



Enabling Specialized Unfolding Methods with Modern Machine Learning (ML)

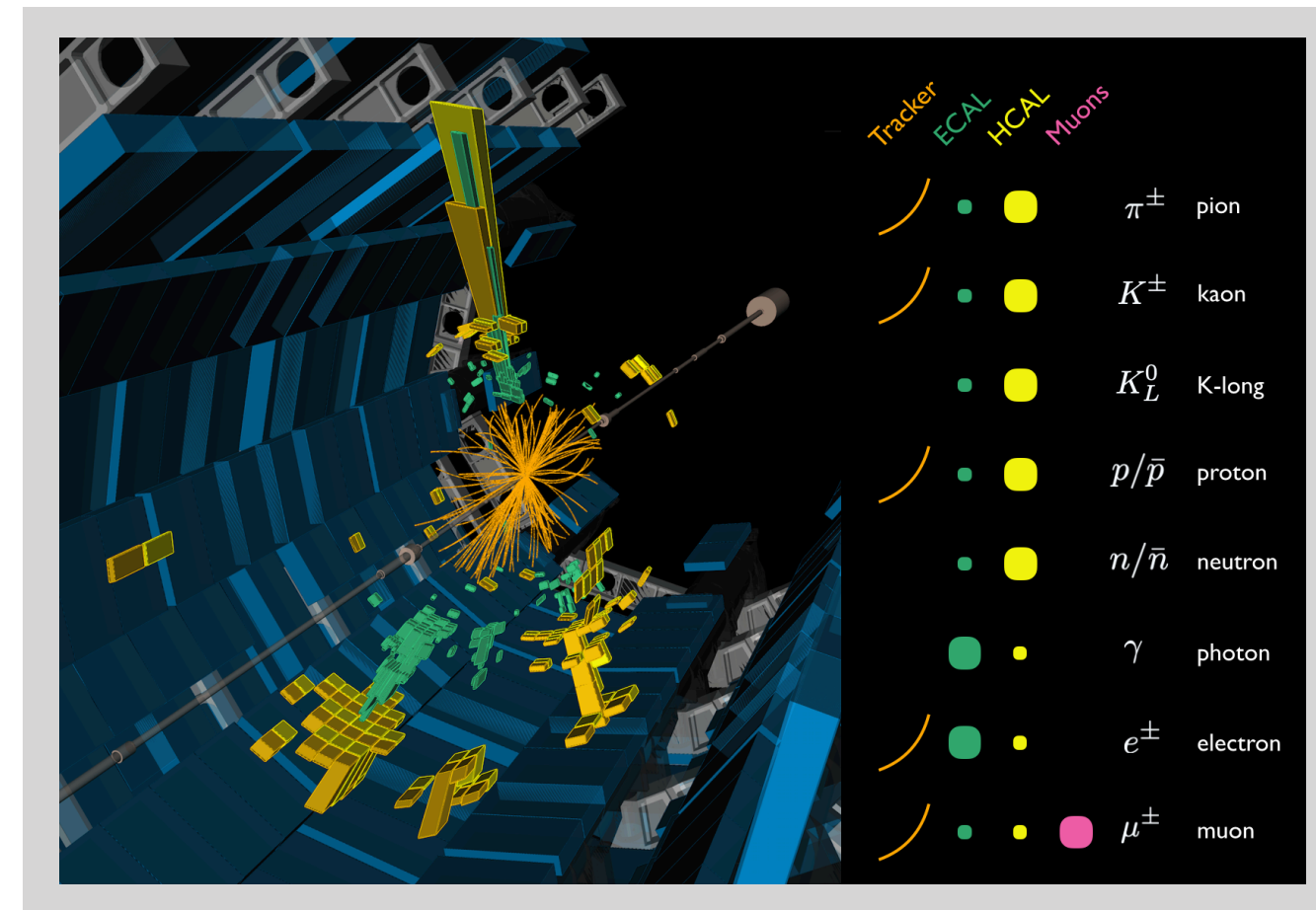
Overview of Binned ML Unfolding Methods

Jingjing Pan (Jing)

France-Berkeley PHYSTAT Workshop, June 11, 2024

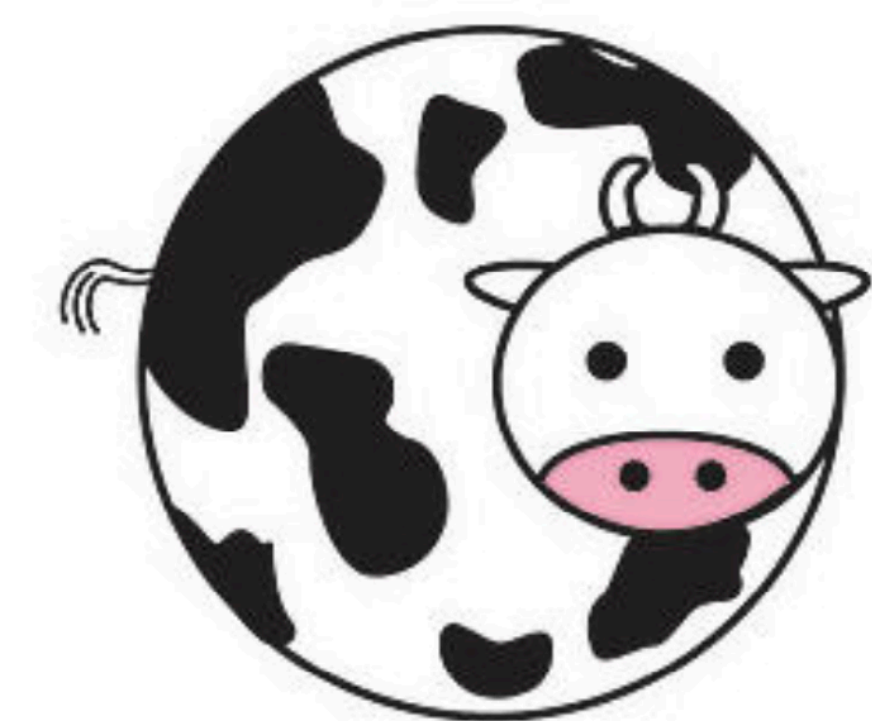
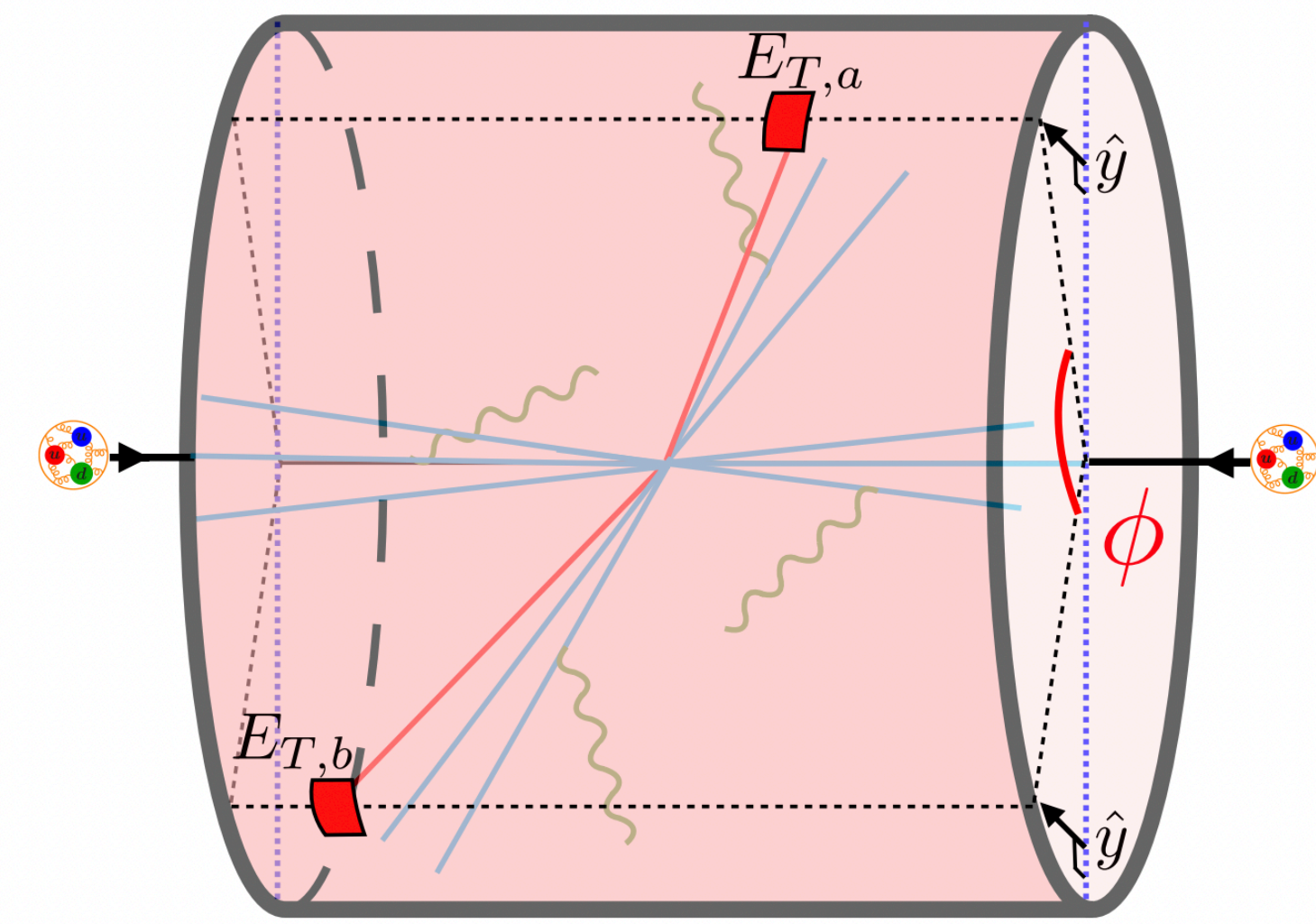
Unfolding: Bridging the Gap...

Necessary to compare data across different experiments / with theory



Experiment

Better preserving data

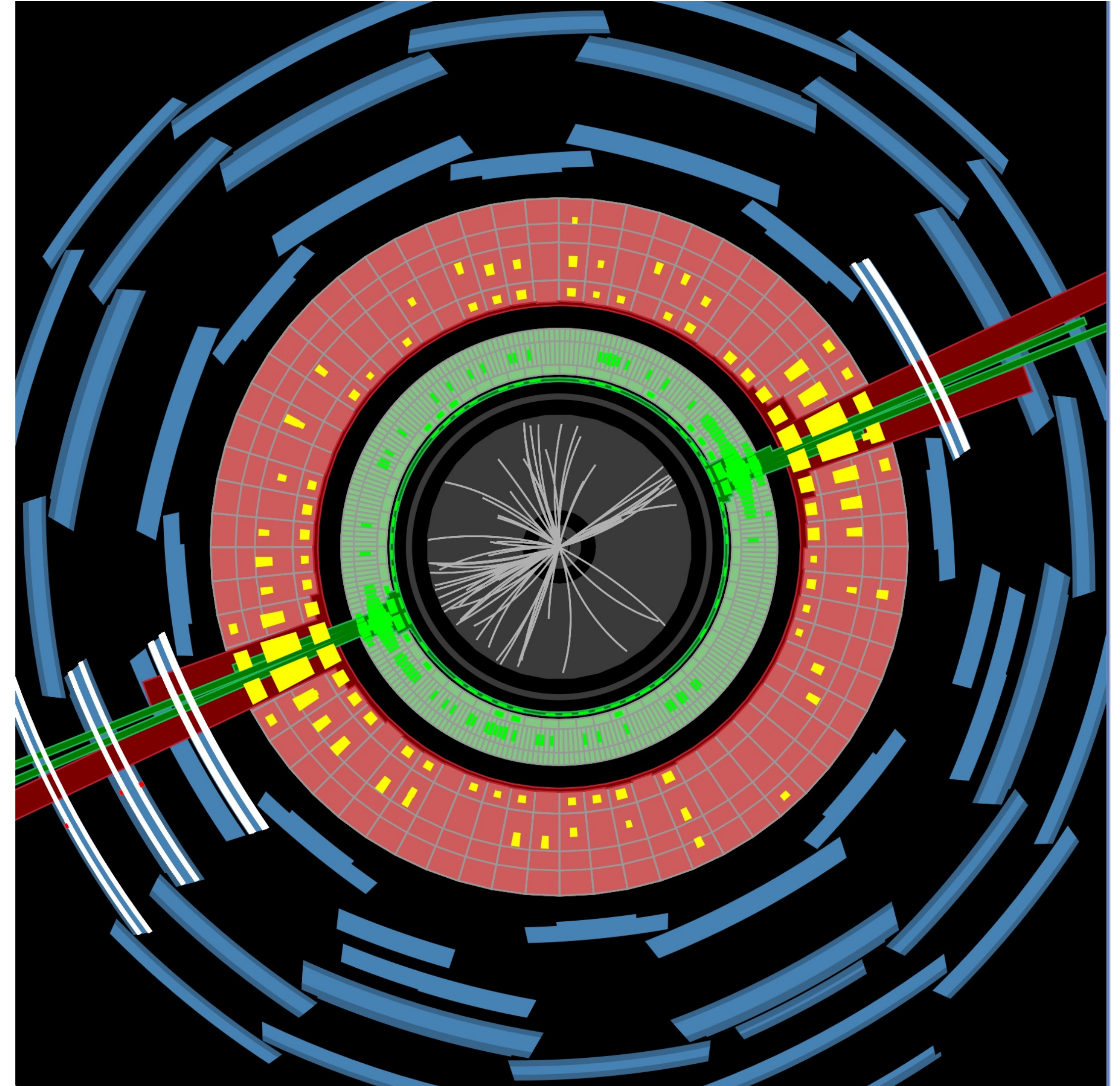


Theory

Figure credit: Wouter Waalewijn (theory overview @BOOST 2020)

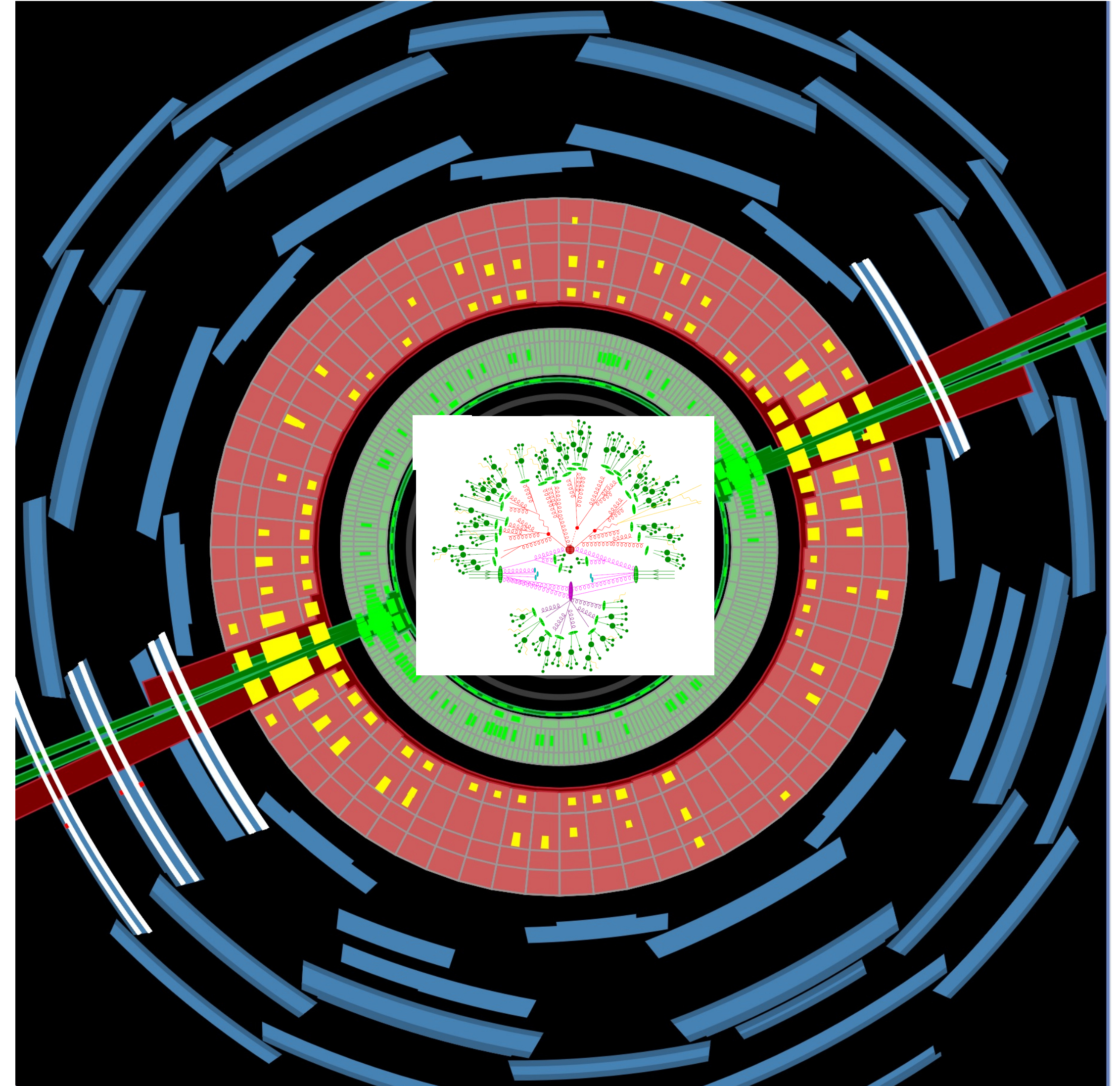
Outline

1. Unfolding as a classification task
2. Optimizing reco-level observables with ML
3. Fast regularized neural posterior estimation with normalizing flows



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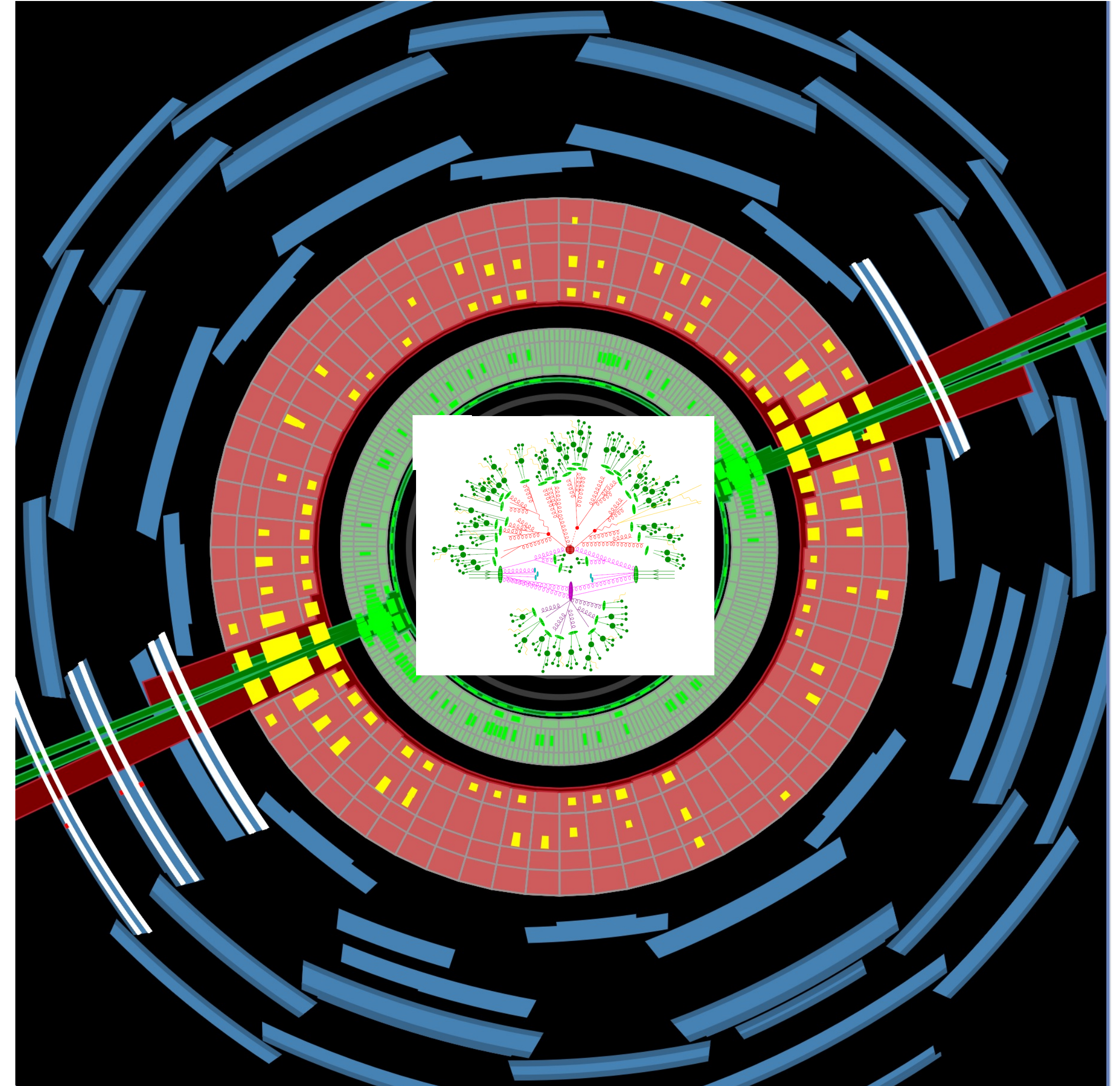
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Outline

1. Unfolding as a classification task

1712.01814



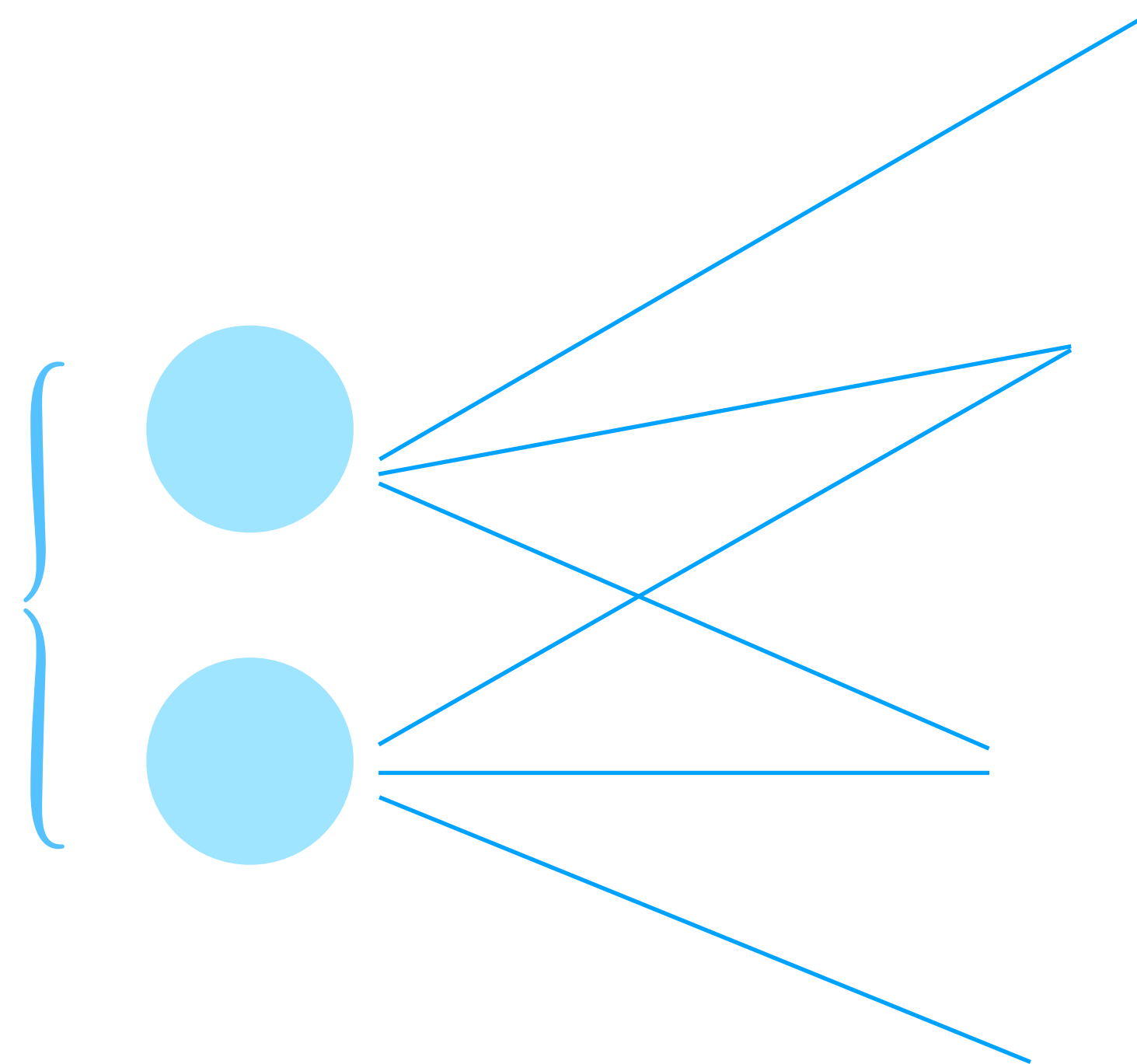
Unfolding as a Classification Task

Classifying the reco-level values into truth-level bins

Unfolding as a Classification Task

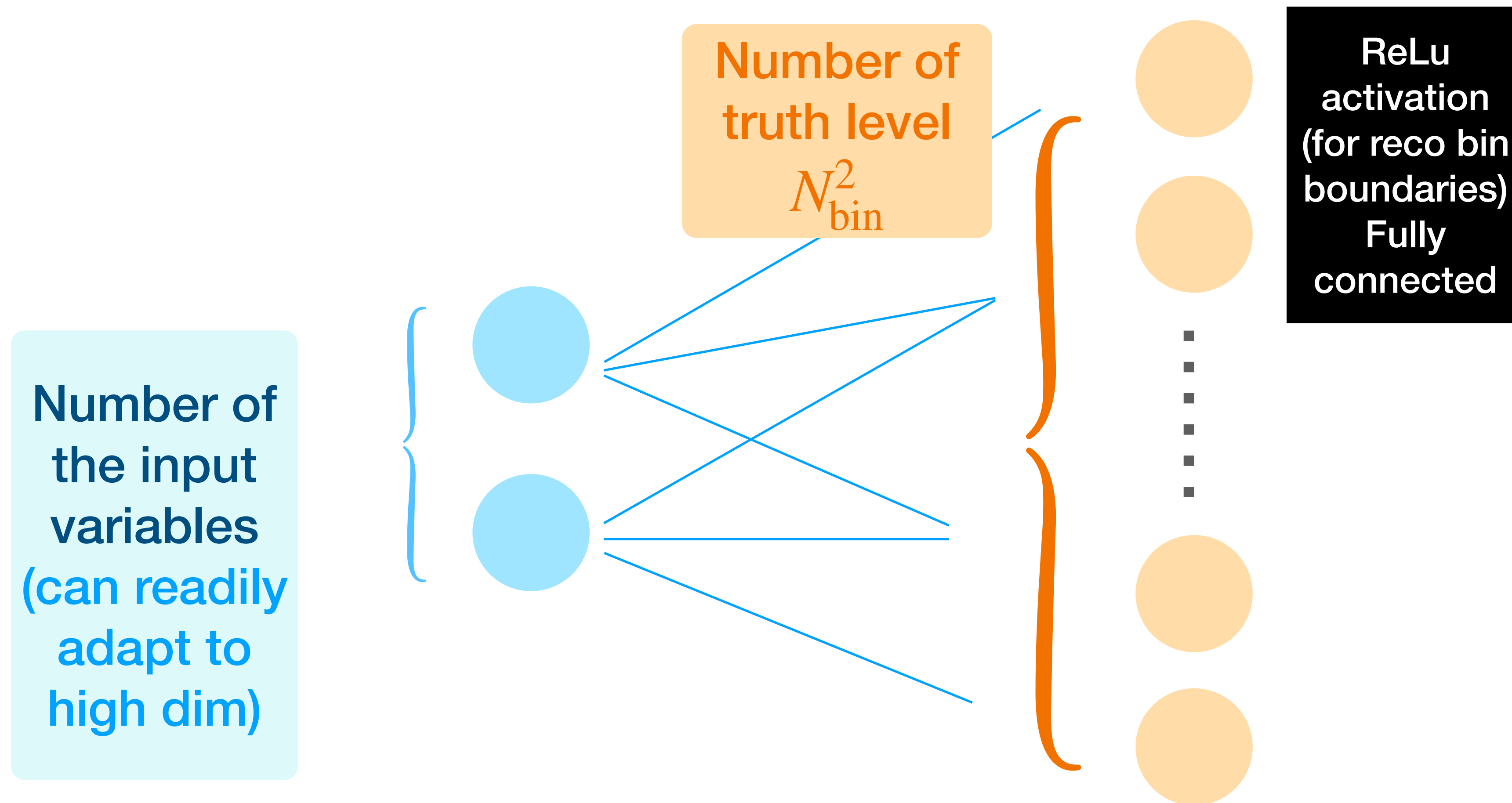
Classifying the reco-level values into truth-level bins

Number of
the input
variables
(can readily
adapt to
high dim)



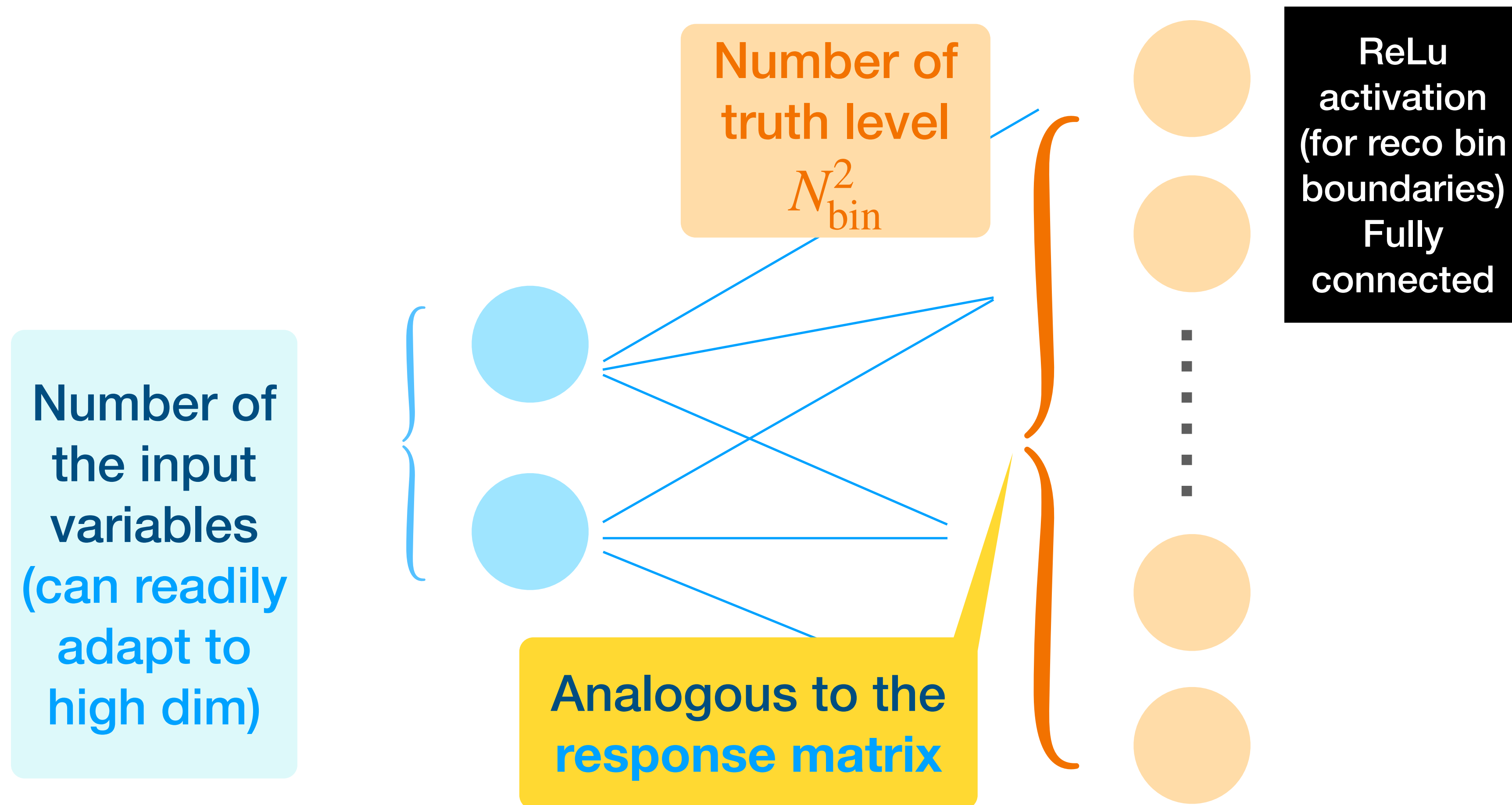
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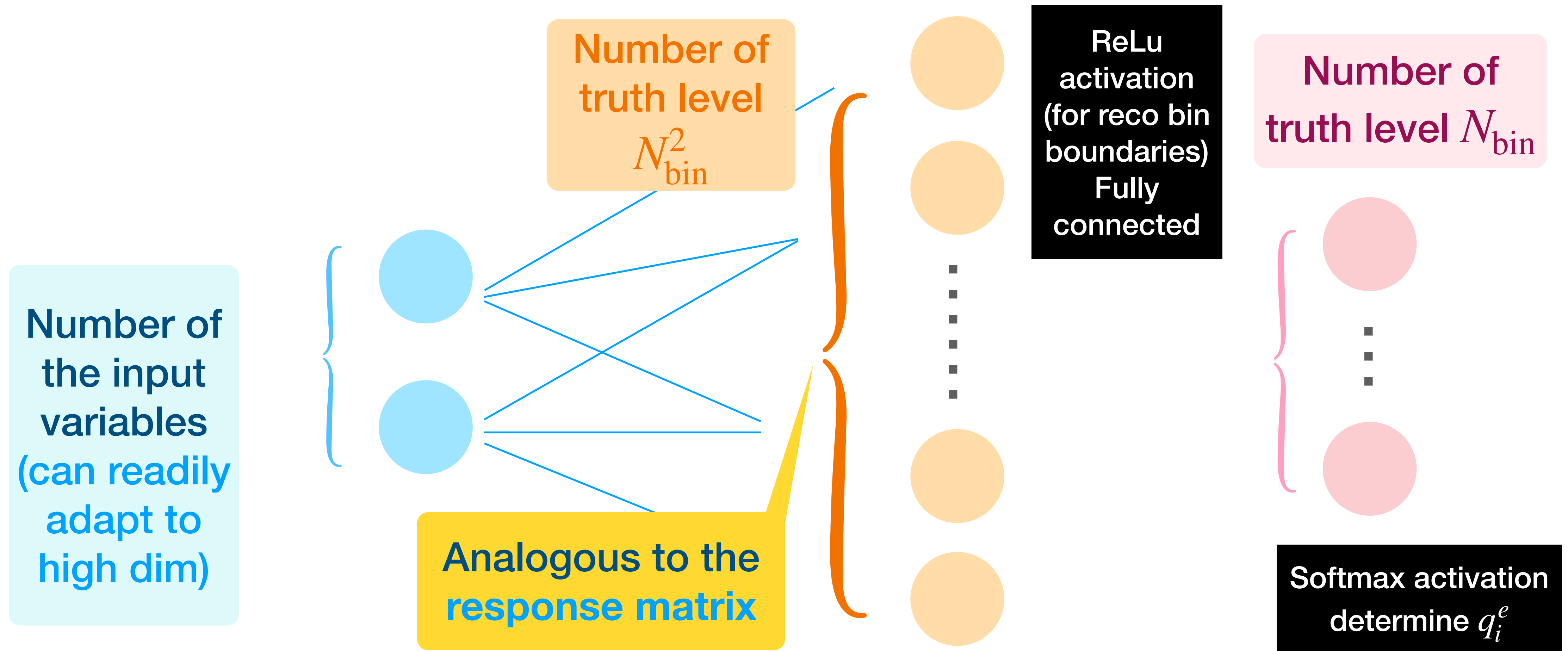
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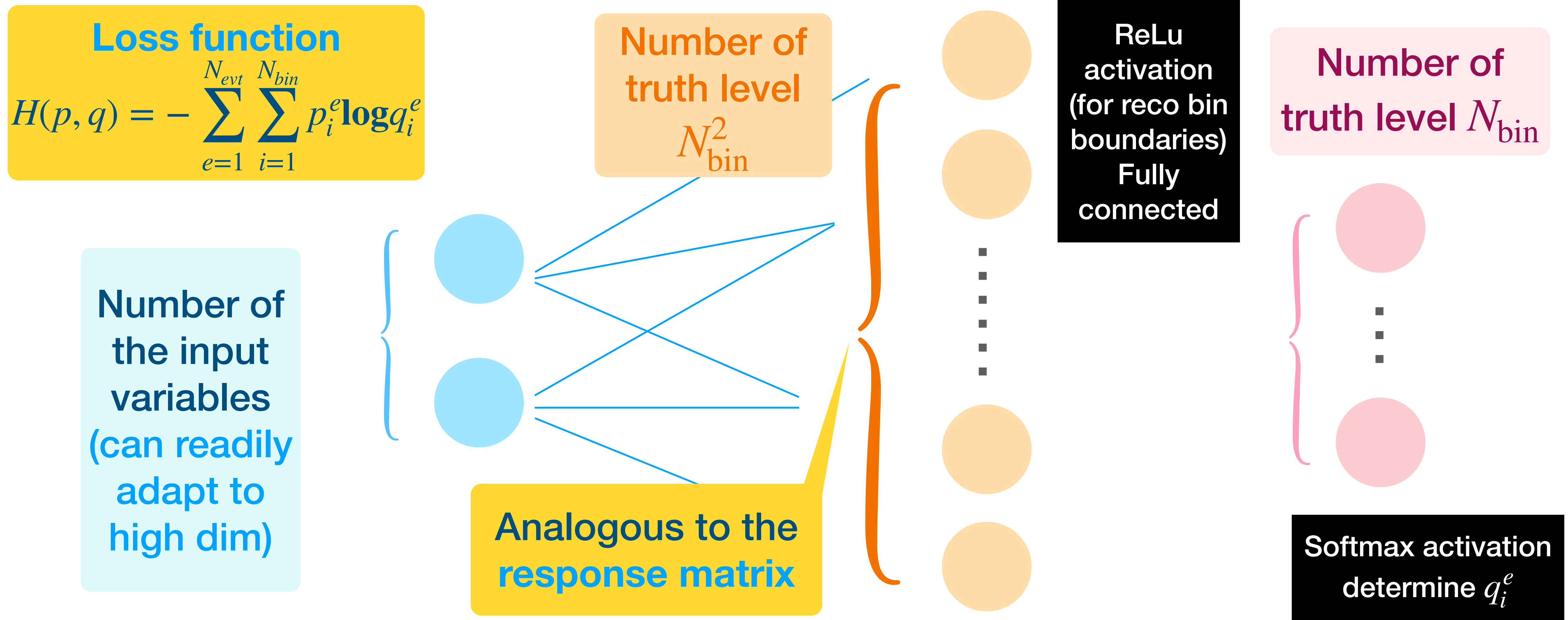
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Unfolding as a Classification Task

Classifying the reco-level values into truth-level bins



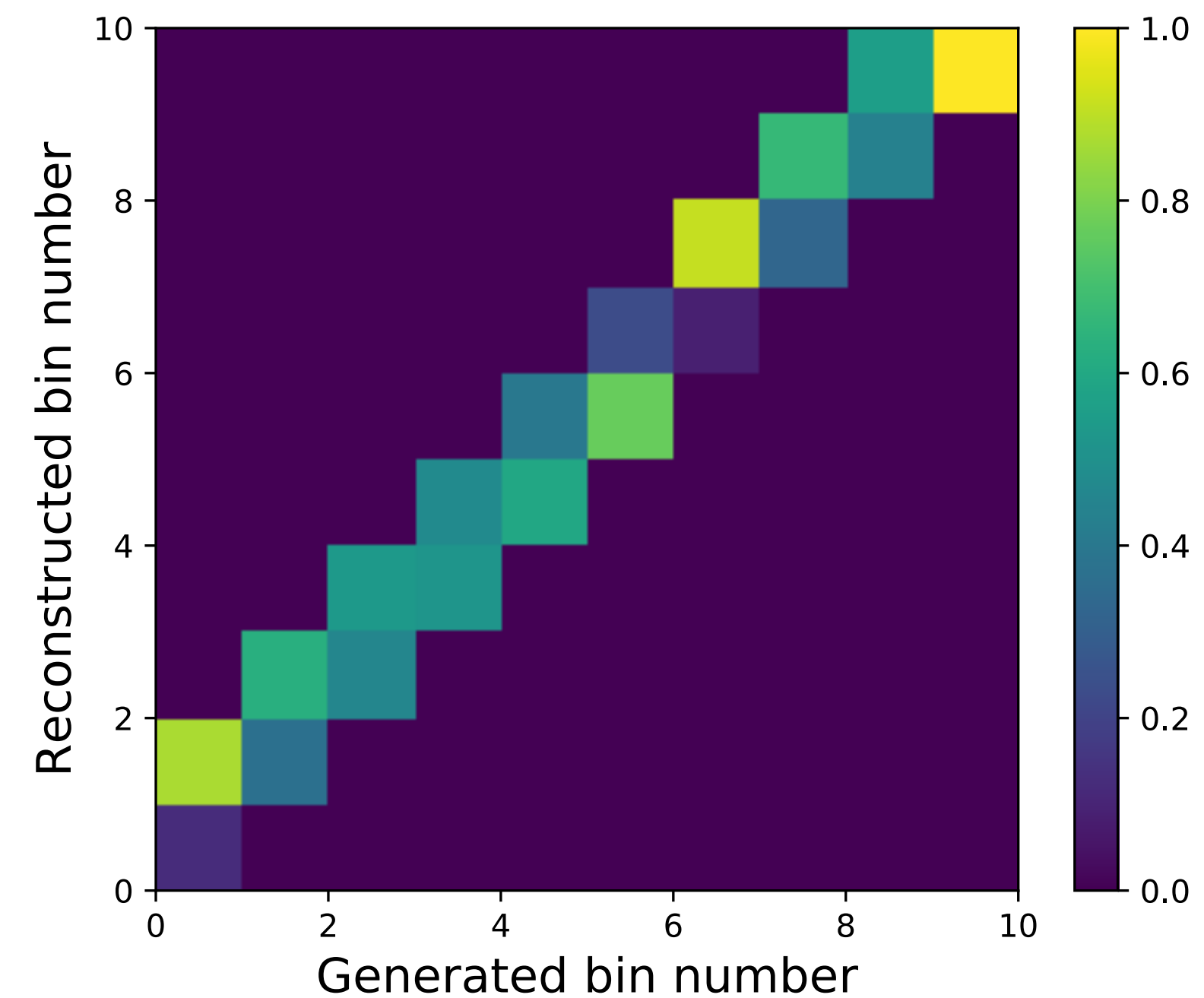
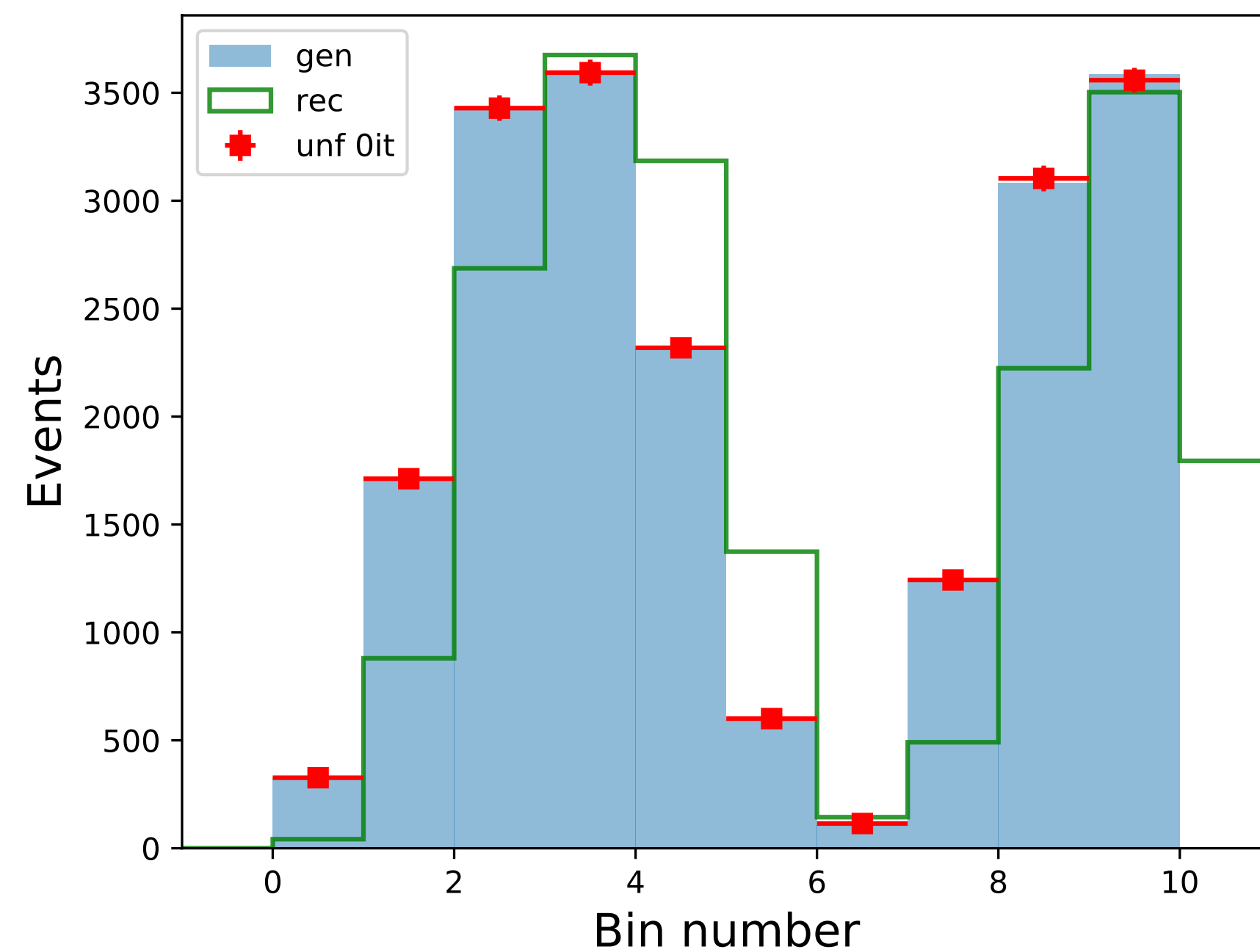
Unfolding as a Classification Task

Classifying the reco-level values into truth-level bins

- **Iterate** to reduce prior dependence
 - Can start with flat prior $F(x_g) = \text{const}$.
 - Trained classifier applied to data $\rightarrow q_i^{e, \text{data}}$ (predicted probability for truth bin i event e)
 - Update and obtain $F'_n(x) = \frac{1}{N_{\text{evt, data}}} \sum_{e=1}^{N_{\text{evt, data}}} q_i^{e, \text{data}}$ for iteration n
 - Re-sample the MC & re-train the classifier
- (**Ensembling** to get the result)

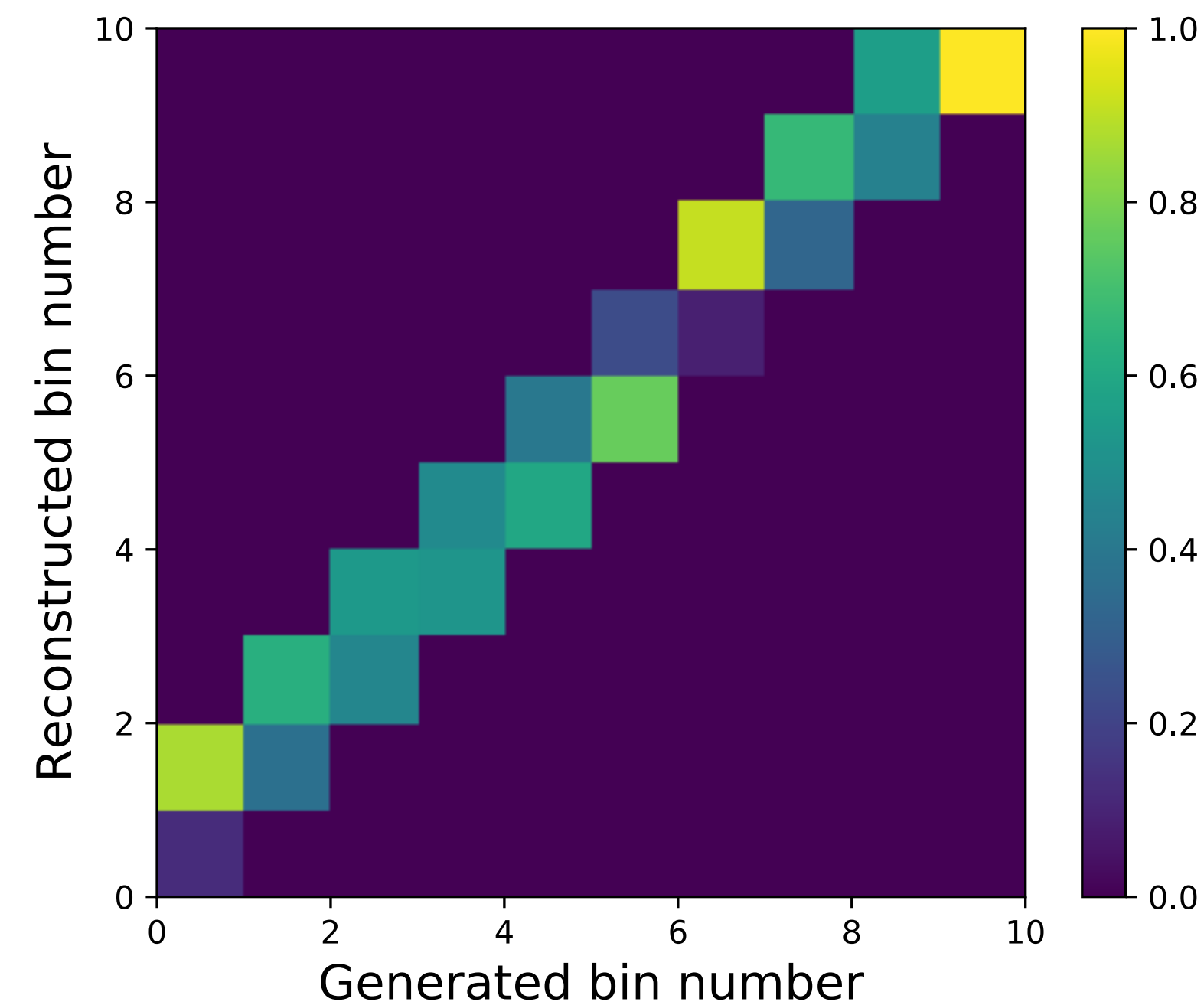
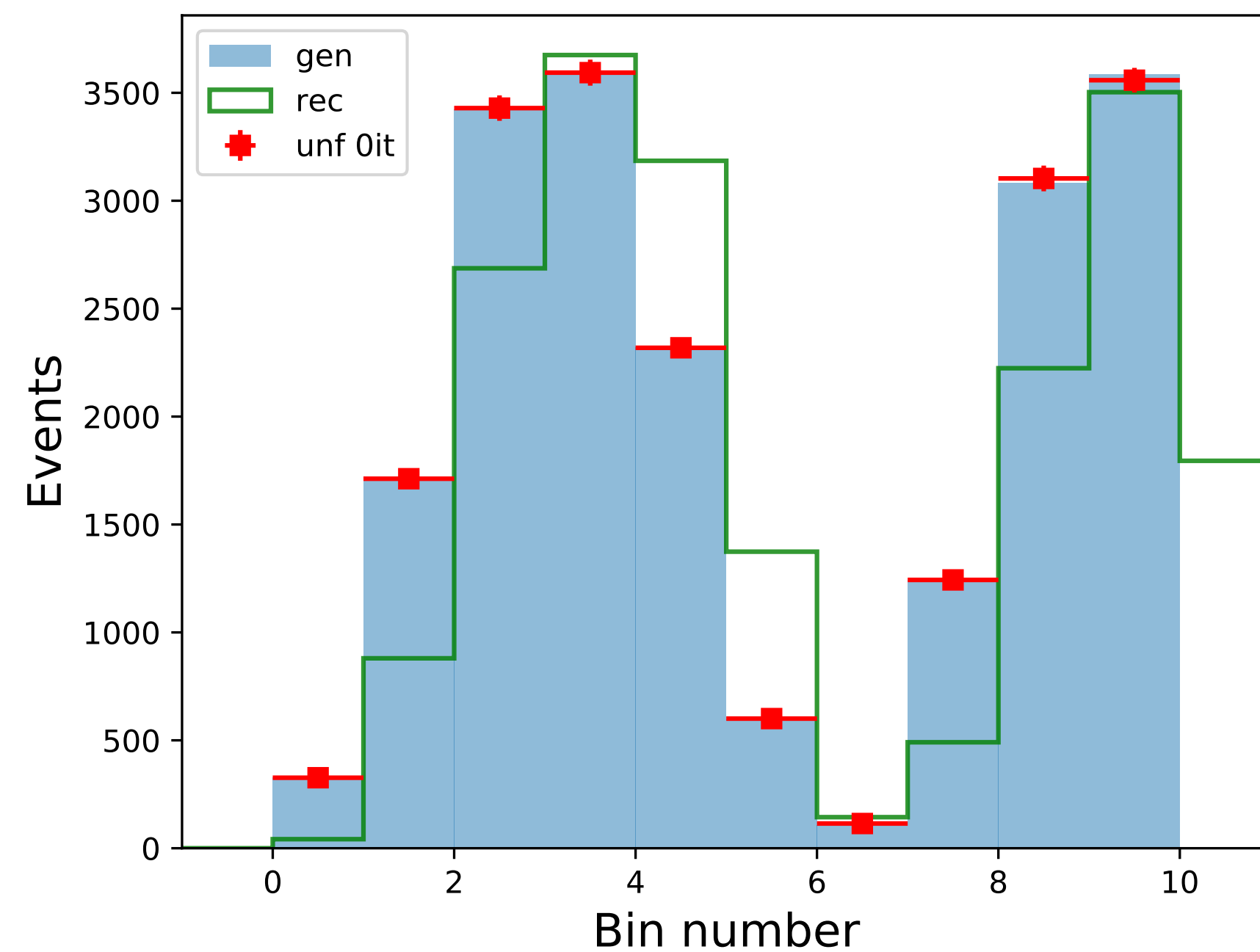
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Unfolding as a Classification Task

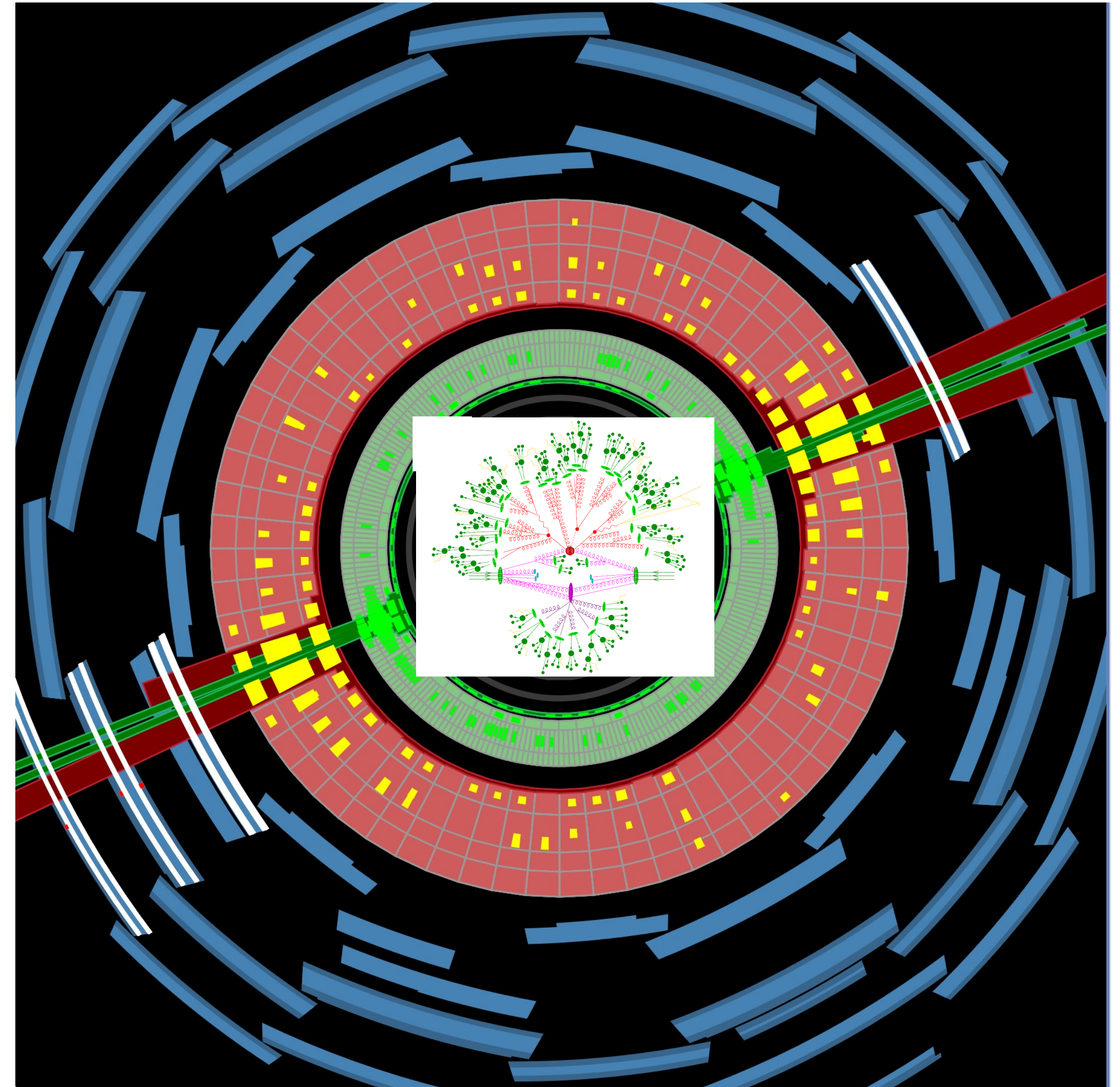
Classifying the reco-level values into truth-level bins



Performs very well even for **huge off-diagonal** response elements from a **shift** ($x_r \rightarrow x_g + 0.05$)!

Outline

1. Unfolding as a classification task
2. Optimizing reco-level observables
with ML [2203.16722](#)
3. Fast regularized neural posterior
estimation with flows
4. (Bonus) Enabling profiling with 1L



Optimizing reco Observable (\mathcal{O}_d) with ML

2203.16722

What to unfold?

Optimizing reco Observable (\mathcal{O}_d) with ML

2203.16722

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- Usually we discuss the art of matrix inversion (i.e. How)

Optimizing reco Observable (\mathcal{O}_d) with ML

2203.16722

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- Step 0: What is the observable?
 - Can we do better than simply adding variables / going to higher dimension?

Optimizing reco Observable (\mathcal{O}_d) with ML

2203.16722

What to unfold?

- Usually we discuss the art of matrix inversion (i.e. How)
- Step 0: What is the observable?
 - Can we do better than simply adding variables / going to higher dimension?
 - YES!
 - Particle-level: from a list of 4-vectors, must be linked to theory for comparison
 - Detector-level: from energy flow objects

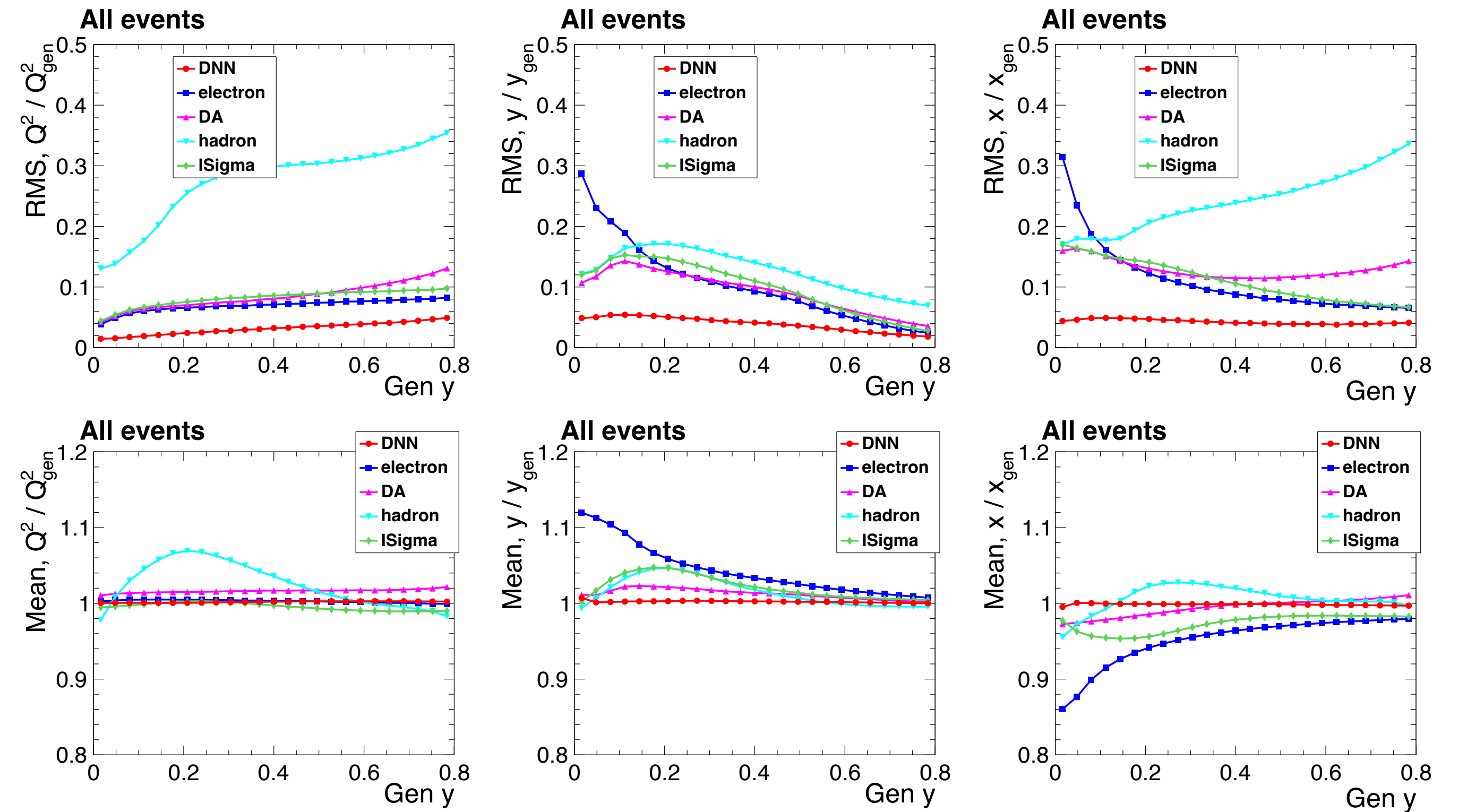
Optimizing reco Observable (\mathcal{O}_d) with ML

2203.16722

2110.05505

What to unfold?

ATHENA fast simulation (Rapgap+Delphes)



Optimizing reco Observable (\mathcal{O}_d) with ML

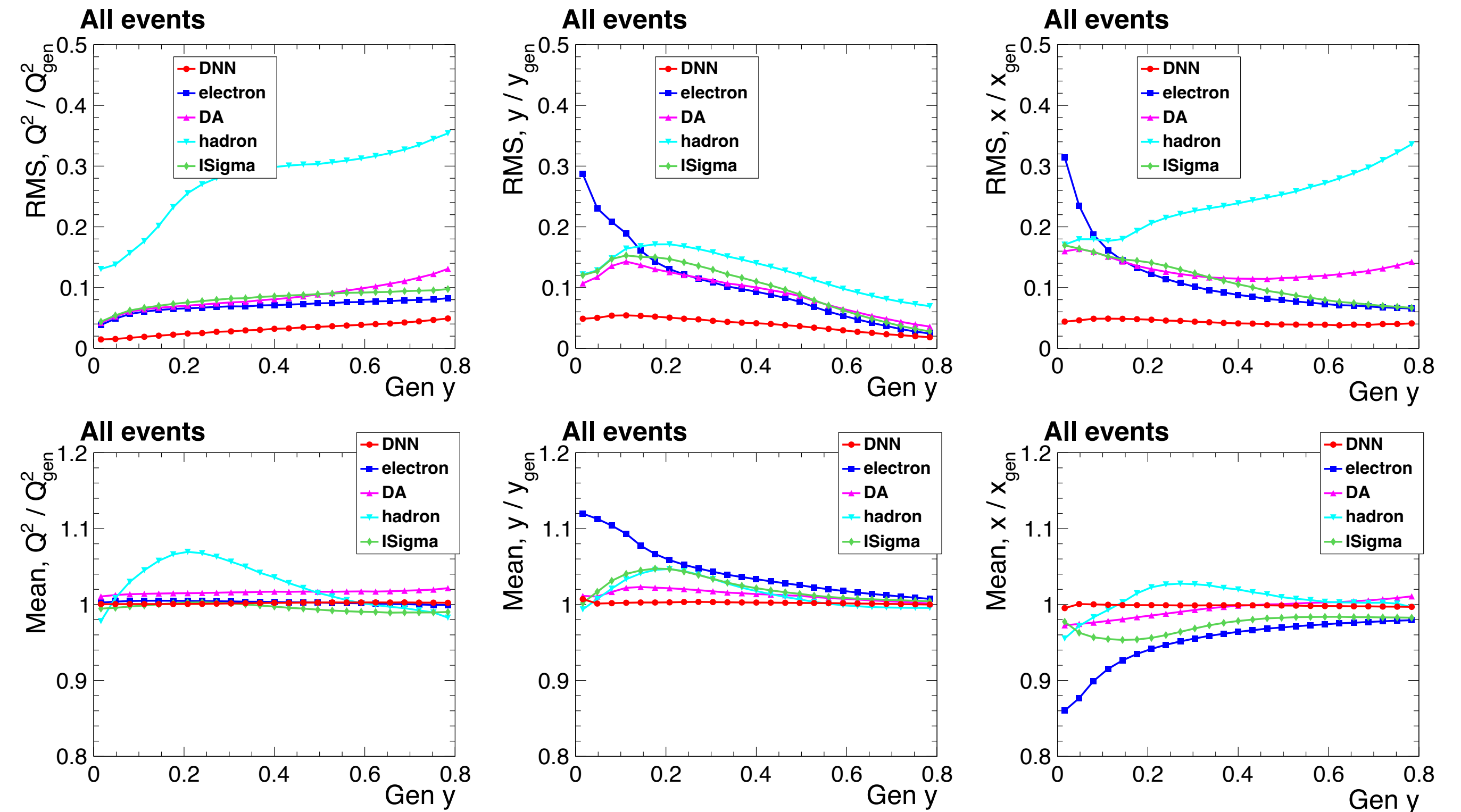
2203.16722

2110.05505

What to unfold?

- ML-assisted reconstruction goals
 - Reduce bias
 - Improve resolution

ATHENA fast simulation (Rapgap+Delphes)



Optimizing reco Observable (\mathcal{O}_d) with ML

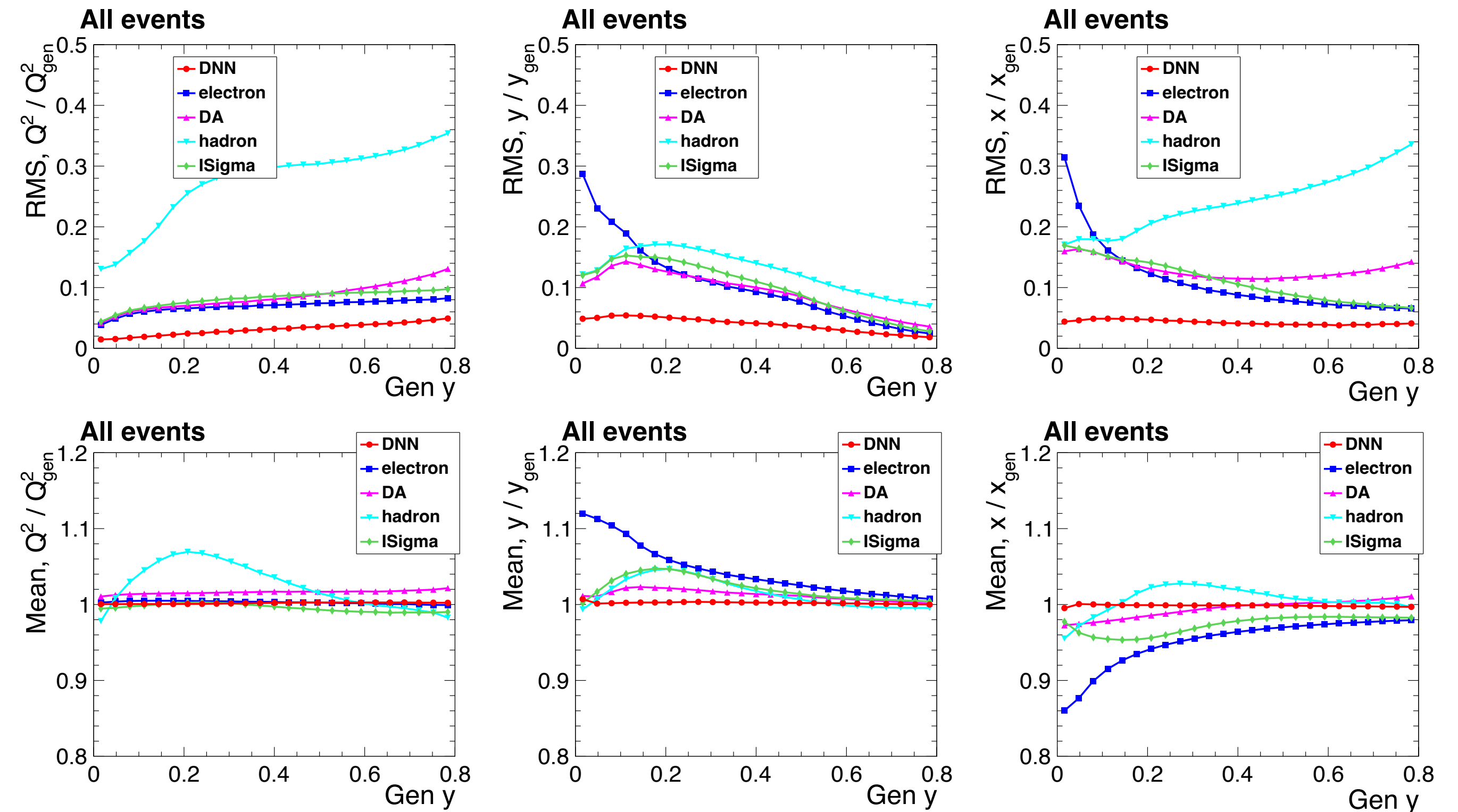
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What to unfold?

- ML-assisted reconstruction goals
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- QED-regression DNN for a Deep Inelastic Scattering (DIS) example: learns Q^2, x, y from distorted inputs

ATHENA fast simulation (Rapgap+Delphes)



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2203.16722

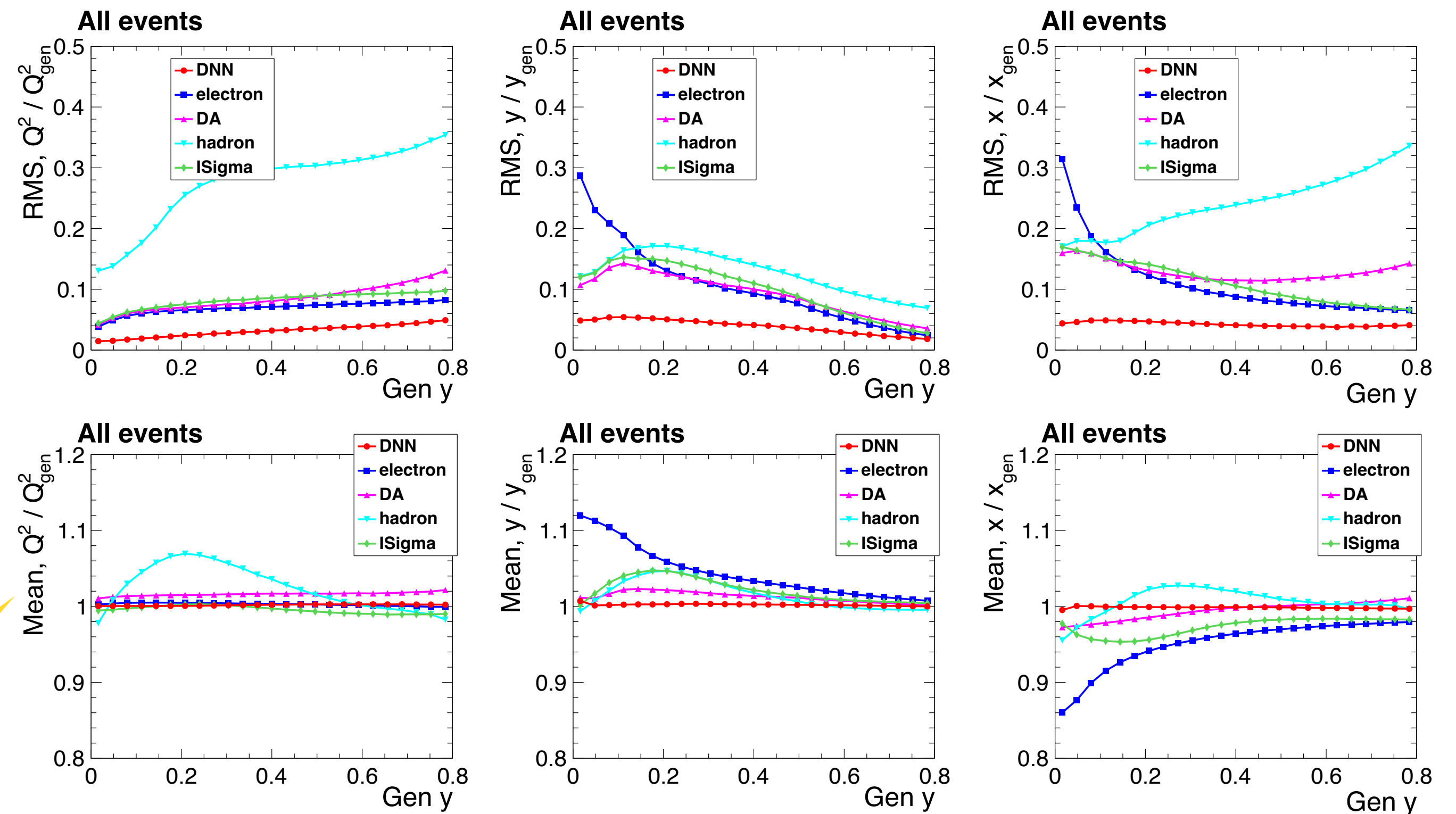
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What to unfold?

- ML-assisted reconstruction goals
 - Reduce bias
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- QED-regression DNN for a Deep Inelastic Scattering (DIS) example: learns Q^2, x, y from distorted inputs

QED-regression DNN gives the finest resolution & corrects for acceptance effects

ATHENA fast simulation (Rapgap+Delphes)

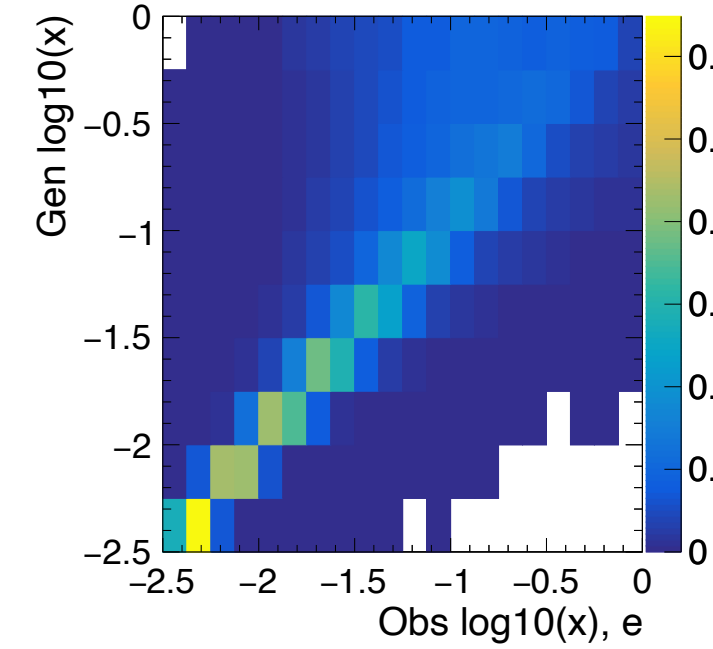


Optimizing reco Observable (\mathcal{O}_d) with ML

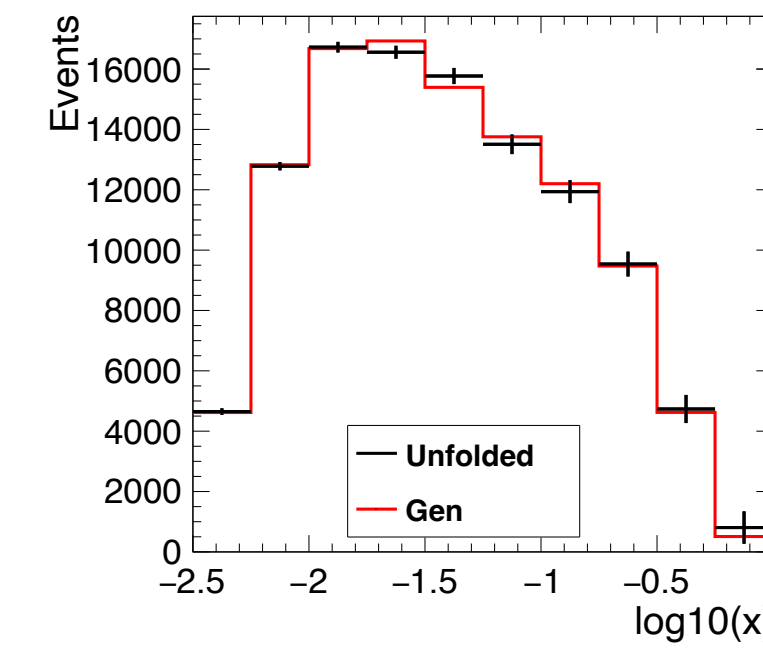
2203.16722

What to unfold?

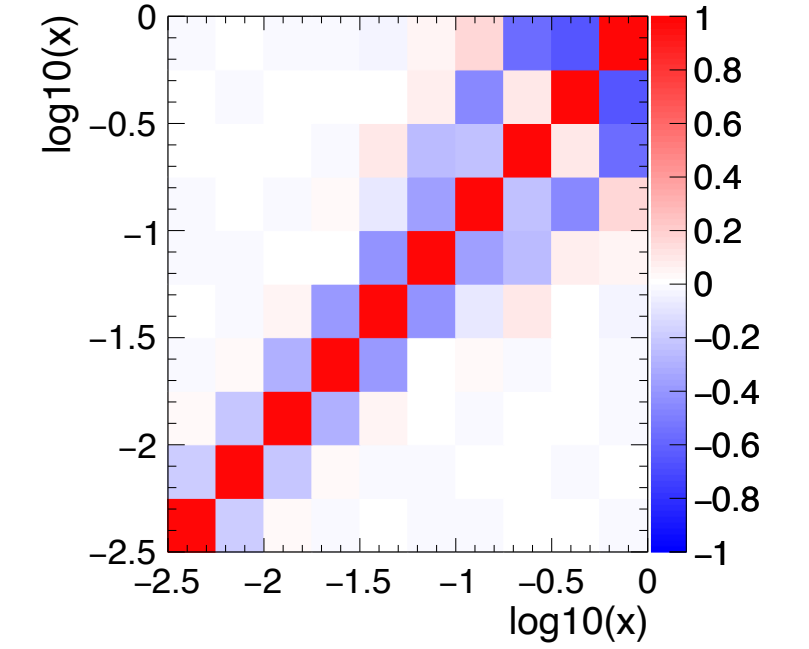
Normalized response matrix, electron



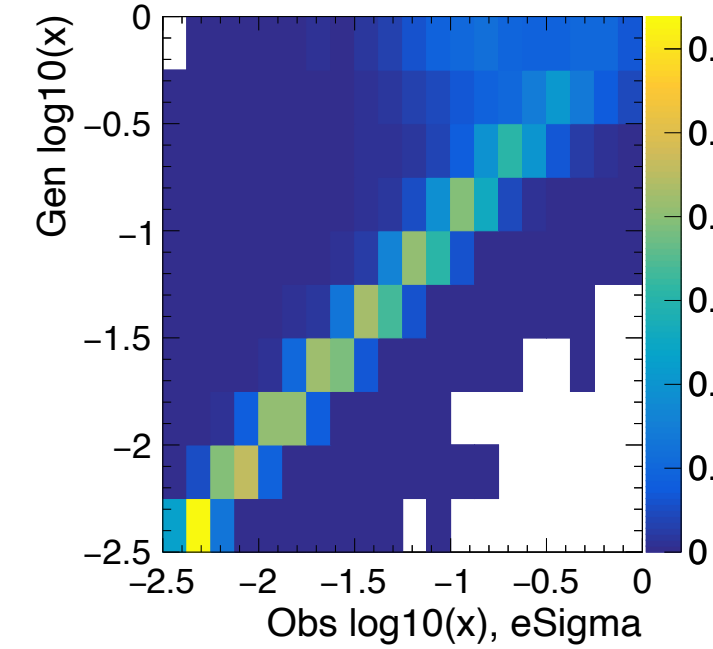
Unfolded distribution, electron



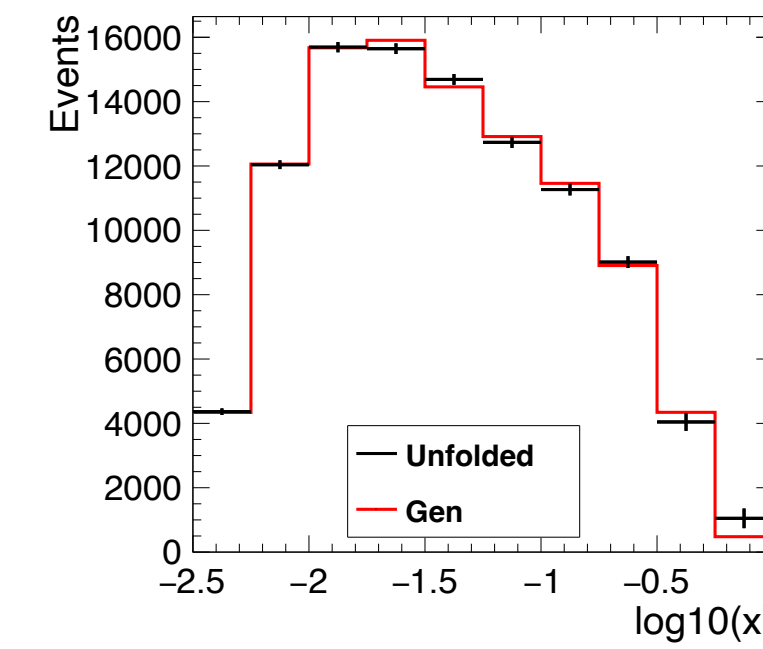
Correlation coefficients, electron



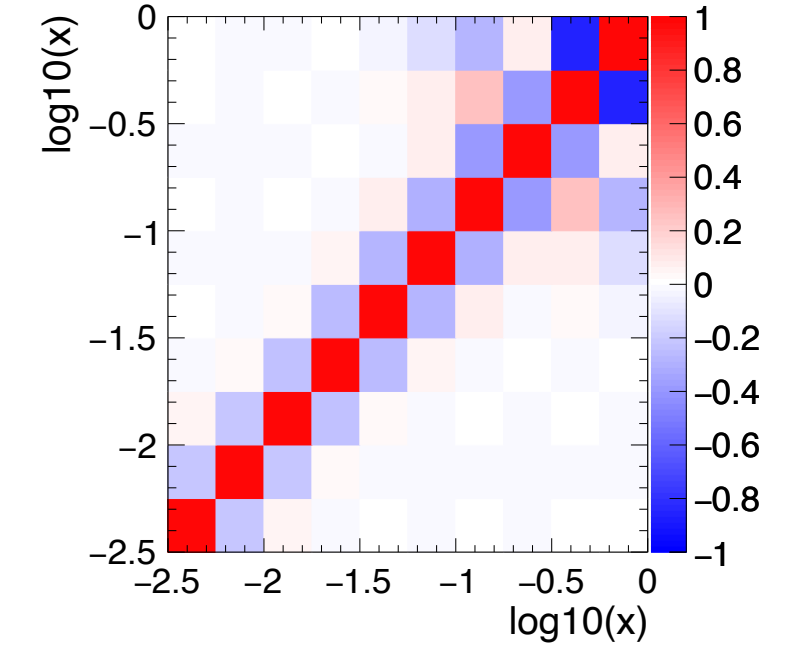
Normalized response matrix, Sigma



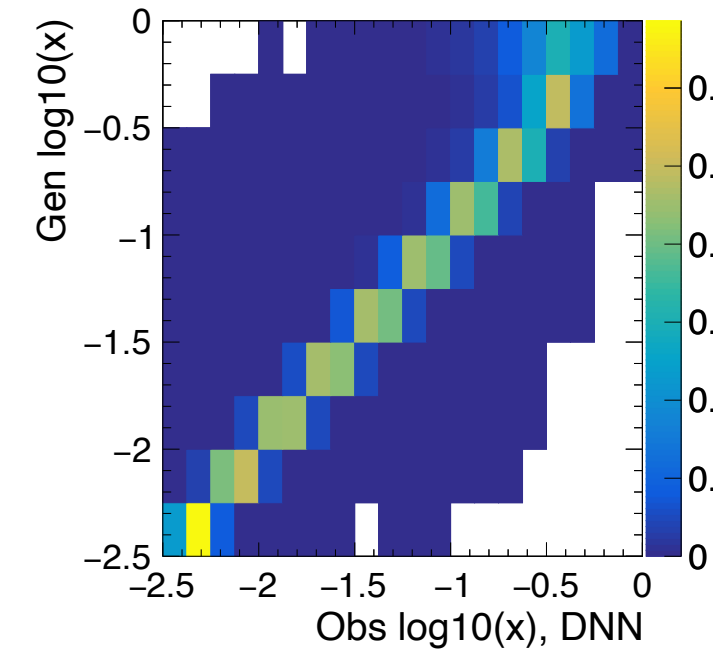
Unfolded distribution, Sigma



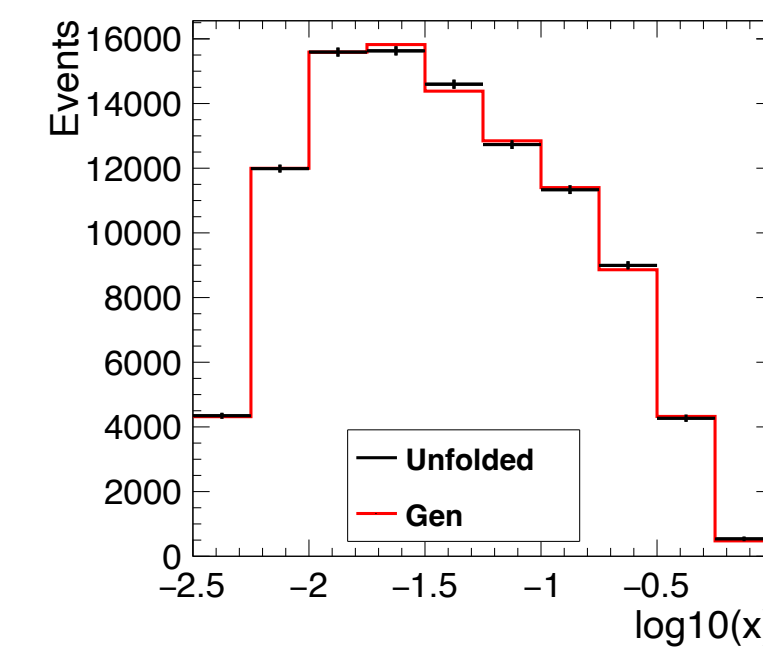
Correlation coefficients, Sigma



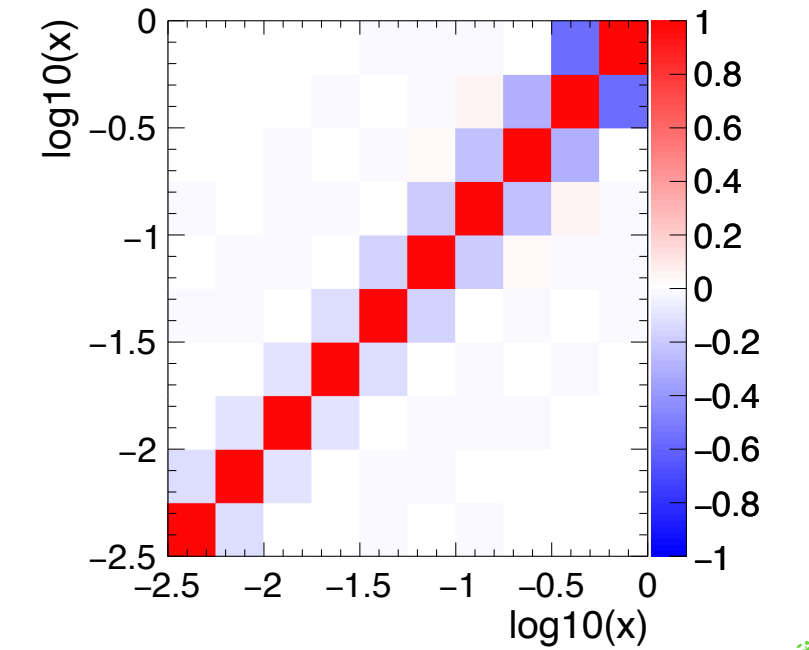
Normalized response matrix, DNN



Unfolded distribution, DNN



Correlation coefficients, DNN



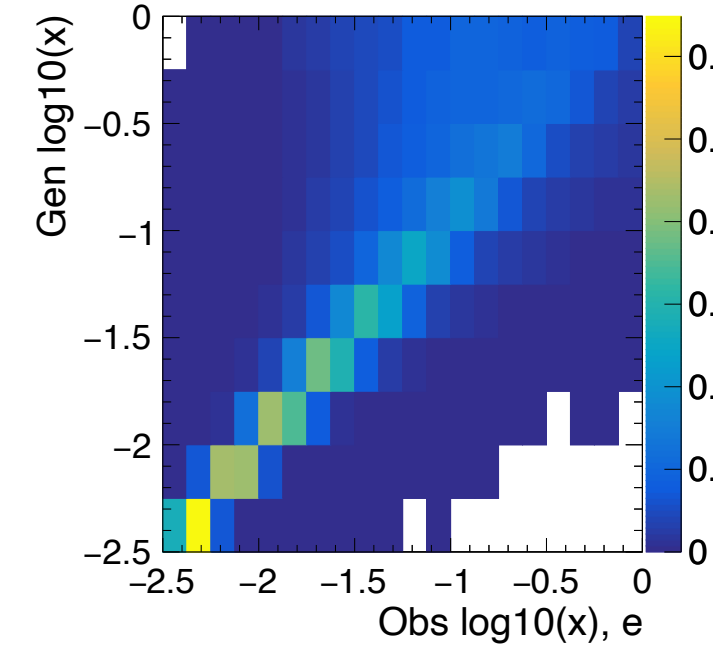
Optimizing reco Observable (\mathcal{O}_d) with ML

2203.16722

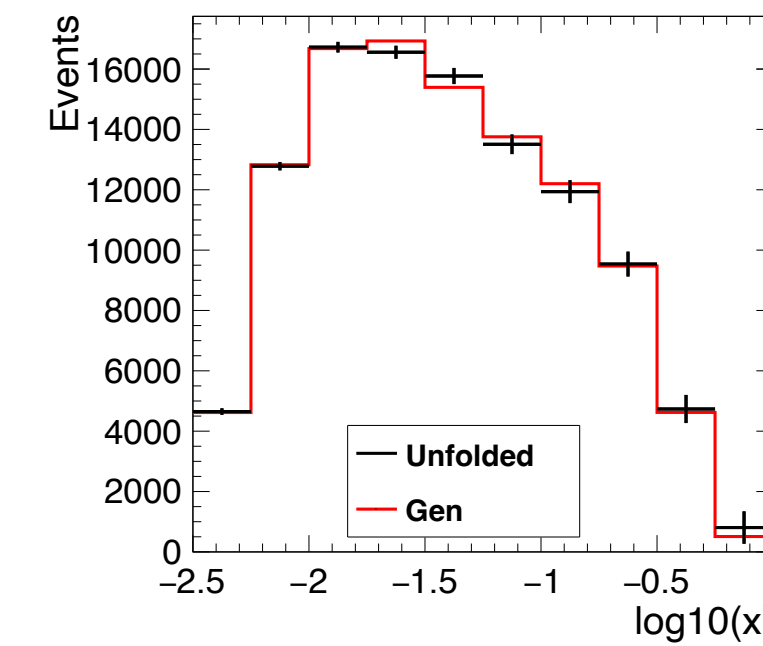
What to unfold?

- ML-assisted reconstruction reco-level observables has the most diagonal fractions throughout phase space

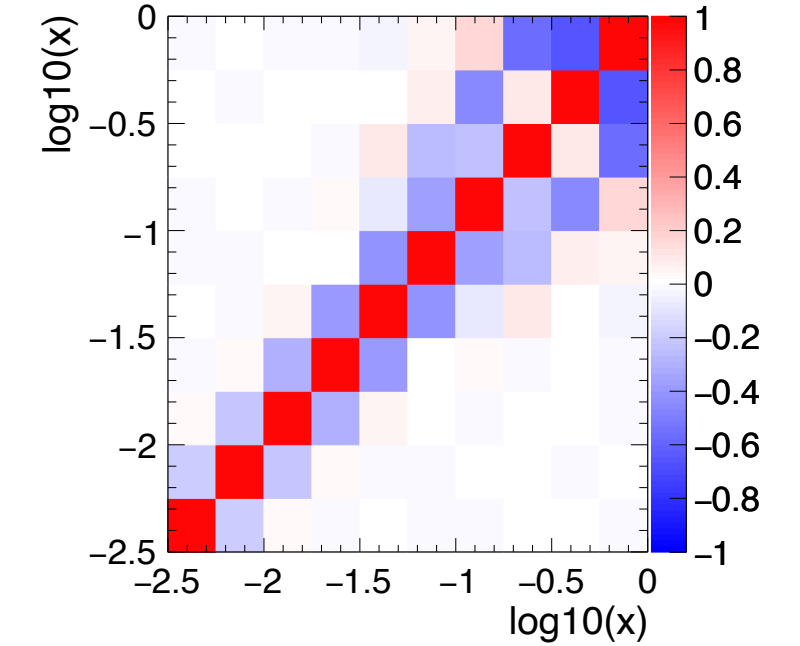
Normalized response matrix, electron



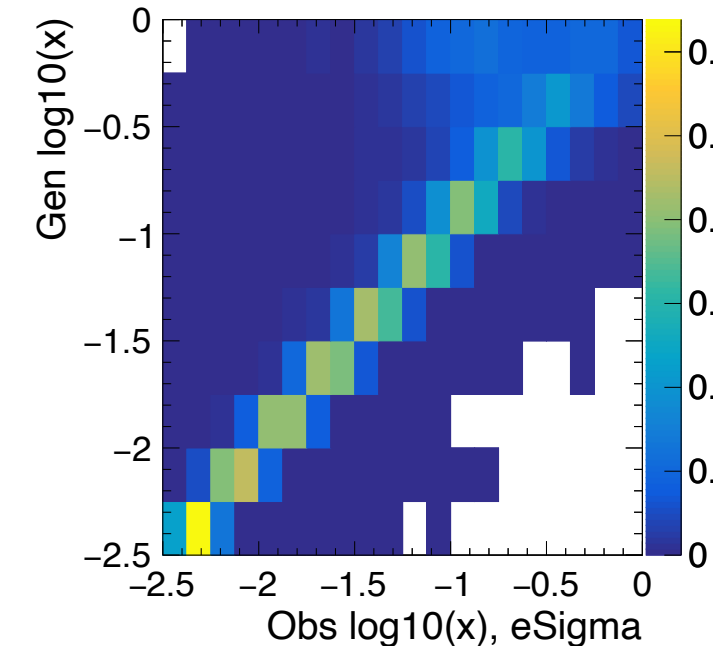
Unfolded distribution, electron



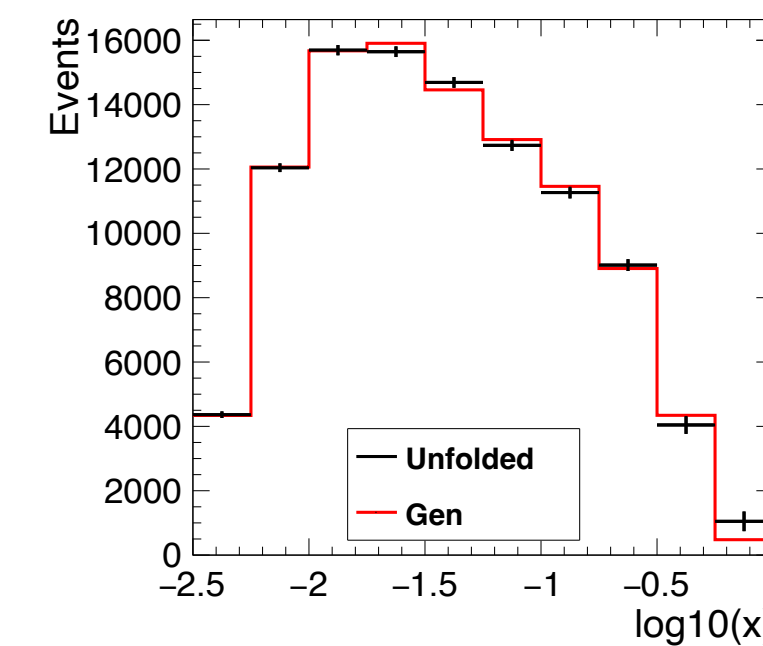
Correlation coefficients, electron



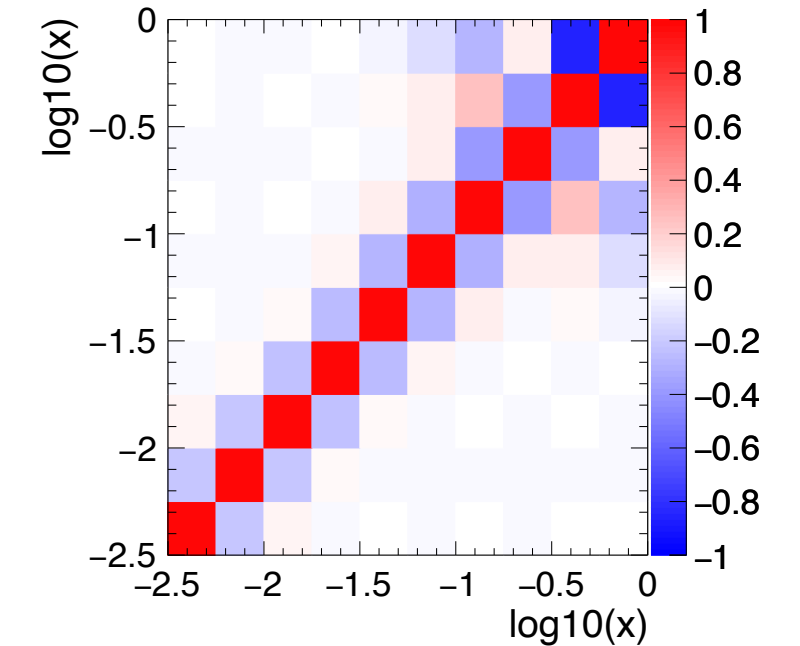
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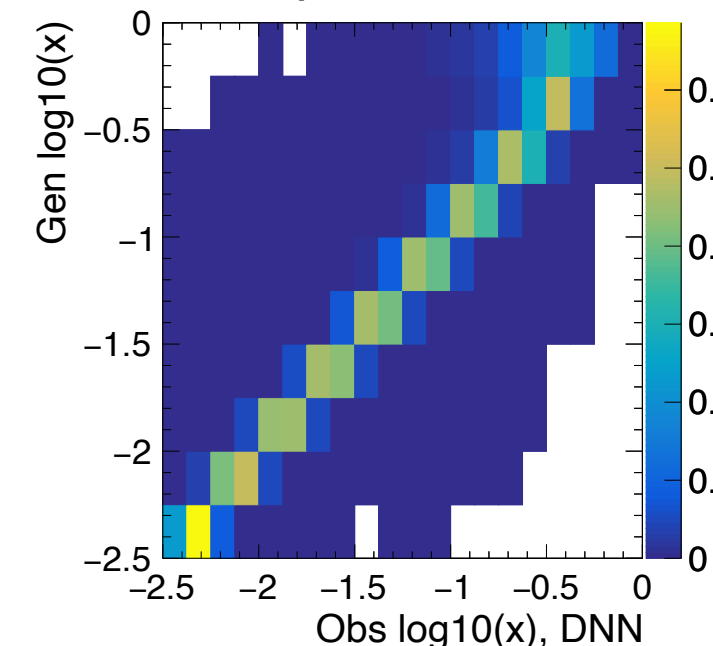
Unfolded distribution, Sigma



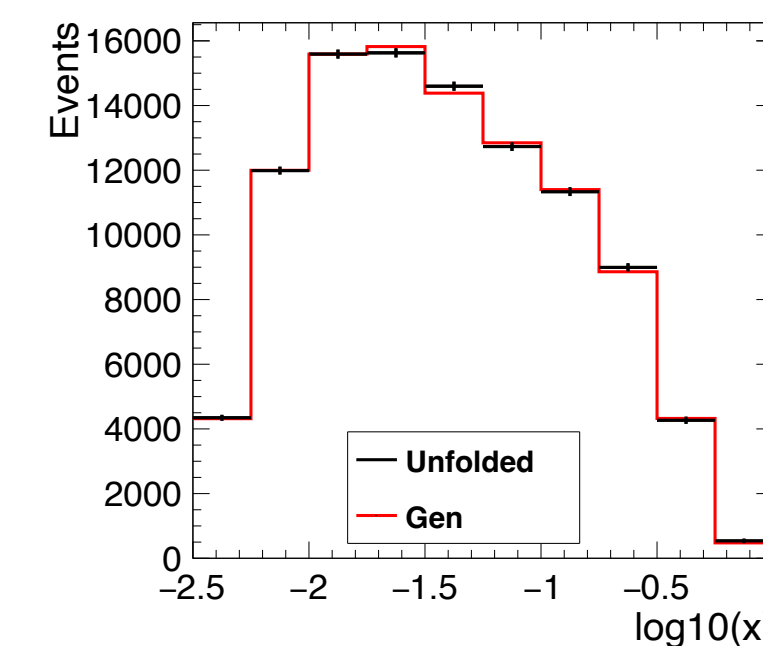
Correlation coefficients, Sigma



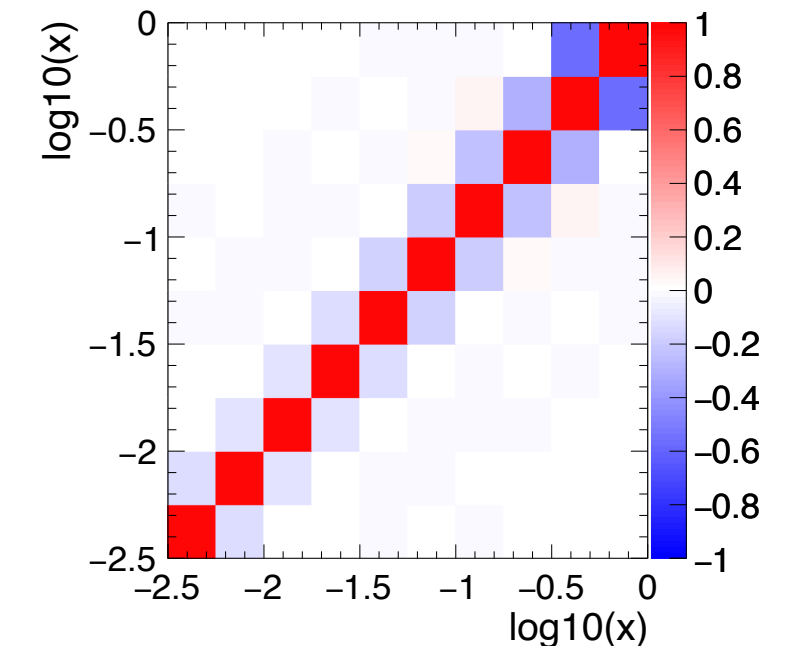
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Correlation coefficients, DNN



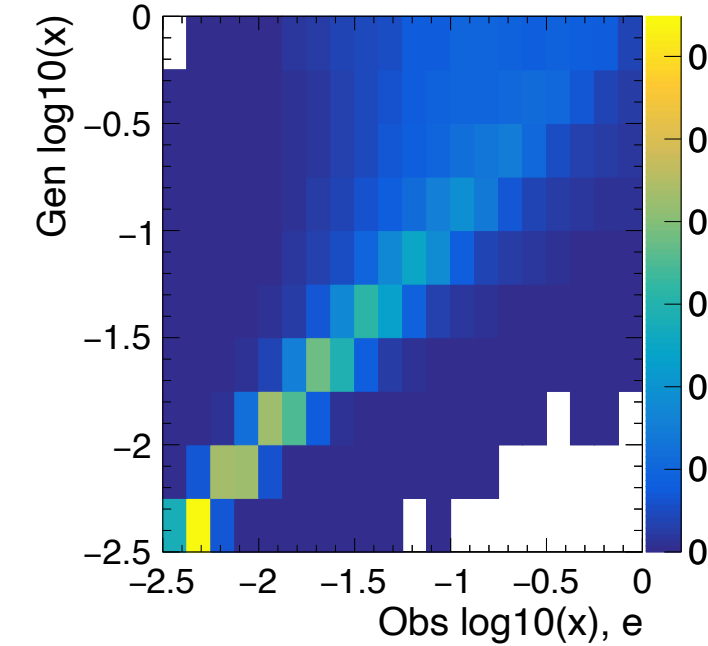
Optimizing reco Observable (\mathcal{O}_d) with ML

2203.16722

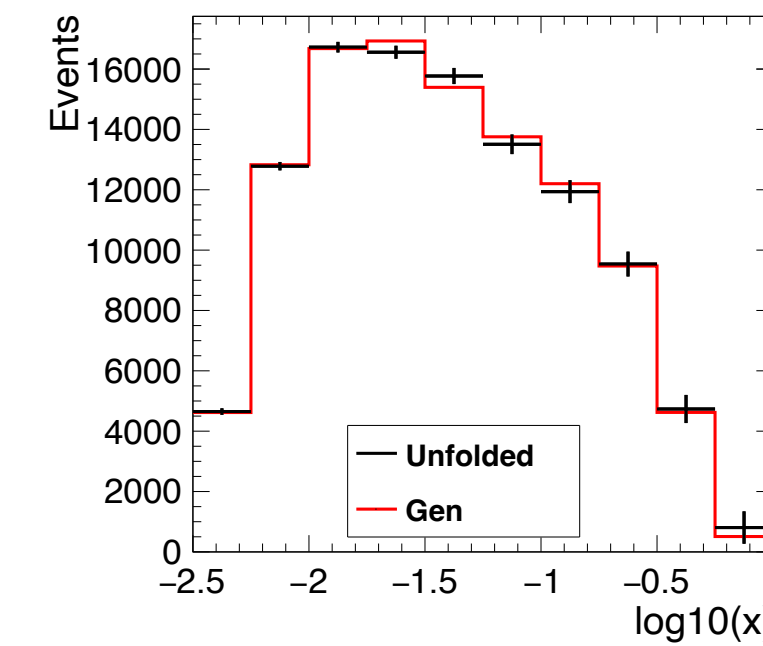
What to unfold?

- ML-assisted reconstruction reco-level observables has the most diagonal fractions throughout phase space
- Loss function = (particle-level target) + (particle-level - detector-level)²

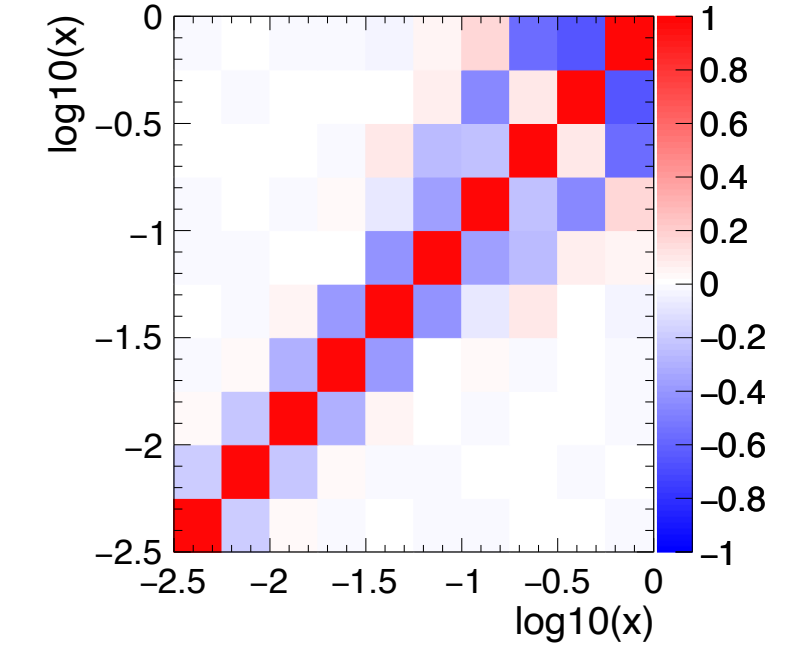
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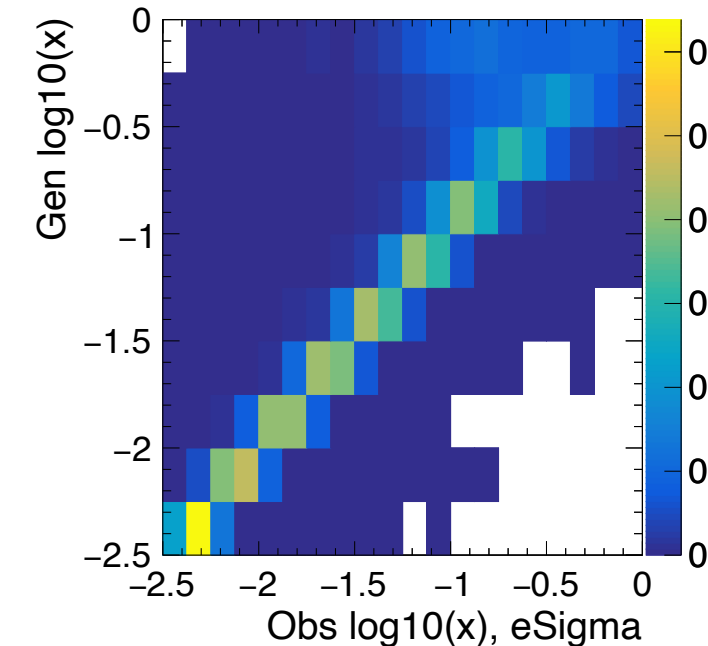
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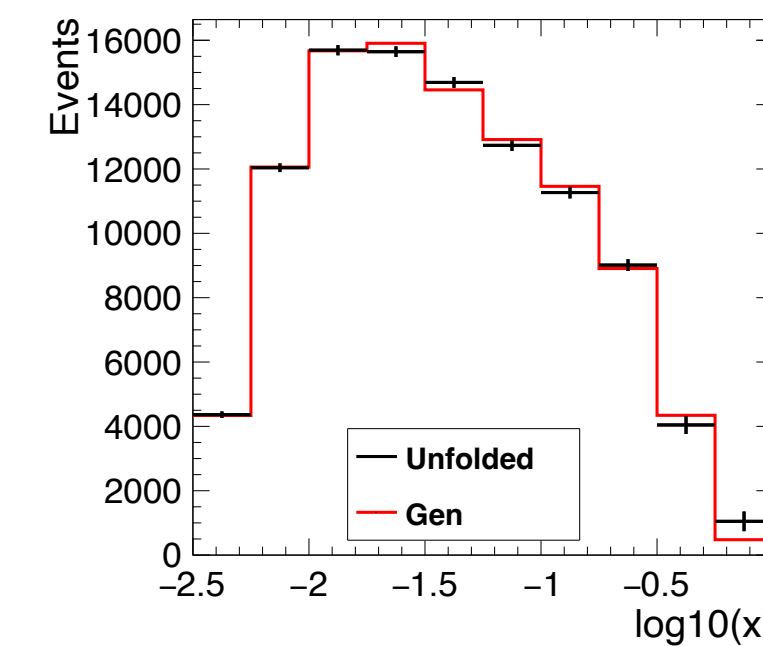
Correlation coefficients, electron



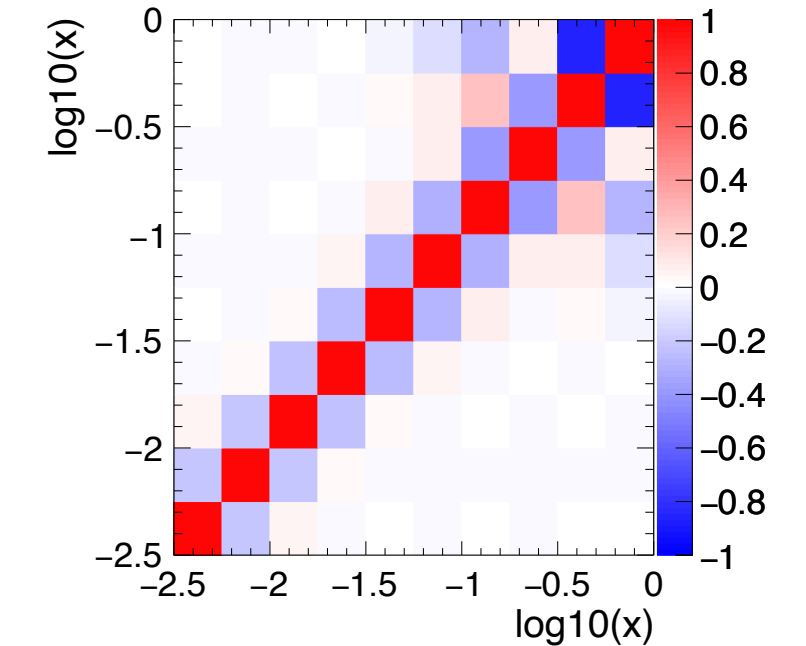
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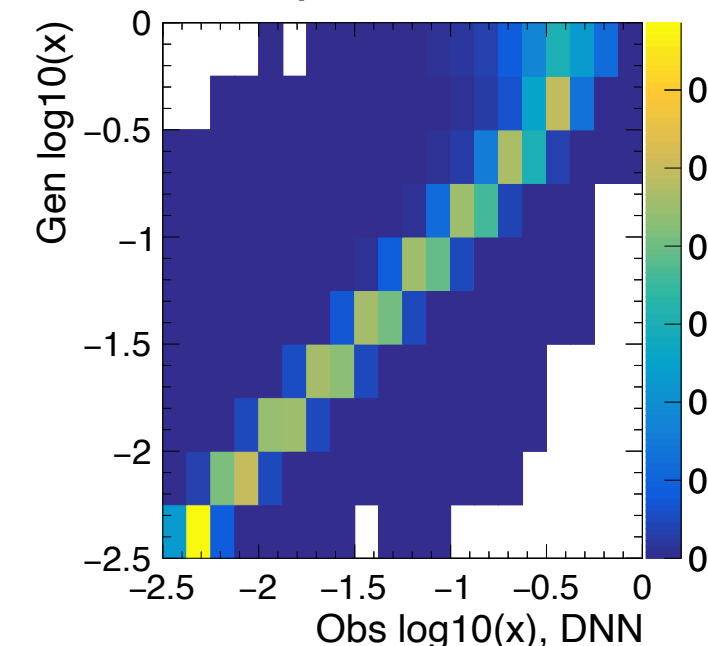
Unfolded distribution, Sigma



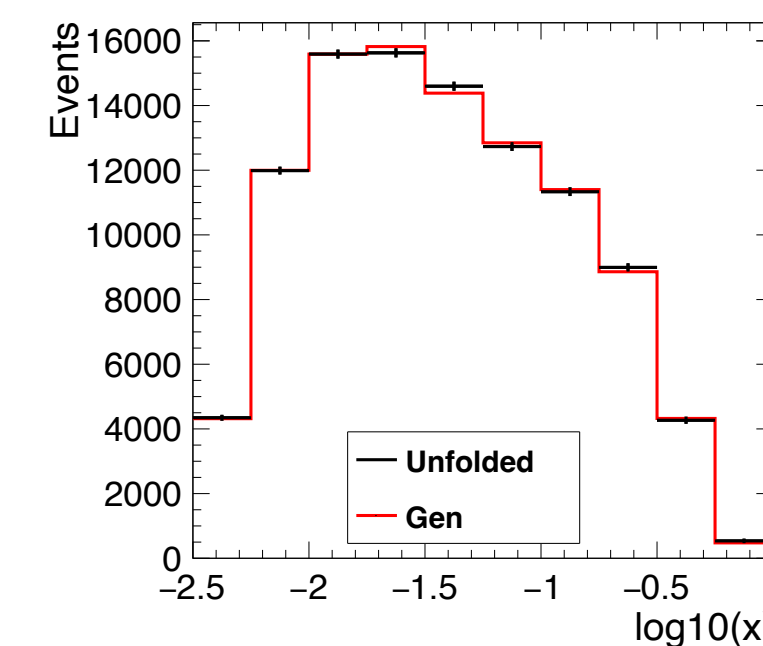
Correlation coefficients, Sigma



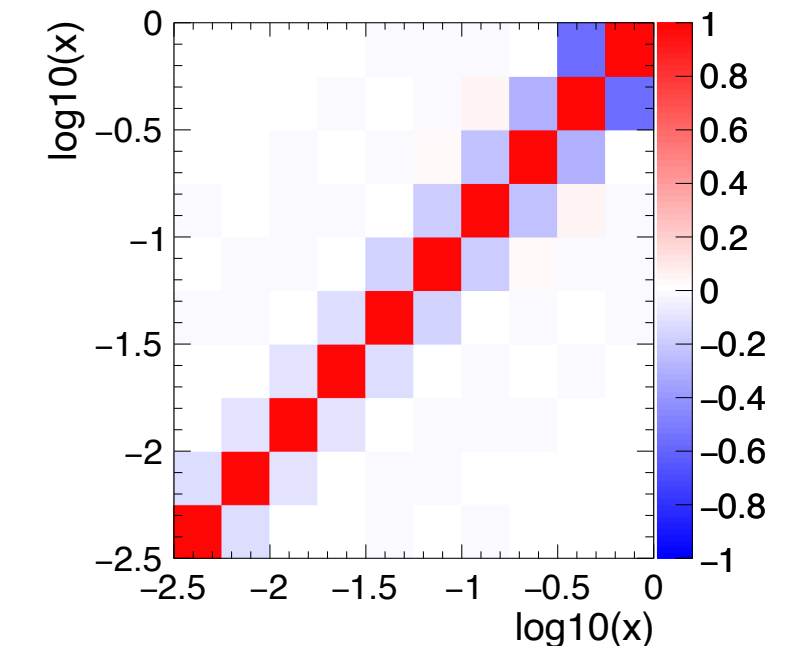
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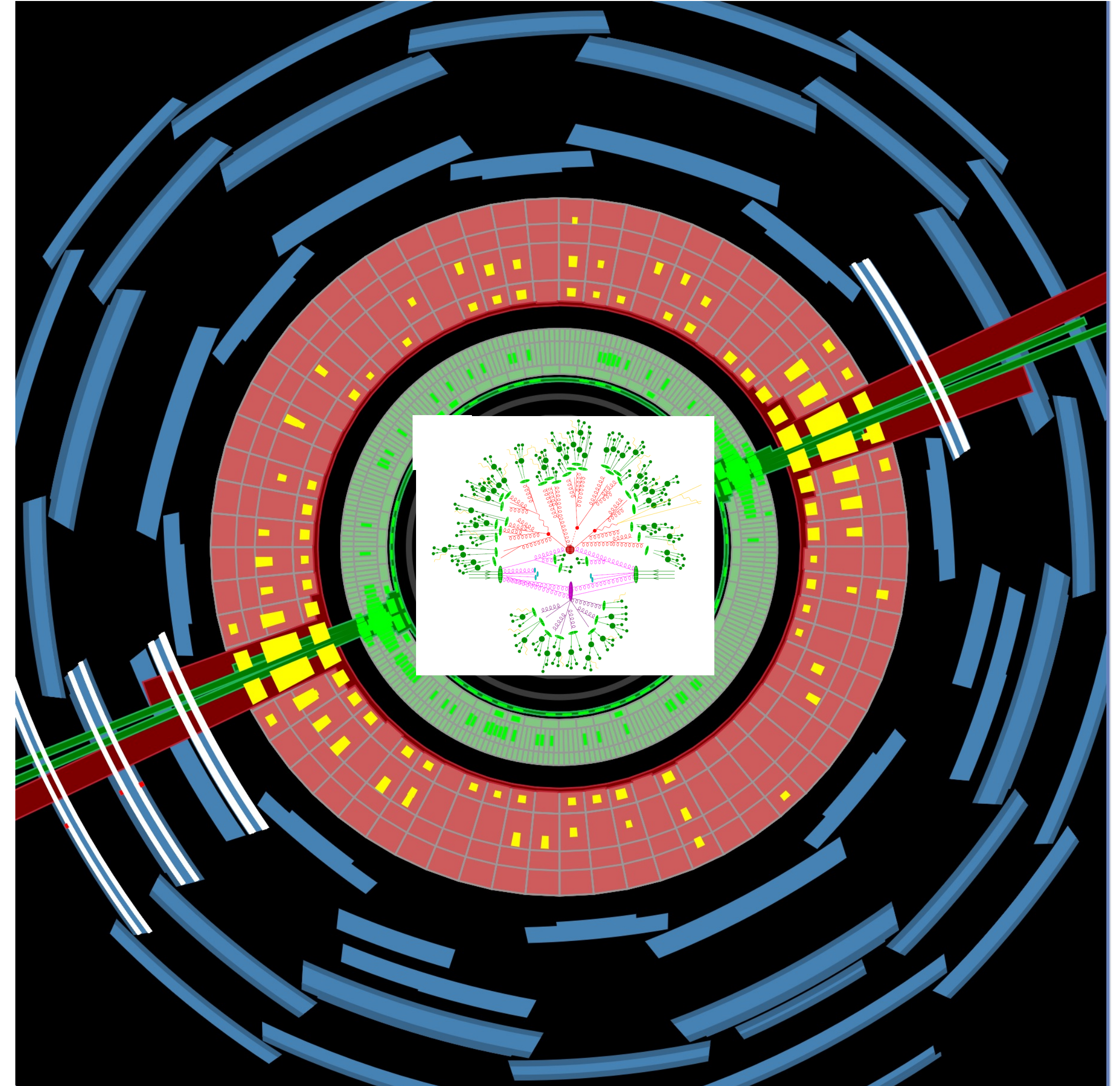


Correlation coefficients, DNN



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3. Fast regularized neural posterior estimation with normalizing flows
4. (Bonus) Enabling profiling with ML



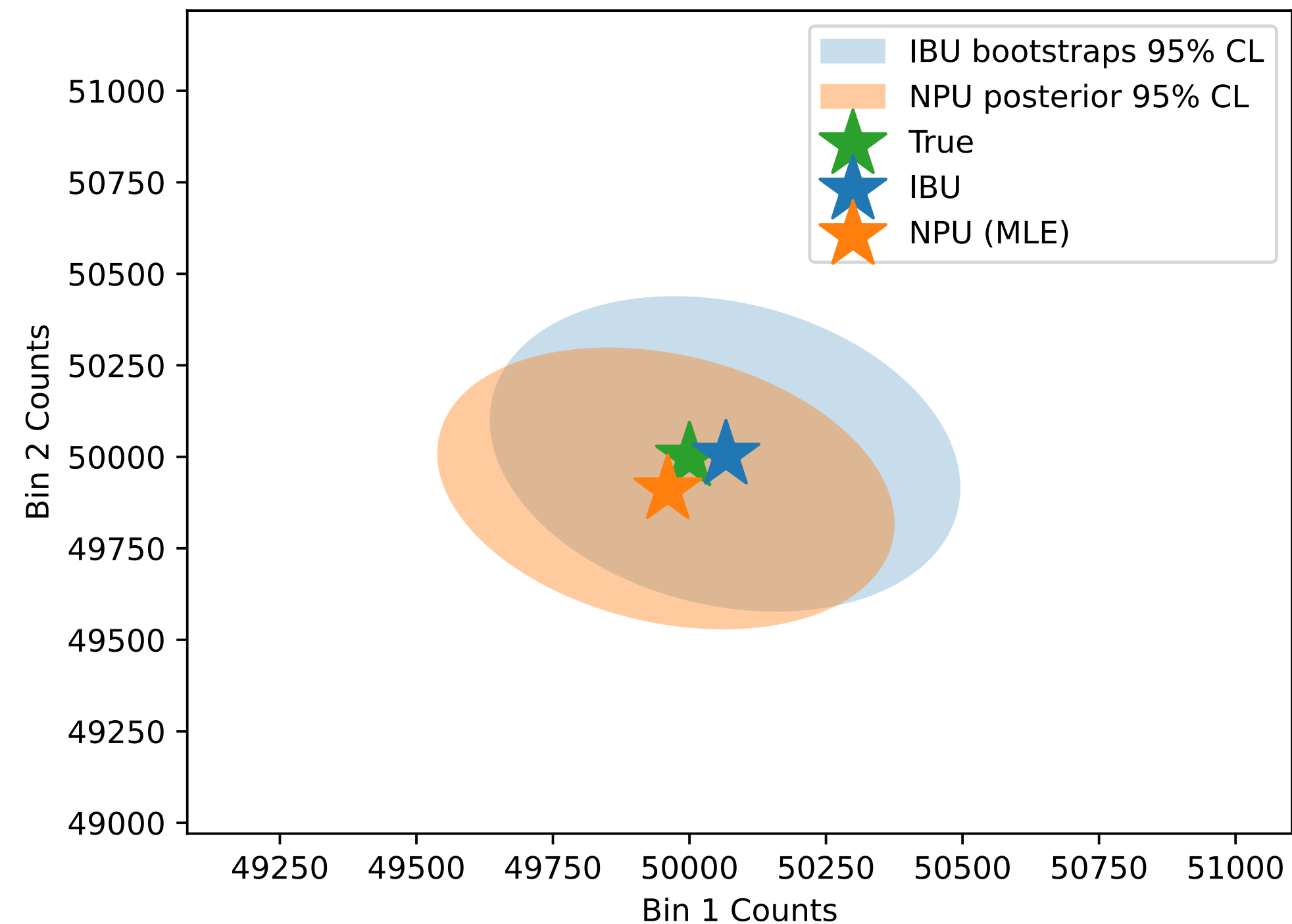
Neural Posterior Unfolding

Fast regularized neural posterior estimation with NFs

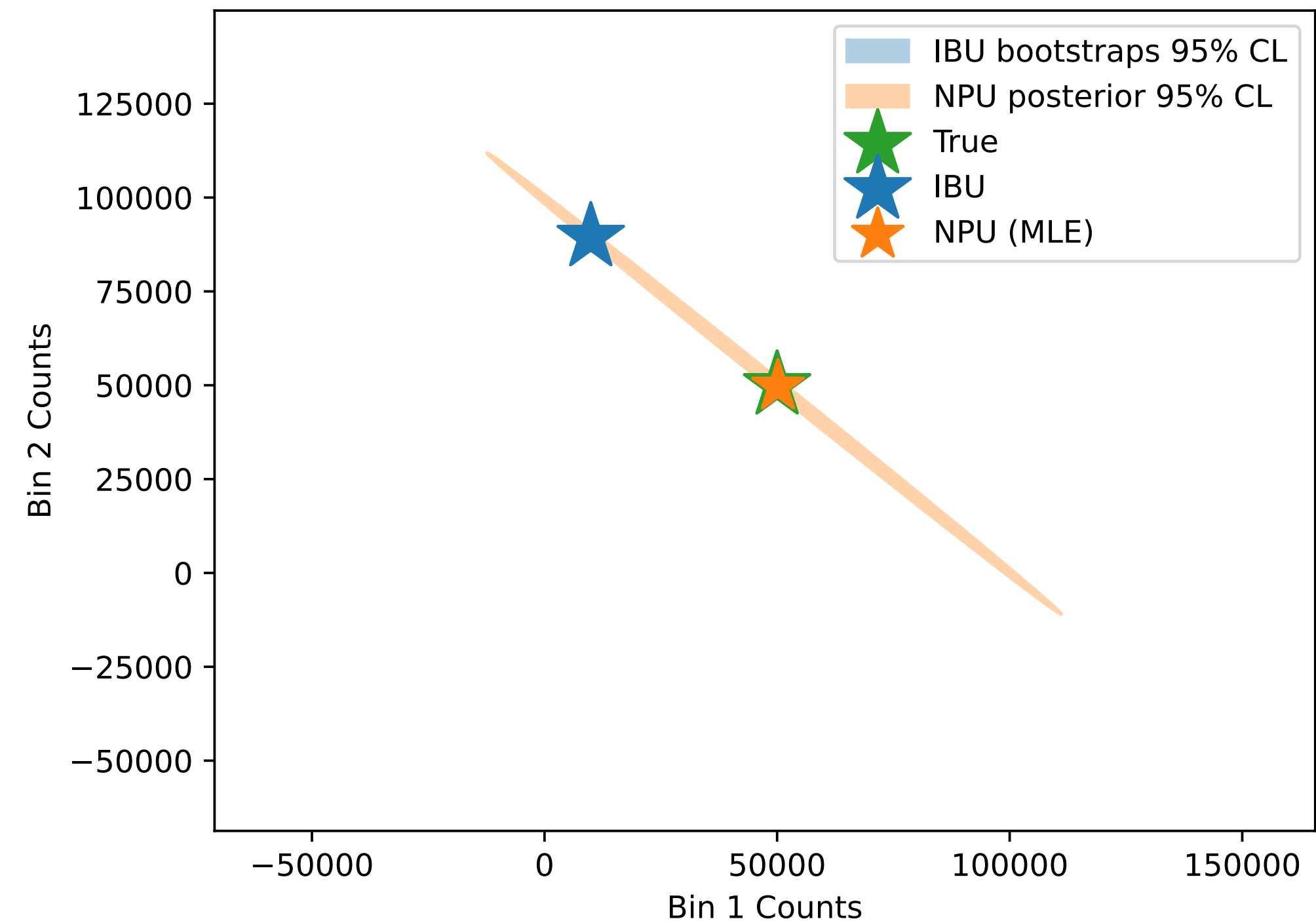
- Motivations
 - **Bayesian**: access to full posterior
 - **Circumvent** MCMC for sampling to fit parameters via **amortized ML**: directly learn $\Pr(t_j | m_i)$ from prior pairs that are passed through R
 - **Normalizing Flows (NFs)** as the density estimator is **inherently regularized** through model selection (i.e. the validation loss)
 - **Still sensible** in phase space poorly constrained by data (i.e. **response matrix with degeneracy**)

Neural Posterior Unfolding

Fast regularized neural posterior estimation with NFs



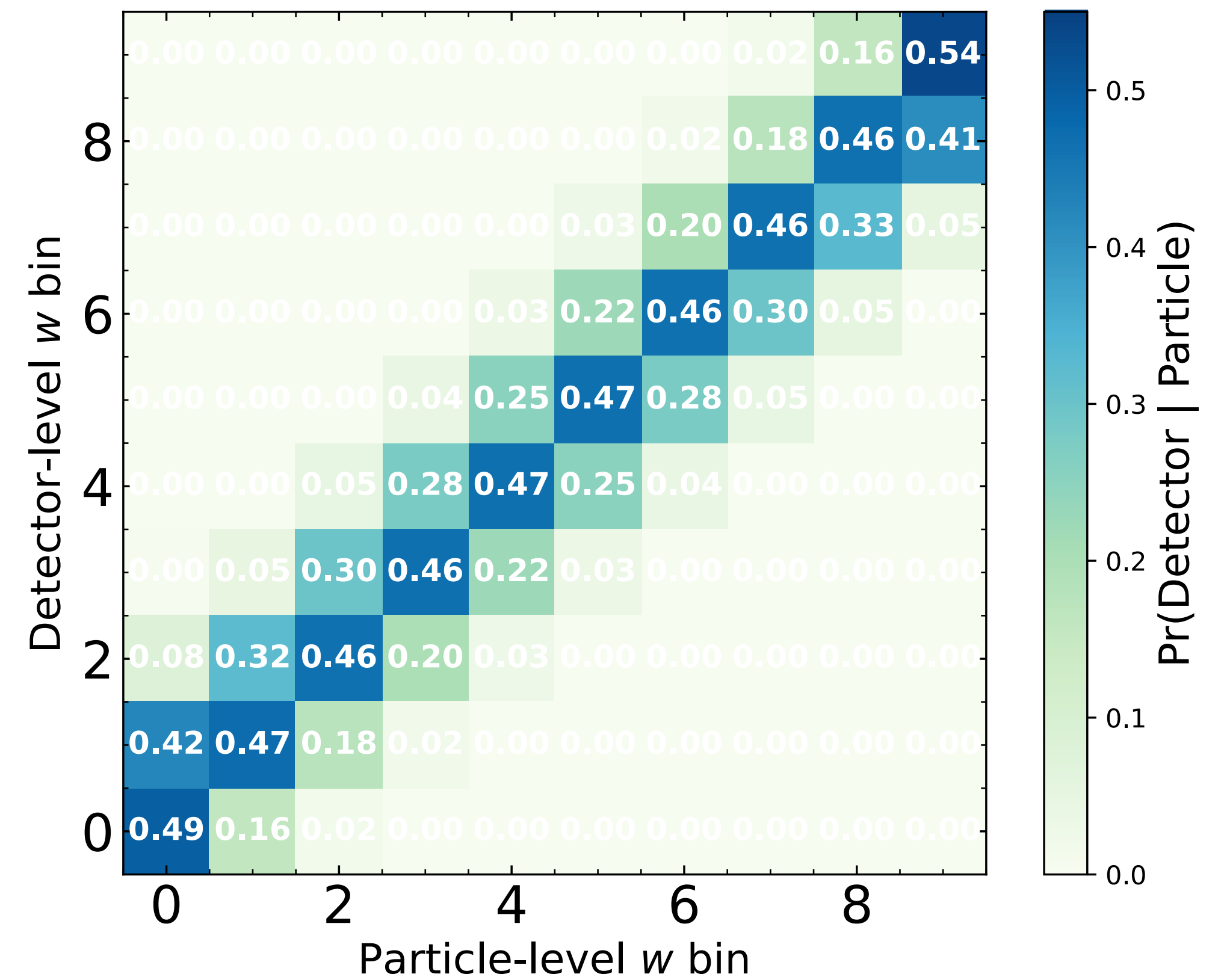
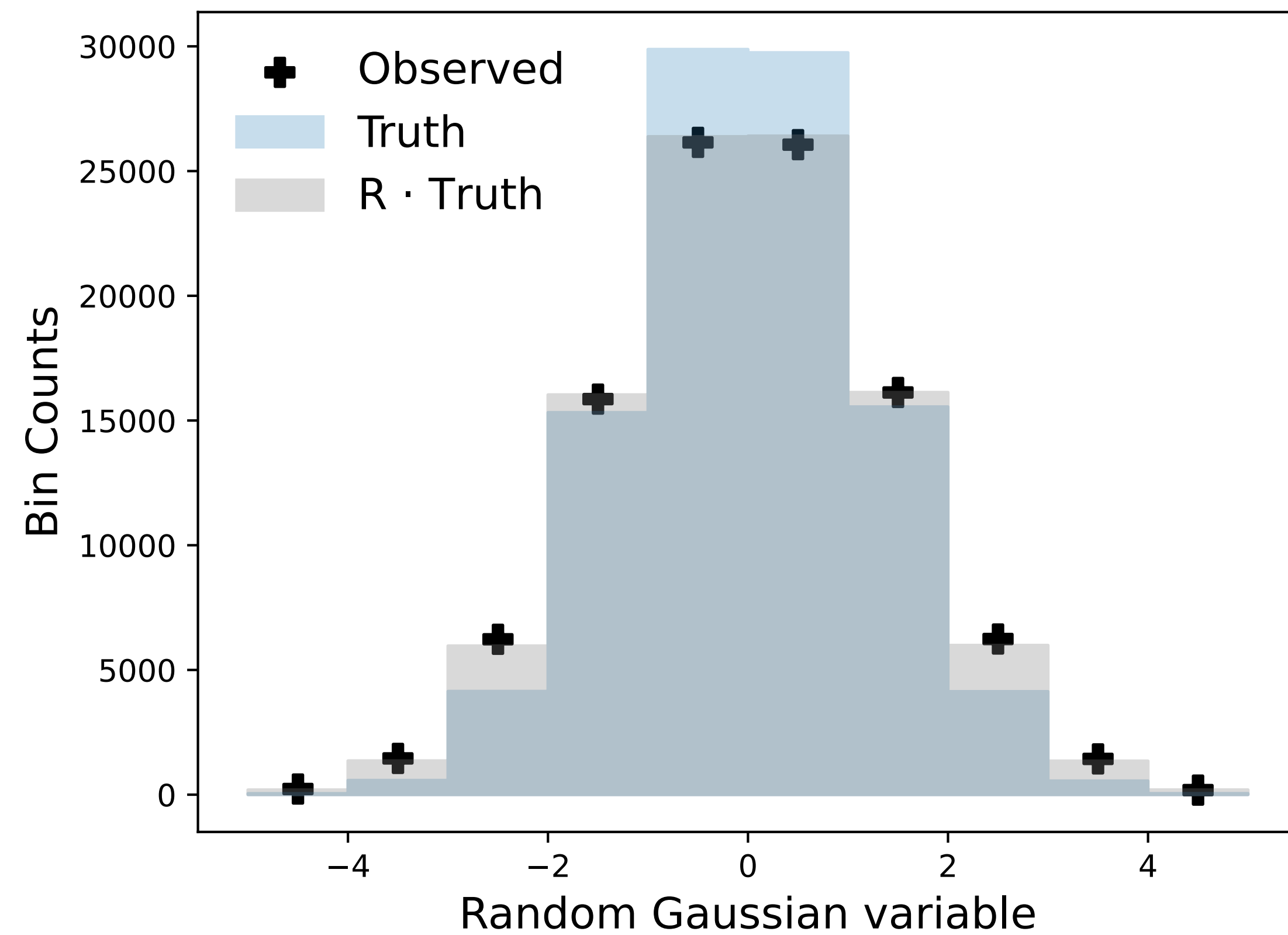
Correlation coefficient = 1
Small migration



Correlation coefficient = 0
Response degenerate

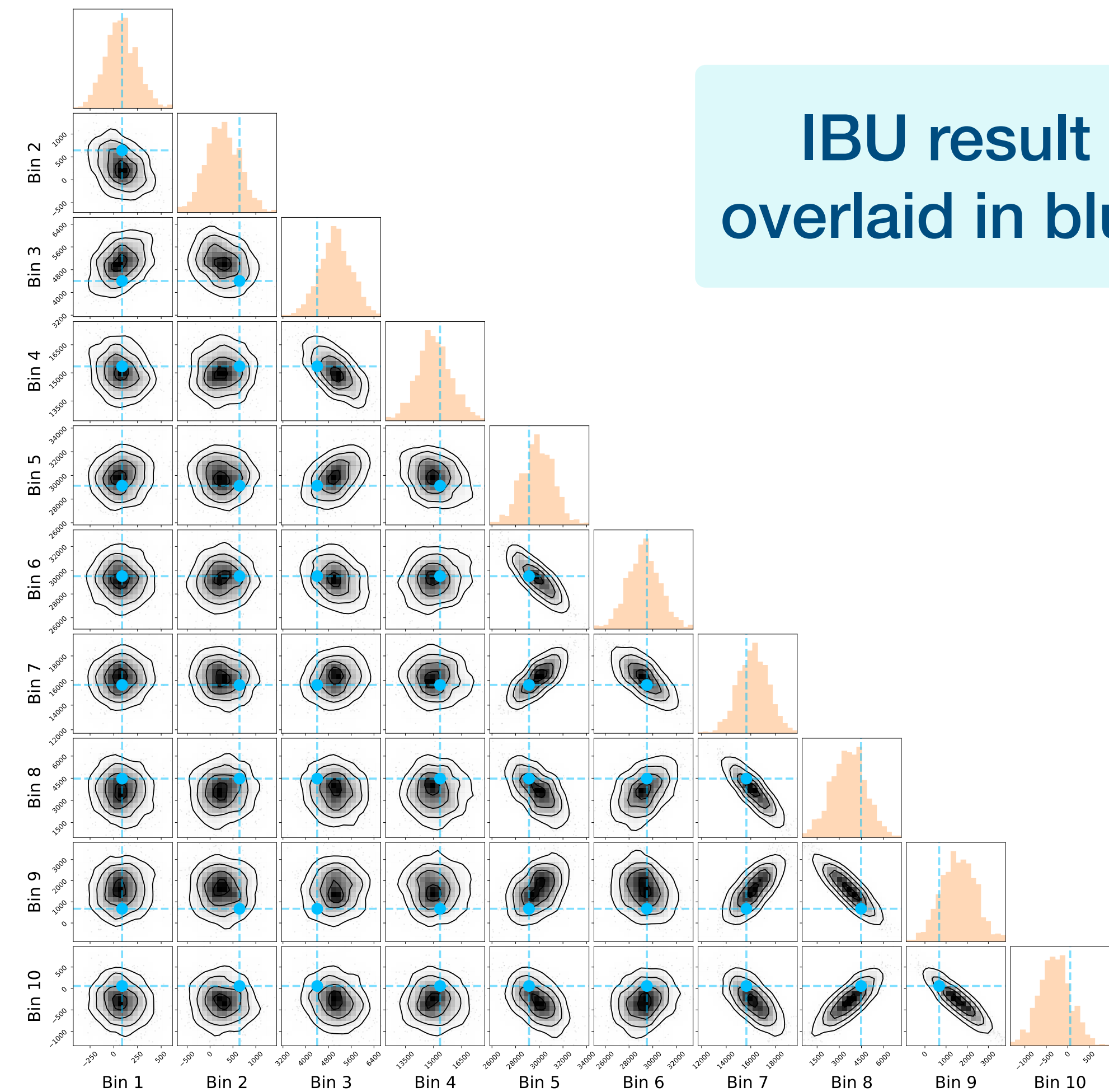
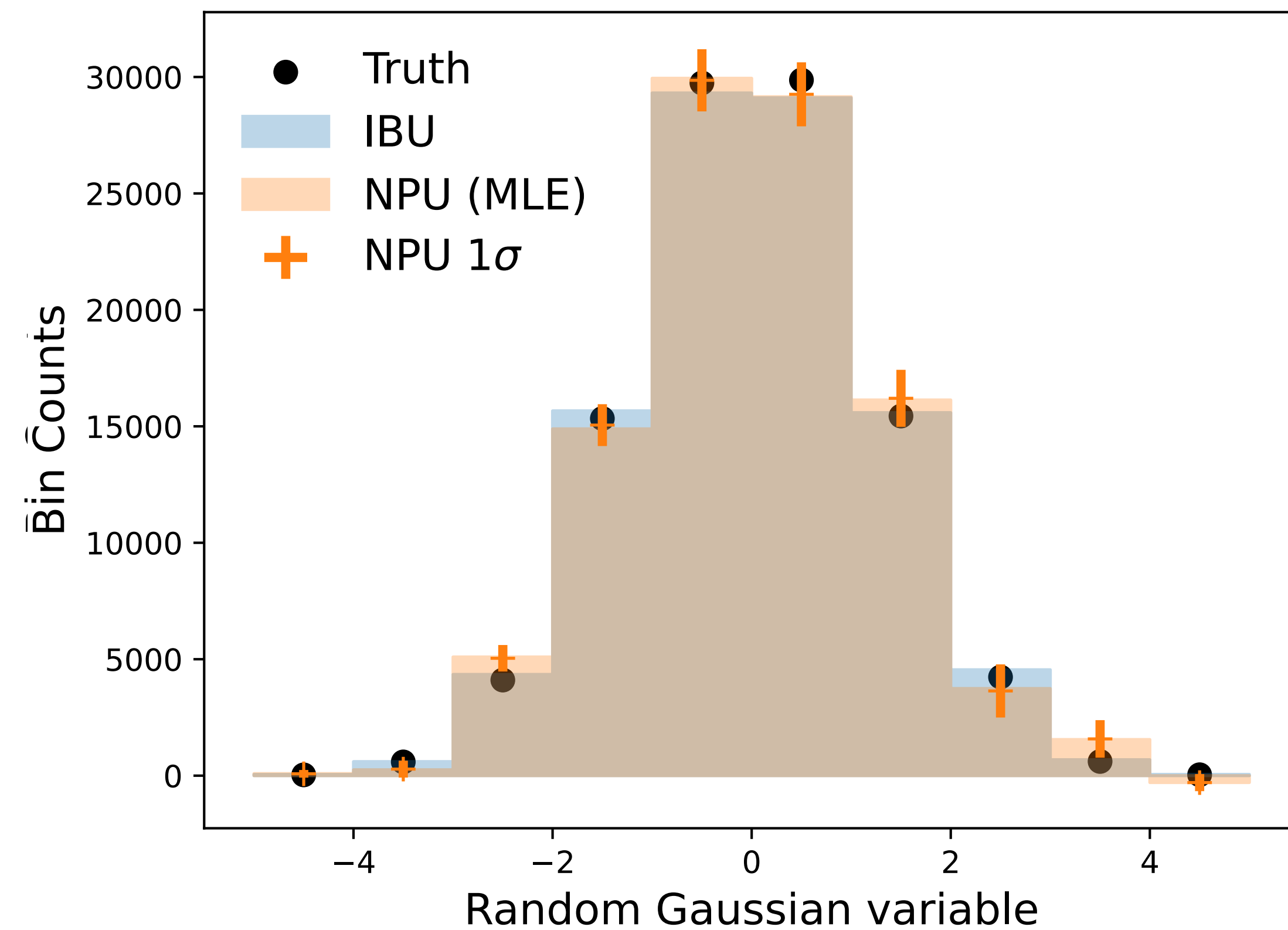
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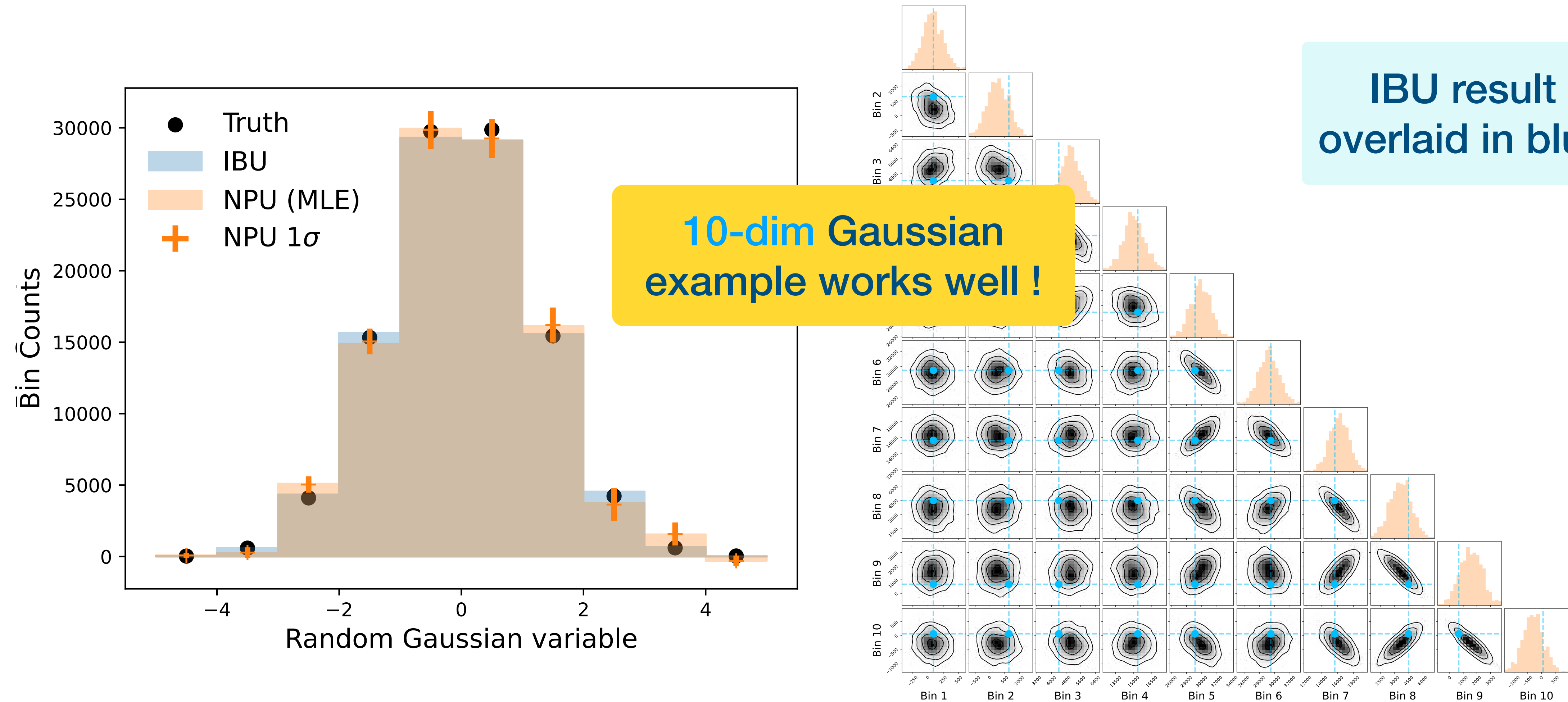
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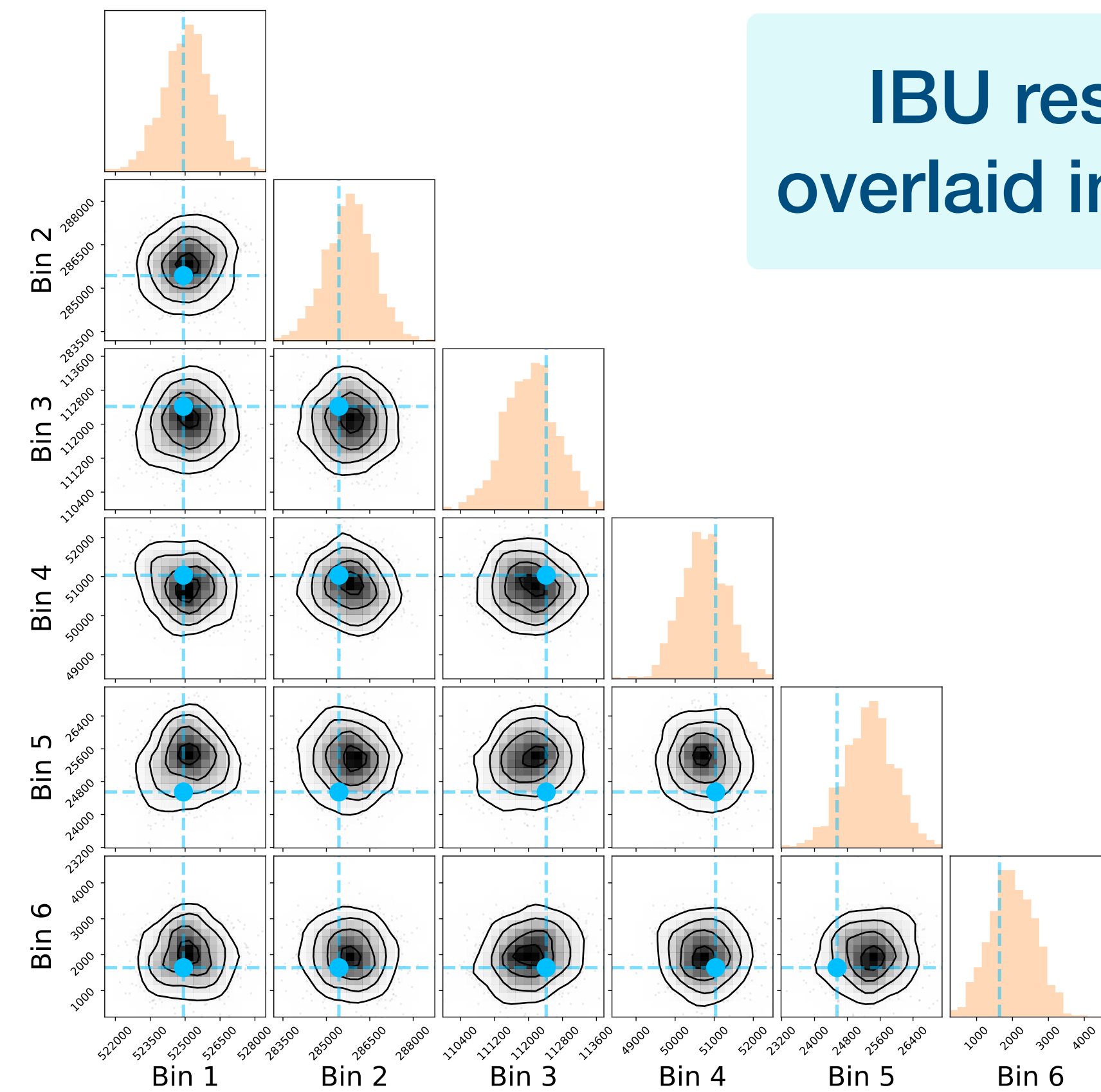
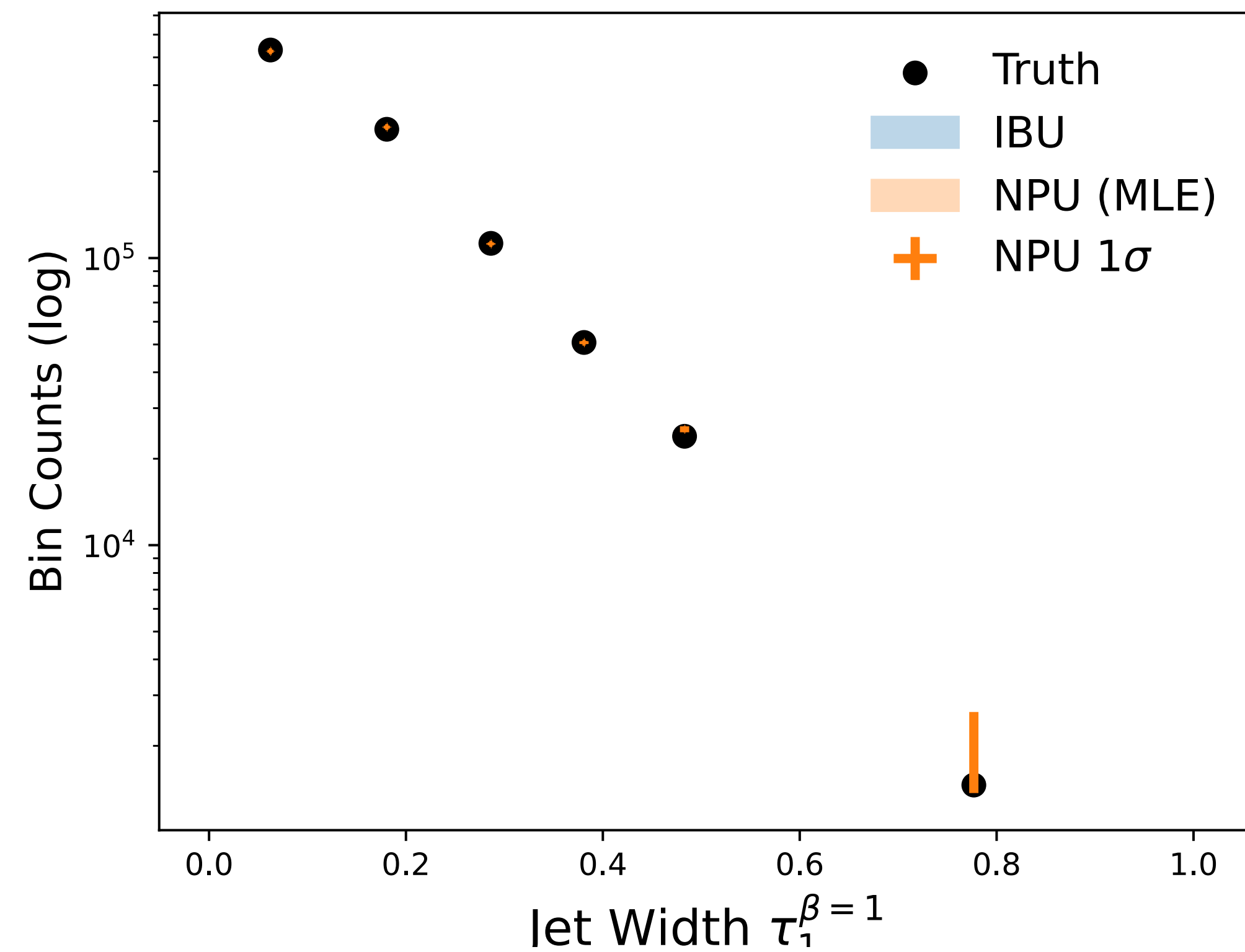
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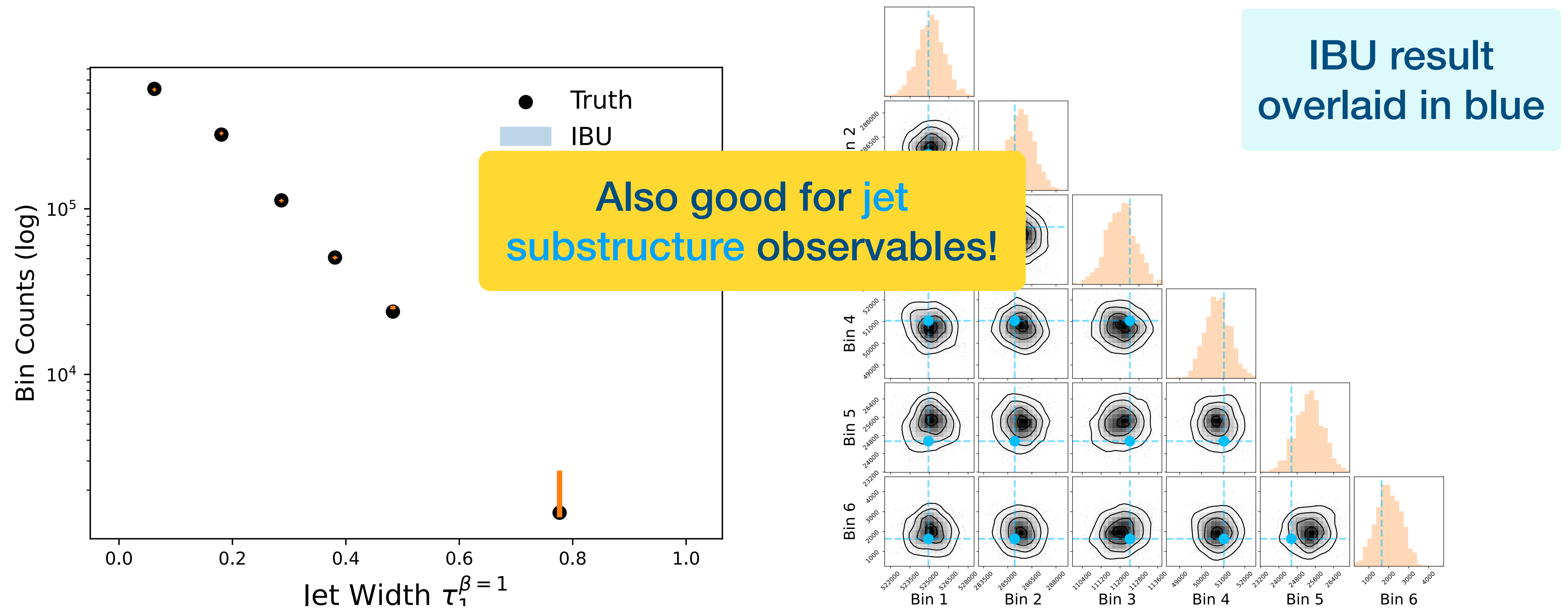
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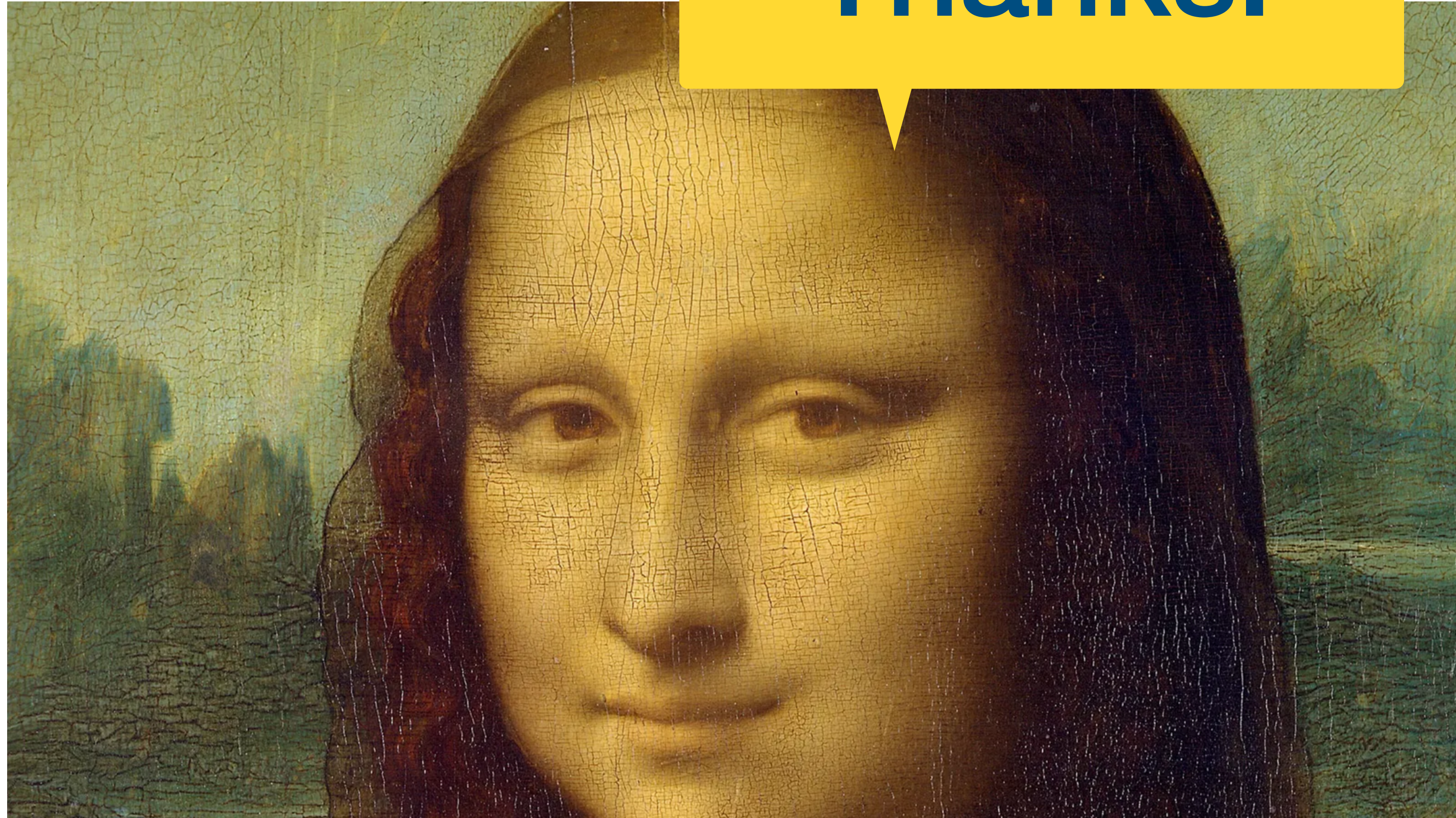


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Fast regularized neural posterior estimation with NFs



Thanks!



Backup