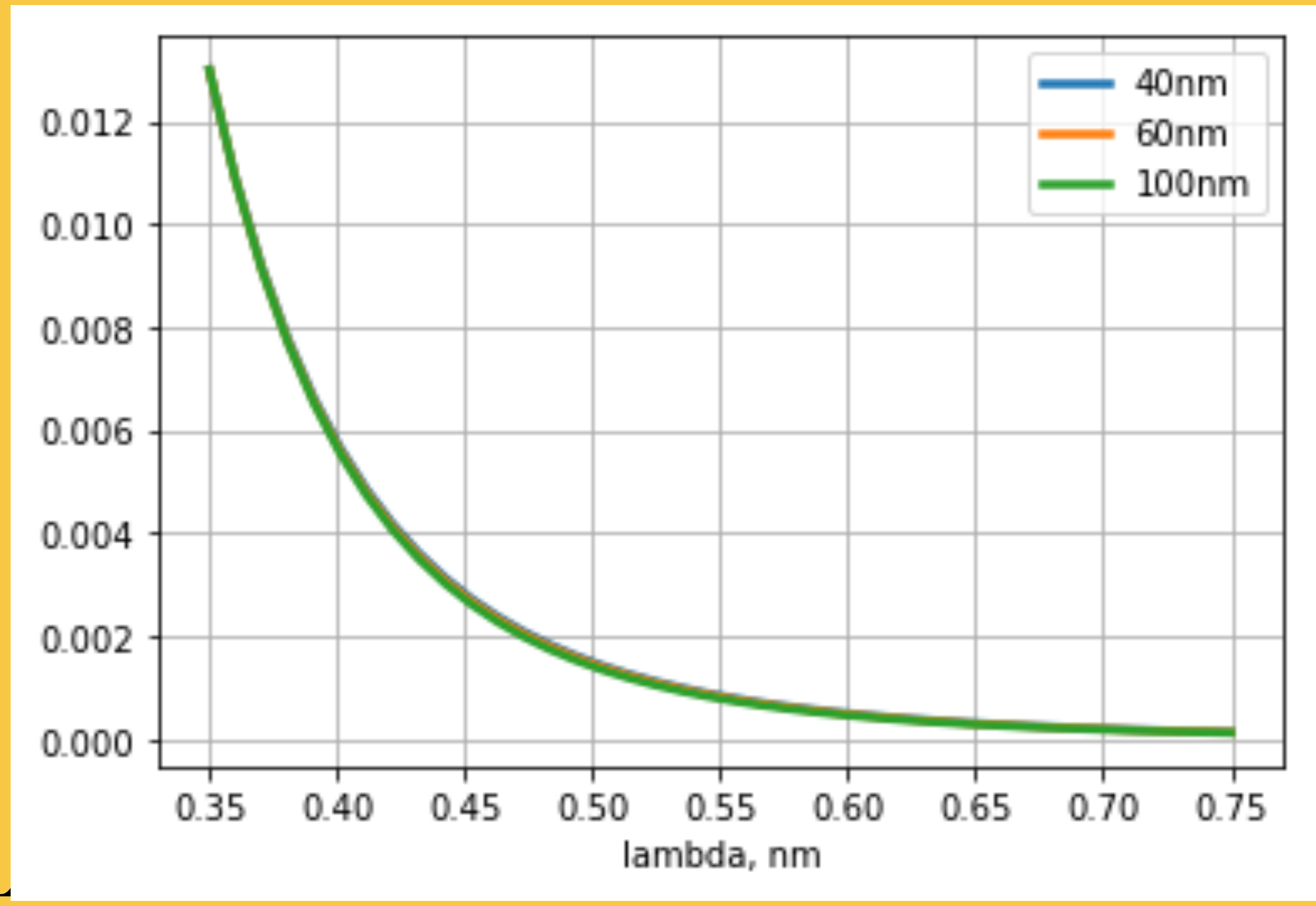


Dielectric

Original

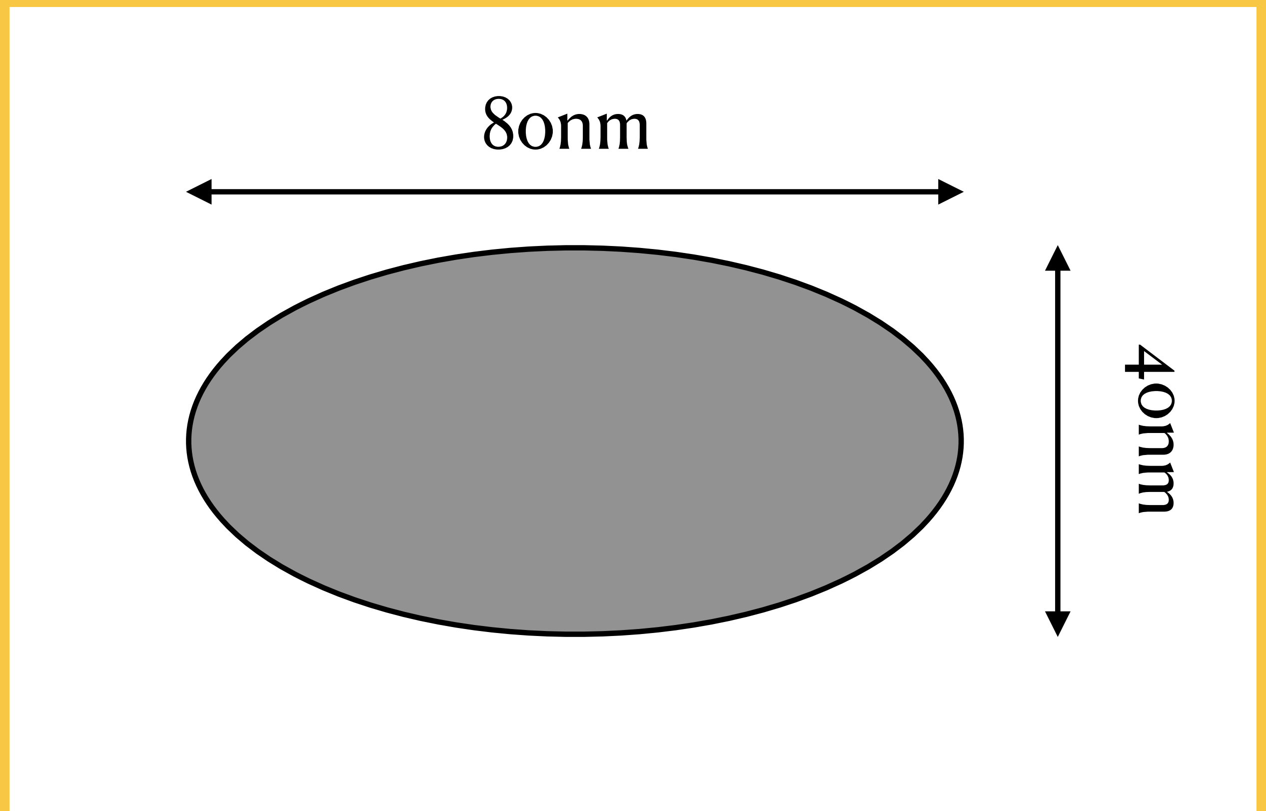


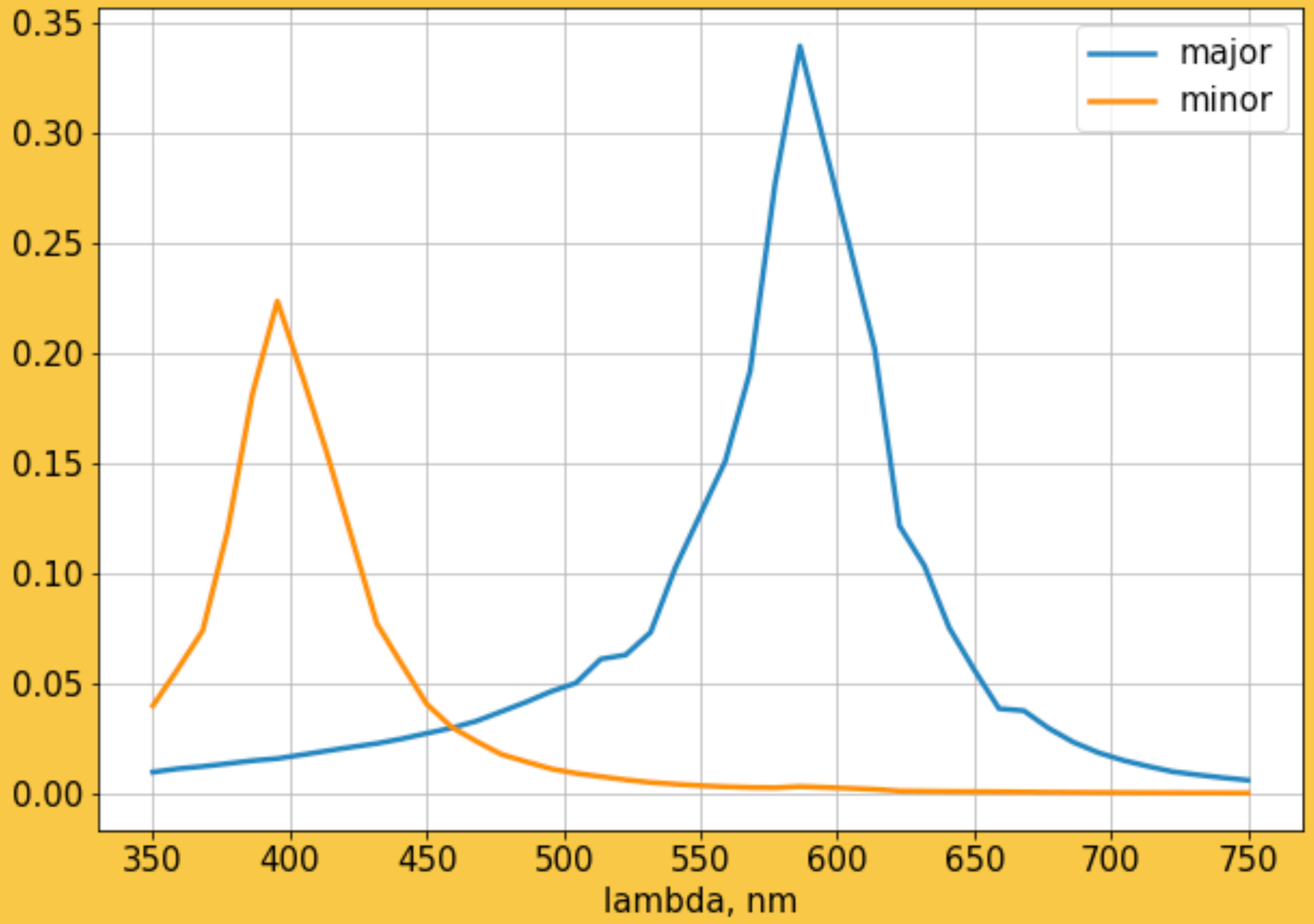
Scaled



Plasmon effect for ellipsoid

Polarisation along major vs minor axis



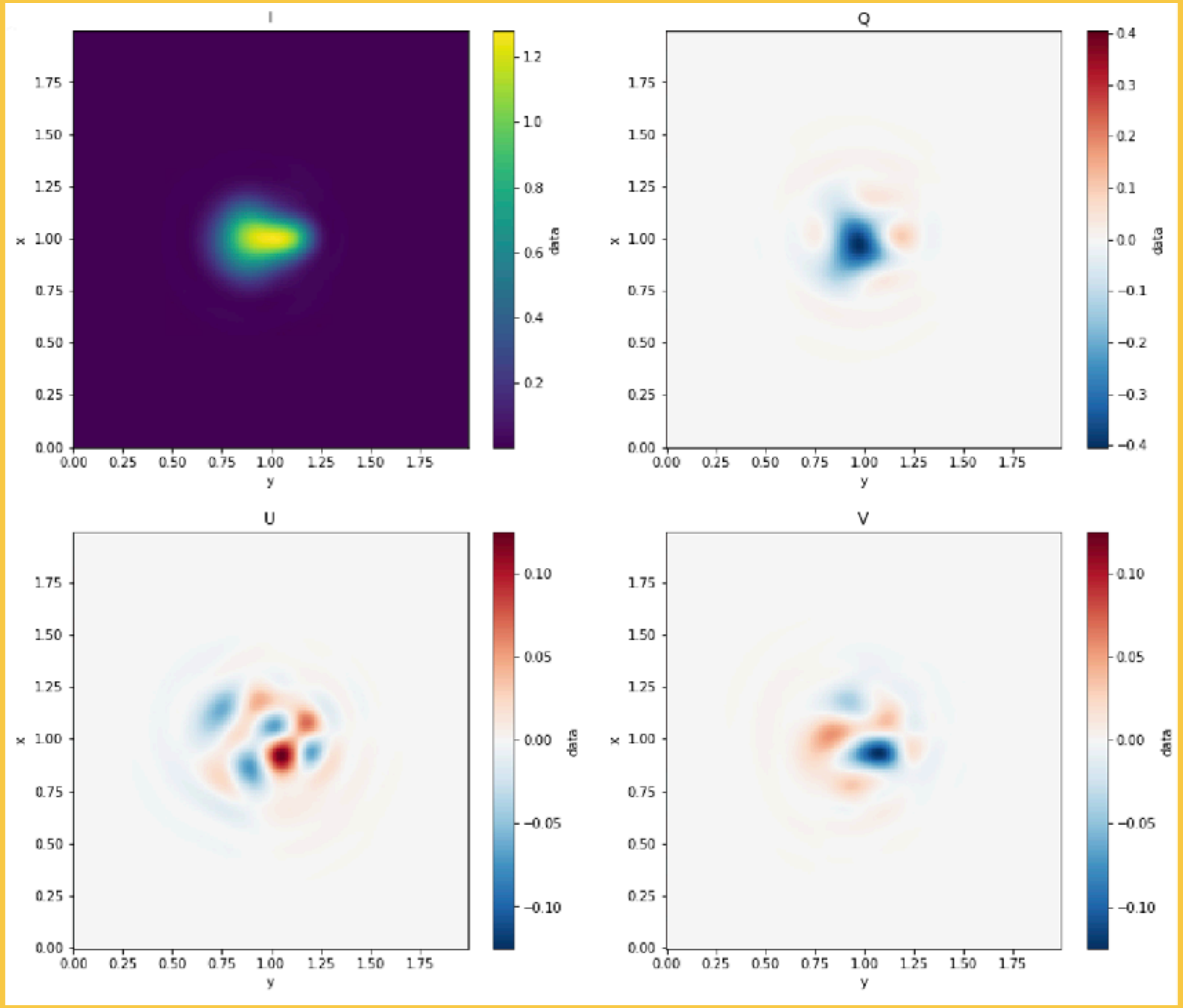


Unpolarised incident light

Combination of X and Y polarisations

- Unpolarised light is a de-coherent combination of $||$ & $\perp$ light.
- $|E|^2_{un} = \frac{1}{2}(|E|^2_{||} + |E|^2_{\perp})$
- Averaging the Stokes vectors will have the similar result.

Unpolarised incident light would have all but first components equal zero. However, scattered light is not truly unpolarised anymore.

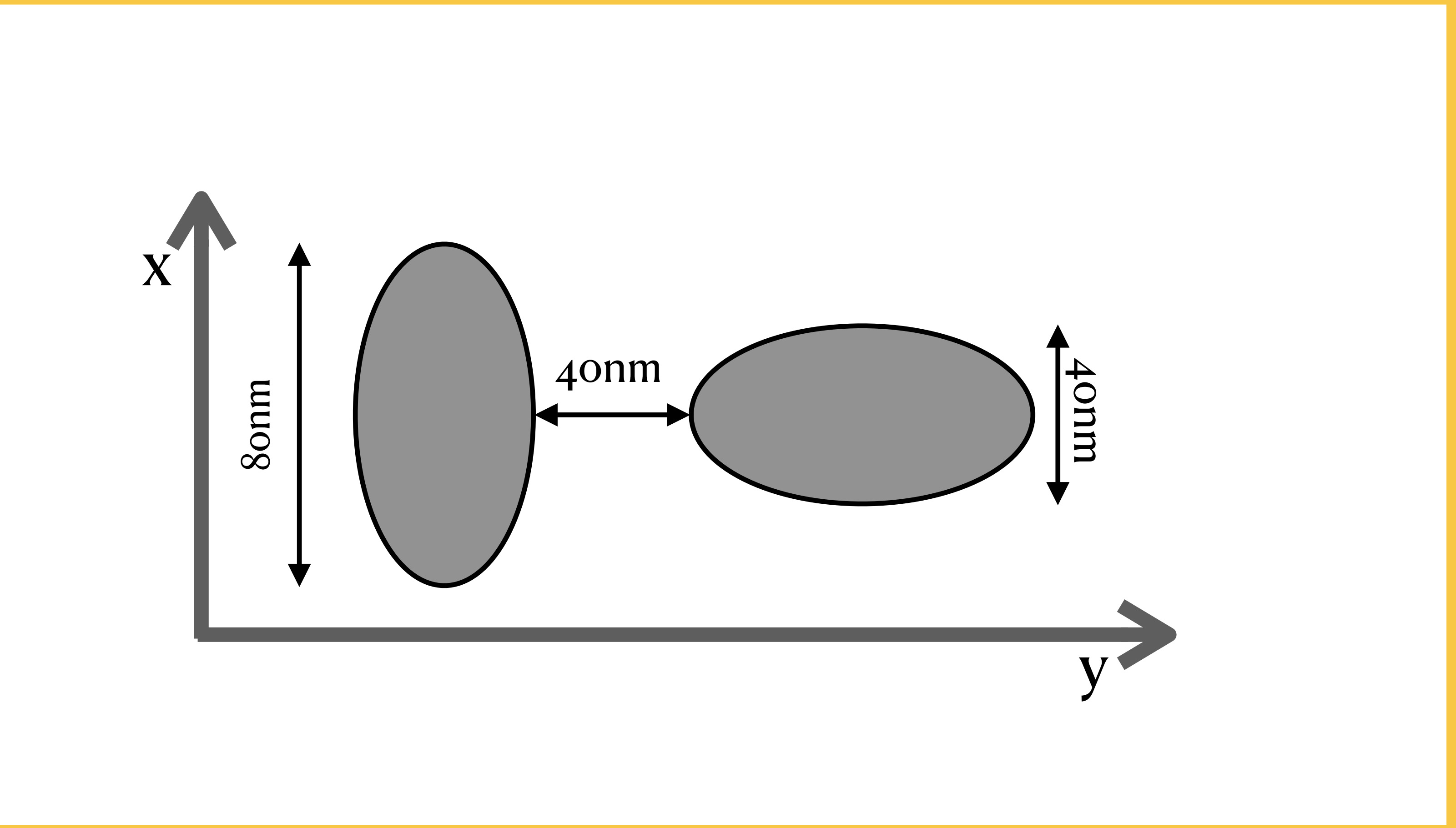


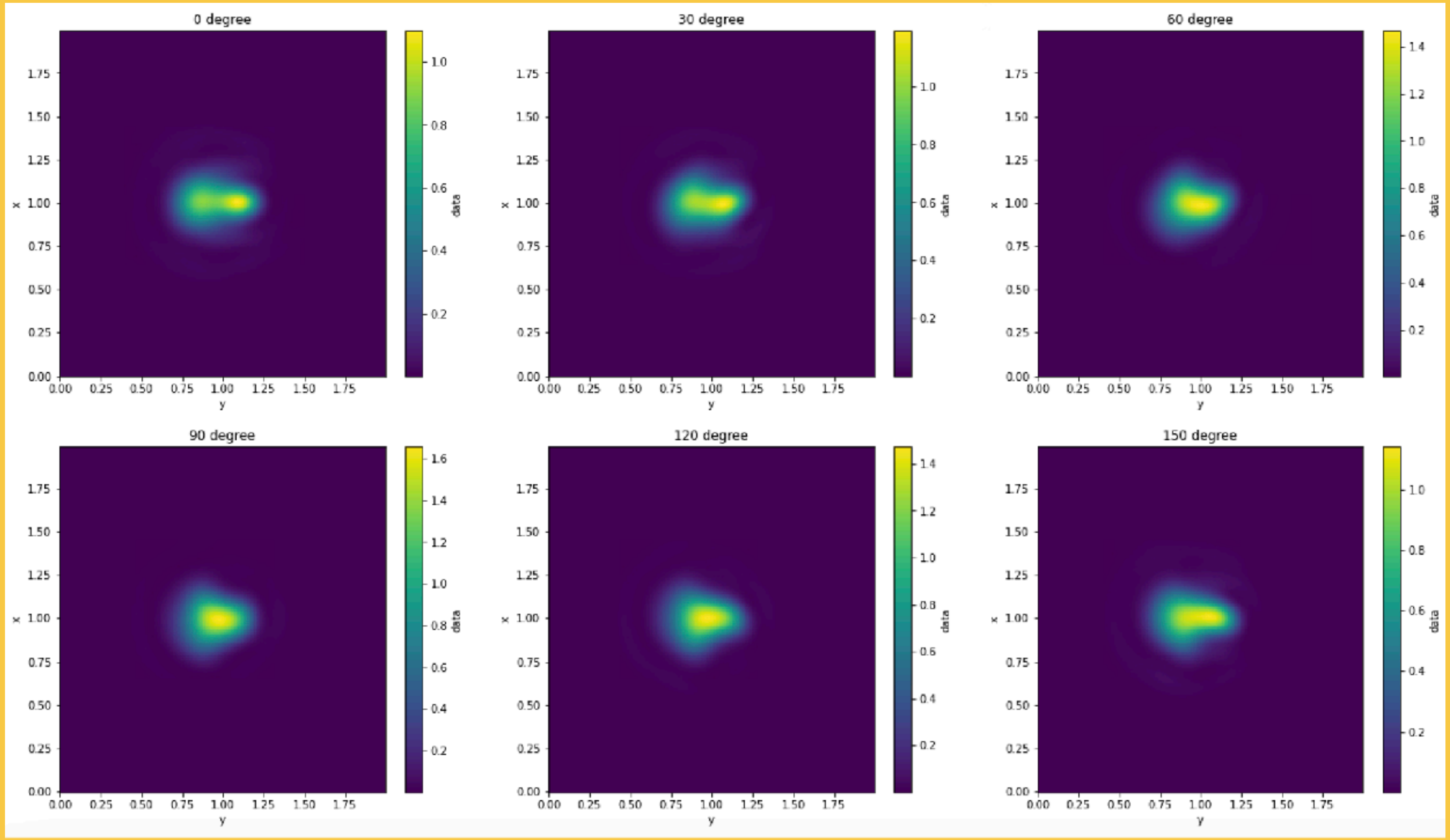
- Stokes vector
  - $I = E_{||}E^*_{||} + E_{\perp}E^*_{\perp}$
  - $Q = E_{||}E^*_{||} - E_{\perp}E^*_{\perp}$
  - $U = E_{||}E^*_{\perp} + E_{\perp}E^*_{||}$
  - $V = i\left(E_{||}E^*_{\perp} - E_{\perp}E^*_{||}\right)$
- To get intensity of linearly polarised light:
  - $I_\xi = \frac{1}{2}\left(I + Q\cos 2\xi + U\sin 2\xi\right)$

Polarised scattered light

Unpolarised incident light

Two silver ellipsoids





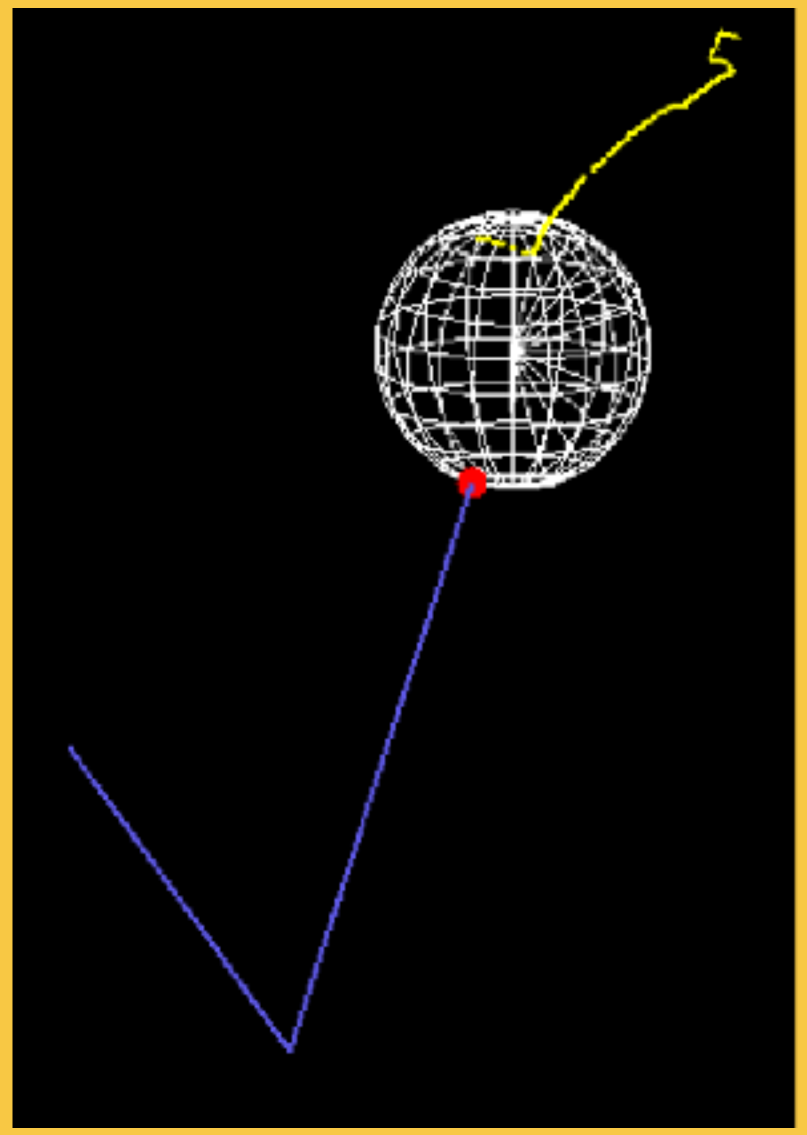
Two simulations for unpolarised light — any number of output polarisations

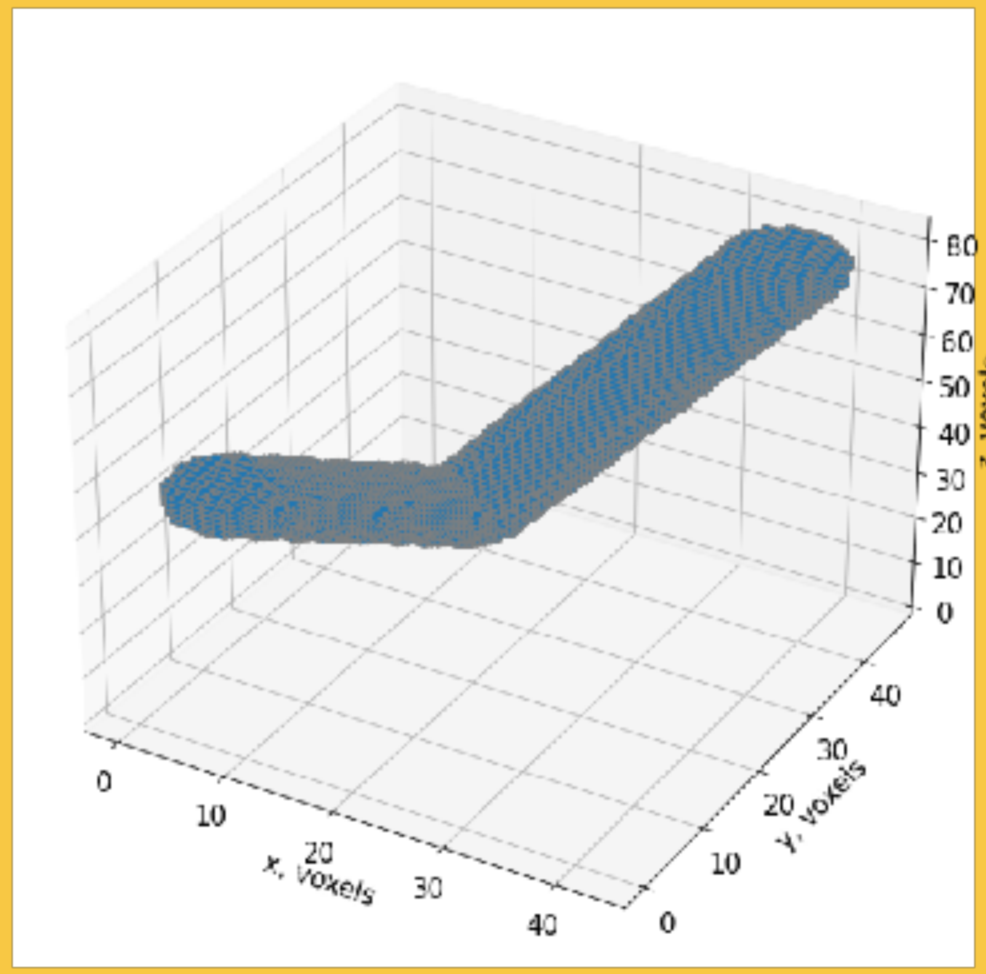
$$I_\xi = \frac{1}{2}\left(I + Q\cos 2\xi + U\sin 2\xi\right)$$

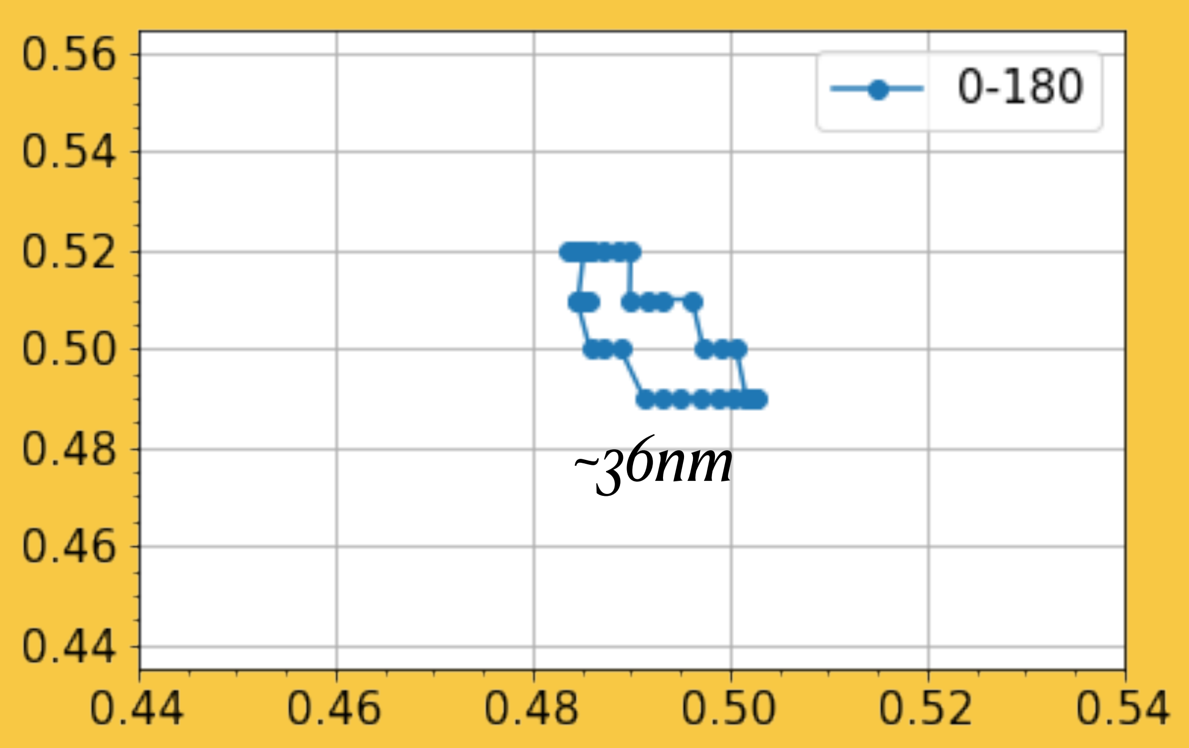
Simulating the filament

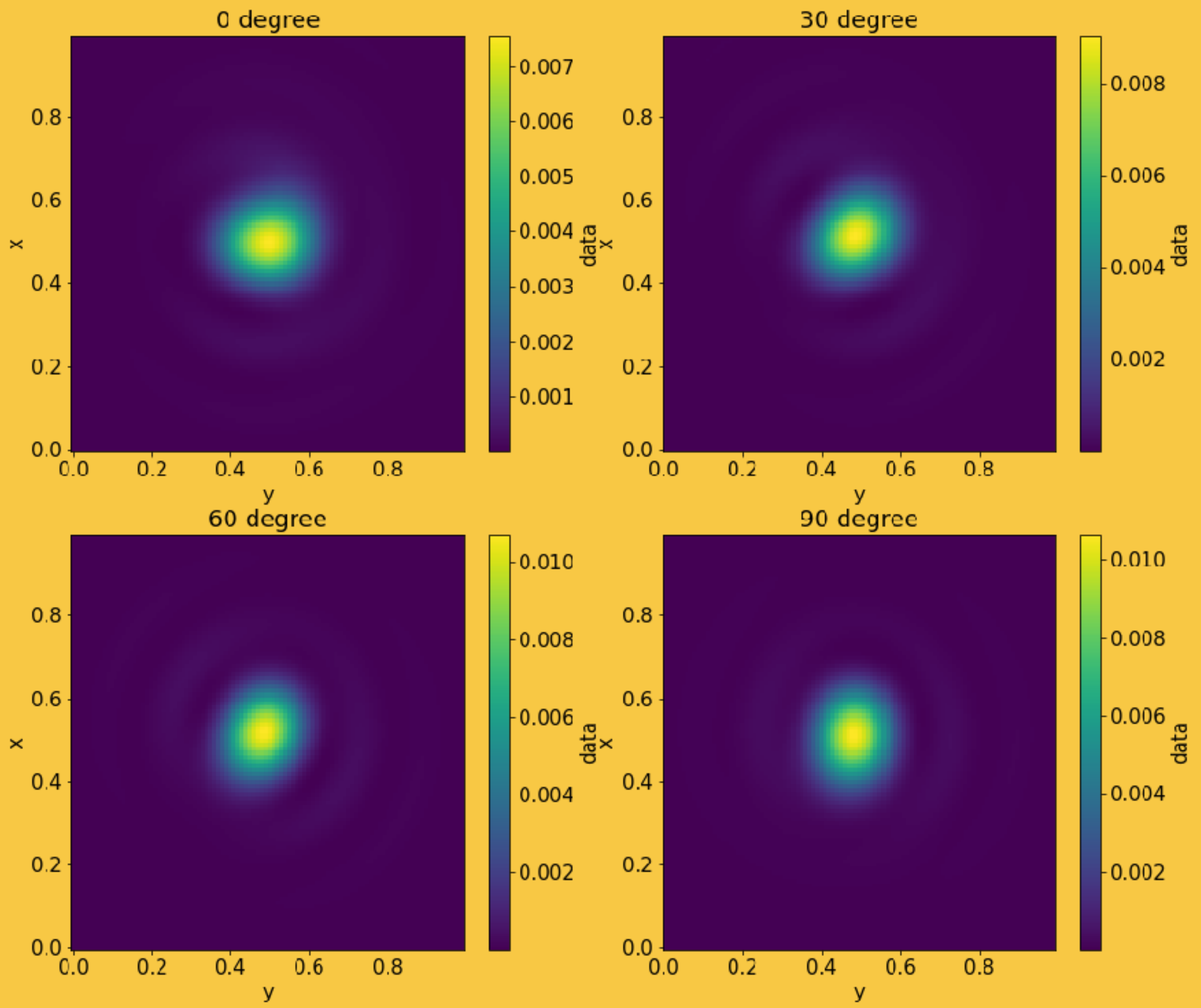
Polarisation rotation

Event view #17





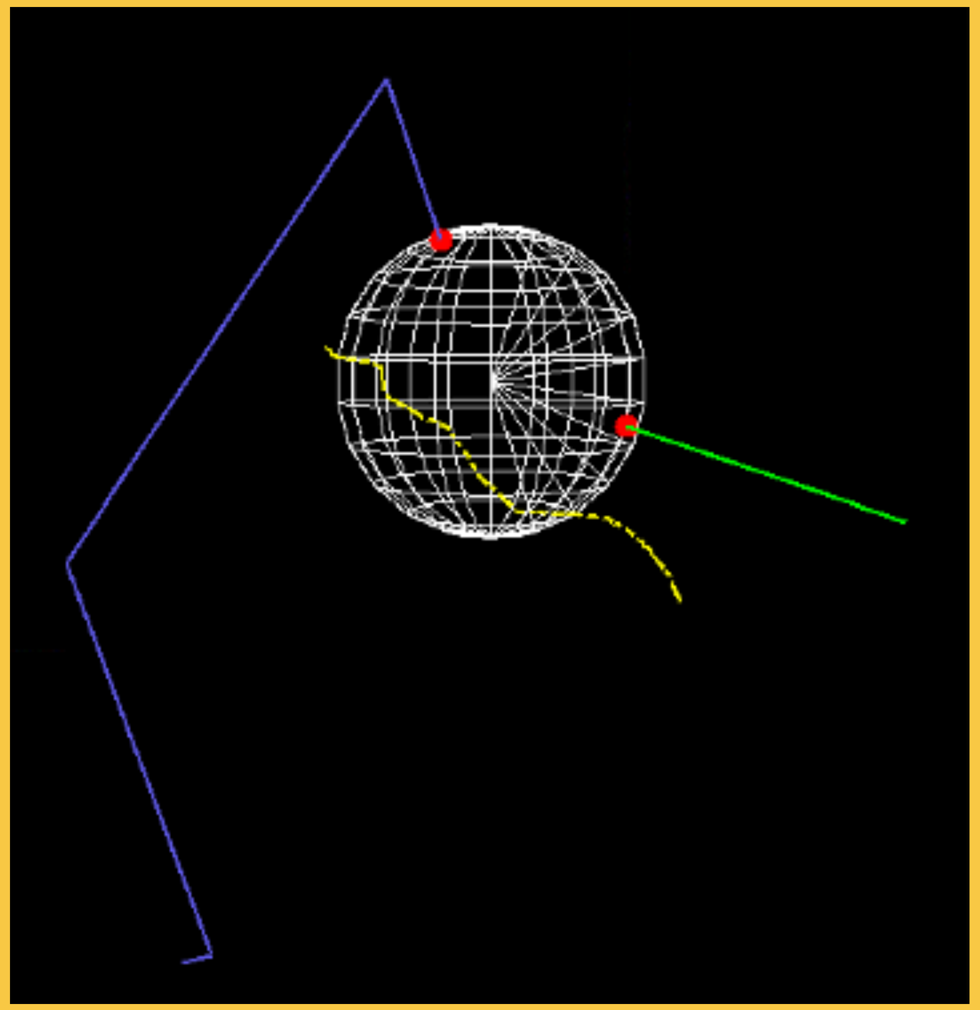


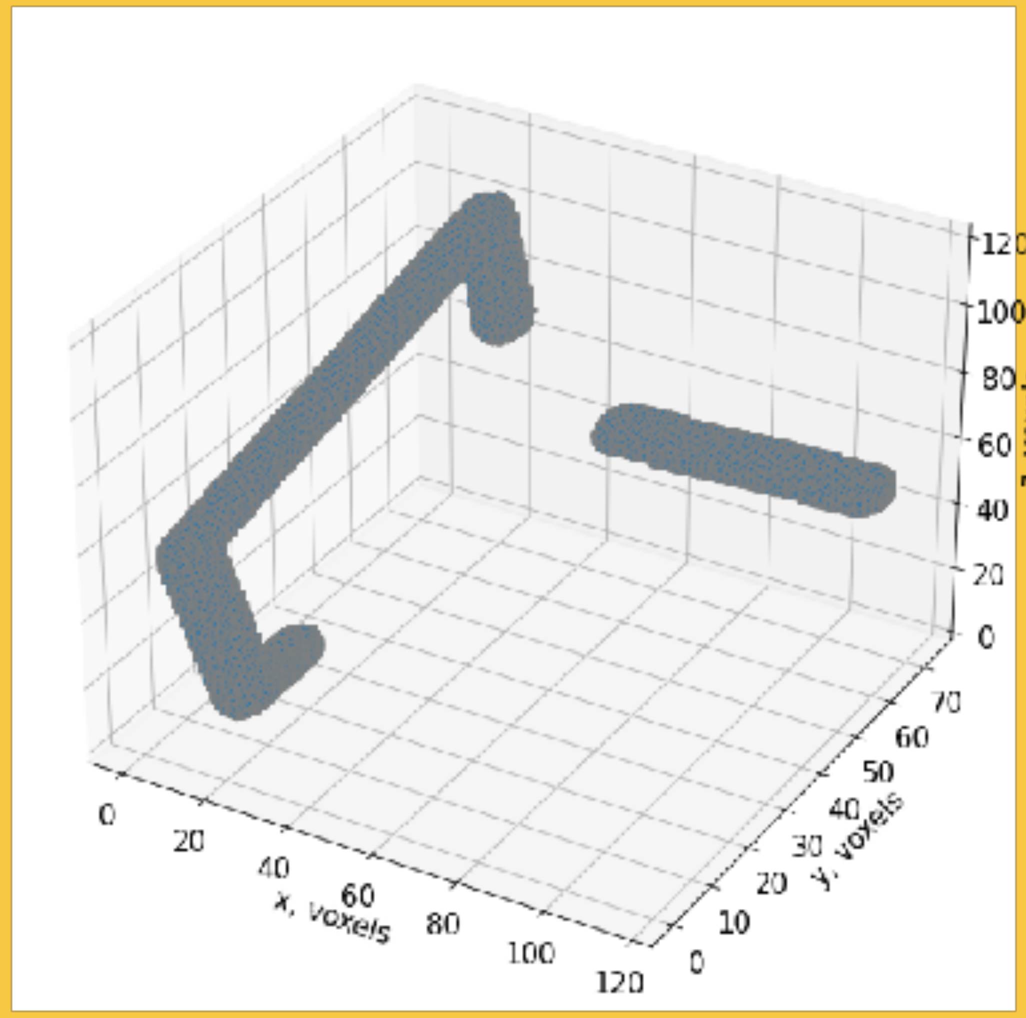


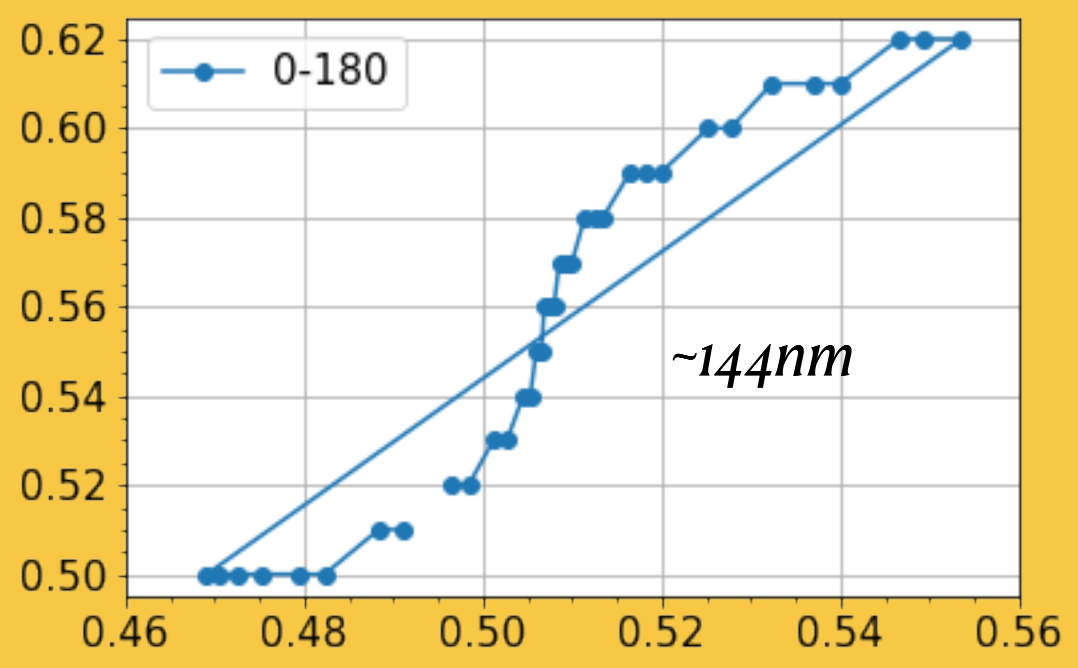
Simulating multi-filament

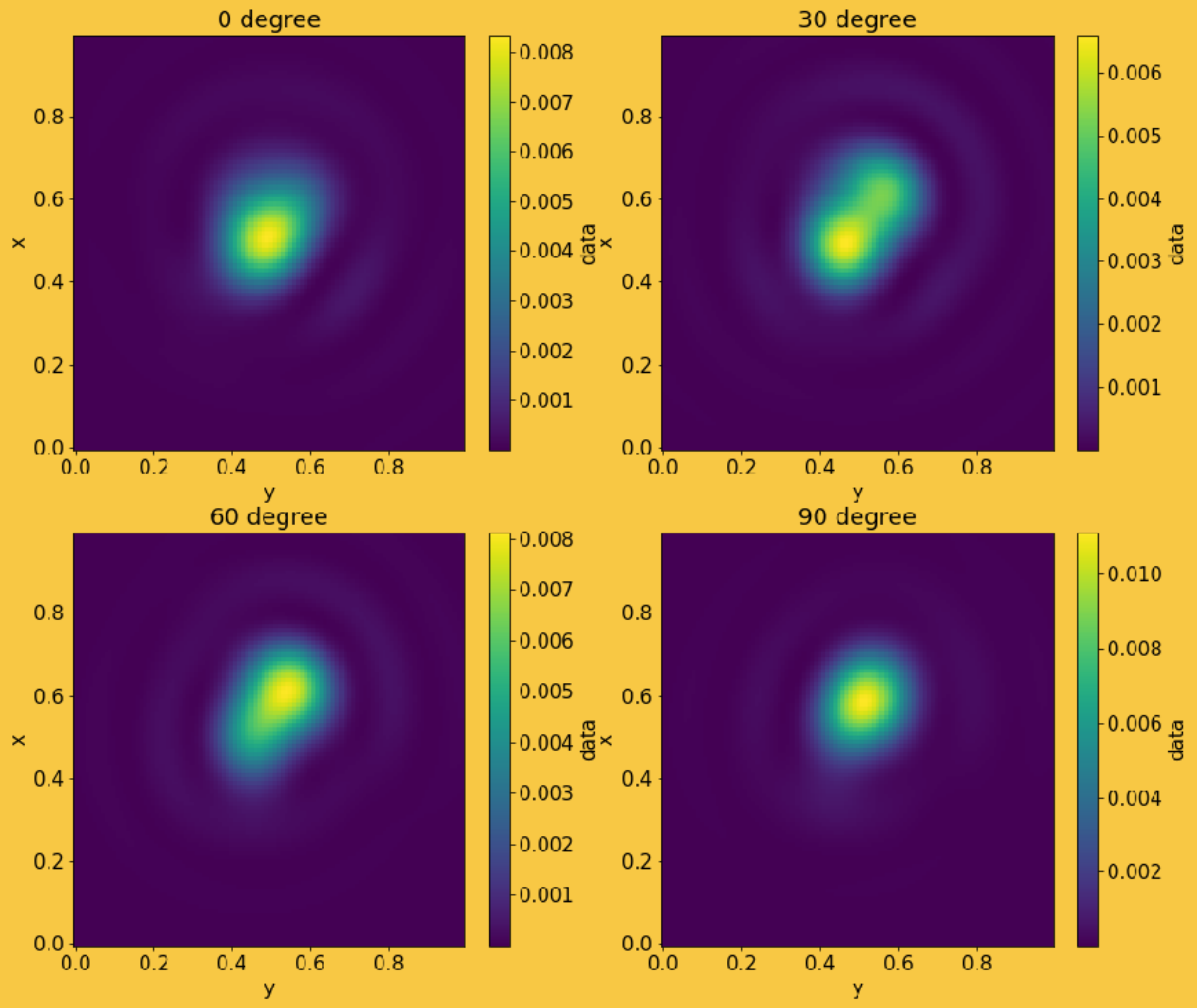
Polarisation rotation

Event view #3



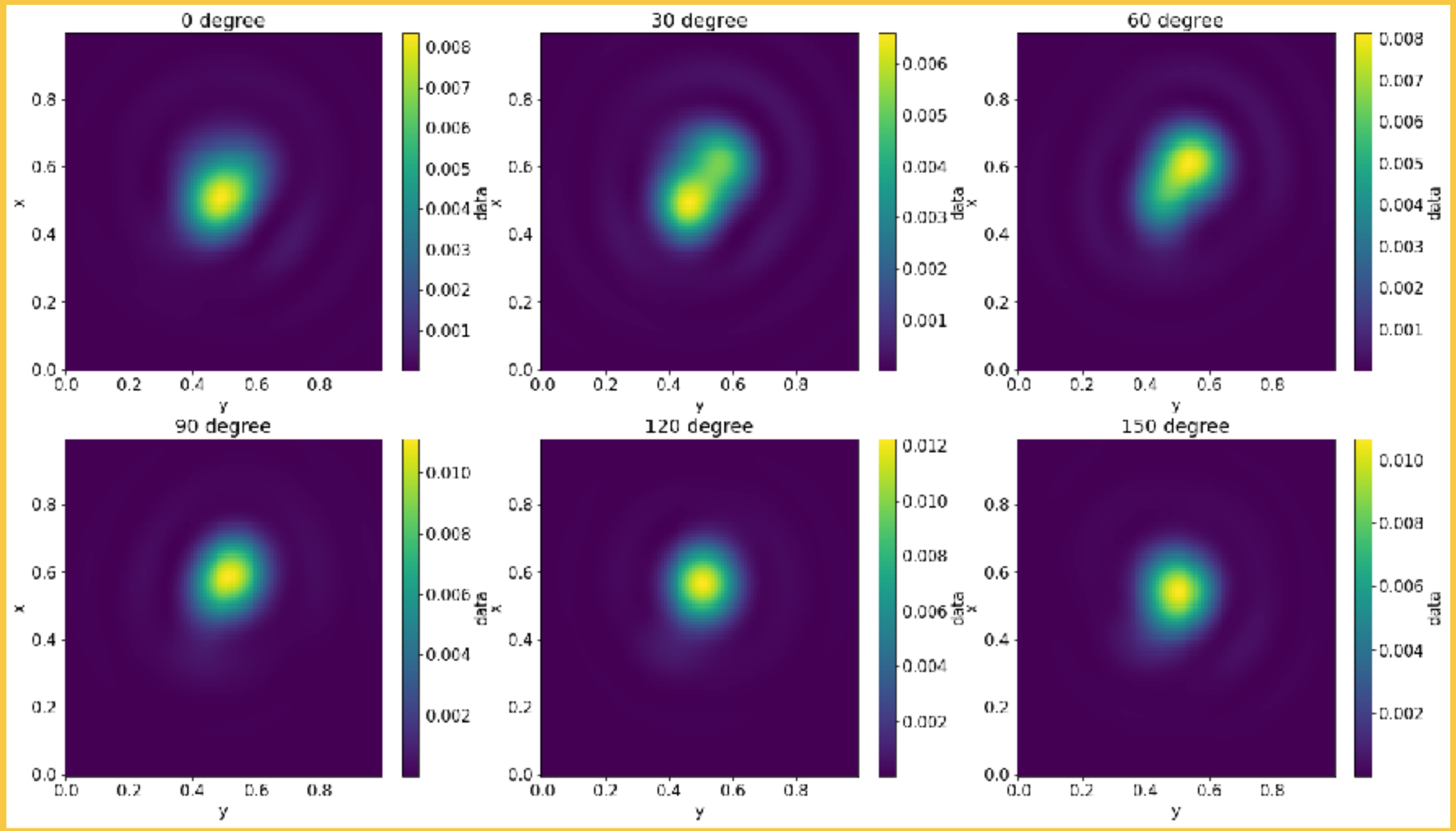


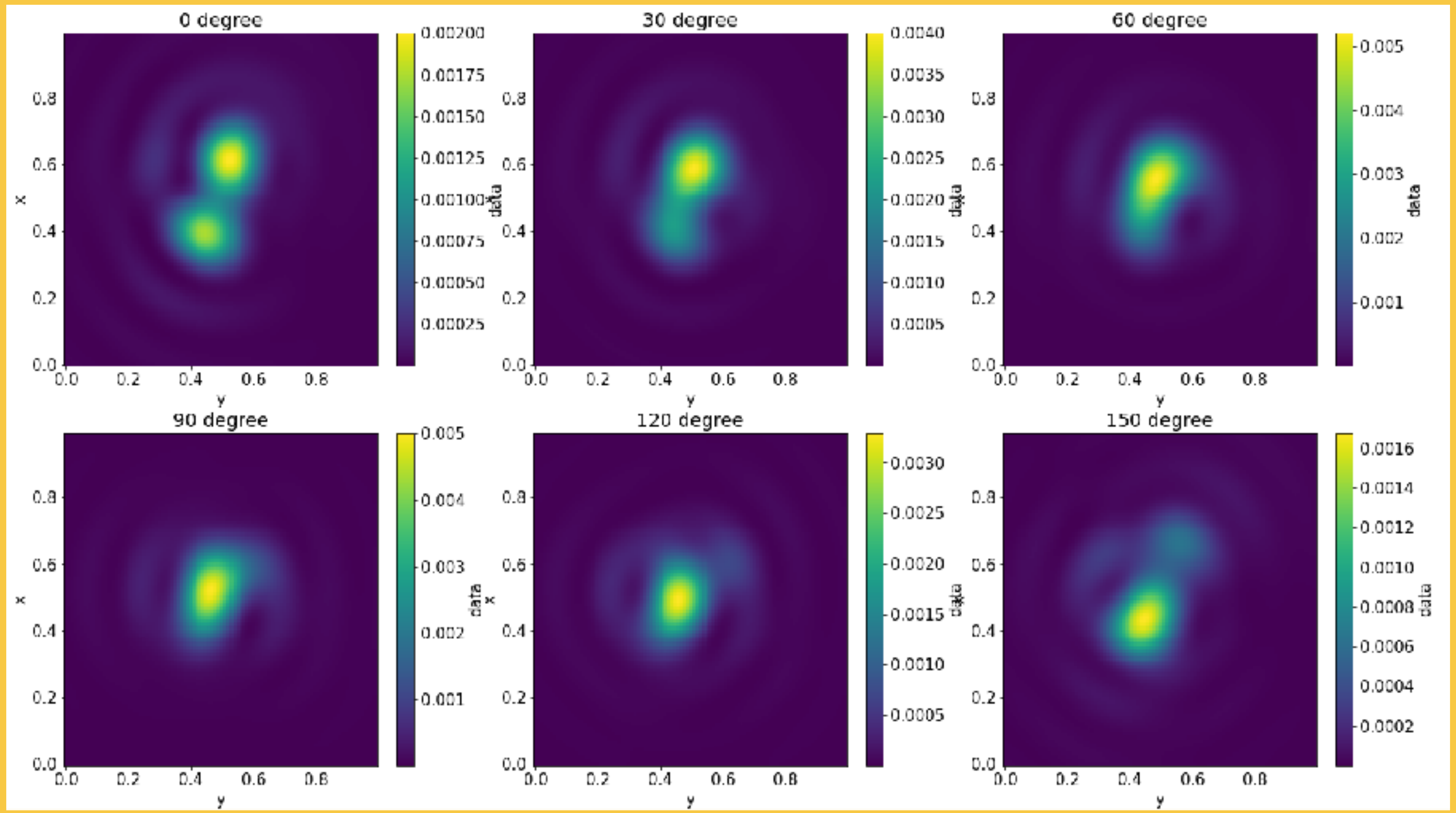




Simulating reflected light

Multi-filament





Scattered light

Reflected light

Image analysis

Machine Learning approach

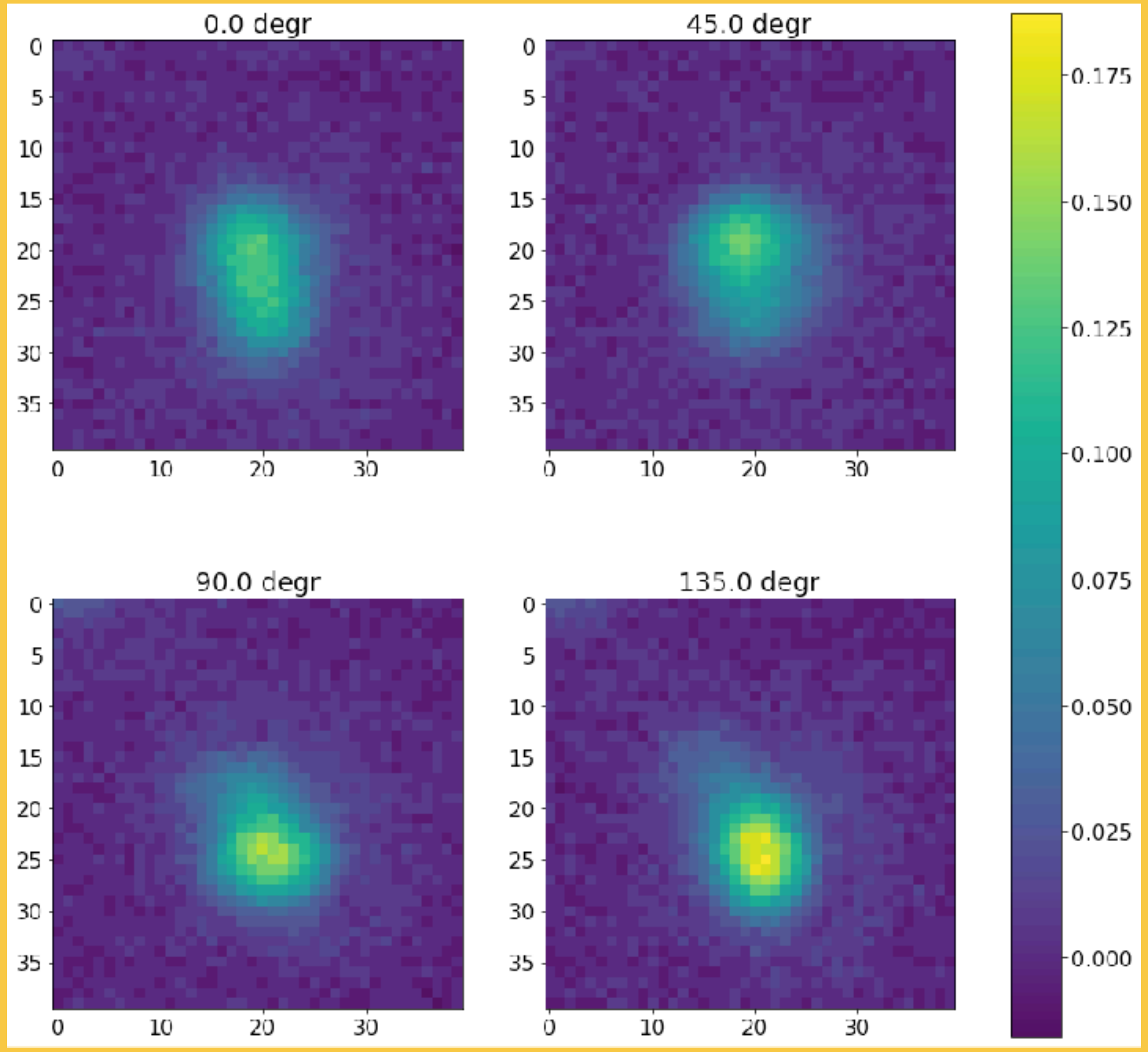
- Two main goals: signal-background classification and directional analysis.
- High background rejection is required, since expected WIMP signal is very rare.
- Signal-like events are represented by ***Carbon*** tracks, main background source is expected to be "***fog***" (thermal fluctuations).

- Machine Learning is capable of detecting complex features directly in pixel images, while barycentre shift analysis and/or elliptical fit use limited subset of image features.
- ML can overfit to instrumental noise instead of physical features of the tracks, so additional checks have to be done to limit the noise impact.

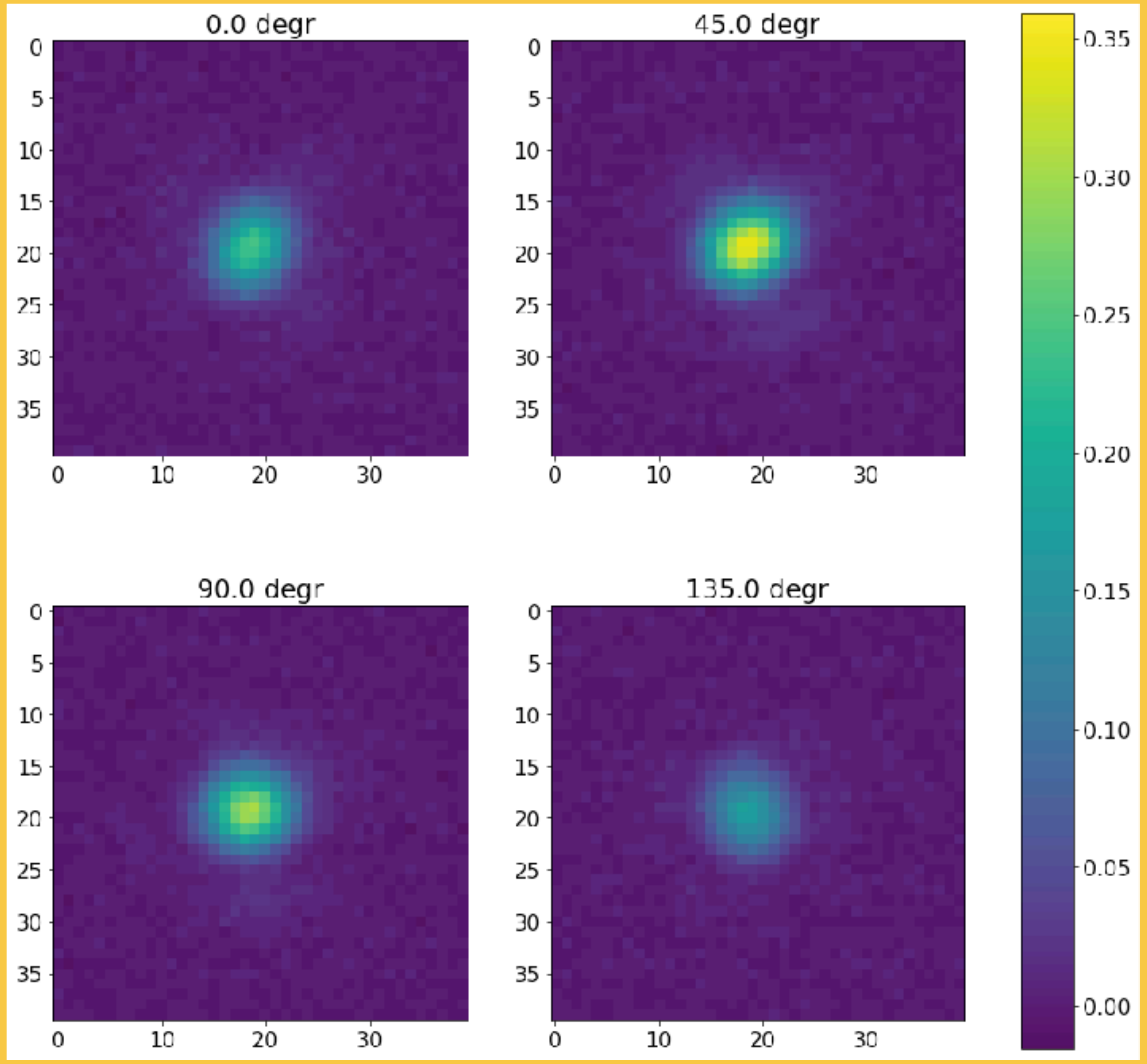
Microscopic images

Polarised light examples

pixel size ~30nm



Carbon 100keV



Fog

Before passing the data to ML

Sample rotations

- Microscope induced features can interfere with track direction in Carbon samples.
- 0^o, 45^o, 90^o rotations and test (0^o) scans of independent areas.
- No sample rotations for isotropic background events.

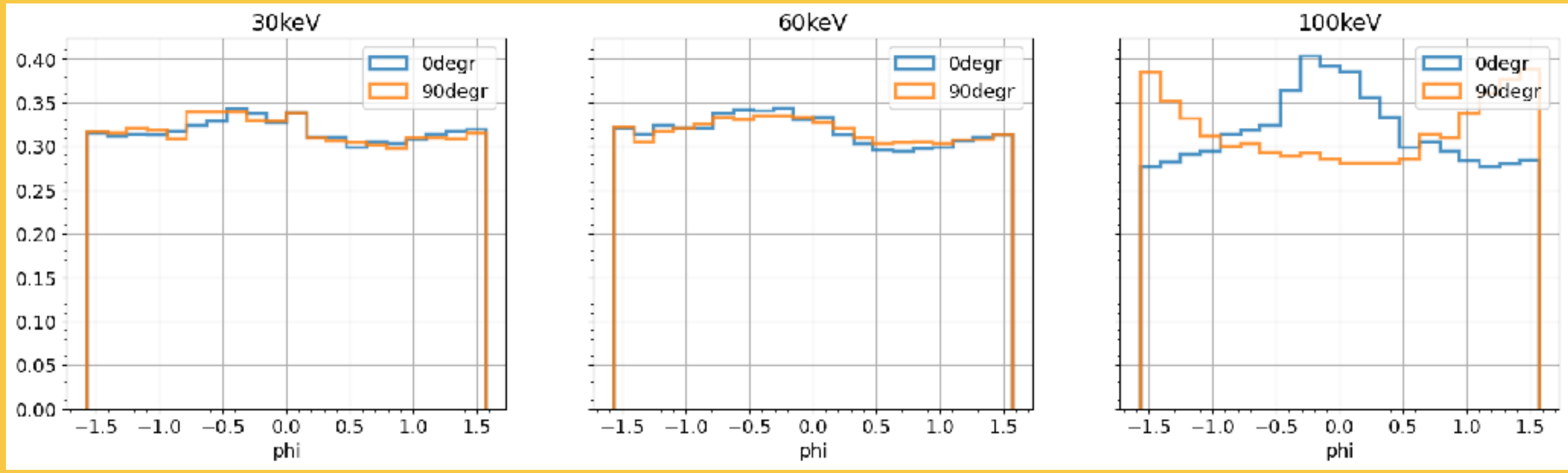


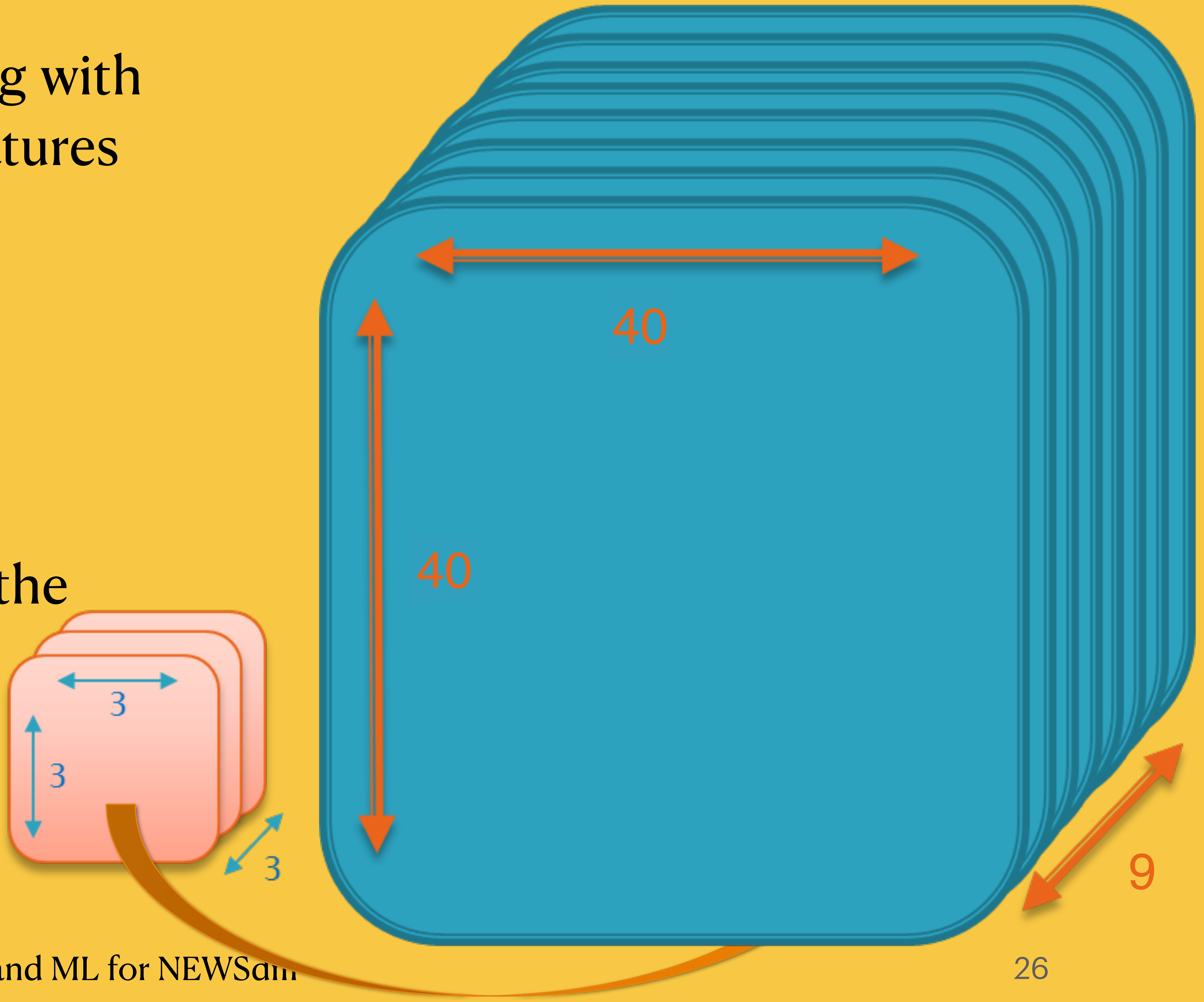
Image preprocessing

- Mean optical background depends on the emulsion sample (amount of reflected background light) and colour -> subtract and scale!
  - Optical noise is distributed around 0
  - Signal to noise ratio is improved
  - Pixel values (~0,1) —> better training
- Periodic boundary conditions -> add a copy of 0^o polarisation as the last 180^o.
- Random rotations for every event -> directionality not used by ML

Polarised images analysis

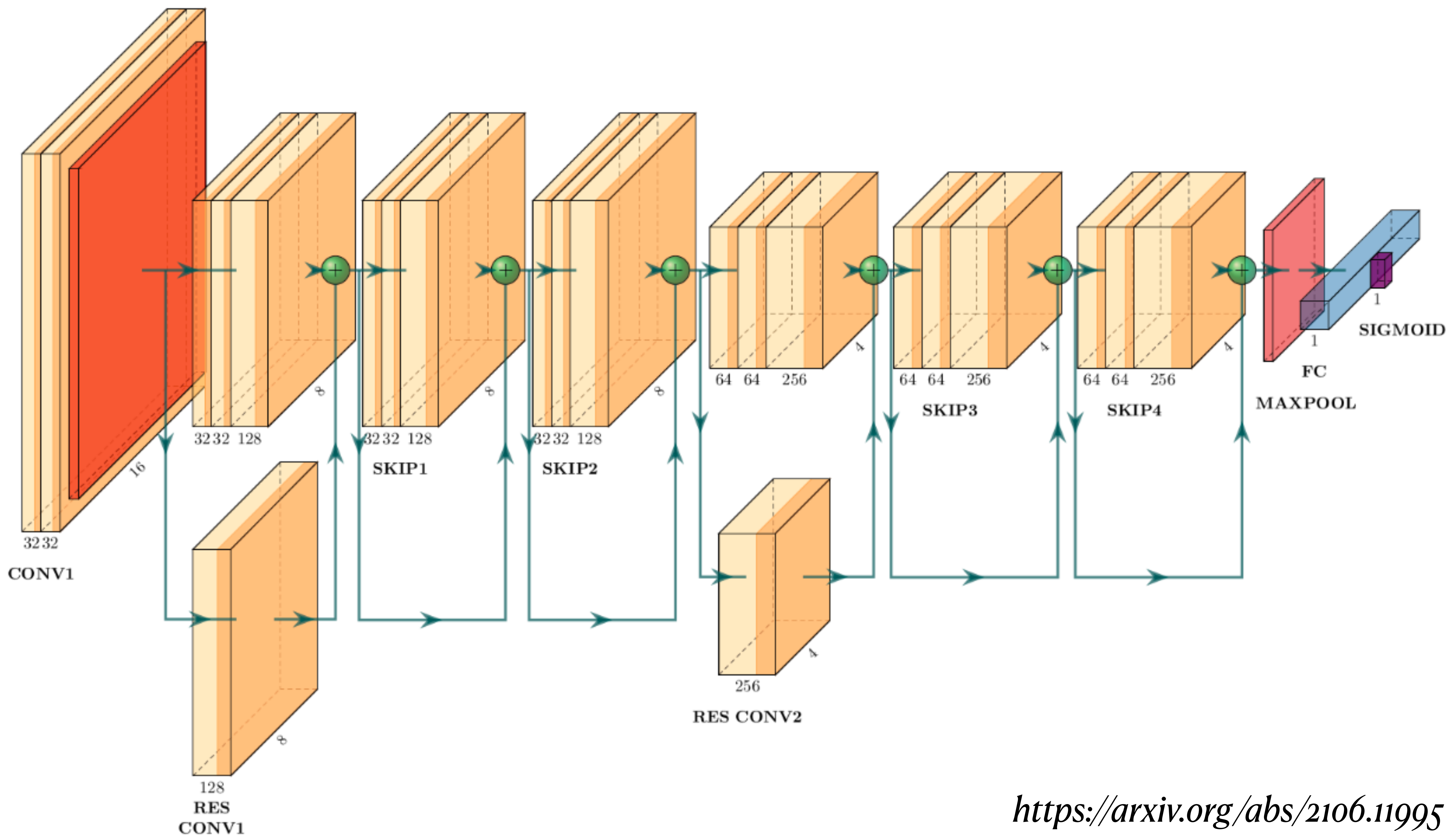
3D Convolutional Neural Networks

- Convolutional approach is designed for working with images. It is capable of discovering complex features of the images and gaining high performance.
- Stacking together images for different light polarisation to obtain a 3D image.
- Empty polarisation images are filled with zeros.
- Network "scans" not only plain image, but also the "polarisation" axis.
- Allows Network to learn correlations between features of different polarisation images.



Polarised and Colour image analysis

Convolutional Neural Network

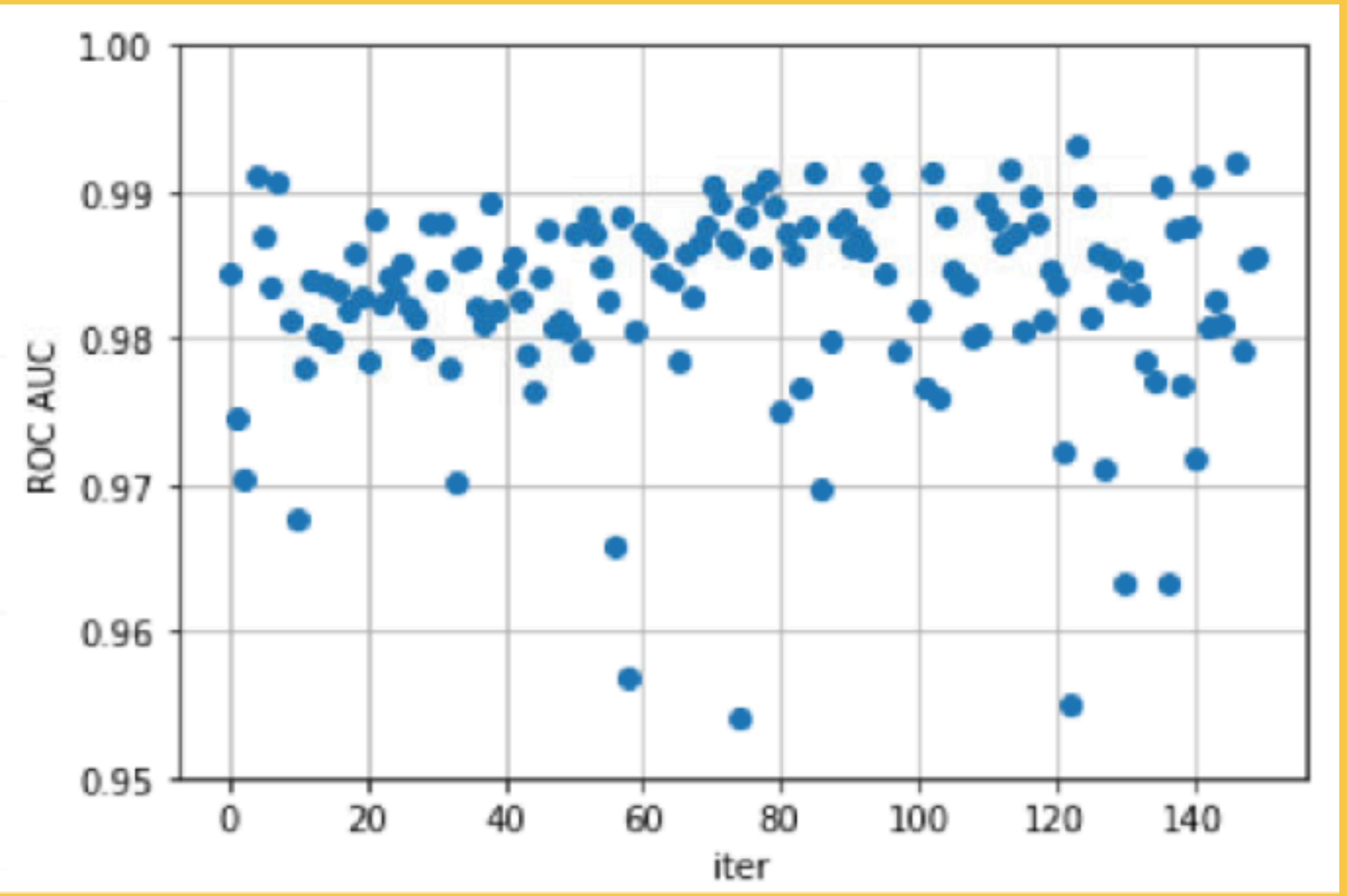


https://arxiv.org/abs/2106.11995

Hyper-parameter optimisation

Bayesian search

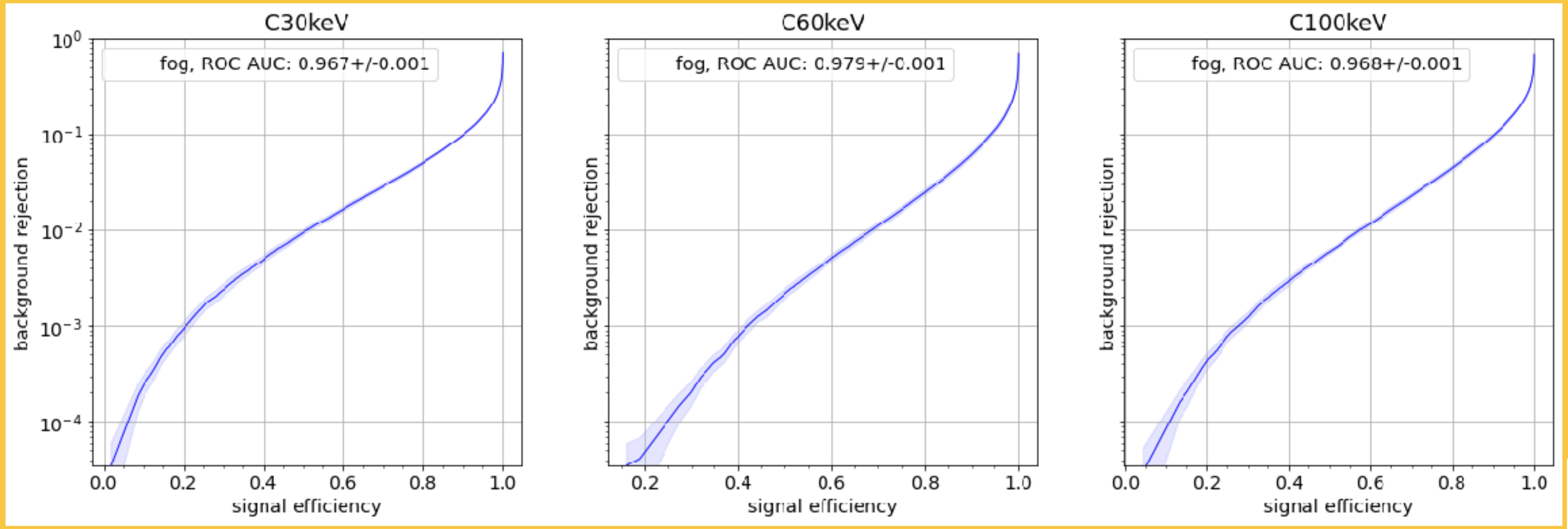
- Bayesian Search is an extension of the random search over the parameter space in more optimal way.
  - For each set of parameters the chosen performance metrics is estimated with Gaussian processes.
  - Every next "sample" of parameters is generated from the area that has more probability to improve the performance metrics.
  - Converges to find the optimal set of parameters.
  - Cross-validation is used to have more confidence in the results.



ML analysis results

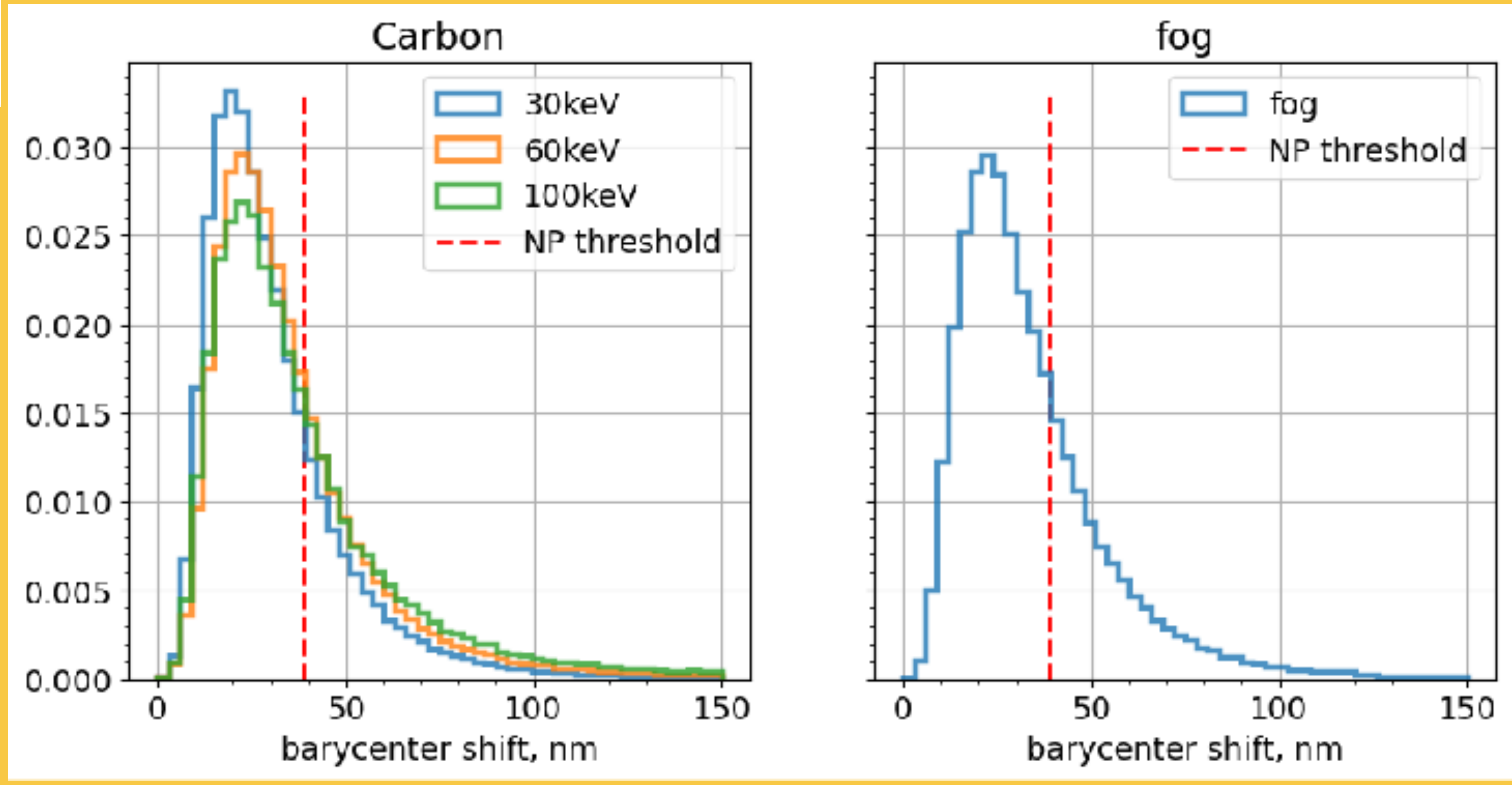
ML comparing to cut-based

https://arxiv.org/abs/2106.11995



- Background reduction factor and efficiency for different thresholds on ML probability-like output on **validation** data

- Barshift threshold rejecting 95% of spherical nano particles



ML analysis results

ML comparing to cut-based

https://arxiv.org/abs/2106.11995

	Barshift		NEWSnet		Shape analysis
	Validation	Test	Validation	Test	
Signal efficiency					
C30keV	$25.3 \pm 1.5\%$	$25.5 \pm 1.7\%$	$29.3 \pm 3.9\%$	$16.2 \pm 3.1\%$	$1.7 \pm 0.1\%$
C60keV	$33.7 \pm 1.8\%$	$35.3 \pm 2.1\%$	$50.4 \pm 3.8\%$	$47.5 \pm 4.0\%$	$13.1 \pm 0.1\%$
C100keV	$38.0 \pm 1.8\%$	$38.2 \pm 1.2\%$	$36.5 \pm 3.4\%$	$37.4 \pm 3.3\%$	$29.7 \pm 0.7\%$
Background reduction factor					
Fog	0.32 ± 0.02	0.39 ± 0.02	$(2.4 \pm 0.74) \cdot 10^{-3}$	$(4.2 \pm 1.3) \cdot 10^{-4}$	0.01

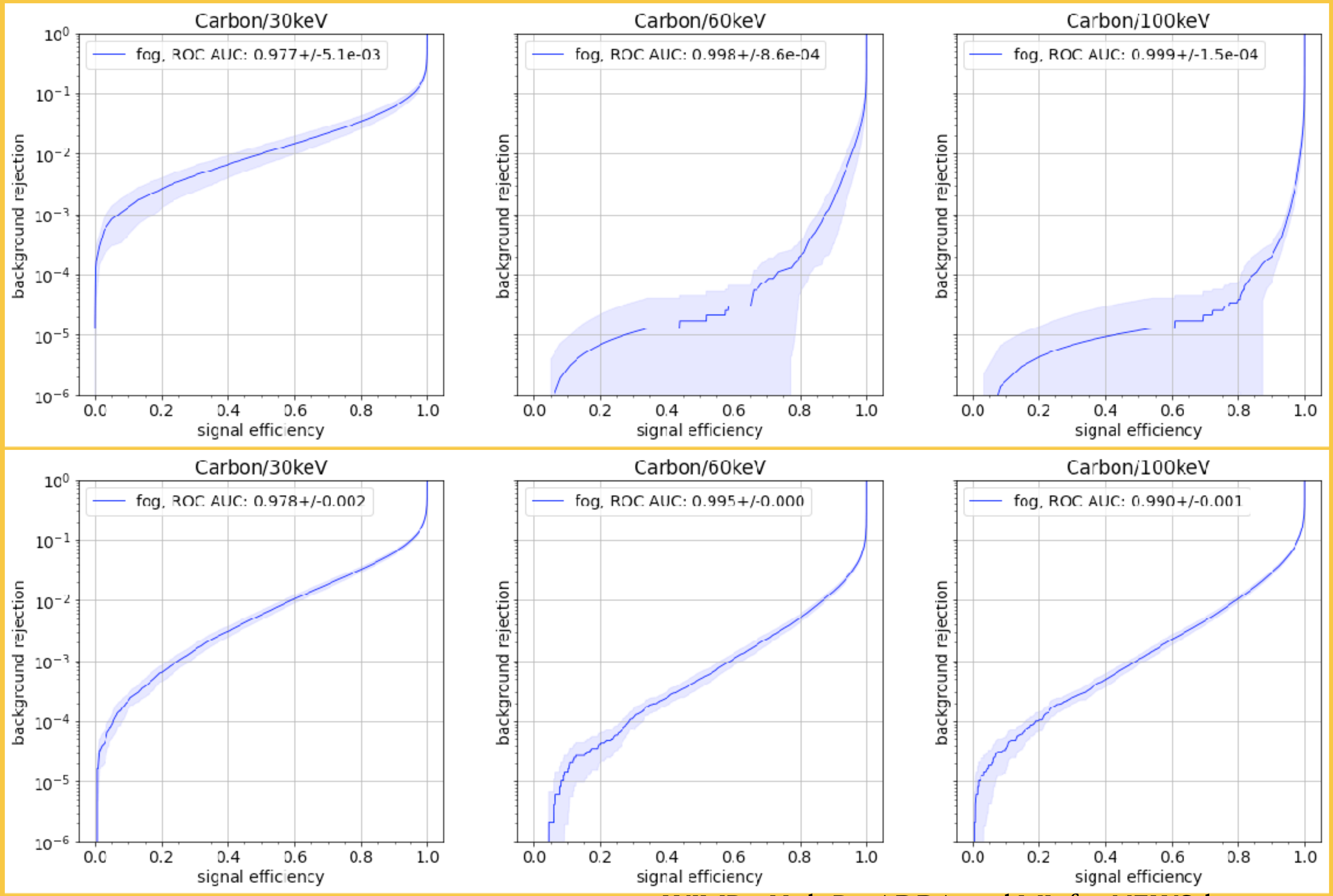
- We fix ML threshold value to obtain similar to barshift signal efficiency on **validation** data and cross-check the reproducibility on **test** data.
- C30keV sample was scratched -> efficiency drop on test. C60keV had suspicious event brightness and density -> not included in the article.

ML analysis results

Colour vs Polarisation (TEST data)

Colour

Polarisation



	Polarised	Colour
	Signal efficiency	
C30keV	$7.4 \pm 2.2\%$	$0.5 \pm 0.7\%$
C60keV	$32.1 \pm 3.7\%$	$72.4 \pm 9.8\%$
C100keV	$22.5 \pm 3.1\%$	$82.8 \pm 6.5\%$
	Background reduction factor	
Fog	$(1.5 \pm 0.6) \cdot 10^{-4}$	$(1.5 \pm 1.1) \cdot 10^{-4}$

- Threshold fixed to provide $\sim 10^{-4}$ background reduction.
- Checked only on test, since validation set did not have enough background to probe strong reduction.

Summary and next steps

WIMP simulation

- WIMP rate and tracks distributions are updated with current DM parameters and form factor.
- Linear combination of Carbon samples can be used to mimic more precise WIMP distribution for specific mass.

Image simulation

- Current simulation with HoloPy and ADDA allows to reproduce most of physical behaviour we can test before comparing directly with real images: *unpolarised/polarised light, reflected light, microscope lens, plasmon effect.*

Next steps

- *Produce updated exclusion curves.*
- *Calibrate image simulation on optical images with the exact 3d models from SEM.*
- *Estimate joint colour-polar ML background reduction potential.*

Image analysis

- Subtracting optical background is important preprocessing step to make sure ML does not focus on unphysical features.
- Colour ML provides strong rejection and can be used before polarised scanning, since colour microscope is much faster.
- Both colour and polar ML can achieve $\sim 10^{-4}$ background reduction, while colour keeps more signal.

Publications

- *Directionality: https://arxiv.org/abs/2102.03125 (published in JCAP)*
- *ML for background reduction: https://arxiv.org/abs/2106.11995 (preparing for CPC)*
- *NEWSdm Conceptual design report: background rejection and image simulation*
- *Muon secondment: https://github.com/golovart/3DmuonProject*

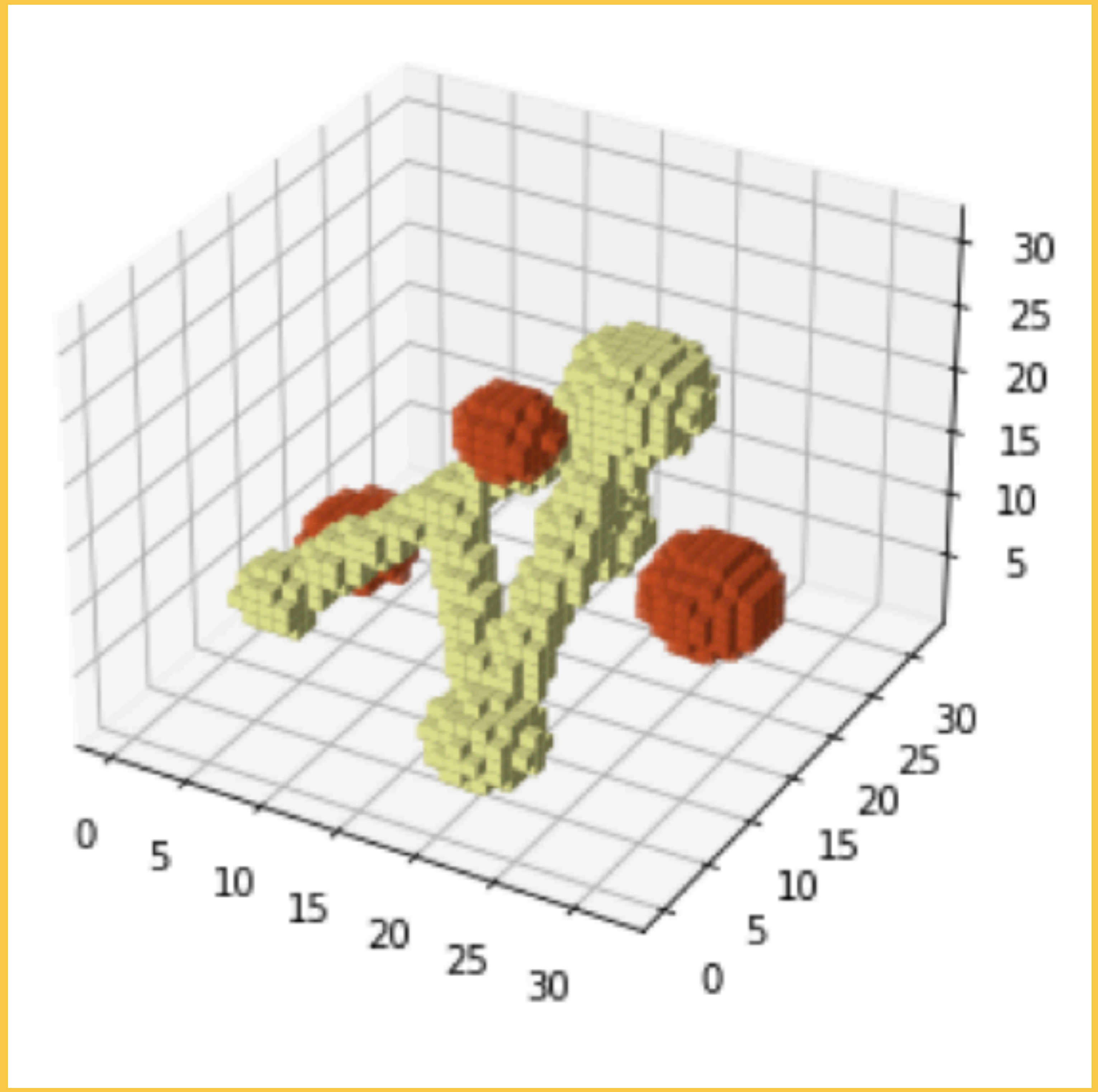
Bonus slides

Muon secondment

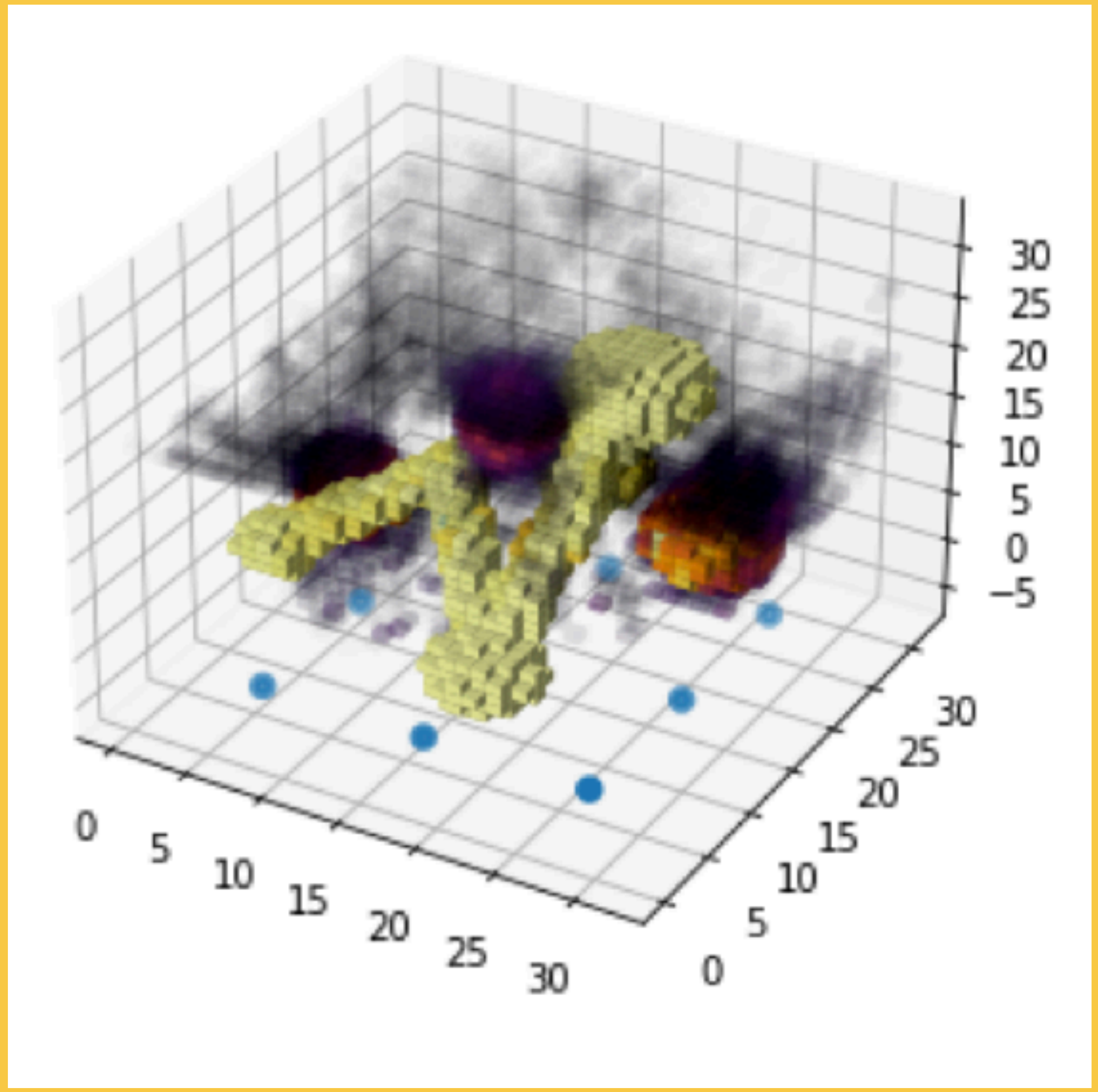
Muon secondment

Numerical solution in Python

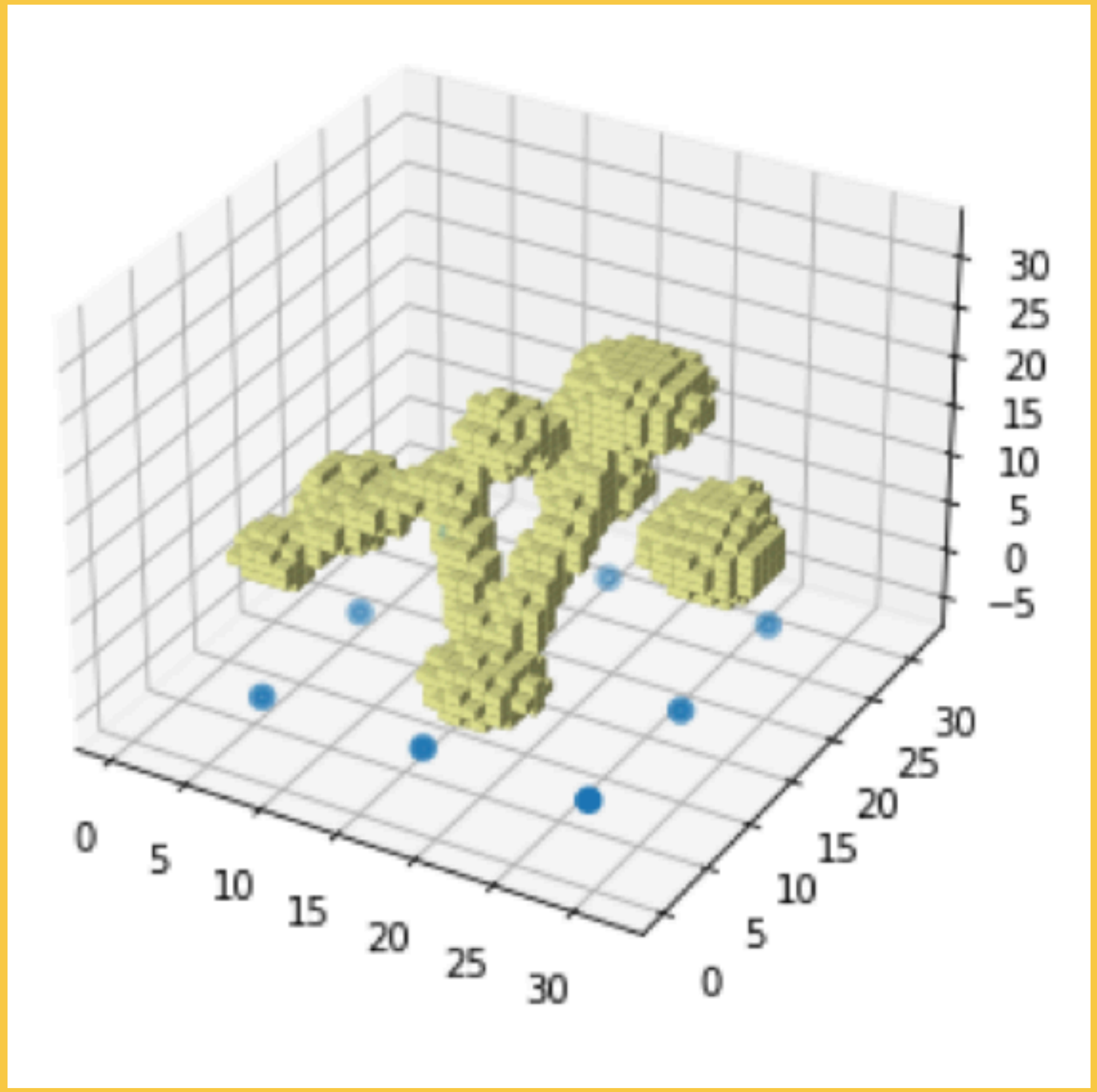
https://github.com/golovart/3DmuonProject



True
(unknown in red)



Predicted
(darker and more transparent = lower anomaly)



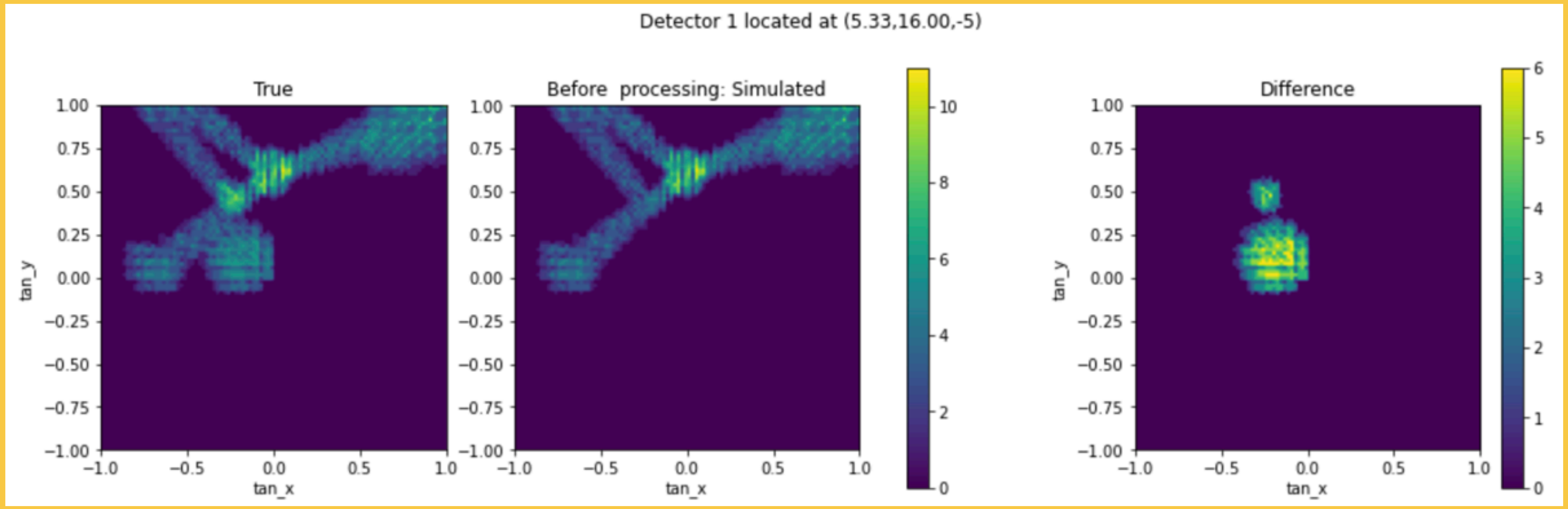
optimal threshold 0.4

Muon secondment

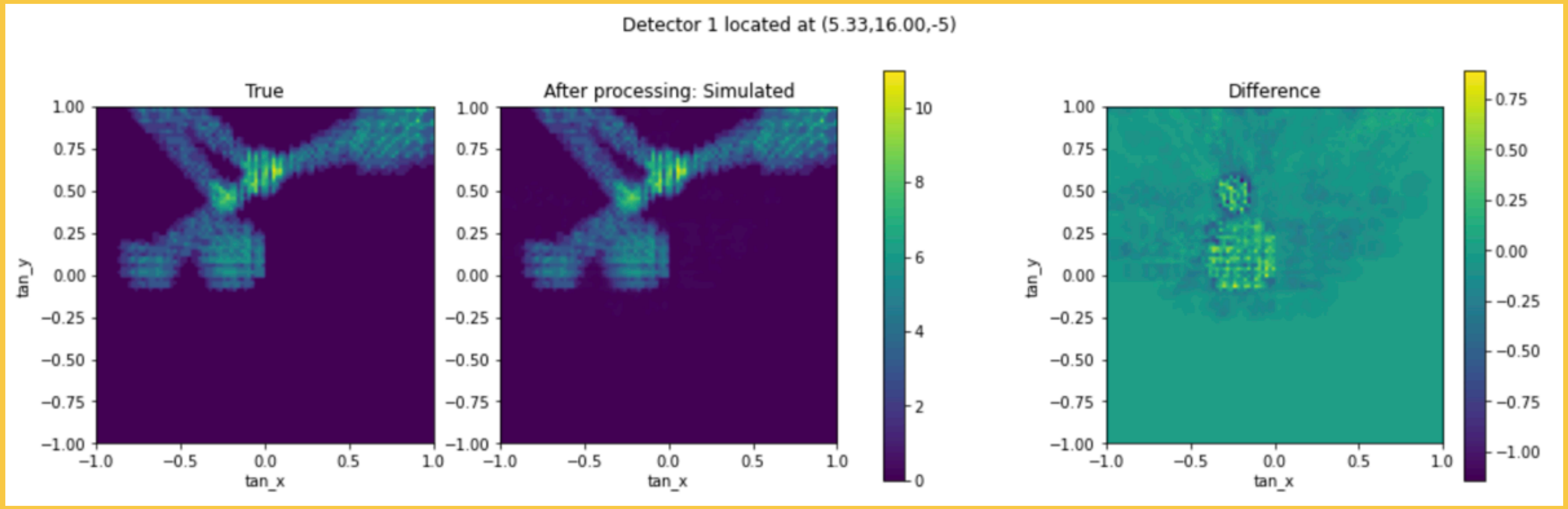
2D angular detector histograms

https://github.com/golovart/3DmuonProject

Before

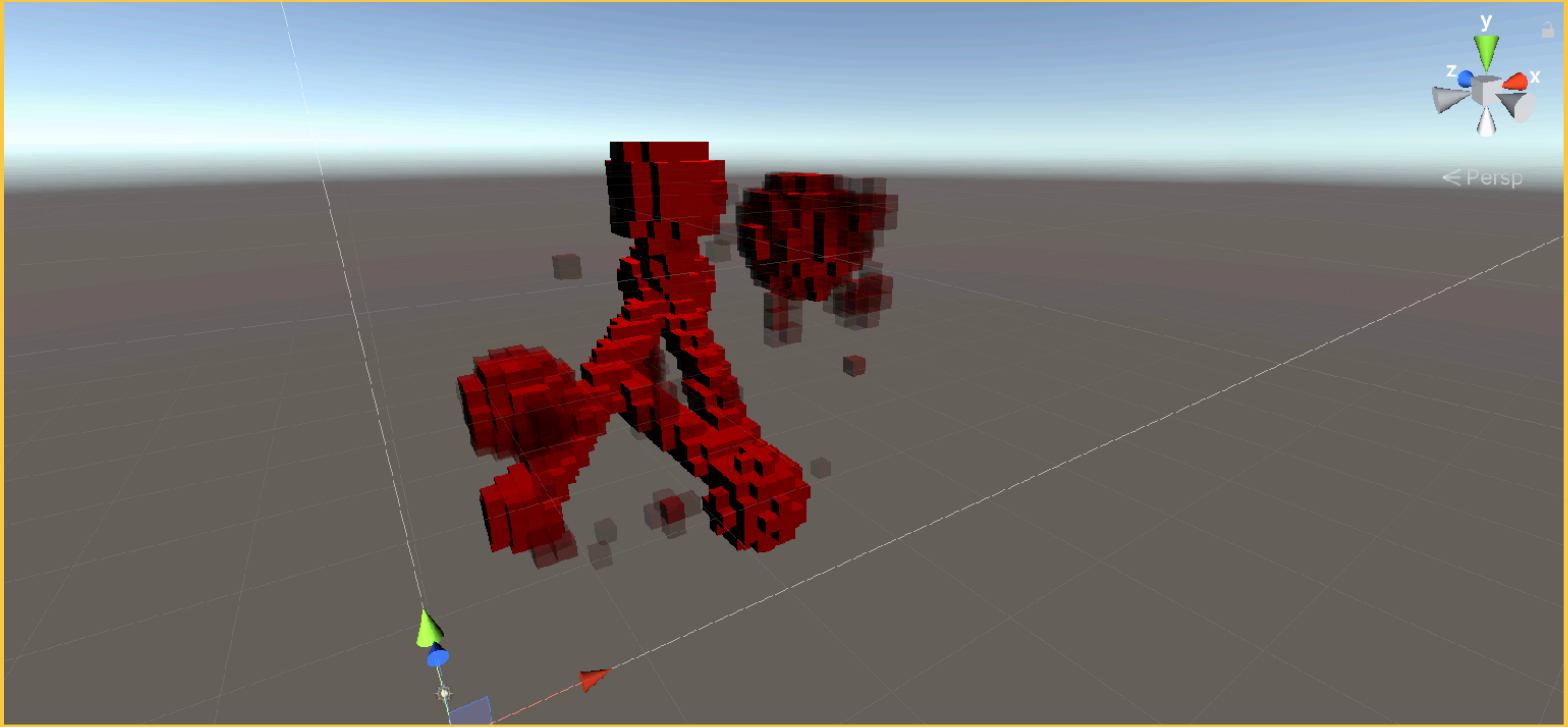


After



Muon secondment

Unity visualisation



Muon secondment

Realistic case