Energy Reconstruction with Autoencoders for Dual-Phase Time Projection Chambers

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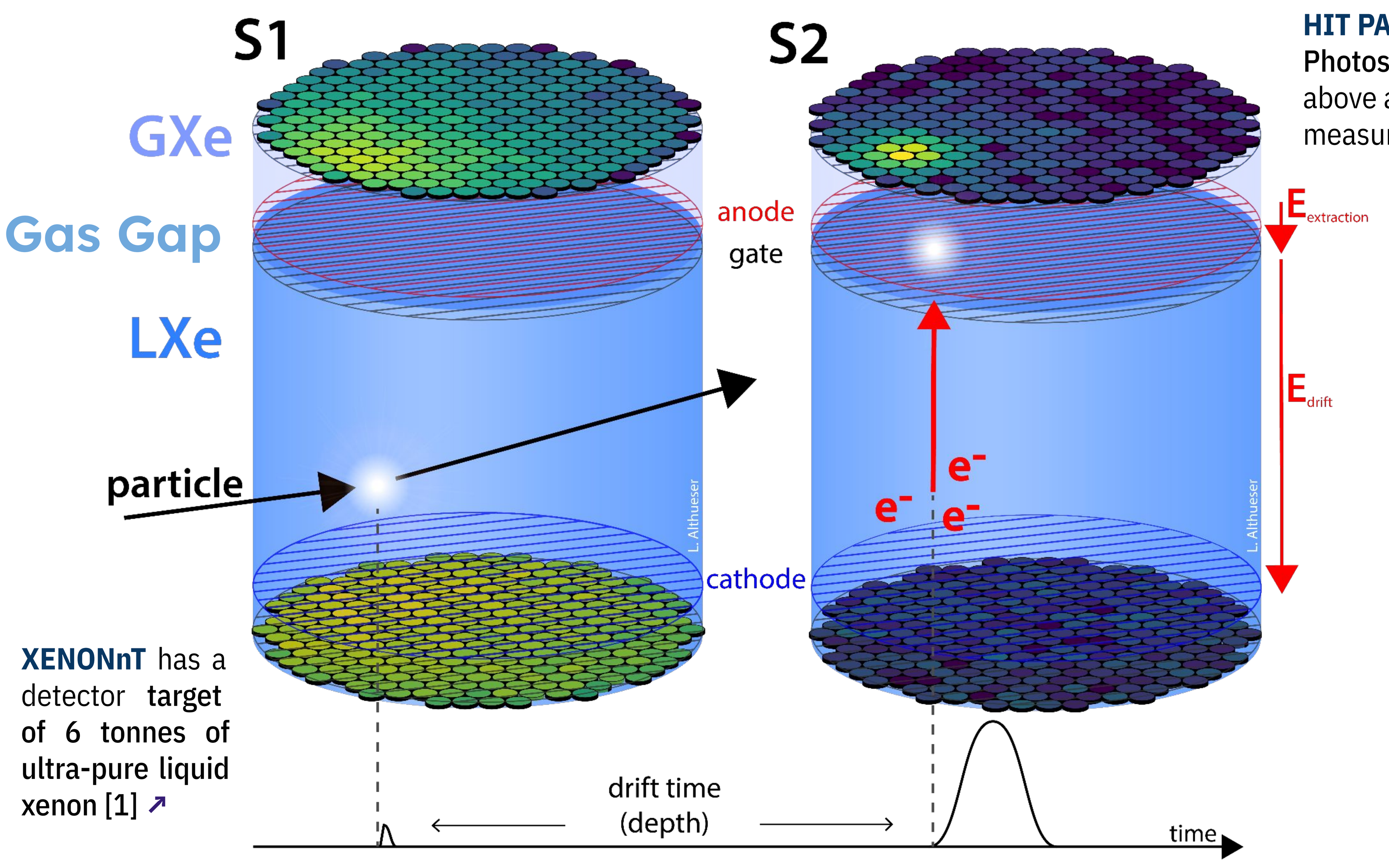
RICE XENON

Energy Reconstruction for XENONnT



HIT PATTERNS: Photosensors above and below measure signals →

XENONnT has a detector target of 6 tonnes of ultra-pure liquid xenon [1] ↗

SCINTILLATION SIGNAL (S1): incoming particle interacts with xenon and causes a **scintillation signal** with energy which is proportional to the initial signal's number of photons

$$E_{S1} \propto n_\gamma$$

ELECTRIC FIELD DRIFTS ELECTRONS TO GAS GAP: not all of the freed electrons from the interaction point reach the **gas gap**

$$n_e \propto n_{e_{\text{int}}} e^{-t/\tau}$$

IONIZATION SIGNAL (S2): electrons which reach the gas gap cause a brighter **ionization signal** with energy which is proportional to the number of electrons at the interaction point

$$E_{S2} \propto n_{e_{\text{int}}}$$

TOTAL ENERGY →

$$\boxed{E_{\text{total}} = n_\gamma + \frac{n_e}{e^{-t/\tau}}}$$

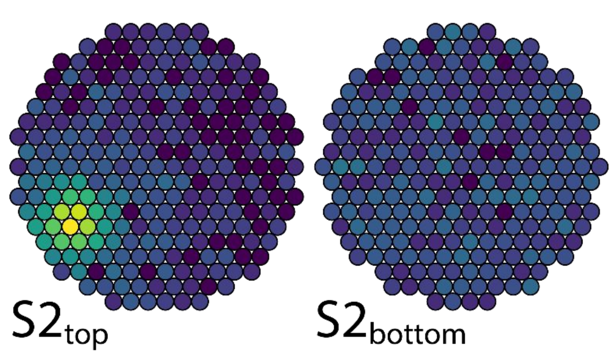
← **NUMBER OF ELECTRONS IN GAS GAP**

Semi-Supervised Autoencoder

DATASET: simulated hit patterns from a given [0, 2000] n_e

INPUT SIZE: 494 photosensors total

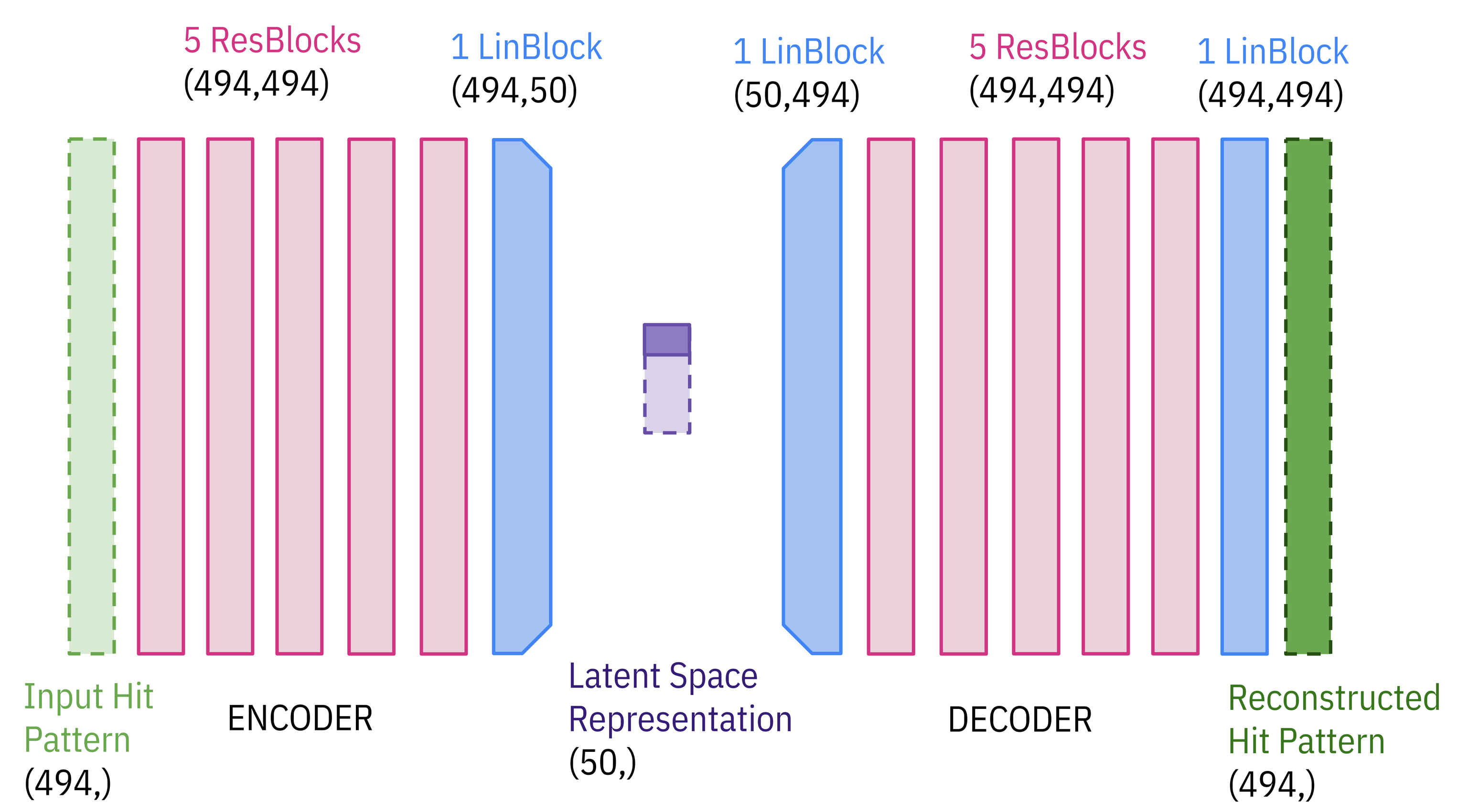
TRAIN/VALIDATION/TEST SPLIT: 447500/447500/100000 hit patterns



6163194 trainable parameters

Adam optimizer, starting learning rate 5e-4

Reduce learning rate by factor of 0.1 if loss does not decrease after 5 epochs

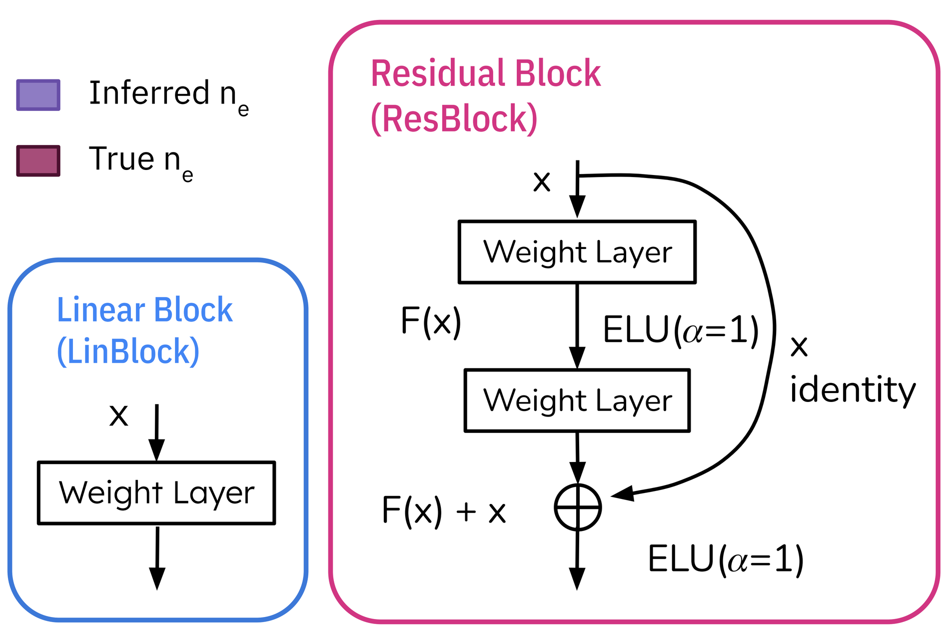


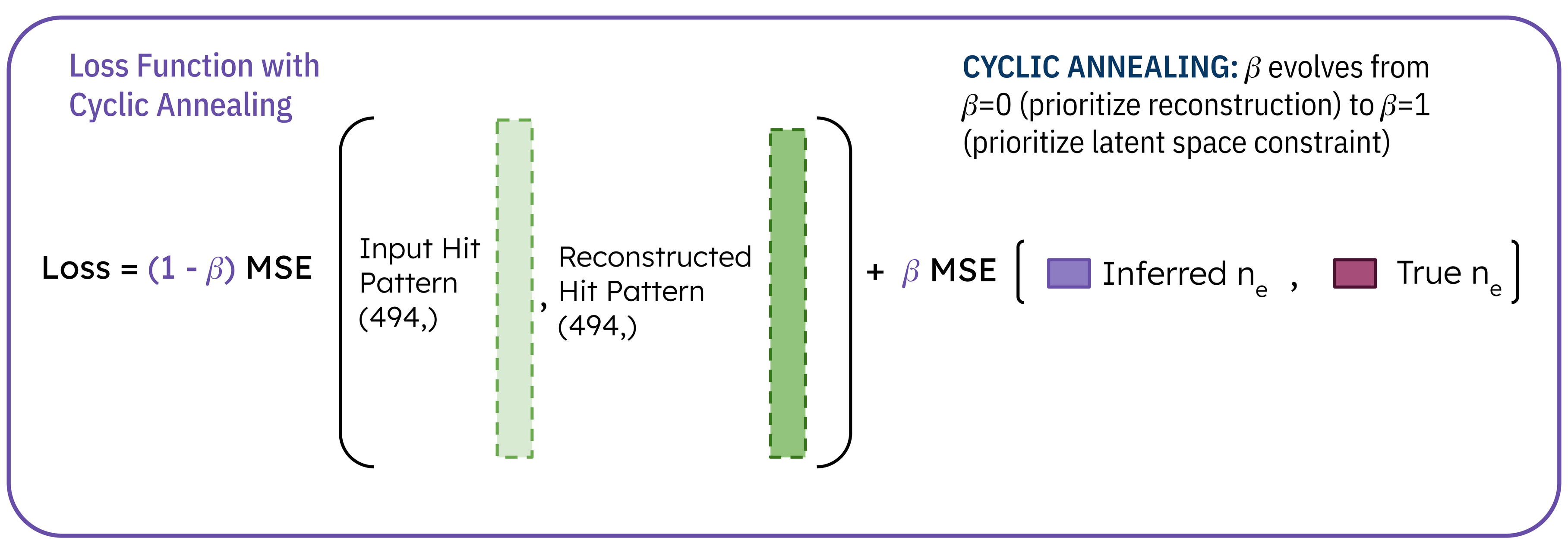
ENCODER: encodes input into a lower dimensional latent space ↑

LATENT SPACE REPRESENTATION: constrains one value **as the number of electrons in the gas gap** but allows the others to evolve freely ↗

DECODER: decodes input from latent space representation ↑

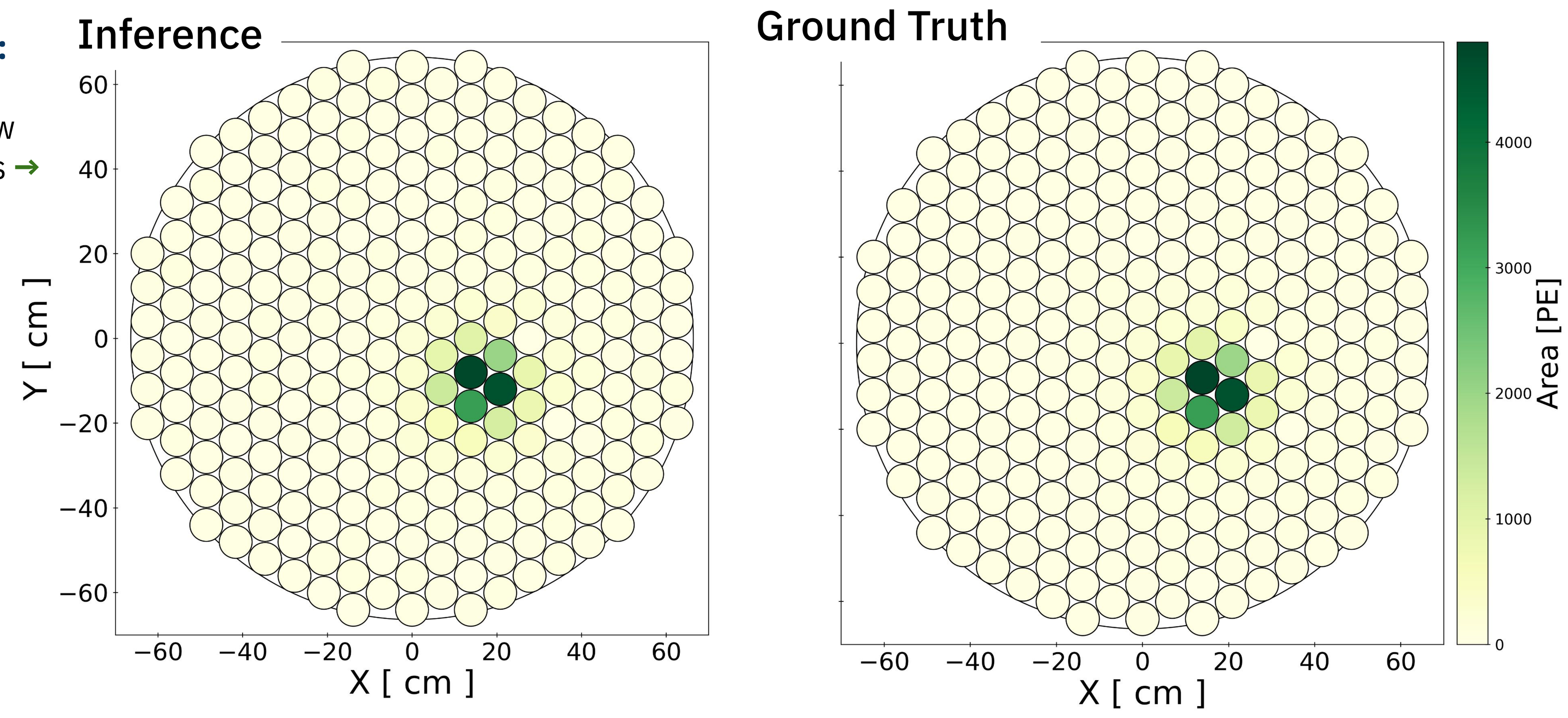
LOSS FUNCTION: weighted sum of the **mean squared error (MSE) losses below** ↓

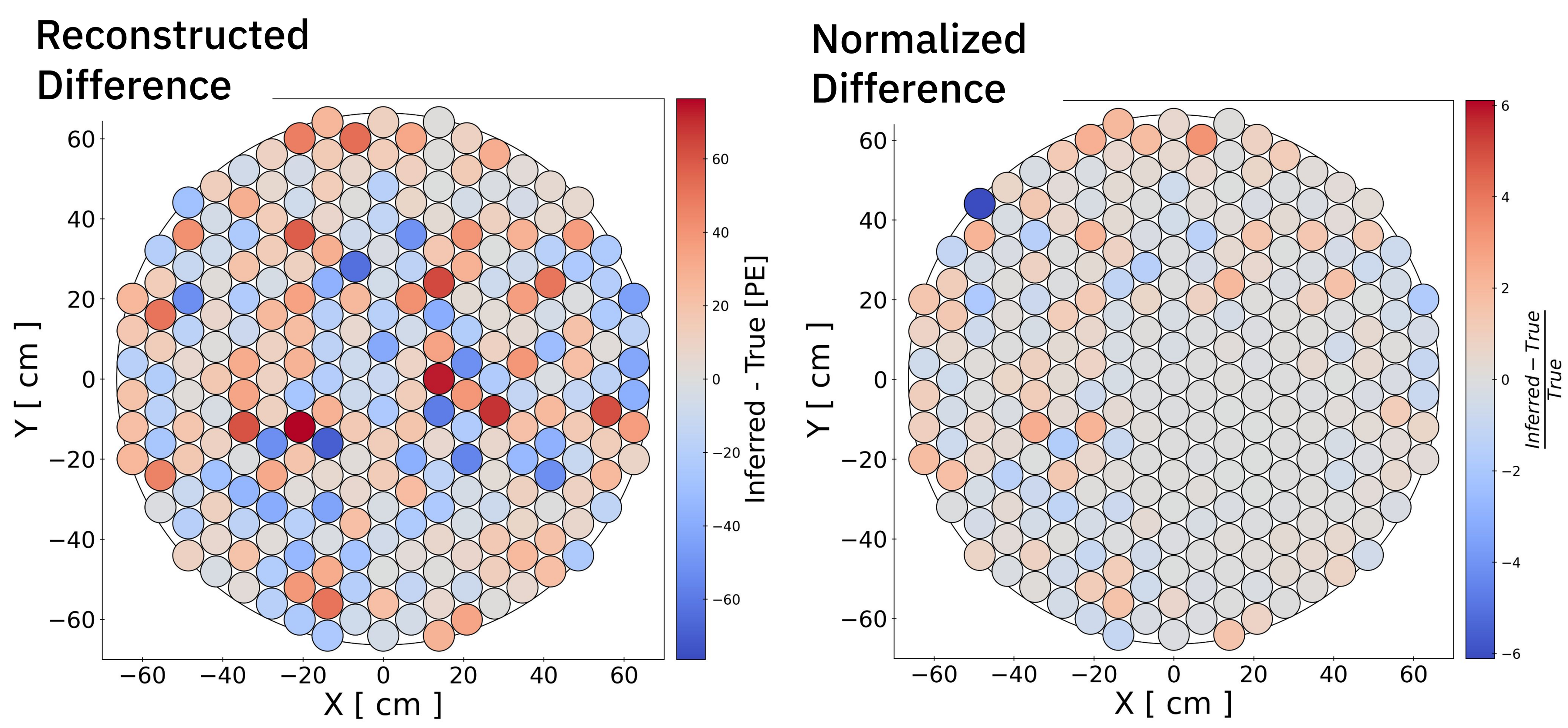




CYCLIC ANNEALING: β evolves from β=0 (prioritize reconstruction) to β=1 (prioritize latent space constraint)

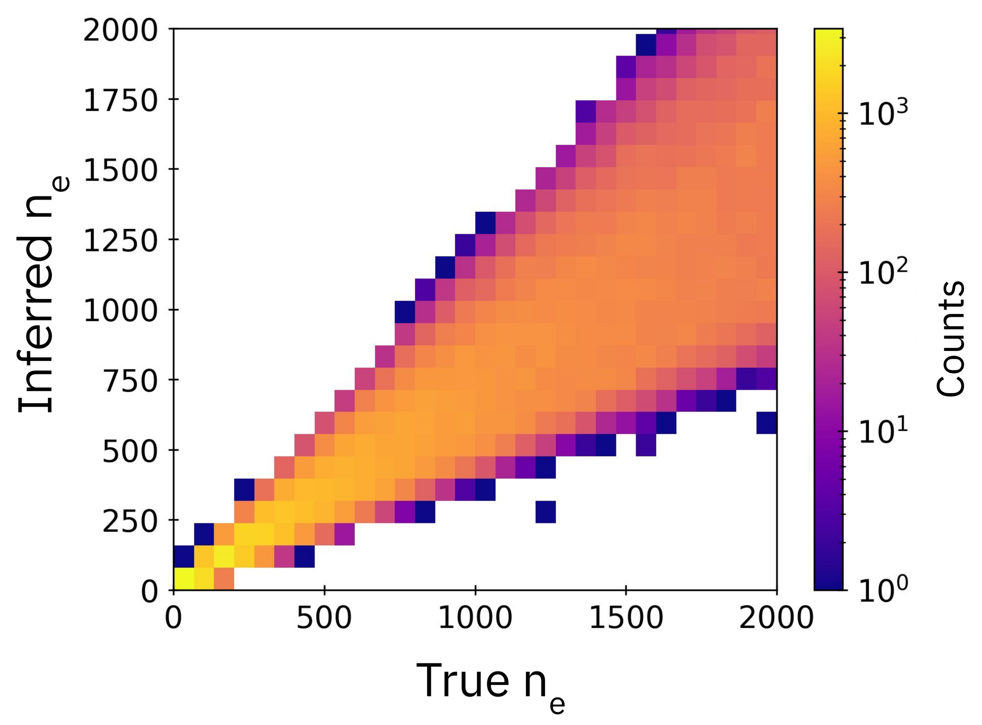
Example Reconstruction of Top Array Hit Pattern

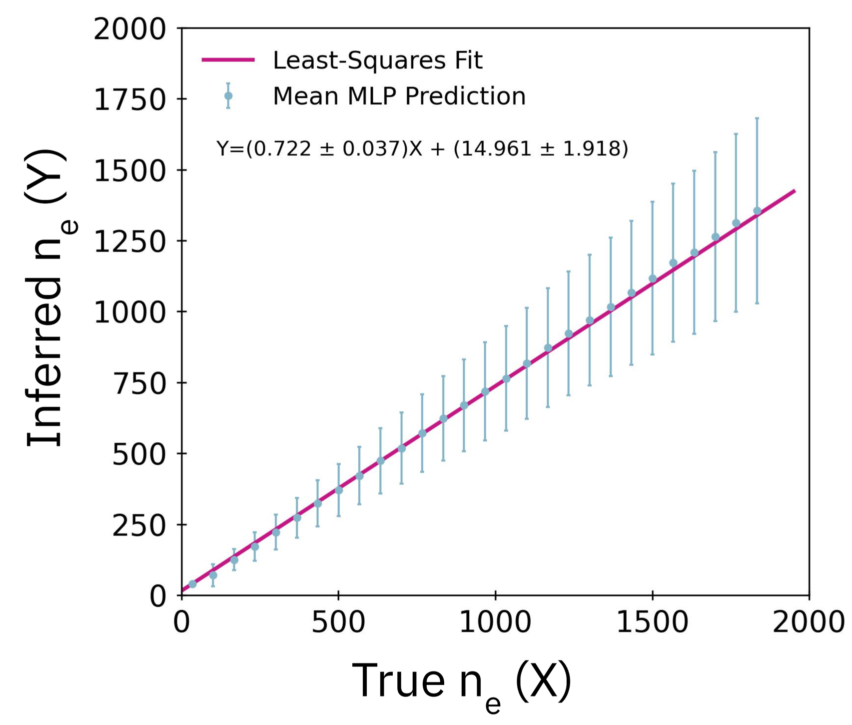


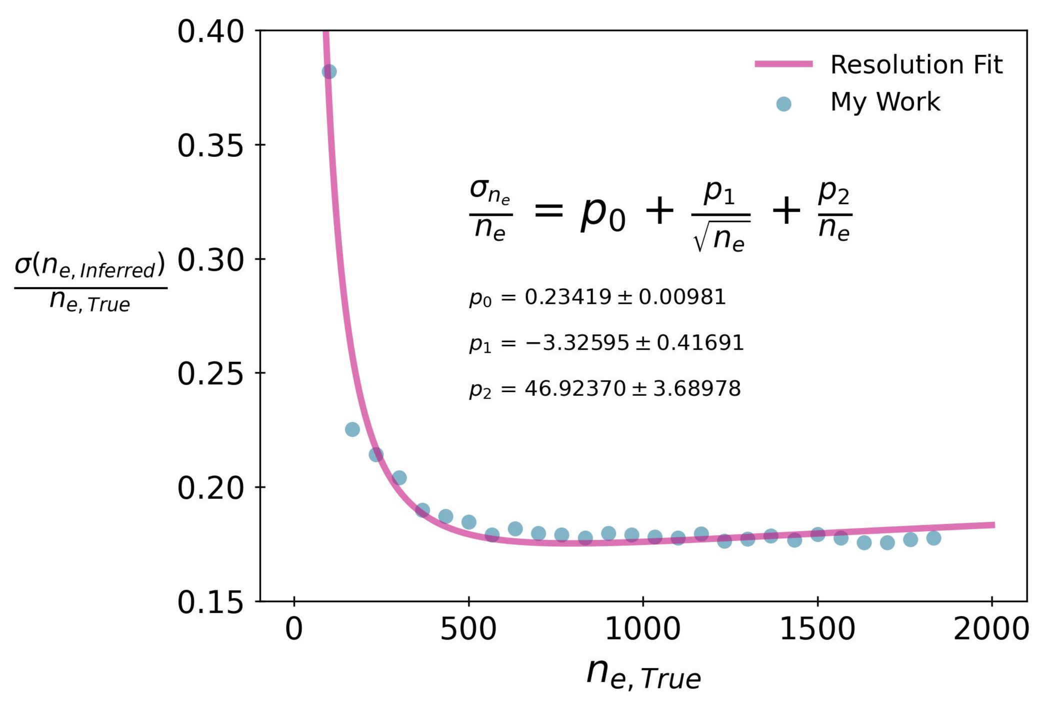


DYNAMIC RANGE: autoencoder can reconstruct hit patterns well without normalizing or log-scaling hit patterns due to skip connections [3]

Inferring Number of Electrons in the Gas Gap







UNDERPREDICTION: WHY? currently the autoencoder underpredicts the number of electrons in the gas gap ↑

GOAL TO IMPROVE RESOLUTION: the spread of the inferred number of electrons in the gas gap decreases as the inverse square root for increasing number of electrons ←

Future Work

ENERGY RESOLUTION: **precise reconstruction is critical for rare event searches** such as the search for dark matter evidence [2]

INTERPRETABILITY: constraining the latent space to be **physically meaningful** e.g. a variational autoencoder constrains latent parameters as probability distributions → **meaningful parameter uncertainties**

COMPUTATIONAL EFFICIENCY: simulating data through Monte Carlo methods is computationally expensive and time-consuming → ongoing efforts to create more efficient machine-learning algorithms for **fast simulation**

References

[0] Check out our experiment! xenonexperiment.org

[1] Aprile, E., et al. "Search for new physics in electronic recoil data from XENONnT." *Physical Review Letters* 129.16 (2022): 161805.

[2] Billard, Julien, et al. "Direct detection of dark matter—APPEC committee report." *Reports on Progress in Physics* 85.5 (2022): 056201.

[3] Dieng, Adji B., et al. "Avoiding latent variable collapse with generative skip models." *The 22nd International Conference on Artificial Intelligence and Statistics.* PMLR, (2019).