Application of generative models for full-detector, whole-event simulated event generation and jet background subtraction in heavy ion collisions

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ML4Jets
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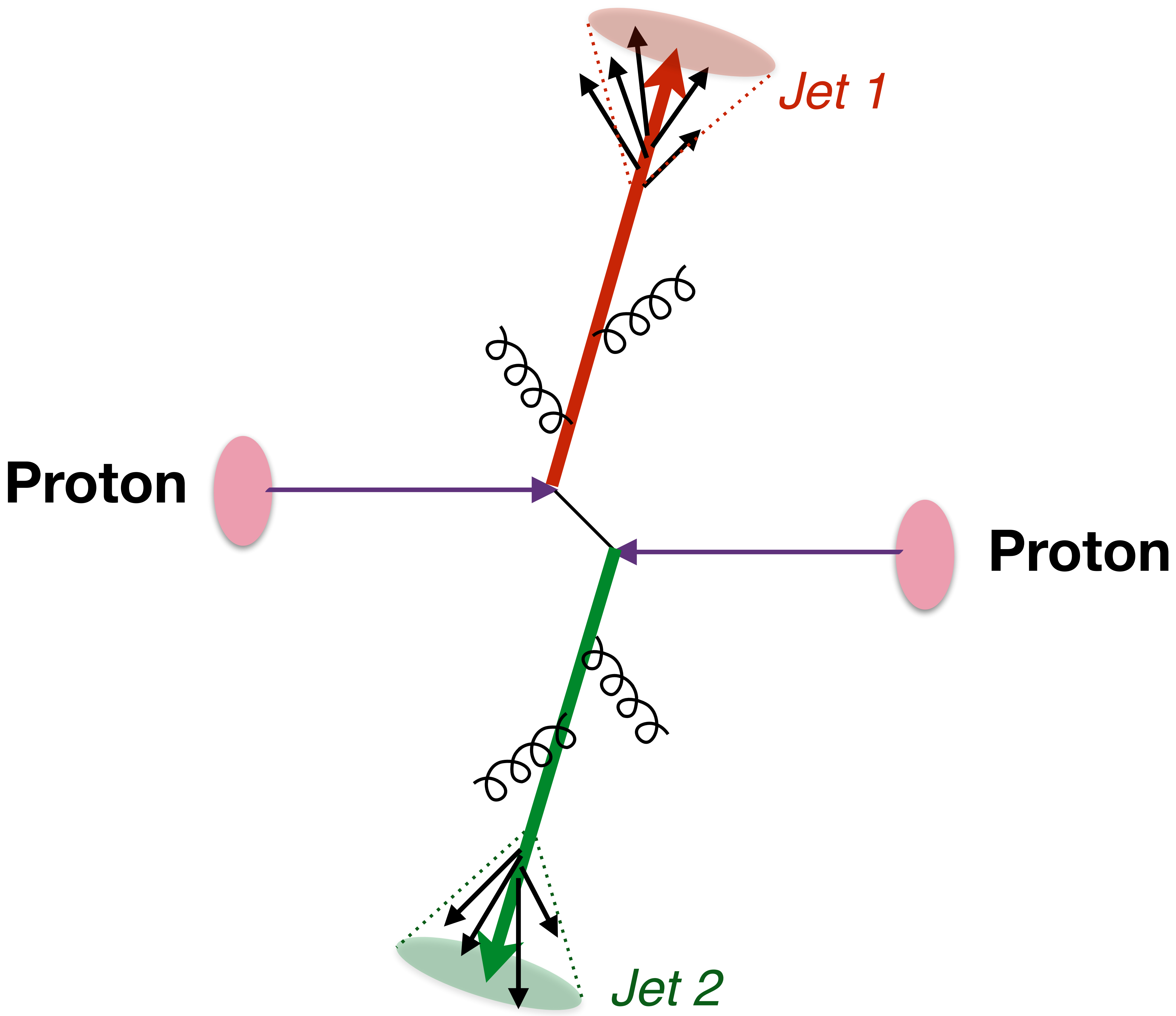
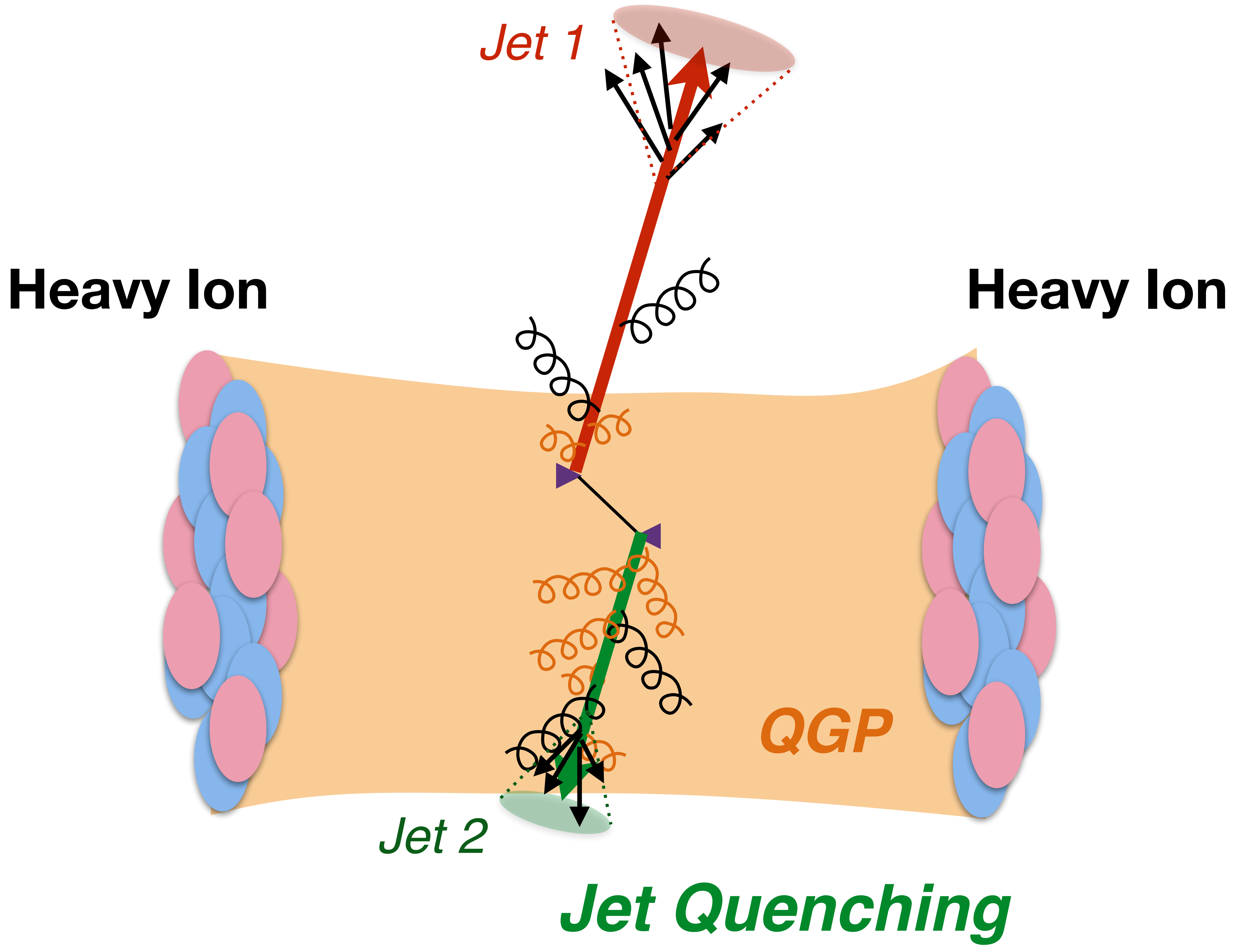
Jets in Heavy Ion Collisions (1)

- **Jet quenching**: a phenomenon of jet energy loss and redistribution that happens when a parton go though a hot and dense ***quark gluon plasma (QGP)*** created by the heavy ion collisions

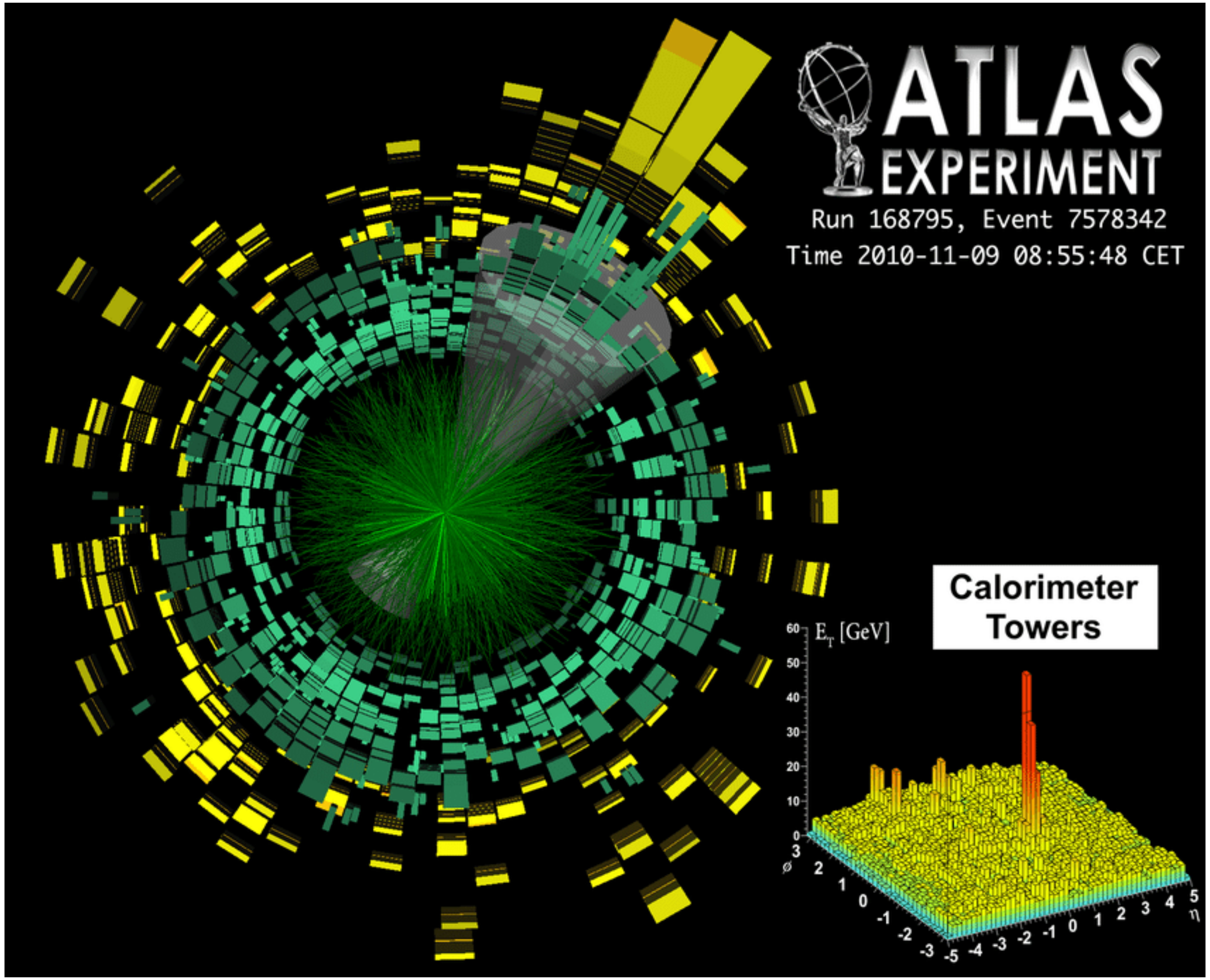




Jets in Heavy Ion Collisions (2)

- MC events with jets in heavy ion collisions
  - ➡ **Pythia jets (signal)** are embedded into minimum-bias heavy-ion MC events e.g. **HIJING (background)**
  - ➡ this bulk medium has properties such as collective motion, e.g. flow

Topic 1: HIJING simulation event generation using diffusion model



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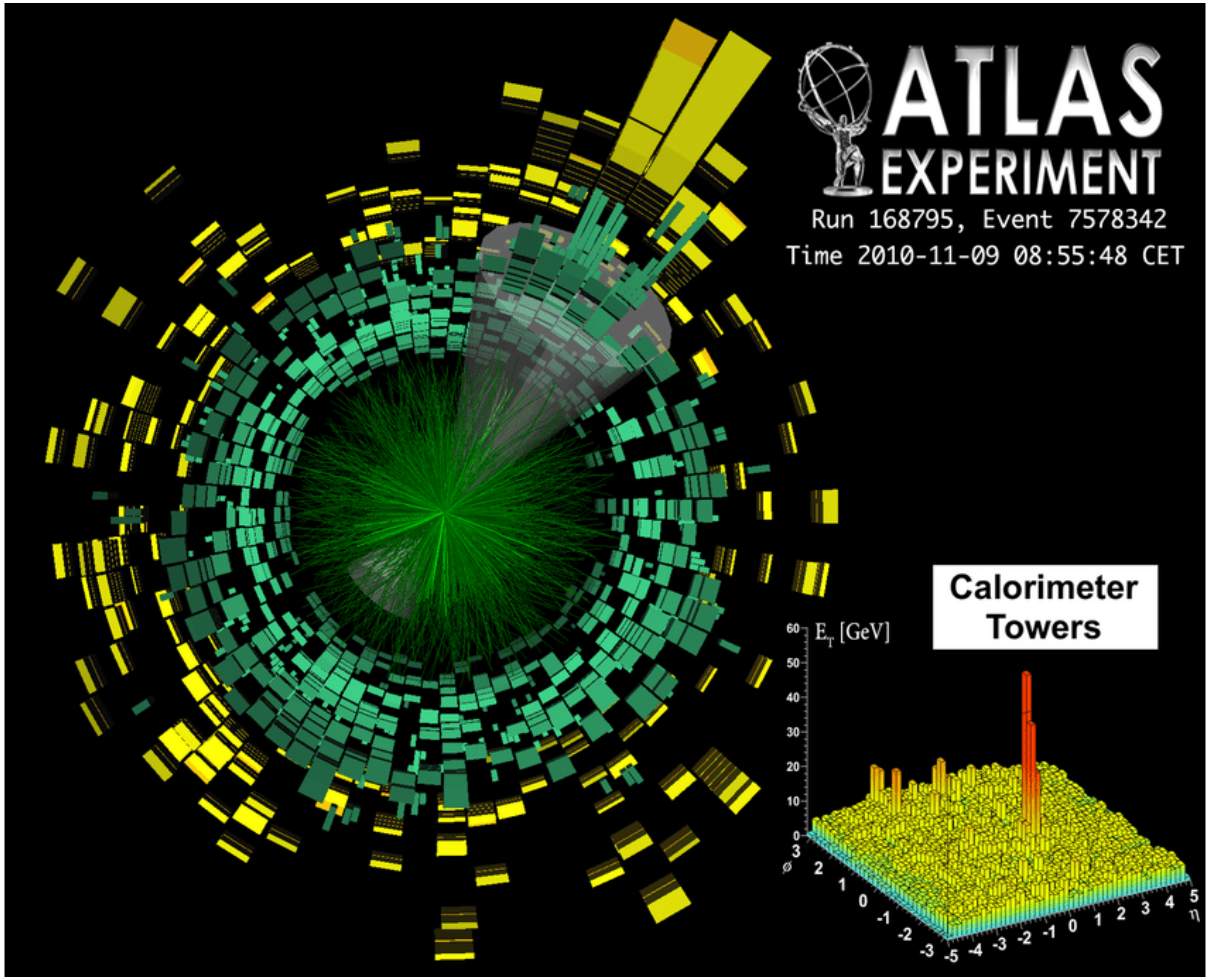
Topic 1: HIJING simulation event generation using diffusion model

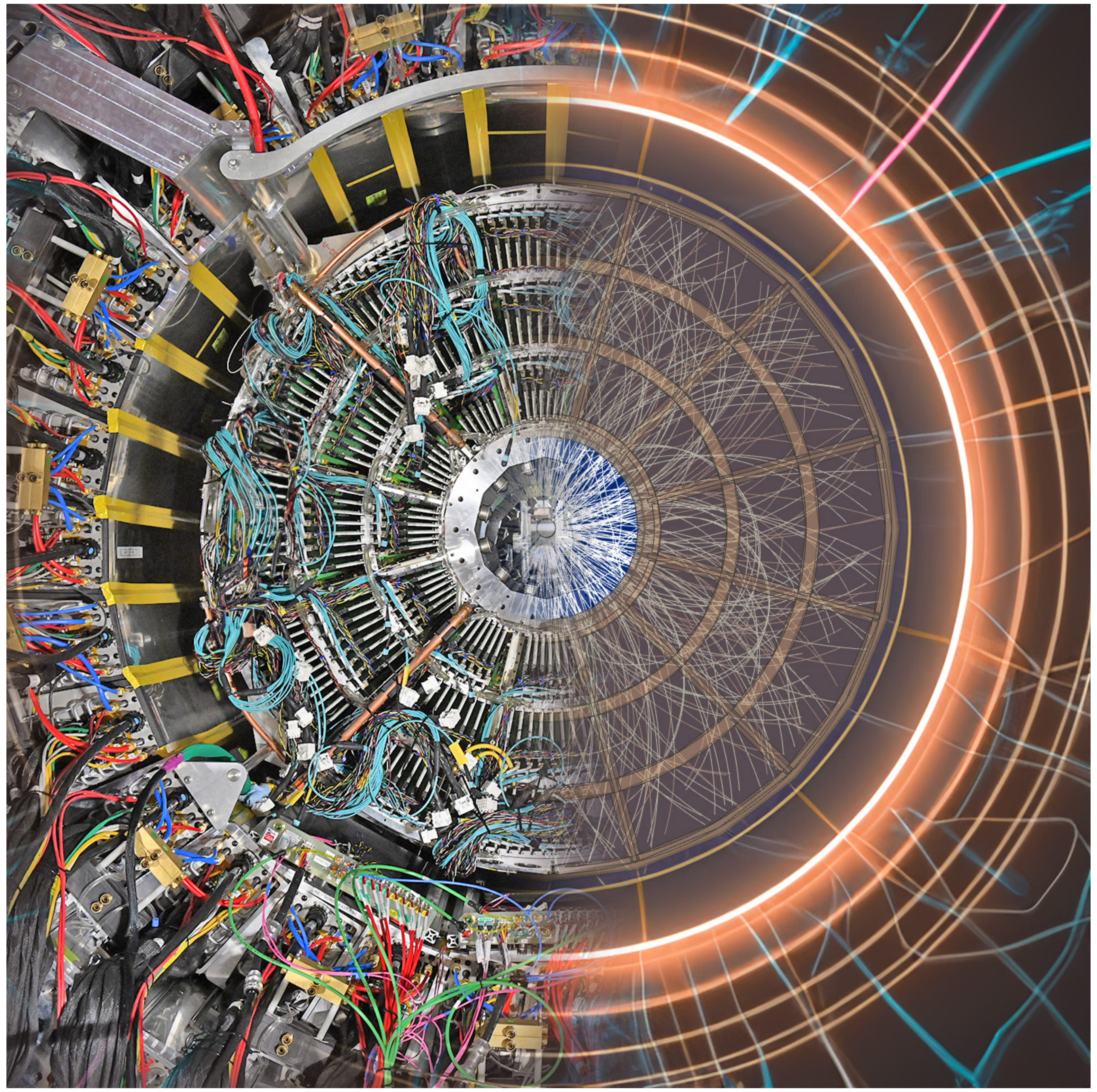
- The huge amount of ***combinatoric background*** produced from multiple nucleon-nucleon collisions **has to be *estimated* and *subtracted*** from **jet reconstruction**

Topic 2: Jet background subtraction using cycleGAN model



Simulations of Relativistic Heavy Ion Collisions

- ***O(1000) particles*** in one nuclear collision event
  + ***thousands shower steps*** per particle
  ➡ Simulation of the interaction of particles with detectors is **high complexity and computationally intensive work**



sPHENIX TPC

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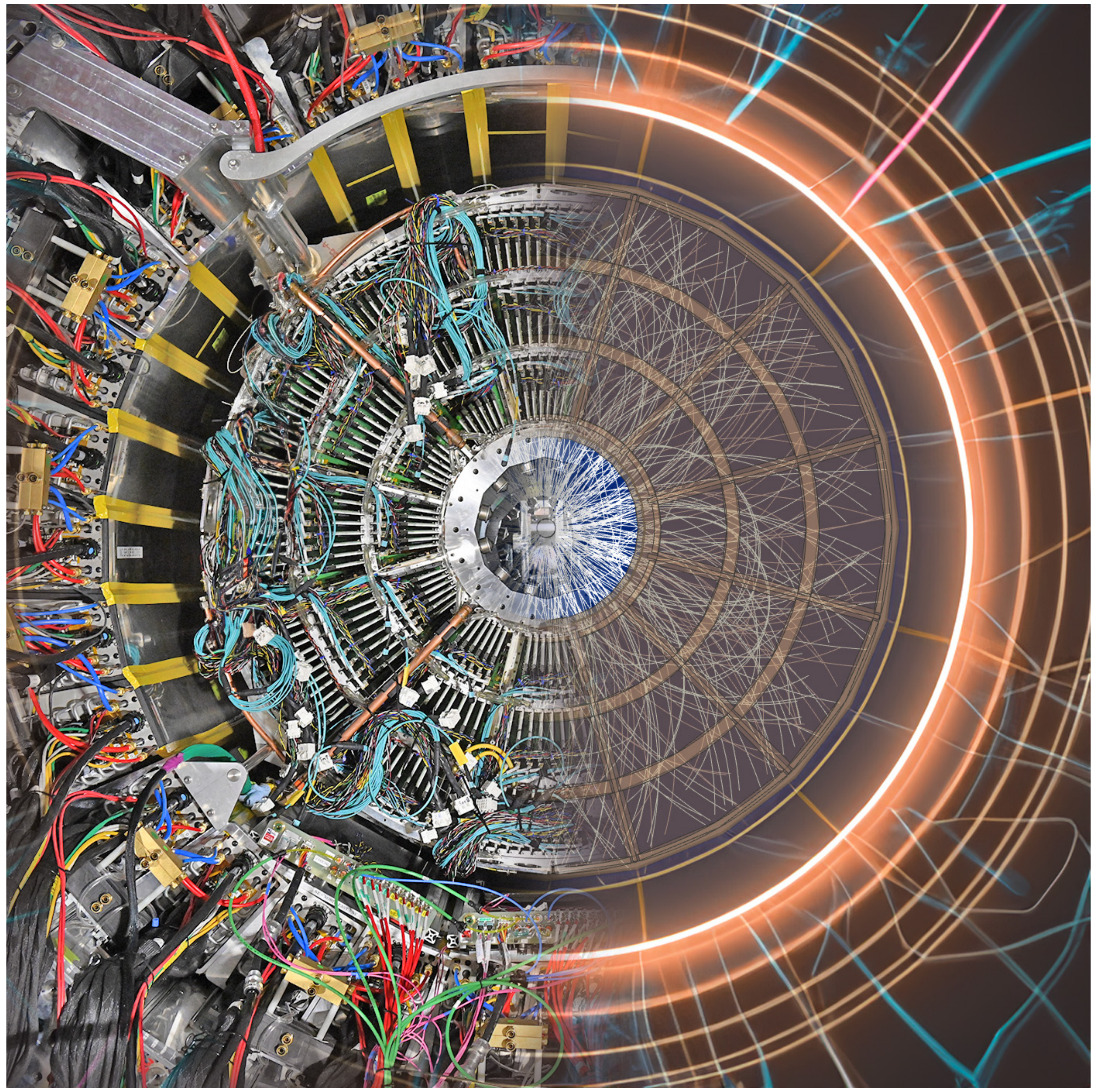

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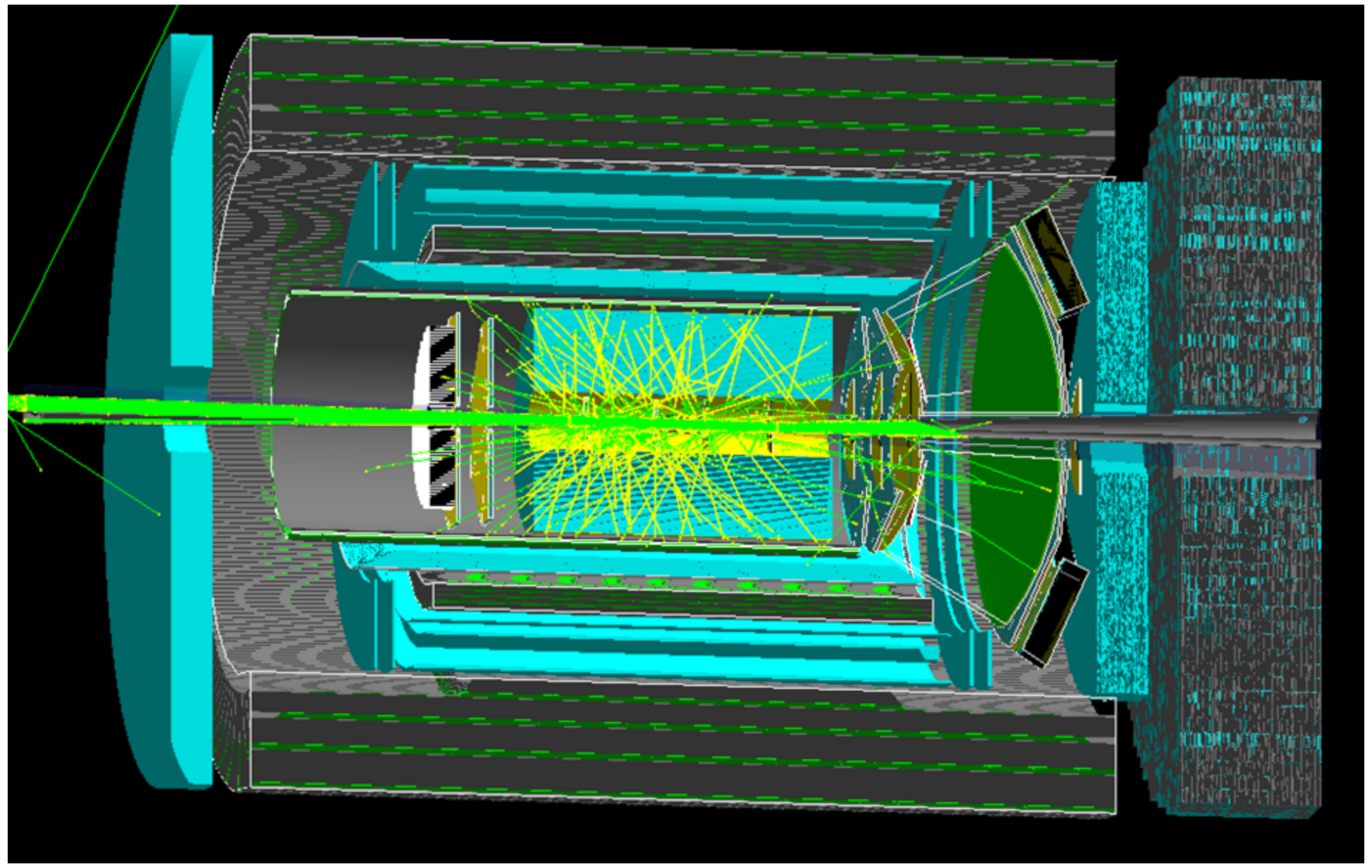

EIC CDR

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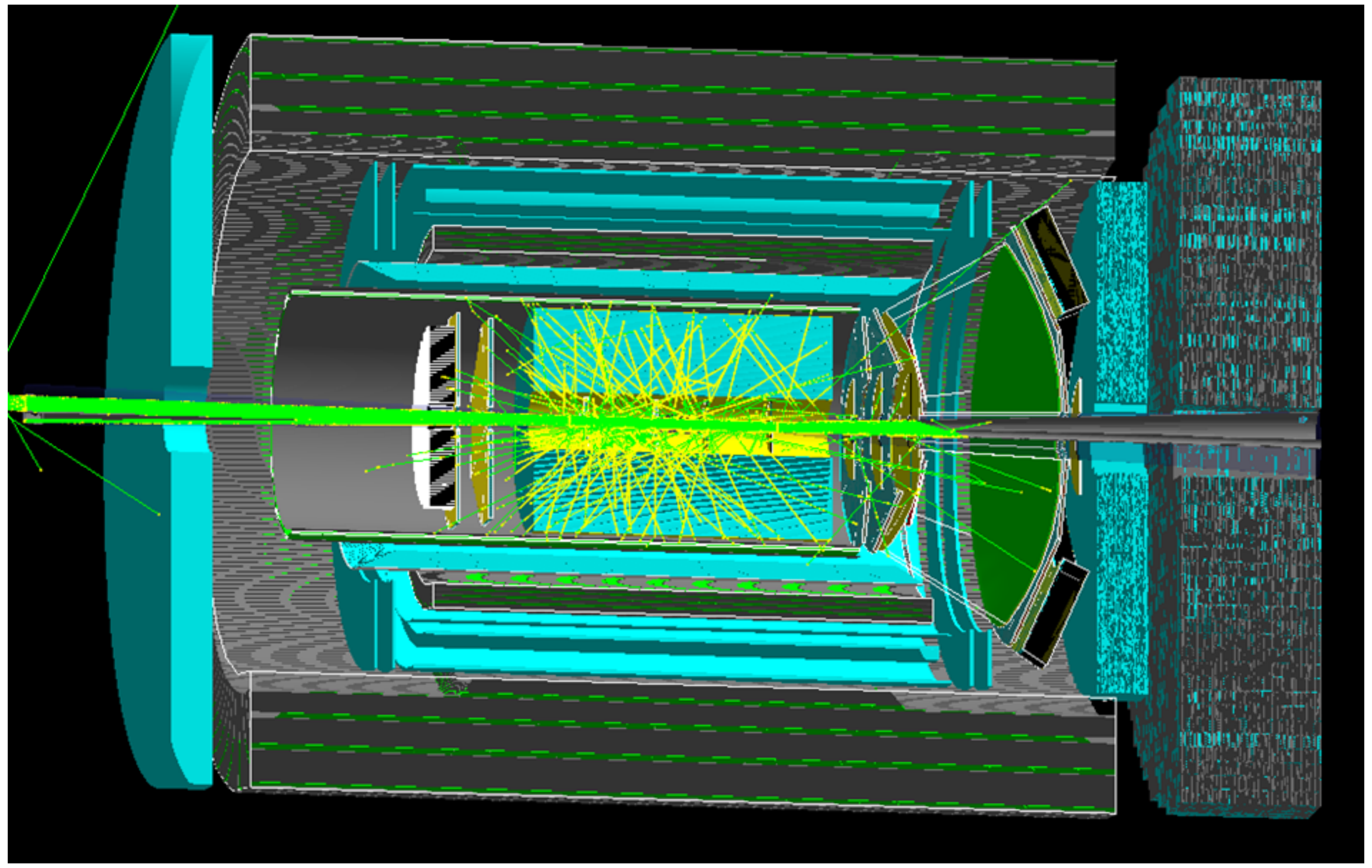
- <u>ML can speed up and produce large amount of the heavy ion event simulations!</u>



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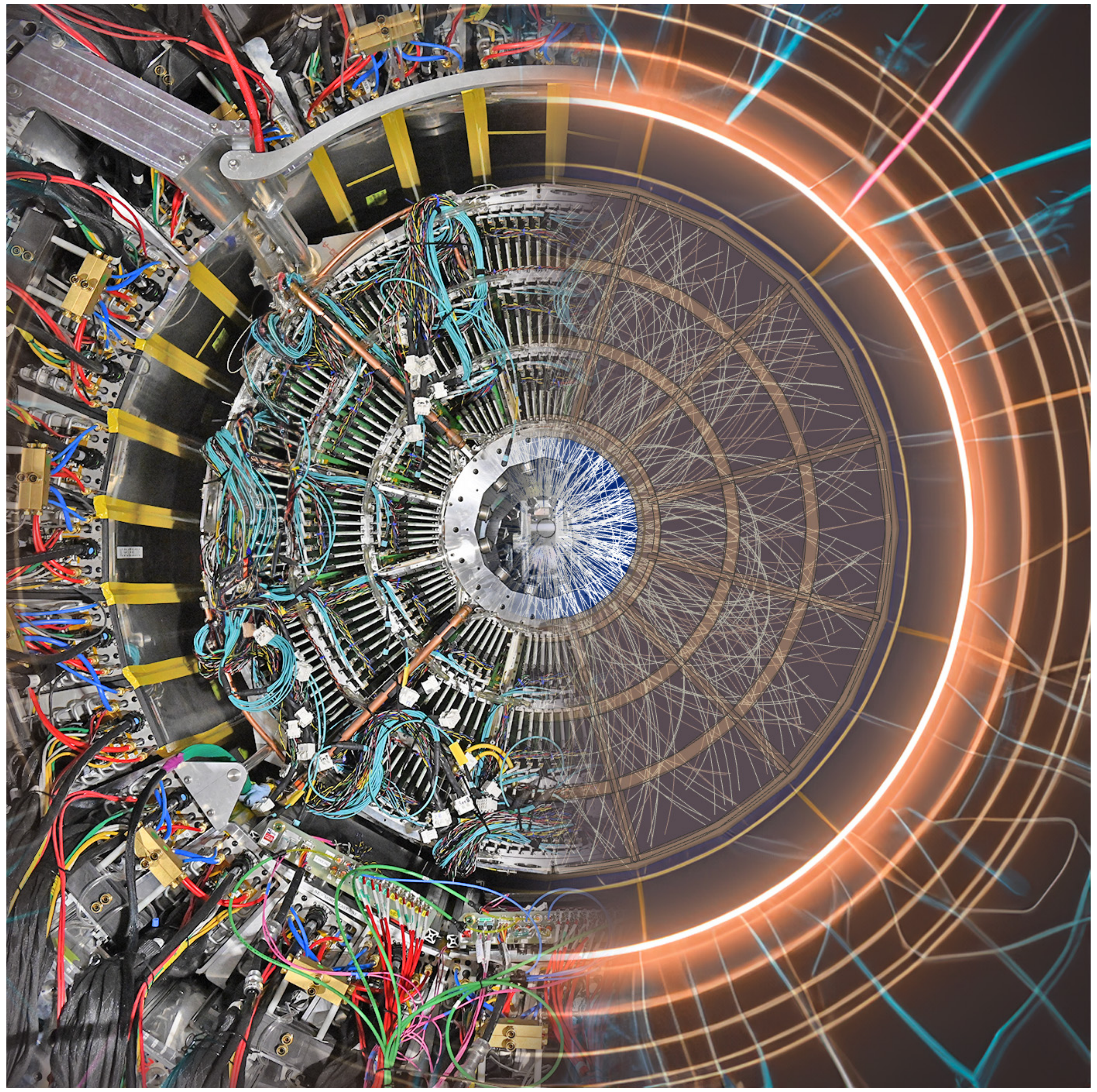

sPHENIX TPC

We introduce ***full detector whole-event ML simulations*** for heavy ion collisions

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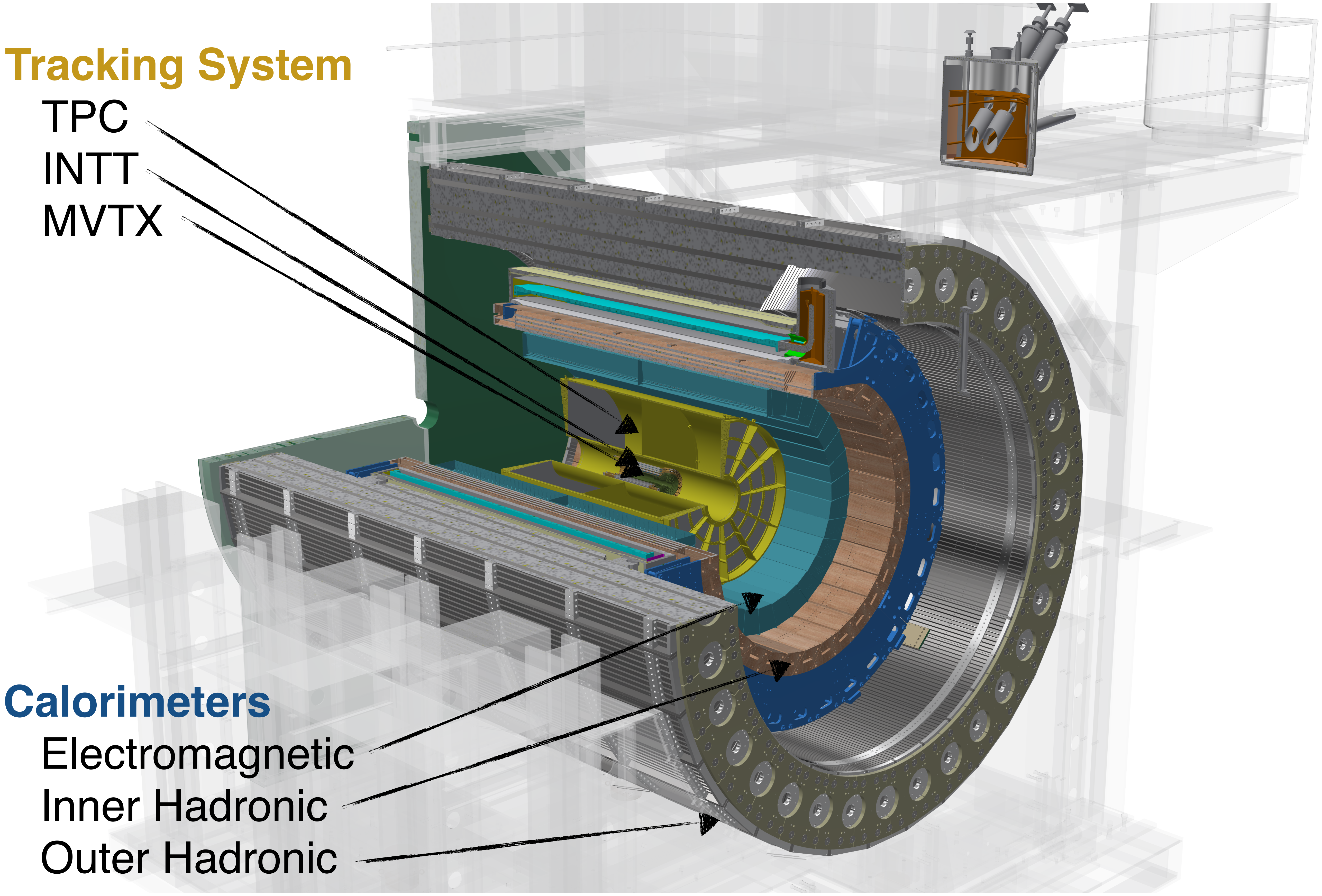
sPHENIX Detector at RHIC

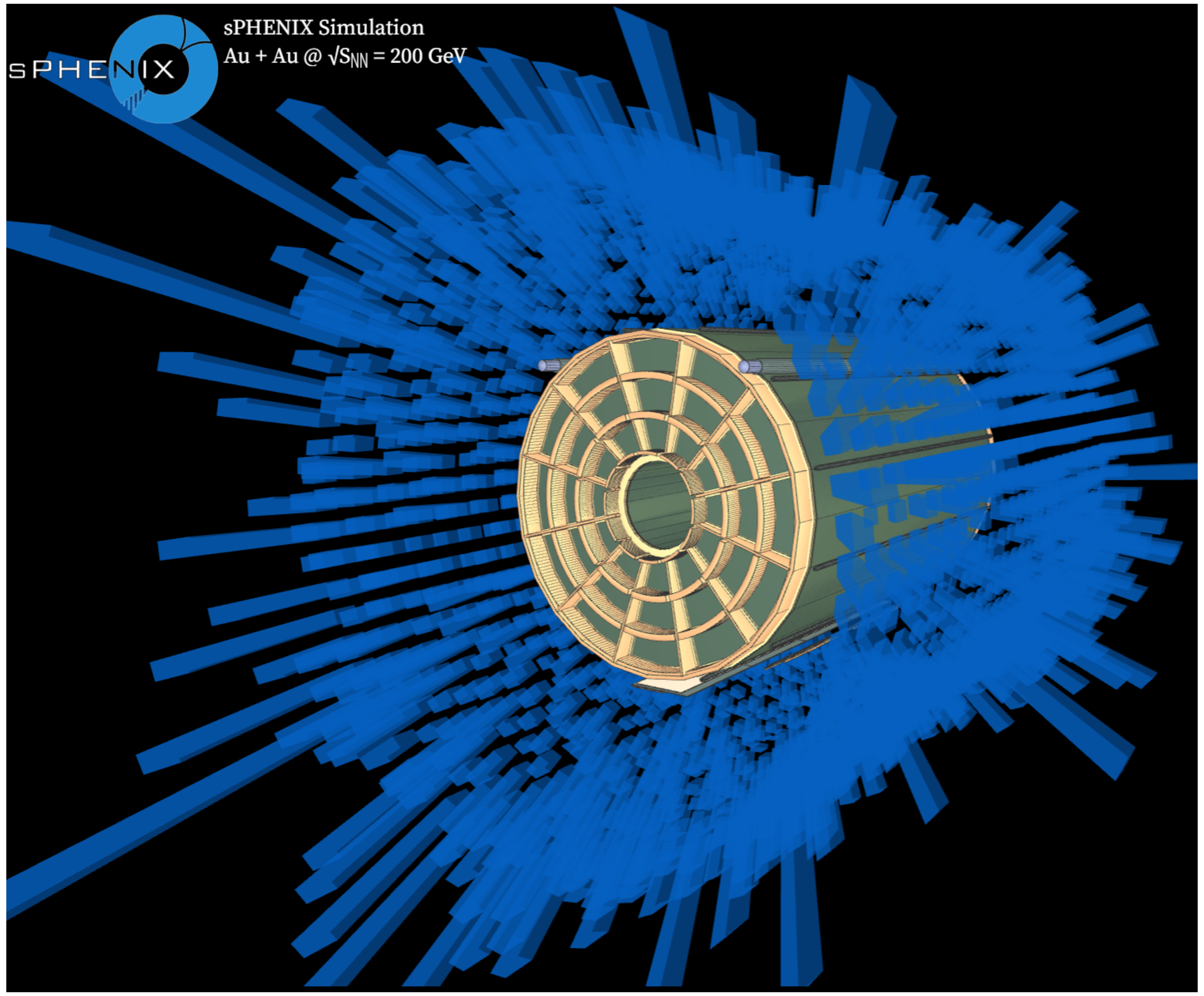


- Data taking began last year!
- High-precision tracking system +
  Hermetic Electromagnetic & Hadronic calorimeters

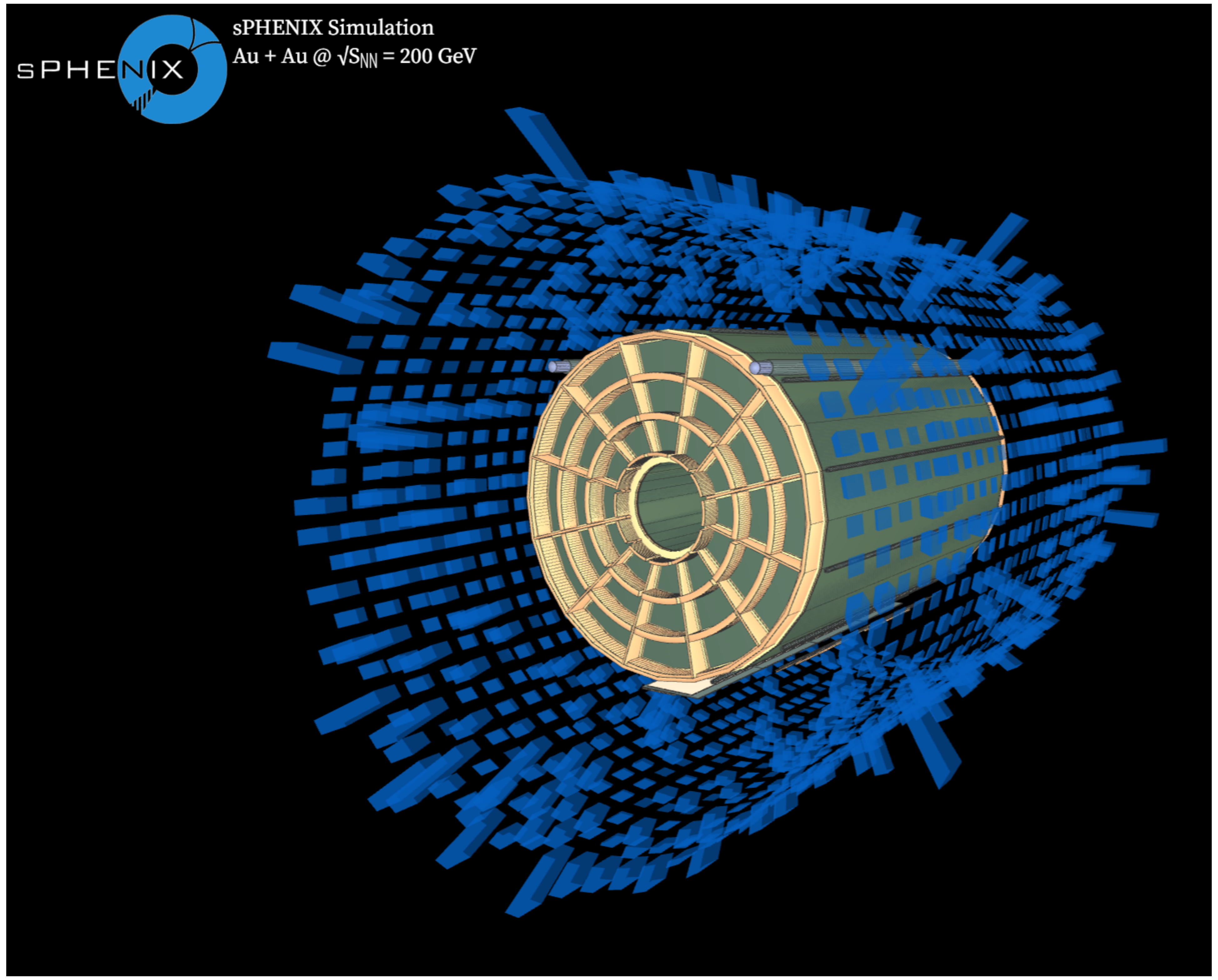
Heavy Ion Collision Event

- **HIJING** Monte Carlo event generator for Au+Au collisions at $\sqrt{s_{NN}}$=200 GeV
- **Geant4** full detector simulation with the sPHENIX geometry

Head-on collision (0-10% Centrality)

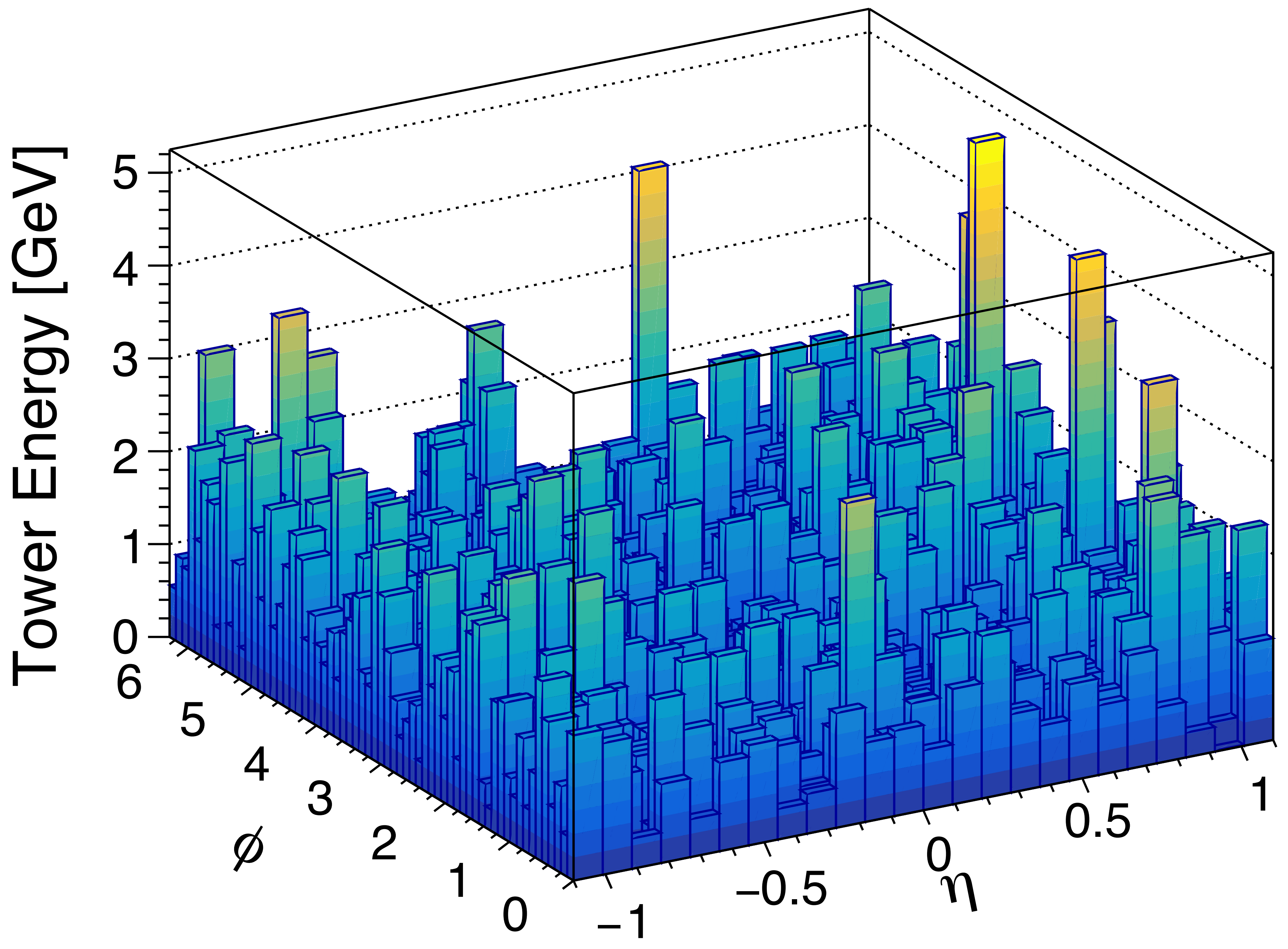


Side collision (40-50% Centrality)

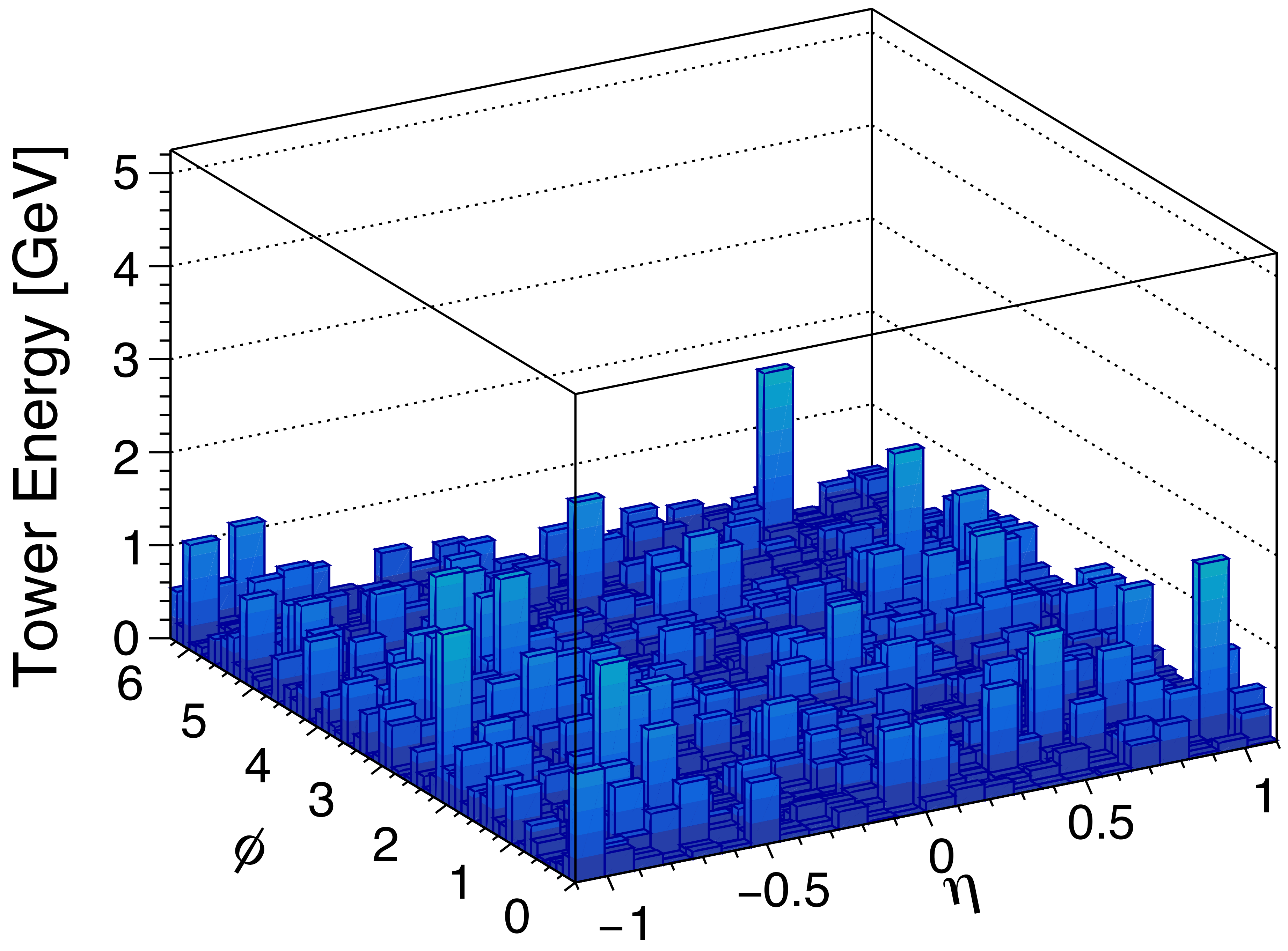


Tower Distributions

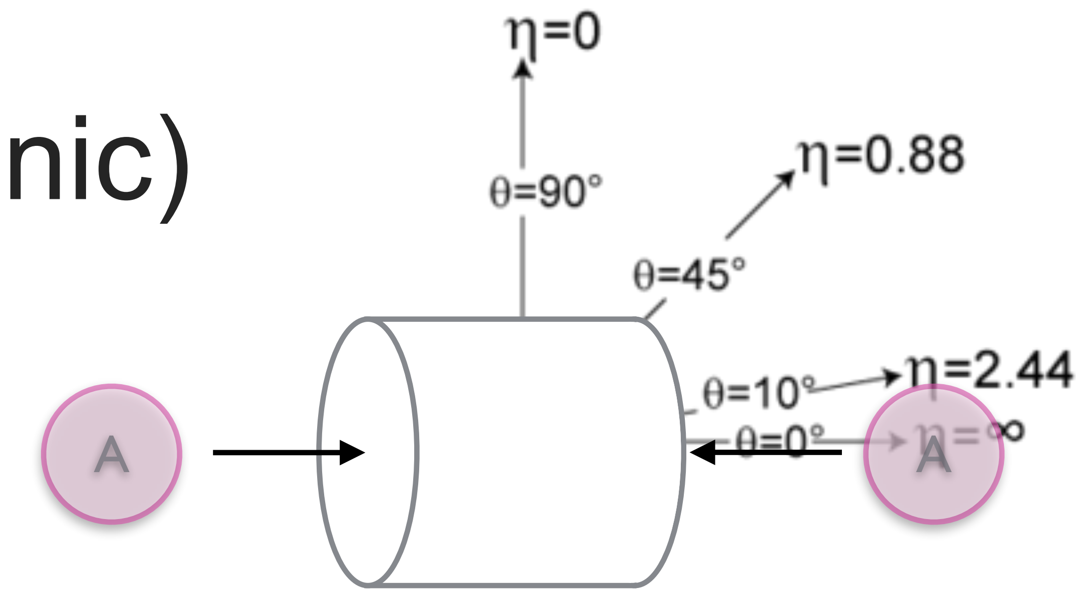
0-10% Centrality



40-50% Centrality



- Full calorimeter **towers** (Electromagnetic + Inner hadronic + Outer hadronic)
  - ➡ $-1.1 < \eta < 1.1, \quad 0 < \phi < 2\pi$
  - ➡ (24 x 64) bins in (η, ϕ)



Generative AI: Diffusion Model

- **Diffusion Models**:
  text-to-image generation
  (e.g. StableDiffusion, Midjourney, Dalle-2)
  - ➡ Popular in industry, yet relatively less used in high-energy physics
  - ➡ known for high fidelity
  - ➡ but, still require improvements for finer details

Diffusion Model (DALL·E3 by OpenAI) generating a sPHENIX meeting
Note difficulty in generating features such as text

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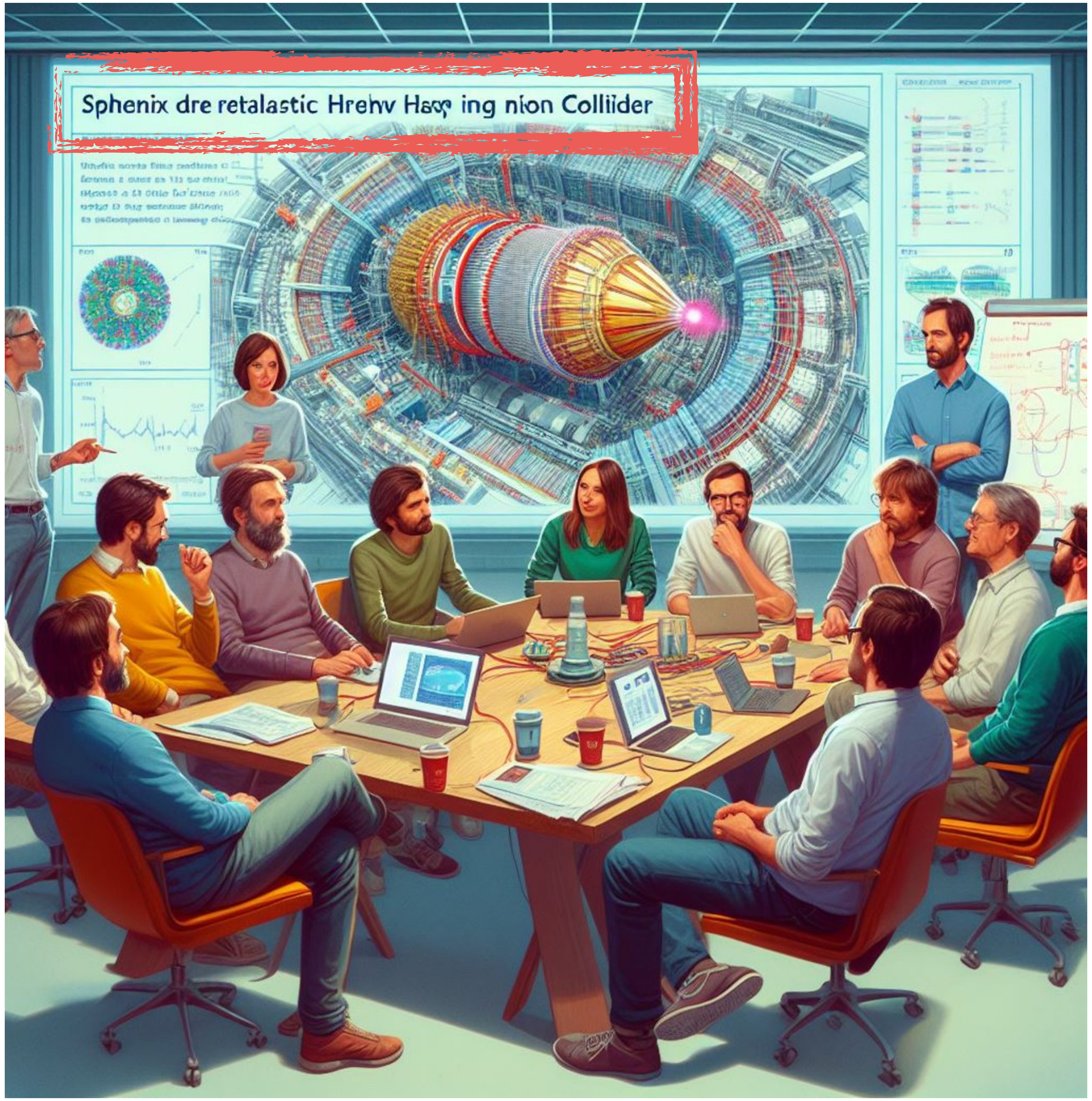

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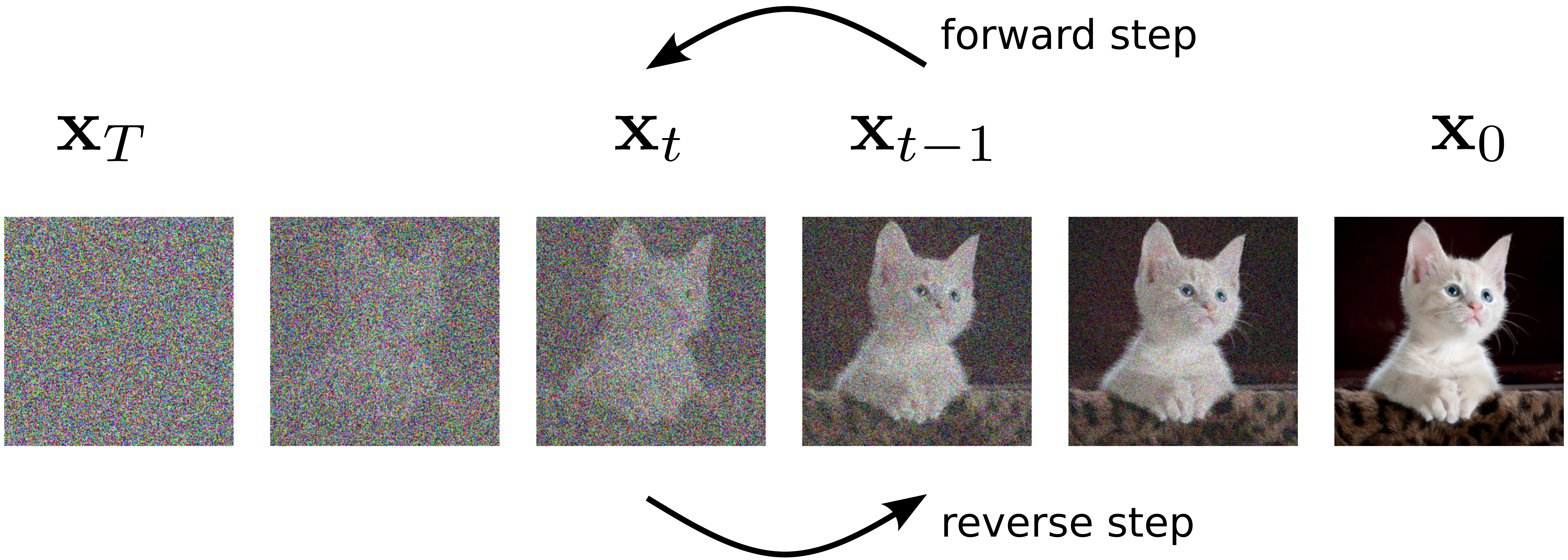
Denoising Diffusion Probabilistic Model (DDPM)

- DDPM provides ***high quality data from random noise***
- **Forward** process: add random gaussian noise
- **Reverse** process: use neural network and <u>generate data</u>
- In real application, O(1,000) steps are used



Display of Generated Events

Training sample (HIJING+GEANT4)

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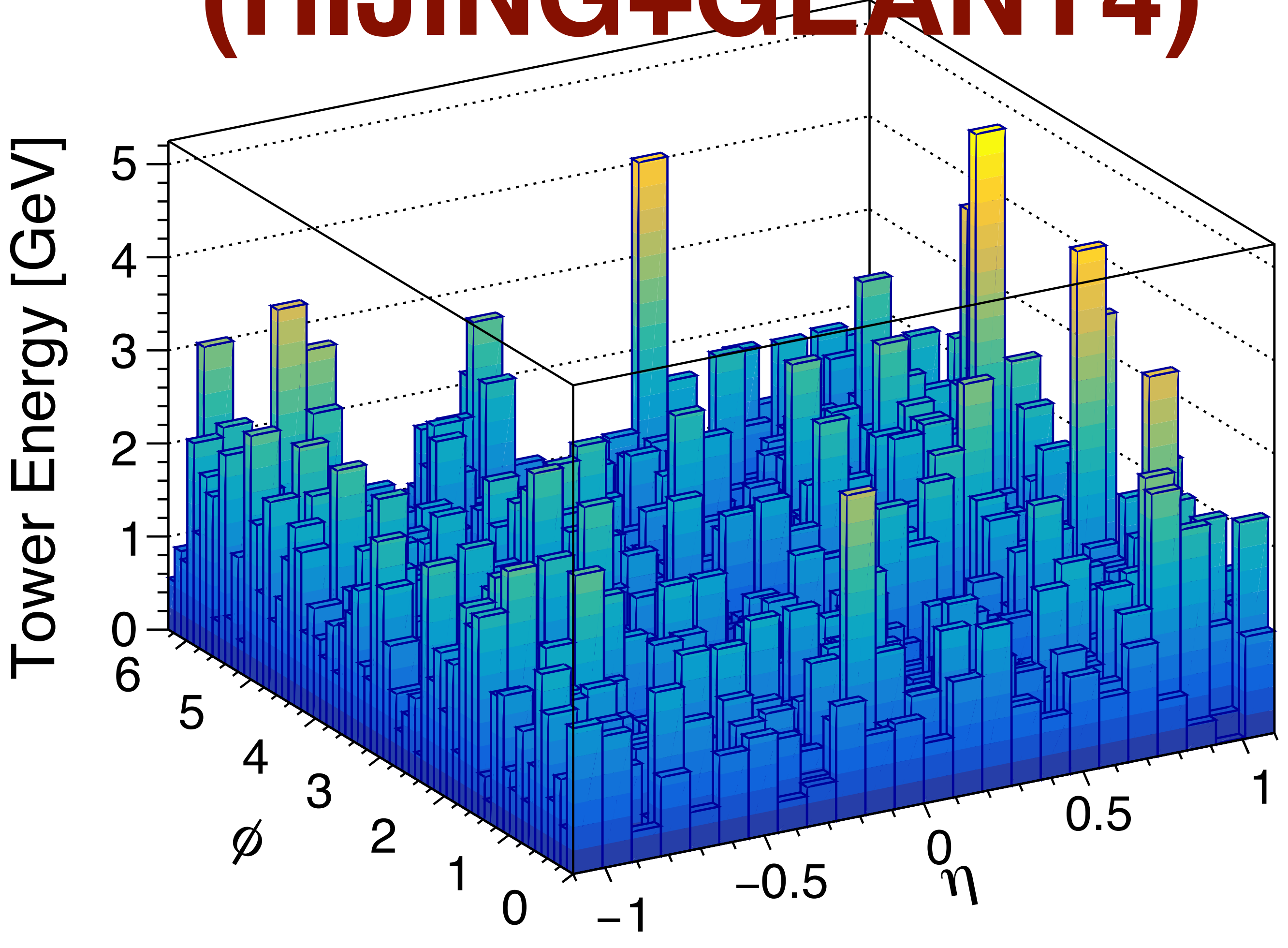

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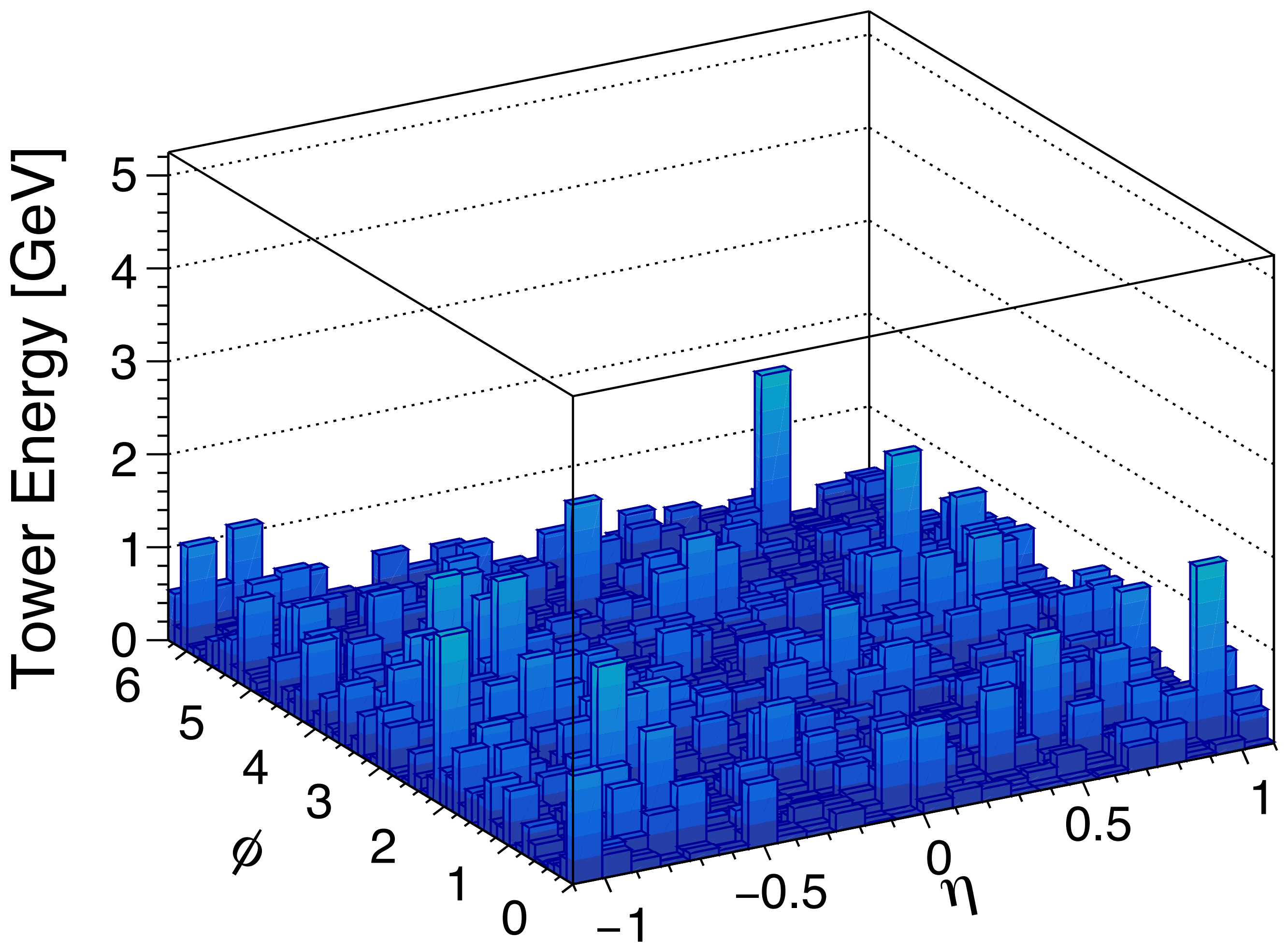
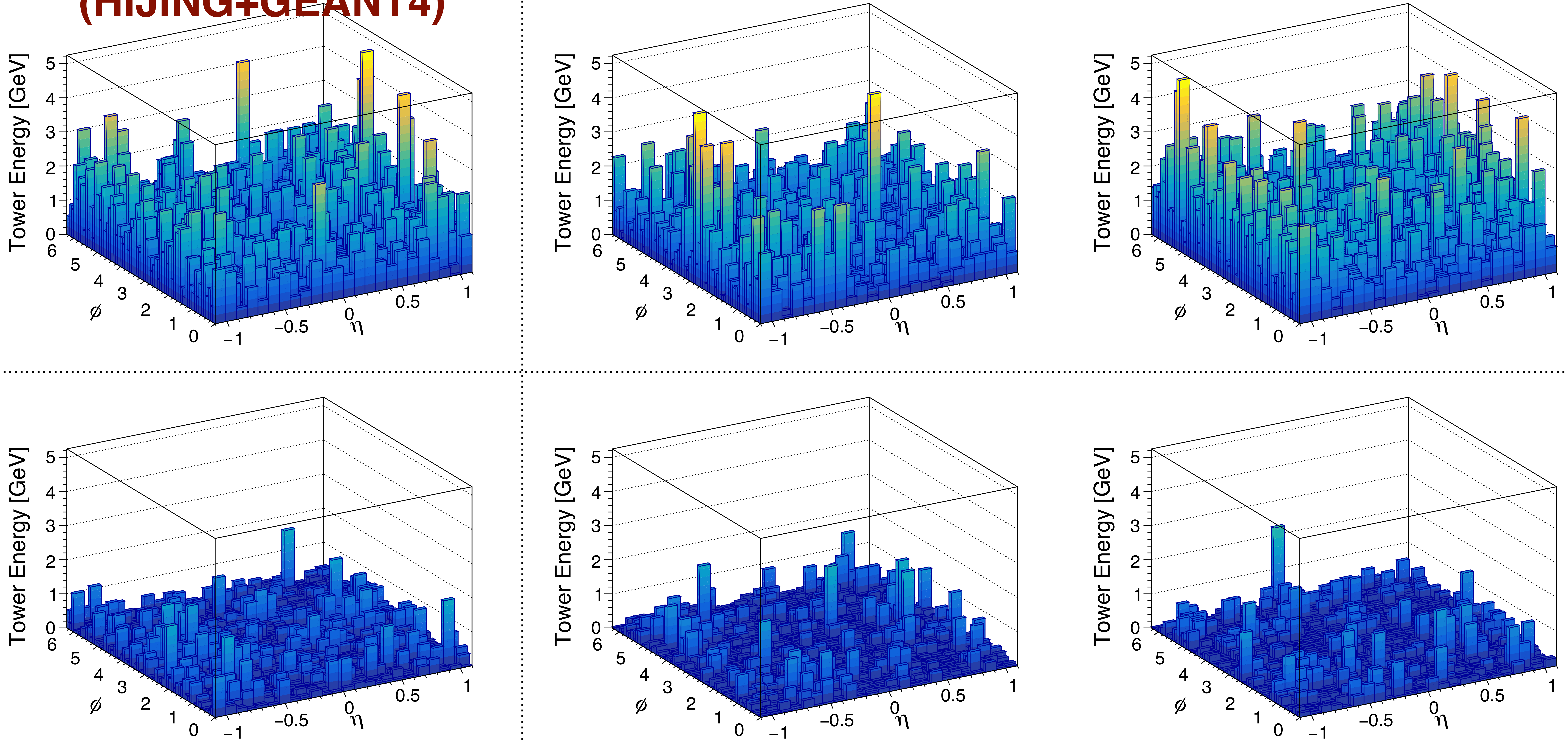


Display of Generated Events

Training sample (HIJING+GEANT4) | **Generated (DDPM)** | **Generated (GAN)**

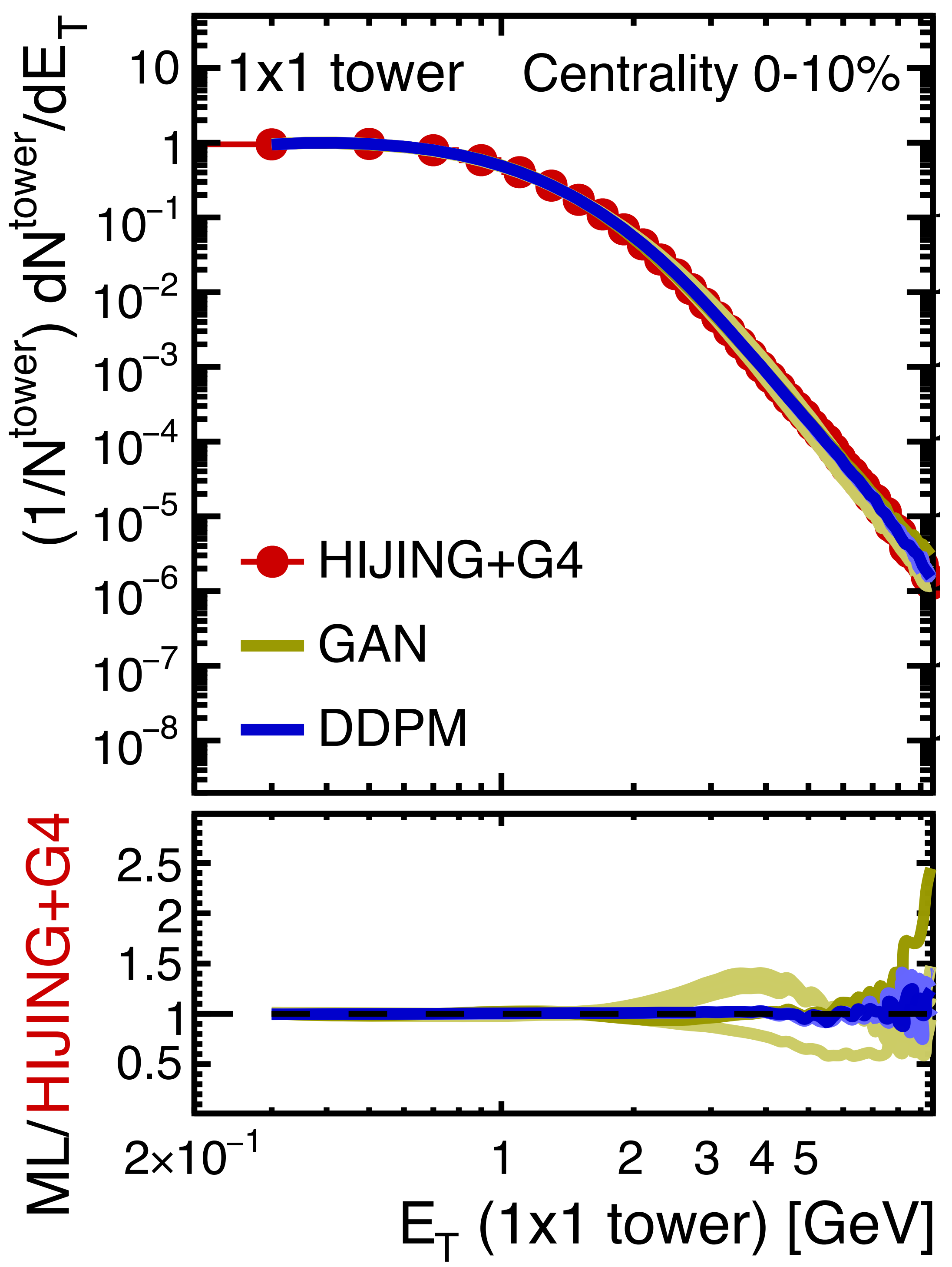


0-10% Centrality

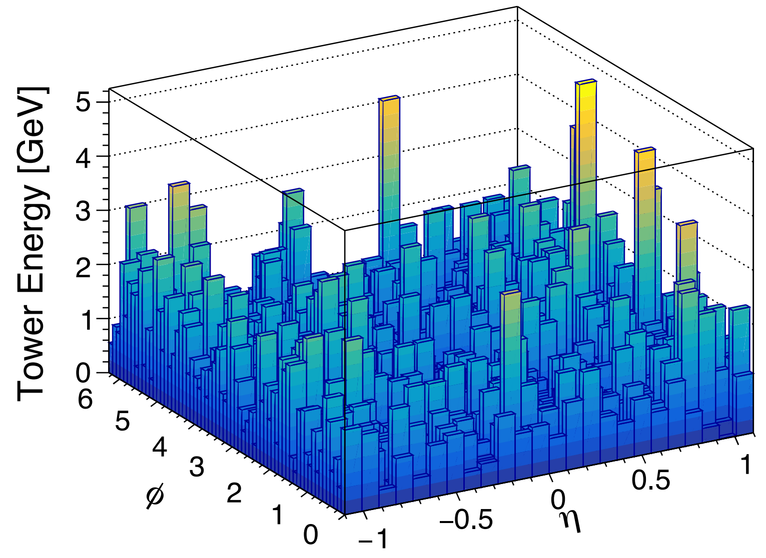
40-50% Centrality

Performance: Transverse Energy (0-10%)

1x1 Tower 4x4 Tower 7x7 Tower 11x11 Tower All Towers



- Each model is retrained 5 times with different random seeds
- HIJING+Geant4 used as training data (600k events) and testing data (100k events)
- Both DDPM and GAN reproduce the data distribution where the data are abundant
- DDPM outperforms GAN in overall distribution w/ great stability and accuracy



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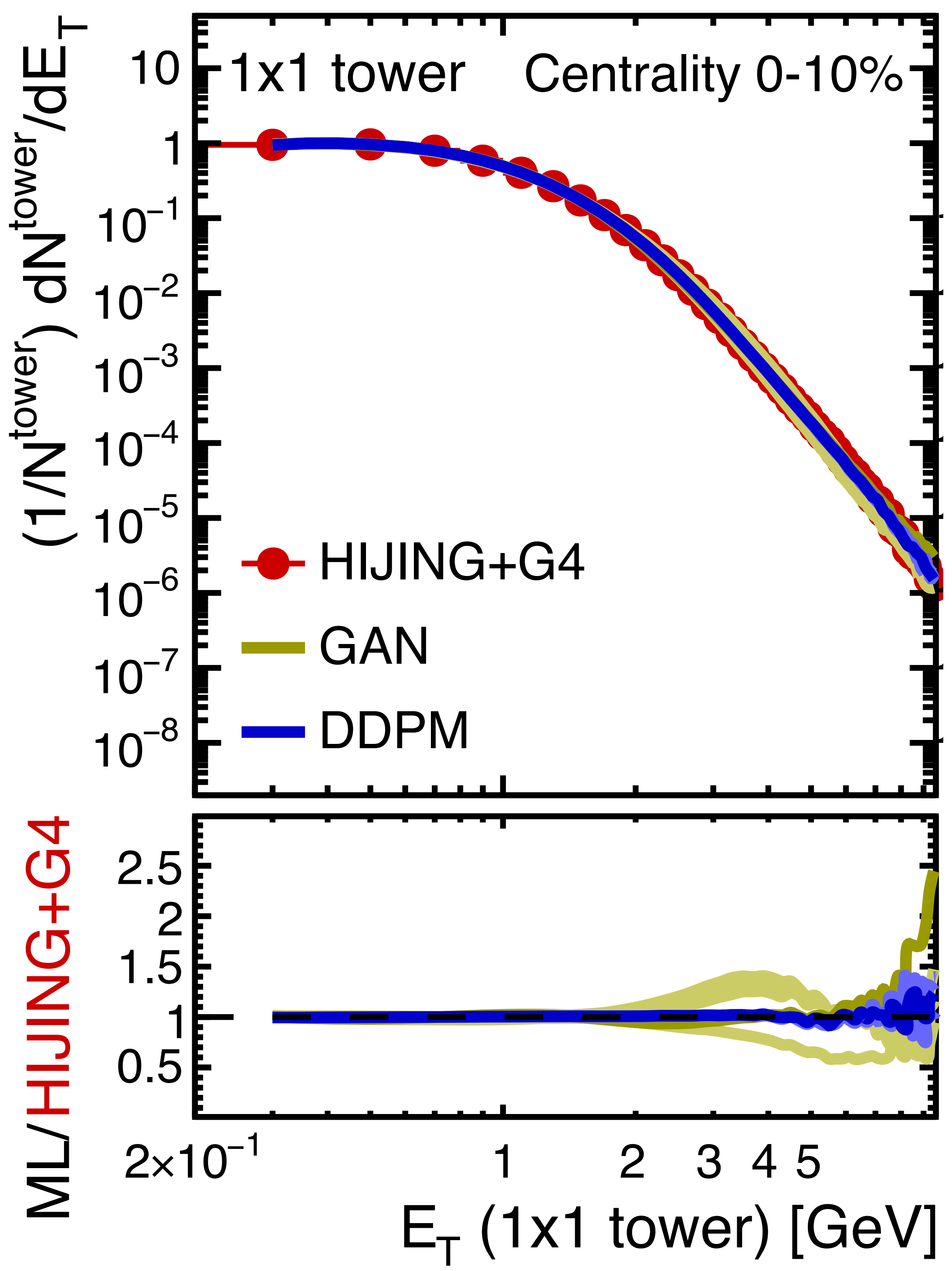

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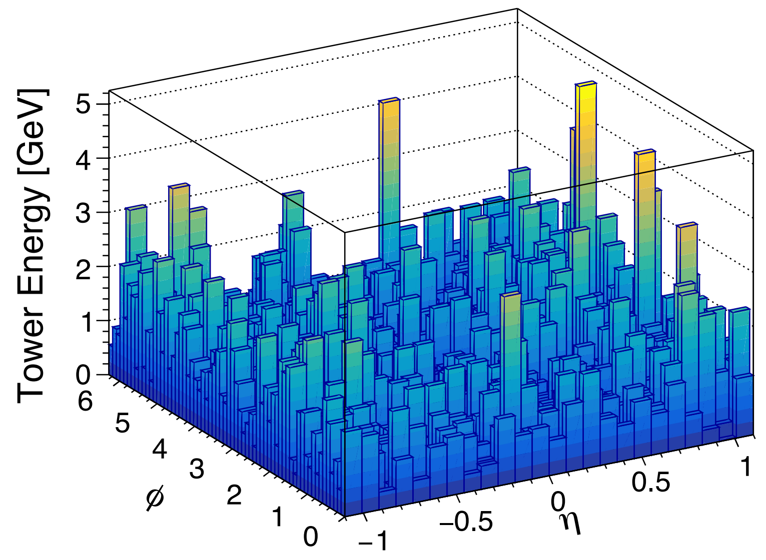

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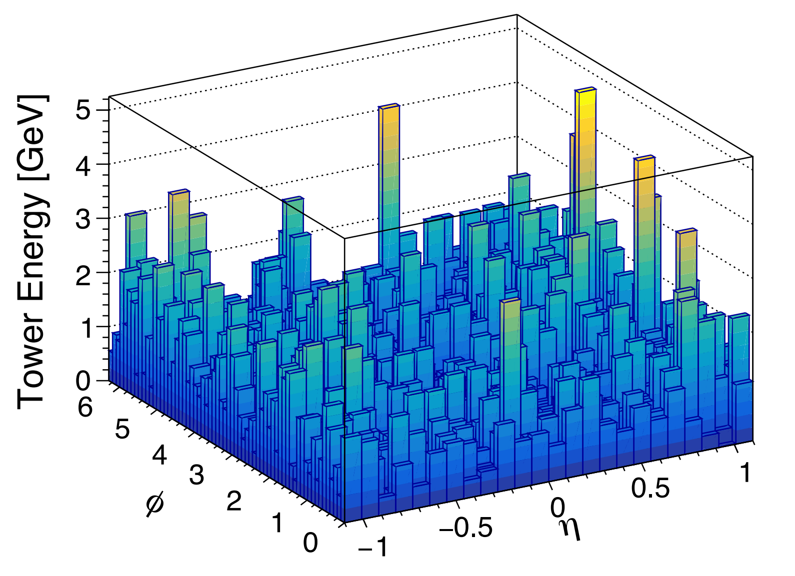
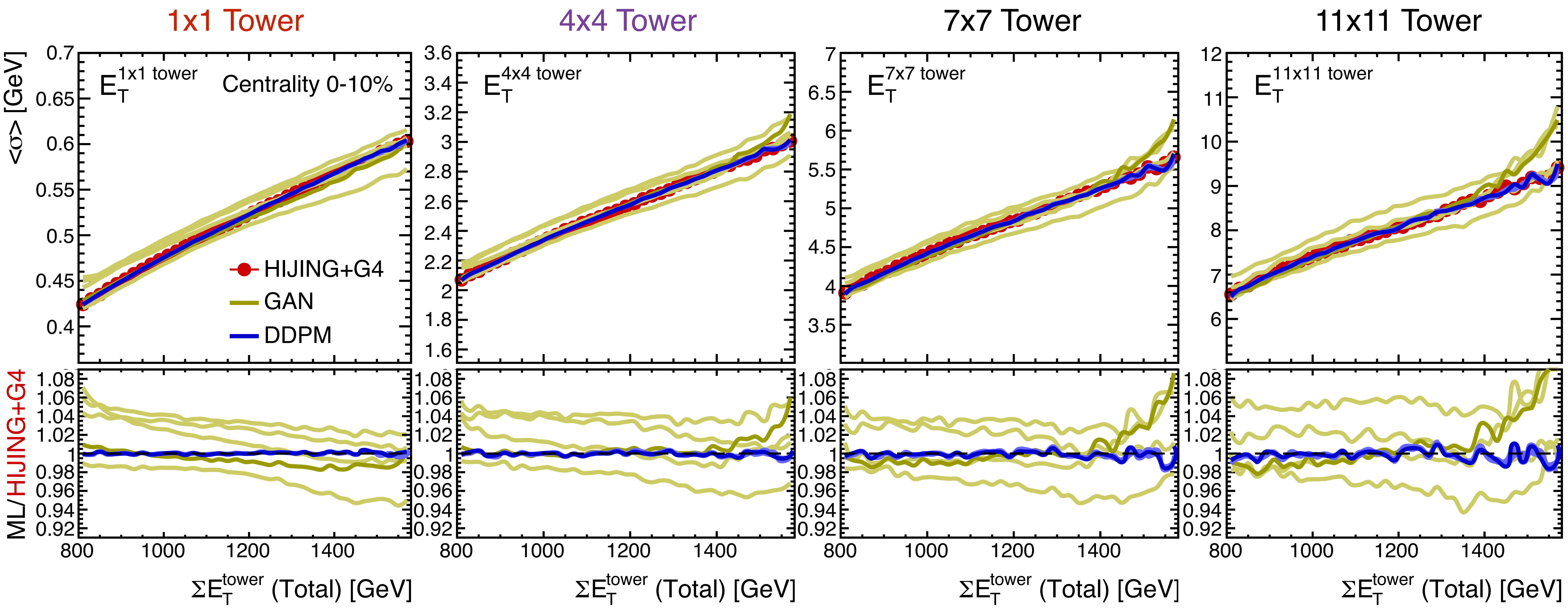
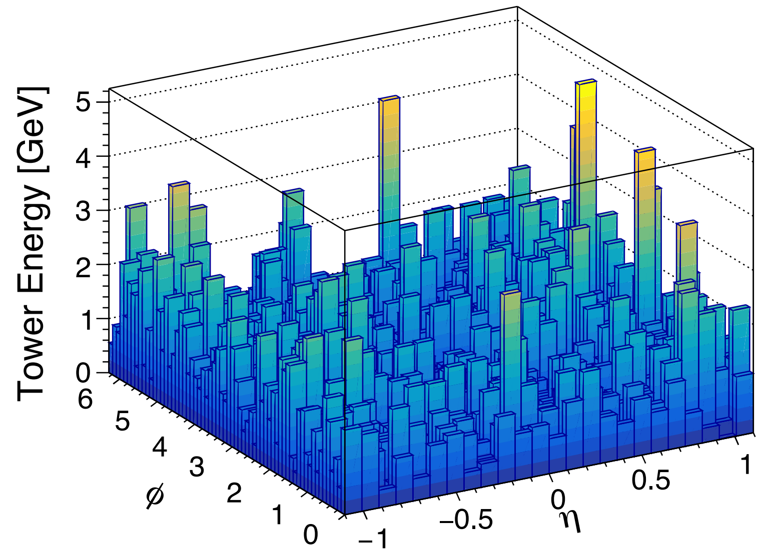


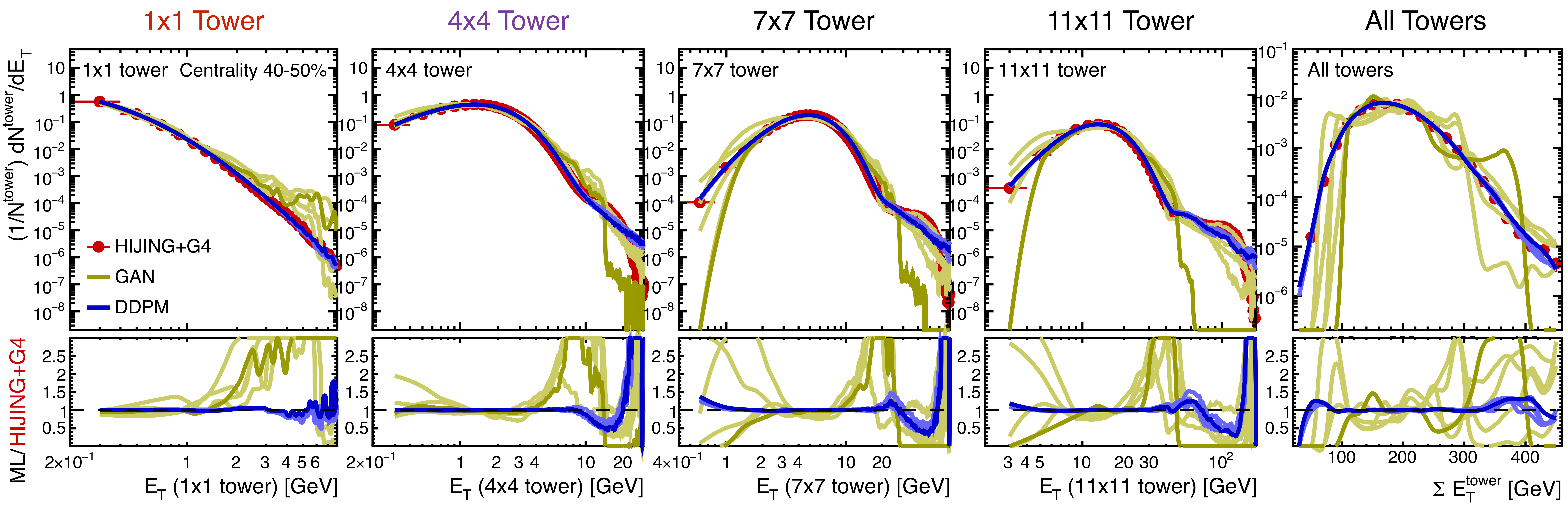
Performance: Transverse Energy Fluctuation (0-10%)



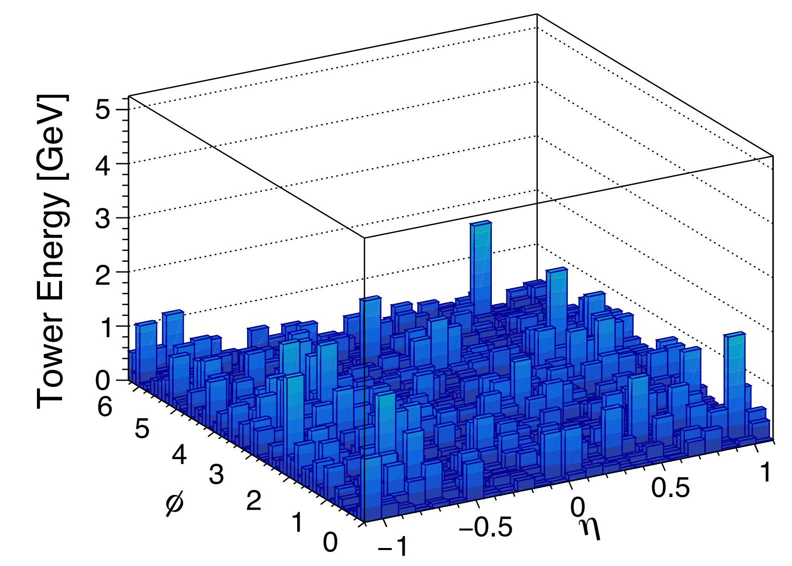
- GAN fails to describe fluctuation
- DDPM outperforms GAN w/ great stability, a few percent-level accuracy



Performance: Transverse Energy (40-50%)



- DDPM outperforms GAN
  - ➡ great stability, good agreement with HIJING+G4 at high probability region



Performance: Transverse Energy (40-50%)

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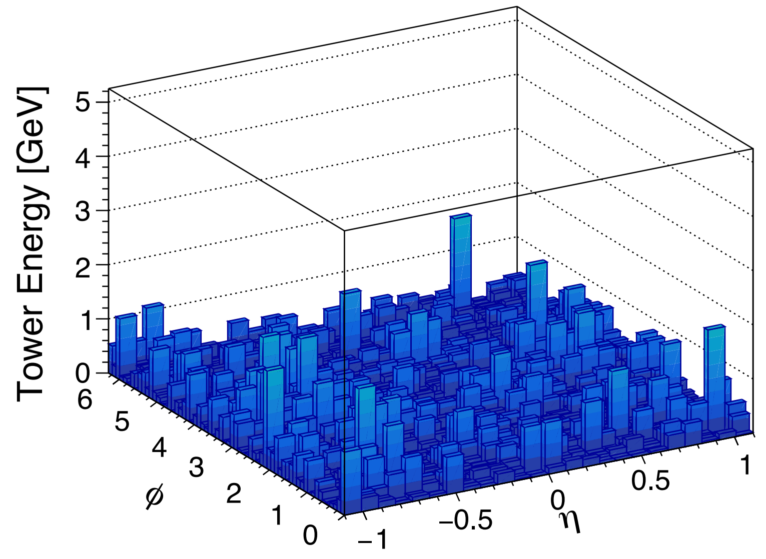
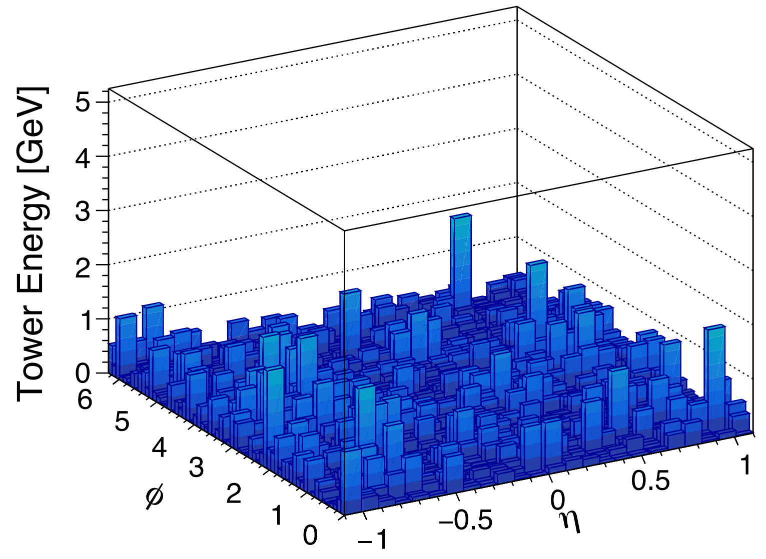
- Non-gaussian rare tail at the high energy region → challenge to reproduce



Trade-off between Training time and Fidelity

- epoch ~ training duration
- **DDPM** models with the higher epochs give **better performance**!
  ➡ but, the higher the epochs, the *longer the training time*



Trade-off between Generation time and Fidelity

- **DDPM** models with the higher de-noising steps give **better performance**!
  - ➡ but, the higher the de-noising, the *longer the generation time*

How long does it take to simulate a large sample?

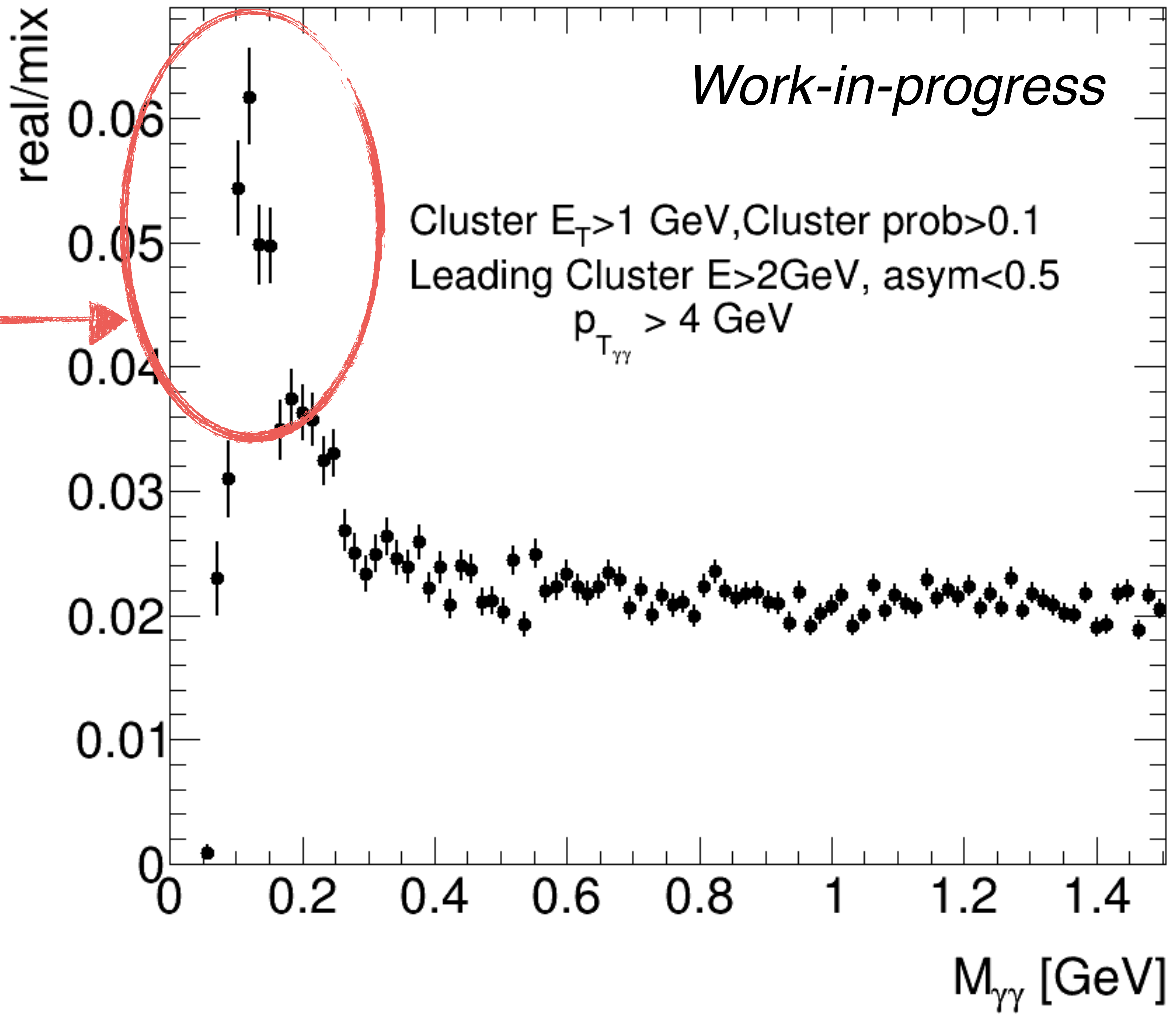
	Generating time	Speedup	CPU/GPU
HIJING + GEANT4 (Conventional)	40 minutes / event	1	Single CPU
DDPM	1.34 s / event	~1,800X	NVIDIA RTX A6000
GAN	0.42 ms / event	~5,700,000X	NVIDIA RTX A6000

- GAN is faster, but the DDPM exhibits high fidelity in describing the truth ground (HIJING+GEANT4)
- DDPM provide a speedup of O(100), considering a 32-core CPU equivalent to a GPU

Application and Future Plan

- We can train the model using a relatively modest number (*at the level of millions*) and then accelerate the production of much larger samples (*at the level of billions*)

π^0 peak reconstructed using simulation samples generated by DDPM



- Can DDPM describe more complex features of heavy ion collisions?
  - ➡ **Resonance, flow** can be reproduced by DDPM!
    (work-in-progress)

Jet Background Subtraction using CycleGAN

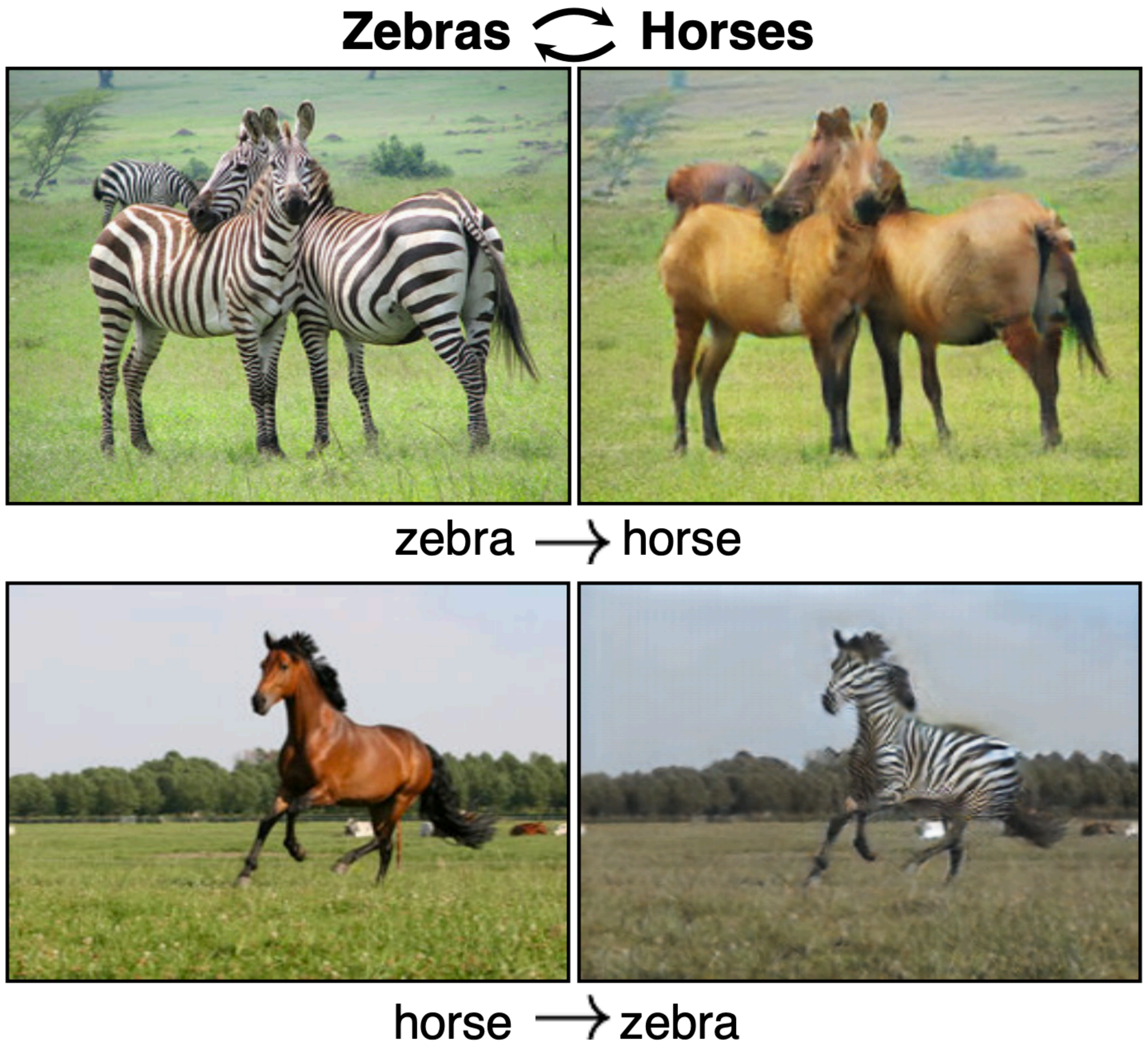
Cycle-consistent GAN

- Self-supervised learning,
  Unpaired image-to-image translation
- Minimizing **cycle-consistency loss** in addition to **adversarial loss**

Domain A ⟷ **Domain B**

Adversarial Loss
- A→B ~ B?
- B→A ~ A?

Cycle-consistency Loss
- A→B→A ~ A?
- B→A→B ~ B?



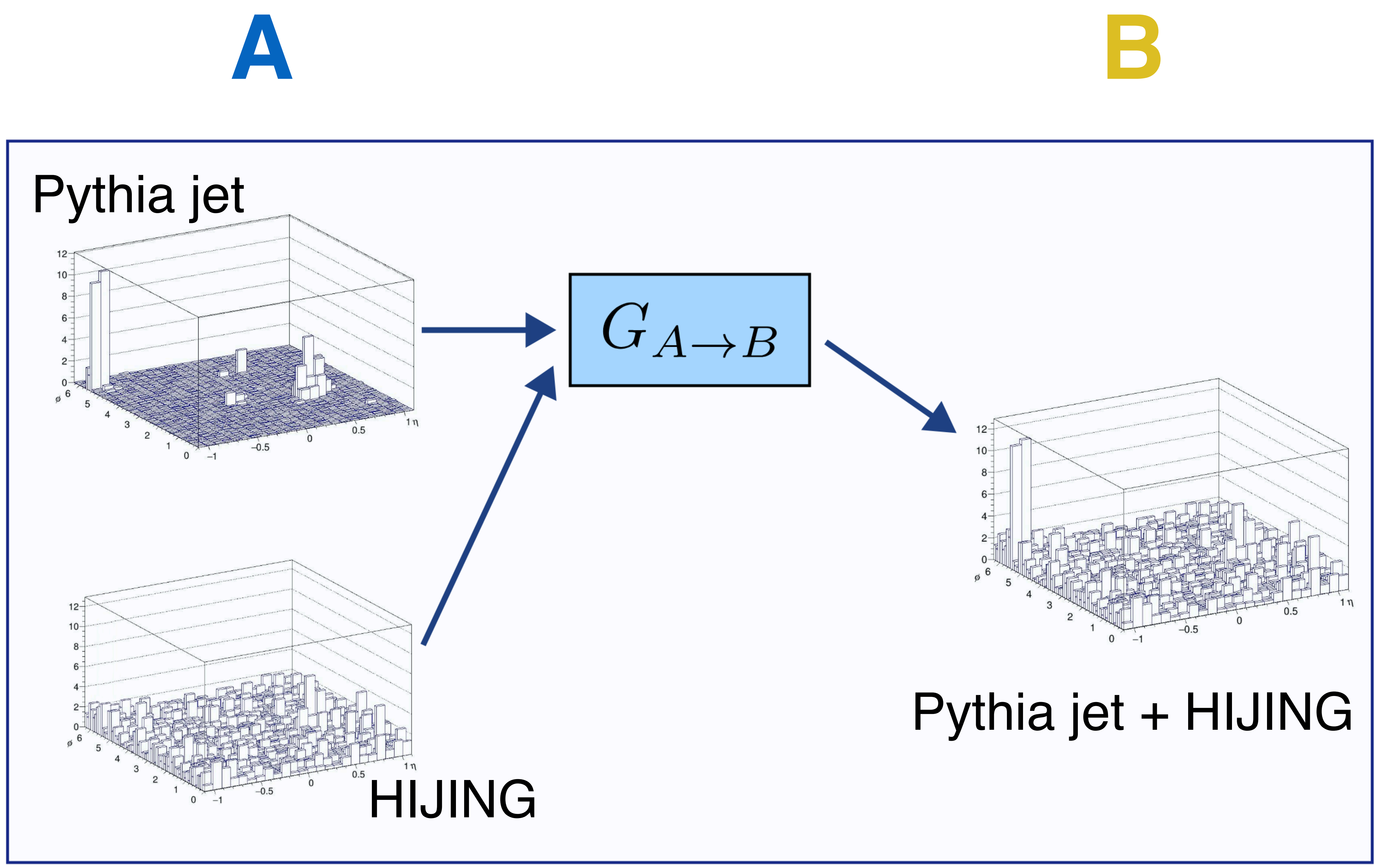
arXiv:1703.10593

UVCGAN

- **UVCGAN** (UNet Vision Transformer cycle-consistent Generative Adversarial Network)
  - ➡ **unpaired** image-to-image translation; bridging gap between simulation and data reference
  - ➡ arXiv:2303.16280 [cs.CV]

Jet Background Subtraction (1)

- Calorimeter η vs ϕ images are generated by UVCGAN for two domains
  - ➡ A domain: Pythia and HIJING, separately
  - ➡ B domain: Pythia + HIJING
- A-to-B is qualitatively described well



Work-in-progress

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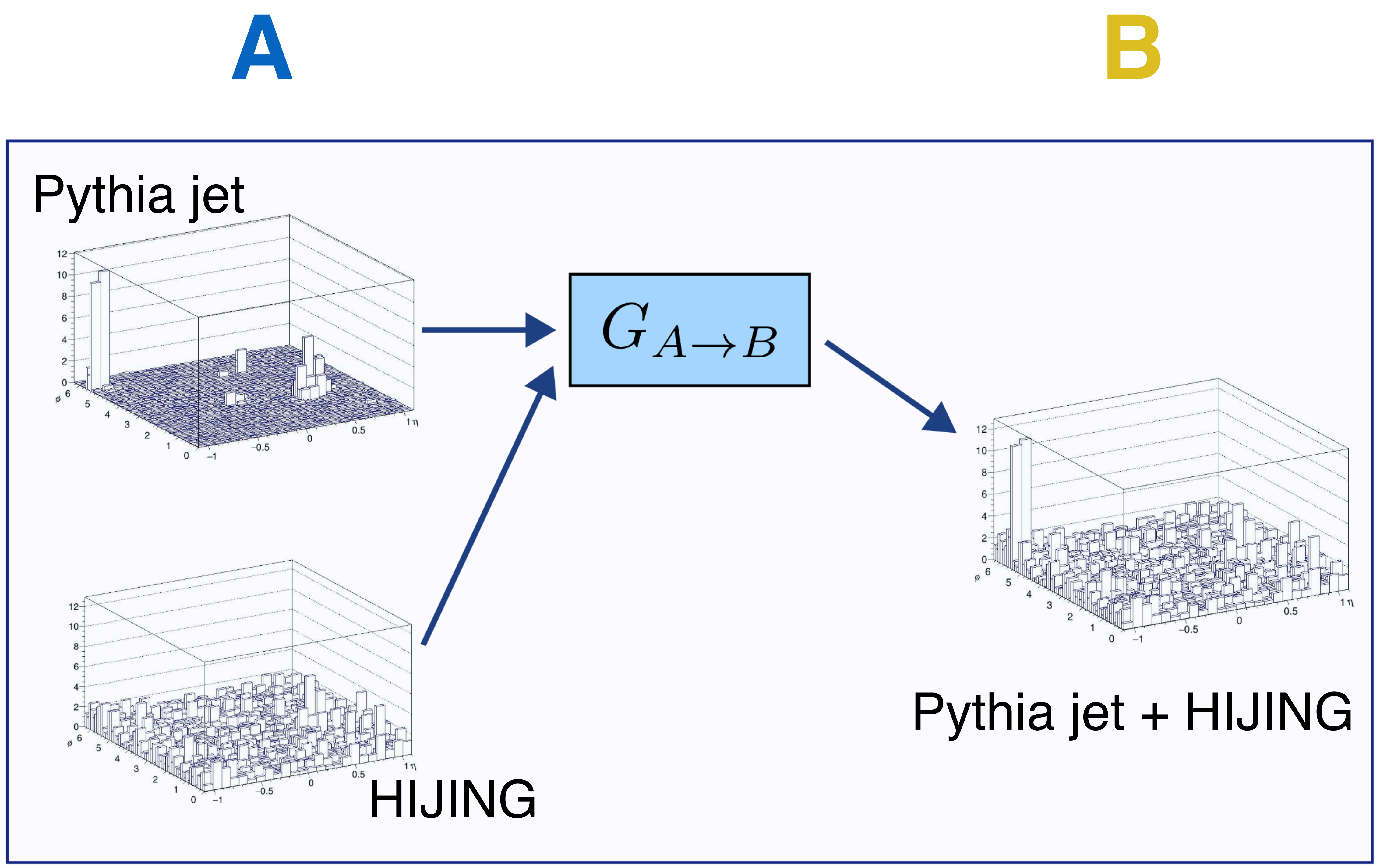

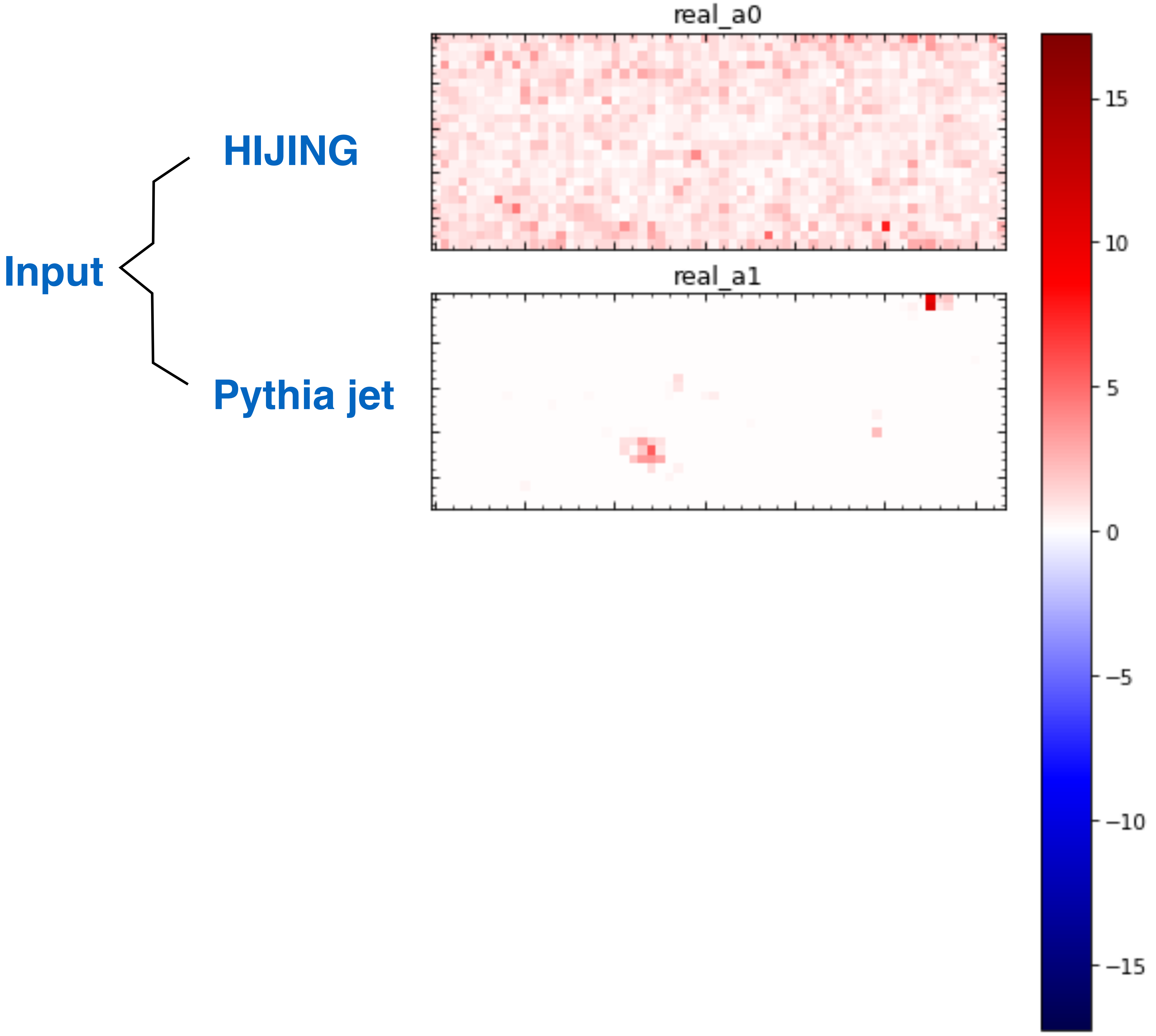

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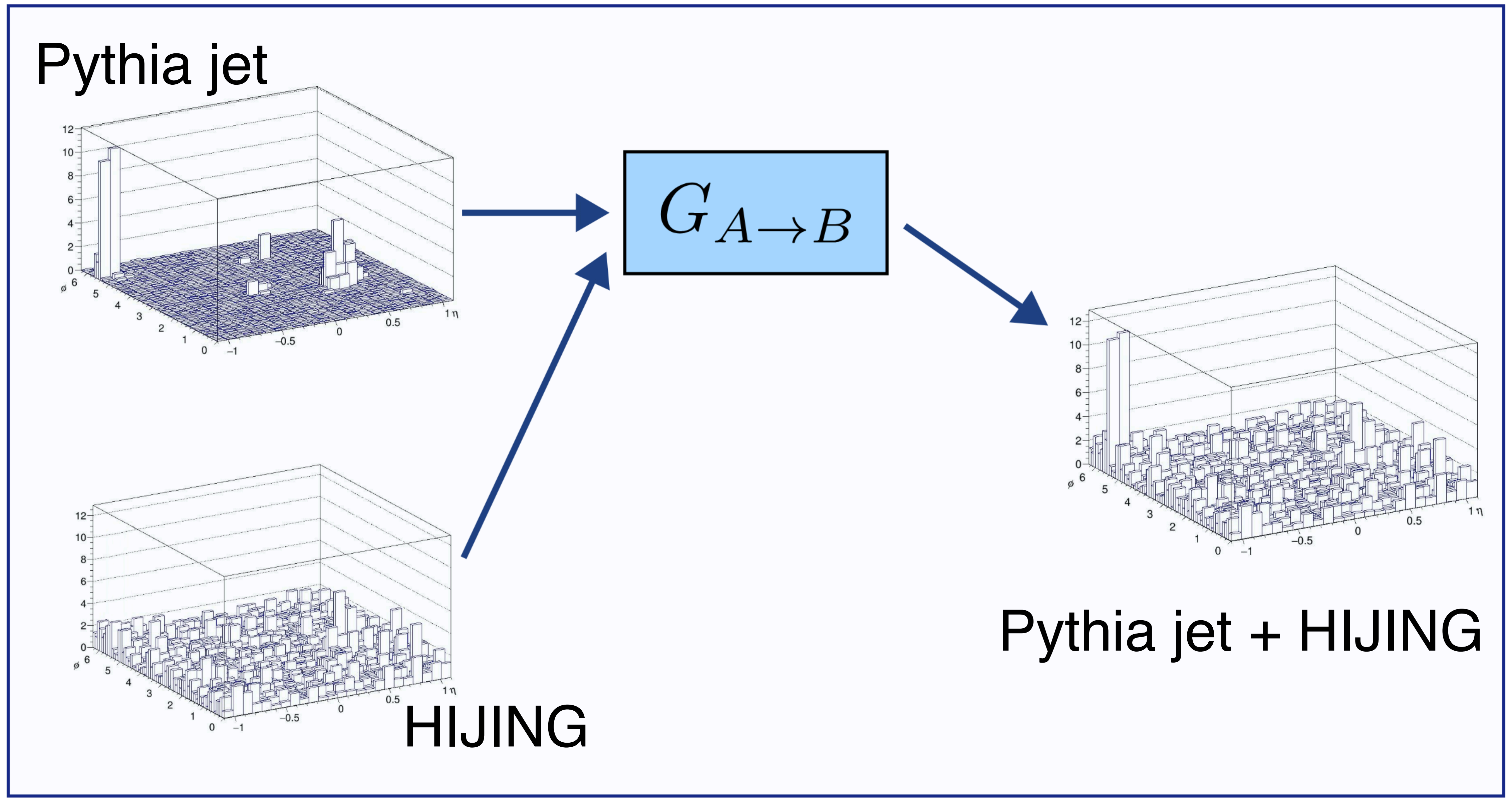
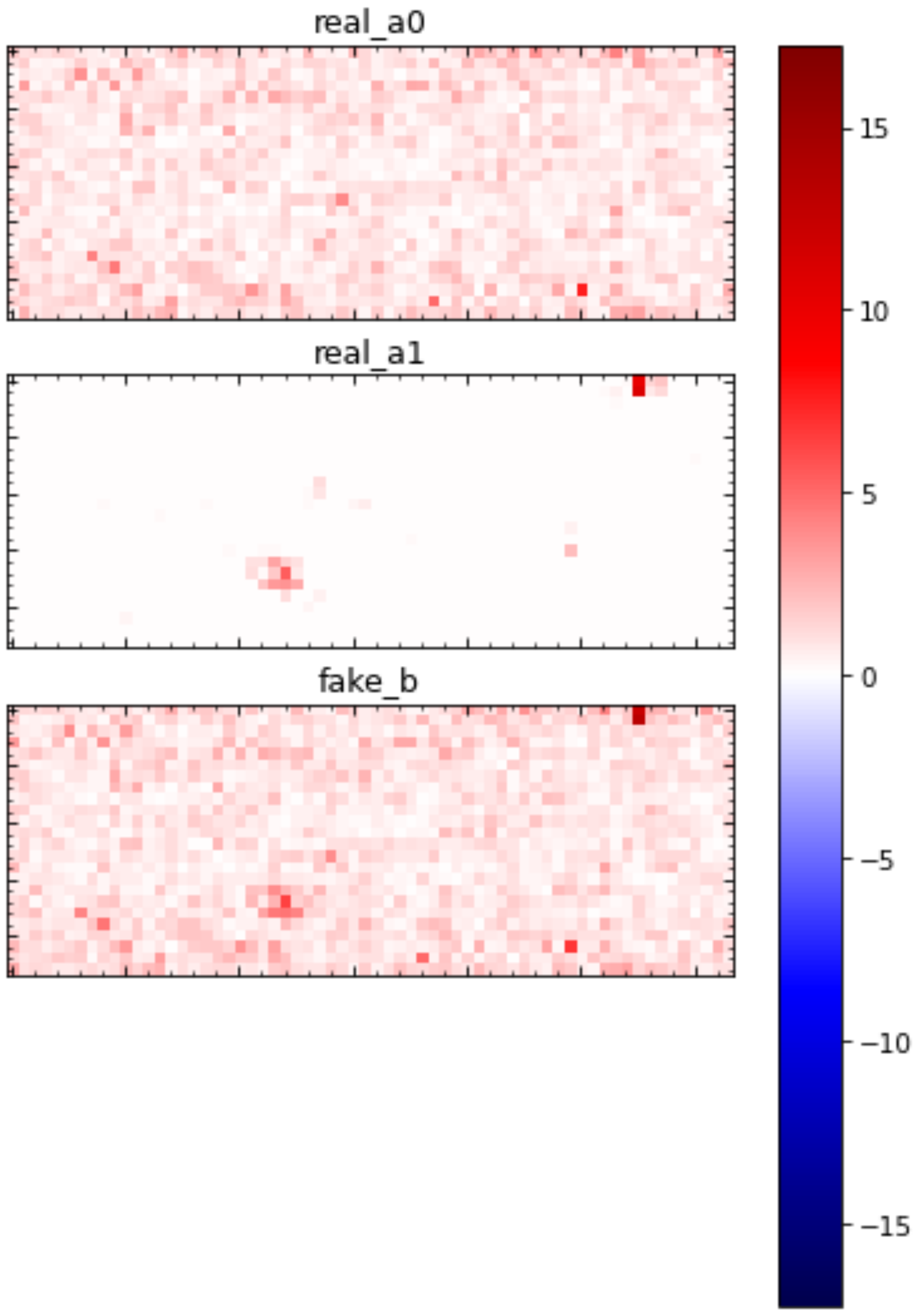
A **B**



Input
HIJING
Pythia jet
A→B Generated by UVCGAN



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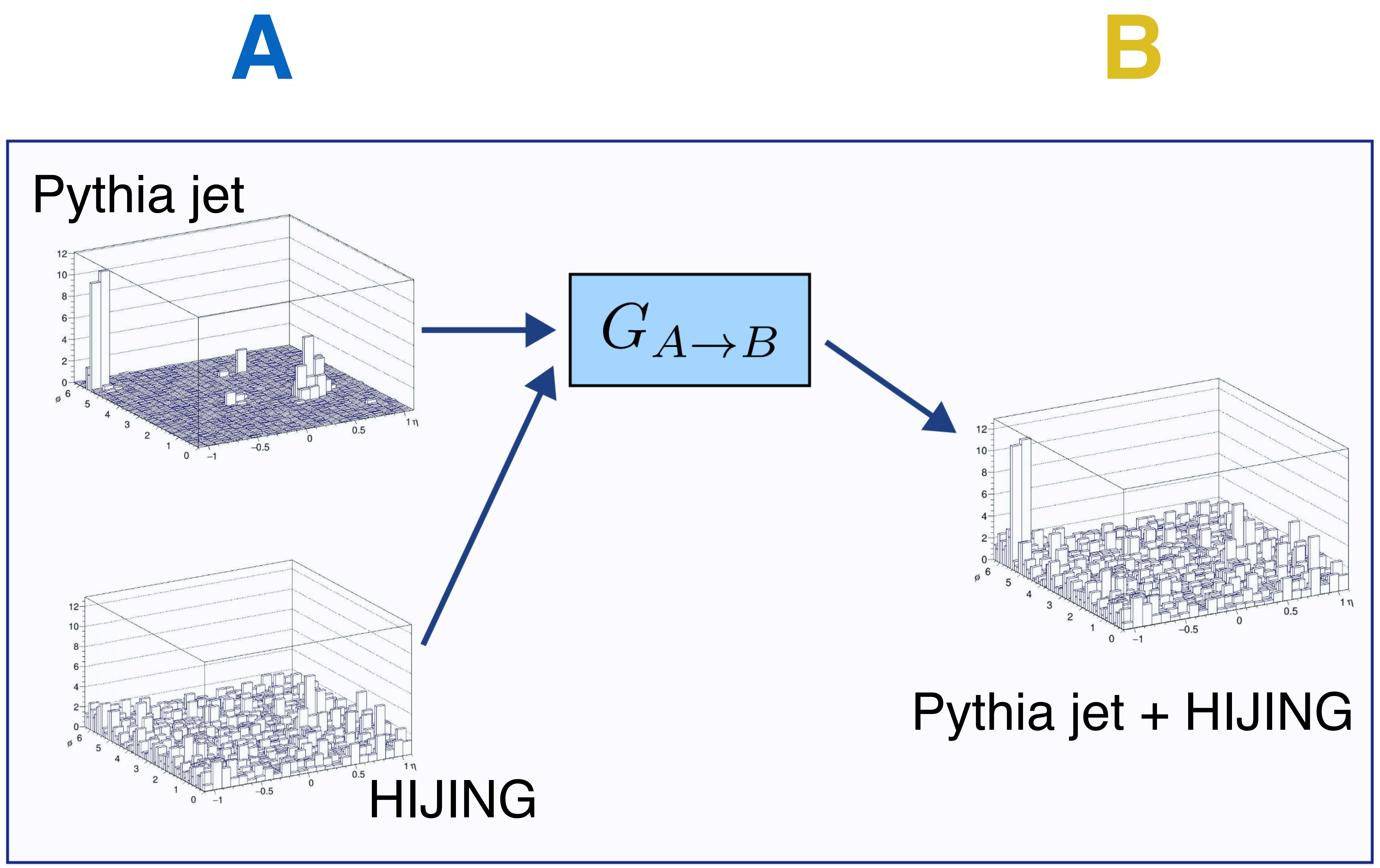
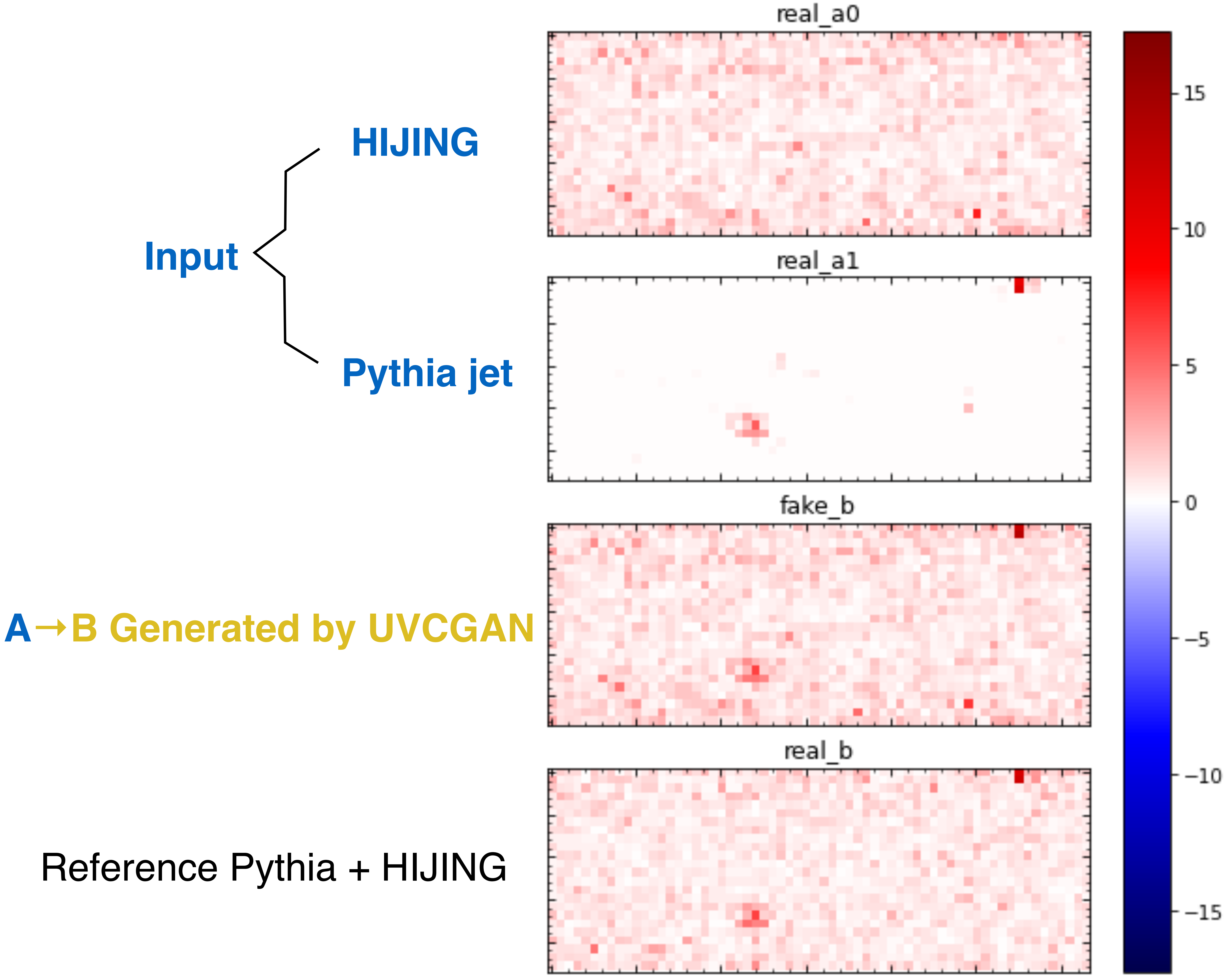




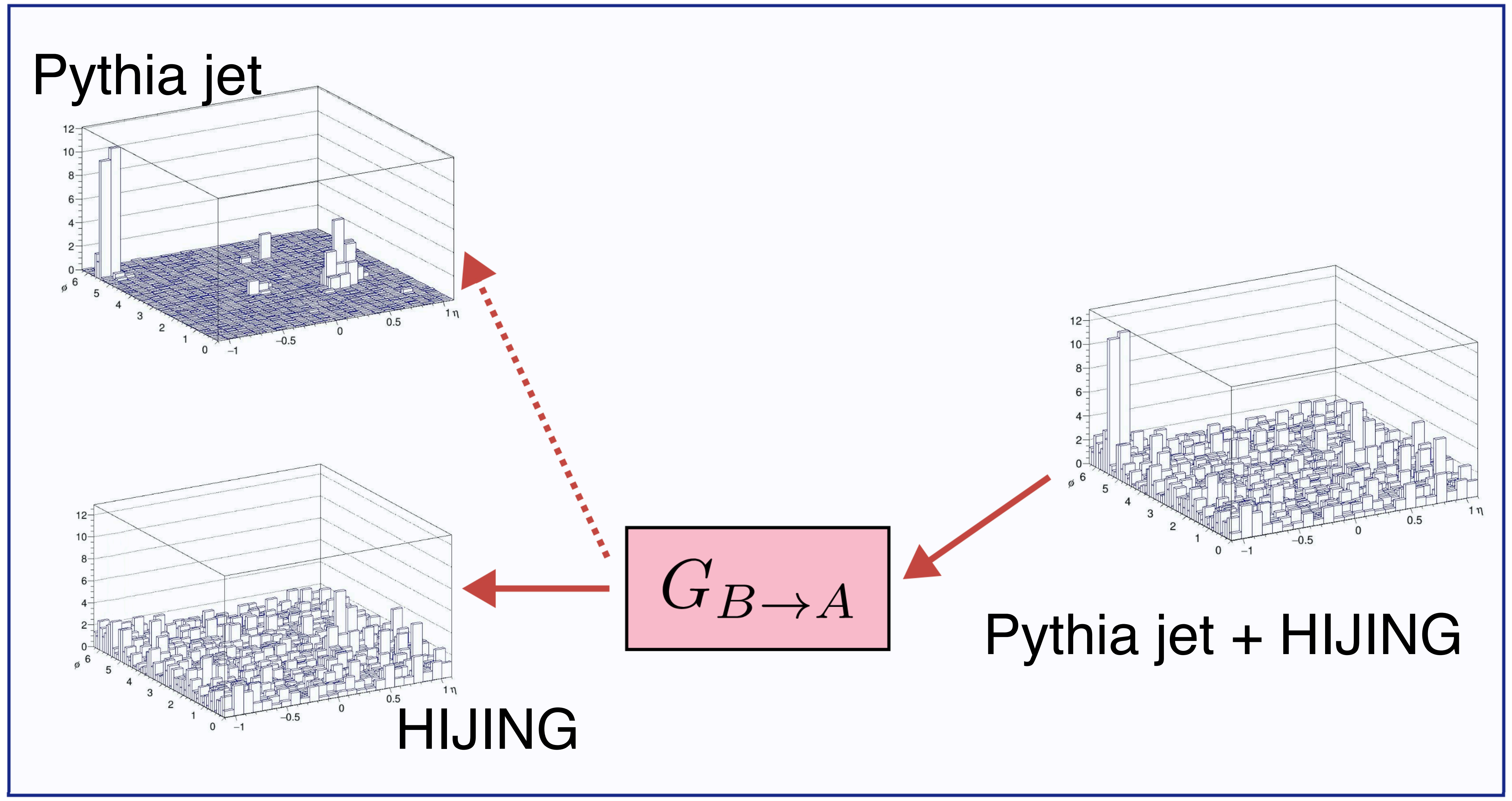
(a) $A \to B$

Work-in-progress

Jet Background Subtraction (2)

- **B-to-A** (**jet background subtraction**) is also qualitatively described well !

A B



Work-in-progress

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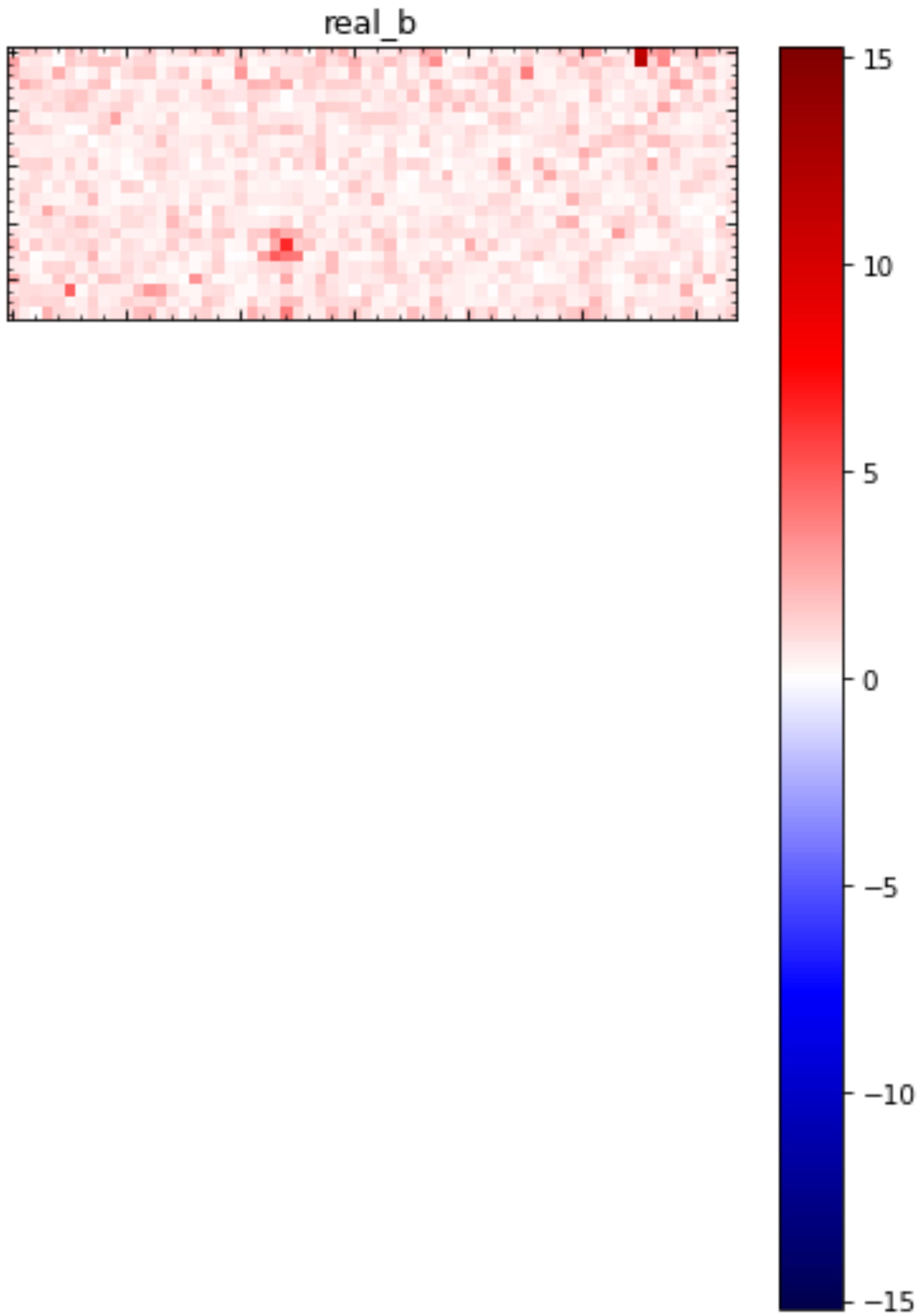
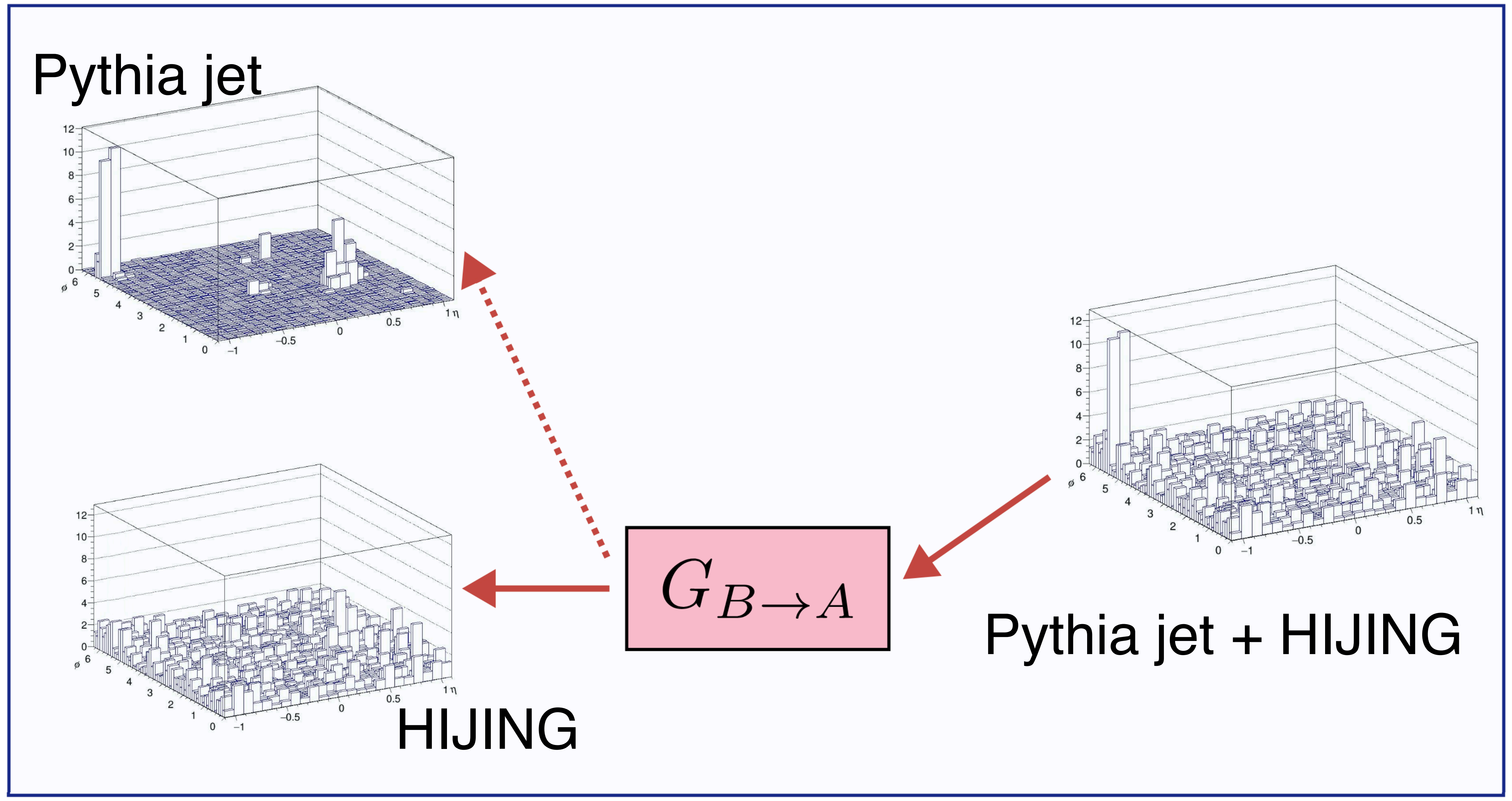
(Input) HIJING+Pythia



A

B



Work-in-progress

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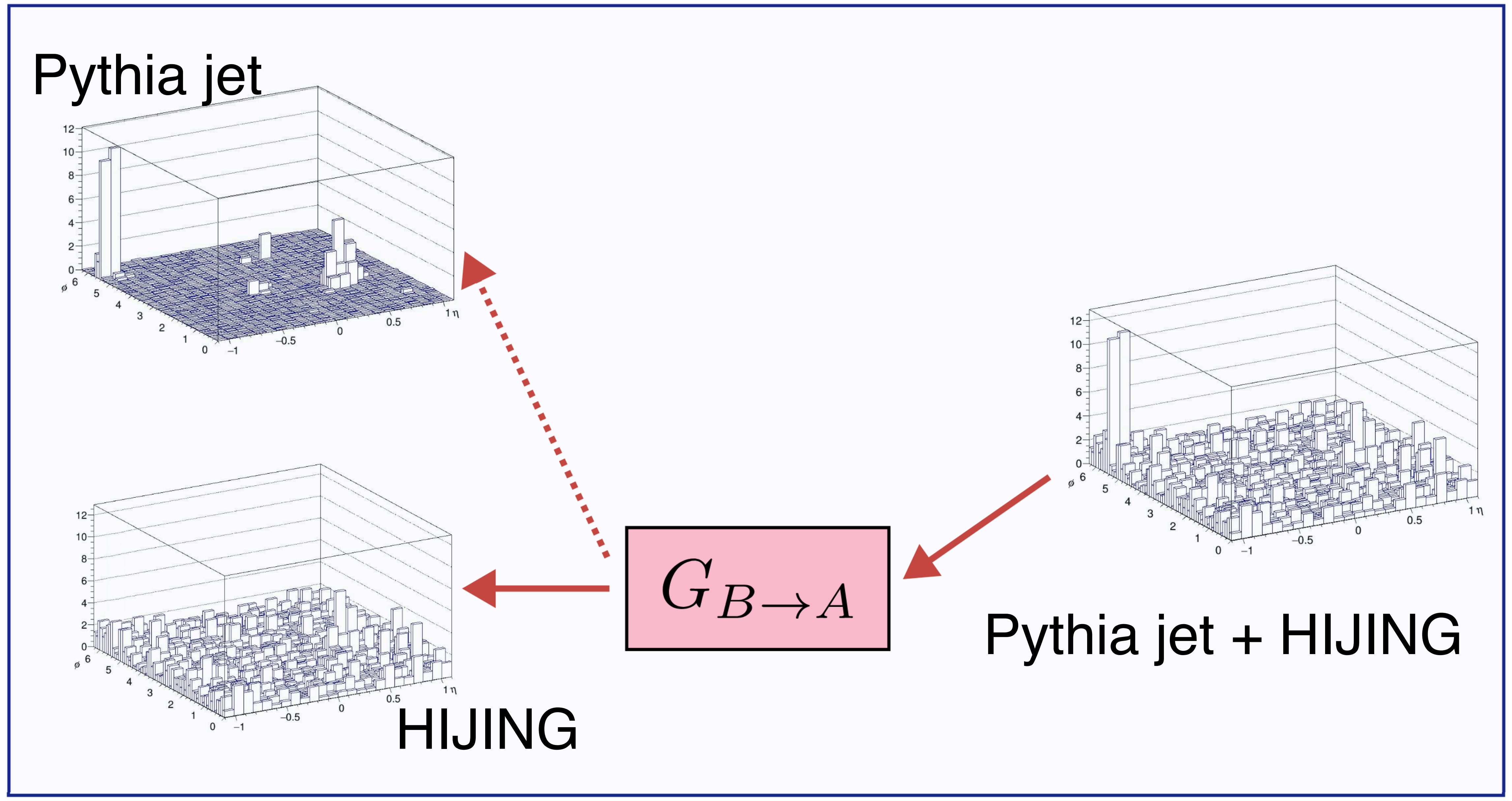
A

B

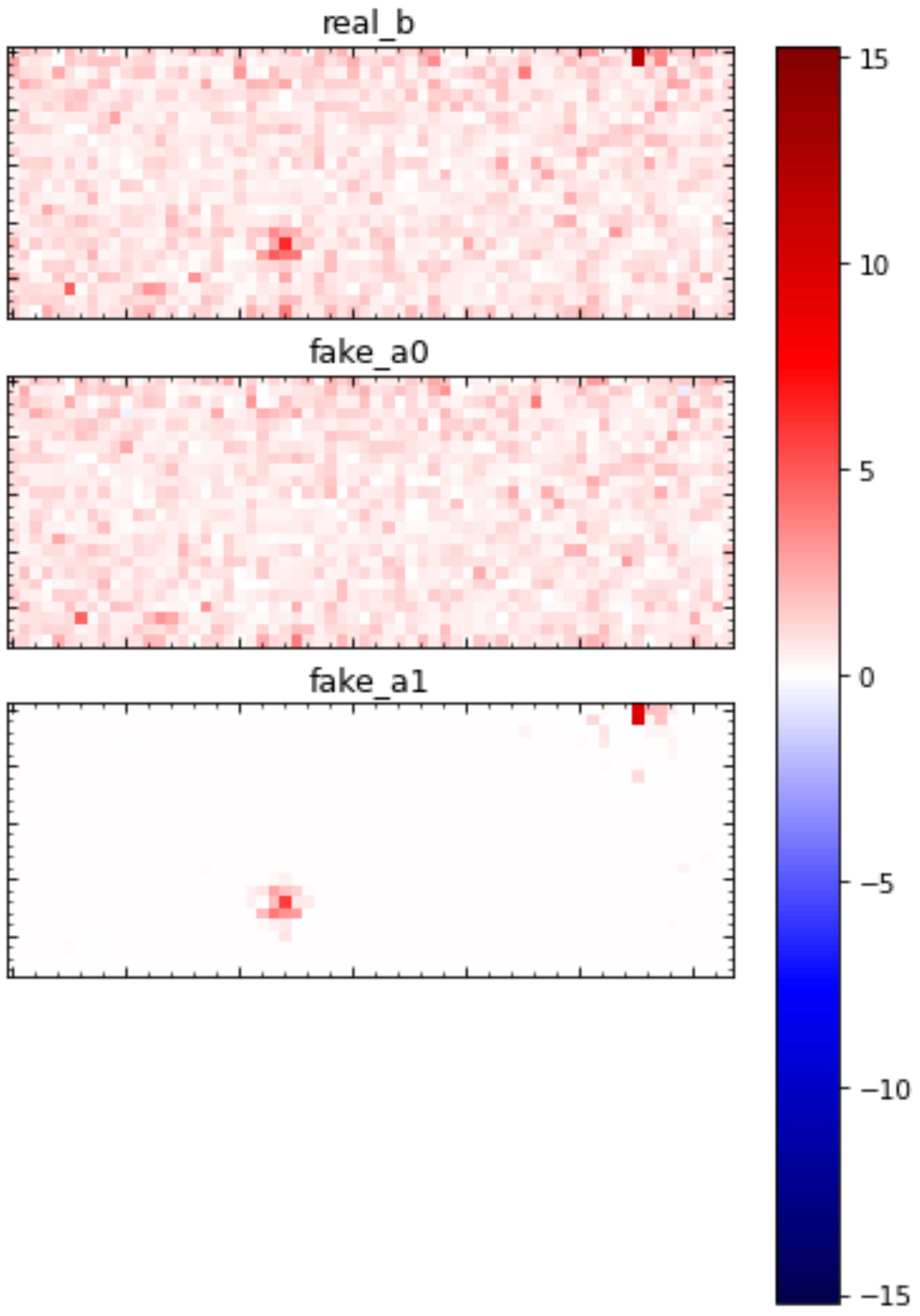
B→A generated by UVCGAN



(Input) HIJING+Pythia

Background (HIJING)

Jets



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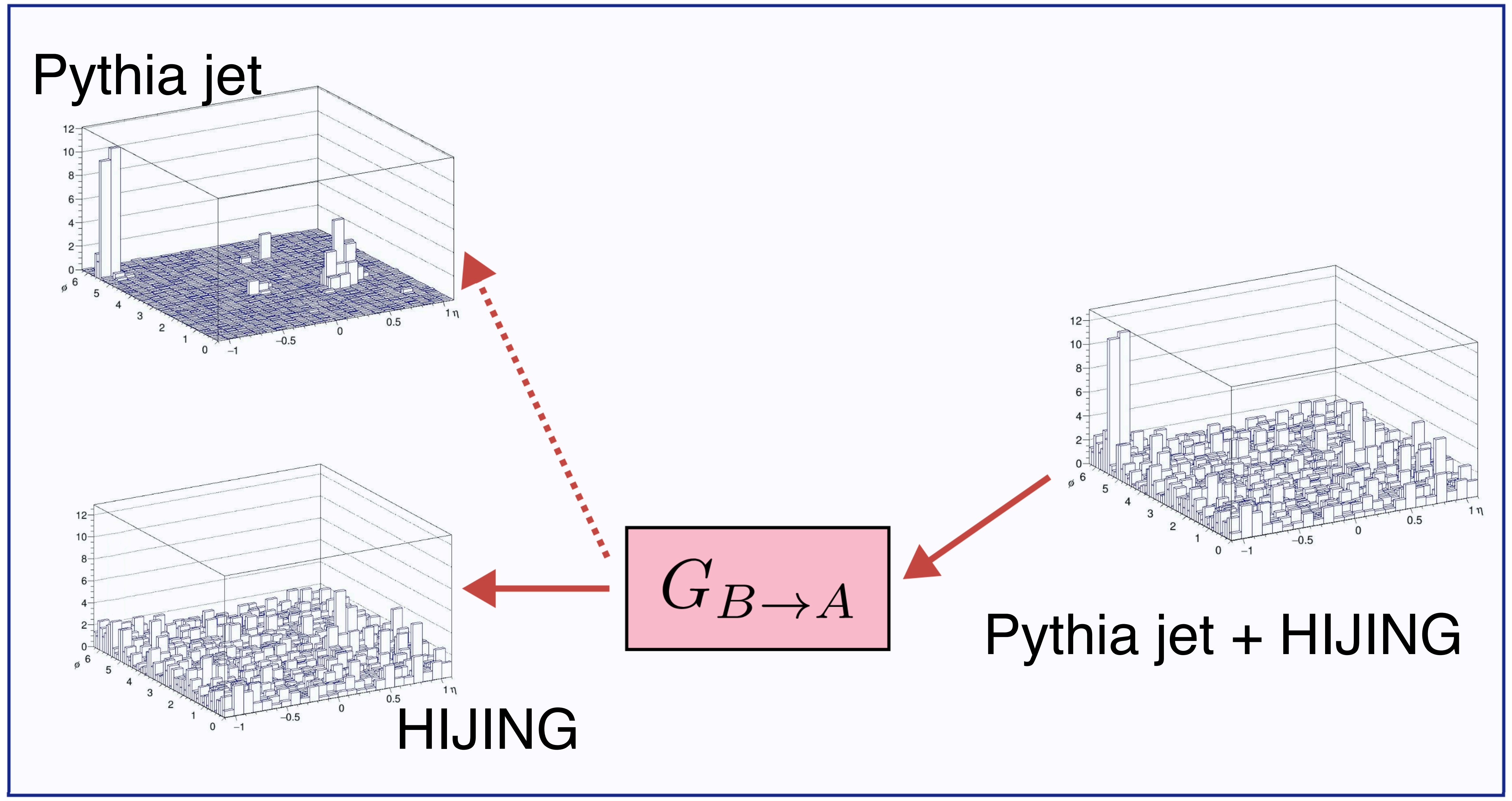
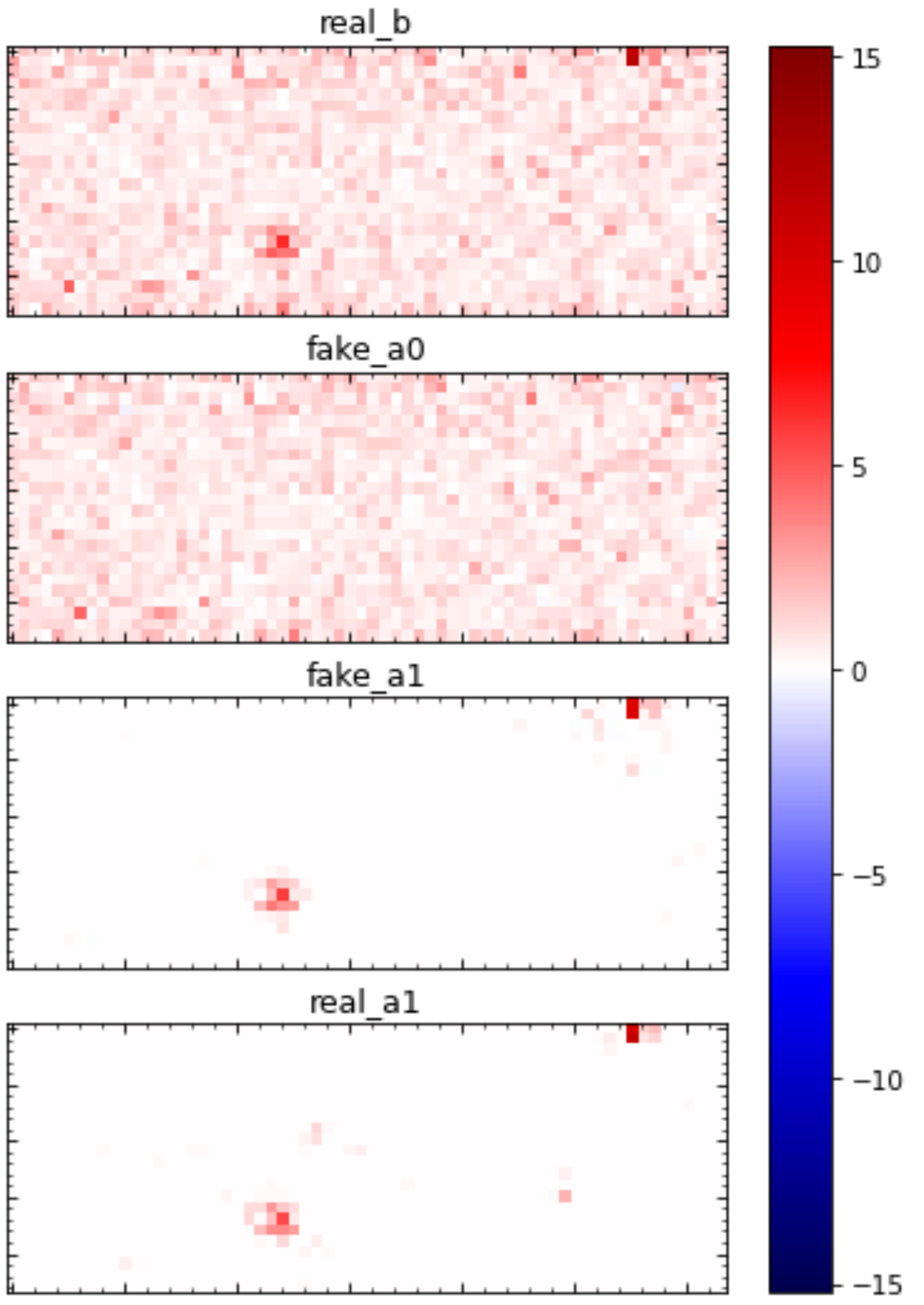


(Input) HIJING+Pythia

Background (HIJING)

Jets

Reference Pythia jet



Work-in-progress

(b) $B \to A$

Summary and Conclusion

- Generative AI Simulations of high energy nuclear experiments
  ➡ **highly complex** and **computationally intensive**
  ➡ both fidelity and speed is important
  ➡ *Generative AI can speed up and produce large amount of the heavy ion event simulations!*

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- **Diffusion model (DDPM)** was used to generate the whole-event, full-detector simulated calorimeter data in high fidelity for the first time in heavy ion collisions *Phys. Rev. C 110, 034912*
  ➡ GAN used as a reference
  ➡ DDPM outperforms GAN for scientific fidelity
  ➡ trade-off found between training / generation duration and the quality of reproducing the rare feature

Summary and Conclusion

- Generative AI Simulations of high energy nuclear experiments
  ➡ **highly complex** and **computationally intensive**
  ➡ both fidelity and speed is important
  ➡ *Generative AI can speed up and produce large amount of the heavy ion event simulations!*

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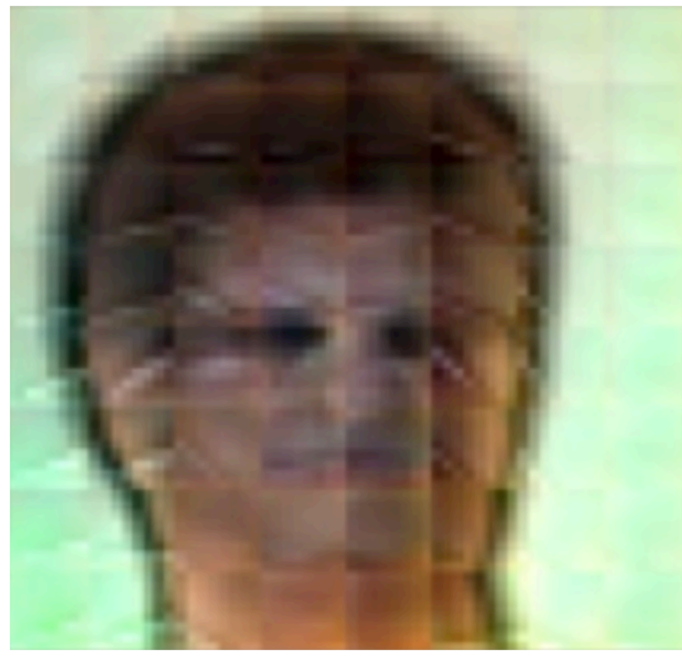
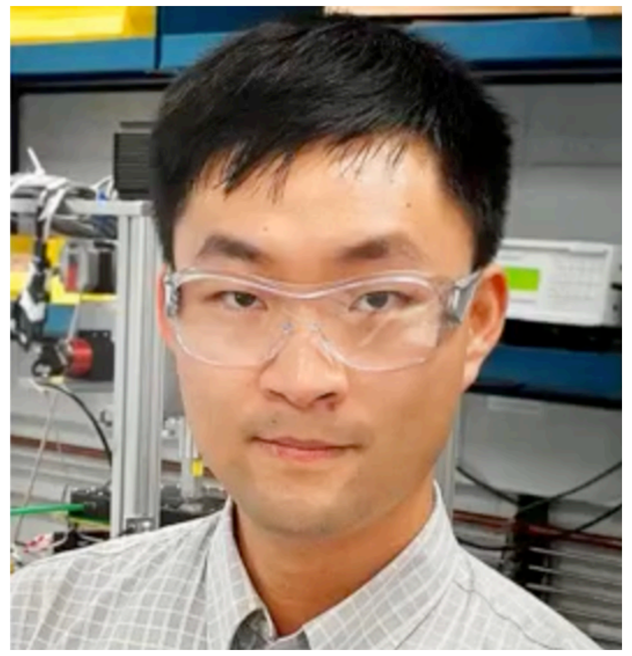
- For the first time, a **self-supervised generative model** is used for **jet background subtraction** in heavy ion collisions; *cycle-consistent GAN for image-to-image translation*
  ➡ *can bridge gap between the data and simulation*
  ➡ *first look is very promising. Stay in tune!*

Our Team

Yeonju Go



Dmitrii Torbunov



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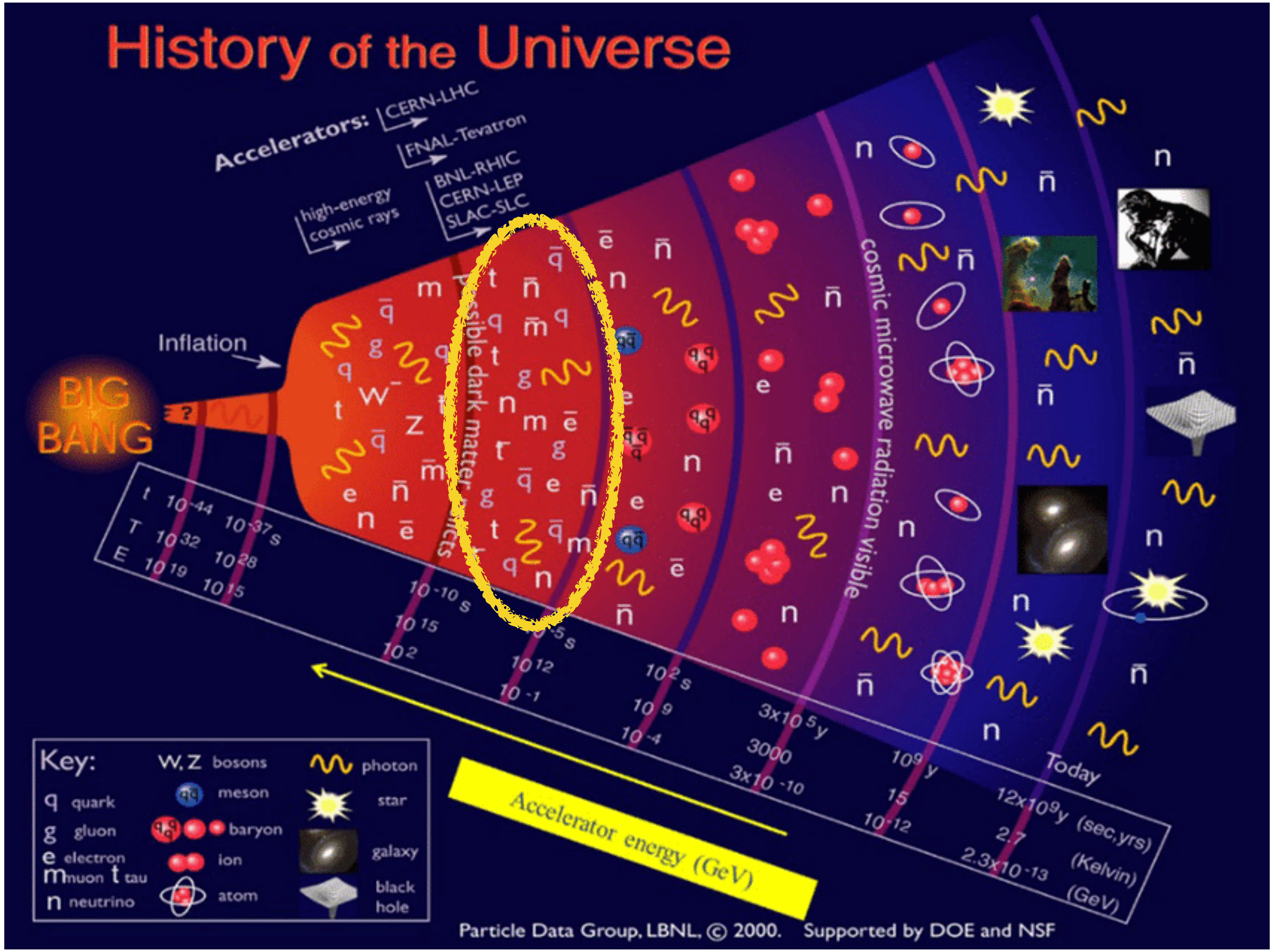
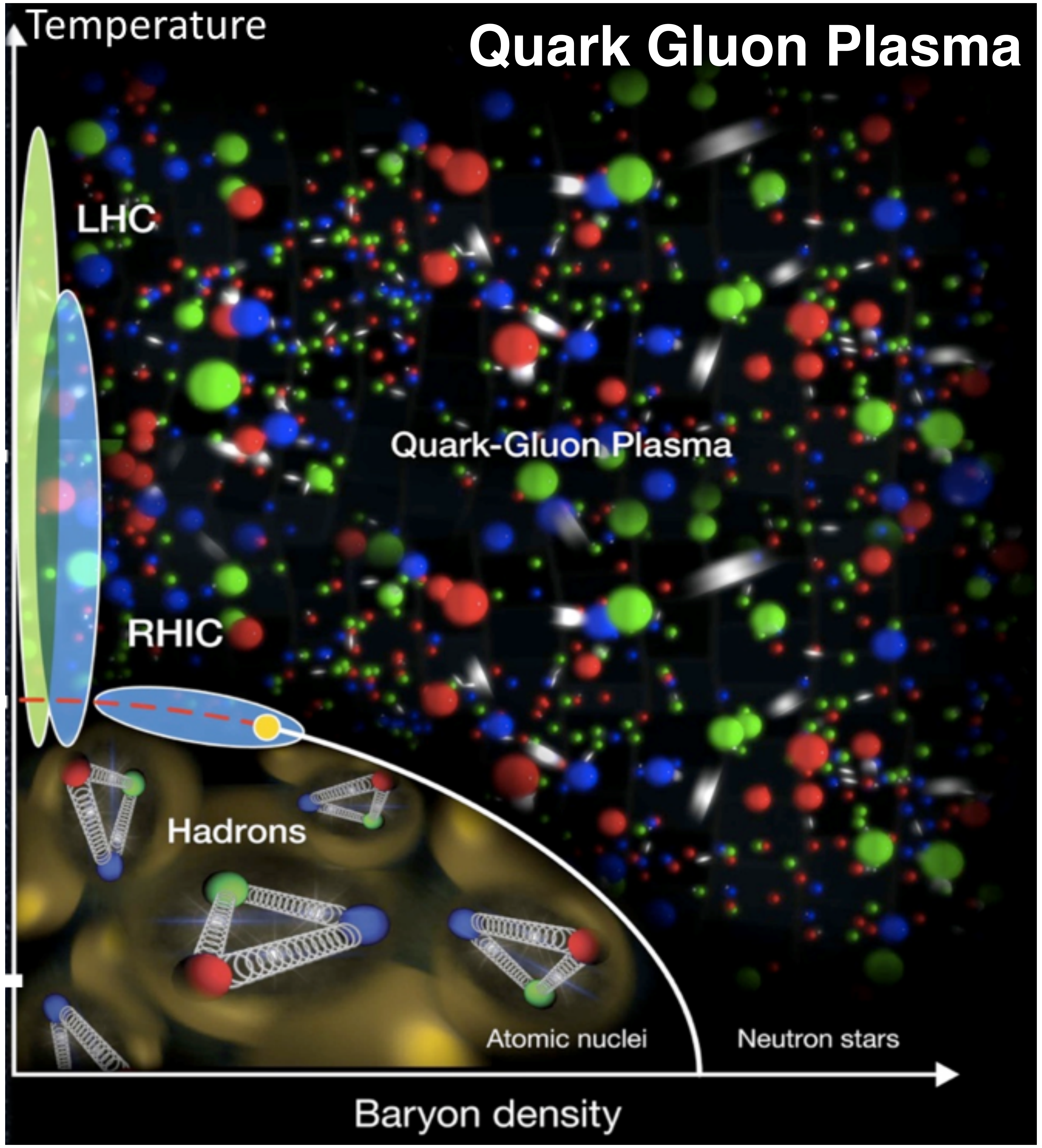
- We thank the sPHENIX collaboration for access to the simulated dataset, which was used in the training and validation of our algorithm.

BACKUP

Early Universe and Quark Gluon Plasma

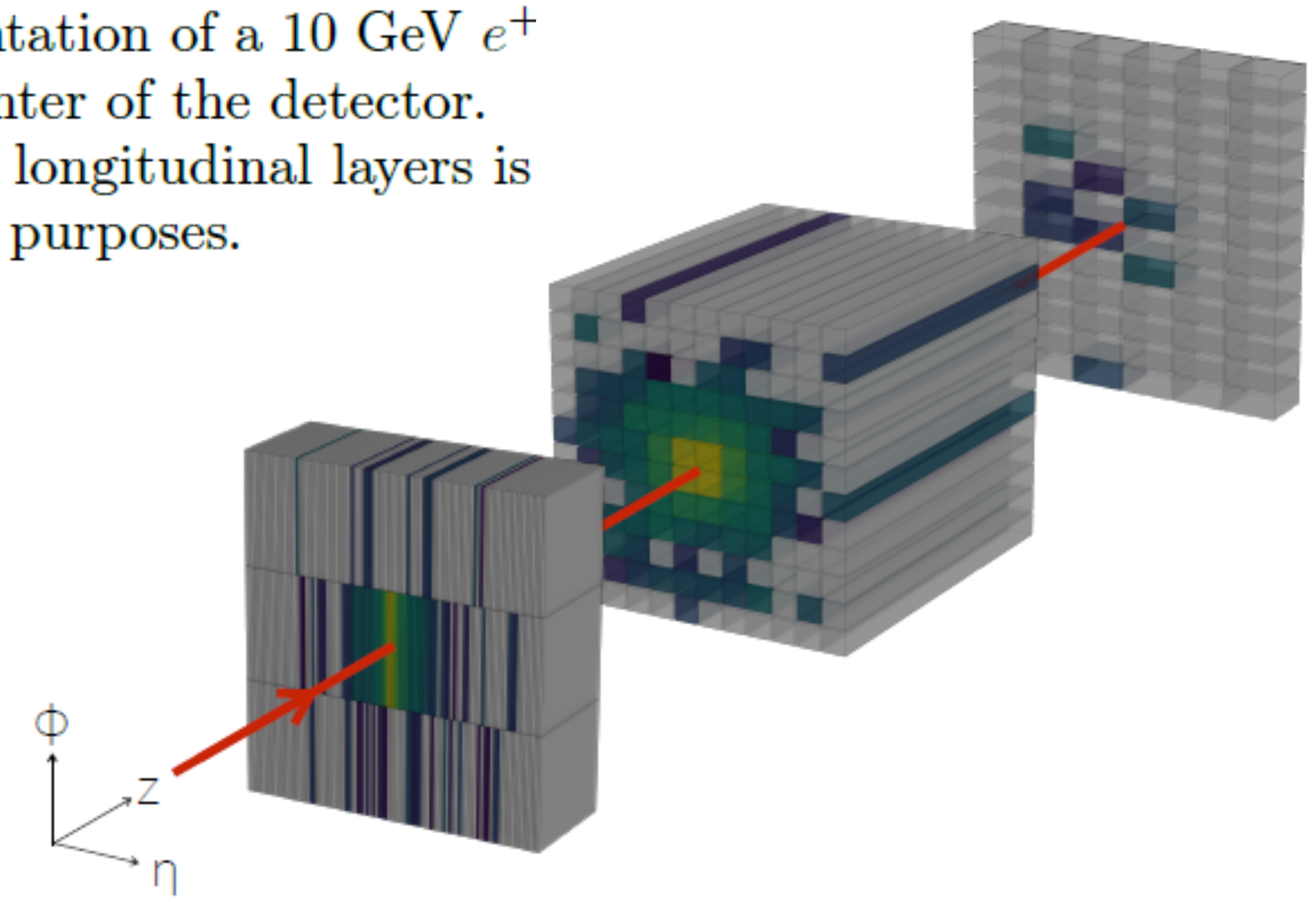




Generative AI

- **Generative Adversarial Networks (GAN)**
  - ➡ actively used in high energy physics *(e.g. arXiv:1712.1032, arXiv:2209.07559, EPJC 80 (2020) 688, arXiv:2210.14245)*

FIG. 2: Three-dimensional representation of a 10 GeV e^+ incident perpendicular to the center of the detector. Not-to-scale separation among the longitudinal layers is added for visualization purposes.



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  ➡ actively used in high energy physics
  (e.g. arXiv:1712.1032, arXiv:2209.07559, EPJC 80 (2020) 688, arXiv:2210.14245)
- **Diffusion Models**: text-to-image generation in industry (e.g. StableDiffusion, Midjourney, Dalle-2)

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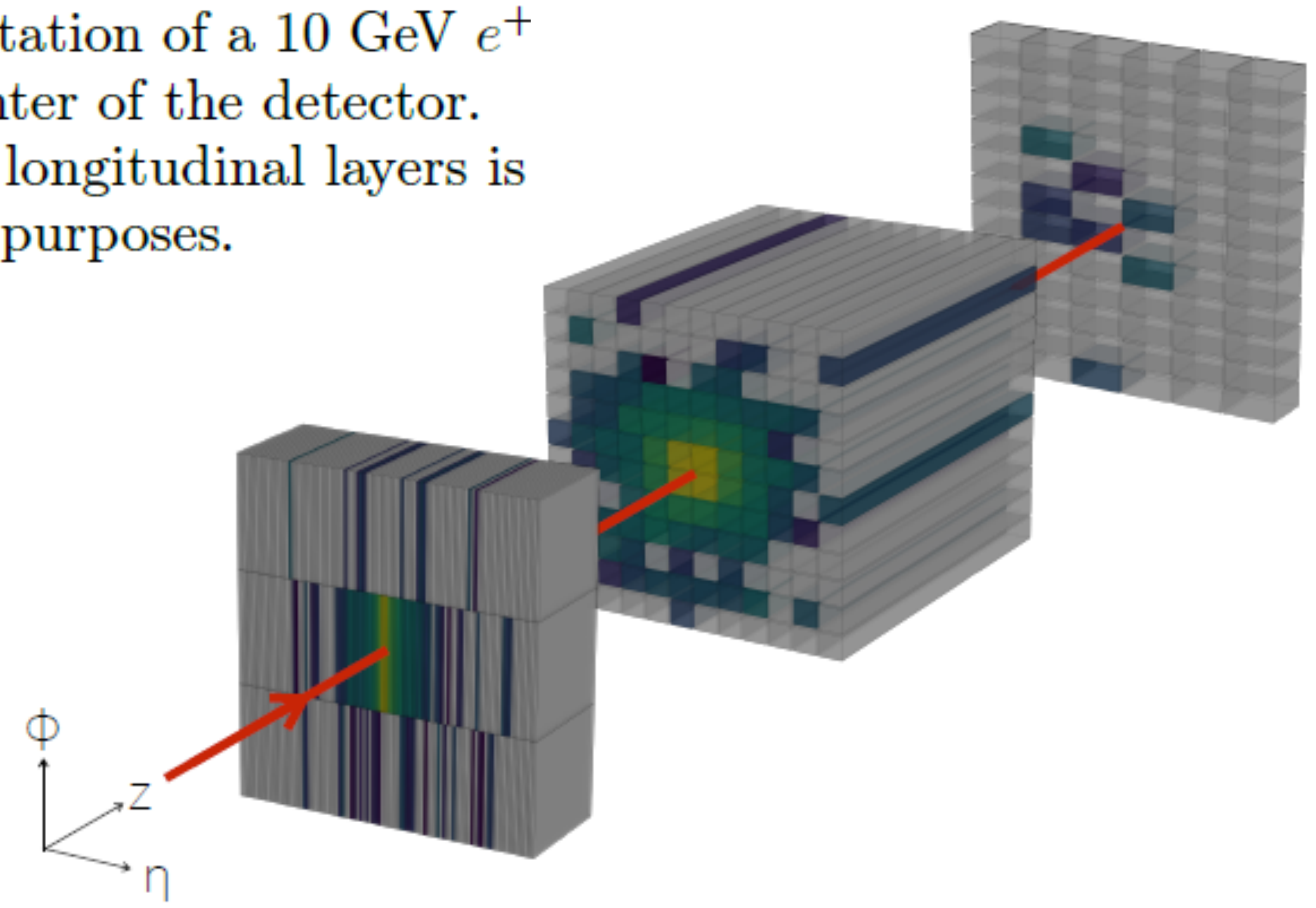
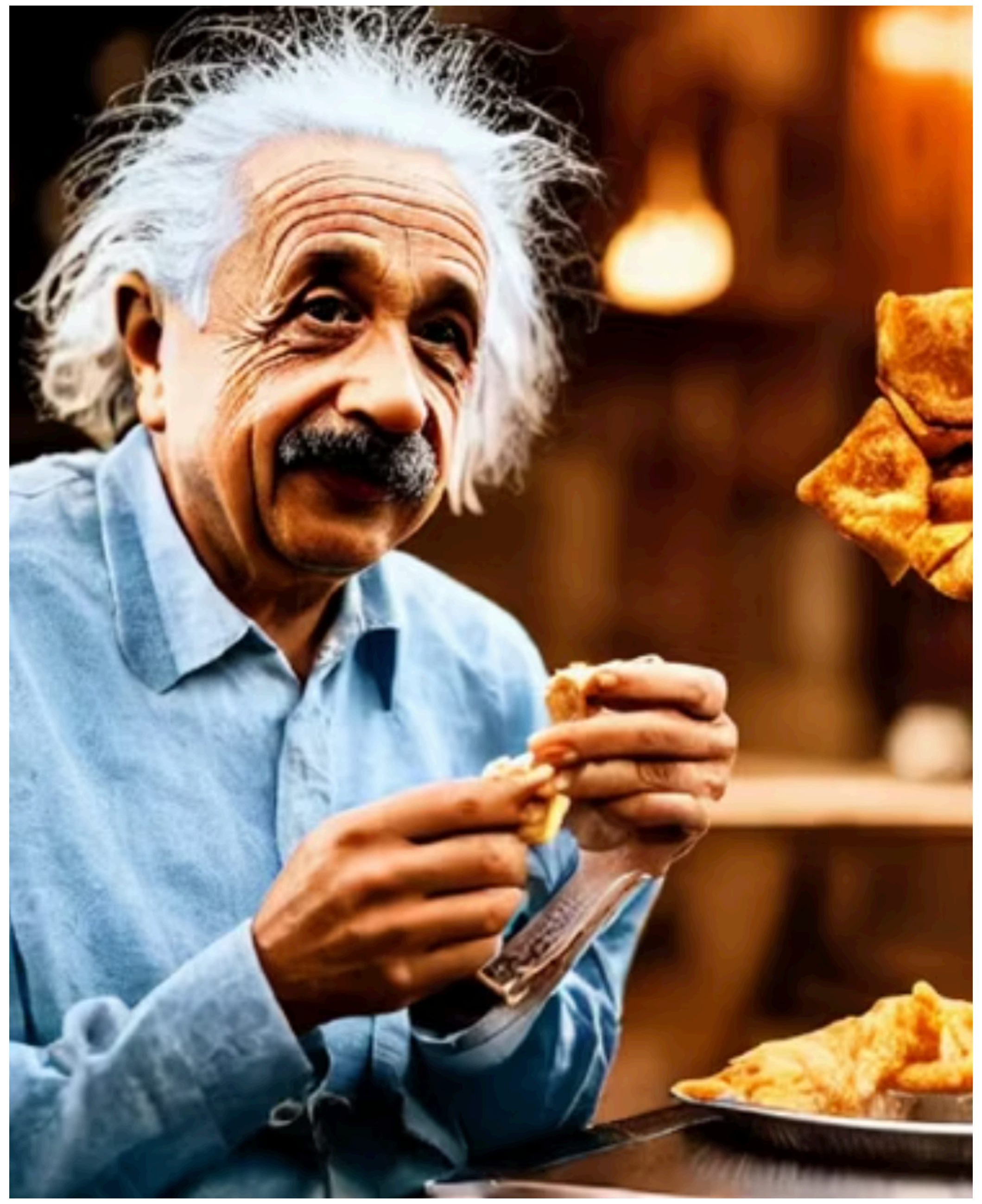
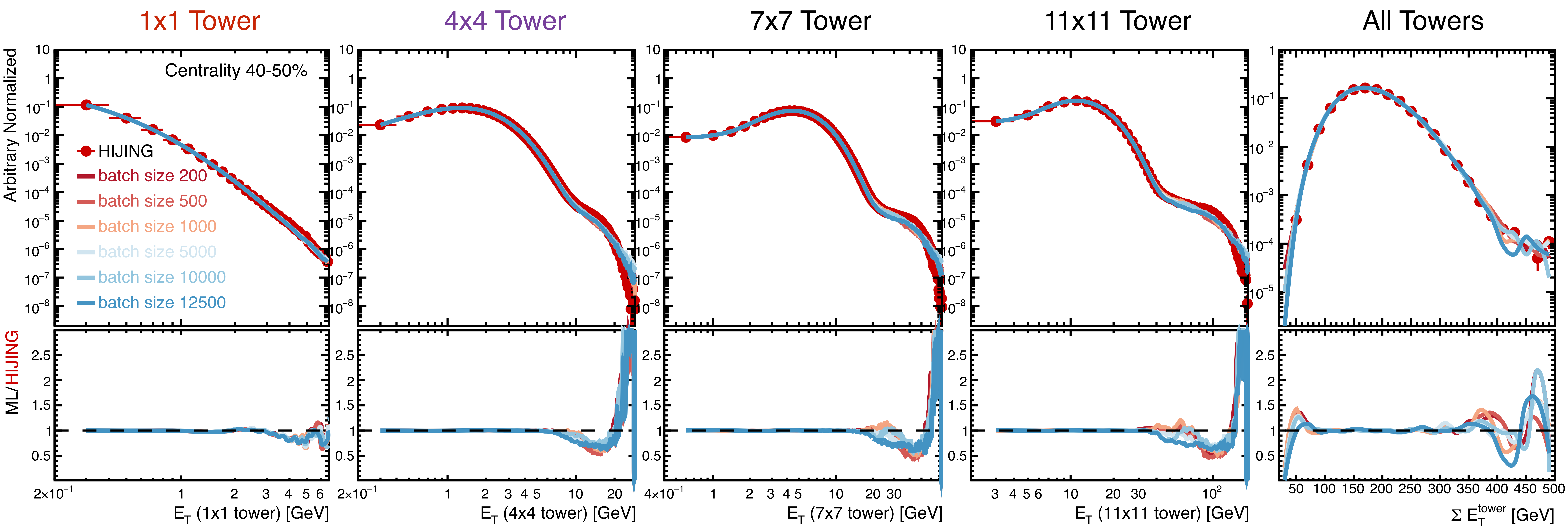




DDPM Configuration

- number of diffusion steps T: default 8000 / variation [1000, 16000]
- variance schedule β_t: default 0.1 / variation [0.02, 0.2]
- training batch size: default 128 / variation [100, 12500]
- training steps per epoch: default 2000
- epoch: default 4000 / variation [100, 4000]
- training with the Adam optimizer with learning rate 10^{-4}
- trained with 600,000 events per each centrality bin
- tested with 100,000 events per each centrality bin
- neural network architecture (U-ResNet + Attention)
- depth/width of the model
  ➡ U-Net encoder-decoder stage, channels per stage: 32, 64, 128
  each of which comprised of two ResNet blocks

Batch Size Dependence



- Batch size not only introduces different random seeds and but also changes variance schedule (β_t)