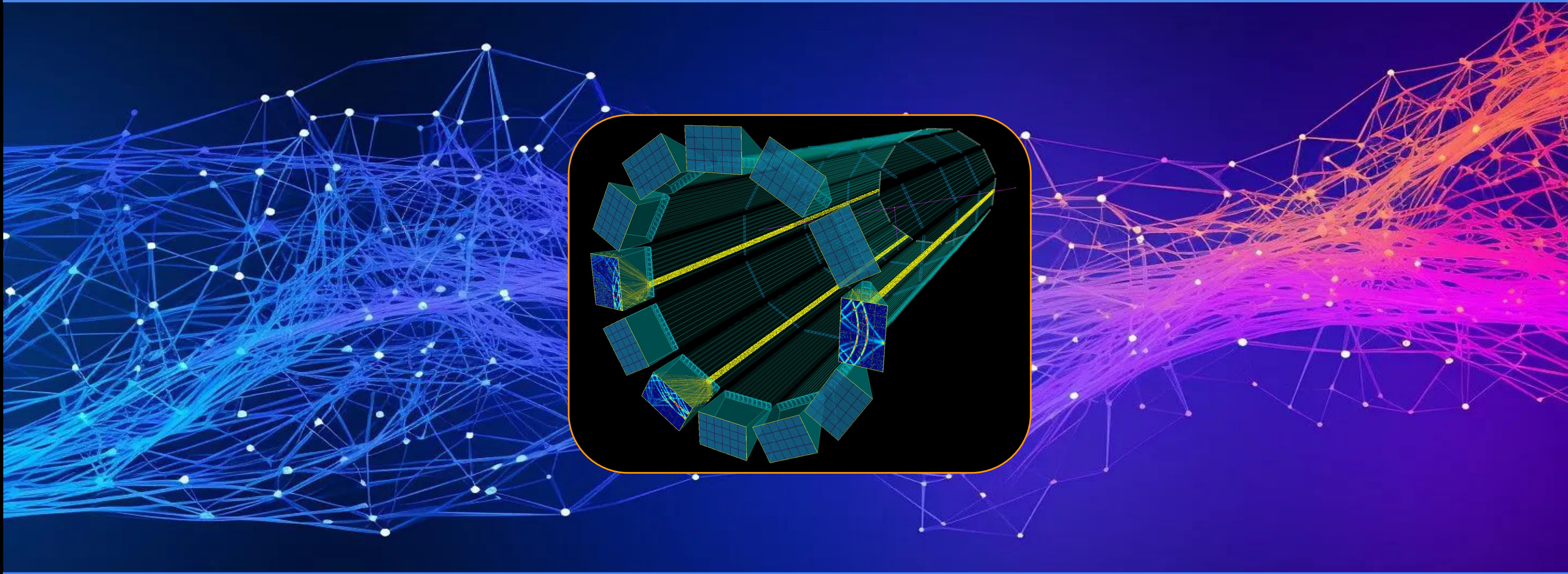
Deeply Learning DIRC Detectors



Cristiano Fanelli, James Giroux

DIRC@EIC, Jefferson Lab, June 26- July 2, 2025

WILLIAM & MARY
CHARTERED 1693

Deep Reco of Imaging CHerenkov (2020)

Deep Learning and DIRC Detector

- Machine learning for imaging Cherenkov detectors has grown significantly in recent years—particularly in the context of the EIC.
- Our 2020 study (link [here]) was the first to explore deep learning approaches for DIRC-like detectors:
    - 2909 Total downloads
    - 30 citations

PAPER • **OPEN ACCESS**

DeepRICH: learning deeply Cherenkov detectors

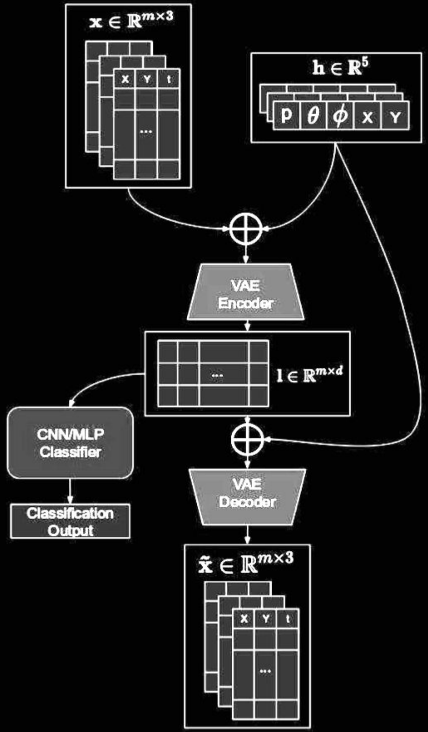
Cristiano Fanelli and Jary Pomponi

Published 27 April 2020 • © 2020 The Author(s). Published by IOP Publishing Ltd

Machine Learning: Science and Technology, Volume 1, Number 1

Citation Cristiano Fanelli and Jary Pomponi 2020 *Mach. Learn.: Sci. Technol.* **1** 015010

DOI 10.1088/2632-2153/ab845a



- This work helped demonstrate the potential of neural networks to:
    - Capture complex optical features directly from photon hit patterns
    - Offer alternatives to traditional reconstruction pipelines
    - Enable faster, data-driven inference for PID

Deeper Reco of Imaging CHerenkov (present)

Modern Architectures and Advances

Since our initial work, we have significantly advanced ML for DIRC by leveraging and integrating modern architectures into novel solutions tailored to the DIRC reconstruction challenges at EIC.

1. **Enhanced Particle Identification:**
   Achieved improved PID performance across the full detector phase space, with reduced computational cost compared to traditional reconstruction methods.

   C. Fanelli, J. Giroux, and J. Stevens. "Deep (er) reconstruction of imaging Cherenkov detectors with swin transformers and normalizing flow models." Machine Learning: Science and Technology 6.1 (2025): 015028. [link]

2. **High-Fidelity Fast Simulation:**
   Developed generative models capable of producing photon hit distributions with fidelity comparable to Geant4, but at a fraction of the computational cost—critical given the expense of tracking optical photons through complex geometries.

   J. Giroux, M. Martinez, C. Fanelli "Generative Models for Fast Simulation of Cherenkov Detectors at the Electron-Ion Collider." arXiv:2504.19042 (2025). — advanced stage of review on Machine Learning: Science and Technology [link]

3. **Towards Foundation Models for DIRC:**
   Recently introduced a unified model architecture capable of performing both reconstruction and fast simulation, enabling simultaneous achievement of (1) and (2) within a single framework.

   J. Giroux, C. Fanelli, "Towards Foundation Models for Experimental Readout Systems Combining Discrete and Continuous Data." arXiv:2505.08736 (2025). — submitted to Machine Learning: Science and Technology [link]

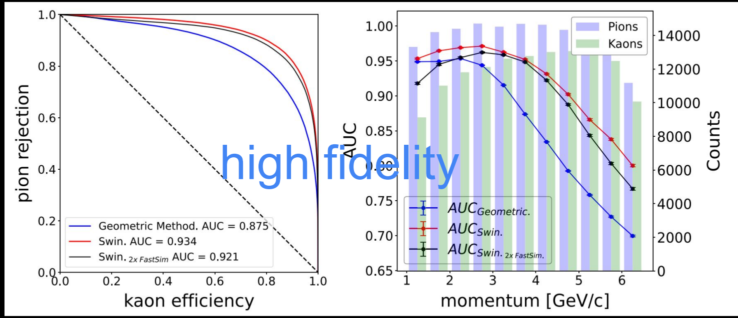
DIRC@GlueX

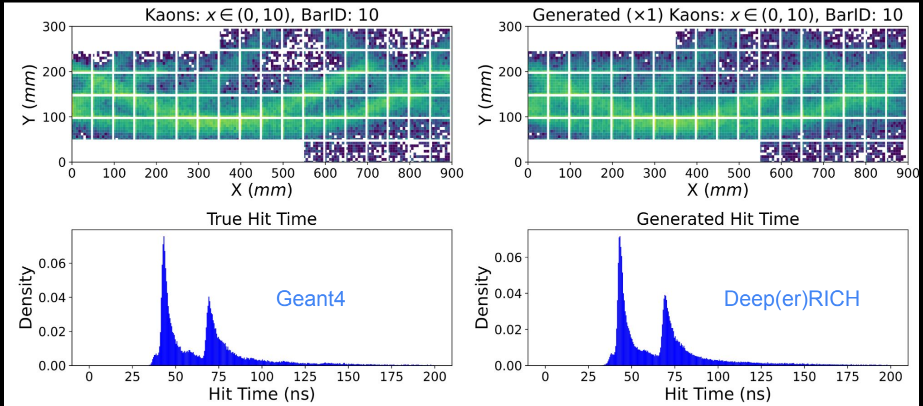
Deep(er)RICH: Fast Sim with NF - GlueX

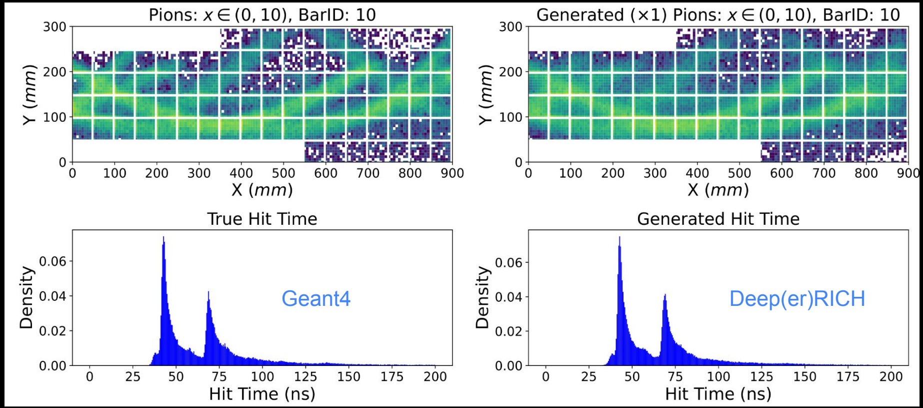
Architecture: Normalizing Flow (NF)

CF, J. Giroux, J. Stevens. “Deep(er)RICH"
Machine Learning: Science and Technology 6.1 (2025): 015028.

- **Density Transformation** – Define a bijective function and apply a change of variables, conditioning on kinematics parameters to maximize likelihood of expected hit pattern under a base distribution
- **Hit-Level Learning** – Model conditioned on kinematic parameters (|p|,θ,ϕ)
- **Agnostic to Photon Yield** – Ensure model independence from photon yield
- **Abstract away Fixed Input Size** – Address NF limitations with discrete distributions; data preprocessing transform DIRC readout (row, col) to (x,y) in mm and uniformly smear over PMT pixels



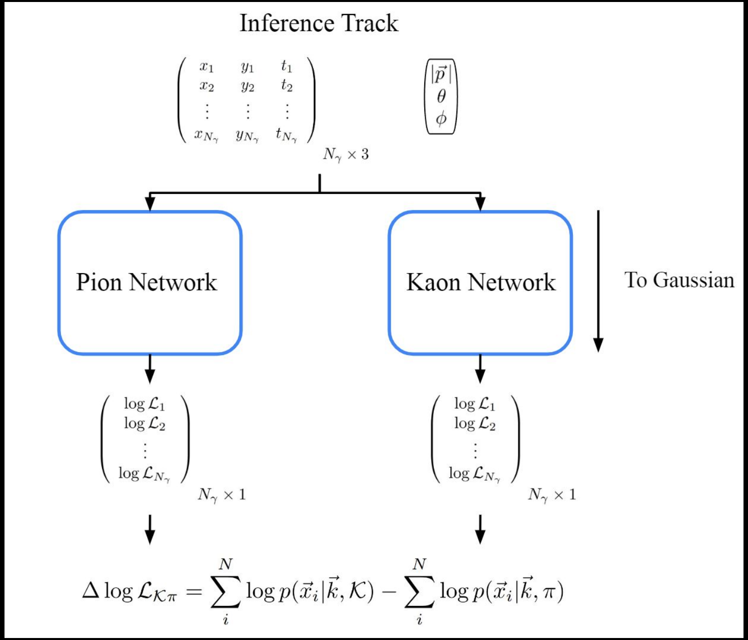




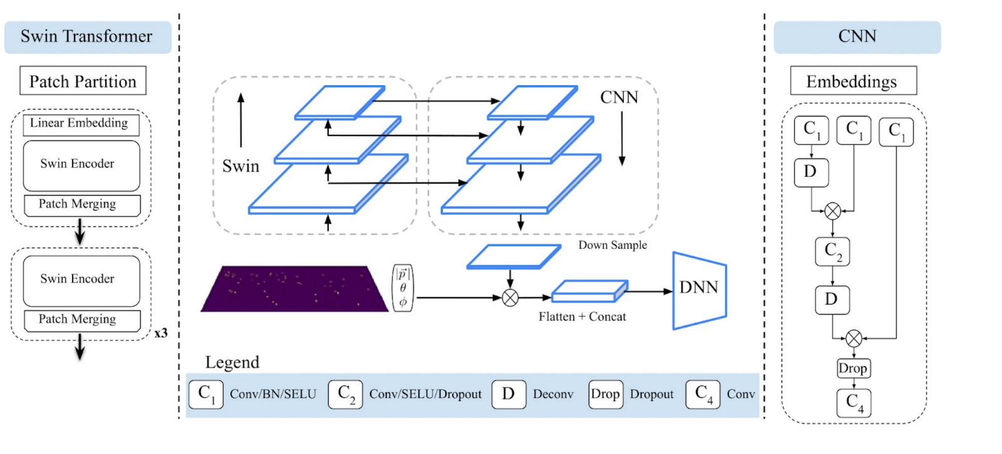
Simulation is fast - O(0.5)μs per hit (effective)

Deep(er)RICH: 2 Methods of PID - GlueX

CF, J. Giroux, J. Stevens. “Deep(er)RICH"
Machine Learning: Science and Technology 6.1 (2025): 015028.



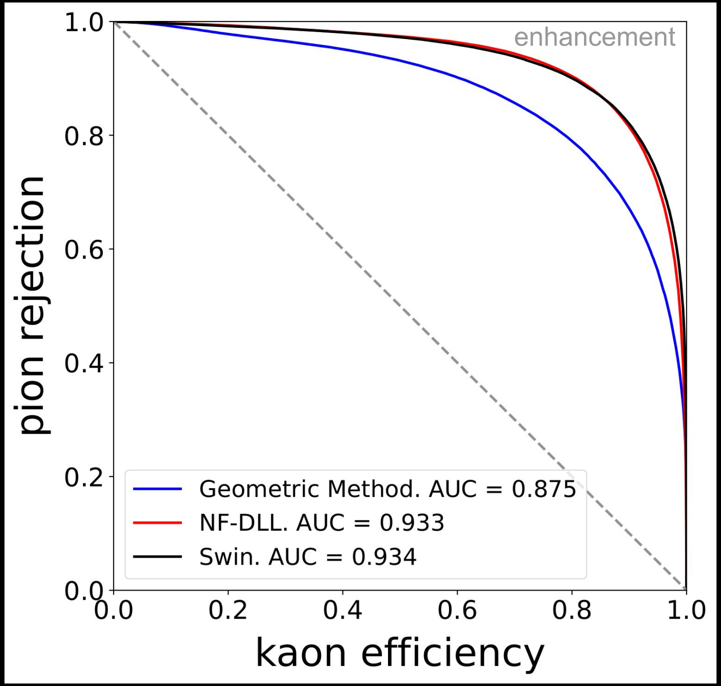
- Normalizing Flow - Likelihood based PID
- PID hypotheses represented through independent models
- Analytic likelihood computation from NF in base distribution
- Compute Delta-Log Likelihood

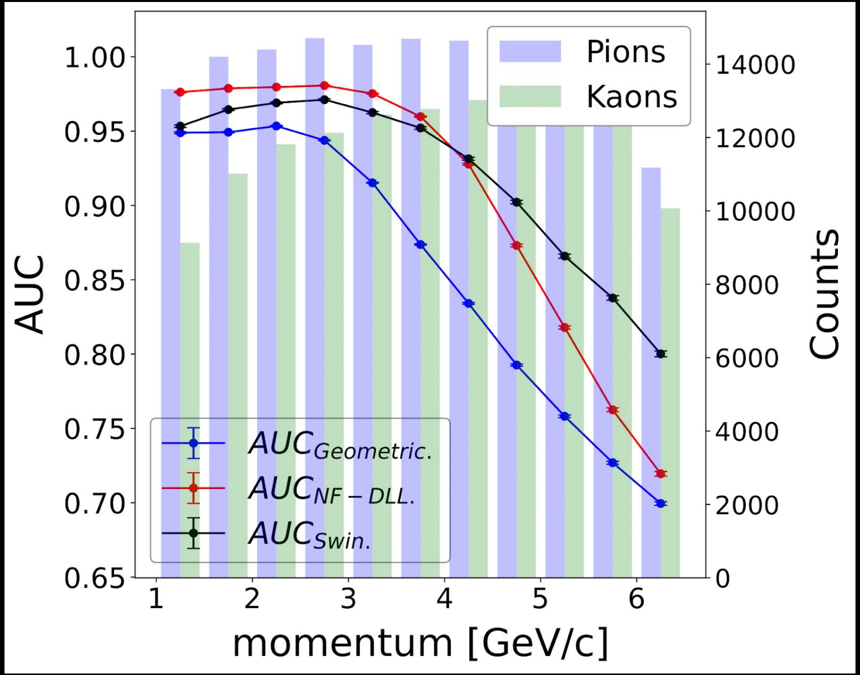


- Hierarchical Vision Transformer (Swin) - encoder style feature extraction
  - Windowed attention - higher throughput
- Combine information through CNN - utilize skip connections for different resolutions
- Inject kinematics as concatenated information to DNN

Deep(er)RICH: 2 Methods of PID - GlueX

CF, J. Giroux, J. Stevens. "Deep(er)RICH"
Machine Learning: Science and Technology 6.1 (2025): 015028.





PID is fast - O(10)μs per track with transformer (effective)

Github

Bonus: NF for PID. This method is slightly slower given additional computation needed

All code is open source and pre-trained models are provided.

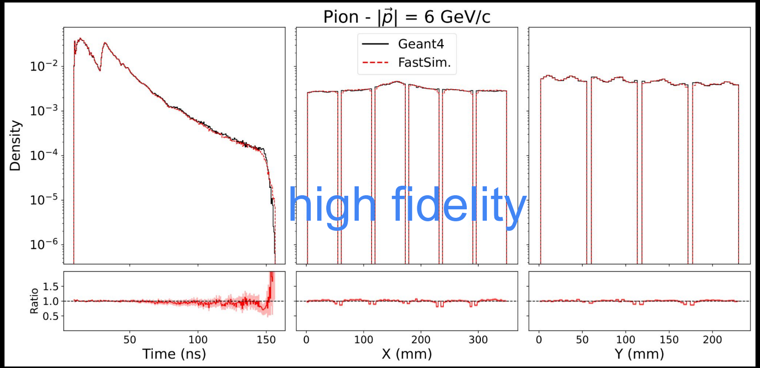
(GlueX DIRC sim)

hpDIRC@EIC

Fast Simulation at EIC - hpDIRC

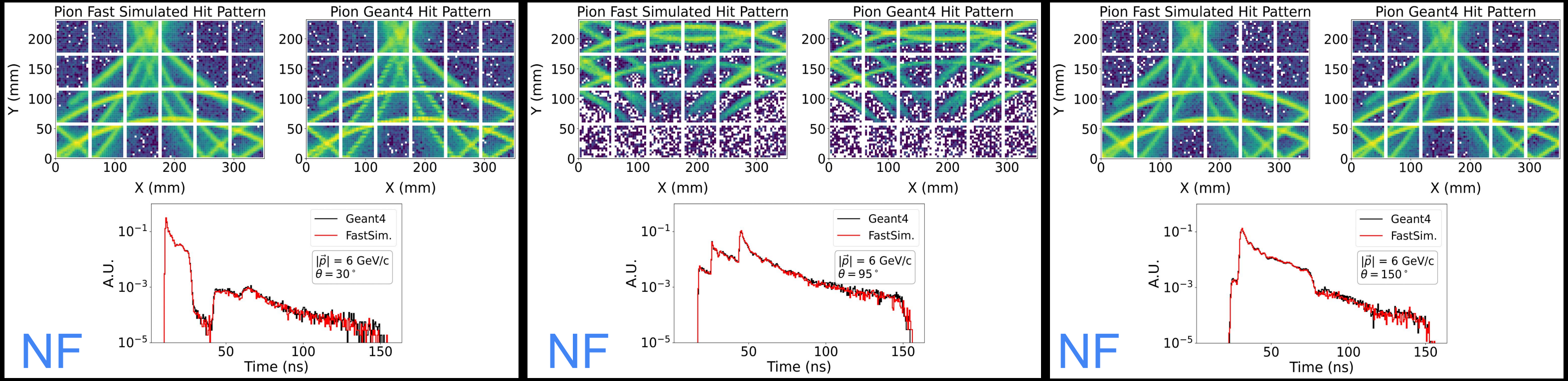
DIRC@EIC

J. Giroux, James, M. Martinez, and CF. "Generative Models for Fast Simulation of Cherenkov Detectors at the Electron-Ion Collider." *arXiv:2504.19042* (2025).



Architectures: Normalizing Flows (NF), Continuous Normalizing Flows (CNF), Conditional Flow Matching (CFM), Denoising Diffusion Probabilistic Models (DDPM), Score Based Generative Models (SB)

- **Suite of SOTA Generative Models** – Compare modern SOTA generative algorithms in the space of DIRC simulation
- **Hit-Level Learning** – Model conditioned on kinematic parameters (|p|,θ)
- **Agnostic to Photon Yield** – Ensure model independence from photon yield
- **Abstract away Fixed Input Size** – Address limitations with discrete distributions; data preprocessing transform DIRC readout (row, col) to (x,y) in mm and uniformly smear over PMT pixels



Simulation is fast - O(0.5)μs per hit (effective)

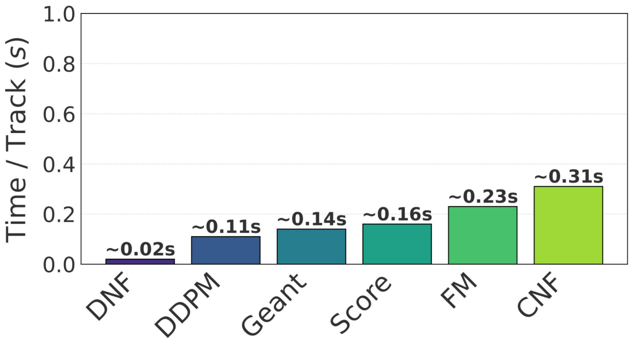
(hpDIRC standalone sim)

Fast Simulation at EIC - hpDIRC

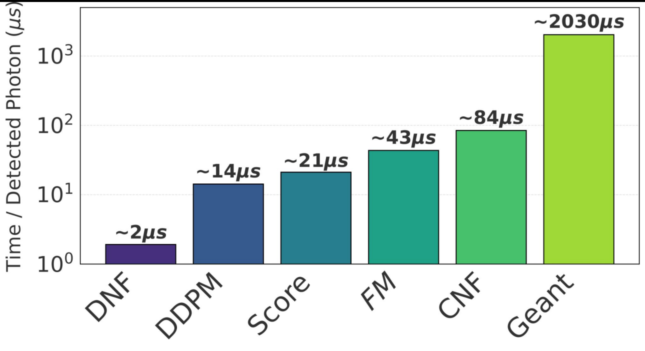
- Ring and time structures follow correct kinematic dependencies for both PIDs
  - See ArXiv for more in depth evaluation
- We have created an open source suite of SOTA algorithms for the hpDIRC (easily adapted to other detectors)
- Our fast simulation is self contained, fast and capable of being run on CPU or GPU

All code is open source and pre-trained models are provided.

Github



Track Generation (CPU)

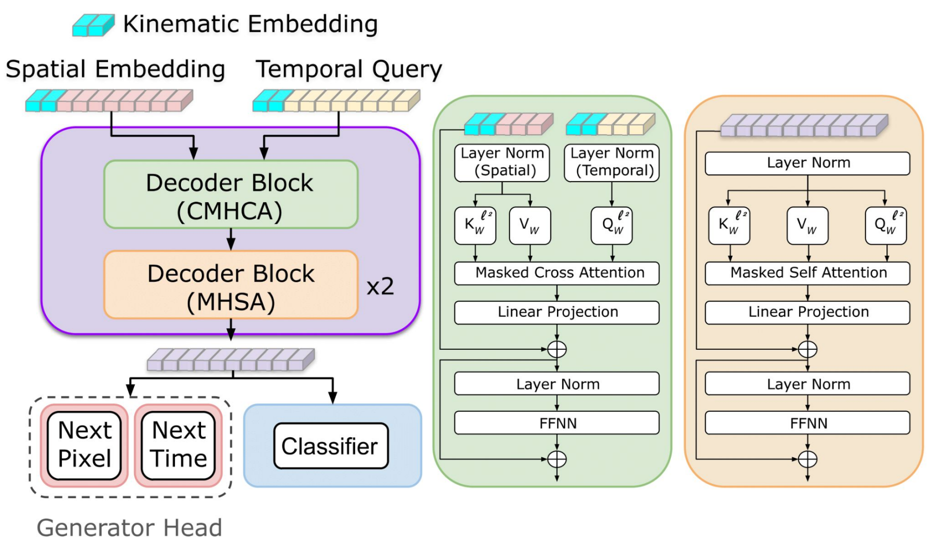


Photon Generation - Large PDFs (GPU)

Foundation Models - hpDIRC

J. Giroux and C Fanelli "Towards Foundation Models for Experimental Readout Systems Combining Discrete and Continuous Data." *arXiv:2505.08736* (2025).

- Foundation Models capable of generalizing to multiple task
  - Pre-trained backbone structure (transformer based)
- *Fine-tune* to different tasks
  - Generation
  - Classification
  - Noise Filtering
- Represent hits in *tokenized* space



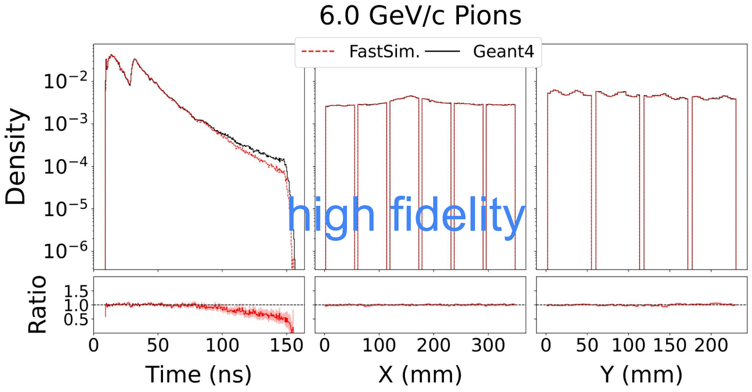
$$\text{spatial} \rightarrow \{|\vec{p}|, \theta, \mathrm{SOS}_p, p_1, \ldots, p_n, \mathrm{EOS}_p\}$$
$$\text{time} \rightarrow \{|\vec{p}|, \theta, \mathrm{SOS}_t, t_1, \ldots, t_n, \mathrm{EOS}_t\}$$

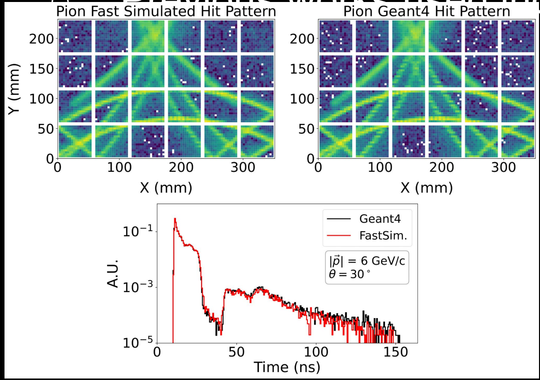
Github

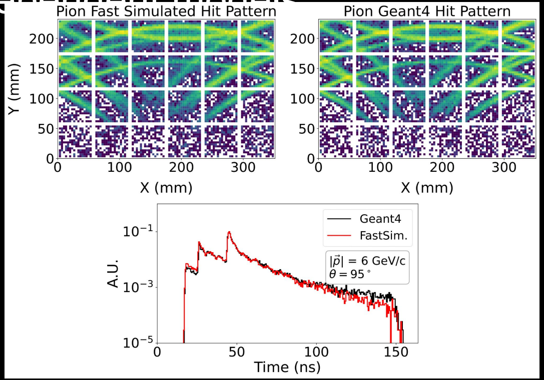
All code is open source and pre-trained models are provided.

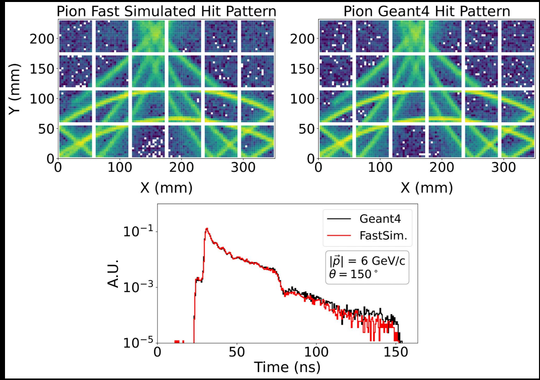
Foundation Models - hpDIRC

- Fast simulation through *next token* prediction
- Directly learns variability in photon yield
  - Model conditioned on kinematic parameters (|p|, θ)
  - No external modeling of photon yield required
- Class conditional (particle type) generation through a *Mixture of Experts* (MoE)
  - Previous works used independent models







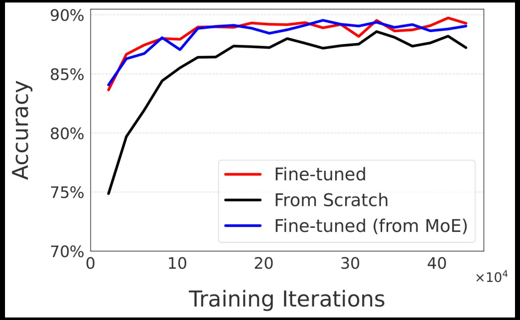


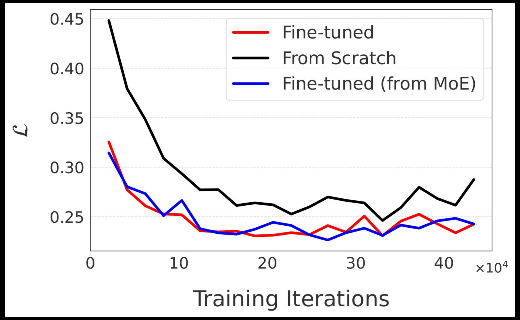
Simulation is fast - O(0.02)s per track (effective)

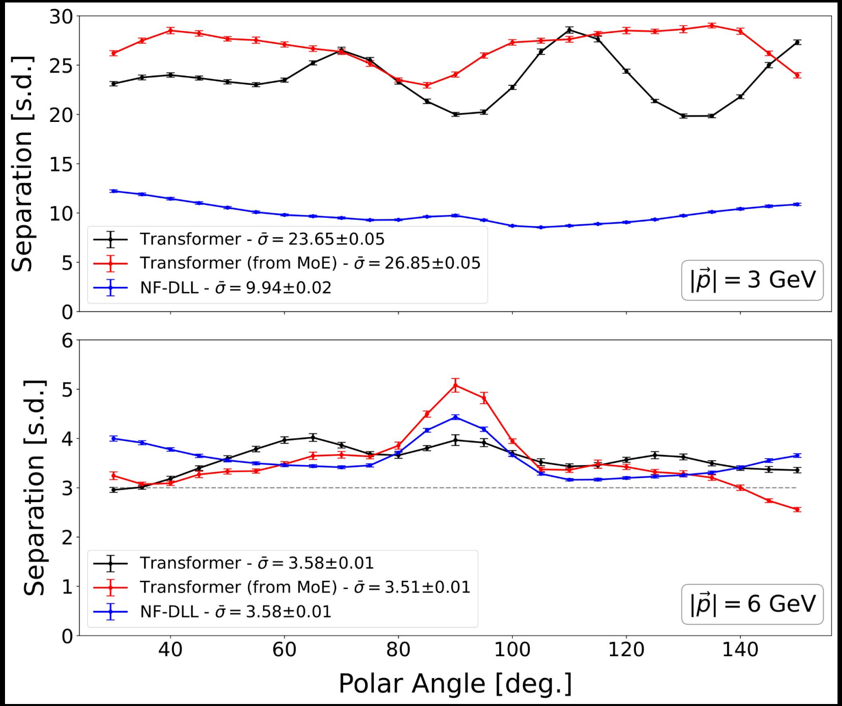
(hpDIRC standalone sim)

Foundation Models - hpDIRC

- Classification (π/K) through fine-tuning fast simulation model (sequence level)
    - Decrease in required training time
    - Increased performance
- Reaching separation requirement of 3σ at 6 GeV/c





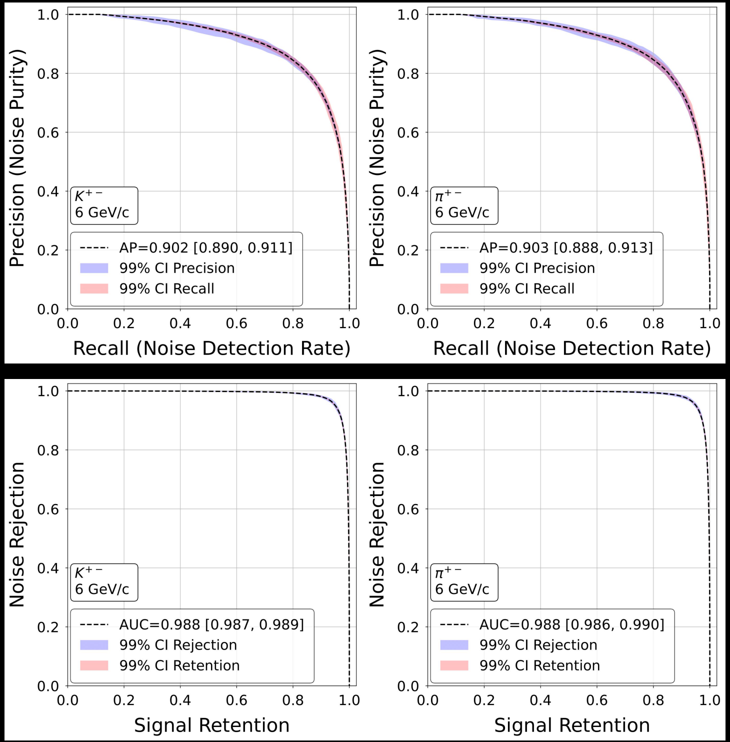


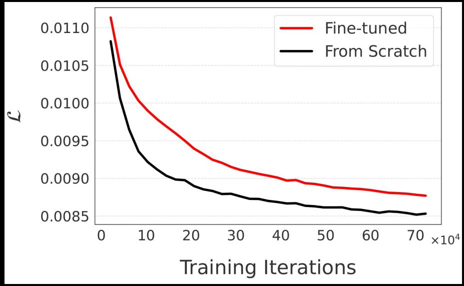
(hpDIRC standalone sim)

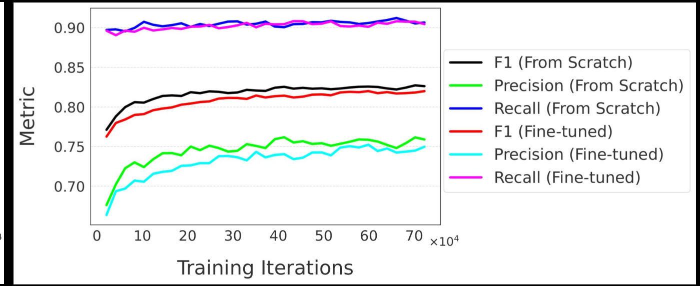
Foundation Models - hpDIRC

Noise filtering (proof of principle)

- Simulated dark rate of ~ 100 khz/cm^2
- Classification of noise hits (token level)
- Fine-tuning not valuable here
    - Prior attention heads have learned information under a more global context







Preliminary Studies

(hpDIRC standalone sim)

Takeaways

Takeaways

- Simulation
  - Order of magnitude faster than Geant4 - we have shown our algorithms (not FM) run extremely well on CPU
  - Simulation is easily usable by users without GPU - PID should use GPU for efficiency
  - Possibility to enable time-imaging - we can simulate PDF’s on the fly on GPU

- PID
  - Increased performance shown at GlueX
  - Also shown increased performance at hpDIRC (very preliminary)
  - Compute wise - Geometric LUT is cheap - but so are we on GPU - mainly depends if we can outperform

- Foundation Model
  - Everything under one architecture - bulk of model remains identical - changes in final layer
  - More computationally intensive than previous models for simulation - requires GPU
  - PID is still very cheap and fast
  - Possibility for noise filtering - possibility of applications to high rate environments such as in the dRICH