Application of Generative AI in Heavy Ion Collisions

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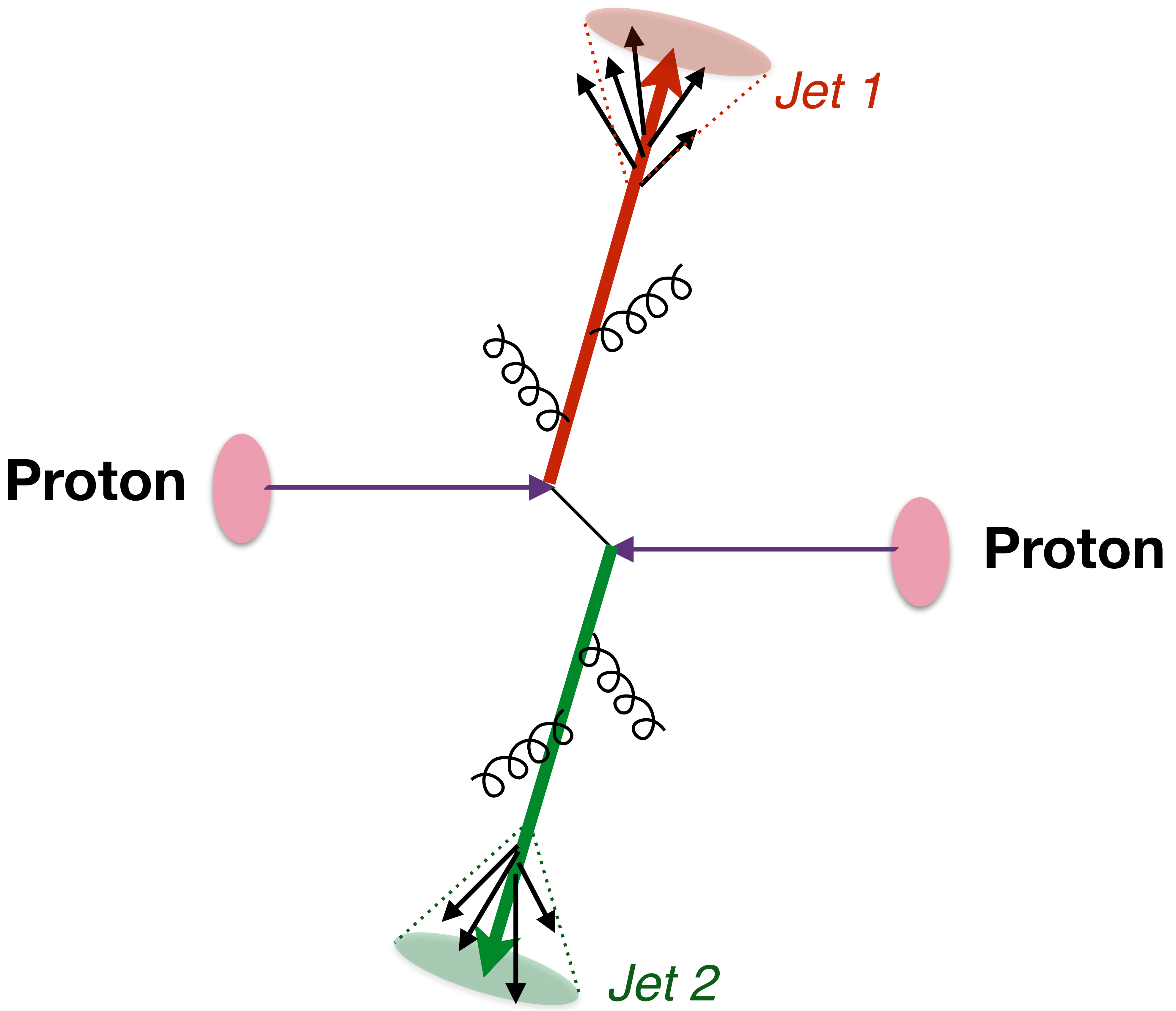
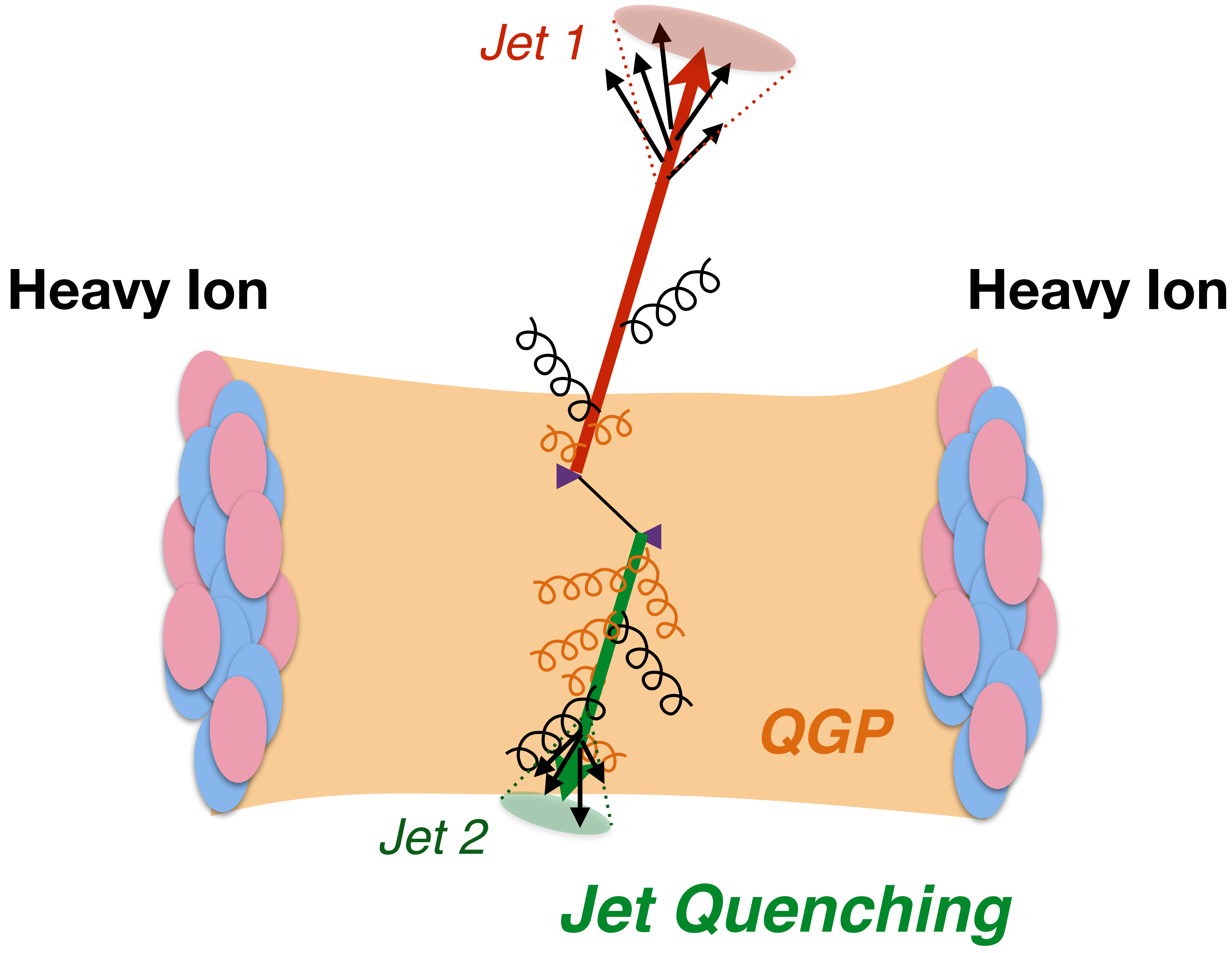
U.S. DEPARTMENT OF ENERGY

Brookhaven National Laboratory

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 in the heavy ion collisions





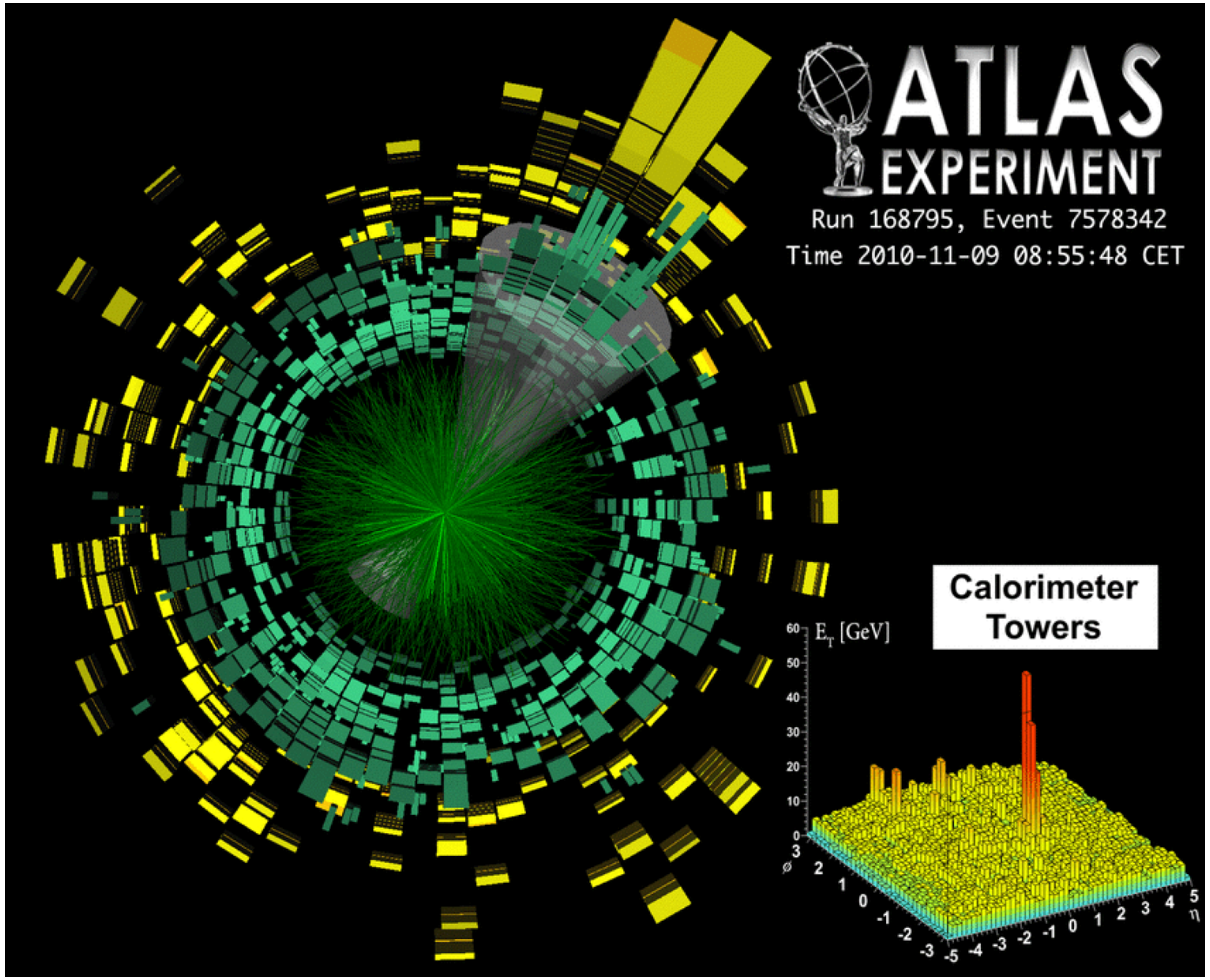
Jets in Heavy Ion Collisions (2)

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

Topic 1: HIJING simulation event generation using diffusion model

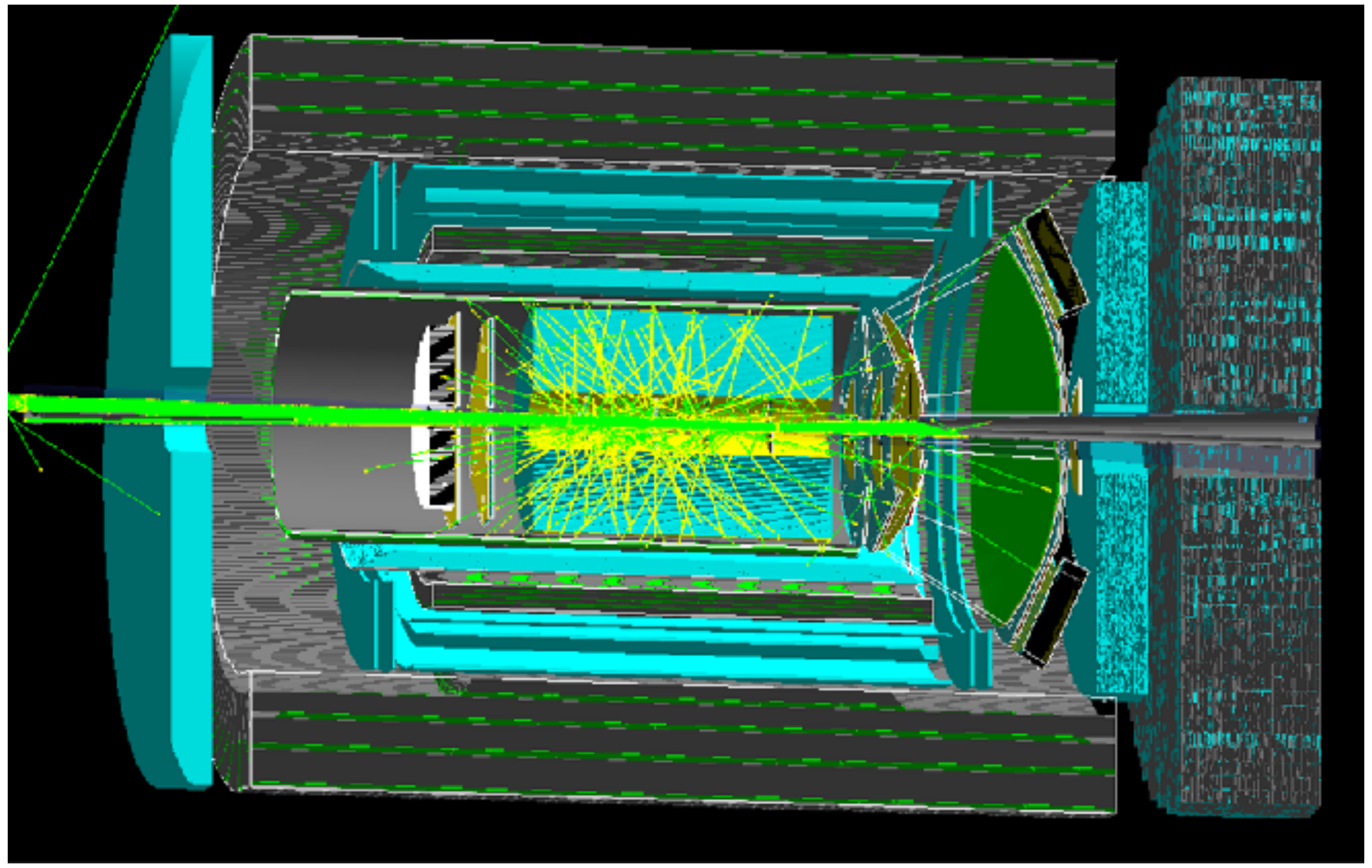
- The huge amount of ***underlying event background*** produced from multiple nucleon-nucleon collisions **has to be *estimated* and *subtracted*** from **jet reconstruction**

Topic 2: Jet background subtraction using cycleGAN model

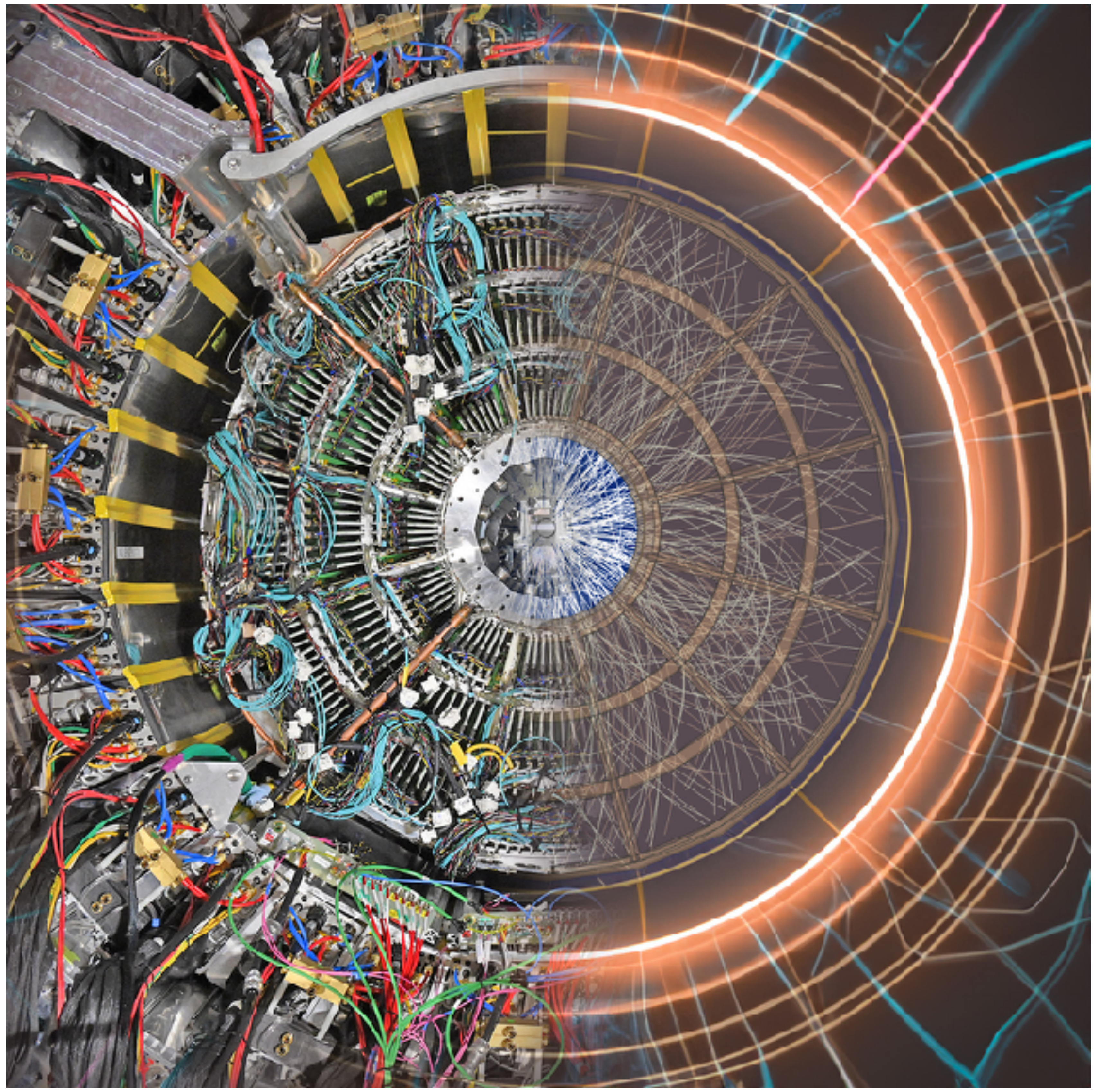


Simulations of Relativistic Heavy Ion Collisions

- ***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**
- *Electron-Ion Collider* will need a large amount of simulations of full detector with both physics and machine background
- <u>ML can speed up and produce large amount of the heavy ion event simulations!</u>



EIC CDR

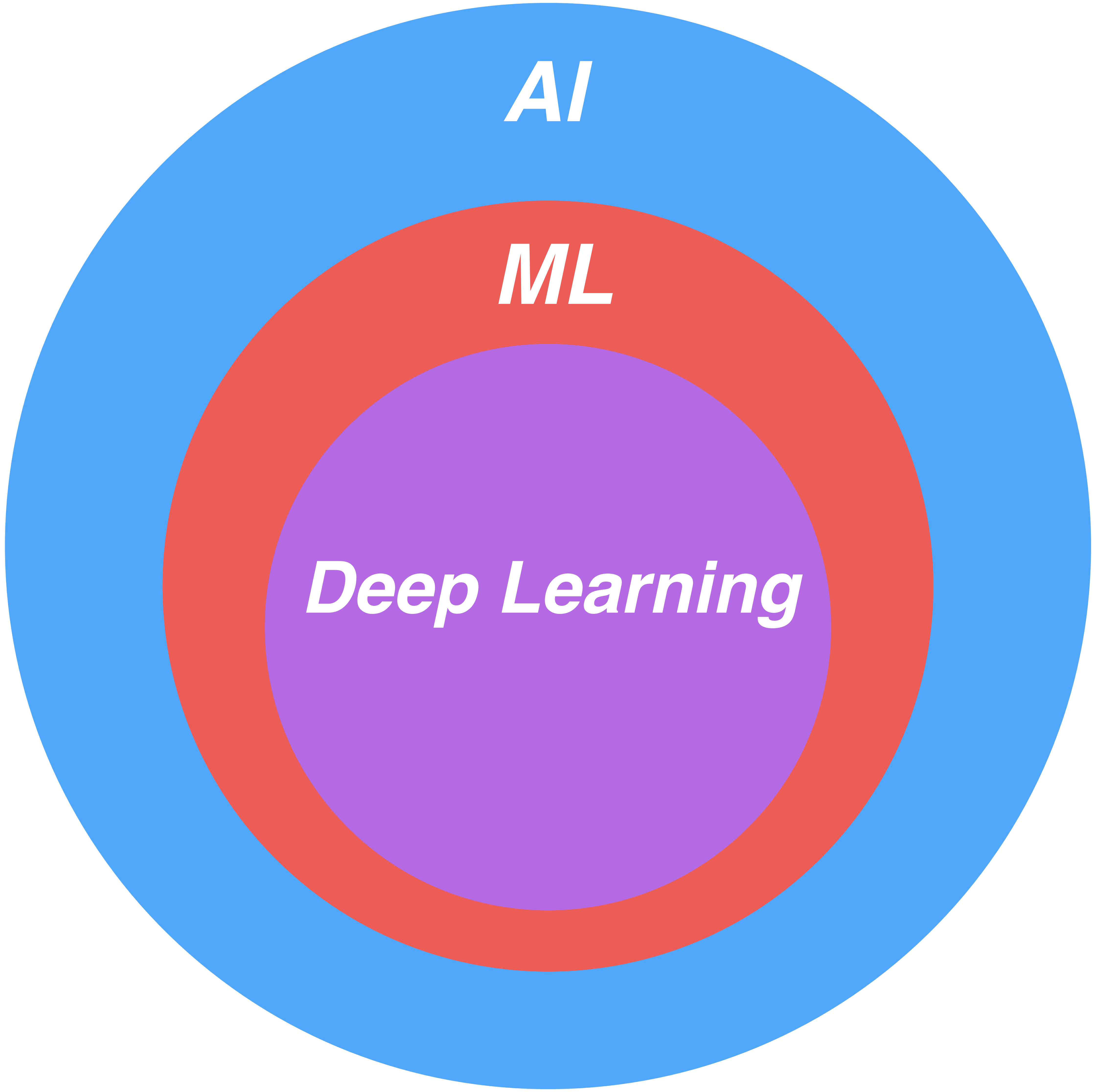


sPHENIX TPC

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

Phys. Rev. C 110, 034912

Artificial Intelligence (AI) and Machine Learning (ML)



Artificial Intelligence (AI)
- mimic cognitive functions associated with human intelligence
e.g. see, understand, respond, analyze data, make recommendations, etc

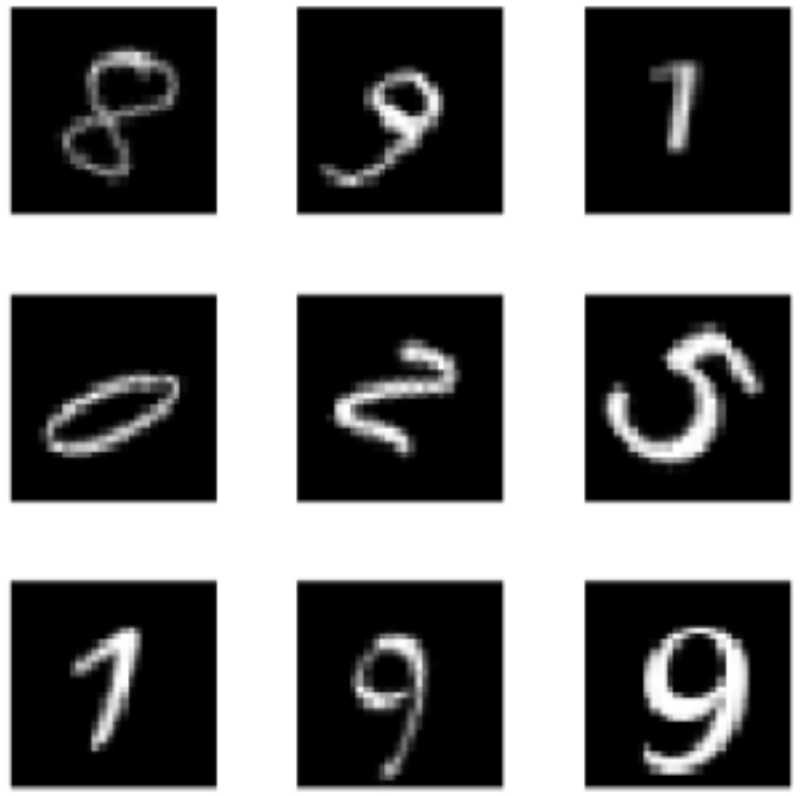
Machine Learning (ML)
- extract knowledge from data and learn from it autonomously
- no explicit programming

Deep Learning (DL)
- learn based on deep neural network

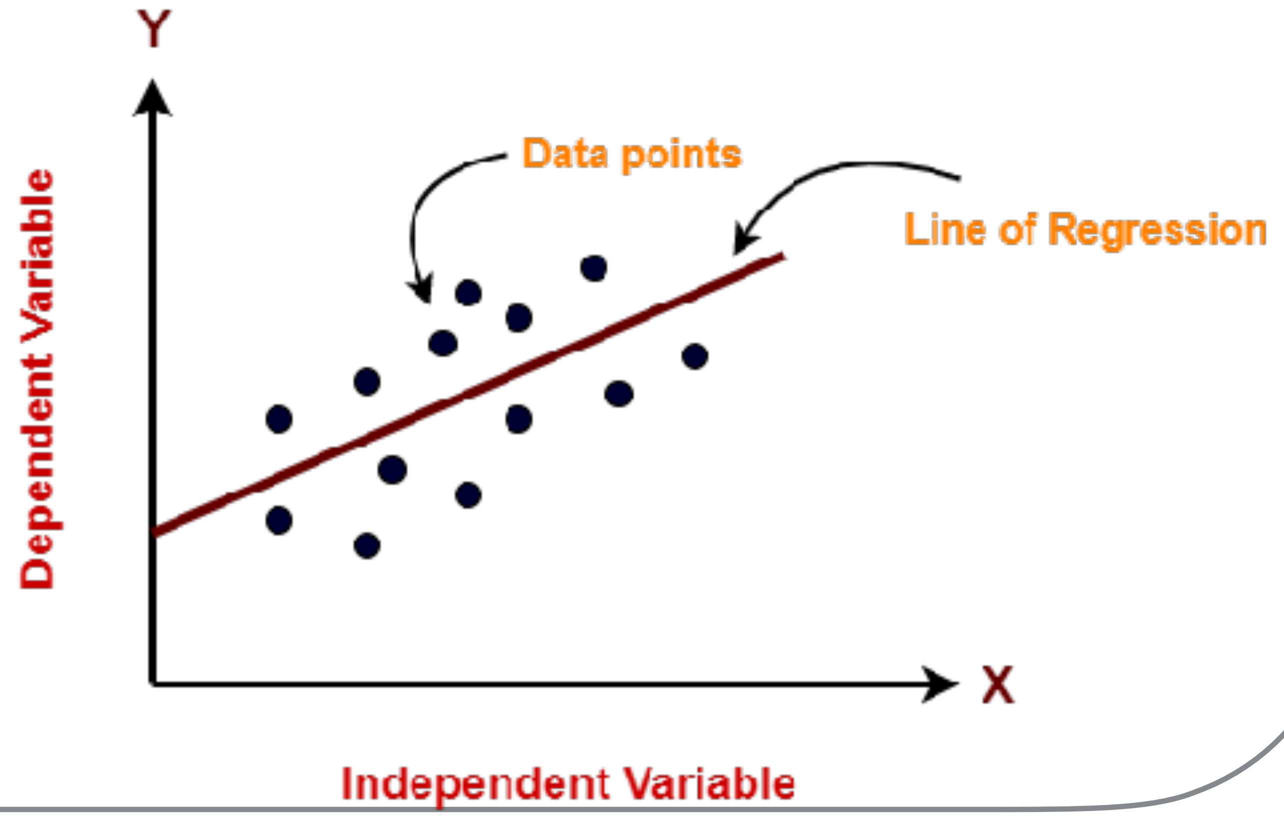
Supervised vs Unsupervised ML

Supervised

- Use labelled data
- Input-output values are given by human
- Forecast outcomes
- Classification …………

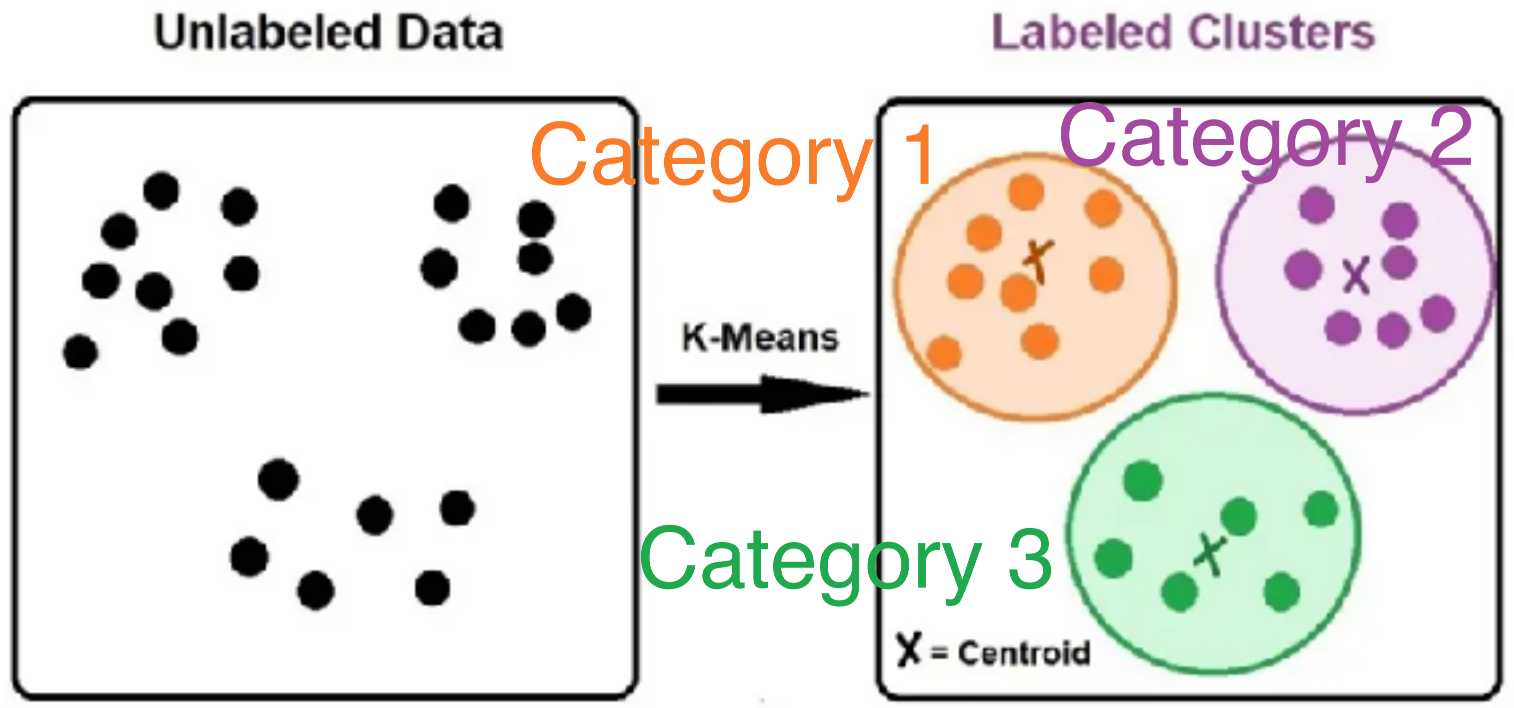


- Regression ……



Unsupervised

- Use unlabelled data
- Grouping and no prediction
- Find hidden patterns w/o human intervention
- Clustering

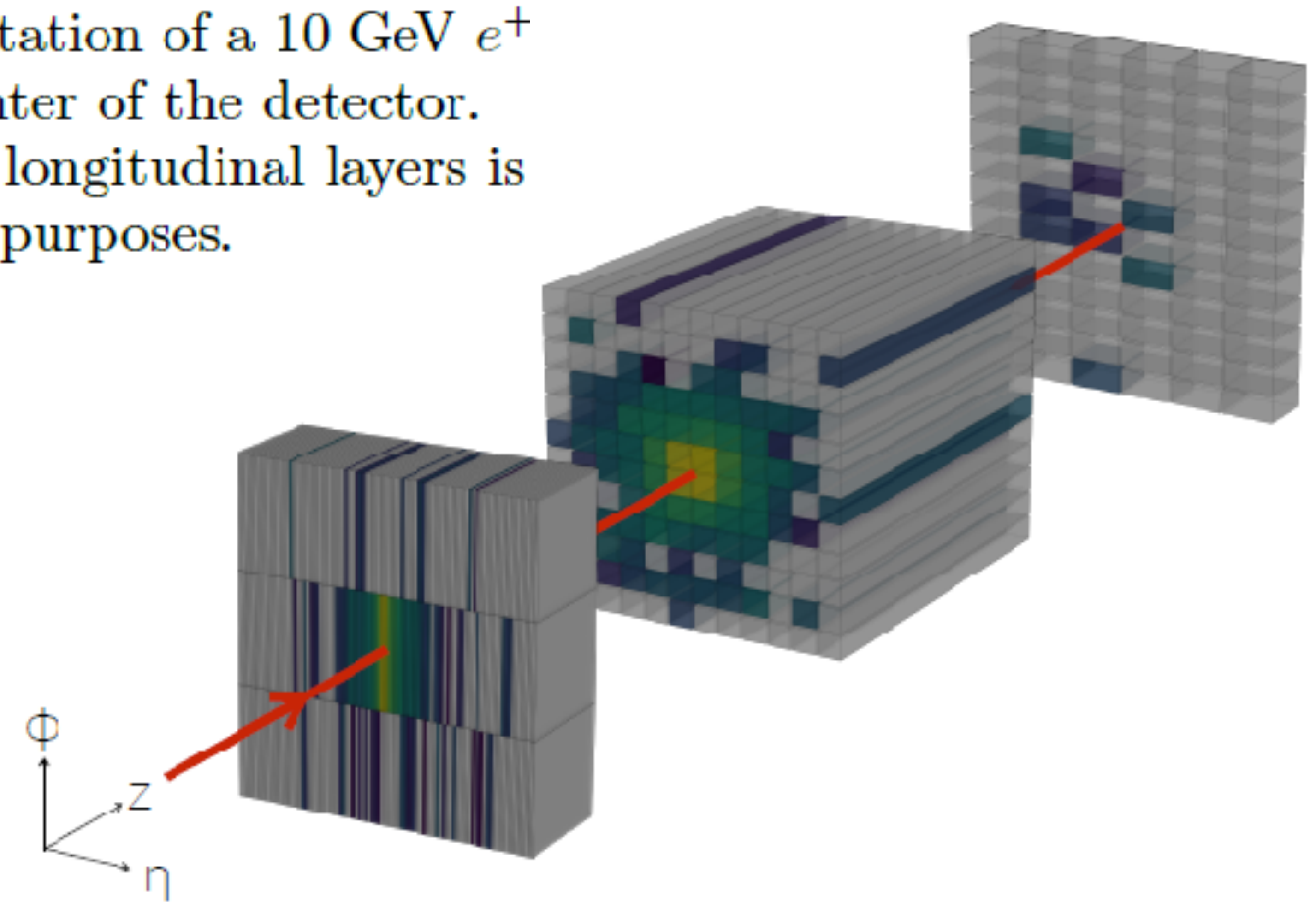


- Association
- Dimension Reduction
- Anomaly detection

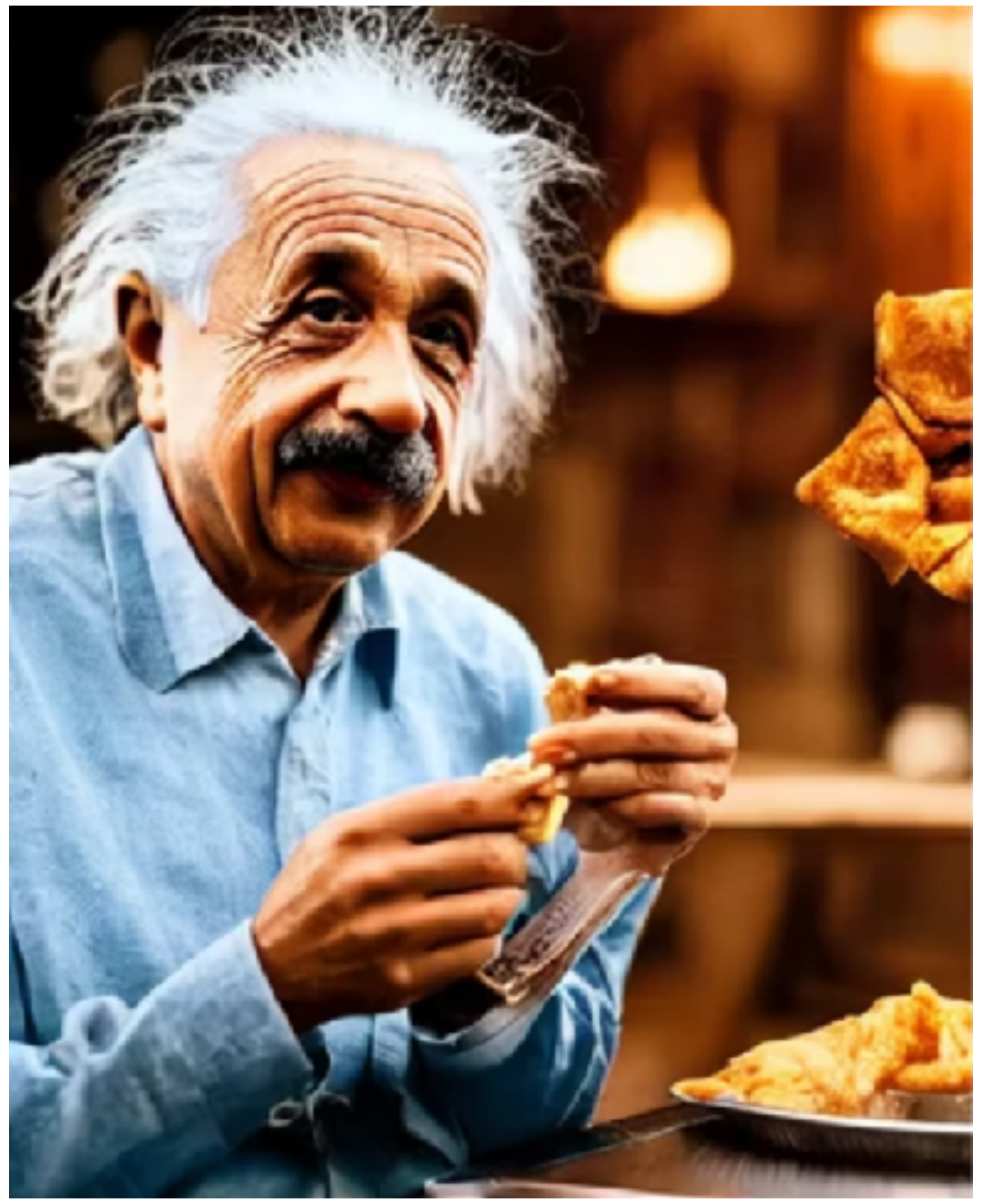
Generative AI Models

- **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.

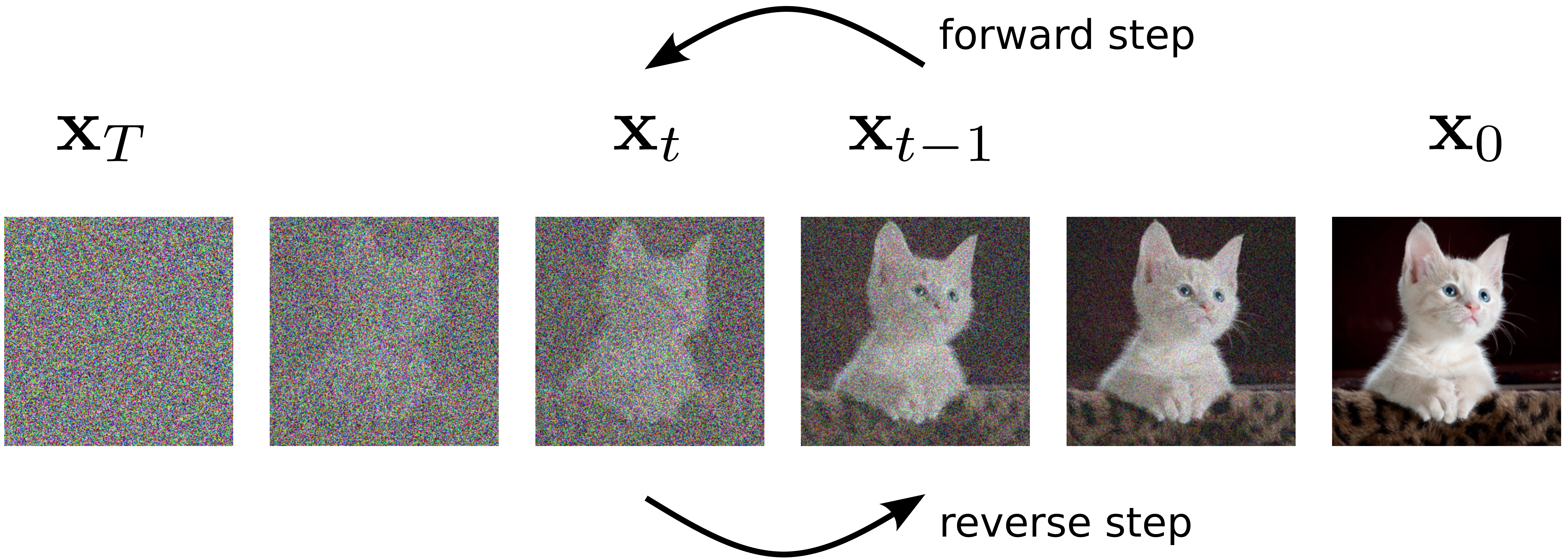


- **Diffusion Models**: text-to-image generation in industry (e.g. StableDiffusion, Midjourney, Dalle-2)

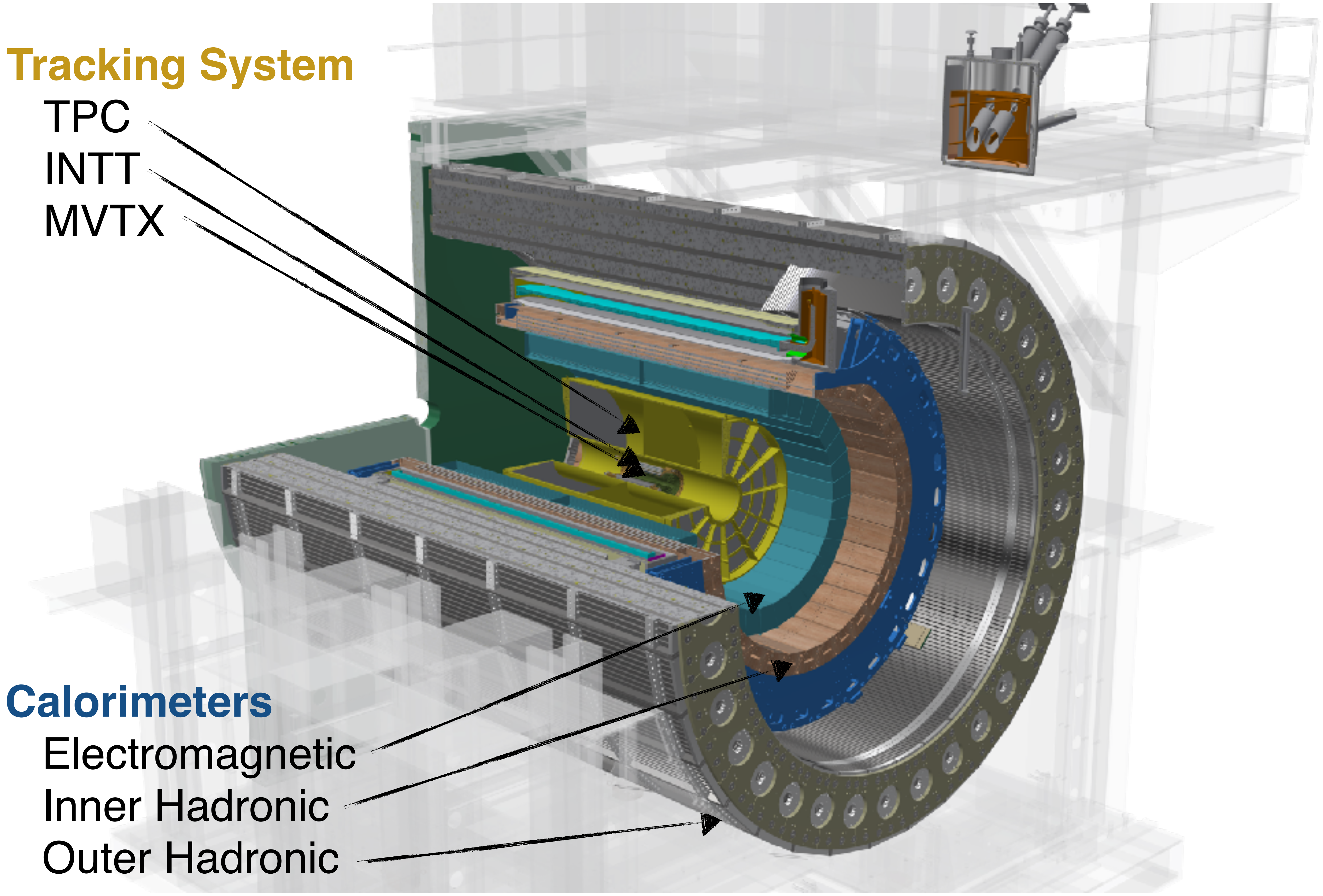


Denoising Diffusion Probabilistic Model (DDPM)

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



sPHENIX Detector at RHIC

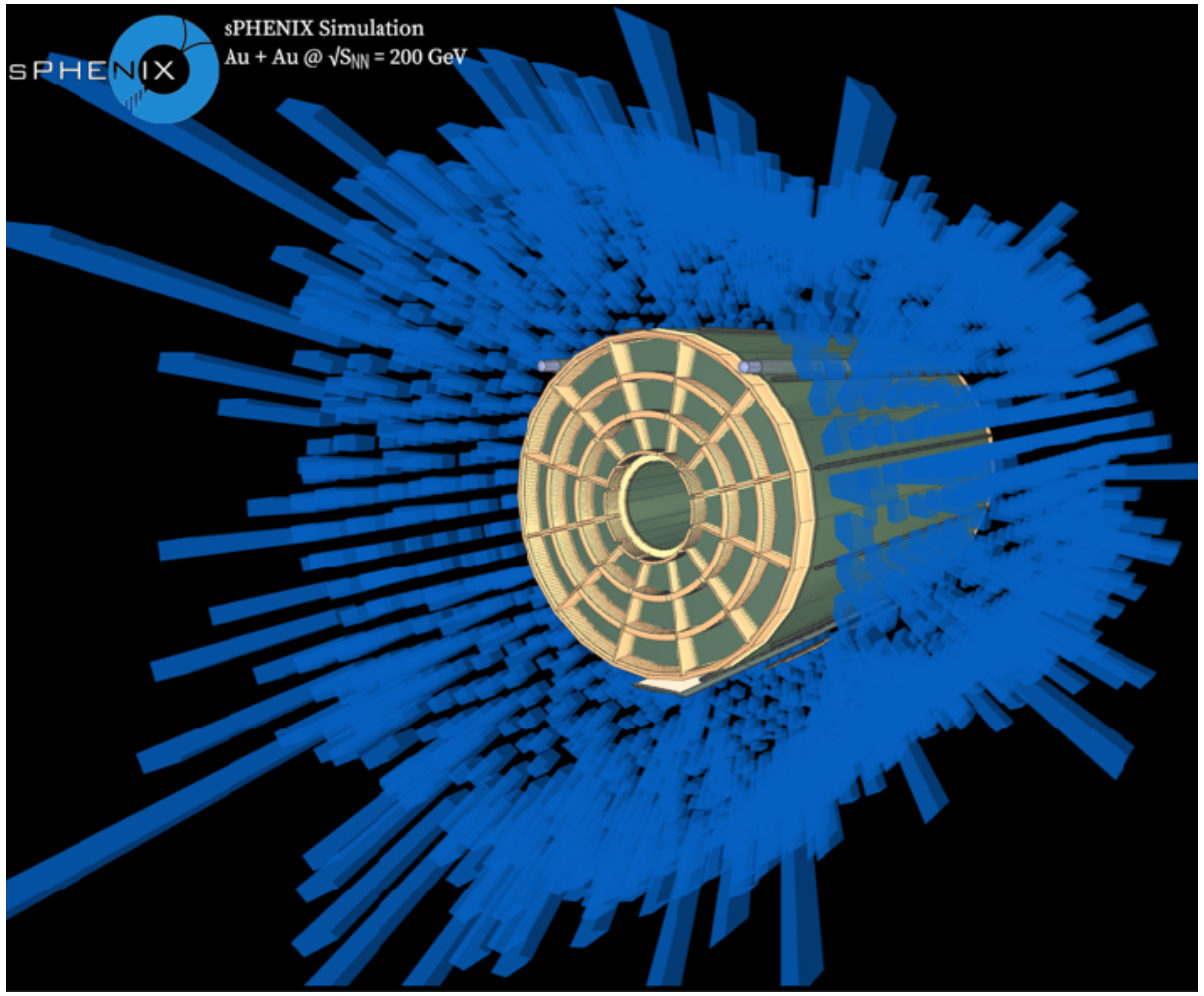


- Data taking began last year!
- High-precision tracking system +
  Hermetic Electromagnetic & Hadronic calorimeters

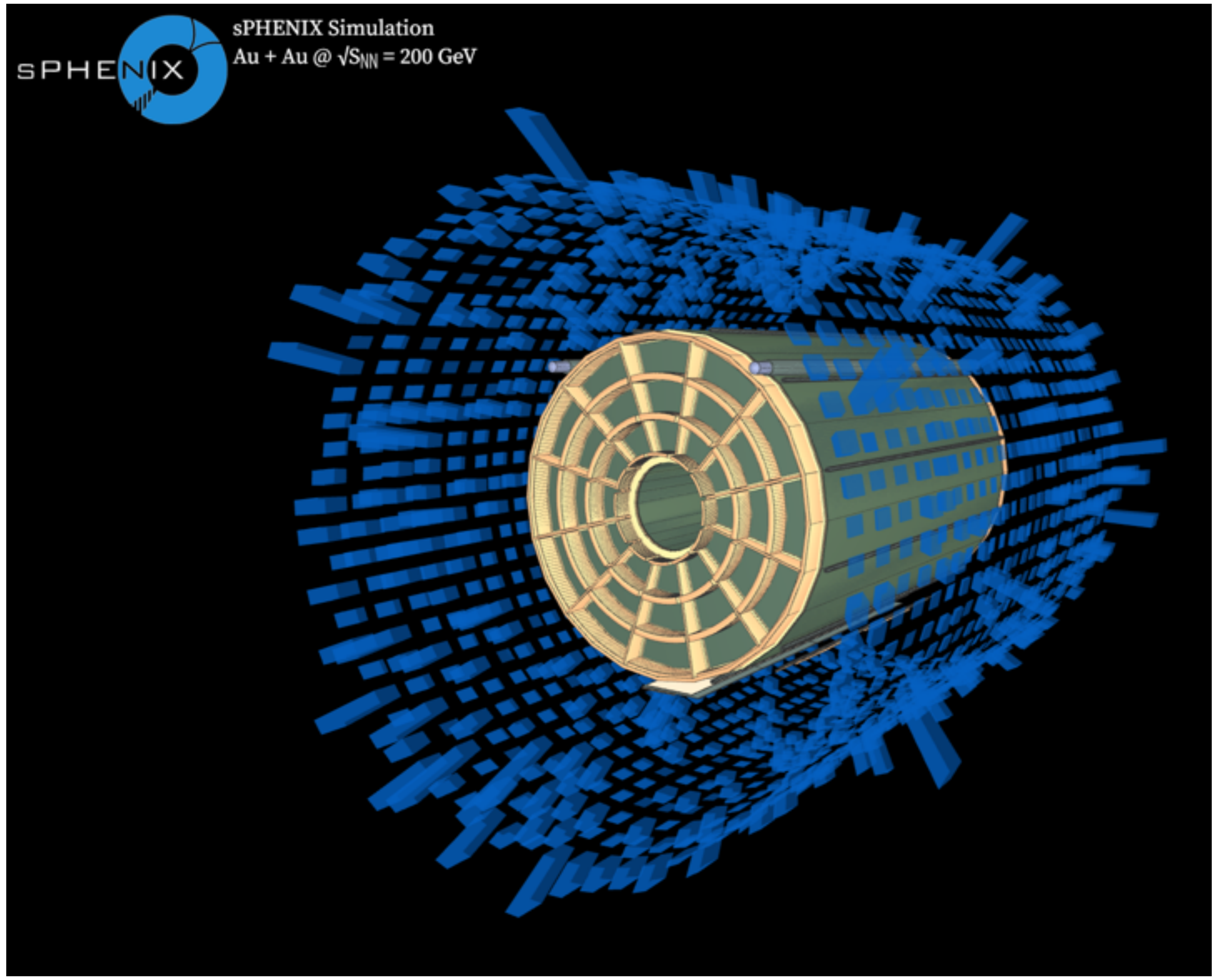
Heavy Ion Collision Event

- **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)

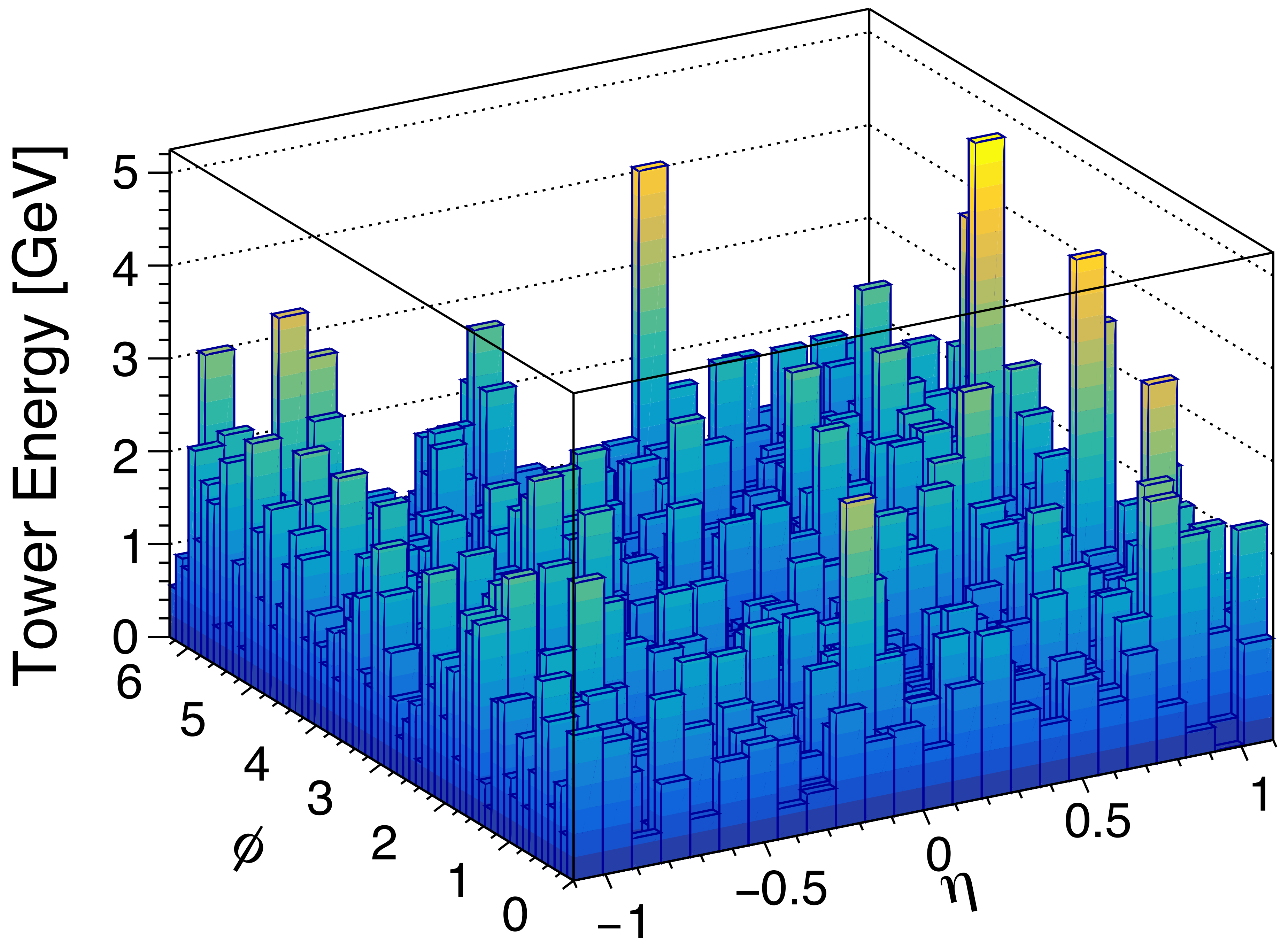


Side collision (40-50% Centrality)

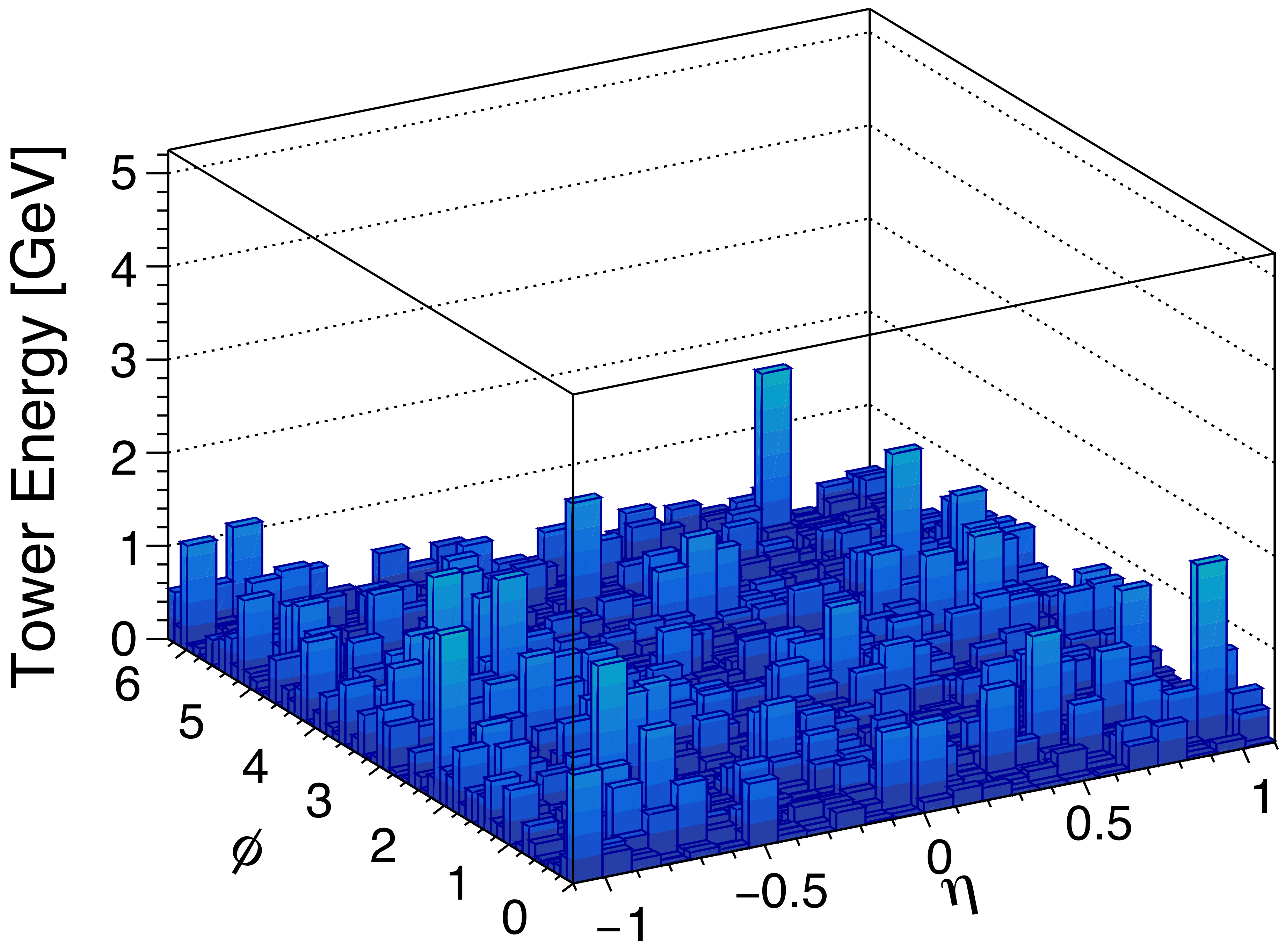


Tower Energy Distributions

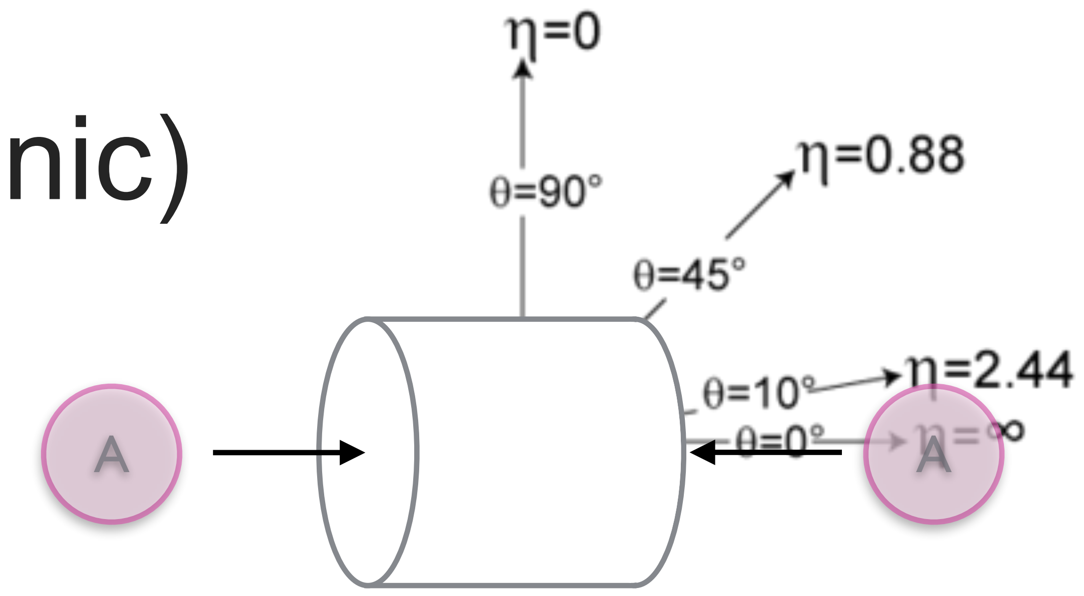
0-10% Centrality



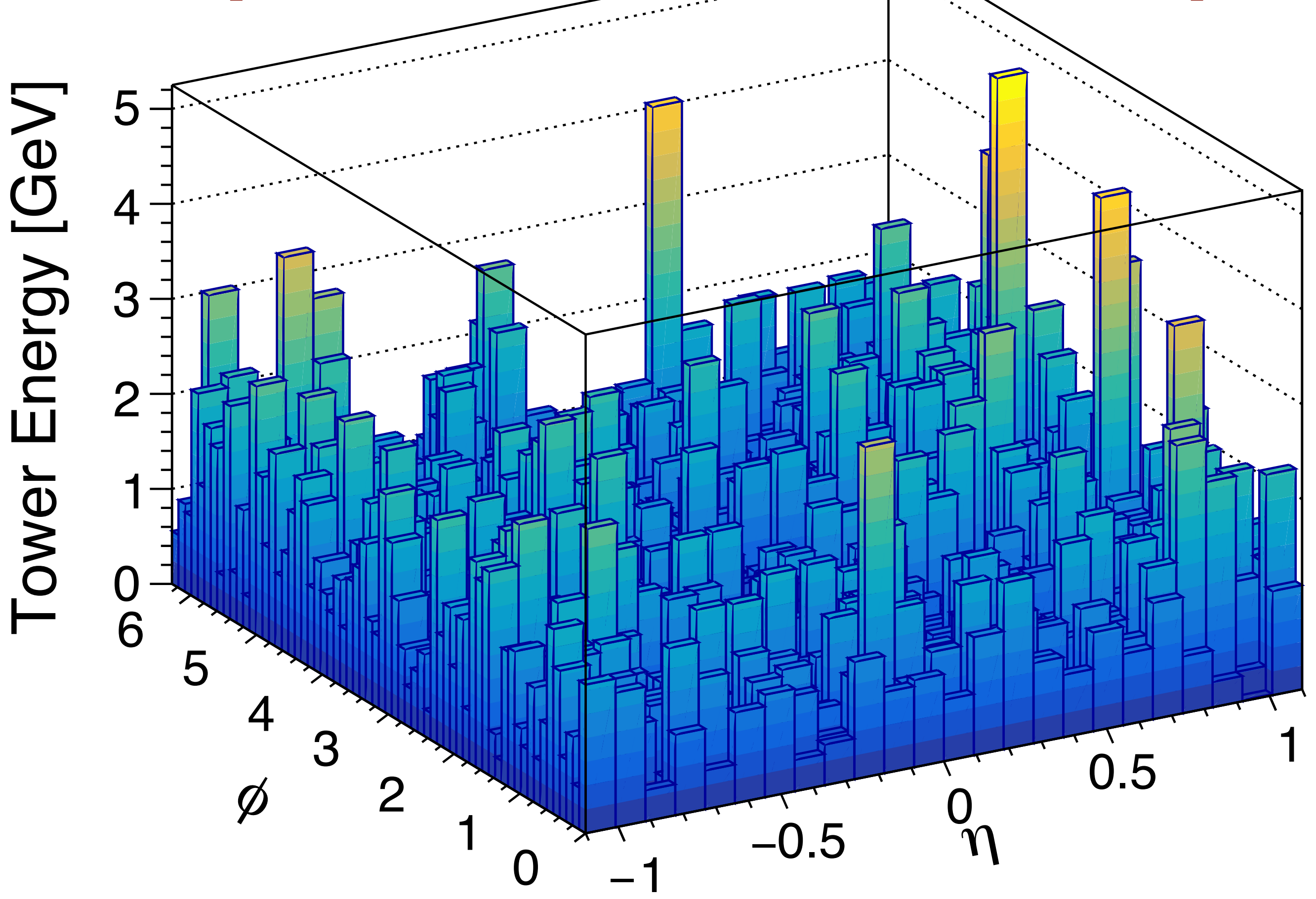
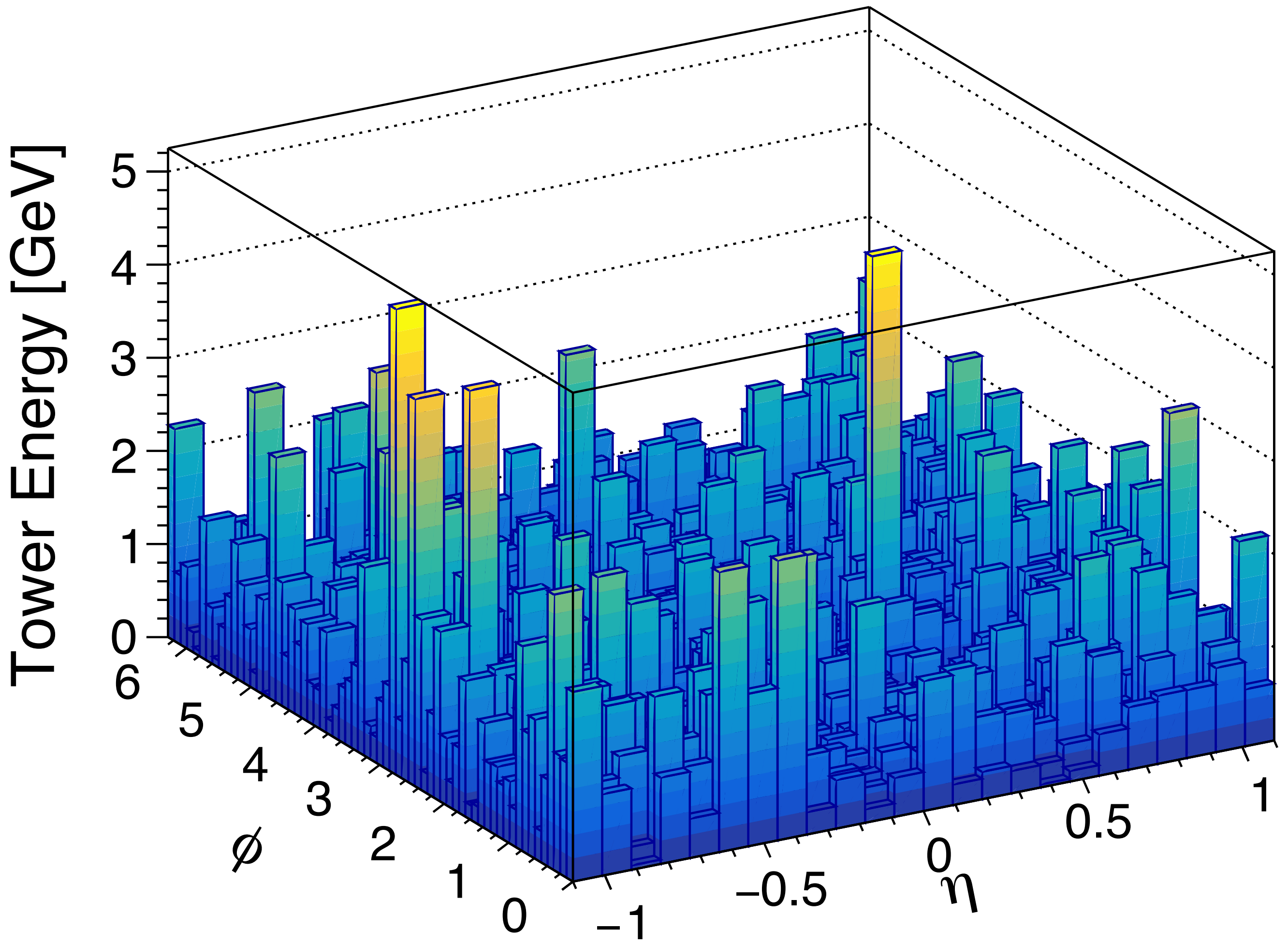
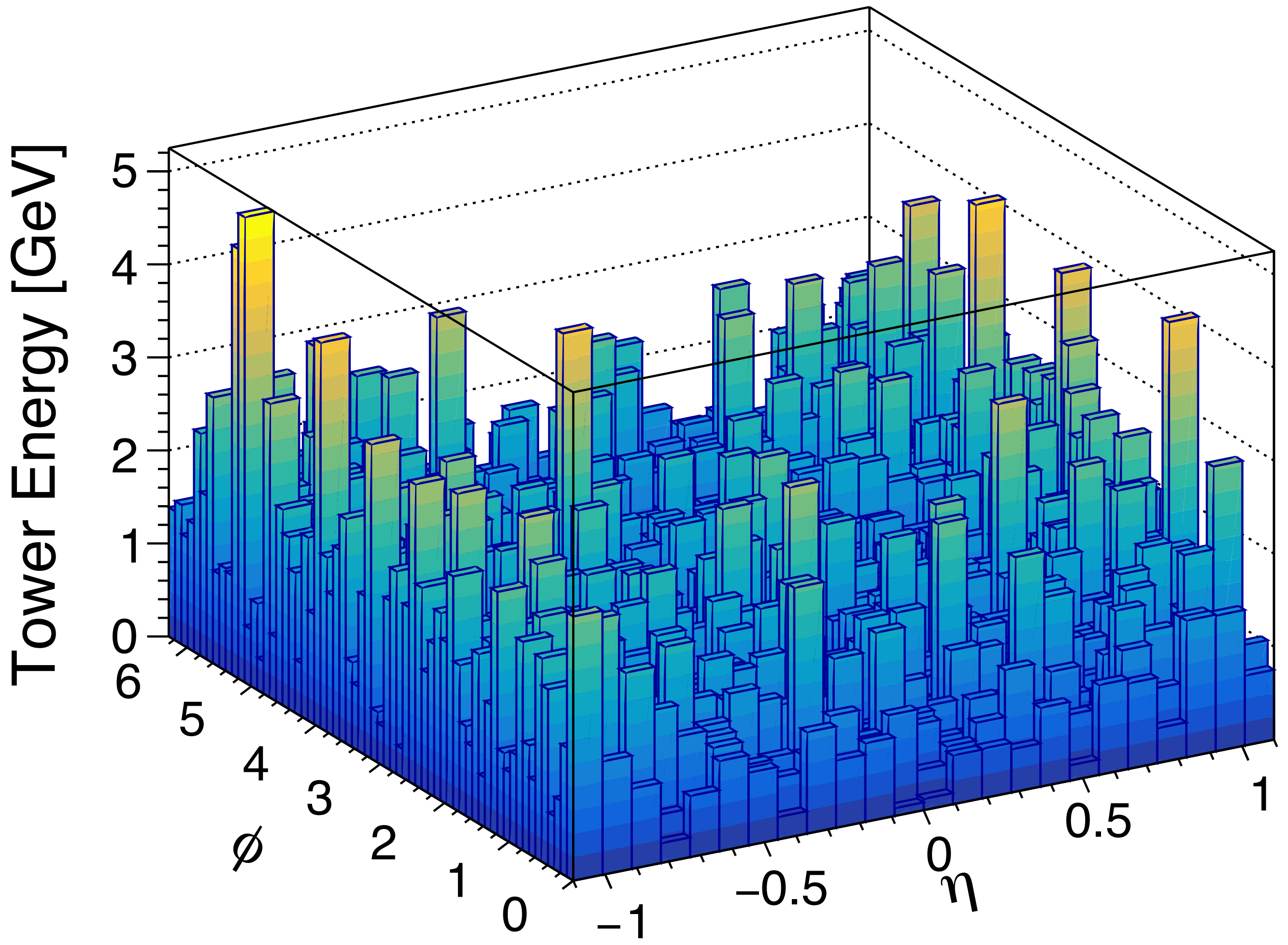
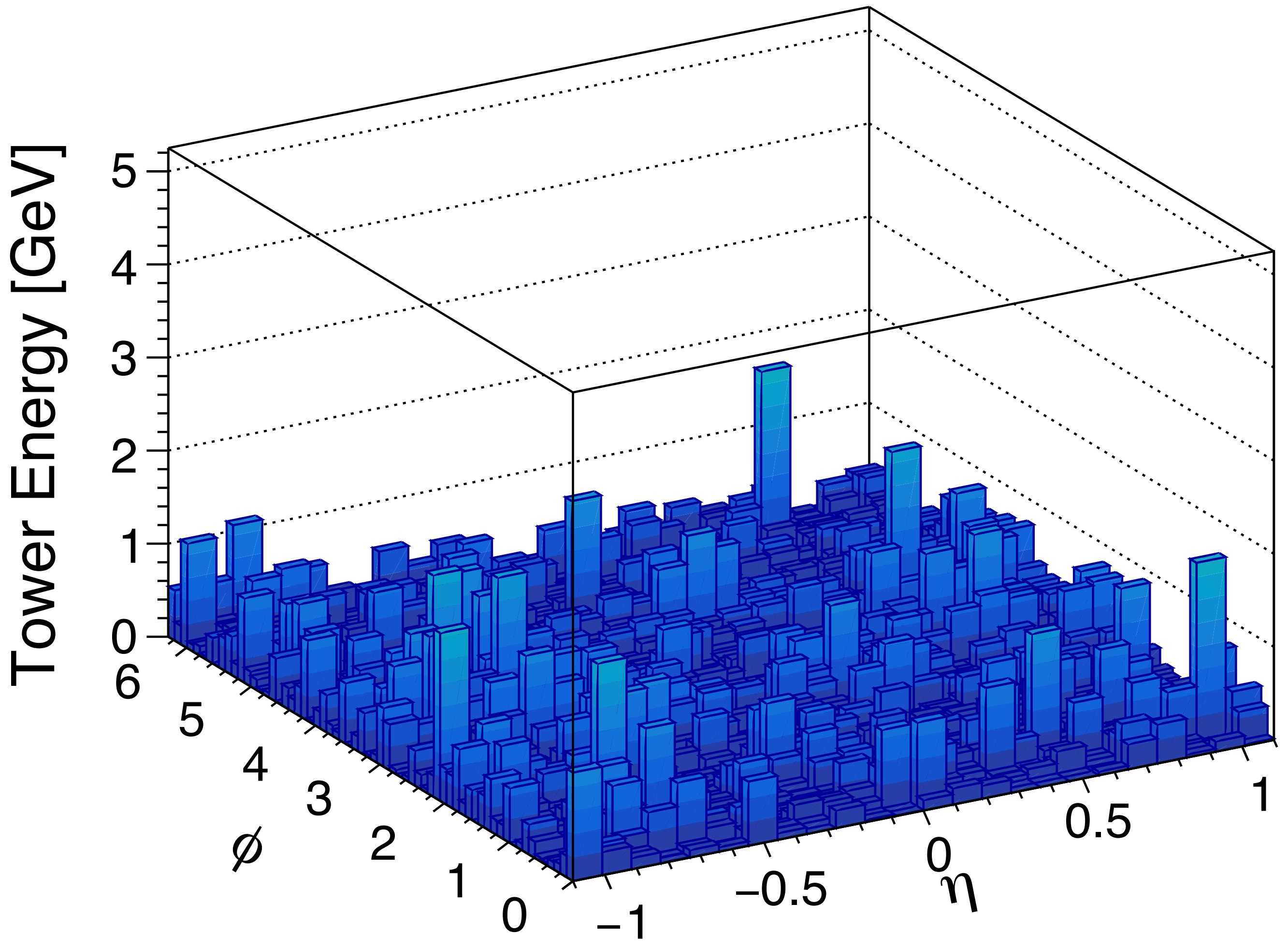
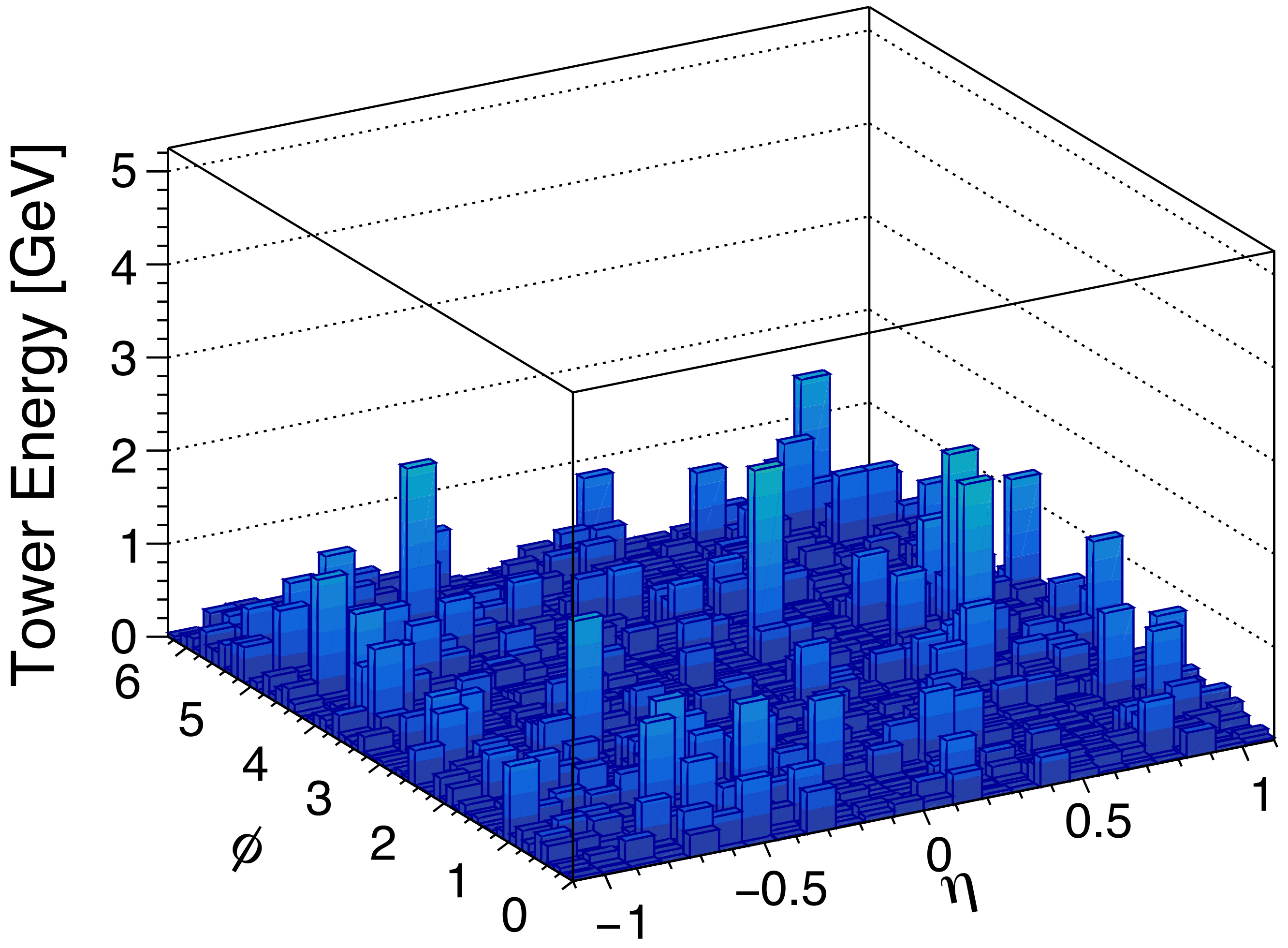
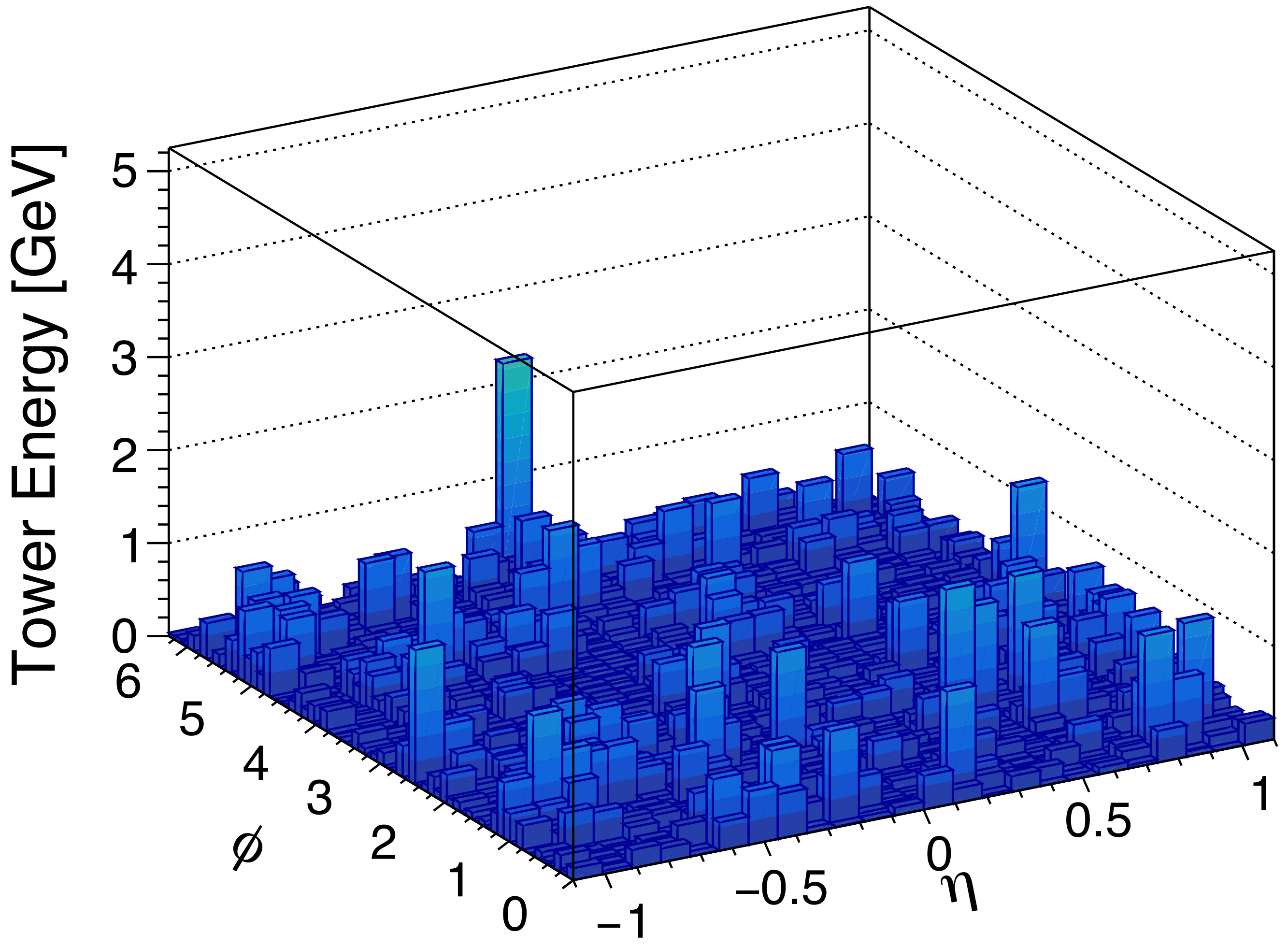
40-50% Centrality



- 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)

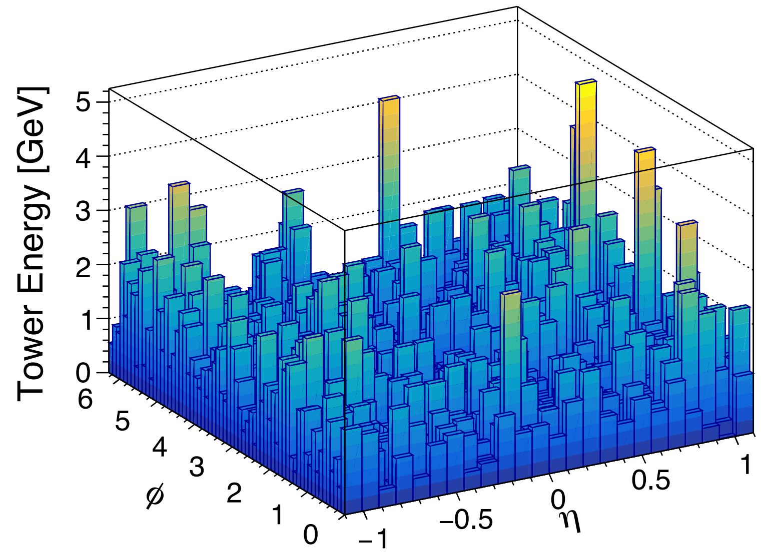


Display of Generated Events

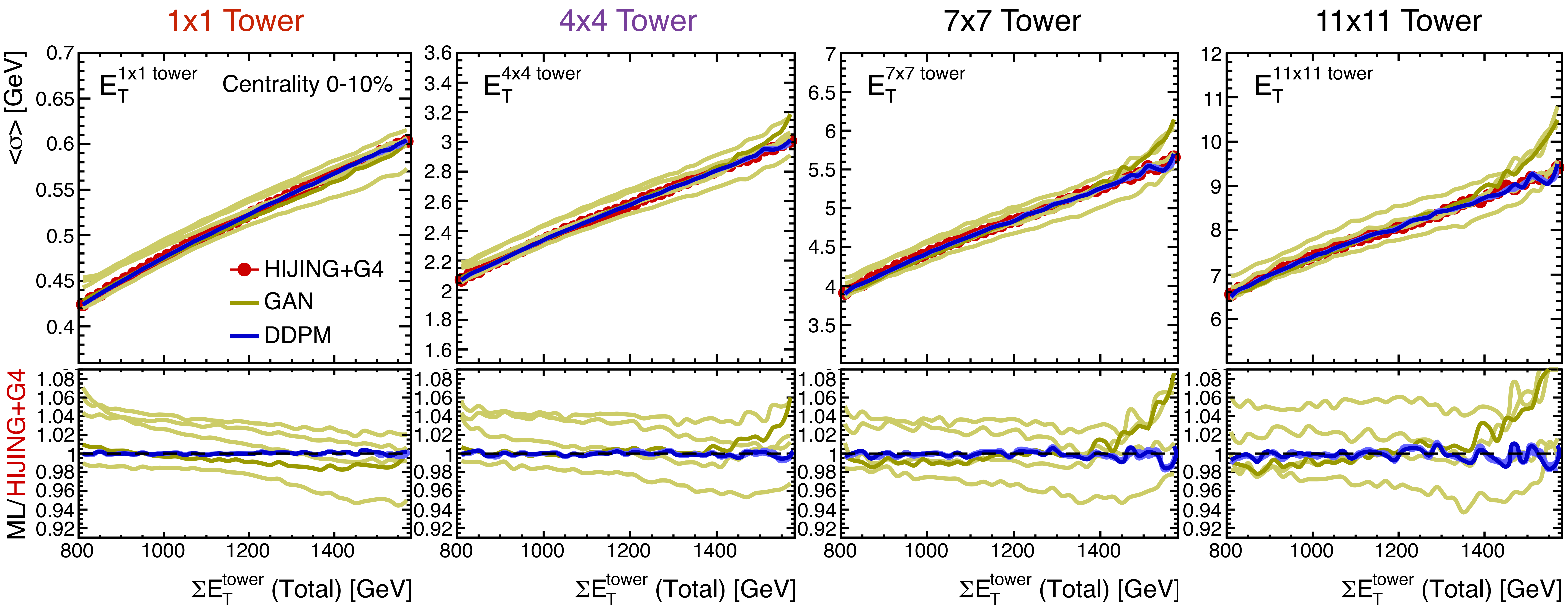
	Training sample (HIJING+GEANT4)	Generated (DDPM)	Generated (GAN)
0-10% Centrality			
40-50% Centrality			

Performance: Transverse Energy (0-10%)

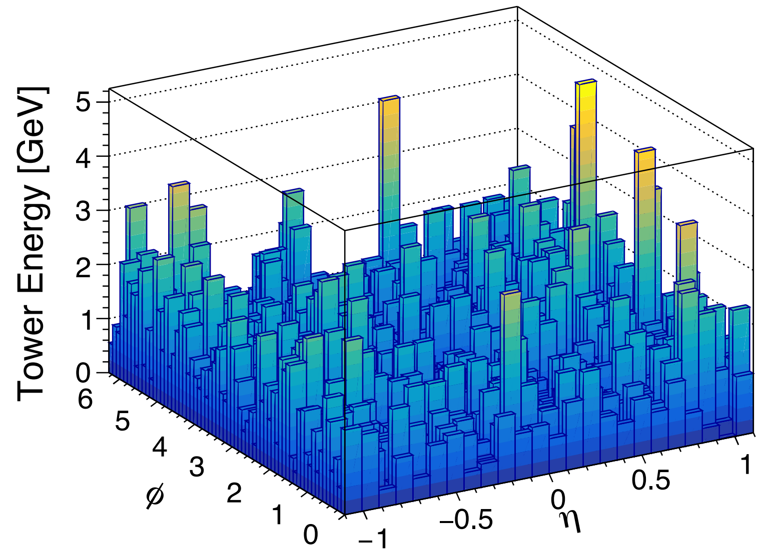
- Each model is retrained 5 times with different random seeds
- HIJING+Geant4 used as training data (600k events) and testing data (100k events)
- Both DDPM and GAN reproduce the data distribution where the data are abundant
- DDPM outperforms GAN in overall distribution w/ great stability and accuracy



Performance: Transverse Energy Fluctuation (0-10%)

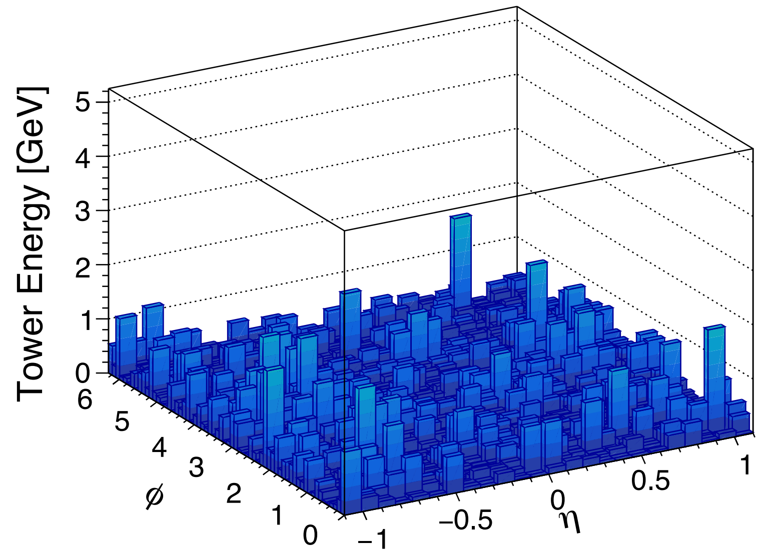


- GAN fails to describe fluctuation
- DDPM outperforms GAN w/ great stability, a few percent-level accuracy



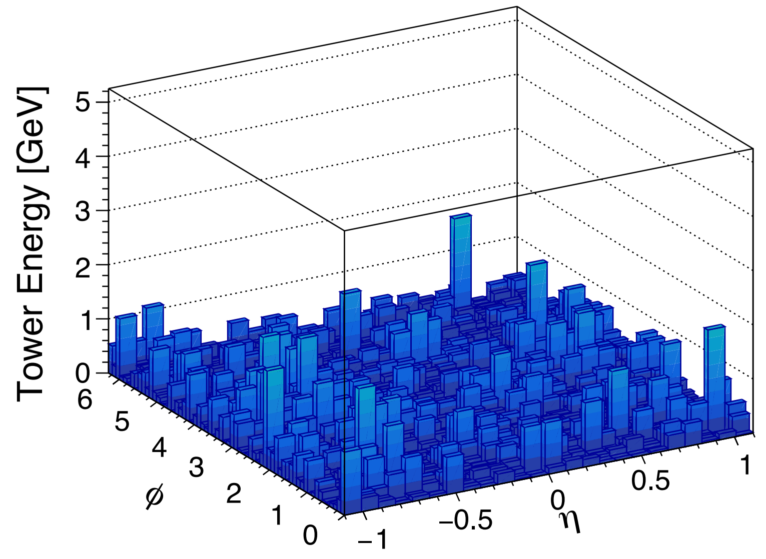
Performance: Transverse Energy (40-50%)

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

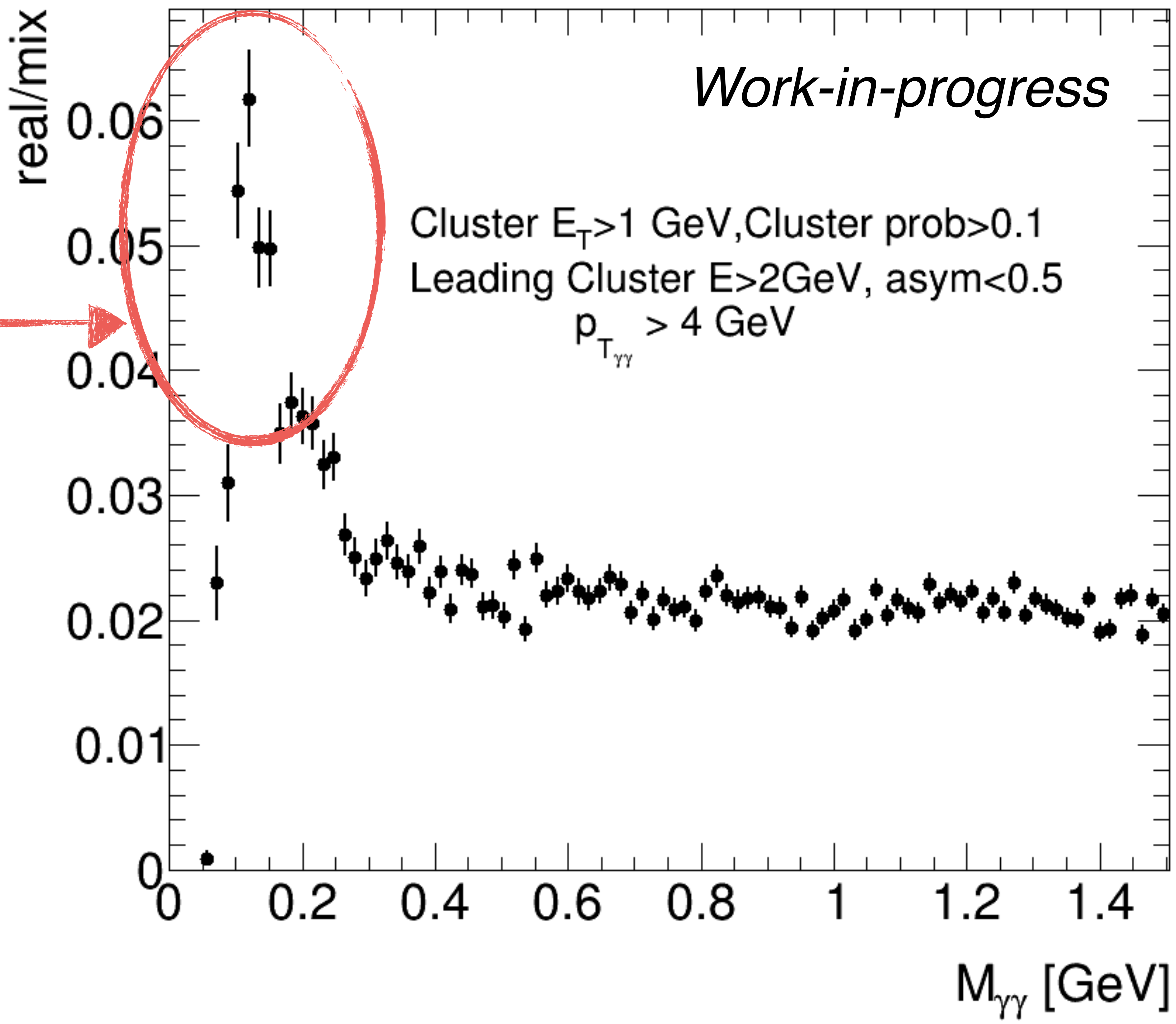
	Generating time	Speedup	CPU/GPU
HIJING + GEANT4 (Conventional)	40 minutes / event	1	Single CPU
DDPM	1.34 s / event	~1,800X	NVIDIA RTX A6000
GAN	0.42 ms / event	~5,700,000X	NVIDIA RTX A6000

- 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)

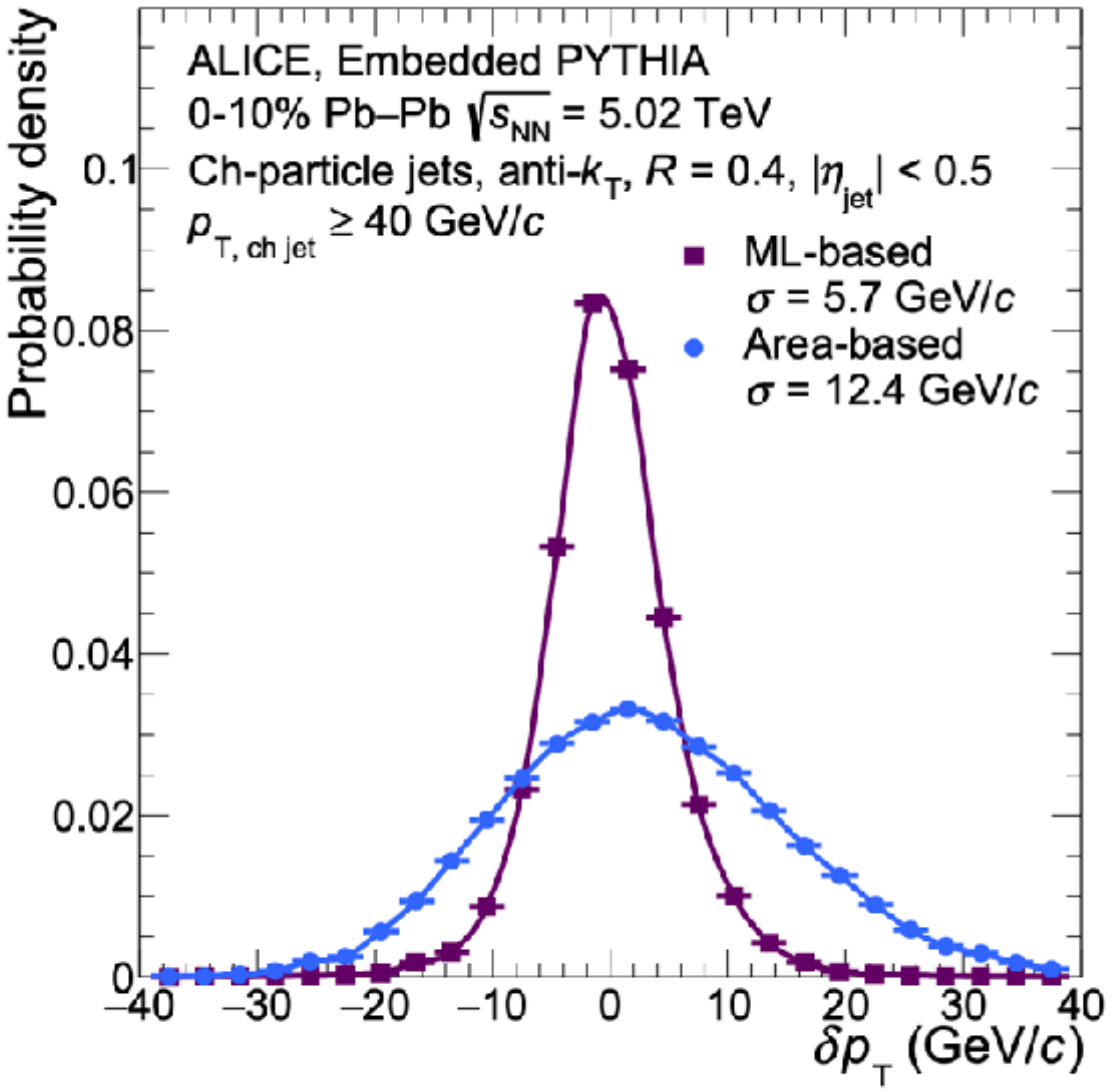
- Similar approach applicable to other experiments e.g. EIC

Jet Background Subtraction using CycleGAN

Jet Background Subtraction Using AI

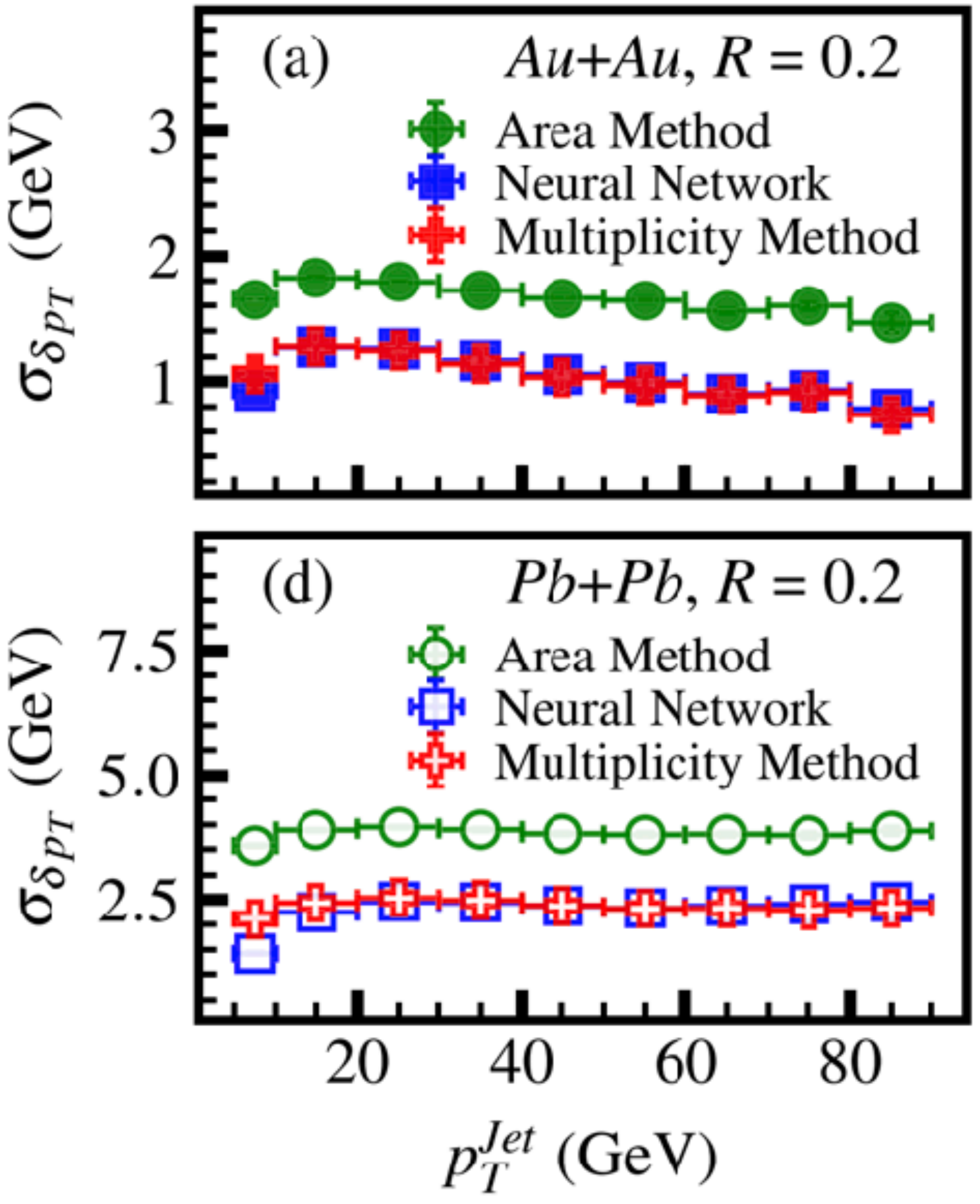
- Previous works on jet background subtraction using ML showed improved jet energy resolution, however,
  - ➡ ***supervised*** *learning*: regression task based on "**labelled**" maps
  - ➡ train using jet substructure; trained on *unquenched jet* substructure, applied on *quenched* jet substructure → **bias**
  - ➡ map to low-dimensional distributions quantity, e.g. p_T, → don't preserve the full substructure information

ALICE: shallow neural network



PLB 849 (2024) 138412

deep neural network



PRC 108, L021901

- *New approach is to use* ***unsupervised generative AI***
  - ➡ *to preserve the higher dimensional information*
  - ➡ *to* ***bridge gap*** *between MC (used in training) and data*

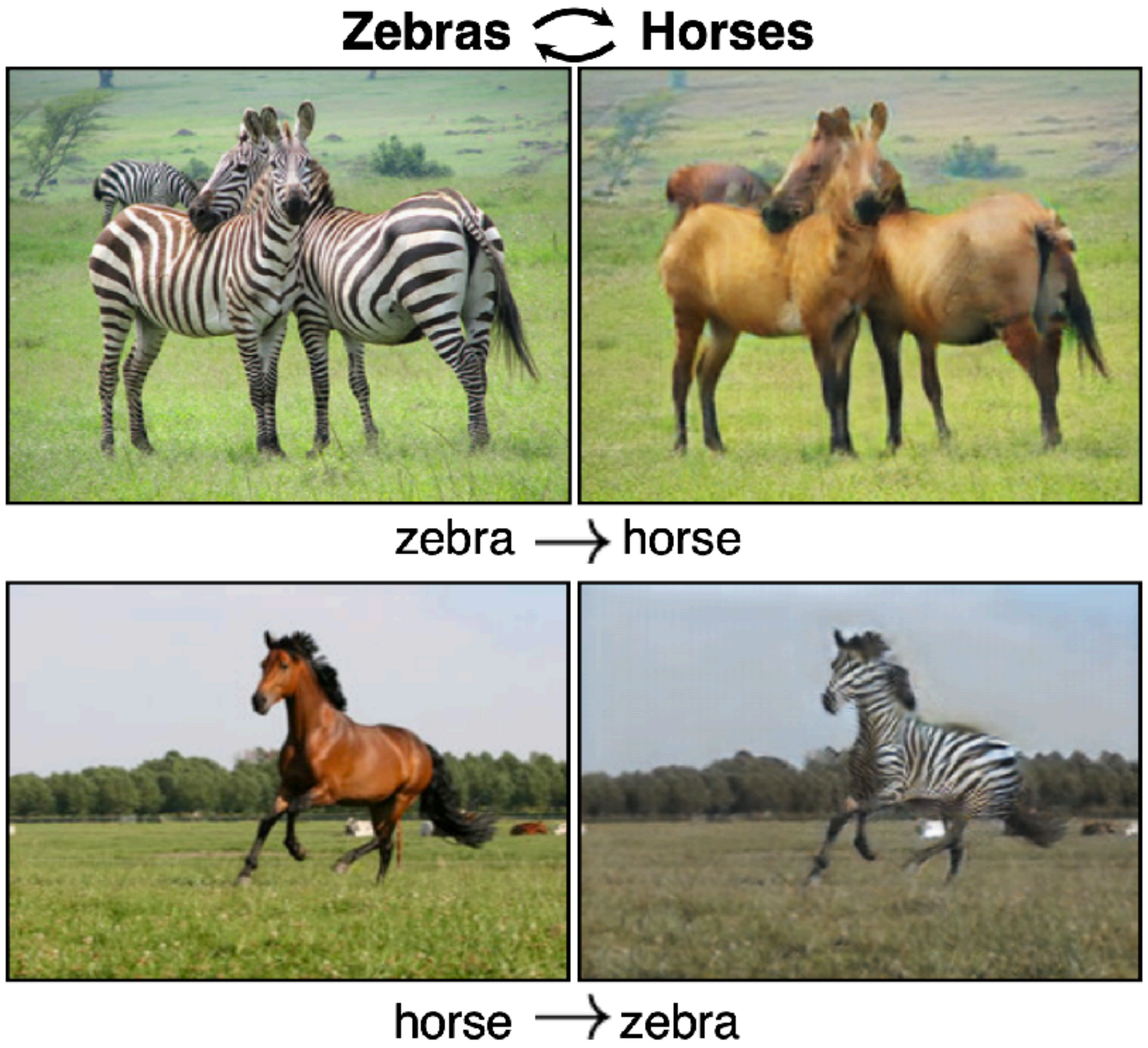
Cycle-consistent GAN

- 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?



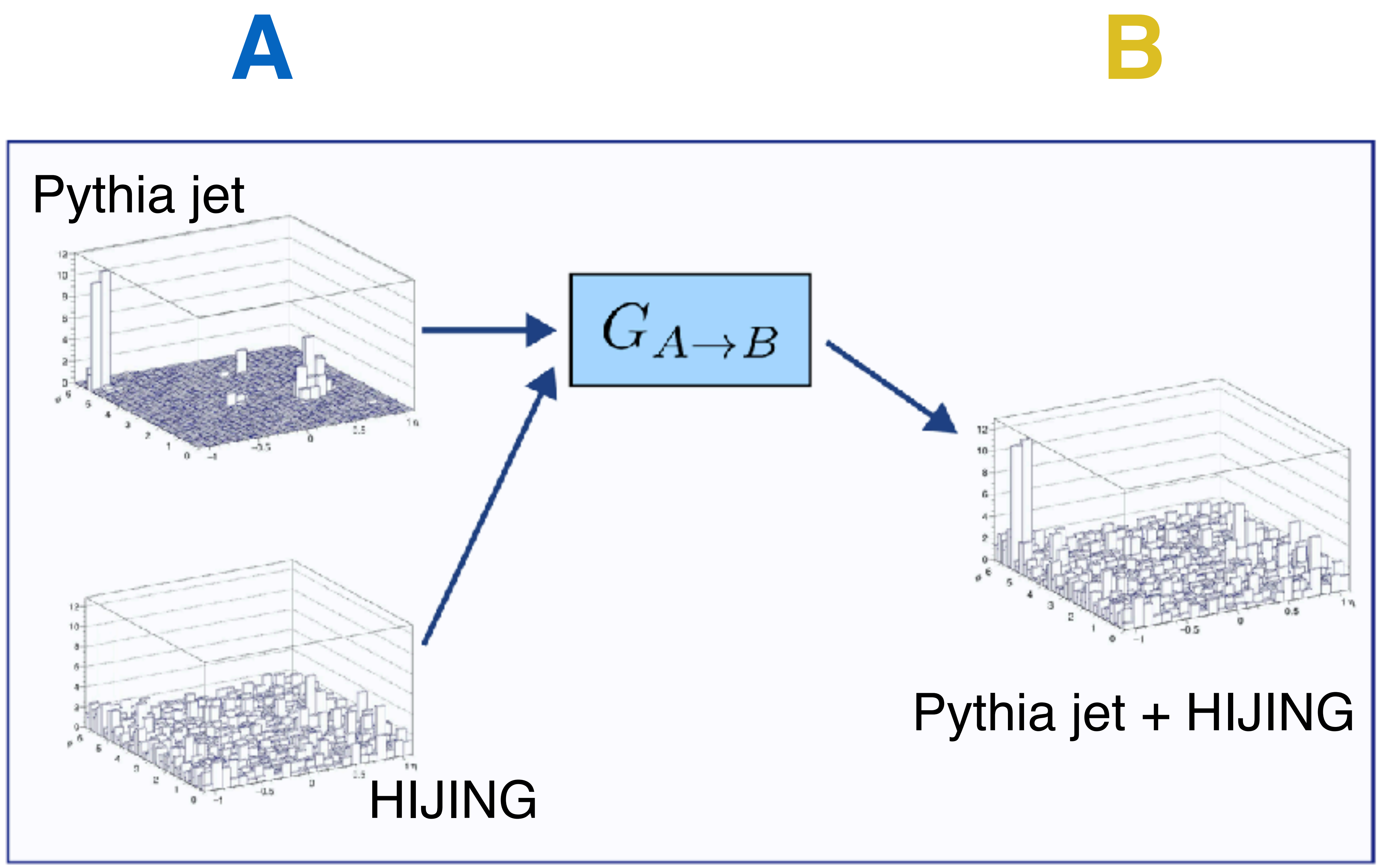
arXiv:1703.10593

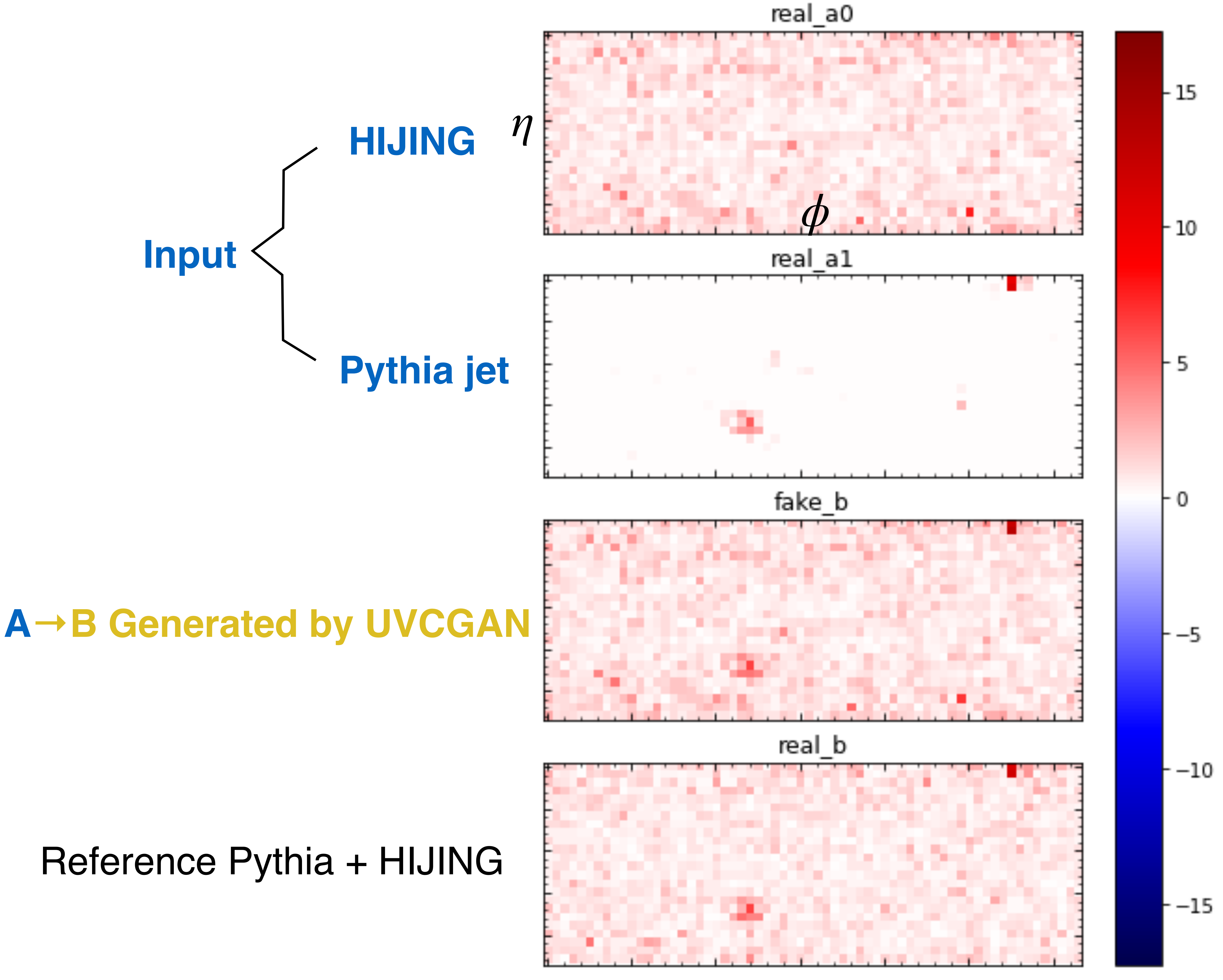
UVCGAN

- **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

(a) $A \to B$

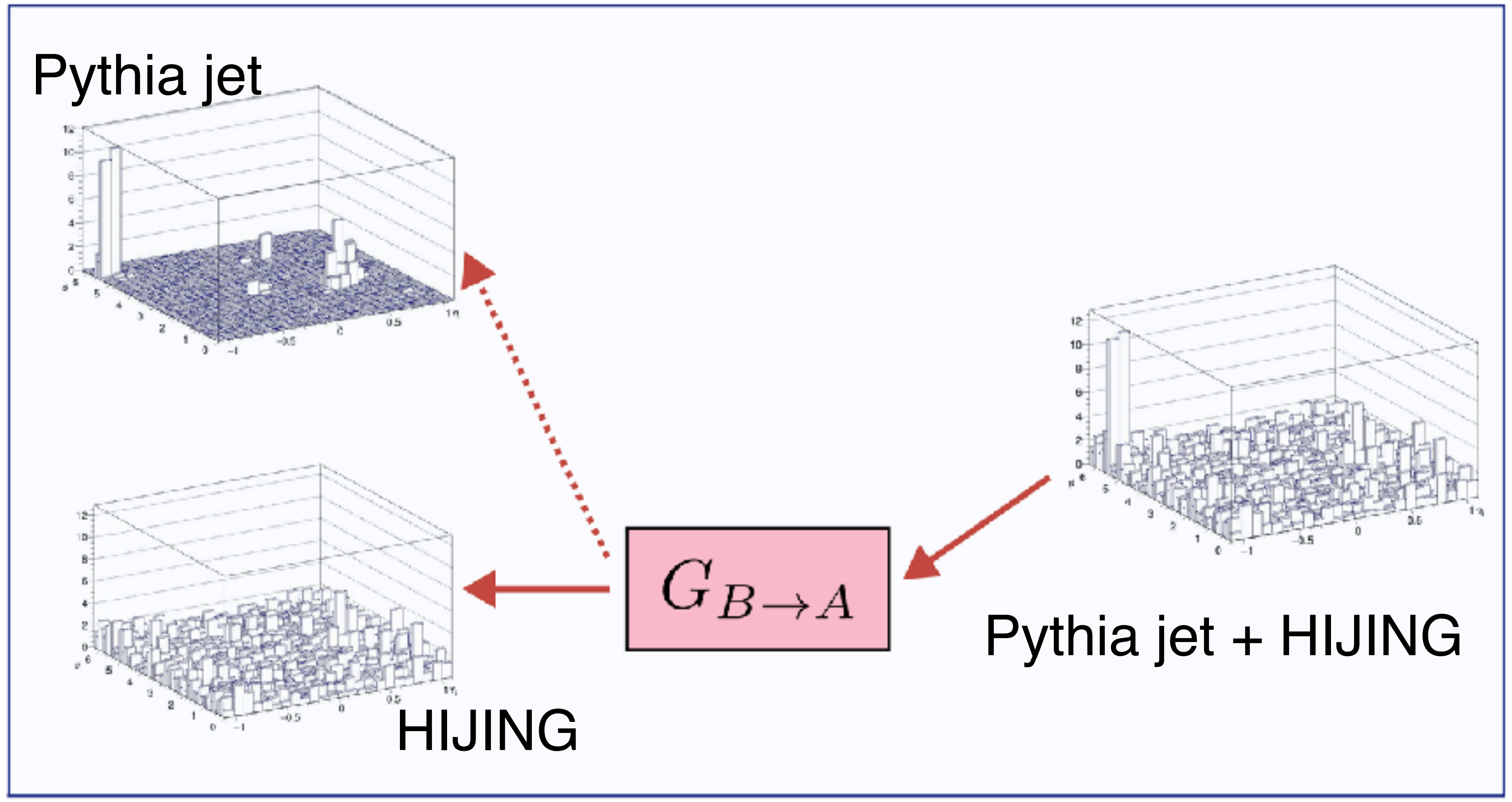
Jet Background Subtraction (2)

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

A

B

B→A generated by UVCGAN

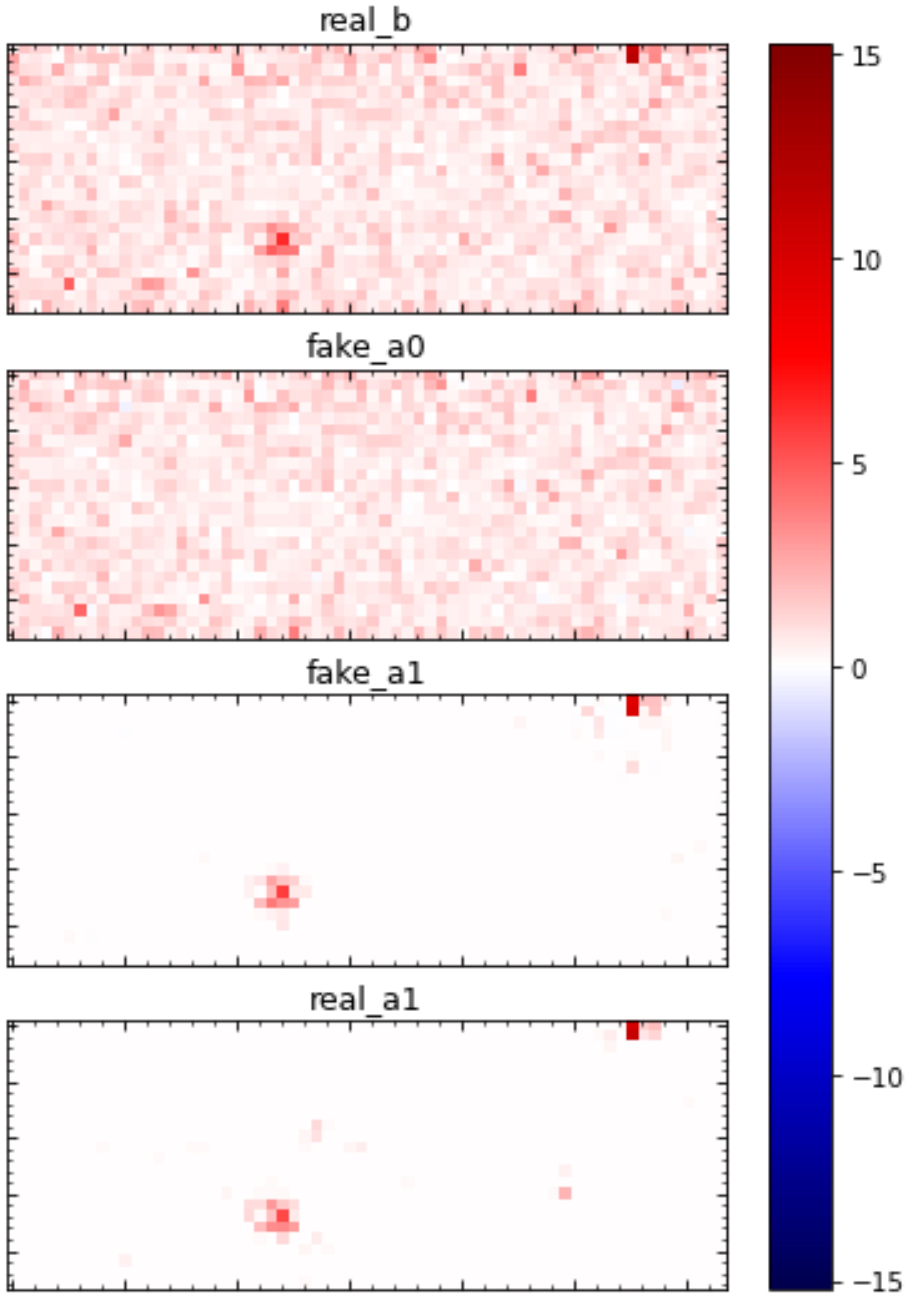


(Input) HIJING+Pythia

Background (HIJING)

Jets

Reference Pythia jet



(b) $B \to A$

Work-in-progress

Summary and Conclusion

- *Generative AI* are useful for high energy (nuclear) experiments, e.g.
  - ➡ speed up and produce large amount of the heavy ion event simulations!
  - ➡ subtract large amount of background from jet event
  - ➡ …

- **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

- For the first time, a **unsupervised generative AI** 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. arxiv:2505.XXXX Stay tuned!*

Our Team

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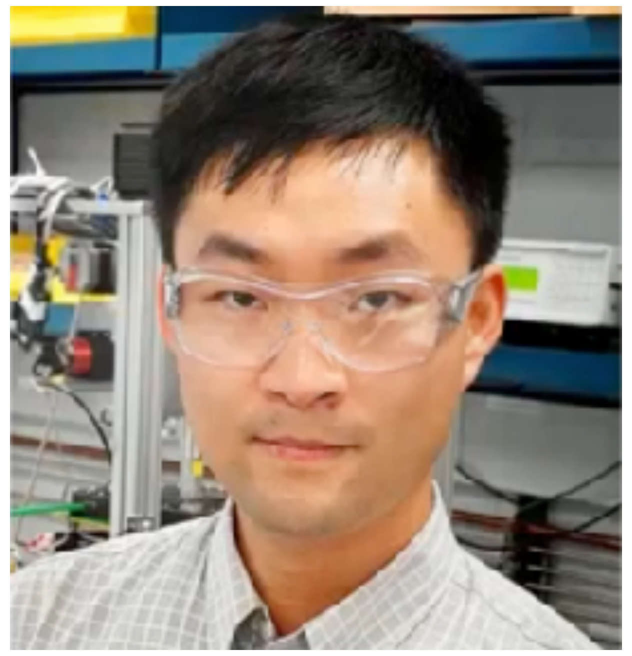

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BACKUP