Development of first level track trigger at Belle II using Deep Neural Network

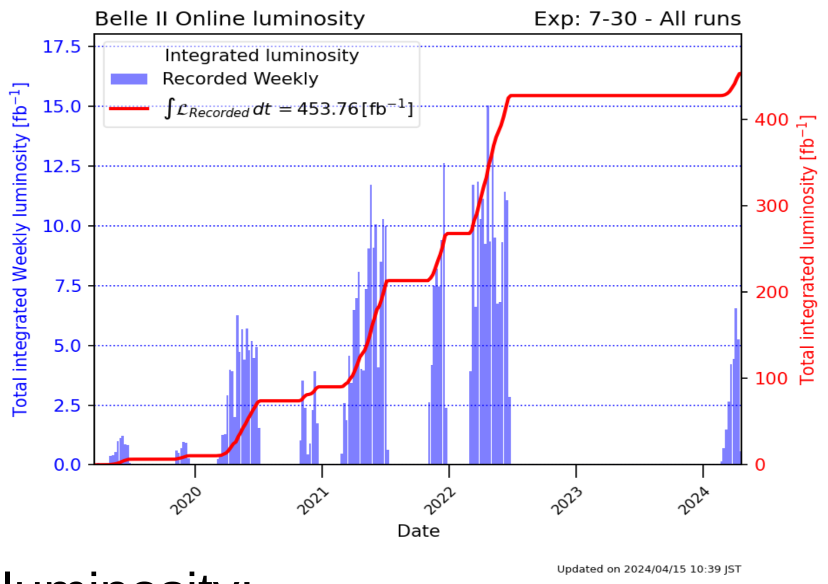
Yuxin Liu, SOKENDAI(KEK)

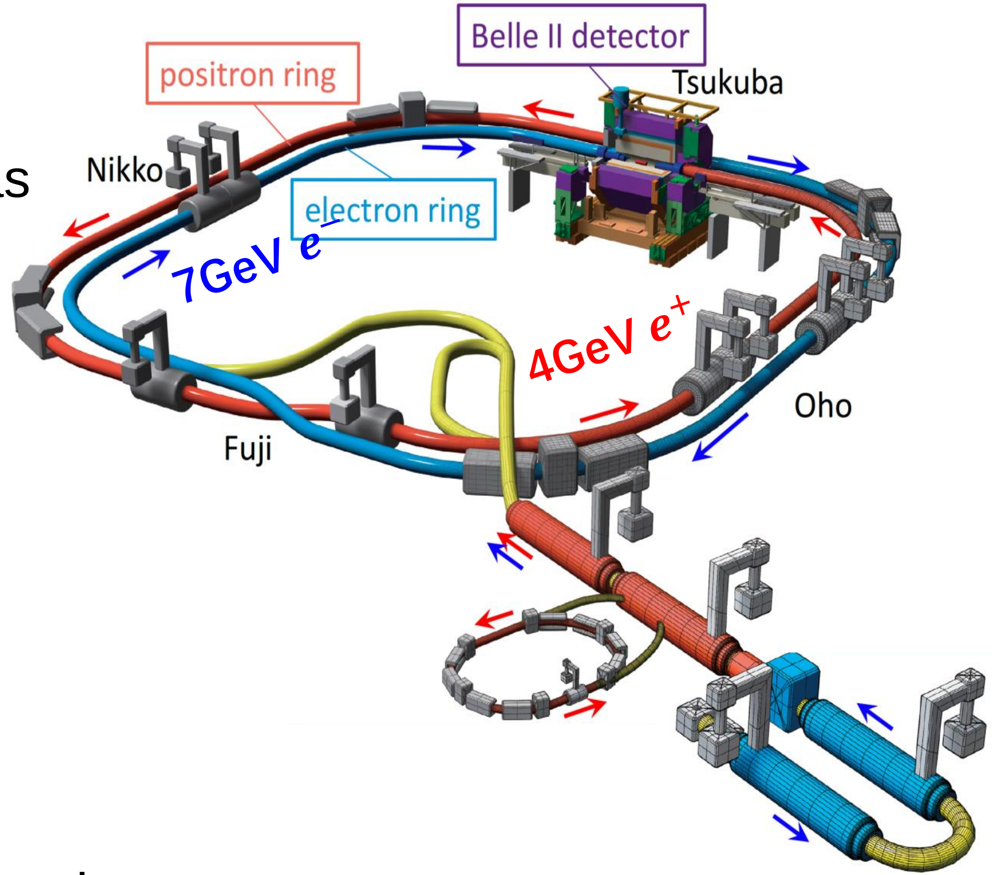
18th May, Workshop of Tracking in Particle Physics Experiments

SuperKEKB

- An asymmetric $e^- \ e^+$ collider, Upgrade from KEKB.
  7.0 GeV e^- and 4.0 GeV e^+ for $\Upsilon(4S)$

- SuperKEKB aimed for a peak luminosity of $6 \times 10^{35}\ \mathrm{cm}^{-2}\mathrm{s}^{-1}$, surpassing KEKB by 30 times and setting a world record; also with the integral luminosity as $50\ ab^{-1}$;





- Achieved luminosity:

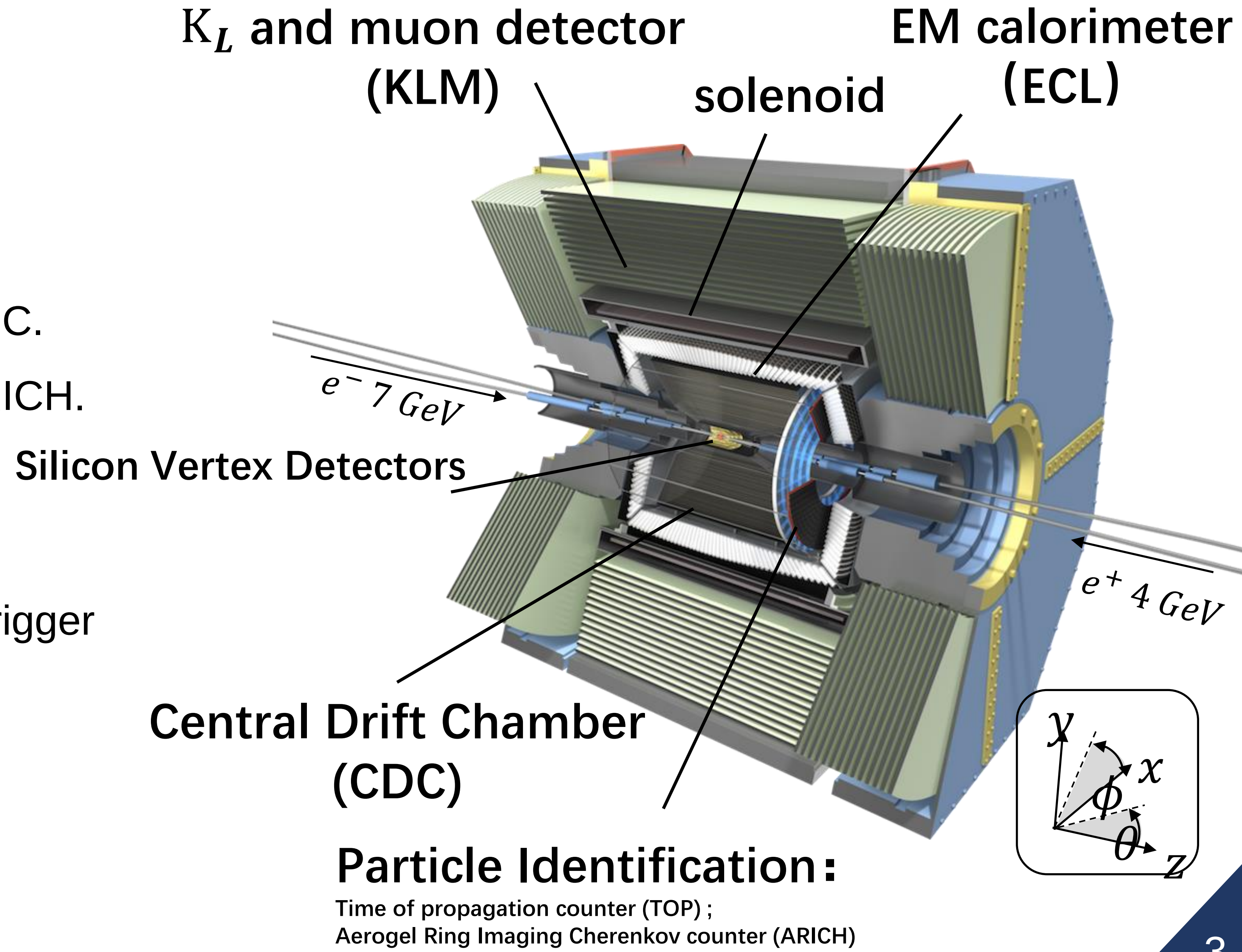
$$\mathcal{L}_{peak} = 4.65 \times 10^{34}\ \mathrm{cm}^{-2}\mathrm{s}^{-1}$$, two time of KEKB record

$$\mathcal{L}_{int} = \ 453\ fb^{-1}$$; till April 2024

Belle II detectors

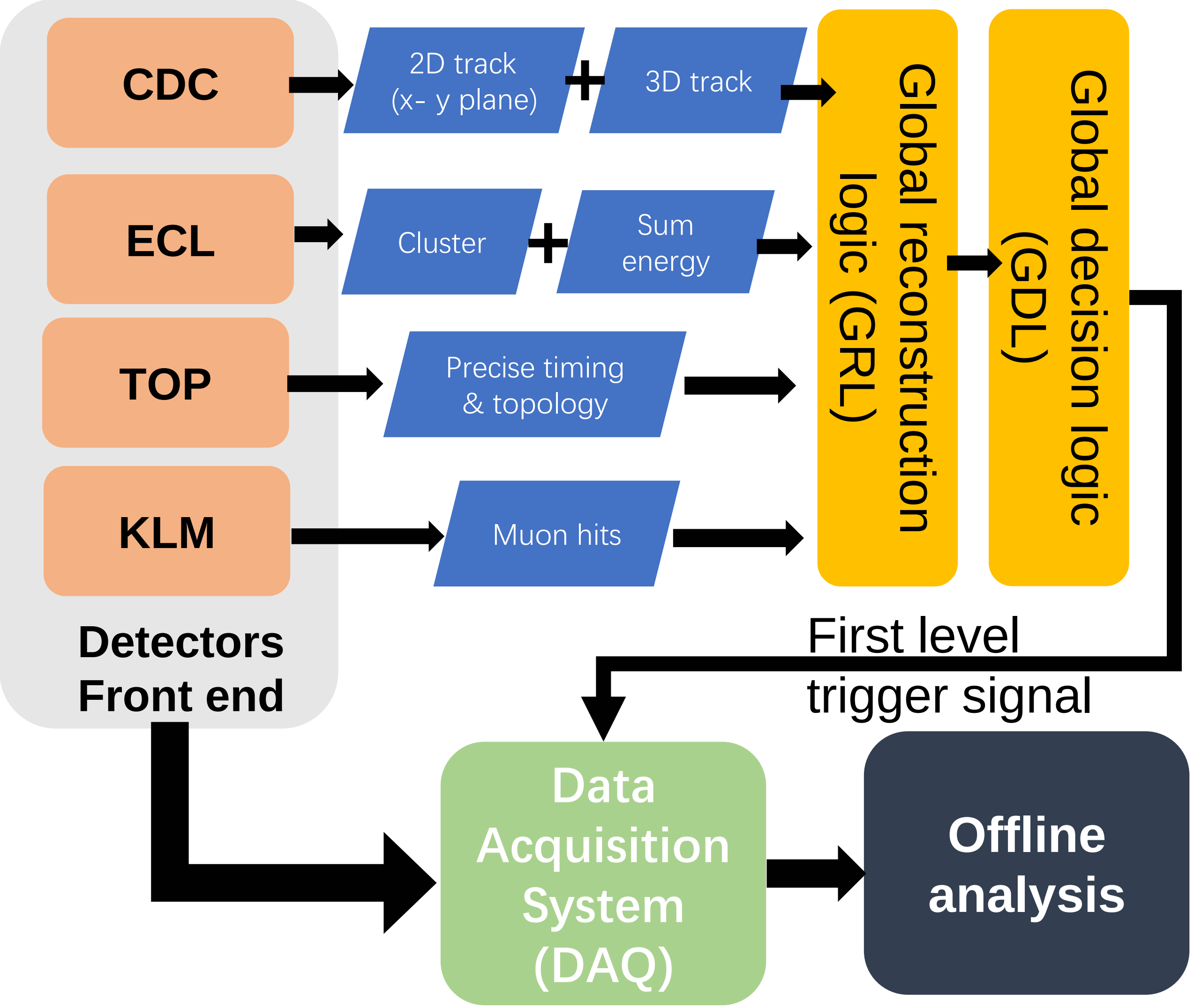
Belle II including:

- Tracking: Vertex detectors and CDC.
- particle identification: TOP and ARICH.
- Calorimeter: ECL.
- KL and muon detector.
- First level (L1) trigger, High level trigger (HLT) and DAQ.



First level trigger

- Collected small set of data from sub-detectors
- Process data in real-time; short dead time
- Decide to record the event or not with fixed latency



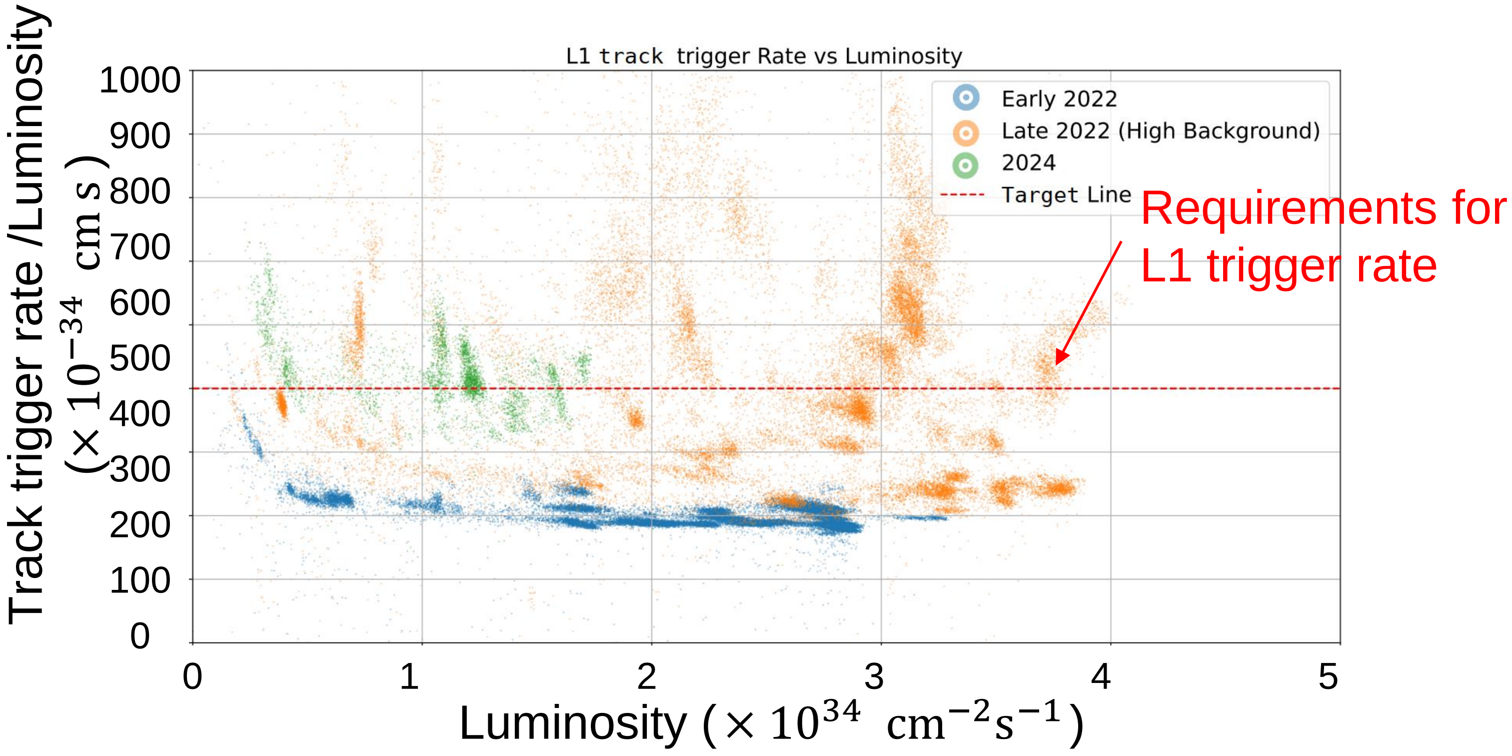
Requirements for first level trigger system

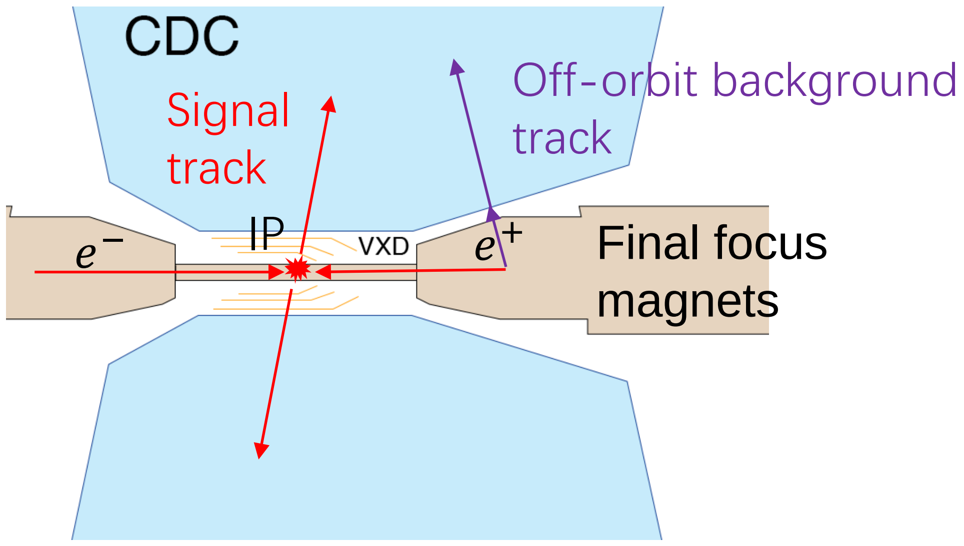
1. High efficiency for hadronic events
2. A maximum average trigger rate of 30kHz
3. A fixed latency of about 4.4 μs

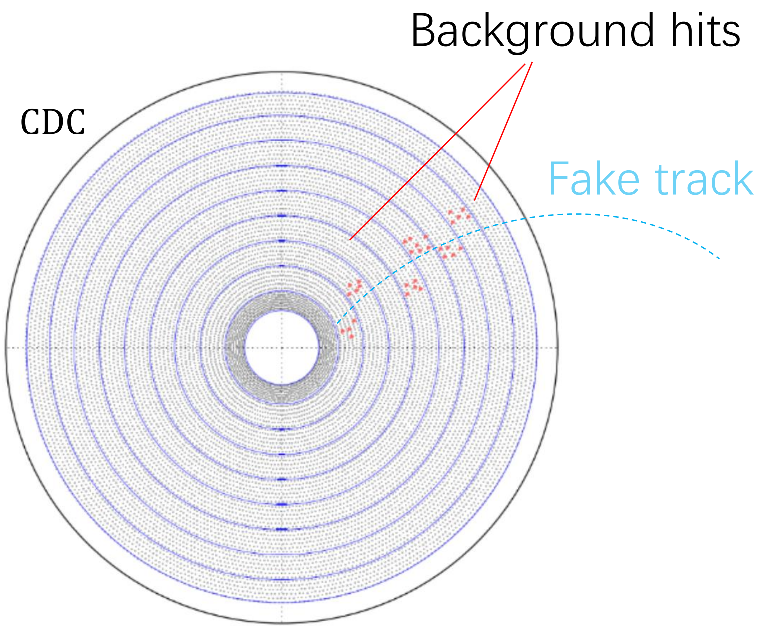
Motivation for track trigger upgrading

Requirements for first level trigger system

1. High efficiency for hadronic events
2. **A maximum average trigger rate of 30kHz**
3. A fixed latency of about 4.4 μs





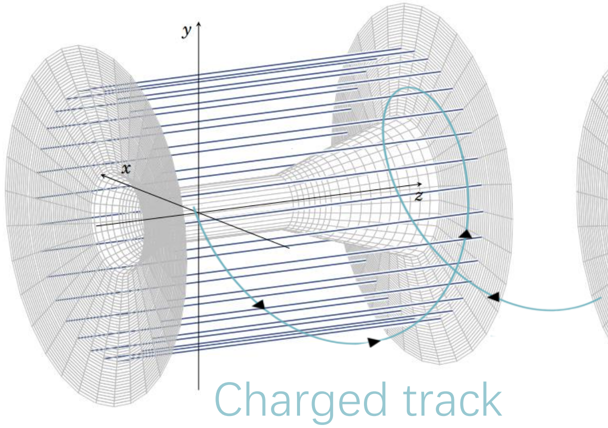


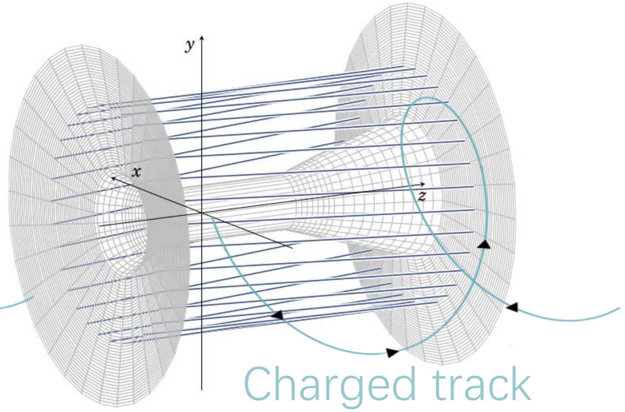
- **we aim to decrease the track trigger rate, thereby lowering the overall trigger rate.**

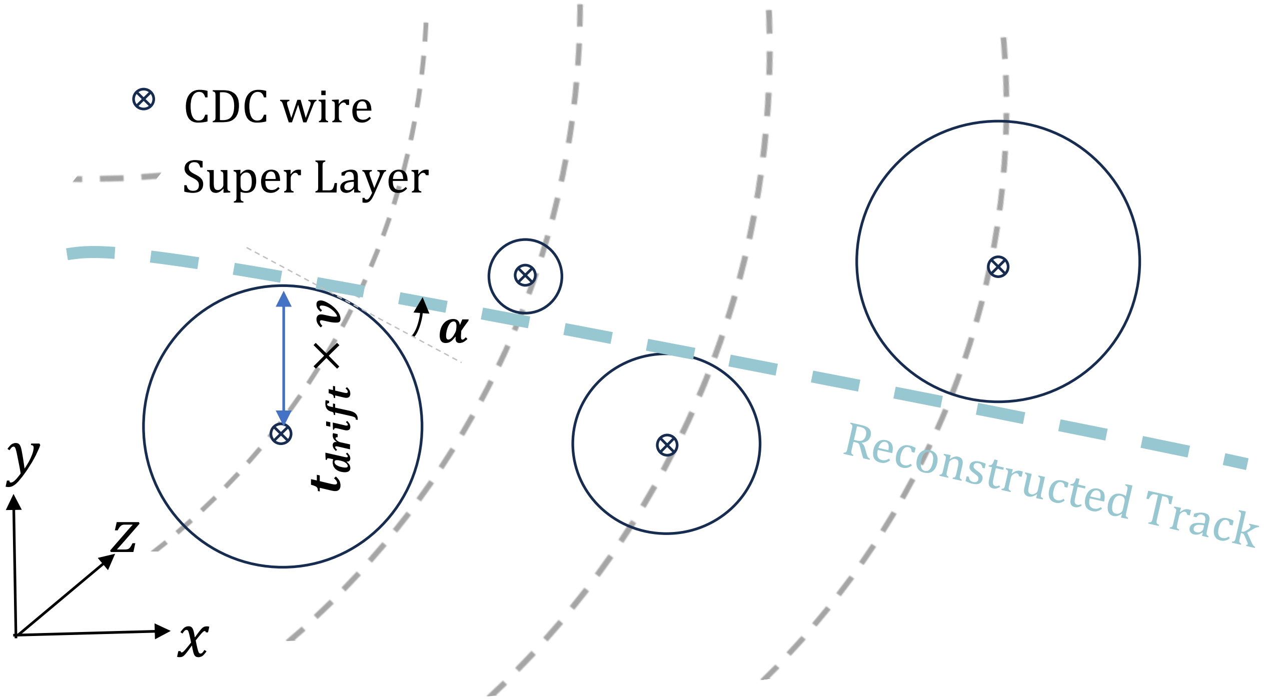
Central drift chamber

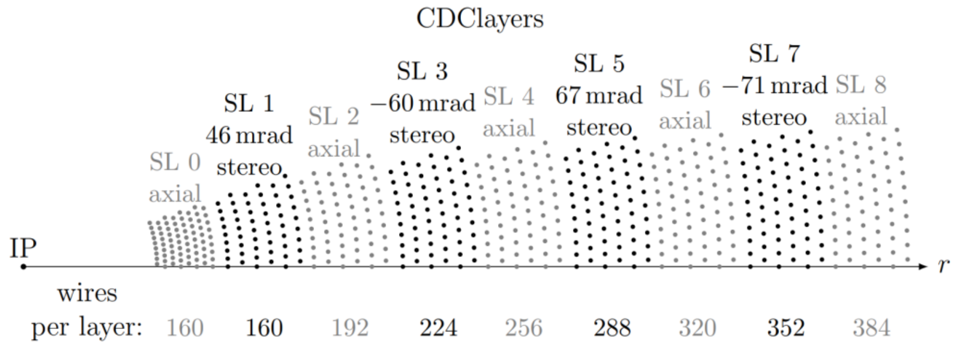
CDC Axial wires
(parallel to beam direction)

CDC Stereo wires
(oblique to beam direction)





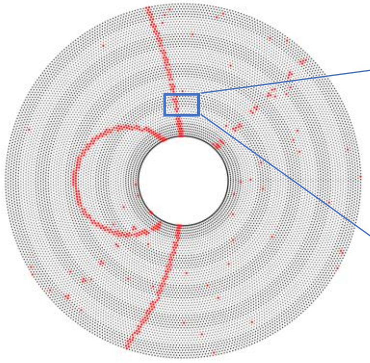


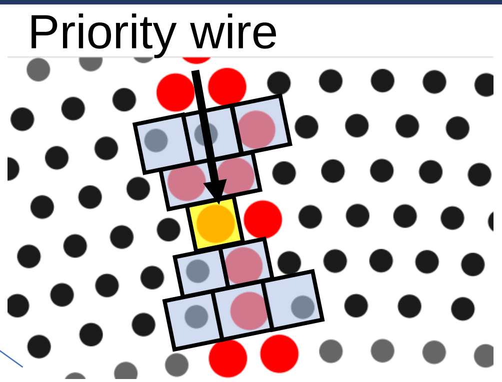


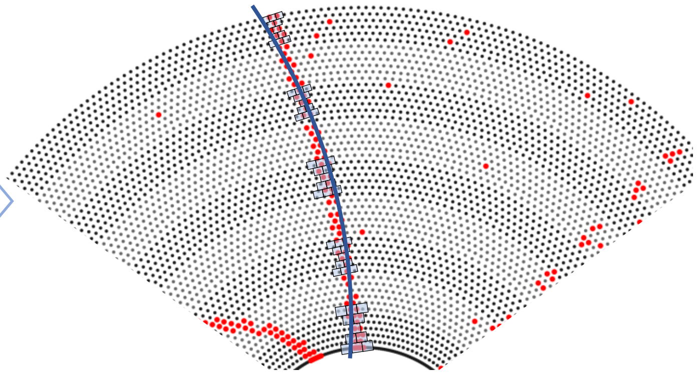
- Track reconstruction information: **location for CDC hits (ϕ and r) , drift time (t_{drift})**

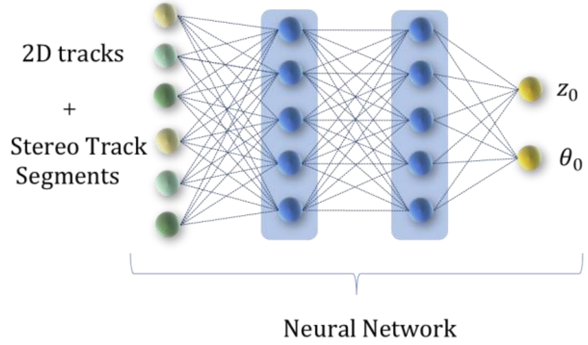
First level CDC track trigger

https://arxiv.org/abs/2402.14962







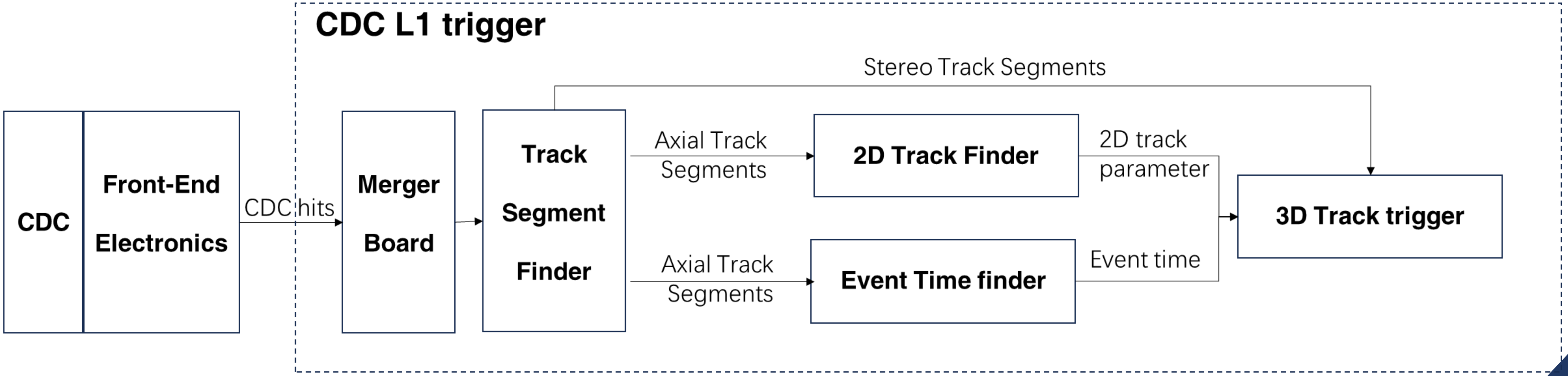


CDC raw hits

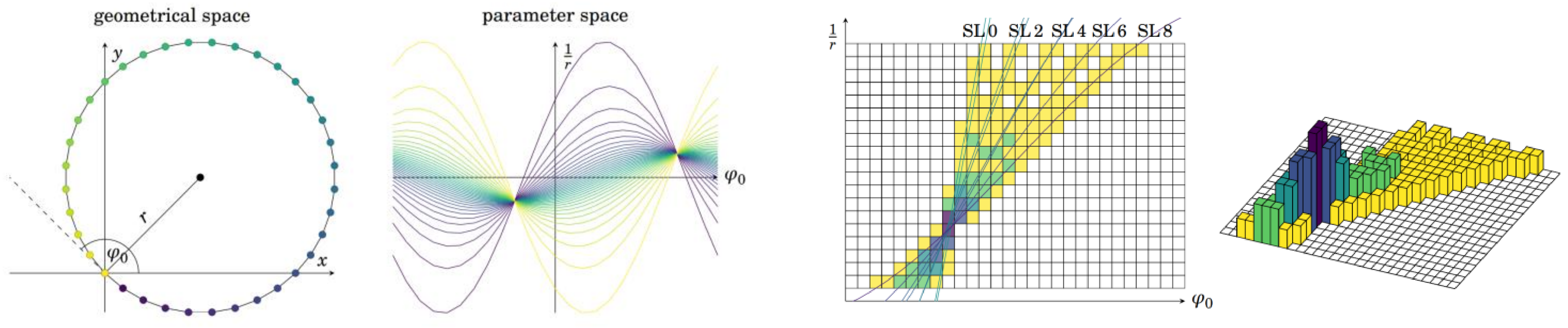
Built **Track Segment** (a set of CDC wires) in every super layer

Build **2D track** with **axial hits** using Hough transformation

Build **3D track** with **stereo hits** and 2D track using **Neural network**

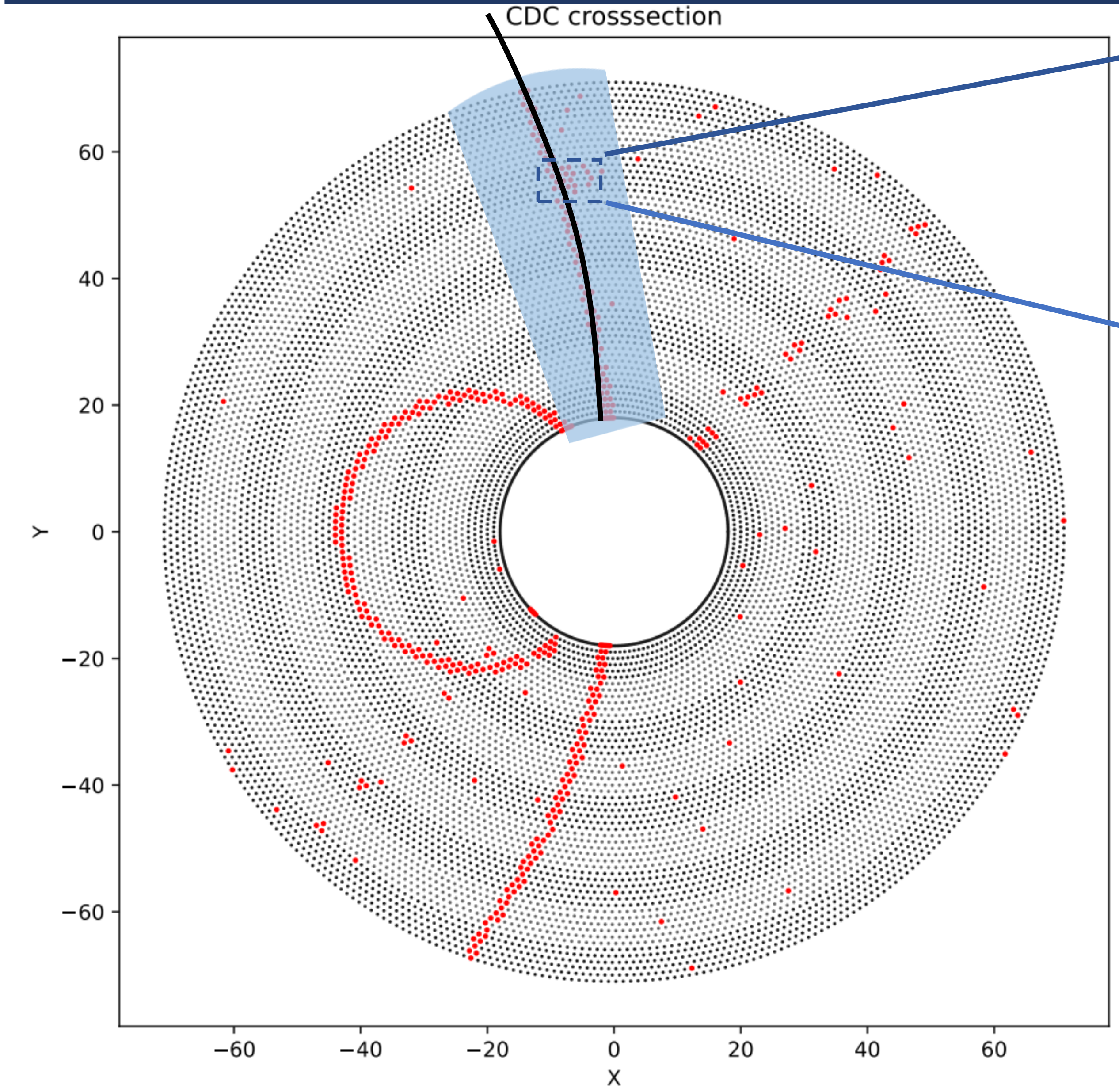


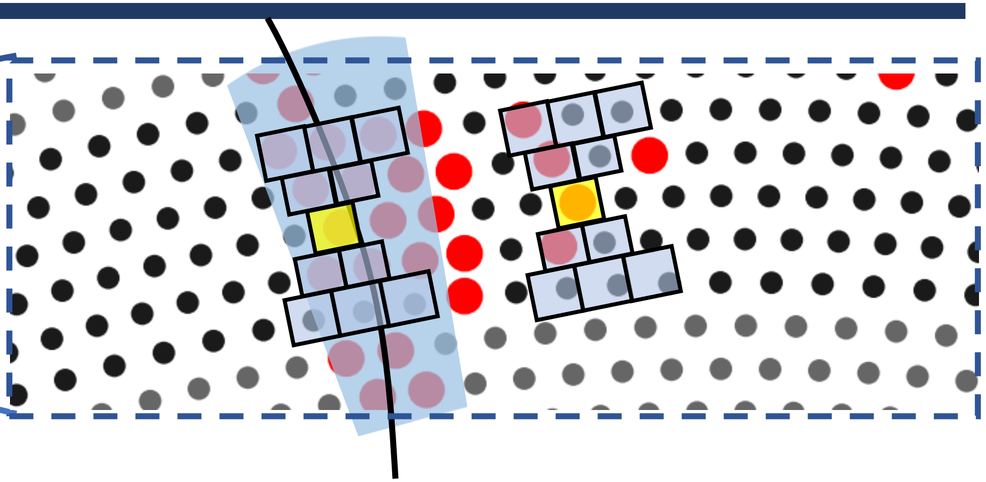
2D Hough transformation

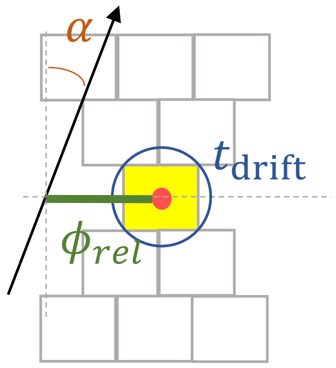


- Mapping points in the geometric space to a parameter space with : $\rho(\phi) = \frac{2}{r_{\mathrm{TS}}} \sin(\phi - \phi_{\mathrm{TS}})$
- Implementing a grid separation on the Hough parameter space.
- Counting hits cell and take the cells exceeding threshold as a track

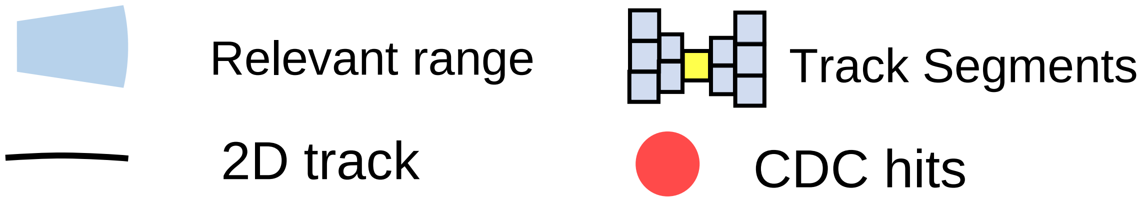
Inputs selection







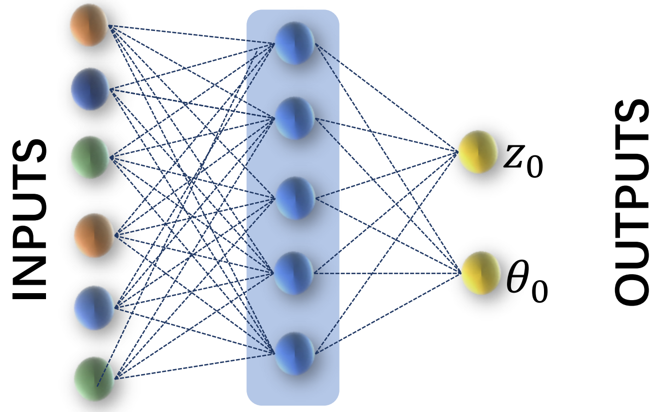
- Selected 1 Track Segments per one Super Layers
- Collected the α, t_{drift} and ϕ_{rel} for each track segment



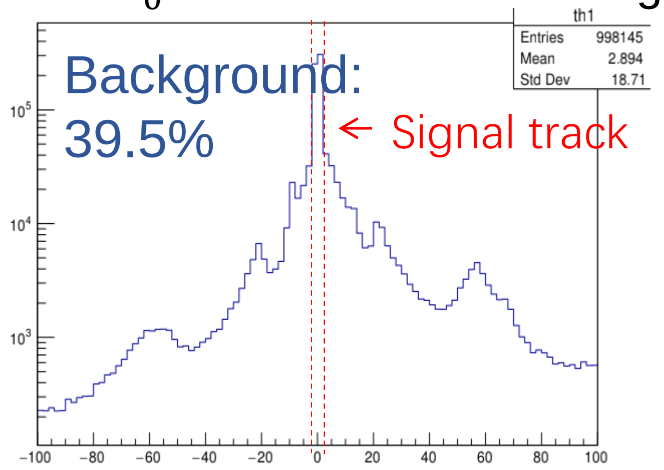
Why use deep neural network

- Background ratio is still high
- Not only "Fitting", but also "selection"
- Fake track problems

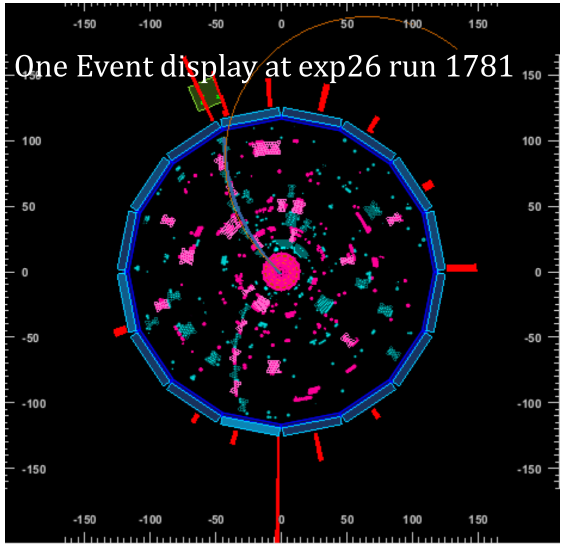
Current used MLP



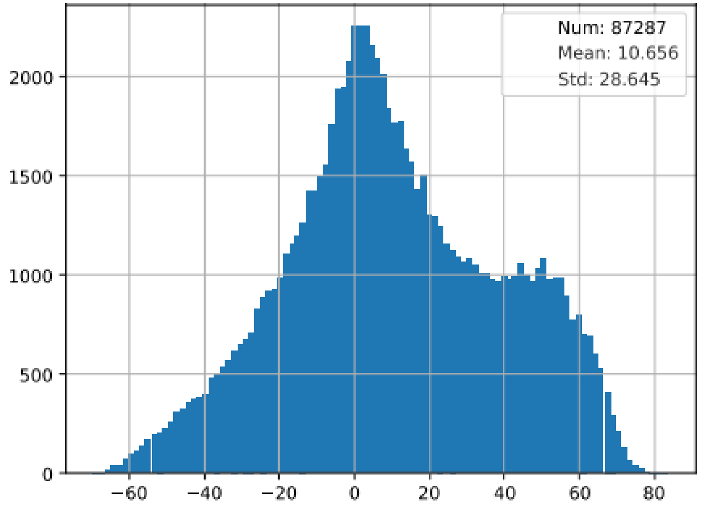
Tracks z_0 distribution after L1 trigger



Offline track vertex z_0(cm)

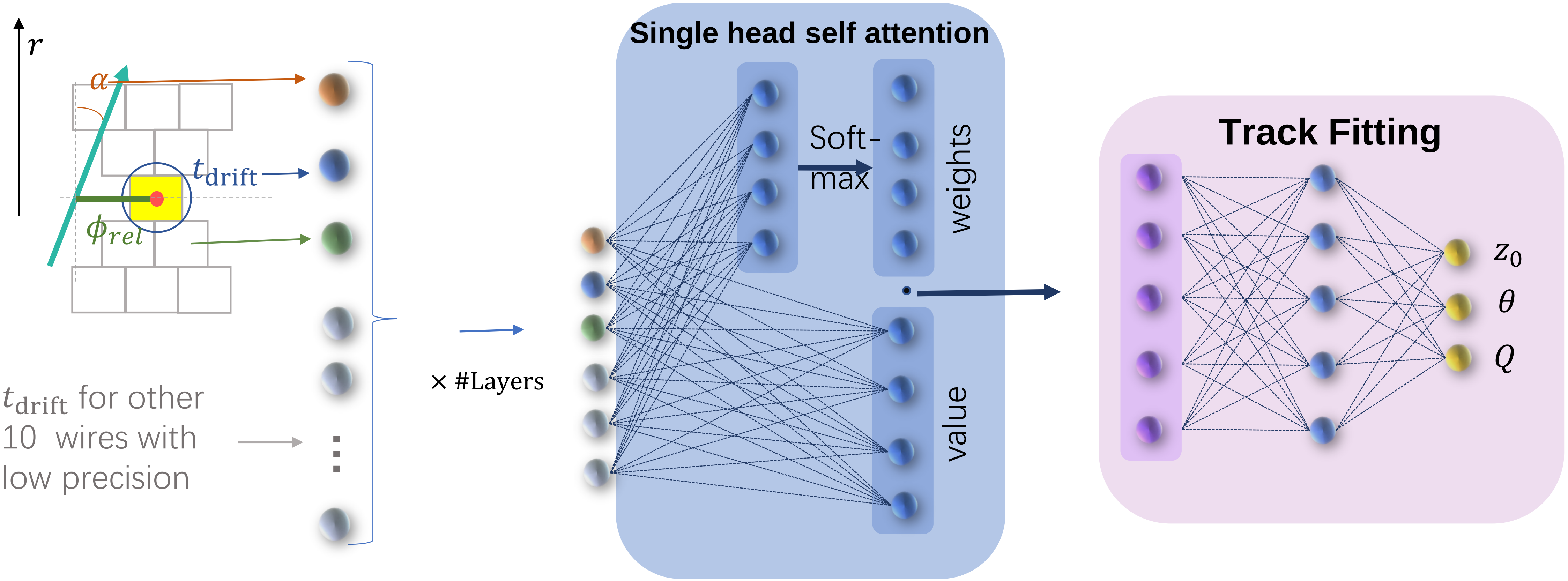


Fake track



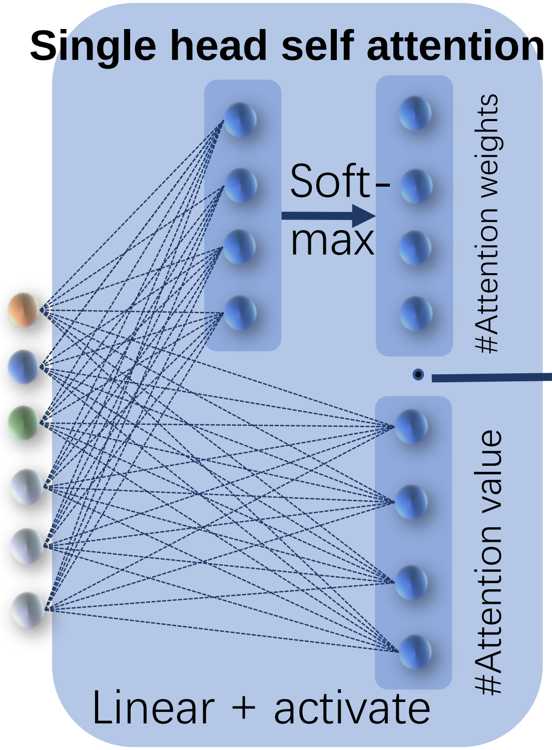
Neural-network track vertex z_0(cm)

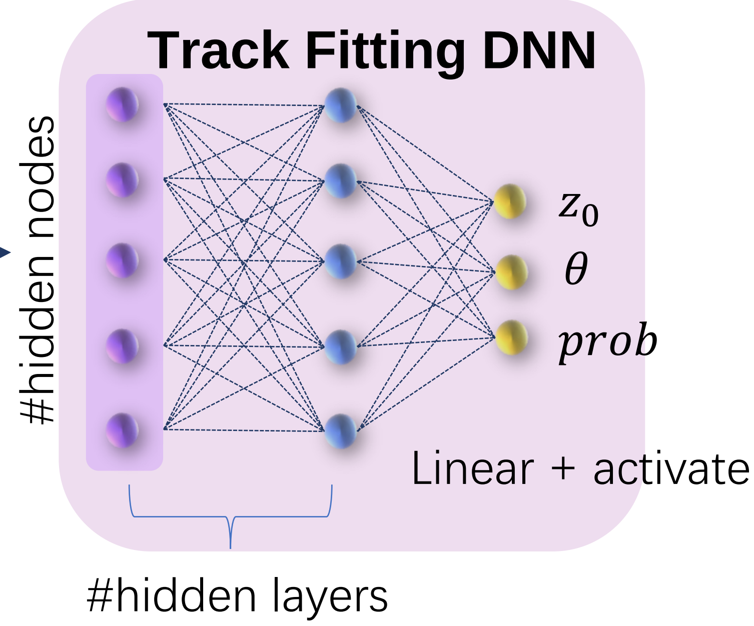
Neural-network inputs and architecture upgrade



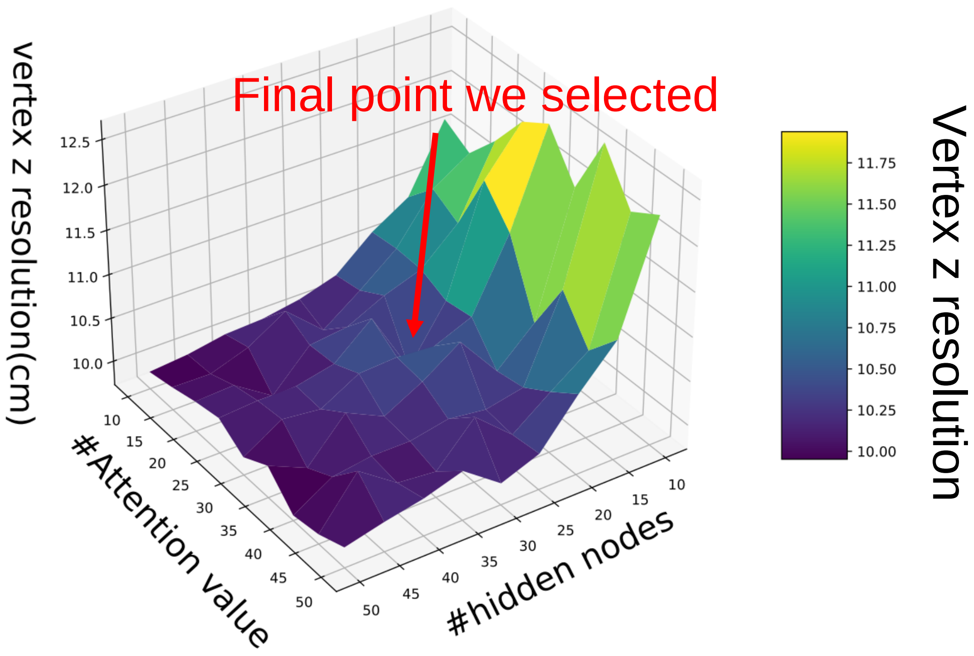
- Inputs: **Drift time t_{drift}**, **wires relative location ϕ_{rel}**, **Crossing angle α** for priority wires
  + **Drift time for all other wires**
- Introduce the **self-attention architecture** to "focus" on certain inputs
- Output track vertex z_0, track θ and **classifier output Q**

Neural-network training, optimization, quantization





Snapshot of optimization process



- Data: real physics run data with high background in late 2022.
- Using PyTorch lib for model building and training, OPTUNA for parameters optimization

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

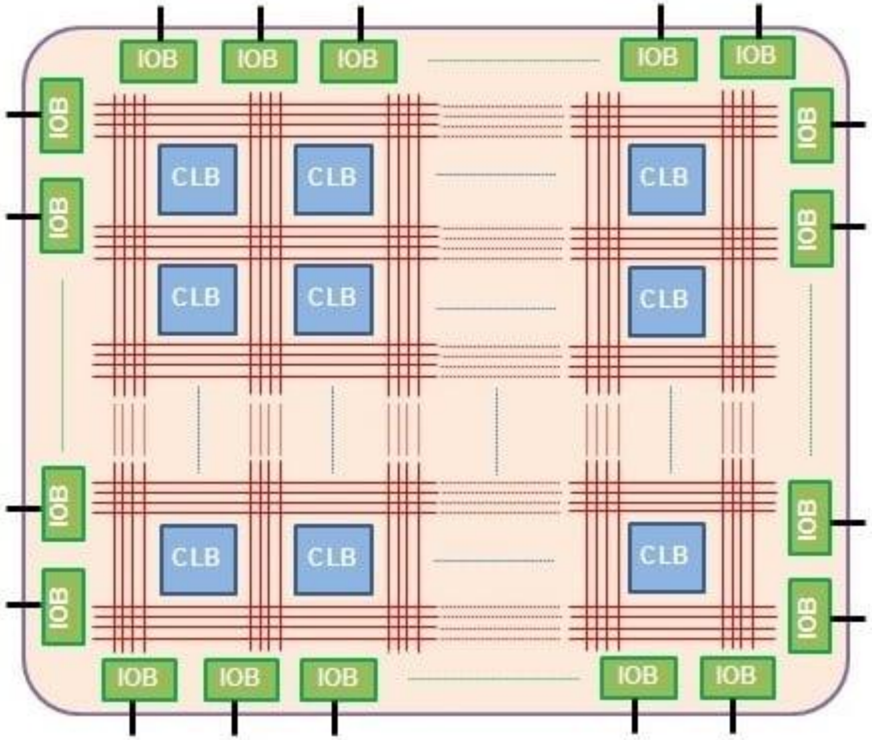
Field Programmable Gate Arrays (FPGA)

FPGA contains:

-IOBs : Programmable in/out pins

-CLBS : Configurable Logic Blocks

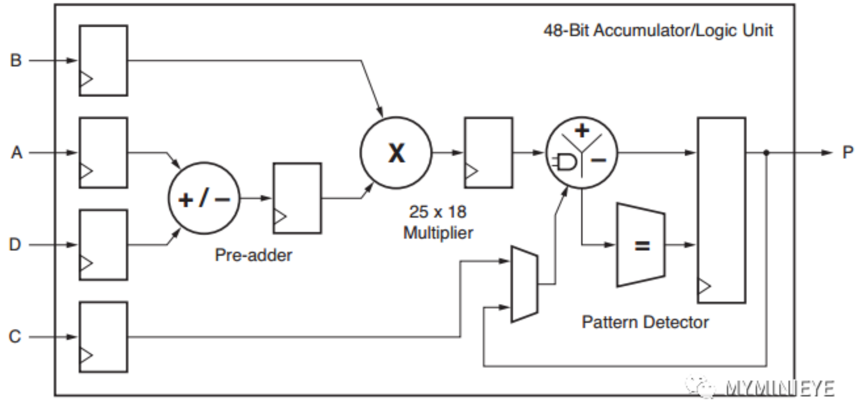
: Programmable interconnect



FPGA Advantage:

- Flexibility
- Extremely fast (~ ns)
- Fixed latency

DSP: a logic unit to process Multiply And Accumulate (MAC)



Digital Signal Processing (DSP) 48E1

Deep neural-network implementation

Upgrade

Universal Trigger board (UT) generation	3rd	4th
FPGA	Virtex 6 XC6VHX380	Virtex UltraScale XCVU160
DSP	864	1560
Logic gates	380k	2026k
Optical bandwidth	530 Gbps	1300 Gbps

Requirements for implementation:

- Latency: ~300ns (3rd) and ~600ns (4th)
- DSP limitation: 864 (3rd) and 1560 (4th)
- More than 5 times logic gates, can be used for multiply

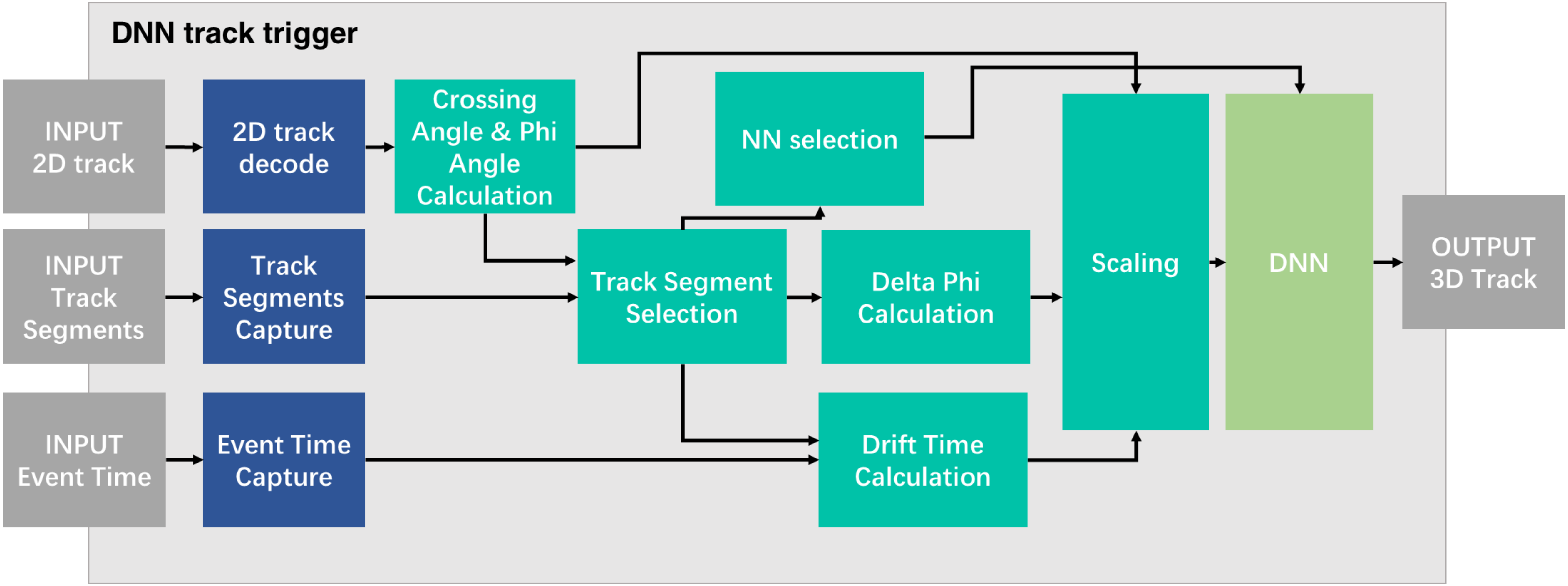
Belle II UT3

Xilinx Virtex-6
xc6vhx380t, xc6vhx565t
11.2 Gbps with 64B/66B

Belle II UT4

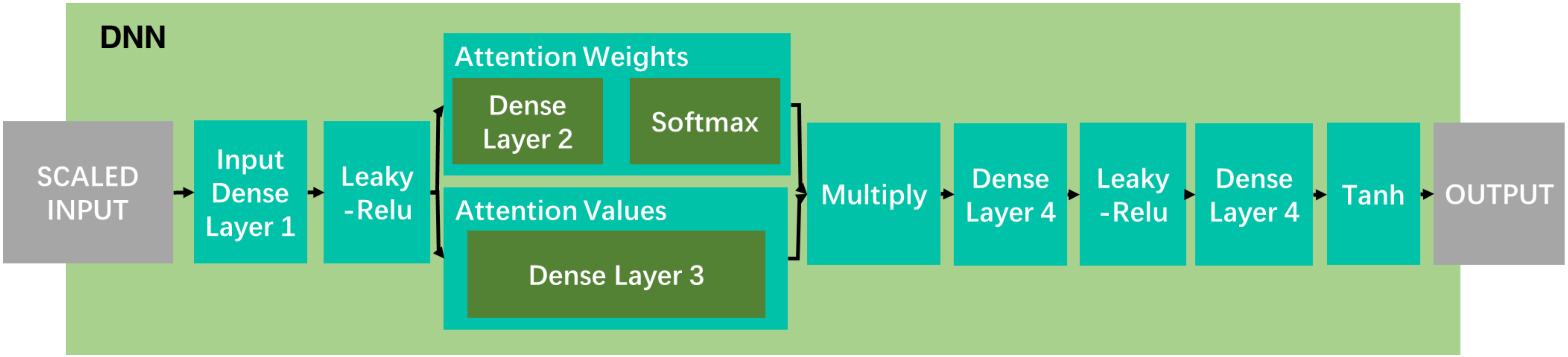
Xilinx UltraScale
XCVU080, XCVU160
25 Gbps with 64B/66B

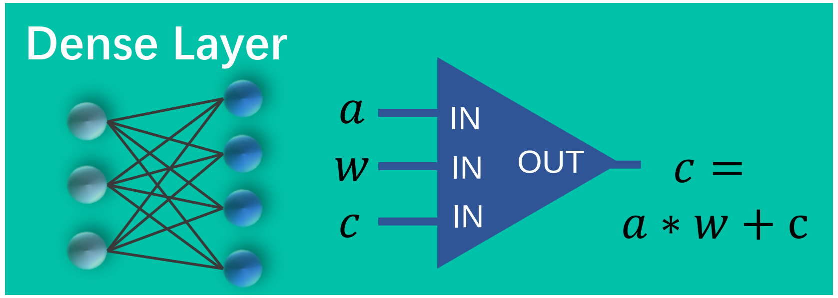
DNN track trigger firmware architecture

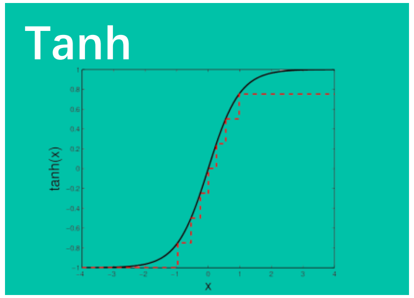


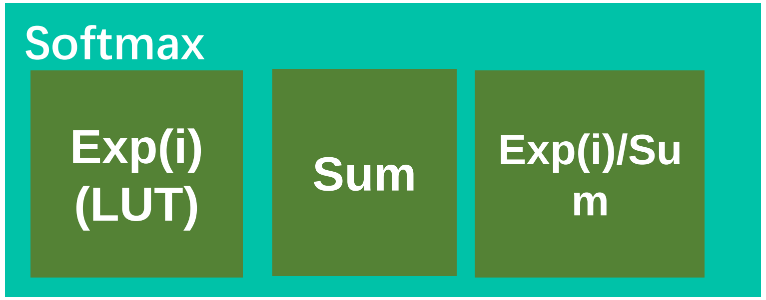
- Input 2D track, track segments and event time pre-processing them to get scaled input for DNN.
- Pre-processing & interface using VIVADO, Core DNN logic using XILINX VITIS

Firmware architecture for DNN TRG







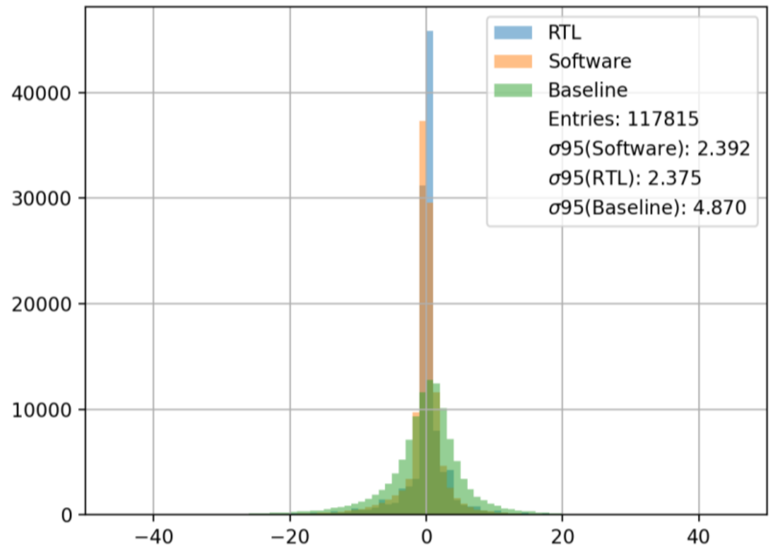


- Using look up table with 18 bits precision for $\exp(x)$ & $\tanh(x)$, refer to the function in hls4ml
- Directly use DSP for Leaky ReLU
- For Dense layer, using specific strategy to fit the requirements (next page)

Performance: Register-transfer level (RTL) simulation

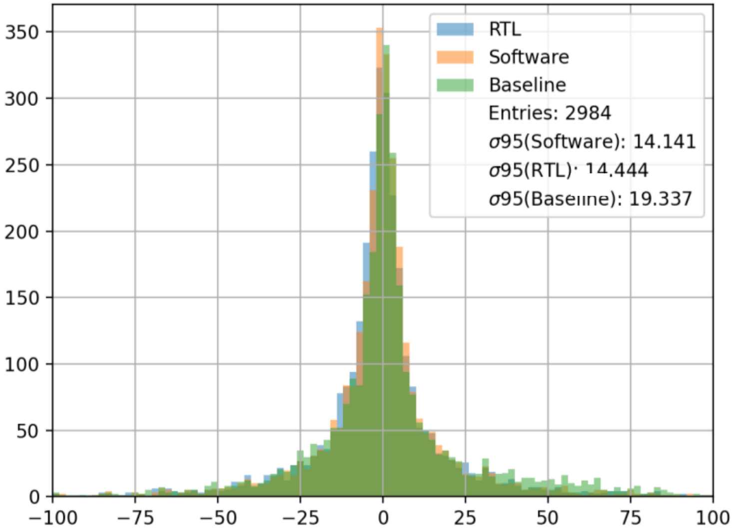
- Performance RTL simulation and comparing performance with pytorch results

track Delta z



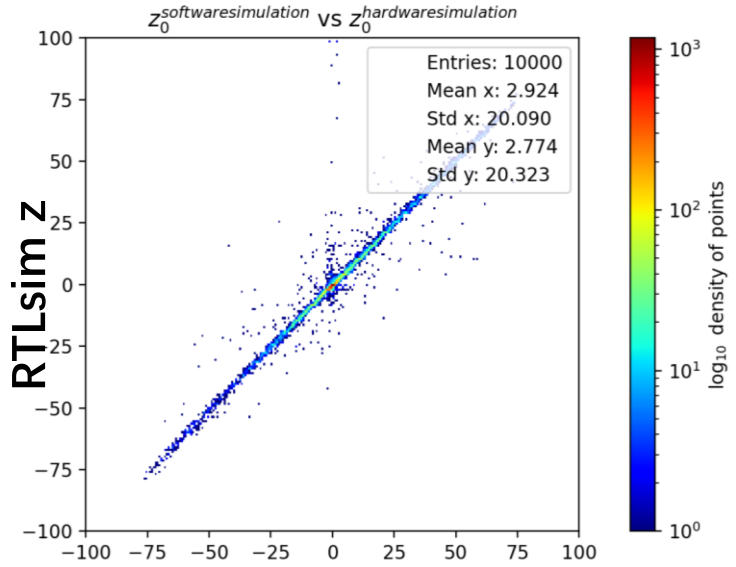
$z_0^{NN} - z_0^{offline}(cm)$

track Delta theta



$\theta_0^{NN} - \theta_0^{offline}(°)$

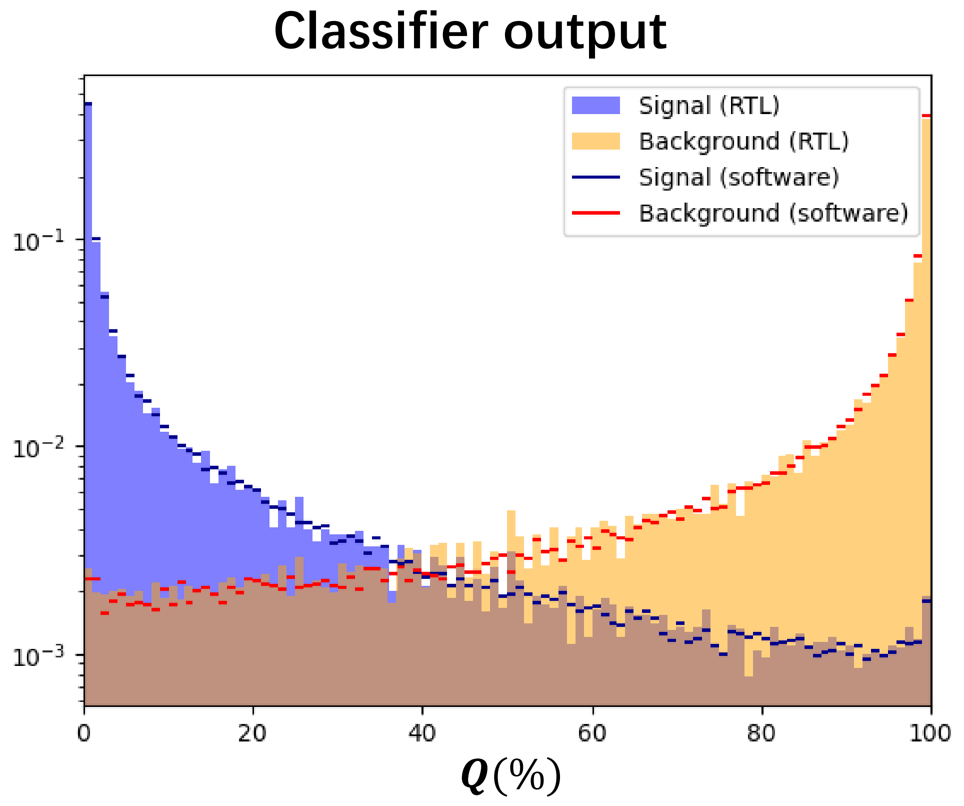
RTL co-sim vs software sim

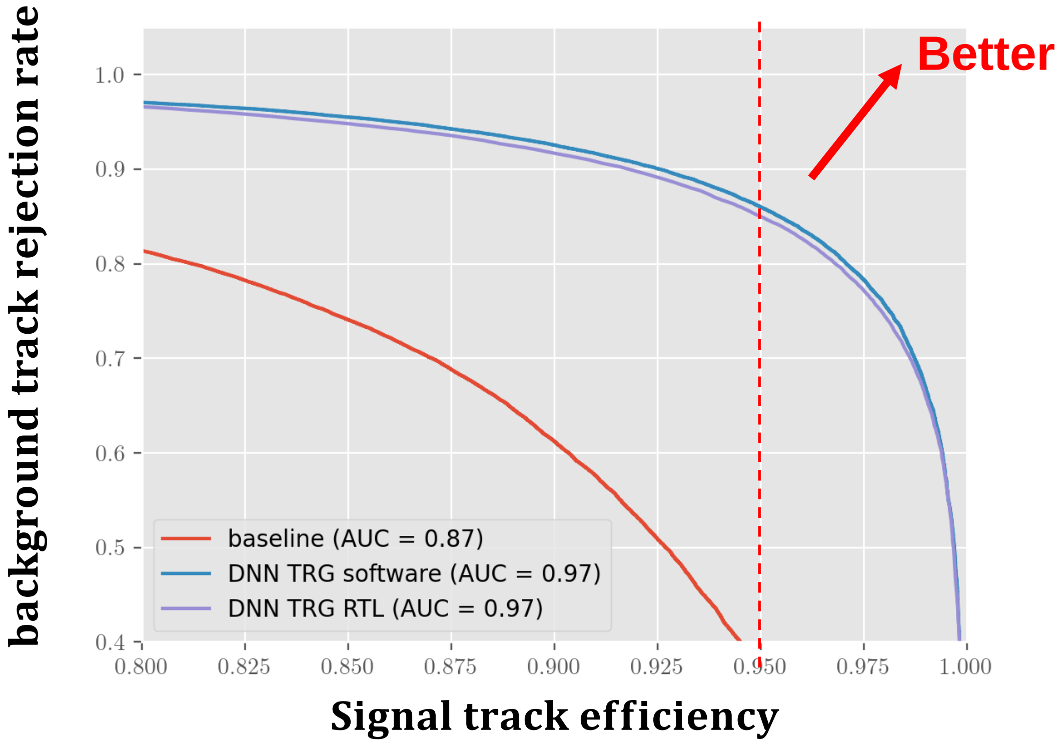


software sim z

- $\boldsymbol{\sigma^{z_0} = 2.4\ cm}$, about ½ as the baseline $\boldsymbol{\sigma^{z_0} = 4.9}$ cm ; and $\boldsymbol{\sigma^{\theta} = 14°}$ (baseline: $\boldsymbol{\sigma^{\theta} = 19°}$)
- RTL and software simulation matched. Reducing precision did not loss the resolution.

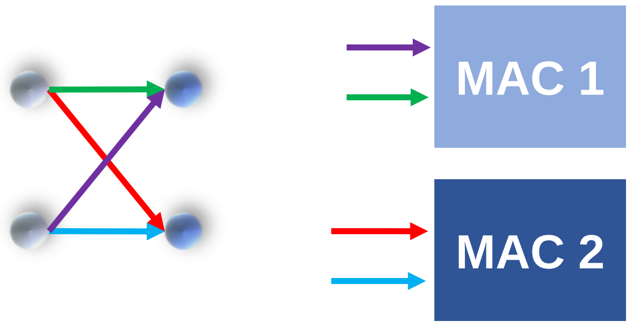
Performance: Register-transfer level (RTL) simulation



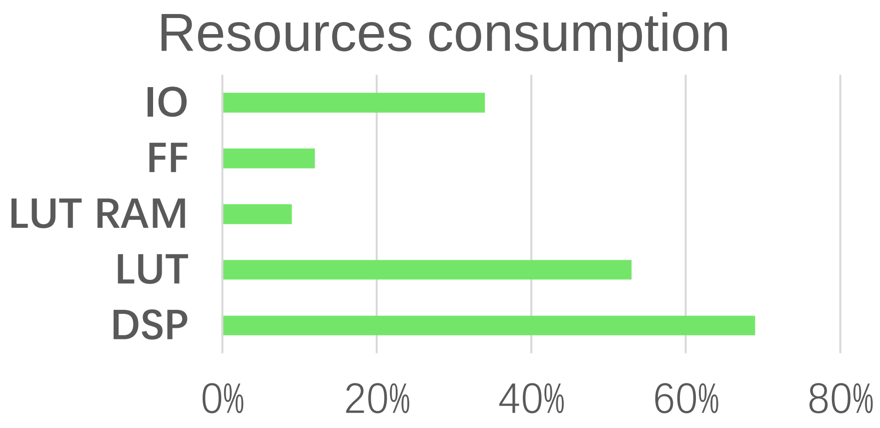


- Q output got consistent with software result
- AUC do not get large drop comparing RTL and software simulation
- At signal track efficiency at ~95% :
  Background rejection rate: **NN track trigger (baseline): 39%; DNN track trigger: 85%**

Implementation result



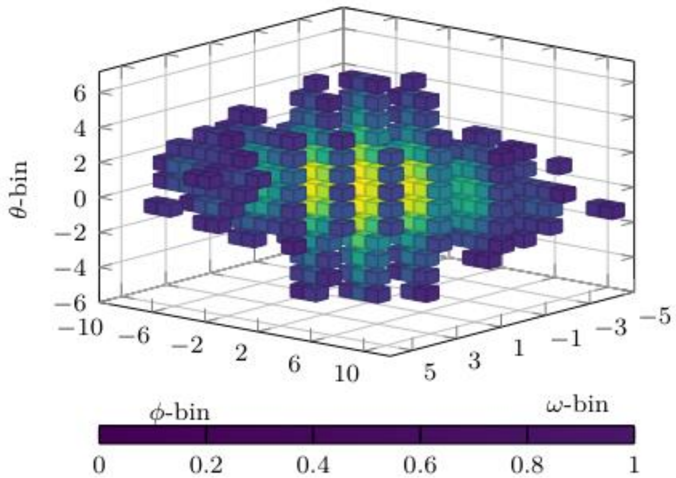
Reuse every multiplier by twice



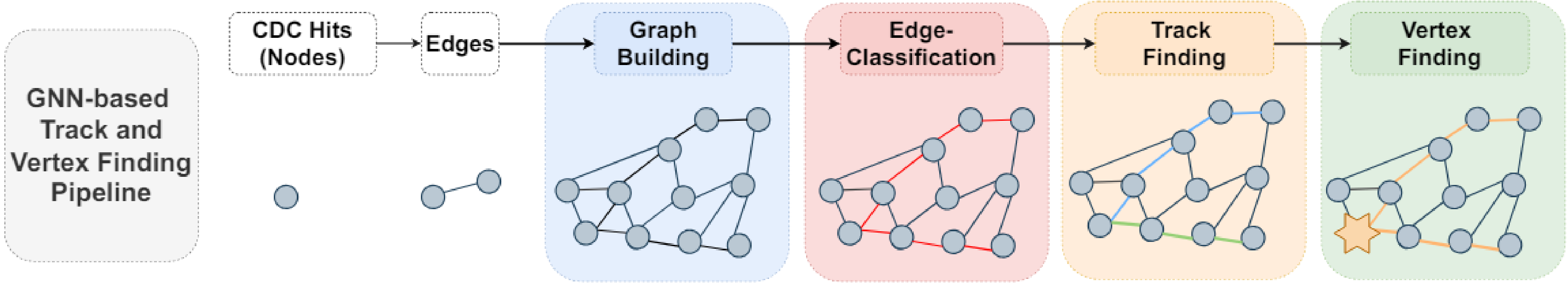
- **4000** multiplier v.s. **1600** DSP
- Using both LUT and DSP to perform Multiply And Accumulate (MAC)
- Reuse each MAC twice.

- Resource matched requirements, not timing violation
- Latency : 76 clock = 592.8 ns ;require: < 600ns
- Pipeline Interval (dead time) = 32ns ;require: 32ns

Next step: 3D Hough and GNN



3D Hough Transformation
$(\boldsymbol{\theta}, \boldsymbol{\phi}, \boldsymbol{\omega})$



GNN track finding

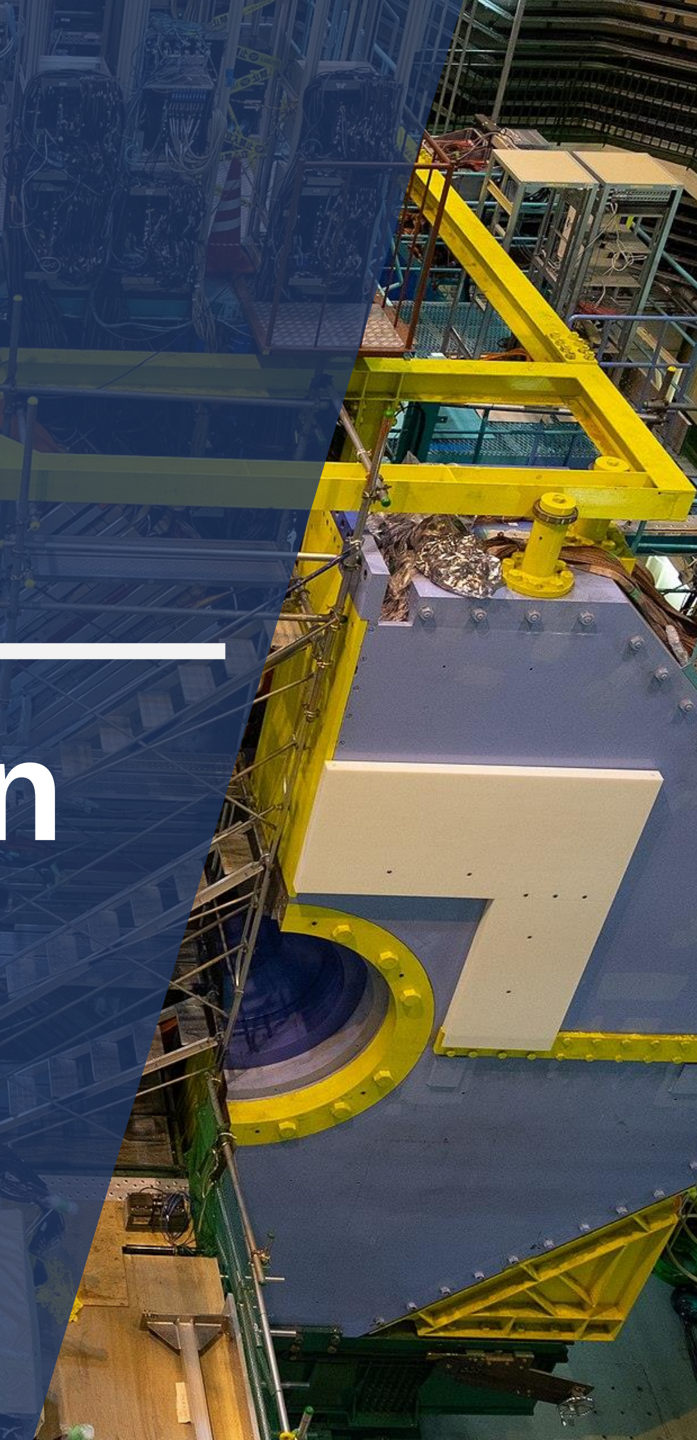
Summary

- The upgrade of Belle II first level track trigger is on-going
- We examined the performance for upgrade trigger with both software and RTL simulation, and achieved a 2.2 times background rejection rate improvement.
- We successfully implemented the DNN track trigger with UT4 module and fulfill the requirements with latency ~ 600ns and II ~ 4 clock.
- We are working on the commission work for the DNN track trigger

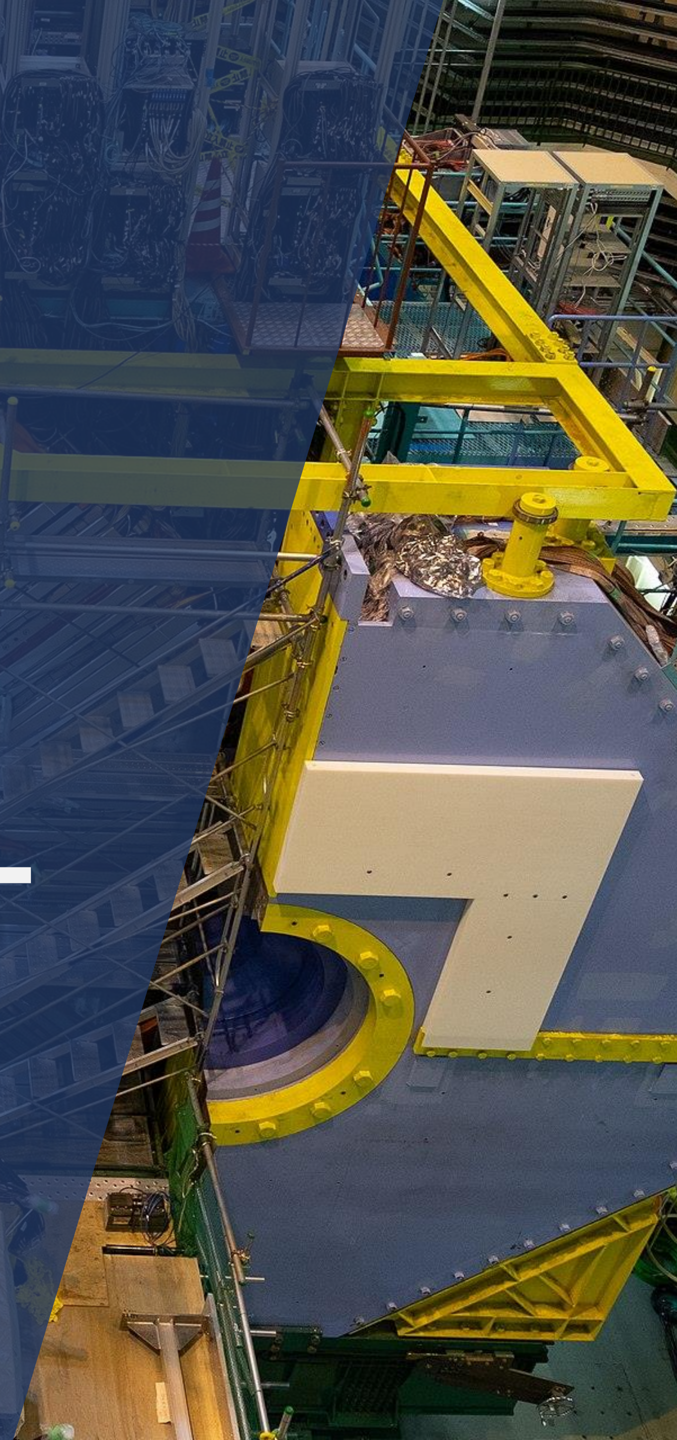
Next Step

- 3D Hough transformation and GNN

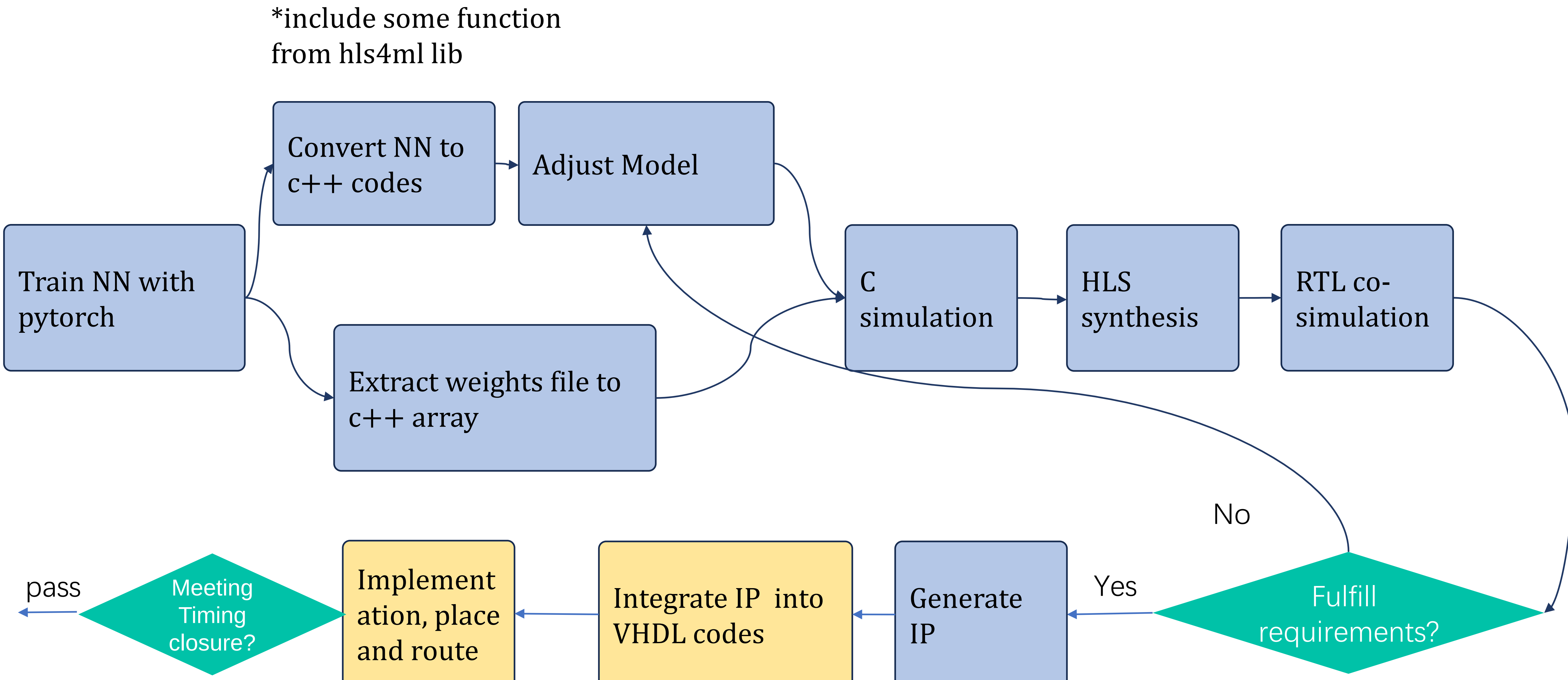
Thanks for your attention



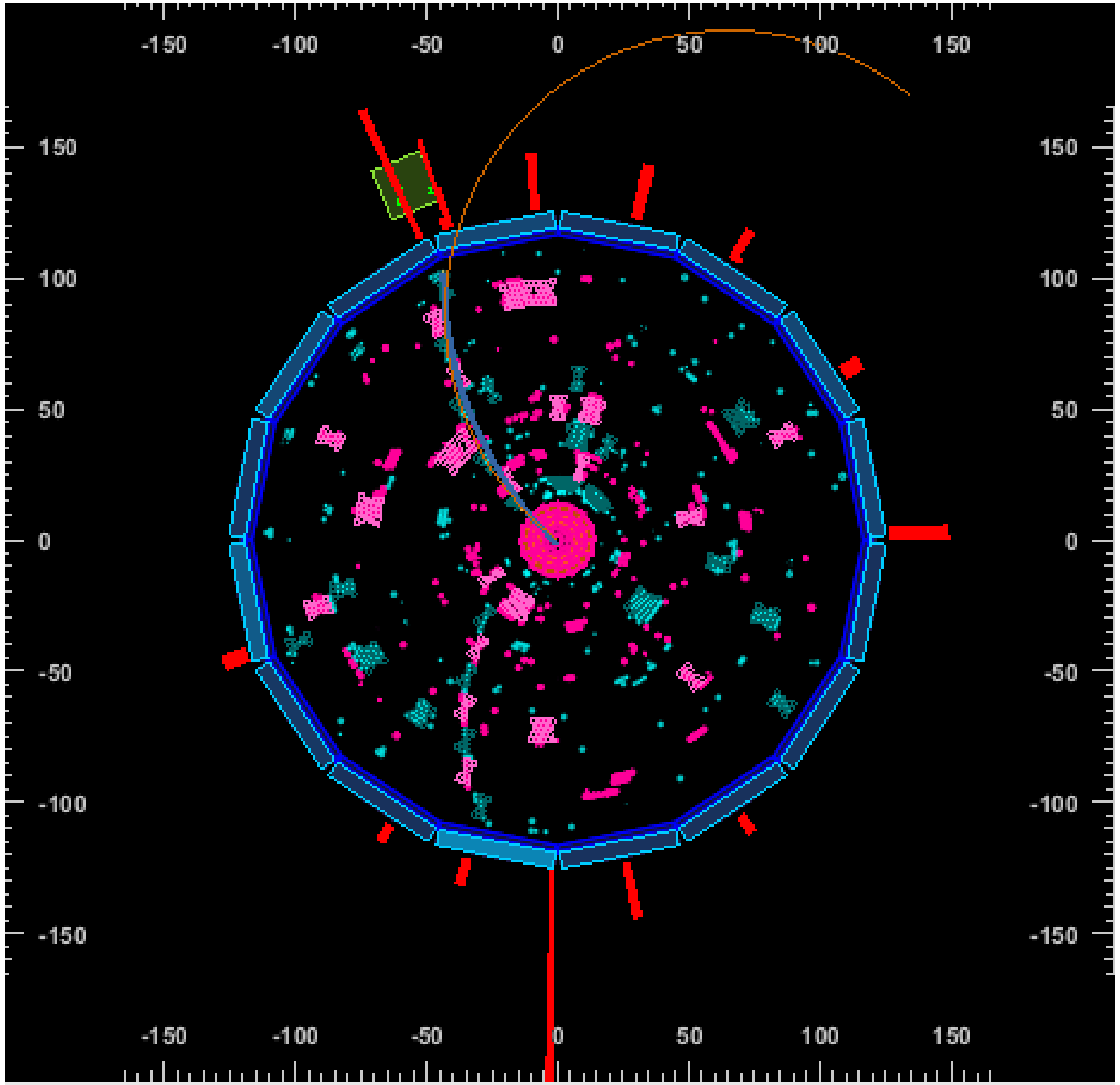
Backup



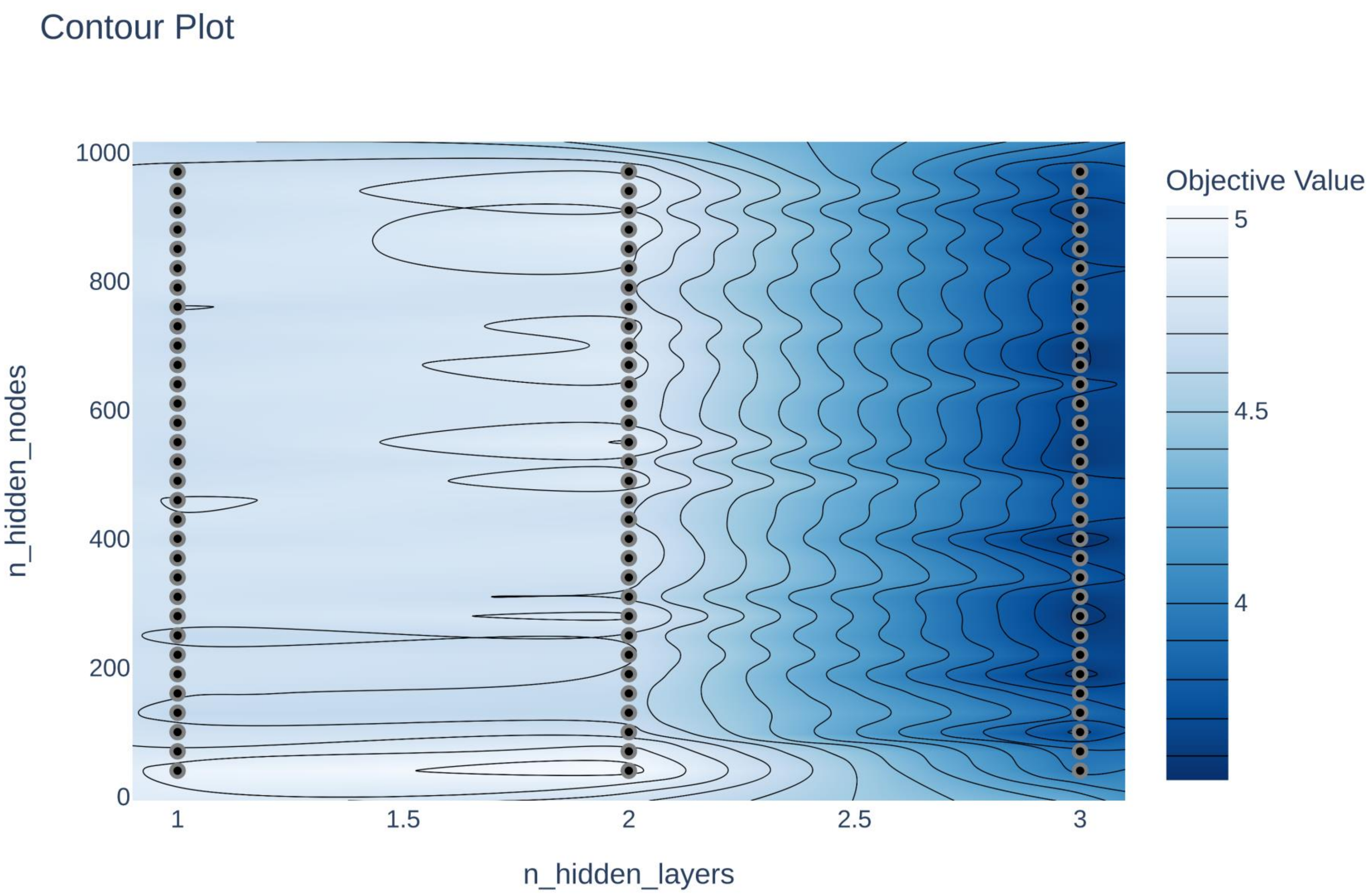
Workflow with HLS



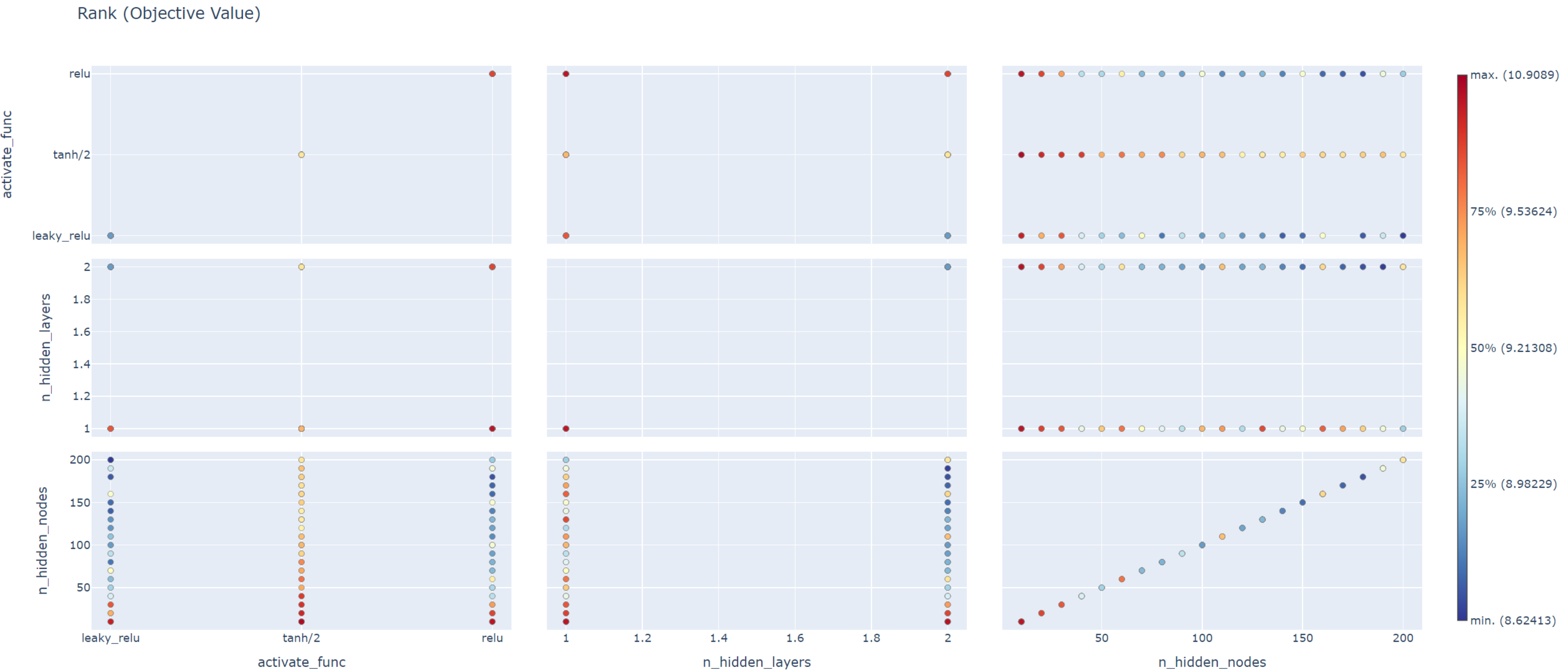
General physics events shape



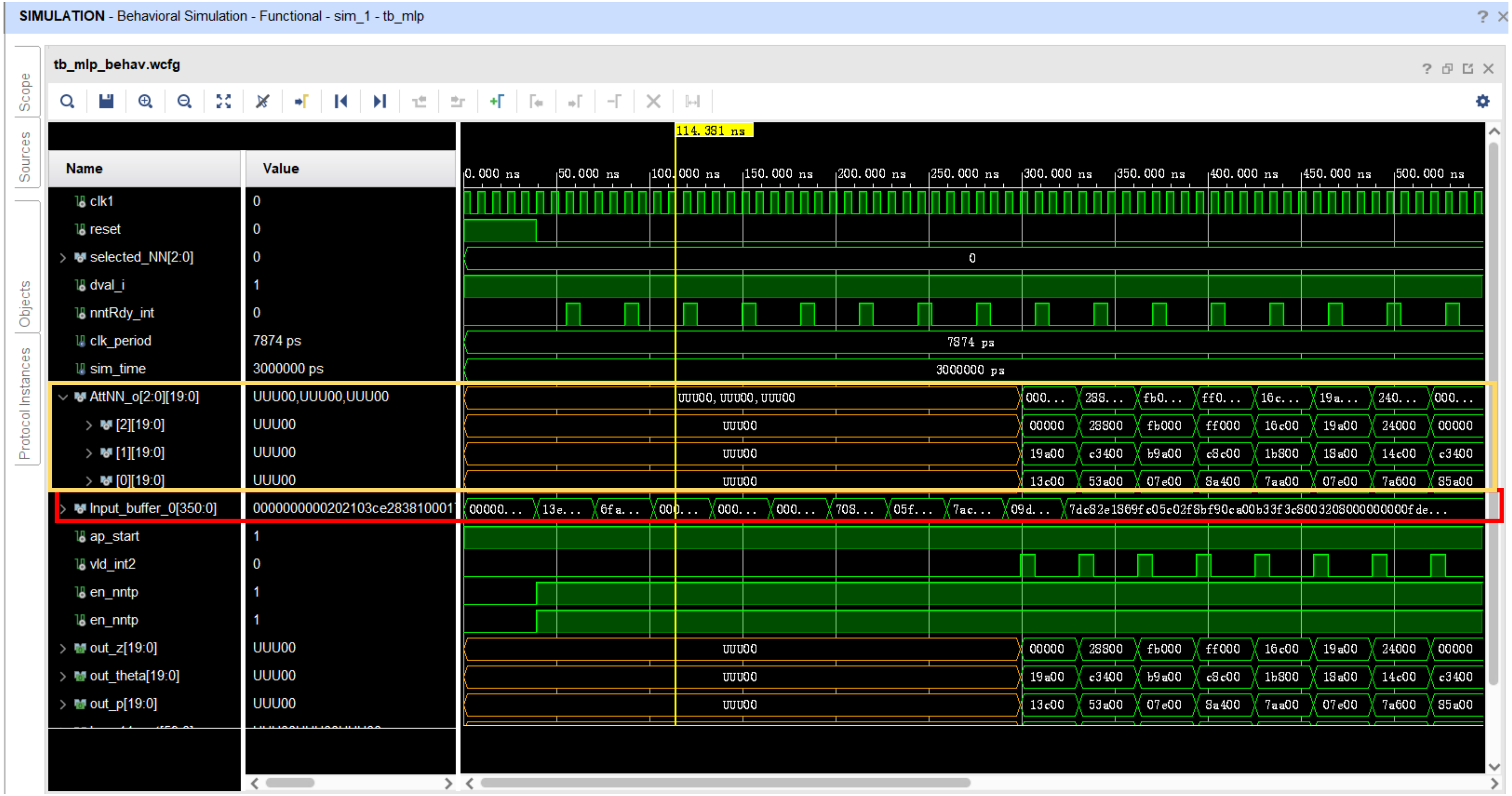
Depth is much more powerful than width



Optimization for Self-attention MLP



Core Logic vivado simulation pass

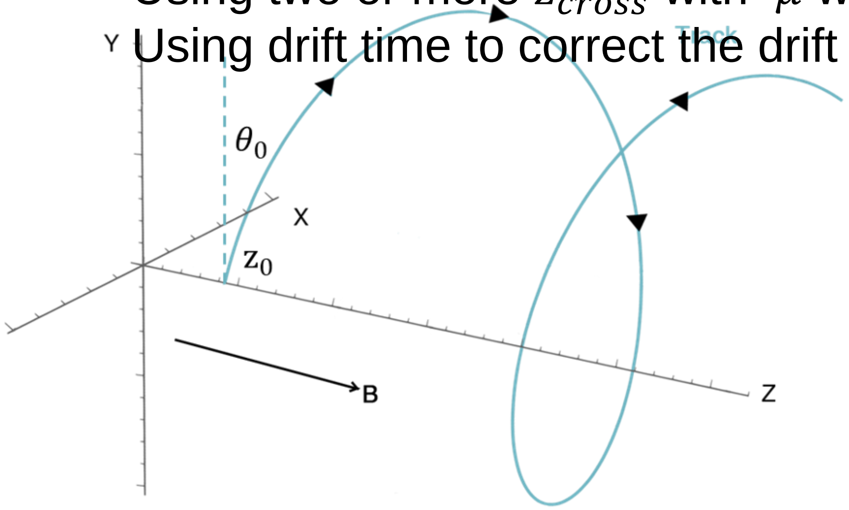


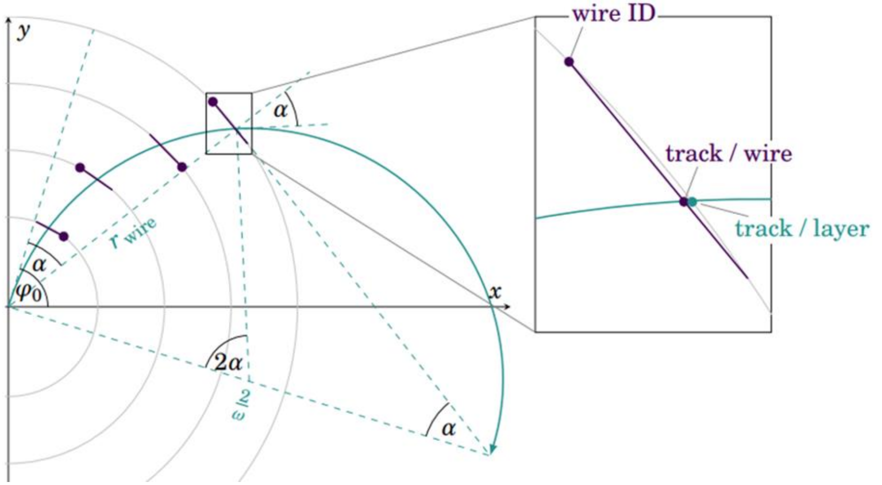
Output: after ~600ns

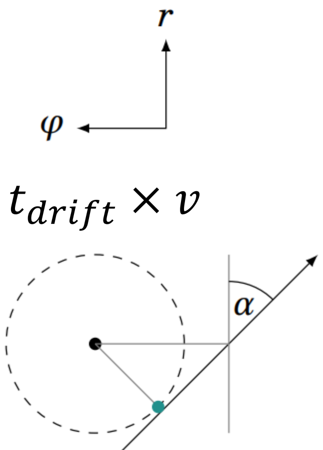
Input: every 4 clock a new input

Introduction CDC trigger - 3D reconstruction

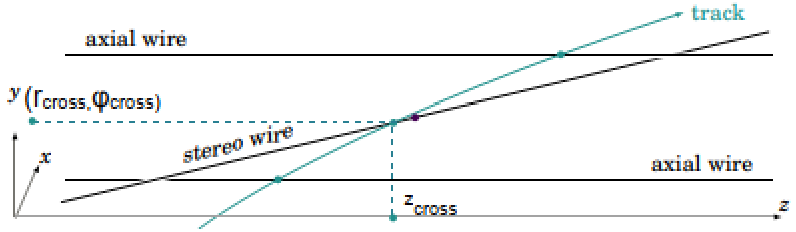
Only θ_0 and z_0 remain unknown for 3D tracks.
With Crossing angle ϕ_{cross} for stereo wire we can get z_{cross} .
Using two or more z_{cross} with μ we can fit the linear track in $\mu - z$ plane and obtain θ_0 and z_0.
Using drift time to correct the drift distance.







Drift correction



$$\begin{pmatrix} x(\mu) \\ y(\mu) \\ z(\mu) \end{pmatrix} = \begin{pmatrix} r \cdot (\sin(\mu/r - \phi_0) + \sin\phi_0 + x_0) \\ r \cdot (\cos(\mu/r - \phi_0) - \cos\phi_0 + y_0) \\ \cot\theta_0 \cdot \mu + z_0 \end{pmatrix}$$

Requirement for new developed NN

Parameters	Target
z_0 resolution at IP (σ_{95}^{IP})	<2 cm
Trigger efficiency	>95%
Extra background rejection rate	>50%

- Reduce the z_0 resolution for signal track to less 2 cm
- Keep same efficiency as before (>95%) and restrict cut to reject further half of background events, which were kept by current trigger.

	CDC $B\overline{B}$ bits	CDC τ & dark bits
Current CDC Background raw trigger rate	2.15 kHz	1.91 kHz
Required CDC Background raw trigger rate	1.07 kHz	0.9 kHz

- New NN algorithm can be implemented on new universal trigger board (called UT4) ,which has about 4 times more logic gates than previous one.

Performance evaluation – Training, validation and testing sample

Data sample generate from special physics run data taken without HLT trigger.

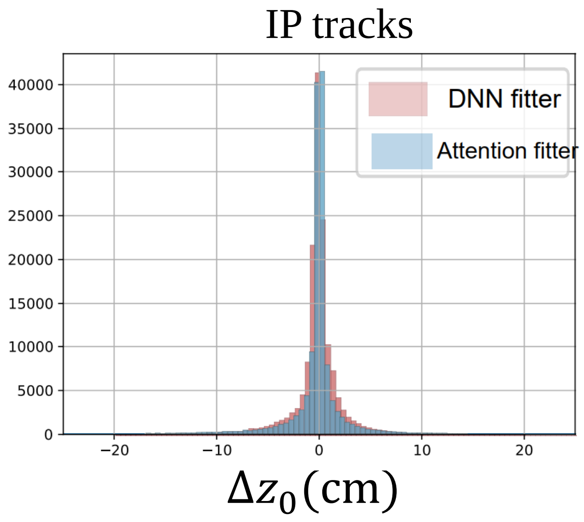
Target z_0 and θ_0 of Tracks are got from offline reconstruction and fed for training

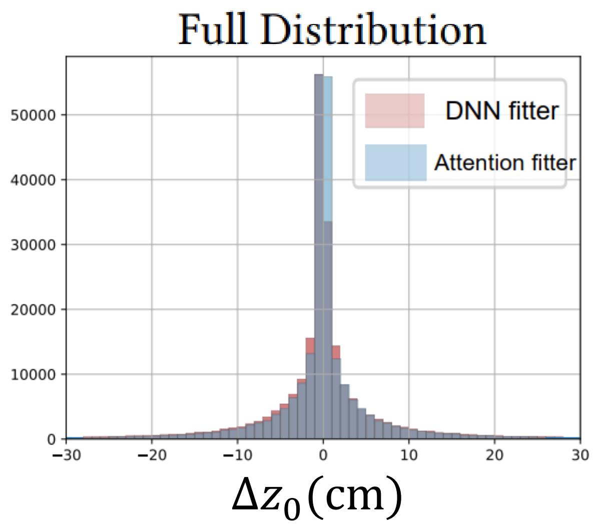
Randomly separate full sample in training validation and test:

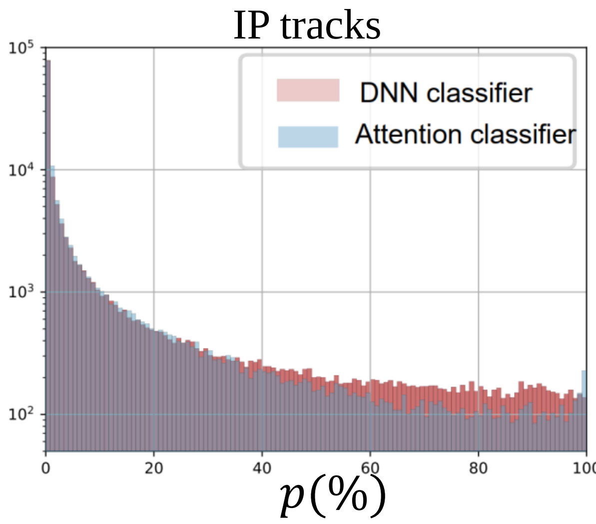
	#Signal Tracks	# Off-IP Tracks	#Fake Tracks
Training sample	935K	284K	0
Validation sample	282K	85K	0
Test sample	180k	53k	87k

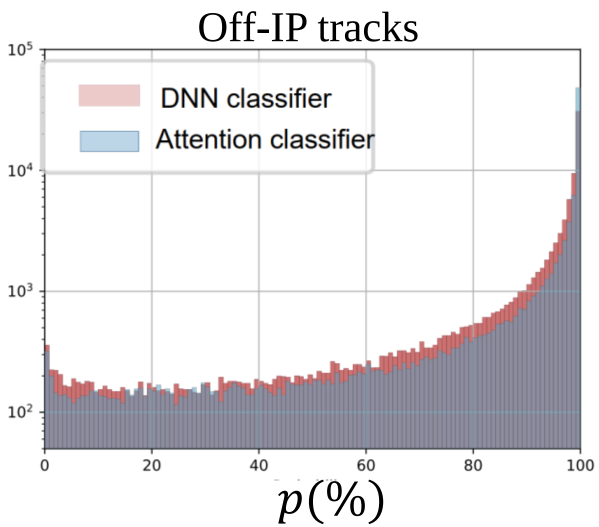
Fake tracks are only included in test sample -- No target z_0 and θ_0

Performance evaluation – Attention based NN









	Cut	σ_{95}^{IP} (cm)	signal track efficiency (%)	off-IP track reject rate(%)
Neurotrigger	$\lvert z_0^{NN}\rvert < 15$	5.53	93.5	52.0
DNN fitter	$\lvert z_0^{NN}\rvert < 15$	2.34	97.5	56.7
Attention fitter	$\lvert z_0^{NN}\rvert < 15$	**1.84**	**97.8**	**59.4**
DNN classifier	$p < 65$	/	95.1	84.4
Attention classifier	$p < 65$	**/**	**96.6**	**86.2**

6%↑

12%↑

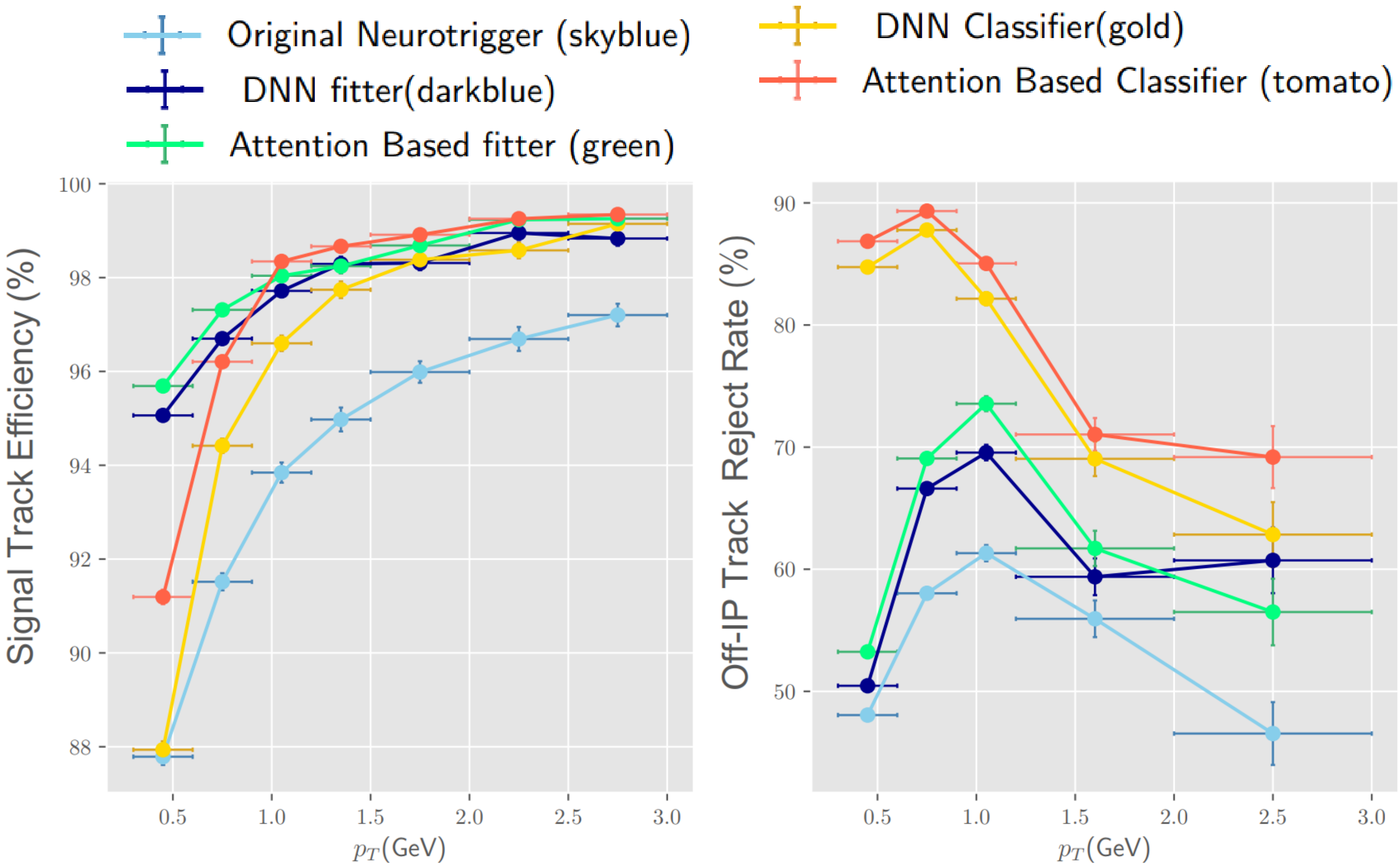
Attention NN gain 0.5 cm IP resolution and ~12% reject rate improvement comparing with DNN

Performance evaluation – Transverse momentum dependency

Check the efficiency and reject rate dependency of Transverse momentum (p_T)

Cut: $p < 65$ OR $|z_0^{NN}| < 15$

- **All new model have better efficiency & reject rate at any p_T**
- **Classifiers improve low p_T reject rate by 30%, while have lower efficiency comparing with fitters**



Performance evaluation – Fake track

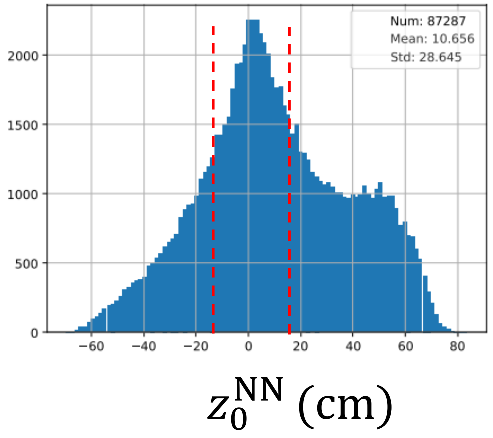
Classifiers can identify fake track well which mainly **concentrate at $p \sim 100$**

For **Fitters**, Fake track have a certain z_0^{NN} distribution **centering at ~0**.

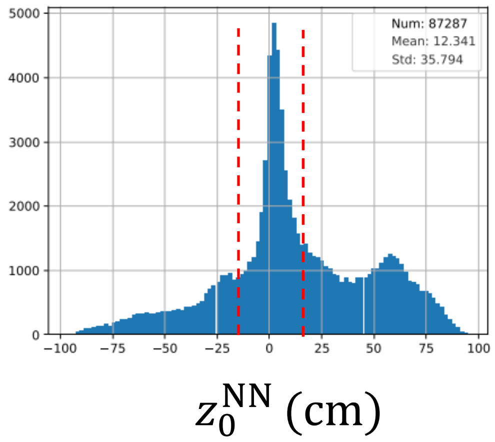
With Cut: $p < 65 \text{ OR } |z_0^{NN}| < 15$

	Fake tracks reject rate
Original Neurotrigger	60.4%
DNN fitter	58.5%
Attention based fitter	59.8%
DNN classifier	68.5%
Attention based classifier	66.5%

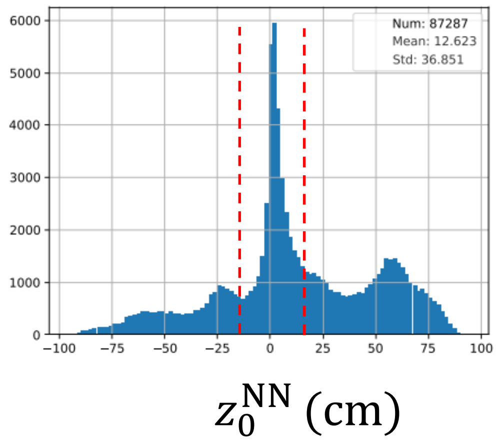
Original Neurotrigger



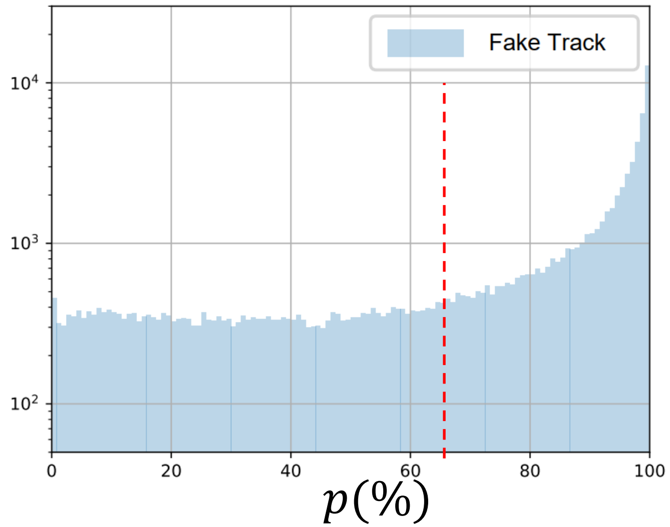
DNN fitter



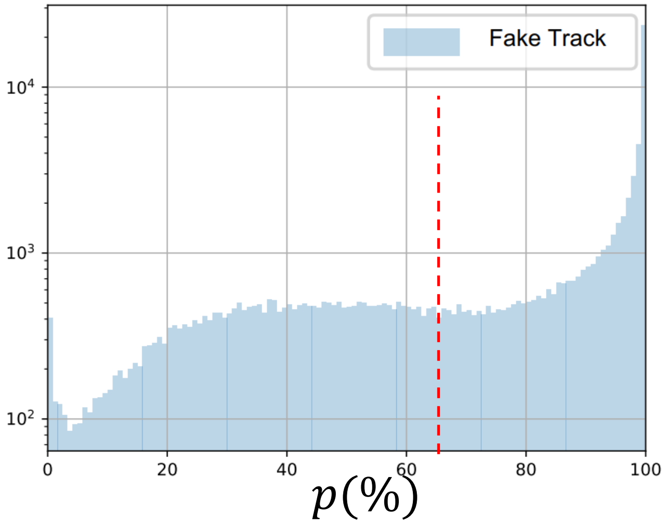
Attention based fitter



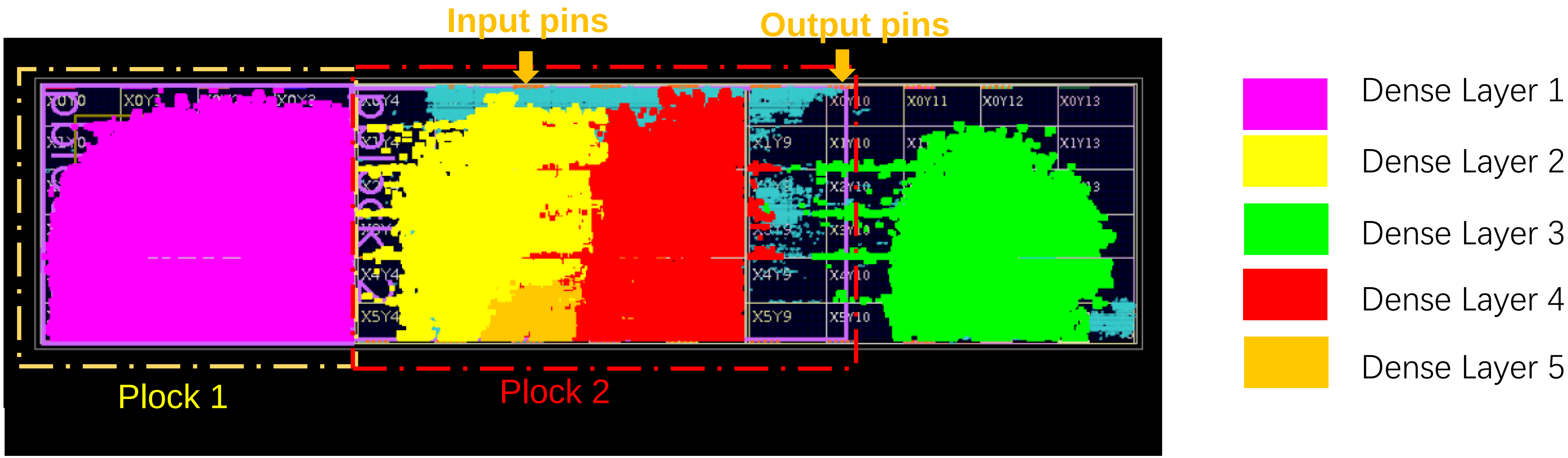
DNN classifier

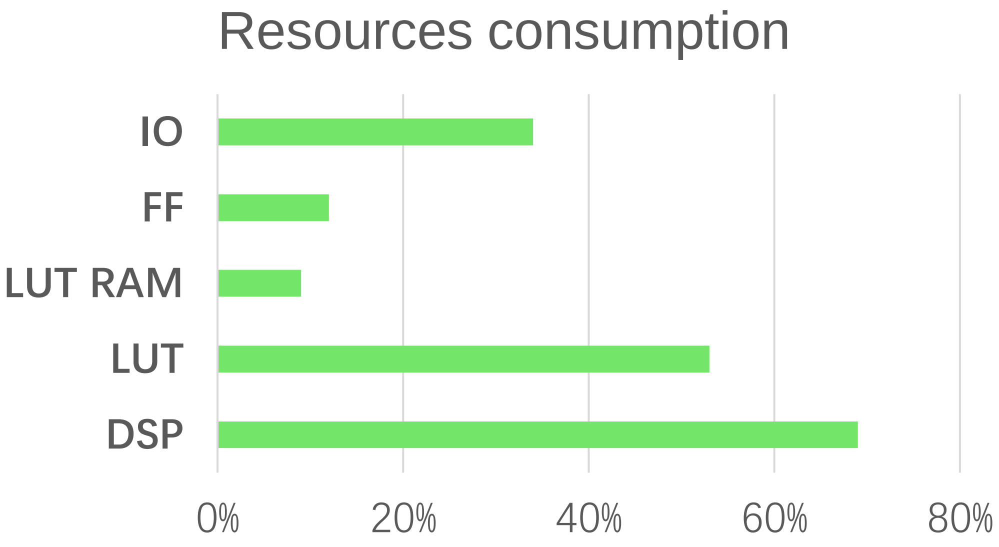


Attention based classifier



Floor planning and Implementation result





- Floor planning the dense layers :
- Resource matched requirements, not timing violation
- Latency : 76 clock = 592.8 ns ;require: < 600ns
- Initial Interval = 4 clocks ;require: 4 clocks