AI for hadron structure studies

Nobuo Sato

Recent workshops of AI/ML for NP

Institute for Nuclear Theory

- (2022) Machine Learning for Nuclear Theory (2022) [link]
- (2024) QCD at the Femtoscale in the Era of Big Data [link]

AI4EIC

- (2022) 2nd workshop on AI4EIC, W&M [link]
- (2023) annual workshop on AI4EIC, Catholic University of America [link]

CFNS

- (2023) Probing the frontiers of NP with AI at the EIC (I) [link]
- (2025) Probing the frontiers of NP with AI at the EIC (II) [link]

INFN

- Digital Twins for Nuclear Particle physics - NPTwins 2024 [link]

POETIC `25

- Talk by Fanelli (Thu)
- Talk by Liuti (Thu)

Maybe more that I missed (sorry)

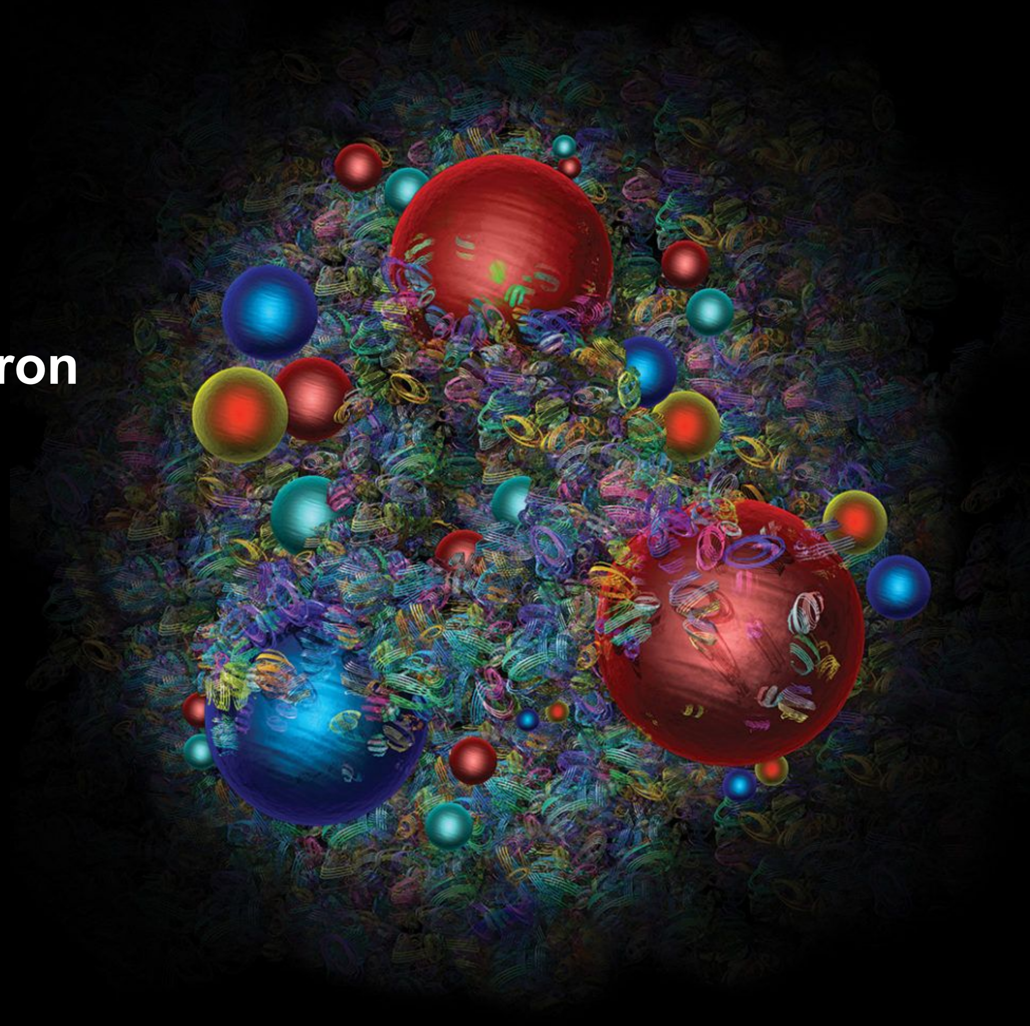
INSTITUTE for NUCLEAR THEORY

AI4EIC

Center for Frontiers in Nuclear Science

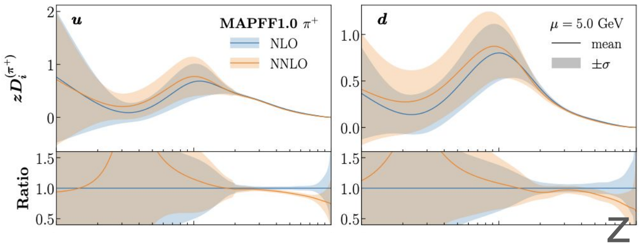
Outline

1. Recent examples
2. Diffusion models for EIC
3. Pixel based analysis for hadron structure
4. Summary

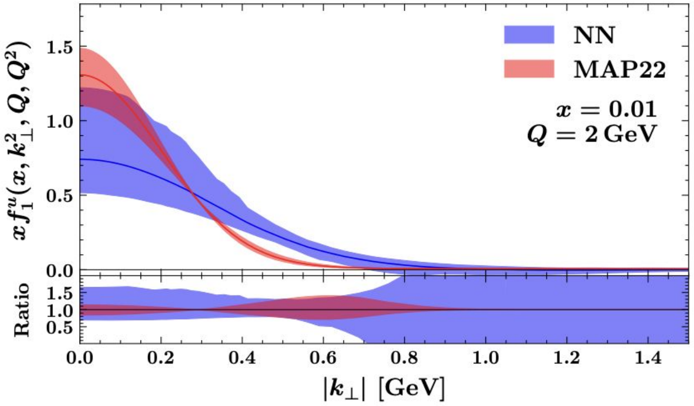


Regression problems Modeling
Non-perturbative functions using ANN

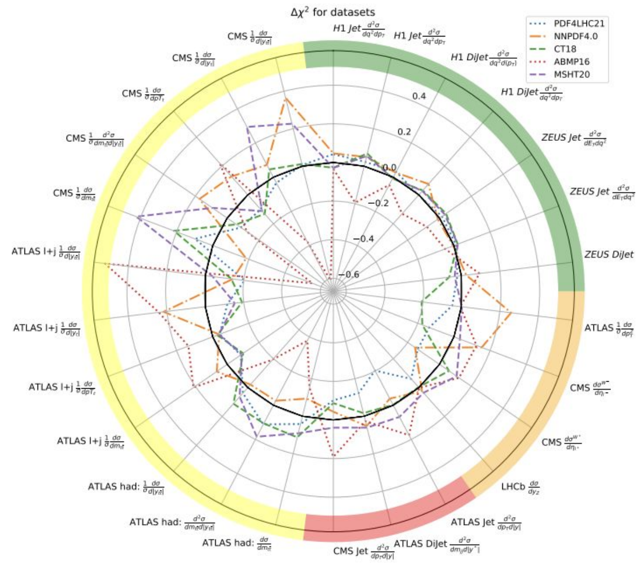
MAP collaboration `22



MAP collaboration `25



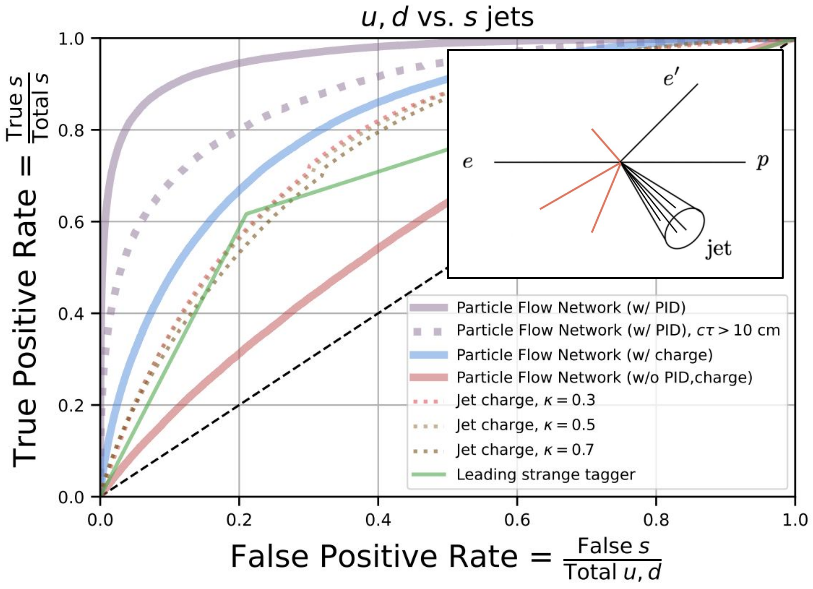
Talk by Nocera @ NPTwins `24



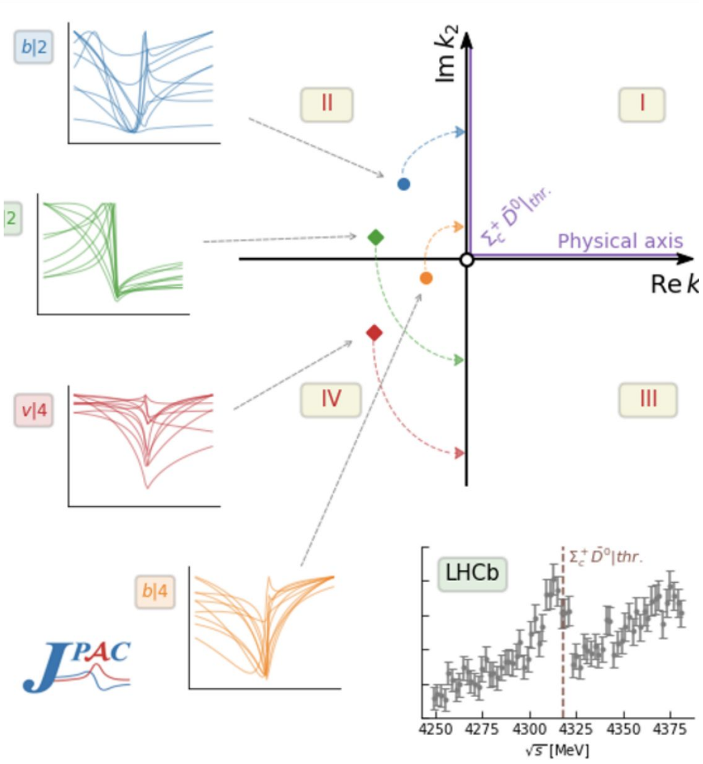
"The PDF set obtained with ML is more precise and more accurate than all the others"

Classification problems

Lee, Mulligan, Ploskon, Ringer, Yuan `23



JPAC `24



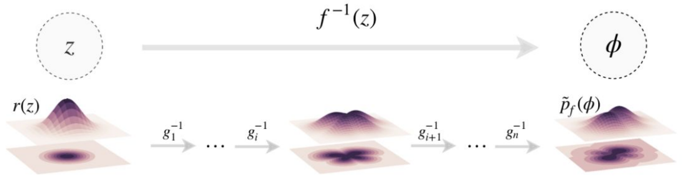
DNN classifiers (Deep sets) for particles inside jets

- Quark and Gluon jets discrimination -> polarized gluons
- Enhance reconstruction of Sivers function in SSA with Jets
- BSM searches
- GPDs from diffractive processes

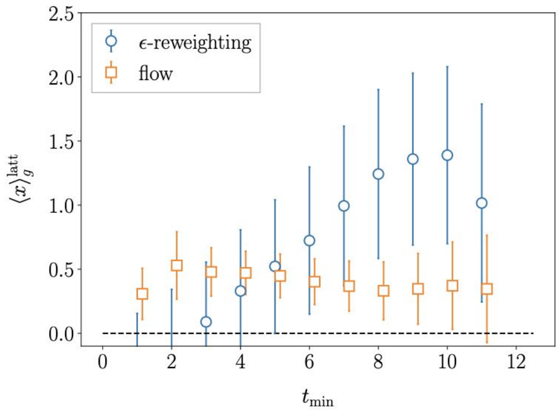
Classifiers for hadron spectroscopy

Sampling problems

Albergo et al `21

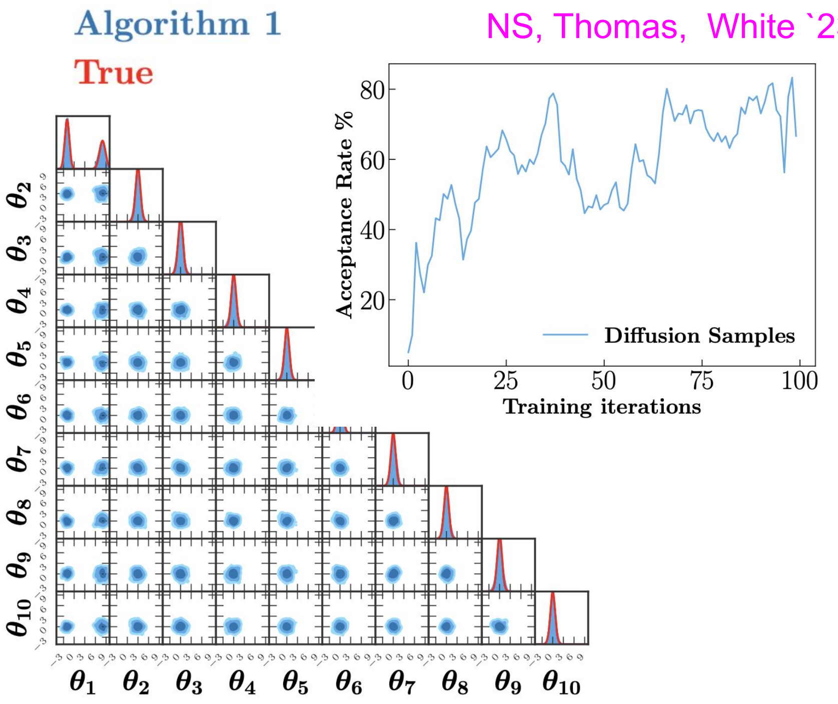


Abbott et al `25



- Flow based application to Feynman-Hellmann techniques
- statistical errors are 2-3 times smaller when using flows

Hunt-Smith, Melnitchouk, Ringer, NS, Thomas, White `23



- Diffusion model application for Bayesian inference
- Significant boost of Acceptance rate over non ML methods

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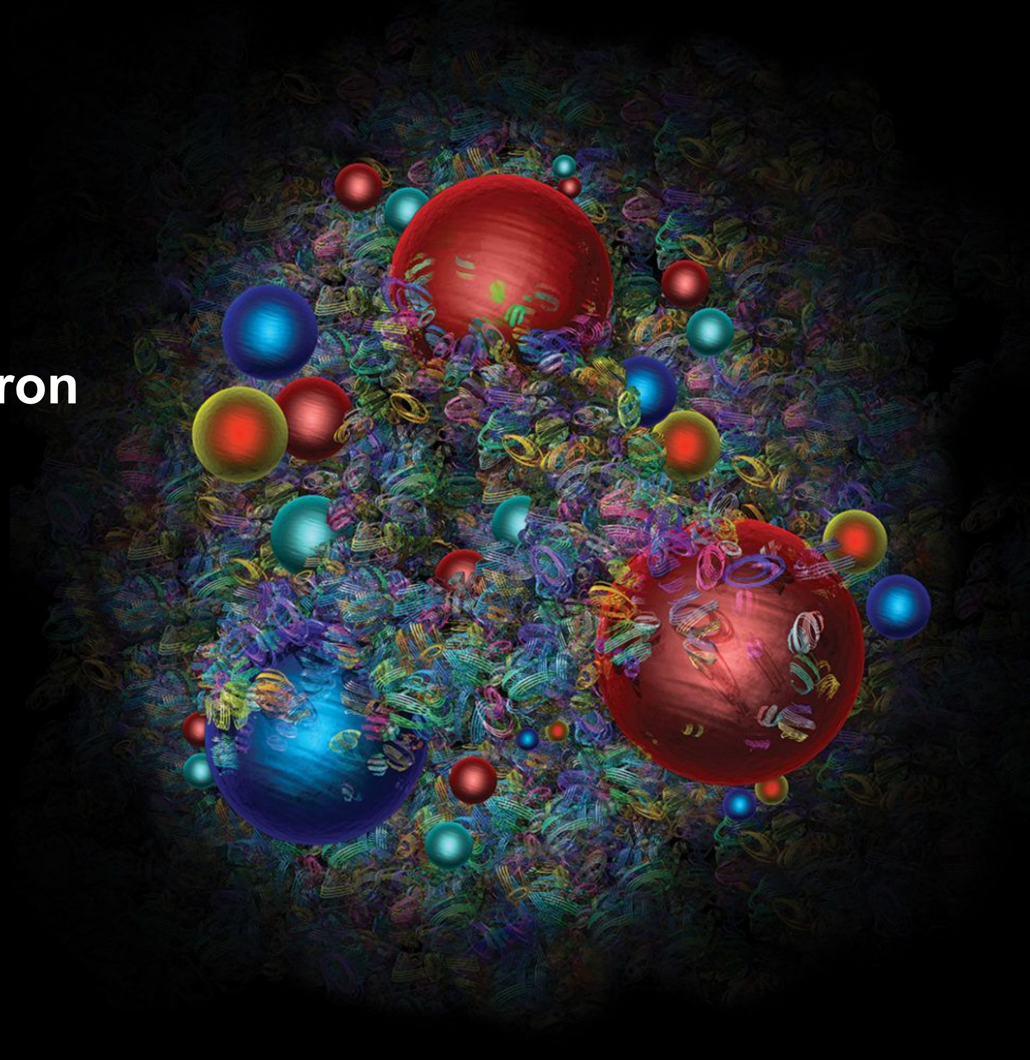
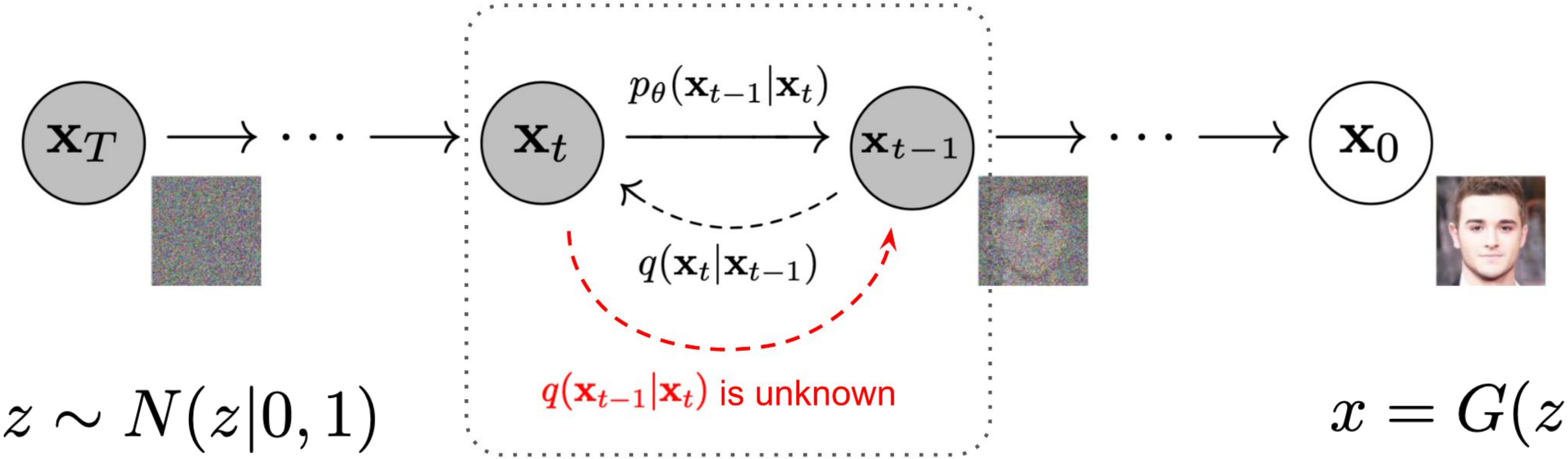


Diffusion models for pedestrians

Ho, Jain, Abeel ‘20



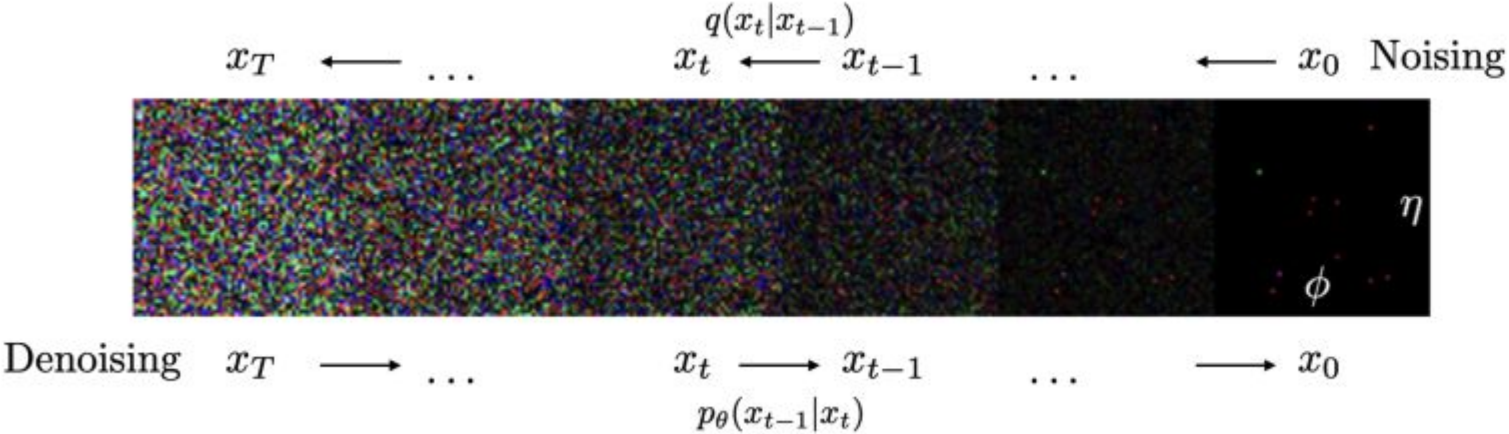
$z \sim N(z|0,1)$

$x = G(z|\theta)$

Even representation

Devlin, Qiu, Ringer, NS '23

Image



Wang, et al '18

Point-clouds

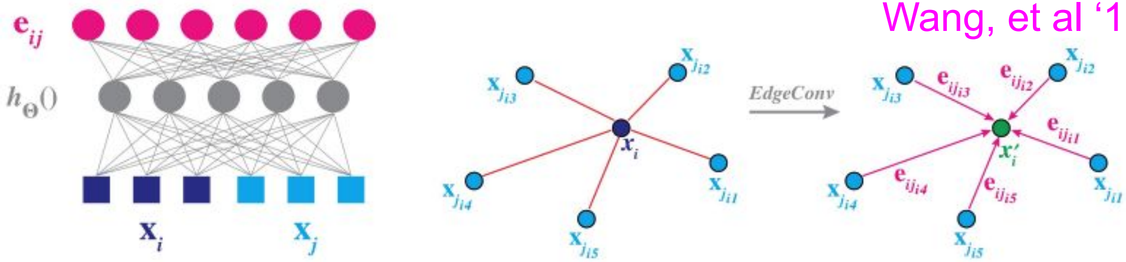
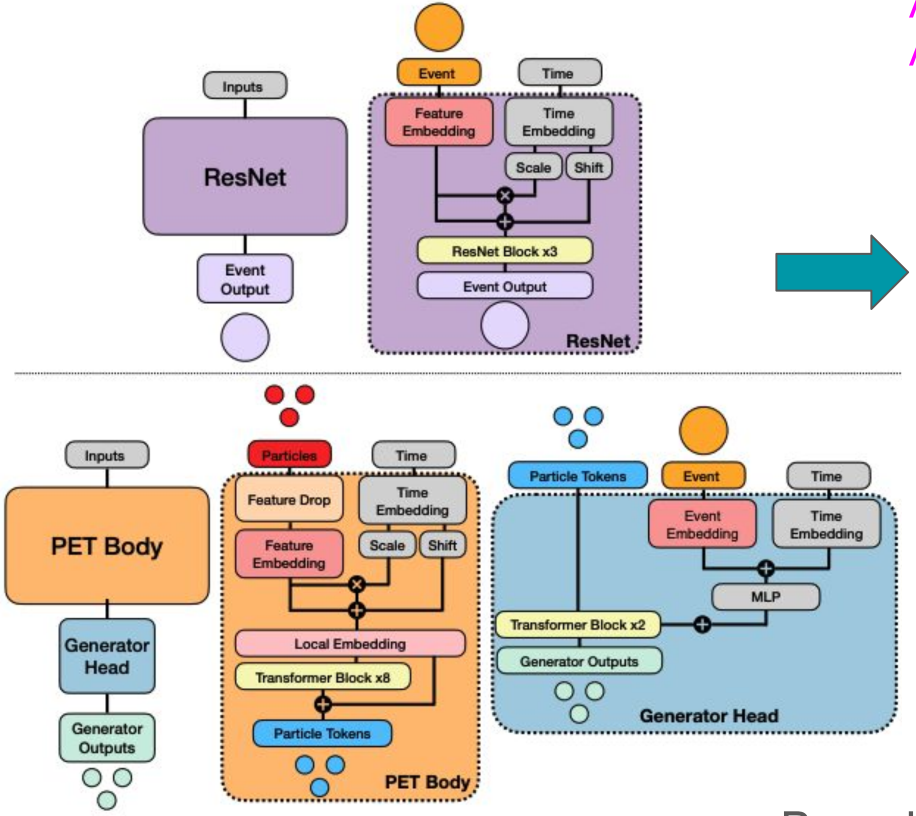
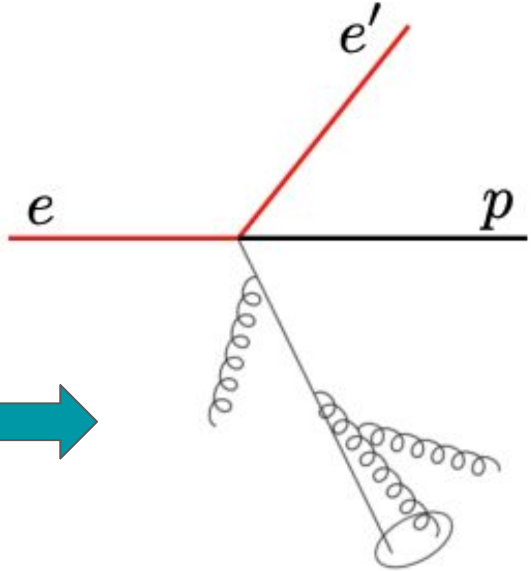


Fig. 2. **Left**: Computing an edge feature, $\mathbf{e}_{ij}$ (top), from a point pair, $\mathbf{x}_i$ and $\mathbf{x}_j$ (bottom). In this example, $h_\Theta()$ is instantiated using a fully connected layer, and the learnable parameters are its associated weights. **Right**: The EdgeConv operation. The output of EdgeConv is calculated by aggregating the edge features associated with all the edges emanating from each connected vertex.

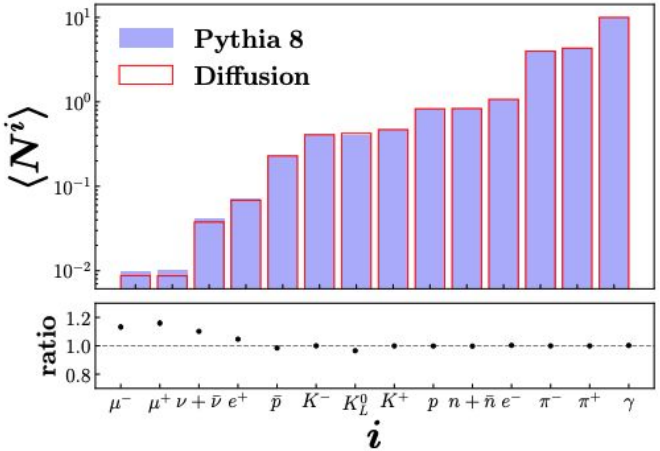
Diffusion models particle generation @ EIC

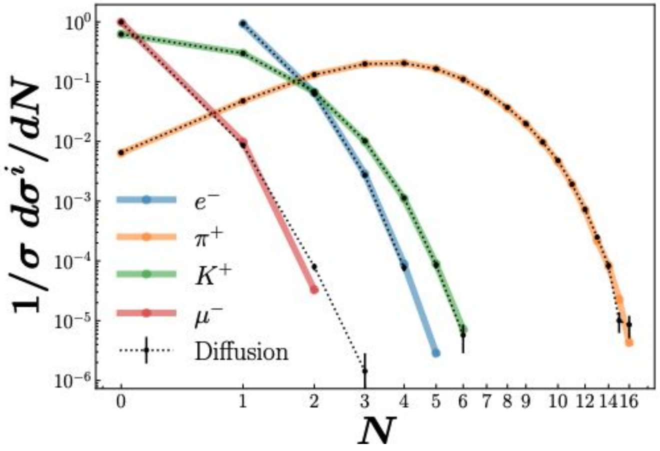
Araz, Mikuni, Ringer, NS, Torales Acosta, Whitehill ‘24

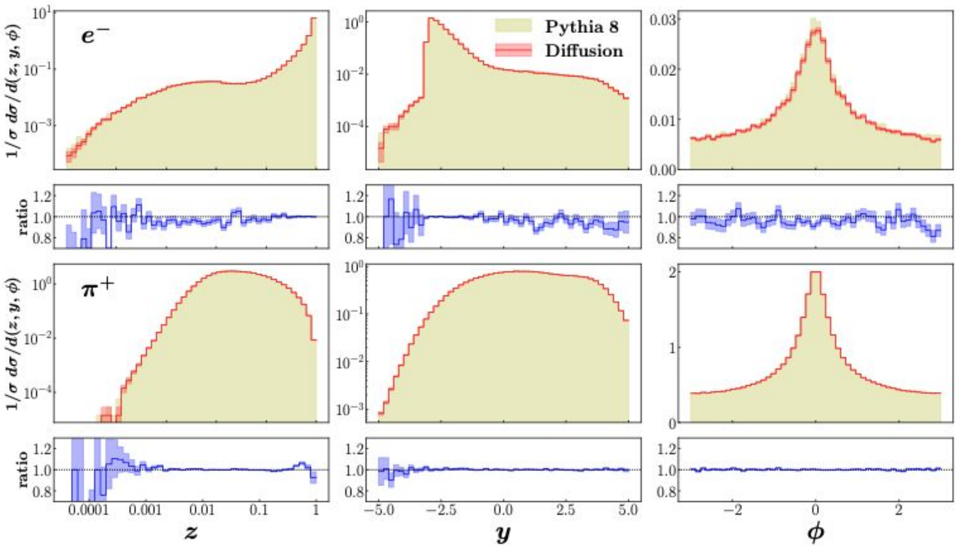


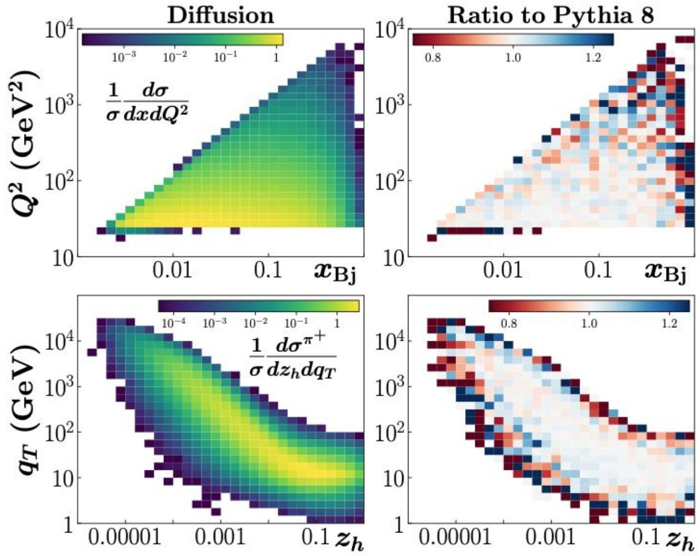


Based on Jet physics model


Pythia 8
Diffusion
$\langle N^i \rangle$
ratio
μ^- μ^+ $\nu+\bar{\nu}$ e^+ $\bar{p}$ K^- K_L^0 K^+ p $n+\bar{n}$ e^- π^- π^+ γ
i


$1/\sigma\, d\sigma^i/dN$
e^-
π^+
K^+
μ^-
Diffusion
N


e^-
π^+
Pythia 8
Diffusion
$1/\sigma\, d\sigma/d(z,y,\phi)$
ratio
z
y
ϕ


Diffusion
Ratio to Pythia 8
$\frac{1}{\sigma}\frac{d\sigma}{dx dQ^2}$
Q^2 (GeV^2)
x_{Bj}
$\frac{1}{\sigma}\frac{d\sigma^{\pi^+}}{dz_h dq_T}$
q_T (GeV)
z_h

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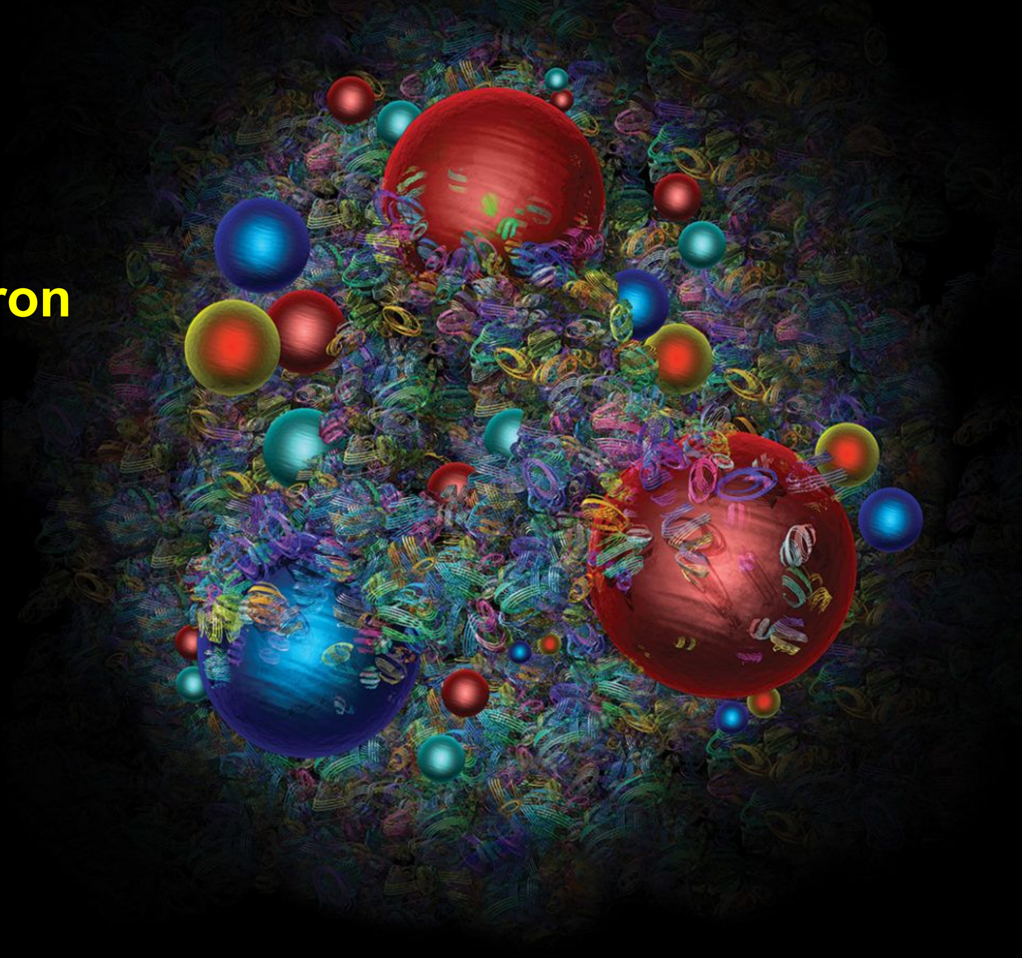
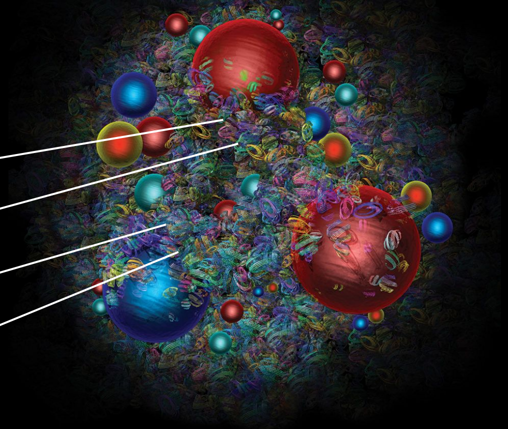


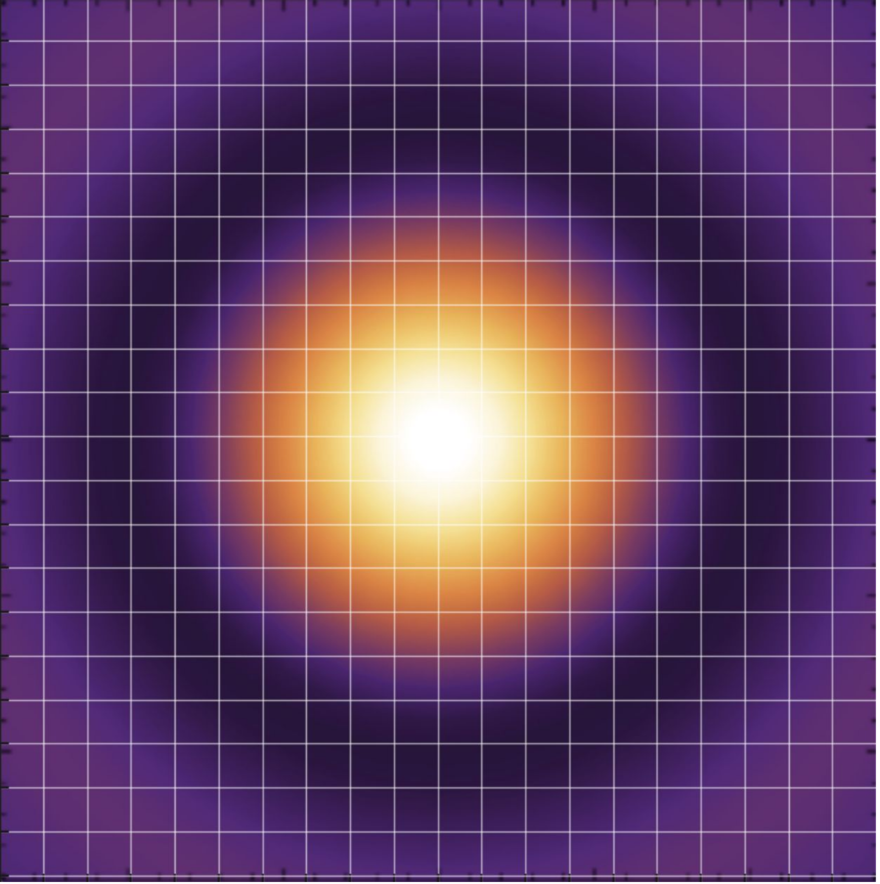
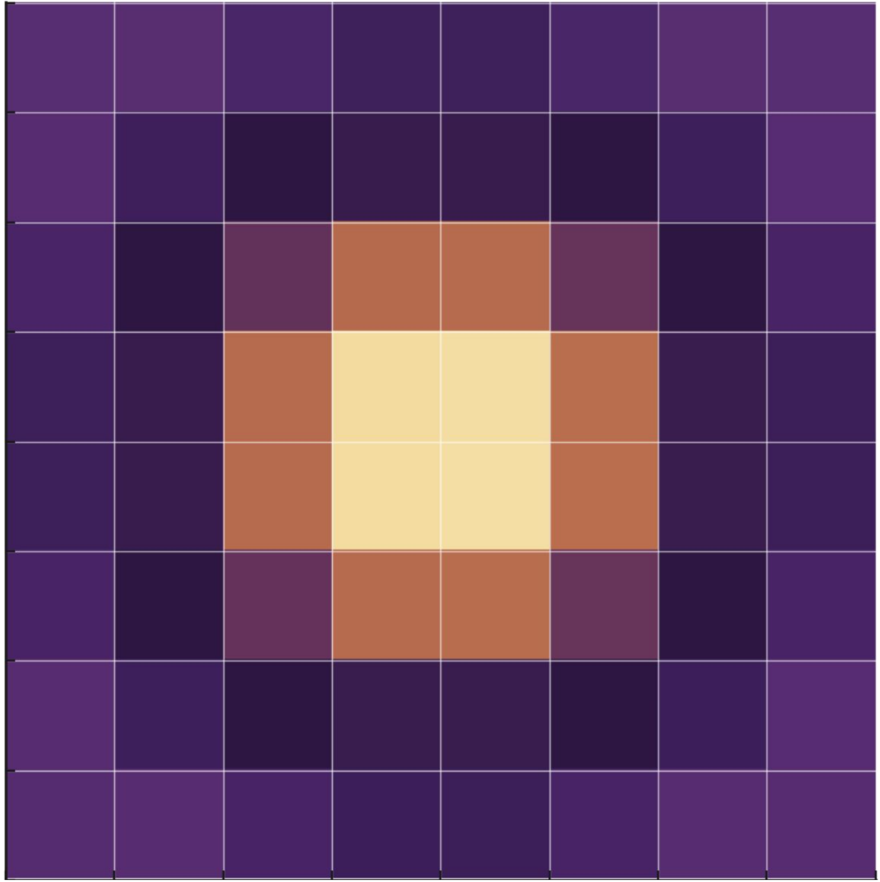
The goal



AI based integrated theory and experimental sub-femtoscale imaging tool for Nuclear physics

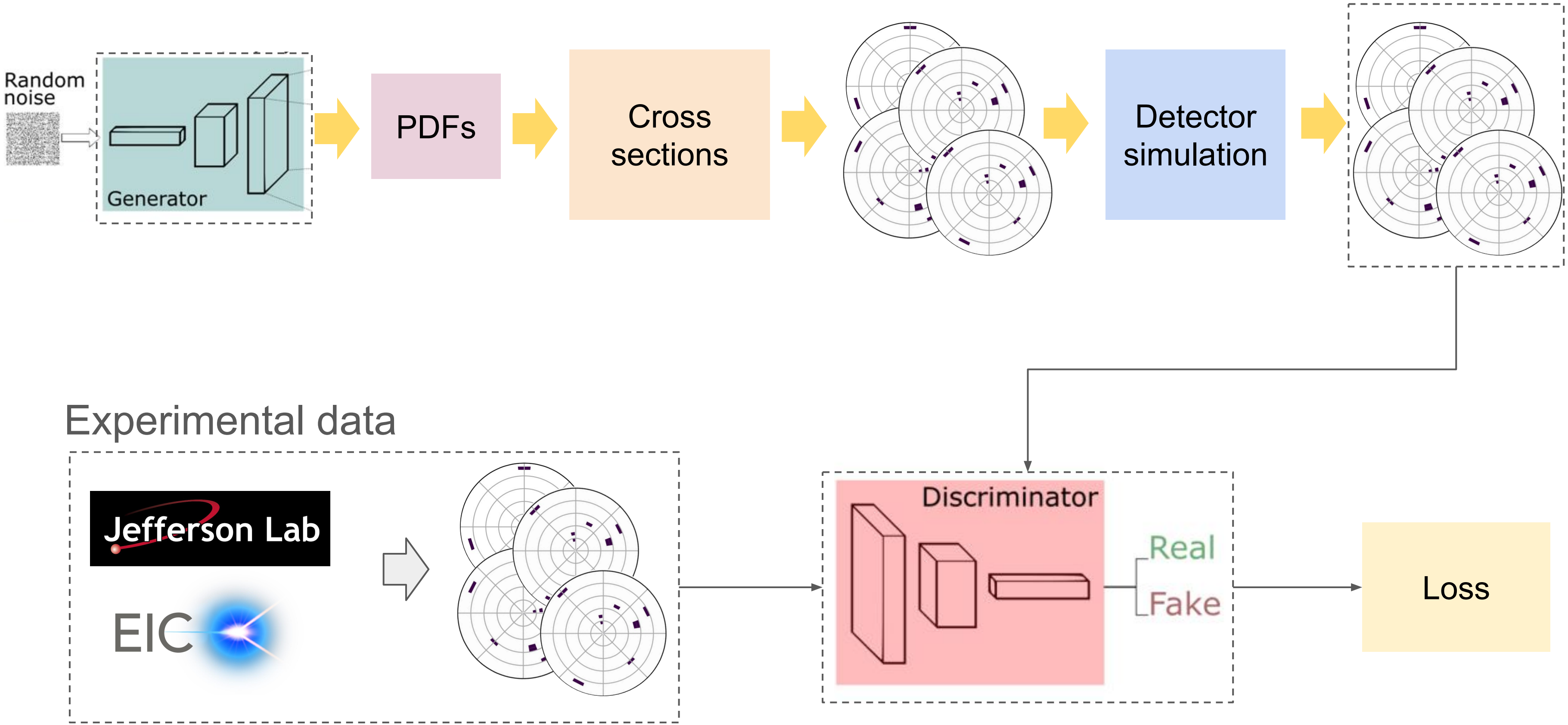
Pixels are the most basic building blocks of imaging

QuantOm Collaboration

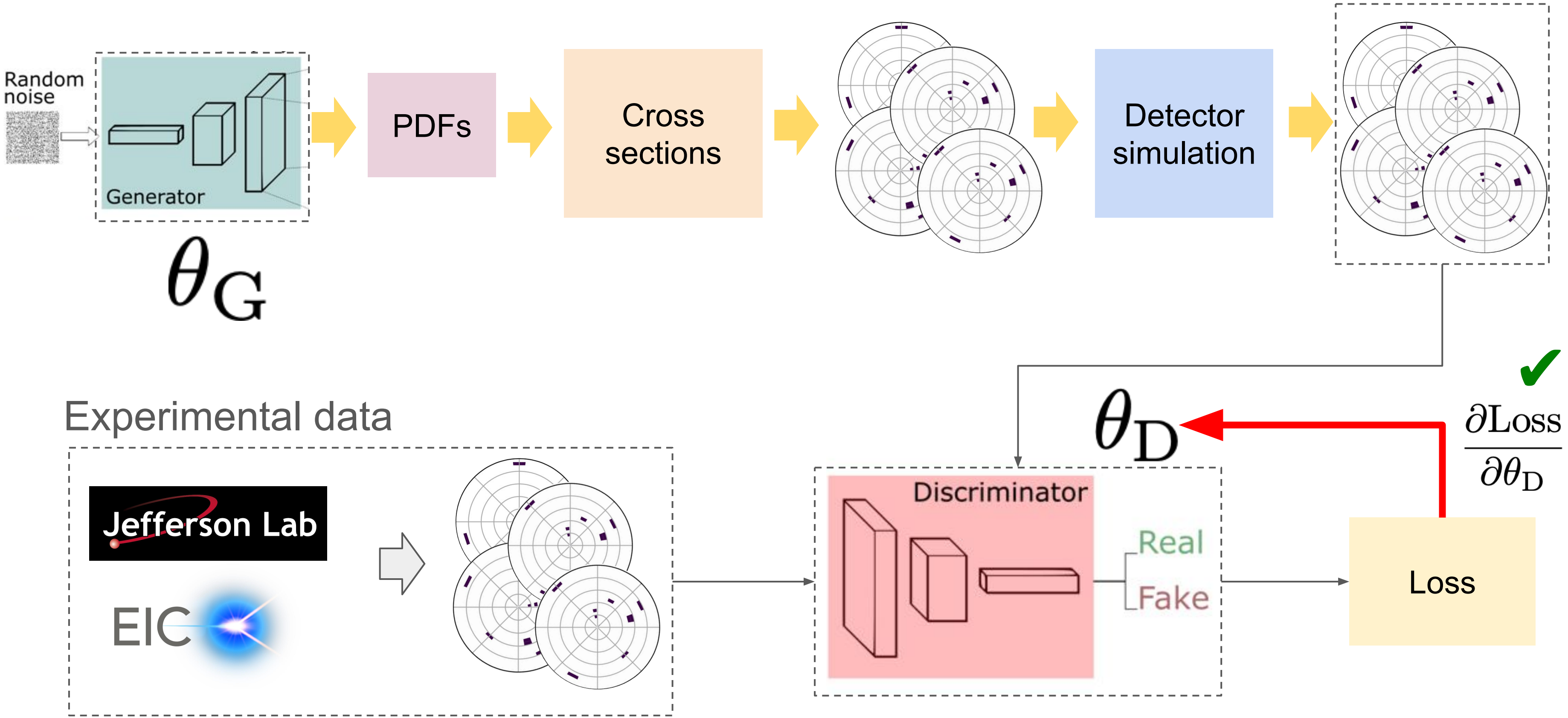
 

Can data differentiate between the two images?

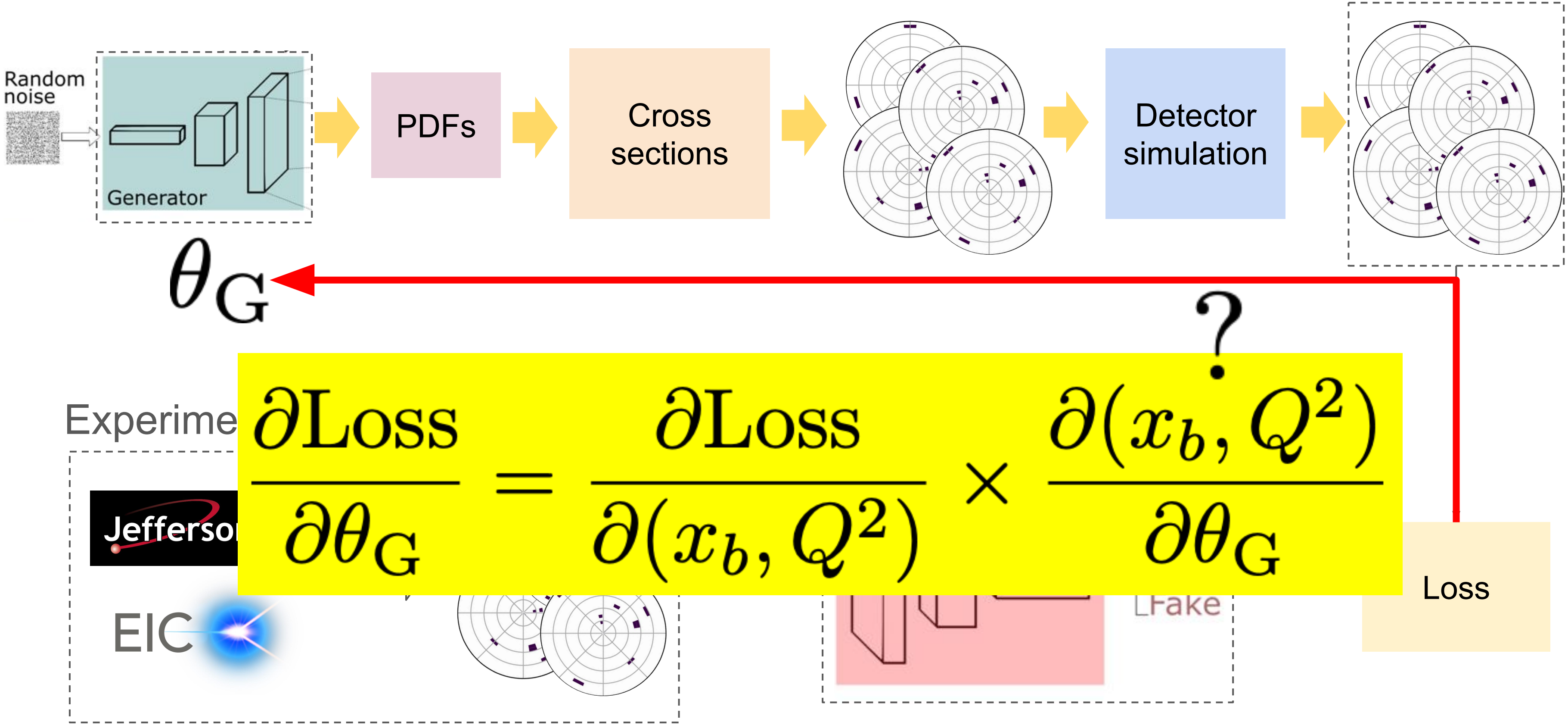
Integrated theory and experimental analysis



Challenge: how to optimize the ML model

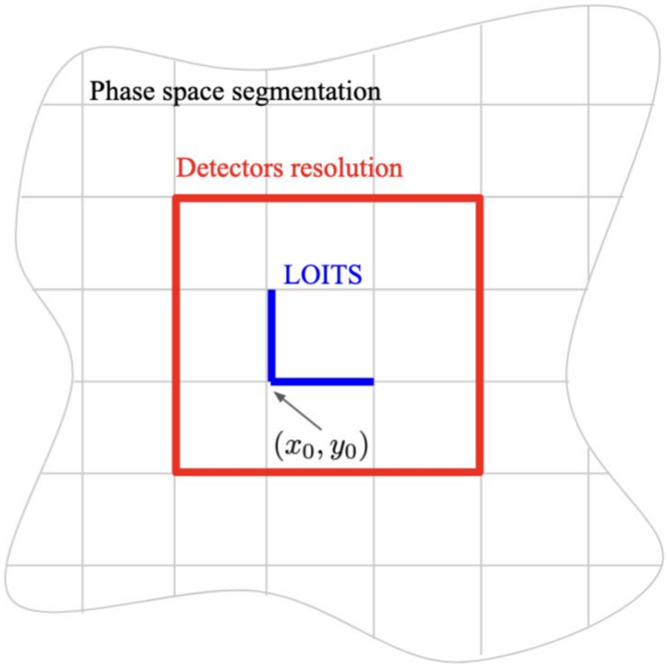


Challenge: how to optimize the ML model



$$\frac{\partial \mathrm{Loss}}{\partial \theta_{\mathrm{G}}} = \frac{\partial \mathrm{Loss}}{\partial (x_b, Q^2)} \times \frac{\partial (x_b, Q^2)}{\partial \theta_{\mathrm{G}}}$$

Local Orthogonal Inverse Transform (LOITS)

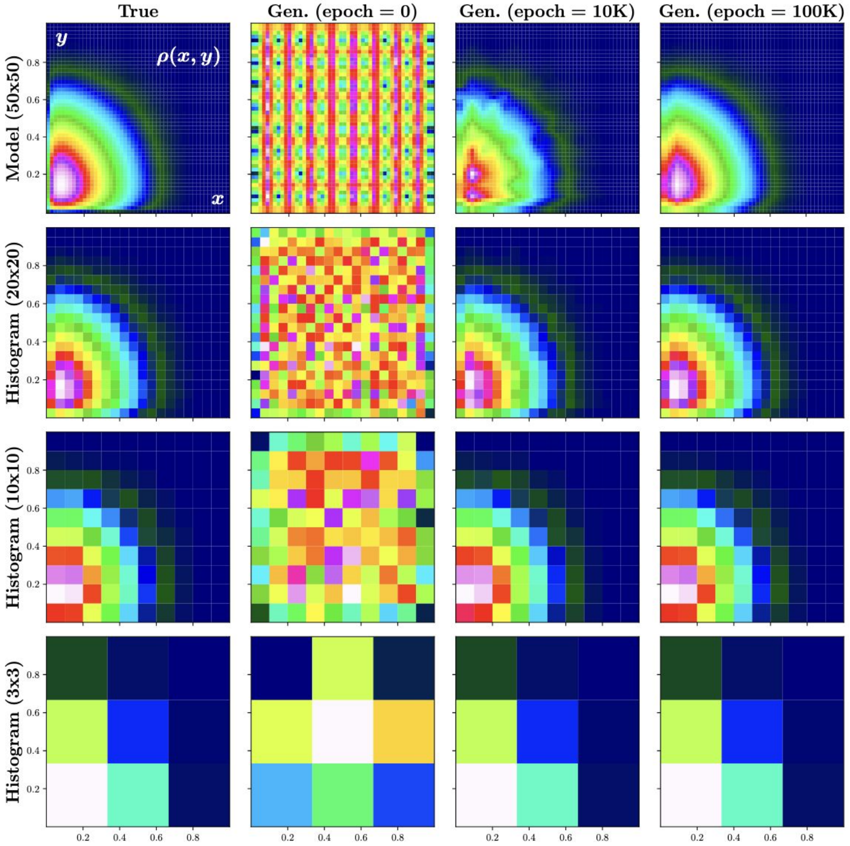


- Inverse transform sampling admits derivatives of phase space samples wrt model parameters
- Inverse transform sampling only works in 1D, but admits interval partition
- We can sample locally in n-D by approximating the phase space density

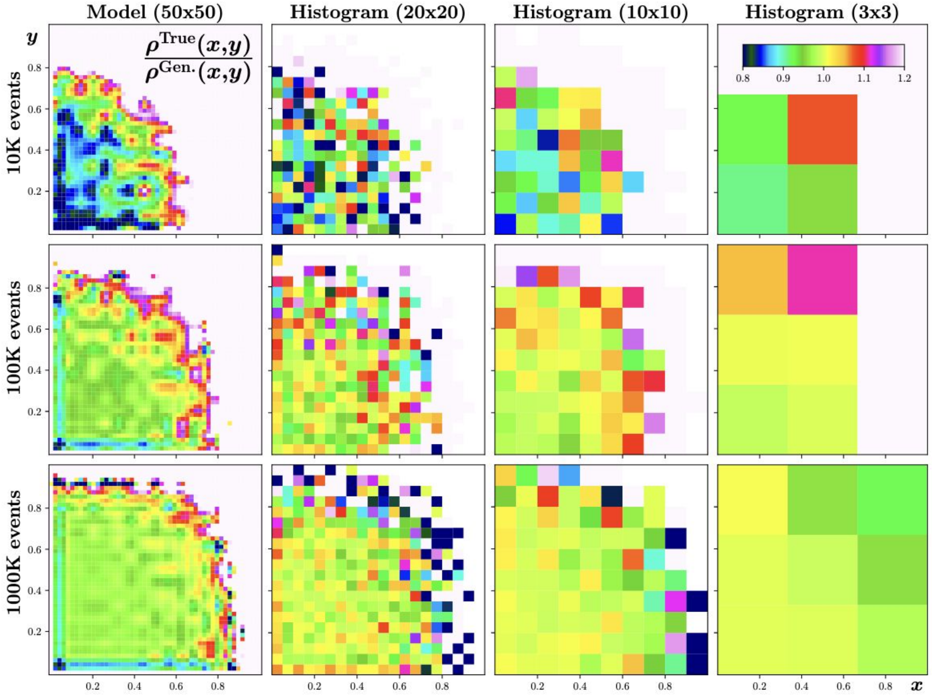
$$\rho(x,y) \sim \rho(x,y_0)\rho(x_0,y)$$

- We can apply metropolis hastings to correct the approximation

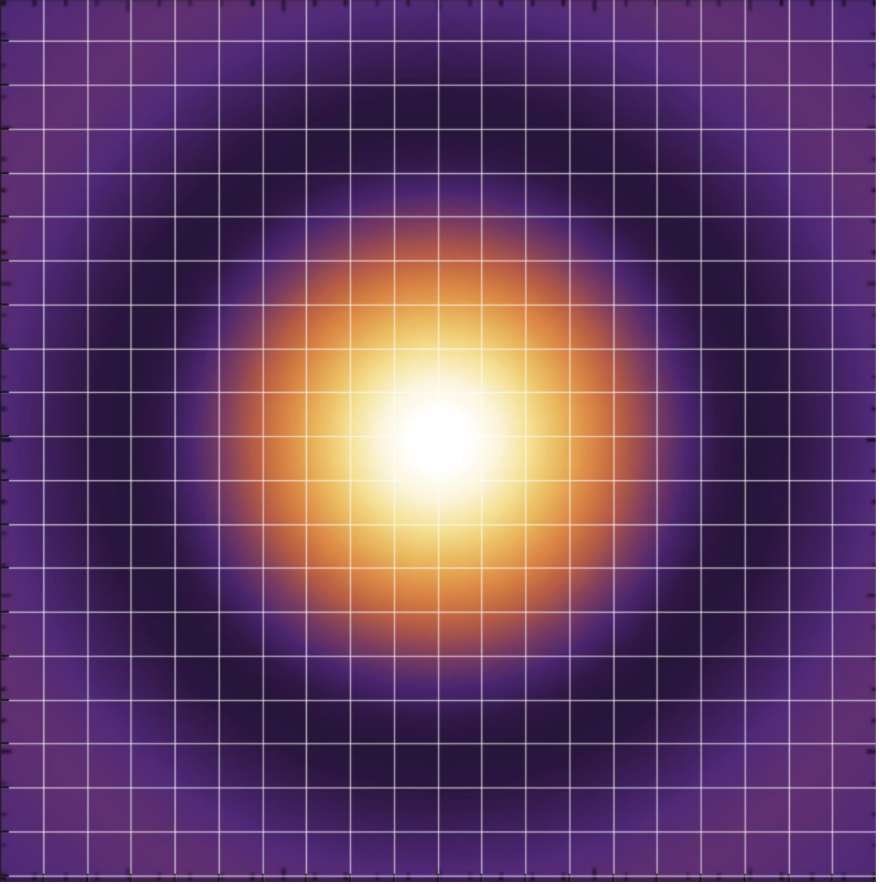
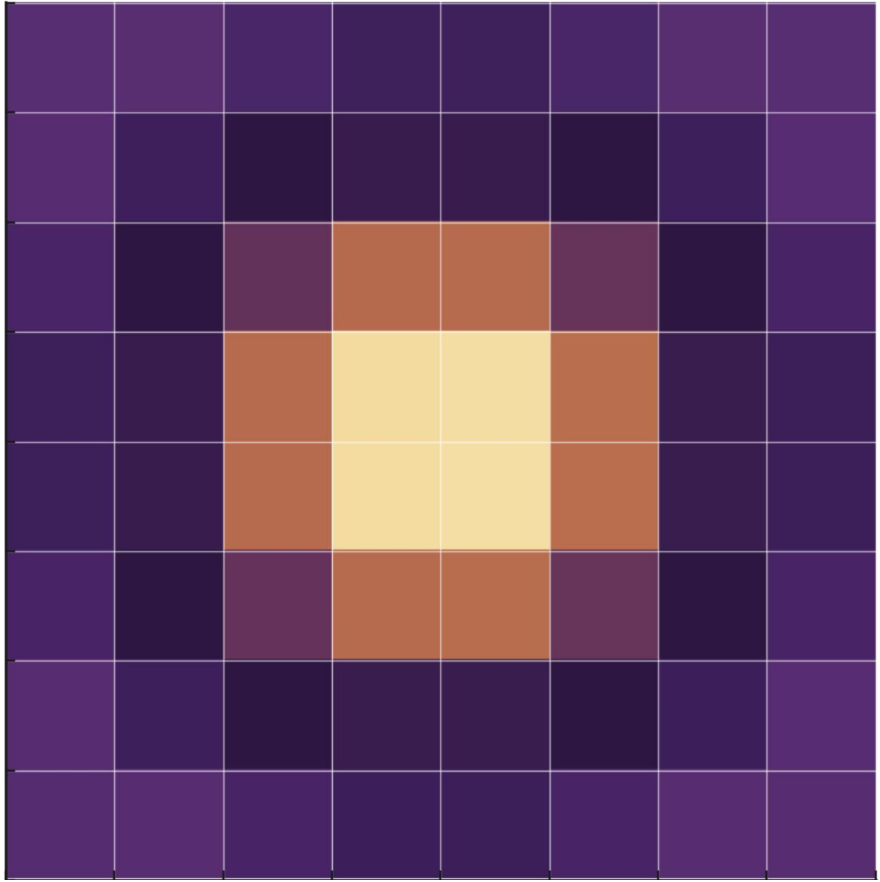
Case study: 2D toy imaging problem



(Paper in preparation)

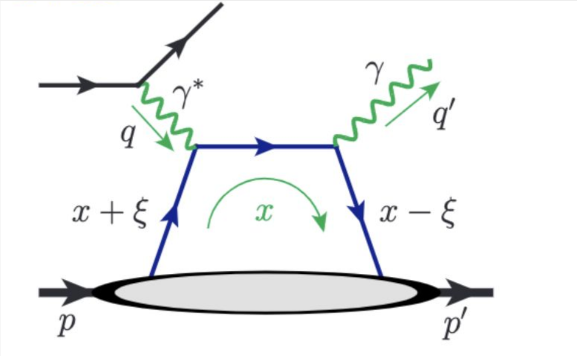


The more events we have, the GAN algorithm learns more as expected

Can data differentiate between the two images? **NO!**

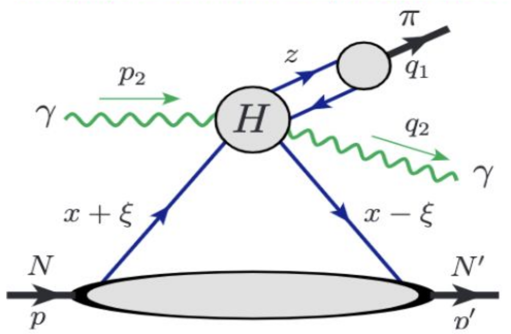
DVCS



- Limited sensitivity to x-dependence
- Presence of shadow GPDs
- Unable to fully reconstruct proton images

$$\mathcal{M}_{\mathrm{DVCS}} \sim \int_{-1}^{1} dx \frac{F(x,\xi,t)}{x-\xi+i\epsilon}$$

Pion-photon Photoproduction

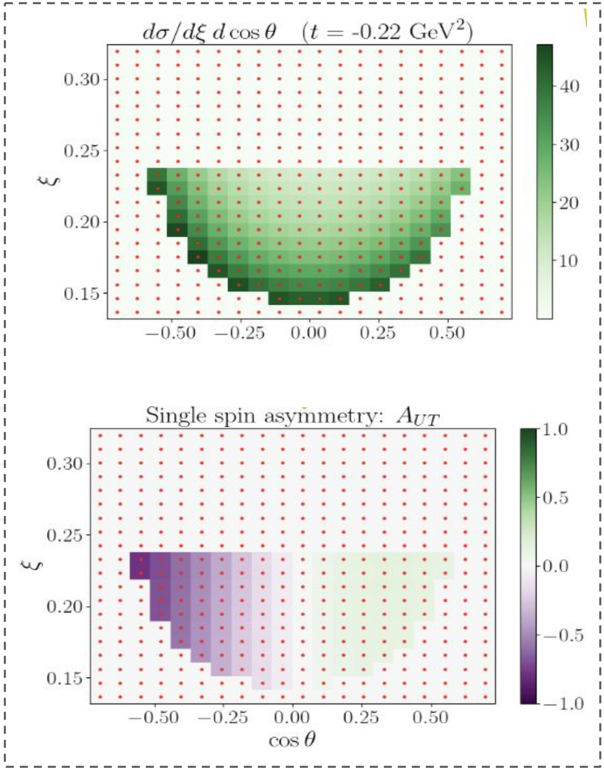


Special pole structure gives enhanced sensitivity to the x-dependence

$$\mathcal{M}_{N\gamma} \sim \int_{-1}^{1} dx \frac{F(x,\xi,t)}{x - x_p(\xi,z,\theta) + i\epsilon}$$

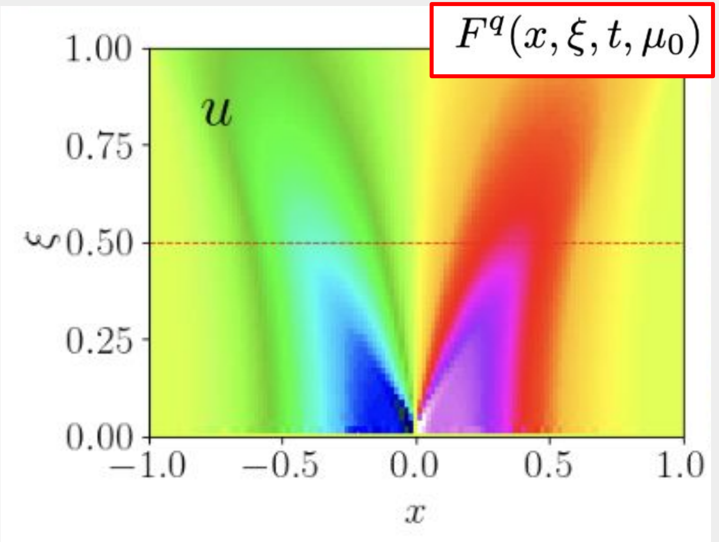
$$x_p(\xi,z,\theta) = \xi \left[\frac{\cos^2(\theta/2)(1-z)-z}{\cos^2(\theta/2)(1-z)+z}\right]$$

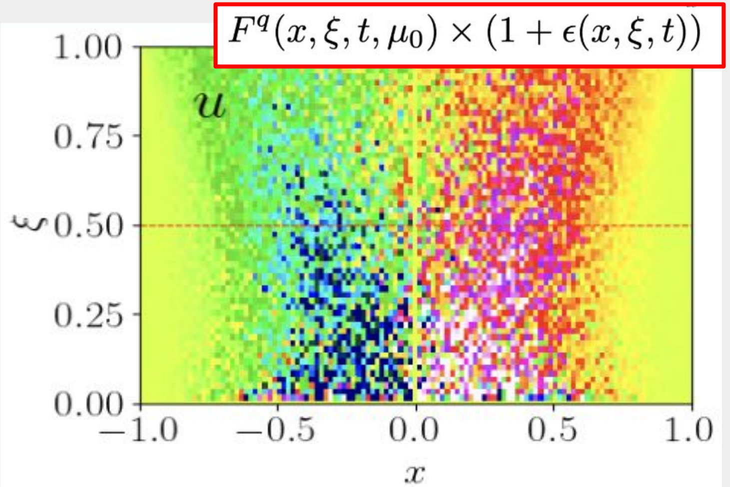
Hall D simulations



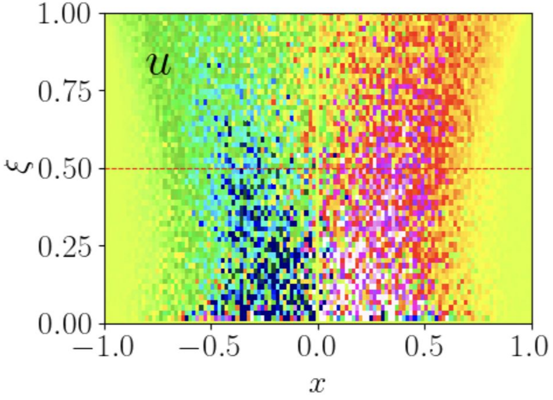
JLab LDRD `23-`24

Optimize $\epsilon(x,\xi,t)$ pixels

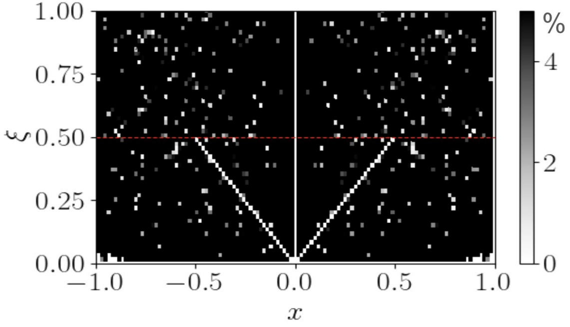




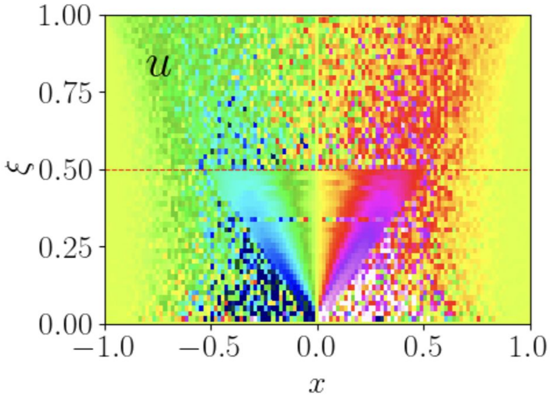
DVCS

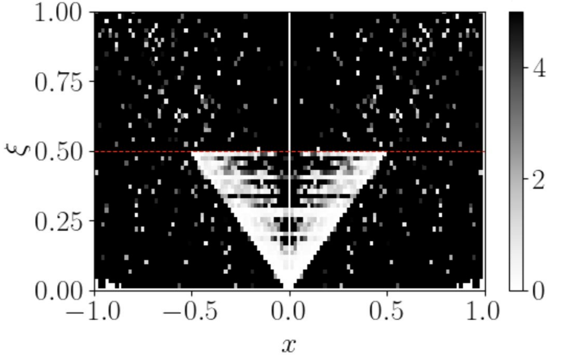


Relative error



DVCS + photoproduction





Summary

- Lots of AI applications for NP
  -> getting ready for EIC

- Is a rapid evolving field, with a very large extended community to benefit from

- Did not have time to event talk about LLMs