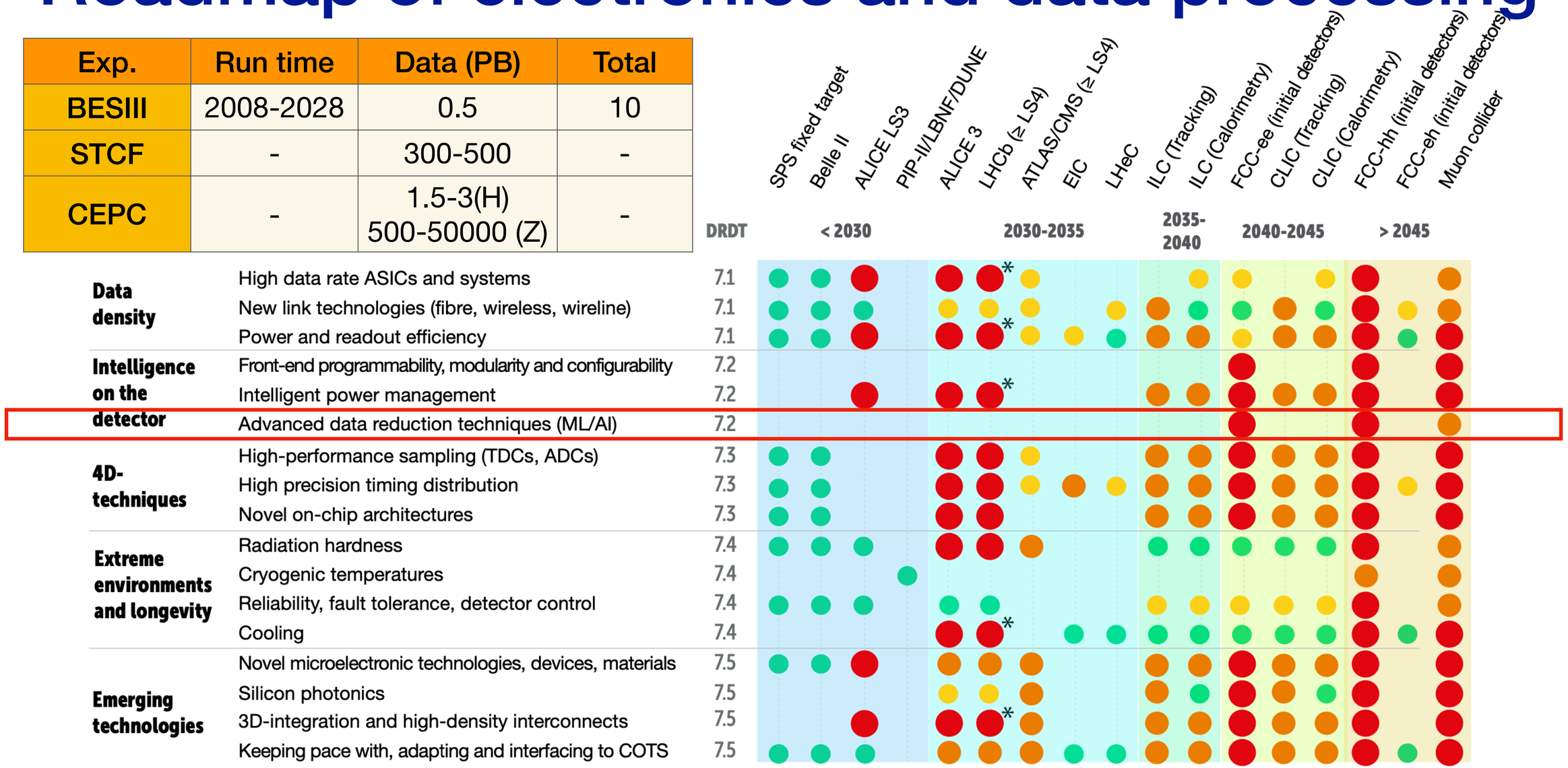
Real-time data processing with ML

周启东(ZHOU Qi-Dong)
Institute of Frontier and Interdisciplinary Science,
Shandong Univ. (Qingdao)

11-12 Jan. 2025, Hefei USTC
量子计算和人工智能与高能物理交叉研讨会

Roadmap of electronics and data processing

Exp.	Run time	Data (PB)	Total
BESIII	2008-2028	0.5	10
STCF	-	300-500	-
CEPC	-	1.5-3(H) 500-50000 (Z)	-

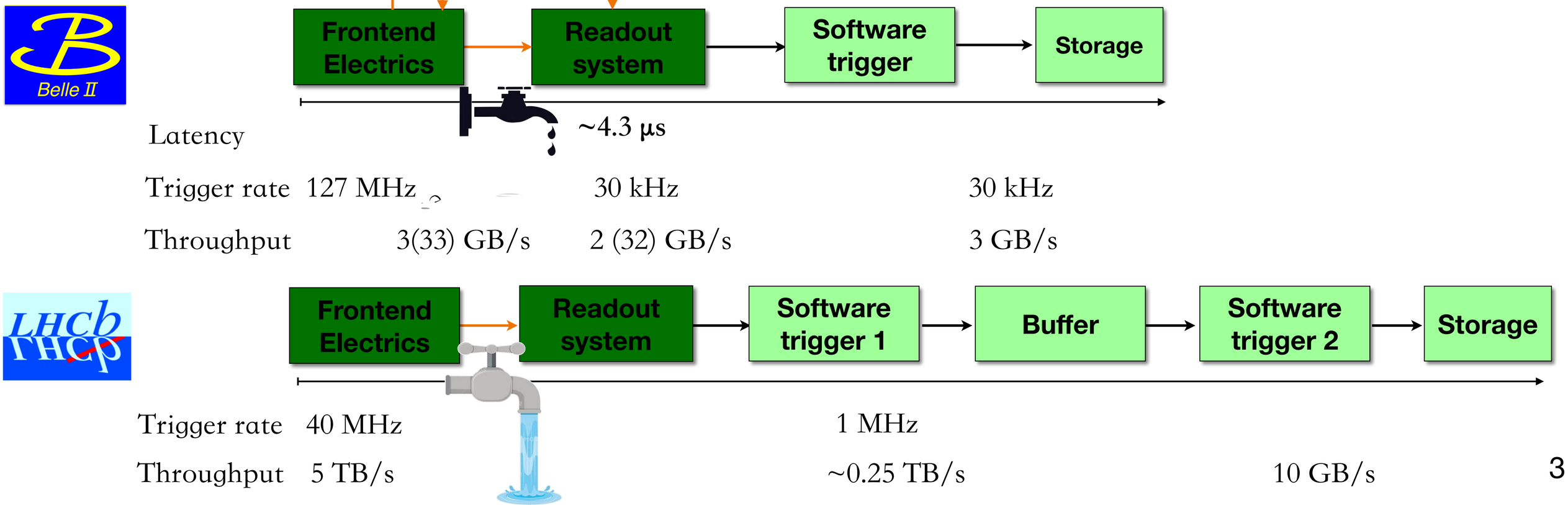


ECFA detector R&D

Readout system (Belle II vs. LHCb)

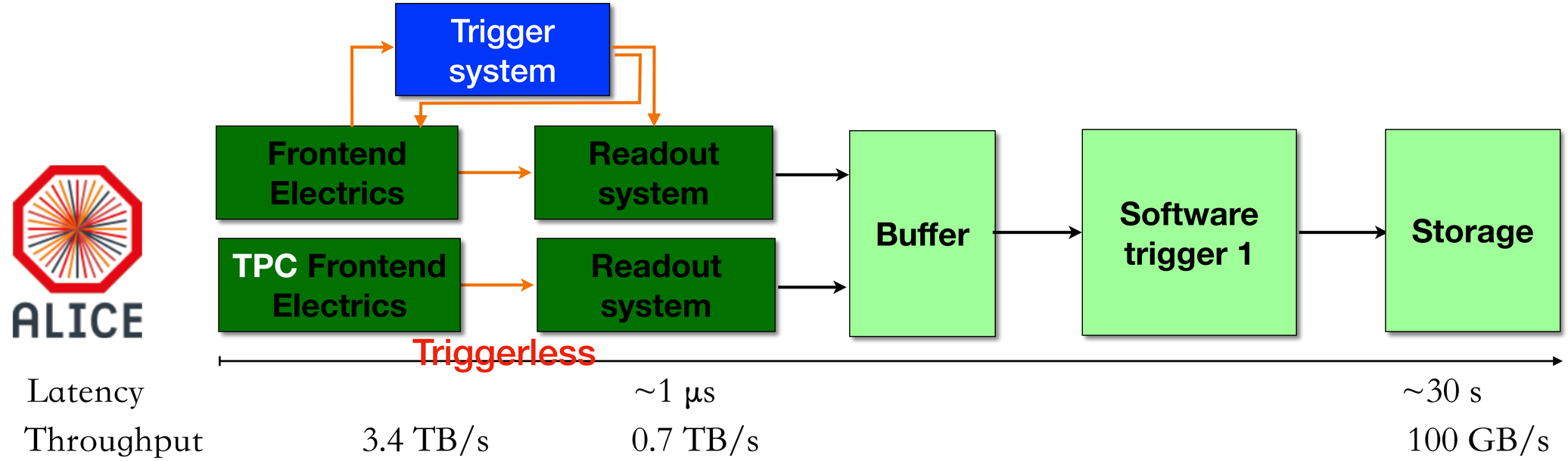
- Belle II: L1 trigger + HLT
  - Trigger efficiency:
    - Had. B physics～100% τ physics

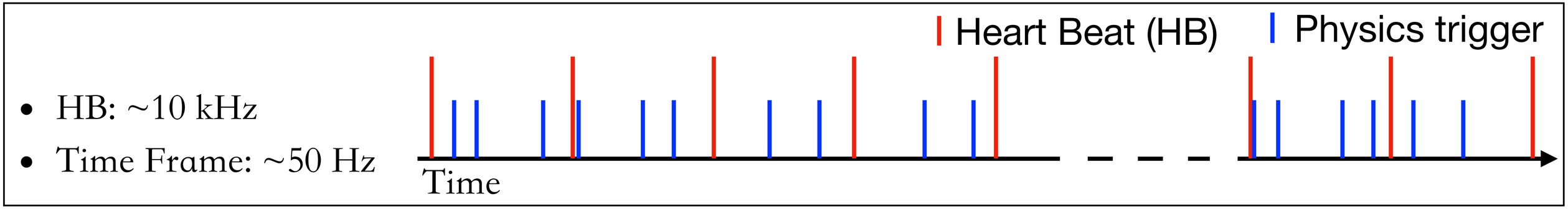
      70~95%
- LHCb: “triggerless” readout & DAQ
  - CPU+GPU based software trigger
  - Rate of physical process: ~MHz
    - No hardware trigger available



Readout and DAQ system(ALICE)

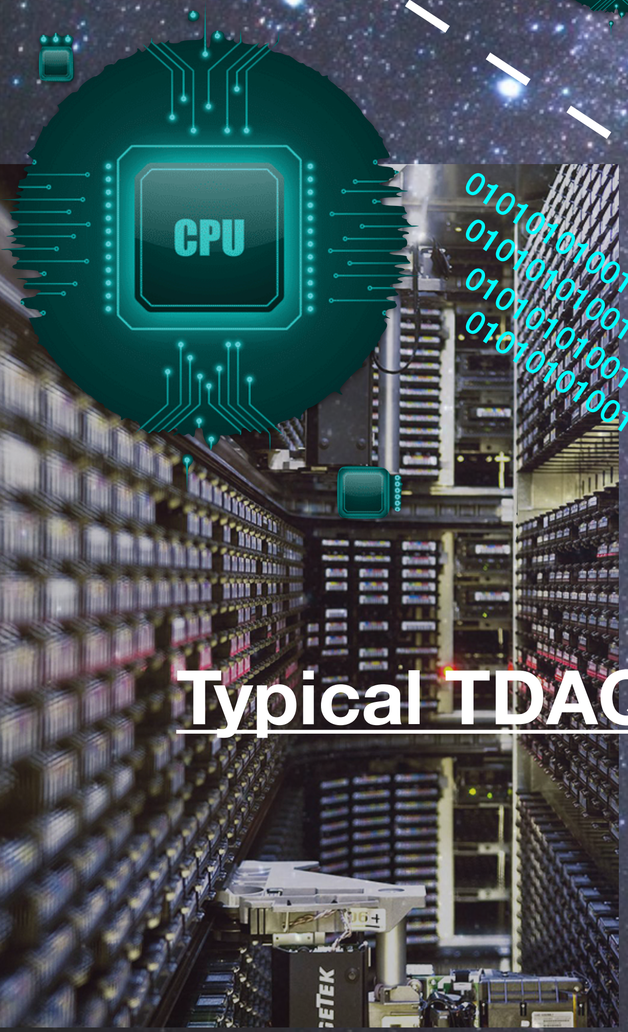
- ALICE: continus readout
  - TPC w/ triggerless readout + others w/ hardware trigger
    - TPC signal: ~100 μs, physical event rate 50 kHz, TPC signal overlap
  - Very basic hardware+ more effective software trigger





Gain power of apparatus with data acceleration

- Continues readout (less-hardware filtering)
- Powered by hardware acceleration
- Heterogeneous computing



Typical TDAQ system

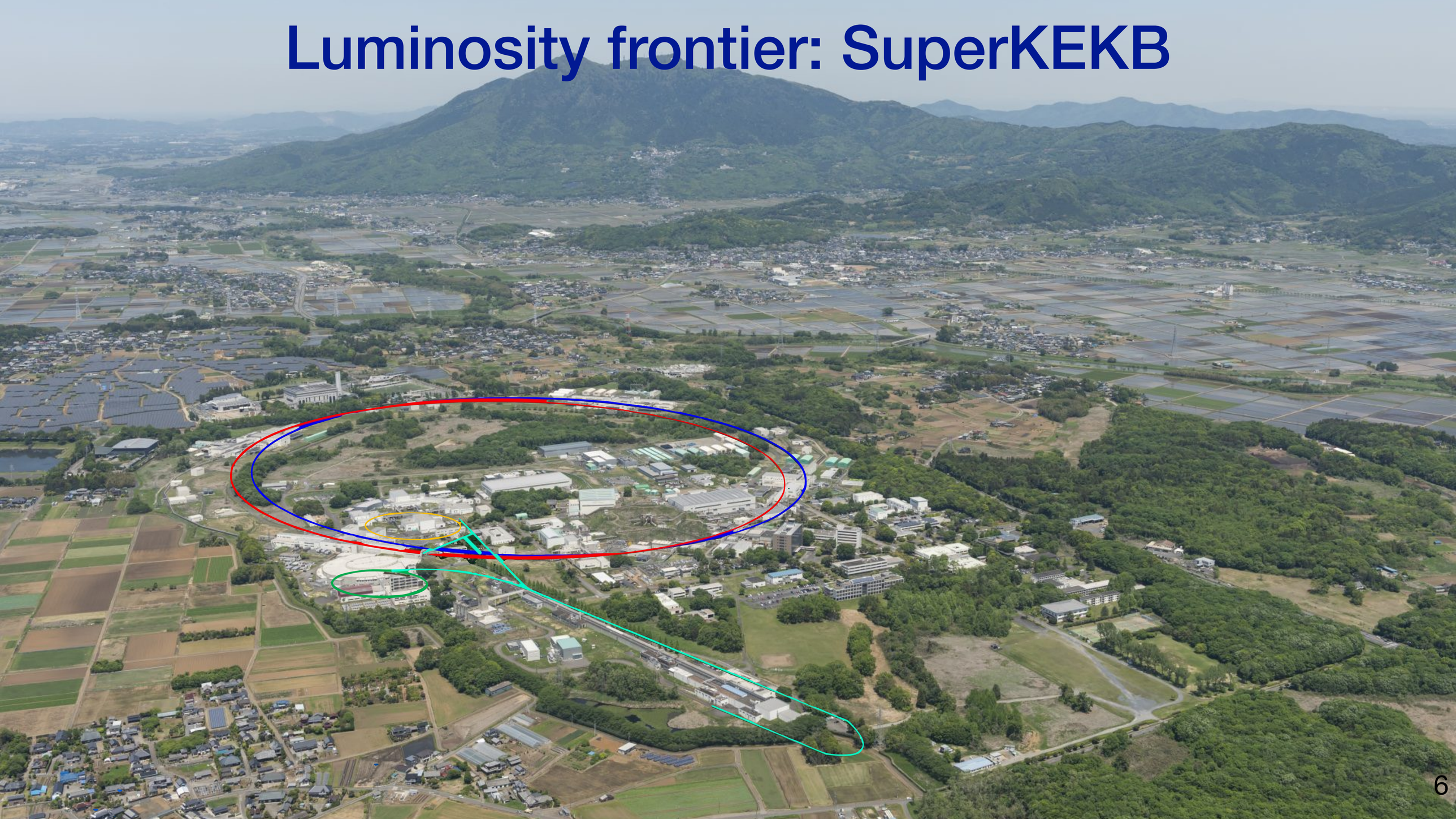
Trigger-less data readout system

Data readout system

Decisions

Trigger system (L1) (hardware filtering)

Luminosity frontier: SuperKEKB



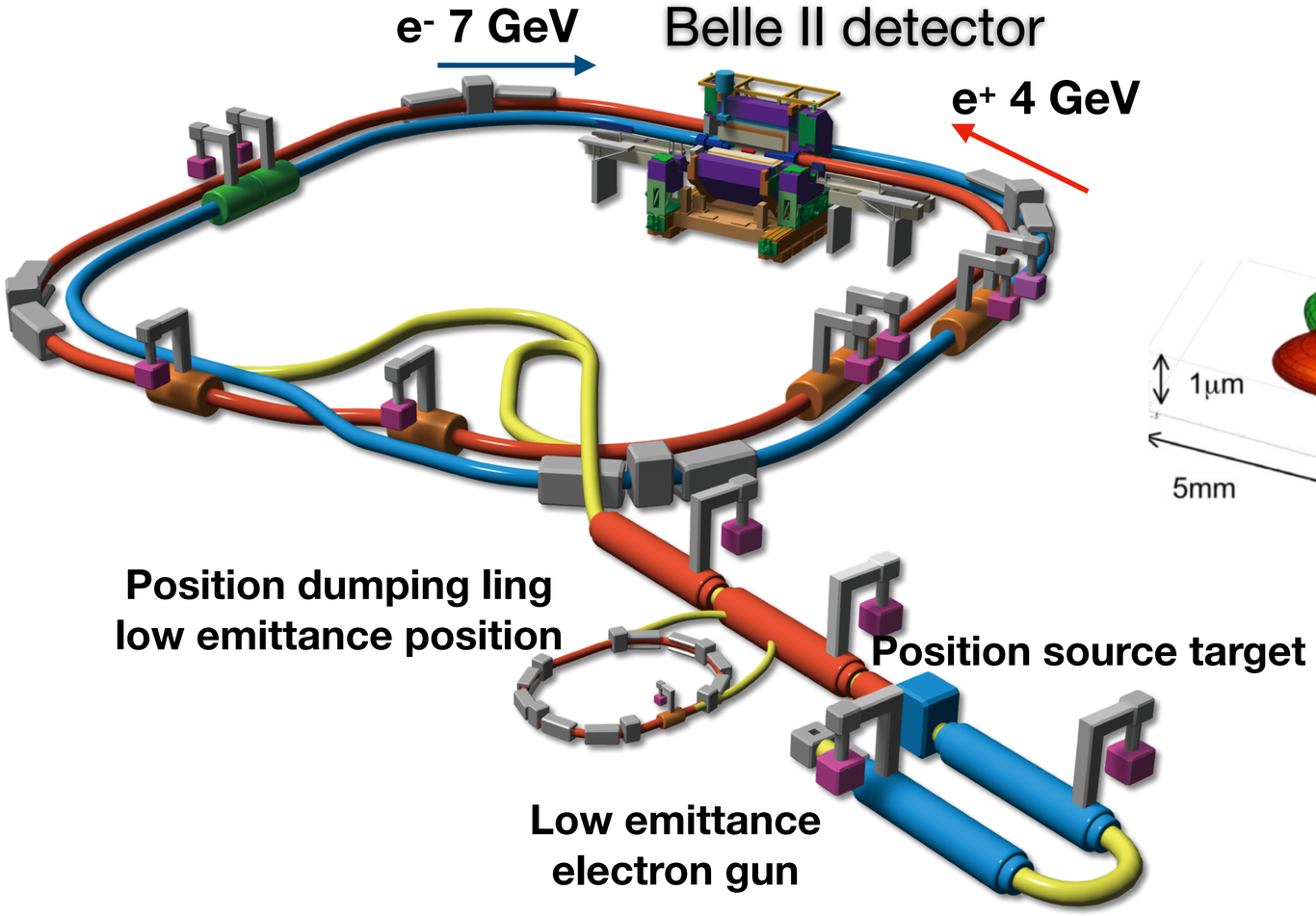
Luminosity frontier: SuperKEKB

- Asymmetric e^+e^- collider
  - $e^+e^- \rightarrow \Upsilon(4S) \rightarrow B\bar{B}$
  - very clean and well-known initial state

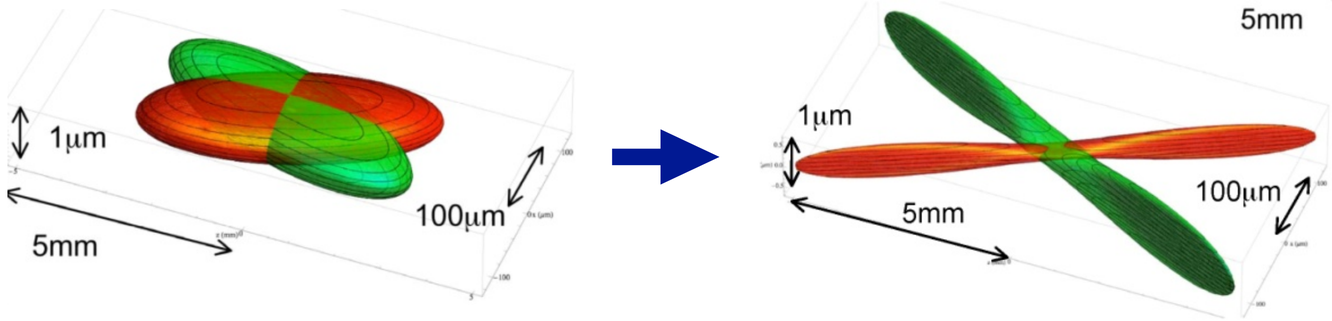
Beam current: KEKB x ~1.5

$$L = \frac{\gamma_\pm}{2er_e}\left(1+\frac{\sigma_y^*}{\sigma_x^*}\right)\frac{I_\pm \xi_{\pm y}}{\beta_y^*}\left(\frac{R_L}{R_y}\right)$$

Beam squeeze: KEKB / ~20



Nano beam scheme



Target: L = 60 x 10^{34} cm^{-2} s^{-1}

Achieved : 5.1 x 10^{34} cm^{-2} s^{-1} (Record)

- Data:
  - **575** fb^{-1} (Belle II) <-> 980 fb^{-1} (Belle)

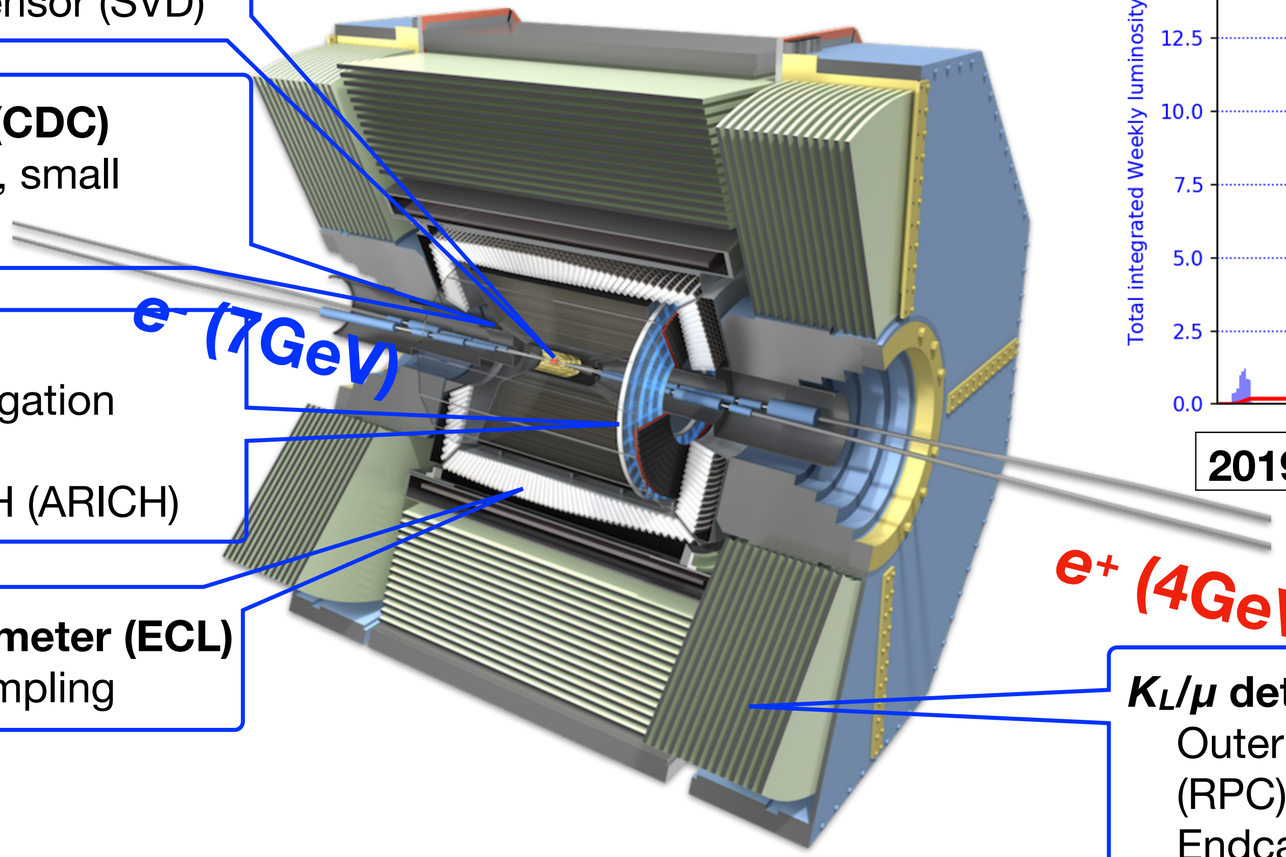
Belle II detector and dataset

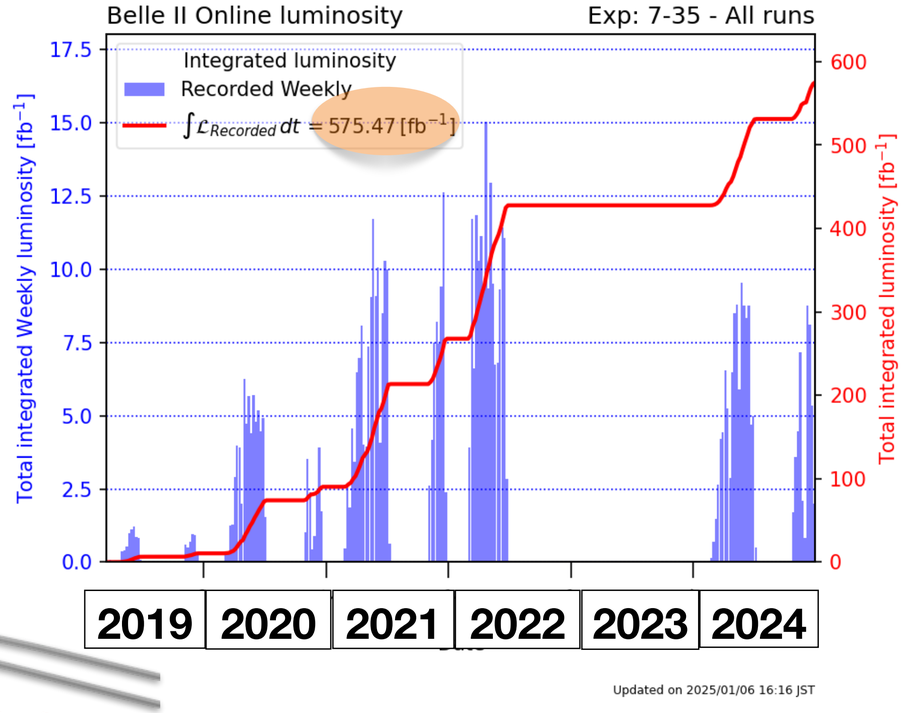
Vertex detector (VXD)
Inner 2 layers: pixel detector (PXD)
Outer 4 layers: strip sensor (SVD)

Central Drift Chamber (CDC)
He (50%), C_2H_6 (50%), small cells, long lever arm

Particle Identification
Barrel: Time-Of-Propagation counters (TOP)
Forward: Aerogel RICH (ARICH)

ElectroMagnetic Calorimeter (ECL)
CsI(Tl) + waveform sampling





K_L/μ detector (KLM)
Outer barrel: Resistive Plate Counter (RPC)
Endcap/inner barrel: Scintillator

- Features:
  - Near-hermetic detector
  - Vertexing and tracking: σ vertex ~ 15μm, CDC spatial res. 100μm $\sigma(P_T)/P_T$ ~ 0.4%
  - Good at measuring neutrals, π^0, γ, K_L… $\sigma(E)/E$ ~ 2-4%

Belle II trigger strategy

- Design requirements: ~100% for $\Upsilon(4S)$->$B\bar{B}$(hadronic decay), Tau/Charm, Exotics
  - No dead-time -> pipeline
  - Single photon trigger
  - Single track trigger
- Max. trigger rate: 30 kHz @ 6 x 10^{35} cm^{-2} s^{-1}
  - Physics trigger ~15 kHz
- Latency limit: ~5 usec (SVD APV25 buffer structure)
  - A fixed latency of about 4.4 usec
- Event timing resolution: 10 nsec

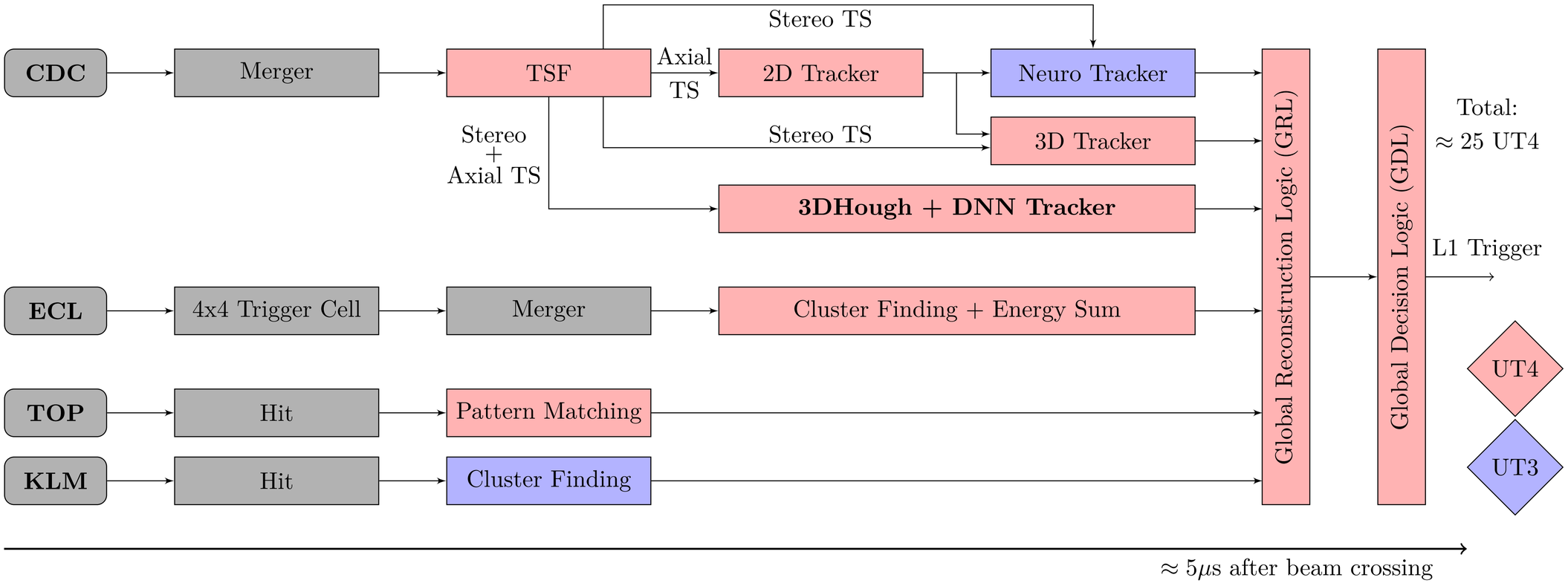
Process	σ(nb)	Rate@L=6x10^{35} (kHz)
Bunch. cross.	-	2x10^5
Beam bkg	-	300-600
Bhabha	44	50
Total->L1	-	200350->~15

Process	σ(nb)	L1@L=6x10^{35} (kHz)
Bhabha	44	0.35*
Two photon	13	10
Upsilon(4S)	1.2	0.96
Continuum	2.8	2.2
μμ	0.8	0.64
ττ	0.8	0.64
γ-γ	2.4	0.019*
Total	67	~15

Belle II trigger system

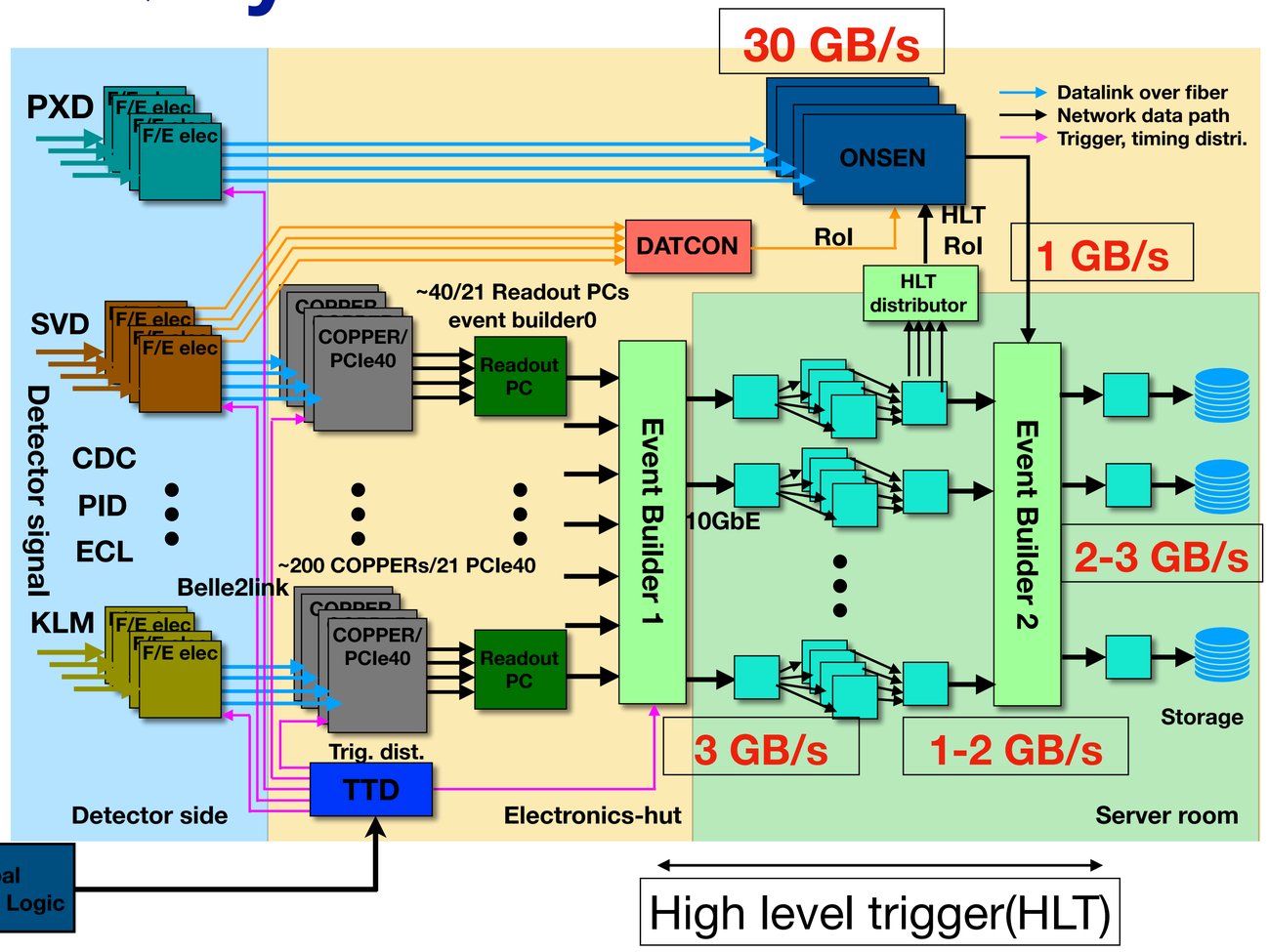
- CDC, ECL: main triggers for tracks and clusters
- KLM: trigger muon
- TOP: event timing
- GRL: matching of sub-triggers
- GDL: final trigger decision

- Challenges:
  - low multiplicity trigger vs. background
  - High track trigger vs. crosstalk
  - Drawback of track trigger at endcap
  - Latency budget vs. transmission and logics
  - …

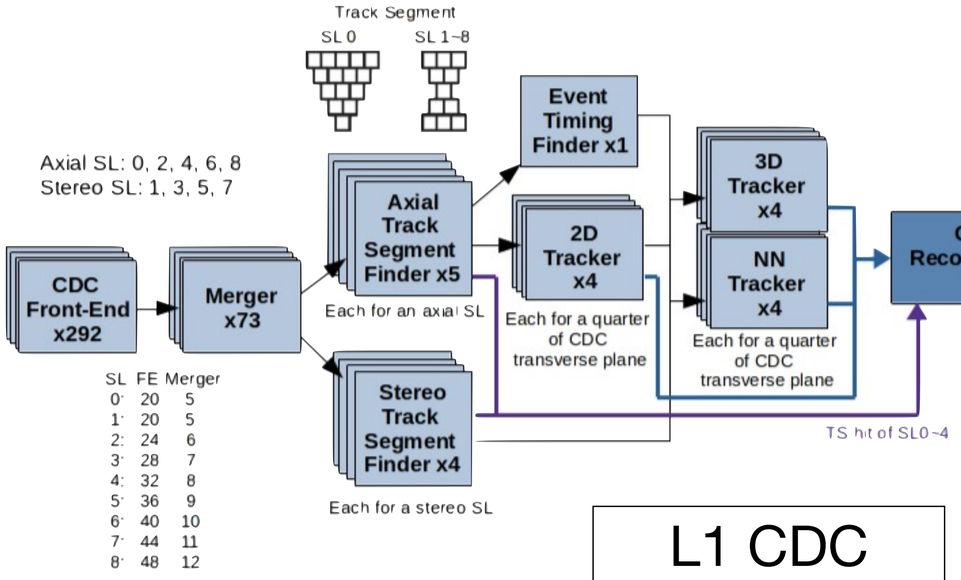


Belle II TDAQ system

- Unified common readout system (except for PXD)
- Unified timing and trigger distribution (TTD) system
- A pipeline readout
- To handle 30 kHz level 1(L1) trigger with O 1% dead time under raw event size of 1 MB



Example: CDC



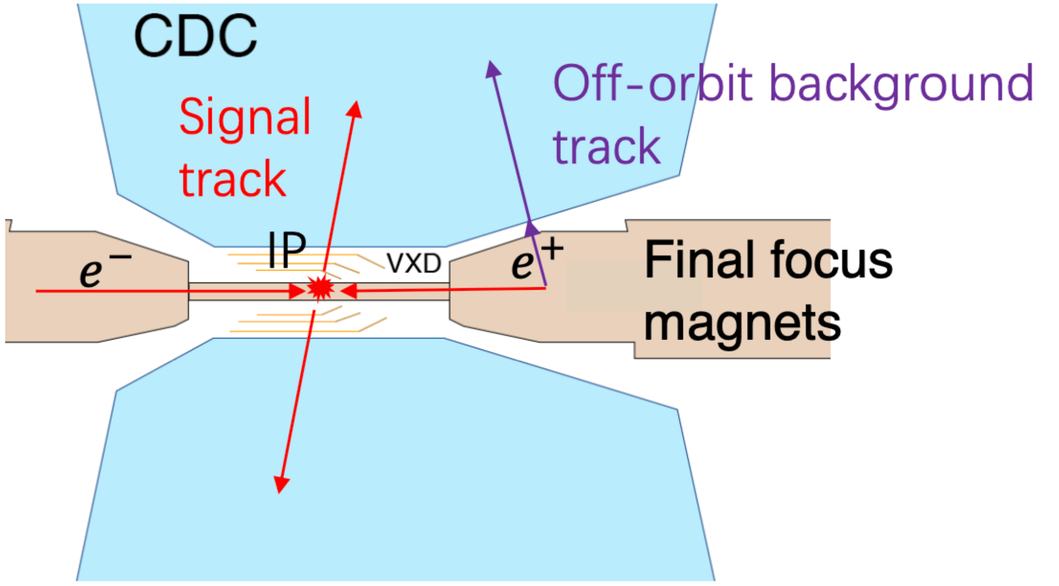
L1 CDC trigger logic

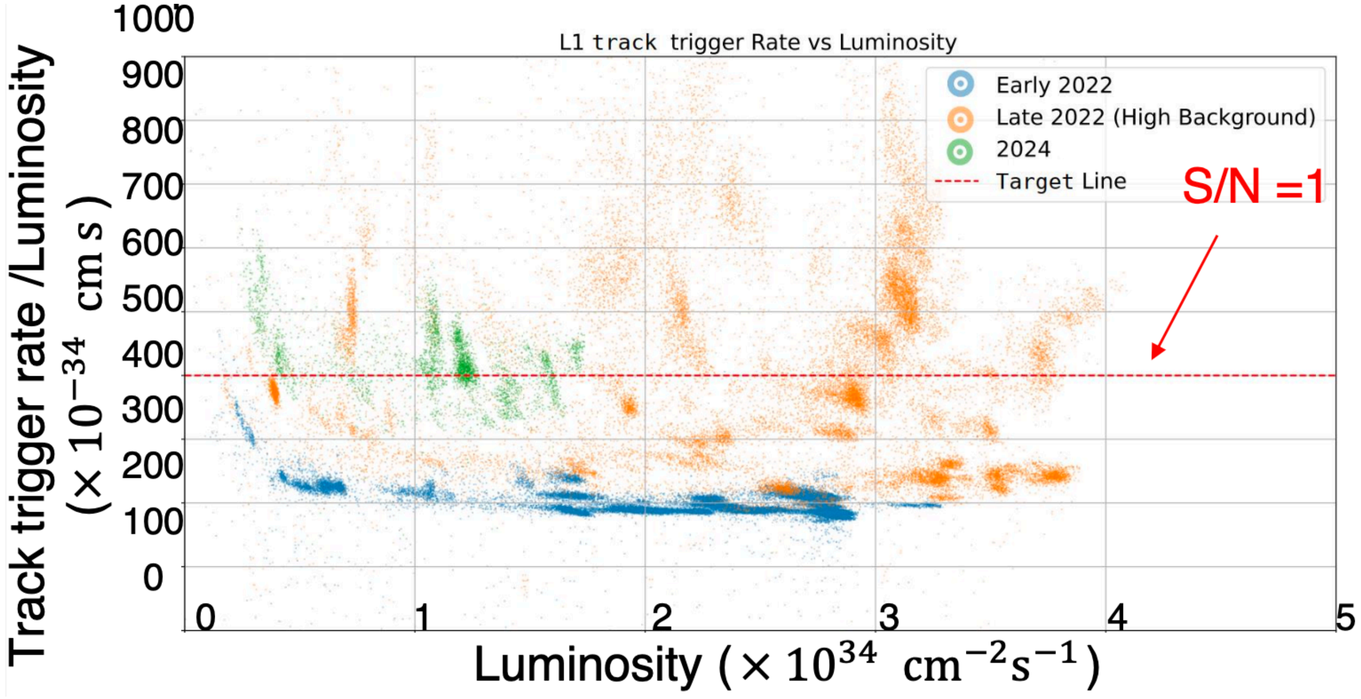
Global Decision Logic

- Provide L1 trigger signal to DAQ using FPGA chips for real-time processing on detector raw data.
- HLT provide Region of Interest (RoI) to PXD for significantly reducing the data size.
  - Latency O sec.

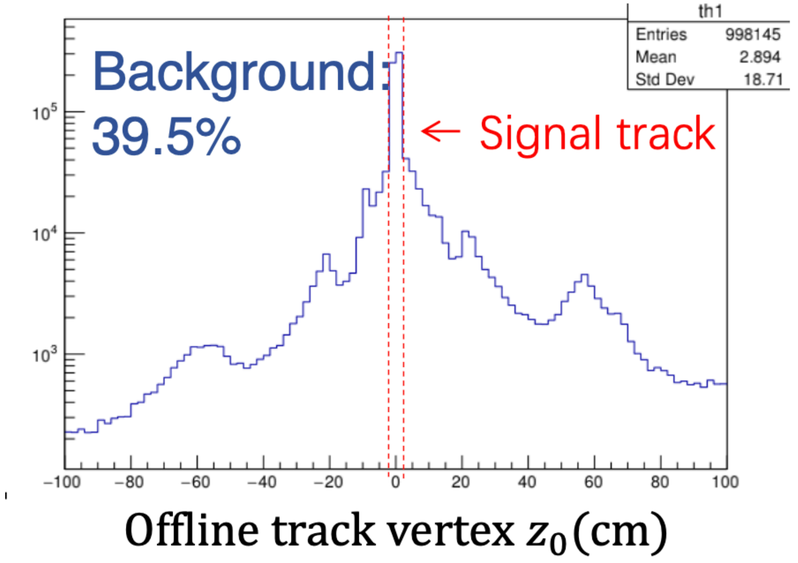
Motivation of Neural Network for L1 Track trigger

- DAQ system is designed to handle 30 kHz
  - Physical trigger ~15 kHz, require S/N = 1
- L1 trigger rate depends significant on background condition
- Advanced CDC algorithm to further suppress background
- A fixed latency of about 4.4 usec



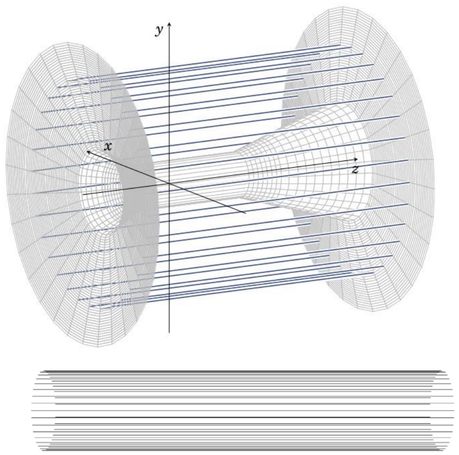


Tracks z_0 distribution after trigger

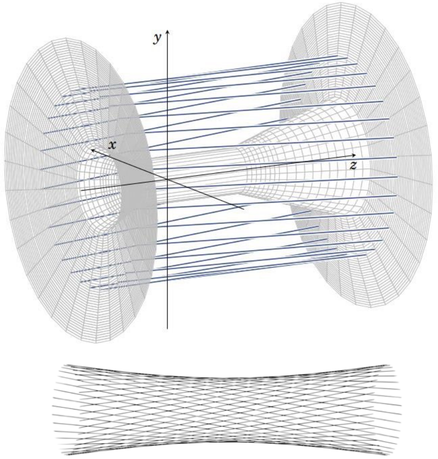


Machine Learning for L1 Track trigger (HARDWARE)

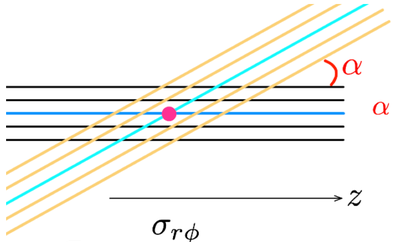
Basics of L1 CDC trigger



Axial wire



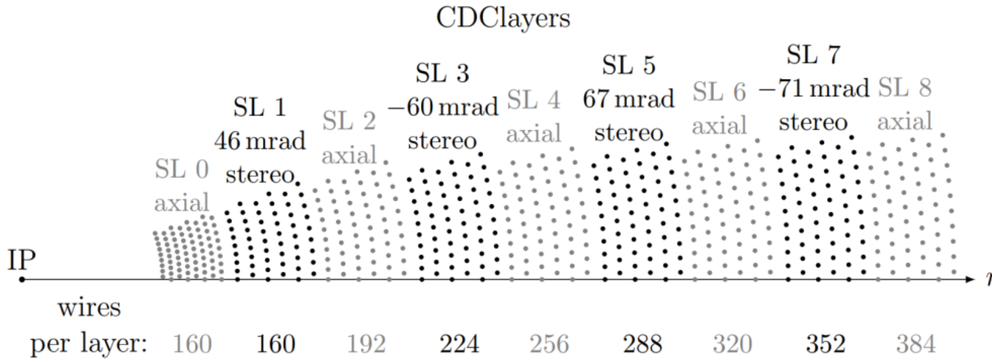
Stereo wire

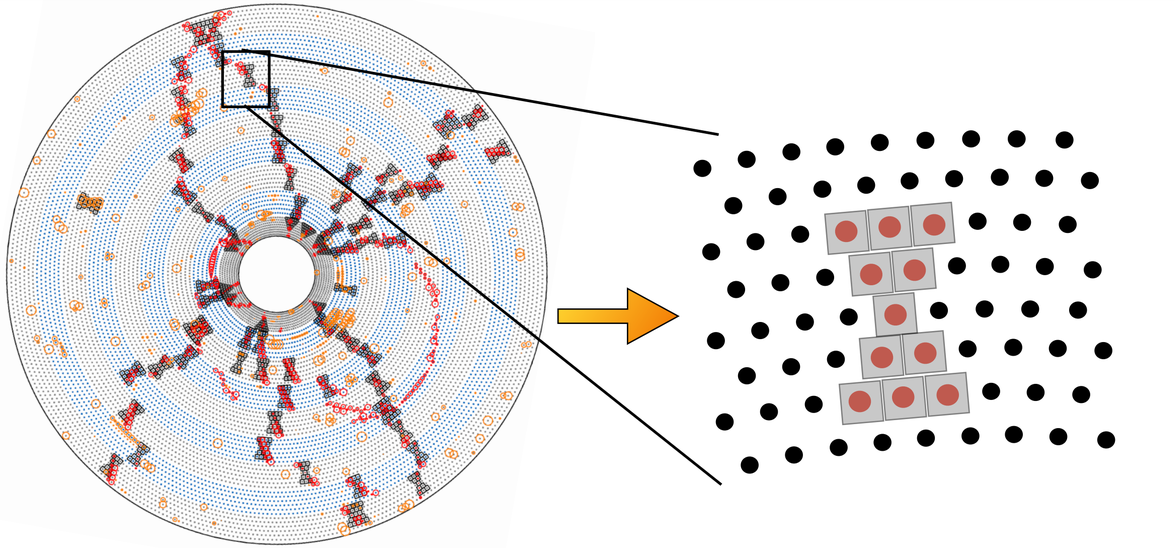


$\alpha = 60 \sim 80\text{mrad}$ (BelleII)

$$\sigma_z = \frac{\sigma_{r\phi}}{\sin\alpha}$$

$$\sigma_z = 1.9 \sim 2.5\text{mm}(\sigma_{r\phi} = 0.15\text{mm})$$





CDC 2D hit map

Track Segment (TS) Finder in every super layer

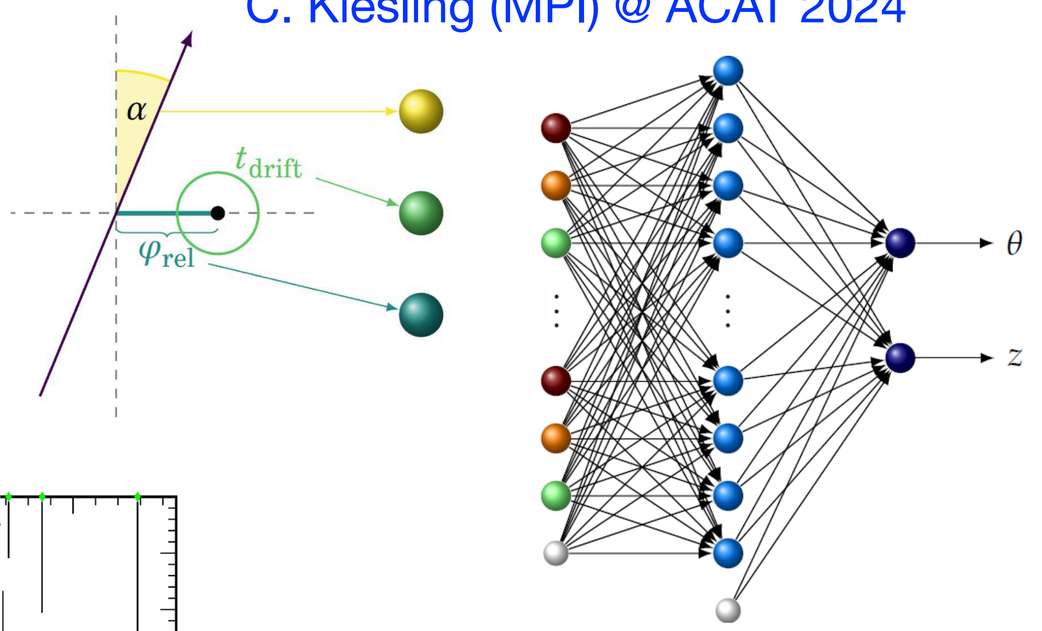
Build 2D track with axial hits using Hough transformation

3D Track trigger base on 2D track and Stereo TS

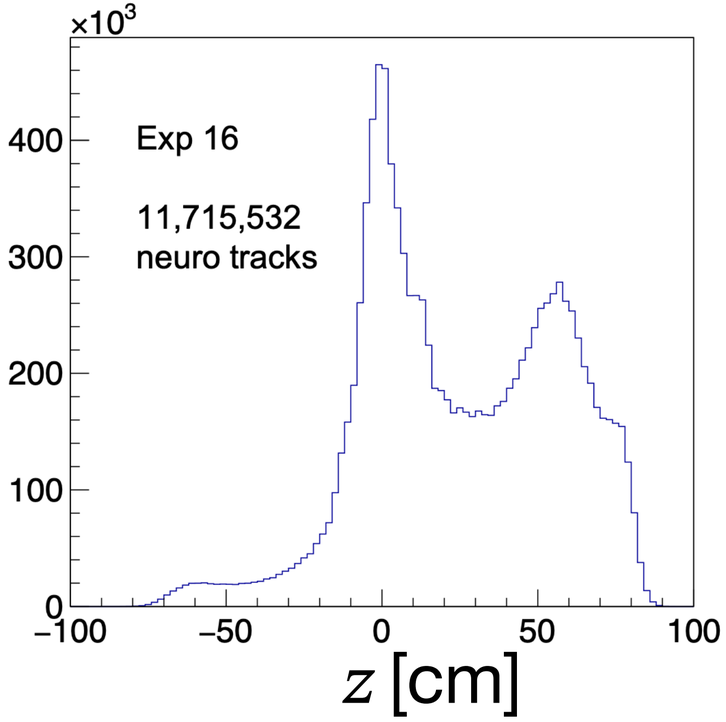
Neural Network z-trigger

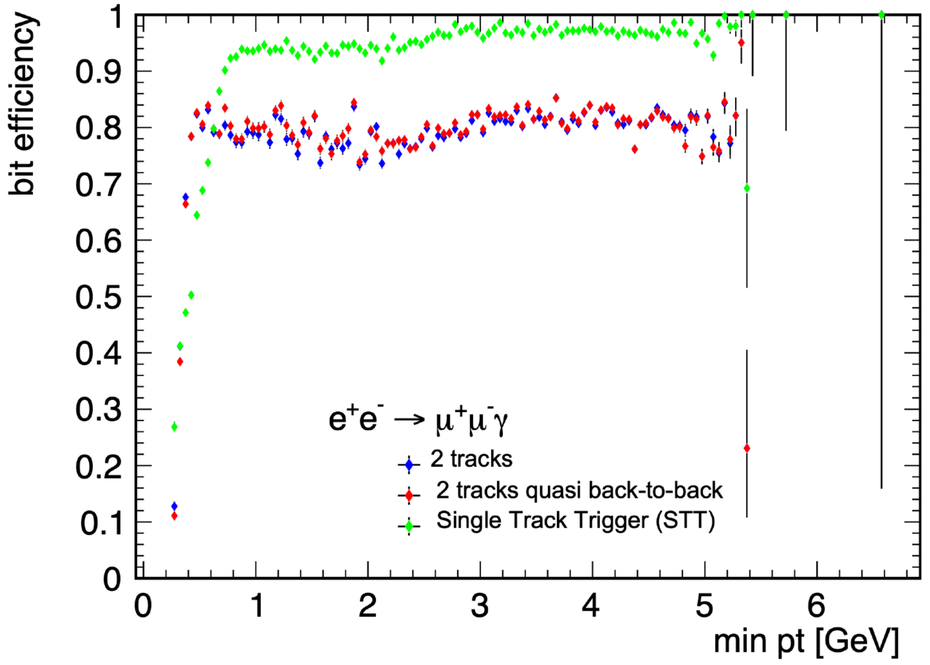
- Pioneer of NN on **HARDWARE** for Belle II trigger
- Inputs: **Drift time t_{drift}**, **wires relative location ϕ_{rel}**, **Crossing angle α** for priority wires
- Outputs: track vertex z_0, track θ
- Selected 1 Track Segment per one Super Layer
- Networks trained with real data from May-June 2020

C. Kiesling (MPI) @ ACAT 2024



arXiv:2402.14962 (submitted to NIMA)

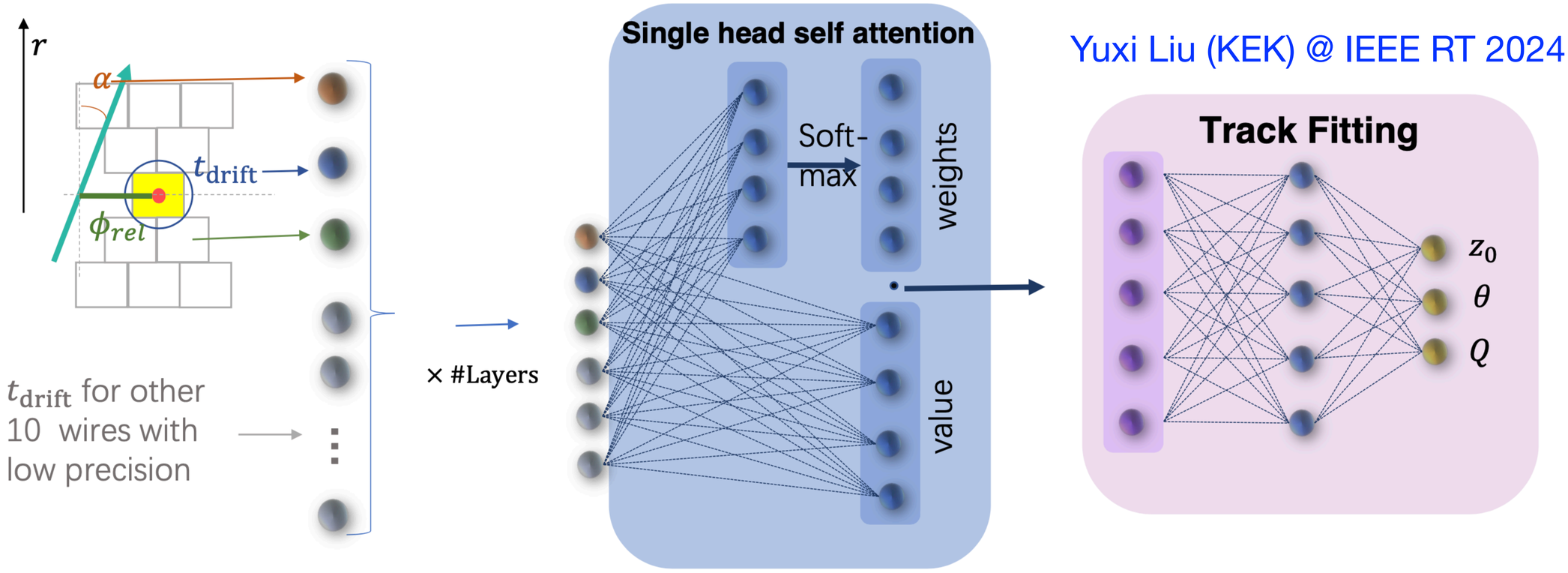




- Backgrounds still high
- Fake background

- Upgrade plan in trigger group:
- Track finding in **3D Hough space**
- network architecture: “deep-learning” + additional inputs

Deep Neural Network



Yuxi Liu (KEK) @ IEEE RT 2024

- Inputs: **Drift time t_{drift}**, **wires relative location ϕ_{rel}**, **Crossing angle α** for priority wires + **Drift time for all other wires**
- Introduce the **self-attention architecture** to "focus" on certain inputs
- Output track vertex z_0, track θ and **signal/ background classifier output (Q)**

Parameter	#Attention value	#hidden nodes	#hidden layer	activate	precision	Total multiplier
Values	**27**	**27**	**2**	**Leaky Relu**	**Float 16**	**4,185**

Development flow of DNN on FPGA

Software → Hardware → FPGA

- Machine Learning model
- Parameter

- C/C++ transition

- Translate into Verilog/VHDL FPGA language

- Start fitter

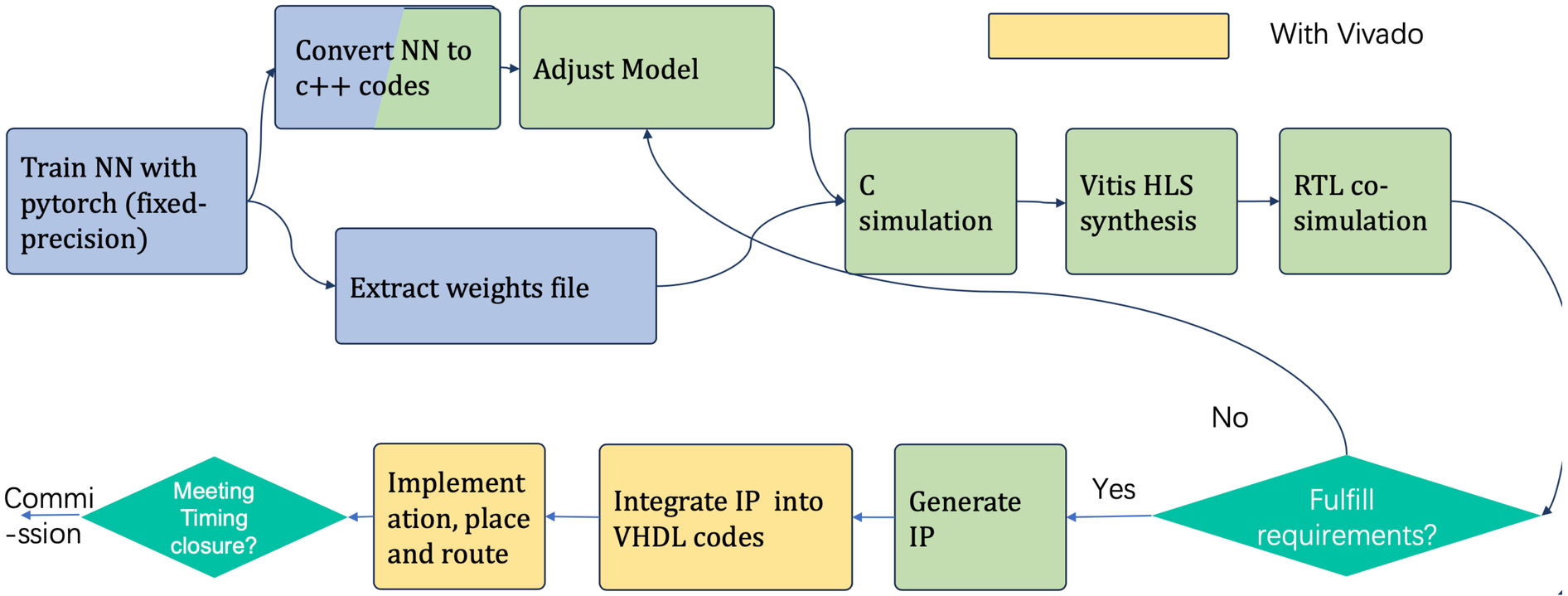
- Evaluation

Belle II UT4

Xilinx UltraScale
XCVU080, XCVU160
25 Gbps with 64B/66B

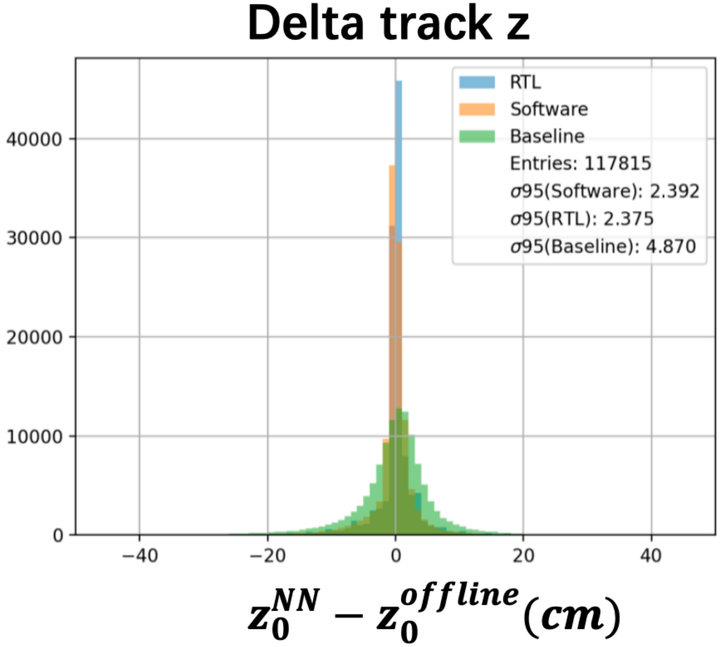
*include some function from hls4ml lib

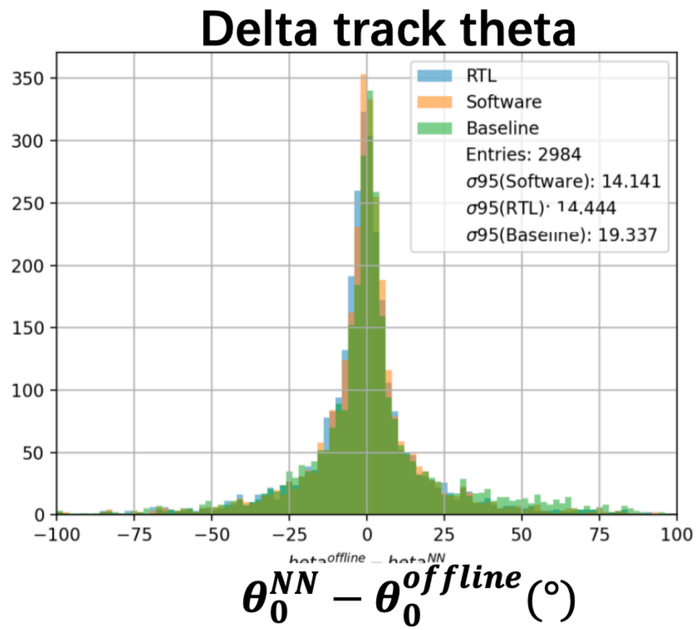
With Python
With Vitis HLS
With Vivado

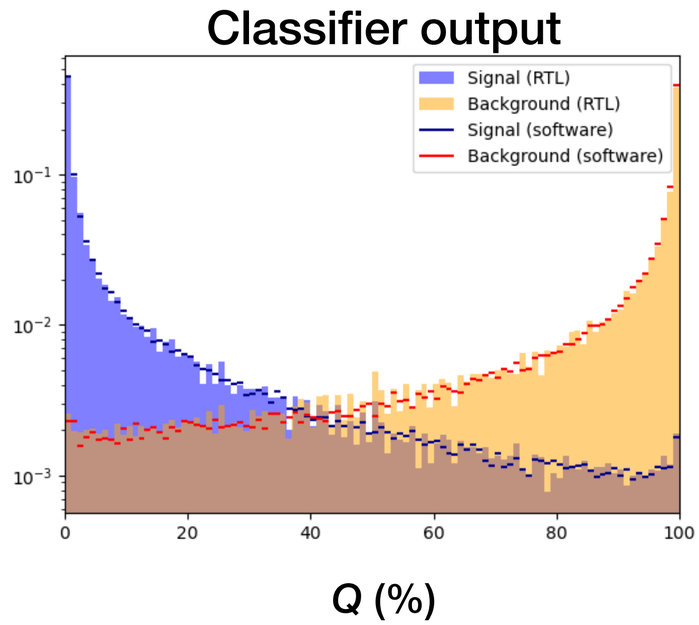


Simulation performance of DNN

Yuxi Liu (KEK) @ IEEE RT 2024

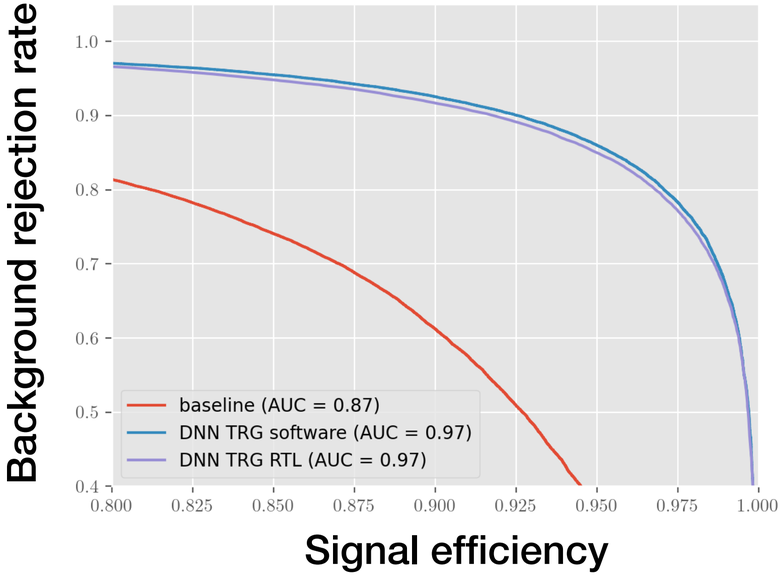






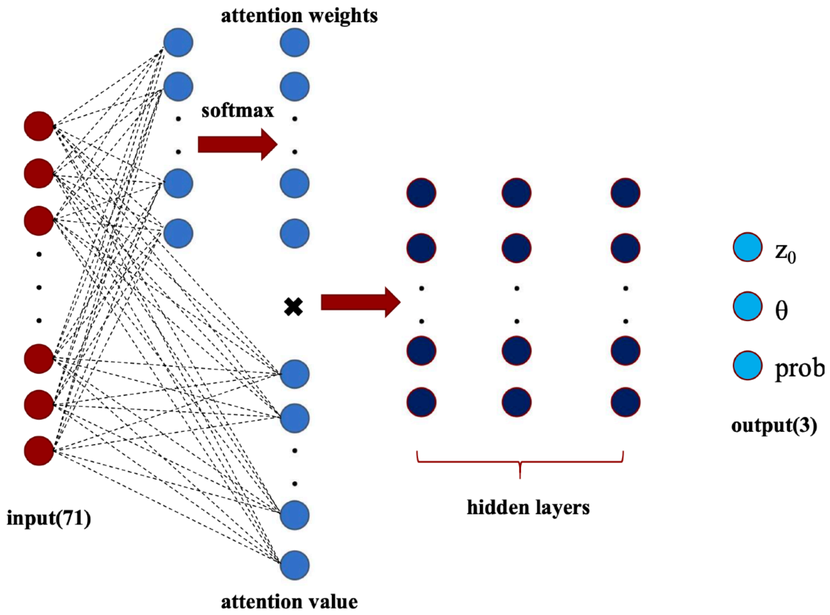
- Latency : 76 clock = 592.8 ns ;require: < 600ns
- FPGA resource (UT4: Virtex UltraScale XCVU160) usage:
  - DSP: ~70%, LUT: ~50%, others <30%
- AUC do not get large drop comparing RTL and software simulation
- At signal efficiency ~95%
  - Background rejection rate ~85%

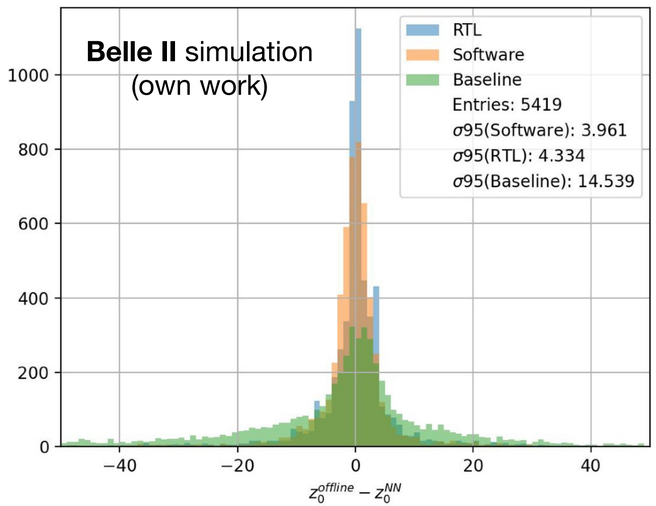
- **DNN trigger with HARDWARE under commissioning, close to operate**

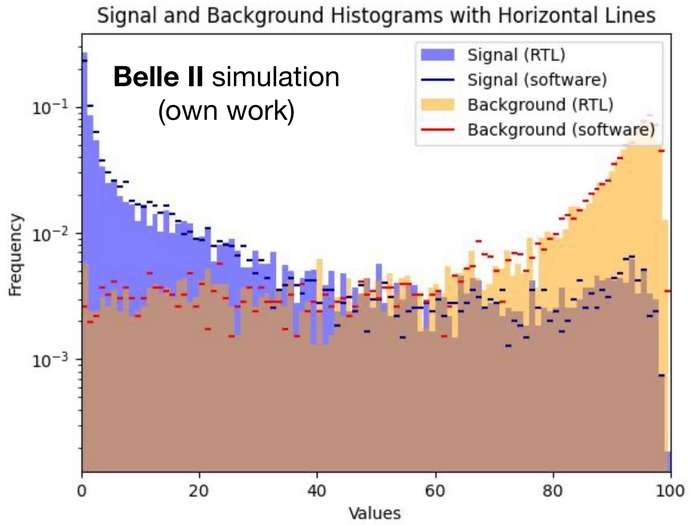


Improvement try for CDC track trigger

- Develop a algorithm improve the performance for the upgrade (10 usec latency)
  - Start from optimization of DNN model
- Modify the number of hidden layers and learning rate
  - Hidden layer: 2 -> 4, learning rate: $1e^{-2}$ -> $1e^{-3}$
  - Others keep the same
  - Latency: 76 clock (592.8 ns) -> 82 clocks (640 ns)
- Next step, change the inputs (CDC hits info.), instead of 2D track parameters

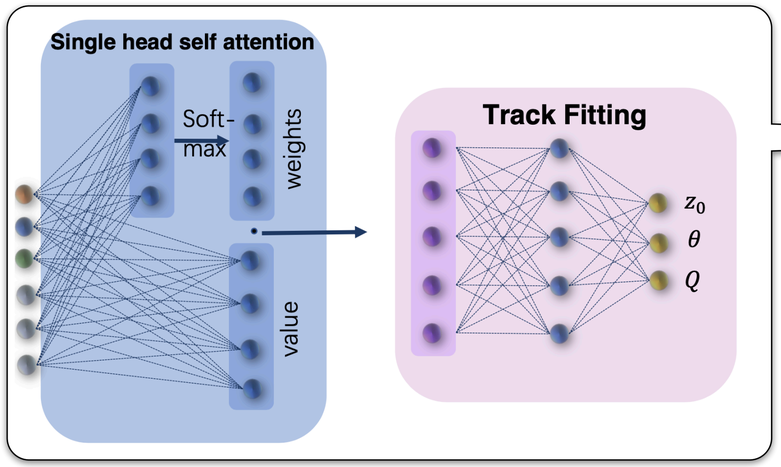


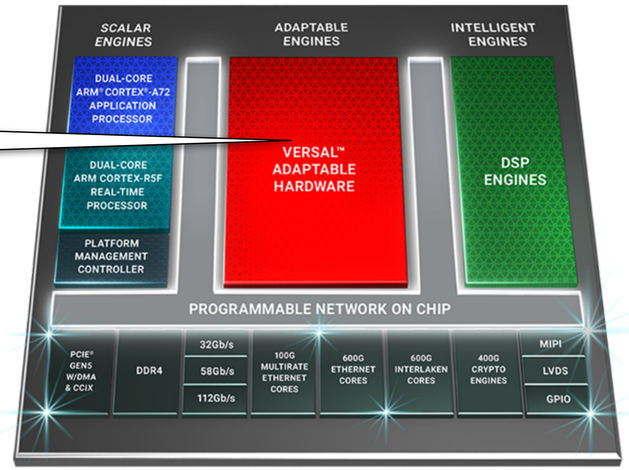




DNN implementation on Versal ACAP

- R&D of a new general FPGA device using the Versal ACAP
  - Heterogenous acceleration (VCK190, VCK5000 evaluation kit)
    - AI engine





UG1079

Figure 2: **AI Engine Array**

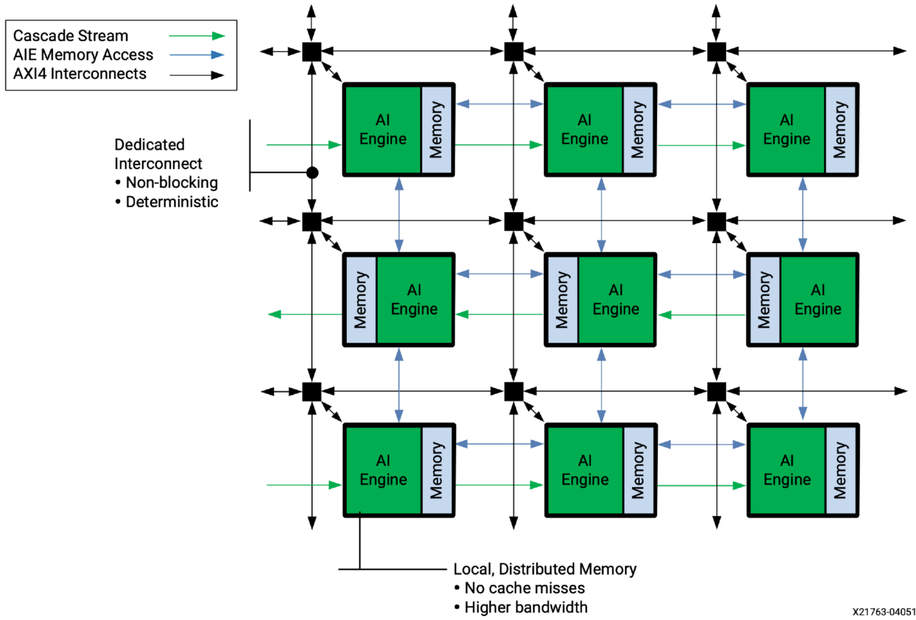
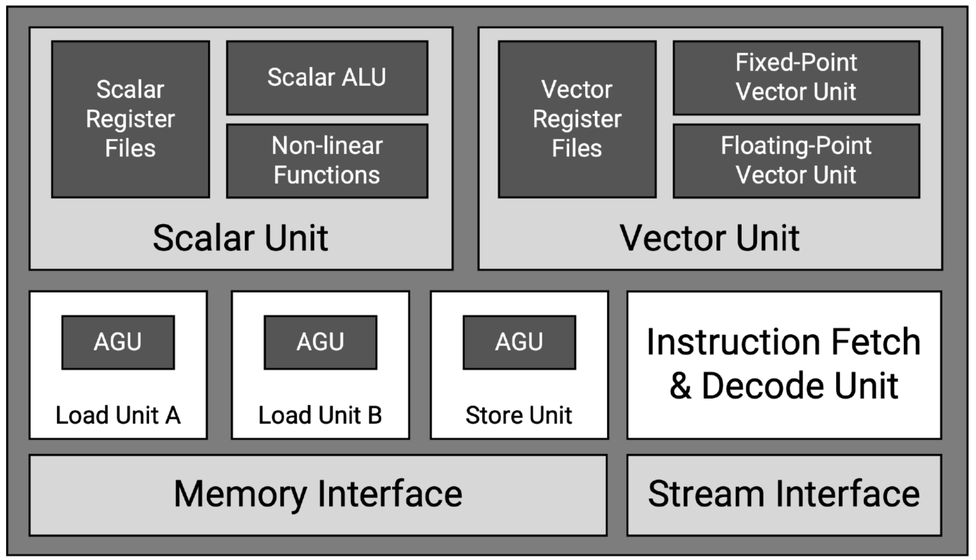
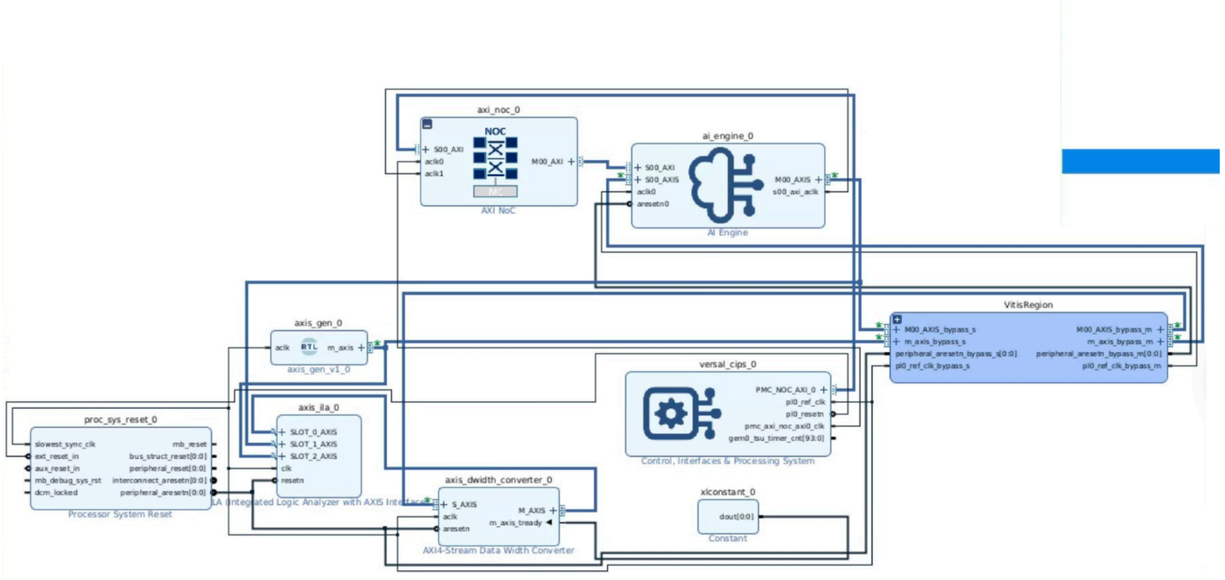
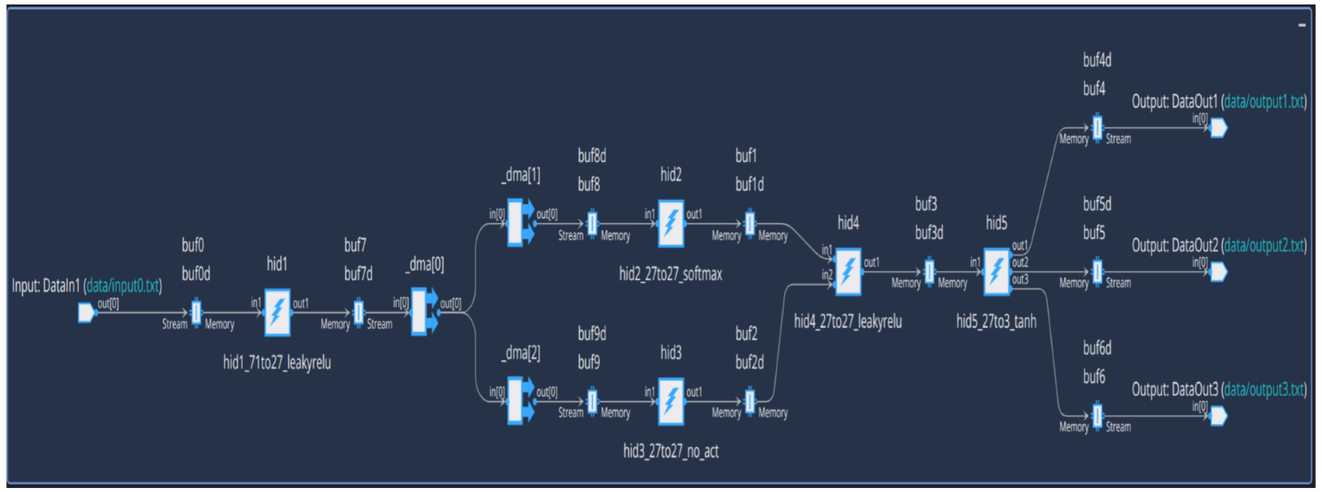


Figure 4: **AI Engine**



DNN acceleration on Versal ACAP





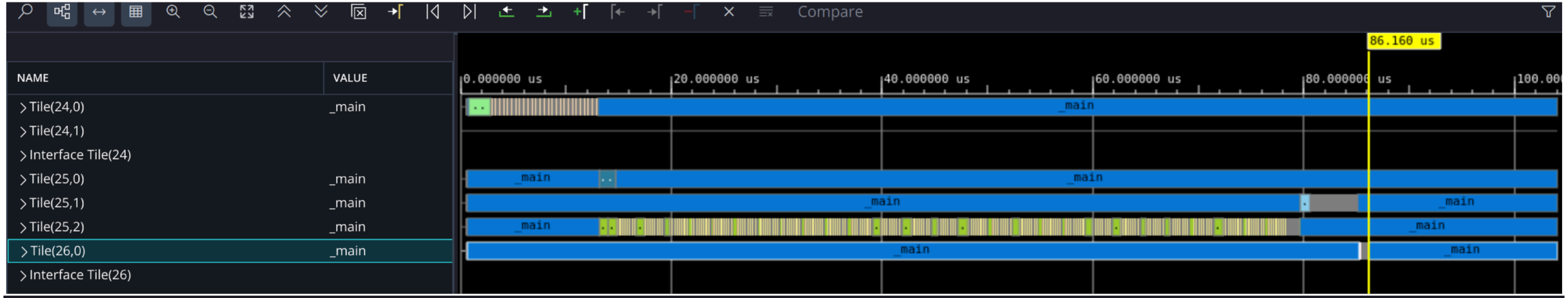
- DNN implementation:
  - Model on a “graph”
  - Dense layer on a “kernel”
- AI engine: C++ based coding on Vitis
  - AI engine libraries
  - AI engine specific functions
  - Scaler, Vector engines, pipelining, etc.

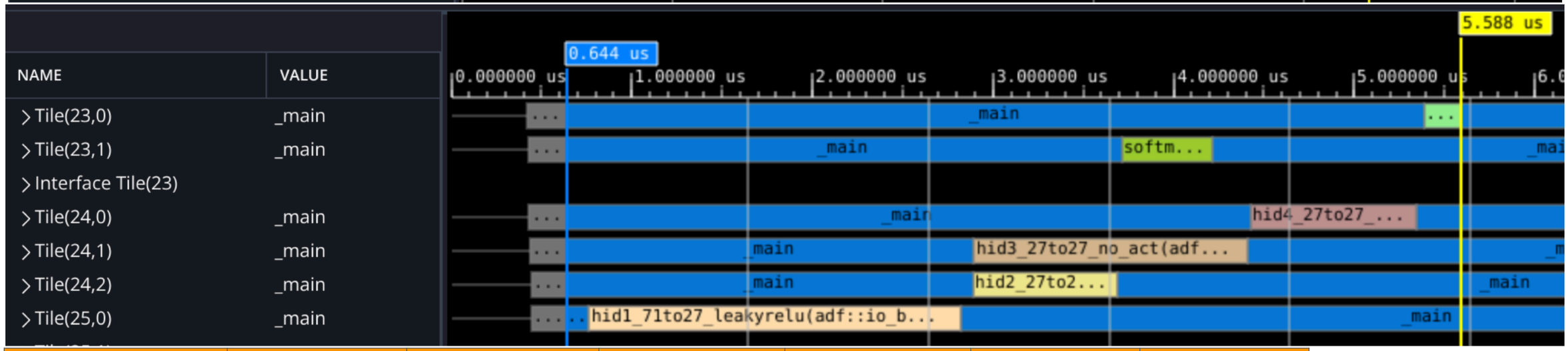
	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
Input nodes	71	27	27	27	27
Output nodes	27	27	27	27	3
Active Func.	LeakyReLU	Softmax	—	LeakyReRU	Tanh

AI Engine Resource Utilization

Tiles used for AI Engine Kernels:	5 of 400 (1.25 %)
Tiles used for Buffers:	7 of 400 (1.75 %)
Tiles used for Stream Interconnect:	8 of 450 (1.78 %)
DMA FIFO Buffers:	0
Interface Channels used for ADF Input/Output:	4 (PLIO: 4)
Interface Channels used for Trace data:	0

Latency optimization on Versal ACAP



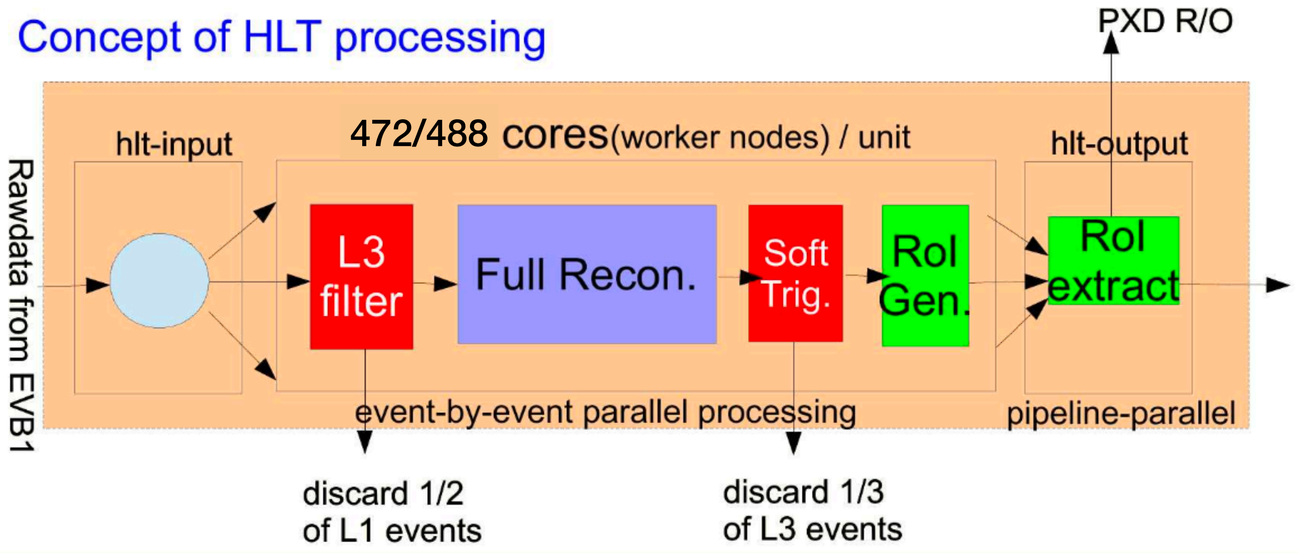


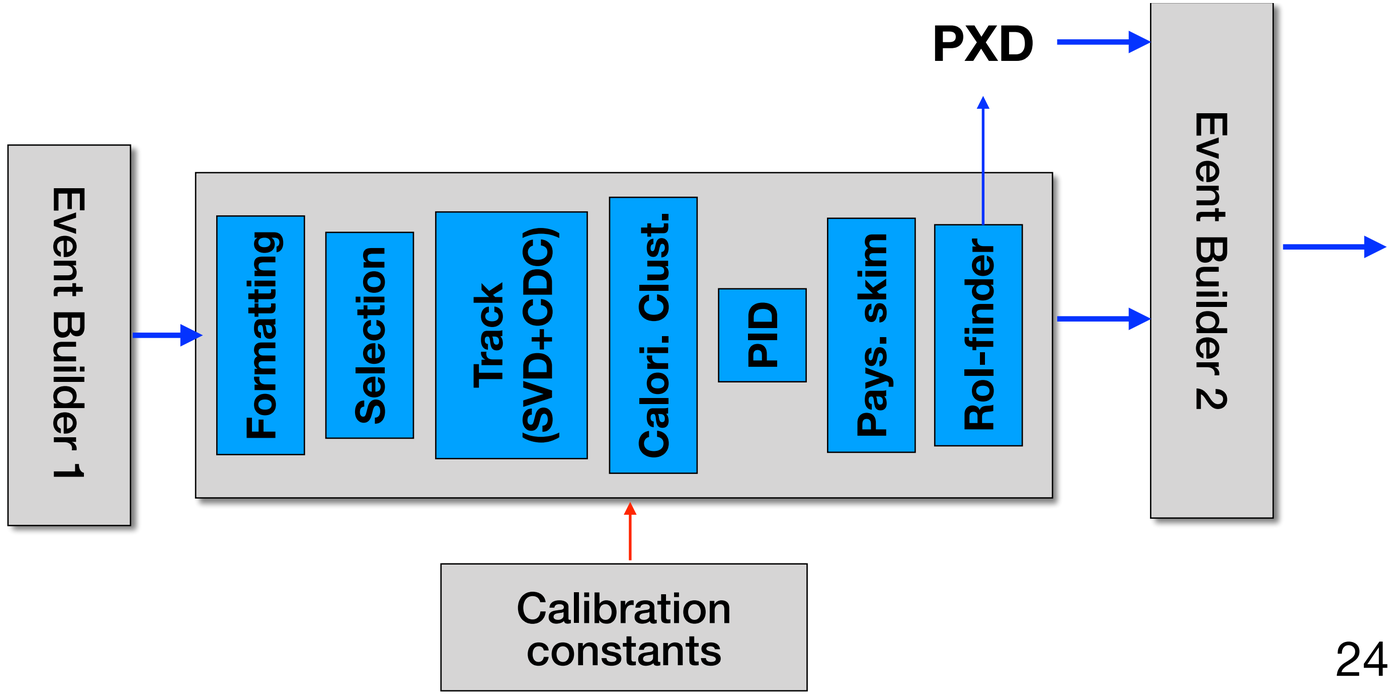
	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5	Total
Input nodes	71	27	27	27	27	—
Output nodes	27	27	27	27	3	—
Active Func.	LeakyReLU	Softmax	—	LeakyReRU	Tanh	—
Ver.0 latency	~12us	~66us	~1.5us	~5.5us	~9.9us	~86us
Ver.1 latency	~2.1us	~1.3us	~1.5us	0.9us	~0.2us	~5us

Machine Learning for software track trigger (SFOTWARE)

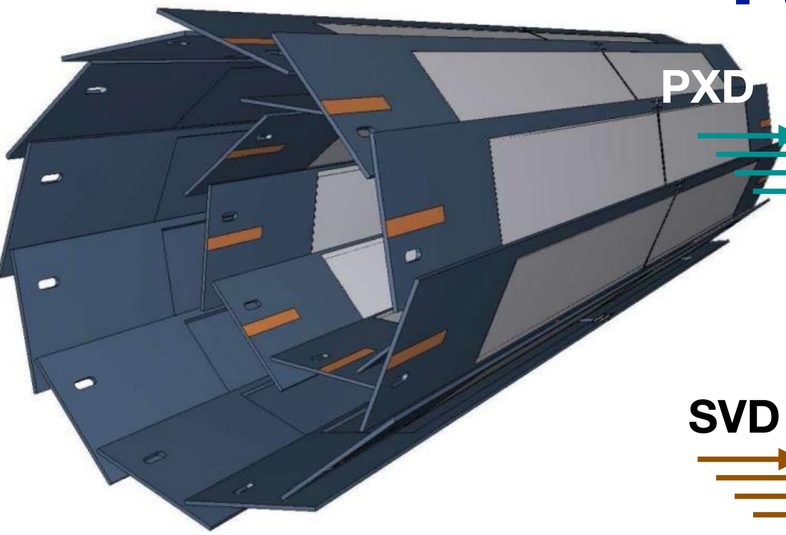
Overview of high level trigger system at Belle II

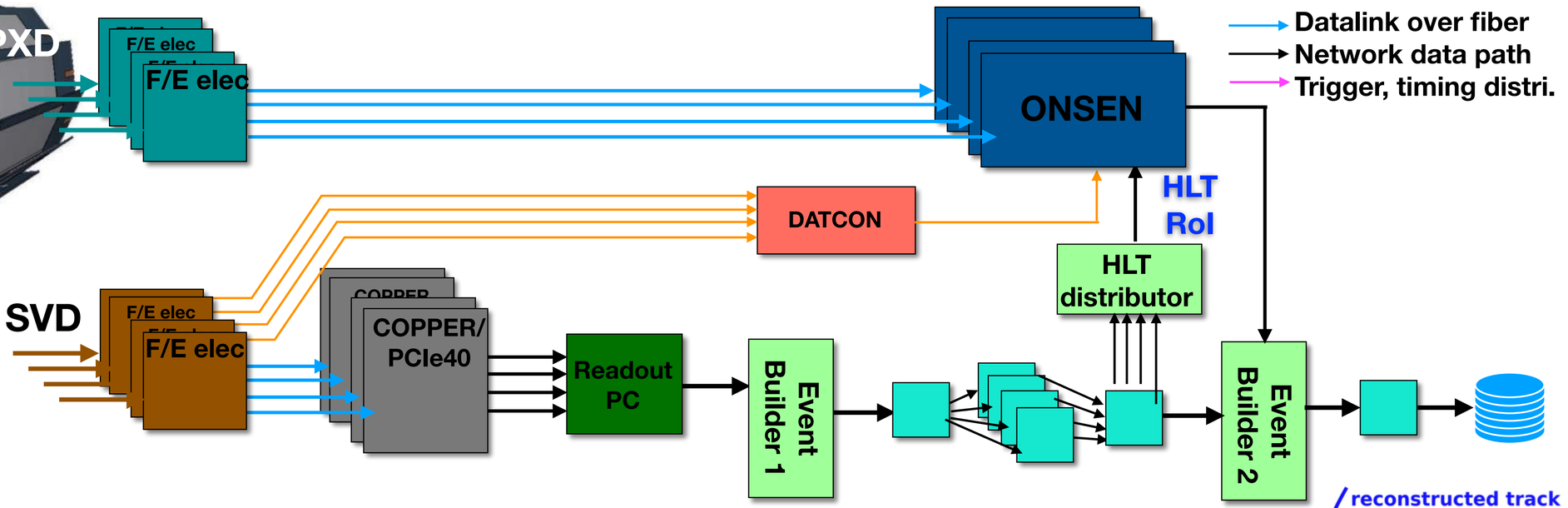
- Full event reconstruction (same as offline processing)
- Crude calibration constant
- 13 HLT units, in total ~6200 CPU cores (design: 7000 cores)
- Data processing: ~ 2.1kHz/ HLT unit w/ hyper-threading
- Event size at HLT in the last run period: ~150 kB/event
- PXD event size = 1MB/event, 10 times larger than the rest of detectors
- Region of interest (RoI) method is effective to reduce the data size
- ROI
  - **Tracking software** running on HLT nodes

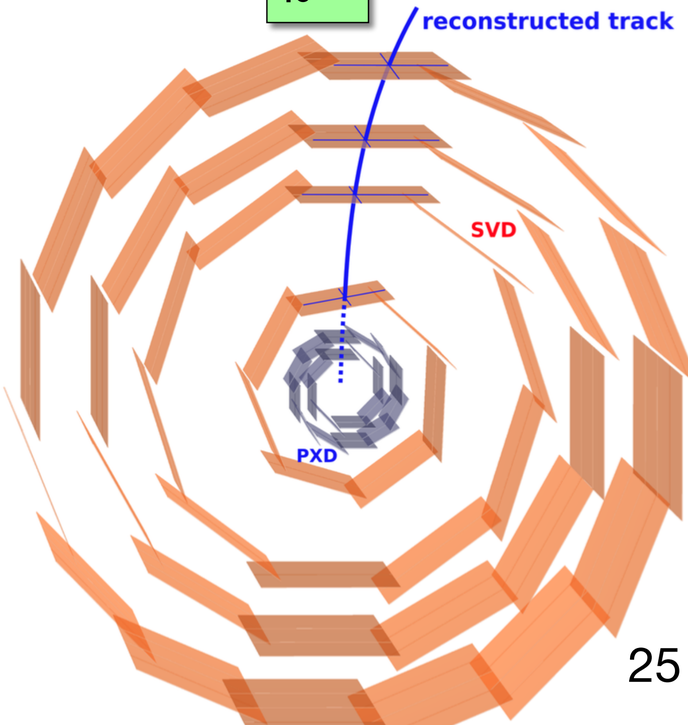




Region Of Interest (ROI)





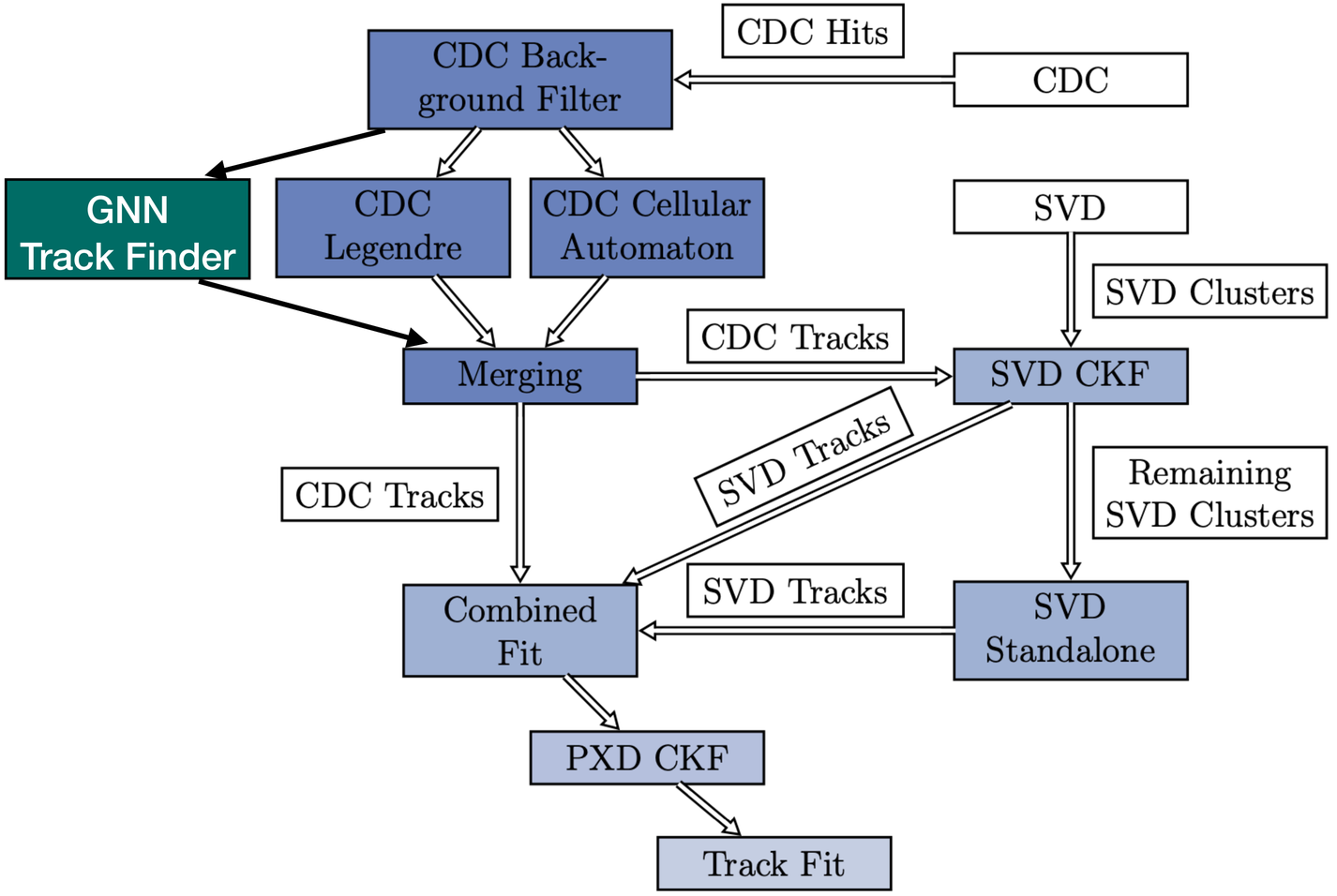


- PXD event size = 1MB/event, 10 times larger than the rest of detectors
- Region of interest method is effective to reduce the data size
- ROI
  - Tracking software running on HLT nodes
- PXD event data size reduced by 1/10 with ROI
  - In addition, trigger rate reduced by 1/3 with HLT ROI

GNN based CDC track finder

- Motivations of introducing a GNN track finder (**SOFTWARE**)
- Low efficiency for displaced vertices
  - Efficiency decrease as displacement increase
  - Important signature for new physics search
- Higher background
- CDC wire inefficiencies
  - Bad wires or electrics
  - Decreased efficiency

Comput.Phys.Commun. 259 (2021) 107610



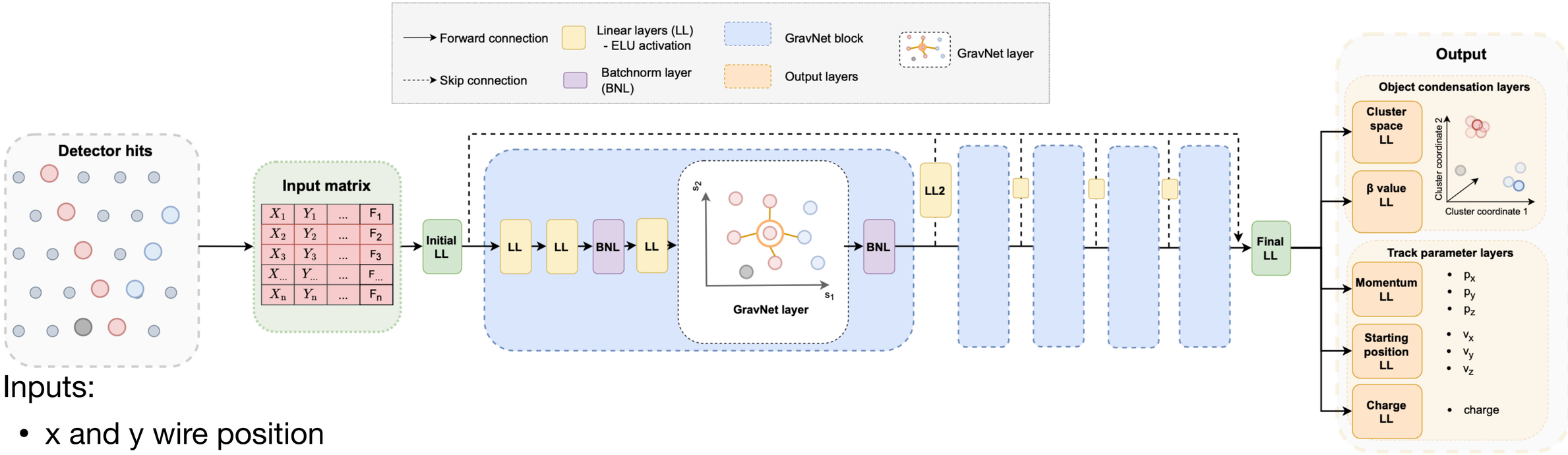
- Modular structure for track finding, with flexible of reconstruction sequence

GNN for offline track finding

- Find track parameters: momentum, starting position and charge
- Find unknown number of tracks → Object Condensation (arXiv:2002.03605)
- Computing resource and time constraint may reducible

Noise filtering → Clustering → Fitting

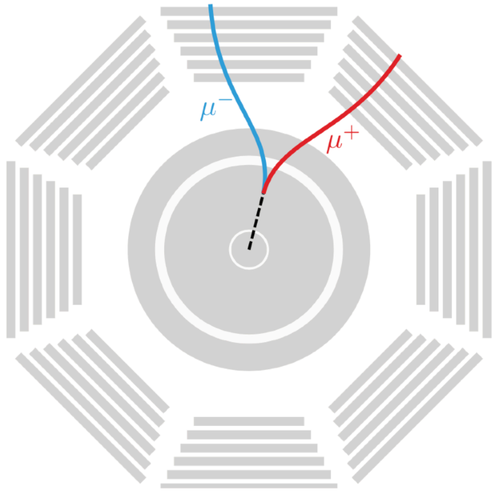
L. Reuter et. at (KIT) arXiv: 2411.13596



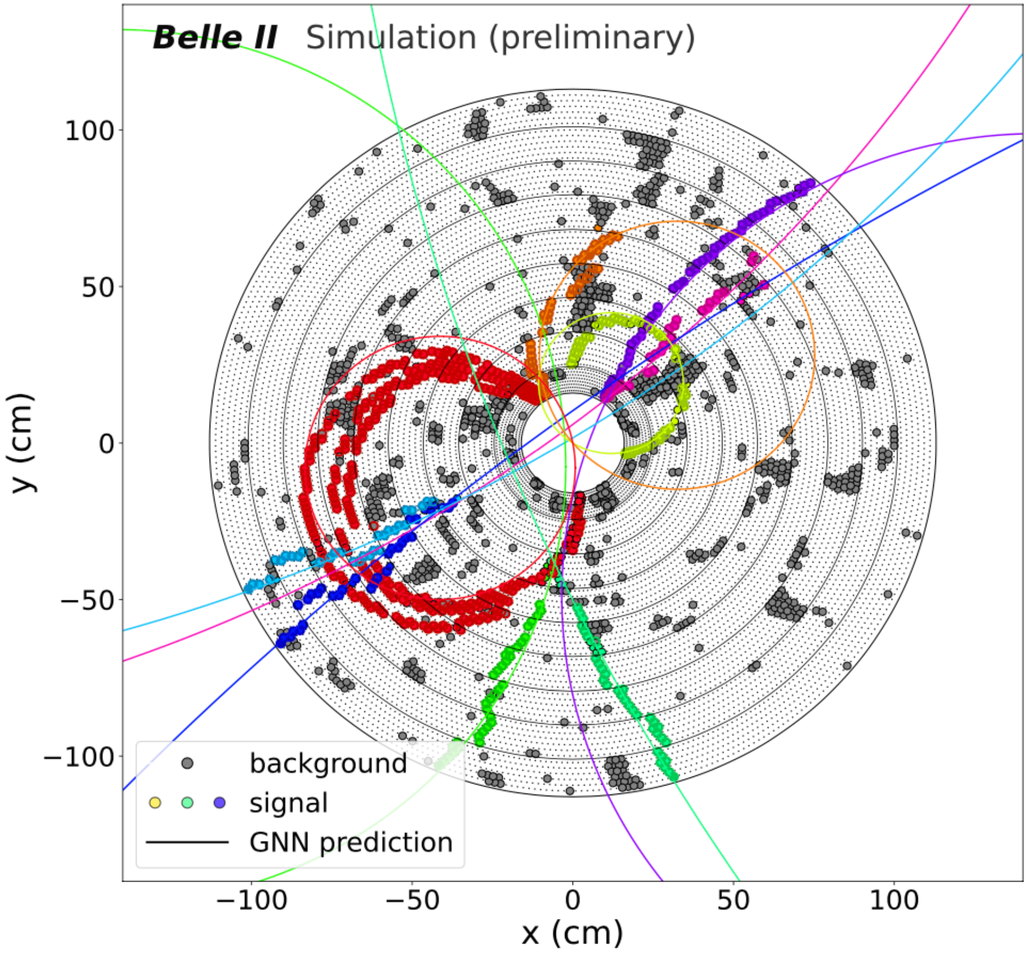
- Inputs:
  - x and y wire position
  - TDC and ADC of signal information
  - layer, superlayer, and layer info. with suprlayer
- Adjustable Parameters
  - 797,812 trainable parameters (3MB weight files)

Performance of GNN

- Efficiency of displaced vertex tracks improved from 85.4% with a fake rate of 2.5%, compared to 52.2% and 4.1%
  - The other performance similar as original algorithm
- Momentum p_x , p_y , p_z starting position v_x , v_y , v_z ,charge
  - Provide initial inputs for GENFIT
- GNN prediction is drawn according to the track parameters predicted by the GNN
- Plan to added as additional track finder for Belle II



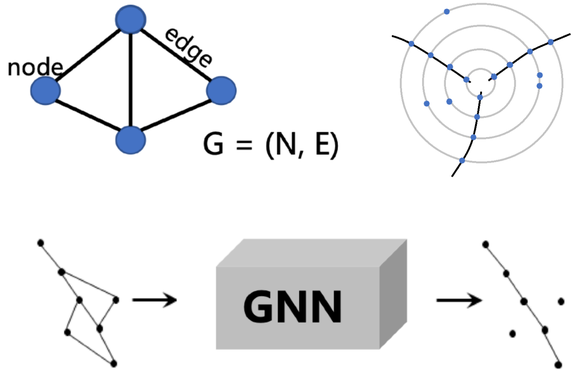
L. Reuter et. at (KIT) arXiv: 2411.13596

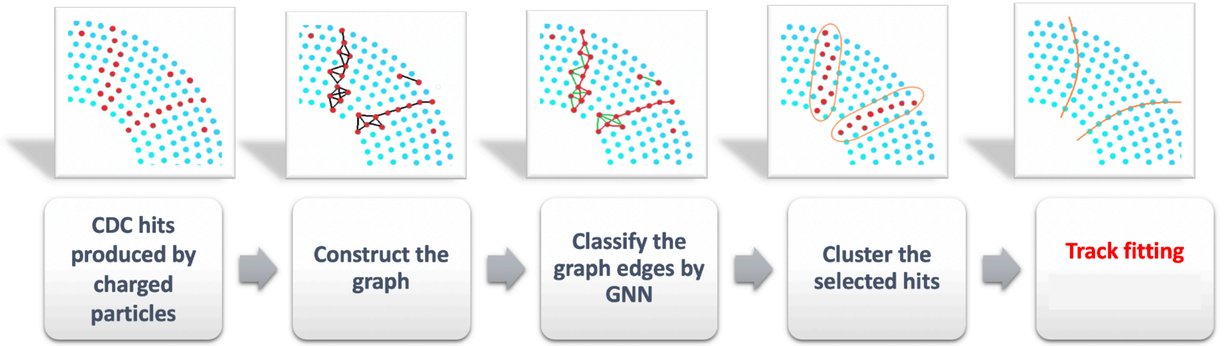


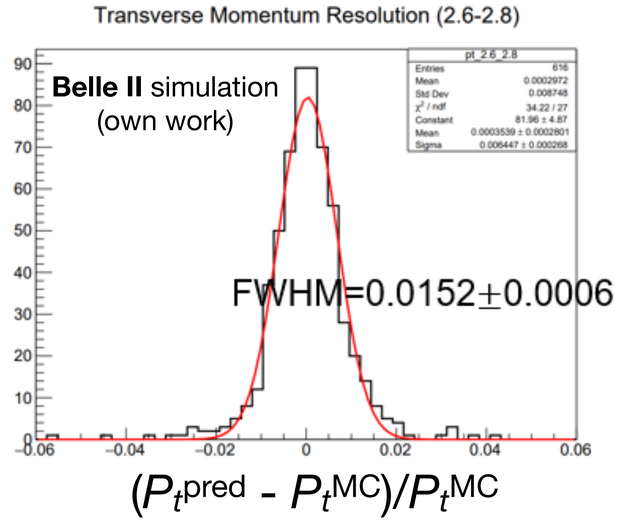
GNN for CDC track background filtering

- Developed a GNN algorithm (based on BESIII's algorithm) for Belle II CDC hits clean up
  - Inputs: TDC, position coordinates r, ϕ

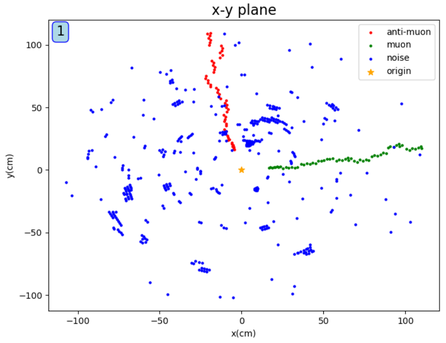
Noise filtering → Clustering → Fitting



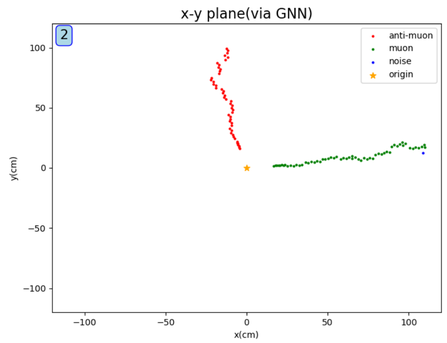




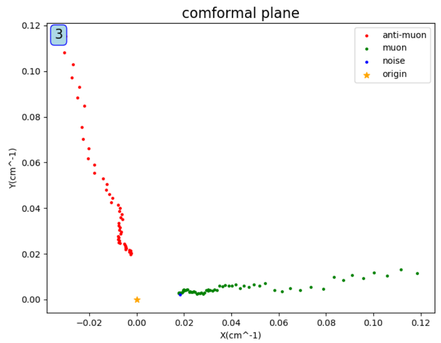
Belle II simulation (own work)



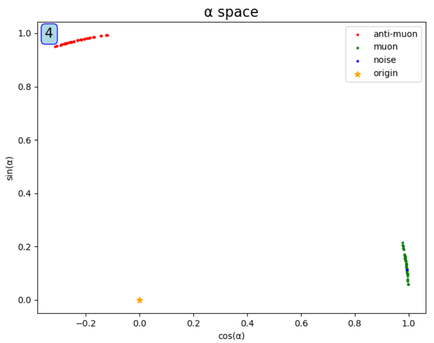
μ+ μ- (particle gun)



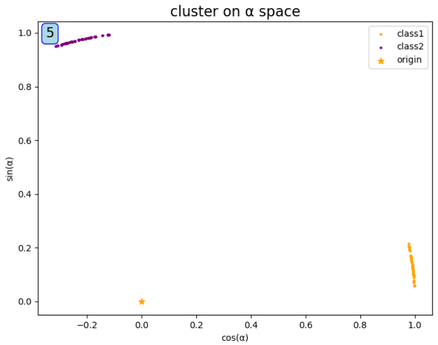
GNN noise filtering



Transform space



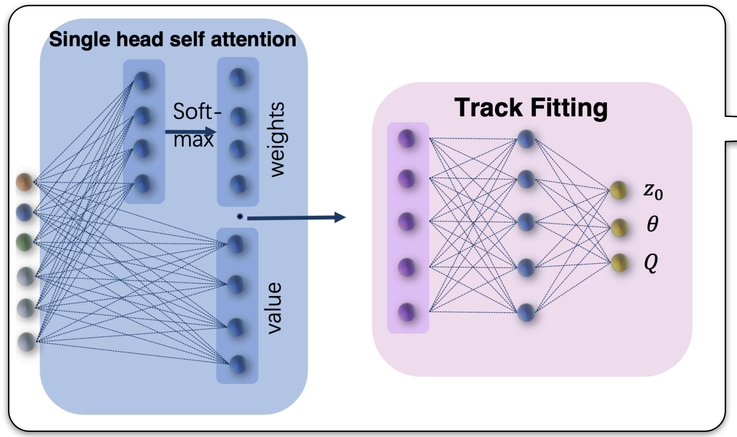
Transform α space

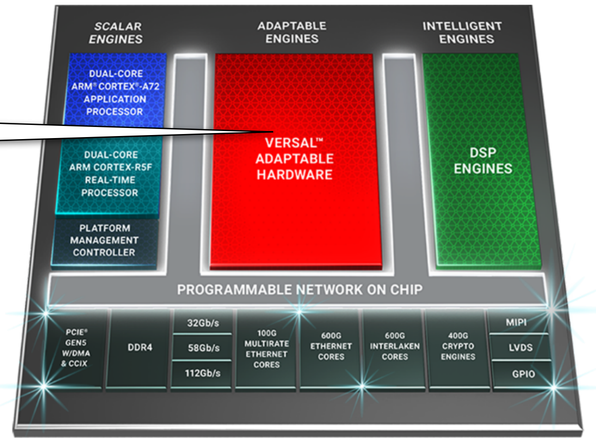


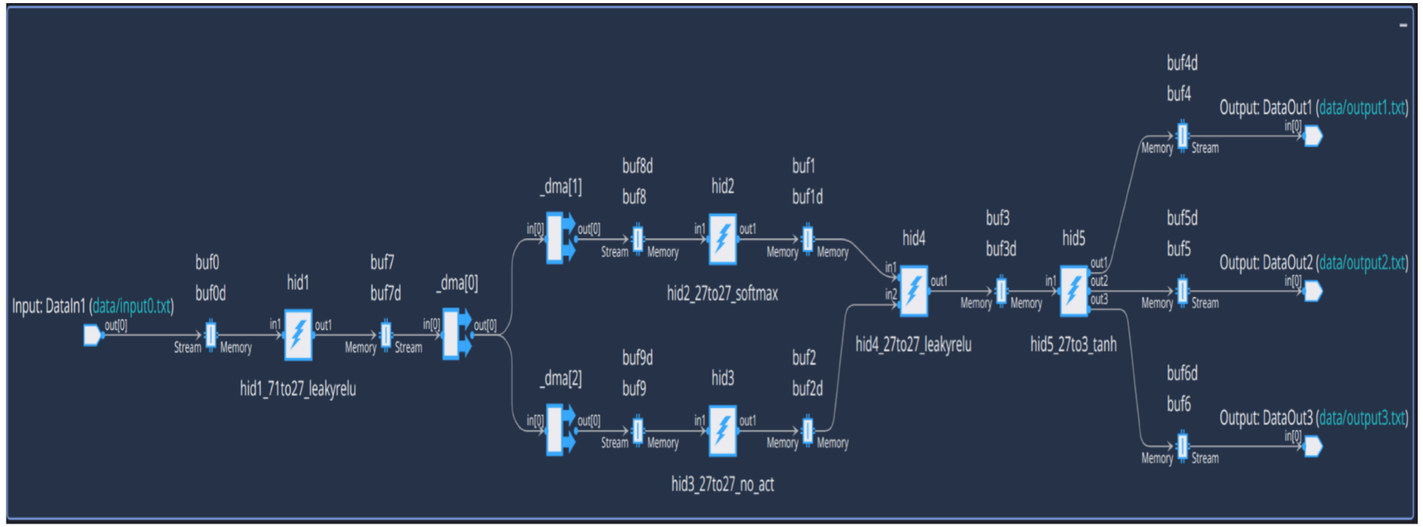
DBSCAN clustering

NN acceleration on Versal ACAP

- Real-time graph building algorithm enables GNN implementation on FPGA for Belle II
  M. Neu et al. Comp. Soft. BigSci. 8, 8(2024)
- R&D of a new general FPGA device using the Versal ACAP
  - Heterogenous acceleration (VCK190, VCK5000 evaluation kit)
    - AI engine, DPU

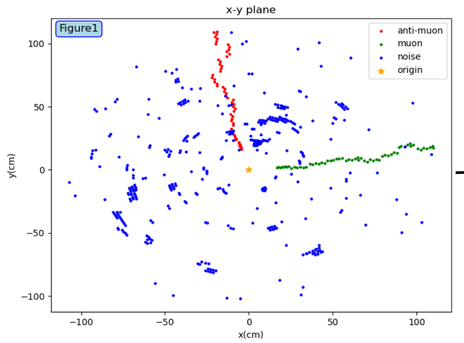


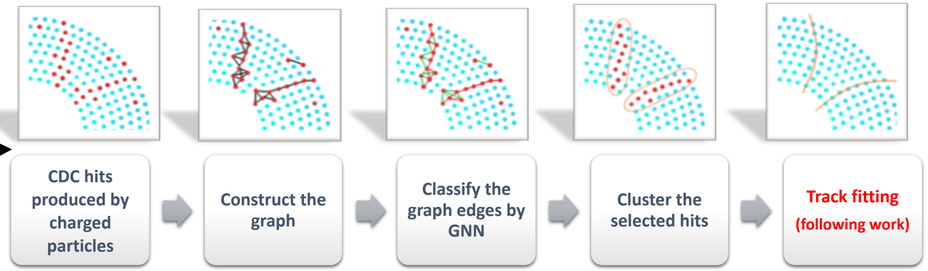


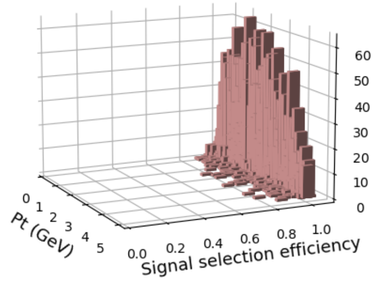


Acceleration on Versal ACAP platform

μ+ μ- (particle gun)





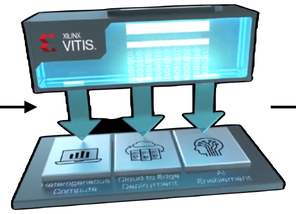


Hit selection efficiency: 98.4%
Hit selection purity : 97.9%

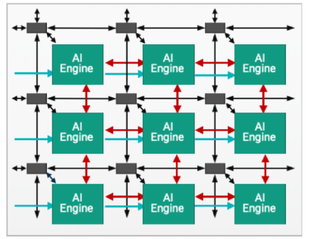
Belle II simulation (own work)

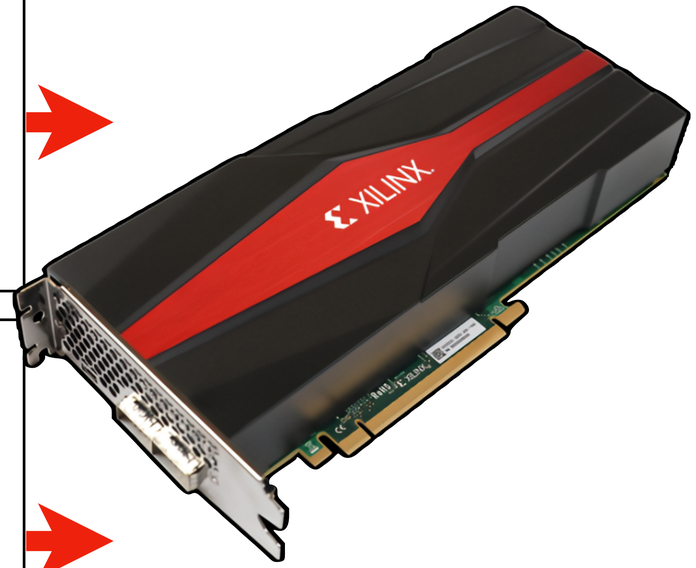
AI engine

C++ software



VIVADO™





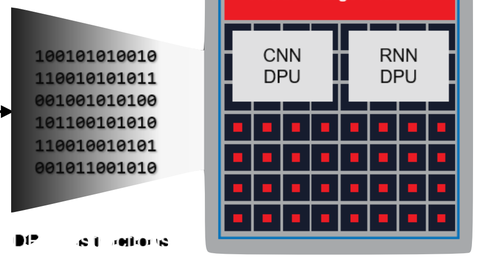
DPU

ML

TensorFlow
QKeras
Keras
PyTorch

C++ software

Vitis AI
XILINX VITIS AI



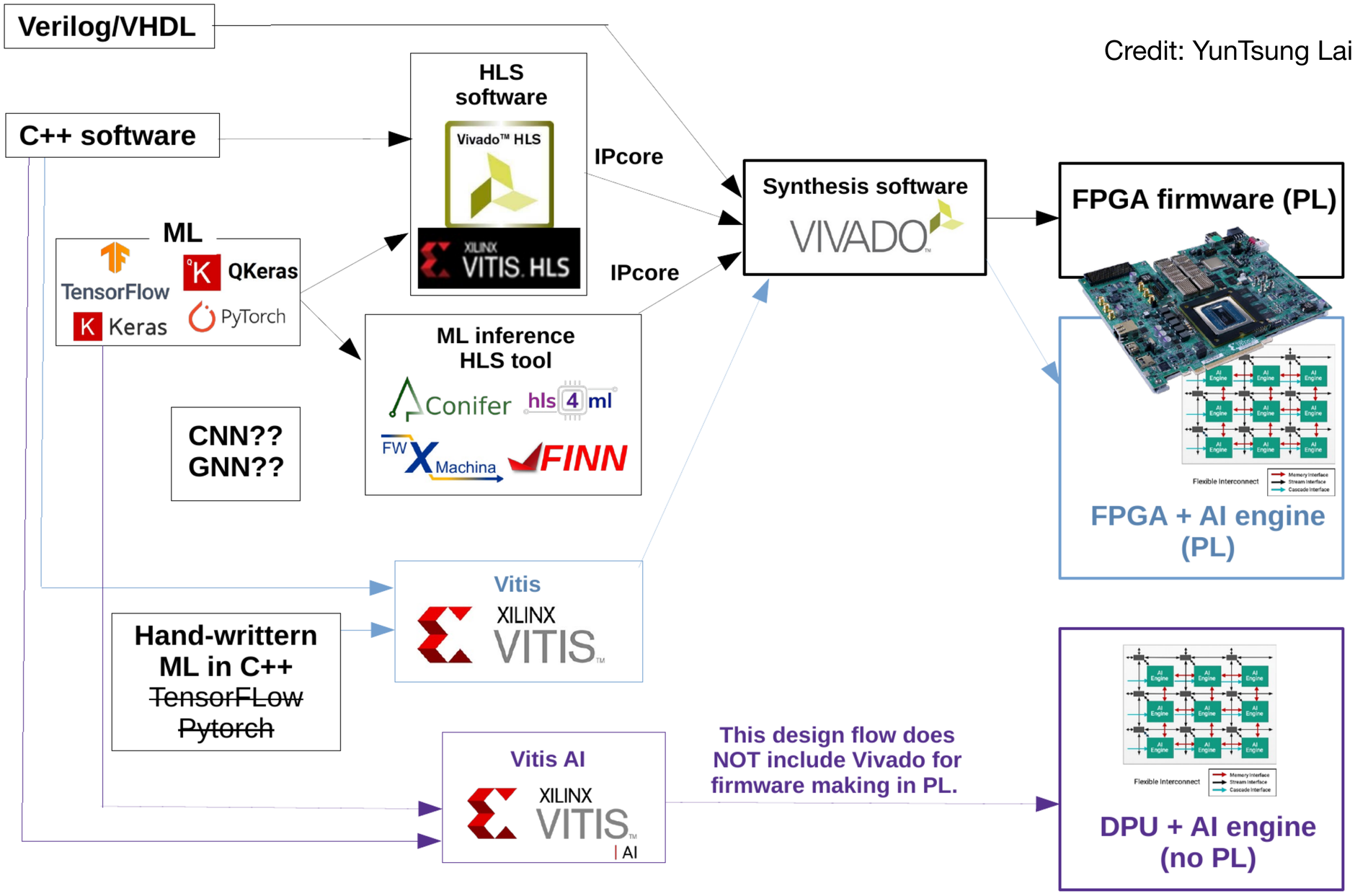
Summary and prospects

- Belle II TDAQ system was designed to handle 30 kHz level 1 trigger
- NN and DNN with hardware based CDC L1 track trigger to improve background rejection
- GNN with software based offline CDC track finder to improve the efficiency of displaced vertex tracks
- Not covered in the talk: GNN with hardware based clustering trigger for Belle II is under commissioning
- Target the upgrade of ongoing and future collider projects
  - ML implementation on heterogenous computing system for acceleration

Backup

FPGA implementation path of ML algorithm

Credit: YunTsung Lai



AI engine structure

UG1079

Figure 1: **Conceptual Overview of the ADF Graph**

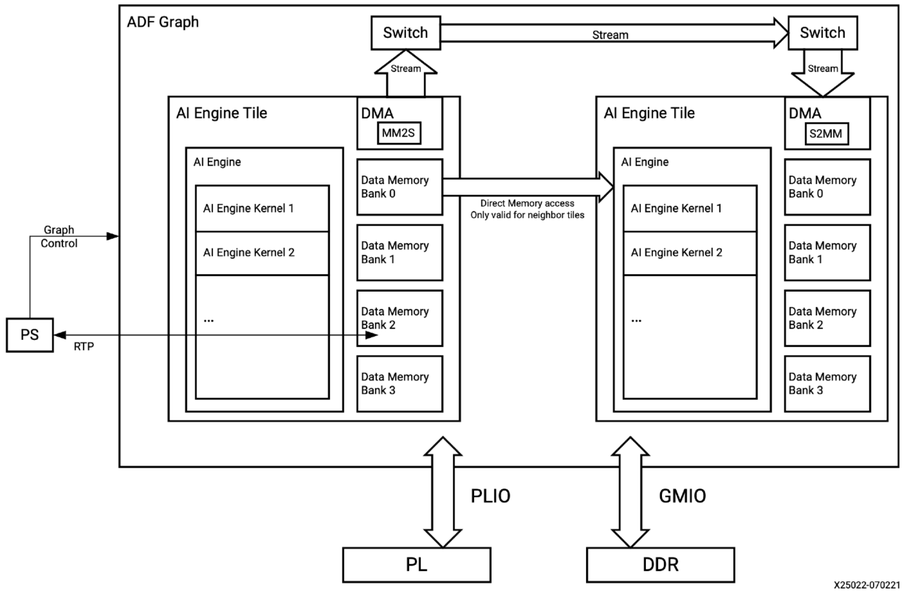


Figure 2: **AI Engine Array**

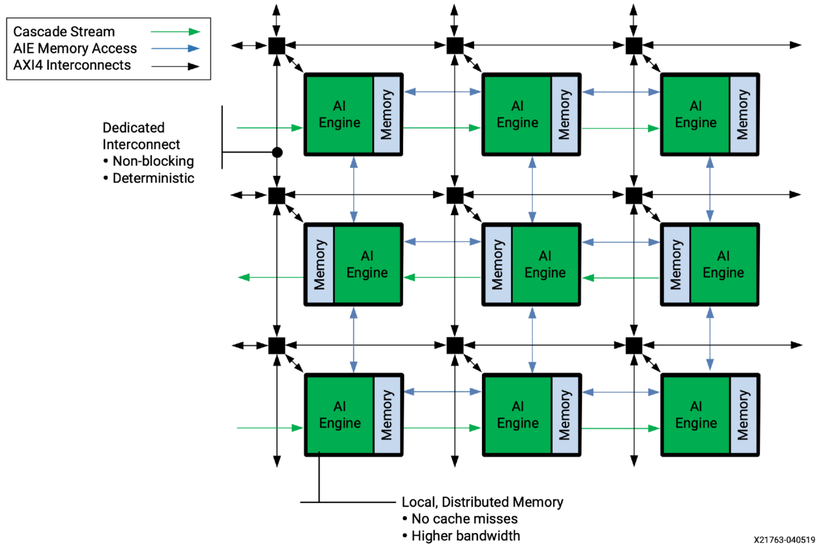


Figure 3: **AI Engine Tile Details**

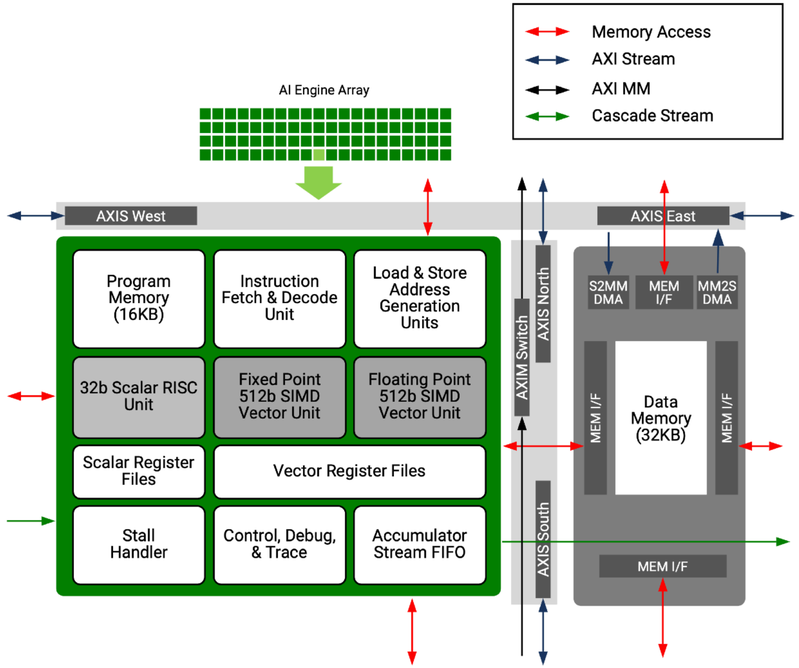
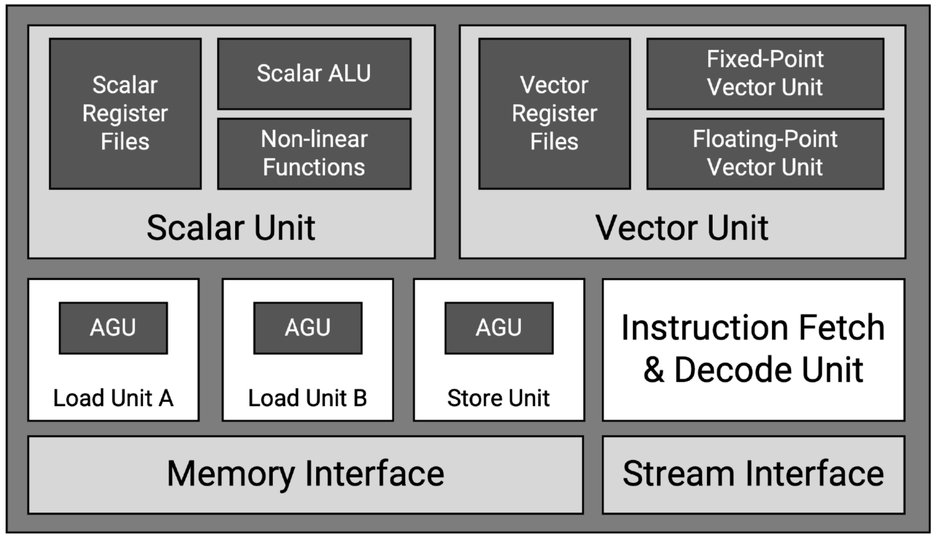


Figure 4: **AI Engine**



Kernel optimization for latency

before

after

Optimization	Before	After
Dense layer	Vector algorithm	Vector algorithm
Act. function	Scalar algorithm	Vector algorithm
Latency	~12us	~1.6us

Motivations of trigger-DAQ upgrade

Physics

- Tau trigger efficiency now is >95% (to be pre-scaled if luminosity is high)
- Low multiplicity trigger efficiency (to be pre-scaled pre-scaled if luminosity is high)
- Low-momentum track trigger efficiency
- “Anomaly” trigger
  - Design a special trigger line for some specific physics channel
- Trigger efficiency of displaced vertex

Current hardware limitation:

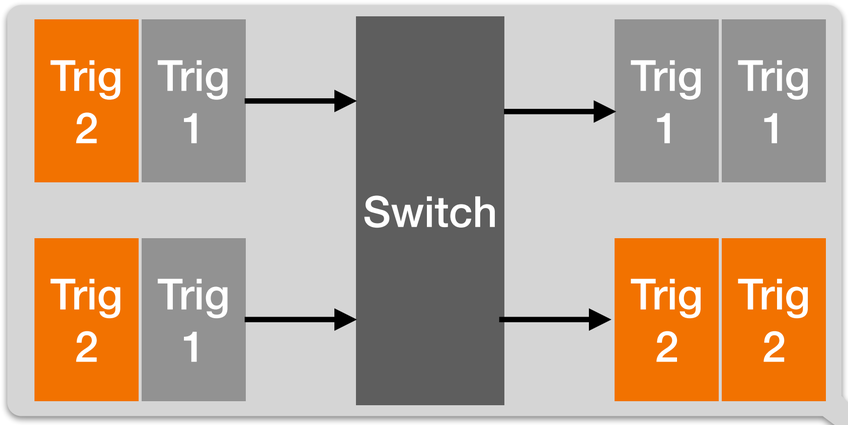
- DAQ system is designed to handle 30 kHz
  - L1 latency 4.4 us (SVD APV25 buffer)
    - CDC DNN trigger latency ~500 ns, latency already limited more large model
- L1 trigger rate will reach to ~20 kHz at 0.9×10^{-35} cm^{-2} s^{-1} (13 HLT units, w/o hyperthreading), planed full HLT: 15 units (7000 CPU cores)
- TTD system: VME bus limit, no more than 3 triggers within 80 clock (624ns)

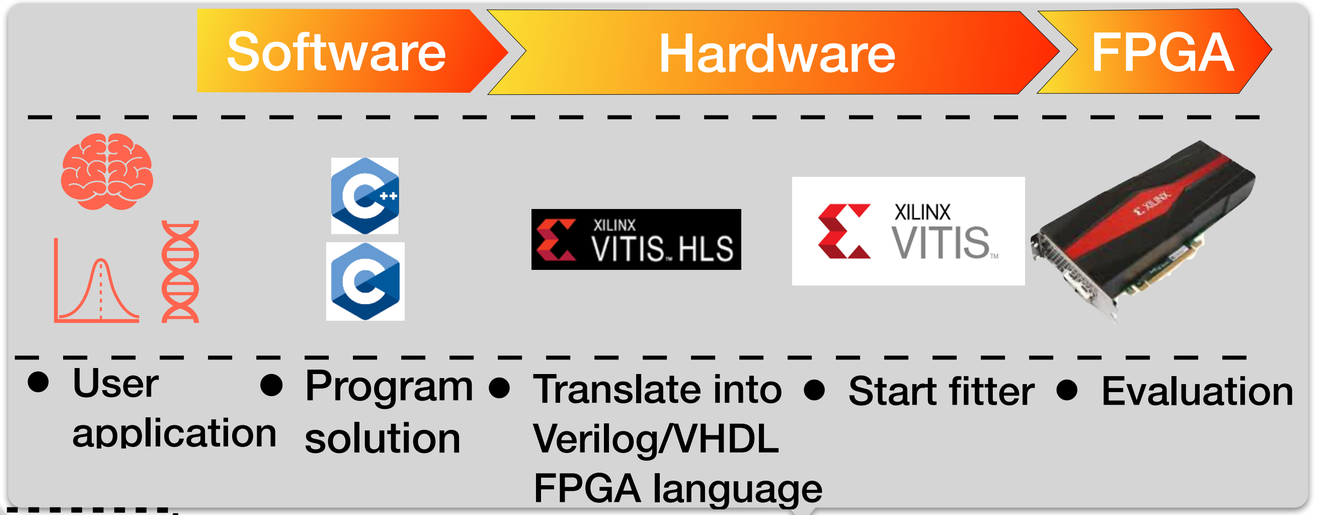
Vertex detector is planed to be upgraded during long shutdown 2 (after 2028)

- Latency limit target: 5 us -> 10 us (5.2 us KLM, 9 us TOP, considering upgrade)
- New TTD hardware: VME bus -> Ethernet
- New trigger board (UT5): Versal ACAP

Idea of upgrade trigger and DAQ system

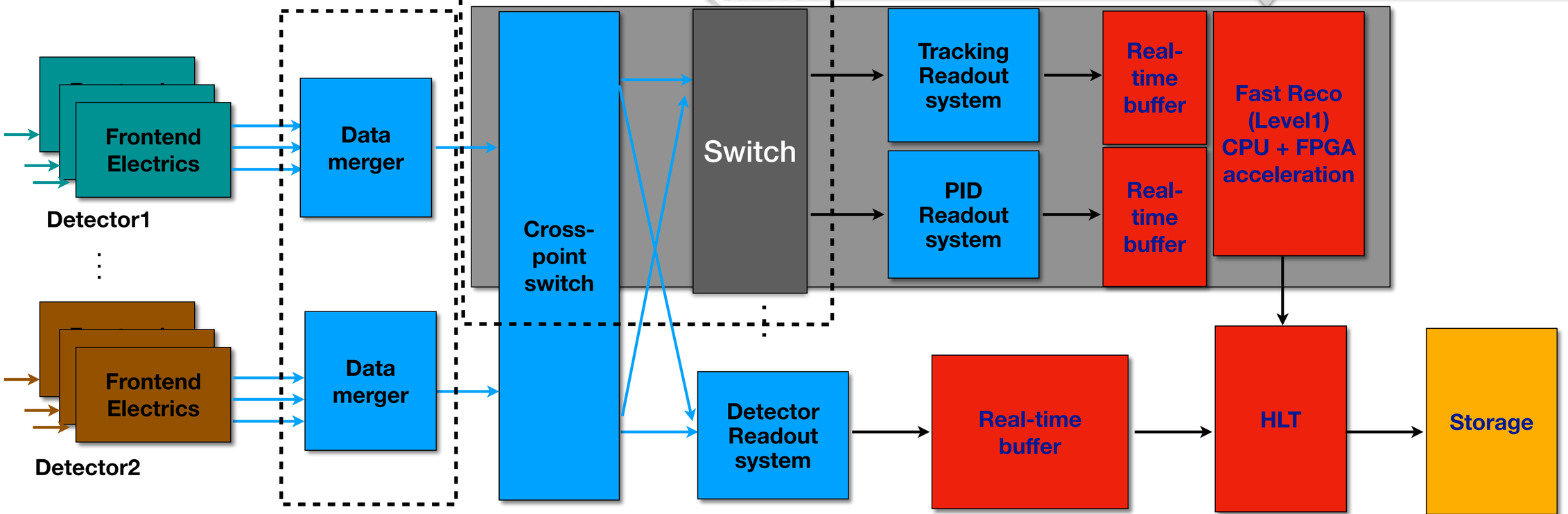
Proposed on Belle II trigger DAQ workshop 2022





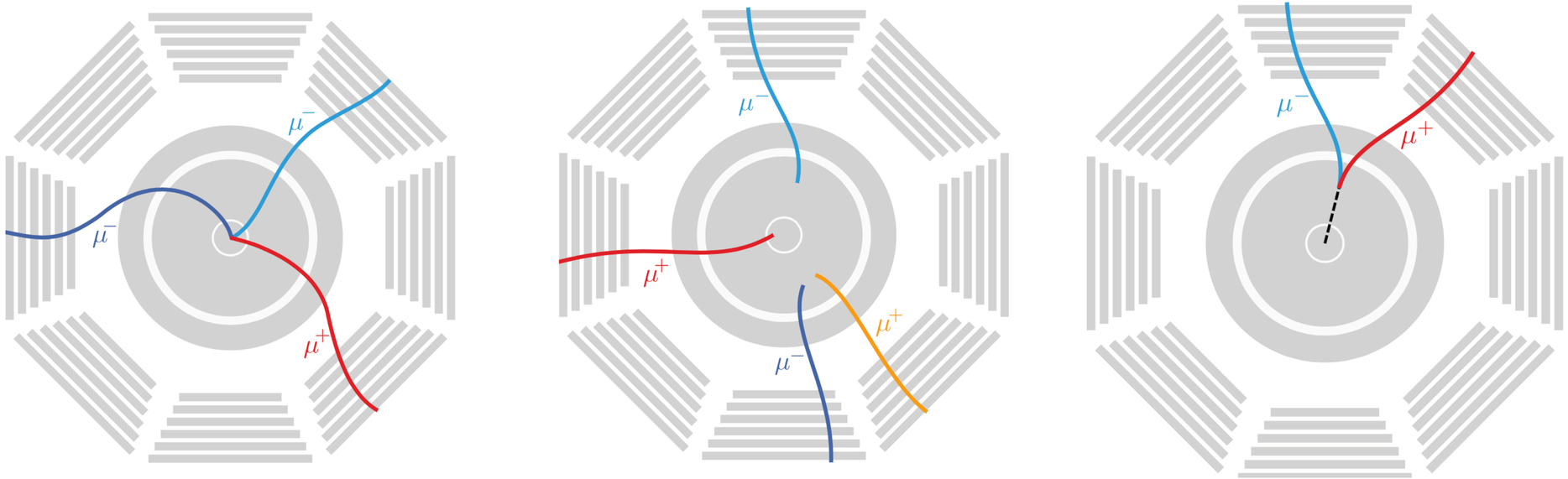
Sorting

Optional



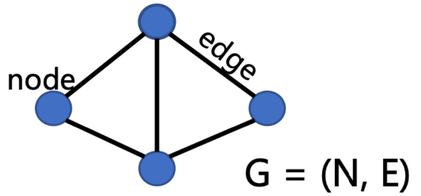
Training of GNN

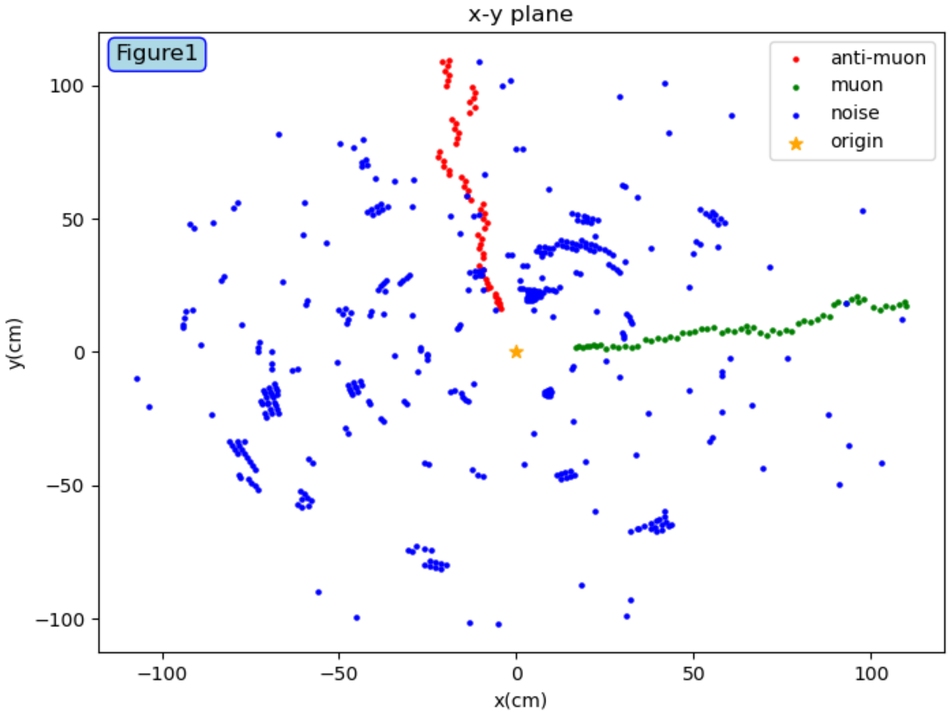
- Simulate 1 million events with over 4 million tracks
  - Train: Validation = 4 :1
- Training samples contain different topologies that cover all interested event features, to not bias the model, **no conservation laws involved here!**
  → crucial step to be agnostic about the physics processes
- Sample features
  - Low momentum tracks forming circles in the CDC ($P_t < 0.4$ GeV) <-> High momentum tracks
  - Short tracks <-> tracks penetrate all CDC layers
  - Small opening angle <-> well isolated two tracks
  - …

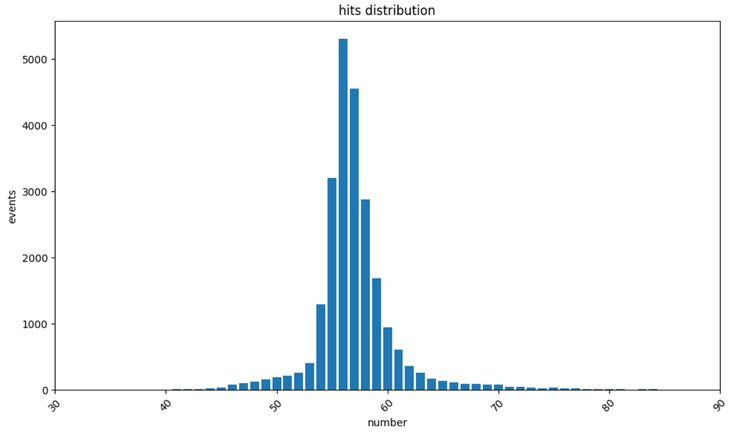


Development of GNN tracking algorithm

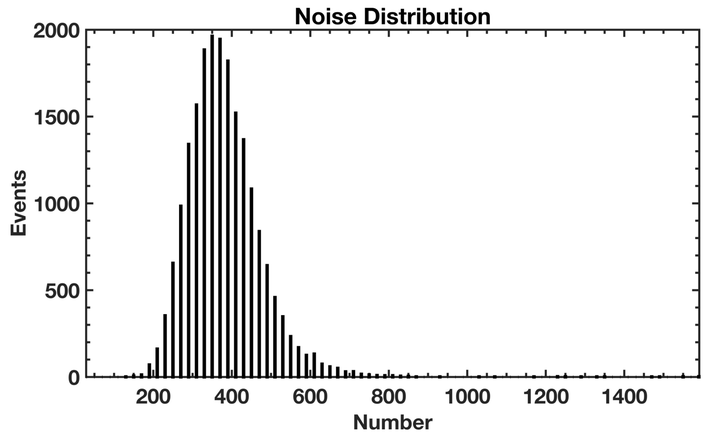
- Belle II MC simulation data-set (Own simulation)
  - μ+ μ- (particle gan)
  - 0.3 GeV/c < *P* < 5.0 GeV/c
  - Theta: 30°-120° , within on barrel CDC
  - Phi: 0-2π
  - Train: Validation: Test = 3: 1: 1
  - noise：/group/belle2/dataprod/BGOverlay/early_phase3/release-06-00-05/overlay/BGx1/set0/







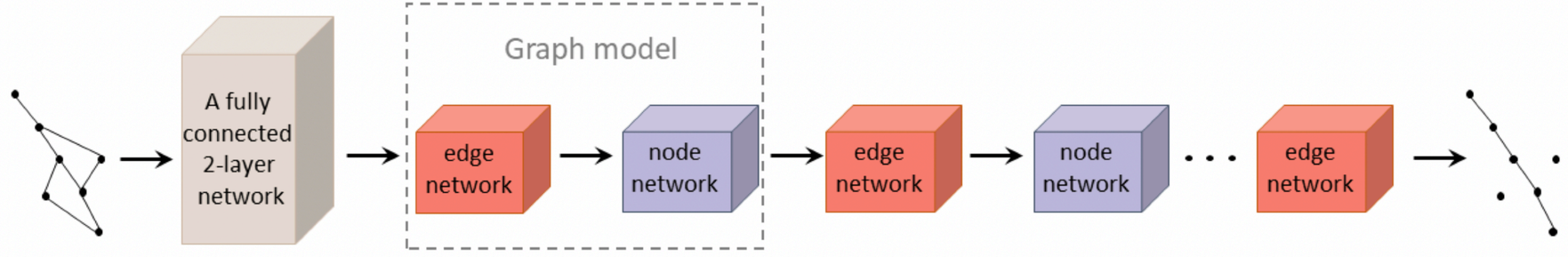
Signal hit No. distribution



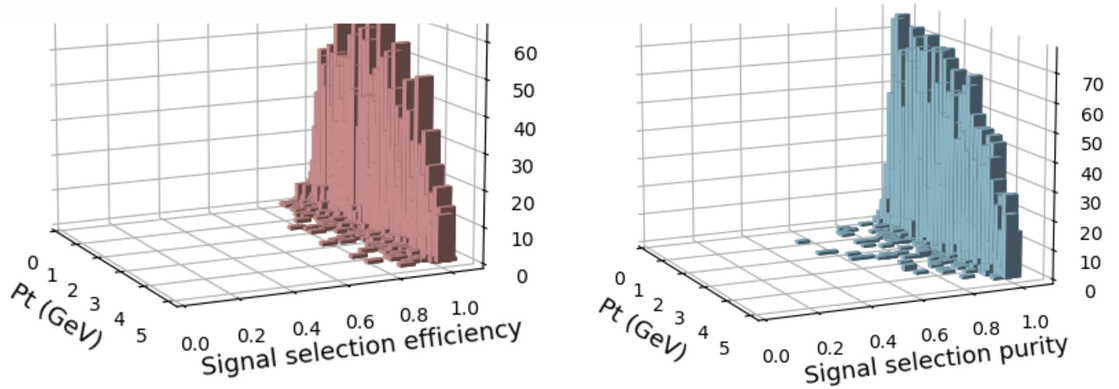
Noise hit No. distribution

Development of GNN tracking algorithm

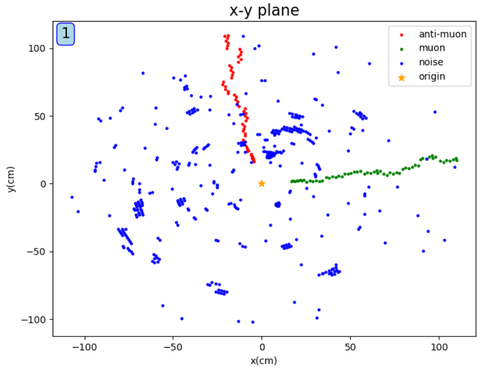
- Graph Neural Network edge classifier
- Input network
  - Node features embedded in latent space
- Graph model
  - Edge network computes weights for edges using the features of the start and end nodes
  - Node network computes new node features using the edge weight aggregated features s of the connected nodes and the nodes' current features
  - MLPs
  - 8 graph iterations
- Strengthen important connections and weaken useless or spurious ones

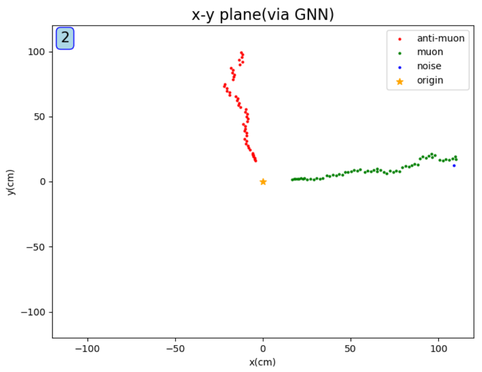


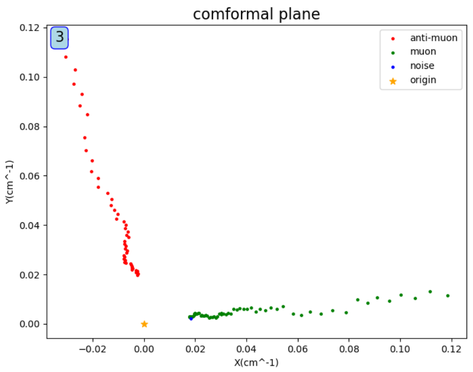
Hit selection efficiency: 98.4%
Hit selection purity : 97.9%

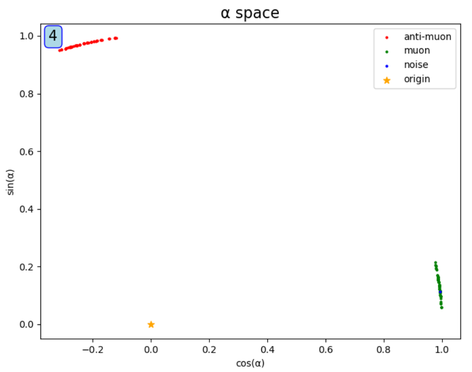


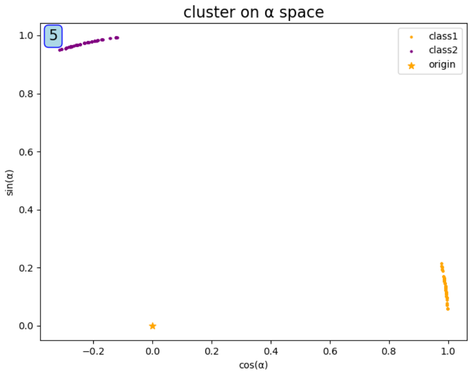
Performance step-by-step











μ+ μ- (particle gan) GNN noise filtering Transform space Transform α space DBSCAN clustering

1. Original MC data sample
   - μ+ μ- (use particle gan)
   - P (0.3GeV - 5.0GeV)
2. Remove noise via GNN
3. Transform to Conformal plane
   - $X=2x/(x^2+y^2)$ $Y=2y/(X^2+y^2)$
   - Circle passing the origin transform into a straight line
4. Transform to ‘α’ parameter plane
   - Hits connected in the X-Y plane in a straight line
   - α as the angle between the straight line and X axis
   - The parameter space as cosα and sinα
5. DBSCAN clustering in ‘α’parameter plane
   - Density-Based Spatial Clustering of Application with Noise
   - Hits in a cluster are considered to be in the same track

Cluster efficiency: 97.7%
Cluster purity : 96.9%