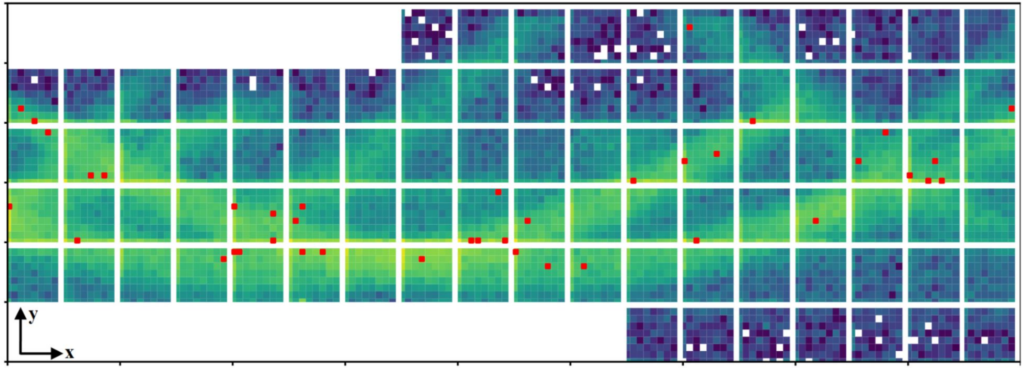
Deep(er)RICH - Deep Reconstruction of Imaging Cherenkov Detectors



James Giroux

Streaming Readout XII, University of Tokyo
December 4, 2024

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[1] Fanelli, Cristiano, James Giroux, and Justin Stevens. "Deep(er) Reconstruction of Imaging Cherenkov Detectors with Swin Transformers and Normalizing Flow Models." arXiv preprint arXiv:2407.07376 (2024).

Overview

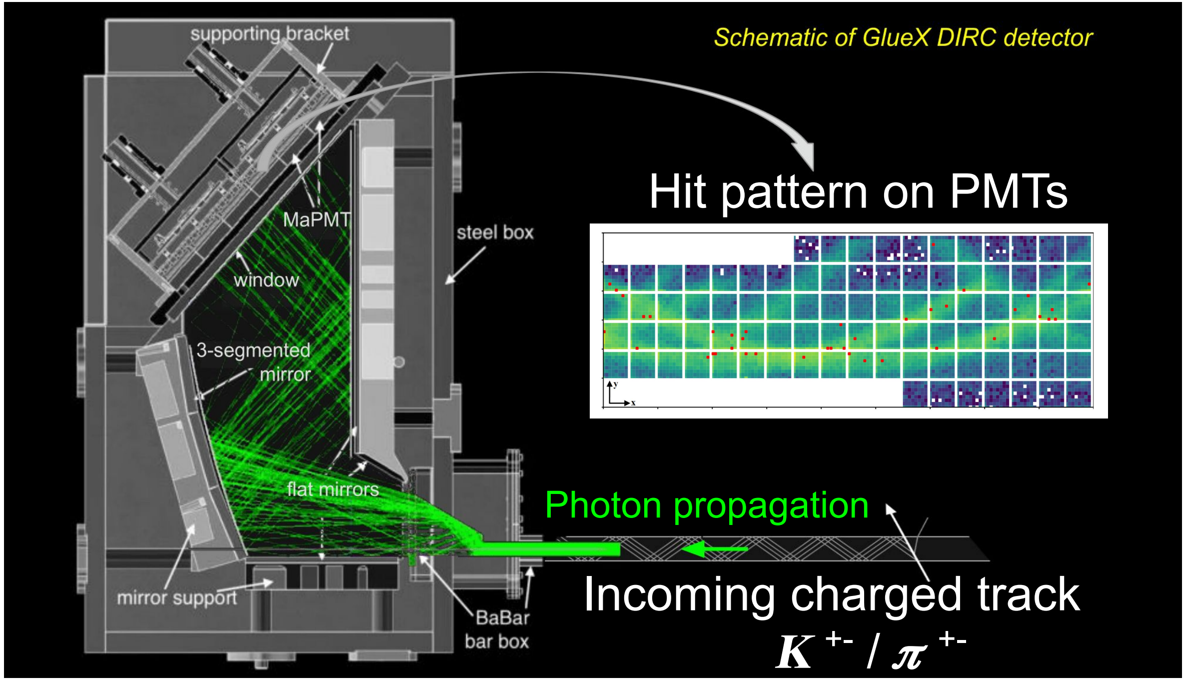
- GlueX DIRC

- Fast and Accurate Simulation

- PID Methods - $\boldsymbol{K}^{+-}$ / $\boldsymbol{\pi}^{+-}$
  - Delta Log Likelihoods
  - Image Classification with Transformers
  - Performance

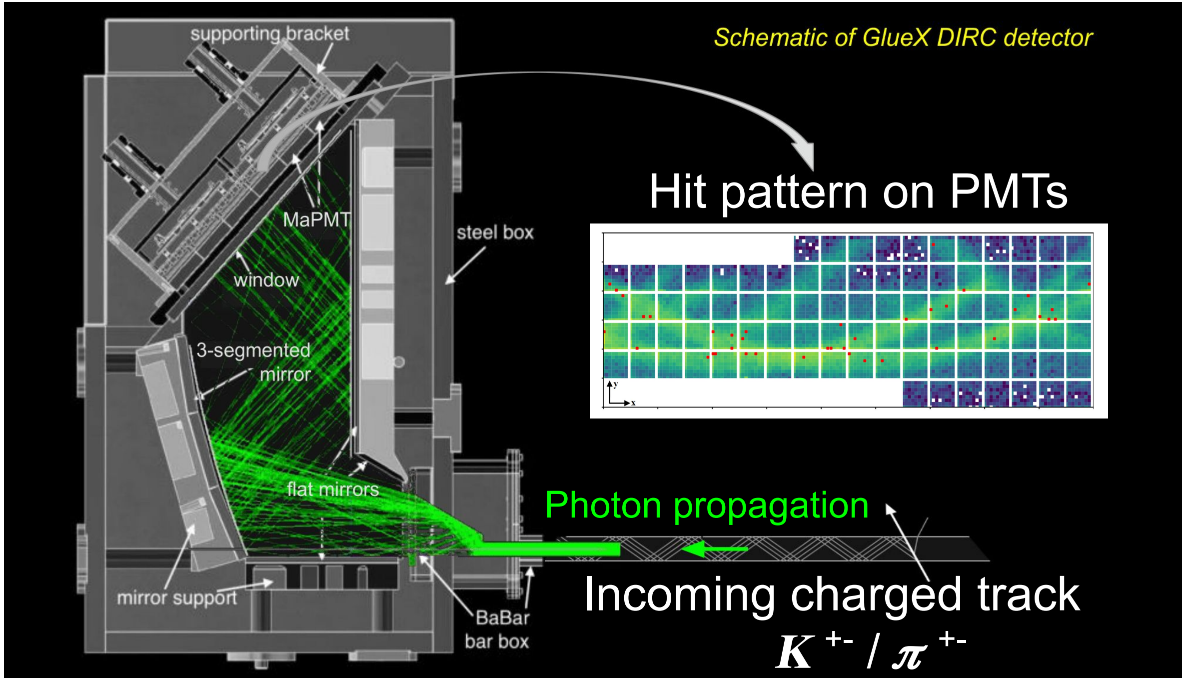
- hpDIRC - Preliminary Fast Simulation

Detection of Internally Reflected Cherenkov Light (GlueX DIRC)



- 48 fused silica bars segmented into 4 bar boxes
- Two readout zones (optical boxes)
- Optical boxes contain distilled water and highly reflective focusing mirrors
- 6 x 18 PMT array for photon detection
  - One PMT - 8 x 8 sensor array
- Provides location and timing information for individual photons

Detection of Internally Reflected Cherenkov Light (GlueX DIRC)



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Goal: Characterize hit patterns from K^{+-} / π^{+-} as a function of < $|p|$, θ , ϕ > (track)

Deep(er)RICH - Fast Simulation with Normalizing Flows

Define a bijective function *f(z), s.t.*

$$\boldsymbol{x} = f(\boldsymbol{z}) = f_N \circ f_{N-1} \circ ... f_1(\boldsymbol{z_0})$$

Transform the density through a change of variables
Conditional on some parameters *k*

$$\log p(\boldsymbol{x}|\boldsymbol{k}) = \log \pi(f^{-1}(\boldsymbol{x})|\boldsymbol{k}) + \sum_{i=1}^{N} \log \left| det \left(\frac{\partial f_i^{-1}(\boldsymbol{x})}{\partial \boldsymbol{x}} \right) \right|$$

Maximize the likelihood of expected hit patterns under a base distribution

$$\mathbf{z} \in N(0,1)$$

Analytic Likelihood Computation

$$\mathcal{L} = -\frac{1}{|\boldsymbol{X}|} \sum_{\boldsymbol{x} \in \boldsymbol{X}} \log p(\boldsymbol{x}|\boldsymbol{k})$$

Deep(er)RICH - Learning at the hit level

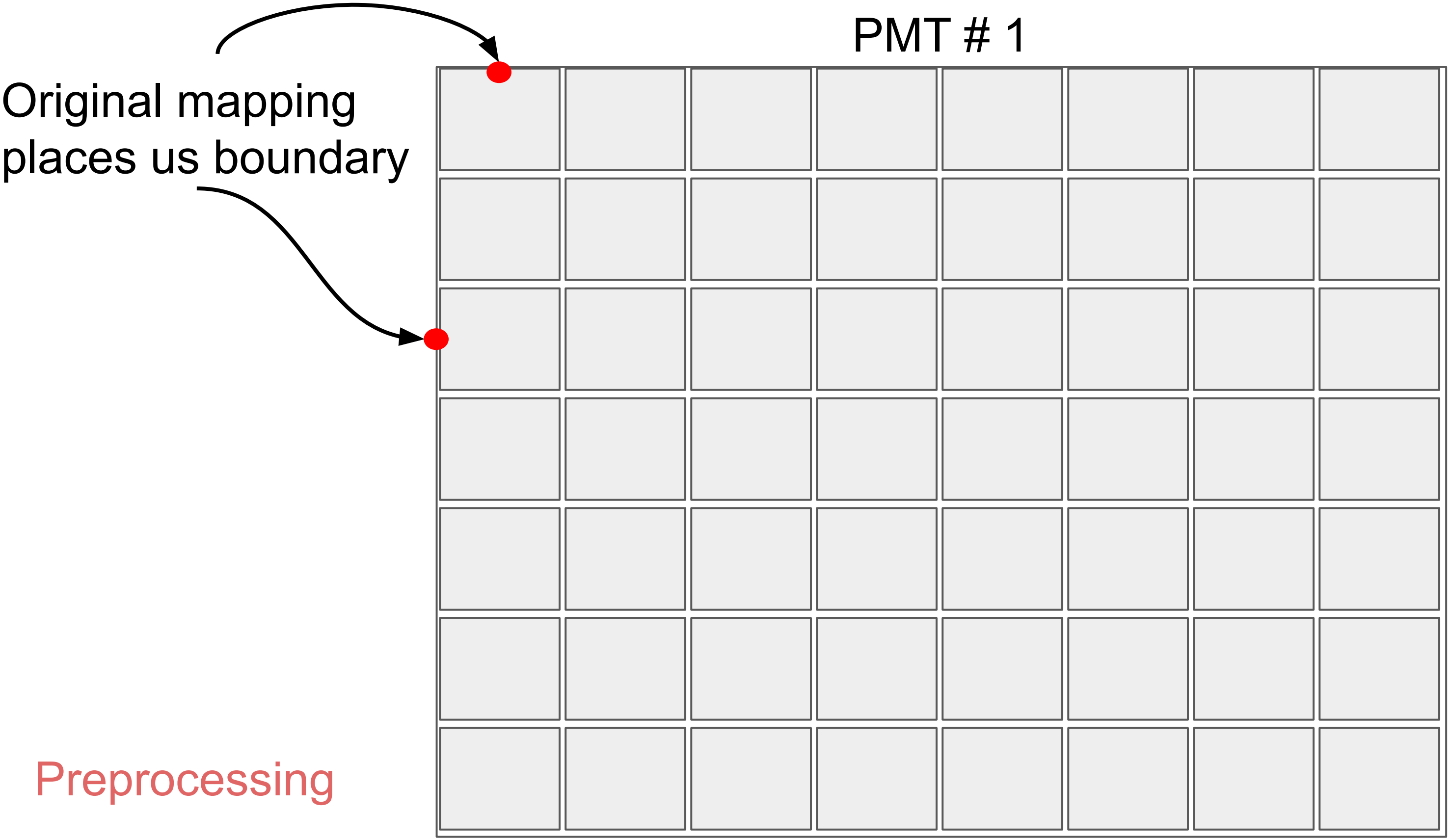
$$D_{i,j} = \begin{cases} \lfloor M_{PMT.}/18 \rfloor \cdot 8 + \lfloor N_{pixel.}/8 \rfloor & (1) \\ (M_{PMT.} \mod 18) \cdot 8 + (N_{pixel.} \mod 8) \end{cases}$$

$$x = D_j \cdot 6\,mm + (M_{PMT.} \mod 18) \cdot 2\,mm + 3\,mm$$
$$y = D_i \cdot 6\,mm + \lfloor M_{PMT.}/18 \rfloor \cdot 2\,mm + 3\,mm \quad (2)$$

- Abstract away from fixed input sizes
  - Remain agnostic to photon yield
- Learn at the hit-level, conditional on < |***p***| , ***θ*** , ***ϕ*** >
- Normalizing Flows unable to deal with discrete distributions
  - DIRC readout has fixed row,col coordinate system (1)
  - Transform to x,y coordinate system (*mm*) (2)
  - Smear uniformly over individual PMT pixels

TrackID	x (mm)	y (mm)	t (ns)	|***p***|	***θ***	***ϕ***
1				3.0	5.0	90.
1				3.0	5.0	90.
…	…	…	…	…	…	…
N				4.0	7.0	-90.
N				4.0	7.0	-90.

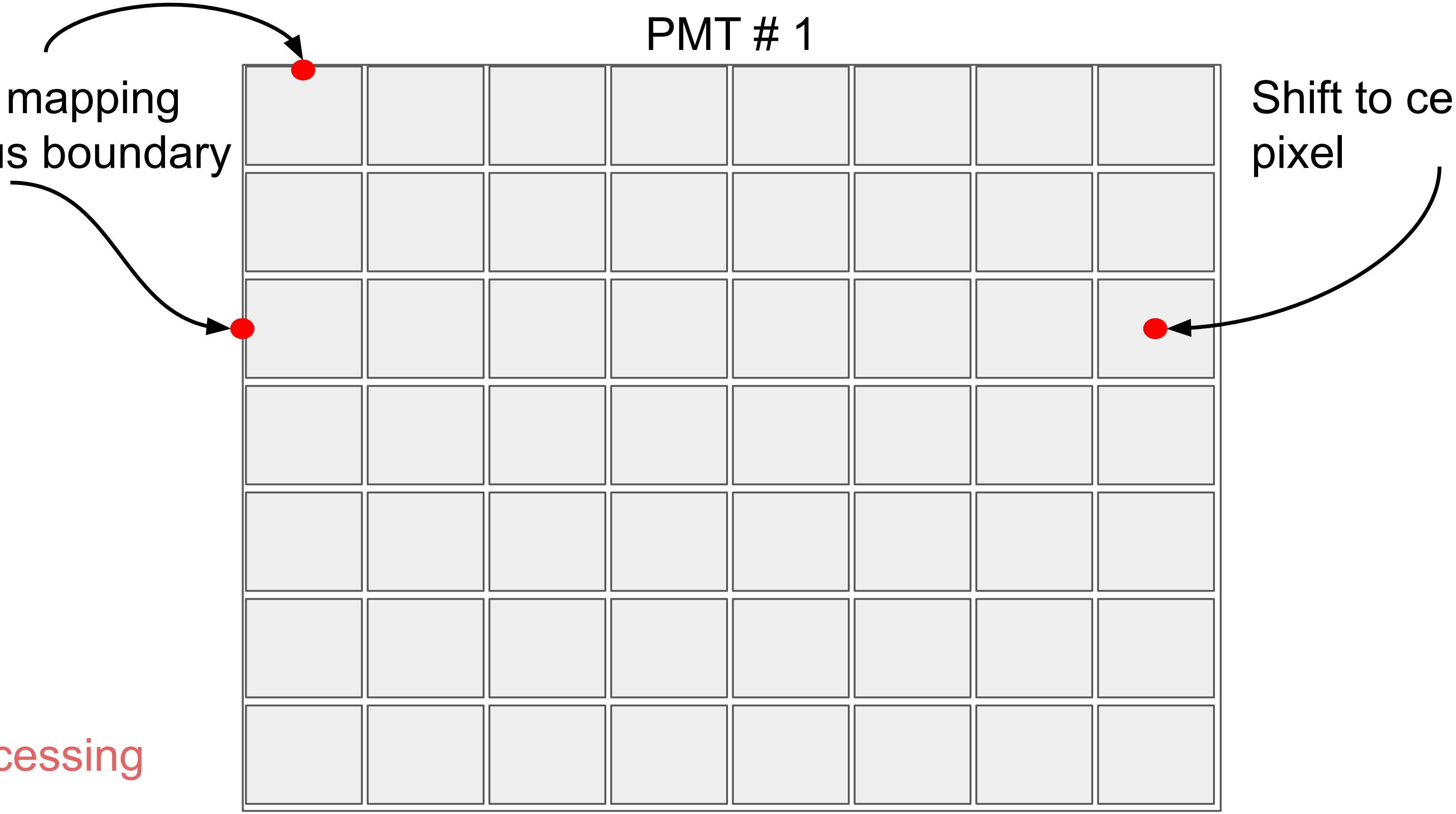
Deep(er)RICH - Learning at the hit level cont'd…



Preprocessing

Deep(er)RICH - Learning at the hit level cont'd…

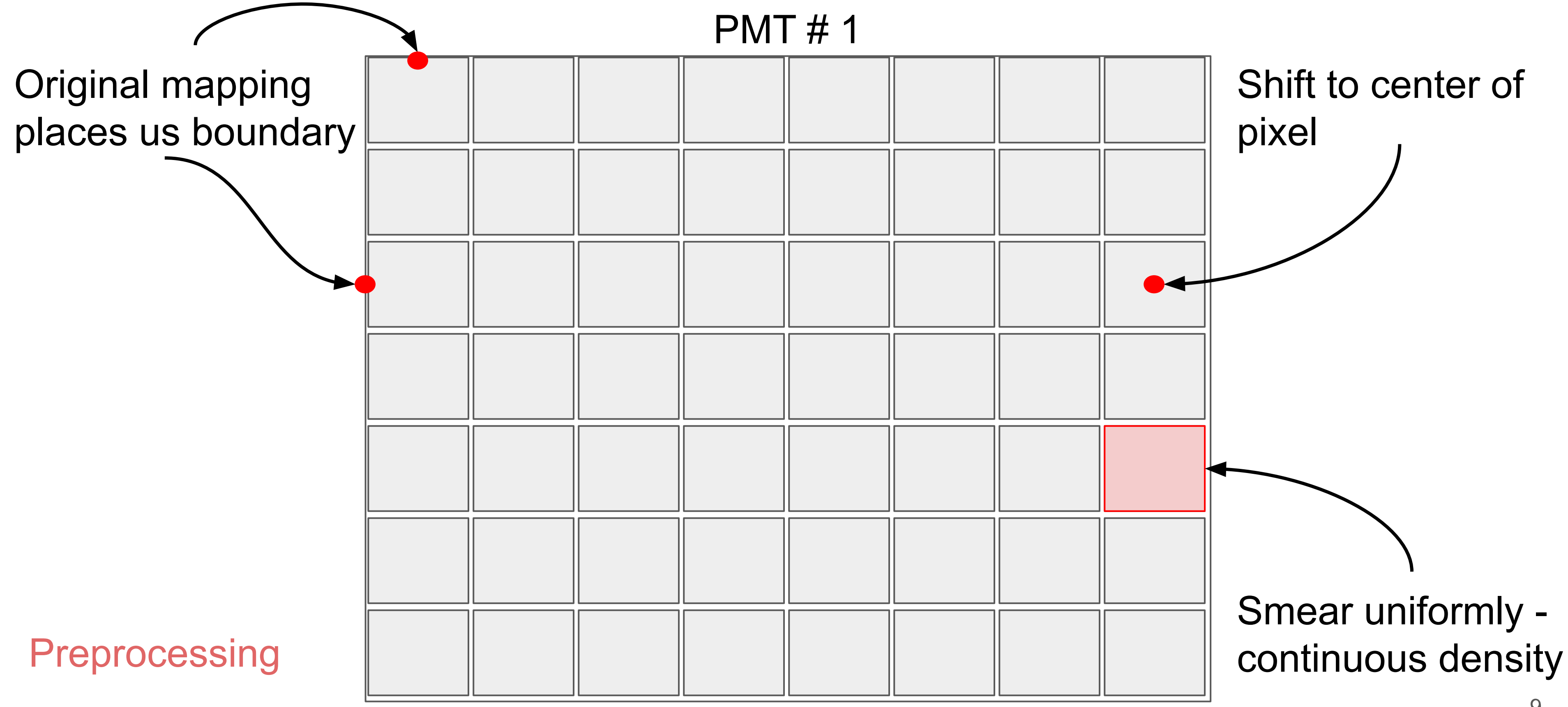
Original mapping places us boundary



Shift to center of pixel

Preprocessing

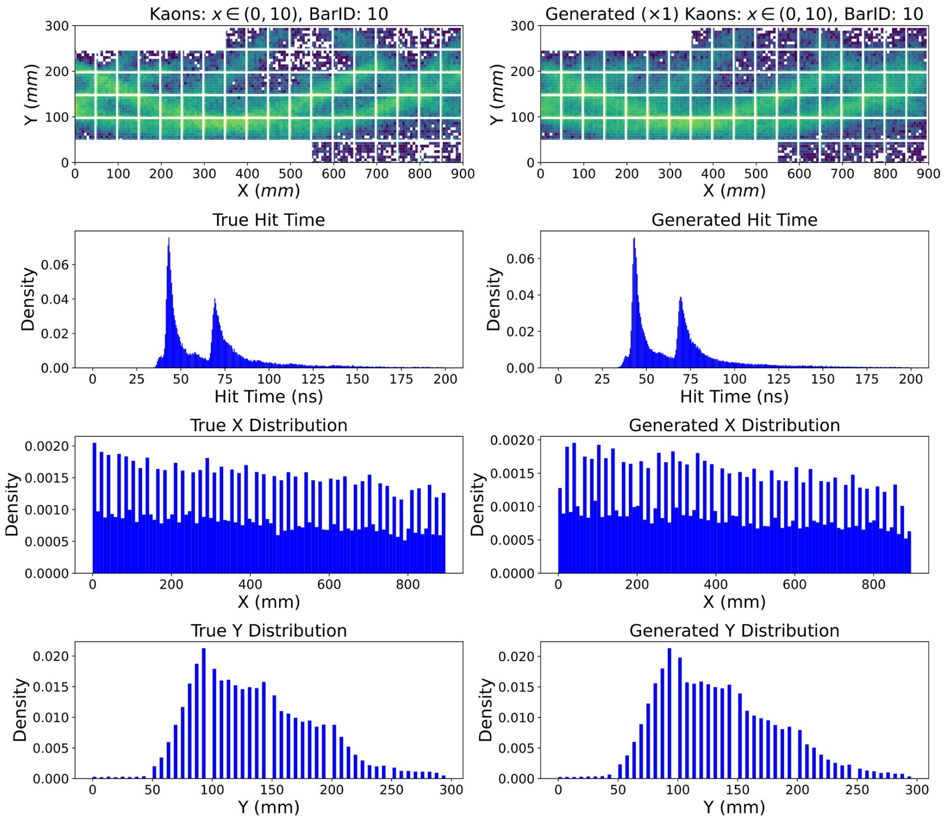
Deep(er)RICH - Learning at the hit level cont'd…



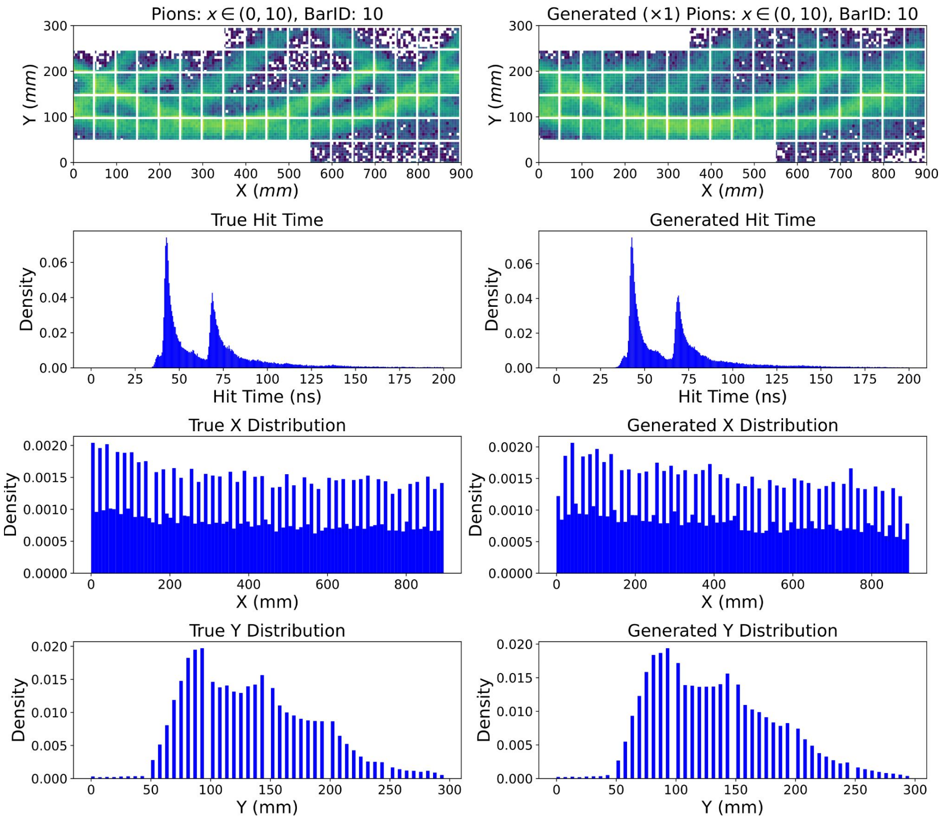
Preprocessing

Fast Simulation - GlueX DIRC

Kaons

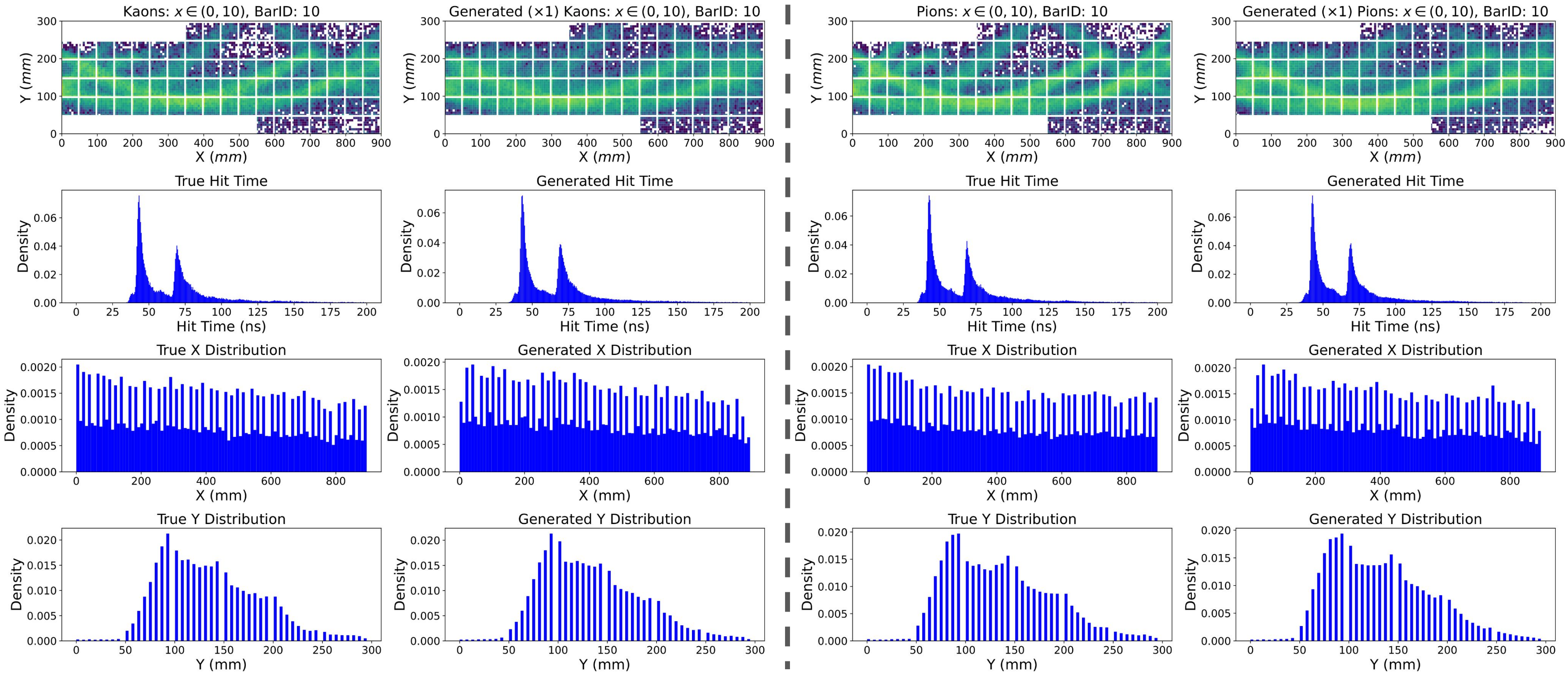


Pions



Fast Simulation - GlueX DIRC

Kaons | Pions



Simulation is fast - O(0.5)*us* per hit (effective)

π/K Separation

PID in the Base Distribution - Normalizing Flow Method

Recall our bijection

$$\boldsymbol{x} = f(\boldsymbol{z}) = f_N \circ f_{N-1} \circ \ldots f_1(\boldsymbol{z_0})$$

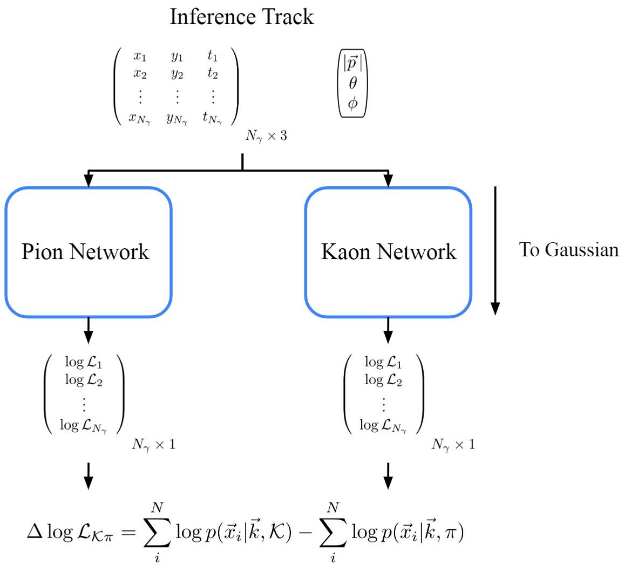
Recall our analytical computation of the likelihood under a change of variables

$$\log p(\boldsymbol{x}|\boldsymbol{k}) = \log \pi(f^{-1}(\boldsymbol{x})|\boldsymbol{k}) + \sum_{i=1}^{N} \log \left| det \left(\frac{\partial f_i^{-1}(\boldsymbol{x})}{\partial \boldsymbol{x}} \right) \right|$$

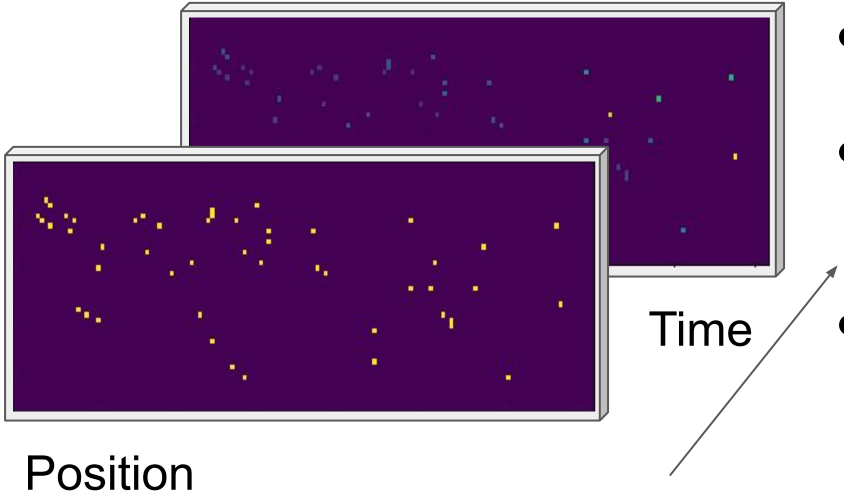
We can compute the DLL under the base distribution - summed contribution over hits

$$\Delta \log \mathcal{L}_{\mathcal{K}\pi} = \sum_{i}^{N} \log p(\vec{x}_i|\vec{k}, \mathcal{K}) - \sum_{i}^{N} \log p(\vec{x}_i|\vec{k}, \pi)$$

Where the hypothesis of a pion/kaon is represented by individual networks



Working with Images - Vision Transformer Method

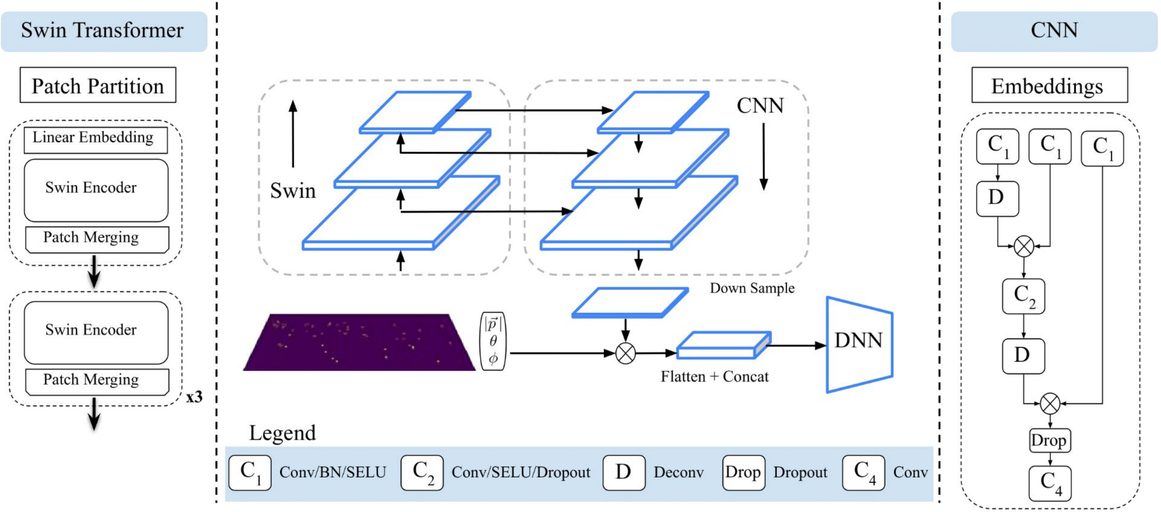


- Remain agnostic to photon yield

- Individual tracks form “images” in optical boxes
  - Sparse point representations

- Possibility of overlapping hits
  - Same *x*,*y* - different times
  - Construct these as images as FIFO
  - Tends to be low percentage of overlap

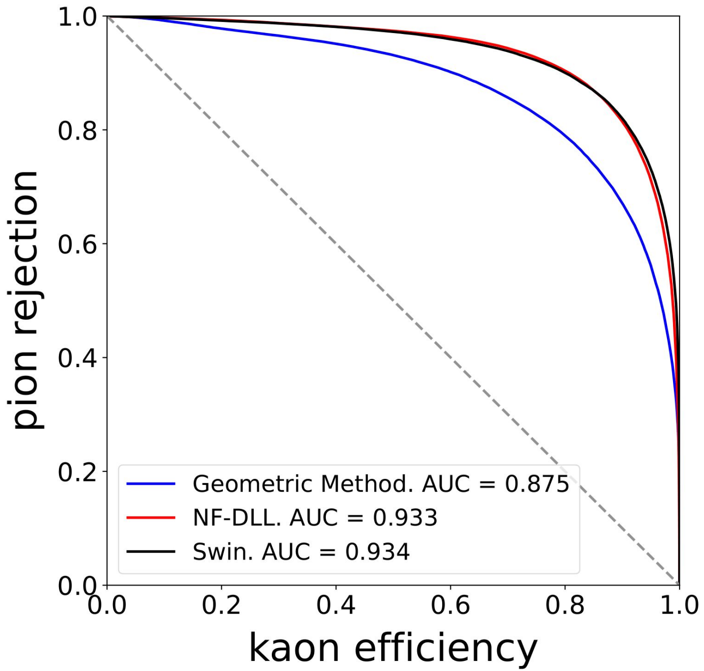
Working with Images - Vision Transformer Method cont'd…

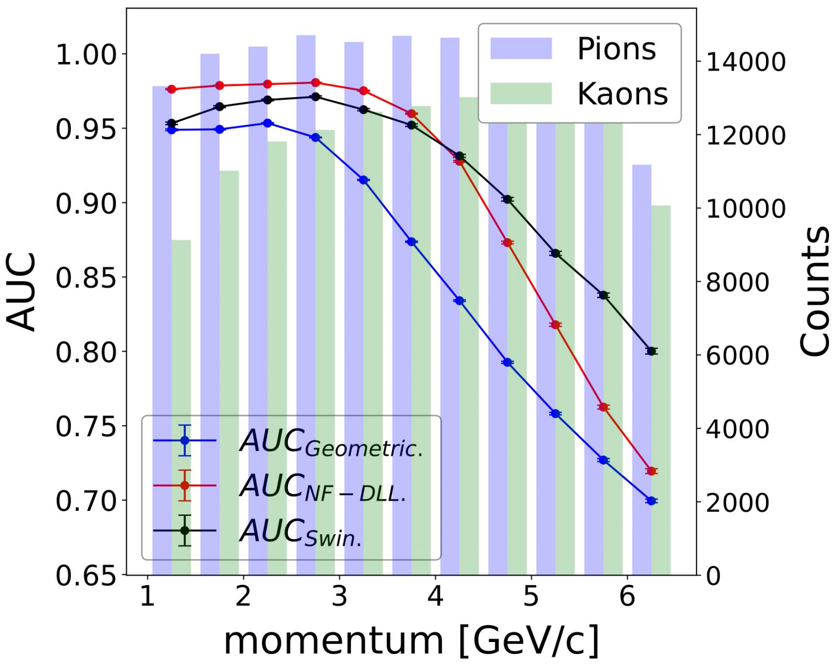


- Hierarchical Vision Transformer (Swin) - encoder style feature extraction
  - Windowed attention - higher throughput
- Combine information through CNN - utilize skip connections for different resolutions
- Inject kinematics as concatenated information to DNN

[2] Liu, Ze, et al. "Swin transformer: Hierarchical vision transformer using shifted windows." *Proceedings of the IEEE/CVF international conference on computer vision*. 2021.

π/K Separation - GlueX DIRC

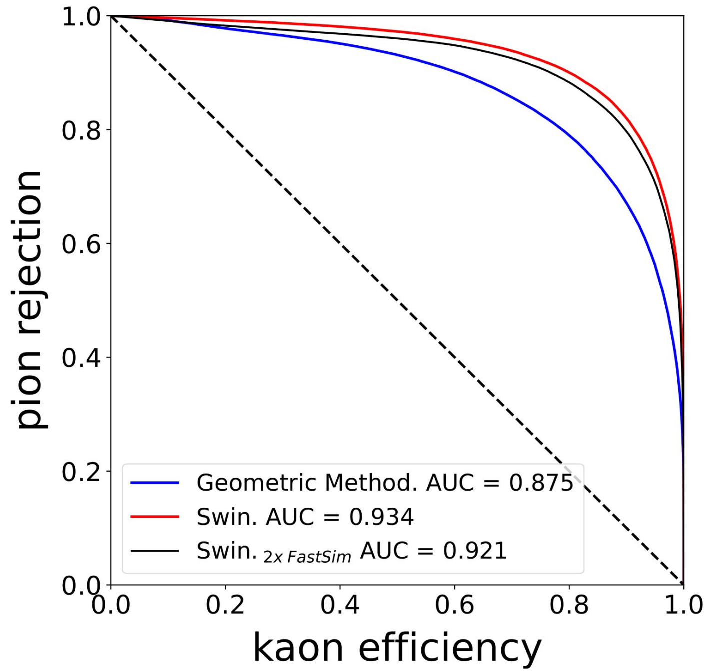


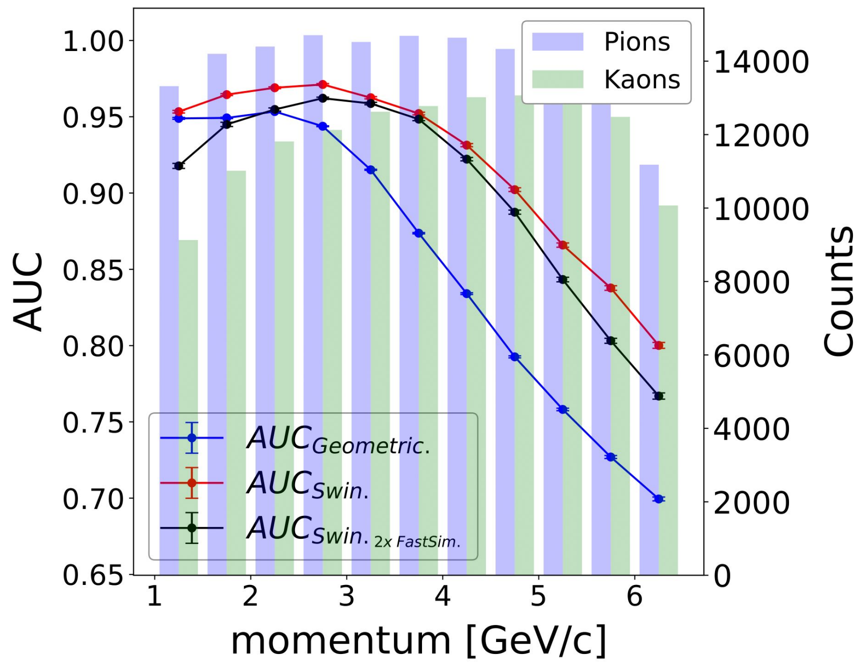


PID is fast - O(9)*us* per track with transformer (effective)

NF method slightly slower given additional computation needed

Validation of Fast Simulation through Transformer





<u>Trained on tracks from NF (fast simulation)</u>
2x Original Dataset

Tested on MC sample

hpDIRC - Preliminary Fast Simulations

$$D_{i,j} = \begin{cases} \lfloor M_{PMT.}/6 \rfloor \cdot 16 + \lfloor N_{pixel.}/16 \rfloor \\ (M_{PMT.} \,\%\, 6) \cdot 16 + (N_{pixel.} \,\%\, 16) \end{cases} \quad (1)$$

$$x = 2 + D_j \cdot p_{width.} + (M_{PMT.} \,\%\, 6) \cdot \text{gap}_x + \frac{1}{2} p_{width.} \quad (2)$$

$$y = 2 + D_i \cdot p_{height.} + \lfloor M_{PMT.} \,/\, 6 \rfloor \cdot \text{gap}_y + \frac{1}{2} p_{height.}$$

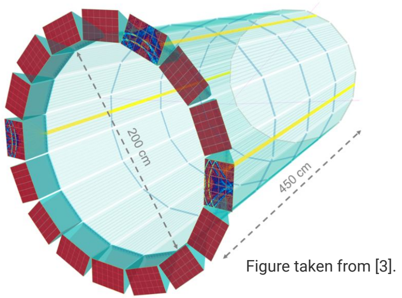
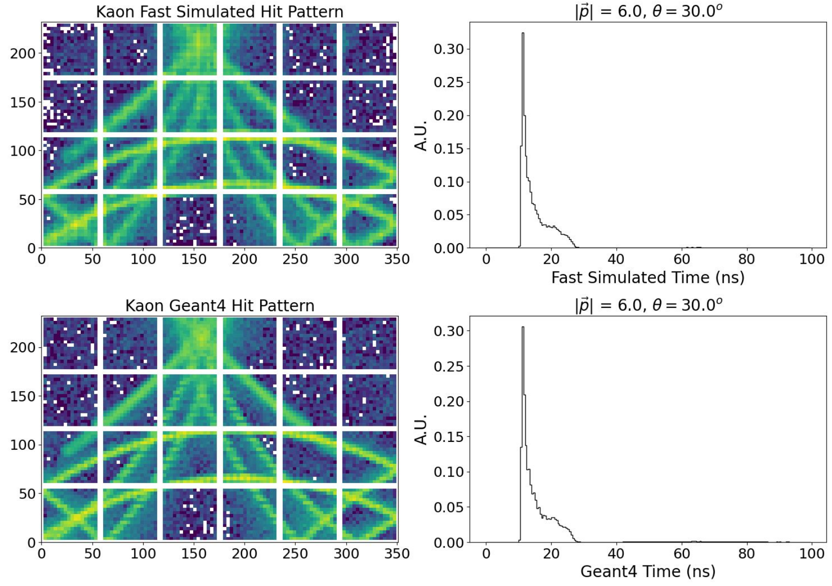
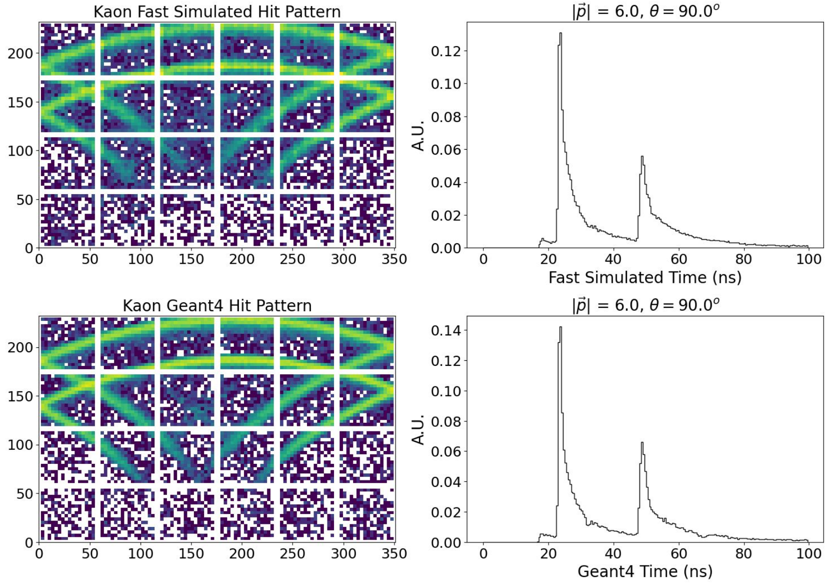


Figure taken from [3].





[3] Kalicy G 2022 Developing high-performance DIRC detector for the Future Electron Ion Collider Experiment (arXiv:2202.06457) URL https: //arxiv.org/abs/2202.06457

Conclusion

- Two Methods of PID
  - Both able to generalize over continuous phase space
  - Initial results show improved PID performance compared to classical methods at GlueX
  - Transformer provides fast inference ~ 9*us* / track (effective)
  - NF method slightly slower - extra computation, overhead due to varying number of photons
  - Working to optimize further for hpDIRC

- Fast and Accurate Simulation
  - Generates optical boxes directly - conditional on track parameters $< |\boldsymbol{p}| , \boldsymbol{\theta} , \boldsymbol{\phi} >$
    - "Skips" all track propagation
    - Fast (NF) and full simulations ~ "indistinguishable"/same performance for a classifier
  - Ability to generate photons in batches - 0.5 *us* / photon (effective)

github.com/wmdataphys/DeeperRICH

References

[1] Fanelli, Cristiano, James Giroux, and Justin Stevens. "Deep (er) Reconstruction of Imaging Cherenkov Detectors with Swin Transformers and Normalizing Flow Models." arXiv preprint arXiv:2407.07376 (2024).

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