RHIC AI/ML Workshop 2024

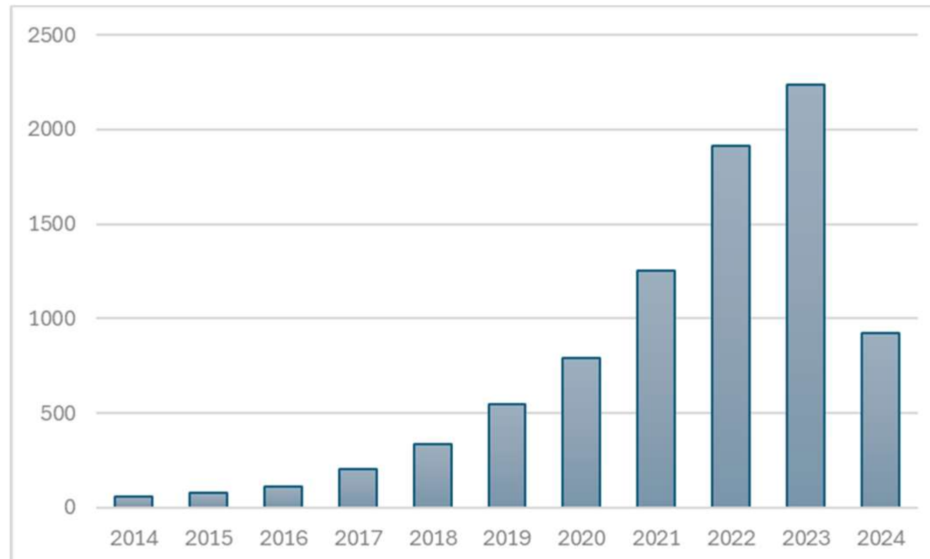
Tanner Mengel

University of Tennessee, Knoxville

THE UNIVERSITY OF TENNESSEE KNOXVILLE

Why should you care?

- **NSAC Long-Range Plan Town Hall Meeting on Hot and Cold QCD**
  - "Increased investments in computational nuclear physics, AI/ML, HPC, HTC, data systems, and interdisciplinary workforce development, are essential for advancing nuclear physics."

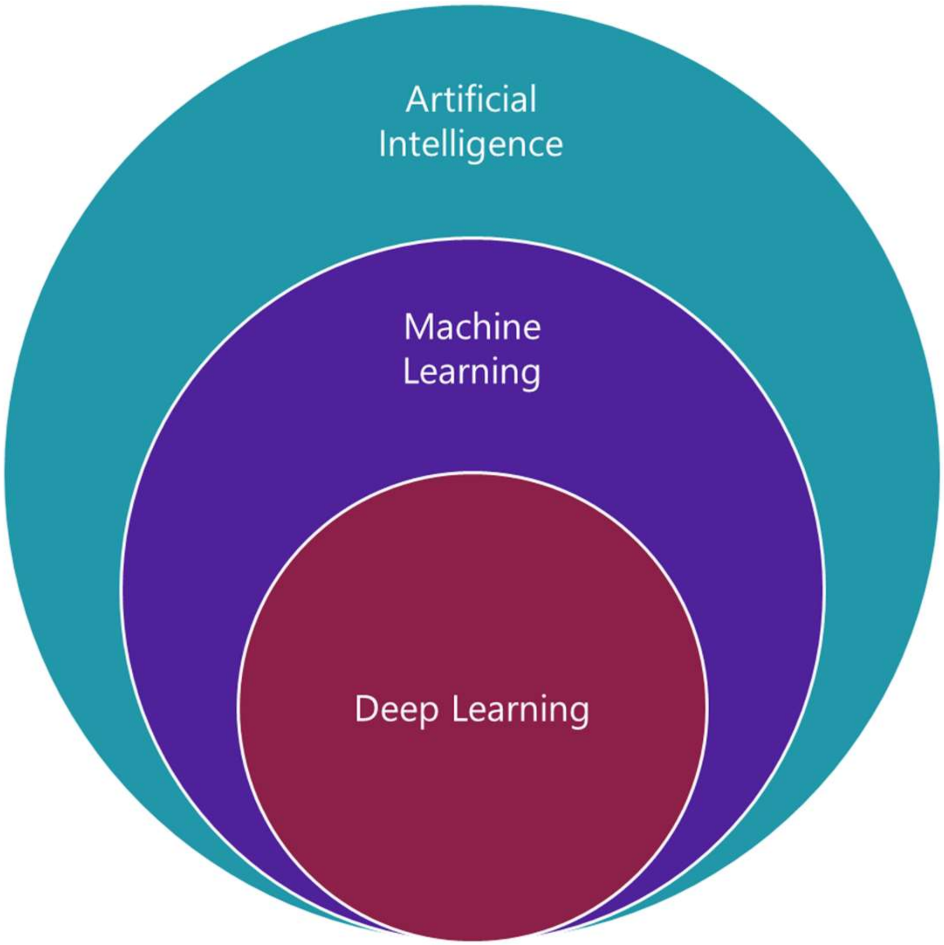


Inspire HEP search results for "machine learning"

THE UNIVERSITY OF TENNESSEE KNOXVILLE

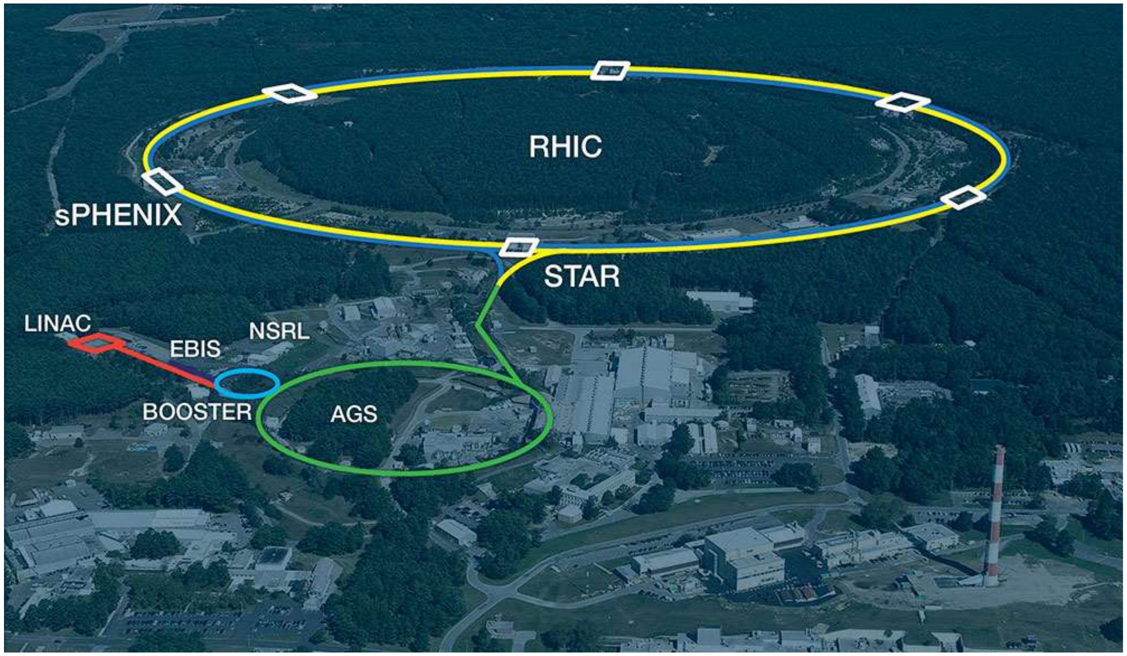
What am I talking about?

- **Artificial Intelligence:** The broad field of creating machines that perform tasks requiring human intelligence
- **Machine Learning**: Algorithms that learn from examples and get better with experience
- **Deep learning**: Modeling complex patterns in large datasets



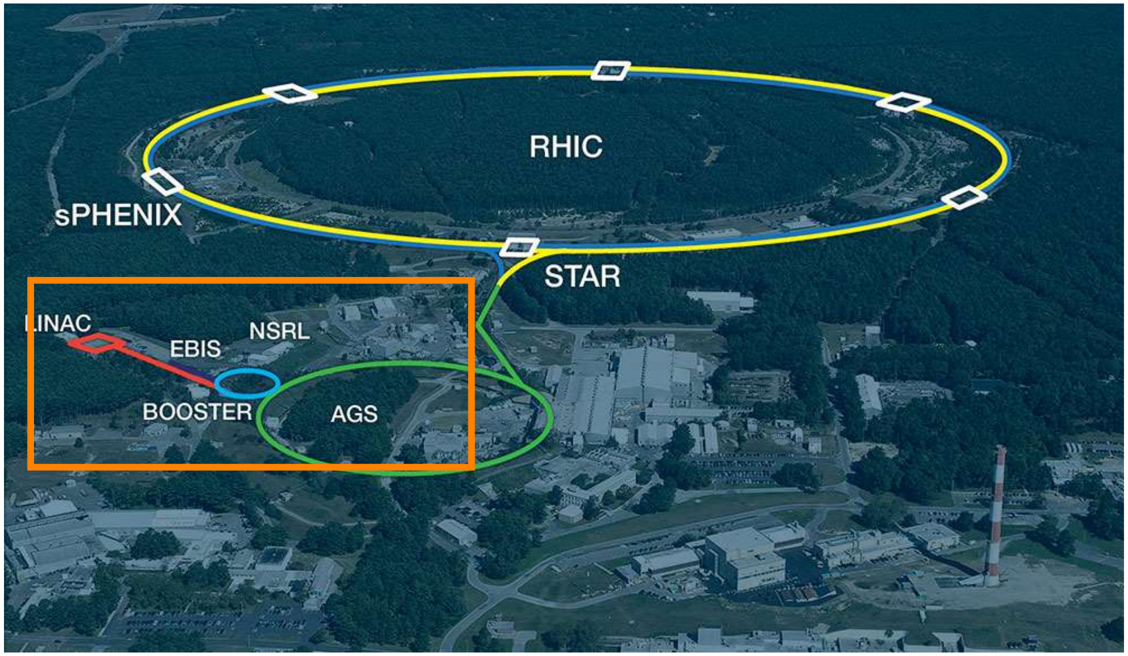
Where is AI/ML used at RHIC?

- ML has applications in all aspects of RHIC
- **Accelerator Facilities**
  - Machine optimization, anomaly detection
- **Data Taking**
  - Event selection, data compression, detector calibration
- **Analysis**
  - Event simulation, background discrimination, detector response



Accelerator Facilities

- EBIS Injection optimization
- Luminosity optimization
- Anomaly detection
- AGS Bunch Merging
- Documentation optimization

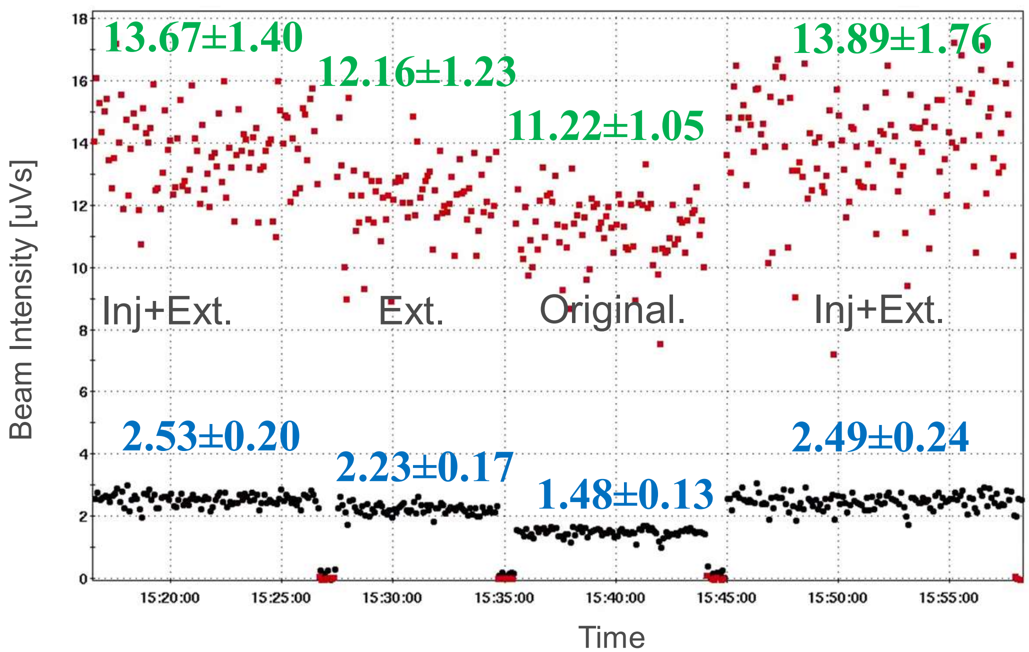


Machine Learning Applications for EBIS Beam Intensity and RHIC Luminosity Maximization
Xiaofeng Gu (CAD, BNL)

Machine learning applications in particle accelerators
Yuan Gao (CAD, BNL)

EBIS Intensity Optimization

- Optimize machine parameters in the EBIS injection line and extraction Line
- Resulted in **22-30%** intensity improvement



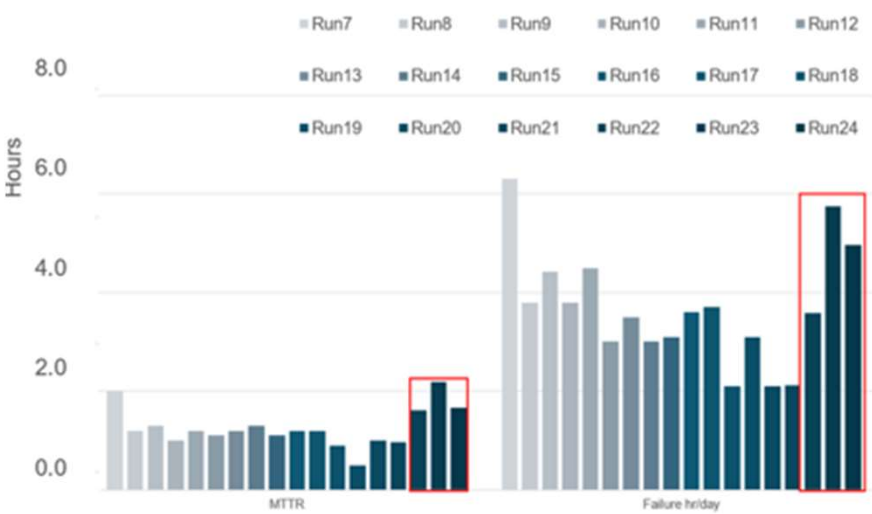
Beam intensity vs fill time for different machine parameters

Machine Learning Applications for EBIS Beam Intensity and RHIC Luminosity Maximization
Xiaofeng Gu (CAD, BNL)

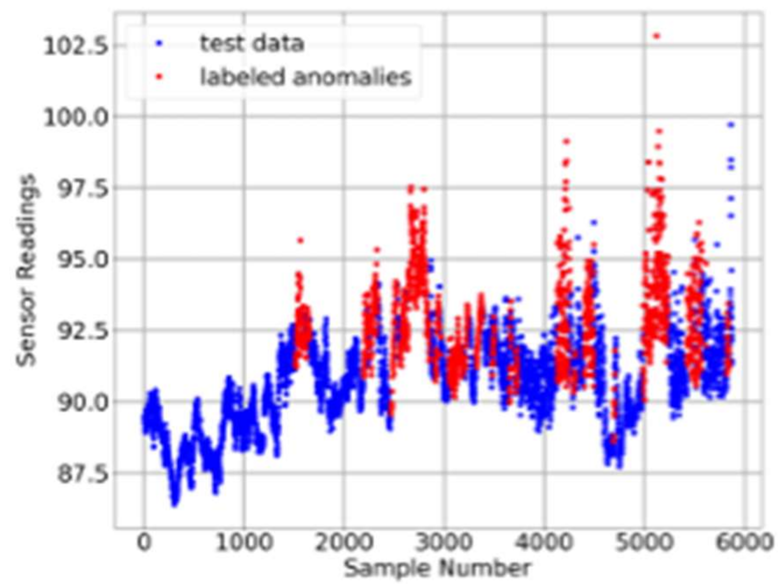
Anomaly Detection

Machine learning applications in particle accelerators
Yuan Gao (CAD, BNL)

- Several future programs planned to reduce number of failures and recovery time
- Predict anomalies before they happen in RHIC Cryogenics systems



Left: Mean repair hours. Right: Average failure hours per day

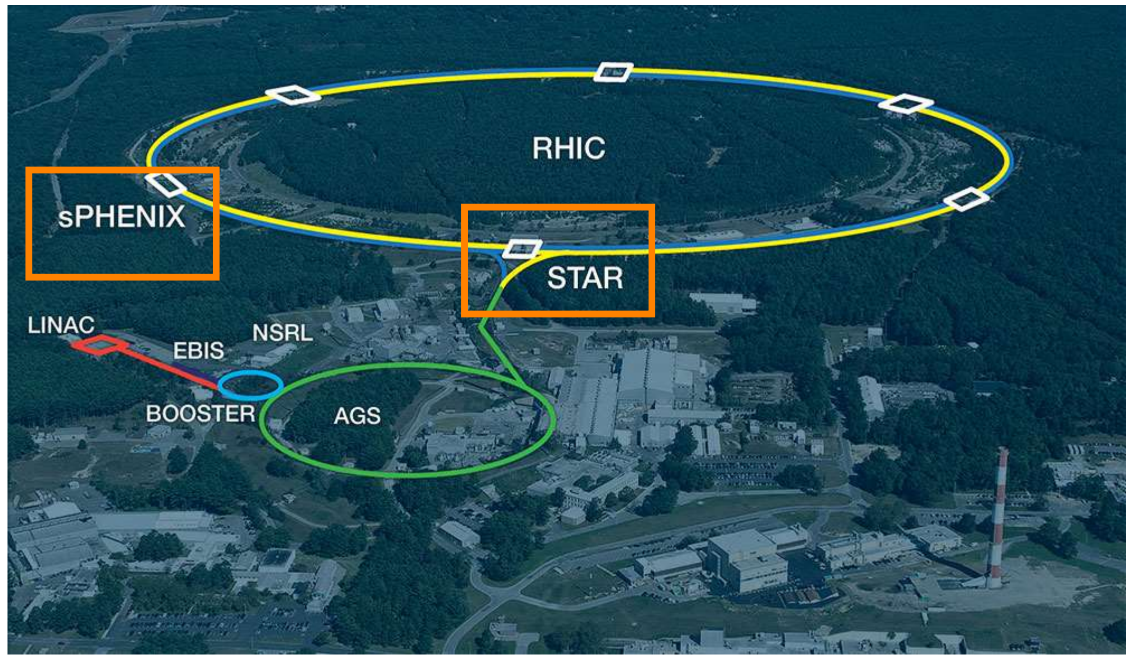


Anomaly prediction of LSTM from Mar. 6th to Apr. 5th, 2022

THE UNIVERSITY OF TENNESSEE KNOXVILLE

Data Taking

- Event selection
- Managing large data volumes



FastML triggering in sPHENIX (Autonomous selection of physics events)
Cameron Dean (MIT)

Real-Time Information Distillation with Deep Neural Network-based Compression Algorithms
Yi Huang (BNL)

Autonomous Event selection

FastML triggering in sPHENIX (Autonomous selection of physics events)
Cameron Dean (MIT)

- sPHENIX DAQ rate is 15 kHz. Can only sample a small fraction of collisions (~0.5%)
- Solution: Put ML on an FPGA to do autonomous event selection. (hls4ml)
- Deploying this year in sPHENIX

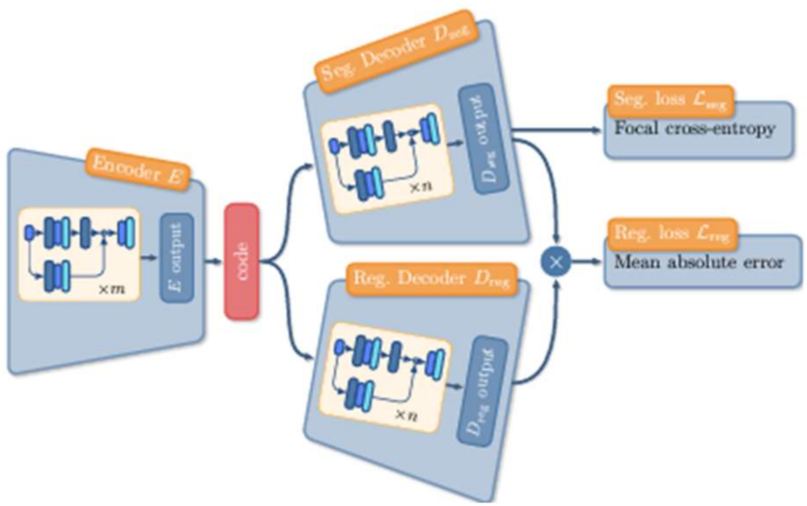
Bkg. track rejection	Signal eff.	Sample purity*
90%	72.5%	7.25%
95%	48.9%	9.78%
99%	15.0%	15.0%

* % of final events with signal you're looking for

Secondary vertex detection in $D^0 \rightarrow K^- \pi^+$ simulation

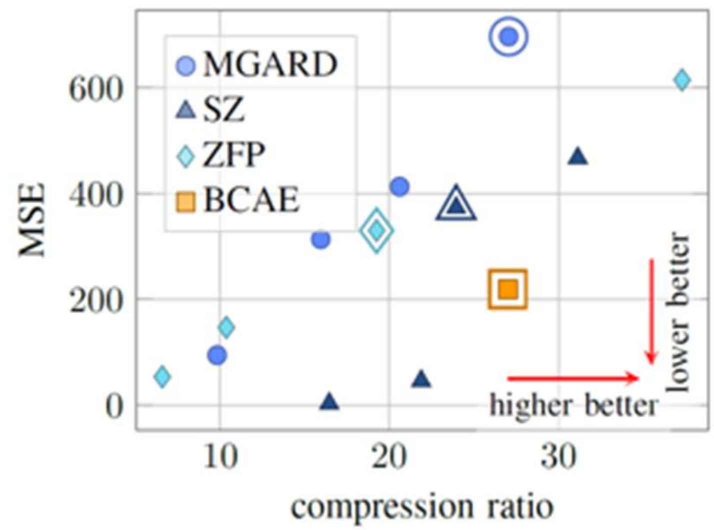
Real-Time Data compression

- sPHENIX TPC dominates streaming readout. All data cannot be saved to disk
- Use a deep neural network-based compression algorithm to reduce data throughput of sPHENIX TPC data



Bicephalous Convolutional Autoencoder for Compressing

Real-Time Information Distillation with Deep Neural Network-based Compression Algorithms
Yi Huang (BNL)



Mean squared error vs compression ratio

https://arxiv.org/abs/2310.15026

Data Analysis

- Event generation
- Background discrimination
- Unfolding with ML

Generative AI for full-detector, whole-event simulation of heavy ion collisions
Yeonju Go (BNL)

Interpretable Machine Learning applications to Jet Background Subtraction
Charles Hughes (ISU)

Machine Learning Application in Jet Quenching Analysis
Yilun Wu (Vanderbilt)

MultiFold
Youqi Song (YALE)

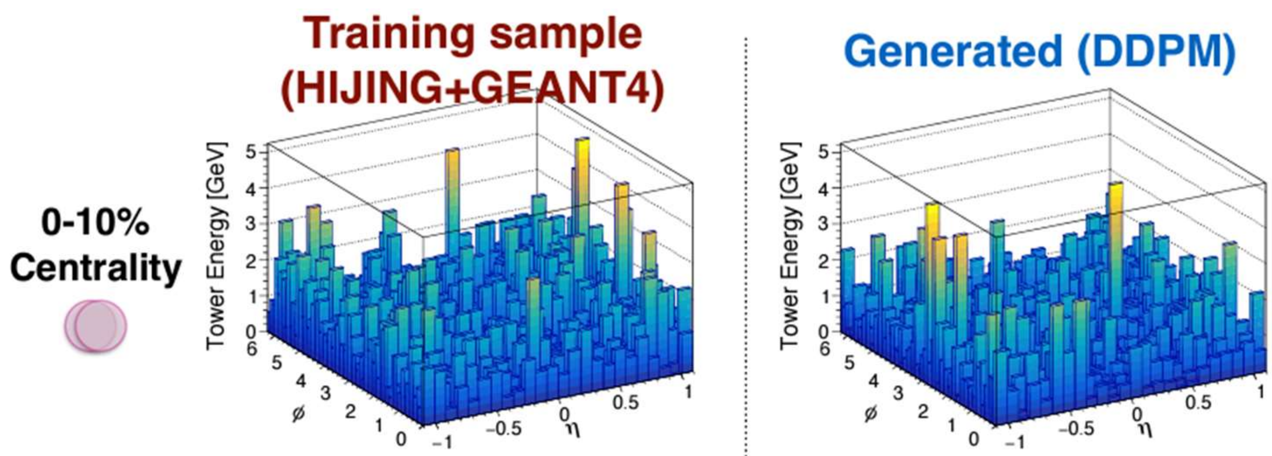
Adventures in Omni Fold: Multivariable Unfolding of Jet-Level Observables with STAR Data
Hannah Harrison-Smith (UK)

High Fidelity Event Generation

Generative AI for full-detector, whole-event simulation of heavy ion collisions
Yeonju Go (BNL)

- Using Denoising Diffusion Probabilistic Model (DDPM) to speed up full event generation in heavy ion collisions
- Comparing to simulations of sPHENIX calorimeters

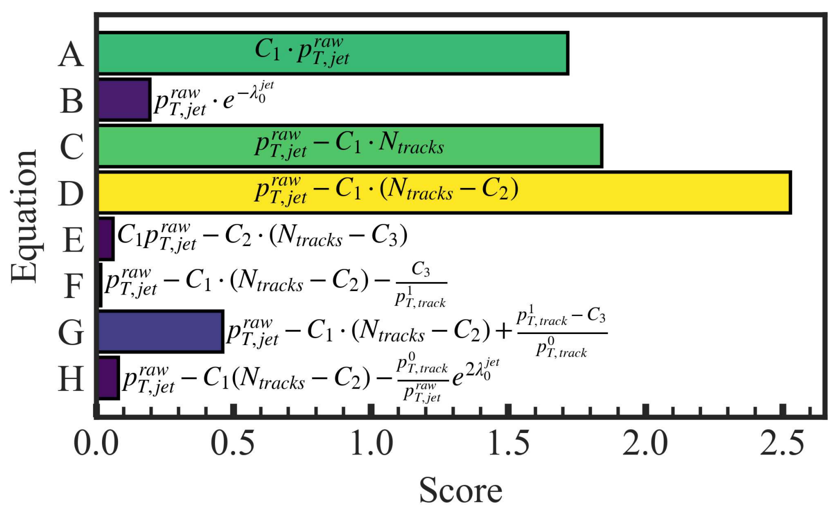
HIJING: ~40minutes / event
DDPM: 1.34s / event



Simulated calorimeter towers compared to diffusive model

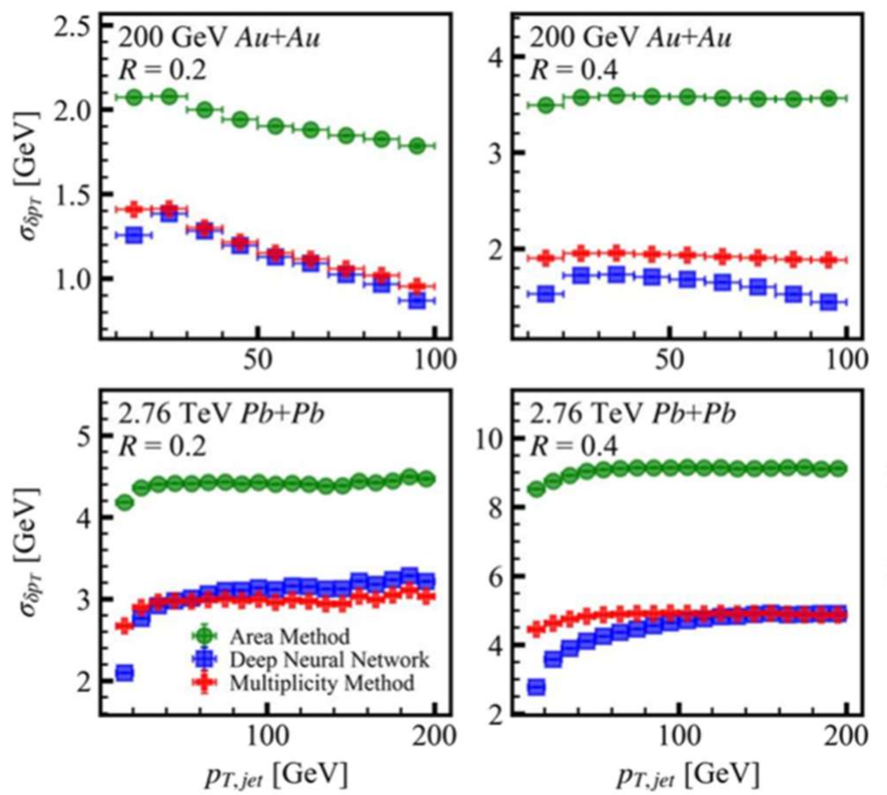
Jet Background Correction

- Using NN to improve jet momentum resolution.
- Learns underlying cause of increase in performance though symbolic regression



Interpretable Machine Learning applications to Jet Background Subtraction

Charles Hughes (ISU)

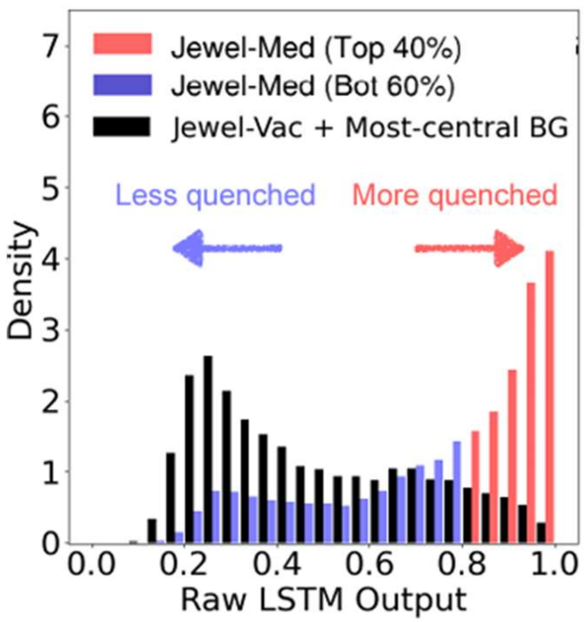


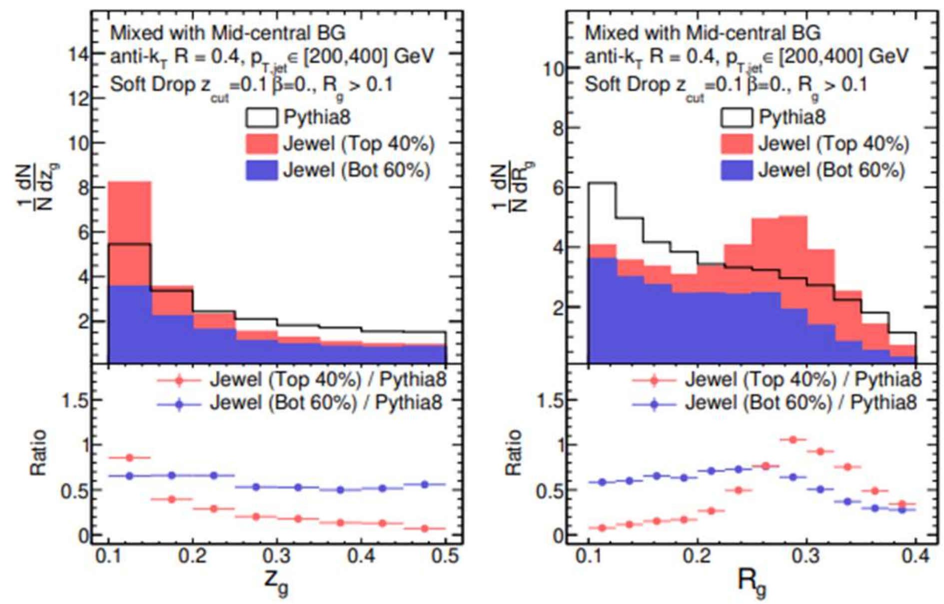
https://journals.aps.org/prc/pdf/10.1103/PhysRevC.108.L021901

Classifying Jet Quenching

Machine Learning Application in Jet Quenching Analysis
Yilun Wu (Vanderbilt)

- LSTM neural network can learn from various jet substructures, and classify jets from heavy-ion collisions based on the diverse extents they quenched to





Substructure variables of groomed jets for ML classification

JHEP04(2023)140

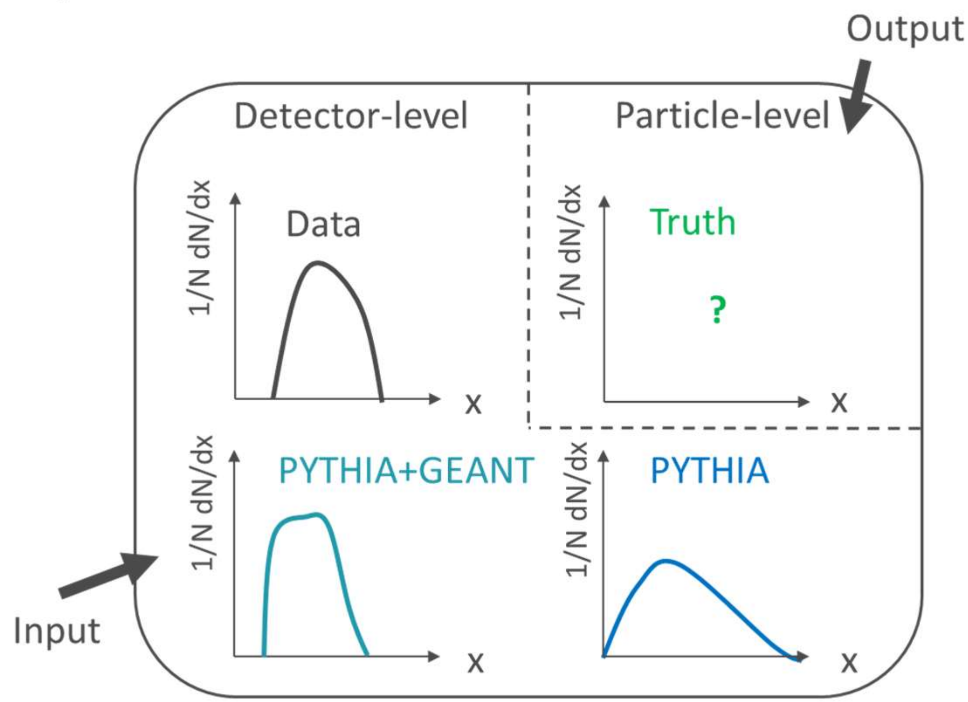
Unfolding with Multifold

Adventures in Omni Fold: Multivariable Unfolding of Jet-Level Observables with STAR Data
Hannah Harrison-Smith (UK)

- Machine learning driven unfolding of multiple observables
- Allows for unbinned unfolding
- **Retains event correlations**

Measurement of CollinearDrop jet mass and its correlation with SoftDrop groomed jet substructure observables in $\sqrt{s} = 200$ GeV pp collisions by STAR
STAR Collaboration • Youqi Song for the collaboration. (Jul 15, 2023)
e-Print: 2307.07718 [nucl-ex]

Generalized angularities measurements from STAR at $\sqrt{s_{\rm NN}} = 200$ GeV
STAR Collaboration • Tanmay Pani (Rutgers U., Piscataway) for the collaboration. (Mar 20, 2024)
Contribution to: Quark Matter 2023 • e-Print: 2403.13921 [nucl-ex]



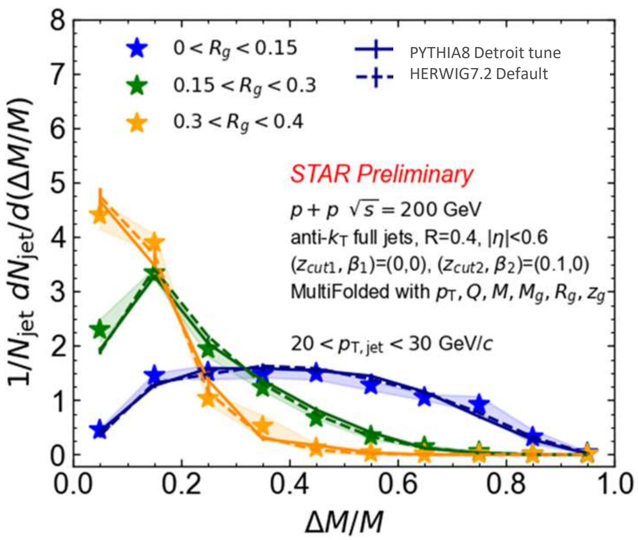
Multifold (*Andreassen et al. PRL 124, 182001 (2020)*)

Picture Credit: Youqi Song (YALE)

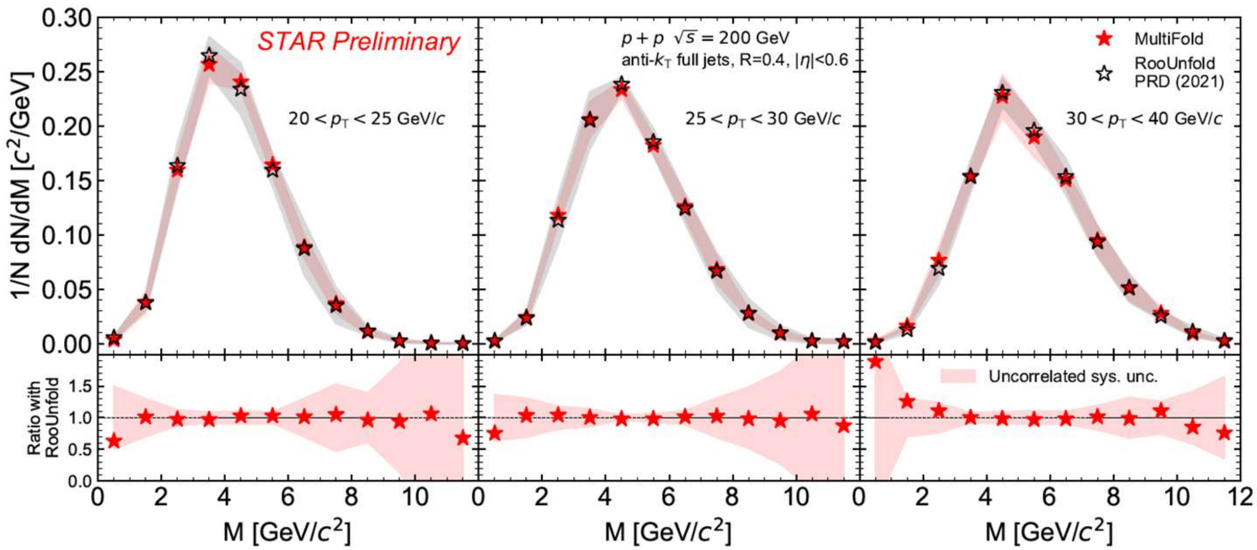
Multifold applications at RHIC

MultiFold
Youqi Song (YALE)

- Probing the correlation between perturbative and nonperturbative components within jets at STAR



Collinear Drop groomed mass fraction



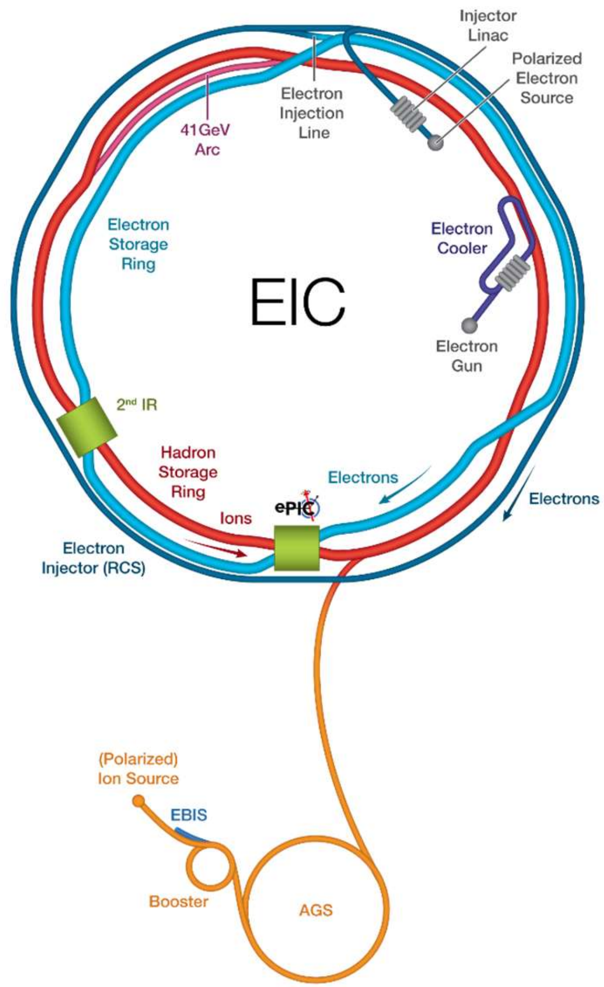
Comparison between IBU and Multifold

The Future: AI @ EIC

- AI-assisted Detector design at EIC
- Reconstruction of Imaging Cherenkov
- Retrieval Augmented Generation
- Streaming readout calorimeters calibrations

AI/ML applications for the EIC
Cristiano Fanelli (William & Mary)

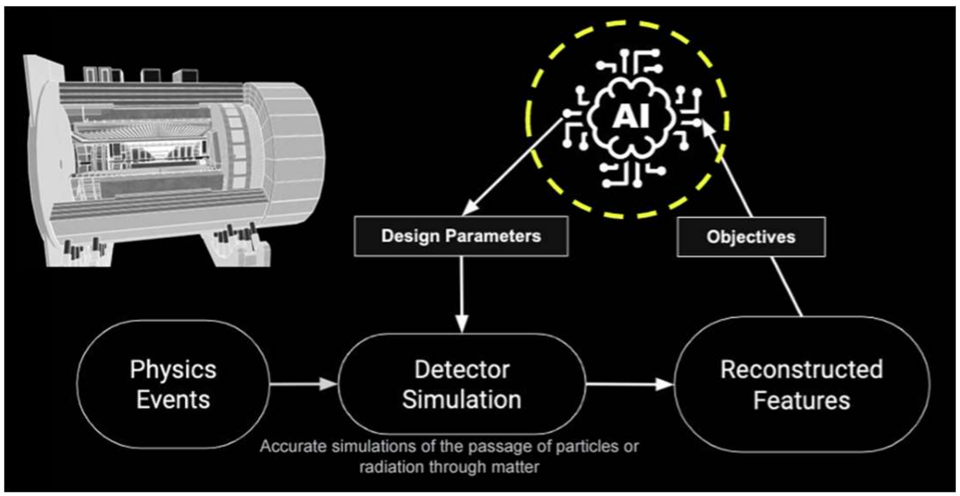
Towards ML Calibration with the ePIC Barrel Hadronic Calorimeter
Derek Anderson (ISU)

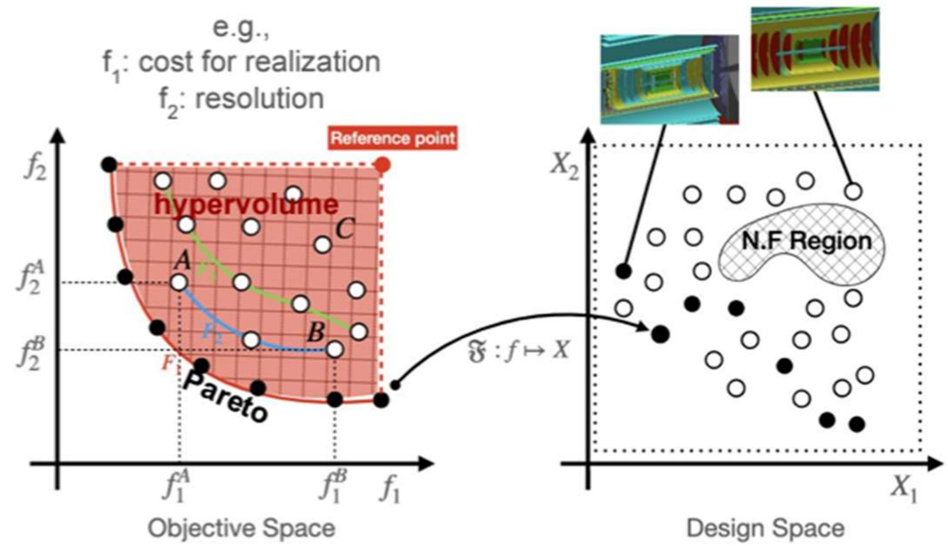


AI-assisted detector design at EIC

AI/ML applications for the EIC
Cristiano Fanelli (William & Mary)

- Uses Bayesian Optimization to optimize detector design

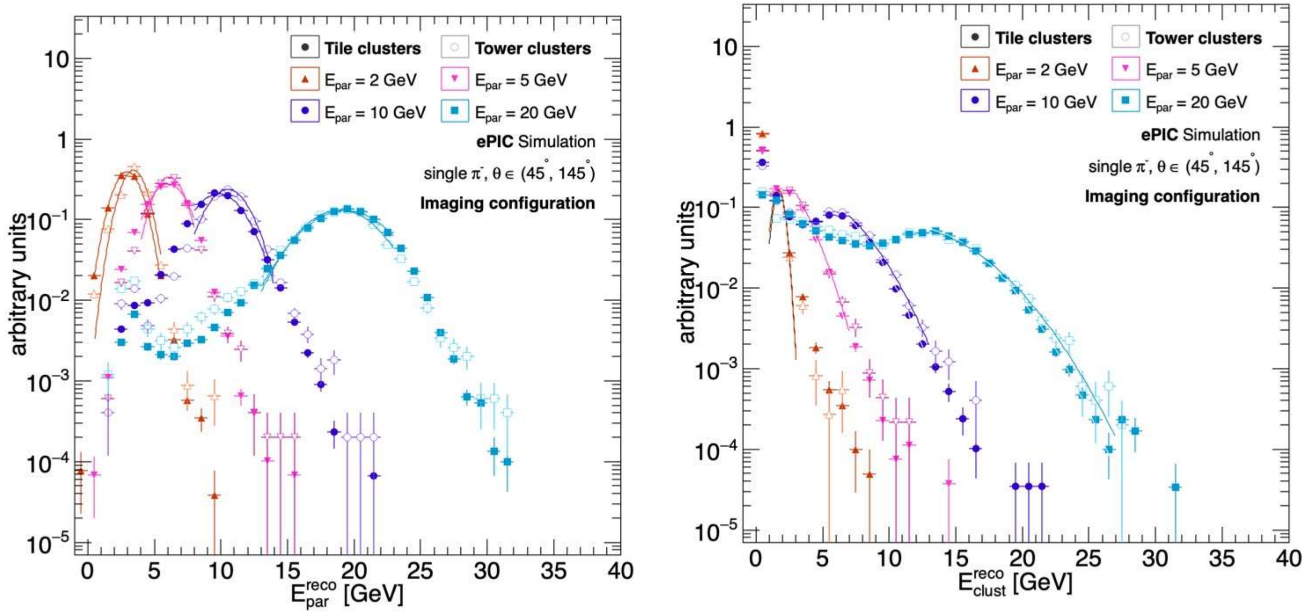




Calorimeter Calibration in ePIC

Towards ML Calibration with the ePIC Barrel Hadronic Calorimeter
Derek Anderson (ISU)

- Full SRO necessities new calibration techniques
- Employ Neural networks to integrate continuous calibrations

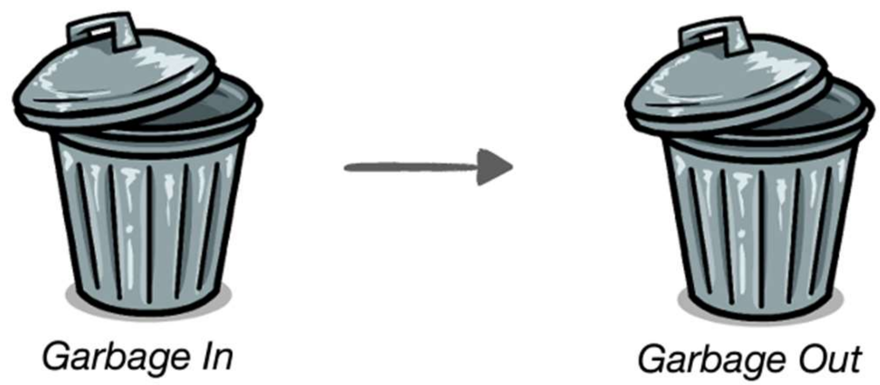


Left: Uncalibrated central calorimeter. Right: Calibrated with TMVA

Final Disclaimer

Overview of Artificial Intelligence at RHIC and Beyond
Hannah Bossi (MIT)

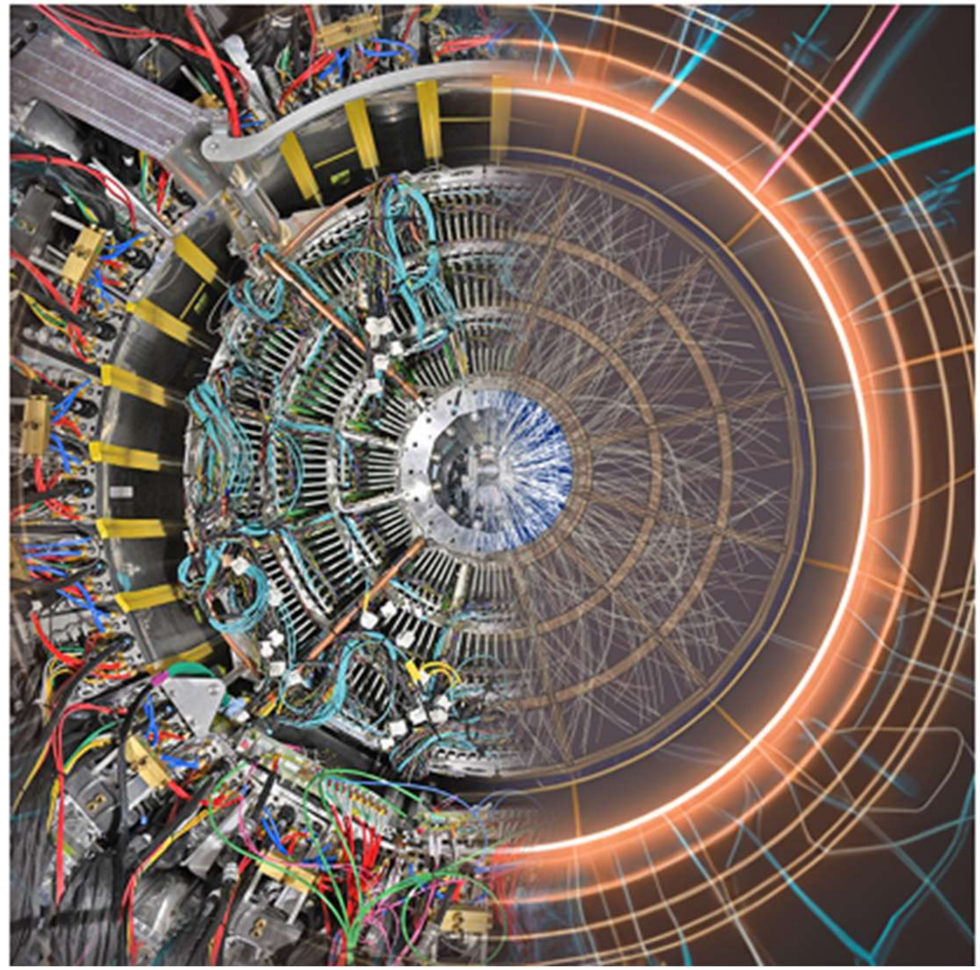
- Machine learning is biased by training data and can often be seen as a black box
- Care needs be taken when applying ML techniques
- Researchers who apply ML to their work need to be able to assess systematics and biases in their method



ML is not a magic fix!

Conclusions

- Applications of AI/ML is being explored in many aspects of RHIC
- ML will only get more prevalent as we move towards the EIC.



Generated image of sPHENIX TPC. Credit Photo based on https://www.growkudos.com/publications/10.1145%25252F3624062.3625127/reader

Shout out!

Machine Learning Applications for EBIS Beam Intensity and RHIC Luminosity Maximization
Xiaofeng Gu (CAD, BNL)

Machine learning applications in particle accelerators
Yuan Gao (CAD, BNL)

AI/ML applications for the EIC
Cristiano Fanelli (William & Mary)

Towards ML Calibration with the ePIC Barrel Hadronic Calorimeter
Derek Anderson (ISU)

FastML triggering in sPHENIX (Autonomous selection of physics events)
Cameron Dean (MIT)

Real-Time Information Distillation with Deep Neural Network-based Compression Algorithms
Yi Huang (BNL)

Generative AI for full-detector, whole-event simulation of heavy ion collisions
Yeonju Go (BNL)

Interpretable Machine Learning applications to Jet Background Subtraction
Charles Hughes (ISU)

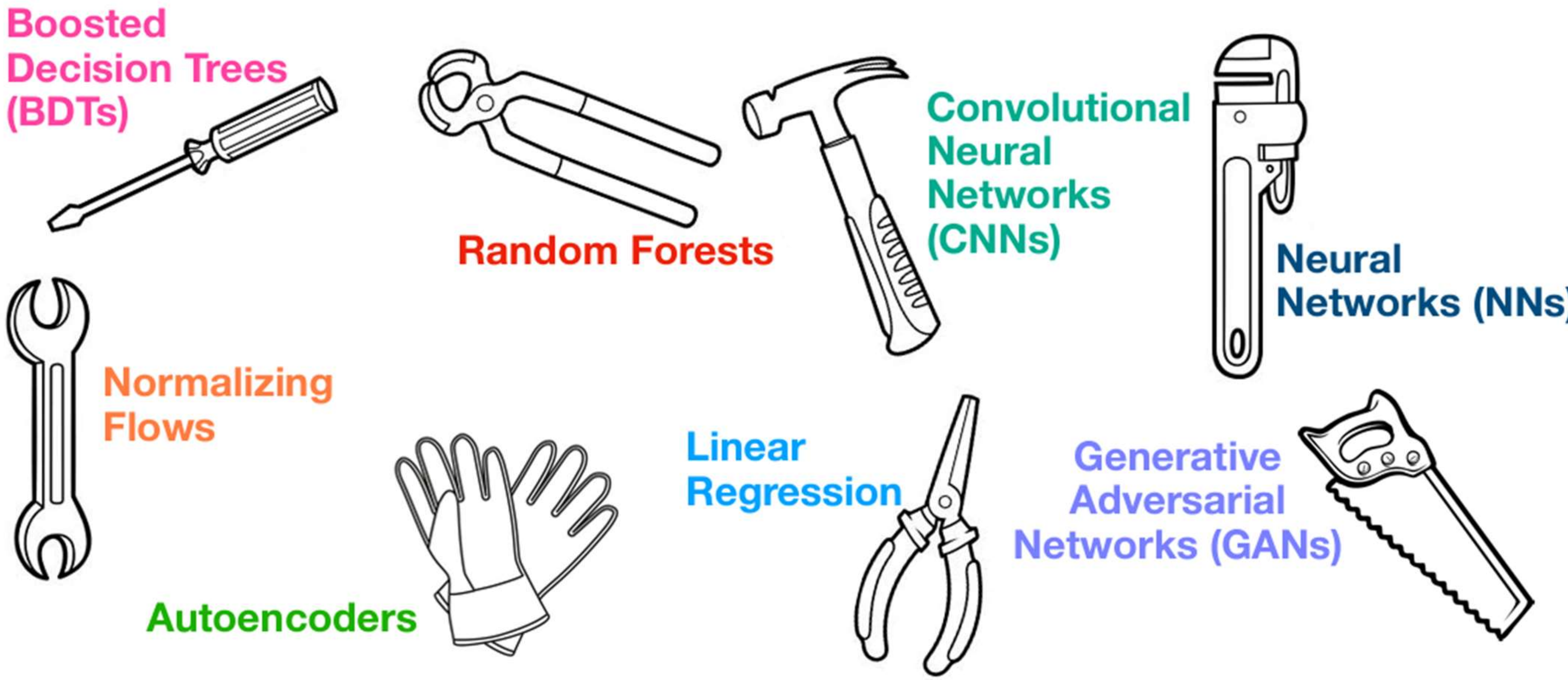
Machine Learning Application in Jet Quenching Analysis
Yilun Wu (Vanderbilt)

MultiFold
Youqi Song (YALE)

Adventures in Omni Fold: Multivariable Unfolding of Jet-Level Observables with STAR Data
Hannah Harrison-Smith (UK)

Overview of Artificial Intelligence at RHIC and Beyond
Hannah Bossi (MIT)

Backup


Boosted
Decision Trees
(BDTs)
Random Forests
Convolutional
Neural
Networks
(CNNs)
Neural
Networks (NNs)
Normalizing
Flows
Linear
Regression
Generative
Adversarial
Networks (GANs)
Autoencoders

Event selection

FastML triggering in sPHENIX (Autonomous selection of physics events)

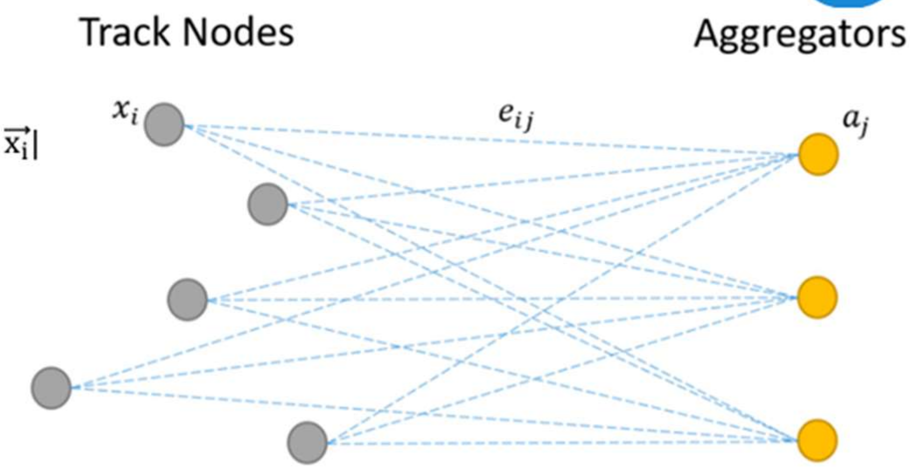
Cameron Dean (MIT)

Tagging with machine learning

sPHENIX

Graph Neural Net design

- Track node input vectors
  1. 5 hits (MVTX + INTT)
  2. Length of each segment: $L = |\overrightarrow{x_{i+1}} - \overrightarrow{x_i}|$
  3. Angle between segments
  4. Total length of segments
- Aggregators
  1. Primary vertex
  2. Secondary vertex
- Current ML tracklet algorithm has
  - Accuracy > 91% for building tracks
  - Area under receiver-operating characteristic curve (AUC) > 97% liken to "probability of combining the correct track elements compared to incorrect elements" – random chance is 50%
  - Purity and rejection studies are underway



$e_{ij} = s_{ij} x_i$ is track-aggregator messages

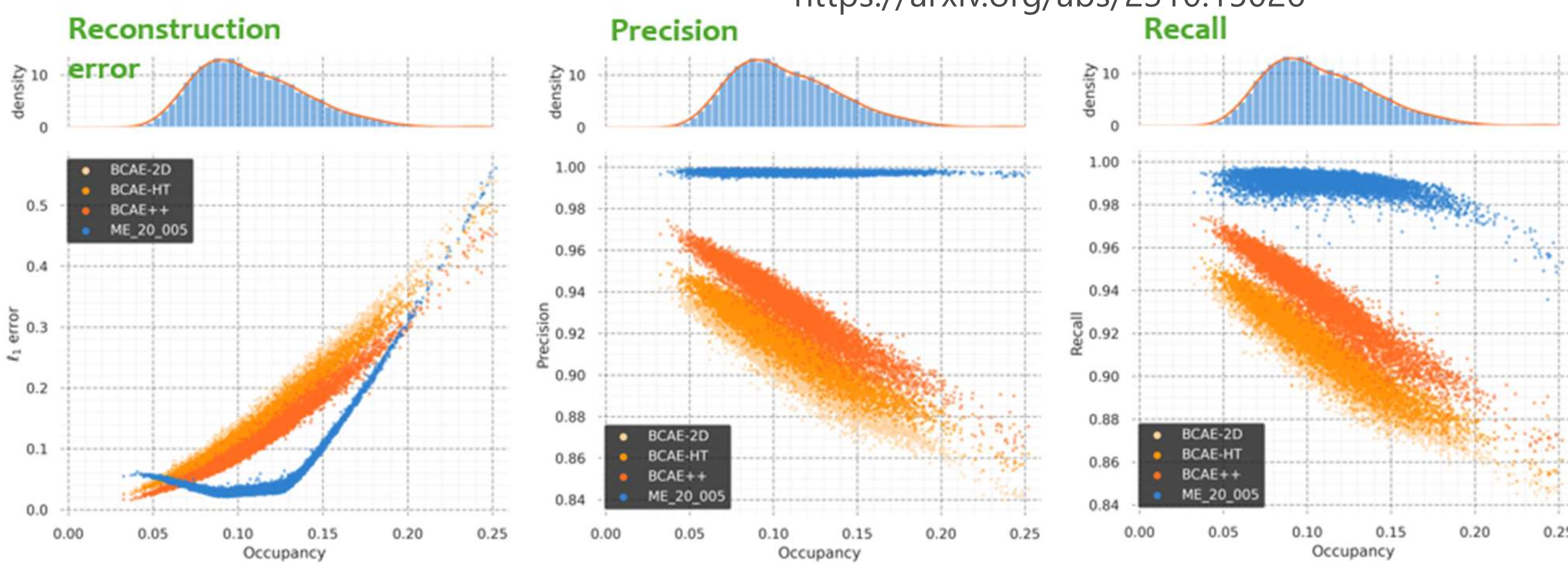
s_{ij} is the weight

ECML PKDD 2022, Sub 1256

MinkowskiEngine

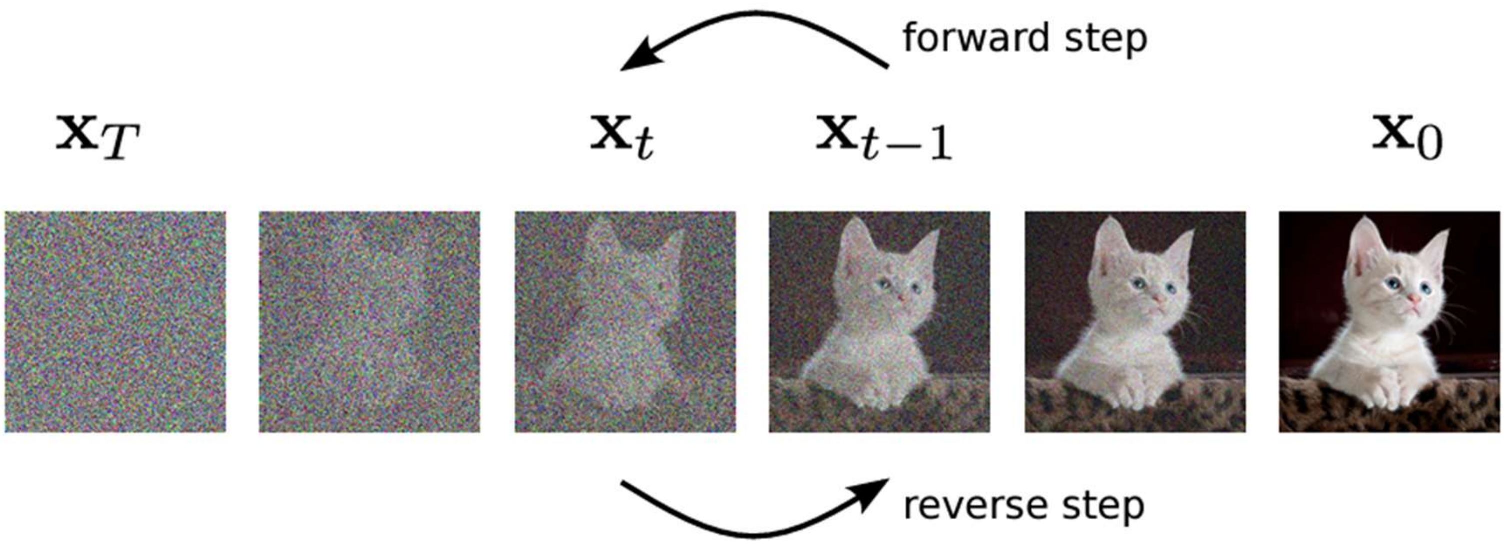
Real-Time Information Distillation with Deep Neural Network-based Compression Algorithms
Yi Huang (BNL)

https://arxiv.org/abs/2310.15026



Diffusive models

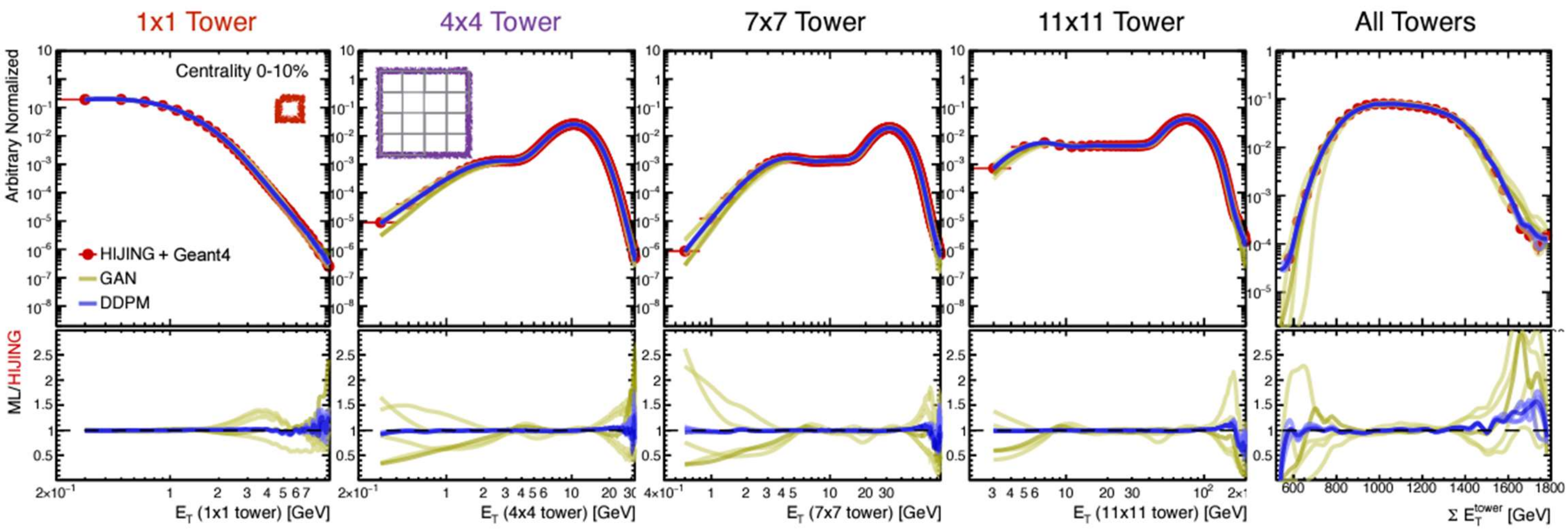
Generative AI for full-detector, whole-event simulation of heavy ion collisions
Yeonju Go (BNL)



Event generation

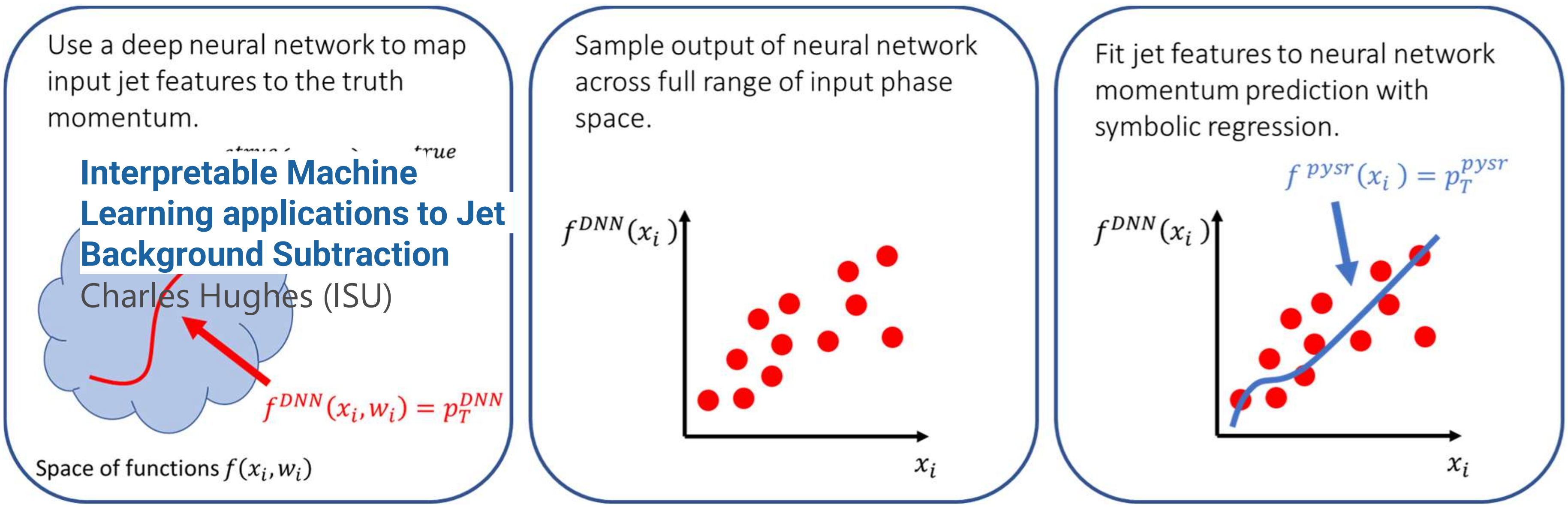
Generative AI for full-detector, whole-event simulation of heavy ion collisions
Yeonju Go (BNL)

	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



Network mapping

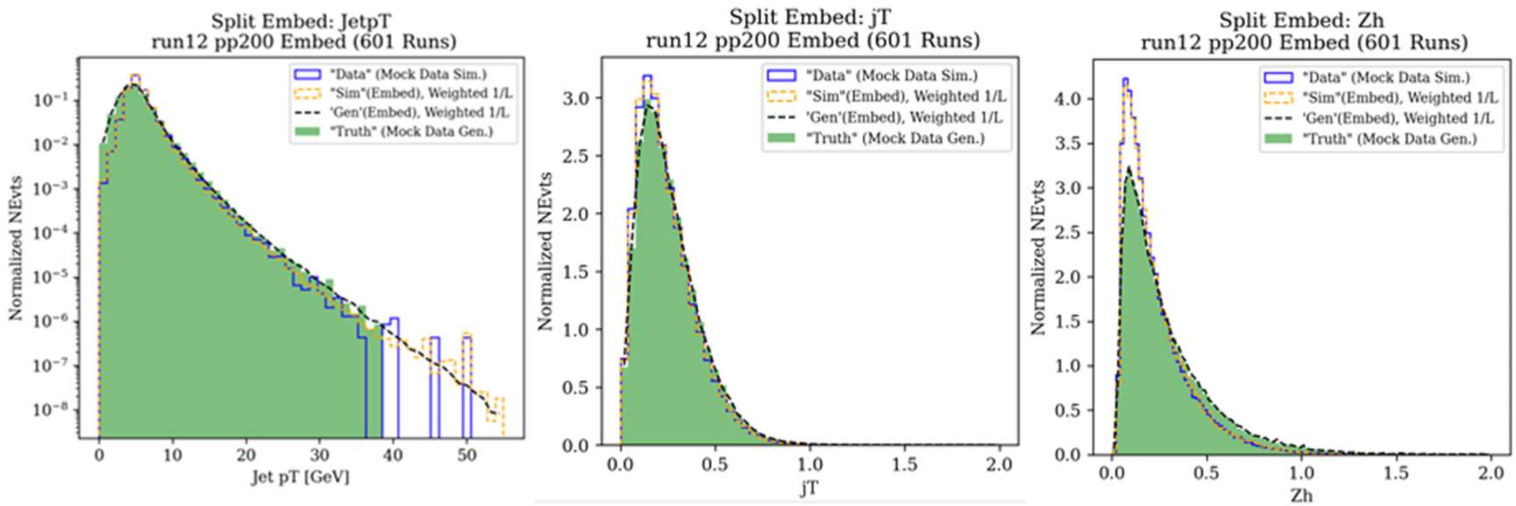
https://journals.aps.org/prc/pdf/10.1103/PhysRevC.108.L021901



More applications of Multifold

Adventures in Omni Fold: Multivariable Unfolding of Jet-Level Observables with STAR Data

Hannah Harrison-Smith (UK)



ePIC calo calibration

Towards ML Calibration with the ePIC Barrel Hadronic Calorimeter
Derek Anderson (ISU)