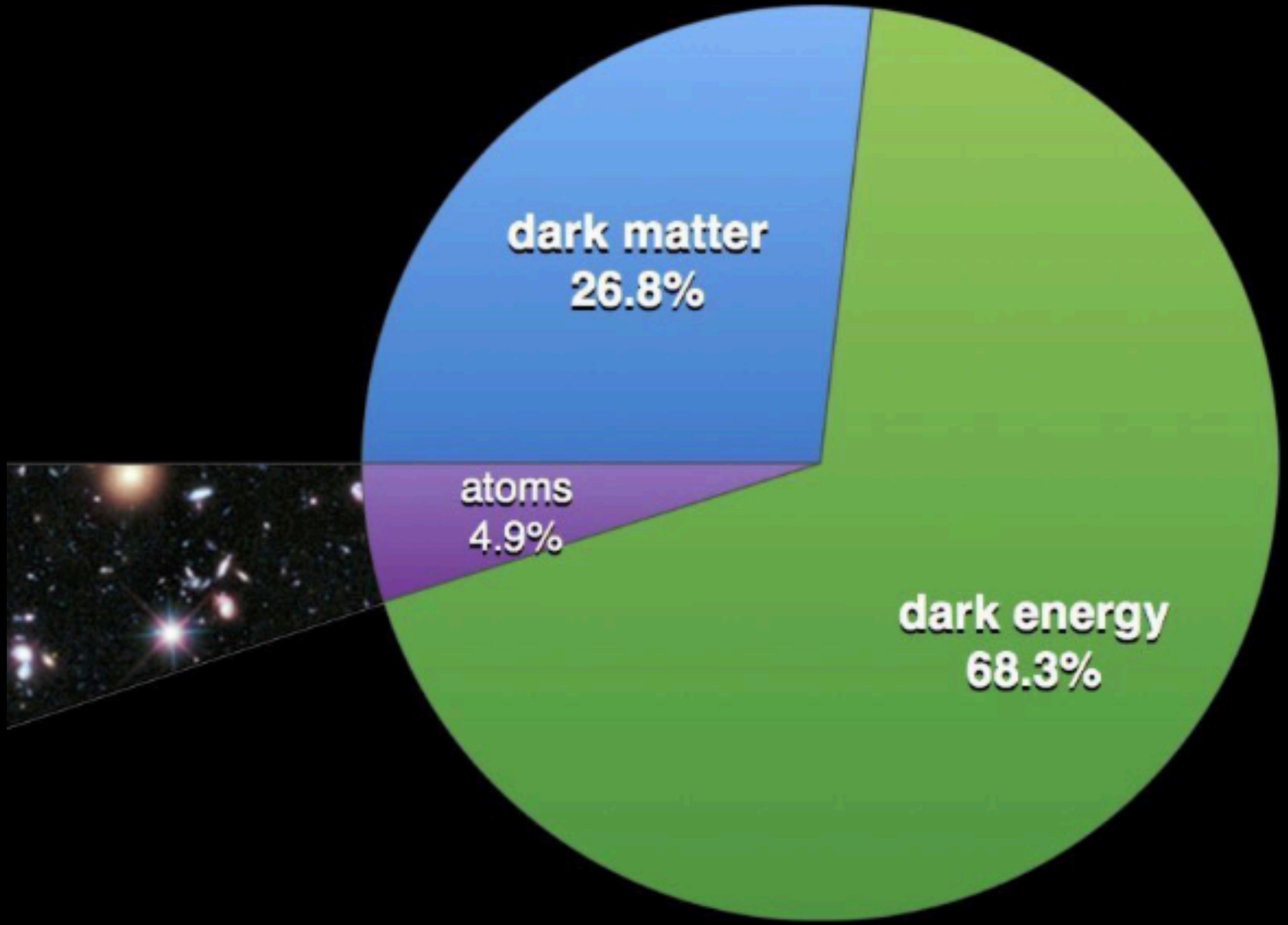
Anomaly aware machine learning for dark matter direct detection at DARWIN

PHYSTAT 10/11/2024, London

Andre Scaffidi and **Roberto Trotta** for the DARWIN collaboration

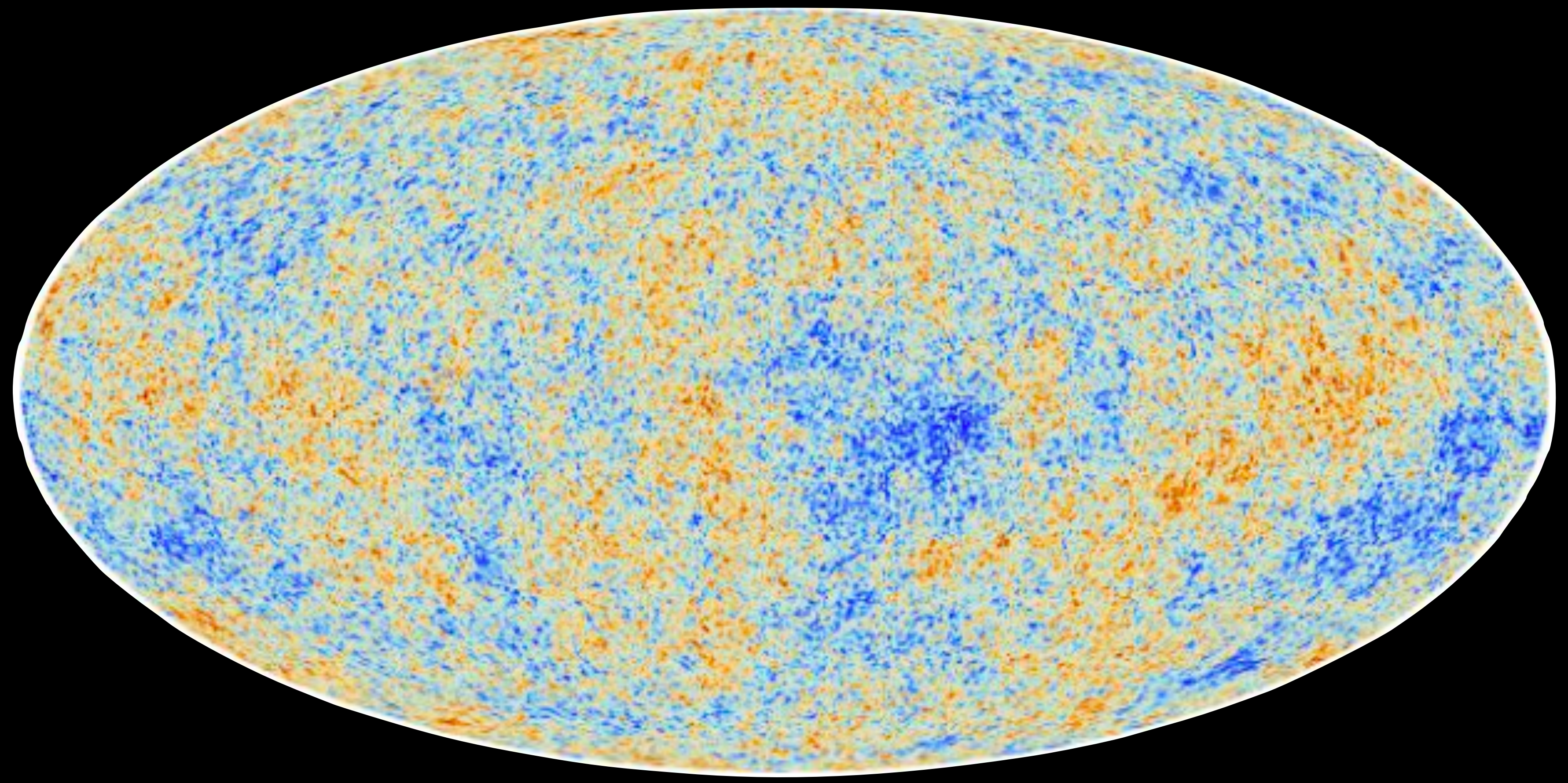


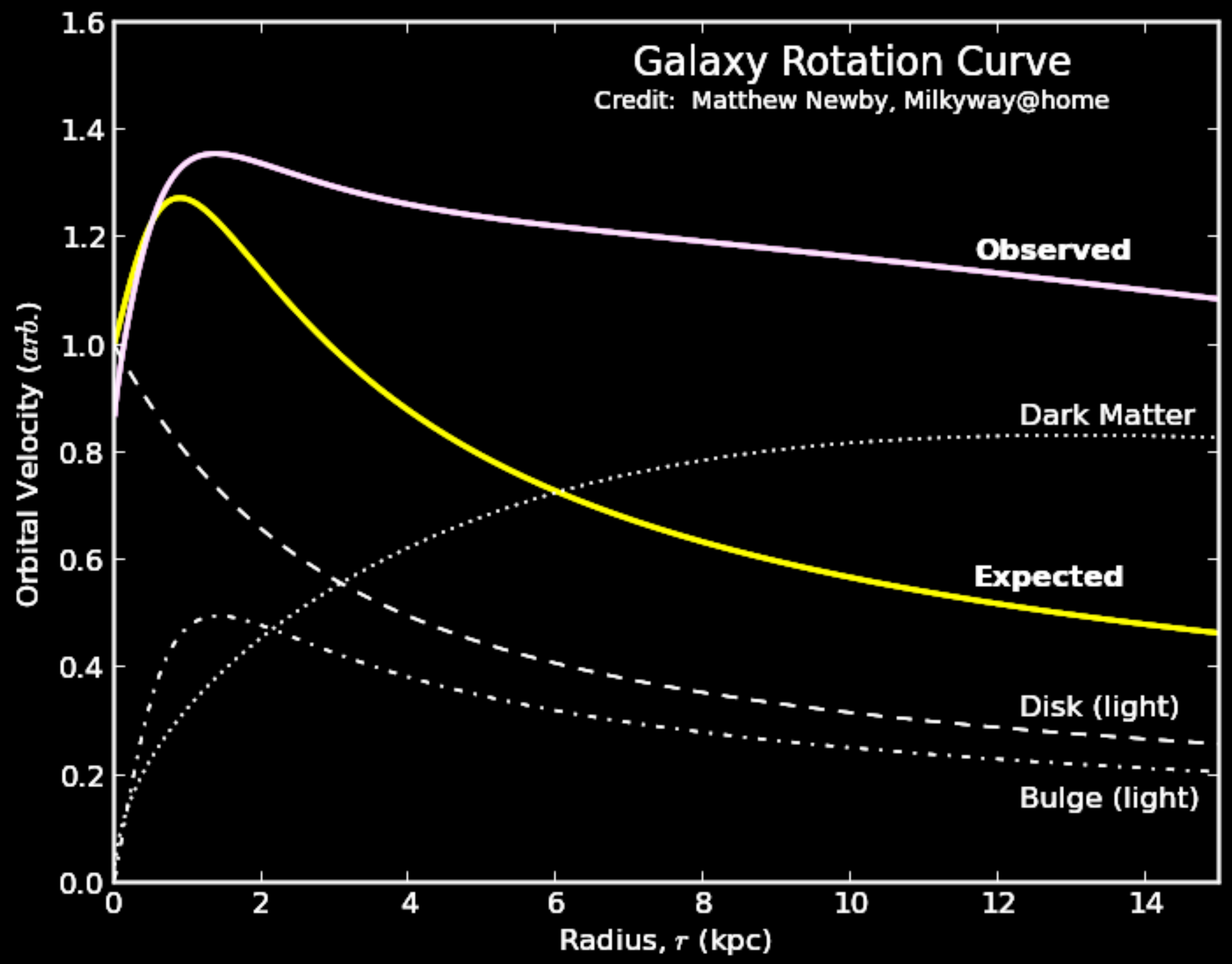
@AstroKatie/Planck13

The search for dark matter

Abundant evidence for DM:

- CMB accoustic oscillations
- Bullet cluster
- Star roation curves

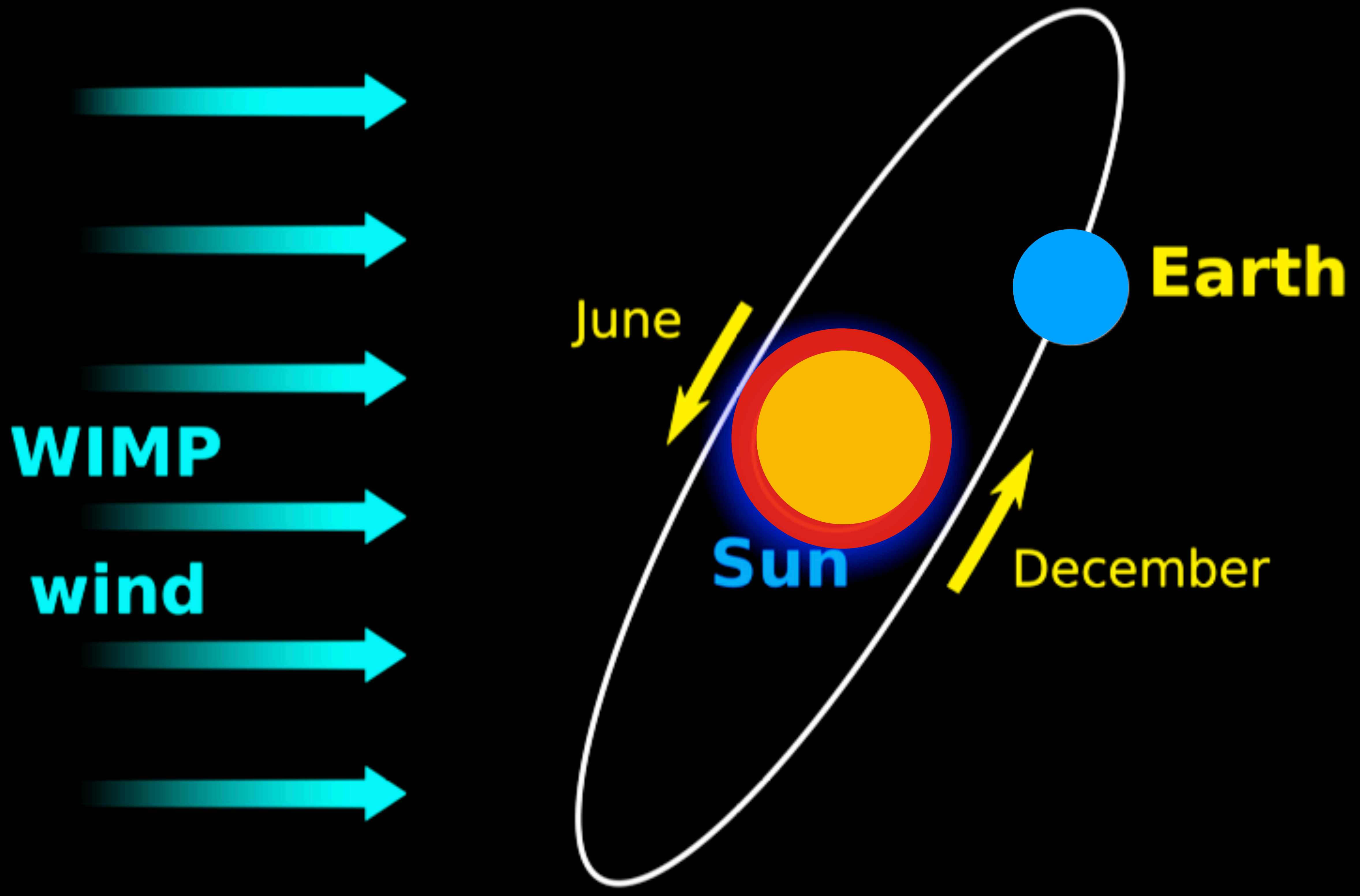




The search for dark matter

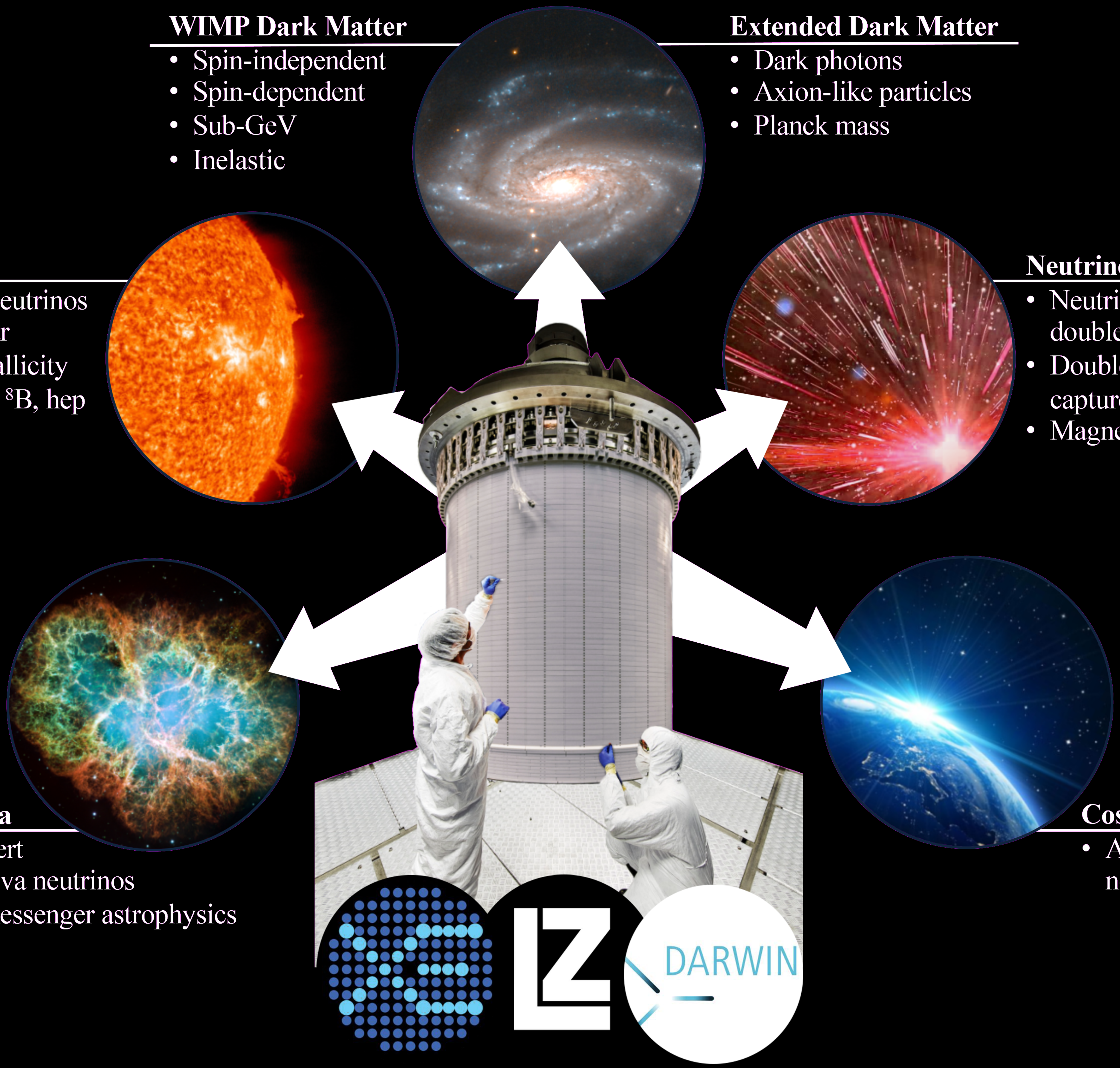
Terrestrial direct detection:

- Earth flying through 'WIND' of dark matter
- Detect it on Earth?



XLZD: XENON-LUX-ZEPLIN-**DARWIN**

(Design book in preparation)



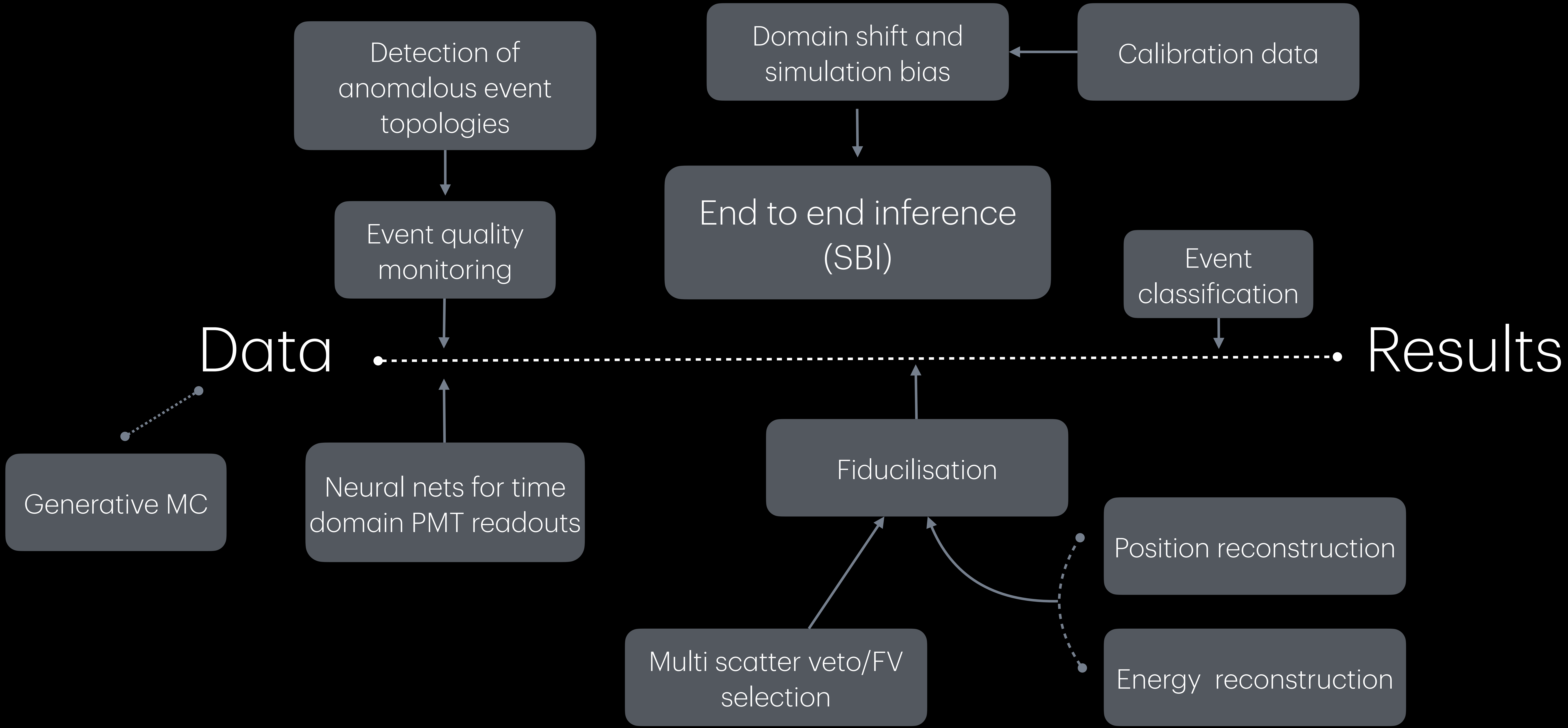
DARWIN

- Leading R&D for 40+ tonne detectors

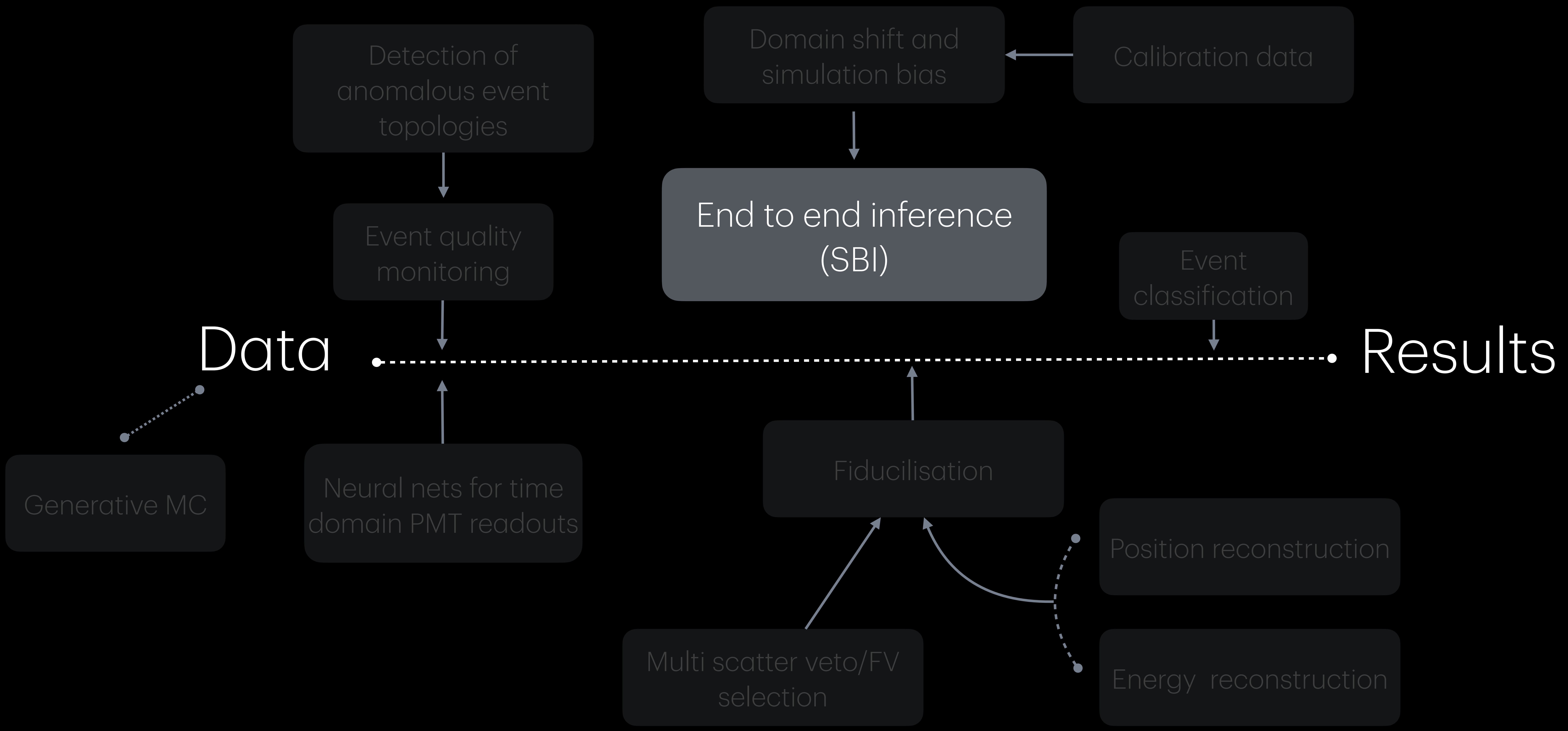
This aim:

- **Develop deep/ML tools for enhancing the analysis pipeline.**
- Collaboration paper out soon!

Current/Future ML scope @ DARWIN/XLZD



Current/Future ML scope @ DARWIN/XLZD

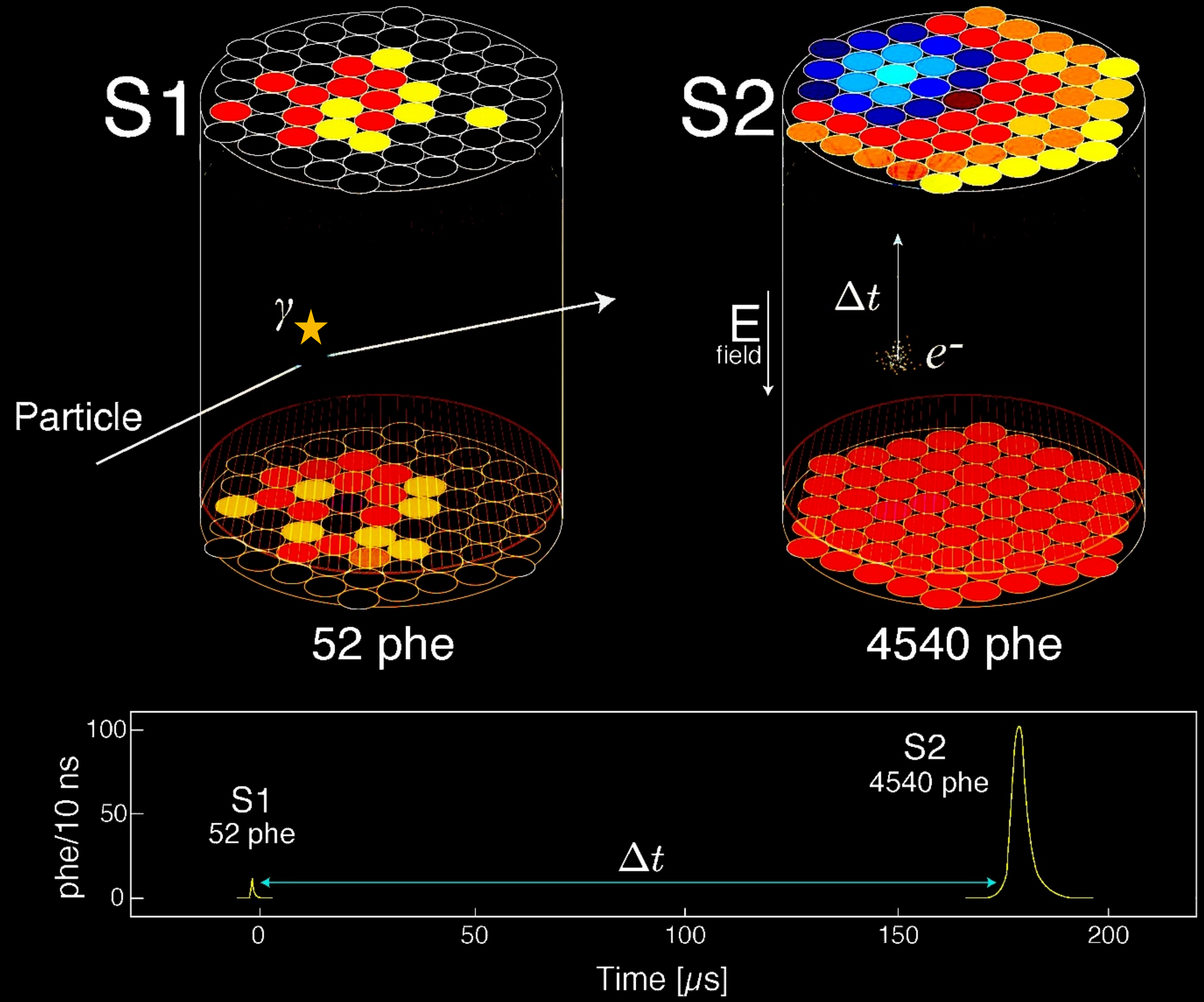


The Time Projection Chamber (TPC)

- Liquid and gaseous Xe
  Two photo sensor arrays (top and bottom)
- Two signals:
  Photons (primary scintillation S1)
  Electrons (ionisation)
- Electrons drifted along electric field into gas phase
  →Secondary scintillation
- Extract high-level 'summary statistics':

  $$\mathbf{cS1, cS2}$$

- Proxy for **recoil energy**
  - $\mathbf{cS1, cS2 \Rightarrow E = g(cS1, cS2)}$

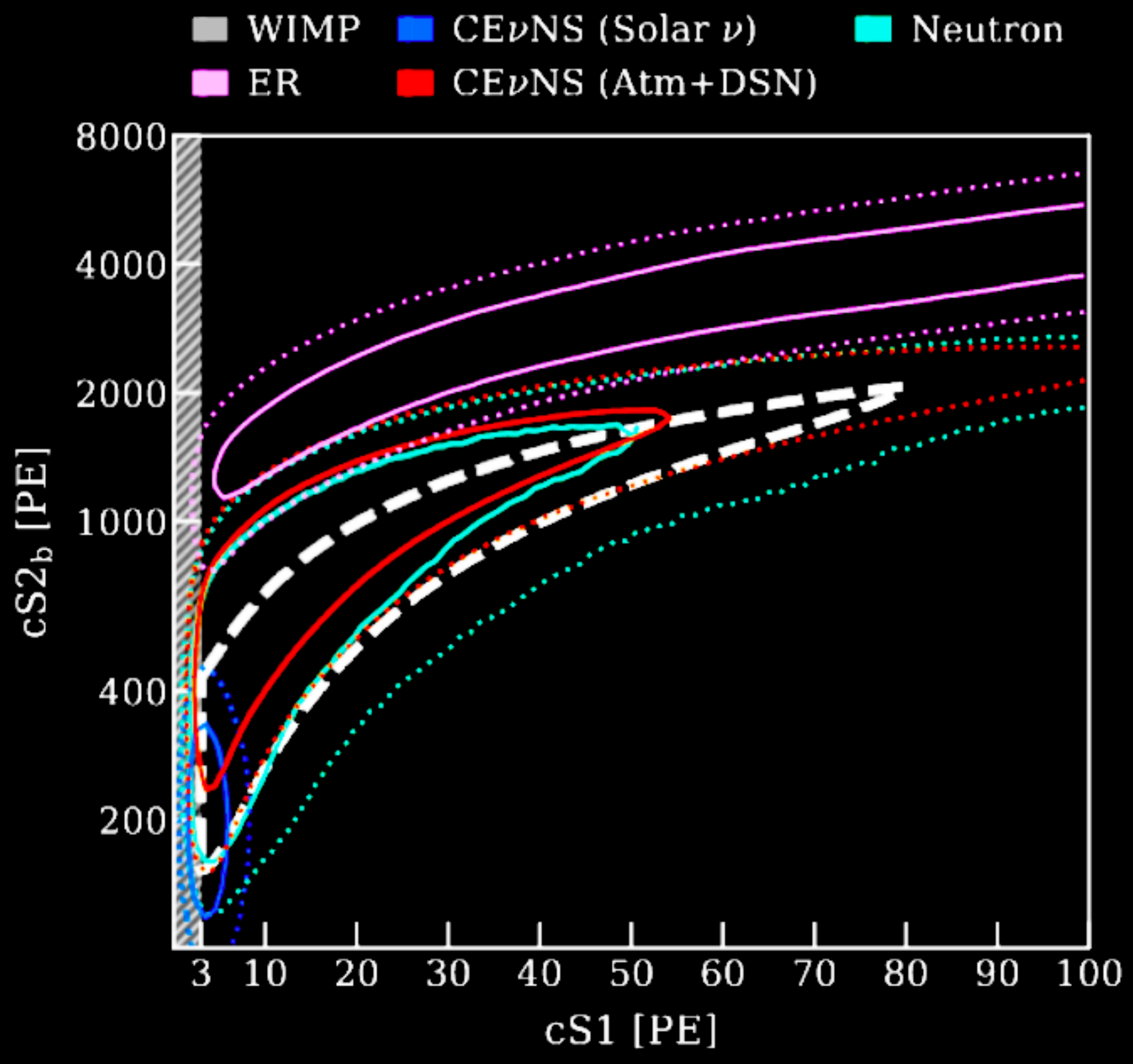


Traditional likelihood-based analysis

$$\log \mathscr{L}(\mathbf{cS1}, \mathbf{cS2} \mid \sigma_{\mathsf{SI}}, \boldsymbol{\theta}) = \log \mathscr{L}_{\text{science}}(\mathbf{cS1}, \mathbf{cS2} \mid \sigma_{\mathsf{SI}}, \boldsymbol{\theta}) + \log \mathscr{L}_{\text{ancillary}}(\boldsymbol{\theta})$$

- Parametrically model dependent
- Derived from 2D templates
- Costly…

Does this likelihood yield an optimal test statistic?

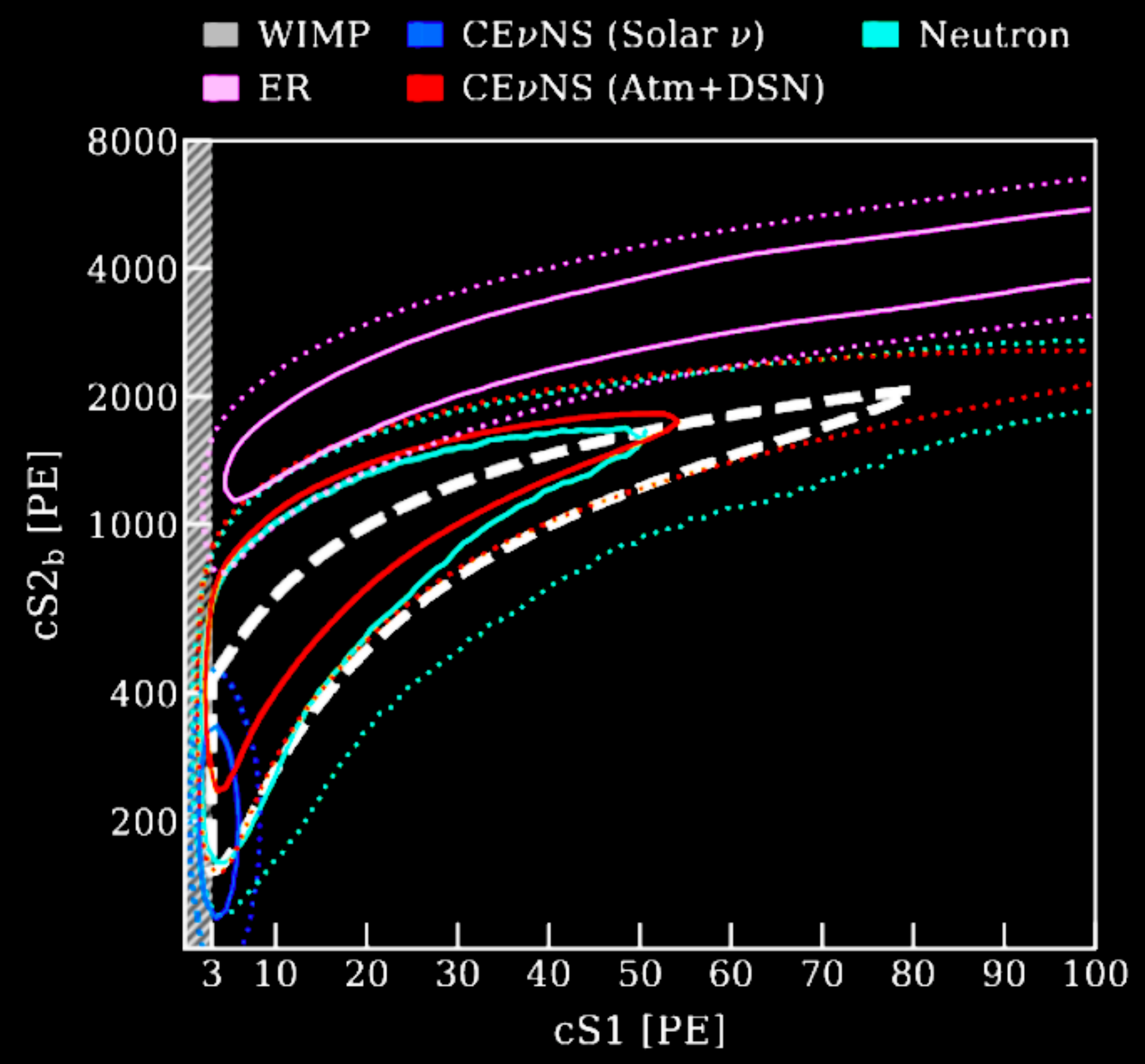


Traditional likelihood-based analysis

$$\log \mathscr{L}(\mathbf{cS1}, \mathbf{cS2} \mid \sigma_{\mathsf{SI}}, \boldsymbol{\theta}) = \log \mathscr{L}_{\text{science}}(\mathbf{cS1}, \mathbf{cS2} \mid \sigma_{\mathsf{SI}}, \boldsymbol{\theta}) + \log \mathscr{L}_{\text{ancillary}}(\boldsymbol{\theta})$$

- Parametrically model dependent
- Derived from 2D templates
- Costly…

Does this likelihood yield an optimal test statistic?



Simulation based inference

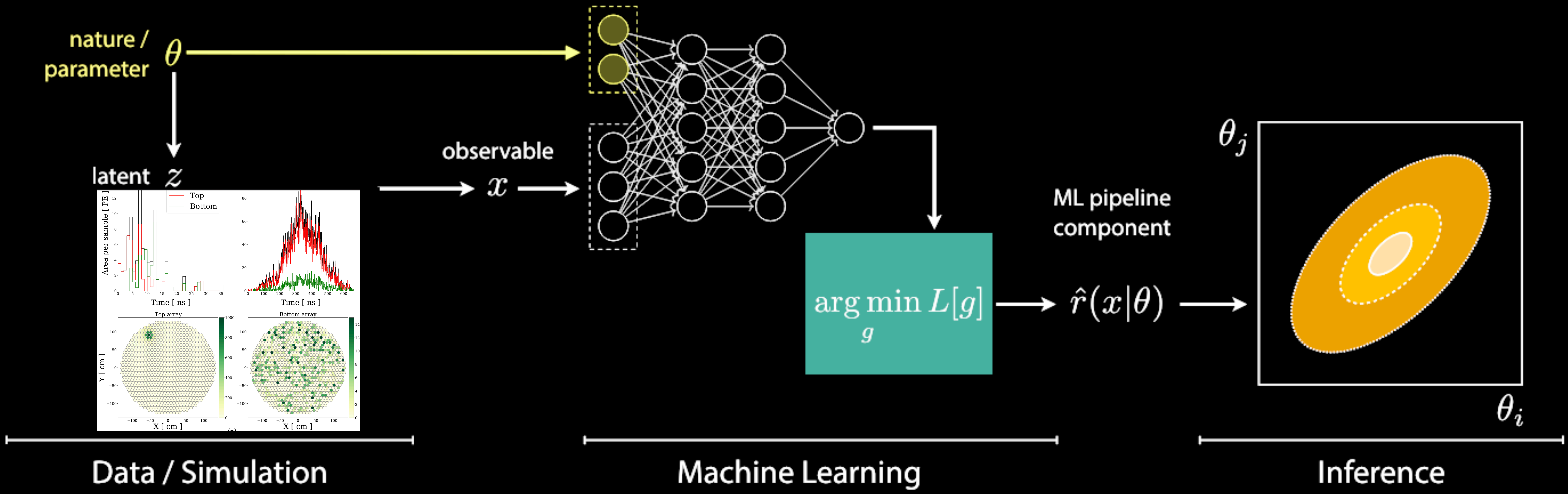


Diagram credit : Kyle Cranmer

**See talk by Will Handley and posters by Giovanni De Crescenzo, Kai Lehman

Simulation based hypothesis testing

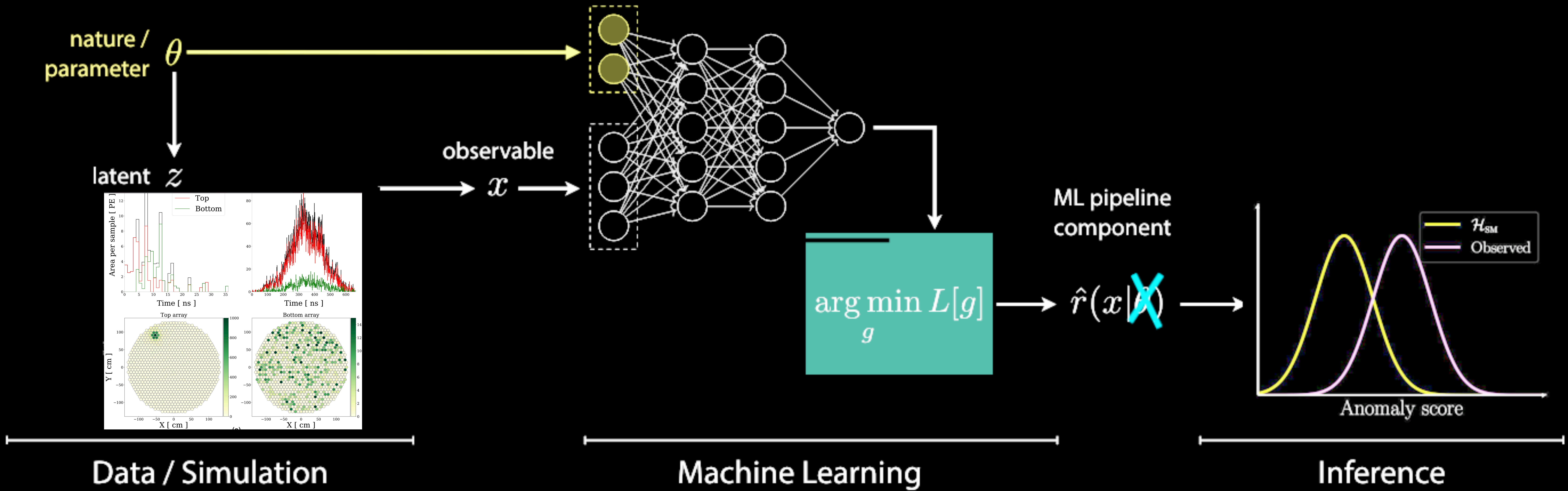
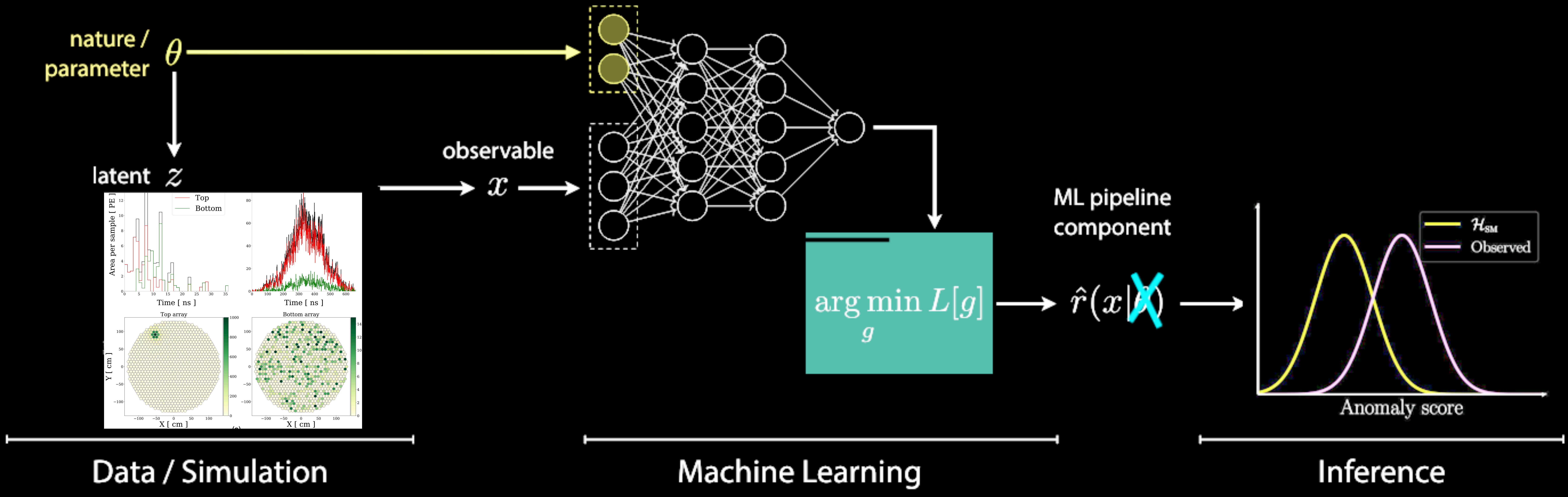


Diagram credit : Kyle Cranmer

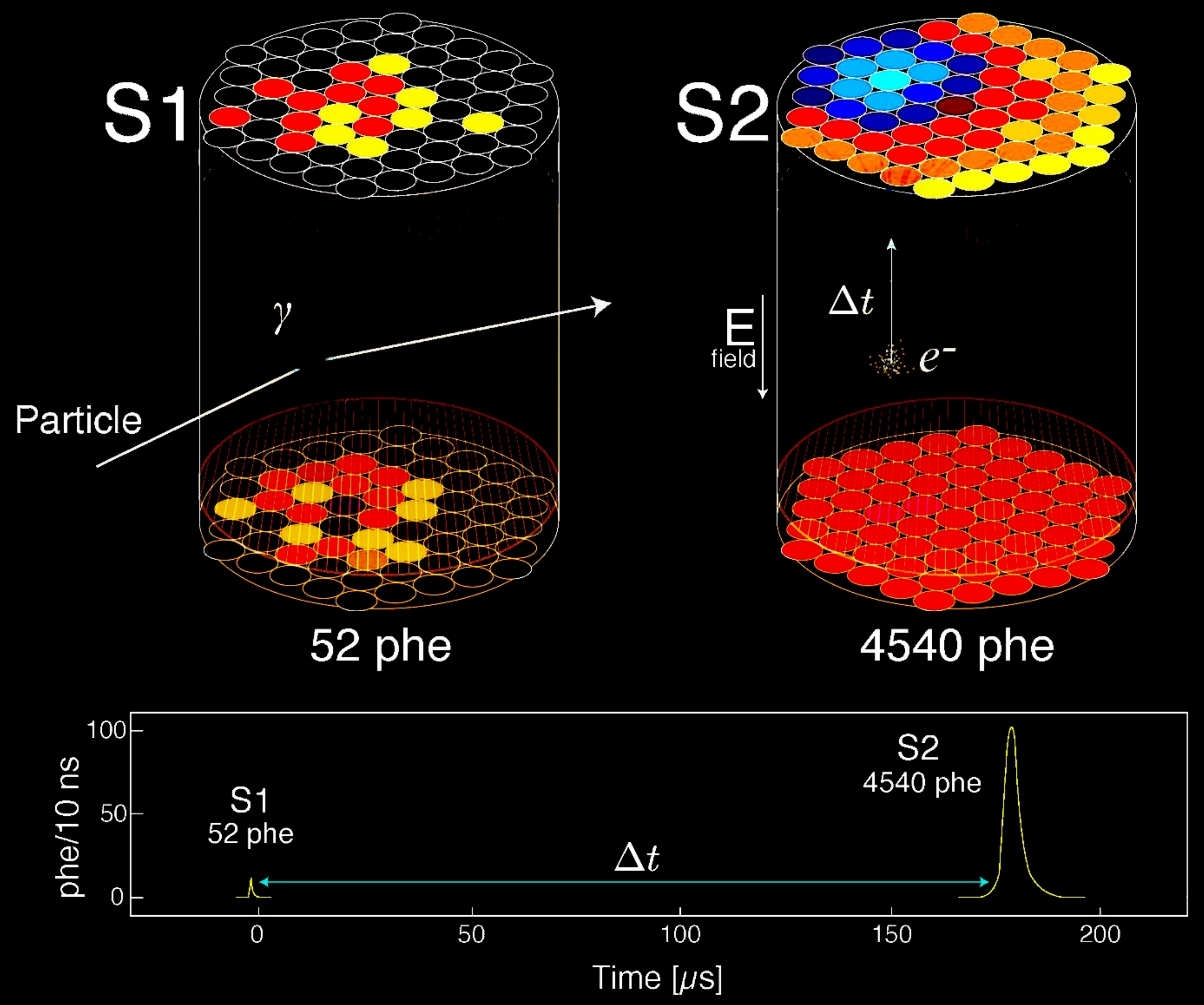
Simulation based hypothesis testing

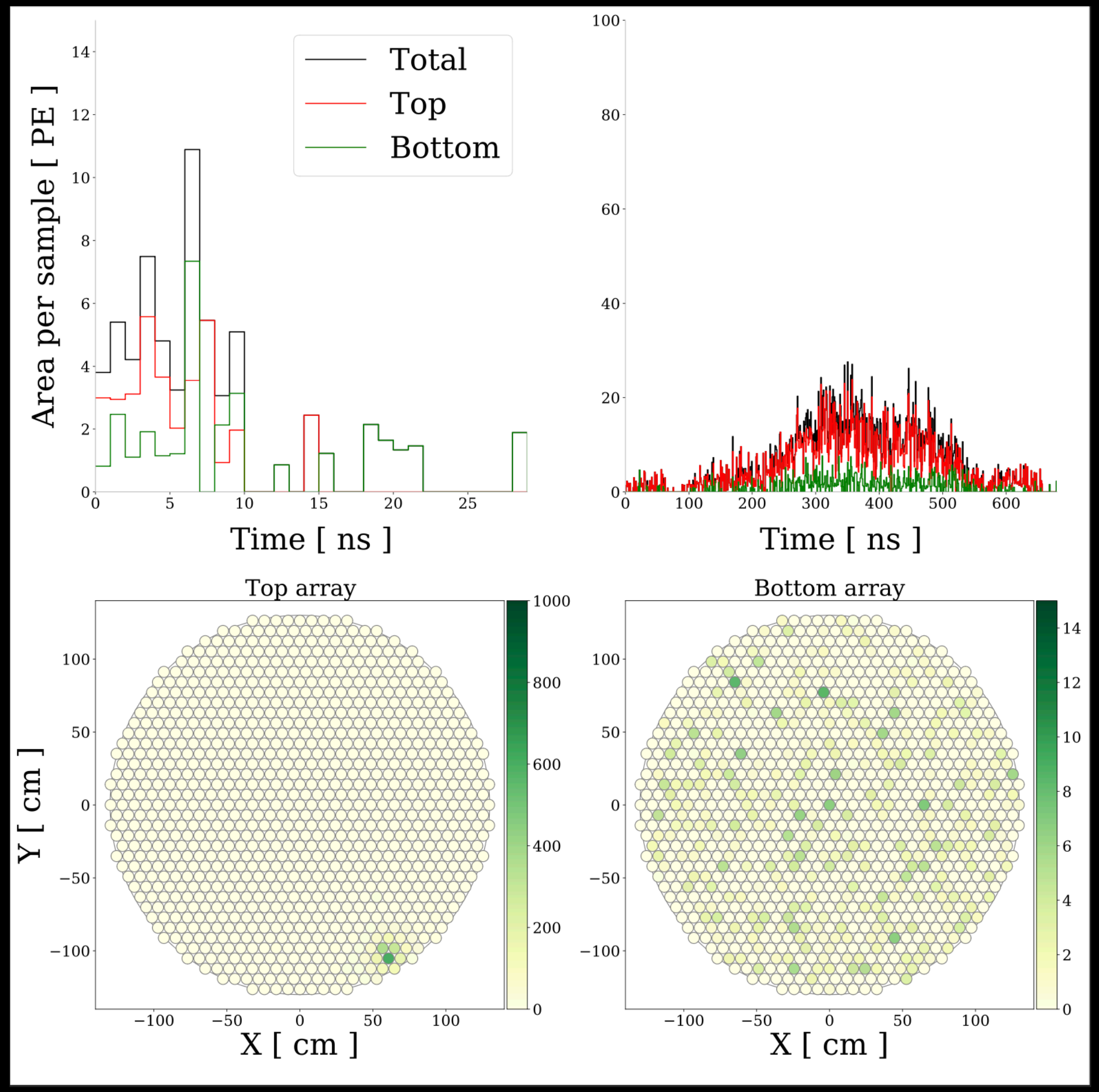


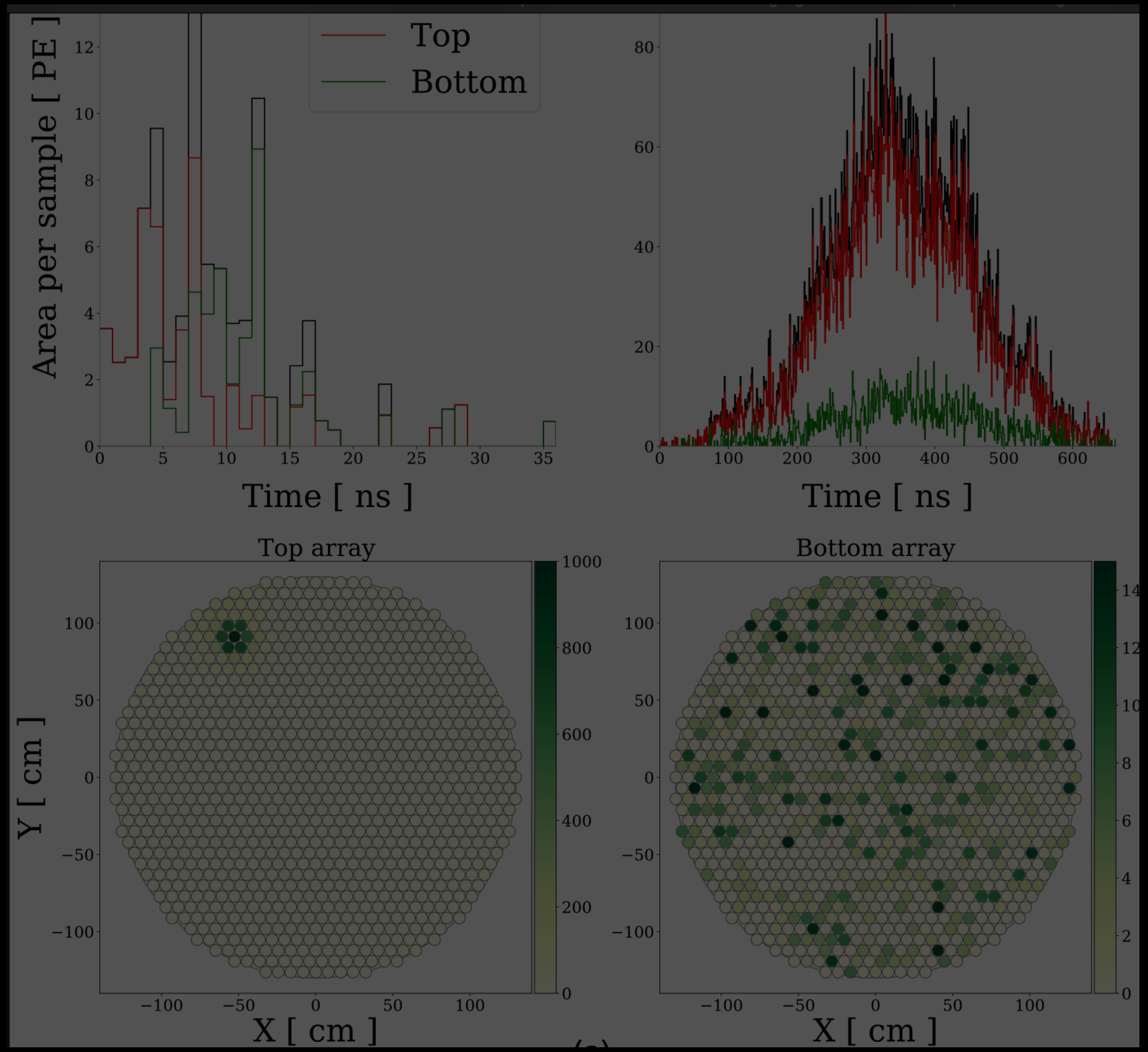
'Anomaly' refers to observation of significantly discrepant anomaly score distribution

Training on Event topologies

- **Nuclear Recoil (NR)** → Associated with WIMPs
- **(Dominant) Background** → Linked to Electron Recoil (ER)
- **S1/S2 Peak Distance & Ratio** → Used to distinguish NR from ER

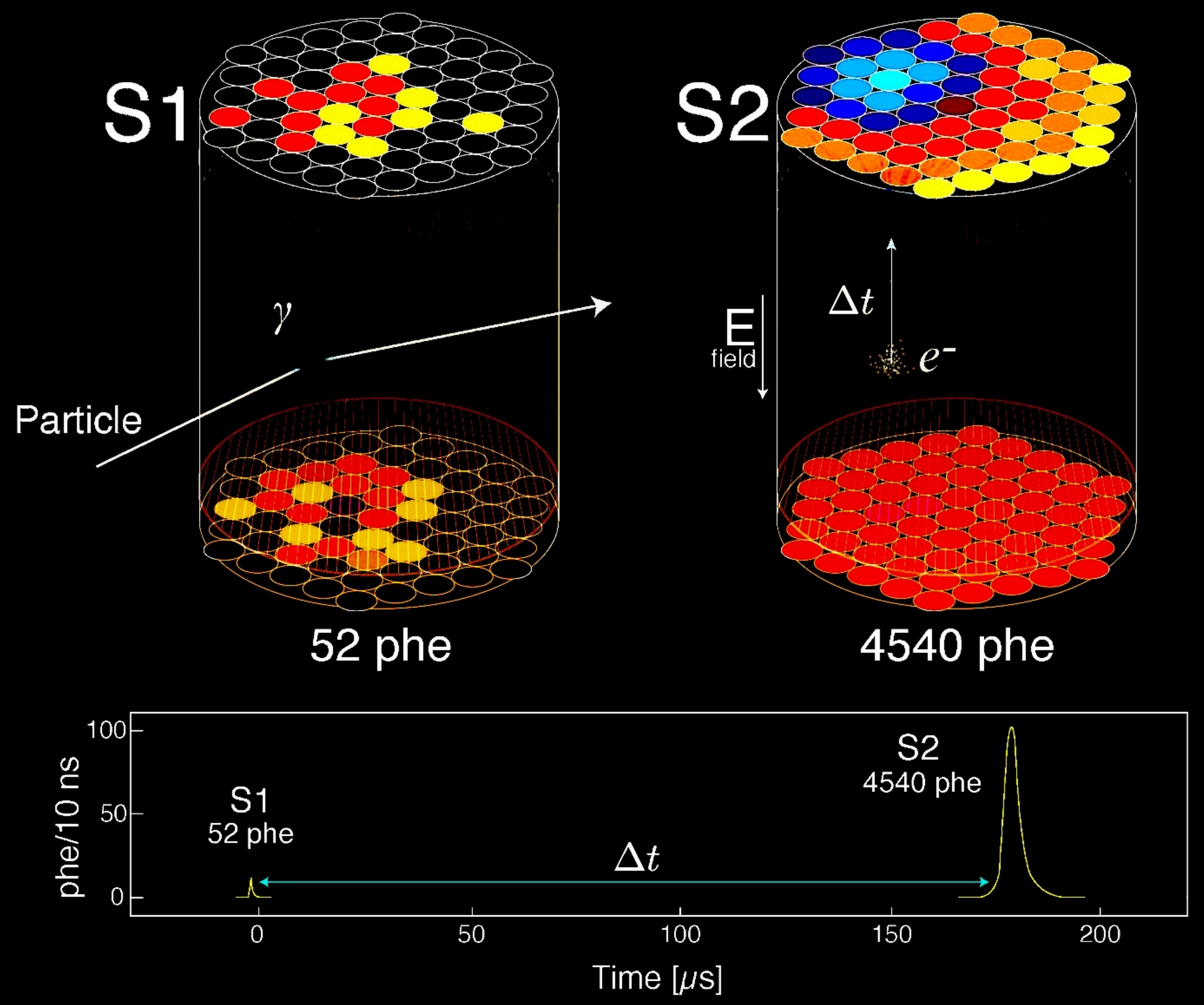


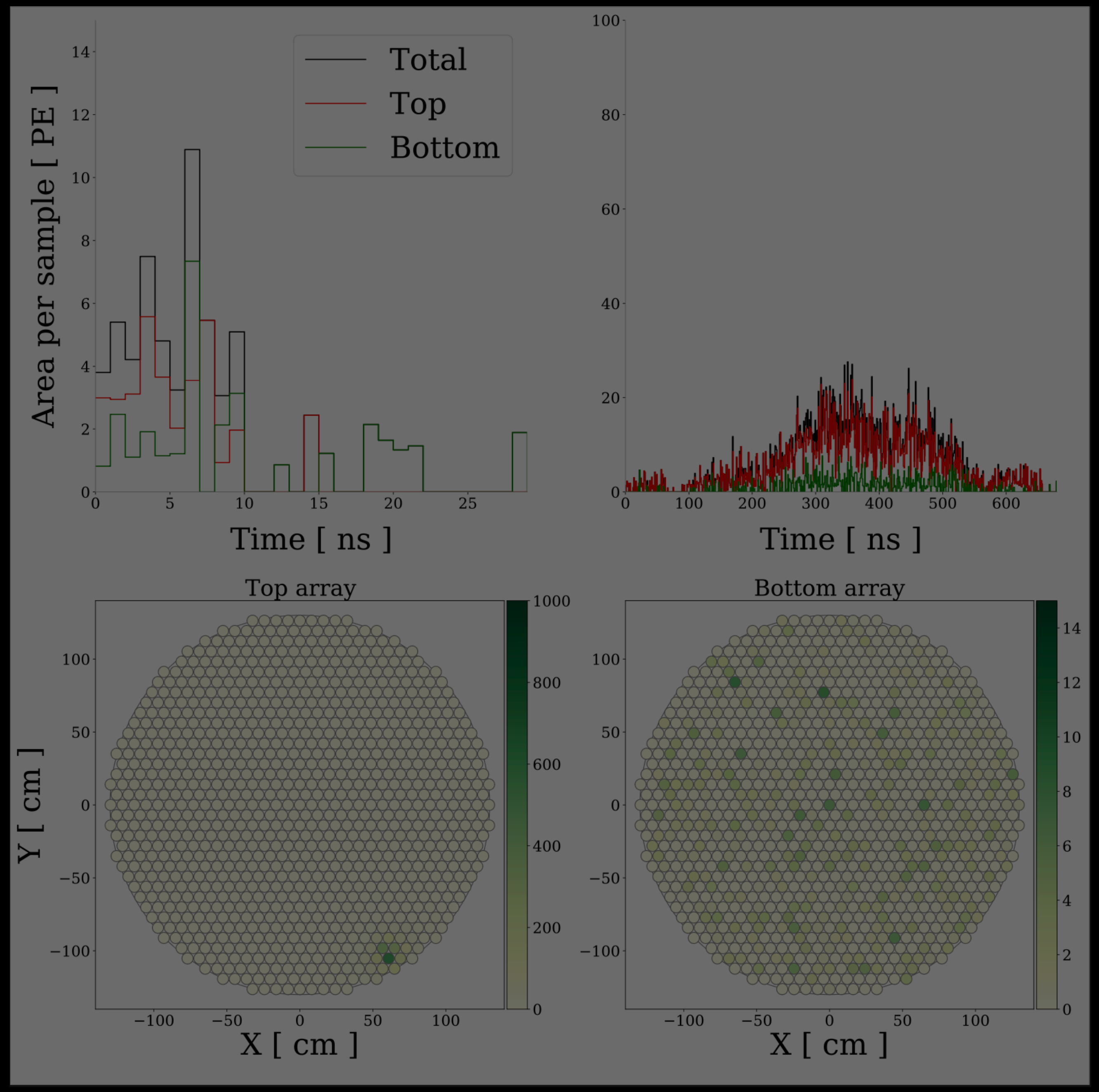


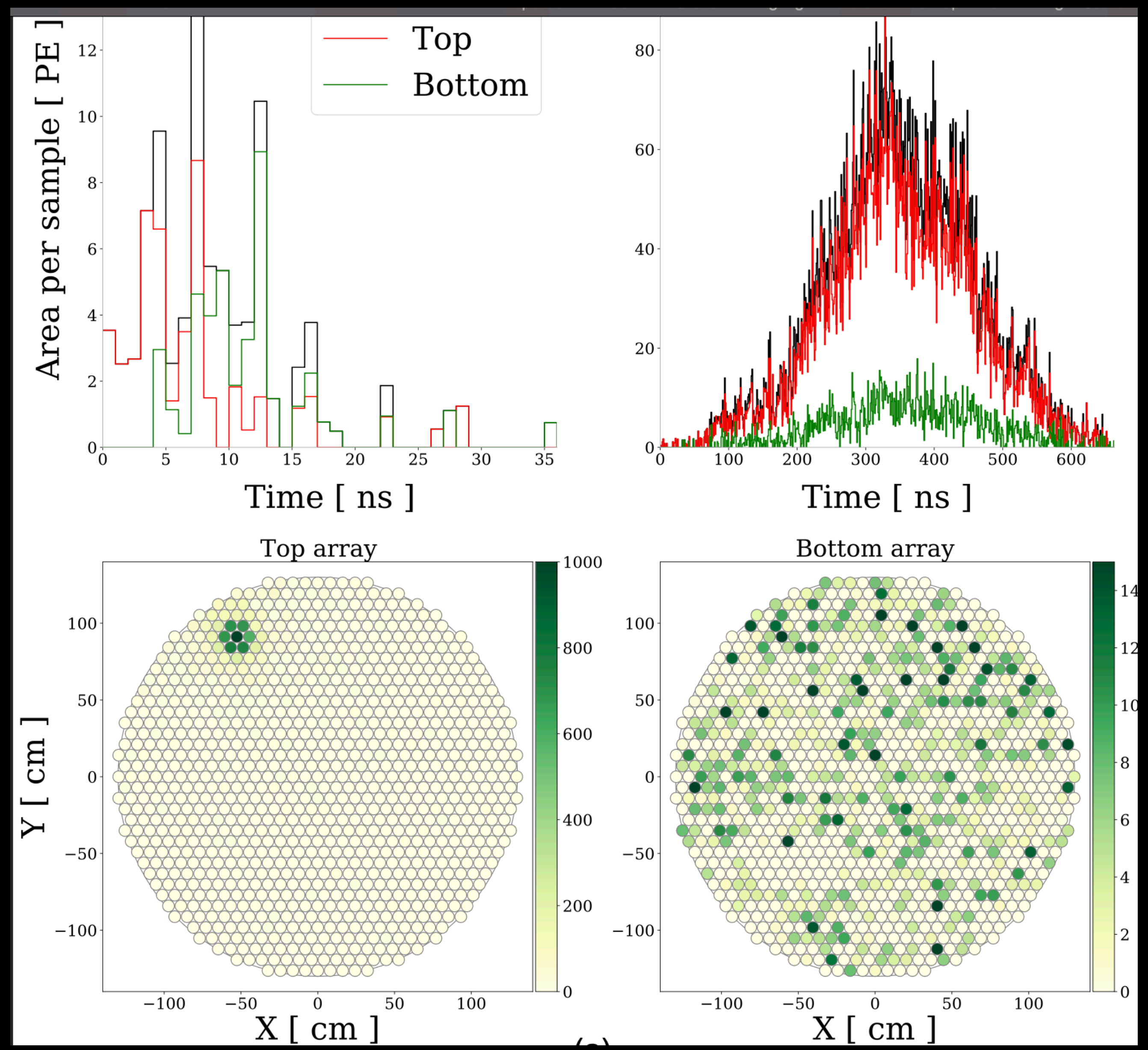


Training on Event topologies

- **Nuclear Recoil (NR)** → Associated with WIMPs
- **(Dominant) Background** → Linked to Electron Recoil (ER)
- **S1/S2 Peak Distance & Ratio** → Used to distinguish NR from ER

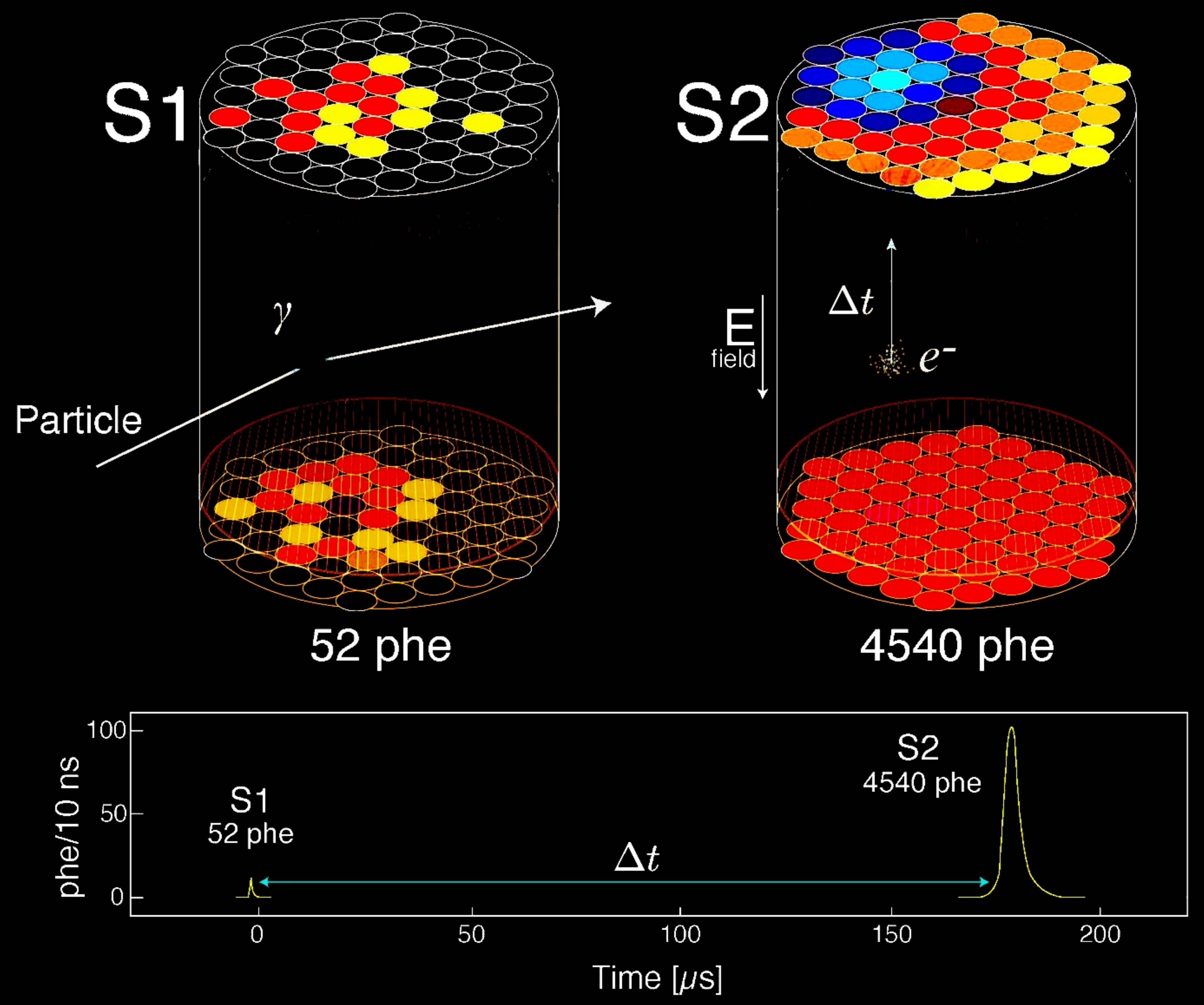


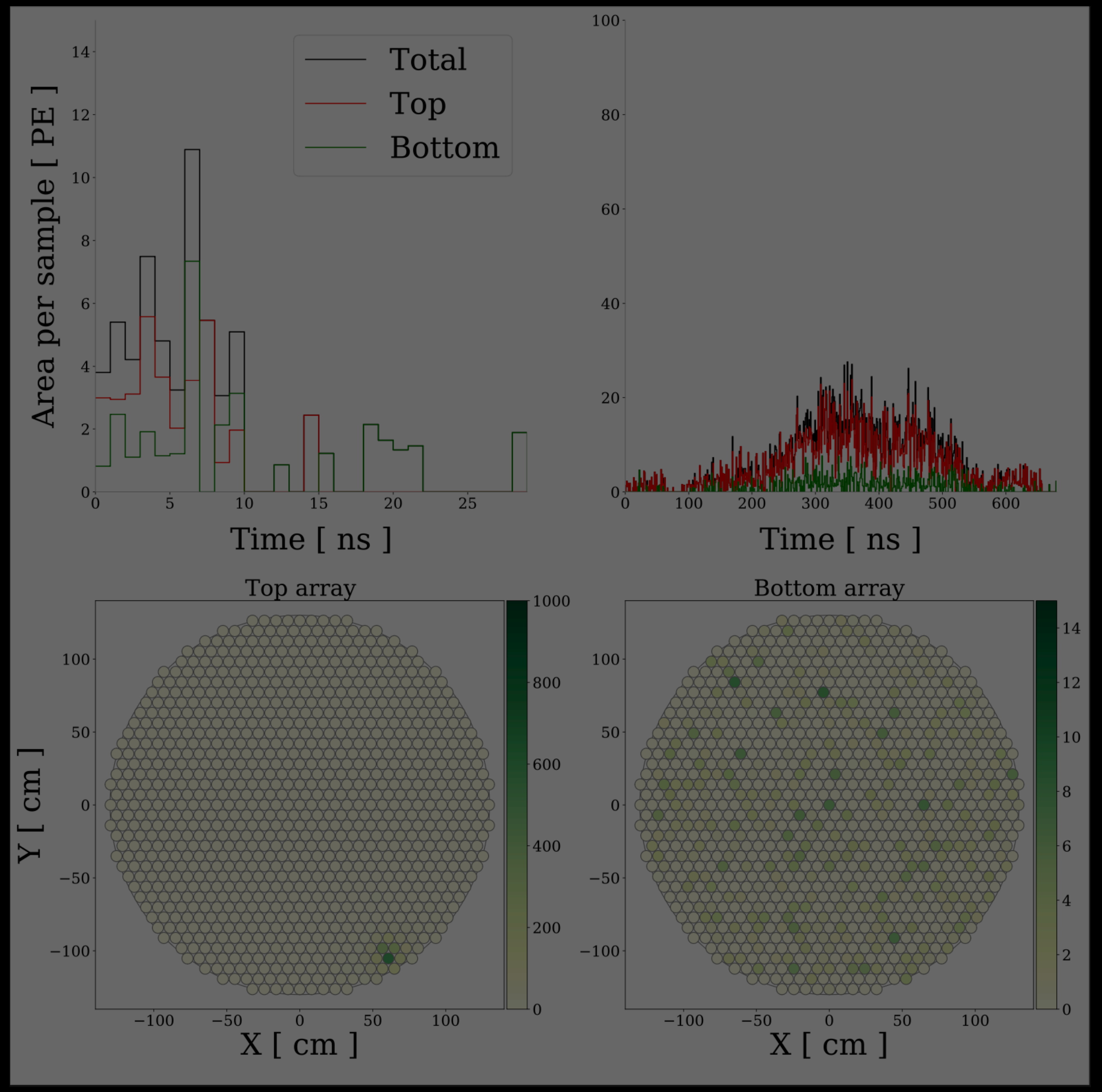


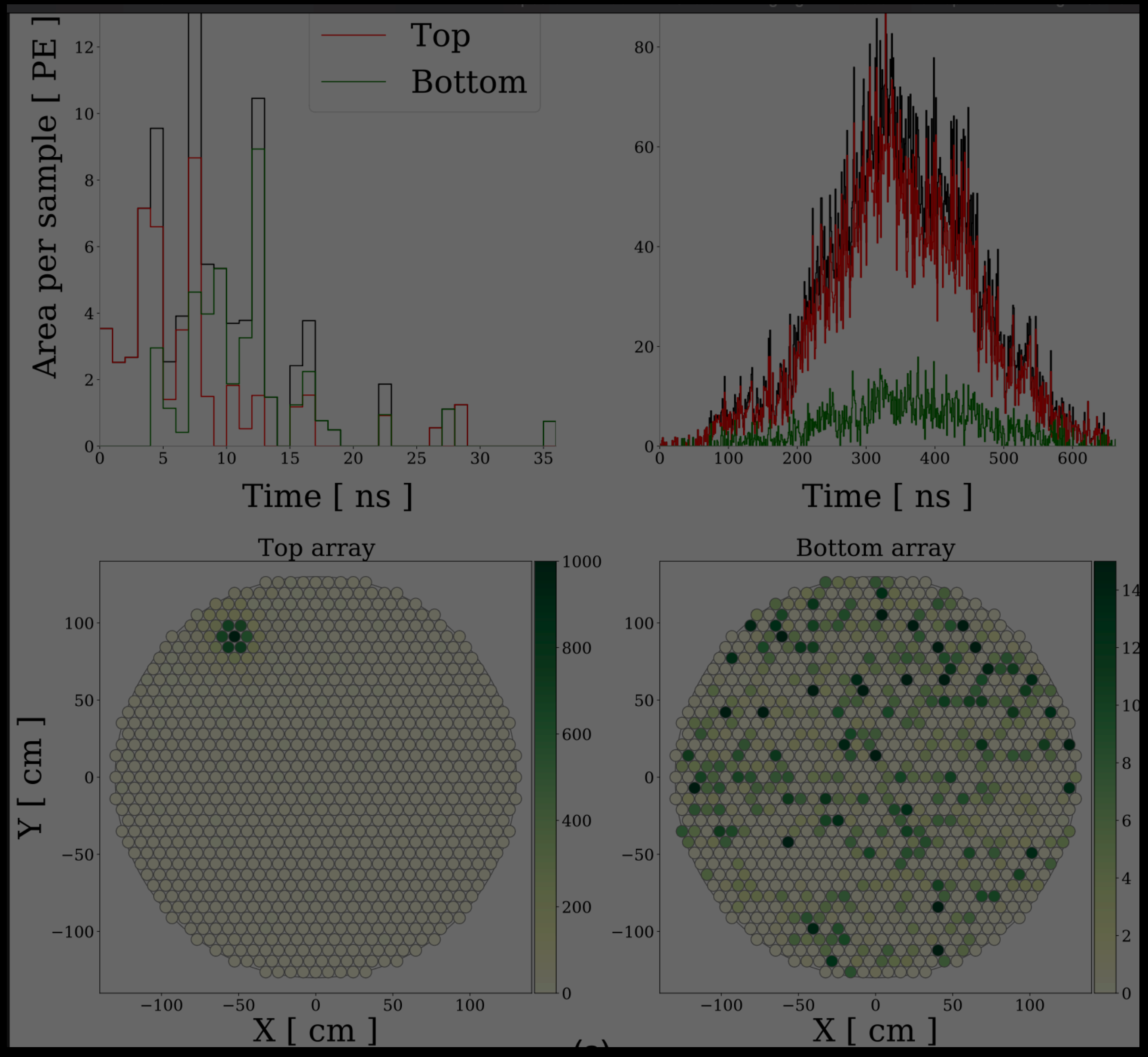


Training on Event topologies

- **Nuclear Recoil (NR)** → Associated with WIMPs
- **(Dominant) Background** → Linked to Electron Recoil (ER)
- **S1/S2 Peak Distance & Ratio** → Used to distinguish NR from ER







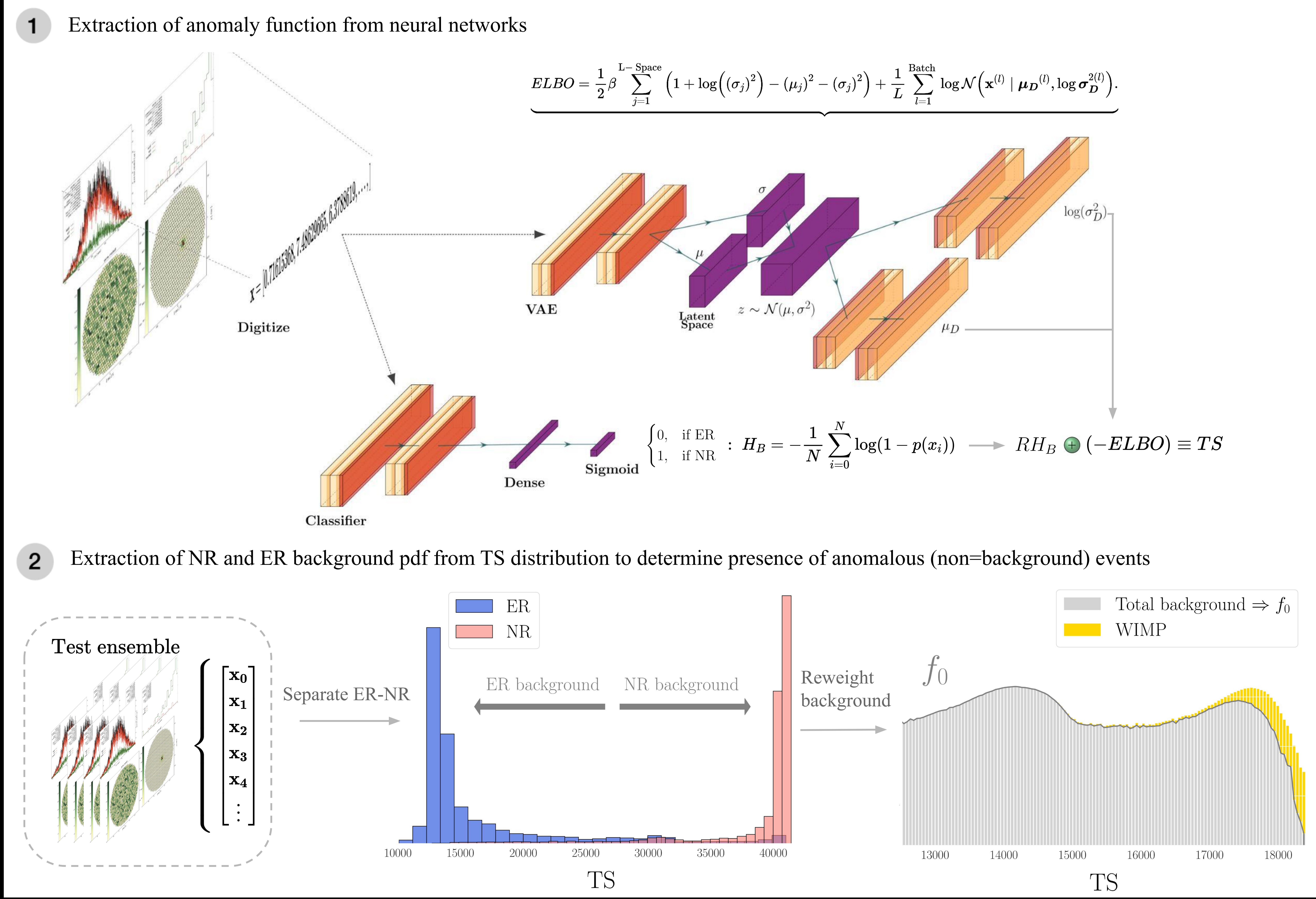
Pipeline

- **Top:** Variational auto-encoder: Train on ER only
- **Bottom:** Fully connected MLP classifier: ER vs NR

- VAE ⇒ Learns spectral info in latent space.
- Classifier ⇒**Lopez-Fogliani et.al 2406.10372**: BDT's MLP and transformers all basically just as good

Quantify presence of anomaly with two sample test to reject f_0

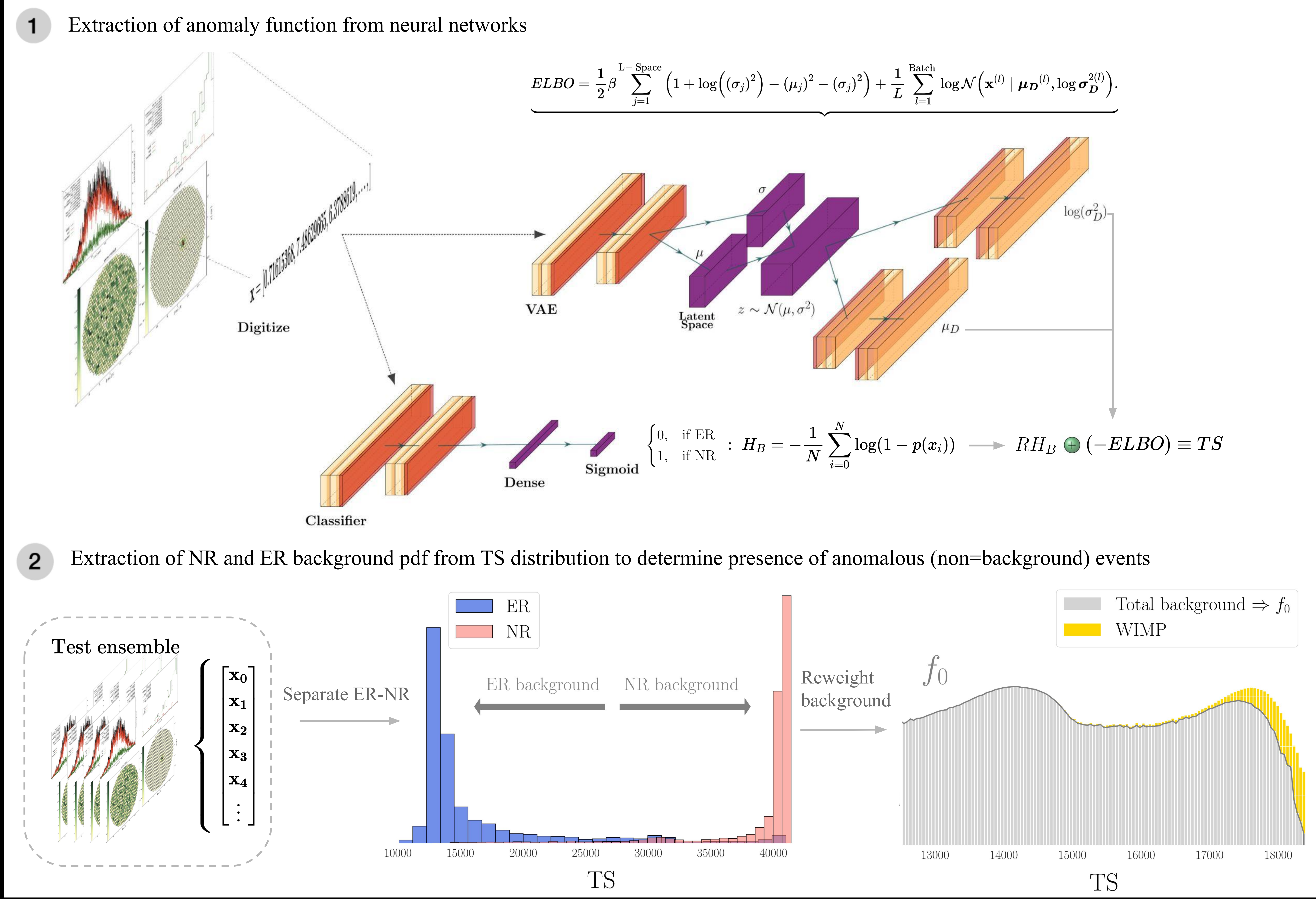
- Using ELBO encodes spectral info
- Using cross entropy 'signal like' NR to the tails



Pipeline

- **Top:** Variational auto-encoder: Train on ER only
- **Bottom:** Fully connected MLP classifier: ER vs NR

- VAE ⇒ Learns spectral info in latent space.
- Classifier ⇒**Lopez-Fogliani et.al 2406.10372**: BDT's MLP and transformers all basically just as good



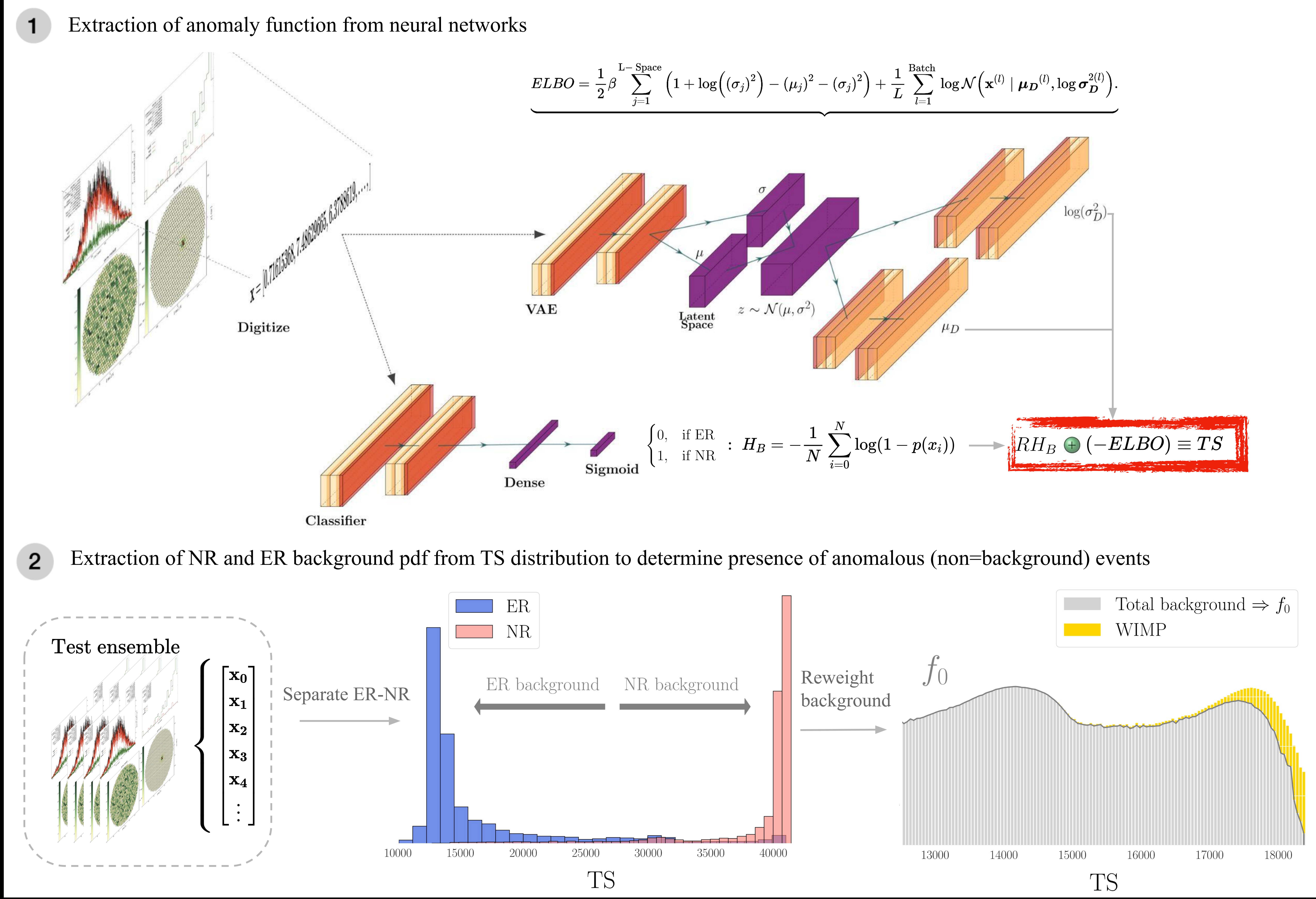
Quantify presence of anomaly with two sample test to reject f_0

- Using ELBO encodes spectral info
- Using cross entropy 'signal like' NR to the tails

Pipeline

- **Top:** Variational auto-encoder: Train on ER only
- **Bottom:** Fully connected MLP classifier: ER vs NR

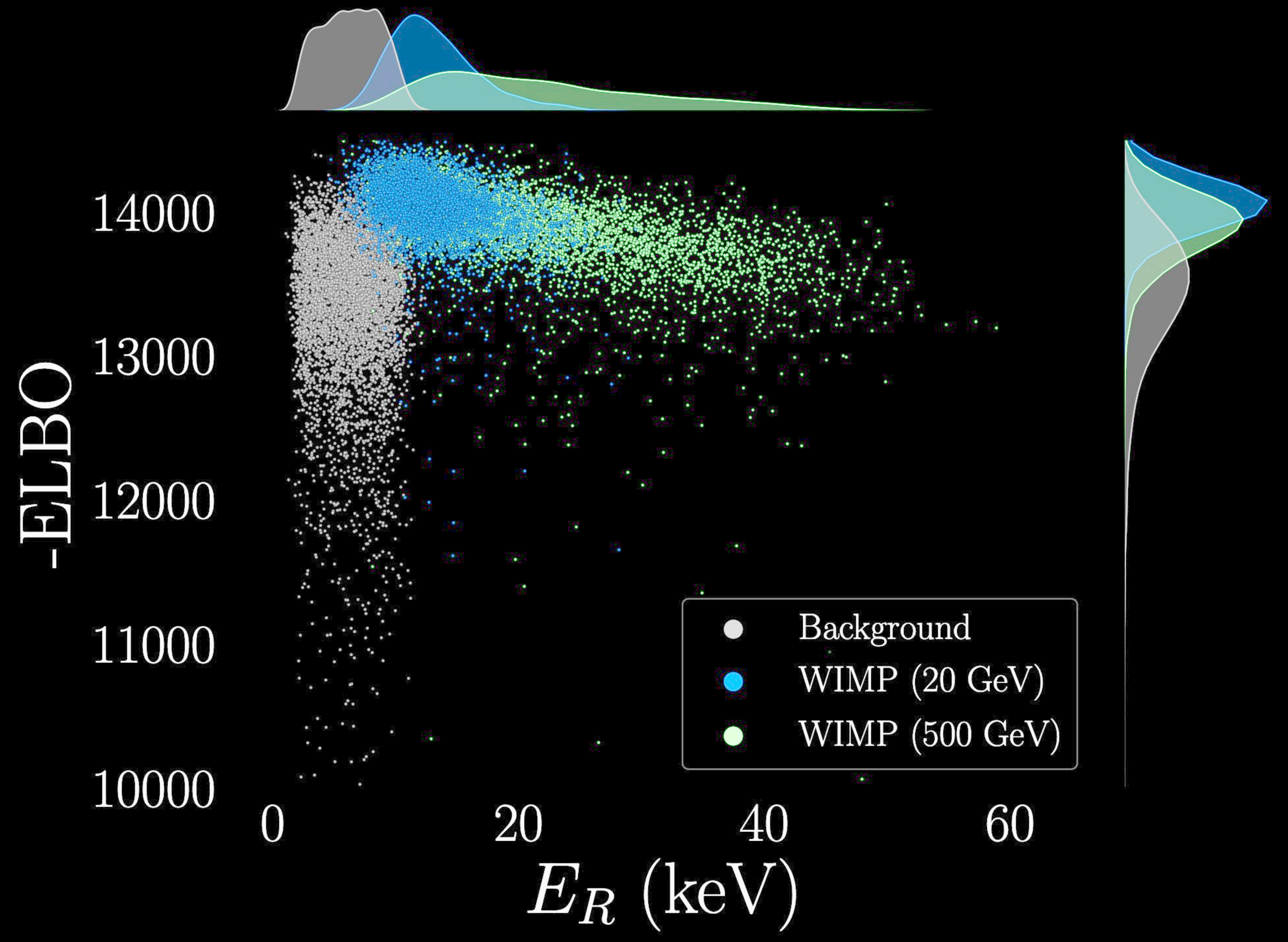
- VAE ⇒ Learns spectral info in latent space.
- Classifier ⇒ **Lopez-Fogliani et.al 2406.10372**: BDT's MLP and transformers all basically just as good

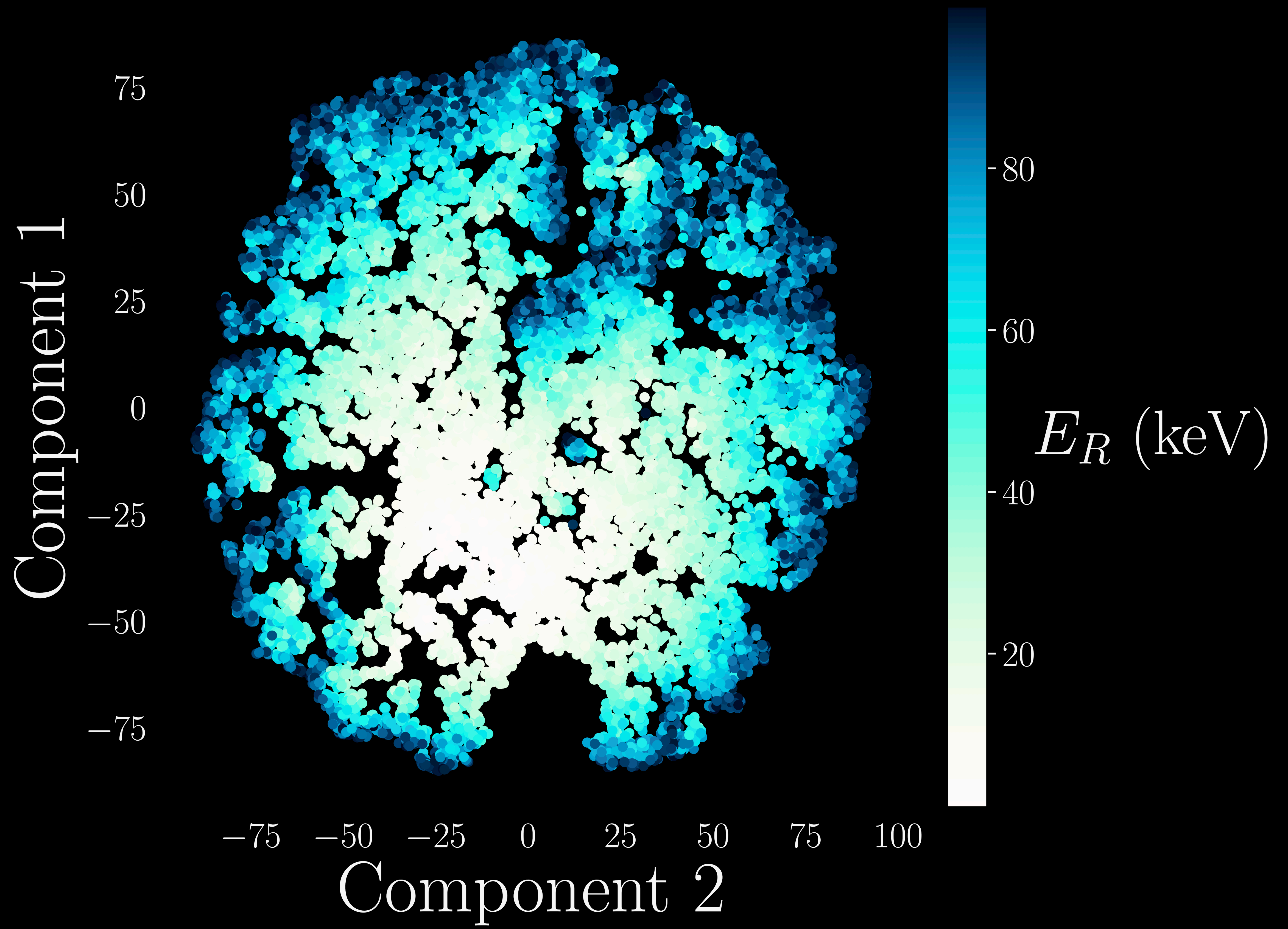


Quantify presence of anomaly with two sample test to reject f_0

- Using ELBO encodes spectral info
- Using cross entropy 'signal like' NR to the tails

ELBO encodes spectral information





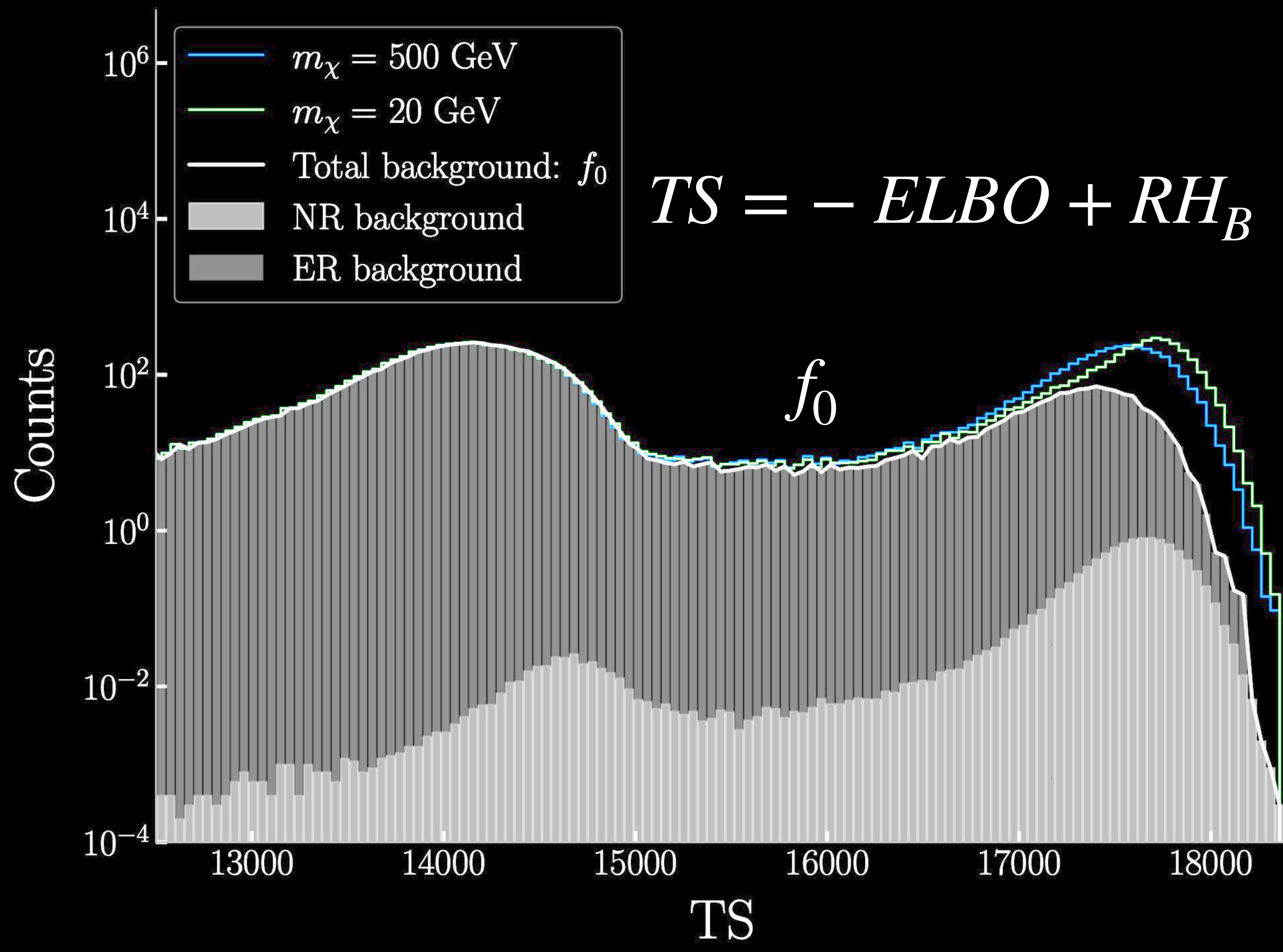
Quantify presence of anomalous events via two sample test

$\Rightarrow$ 1D analysis in TS space:

Accept/reject

$$\mathscr{H}_0 : X \sim f_0\left(TS \mid \text{No signal}\right)$$

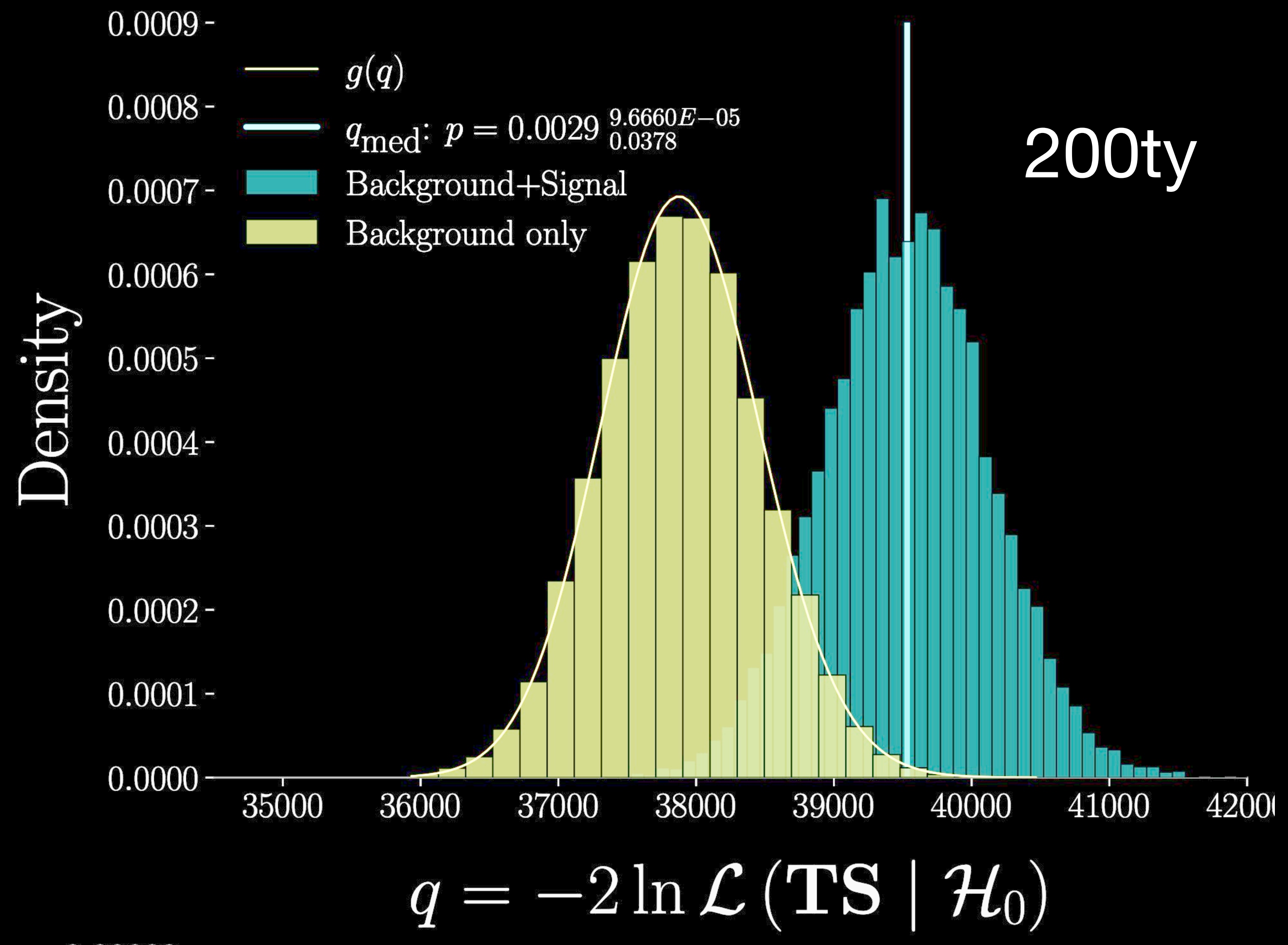
$$\mathscr{L}(\mathbf{TS} \mid \mathscr{H}_0) \propto e^{-B} \prod_{i=1}^{N} \left(B f_0\left(TS_i\right) \right)$$

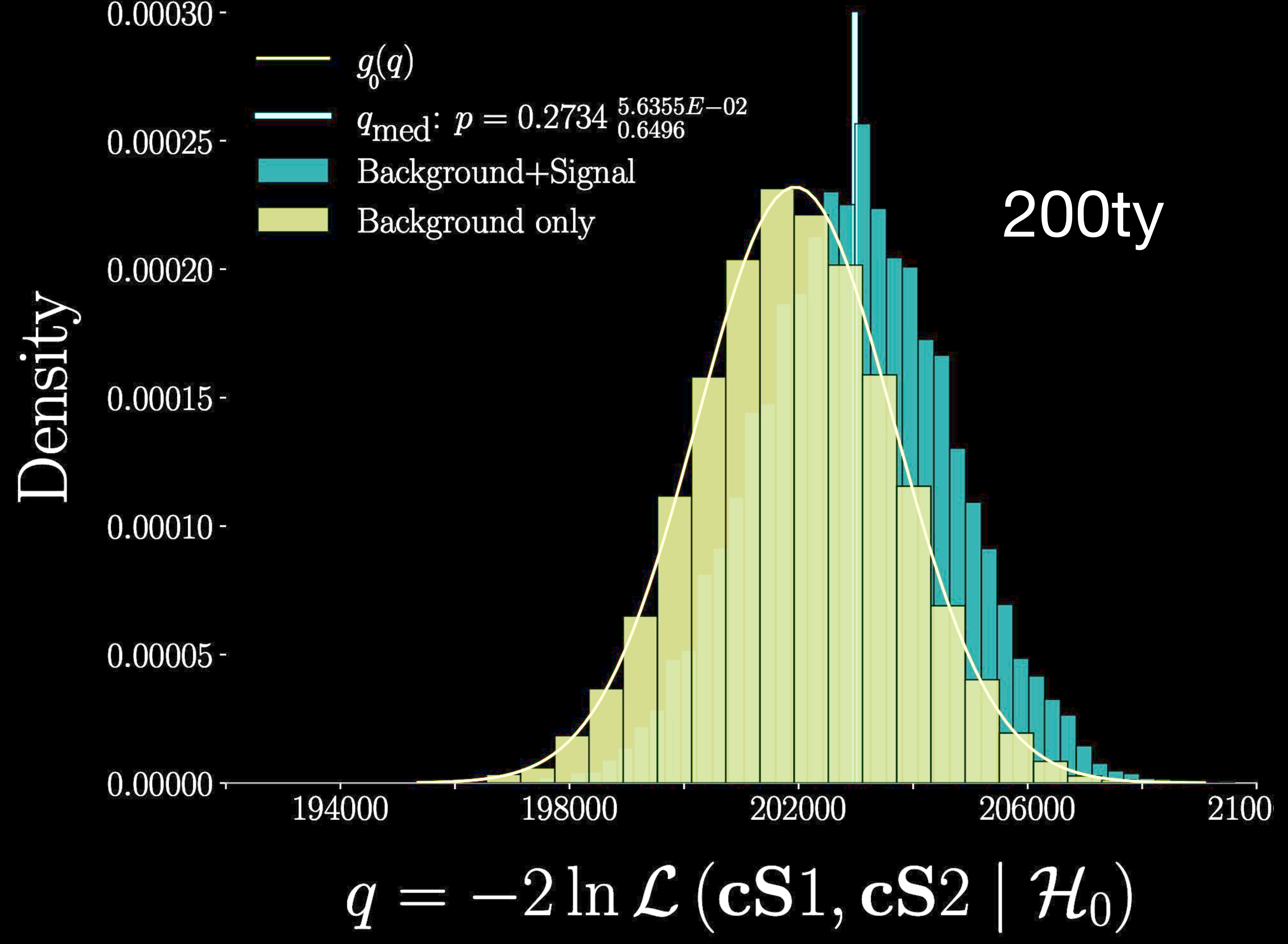


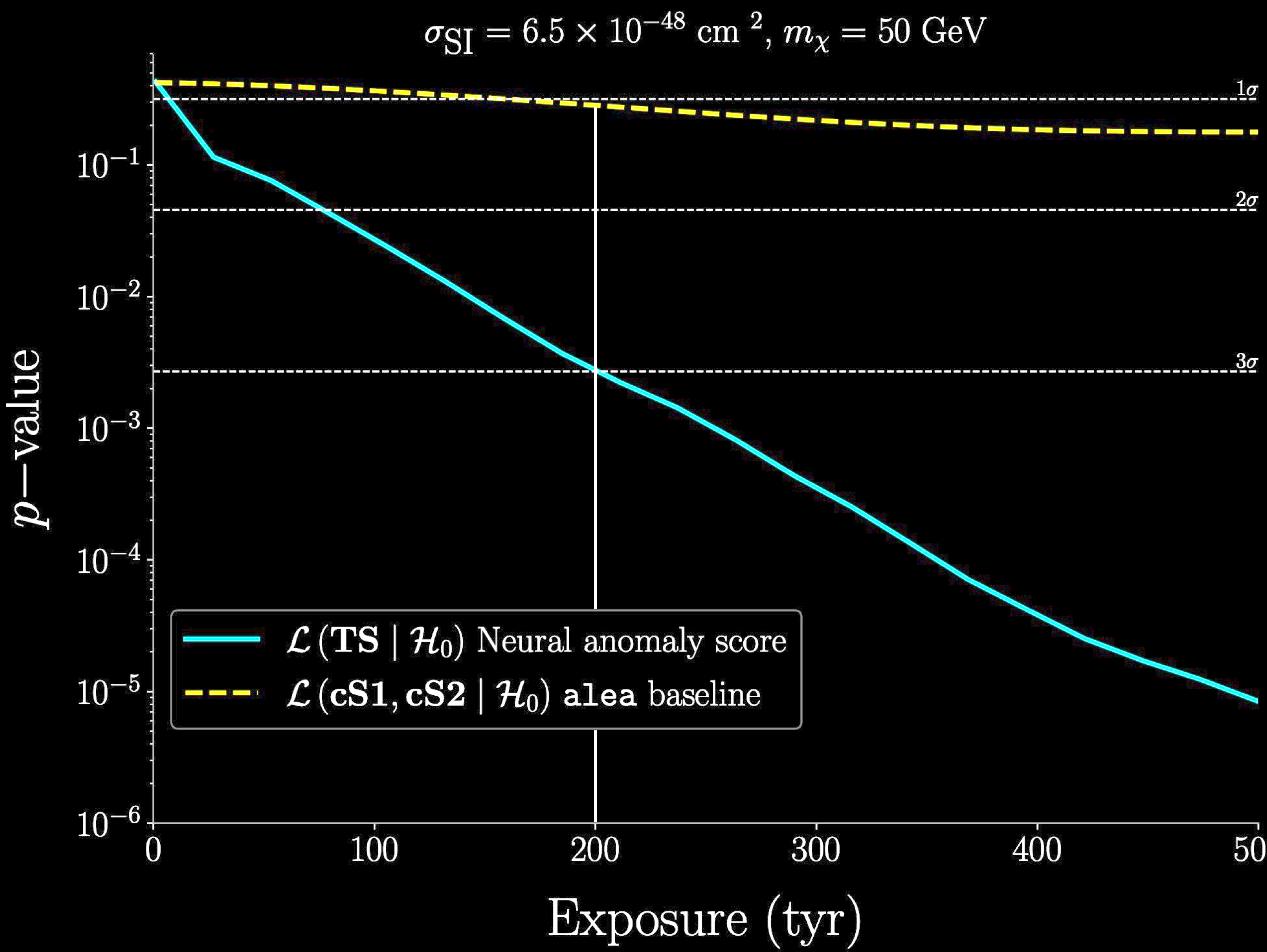
Pros

- Un-binned.
- Parametrically independent on WIMP model.
- No auxiliary terms required assuming simulations have suitably descriptive coverage.
- Can be augmented with more fundamental data representation or calibration. (Current work!)
- Rapid increase in end-to-end computational efficiency

Forecast background rejection sensitivity







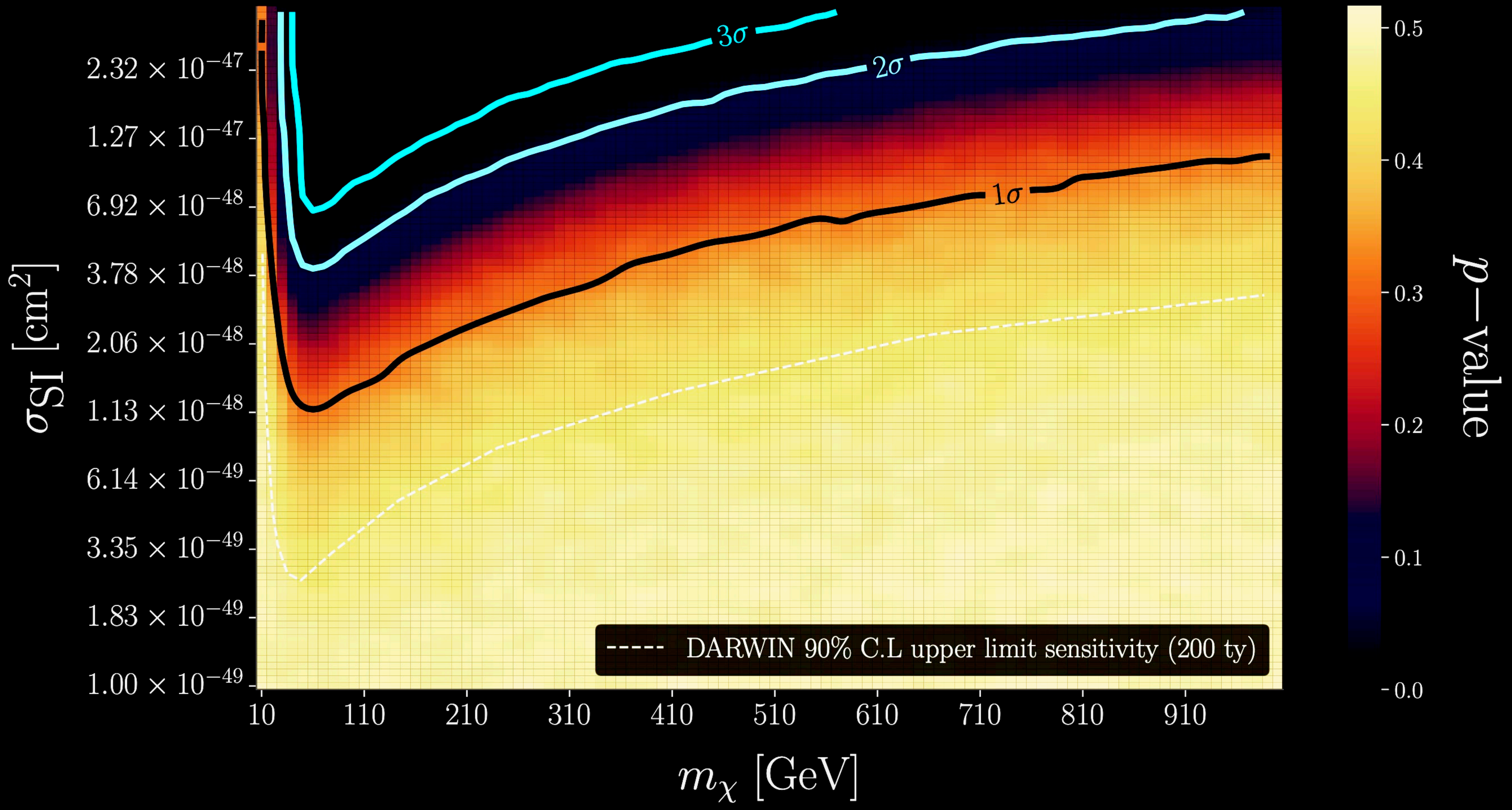
Summary

- XLZD ML program making way
- Focussed on end-to-end anomaly detection (background rejection) task
- Works!
- Outperforms baseline likelihood approach for analogous test.
- Drastic increase in computational efficiency
- Novel baseline for future modular additions: Calibration DA, energy recon., time domain PMT readout handling.

Backup

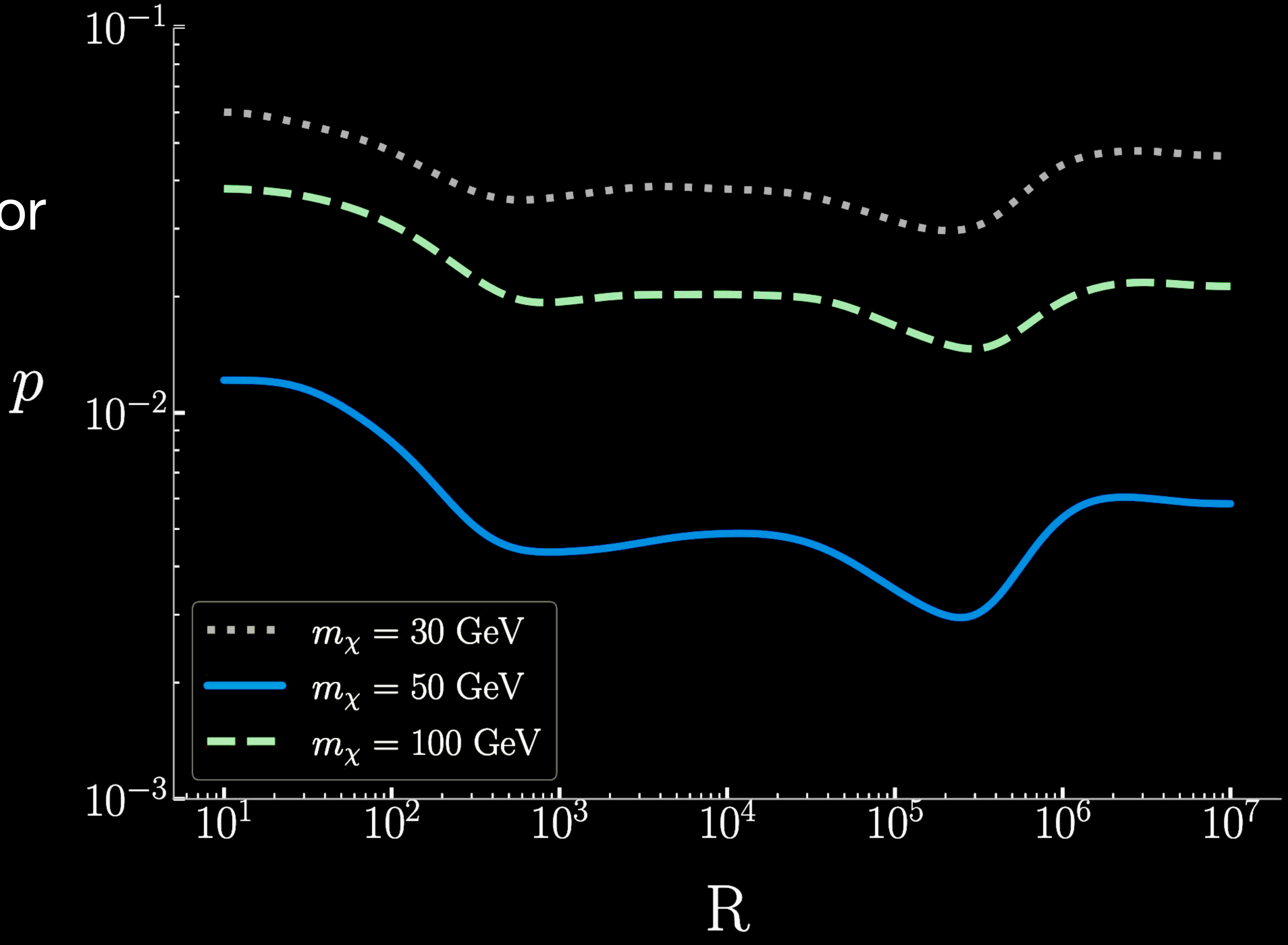
Forecasting background rejection

2D plane



Influence of R

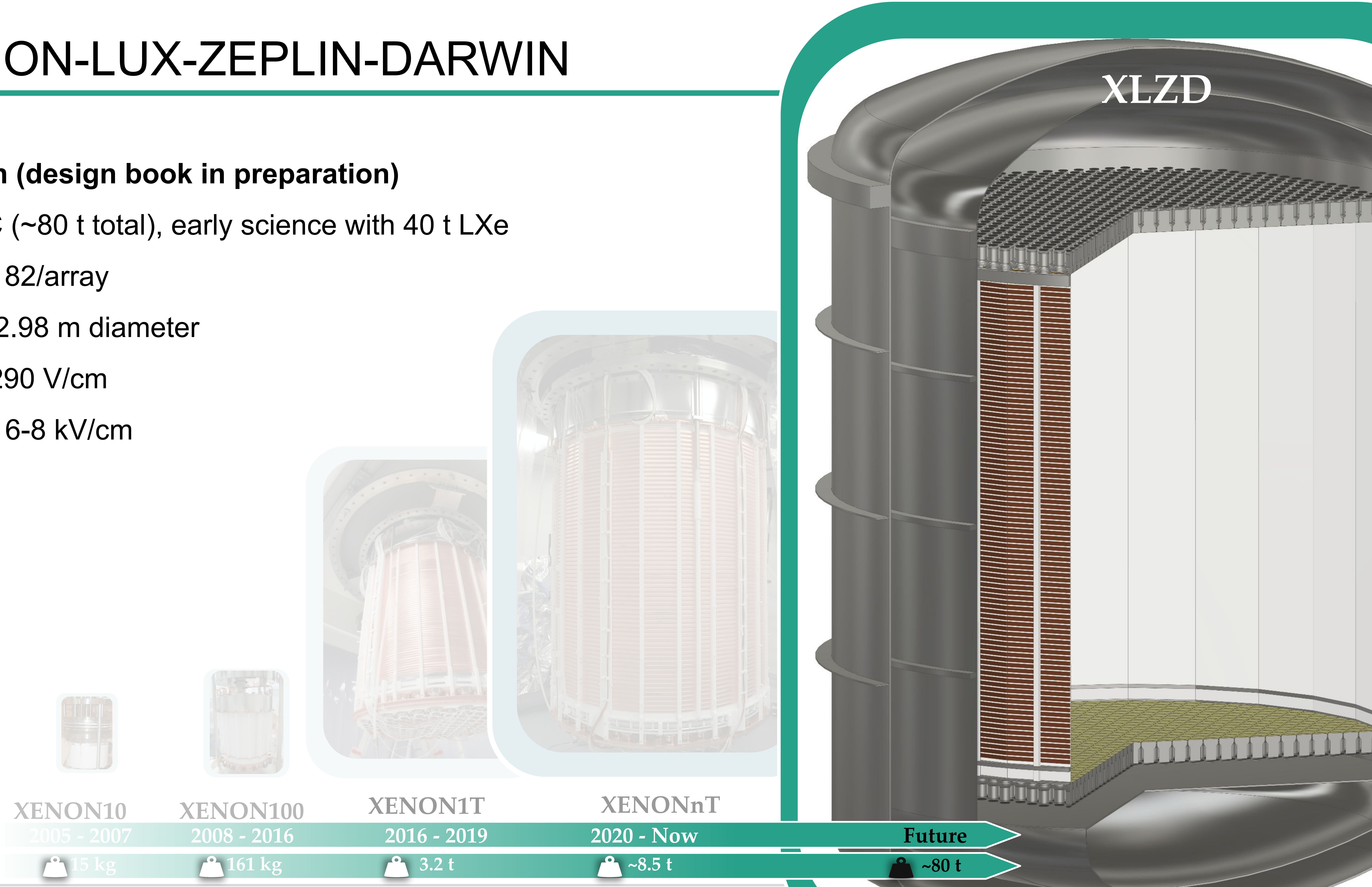
There seems a universal value for which anomaly awareness is maximised: $R = 2.5 \times 10^5$



XLZD - XENON-LUX-ZEPLIN-DARWIN

XLZD nominal design (design book in preparation)

- ❖ 60 t LXe in TPC (~80 t total), early science with 40 t LXe
- ❖ 3-inch PMTs, 1182/array
- ❖ 2.97 m e- drift, 2.98 m diameter
- ❖ Drift field: 240-290 V/cm
- ❖ Extraction field: 6-8 kV/cm



Credit: Alexey Elykov