

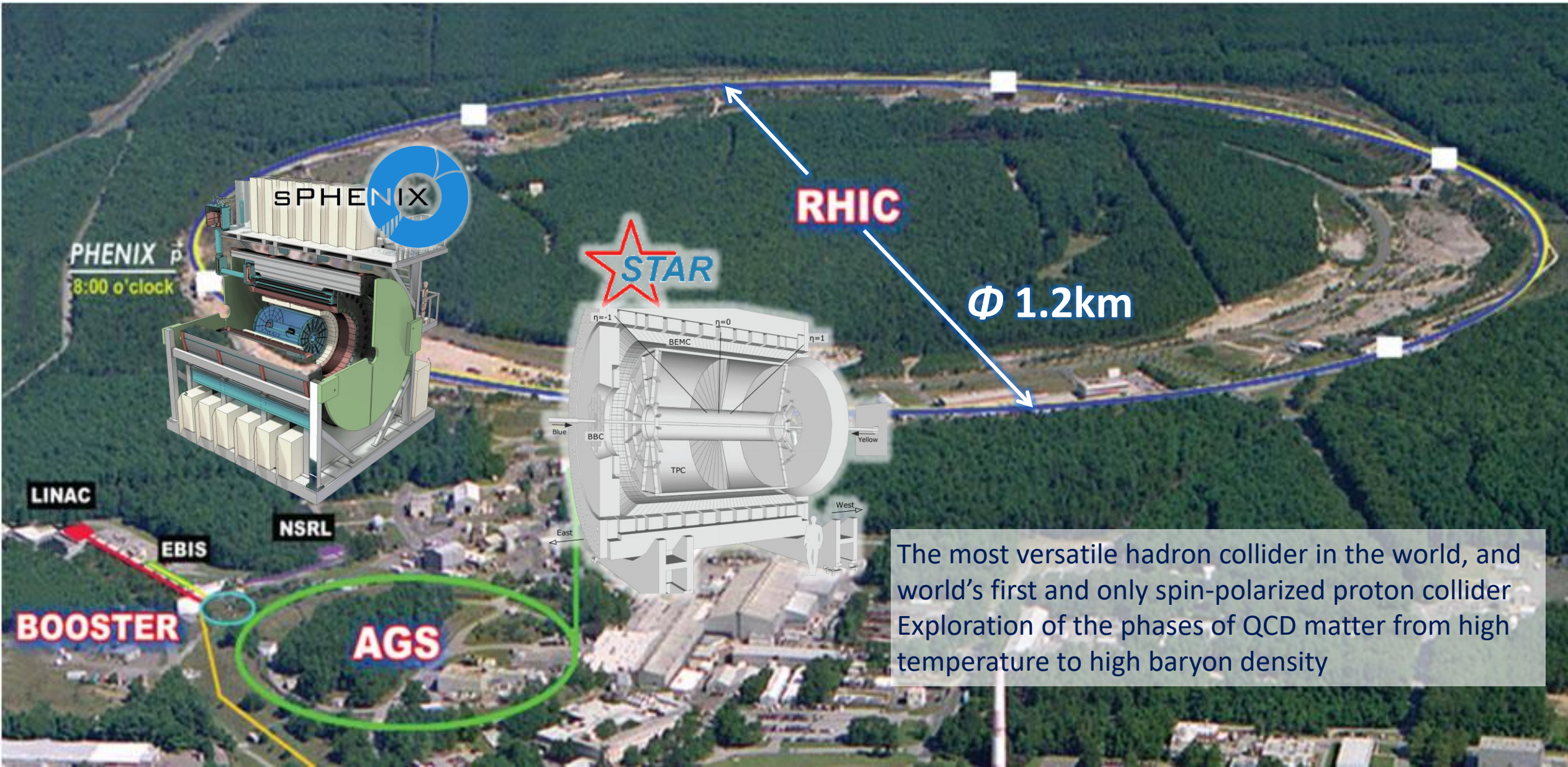
# BNL: sPHENIX SRO DAQ

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# Relativistic Heavy Ion Collider (RHIC) in 2023+





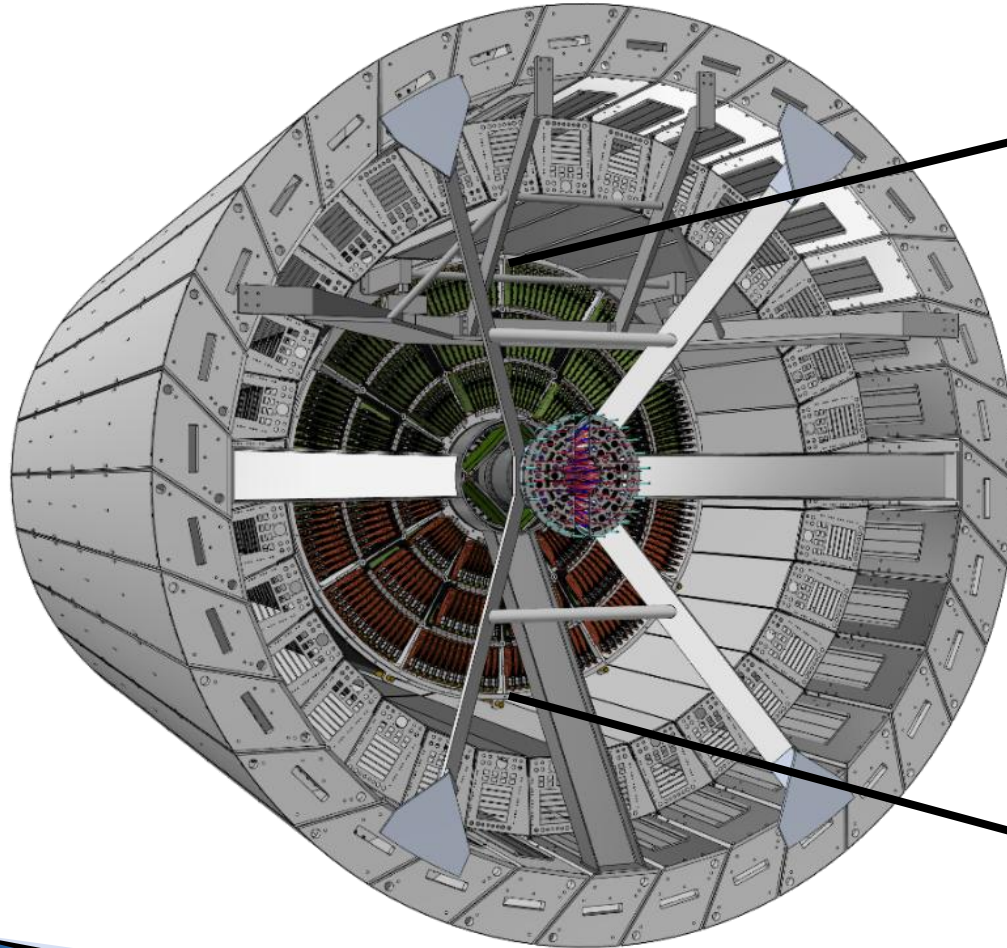
# sPHENIX experiment

Completed first/commissioning run in 2023!

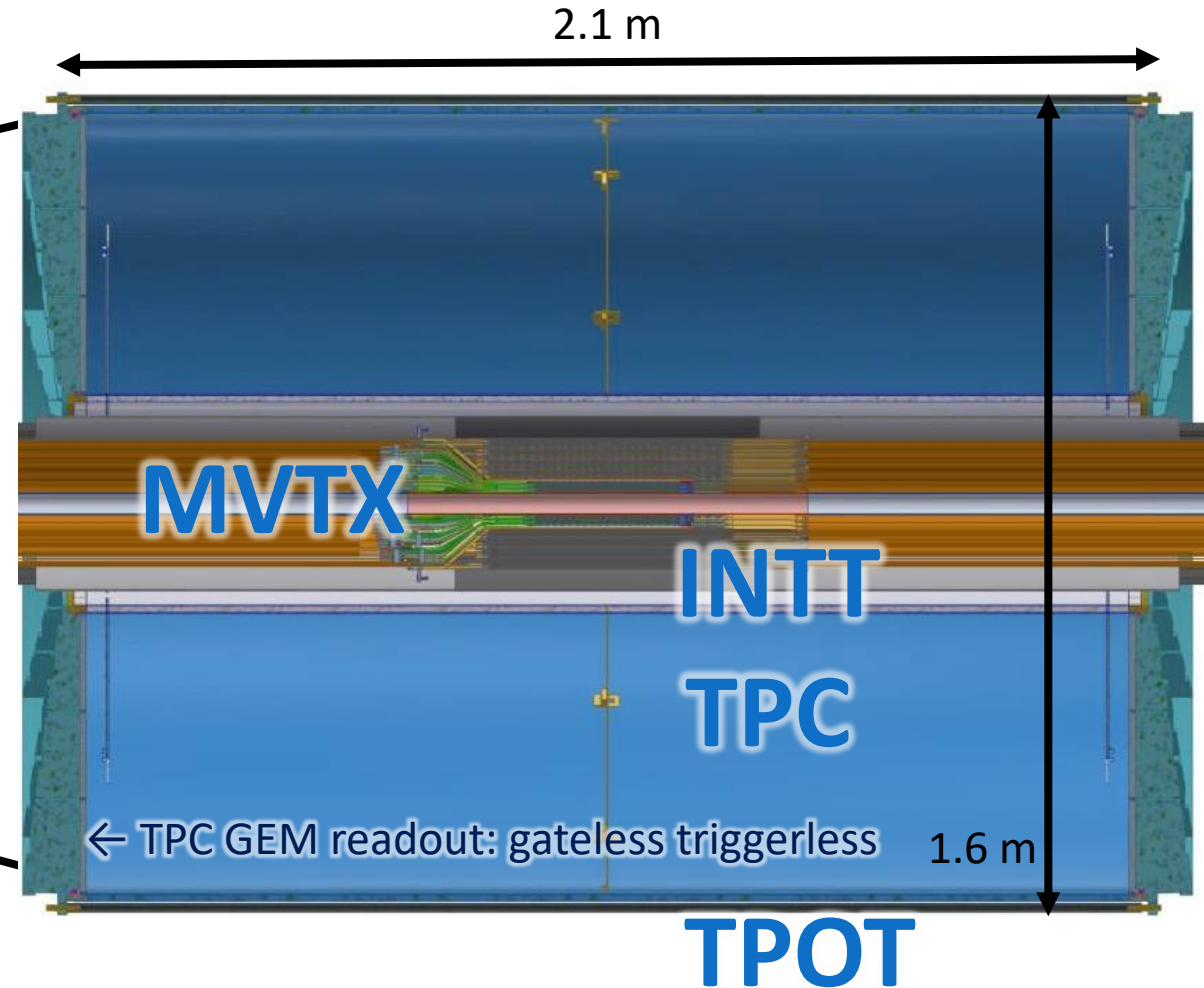




# sPHENIX Tracking Detectors: all supports streaming mode



Detectors inside the magnet





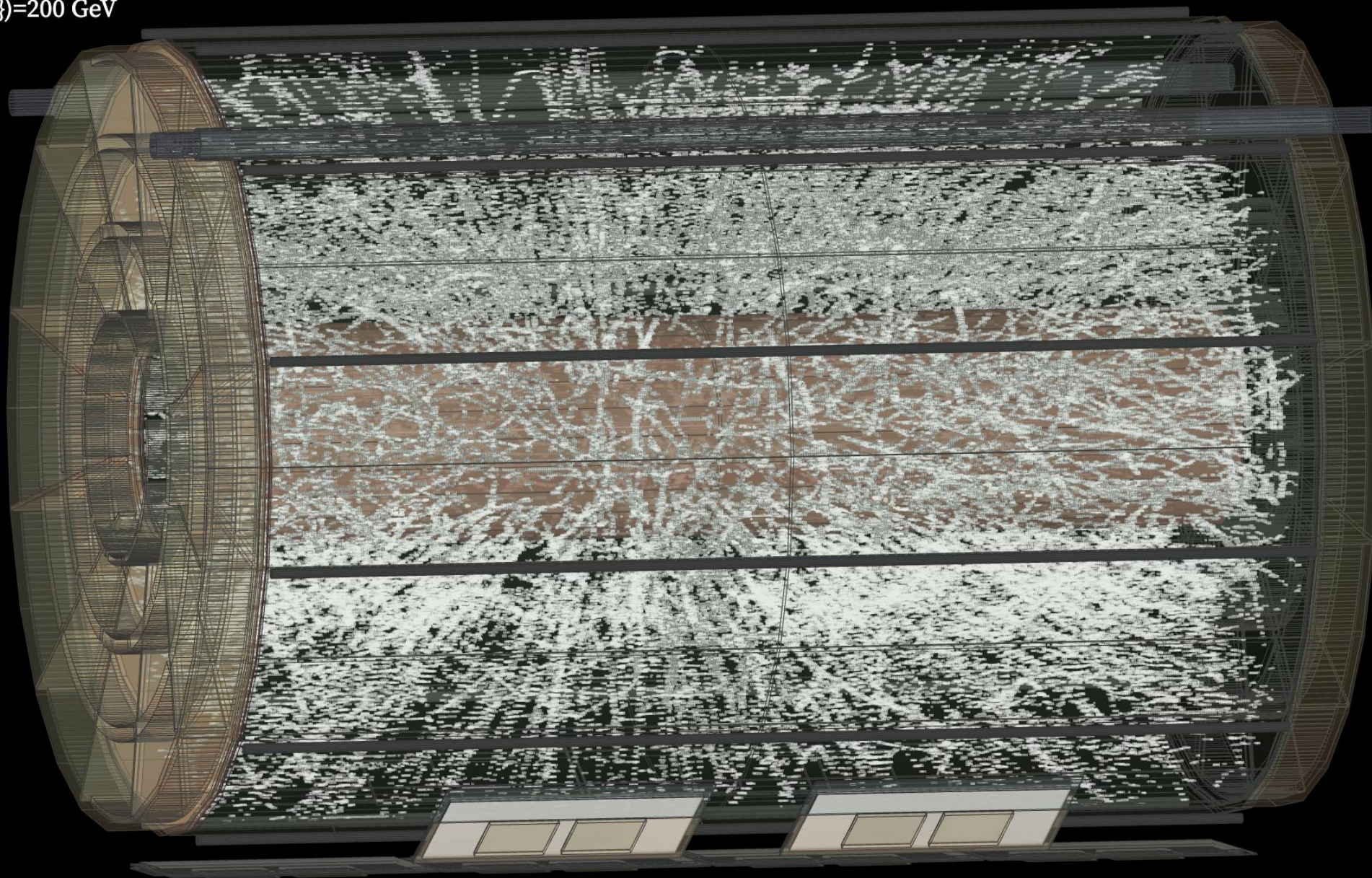


sPHENIX Time Projection Chamber

100 Hz ZDC, MBD Prescale: 2, HV: 4.45 kV GEM, 45 kV CM, X-ing Angle: 2 mrad

2023-06-23, Run 10931 - EBDC03 reference frame 43

Au+Au  $\sqrt{s_{NN}}$ =200 GeV

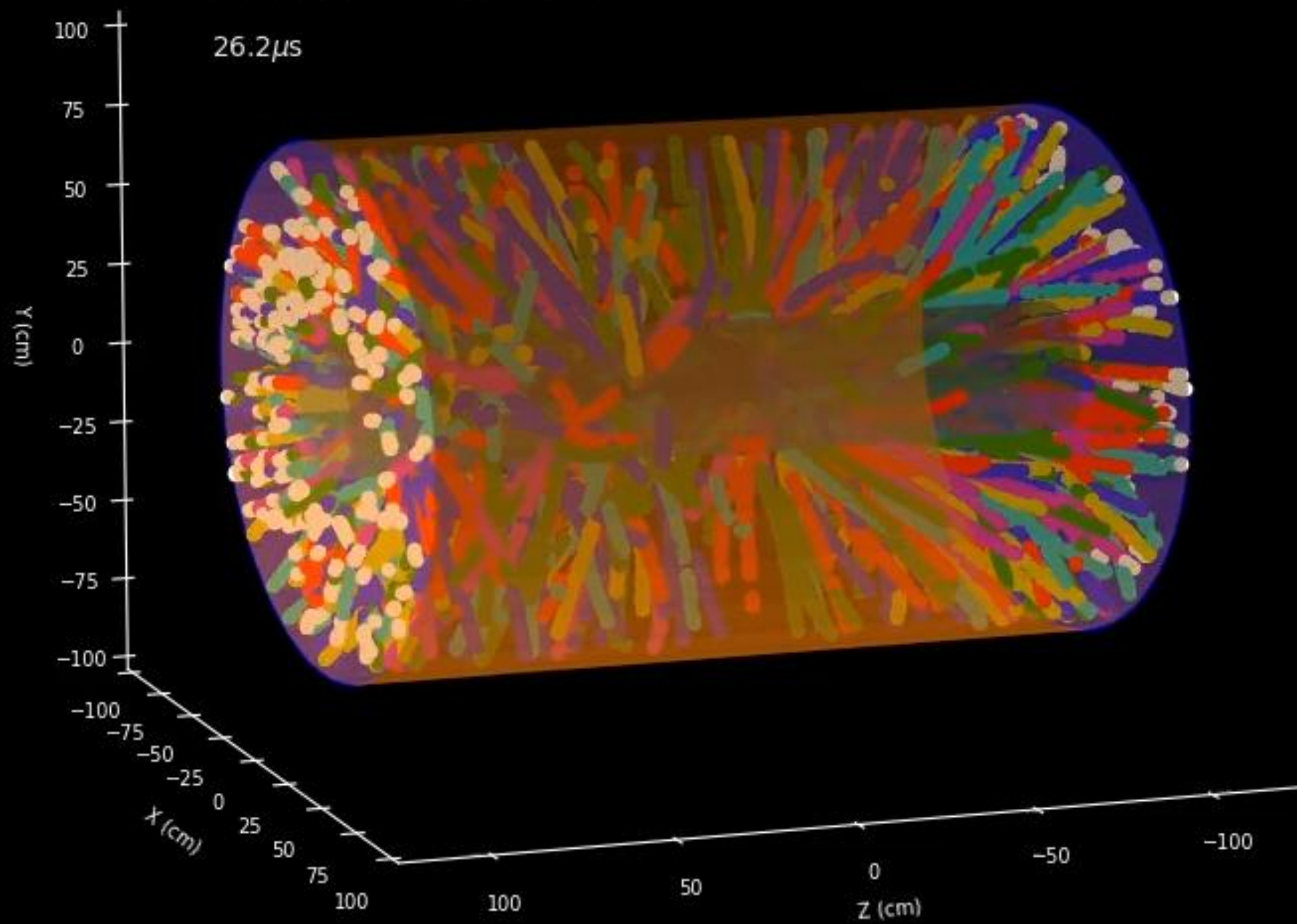




**sPHENIX** TPC simulation

p+p,  $\sqrt{s_{NN}} = 200$  GeV 4MHz

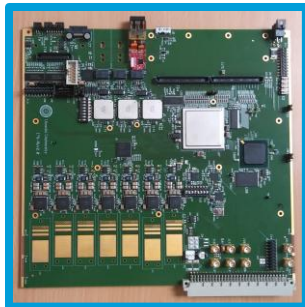
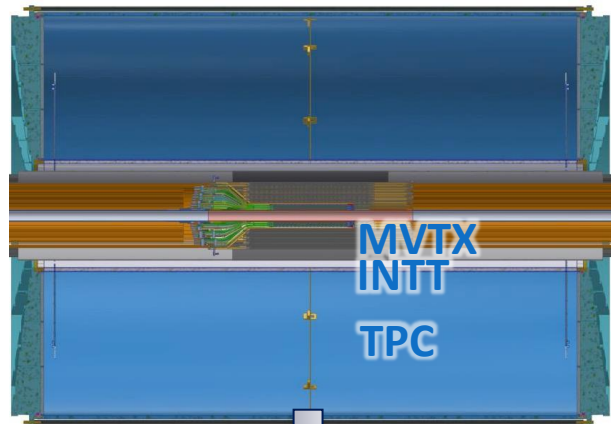
26.2  $\mu$ s



# Streaming readout electronics

## Driven by common DAQ software: RCDAQ

sPHENIX streaming DAQ for tracker



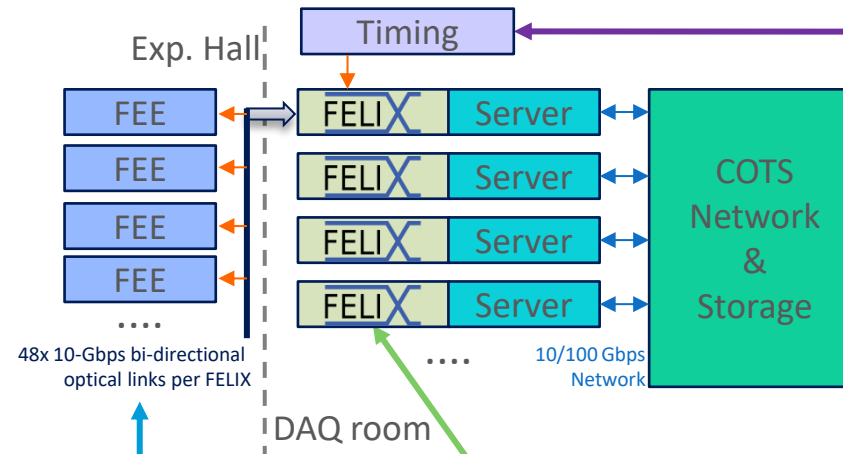
MVTX RU, 200M ch INTT ROC, 400k ch  
ALPIDE (ALICE/sPHENIX), FPHX (PHENIX)



TPC FEE, 160k ch  
SAMPv5 (ALICE/sPHENIX)



BNL-712 / FELIX v2 x38 (ATLAS/sPHENIX)  
FELIX Ref: [10.1109/tim.2019.2947972](https://tim.2019.2947972)



Global Timing  
Module  
(NSLS II/sPHENIX)  
Receiving from RHIC RF  
low jitter clock source

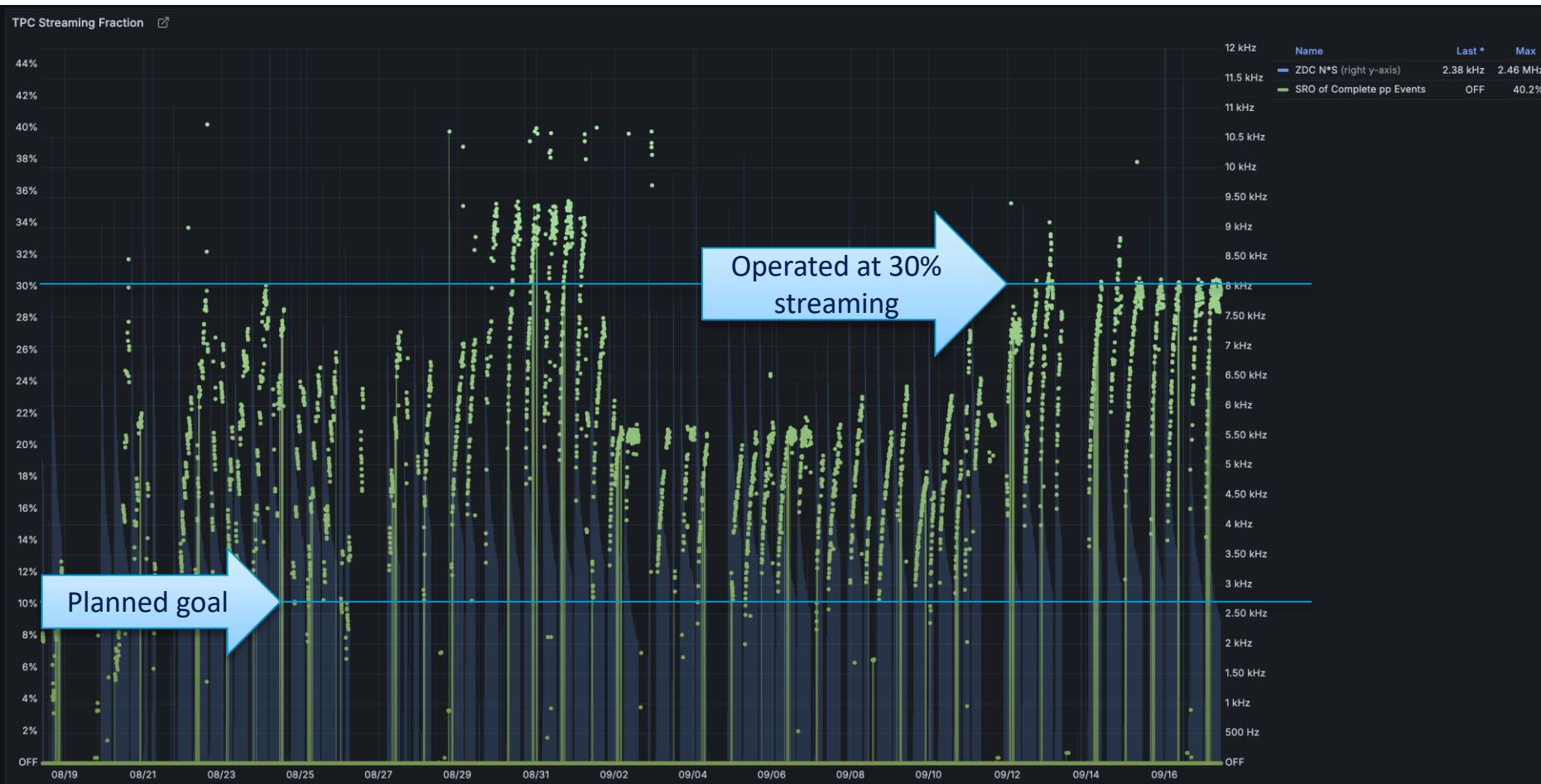
# First physics run in 2024!

## RHIC Program Advisory Committee 2020 Report

The PAC commends sPHENIX for developing the continuous streaming readout option that will increase their data collection in Run-24 by orders of magnitude. This is particularly important and allows unique access to novel open heavy flavor measurements.

## RHIC Program Advisory Committee 2024 Report

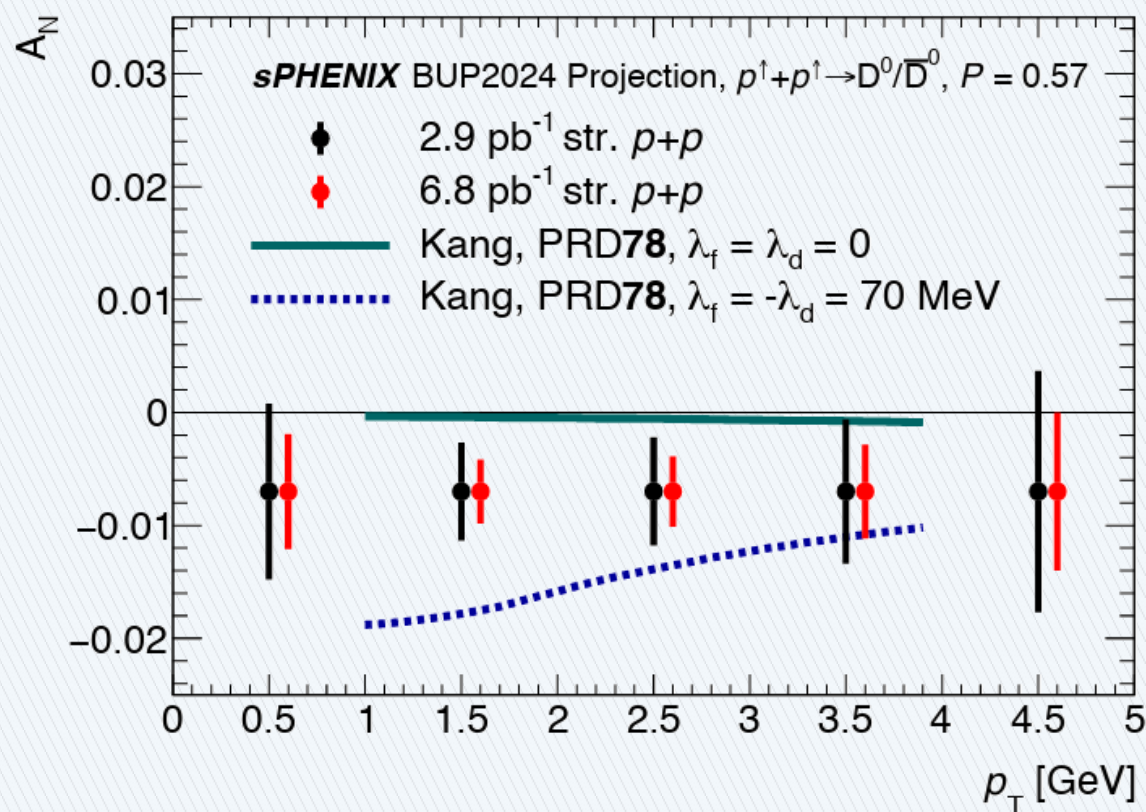
sPHENIX... The streaming readout rate for the tracking detectors (MVTX, INTT and TPC) exceeded the original goal of 10% by a factor of three on average during the run enabling acquisition of a significant amount of data for open heavy flavor physics.



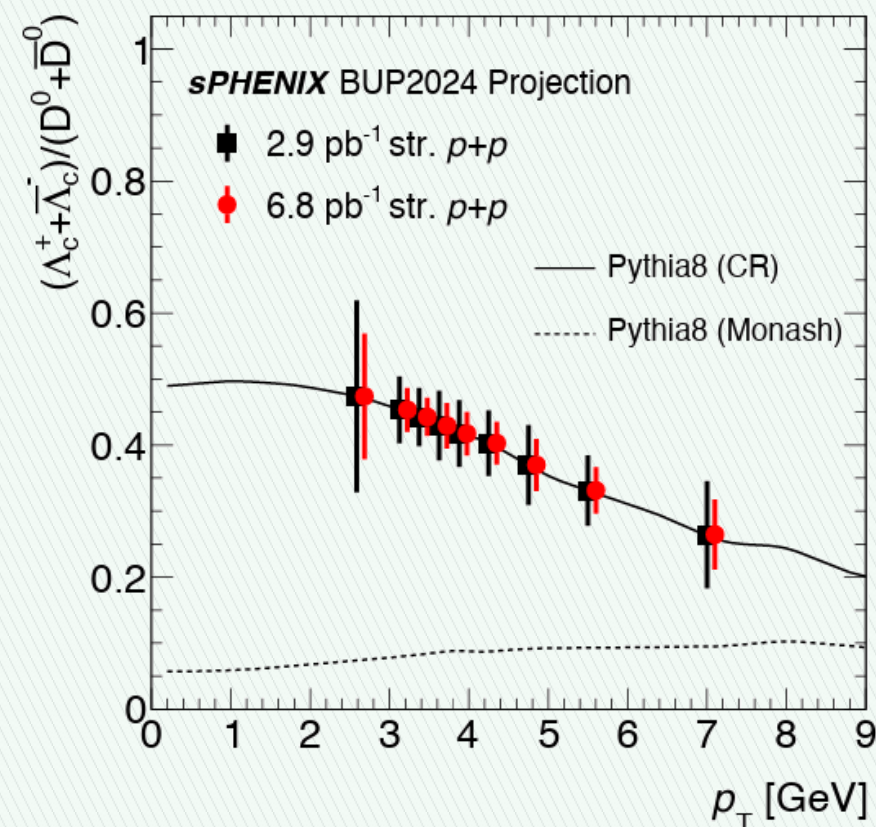


# Physics made only possible by streaming DAQ

First  $D^0$  trans. spin asymmetry,  $A_N$   
 → Gluon Sievers via tri- $g$  cor.



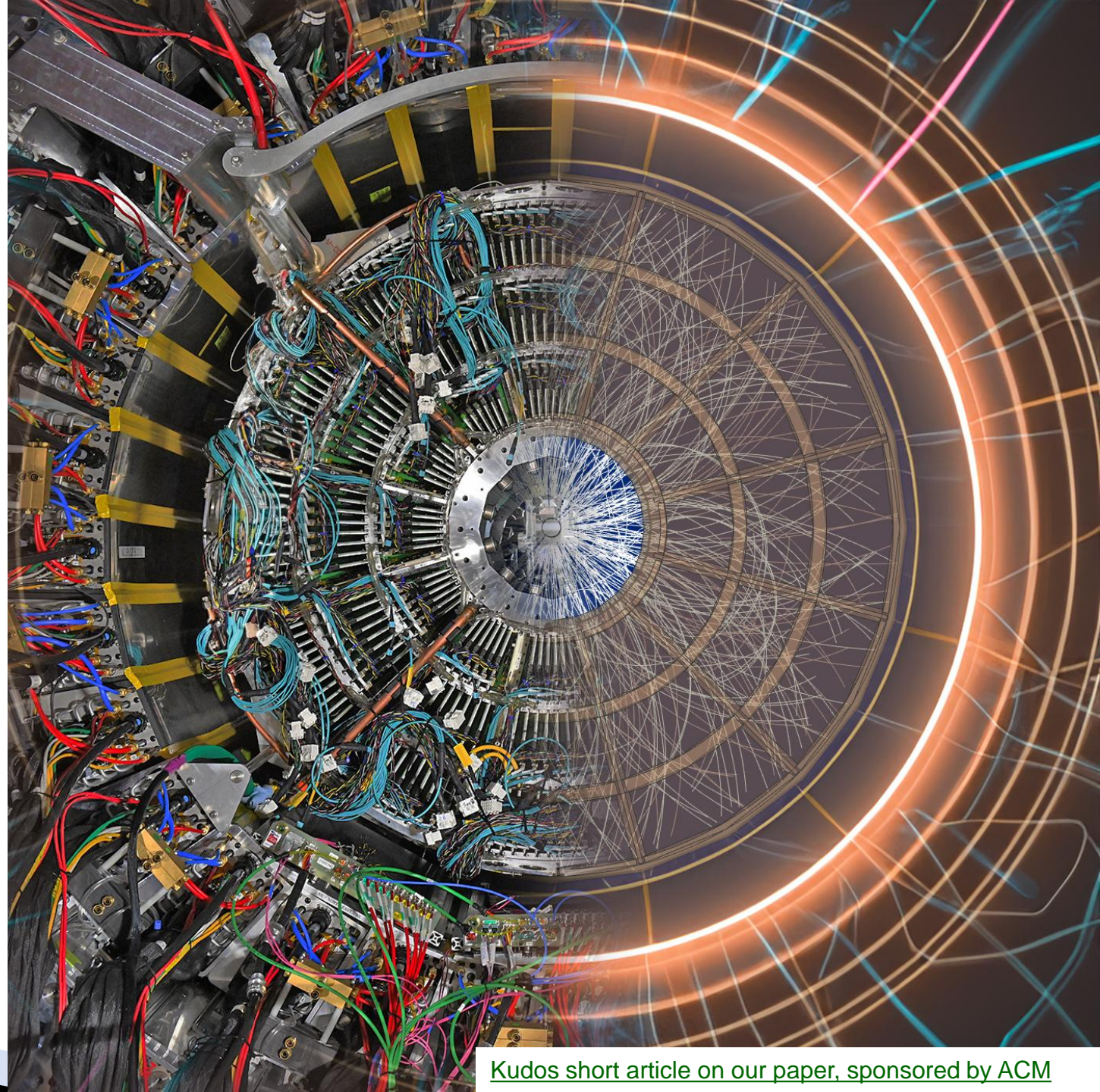
First Charm baryon to meson ratio at RHIC  
 → charm hadronization





# AI in sPHENIX streaming

- ▶ sPHENIX simulation data used for exploring AI-driven data reduction
- ▶ NP-data optimized auto-encoder data reduction:
  - [arXiv:2411.11942](https://arxiv.org/abs/2411.11942) [physics.ins-det]
  - [arXiv:2412.01754](https://arxiv.org/abs/2412.01754) [cs.AI]
  - DOI: 10.1145/3624062.3625127
  - DOI: 10.1109/ICMLA52953.2021.00179
  - [https://github.com/BNL-DAQ-LDRD/NeuralCompression\\_v3](https://github.com/BNL-DAQ-LDRD/NeuralCompression_v3)
  - [https://github.com/BNL-DAQ-LDRD/NeuralCompression\\_v2](https://github.com/BNL-DAQ-LDRD/NeuralCompression_v2)
- ▶ Tagging/triggering on FPGA
  - [arXiv:2501.04845](https://arxiv.org/abs/2501.04845) [physics.ins-det]
  - [arXiv:2312.15104](https://arxiv.org/abs/2312.15104) [physics.ins-det]





# Summary

- ▶ sPHENIX just completed the first successful run with streaming tracker
  - Tripled the target streaming fraction (to 30% delivered pp collision recorded)
  - The streaming capability enables a wide spectrum of low  $p_T$  HF physics program by increasing their statistics by orders of magnitudes, commended by the PAC for years
- ▶ Few thoughts for future streaming experiments
  - Application of Streaming DAQ carries cost and risks, adoption (or not) should be justified by physics program
  - A noisy piece of streaming detector likely become a dead piece of detector in streaming data
  - A streaming data pipeline can become full sooner or later (high instantaneous rate from Poisson distribution of collision, background, and noise), therefore it by design needs to handle congestion gracefully.
  - Many ideas work at small scales, but our streaming system need to be designed at the scale for the entire experiment and robust against multiple failure mode
- ▶ If you would like to prototype streaming system: come to join sPHENIX 😊
  - Real streaming data, 4D tracking, high fidelity streaming simulation, 40x(FELIX+EBDC), MAPS+SAMPA (current generation of the ePIC SVT/MPGD chip family)



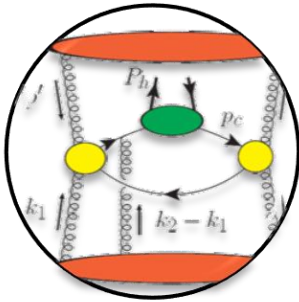
# Extra information





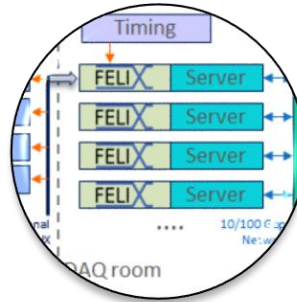
# Streaming DAQ and real-time AI:

## A new and paradigm shift for experiments in next NP LRP



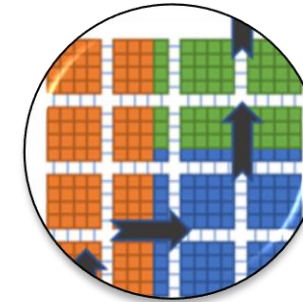
### NP Physics

- Diverse topology
- Stringent sys. Ctrl
- Max data preservation



### Streaming DAQ

- New physic capability accessible only via streaming DAQ
- Example: adopted for sPHENIX and EIC
- Require data reduction computationally



### Opportunities for AI enhancement

- Specialized AI algorithm for reliable and high-performance data reduction
- Novel hardware emerging for high-throughput AI computing

Physics need → Streaming DAQ → Opportunity for real-time AI → Enhanced physics program



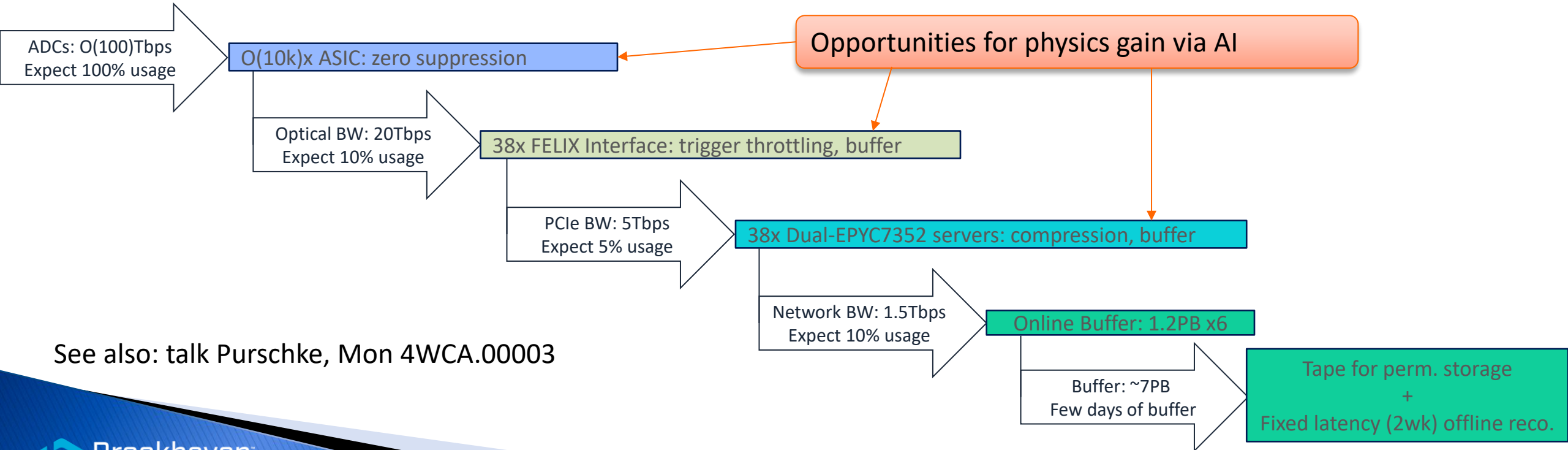
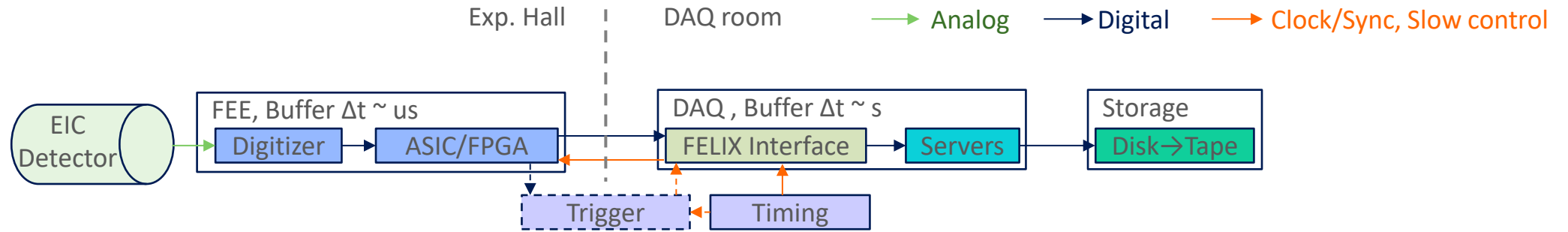
# Nuclear collider experiments: unique real-time system challenges leads to streaming DAQ

	EIC	RHIC	LHC → HL-LHC
Collision species	$\vec{e} + \vec{p}, \vec{e} + A$	$\vec{p} + \vec{p}/A, A + A$	$p + p/A, A + A$
Top x-N C.M. energy	140 GeV	510 GeV	13 TeV
Bunch spacing	10 ns	100 ns	25 ns
Peak x-N luminosity	$10^{34} \text{ cm}^{-2} \text{ s}^{-1}$	$10^{32} \text{ cm}^{-2} \text{ s}^{-1}$	$10^{34} \rightarrow 10^{35} \text{ cm}^{-2} \text{ s}^{-1}$
<b>x-N cross section</b>	<b>50 <math>\mu\text{b}</math></b>	<b>40 mb</b>	<b>80 mb</b>
Top collision rate	500 kHz	10 MHz	1-6 GHz
$dN_{\text{ch}}/d\eta$ in p+p/e+p	0.1-Few	$\sim 3$	$\sim 6$
<b>Charged particle rate</b>	<b>4M <math>N_{\text{ch}}/\text{s}</math></b>	<b>60M <math>N_{\text{ch}}/\text{s}</math></b>	<b>30G+ <math>N_{\text{ch}}/\text{s}</math></b>

- ▶ Signal data rate is moderate → possible to streaming recording all collision signal
- ▶ But events are precious and have diverse topology → hard to trigger on all process
- ▶ Background and systematic control is crucial → avoiding a trigger bias; reliable data reduction



# sPHENIX Streaming data flow



See also: talk Purschke, Mon 4WCA.00003



# AI in streaming readout DAQ

- ▶ Main challenge: data reduction
  - Traditional DAQ: triggering was the main method of data reduction, assisted by high level triggering/reconstruction, compression
  - Streaming DAQ need to reduce data computationally: zero-suppression, feature building, lossy compression
- ▶ Opportunities for Real-time AI
  - Emphasize on reliable data reduction, applicable at each stages of streaming DAQ: Front-end electronics, Readout Back-end, Online computing
  - Data quality monitoring, fast calibration/reconstruction/ feedback
    - Has many AI application too
    - Not focus of this talk, nonetheless important for NP experiments

