Autonomous selection of physics events

A RHIC demonstrator for EIC physics

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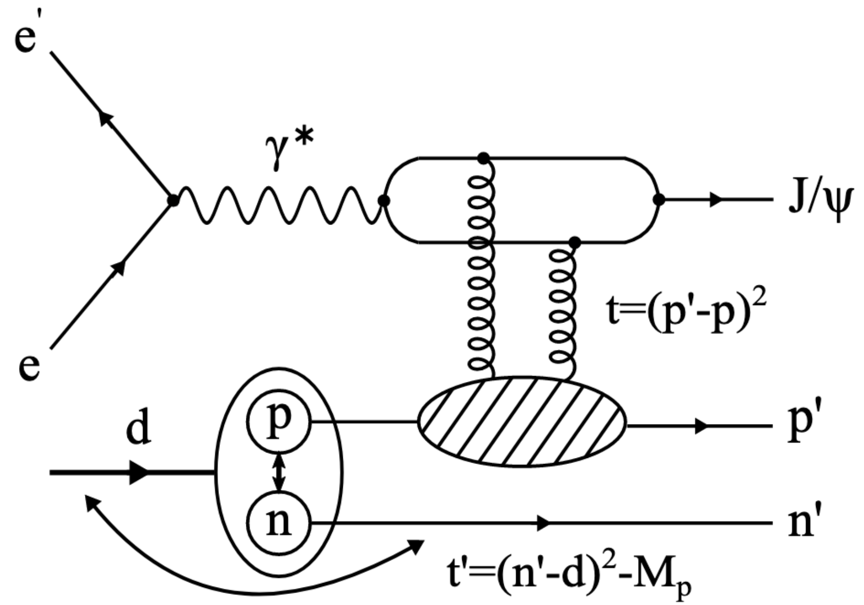
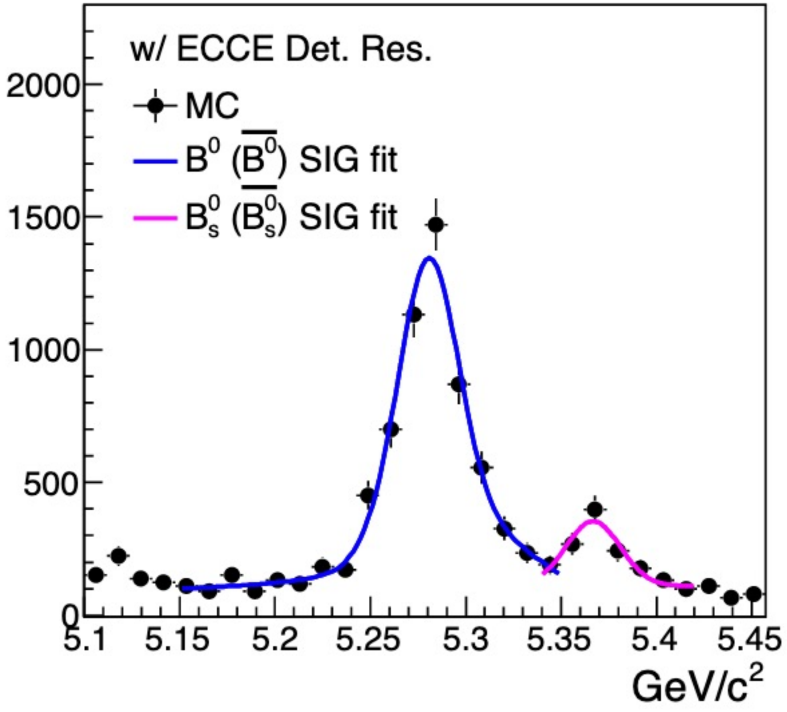
RHIC & AGS Users Meeting

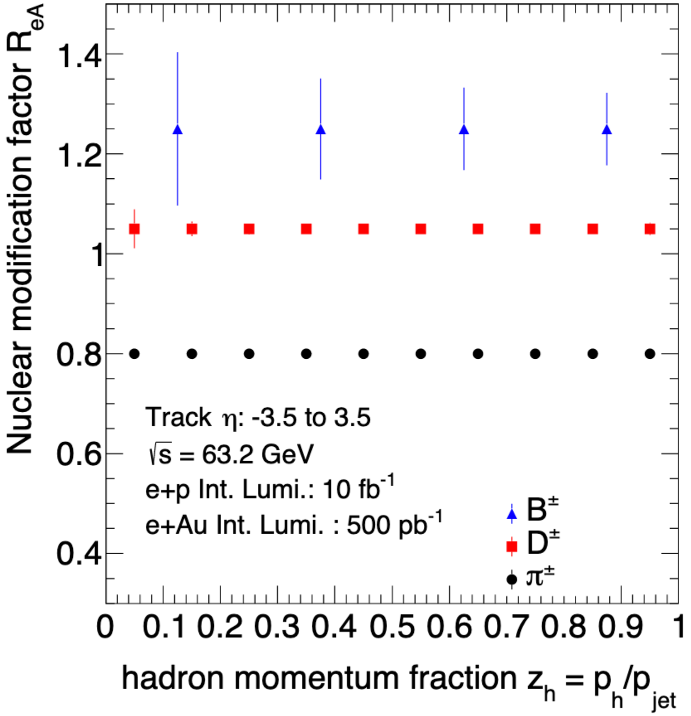
06/11/24

Heavy flavor at the EIC

- Why?
  - Main HF production is through photon-gluon processes
  - Good probe of gluon parton distribution function



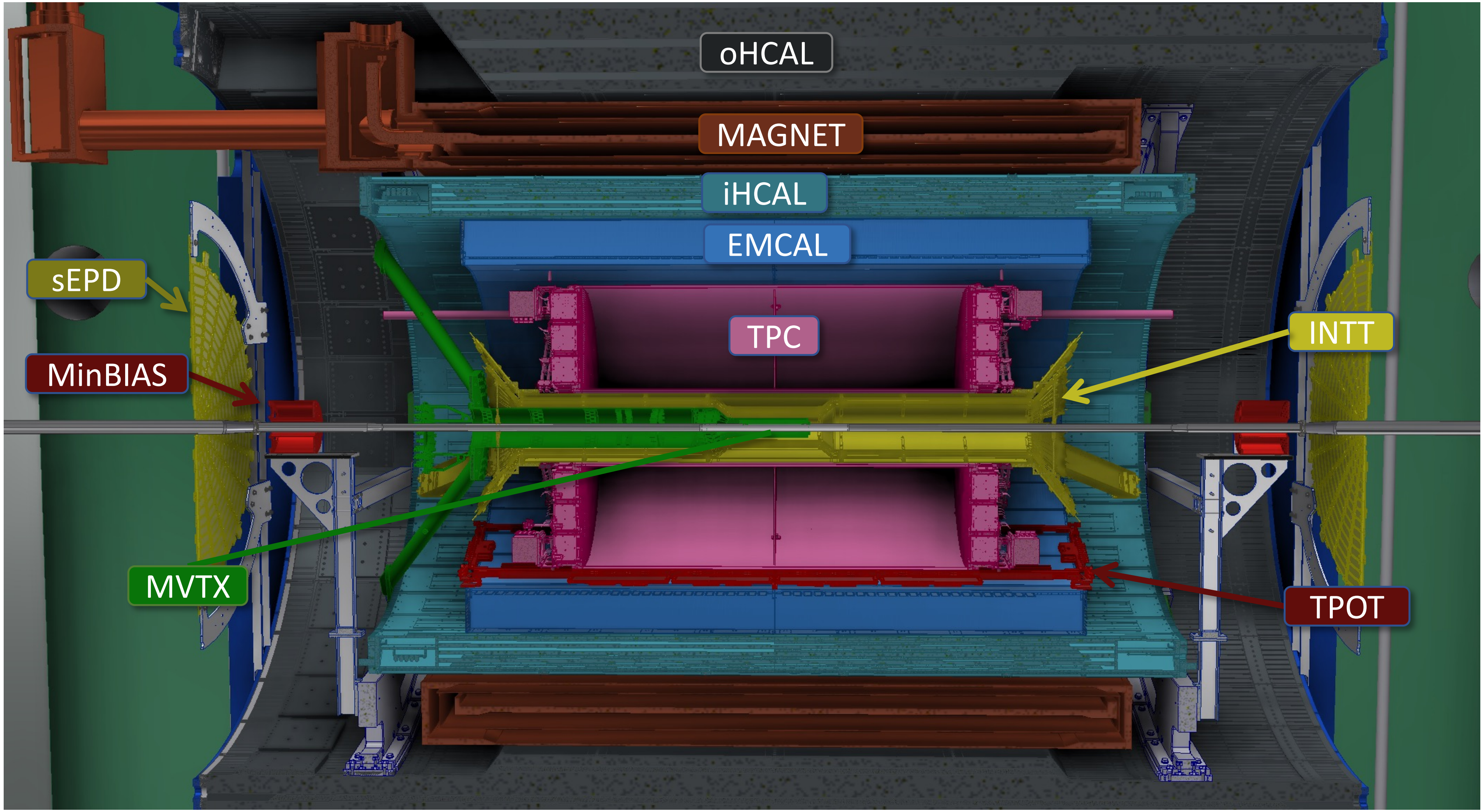




arXiv.2207.10632
arXiv:2103.05419

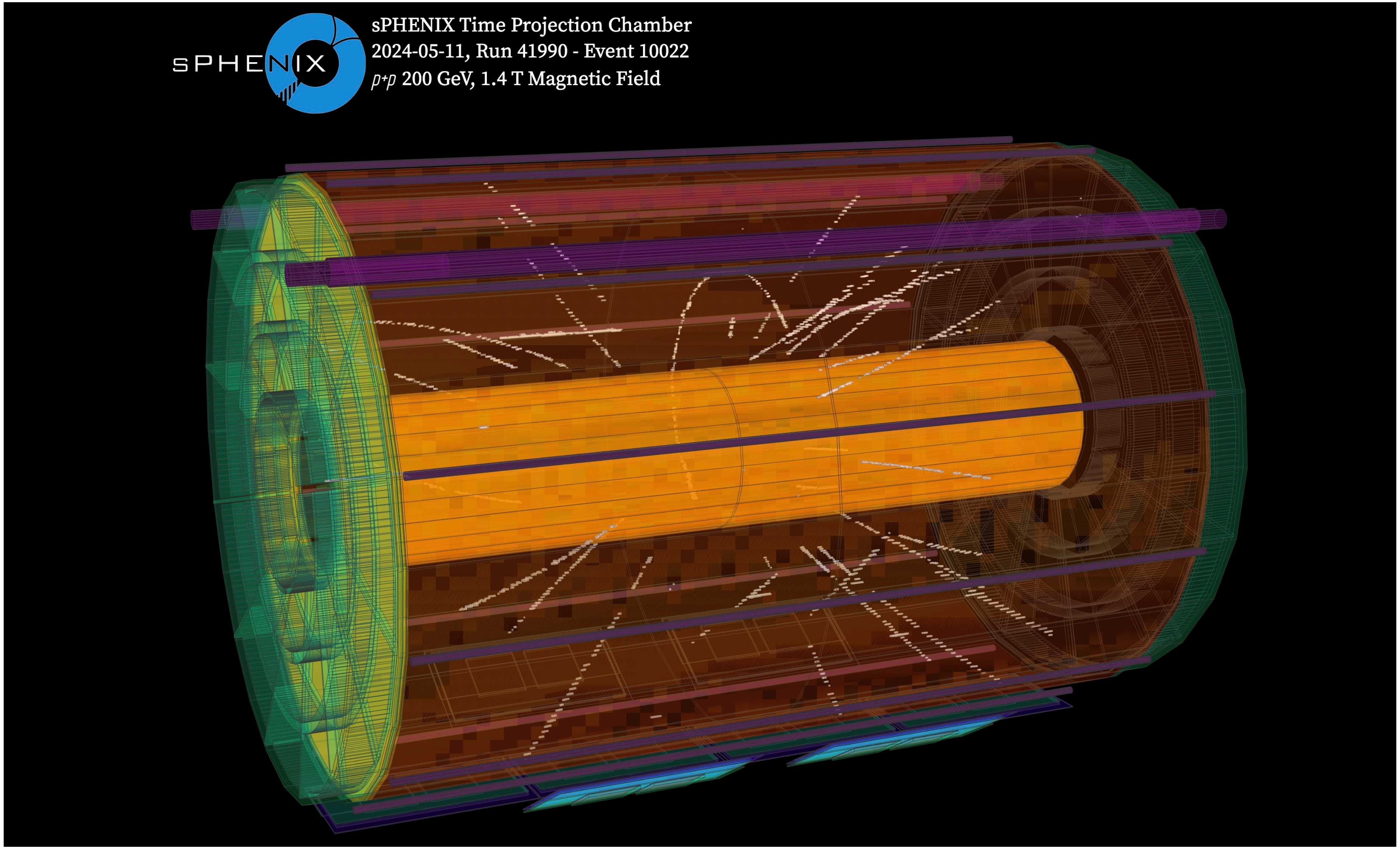
Our playground

ZDCs on either side of IR

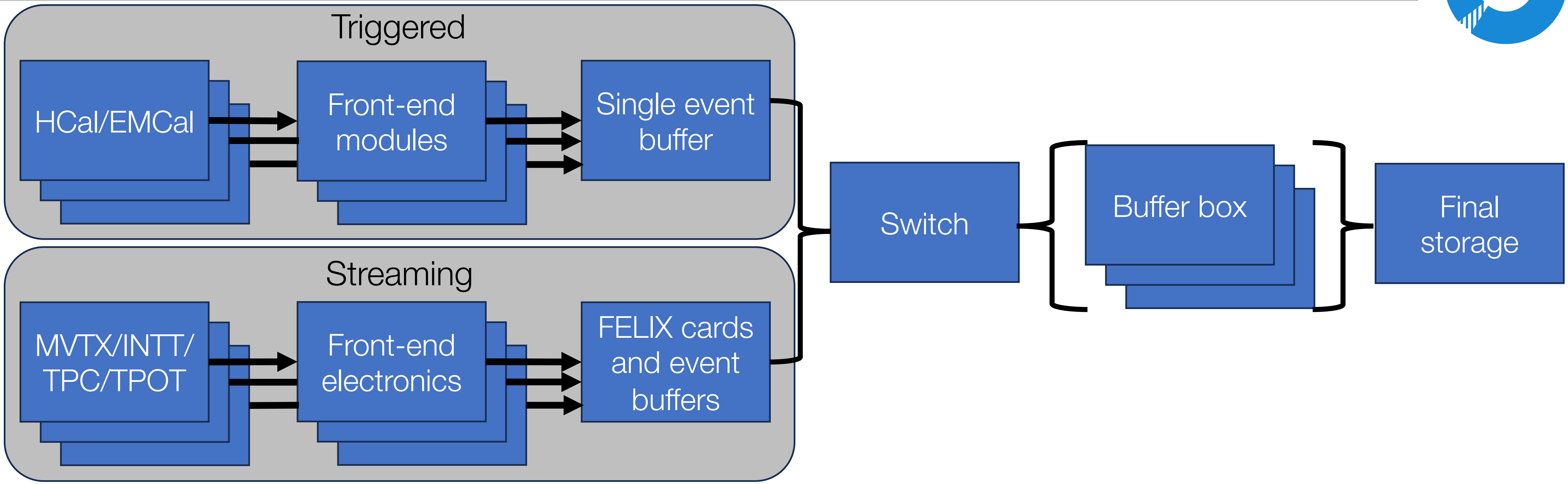


ZDCs on either side of IR

Seeing physics events



Current trigger system



- RHIC pp collision rate is 3 MHz
- sPHENIX calorimeter DAQ max. rate is 15 kHz
  - Limits sPHENIX to recording ~0.5% of triggered proton-proton collisions
- Trackers are all streaming readout (SRO) capable
  - TPC dominates data rate, can't save all streamed data
  - 10% trigger-enhanced SRO increases open HF MB rate ~300 kHz

The proposal

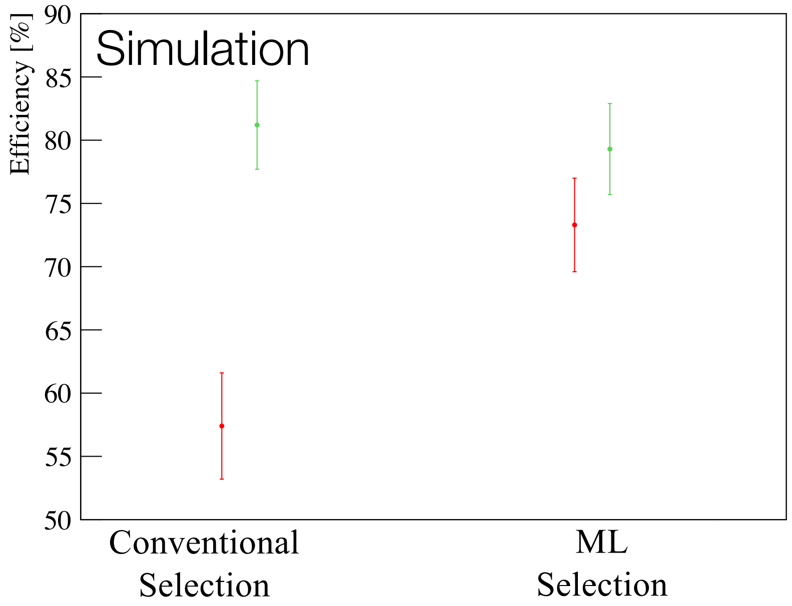
Intelligent experiments through real-time AI: Fast Data Processing and Autonomous Detector Control for sPHENIX and future EIC detectors

A proposal submitted to the DOE Office of Science
April 30, 2021

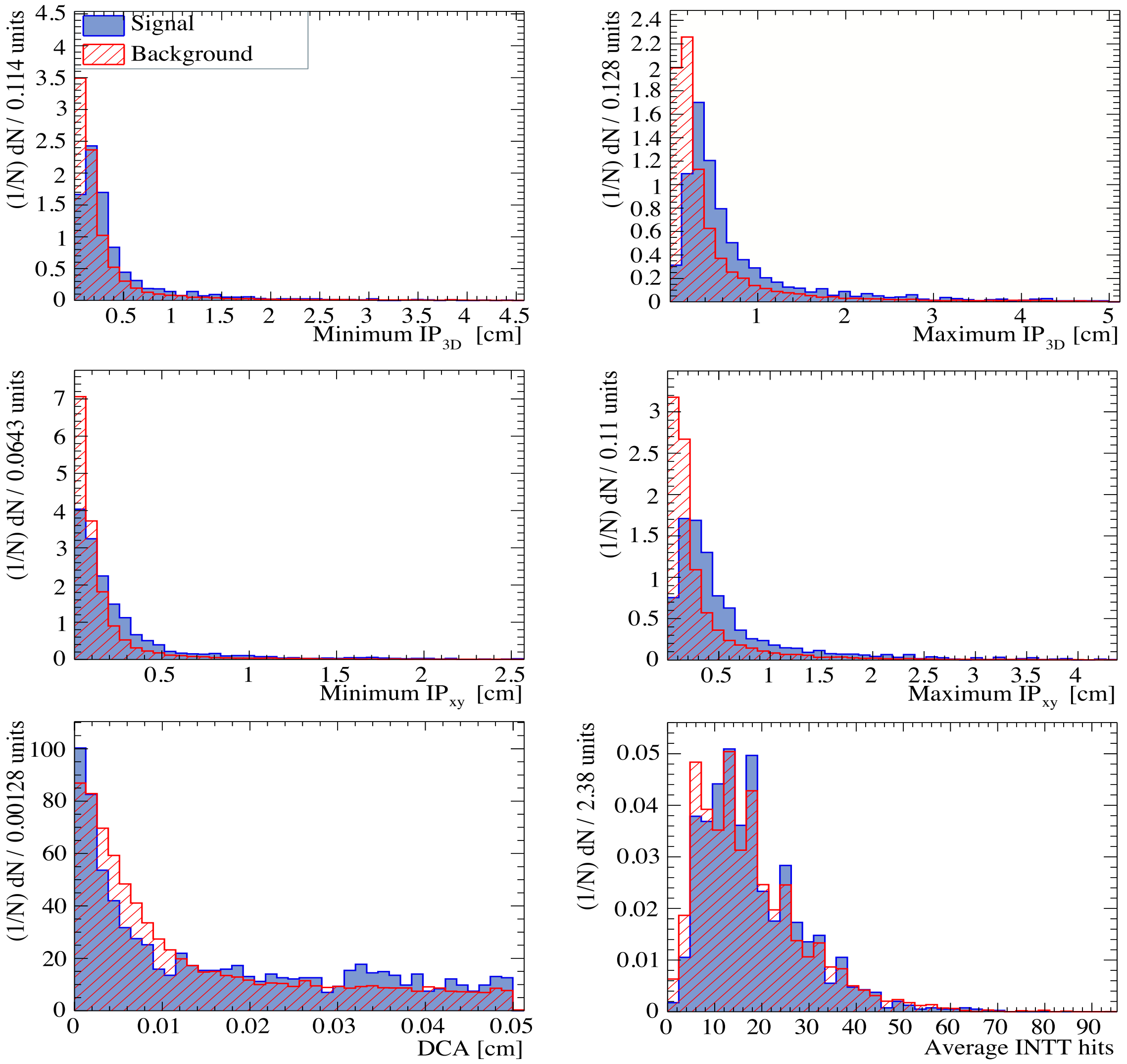
- Embed ML algorithms on FPGAs
- Stream MVTX and INTT to FPGAs and determine if HF event is present through topology
- Send tag downstream to readout TPC
- Allows us to sample remaining 90% of collisions

Case study: AI HF selections

- Question: Is ML better for selecting HF decays over conventional selections?
- Challenge: Must run online, in FPGA. Hence variables must be “simple”



Green – The signal selection efficiency
Red – The background rejection efficiency
1000 signal & 1000 background events used



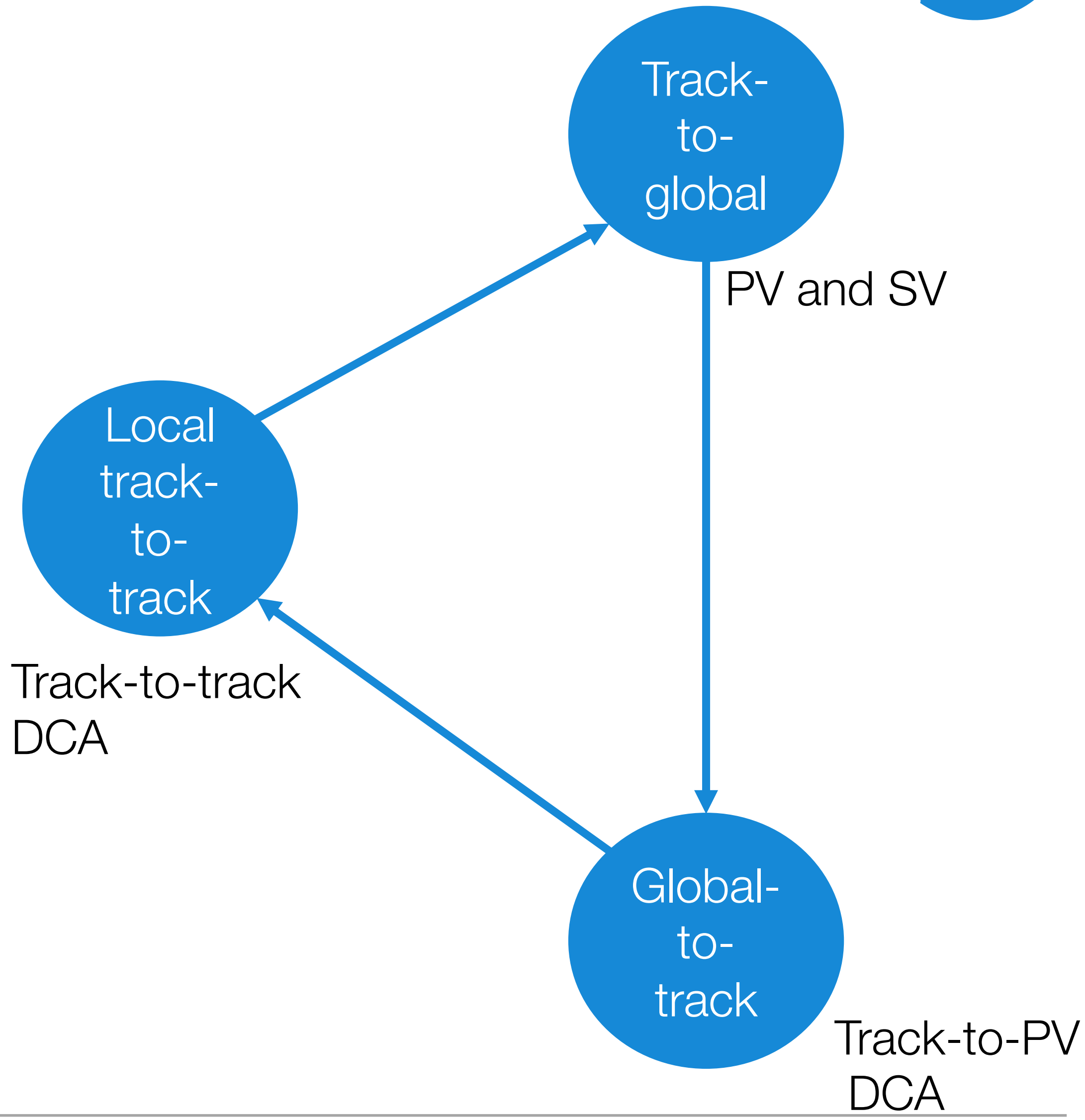
Constructing ML algorithms

- Developed algorithms as Graph Neural Networks (GNN)
- Advantageous over Convolutional Neural Networks (CNN) by adding edge information
- Detector and physics knowledge will improve predictions
- Algorithms deployed at several points on FPGAs:

1. Data decoding – conventional logic
2. Hit clustering – conventional logic
3. Fast tracking – machine learning
4. Topological separation of HF signal from background – machine learning

Feedback algorithms

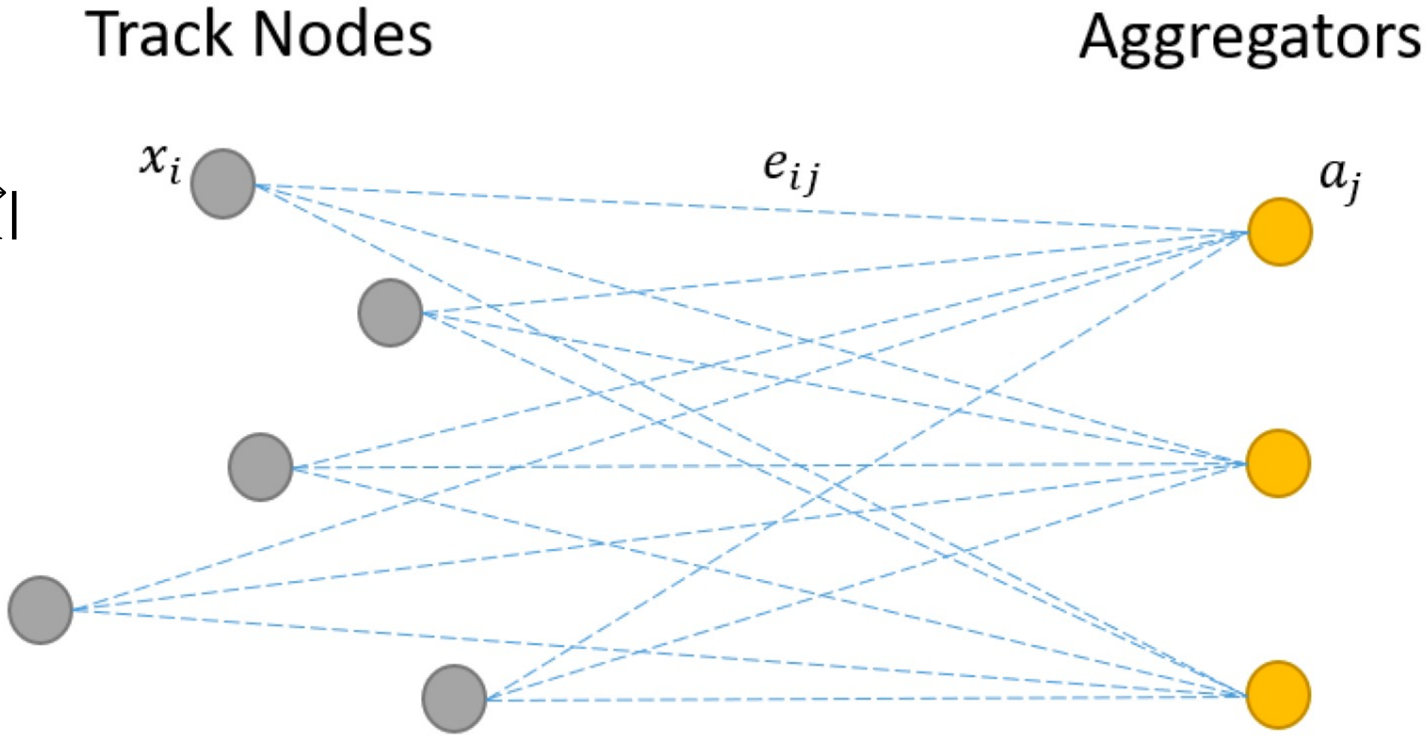
- Tracking algorithms developed using simulated signal and background events in the MVTX and INTT
- Used these models to feed into physics selection models to select interesting events
  - Models are bi-directional, local information is passed to global and global information is passed back to local to refine
- Initial trainings and models are developed on GPU
  - NVIDIA Titan RTX, A5000, and A6000
  - Will take the model and convert it to IP block for FPGA deployment
  - Models developed with PyTorch and PyTorch Geometric



Tagging with machine learning

Graph Neural Net design

- Track node input vectors
  1. 5 hits (MVTX + INTT)
  2. Length of each segment: $L = |\overrightarrow{x_{i+1}} - \vec{x_i}|$
  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

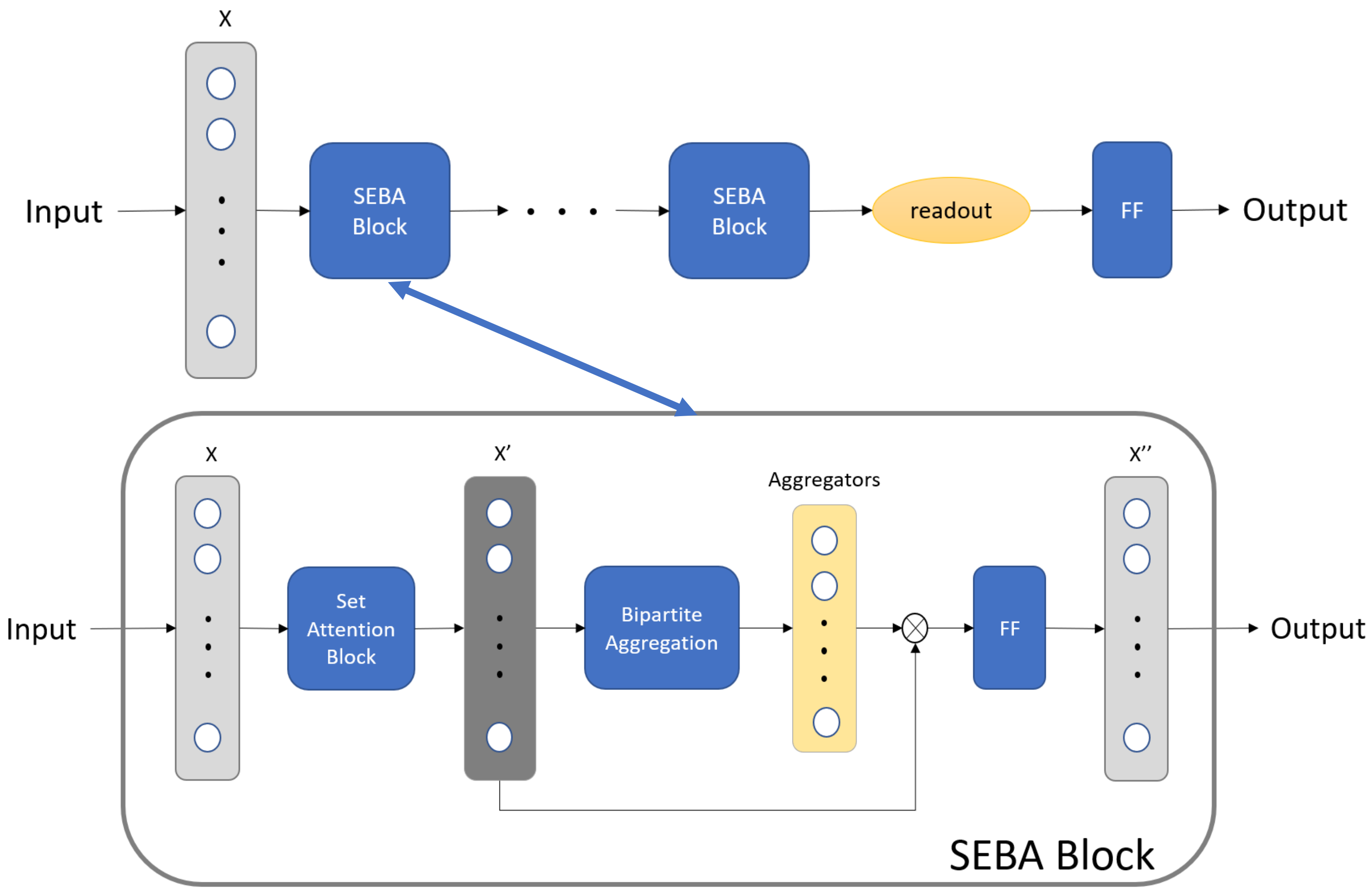


$e_{ij} = s_{ij} x_i$ is track-aggregator messages

s_{ij} is the weight

ECML PKDD 2022, Sub 1256

GNNs with set transformers

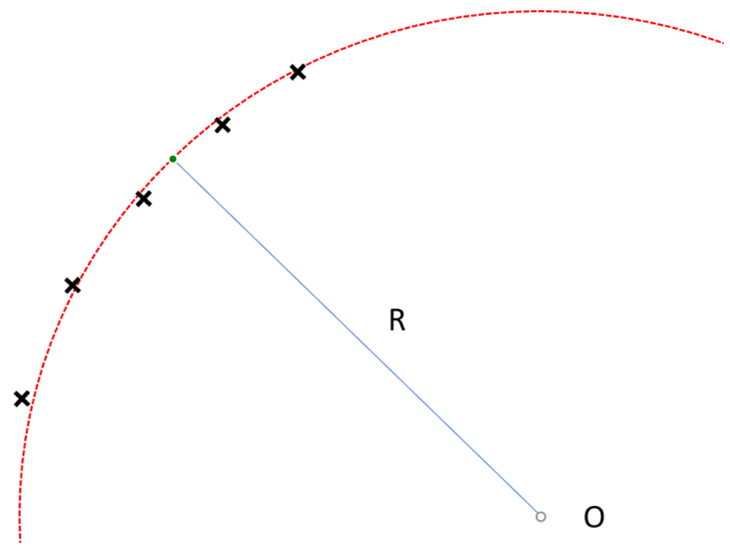


The cycle

1. Track information is initially defined
2. This is relayed to all primary and secondary vertex information
3. Weights are assigned to each link
4. The PV and SV information go through a feedforward NN
5. This updates the track information

pT estimation

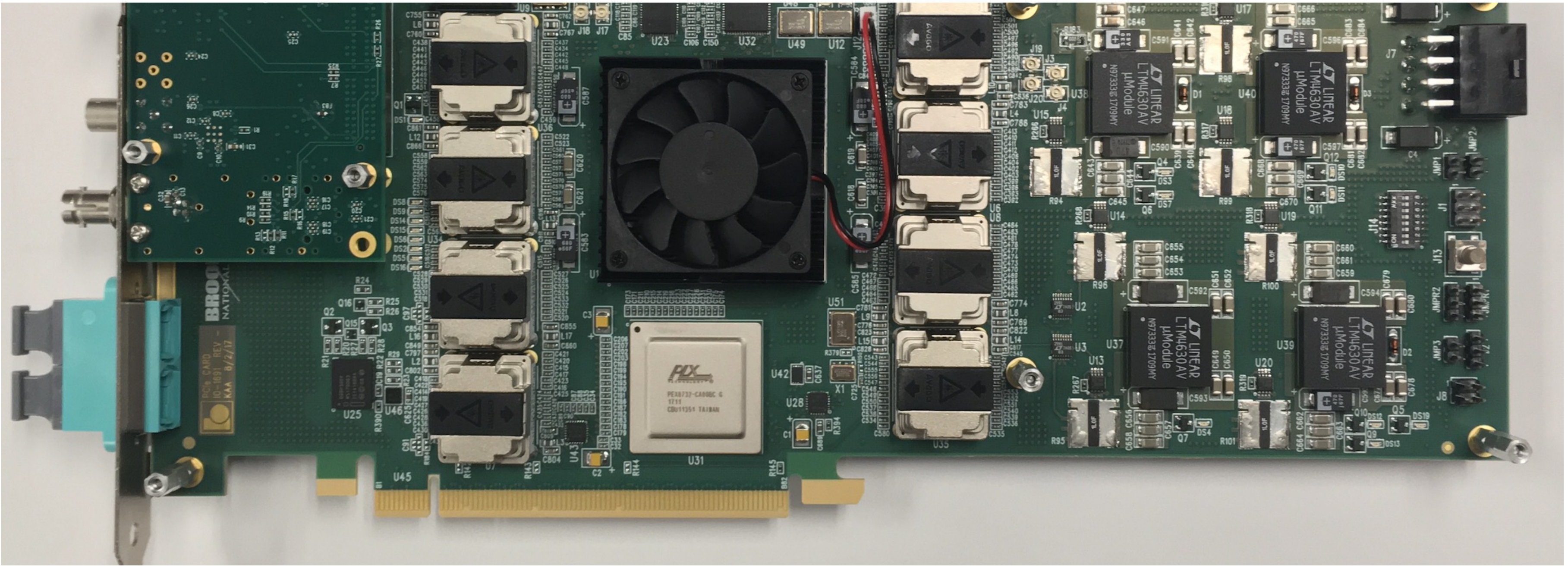
- A feed-forward neural net is used to predict the pT
- Uses least-squares method to estimate track radius
- ~15% improvement in tracking with pT estimation



Model	with LS-radius #Parameters	with LS-radius Accuracy	with LS-radius AUC	without radius #Parameters	without radius Accuracy	without radius AUC
Set Transformer	300,802	84.17%	90.61%	300,418	69.80%	76.25%
GarNet	284,210	90.14%	96.56%	284,066	75.06%	82.03%
PN+SAGPool	780,934	86.25%	92.91%	780,678	69.22%	77.18%
BGN-ST	355,042	**92.18%**	**97.68%**	354,786	**76.45%**	**83.61%**

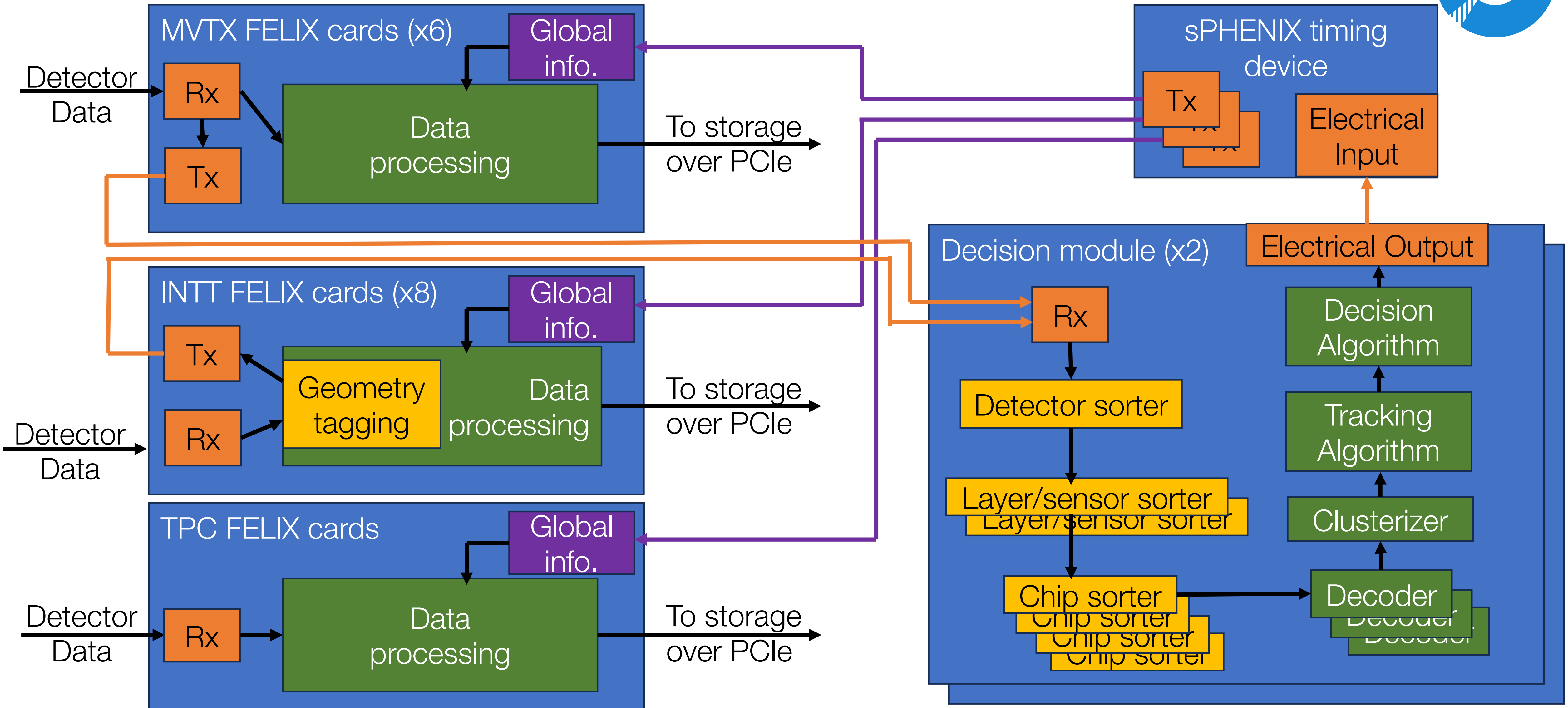
Hidden dim	LS Accuracy	LS AUC	MLP Accuracy	MLP AUC
32	91.52%	97.33%	91.48%	97.31%
64	92.18%	97.68%	92.23%	97.73%
128	**92.44%**	**97.82%**	**92.49%**	**97.86%**

Hardware design



- Decision hardware is currently a BNL-712 FELIX board
  - Same as deployed at sPHENIX for ease of integration
  - Team can successfully transfer data from BNL-712 to KC-705 evaluation board
- Ongoing work on reducing resource usage

Realizing in firmware

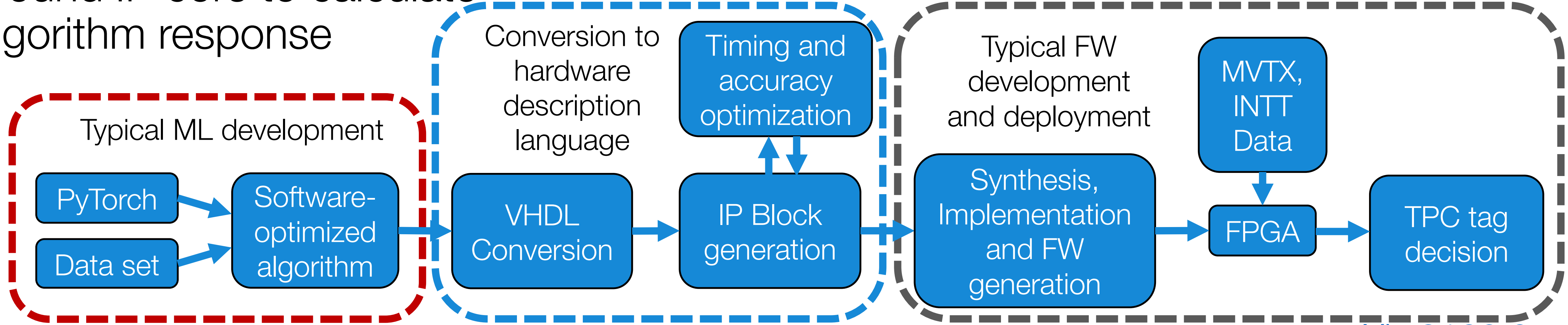


Tagging with machine learning

- Algorithms must have low latency and resource use
- hls4ml translates NN algorithms into high level synthesis
- Also generates IP cores for easy implementation
- Rest of firmware can be built around IP core to calculate algorithm response

Server for algorithm conversion and FW generation

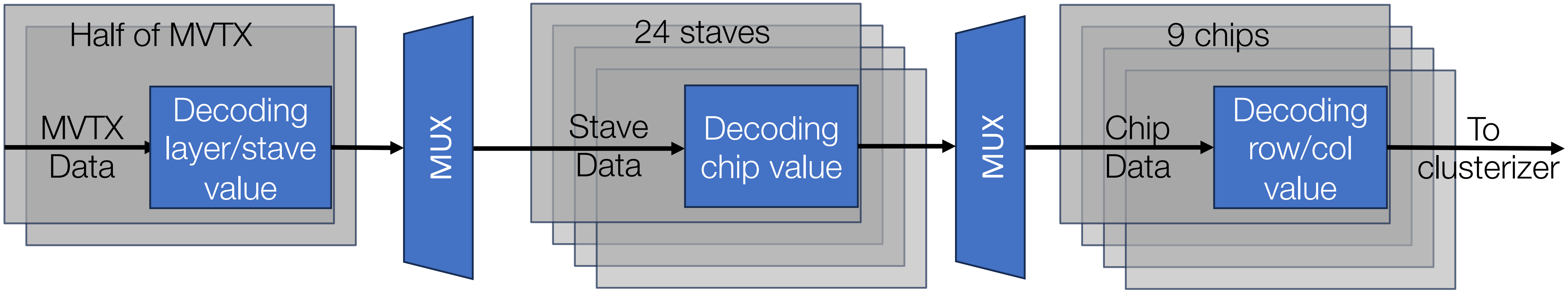
FELIX card (712) on server for FW testing



arXiv 2103.05579

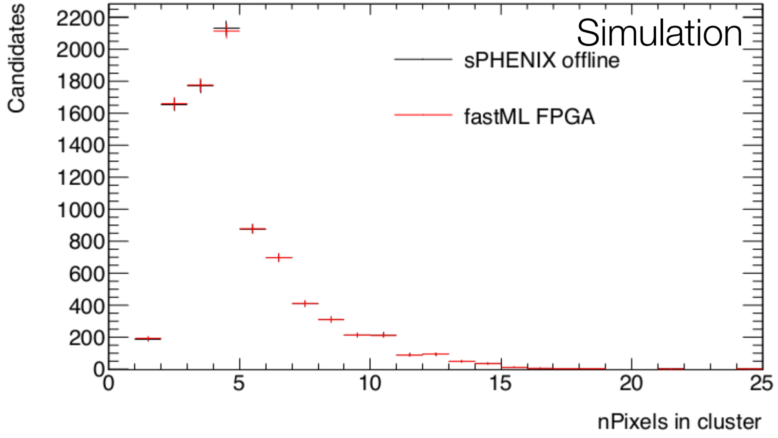
Decoding

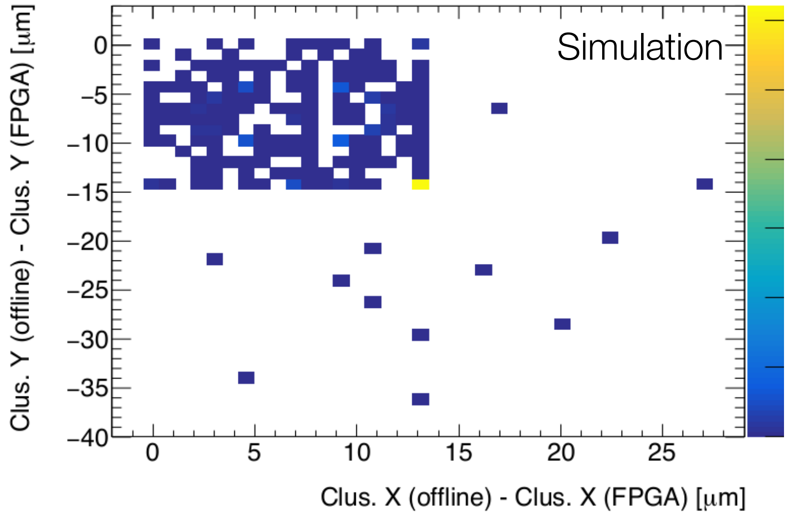
- Entire decision making must be performed in roughly 10 μs to allow recording of TPC hit
  - Parallelization of complex tasks in necessary to achieve this
- MVTX alone consists of 432 pixel chips with > 500k pixels / chip
  - 48 staves x 9 chips / stave
- Luckily, occupancy is low, ~ 20 hits / chip / collision for proton-proton collisions
- Each chip's information is sent to its own decoder to find active pixels



Clustering

- ALPIDE reads data out in double columns from 0 to 1023
  - Decoded hits thus arrive double column-by-double column
- Clusters can be assembled as they arrive
  - No hits in the next columns three adjacent pixels means cluster is ready to be sent out
- After finding pixel with centroid, pixel can be divided into grids to improve resolution using only 2 more bits
- Can get 13.5 μm cluster resolution at the global level from 31 bits
  - 6 bits to define layer and sensor number
  - 4 bits to define chip number on the sensor
  - 21 bits for cluster position on chip (9 for row, 10 for column, 2 for quadrant)
- After changing to global cluster position, detector layout has become abstracted

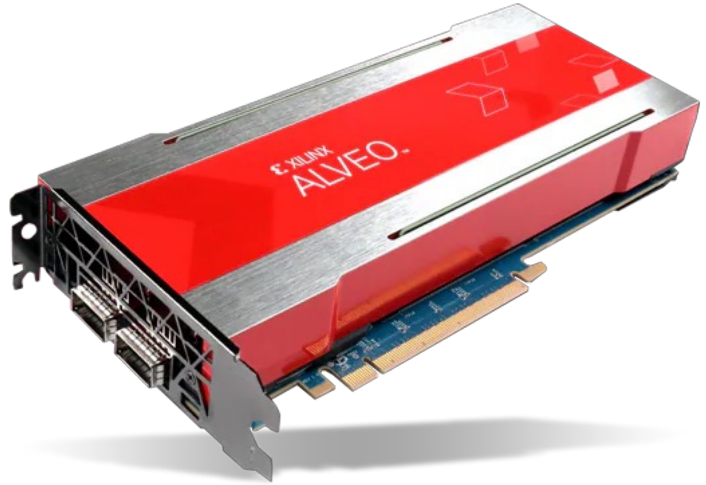




Putting it all together

- Tracking GNN has been synthesised and benchmarked on Alveo U280 accelerator card using simulations

Look up tables	23.7% (308k)
Flip flops	14.5% (378k)
Block RAM	50.8% (1025)
Digital signal processing	15.8% (1426)



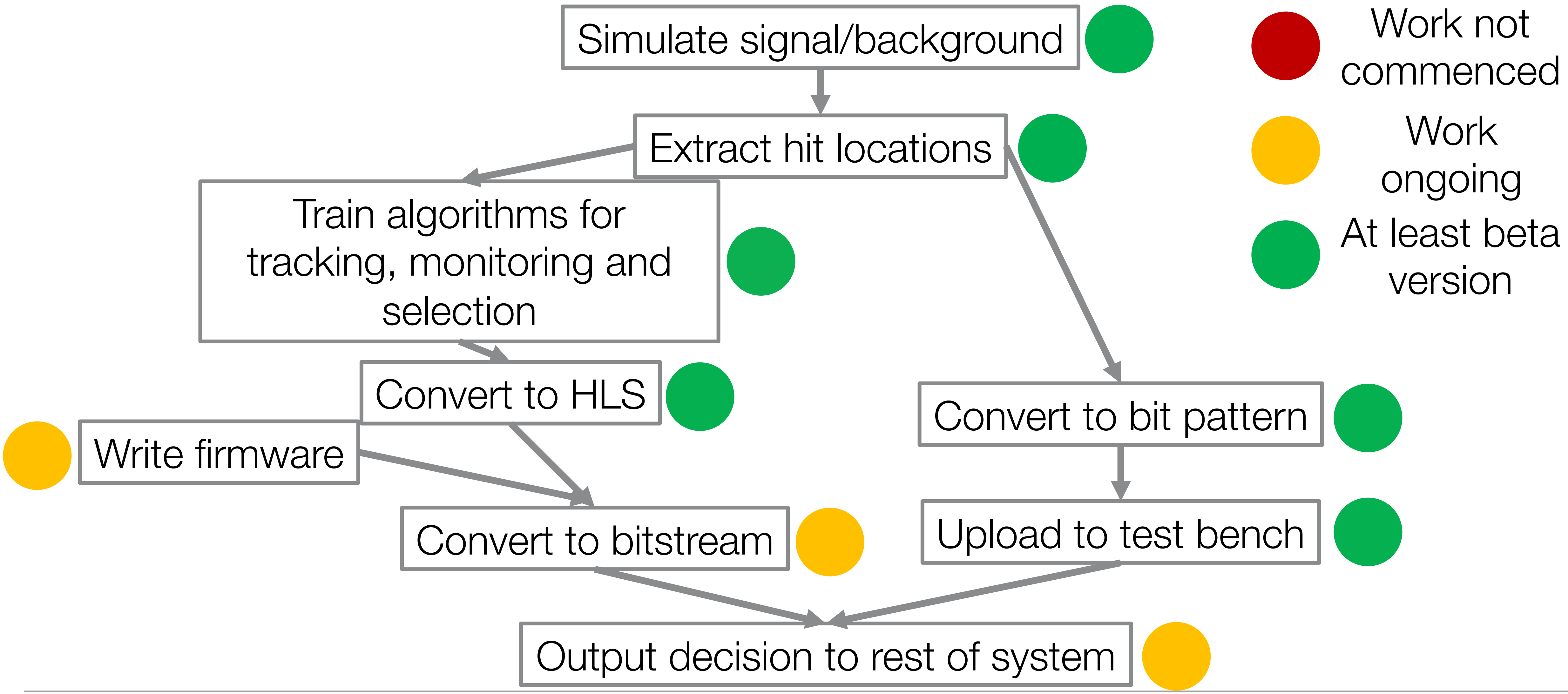
- Processing time is undergoing rapid improvements
  - 380 μs in August 2023
  - 8 μs in May 2024
- Second stage of the algorithm uses tracks to construct secondary vertices, a signature of particle decays

Secondary vertex finding with sim. $D^0 \rightarrow K^-\pi^+$ signal and random background for 1% sig. to bkg. tuning

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

Workflow


Simulate signal/background
Extract hit locations
Train algorithms for tracking, monitoring and selection
Convert to HLS
Write firmware
Convert to bitstream
Convert to bit pattern
Upload to test bench
Output decision to rest of system
Work not commenced
Work ongoing
At least beta version

Predicted timeline

2021

- Project started
- Initial simulations constructed
- First data for algorithm training

2022

- SRO development
- Fast tracking algorithms in place
- GPU feedback machine design
- Initial bitstream synthesis

2023

- Refine interface between system and detectors
- Improve algorithms with latest data stream and commissioning info

2024

- Deploy device at sPHENIX

- Design updated system
- Take advantage of new technology if required

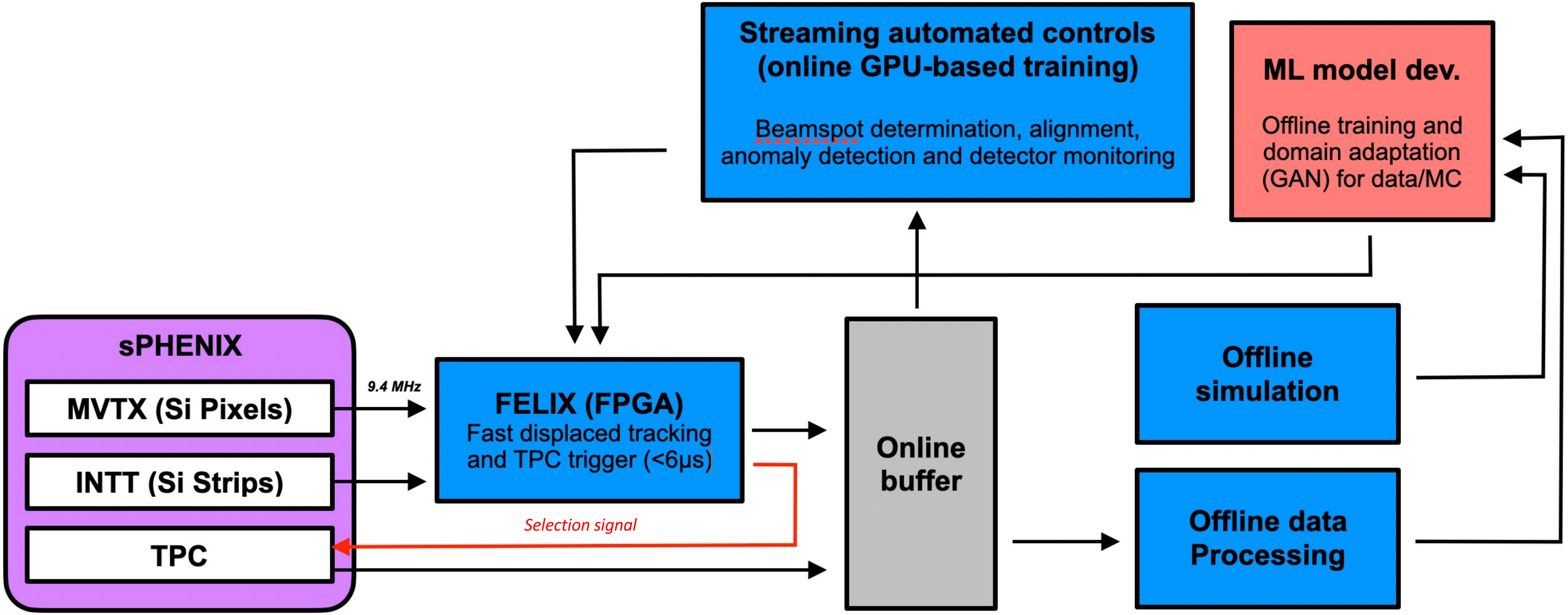
- Deploy device at EIC

Backup

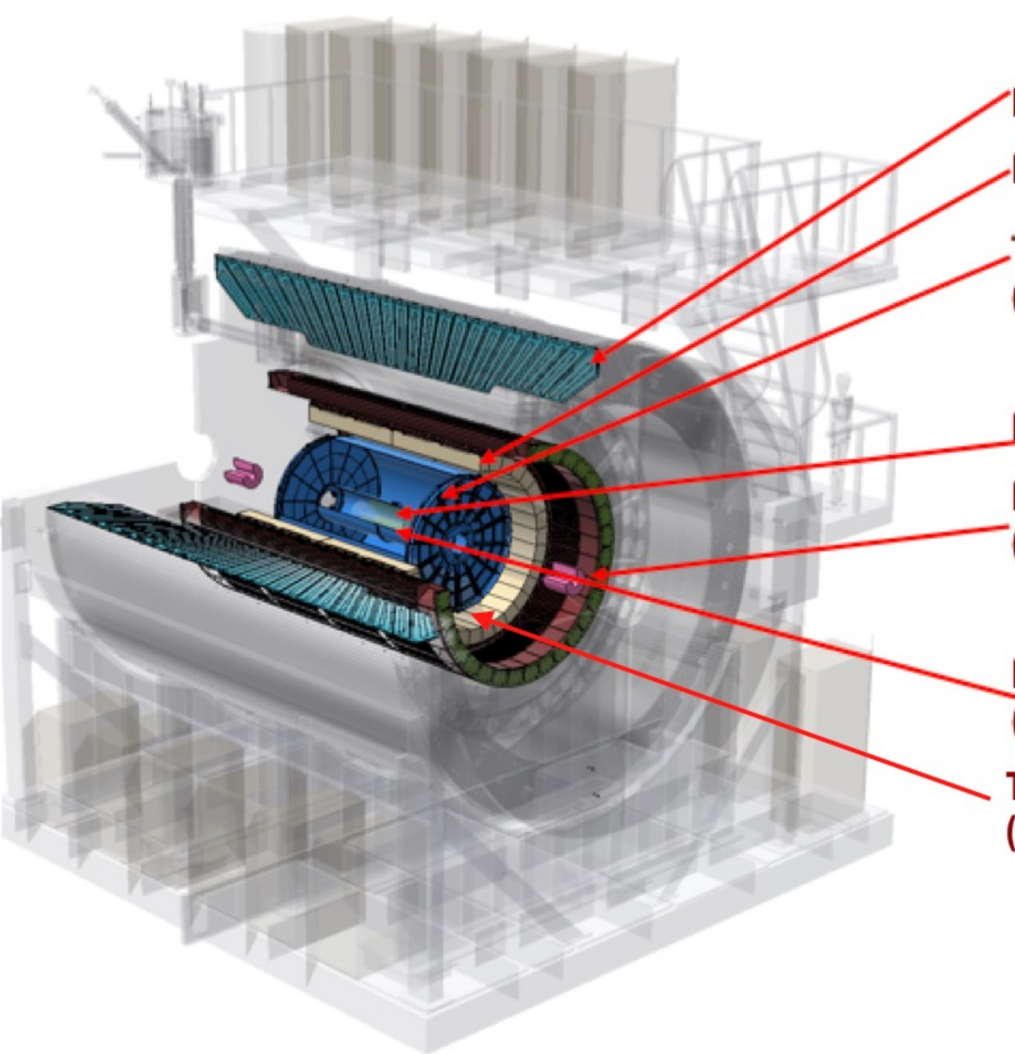
The FastML Team

- Cross-discipline group of computer scientists, engineers and physicists
- Formed in 2020 from DE-FOA-0002490
- Consists of groups from
    - Los Alamos National Laboratory
    - Massachusetts Inst. of Technology
    - New Jersey Institute of Technology
    - Fermilab
    - Oak Ridge National Laboratory
    - Stony Brook
    - Georgia Institute of Technology
    - University of North Texas
    - Central China Normal University

Overcoming with AI



sPHENIX

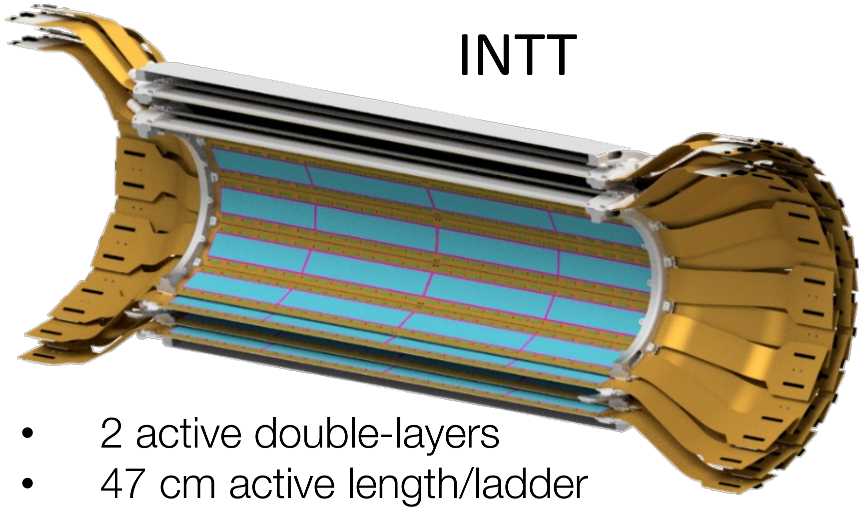


First run year	2023
$\sqrt{s_{NN}}$ [GeV]	200
Trigger Rate [kHz]	15
Magnetic Field [T]	1.4
First active point [cm]	2.5
Outer radius [cm]	270
$\lvert\eta\rvert$	$\leqslant 1.1$
$\lvert z_{vtx}\rvert$ [cm]	10
N(AuAu) collisions*	1.43×10^{11}

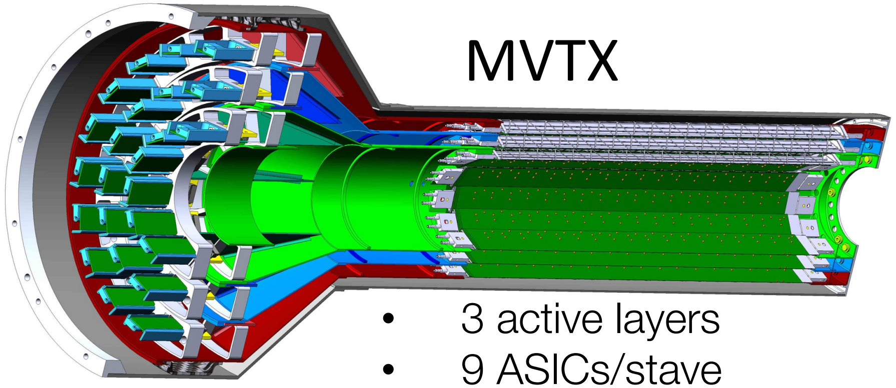
* In 3 years of running

Tracking at sPHENIX

- Tracking consists of 3 sub-detectors:
  - Pixel Vertex Detector (MVTX)
  - Intermediate Silicon Tracker (INTT)
  - Time Projection Chamber (TPC)
- MVTX and INTT are both capable of streaming readout
- Combined tracking to r = 10.3 cm



- 2 active double-layers
- 47 cm active length/ladder
- Silicon strip detector



- 3 active layers
- 9 ASICs/stave
- 27 cm active length/stave
- Pixel detector