

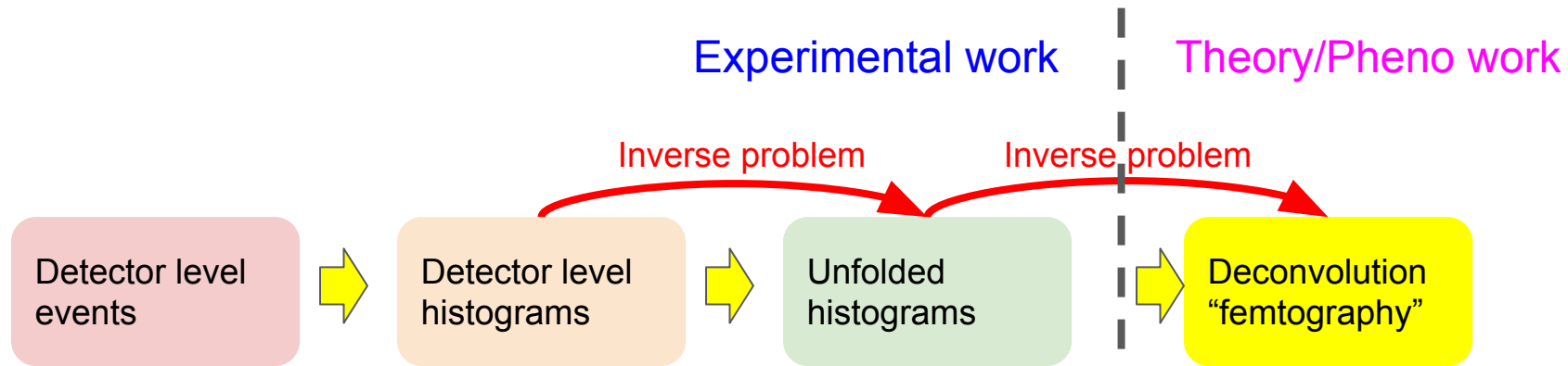
Reconstructing GPDs using pixel based approach

Nobuo Sato

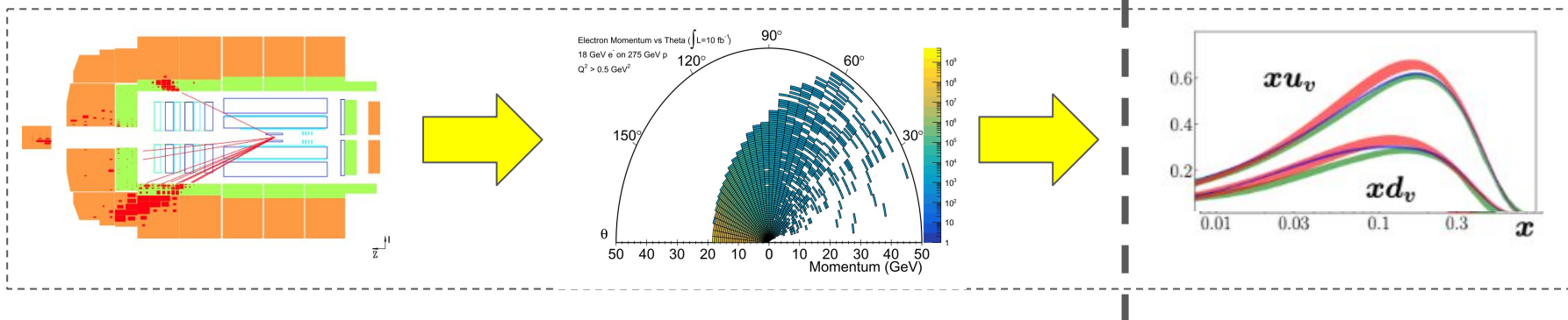
In collaboration with: Kevin Braga, Markus Diefenthaler,
Steven Goldenberg, Daniel Lersch, Yaohang Li, Jian-Wei Qiu,
Kishansingh Rajput, Felix Ringer, Nobuo Sato, Malachi Schram



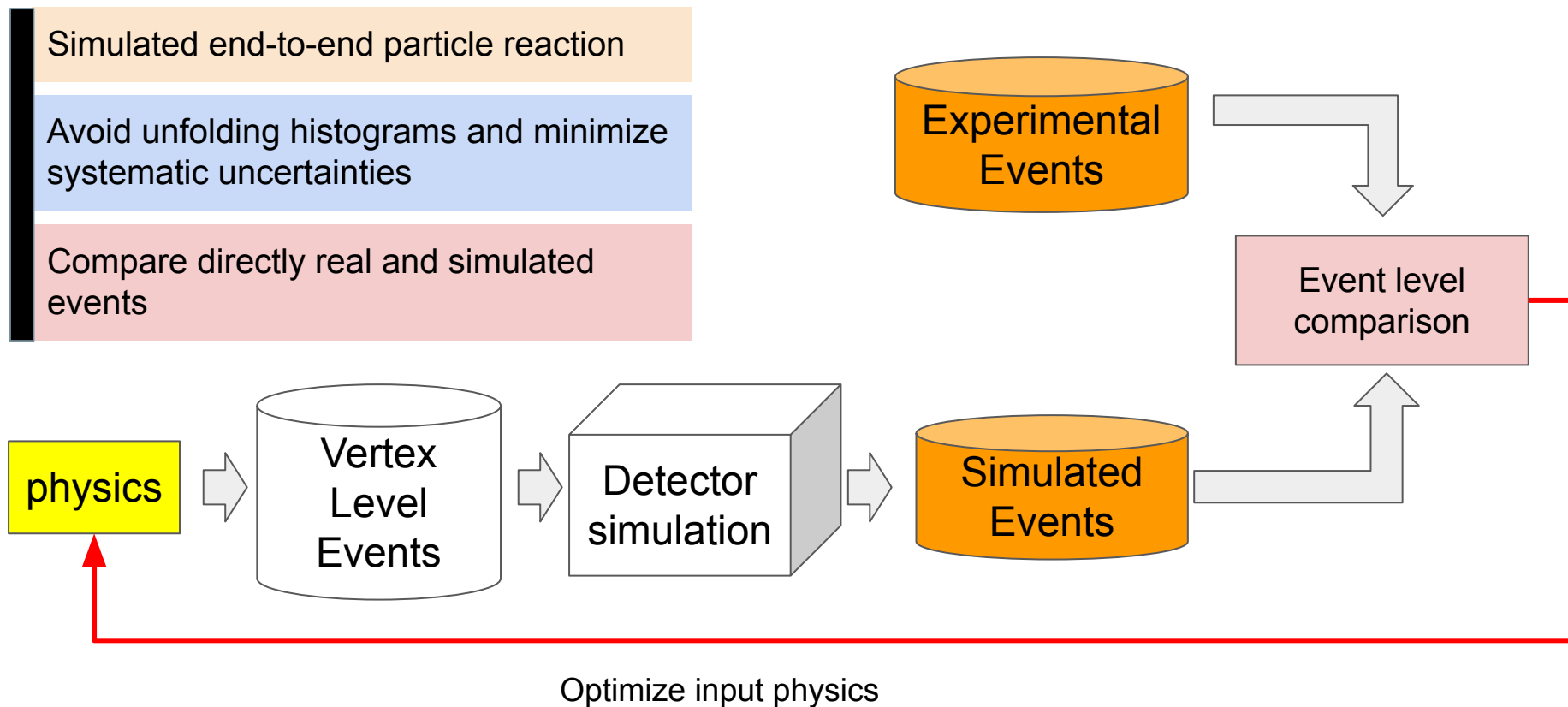
Motivations



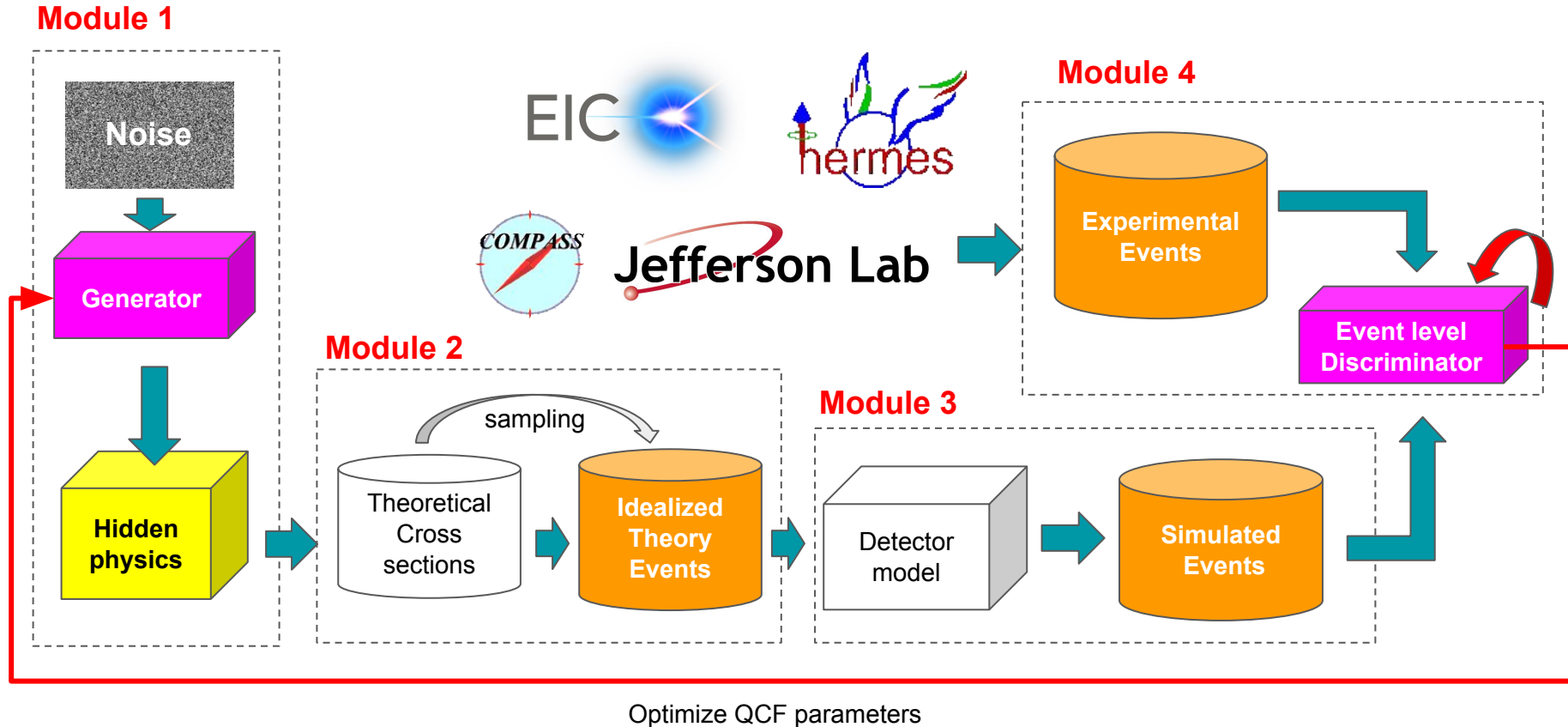
An example in inclusive DIS



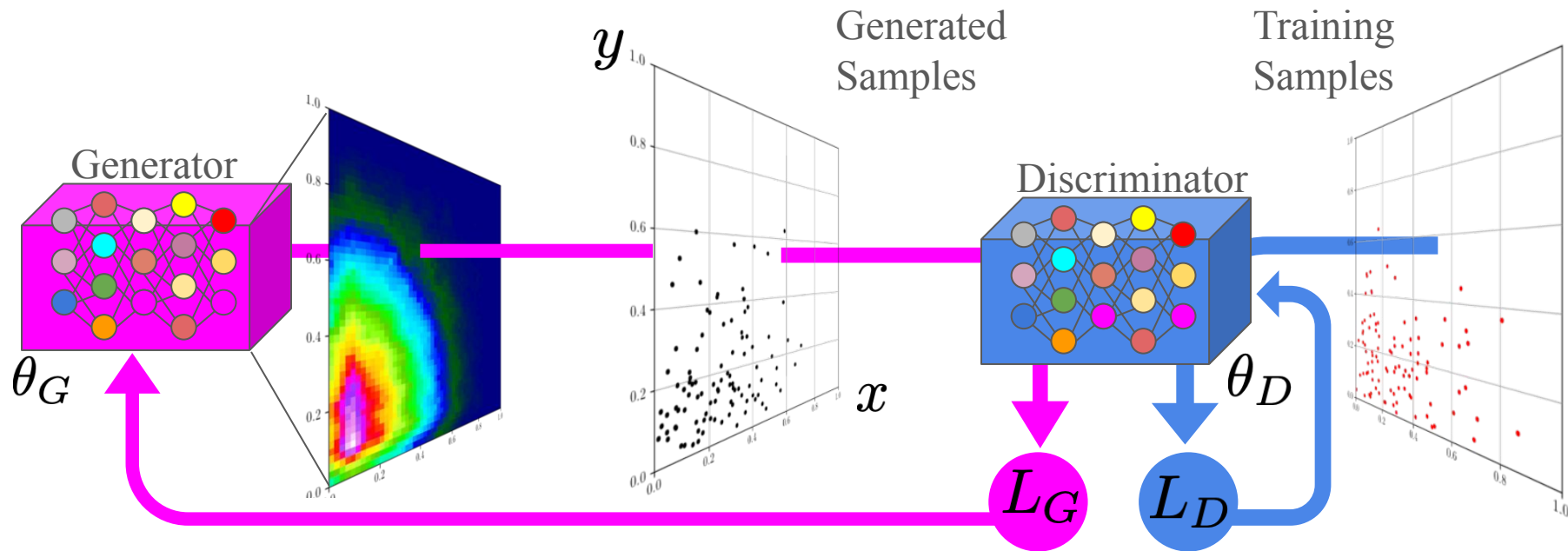
Event-based analysis



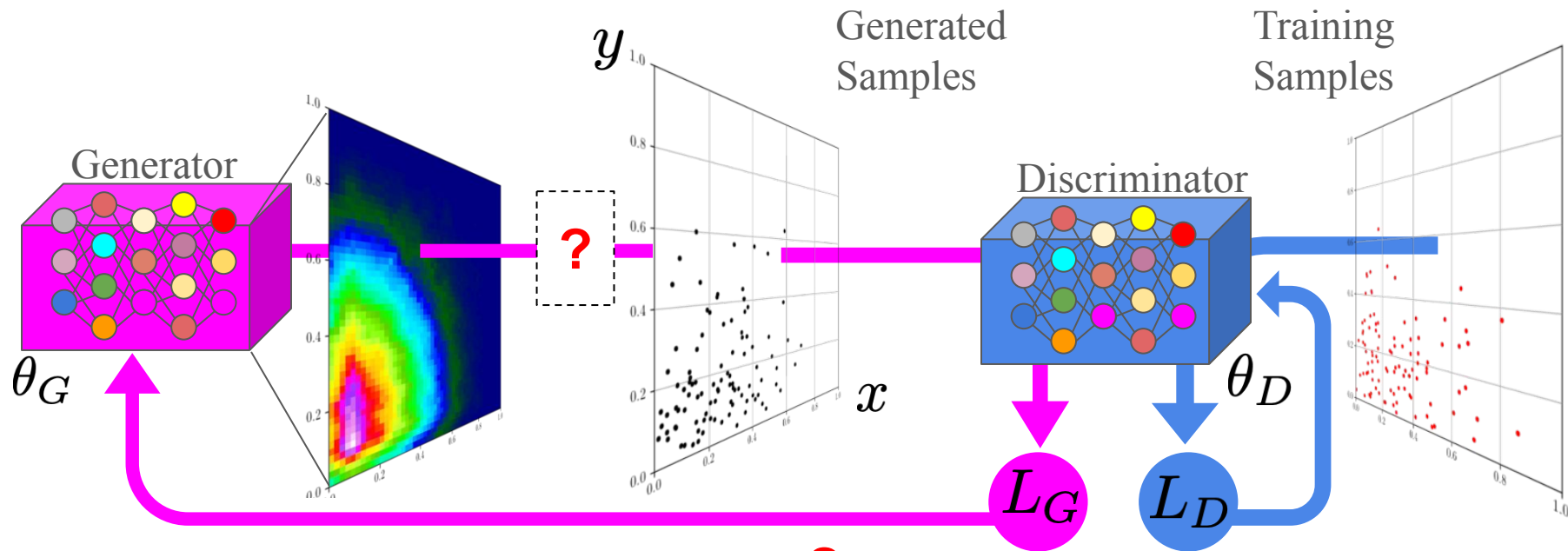
Gen AI approach via GANs



Simplified version of the problem

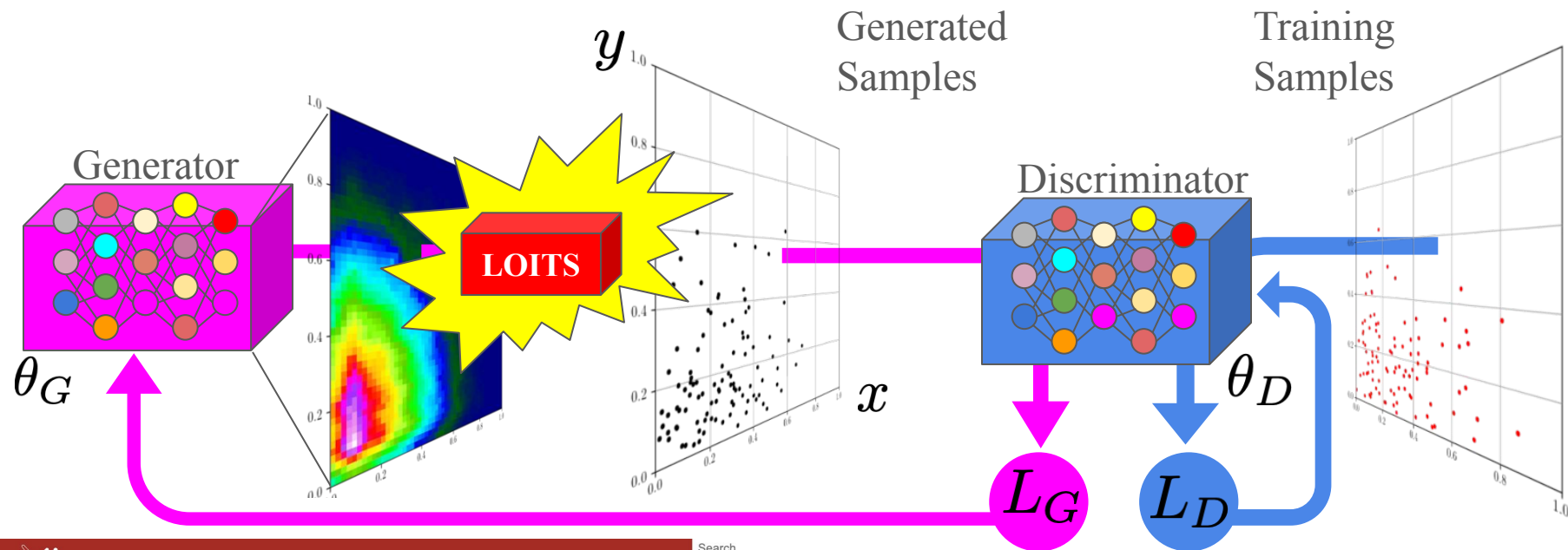


Simplified version of the problem



$$\Rightarrow \frac{\partial L_G}{\partial \theta_G} = \frac{\partial L_G}{\partial x} \frac{\partial x}{\partial \theta_G} + \dots$$

Simplified version of the problem



arXiv > hep-ph > arXiv:2507.15768

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High Energy Physics – Phenomenology

[Submitted on 21 Jul 2025]

Toward an event-level analysis of hadron structure using differential programming

Kevin Braga, Markus Diefenthaler, Steven Goldenberg, Daniel Lersch, Yaohang Li, Jian-Wei Qiu, Kishansingh Rajput, Felix Ringer, Nobuo Sato, Malachi Schram

Key idea: inverse transform sampling

$$\text{CDF}(x, \theta) = \int_0^x dz \, p(z|\theta)$$

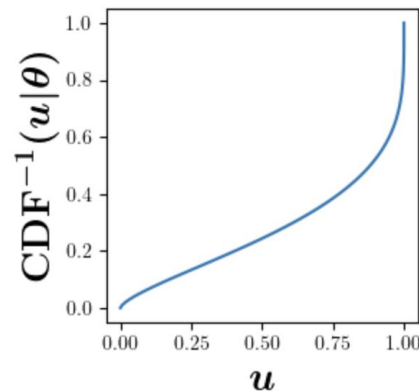
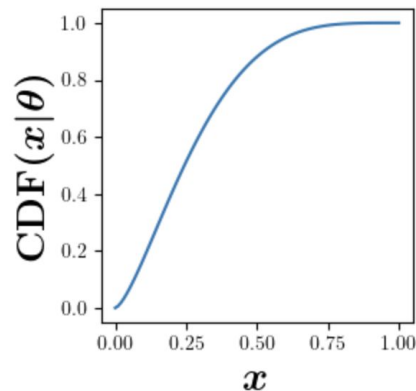
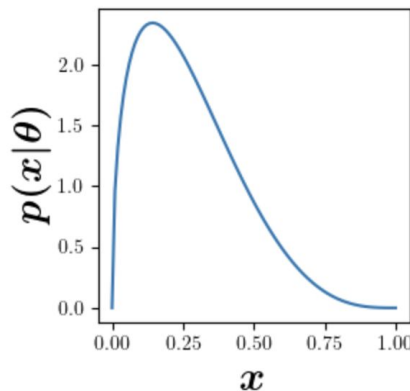


$$x_\theta(u) = \text{CDF}^{-1}(u, \theta)$$

$u \sim \mathcal{U}[0, 1]$



$$\begin{aligned} \frac{\partial x_\theta}{\partial \theta_i} &= \frac{\partial \text{CDF}^{-1}(u, \theta)}{\partial \theta_i} \\ &= \frac{\partial \text{CDF}^{-1}(u, \theta)}{\partial \text{CDF}(x_\theta, \theta)} \frac{\partial \text{CDF}(x_\theta, \theta)}{\partial \theta_i} \end{aligned}$$



In general we don't know the inverse CDF

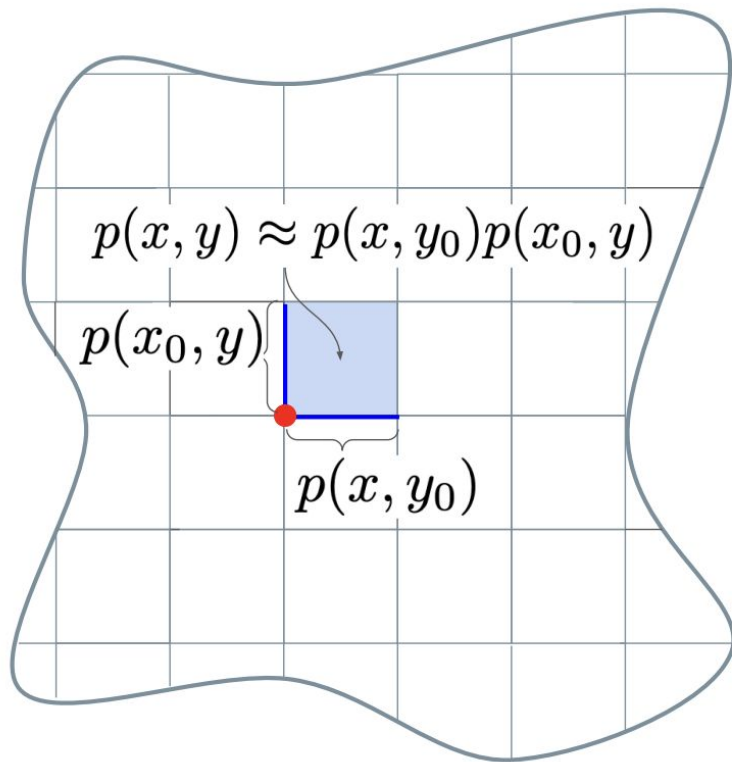
But we can interpolate the inverse once we evaluate CDFs on a grid in x

Interpolation is differentiable

How do we extend to n -dimensions?

Local Orthogonal Inverse Transform Sampling

LOITS

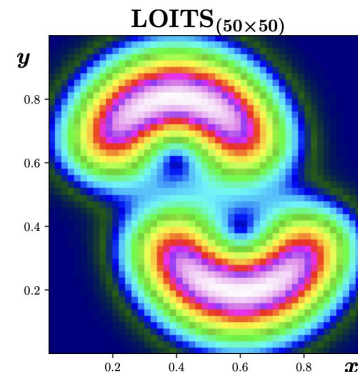
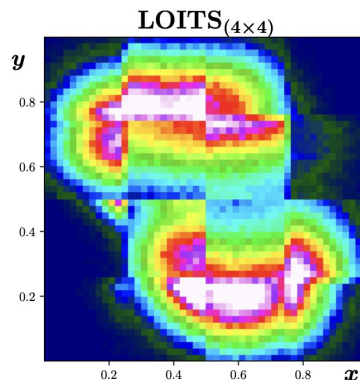


Approximate PDF using orthogonal segments

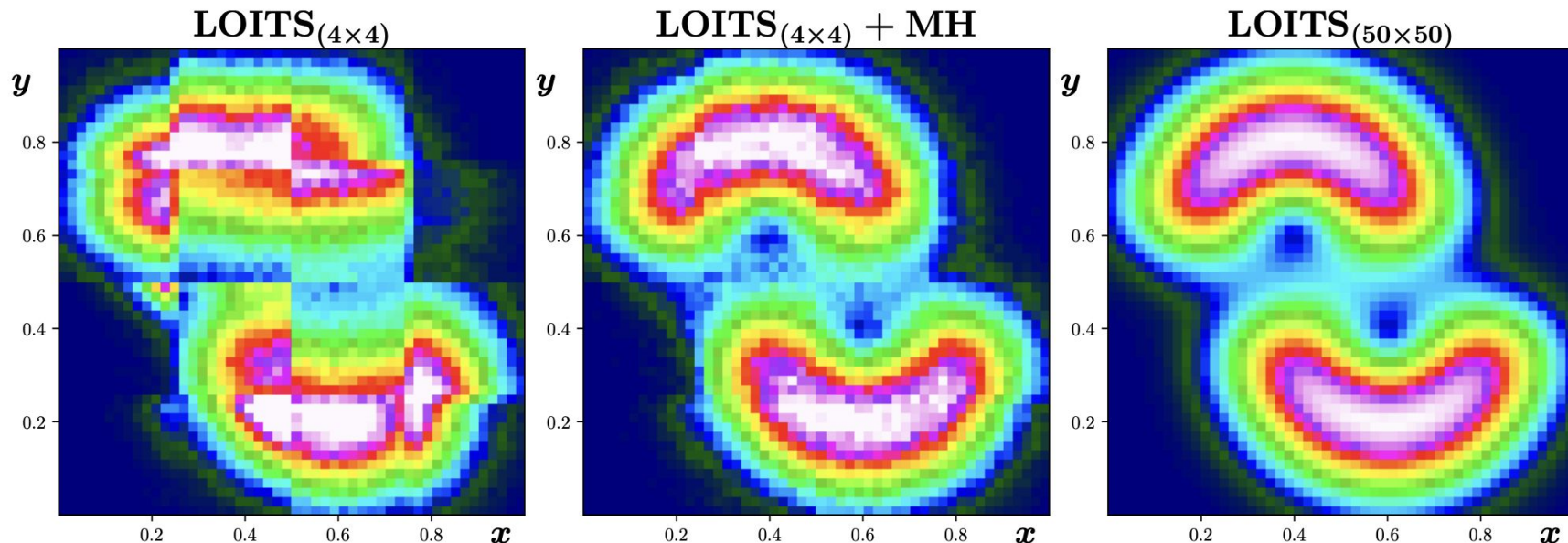
Pair the samples randomly from each of the segments

By construction the 2dim samples are differentiable

NOTE: LOITS is only an approximation



Correcting LOITS with Metropolis Hastings



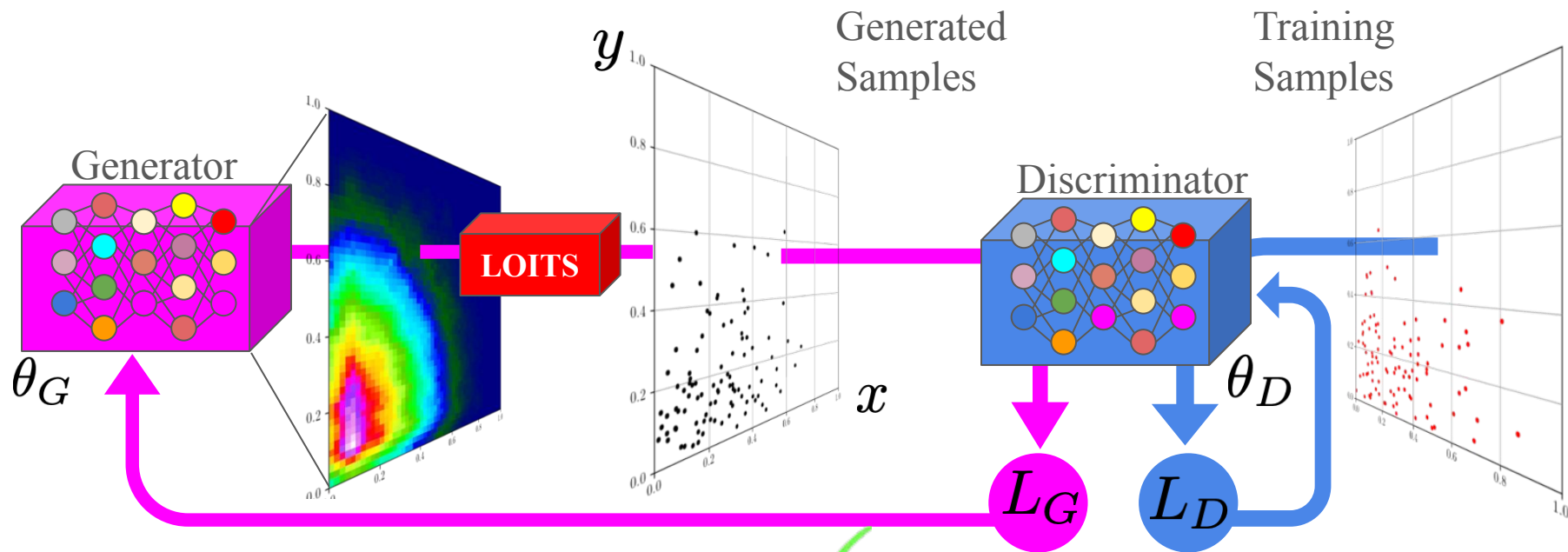
LOITS provides the PDF for each sample

We can use LOITS as independent proposal

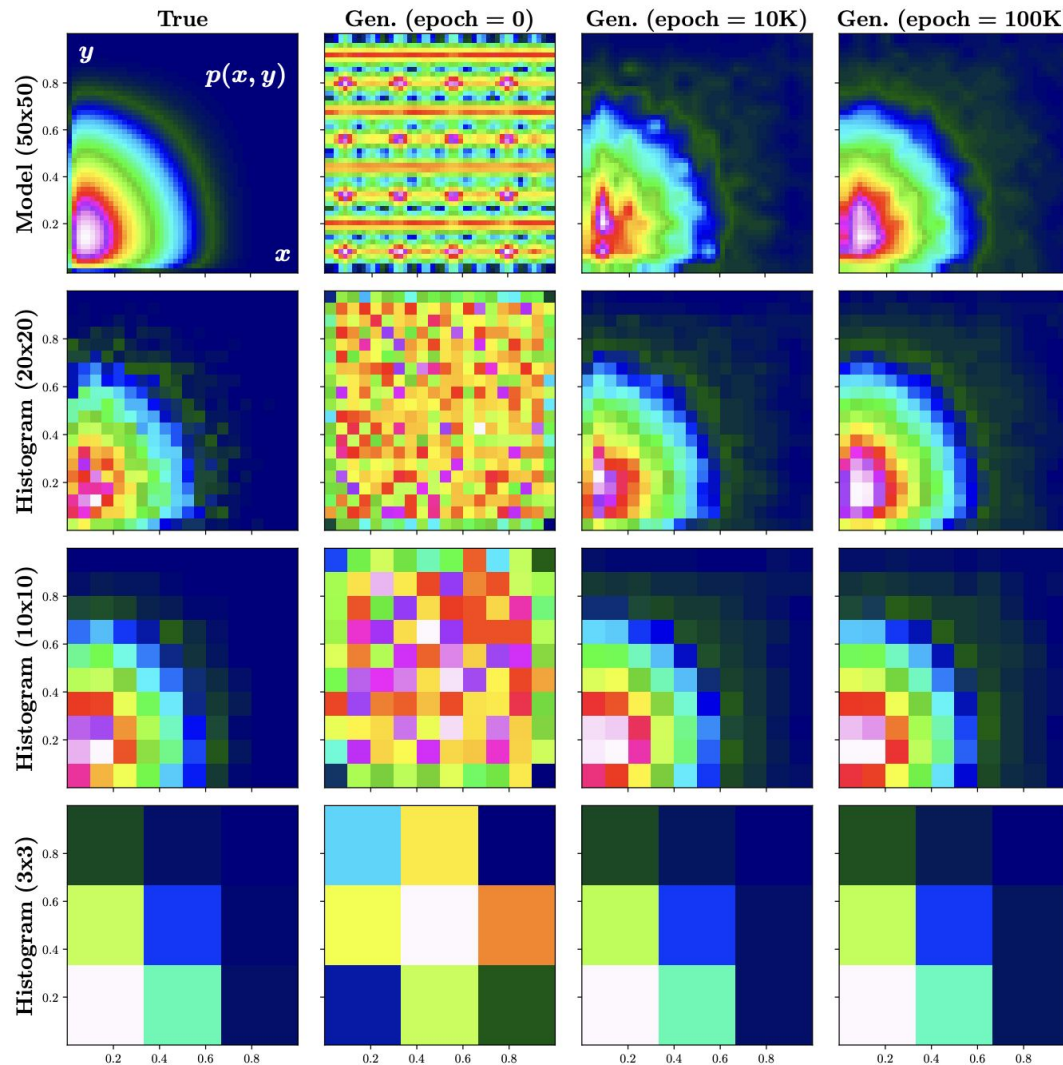
LOITS+MH = differentiable MCMC

$$A = \min \left[u, \frac{p(x_{i+1}, y_{i+1} | \theta)}{p(x_i, y_i | \theta)} \cdot \frac{p^*(x_i, y_i | \theta)}{p^*(x_{i+1}, y_{i+1} | \theta)} \right]$$

Does it work?



$$\Rightarrow \frac{\partial L_G}{\partial \theta_G} = \frac{\partial L_G}{\partial x} \frac{\partial x}{\partial \theta_G} + \dots$$



Gen AI can learn the underlying density using the LOITS gradients

There are yet visible deviations from ground truth

Recombination of pixels indicates that the learned resolution is lower than the original pixel density

Pixel based approach enables to ask resolution of the reconstructed densities

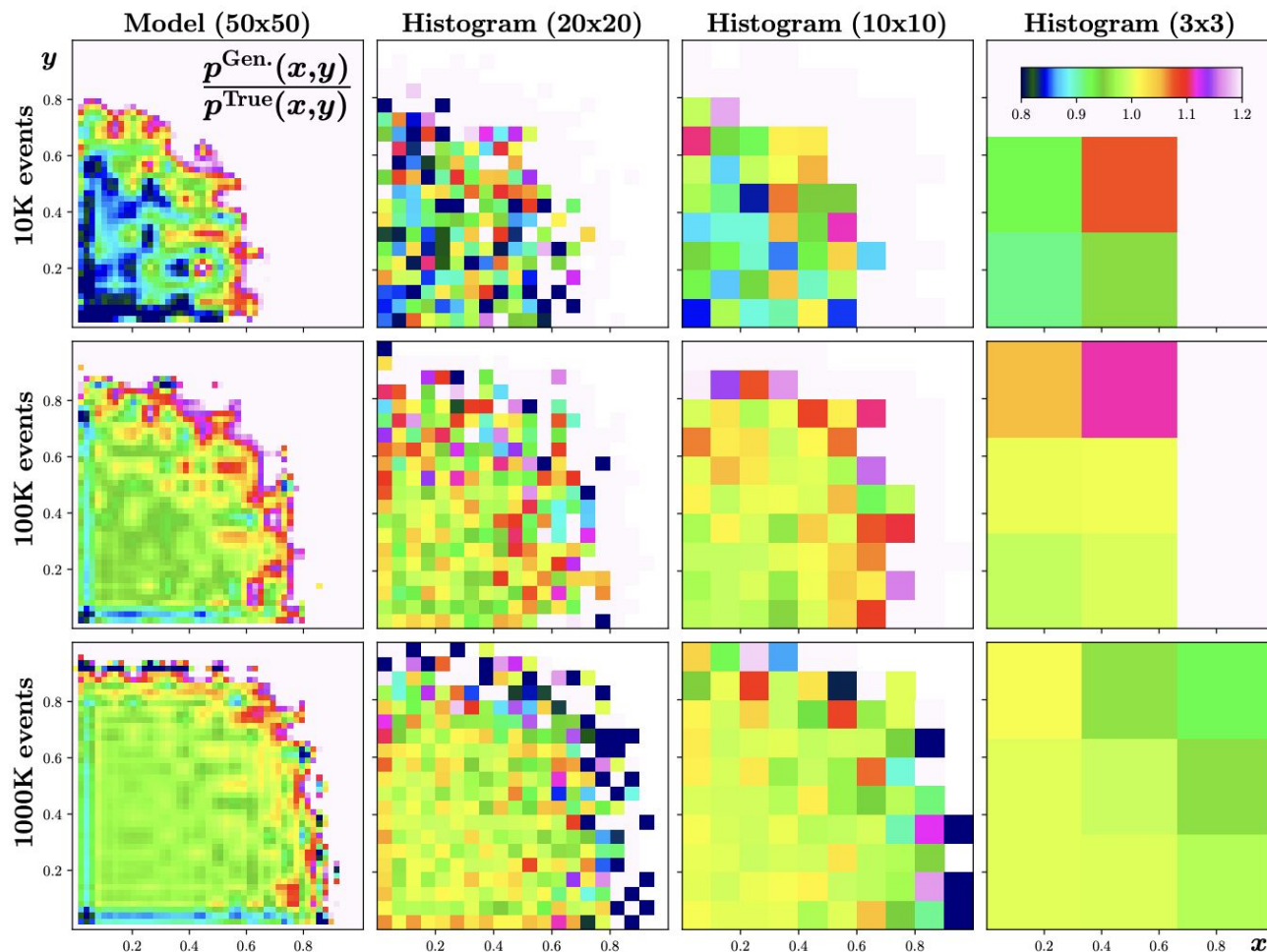
Post analysis: convert density into samples and histogram with different binning

Potential limiting factor includes: data size, model uncertainty, GAN training

We performed test on different data sizes

The results indicates that Gen AI can improve the resolution as the data size increases

The pixel approach provides new venues to quantify required luminosity to reconstruct hadron structure



Summary

Pixel based approach with Generative AI is very suited to reconstruct hadron structure (multidimensional densities).

One of the challenges is backpropagation. Many possibilities might exist. We proposed LOITS and demonstrated its usage on a controlled example

LOITS is an approximation, but it can be corrected using Metropolis-Hasting algorithm

Image resolution for hadron structure is to our knowledge a new form of UQ

