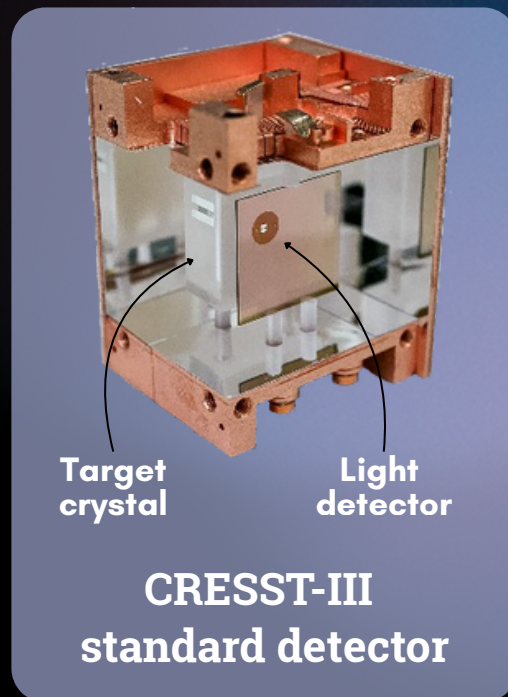
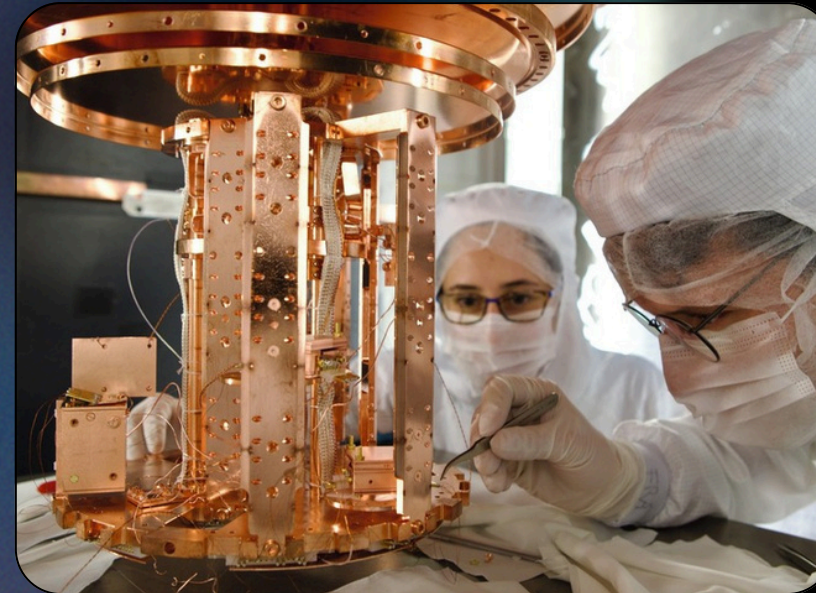


Exploring data-driven likelihood estimation with normalizing flows for CRESST

Presented by **Danaé Valdenaire**

danae.valdenaire@oeaw.ac.at

THE CRESST EXPERIMENT

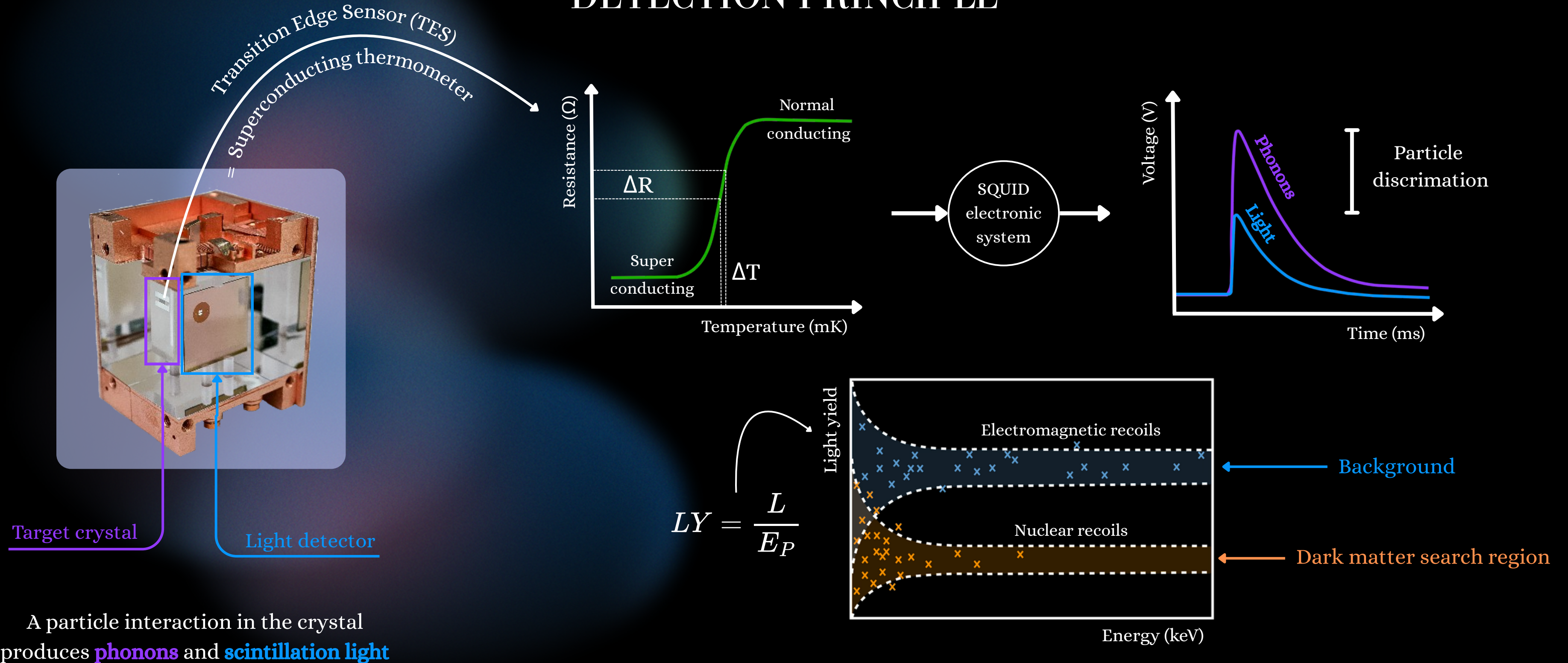


CRESST → **Cryogenic** Rare Event Search
with **Superconducting** Thermometers

Leading direct detection experiment
searching for **low-mass dark matter**

Collaboration of 90 members and
10 institutions accross the world

DETECTION PRINCIPLE



LIKELIHOOD FRAMEWORK

Eur. Phys. J. C 84, 922 (2024)

1. SIGNAL + BACKGROUND MODEL

$$\frac{dN_{\chi,x}}{dE} = \frac{\rho_\chi}{2m_\chi\mu_N^2} \sigma_0 F^2(E) \int_{v_{\min}(E)}^{v_{\text{esc}}} d^3v \frac{f(\vec{v})}{v}$$

$x \in \{O, Ca, W\}$

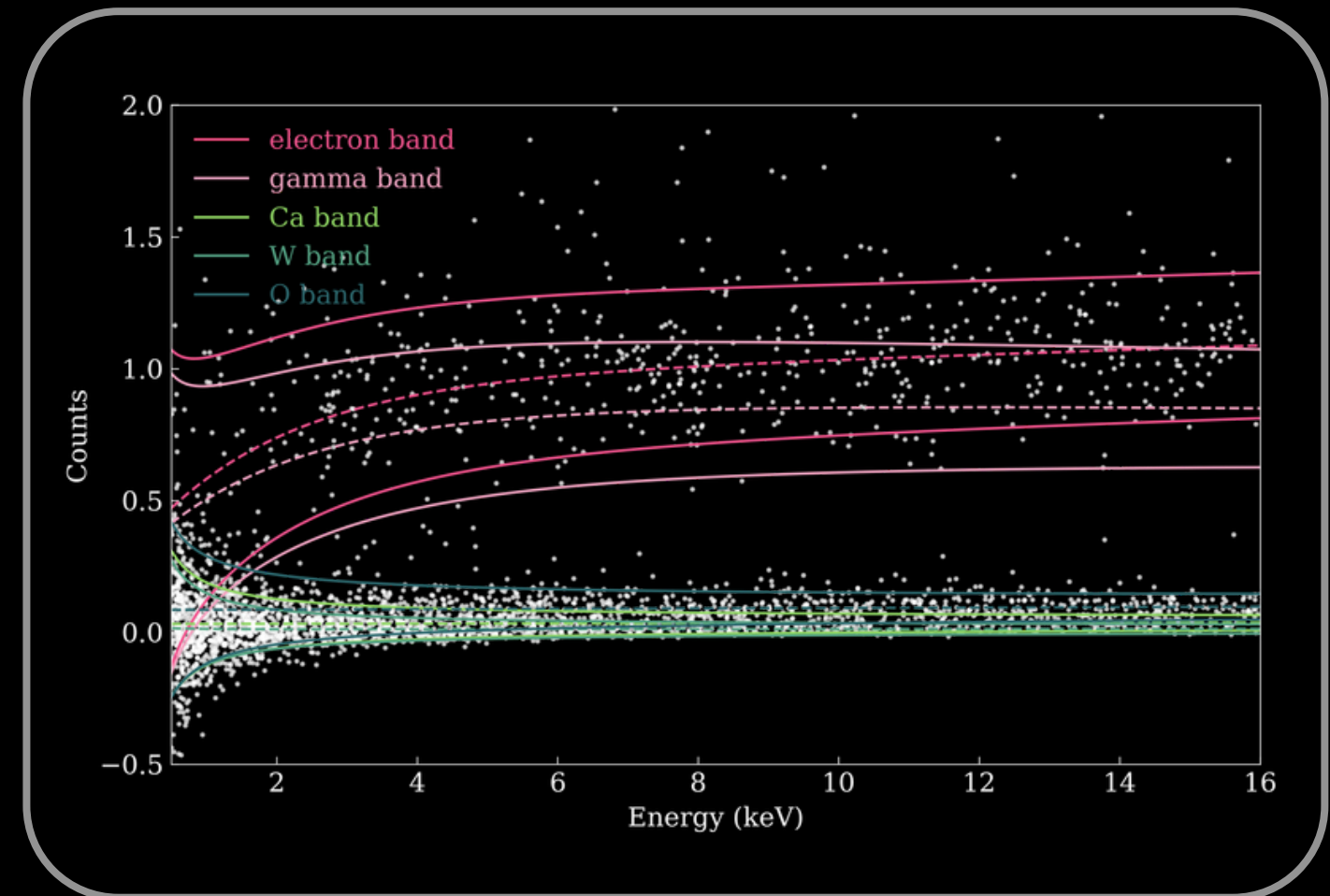
+

β/γ – spectra

+

...

2. BAND FIT



$$\rho_x(E, L) = \frac{dN_x}{dE} \mathcal{N}(L_x(E), \sigma_x^2(E))(L)$$

$\mathcal{N}$: Gaussian function

LIKELIHOOD FRAMEWORK

3. EXTENDED POISSON LIKELIHOOD

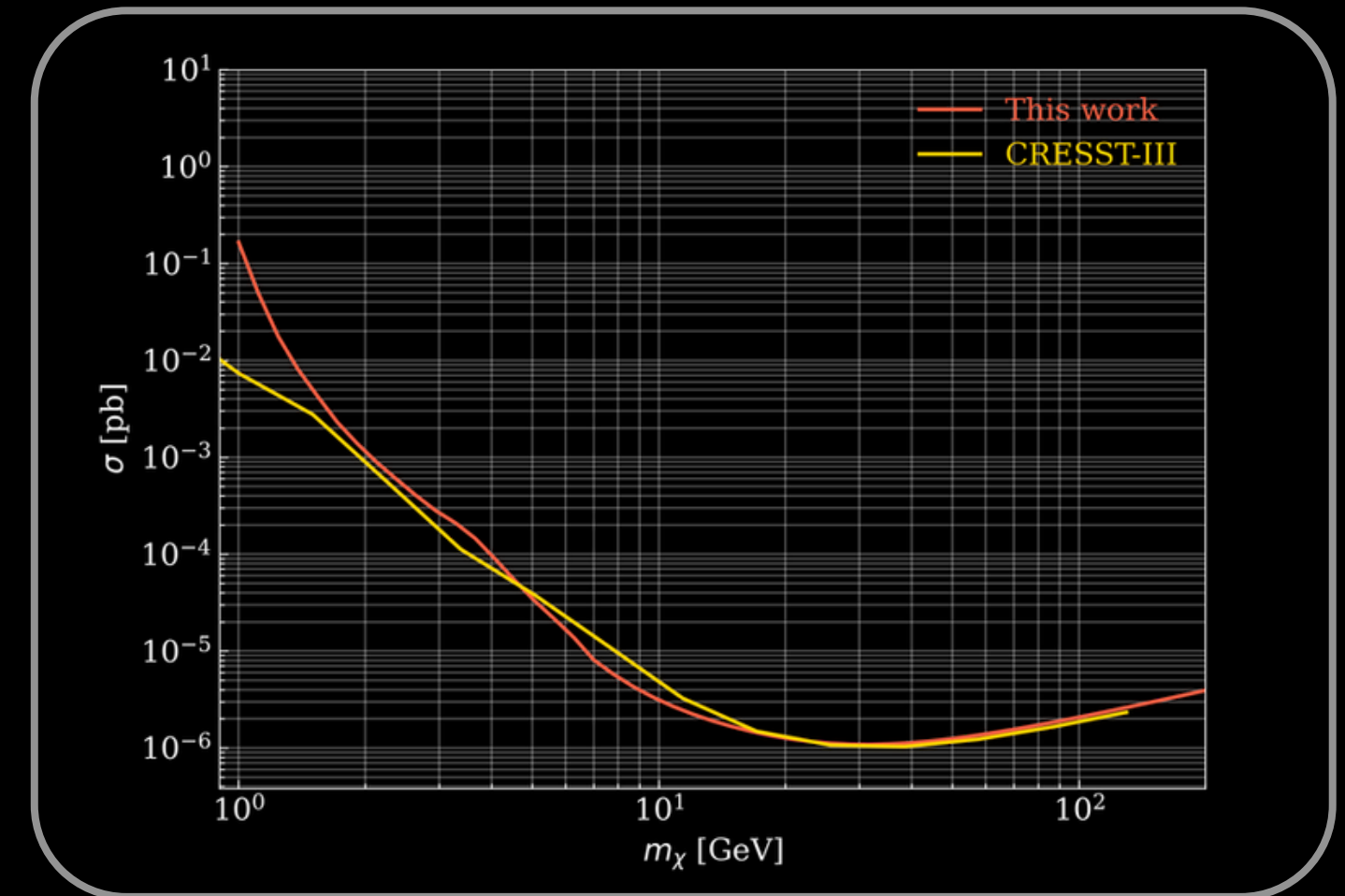
$$\begin{aligned}
 -\log \mathcal{L} = & \sum_{i=0}^{i=N_{\text{bck}}} -\log \left[\text{eff}(E_i) \cdot \left(\sum_{j=0}^{j=N_{\rho_{\text{bck}}}} \rho_j(E_i, L_i) \right) \right] \\
 & + \sum_{k=0}^{k=N_{\text{ncal}}} -\log \left[\text{eff}(E_k) \cdot \left(\sum_{l=0}^{l=N_{\rho_{\text{ncal}}}} \rho_l(E_k, L_k) \right) \right] \\
 & + \sum_{j=0}^{j=N_{\rho_{\text{bck}}}} \iint_{\text{acc.region}} dE dL \text{eff}(E) \rho_j(E, L) \\
 & + \sum_{l=0}^{l=N_{\rho_{\text{ncal}}}} \iint_{\text{acc.region}} dE dL \text{eff}(E) \rho_l(E, L)
 \end{aligned}$$

←
Expected
number of events
for each data set
←

Ncal: neutron calibration data set

Bck: background data set

4. EXCLUSION LIMITS

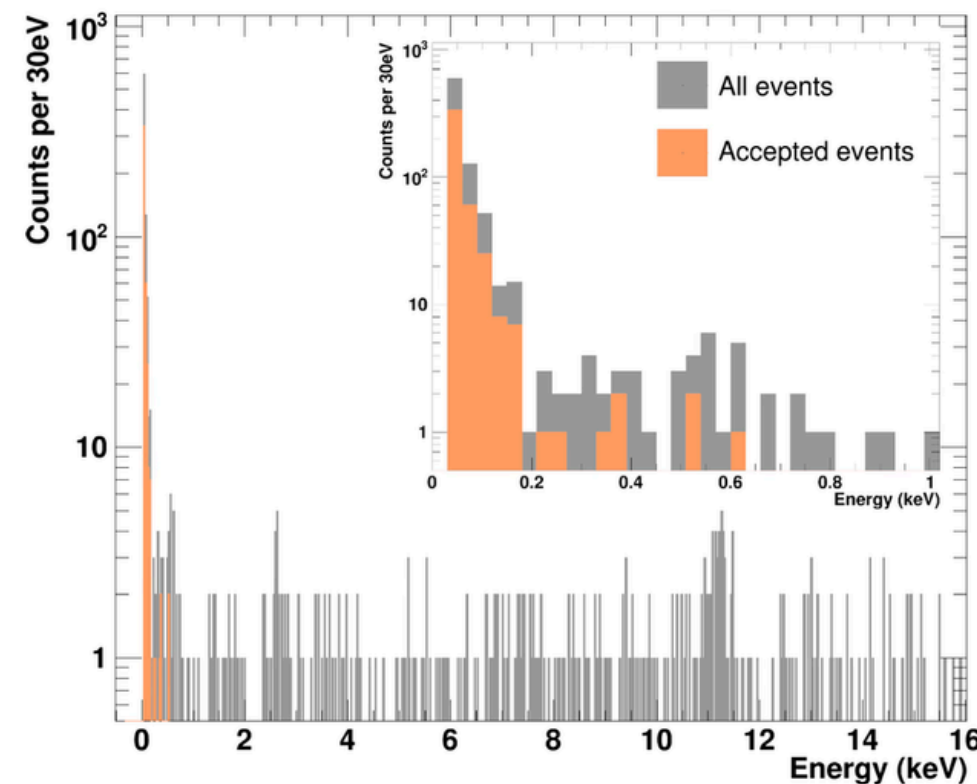


THEN, WHY DO WE NEED MACHINE LEARNING HERE?

LOW-ENERGY EXCESS

The low-energy excess is a **rise in event rate** below 200 eV.

Phys. Rev. D 100, 102002 (2019)



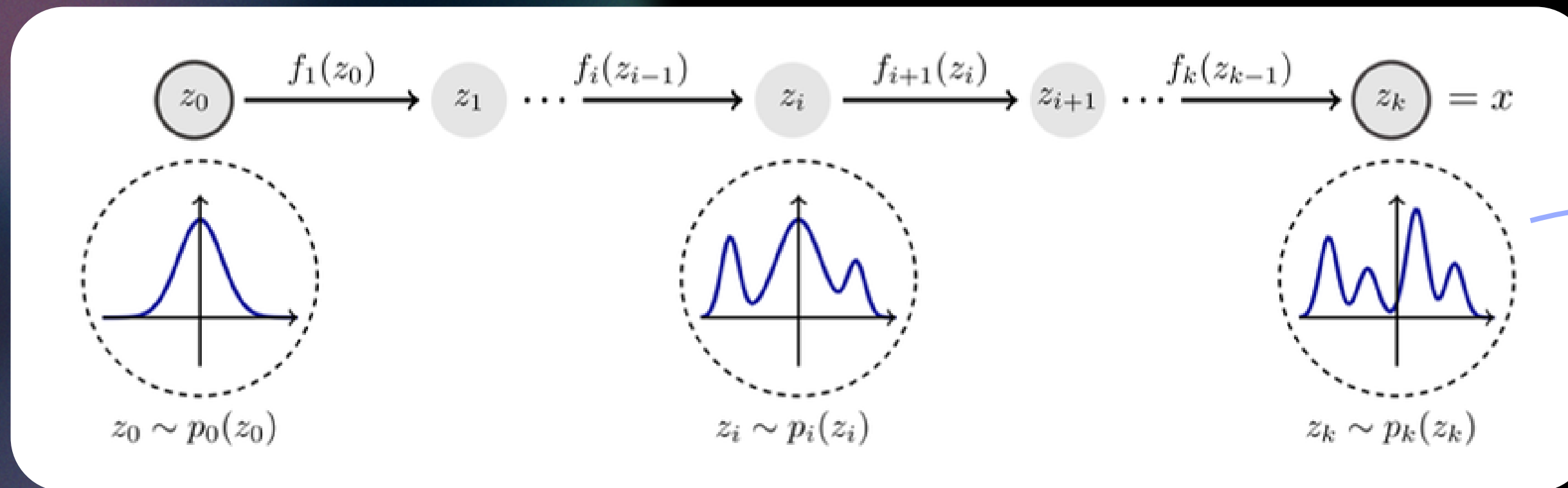
- **Dark matter** or external **radiactivity** origin are **excluded**.
- Other **low-threshold experiments** are also seeing an excess.

With an **unknown background** in our data,
we cannot use the likelihood anymore...

LET'S TRY TO SOLVE THIS WITH
NORMALIZING FLOW!

NORMALIZING FLOW

A **normalizing flow** learns a **complex probability distribution** by **transforming a simple one** through a **series of invertible mappings**.



The likelihood is computed
at each step

you start with a
known distribution

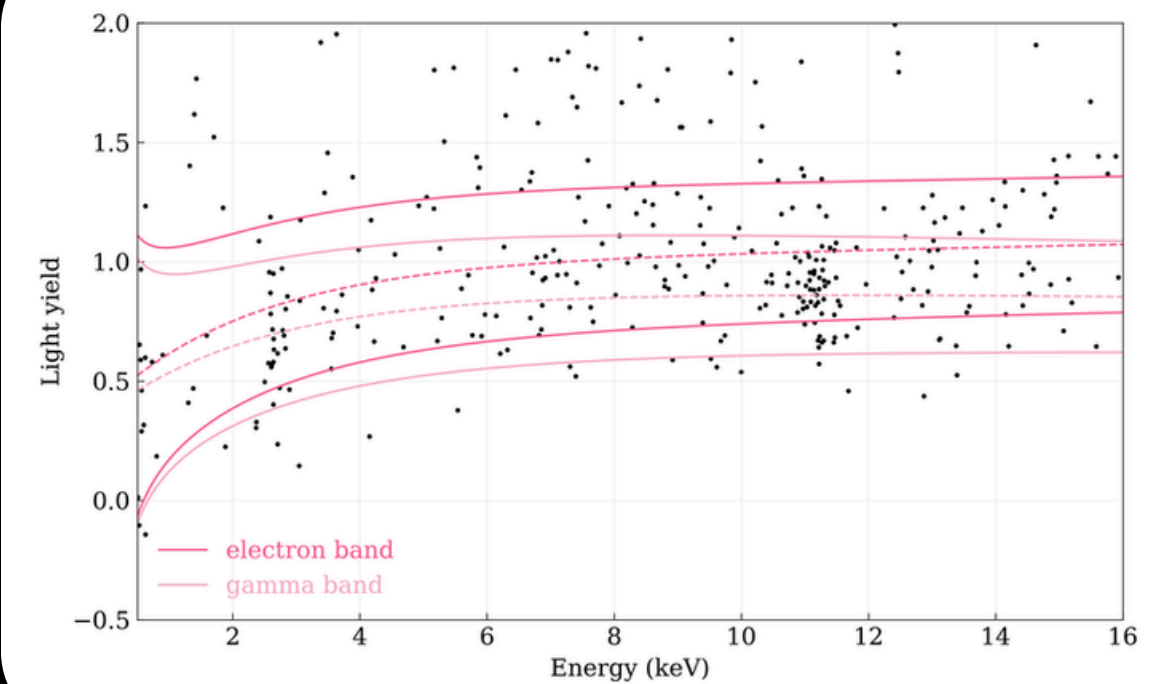
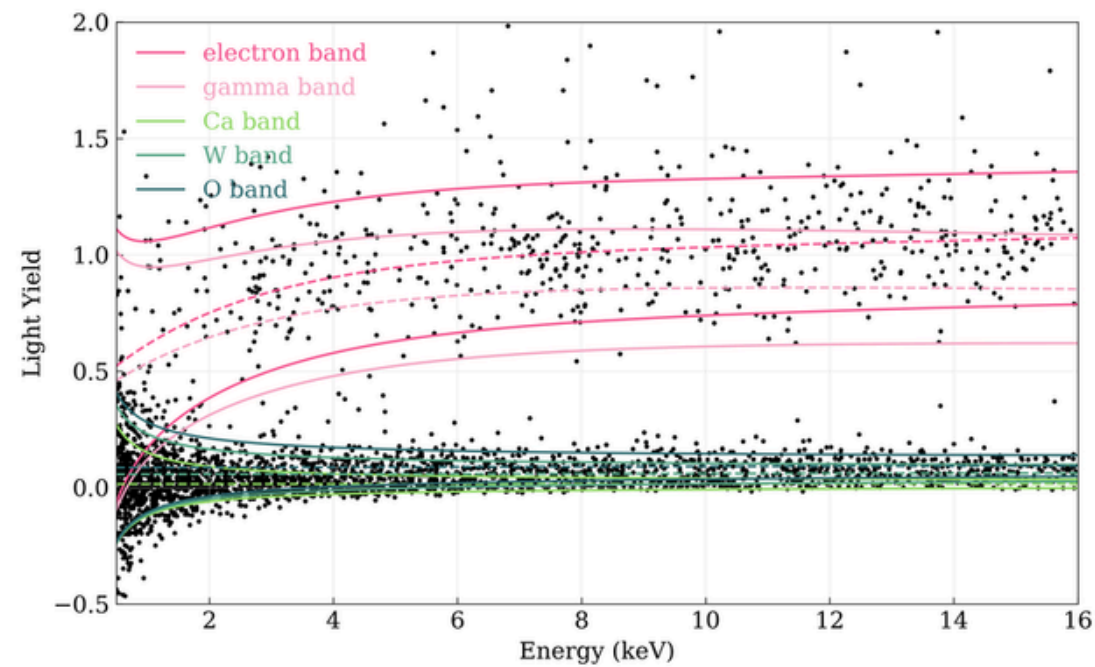
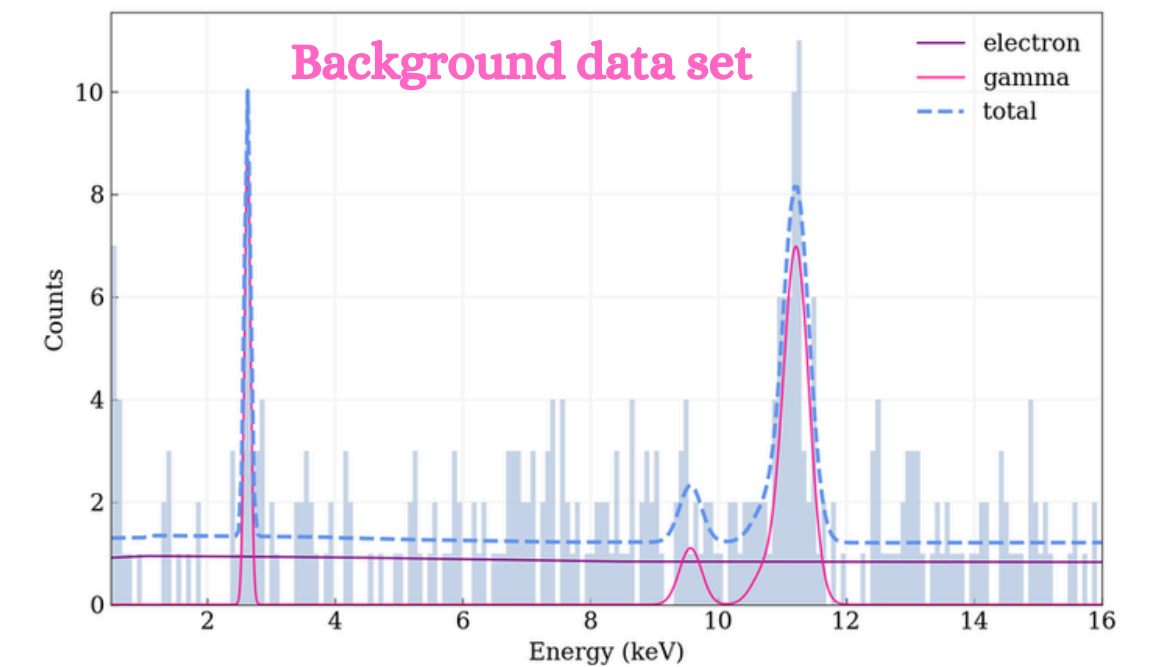
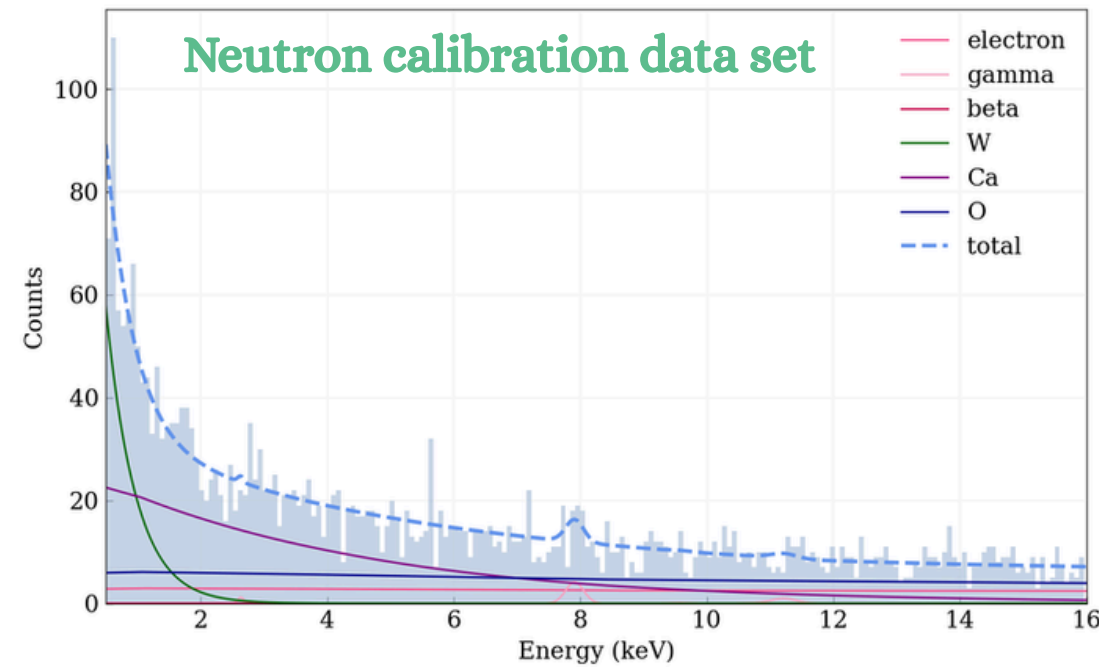
you transform,
you transform,
you transform,

$$\log p_K(z_K) = \log p_0(z_0) - \sum_{i=1}^K \log \left| \det \frac{df_i(z_{i-1})}{dz_{i-1}} \right|$$

CRESST-III DATA

Phys. Rev. D 100, 102002 (2019)

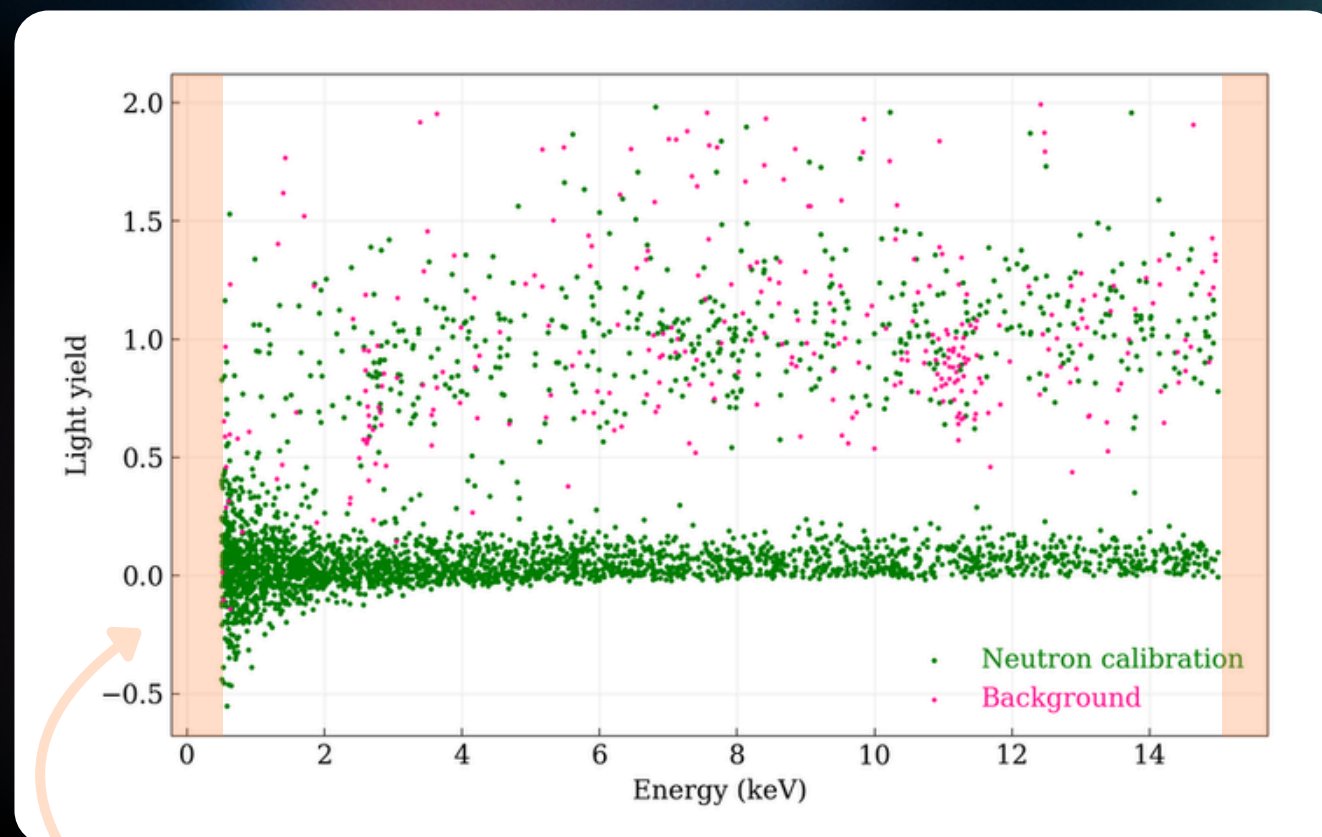
Energy spectrum (1D)



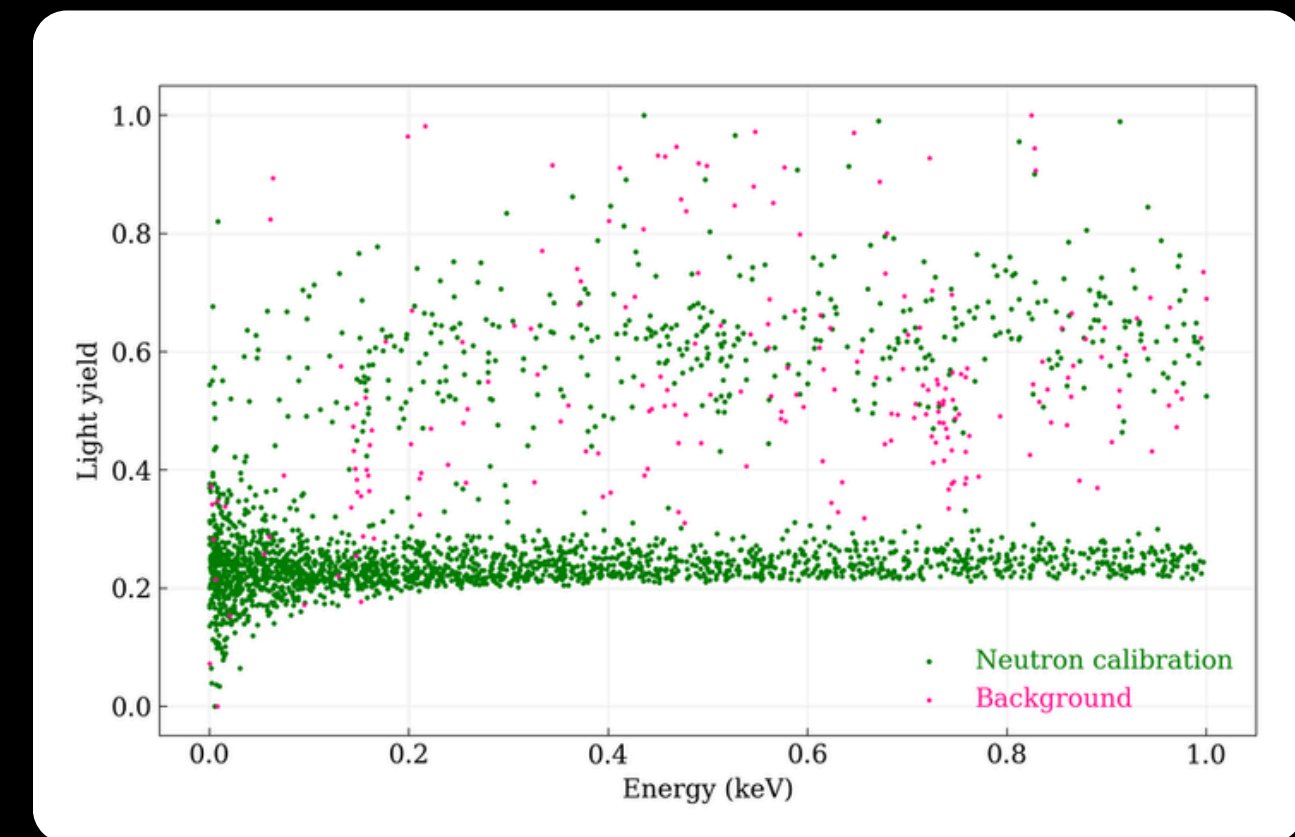
We want to
learn the density
of the bands
for each data set

PRE-PROCESSING STEPS

Before giving to the flow, we need to give a **little hair cut** to our data

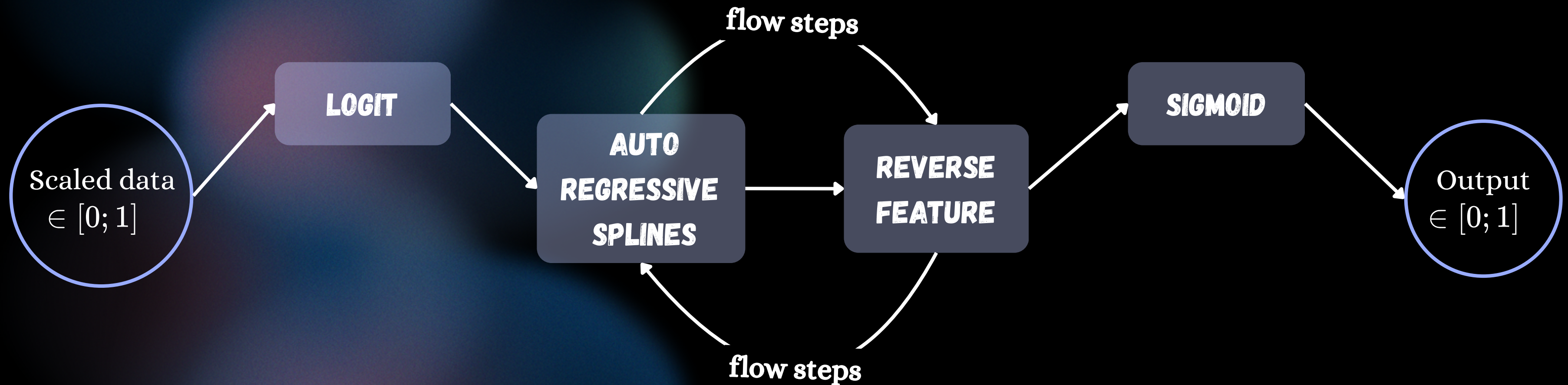


Cut the low-energy excess
 $E > 0.5 \text{ keV}$



Rescaling between 0 & 1

TRAINING THE FLOW



<https://github.com/bayesiains/nflows>

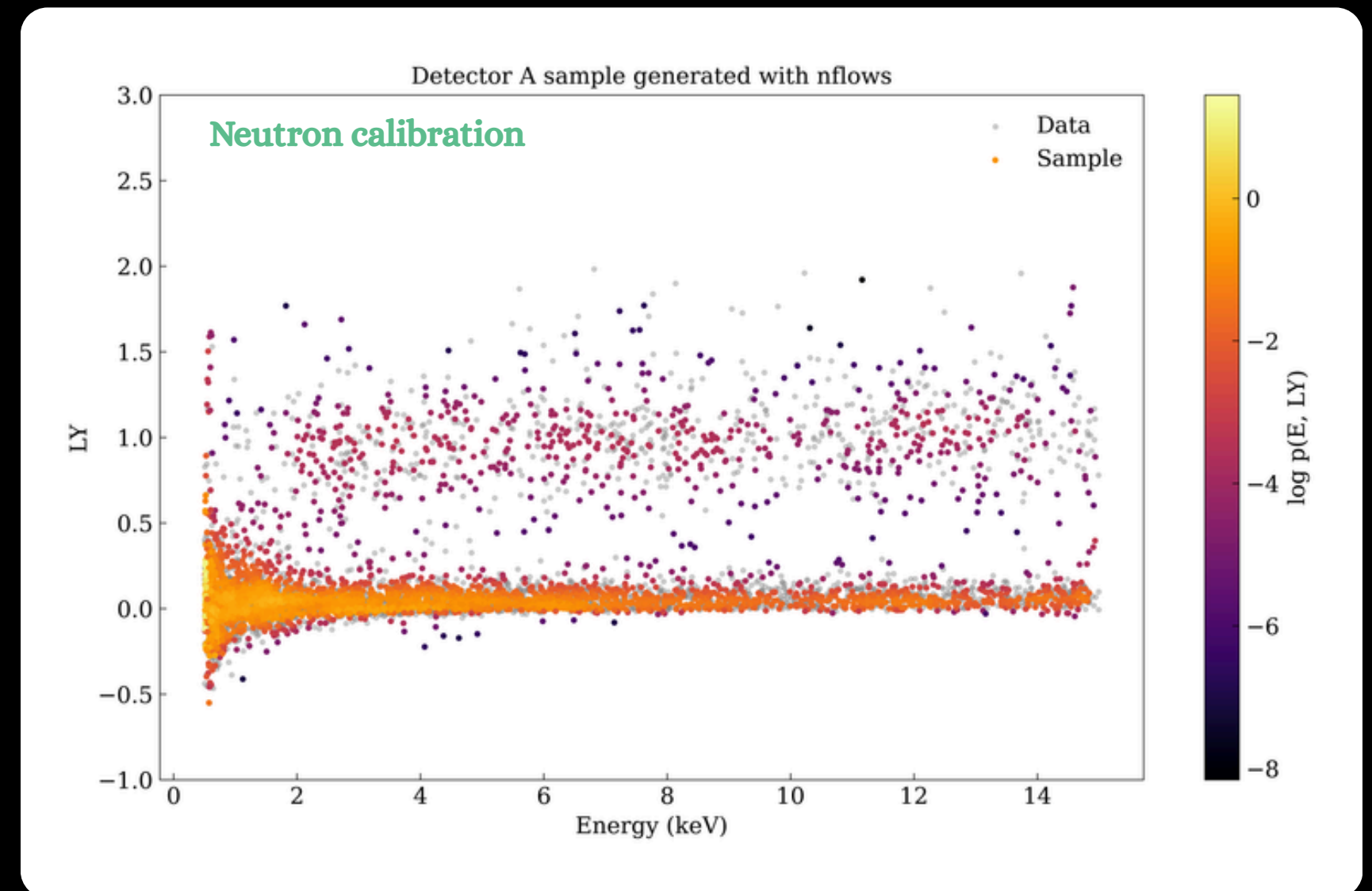
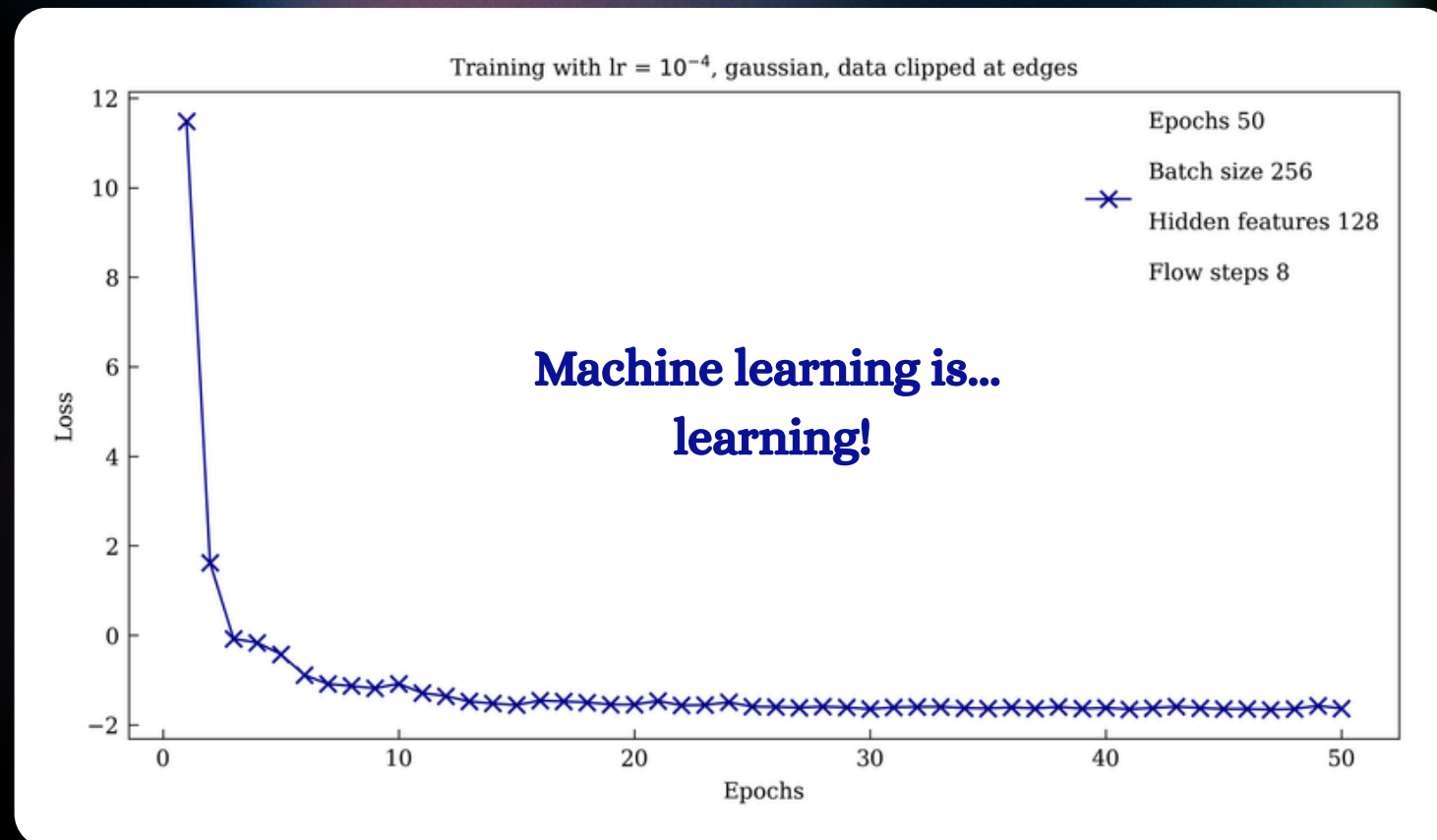
Neural Spline Flows

Conor Durkan, Artur Bekasov, Iain Murray, George Papamakarios

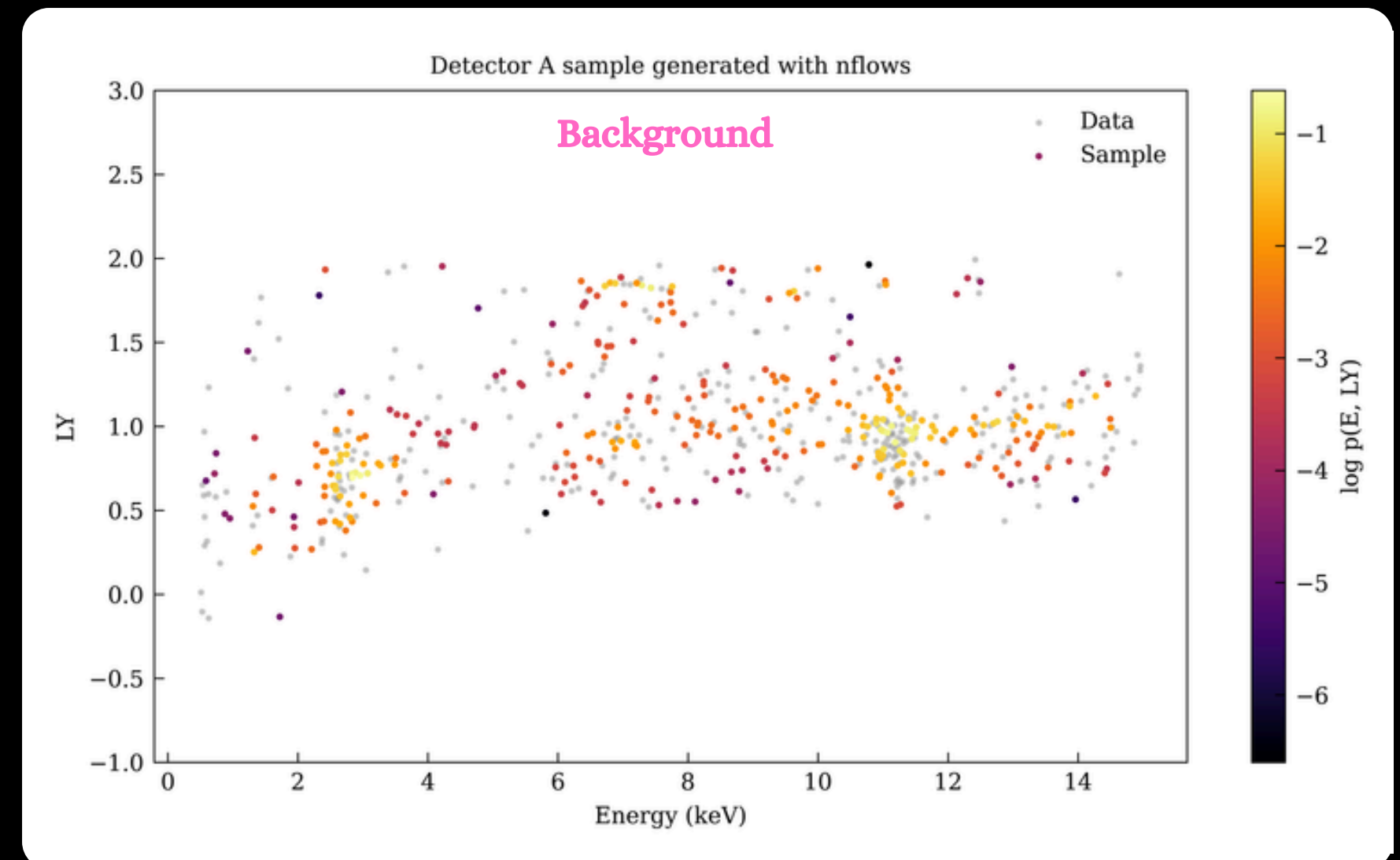
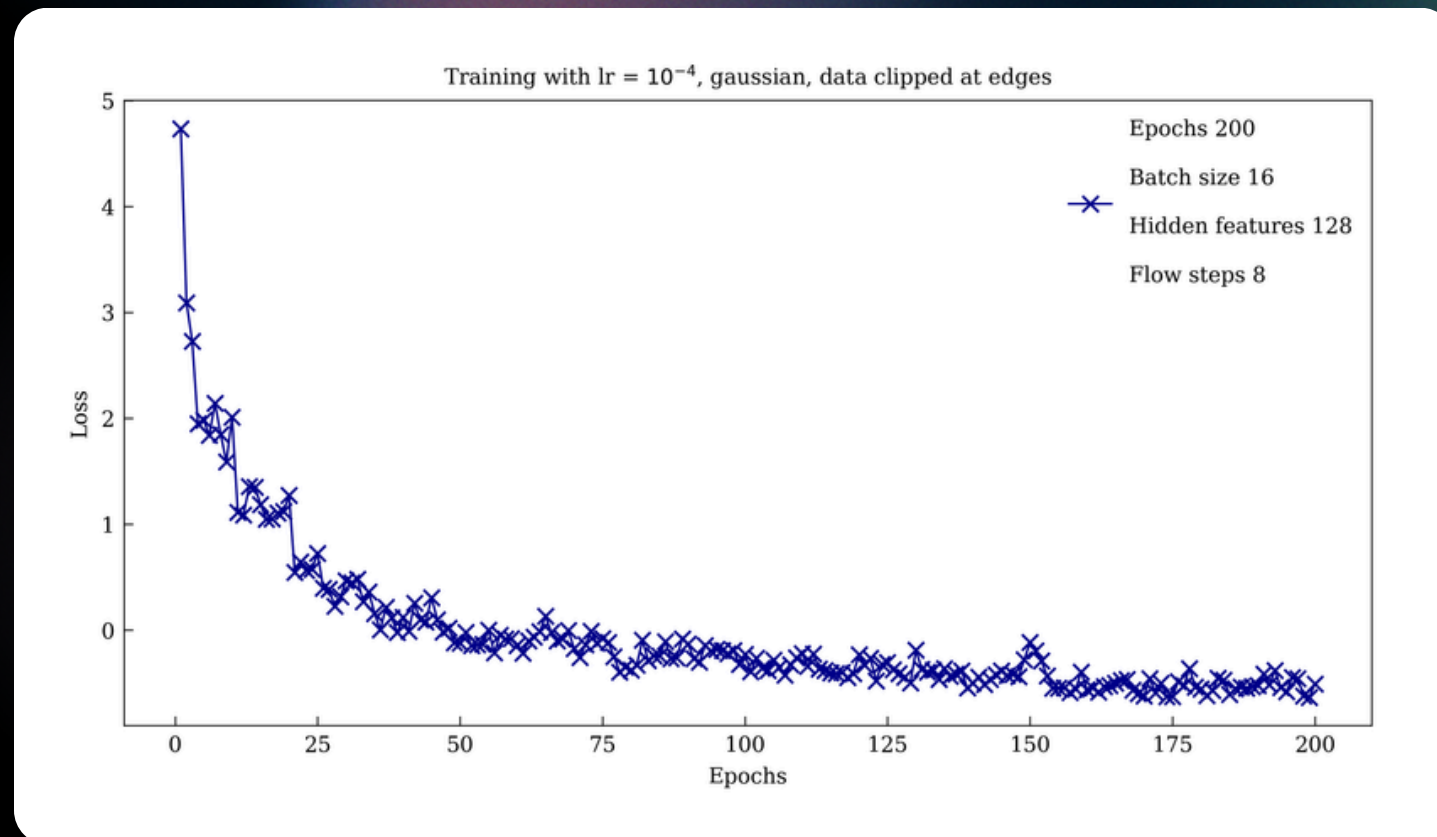
Masked Autoregressive Flow for Density Estimation

Conor Durkan, Artur Bekasov, Iain Murray, George Papamakarios

RESULTS FOR NEUTRON CALIBRATION

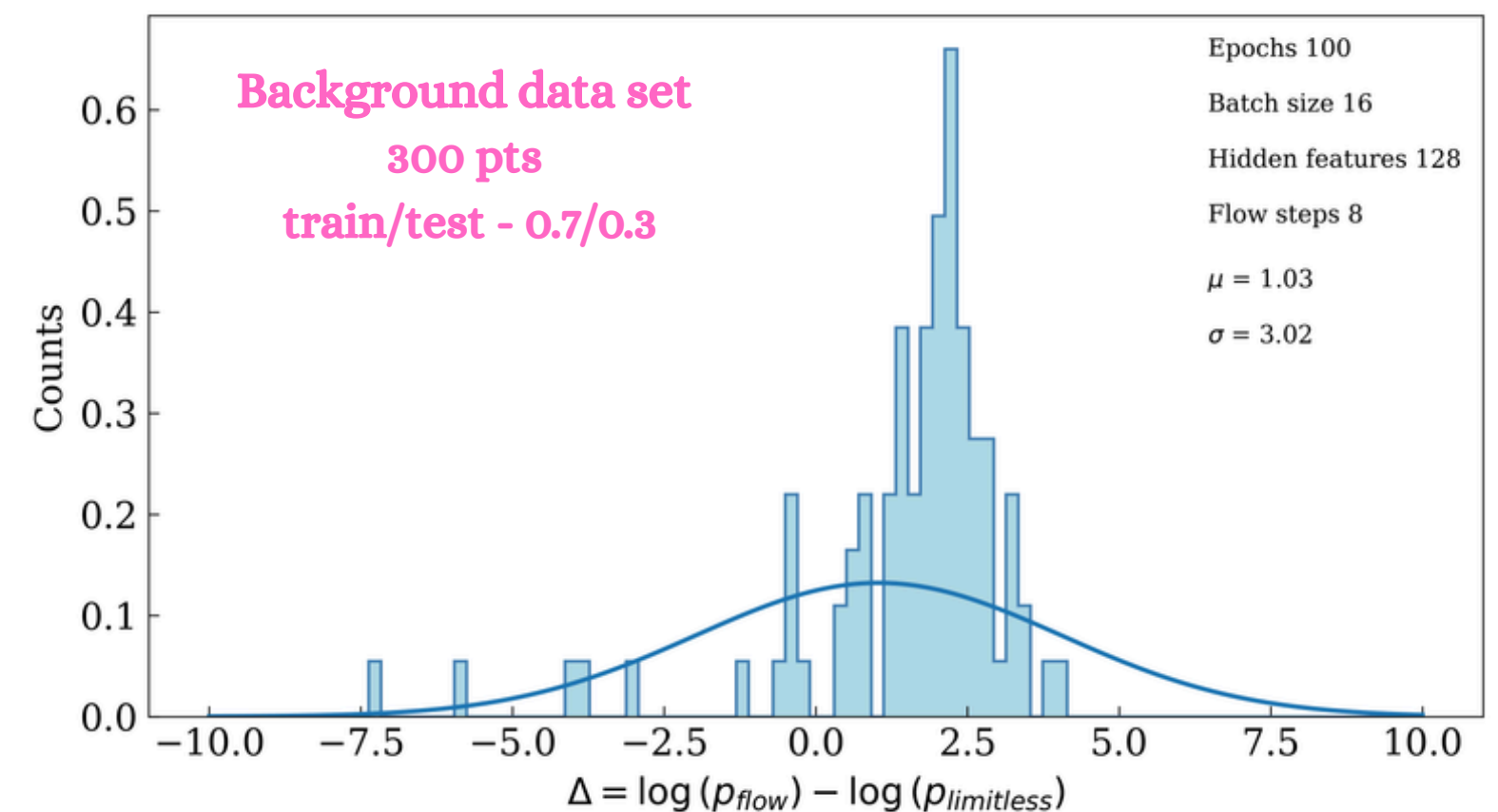
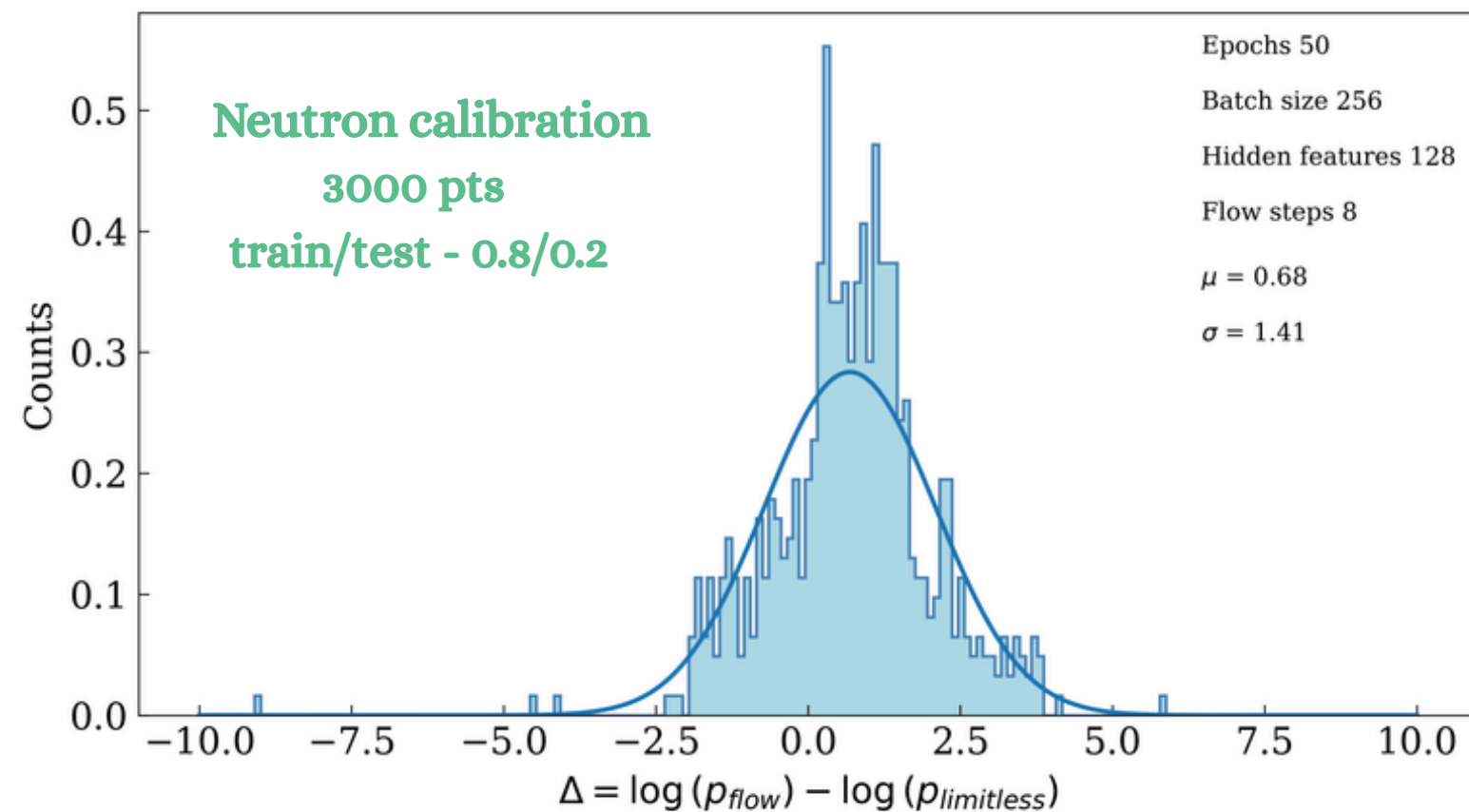


RESULTS FOR BACKGROUND DATA



DENSITIES COMPARISON

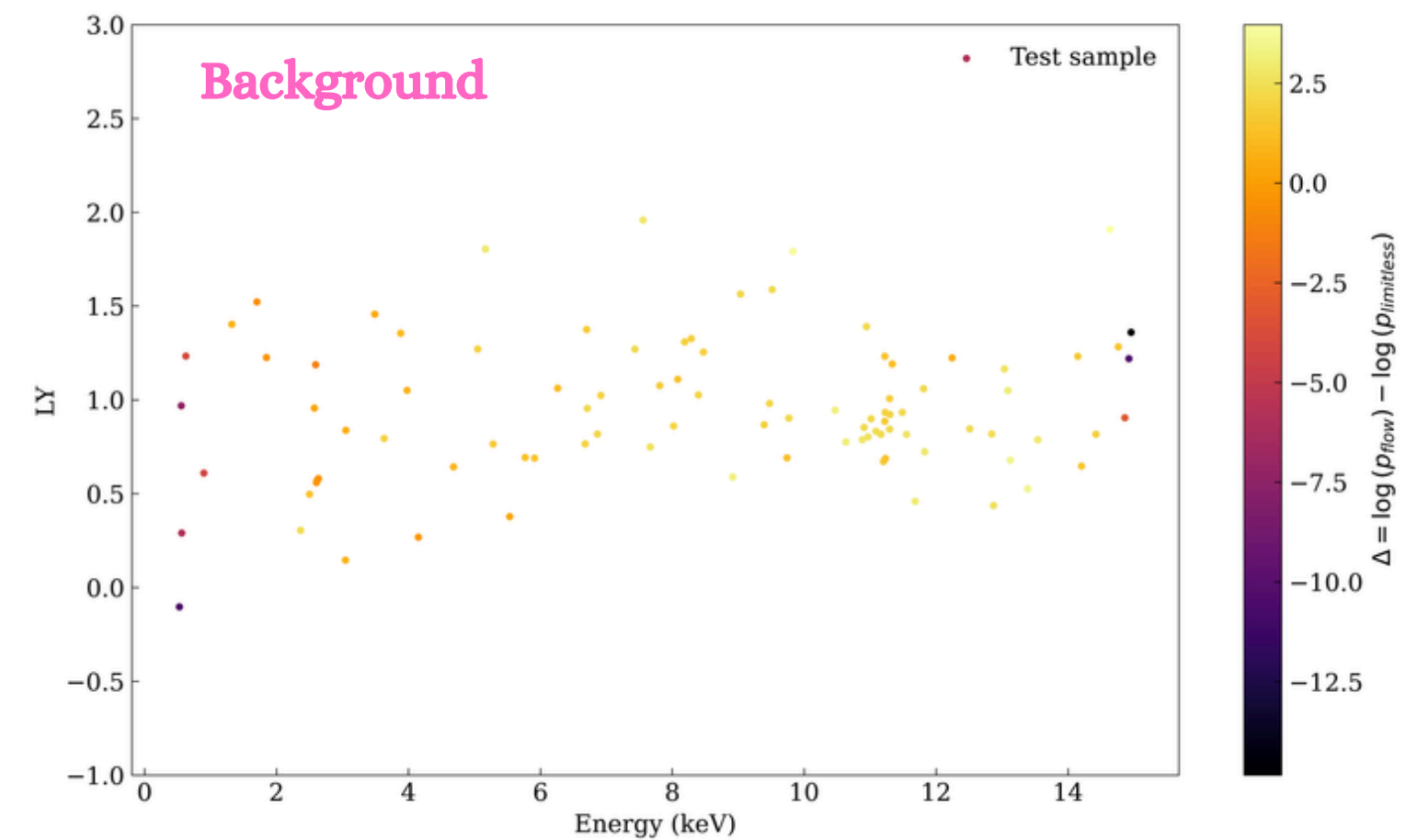
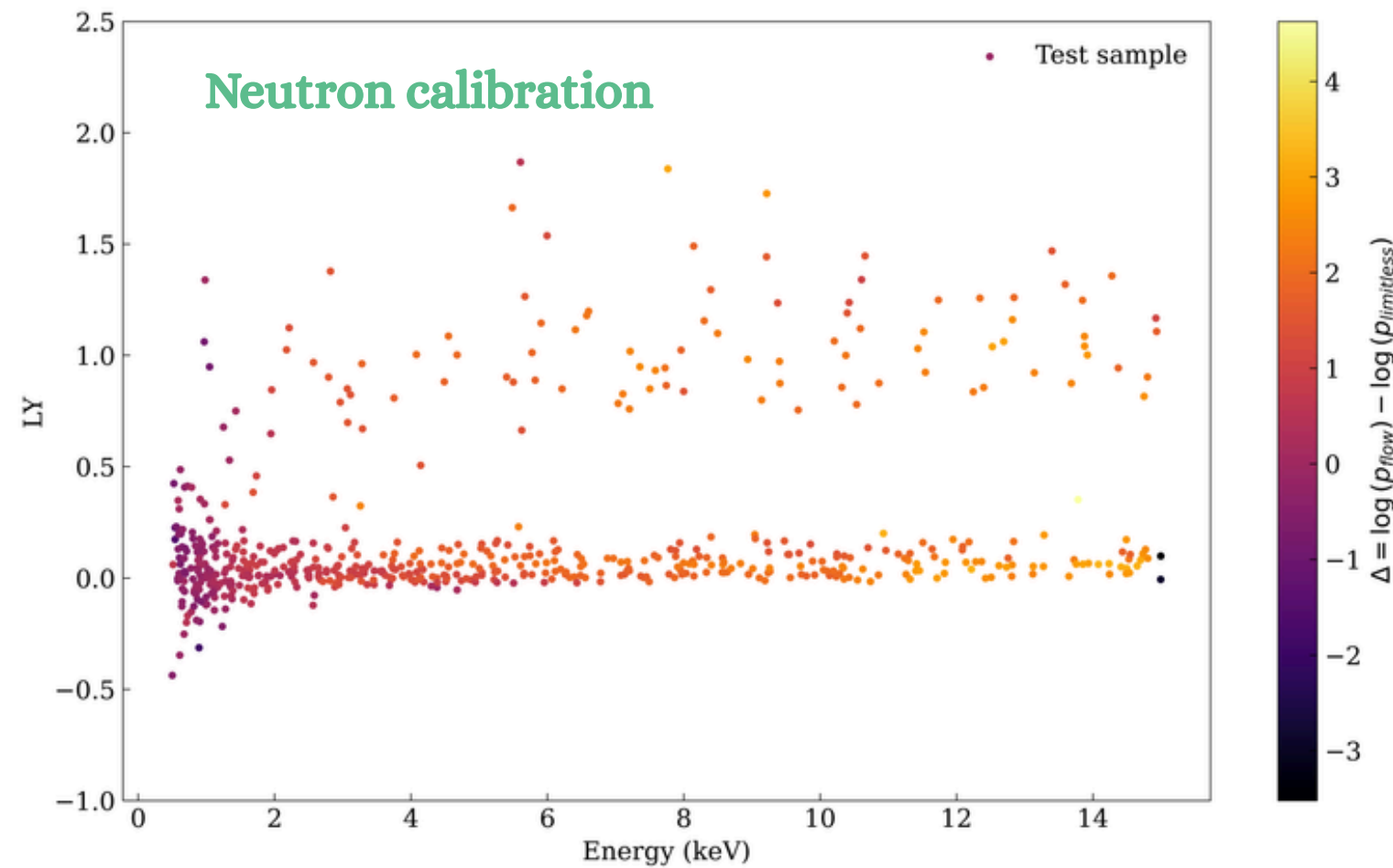
$$\Delta = |\log p_{flow} - \log p_{data}|$$



Suffers from the low statistics

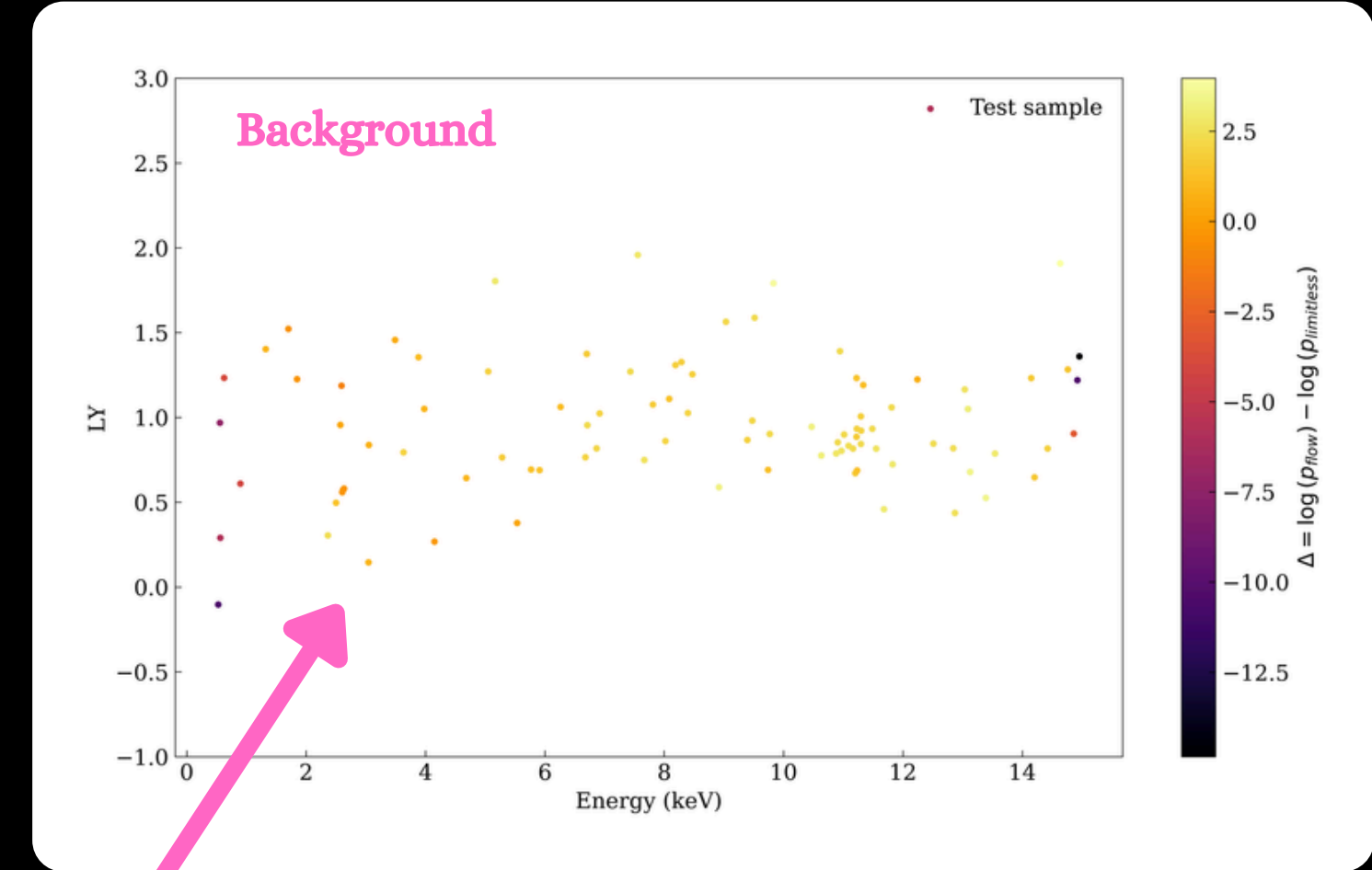
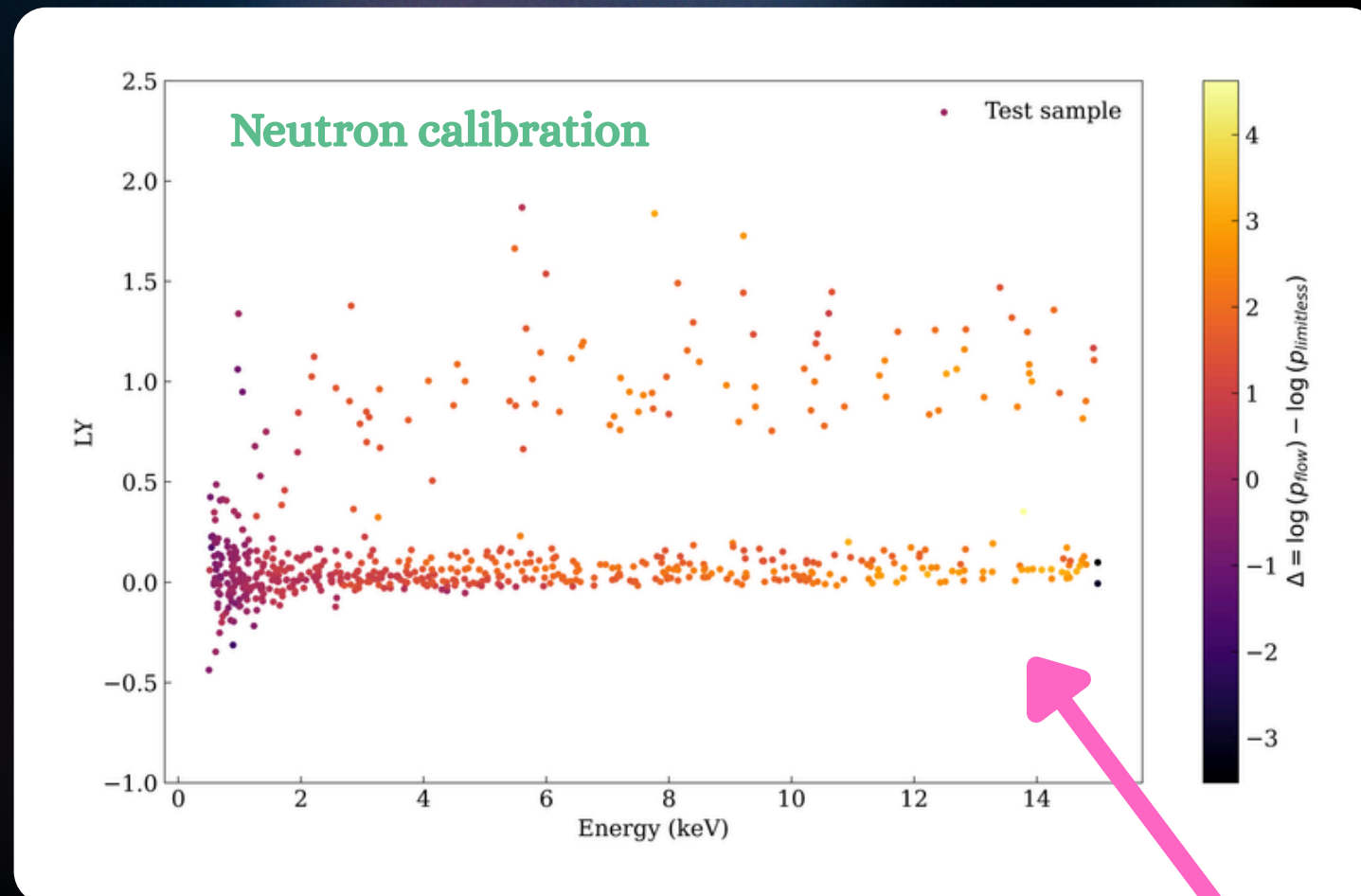
DENSITIES COMPARISON

$$\Delta = |\log p_{flow} - \log p_{data}|$$



DENSITIES COMPARISON

$$\Delta = |\log p_{flow} - \log p_{data}|$$



Next: map the density difference on the all plane to understand better where the discrepancies are coming from

CONCLUSION

Is there **enough statistics** for the flow to learn properly?

Are the densities of our data well captured by the **gaussian model**?

Can we derive **sensitivity limits** with the density computed by the flow?

Did LZ just detected **dark matter**?

arXiv:2609.02823

