MAX-PLANCK-INSTITUT
FÜR KERNPHYSIK

A HYBRID MACHINE LEARNING-LIKELIHOOD APPROACH TO EVENT RECONSTRUCTION FOR IACTS

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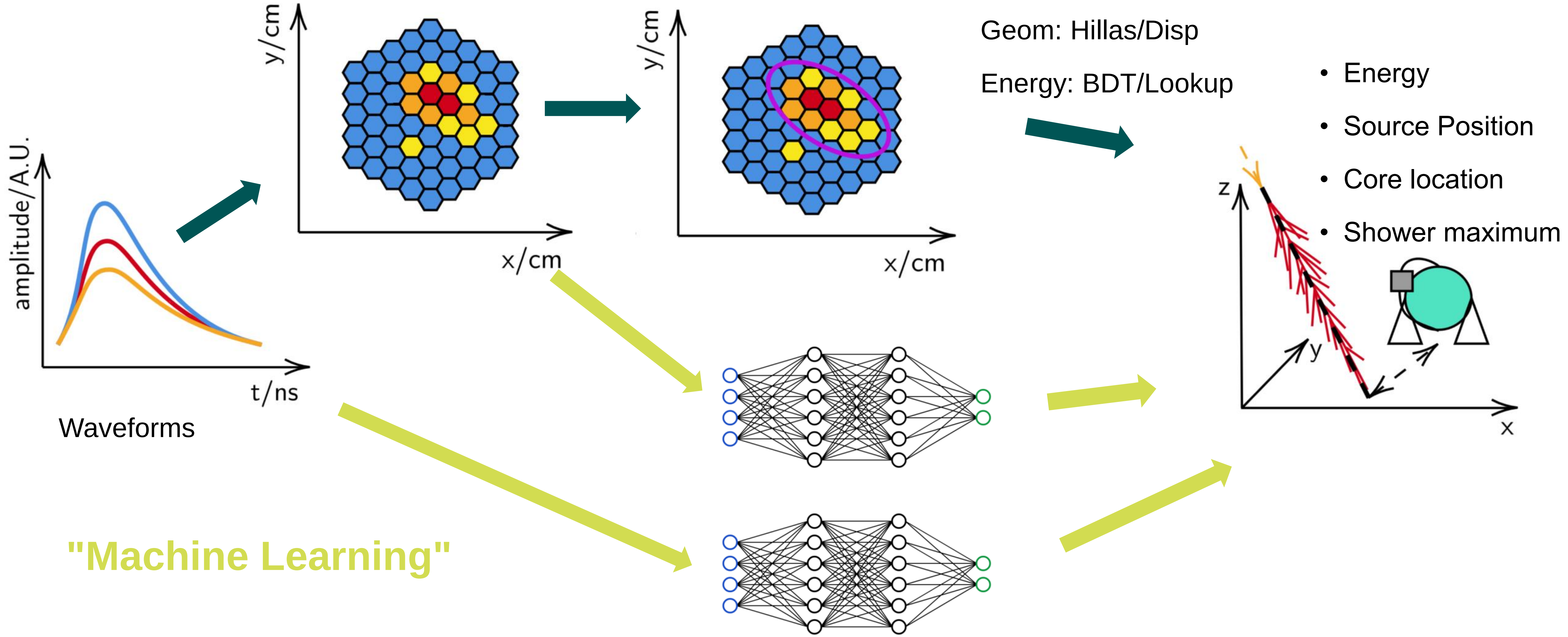
Workshop on Machine Learning for Analysis of High-Energy Cosmic Particles

Bartol Research Institute (Online), 28.01.2025

IACT EVENT RECONSTRUCTION



"Classical"

Image extraction

Image parametrization

Geom: Hillas/Disp

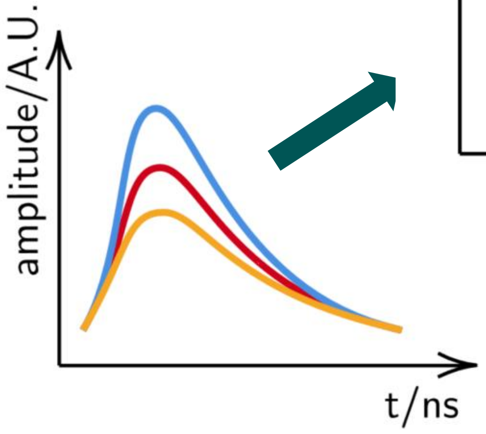
Energy: BDT/Lookup

- Energy
- Source Position
- Core location
- Shower maximum

Waveforms

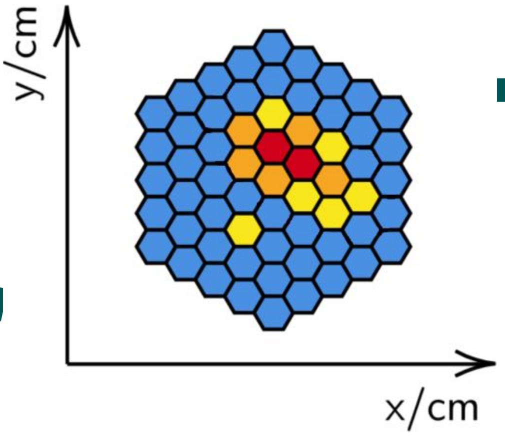
"Machine Learning"

LIKELIHOOD-FITTING RECONSTRUCTION



Waveforms

Image extraction



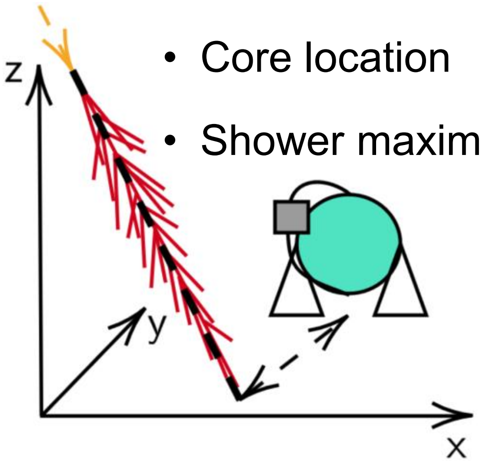
Pixel-wise charge likelihood

$$\mathcal{L} = \prod_{i=1}^{N_{\mathrm{tel}}} \prod_{j=1}^{N_{\mathrm{pix}}} p(c_{ij} | \vec{r}^{\,ij}_{\mathrm{pix}}, \vec{r}^{\,i}_{\mathrm{tel}}, \vec{\eta})$$

- Use full image information
- Fully traceable
- Optimal for **correct** likelihood

ImPACT:

- Analytical (asymmetric) gaussian likelihood
- Expectation values from MC templates

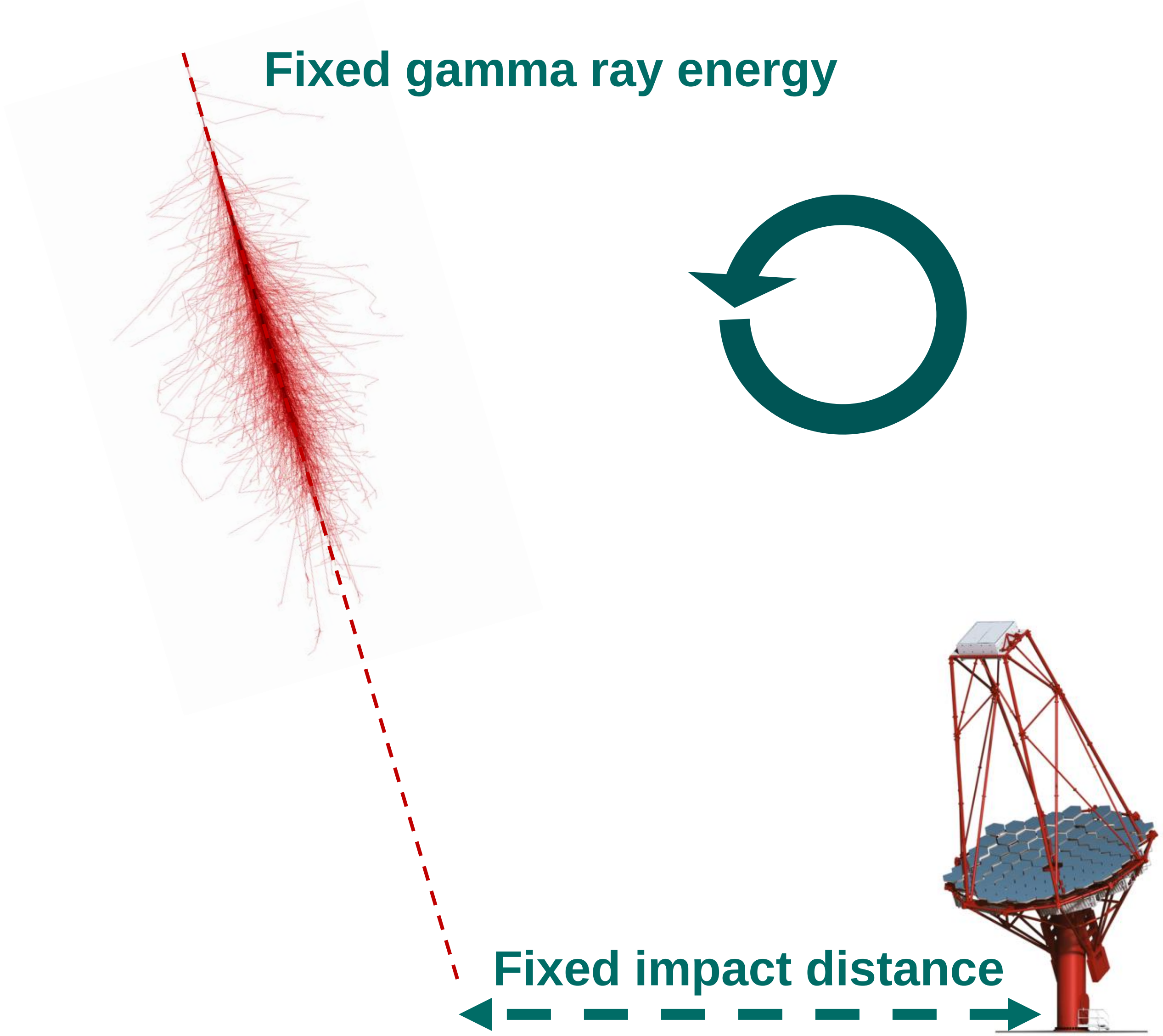


- Energy
- Source Position
- Core location
- Shower maximum

How good is the ImPACT likelihood?

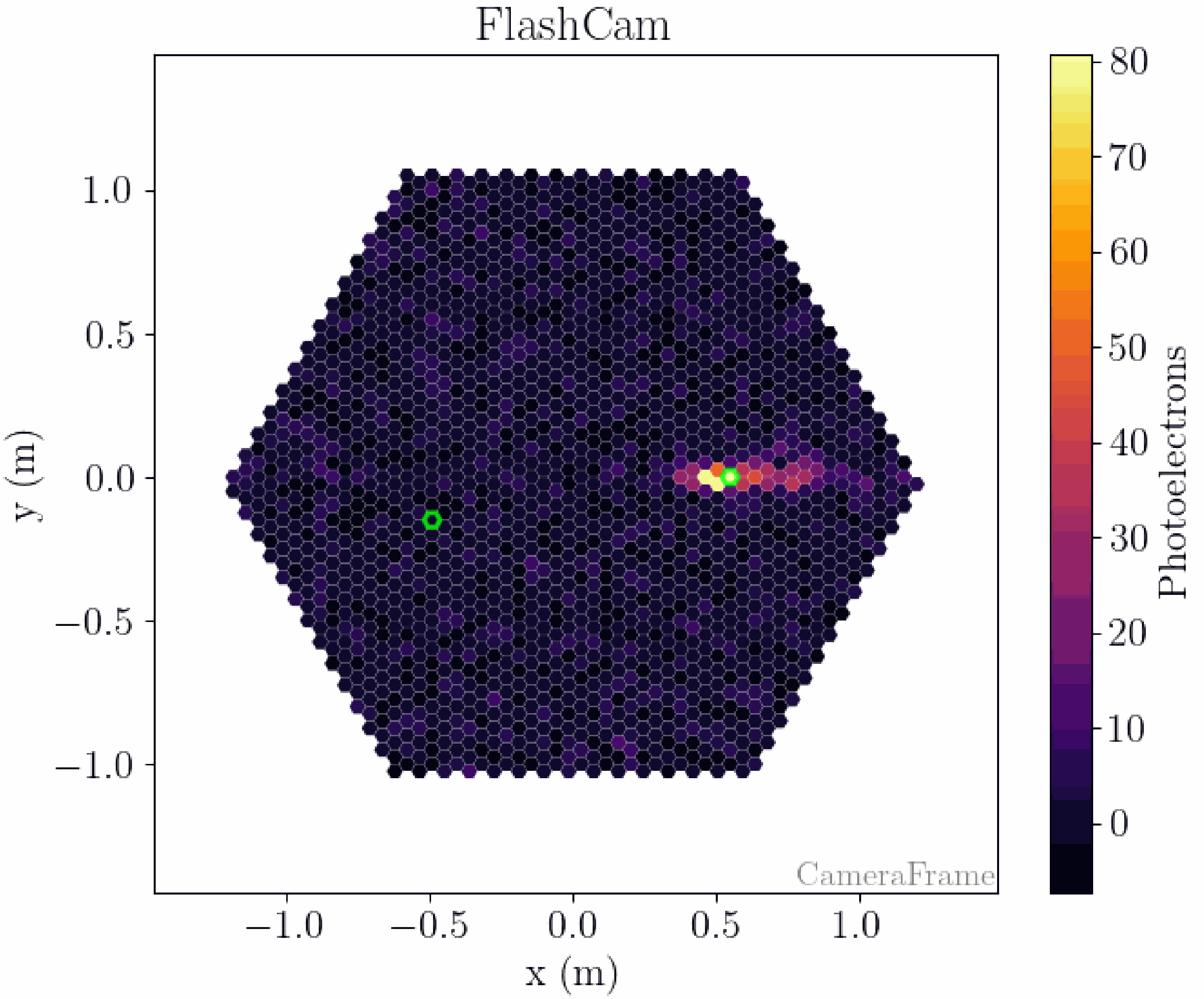
CHARGE PROBABILITY DISTRIBUTION

FLASHCAM-MST



Fixed gamma ray energy

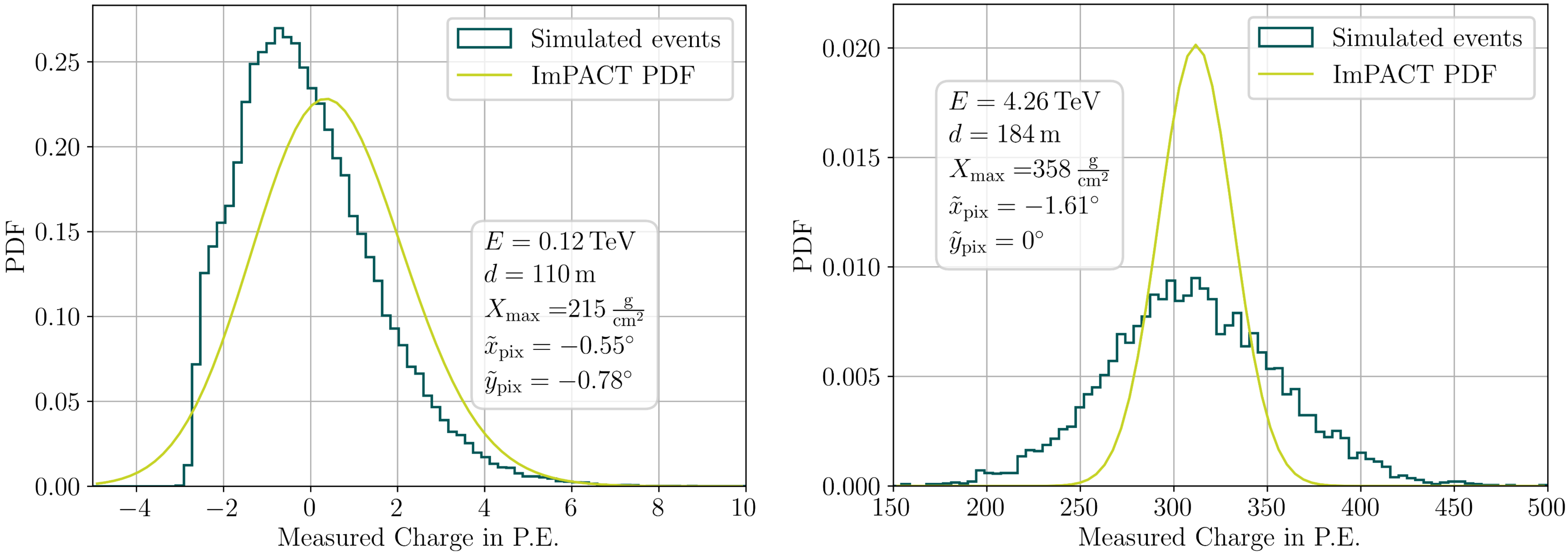
Fixed impact distance



Inspect distributions in individual pixels

CHARGE PROBABILITY DISTRIBUTION

FLASHCAM-MST



NEURAL RATIO ESTIMATION

ARXIV:2208.10166, ARXIV1903:04057

Goal: Estimate likelihood $p(x|\theta)$

$x \;\hat{=}\;$ Measured Pixel Charge

$\theta \;\hat{=}\;$ Telescope and shower parameters

For optimization for θ

$$p(x|\theta) \Longleftrightarrow \underbrace{\frac{p(x|\theta)}{p(x)}}_{\text{Likelihood-to-evidence (LtE) ratio}}$$

Trick: LtE ratio from binary classifier function $d(x,\theta)$

$$\frac{p(x|\theta)}{p(x)} \overset{\text{Bayes}}{=} \frac{p(x,\theta)}{p(x)p(\theta)} = \frac{d(x,\theta)}{1-d(x,\theta)}$$

with $$\underbrace{d(x,\theta) = \frac{p(x,\theta)}{p(x,\theta)+p(x)p(\theta)}}_{\text{Approximate with } \textbf{Binary Classifier Neural Network}}$$

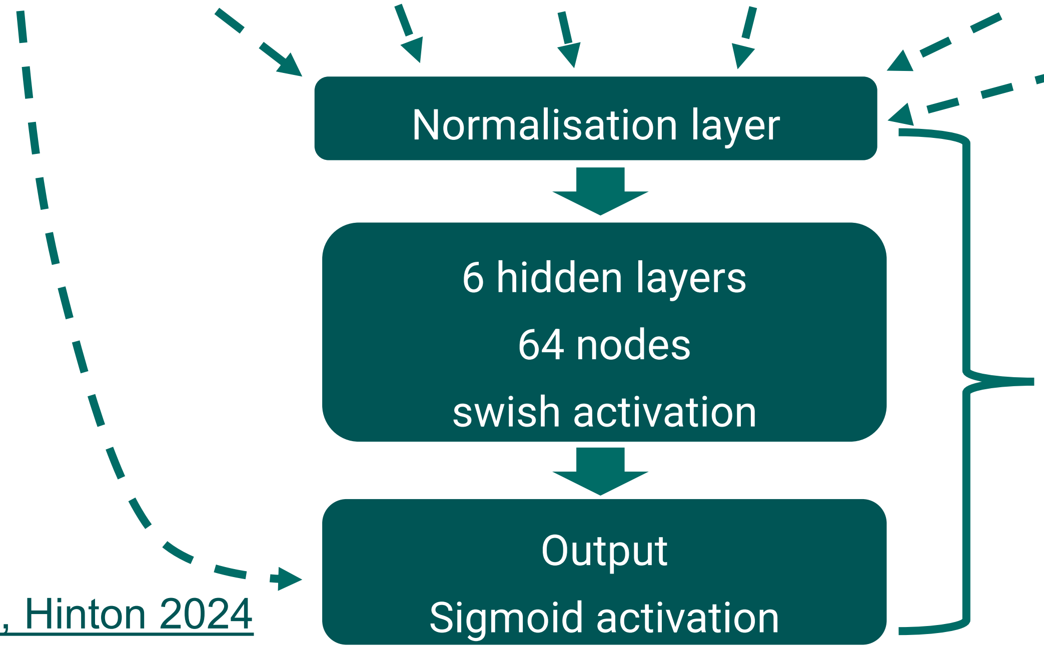
BINARY CLASSIFIER NEURAL NETWORK

$\underbrace{\text{Pixel x, Pixel y, Energy, Impact D., Xmax}}_{\theta}$ $\underbrace{\text{Charge}}_{x}$

	Class	Pixel x	Pixel y	Energy	Impact D.	Xmax	Charge
$p(x,\theta)$	1	0.5 deg	1 deg	1 TeV	100 m	250 g/cm2	20 p.e.
	1	...	...	...	...	...	...
$p(x)p(\theta)$	0	-2 deg	0.3 deg	80 GeV	50 m	150 g/cm2	10 p.e.
	0	...	...	...	...	...	...

Class 1:
Pixels from MC events

Class 0:
Shuffle charge between rows



Normalisation layer

6 hidden layers
64 nodes
swish activation

Output
Sigmoid activation

Training:

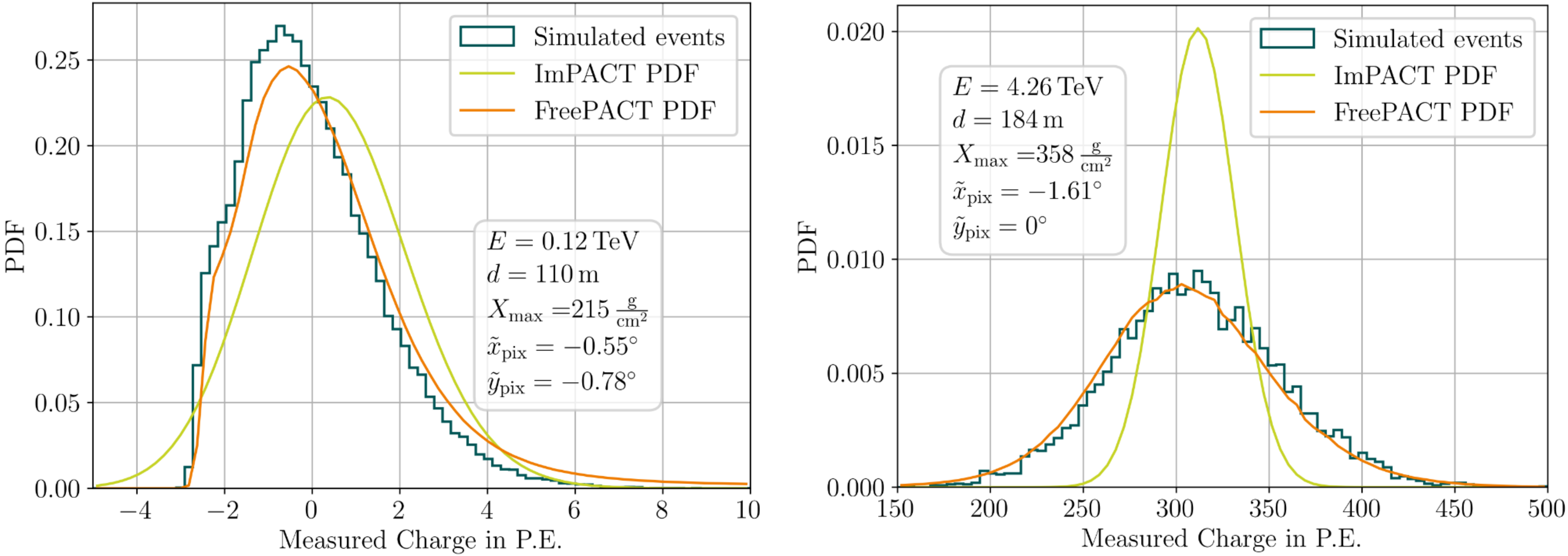
- ~20000 trainable parameters
- Binary cross-entropy loss
- Convergence in an hour on 10 cores

FreePACT: Likelihood-free ImPACT

Schwefer, Parsons, Hinton 2024

LEARNED CHARGE PROBABILITY DISTRIBUTION

FLASHCAM-MST

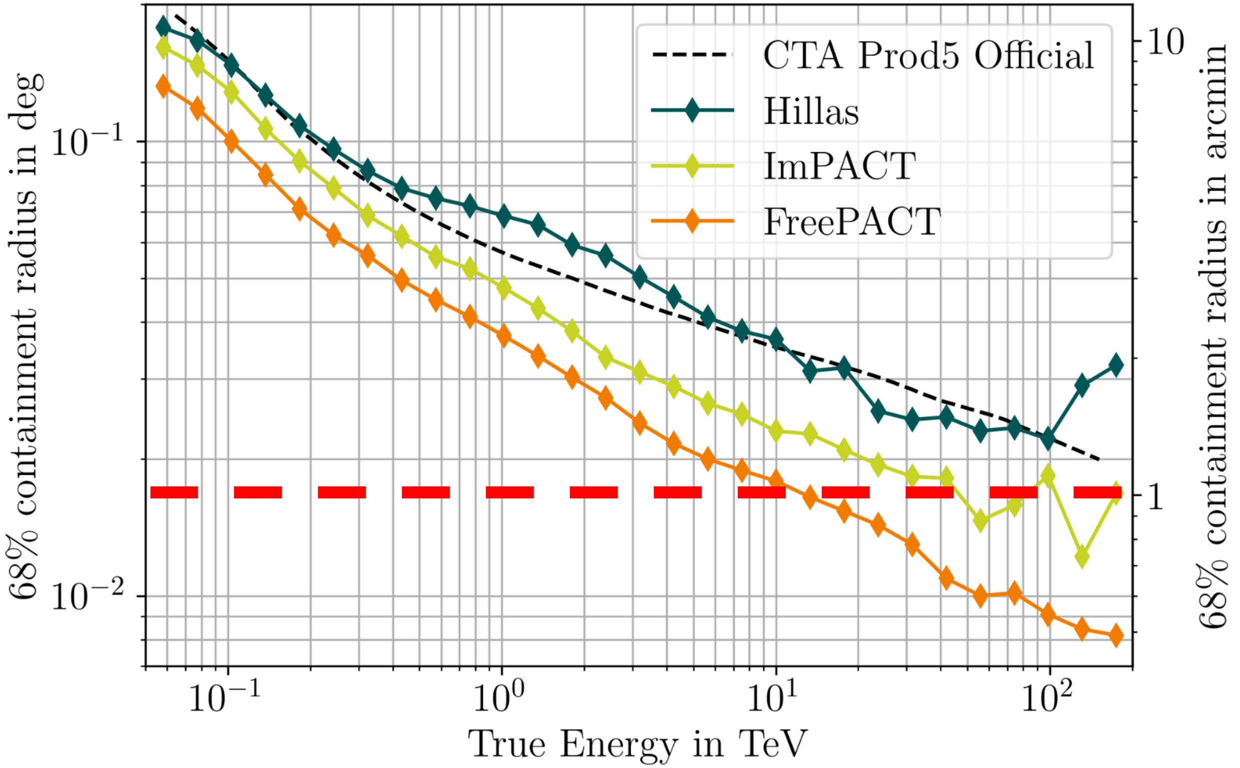


Schwefer, Parsons, Hinton 2024

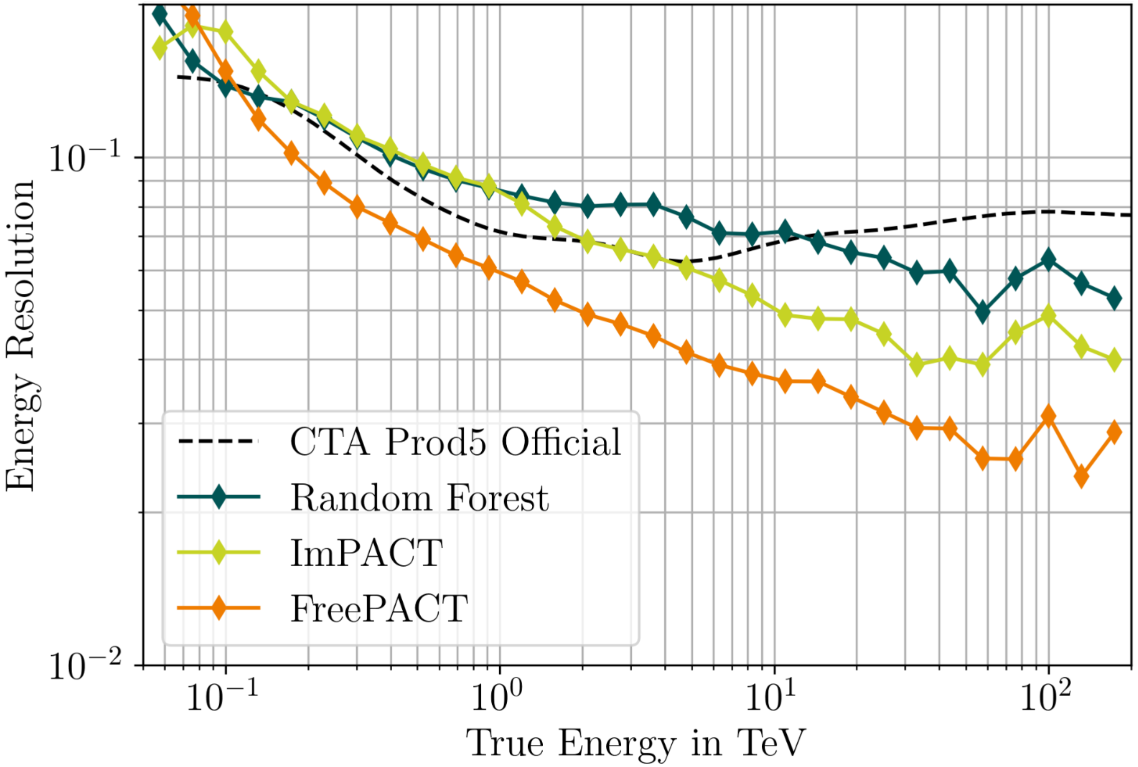
RESOLUTION CURVES

- CTA south alpha array: 14 MSTs + 37 SSTs
- On-axis gamma rays at 20 deg zenith

Angular Resolution



Energy Resolution



Sub-arcminute resolution above 10 TeV

Schwefer, Parsons, Hinton 2024

SUMMARY

FreePACT: Hybrid machine learning-likelihood reconstruction for IACTs

- Likelihood reconstruction is a proven method for IACTs
- Idea: Replace analytical likelihoods with proxy from Neural Ratio Estimation
- Significant gain in energy and angular resolution + operational advantages
- Taking this further
    - Goodness-of-fit for improving g/h separation
    - Using image timing in reconstruction

Check out the paper: Schwefer, Parsons, Hinton 2024