

sPHENIX TPC and Real-time AI

Outline: • sPHENIX TPC Year-1 Commissioning • Applications of Realtime AI (LDRD 23-048) • Summary

Jin Huang

Brookhaven National Lab

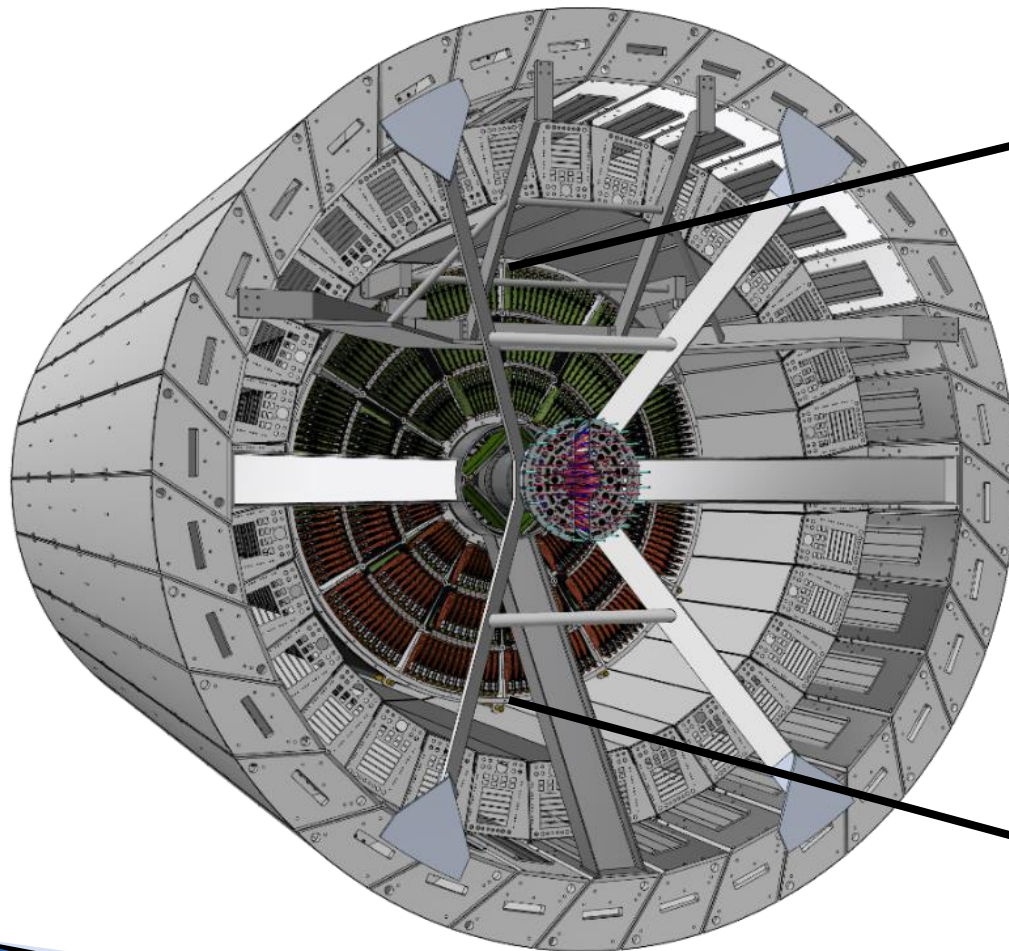
sPHENIX experiment

Completed first/commissioning run in 2023!

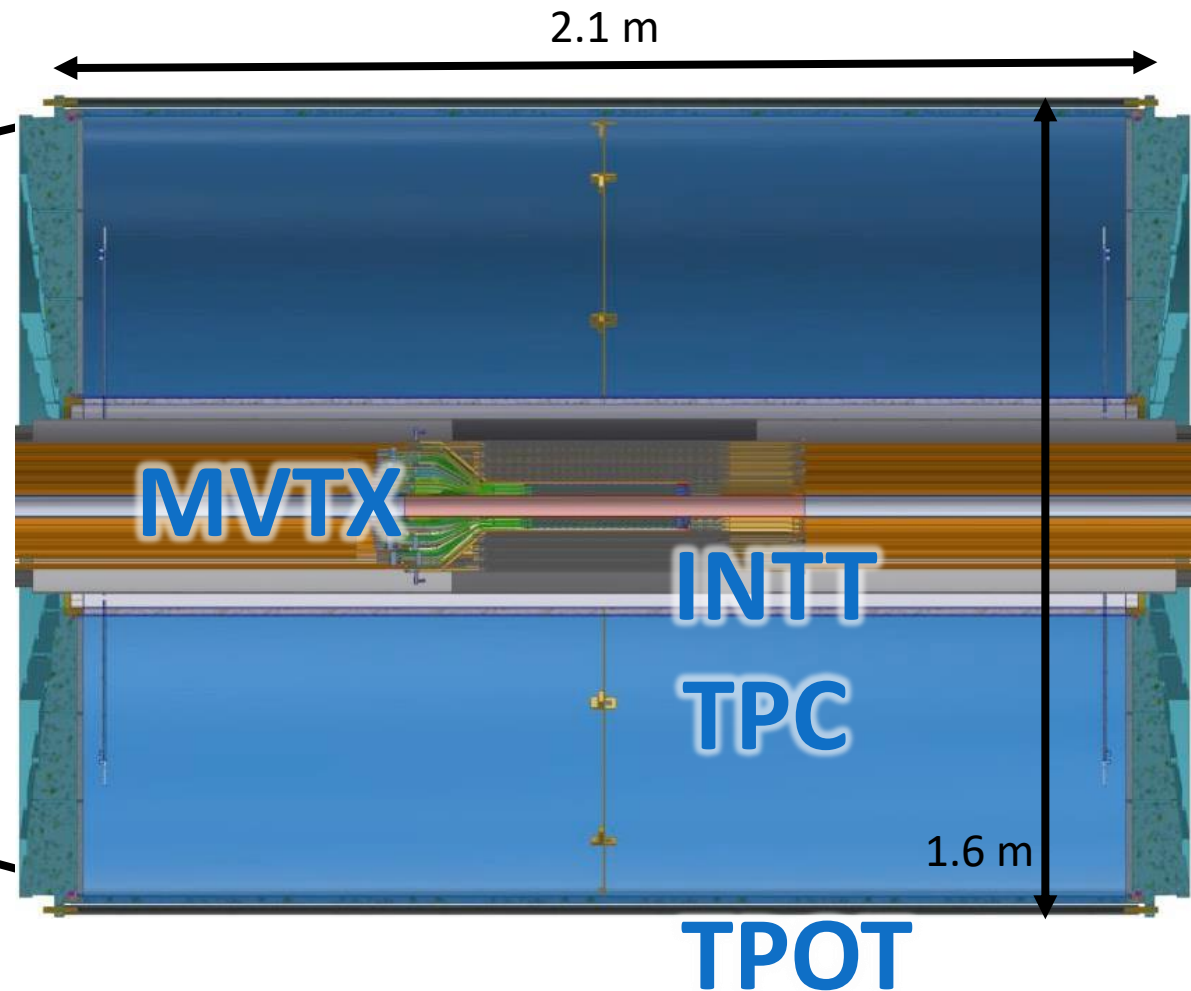
See also: M. Purschke's talk Just now



sPHENIX Tracking Detectors



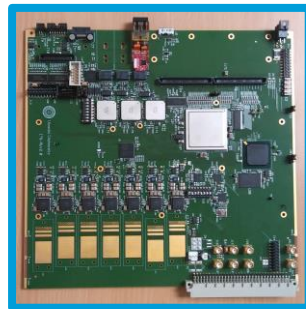
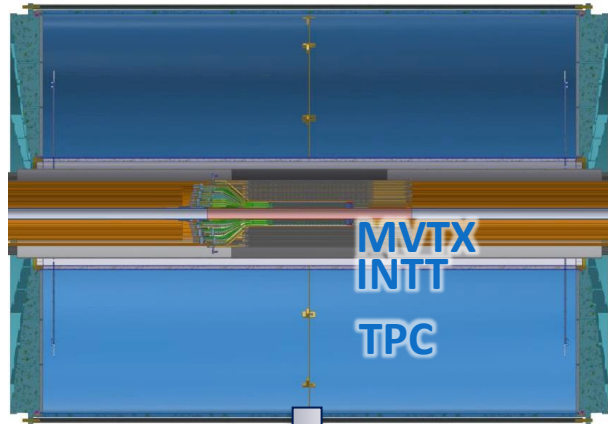
Detectors inside the magnet



Streaming readout electronics

Plan to recording 10% p+p collisions in hybrid streaming DAQ
 → 2-3 orders of magnitude increase in soft-HF statistics

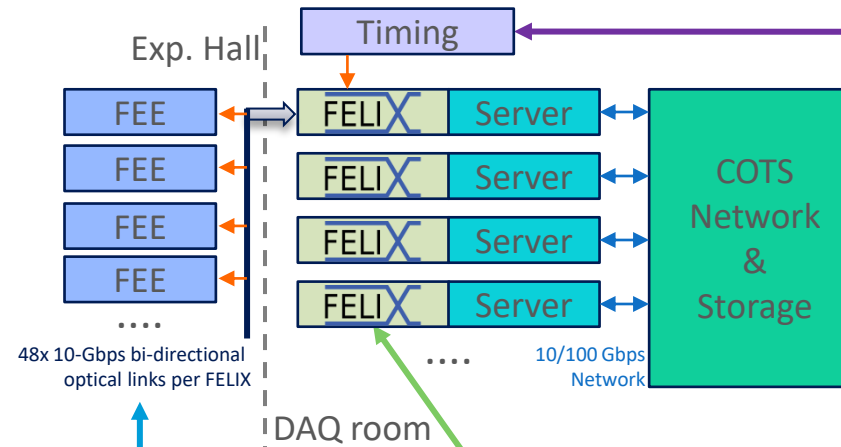
sPHENIX streaming DAQ for tracker



MVTX RU, 200M ch
 ALPIDE (ALICE/sPHENIX), FPHX (PHENIX)



INTT ROC, 400k ch



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



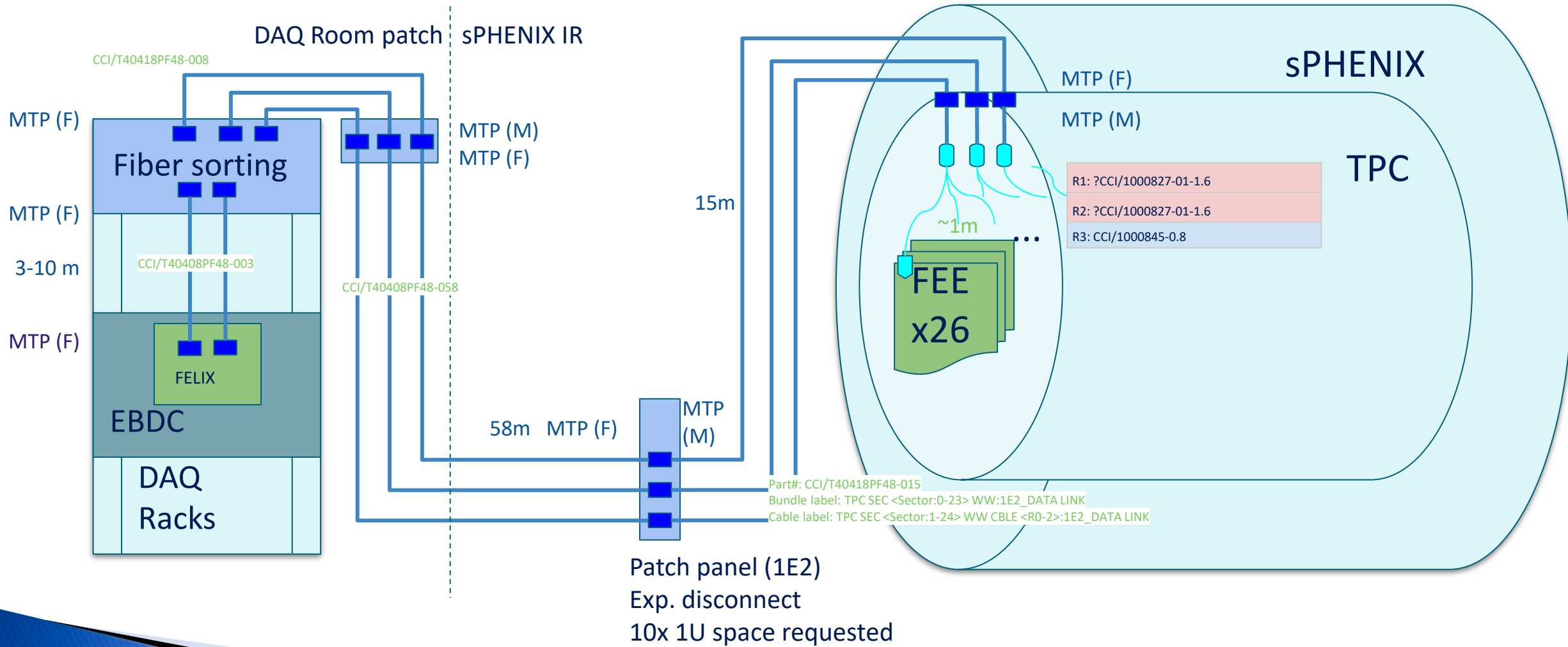
TPC FEE

INTT ROC

MVTX

Beam pipe

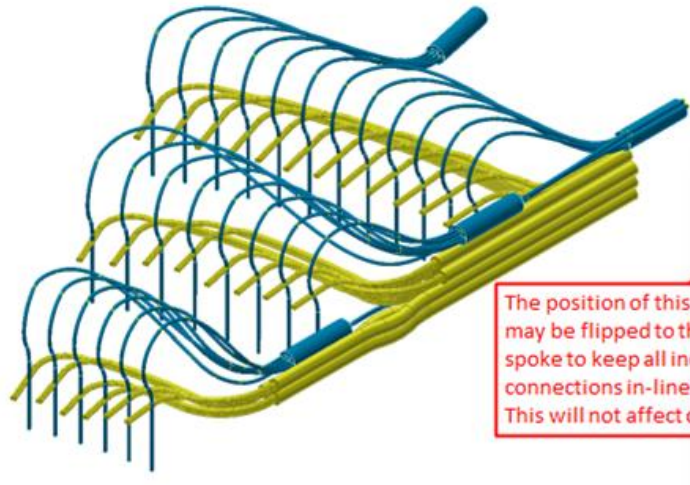
sPHENIX TPC Data Fiber Cabling Plan, 1 of 24 sectors shown



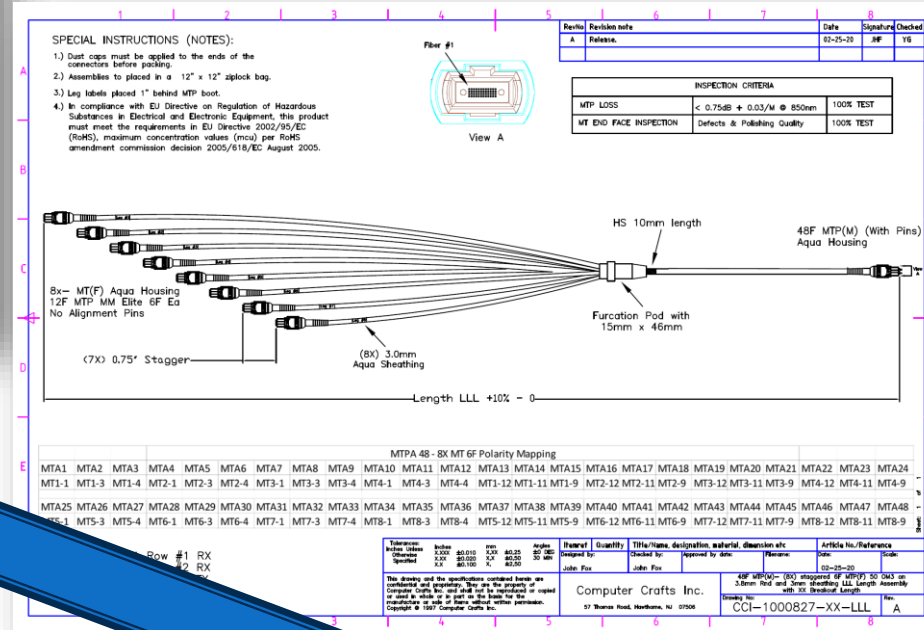
Custom MTP-48 to MTP-12 breakout

Mechanical and channel-mapping design at BNL

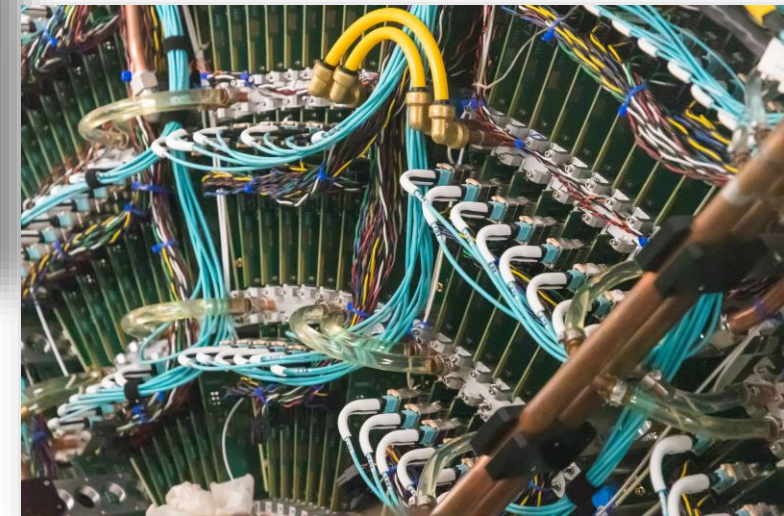
Drawing and manufacture/QA at CCI: ~\$500 + 4wk LT



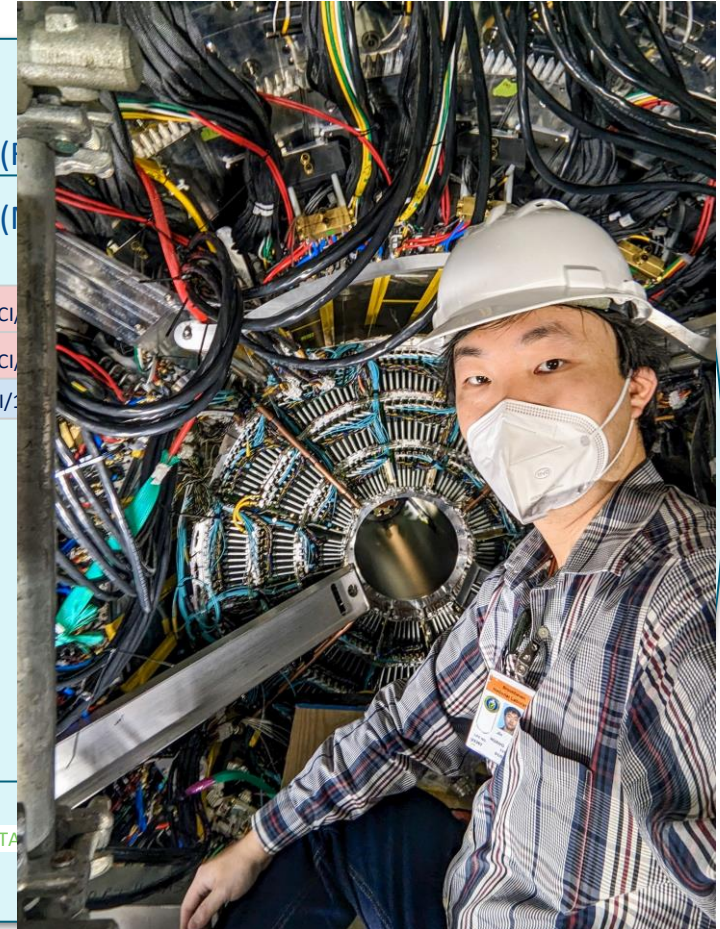
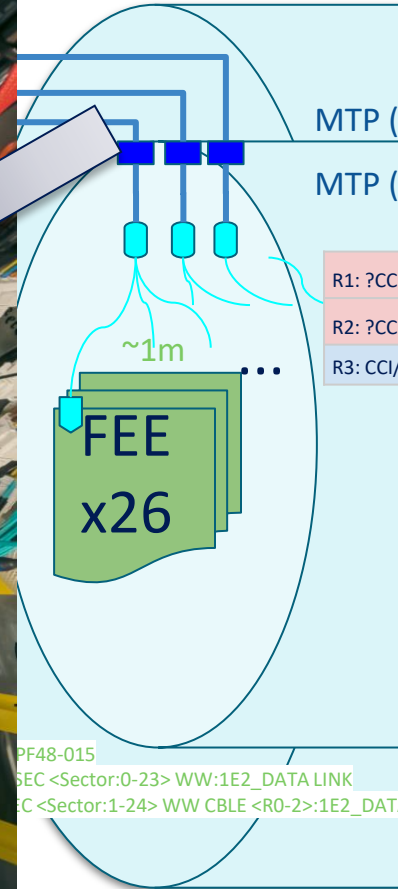
The position of this may be flipped to the spoke to keep all in-line connections in-line. This will not affect



Installation at sPHENIX



sPHENIX TPC Data Fiber Cabling Plan, 1 of 24 sectors shown

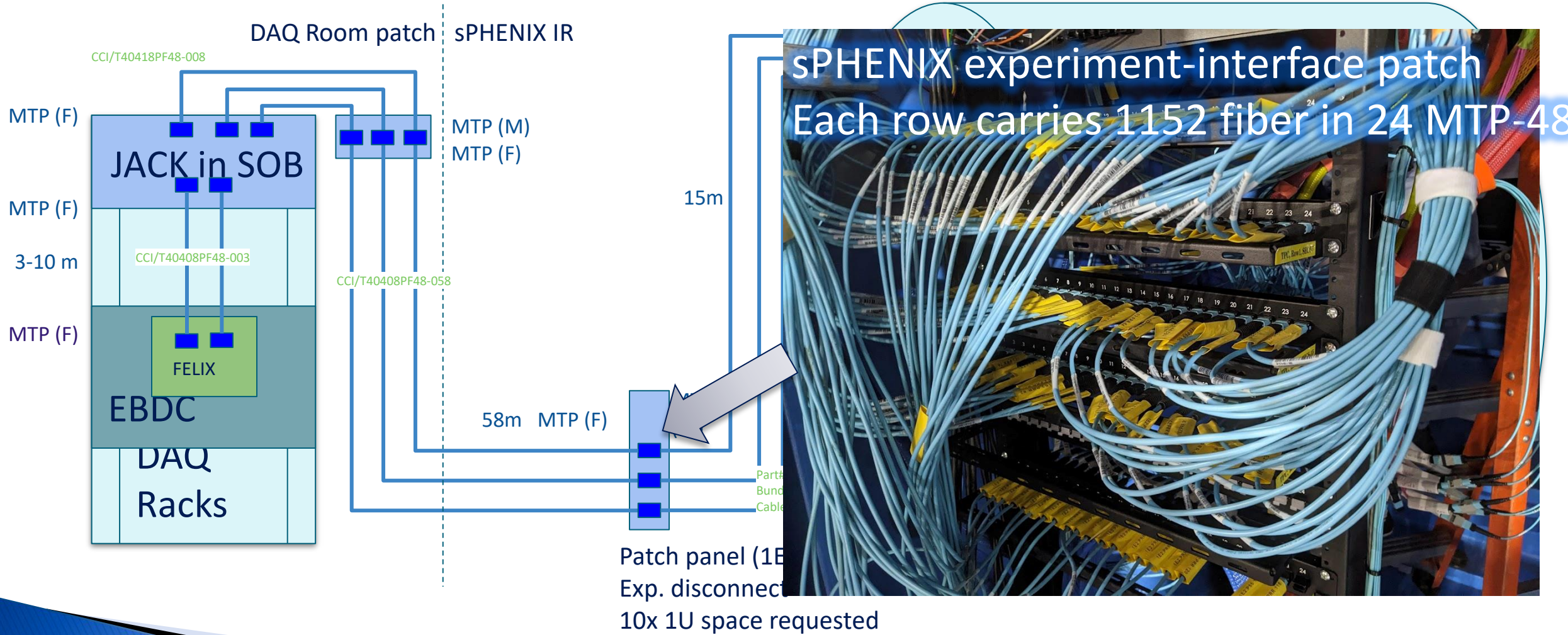


Exp. disconnect
10x 1U space requested

 48F MTP Cable
  MTP coupler
  MTP-QSFP breakout
  QSFP MTP cable
  QSFP Transceiver

One-way optical loss: 1.5dB

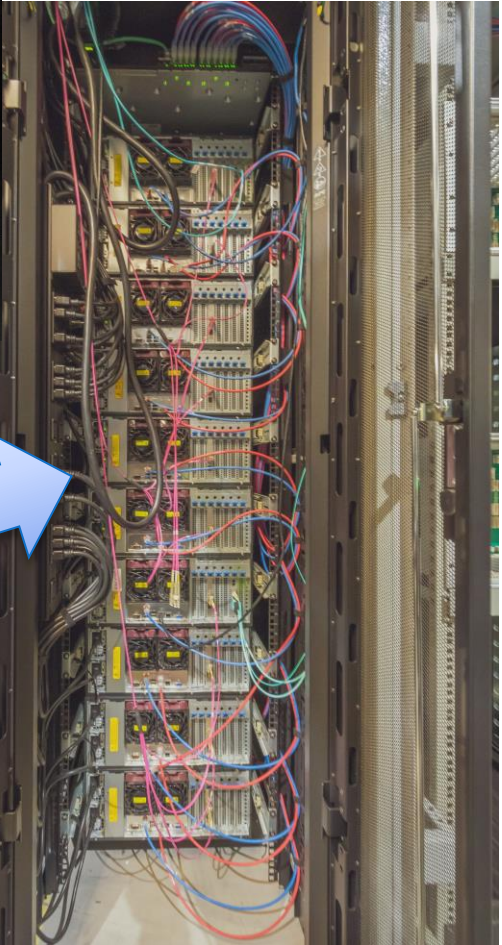
sPHENIX TPC Data Fiber Cabling Plan, 1 of 24 sectors shown



Rack room layout

Row 3, viewed outside in

Assignment Rack	RHIC infrastructure 3.1	LL1 3.2	EBDC TPC South 3.3	Patch/ TPC SOB South 3.4	EBDC TPC North/Sou 3.5	Patch/ TPC SOB North 3.6	EBDC TPC South 3.7	EBDC Other 3.8
1		1		1 Fiber Patch MVTX		1 Fiber Patch INTT		1
2		2		2 Fiber Patch		2 Fiber Patch INTT		2
3		3		3 Fiber Patch		3 Fiber Patch		
4		4	4 EBDC MVTX 1	4 Fiber Patch	4 EBDC TPC S5	4 Fiber Patch	4 EBDC TPC S1	
5		5		5 Fiber Patch TPC S1-4		5 Fiber Patch TPC N1-4		
6		6		6 Fiber Patch TPC S5-8		6 Fiber Patch TPC N5-8		6
7		7		7 Fiber Patch TPC S9-12		7 Fiber Patch TPC N9-12		7
8		8	8 EBDC MVTX 2		8 EBDC TPC S6		8 EBDC TPC N4	8 EBDC INTT1
9		9						
10		10		10 SOB Spare		10 SOB TPOT		
11		11						
12		12	12 EBDC MVTX 3	12 SOB S1	12 EBDC TPC S7	12 SOB N1	12 EBDC TPC N5	12 EBDC INTT2
13		13		13 SOB S2		13 SOB N2		
14		14		14 SOB S2		14 SOB N2		
15		15		15 SOB S3		15 SOB N3		
16		16	16 EBDC MVTX 4	16 SOB S3	16 EBDC TPC S8	16 SOB N3	16 EBDC TPC N6	16 EBDC INTT3
17		17		17 SOB S4		17 SOB N4		
18		18		18 SOB S4		18 SOB N4		
19		19		19 SOB S5		19 SOB N5		
20		20	20 EBDC MVTX 5	20 SOB S5	20 EBDC TPC S9	20 SOB N5	20 EBDC TPC N7	20 EBDC INTT4
21		21		21 SOB S6		21 SOB N6		
22		22		22 SOB S6		22 SOB N6		
23		23		23 SOB S7		23 SOB N7		
24		24	24 EBDC MVTX 6	24 SOB S7	24 EBDC TPC S10	24 SOB N7	24 EBDC TPC N8	24 EBDC INTT5
25		25		25 SOB S8		25 SOB N8		
26		26		26 SOB S8		26 SOB N8		
27		27		27 SOB S9		27 SOB N9		
28		28	28 EBDC TPC S1	28 SOB S9	28 EBDC TPC S11	28 SOB N9	28 EBDC TPC N9	28 EBDC INTT6
29		29		29 SOB S10		29 SOB N10		
30		30		30 SOB S10		30 SOB N10		
31		31		31 SOB S11		31 SOB N11		
32		32	32 EBDC TPC S2	32 SOB S11	32 EBDC TPC S12	32 SOB N11	32 EBDC TPC N10	32 EBDC INTT7
33		33		33 SOB S12		33 SOB N12		
34		34		34 SOB S12		34 SOB N12		
35		35		35 SOB Spare		35 SOB Spare		
36		36	36 EBDC TPC S3	36 SOB Spare	36 EBDC TPC N1	36 SOB Spare	36 EBDC TPC N11	36 EBDC INTT8
37		37		37 SOB Spare		37 SOB Spare		
38		38		38 SOB Spare		38 SOB Spare		
39		39		39		39		
40		40	40 EBDC TPC S4	40	40 EBDC TPC N2	40	40 EBDC TPC N12	40 EBDC Spare
41		41		41		41		
42		42		42		42		



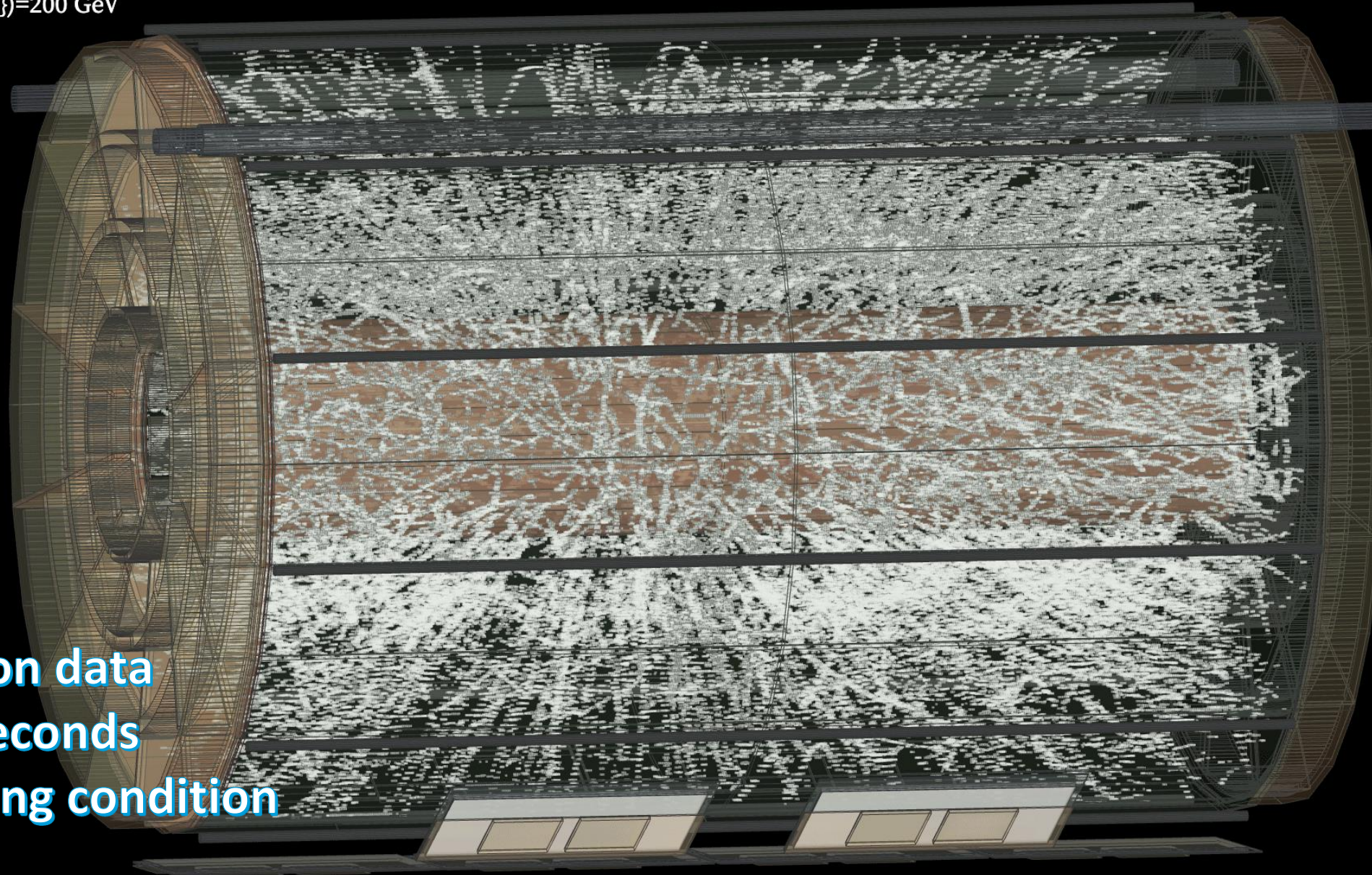


sPHENIX Time Projection Chamber

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



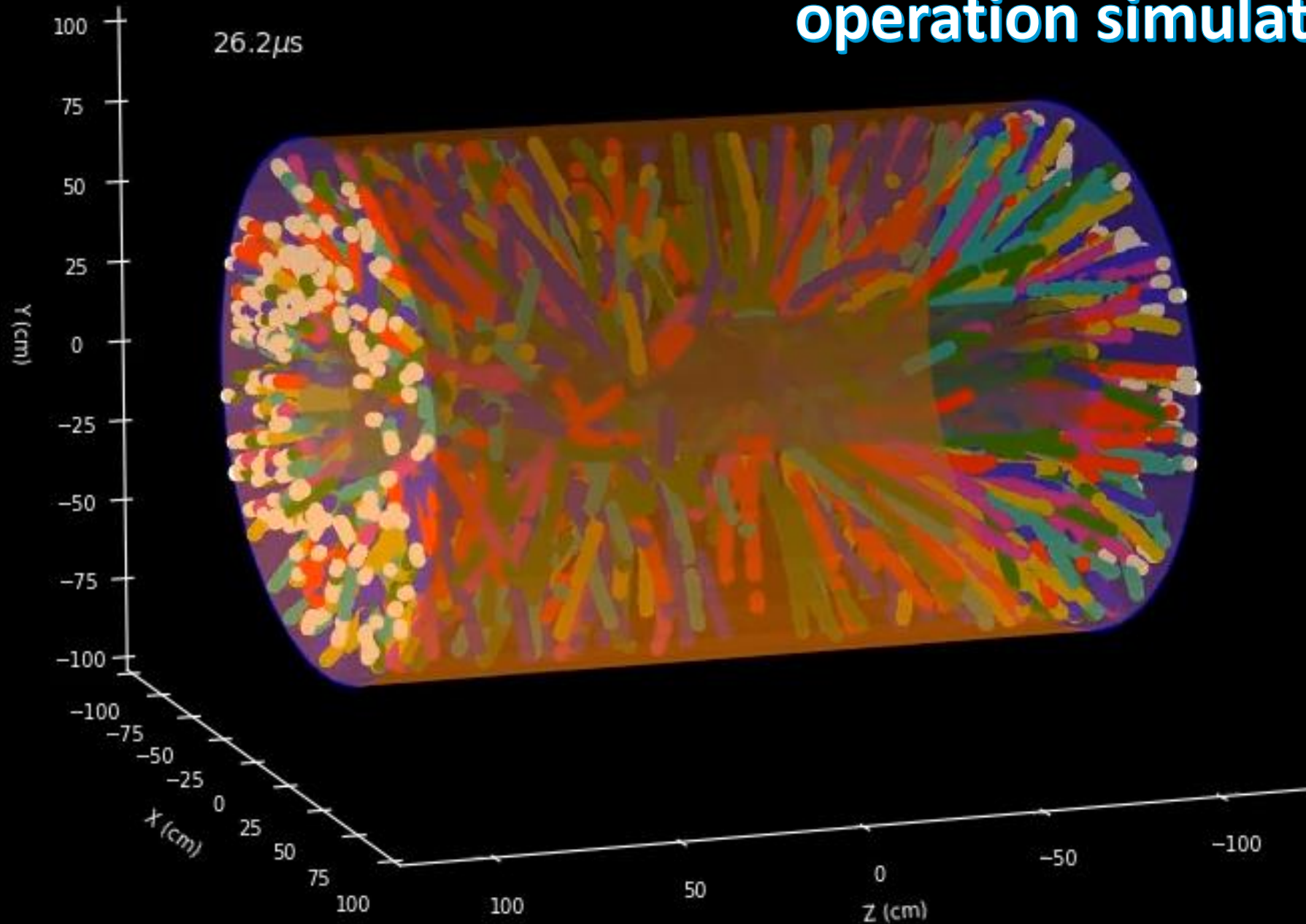
Run23 AuAu collision data
Taken in first few seconds
after TPC in operating condition

*s*PHENIX TPC simulation

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

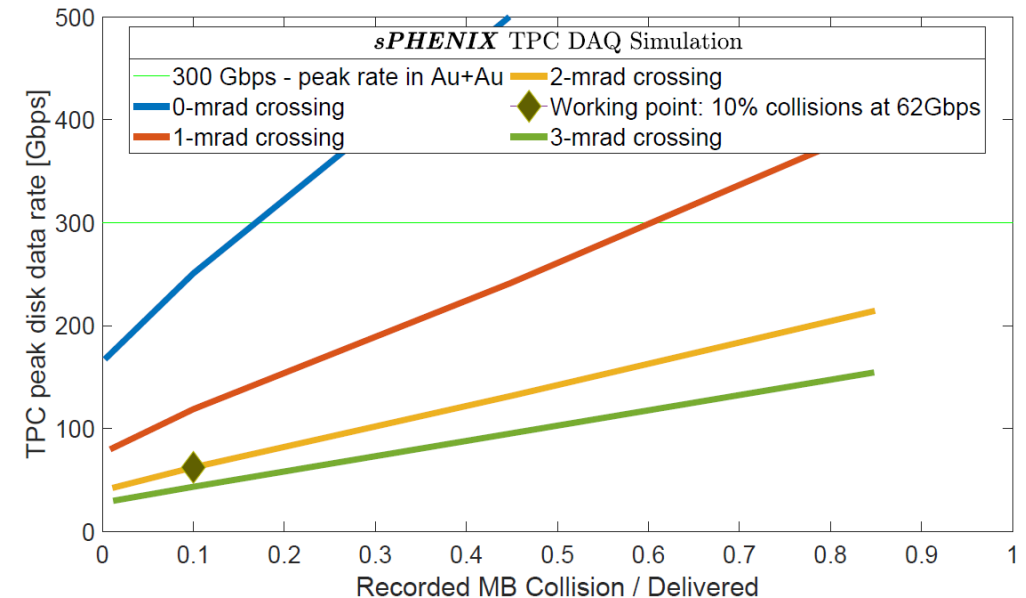
26.2 μ s

Run24 p+p streaming operation simulation



Streaming readout status at sPHENIX

- ▶ All three sPHENIX tracking detector uses streaming readout
- ▶ Developed plan to take 10% streaming data for heavy flavor physics program commended by RHIC PAC.



RHIC PAC 2020 report

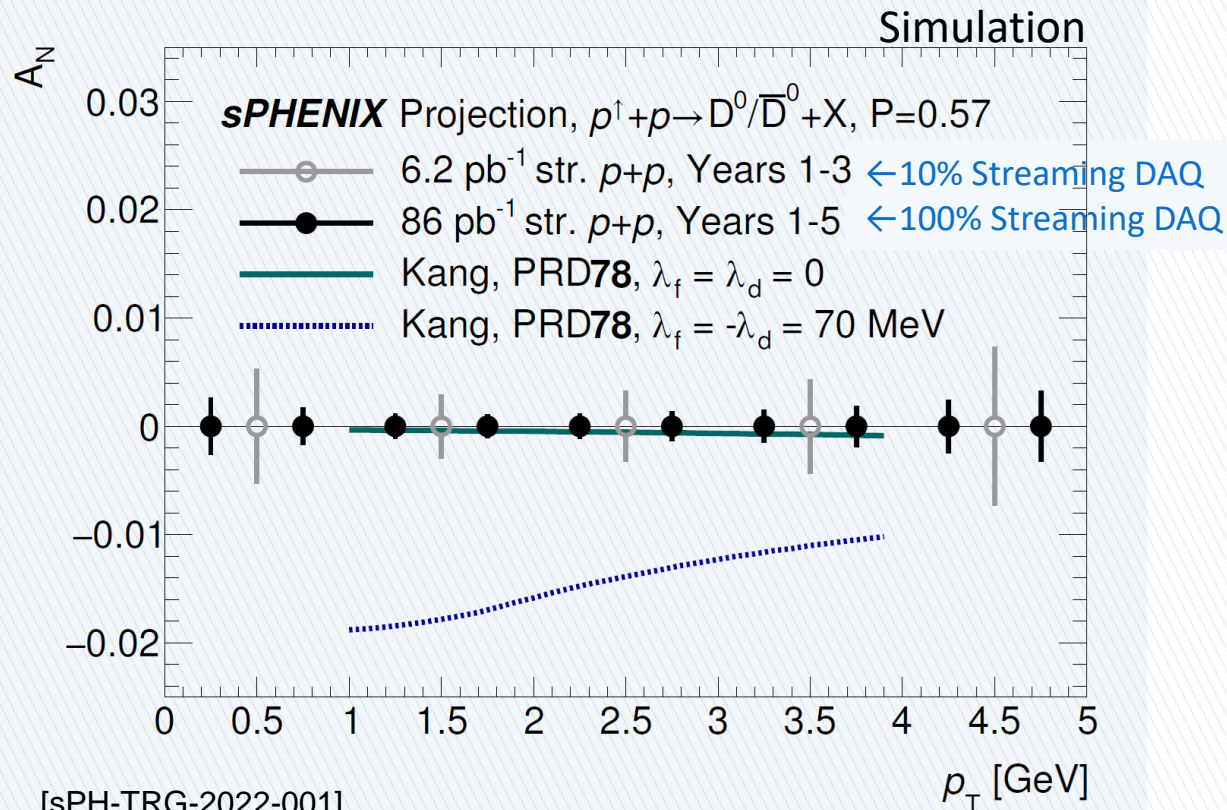
We commend sPHENIX for developing the continuous streaming readout option for the detector, which increases the amount of data that can be collected in Run-24 by orders of magnitude. In particular in the sector of open heavy flavor, this technique will give access to a set of qualitatively novel measurements that would otherwise not be accessible. Given the tight timeline for completing the RHIC physics program before construction of the EIC begins, this is a tremendous and highly welcome achievement.

Streaming-DAQ enabled scientific connection: e.g. gluon dynamics via heavy flavor transverse spin asym.

← Universality test on gluon Sievers →

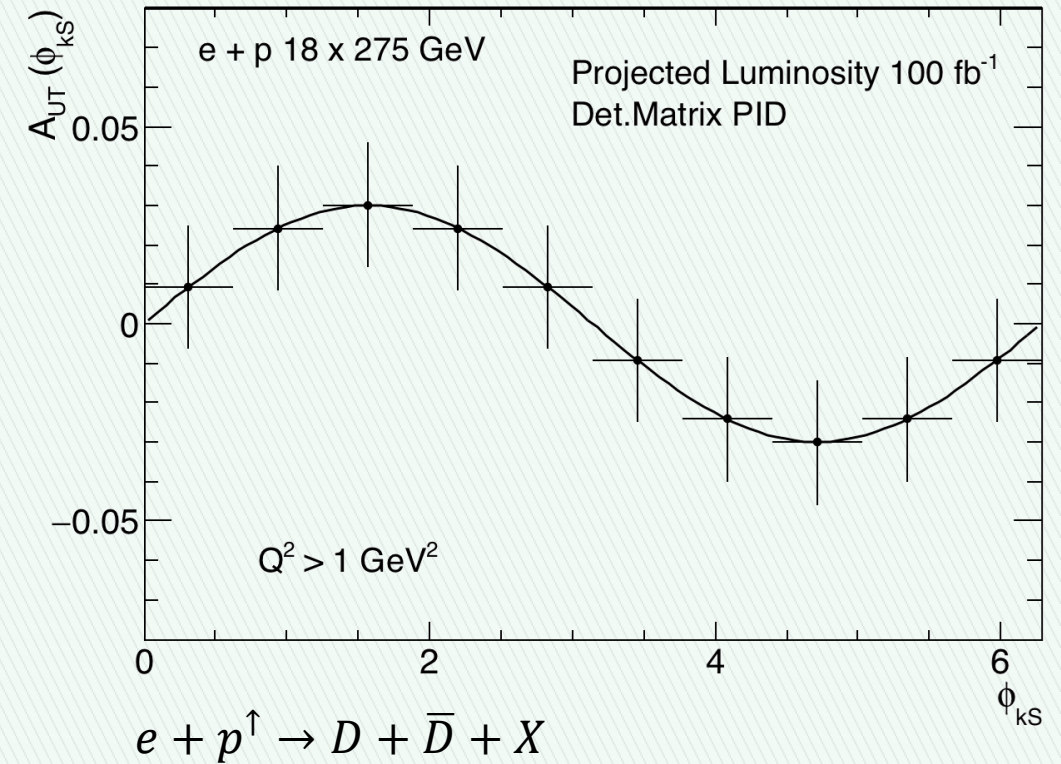
sPHENIX D^0 trans. spin asymmetry, $A_N \rightarrow$ Gluon Sievers via tri-g cor.

EIC SIDIS D^0 transverse spin asymmetry \rightarrow Gluon Sievers



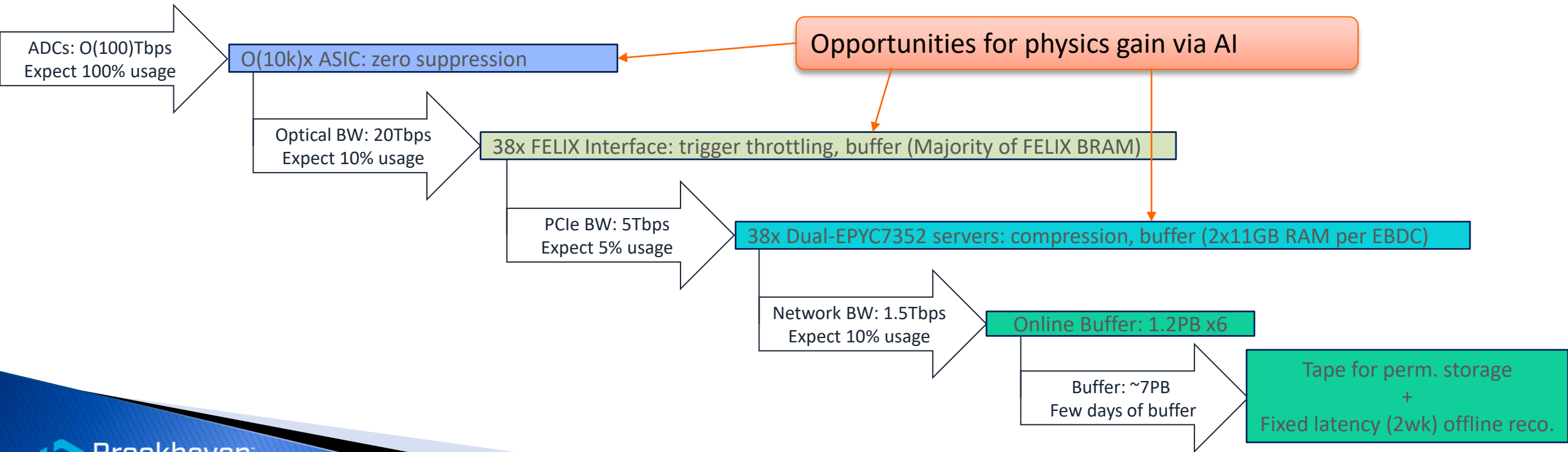
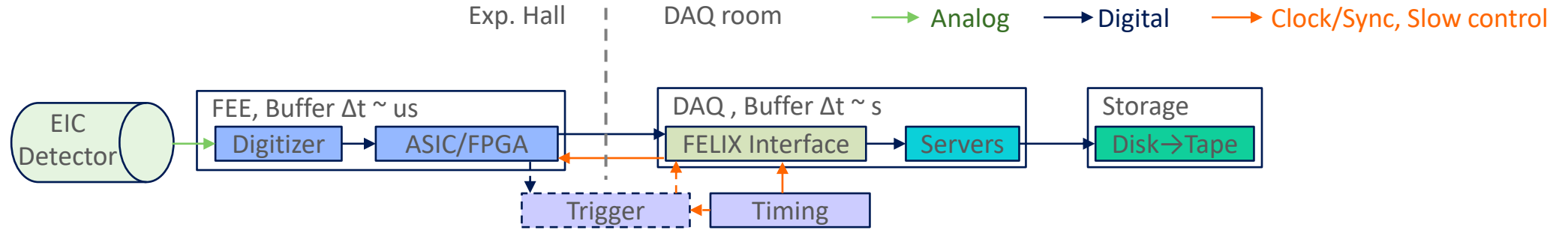
[sPH-TRG-2022-001]

Model: 10.1103/PhysRevD.78.114013

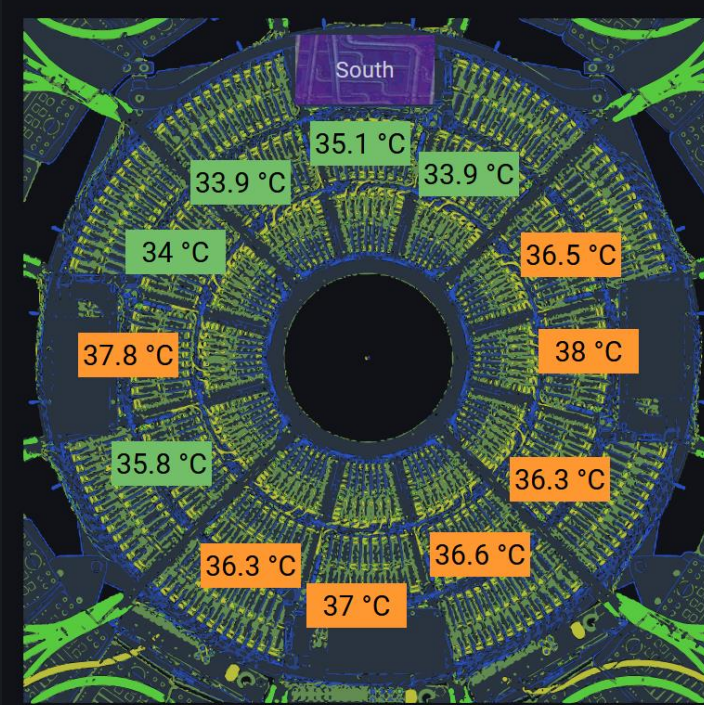


[CNFS HF@EIC workshop, Nov 4-6, 2020]

sPHENIX Streaming data flow



SRO pipeline monitoring via TSDB + Grafana



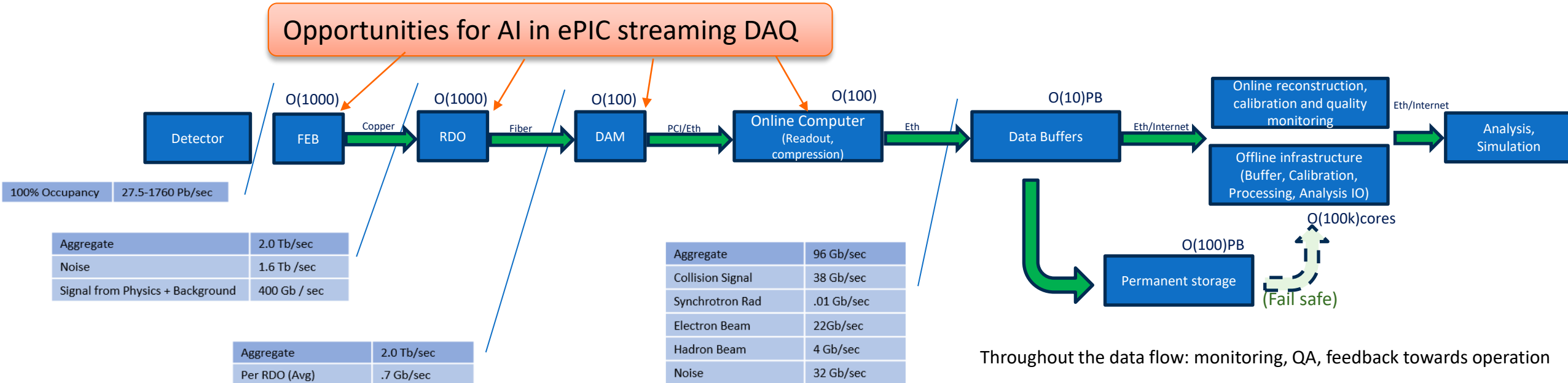
FEE PCB temperature during first collision data taking
Part of SRO control data stream

Data pipeline monitoring during the max throughput stress test at 7GBps for each PCIe EP
→ 2.7Tbps FEE to server memory readout (without the limit of file logging)

ePIC streaming DAQ-computing

See also: Jeff Landgraf's talk later today

Opportunities for AI in ePIC streaming DAQ



Latency :

Ons O(100)ns O(1)us O(10)us O(1)min O(1)min-O(1) day O(1)day-O(1)week

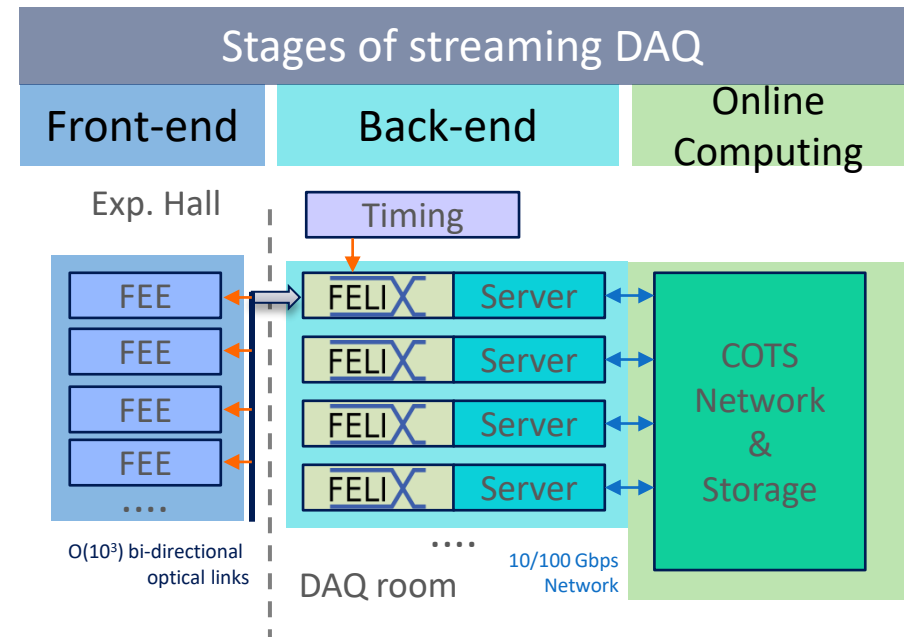
Possible facilities:

On detector On detector/rack DAQ room Host labs/Echelon 1 facility Remote resources

- Reference:
- ePIC DAQ wiki: <https://wiki.bnl.gov/EPIC/index.php?title=DAQ>
 - ECCE computing plan, [Nucl.Instrum.Meth.A 1047 \(2023\) 167859](#)

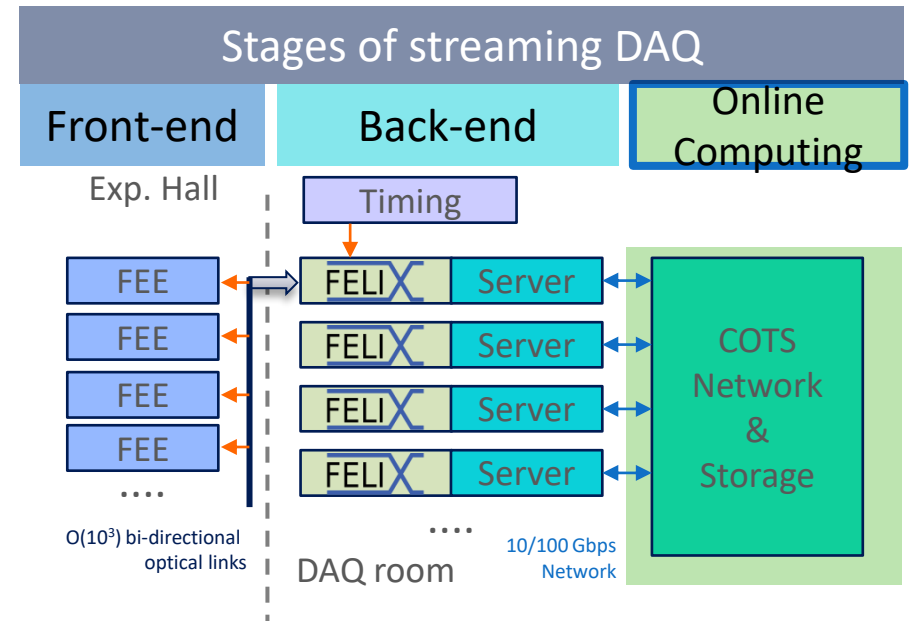
AI in streaming readout DAQ

- ▶ 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



Streaming DAQ stage 3: Online computing

- ▶ Online computing is an integral part of streaming DAQ
 - Blending the boundary of online/offline computing
- ▶ AI opportunities:
 - Lossy compression
 - Noise and background filtering
 - Higher level reconstruction
- ▶ Target hardware:
 - Traditional computing: CPU, GPU
 - Novel AI Accelerators



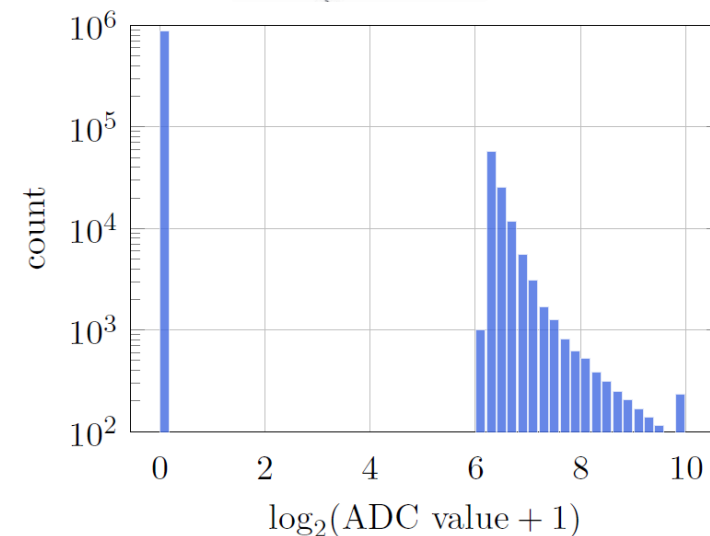
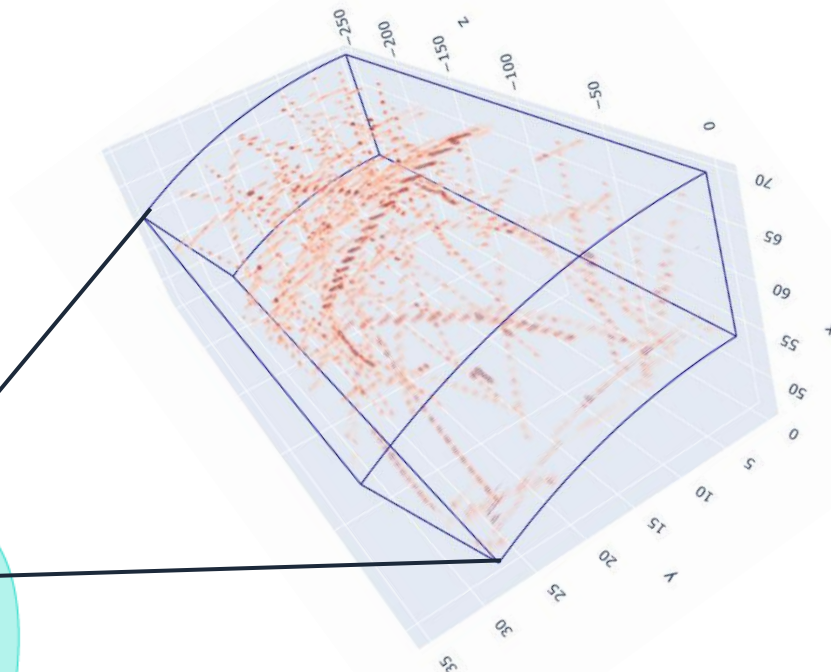
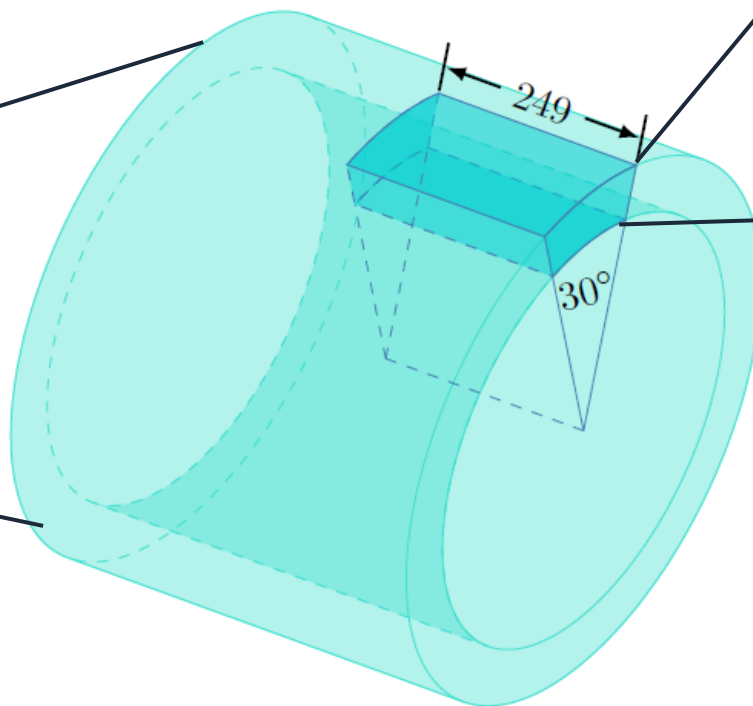
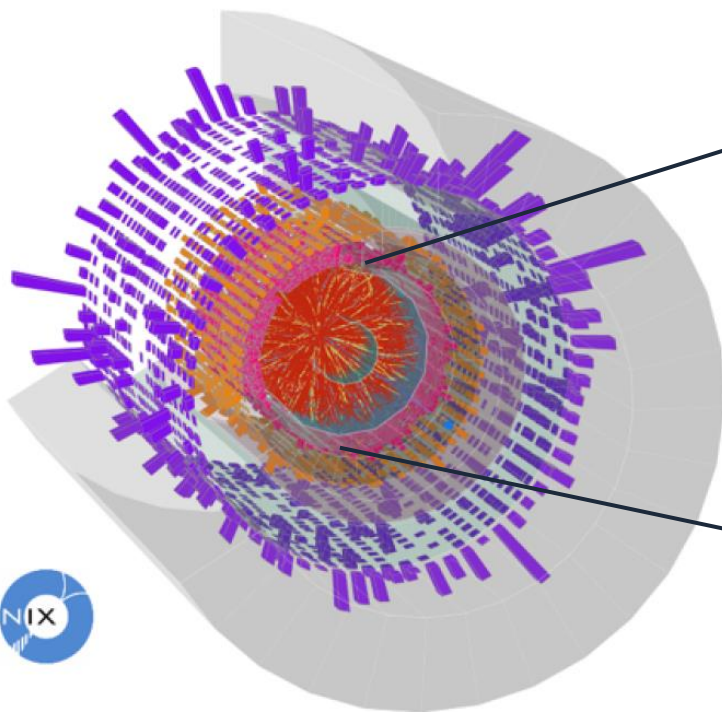
TPC Data Frames

Busiest event in sPHENIX TPC

3D X-Y-Time time frame at 50Tbps prior to zero-suppression

10% central Au + Au collision with 170kHz pile up

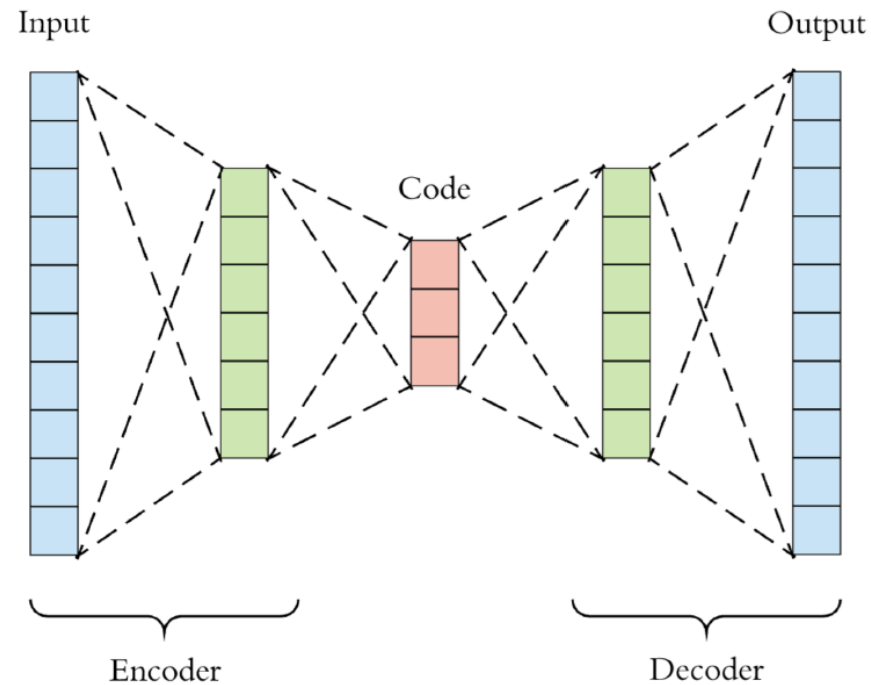
Data frame for 1/12 azimuth sector shown here



Lossy compression of data, noise filtering

Auto-encoder (AE) is a natural choice for self-supervised learning for lossy data compression and noise removal

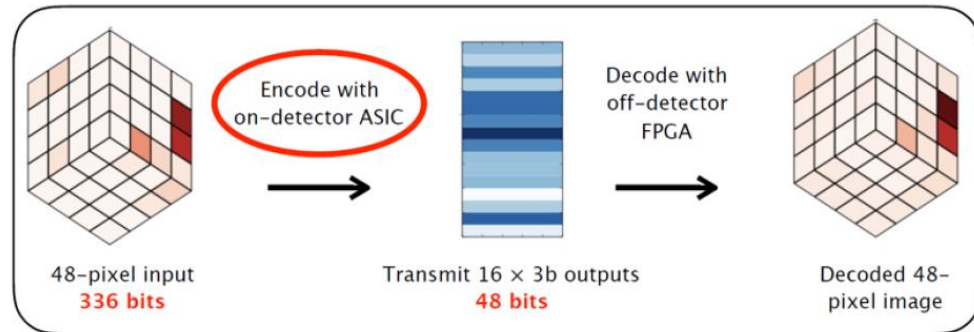
Simple auto-encode neural network



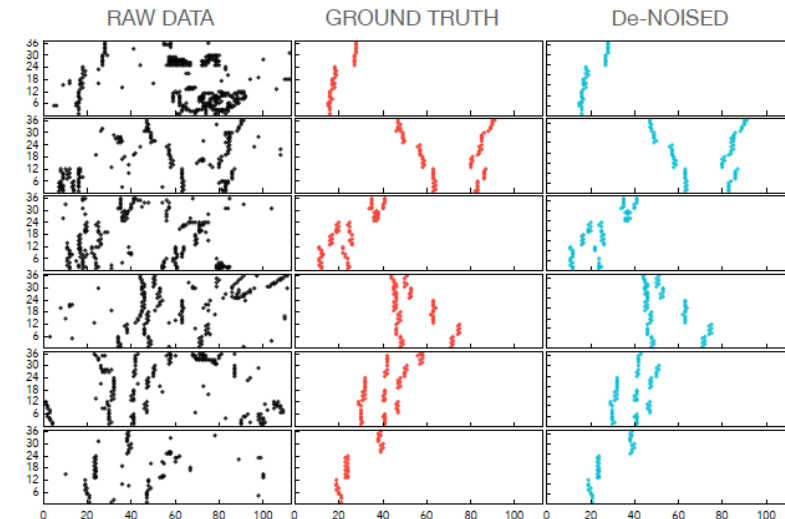
Lossy compression of data, noise filtering

- ▶ Auto-encoder (AE) is a natural choice for unsupervised learning for lossy data compression: streaming data reduction
- ▶ Same network architecture can be adopted with supervised learning to filter out noise: further data reduction, speed up reconstruction

CMS HGCal compression ASIC, [\[10.1109/TNS.2021.3087100\]](#), talk by Maximilian J Swiatlowski]



CLAS12 Drift Chamber offline AE de-noise [\[link\]](#)
See also: talk by Diana McSpadden



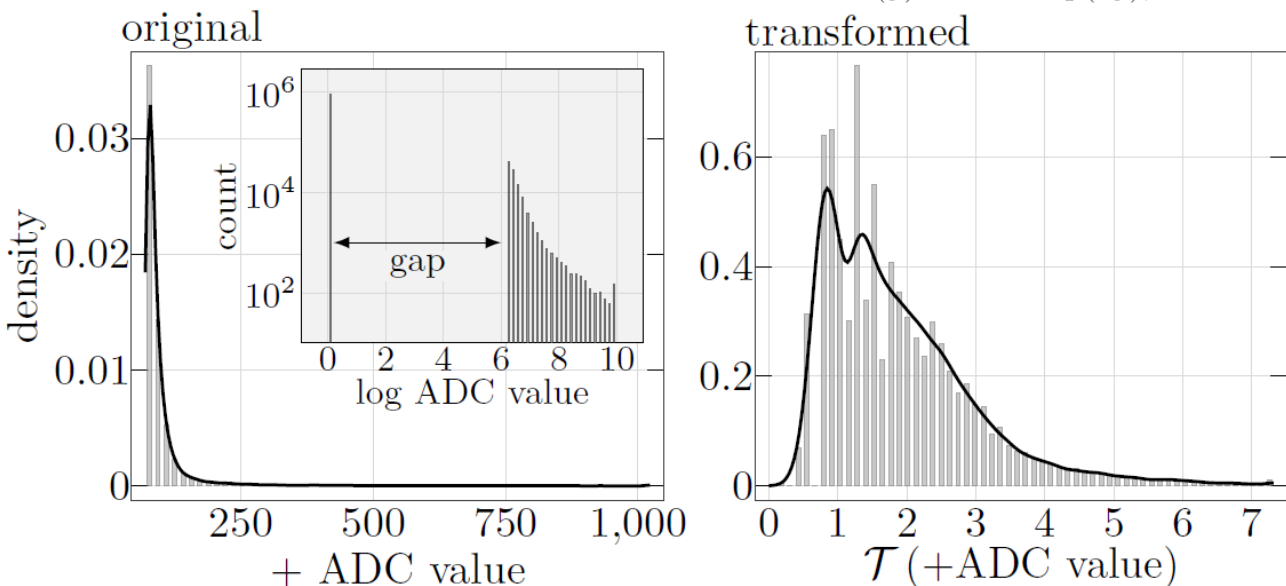
Bicephalous Convolutional Auto-Encoder (BCAE) and

input transform

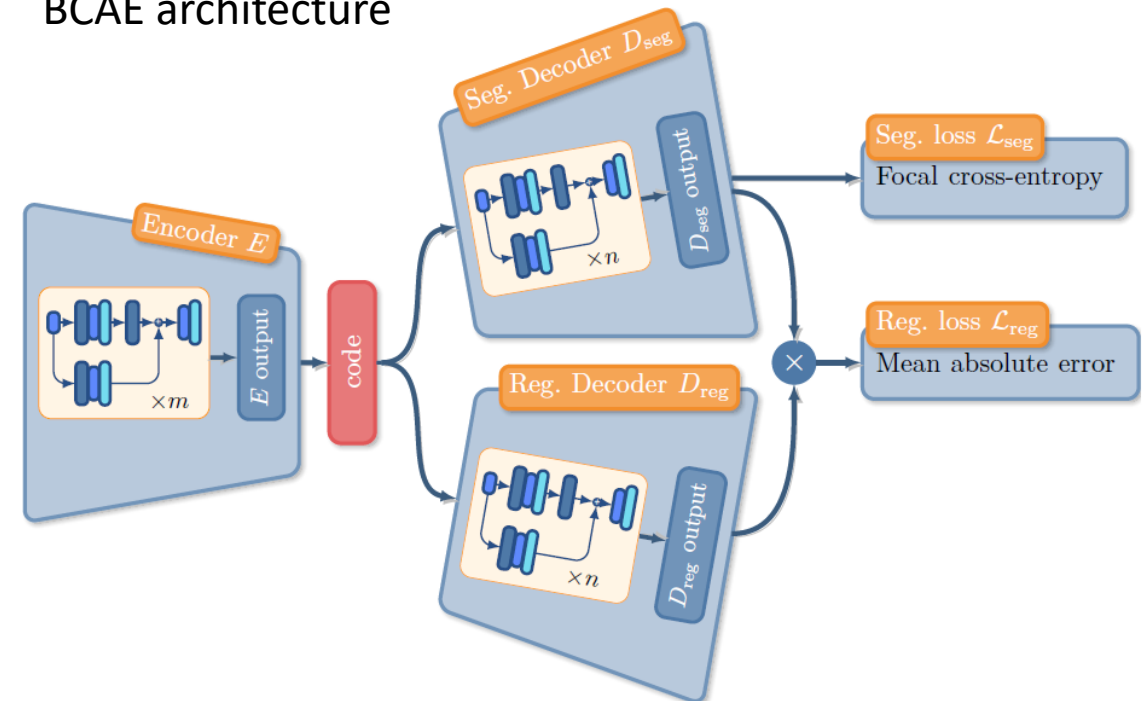
[Huang et al ICMLA21, DOI: 10.1109/ICMLA52953.2021.00179 arXiv:2111.05423]

- ▶ Input transform: fill in the zero-suppression gap and make ADC distribution much less steep
- ▶ Bicephalous decoder: +classification decoder to note the zero-suppressed ADC voxels and +noise voxels in TPC

Input transform: $\mathcal{T}(x) = \log(x - 64)/6, \quad x > 64$
 Inverse transform: $\mathcal{T}^{-1}(y) = 64 + \exp(6y), \quad x \in \mathbb{R}$



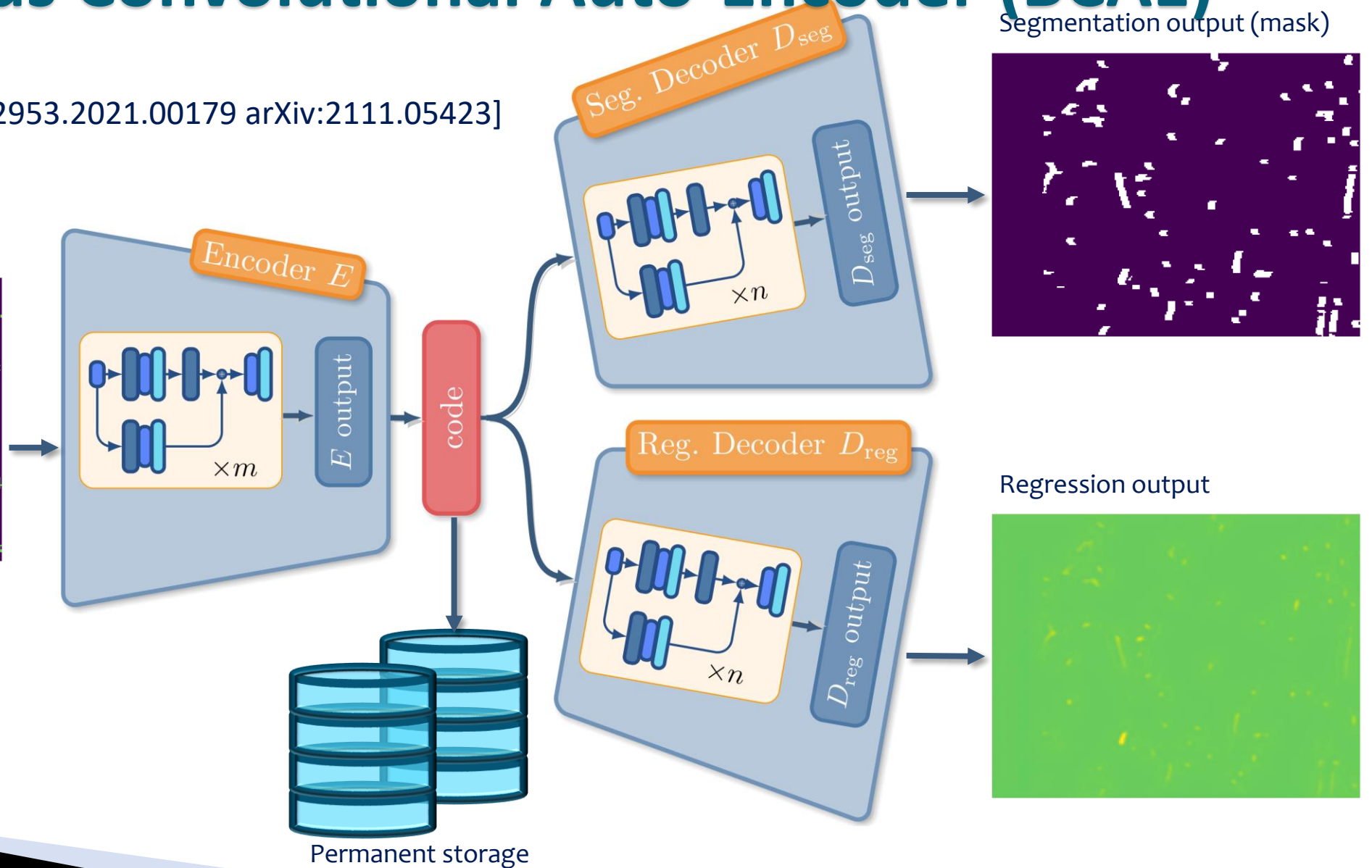
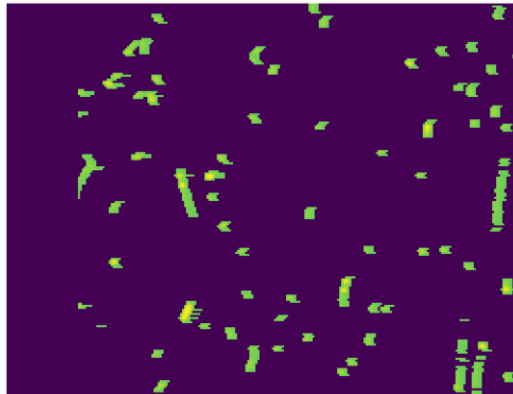
BCAE architecture



Bicephalous Convolutional Auto-Encoder (BCAE)

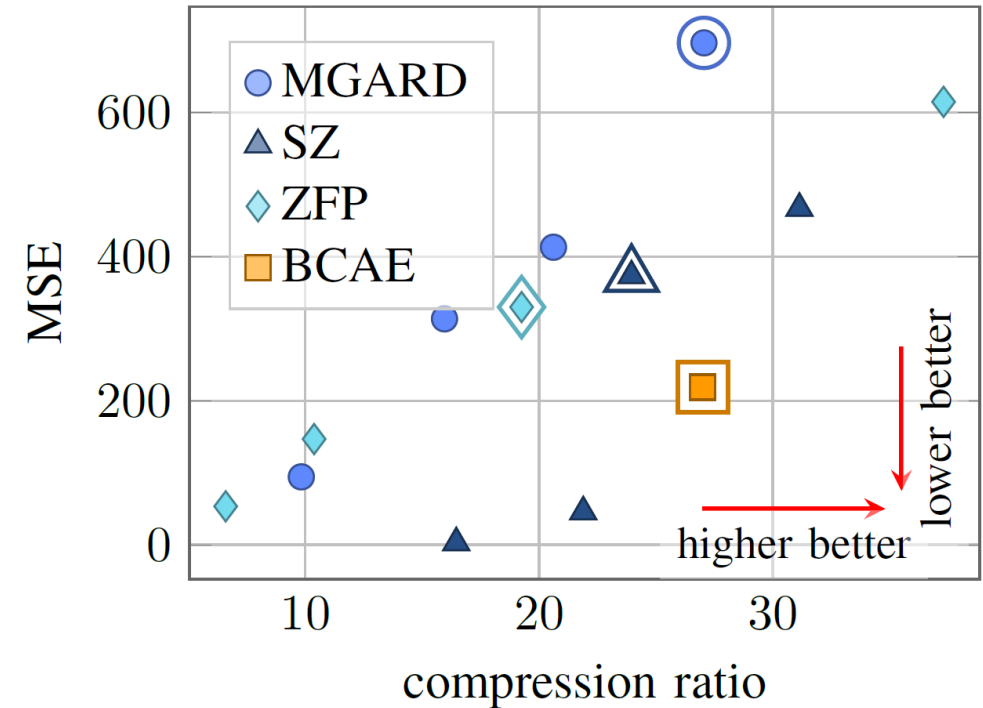
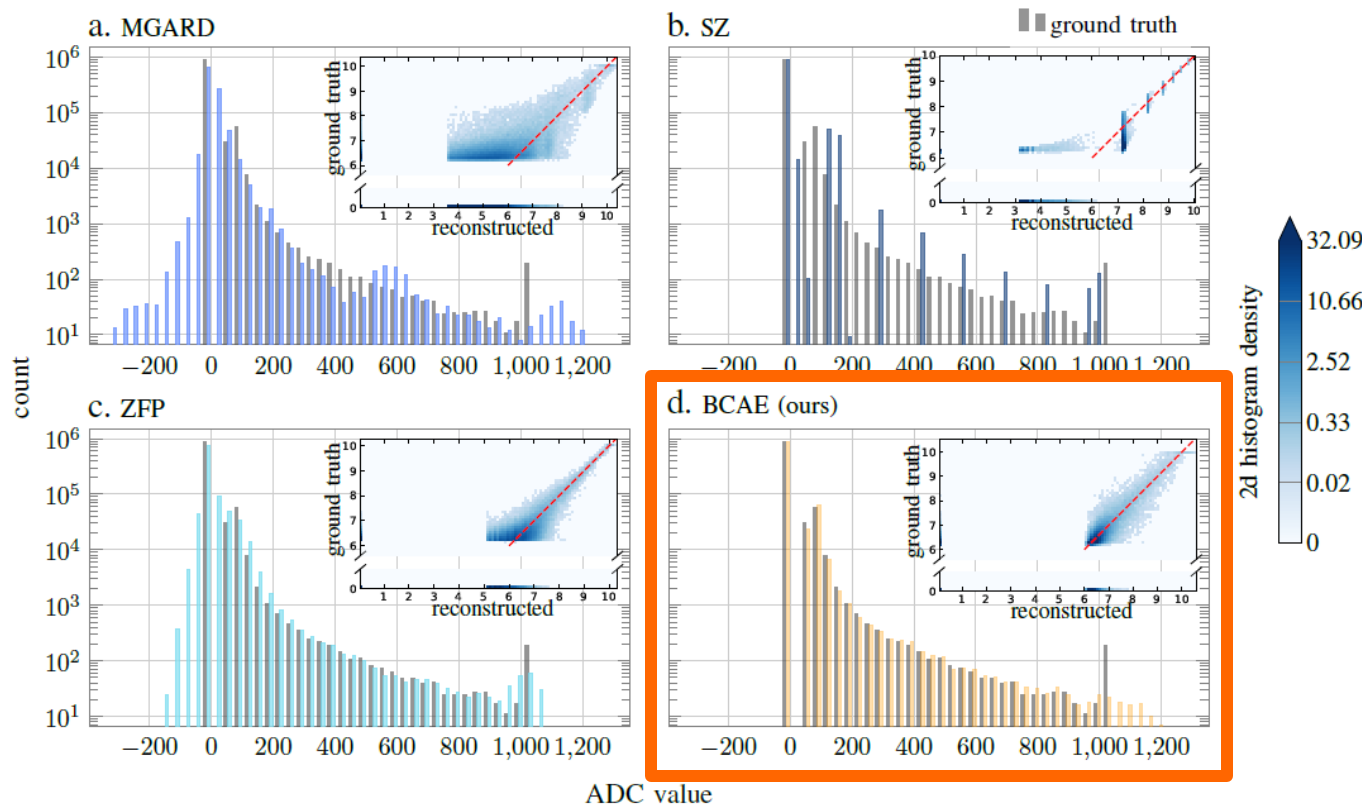
[Huang et al ICMLA21,
DOI: 10.1109/ICMLA52953.2021.00179 arXiv:2111.05423]

input



Comparison with existing algorithm

[Huang et al ICMLA21, DOI: 10.1109/ICMLA52953.2021.00179, arXiv:2111.05423]

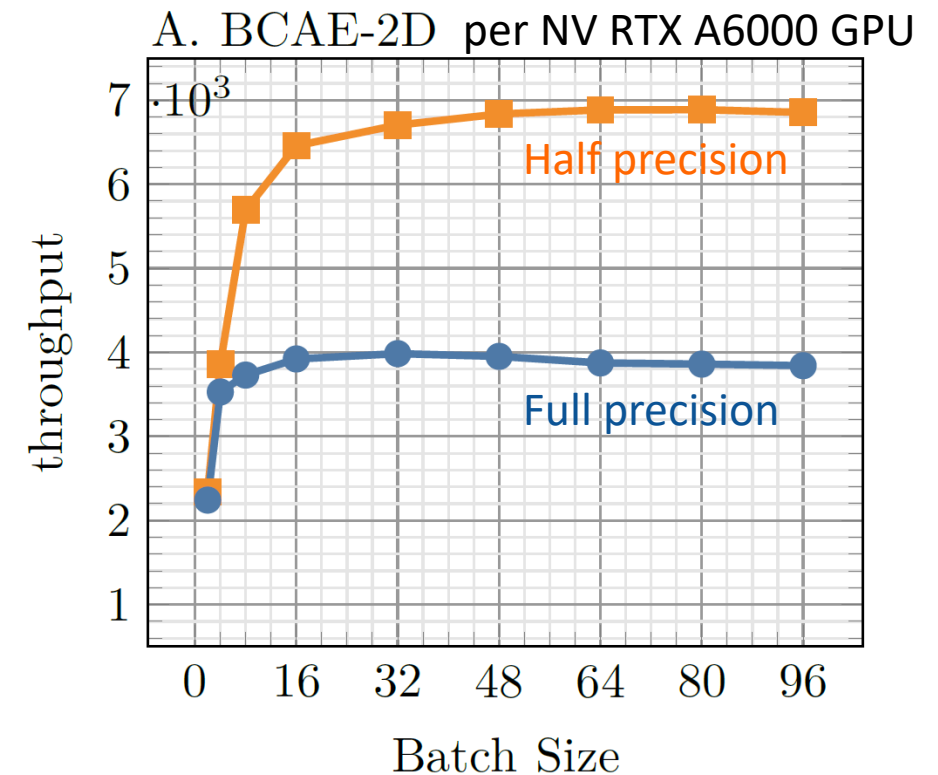
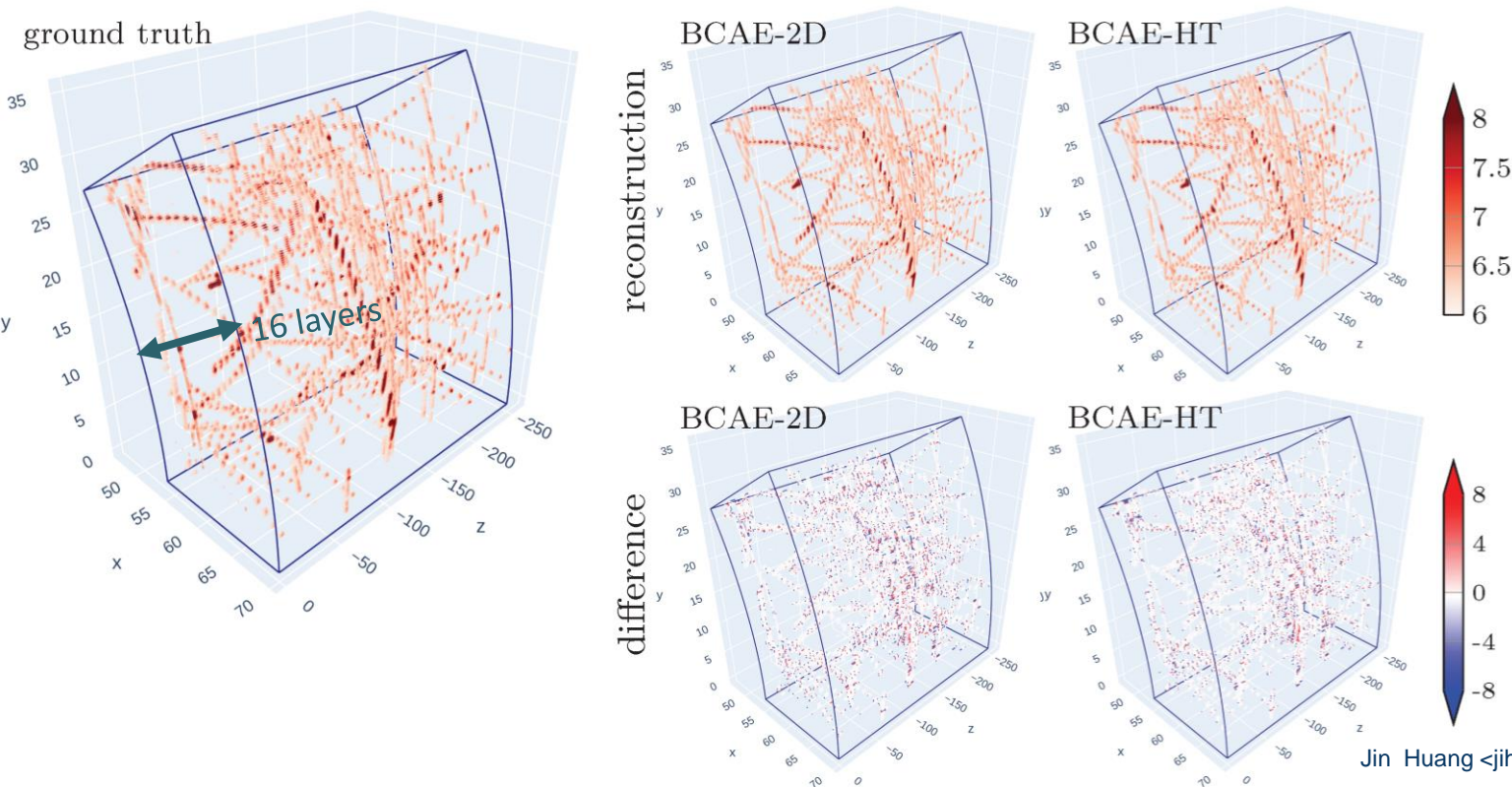


Real-time speed optimization for BCAE

[Huang et al DRBSD9@SC23, DOI: 10.1145/3624062.3625127 arXiv:2310.15026], received paper award

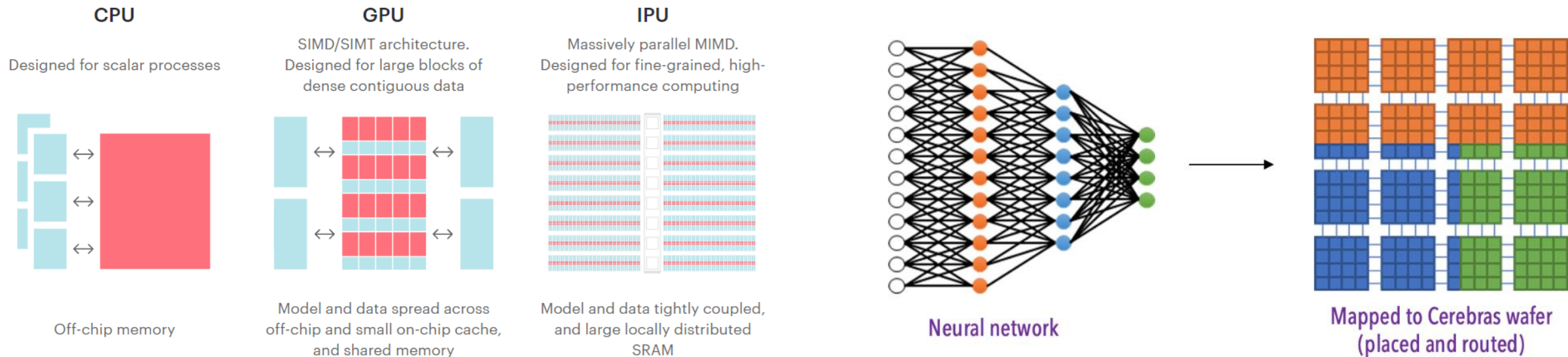
Optimization of inference speed of BCAE while maintaining better MAE than first version:

- ▶ BCAE-2D: 3D convolution -> 2D convolution with 16 color channels
- ▶ BCAE-HT: smaller intermediate output channels, 1/20 in size for encoder
- ▶ NN use of **half-precision** float (16bit) operations

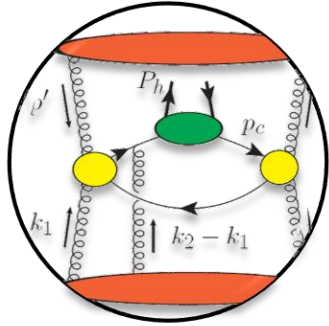


Novel AI Accelerators for streaming DAQ

- ▶ A new family of AI chips is emerging with **non-von Neumann Architectures**
 - Designed for NN computing, similarities to ML on FPGA
 - **Massive on-chip activation/weight storage on sRAM**
 - Good integration with popular AI tools
 - Energy efficient and high throughput
- ▶ Significant throughput gain with testing of BCAE on Graphcore IPU, a **Dataflow Architectures processor for AI application**

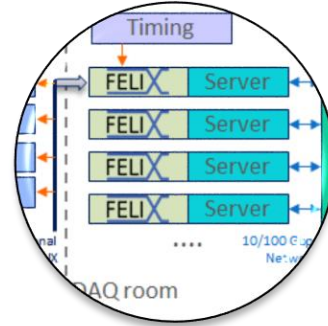


Summary



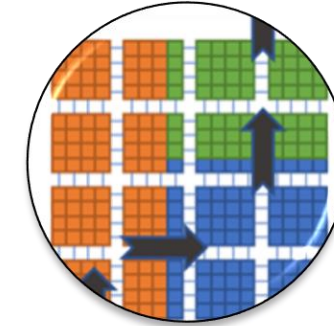
NP Physics

- 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

Questions?



Extra information



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

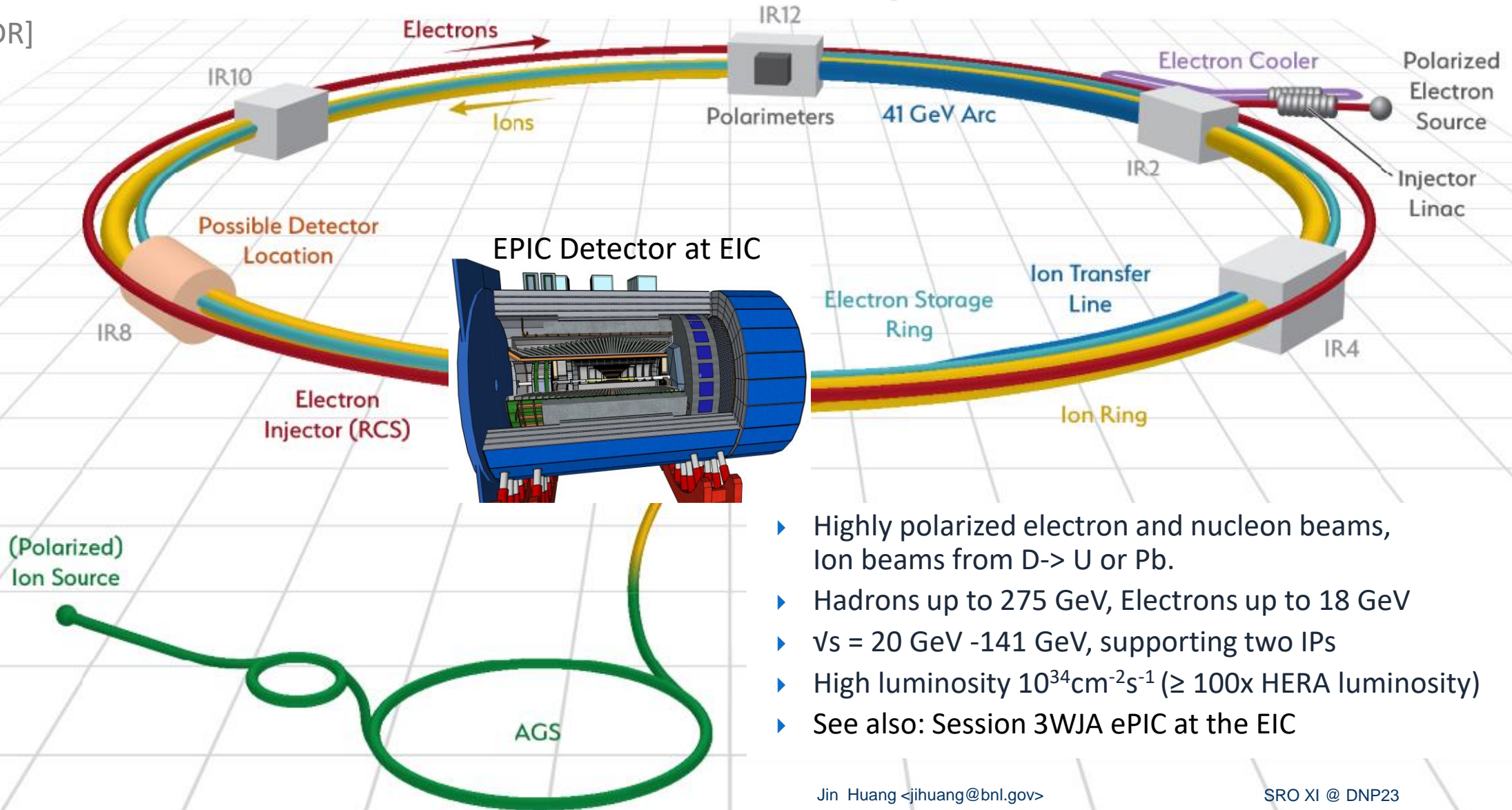
	EIC	RHIC	LHC → HL-LHC
Collision species	$\vec{e} + \vec{p}, \vec{e} + A$	$\vec{p} + \vec{p}/A, A + A$	$p + p/A, A + A$
Top x-N C.M. energy	140 GeV	510 GeV	13 TeV
Bunch spacing	10 ns	100 ns	25 ns
Peak x-N luminosity	$10^{34} \text{ cm}^{-2} \text{ s}^{-1}$	$10^{32} \text{ cm}^{-2} \text{ s}^{-1}$	$10^{34}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

- ▶ 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

RHIC transition to the Electron Ion Collider (EIC)

Just had a successful CD3-A review, Science Phase in 2030+

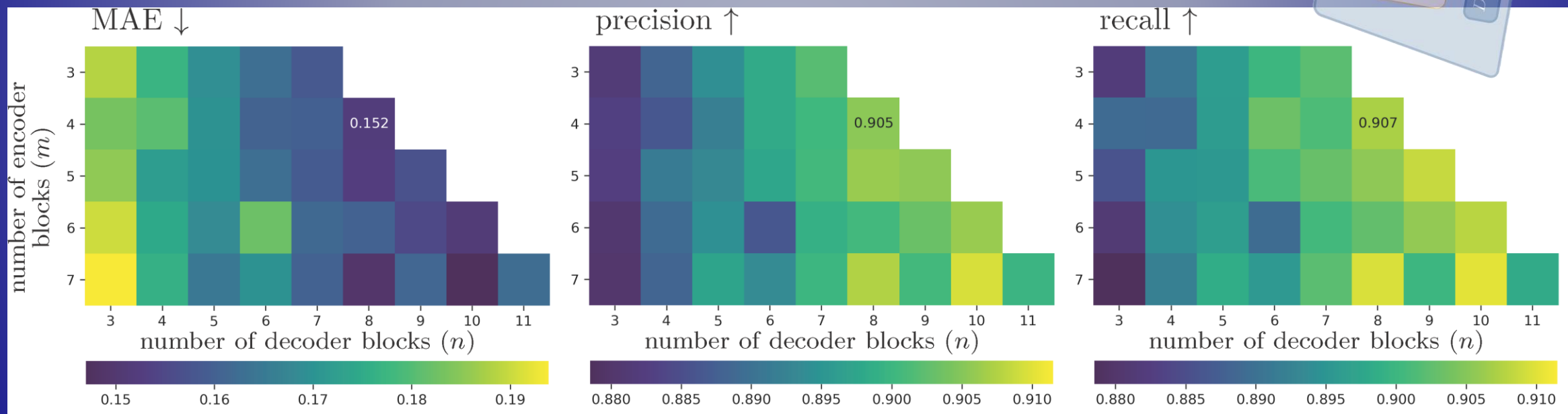
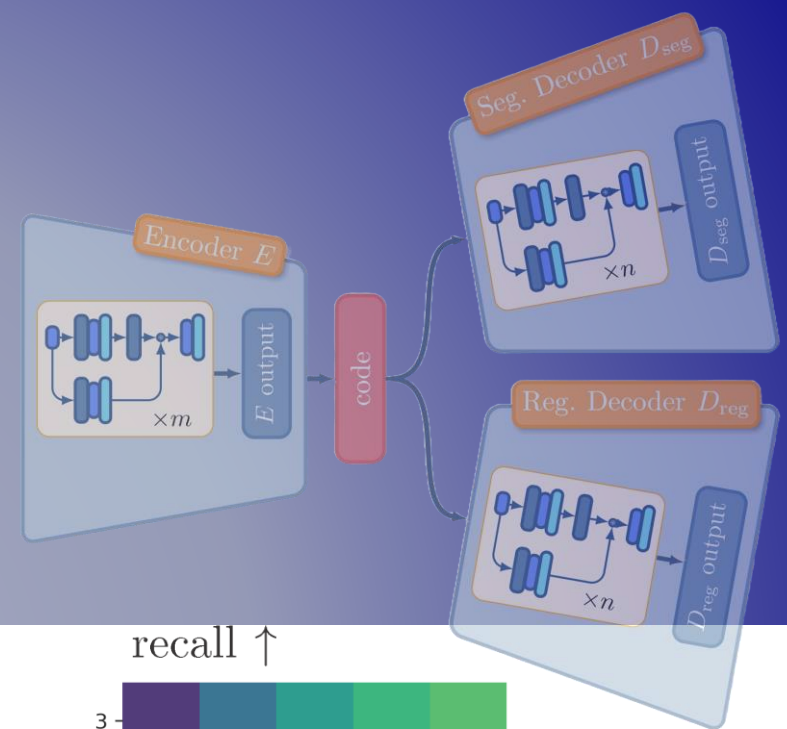
[EIC CDR]



- ▶ Highly polarized electron and nucleon beams, Ion beams from D- \rightarrow U or Pb.
- ▶ Hadrons up to 275 GeV, Electrons up to 18 GeV
- ▶ $\sqrt{s} = 20 \text{ GeV} - 141 \text{ GeV}$, supporting two IPs
- ▶ High luminosity $10^{34} \text{ cm}^{-2} \text{ s}^{-1}$ ($\geq 100 \times$ HERA luminosity)
- ▶ See also: Session 3WJA ePIC at the EIC

2D Encoder and Decoder

tunable encoder decoder sizes



Performance comparison

better 3D BCAE

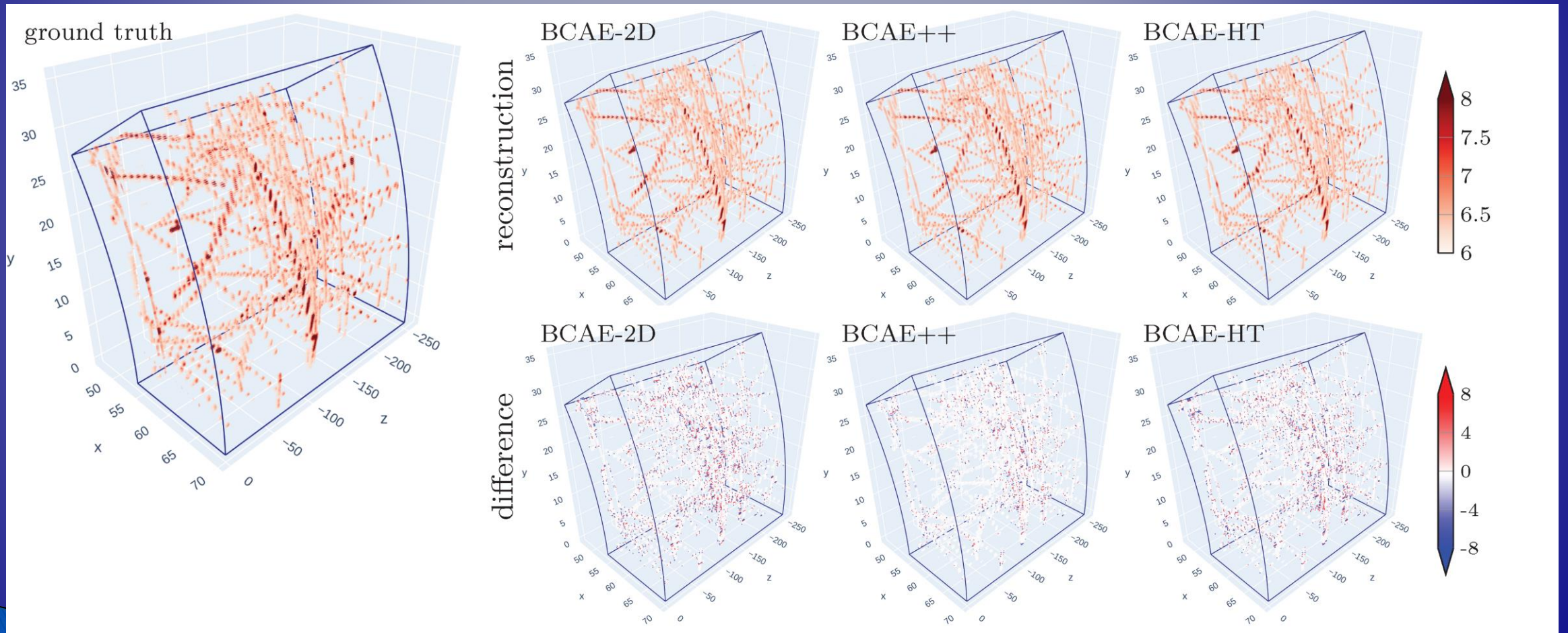
model	MAE ↓	PSNR ↑	Precision ↑	Recall ↑	Encoder size ↓	Compr. Ratio ↓
BCAE	0.198	9.923	0.878	0.861	201.7k	27.041
BCAE-2D	0.152	11.726	0.906	0.907	169.0k	31.125
BCAE++	0.112	14.325	0.934	0.936	226.2k	31.125
BCAE-HT	0.138	12.376	0.916	0.915	9.8k	31.125

From BCAE to BCAE-HT

1. 3D convolution
2. Pad (16, 192, 249) to (16, 192, 256) for easy halving and an increased compression ratio
3. Remove normalization
4. Much smaller intermediate output channels for higher throughput

- Slightly better reconstruction performance
- Super small model size
- Higher throughput

Performance comparison



Throughput comparison

two computing modes

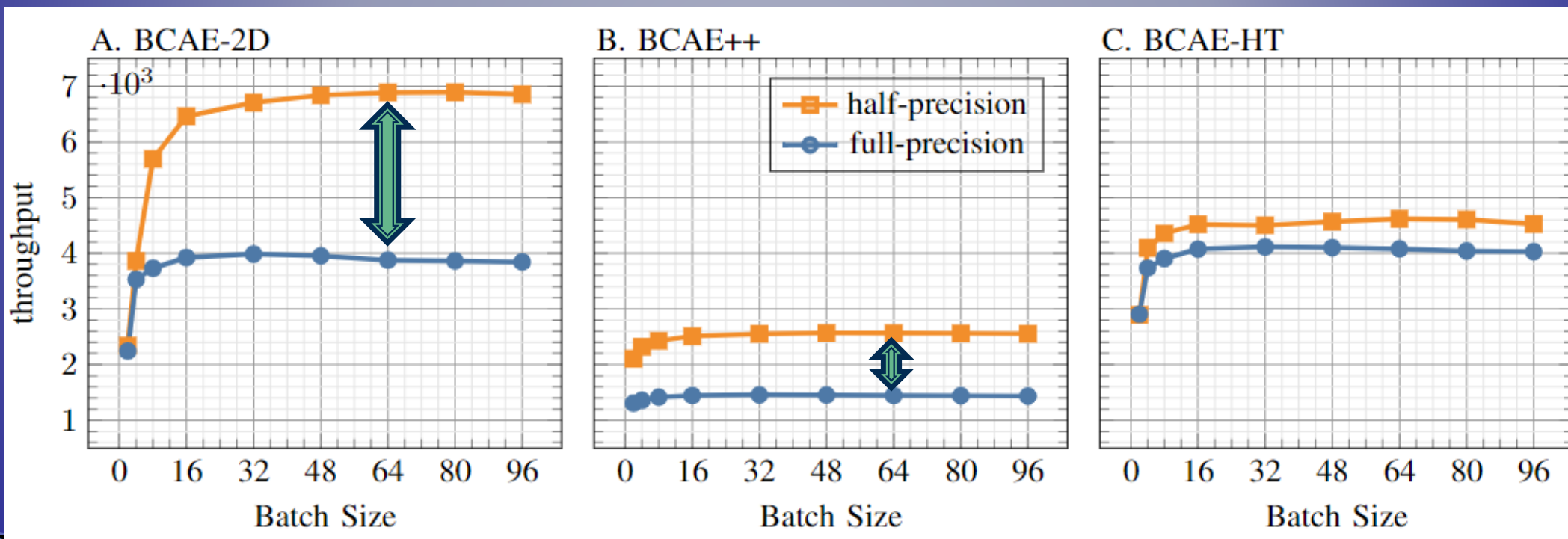
- **Full:** encode with float 32, save code as float 16, decode with float 32
- **Half:** encode with float 16, save code as float 16, decode with float 32

model	mode	MAE	precision	recall
BCAE-2D	Full	0.151937	0.905469	0.906916
	Half	0.151965	0.905326	0.907050
BCAE++	Full	0.112347	0.933817	0.935779
	Half	0.112342	0.933852	0.935741
BCAE-HT	Full	0.138443	0.915391	0.914562
	Half	0.138441	0.915780	0.914701

Throughput comparison

two computing modes

Why don't we have the same speedup here?



Why the Lack of Speedup

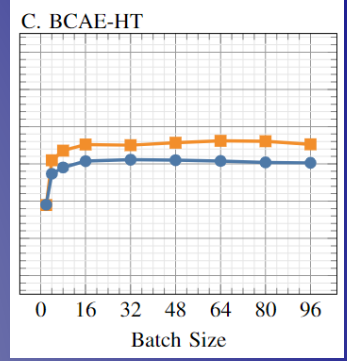
Nsight System Profiling

Full precision

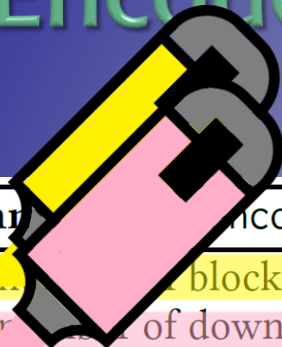


7.3 ms

Half precision



2D Encoder and Decoder



Algorithm encoder_2D

Input: number of blocks m ,
number of downsampling layers d

Output: A PyTorch module

- 1 Initialize network N to be an empty module list;
- 2 Append N with $L_{in} = \text{Conv2D} (i = 16, o = 32, k = 7, p = 3)$
- 3 **for** $i \leftarrow 1$ **to** m **do**
- 4 **if** $i \leq d$ **then**
- 5 Append N with $\text{AvgPool2D} (k = 2, s = 2)$;
- 6 Append N with two residual block
 $\text{Res} (i = 32, o = 32, k = 3, p = 1)$;
- 7 Append N with $L_{out} = \text{Conv2D} (i = 32, o = 16, k = 1)$;
- 8 **return** N ;

4 convolutions per block

Algorithm decoder_2D

Input: number of blocks n , number of upsampling layers d ,
output activation function A

Output: A PyTorch module

- 1 # NOTE: a decoder must have the same number of upsampling steps as the downsampling steps in its corresponding encoder
- 2 Initialize network N to be an empty module list;
- 3 **for** $i \leftarrow 1$ **to** n **do**
- 4 **if** $i \leq d$ **then**
- 5 Append N with $\text{Upsample} (\text{scale_factor} = 2)$;
- 6 Append N with two residual block
 $\text{Res} (i = 32, o = 32, k = 3, p = 1)$;
- 7 Append N with $L_{out} = \text{Conv2D} (i = 32, o = 16, k = 1)$;
- 8 Append N with output activation function A ;
- 9 **return** N ;

Results from Bicephalous AE with transform [arXiv:2111.05423]

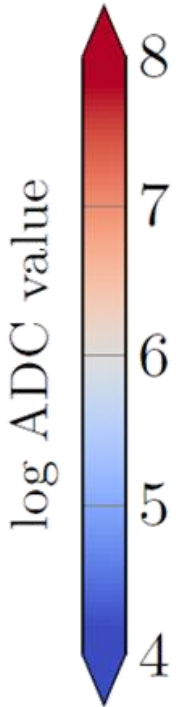
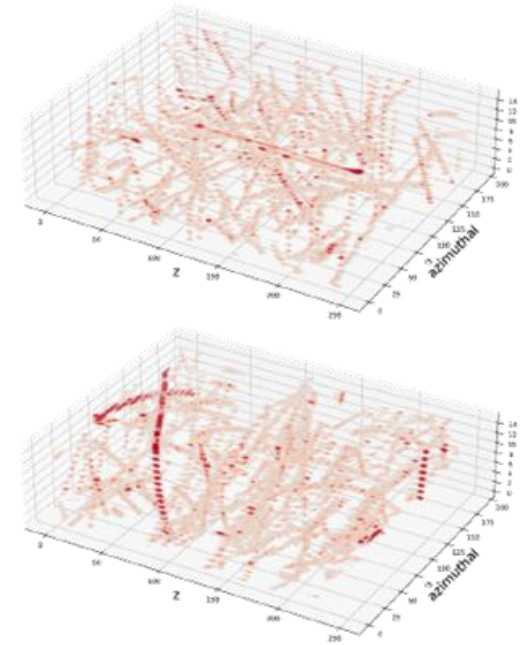
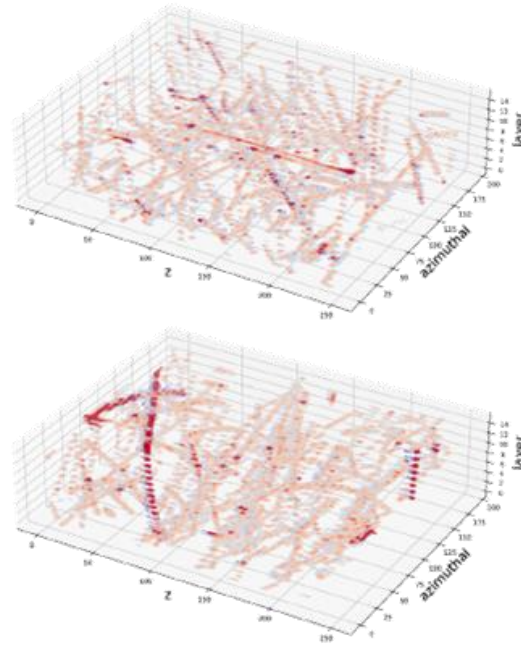
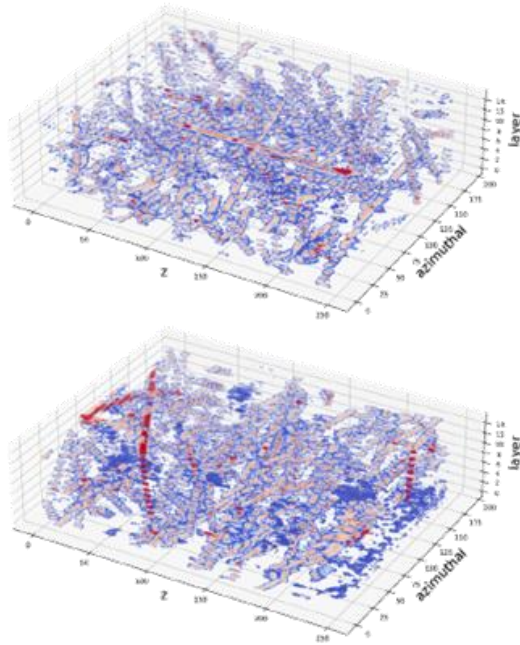
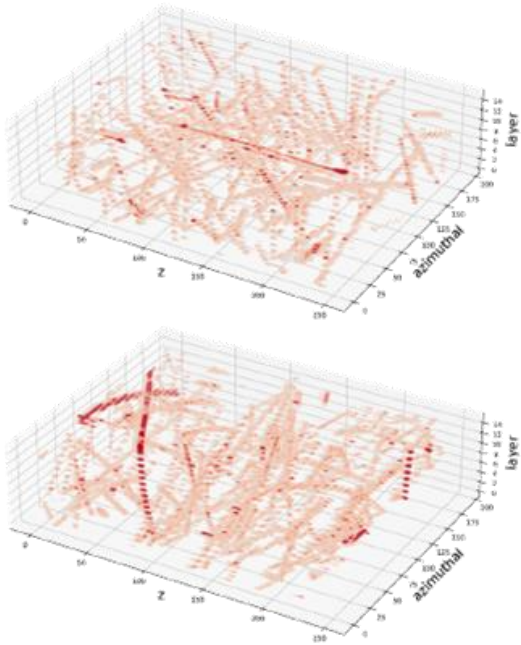
example 1
example 2

ground truth

AE

bicephalous AE

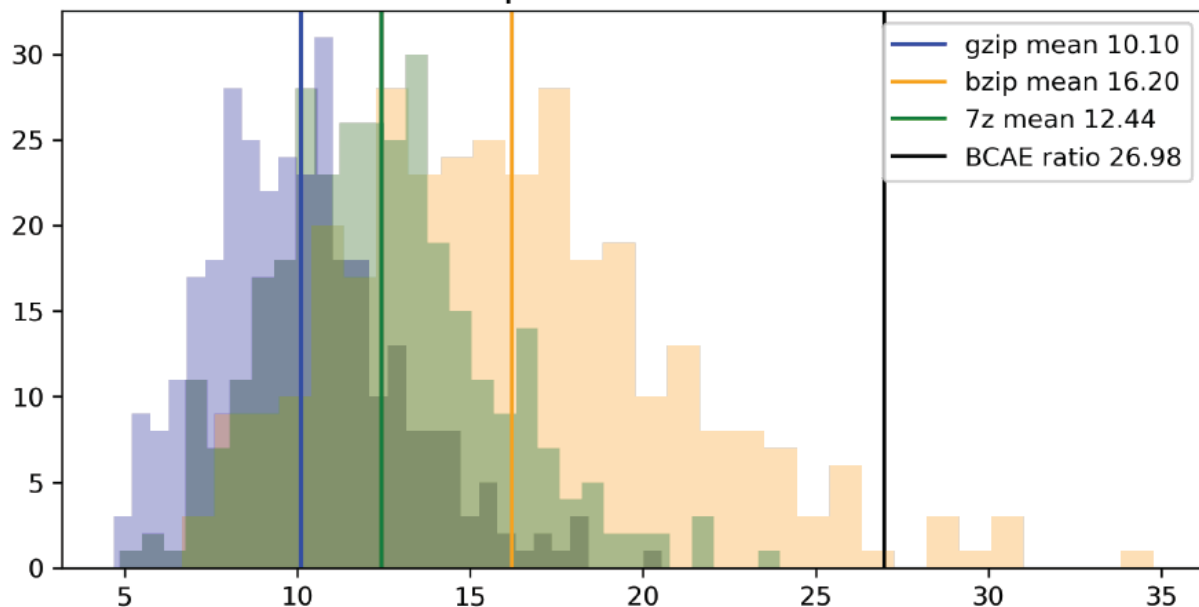
bicephalous AE
w. transform



Compressibility check: thanks to suggestion from Brett!

- ▶ The lossy-compressed code is hardly compressible further losslessly

Zip Ratios of Raw



Zip Ratios of BC AE-compressed

