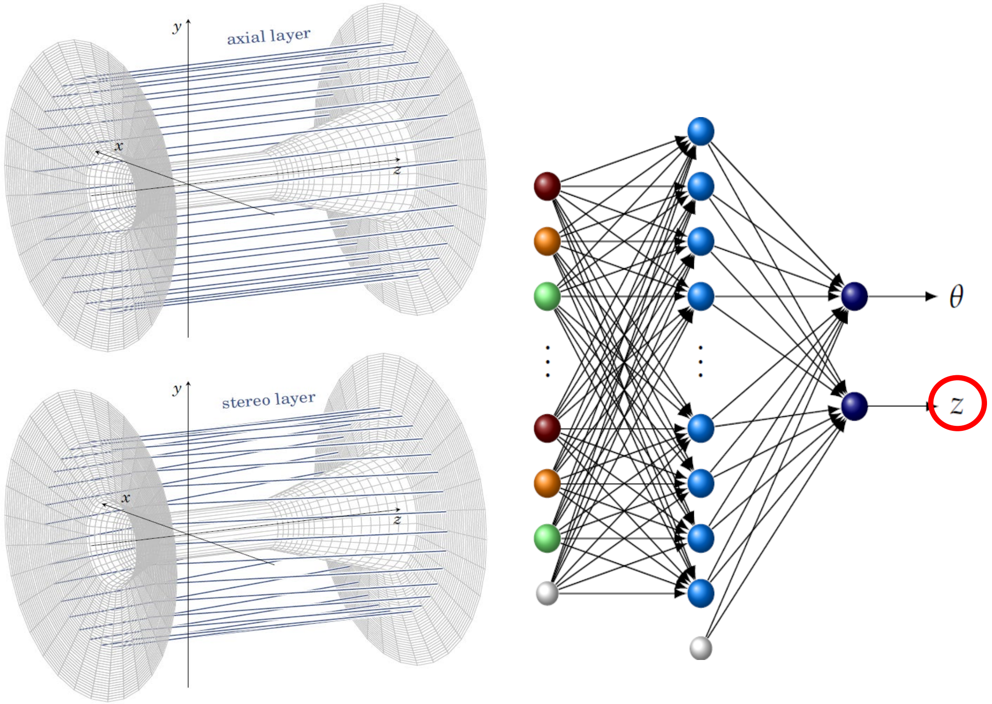
The Neural Network First-Level Hardware Track Trigger of the Belle II Experiment

Christian Kiesling
Max-Planck-Institute for Physics

Overview:

- SuperKEKB & Belle II‘s „Conventional“ Track Trigger
- Principles of the Neural Approach to Track Triggers
- Physics-motivated Preprocessing of Input Variables
- Performance of the Neural Track Trigger
  -> Launch of a Minimum Bias Single Track Trigger (STT)
- Problems and Solutions -> Upgrade program
- Summary and Conclusions

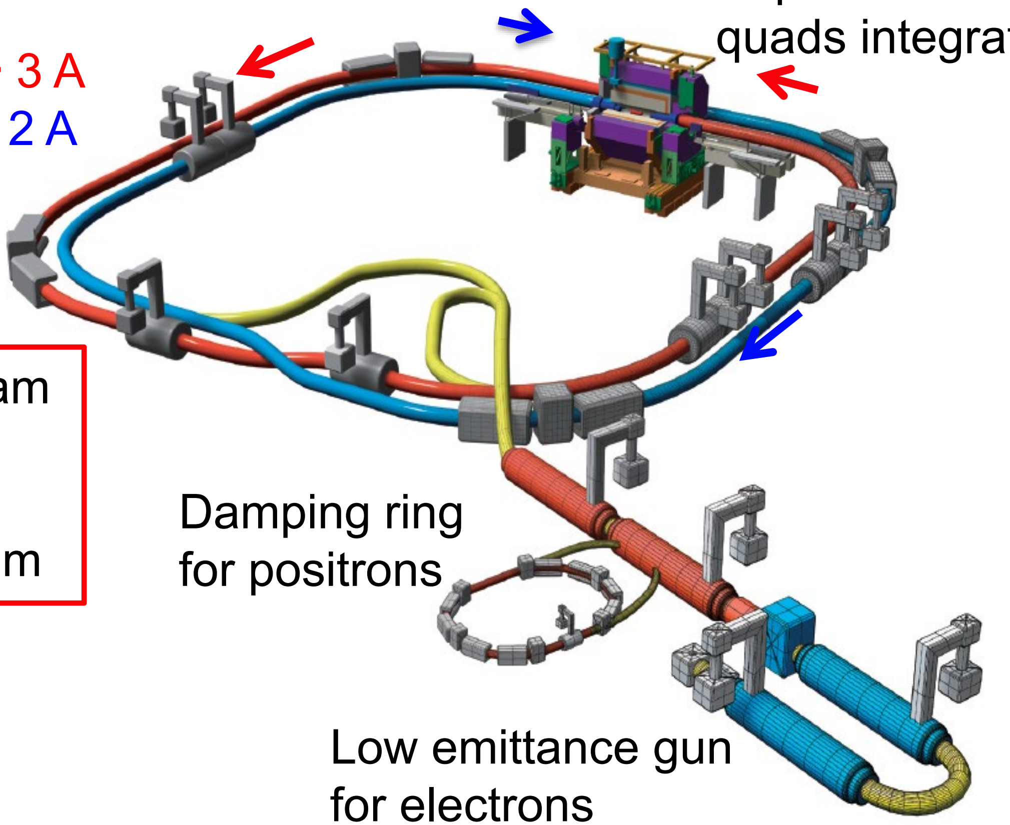


SuperKEKB & Belle II

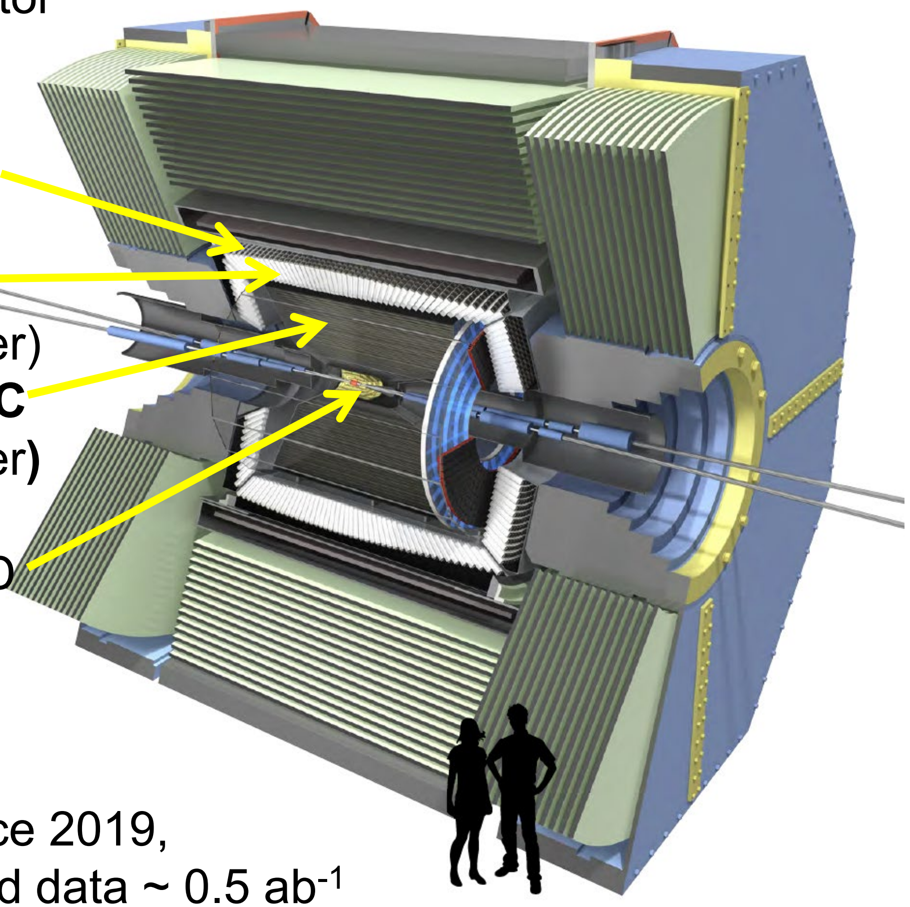
e^+ 4GeV ~ 3 A
e^- 7GeV ~ 2 A

Nano-beam scheme:

σ_y ~ 50 nm



target $\mathcal{L}$ = 6x10^{35}/cm^2/s

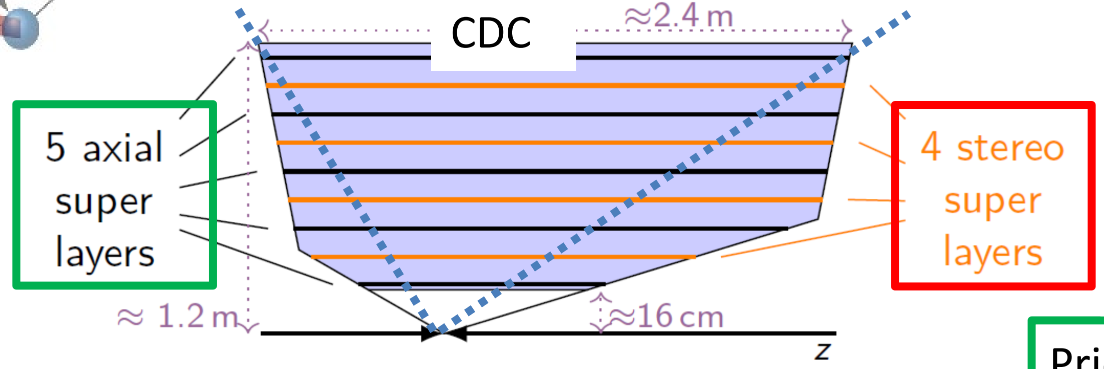


running since 2019,
accumulated data ~ 0.5 ab^{-1}

peak luminosity $\mathcal{L}$ = 4.7 x 10^{34} /cm^2/s
I(e^+ / e^-) = (1.4/1.2 A) , β^* = 1 mm

located @ KEK, Tsukuba, Japan

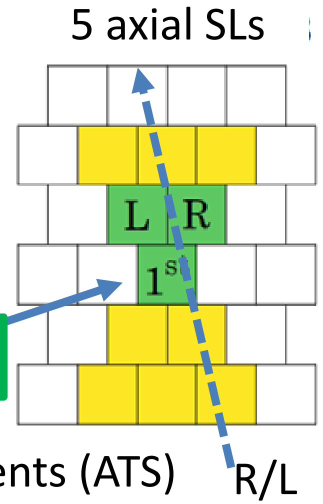
The „Conventional“ Belle II L1 Track Trigger („2D“)



- 56 layers combined to 9 super layers (SL)
- 2336 track segments (TS) in 9 SL

Track Segments:
Hit patterns compatible with traversing track (LUT)

Priority wire = „hit“



Axial track segments (ATS)

L1 Pipeline

CDC front end

Track Segment Finder (TSF)

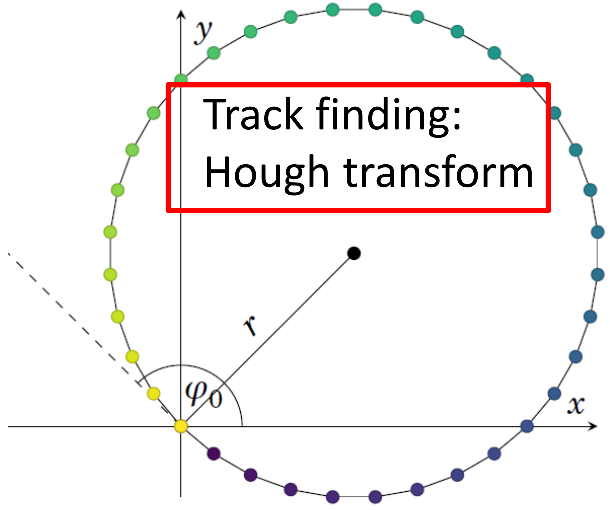
HoughTransform + peak finding

Global Decision Logic (GDL)

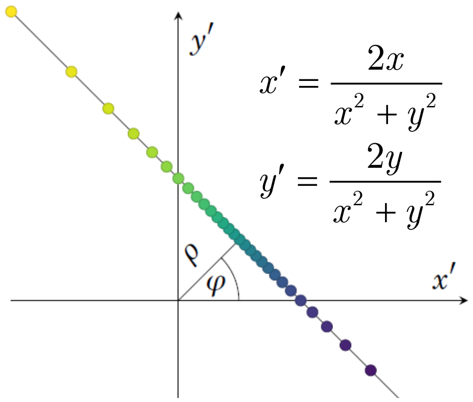
5µs

algos on FPGA boards „UT(3)“
Virtex 6 XC6VHX380/565T

geometrical space → conformal space → parameter space



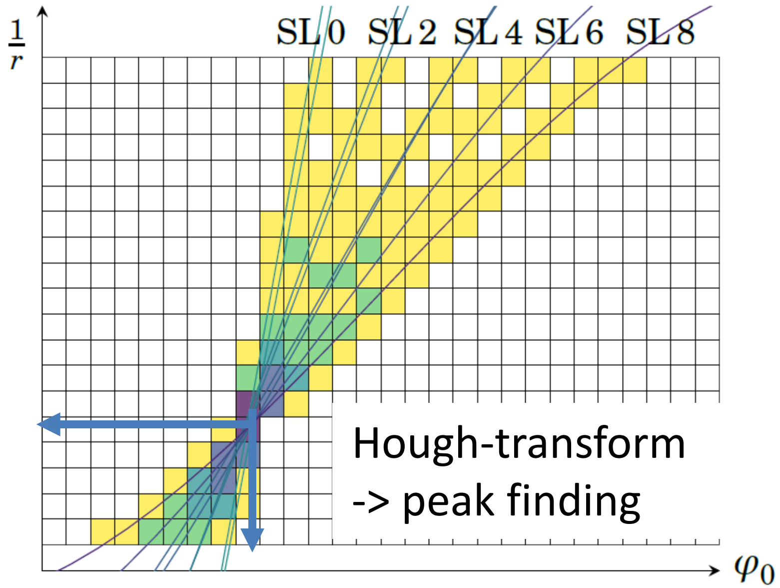
Tracks from IP by definition



$$x' = \frac{2x}{x^2 + y^2}$$

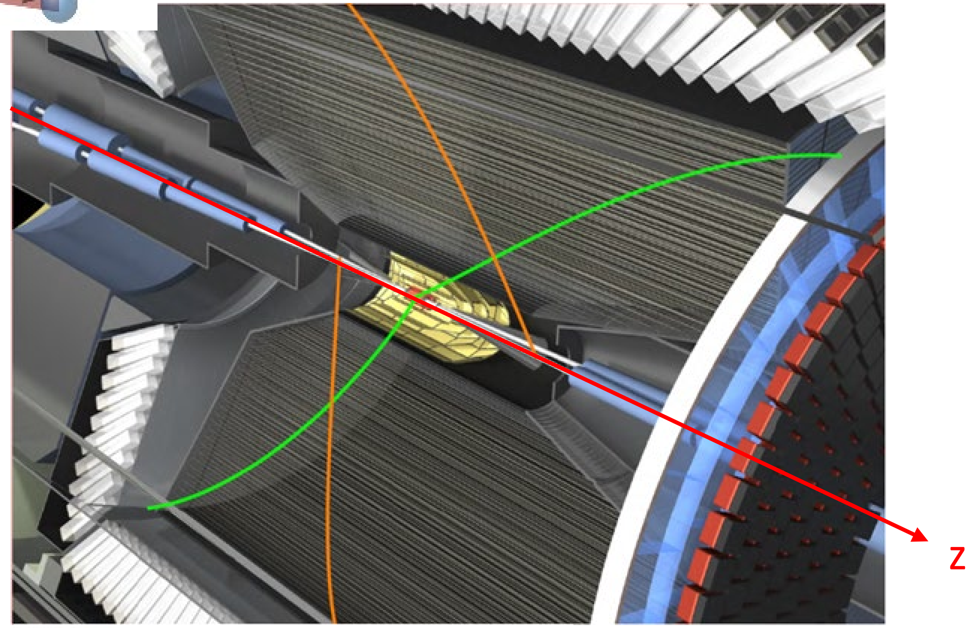
$$y' = \frac{2y}{x^2 + y^2}$$

Each {hit + IP} produces a set of [1/r, ϕ] points, basically on a straight line

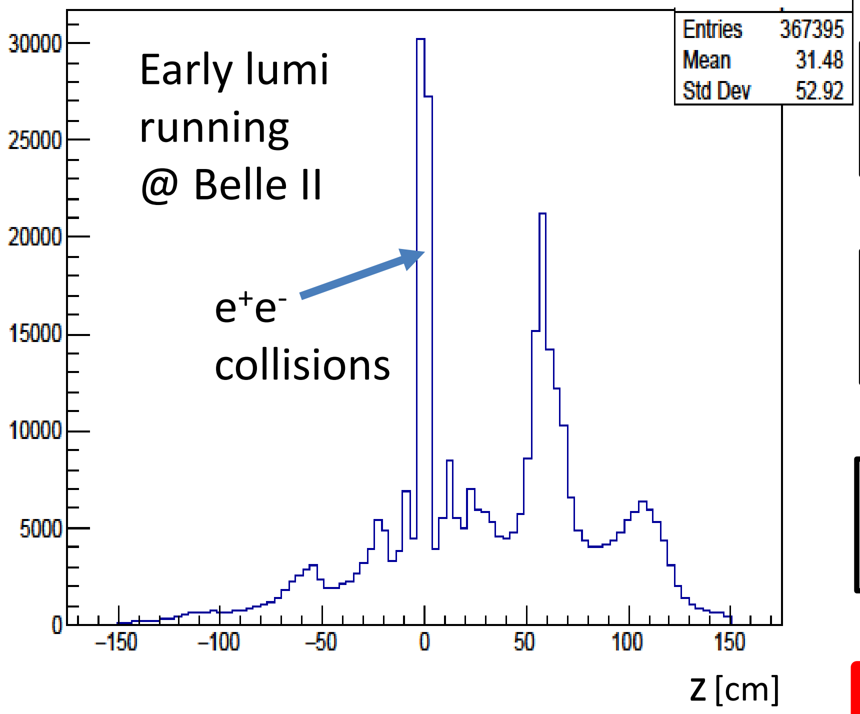


Hough-transform
-> peak finding

Challenge of the Conventional Track Trigger



z-vertex distribution (offline) :



L1 Pipeline

CDC front end

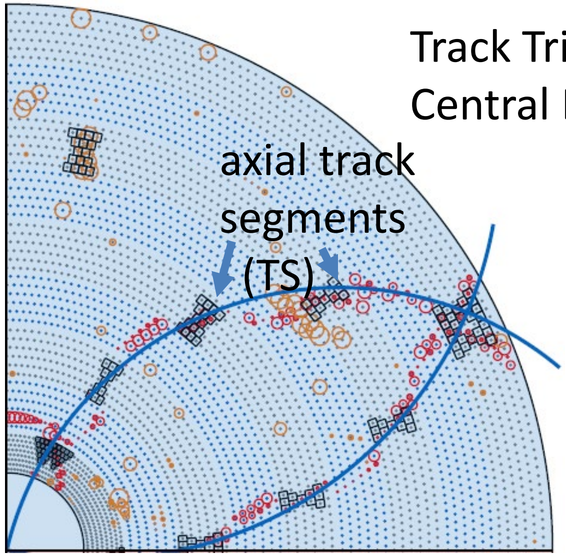
Track Segment Finder (TSF)

Hough transform „2D tracks“

3D track fit:
iterative process
- Latency ??
- precision ??

-> Machine Learning

5µs



Track Trigger derived from Central Drift Chamber:

Belle II:
Initially, track trigger only in 2D, using Hough transforms

2D tracks >= 2

Majority of tracks from „obstacles“ outside of the interaction region (IP) (|z| >> 1 cm): only ~10% from IP

→ „z-vertex“ trigger mandatory

AI Trigger Group at Belle II

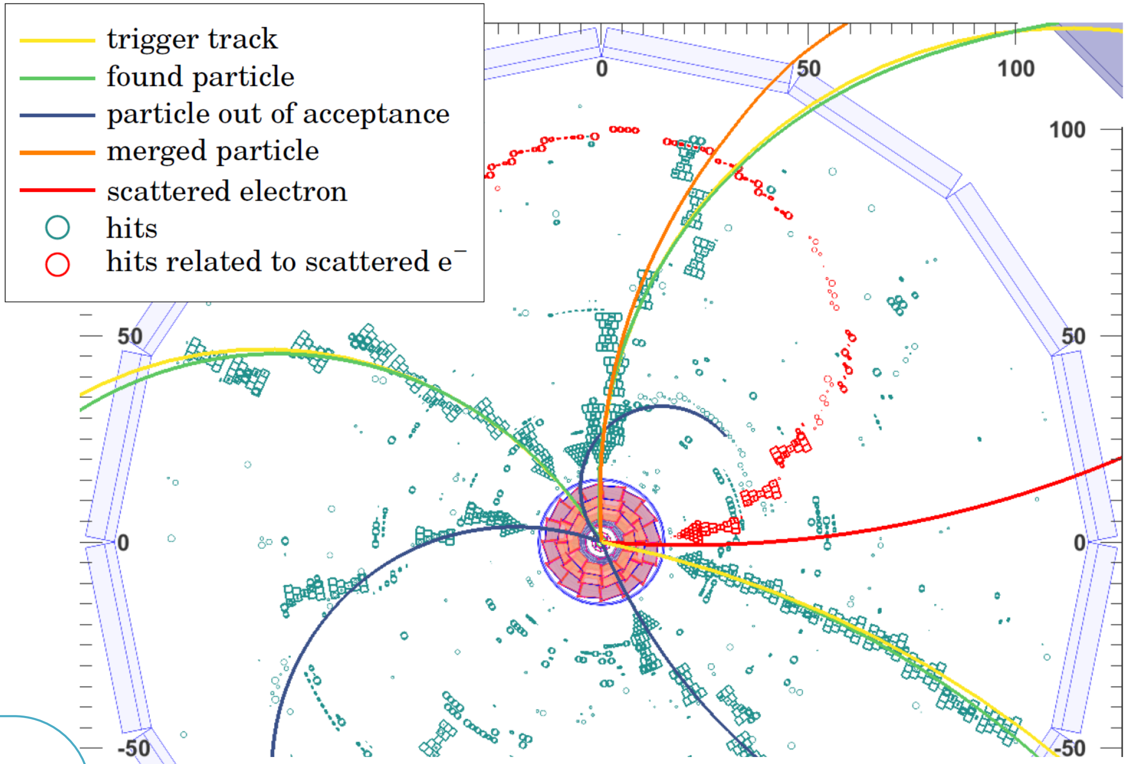
KIT ITIV
- Marc Neu
- Kai Unger
- **Jürgen Becker**

Institut für Experimentelle Teilchenphysik

KIT ETP
- Lea Reuter
- Greta Heine
- Slavomira Stefkova
- **Torben Ferber**

MAX-PLANCK-GESELLSCHAFT

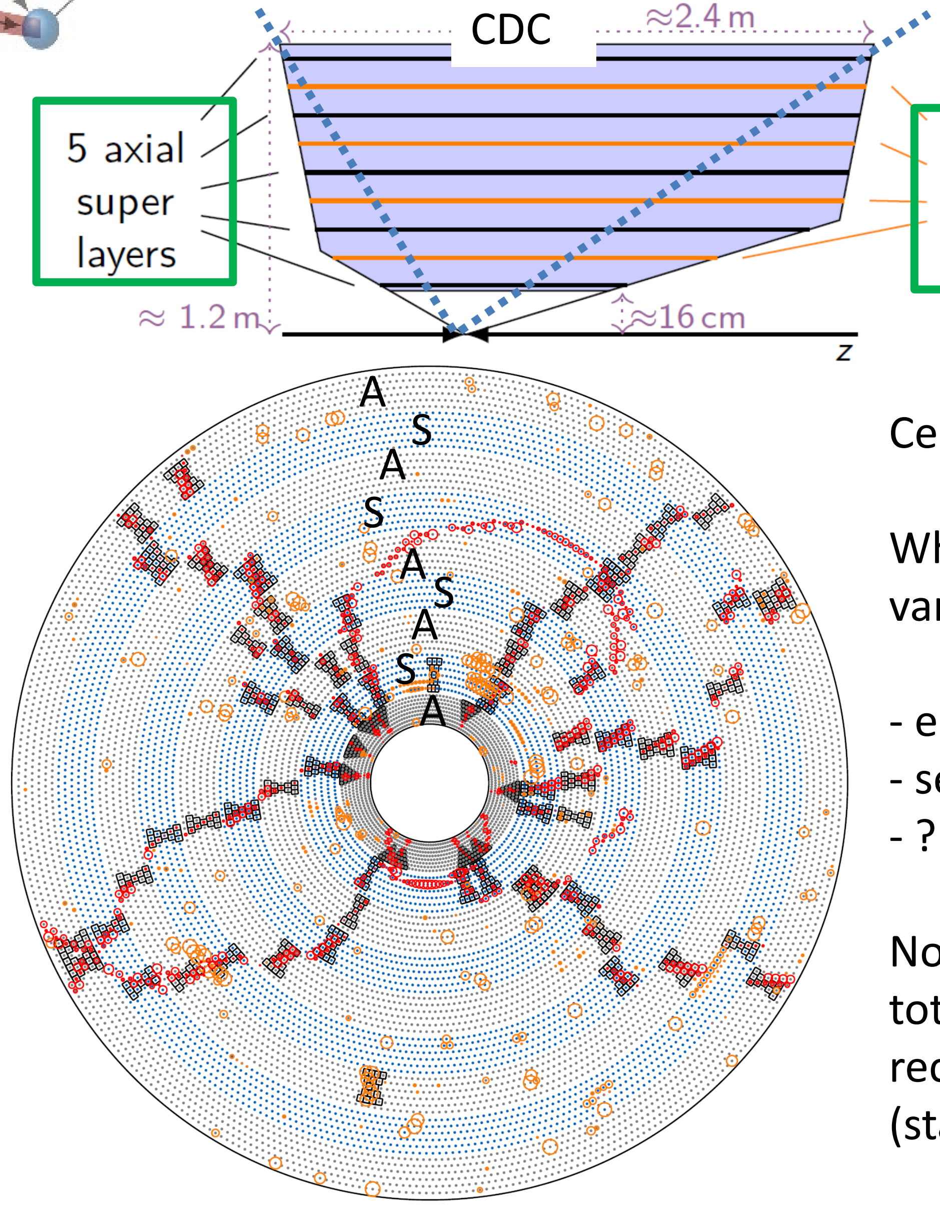
MPI / LMU / TUM
- Felix Meggendorfer
- Simon Hiesl
- Timo Forsthofer
- **Christian Kiesling**
- Alois Knoll



Projects:
Machine learning methods for triggering
-> calorimeter (ECL)
-> tracker (CDC)

here: Neural Network „z“ Trigger @L1

Principle of the Neural L1 Track Trigger



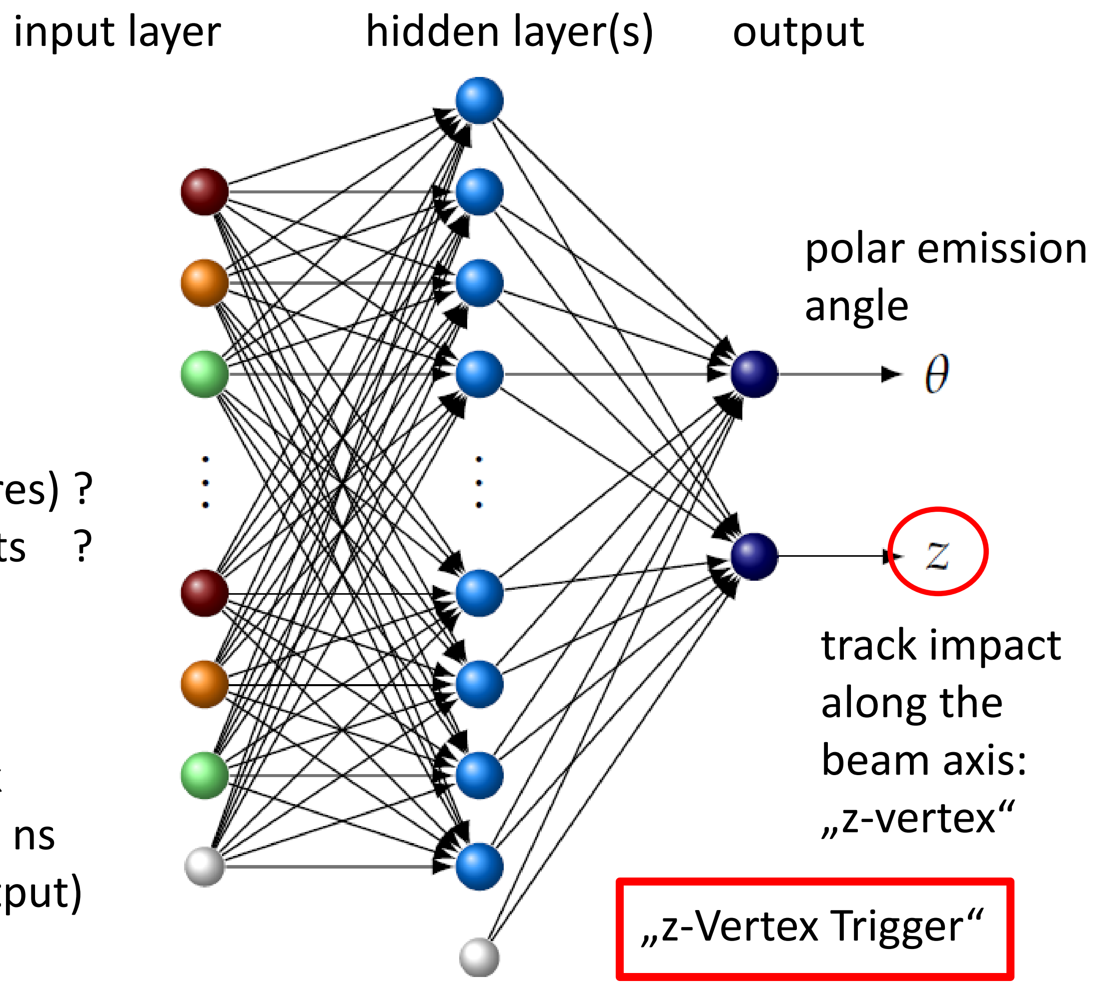
Central question:

What are the input variables:

- entire „picture“ (wires) ?
- set of track segments ?
- ?

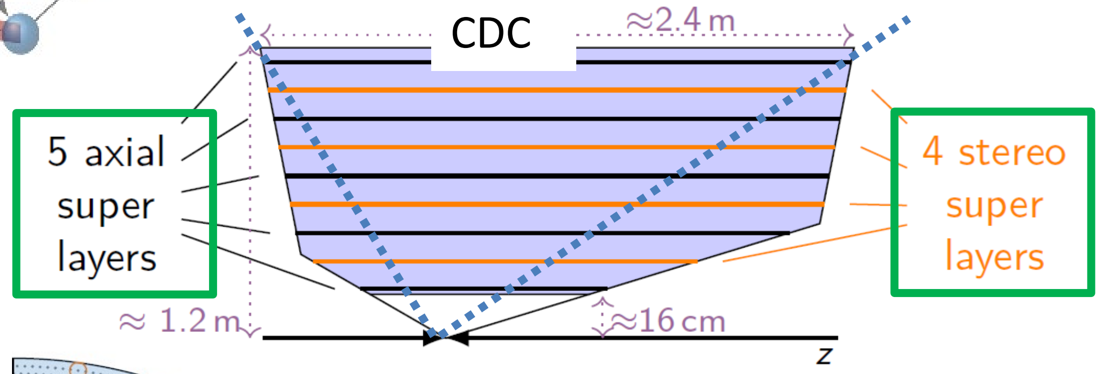
Note:
total latency for track reconstruction ~ 700 ns (starting with TSF output)

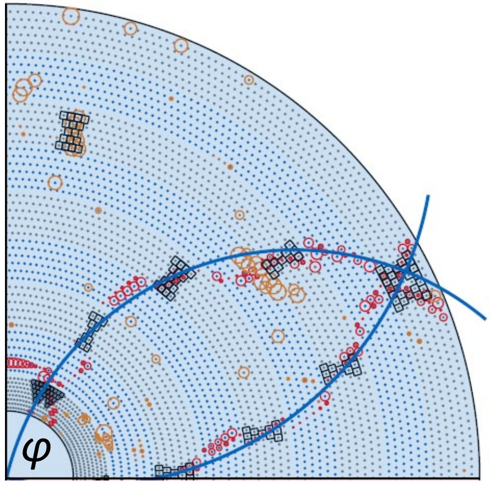
Architecture for each track candidate (networks to solve a regression task)



„z-Vertex Trigger“

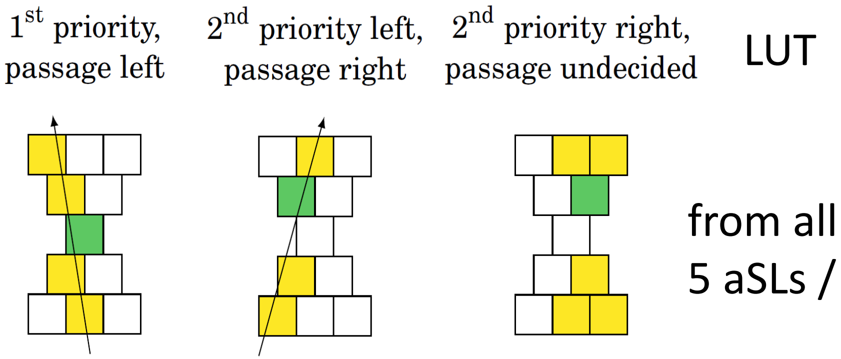
Input Preprocessing & Neural Networks





Target: tracks = well-known geometrical objects

patterns in known B-field:
- helices in space
- circles in transverse plane

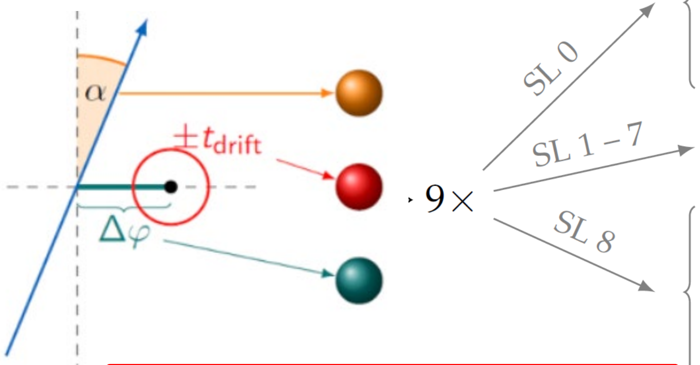


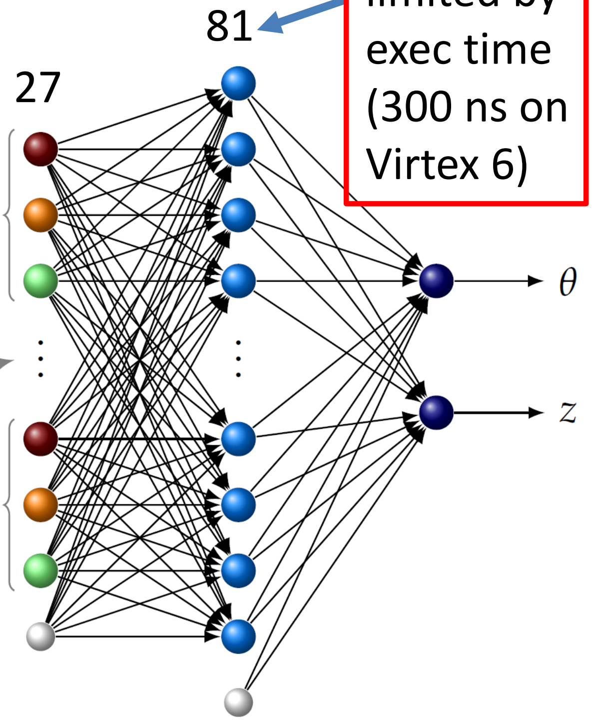
from all 5 aSLs / 4 sSLs

3 preprocessed inputs per TS in each of the 9 SLs:
- crossing angle α (calculation)
- signed drifttime (LUT)
- stereo wires selected from predef. range Δϕ (LUT)

limited by exec time (300 ns on Virtex 6)

„Natural input“: 2D track candidates in each of 4 quadrants from Hough transforms (-> azimuth ϕ and $1/R = 1/p_T$)
- calculate crossing angle α through TS
- determine „sign“ of drifttime (from wire pattern in TS)

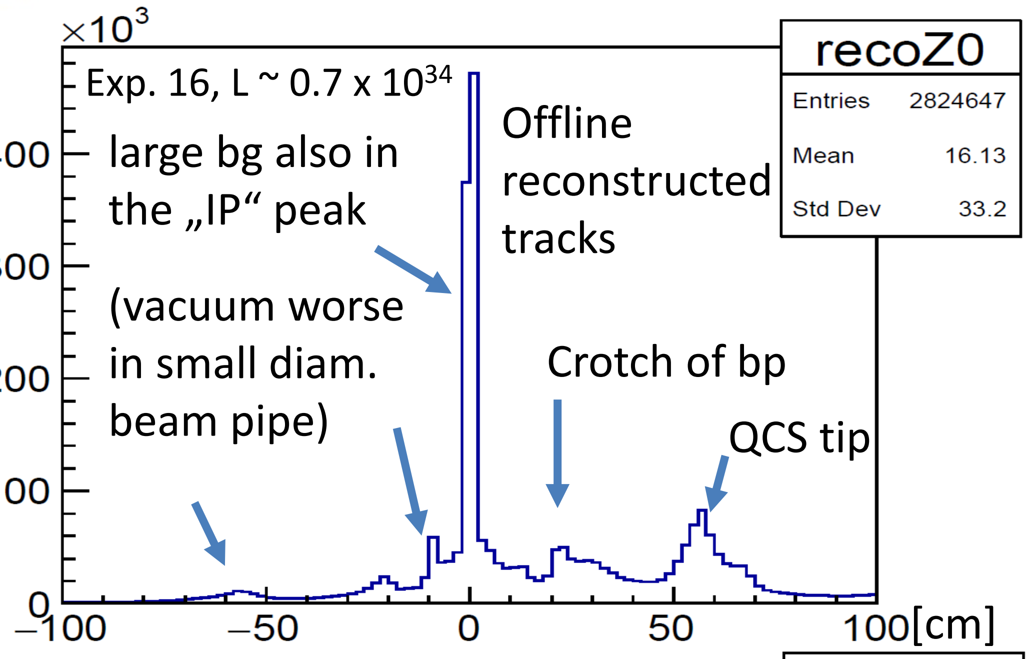


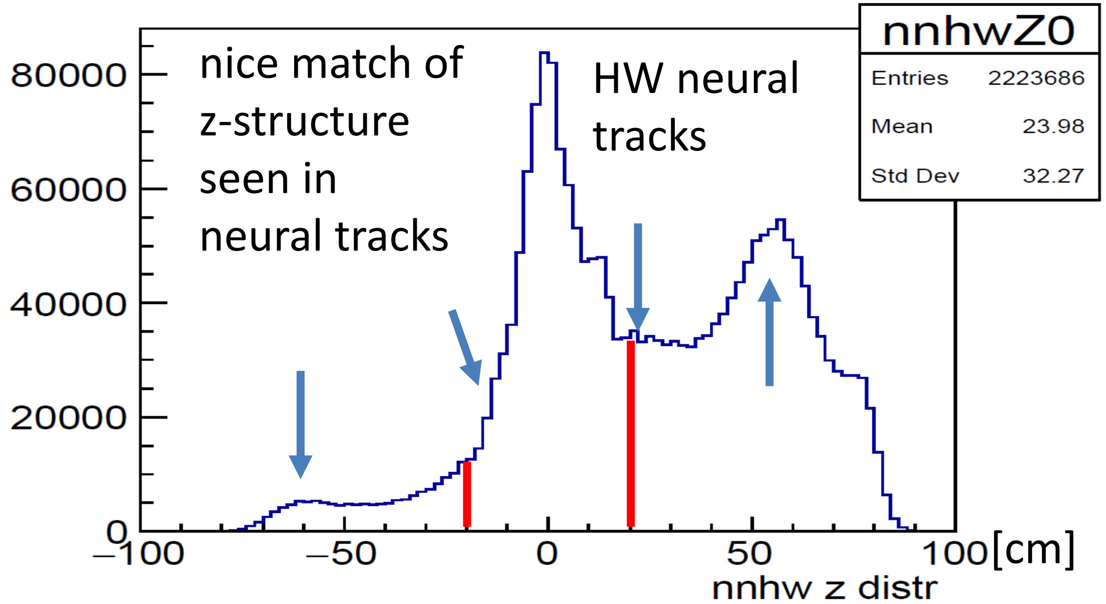


Felix Meggendorfer (TUM/MPI)

Networks trained with fully reconstucted offline tracks

Commissioning the Neural z-Trigger in 2020





Fall 2020 running

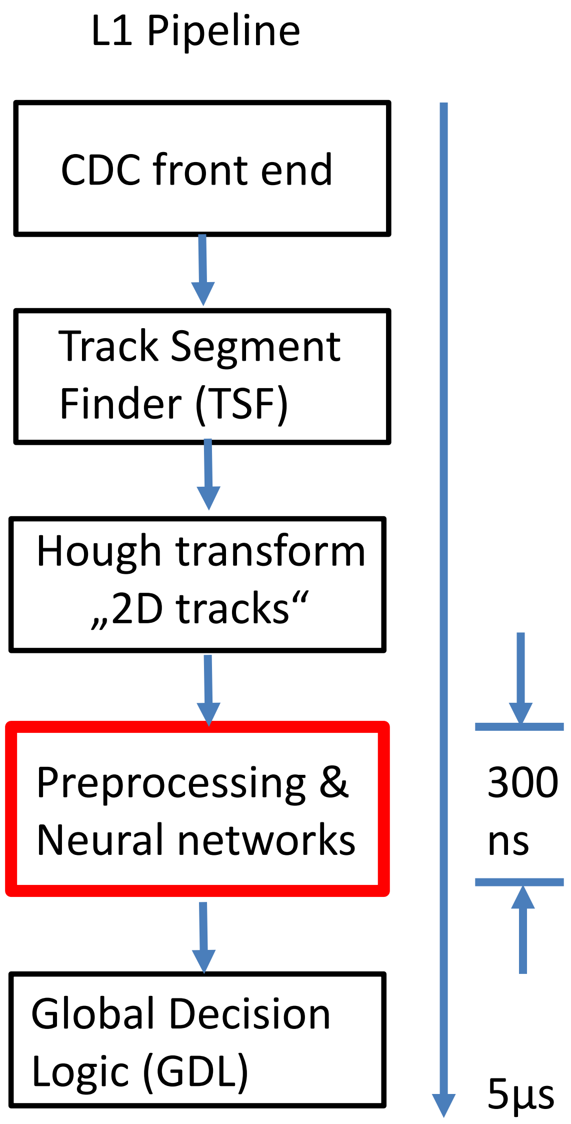
Reco tracks:
z-distribution after full off-line reconstruction,
including VXD space points

Networks trained with real data from May-June 2020

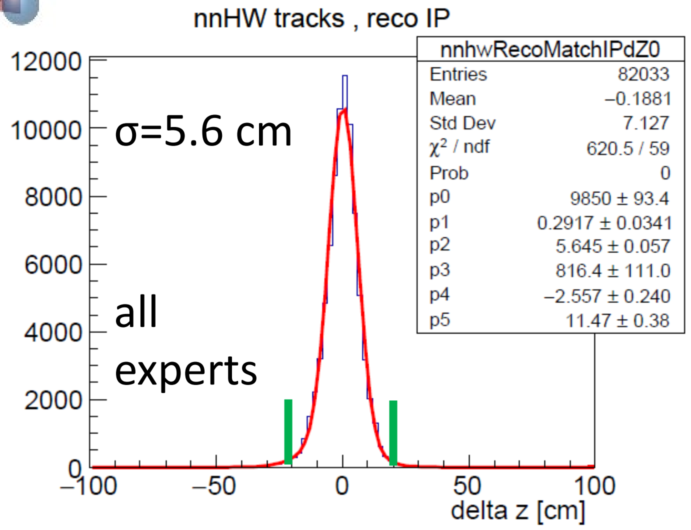
The „Expert Networks“:

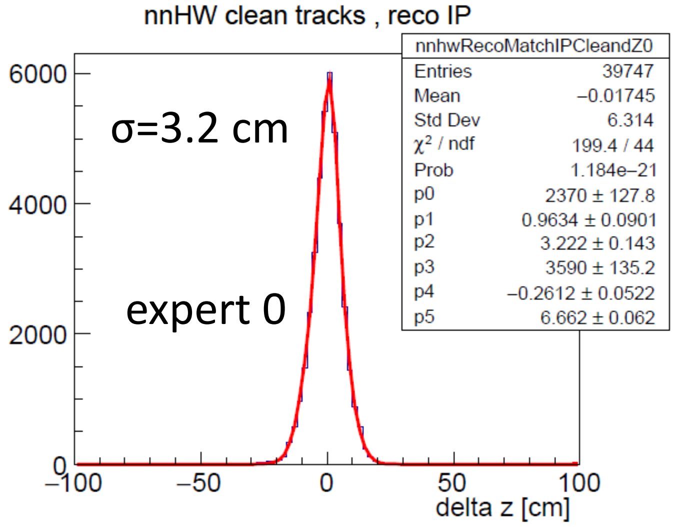
5 different networks trained, depending on the number of available stereo TS

Expert 0: all 4 stereo TS
Expert 1-4: one of the stereo TS missing



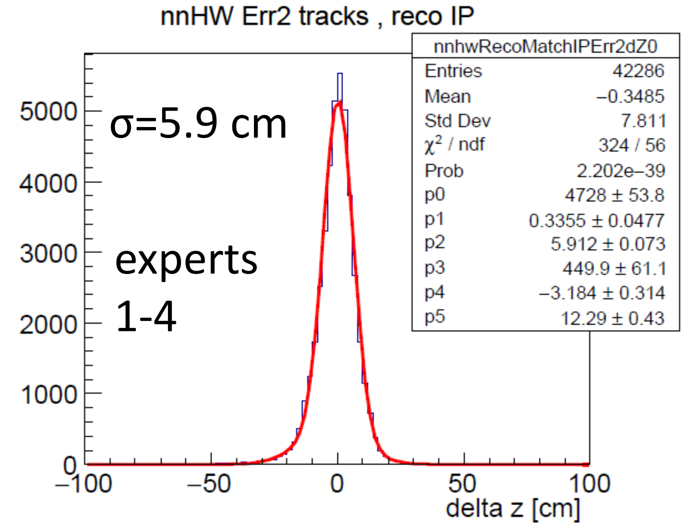
Performance of the Neural z-Trigger (I)





Belle II Track Trigger 2021 running

Large 2D trigger rate in 2021 ->
„y“ bit: ≥ 1 track, |z| < 20 [cm],
require ≥ 2 (2D) tracks && y=1

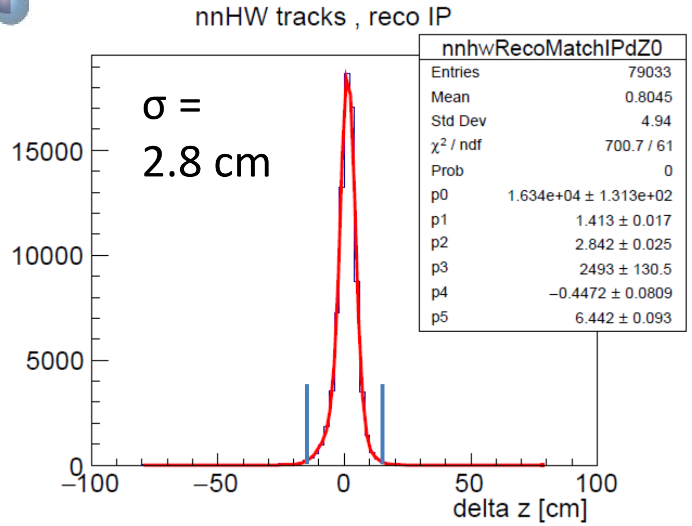


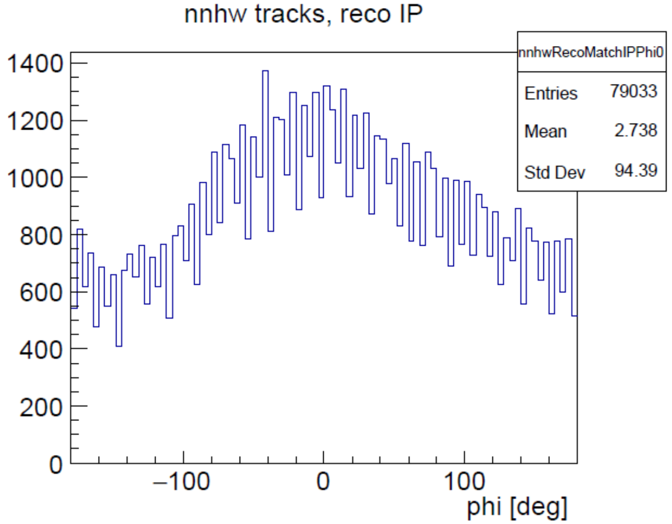
Instantaneous lumi = (3.8 x 10^{34}) end of 2021,
background rising with luminosity in 2021

NN resolution of IP tracks very stable, proving robustness of the neural network technique against changing conditons

Fundamental change at Belle II wrt Track Triggers:
due to overwhelming BG,
all 2-Track Triggers require
at least one neural track: „y=1“

Performance of the Neural z-Trigger (II)

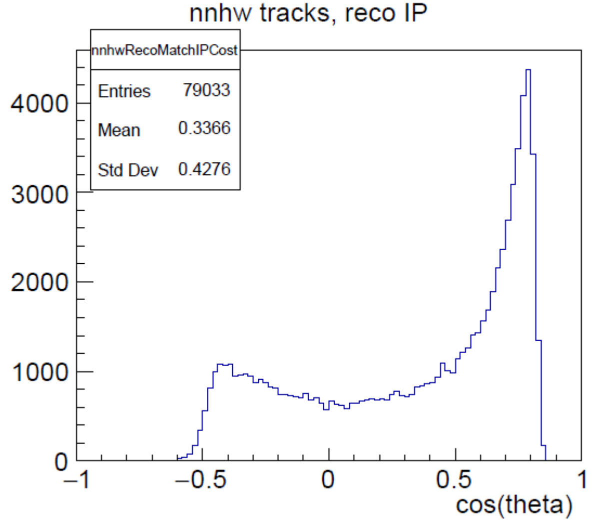




Retraining of neural networks with data from the end of 2021 (increased background)

Now use training library **PyTorch** (previously used FANN, integrated into Belle II software library)

Results from improved training



Exp 24, runs 790 - 890, New FW

Gaussian fits to neuro tracks associated with reco tracks from IP (|z|<1 cm, d < 1.5cm)

Central Gauss: σ = 2.8 cm

2nd Gauss: σ = 6.4 cm (13.2 %)

2020 training:
central Gauss σ = 5.6 cm
2nd Gauss σ = 11.5 cm

PyTorch training improves FANN results by factor 2 !!

Minimum Bias Single Track Trigger in Belle II : STT

Can we launch a track trigger requiring only one track?

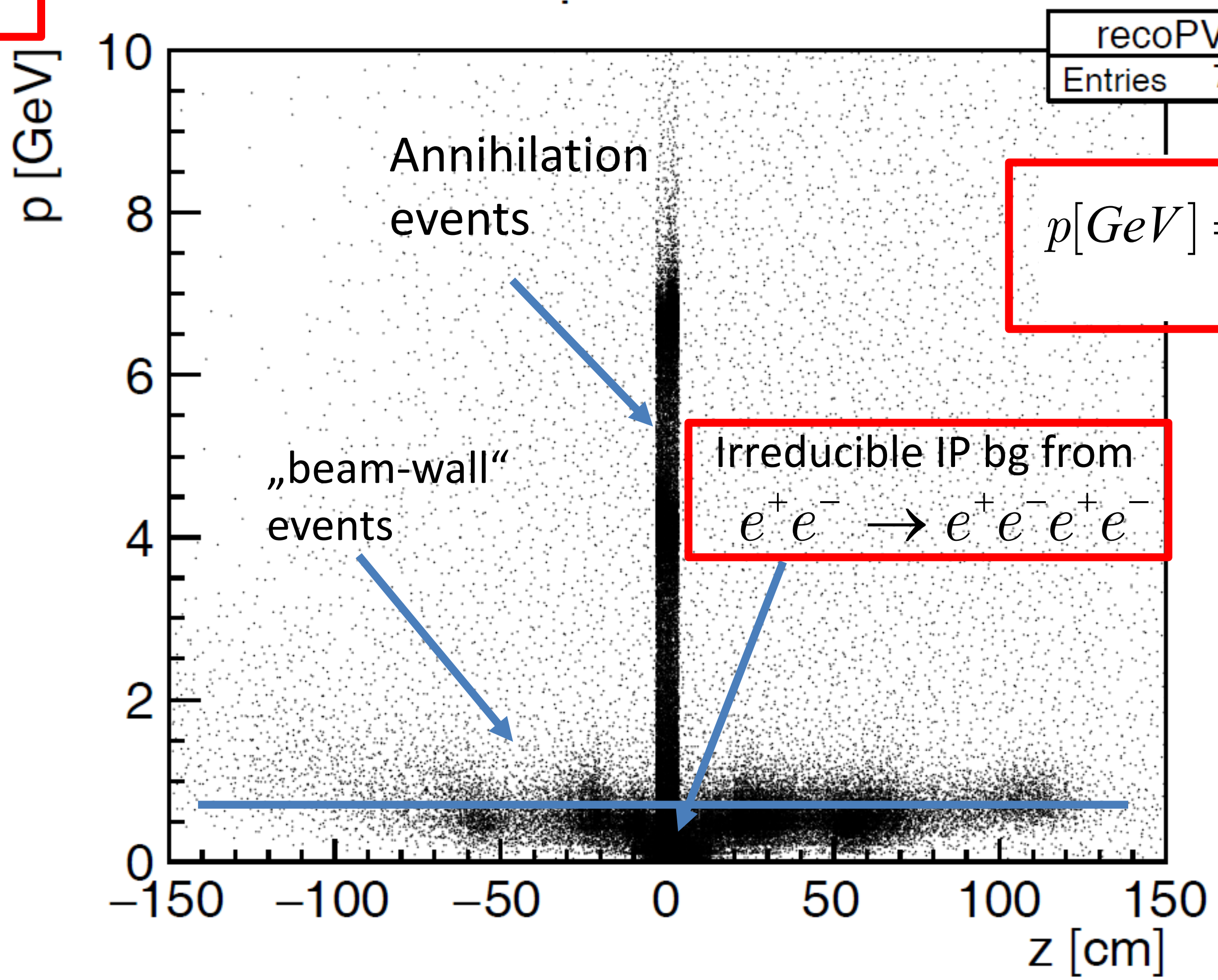
Sources of Background:

Collisions of electrons/positrons with elements of the beam guide system,
mostly producing protons from nuclear spallation

(momentum of particles outside of IP mostly below 1 GeV !!)

from IP (!!): QED events

Distribution of Reco Track momentum vs z



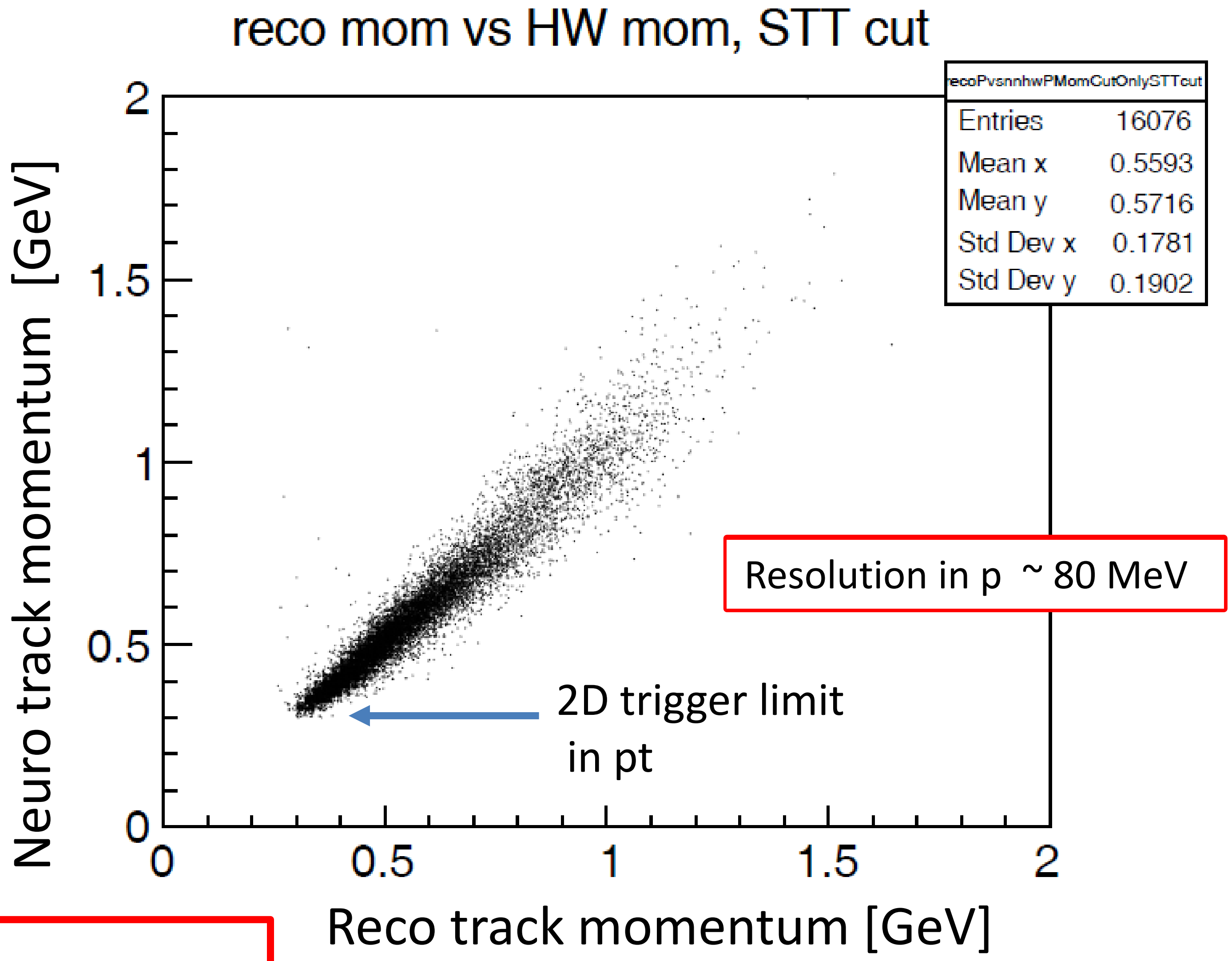
$$p[GeV] = \frac{1}{|\omega|[1/m]\sin(\theta)} 0.3B[T]$$

use the second output („θ“) of the networks

Cut on p > 0.7 GeV

Reducing STT Trigger Rate: Neuro Track p

momentum correlation of neuro tracks and reco tracks

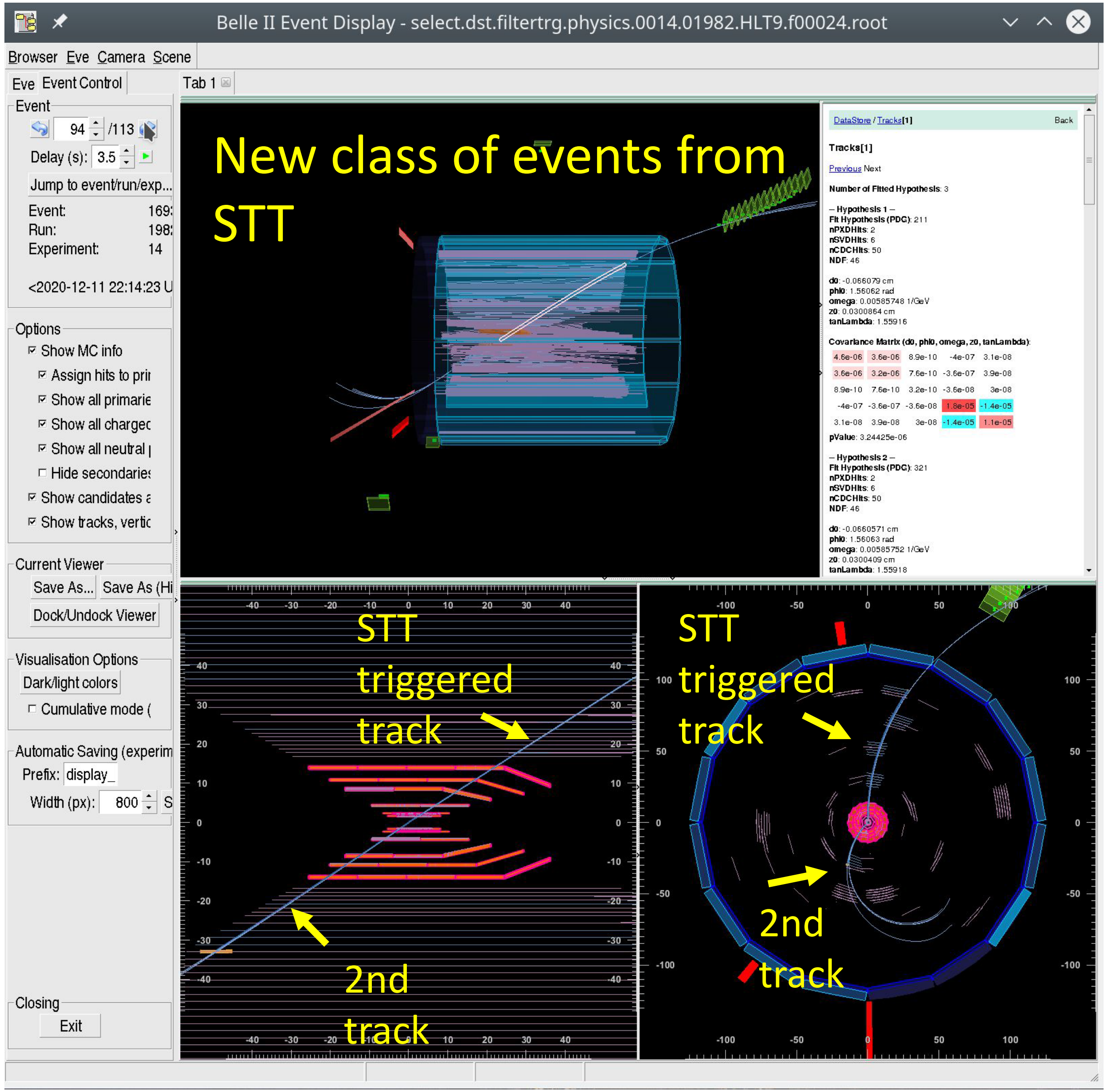


calculate the neuro track momentum:

$$p[GeV] = \frac{1}{|\omega|[1/m]\sin(\theta)} 0.3B[T]$$

ω ~ 1/transverse momentum (from 2D track)

STT Triggers ONLY



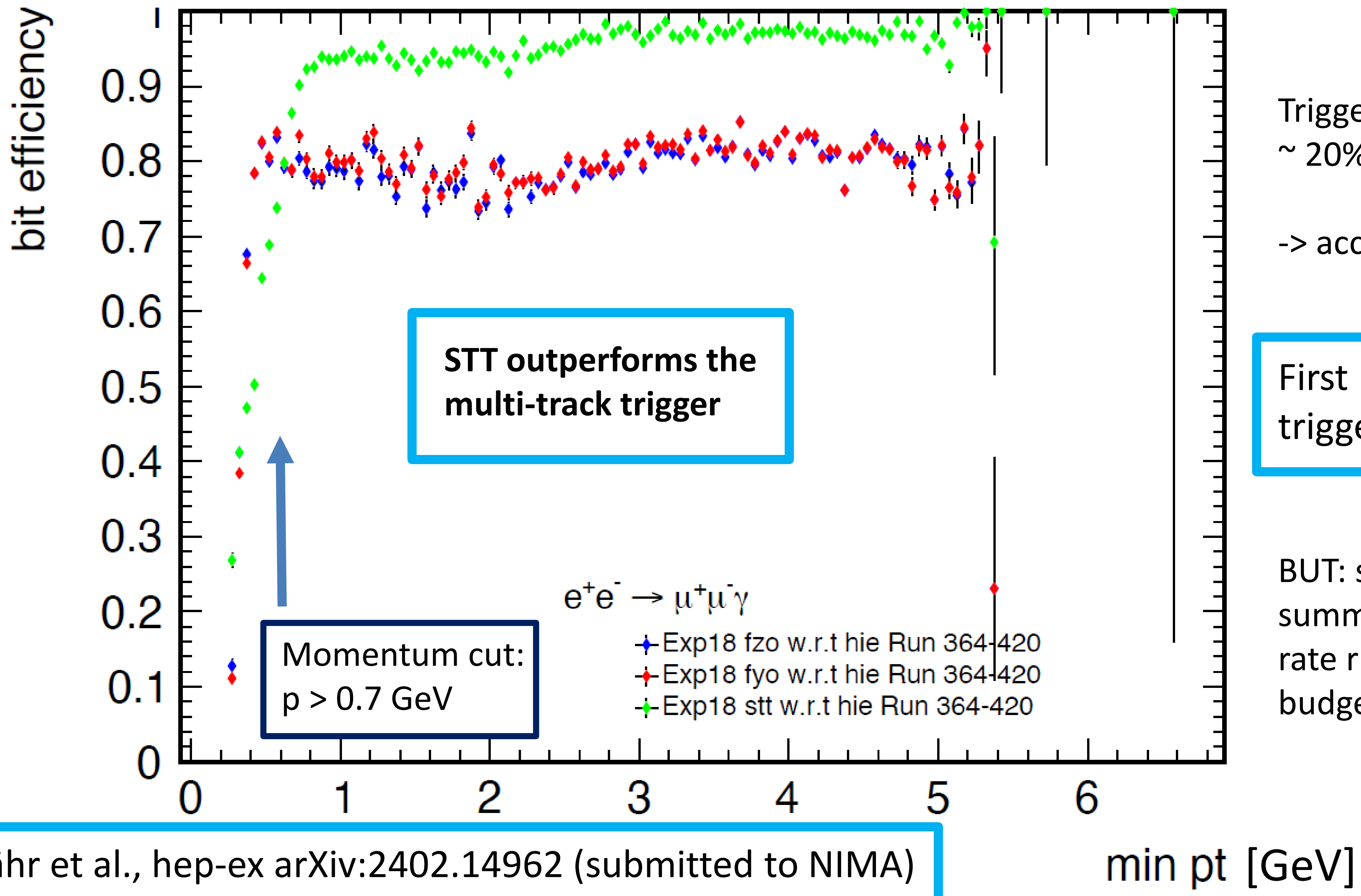
Event display shows the reco tracks

2nd track at shallow Θ cannot be seen by CDC trigger

Note:
2nd track is unbiased
(can be anywhere in the detector, usually reconstructed by silicon tracker)

Event class only triggered by STT
(~12% of STT events)

STT: Superior Efficiency



Trigger rate of the STT
~ 20% -25% of total rate budget

-> acceptable

First minimum bias track trigger in HEP

BUT: some problems during summer 2022 running:
rate rising to ~50% of total budget -> ??

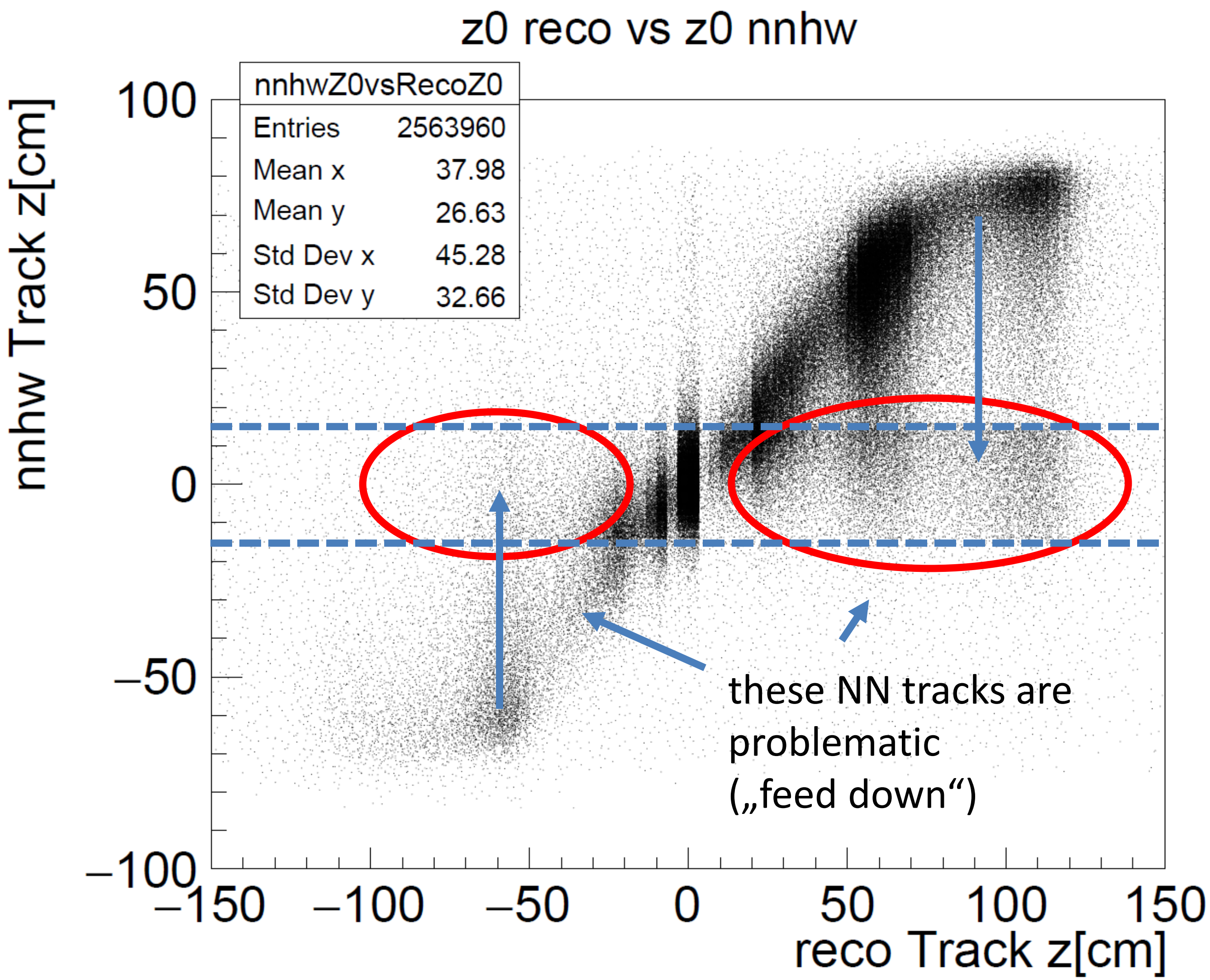
S. Bähr et al., hep-ex arXiv:2402.14962 (submitted to NIMA)

Problems of the STT (I) : „Feed-Down Effect“

Increase of machine-induced background
with rising luminosity

-> increase of STT trigger rate observed
(but efficiency stable !!)

Excess rate may saturate DAQ and increase deadtime



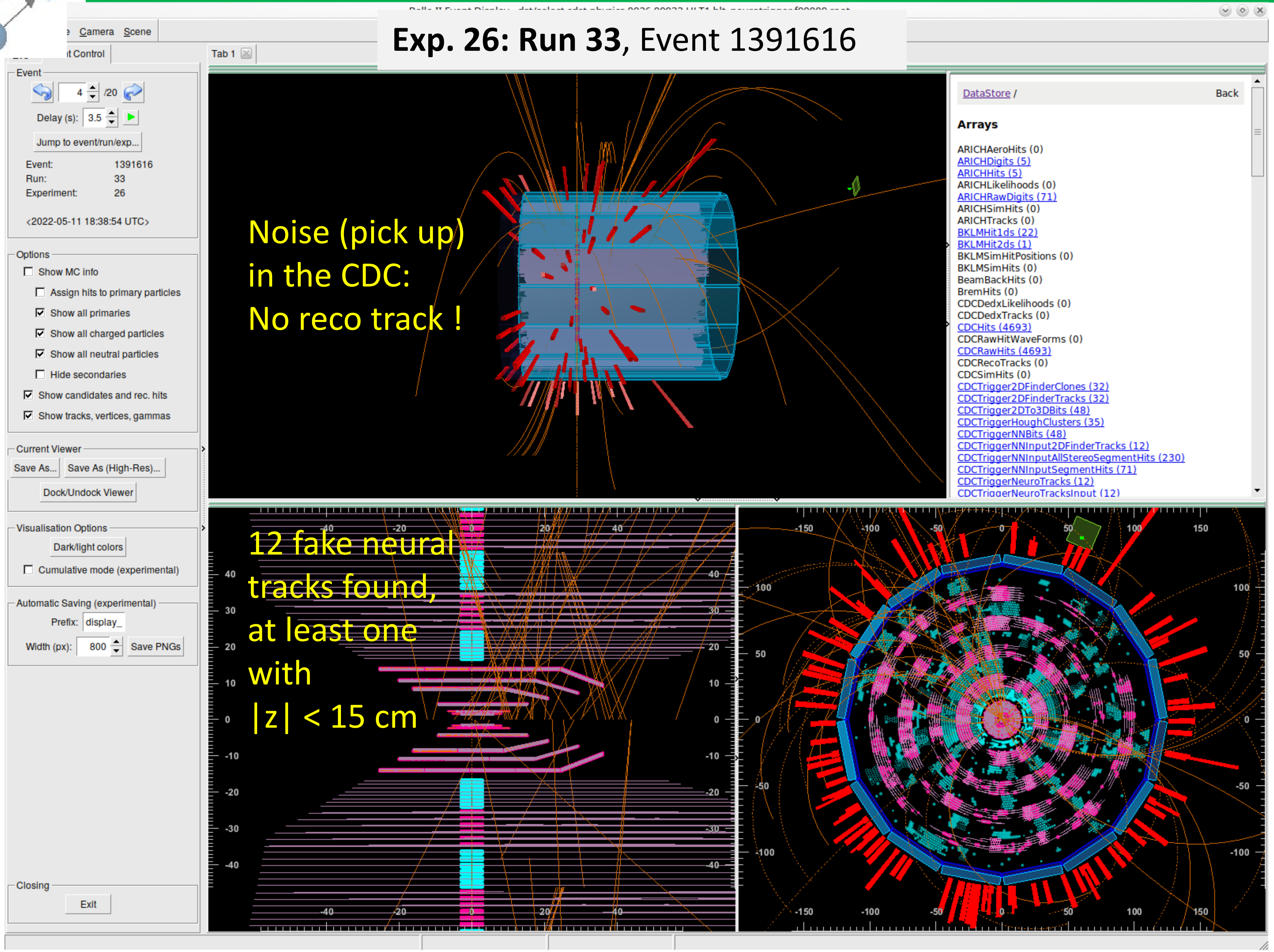
Band at |z|<15cm: acceptance for a valid neural track

Large |z|: a certain fraction of tracks shifted into IP region
-> increase of rate

Why are tracks predicted around IP while coming from large |z| ?

feed-down especially strong for expert 4 (inner stereo SL missing)

Problems of the STT (II) : „Fake Tracks“



Feed-Down and Fake Tracks have the same source:

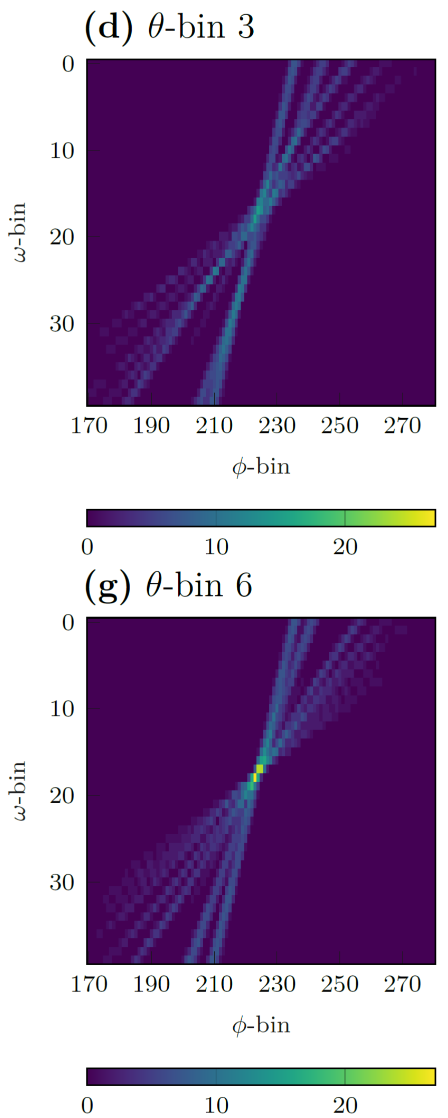
Large number of fake 2D track candidates (require 4 out of 5 SLs), formed by „random“ noise in the CDC, mostly synchrotron radiation photons and electronic cross talk

Neural tracks formed by: noisy 2D track candidates & noise in the stereo layers

Upgrade Program for the STT

-> keep efficiency of STT & low rate budget with rising luminosity (BG)

3D track model



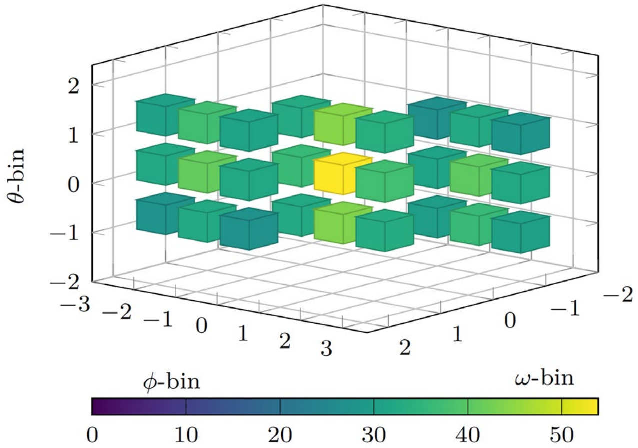
Physics goals: low charged multiplicity, e.g. τ 1-prong decays (- > τ EDM, LFV),

- $e^+e^- \rightarrow \pi^+\pi^-(\gamma)$ for g-2 (hadronic vaccum polarization) etc.
- quite generally: determination of lepton ID, tracking efficiency for the „other track“
- **STT is a minimum bias track trigger**

New FPGA Hardware now available: „UT4 Board” with Virtex Ultrascale 160/190

Improved track model for neural input / training algorithms:

- **track finding in 3D Hough space** -> this is **really new** (S. Skambraks, S. Hiesl)
- network architecture: „deep-learning“ + additional inputs (T. Forsthofer)
- -> improve resolutions @ IP and for larger |z|
- -> reduce feed-down & fake tracks



FPGA Implementation (Kai Unger):

- new algorithms on new UT4-Boards using hls4ml
- optimize latency: e.g. move STT decision to NN

Hough Clustering in 3 Dimensions

Variables for standard 2D Hough transformation: track curvature ω and azimuth angle ϕ
Extension to 3 dimensions: additional variable -> polar emission angle θ

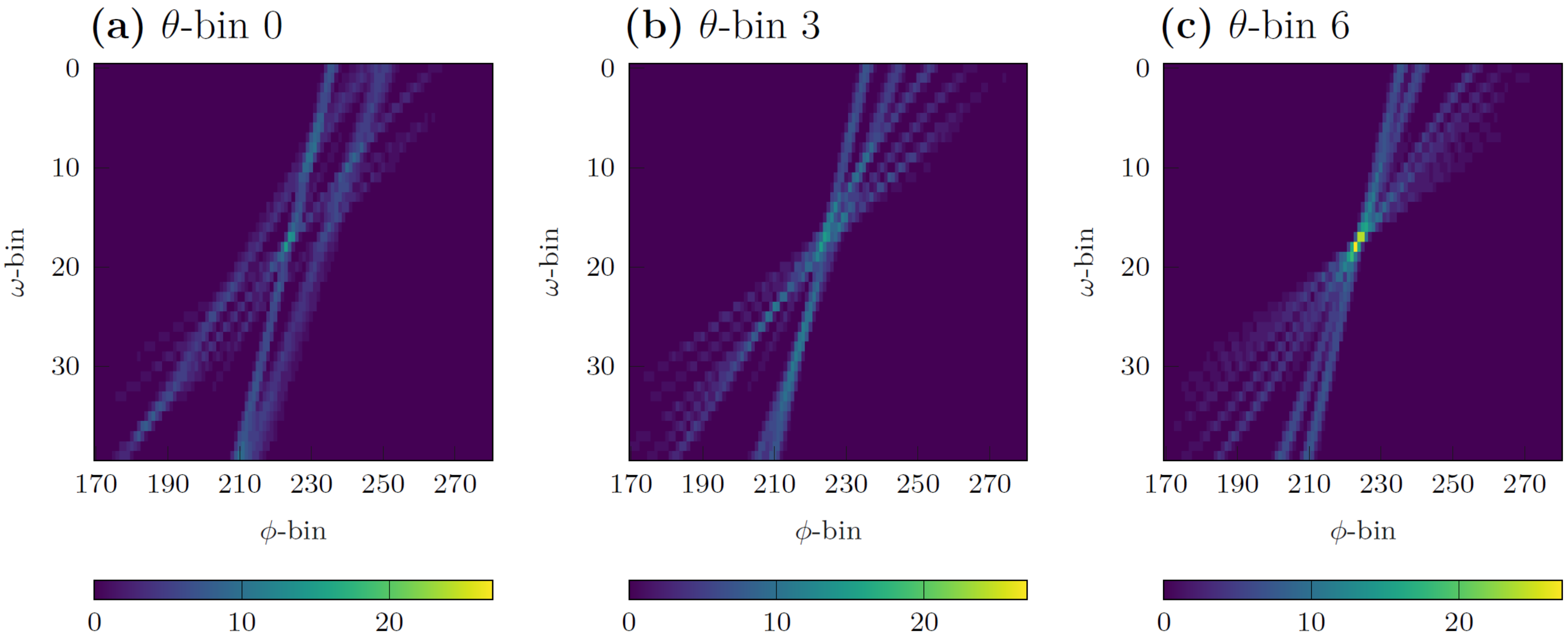
Implicit Hough constraint: track origin = IP (0,0,0) -> „natural" suppression of tracks from „outside" of IP

Binning:

ϕ: 384
[0,360°]

ω: 40
pt ~ q/ω

θ: 9
[19, 140°]



Simon Hiesl (MPI & LMU)

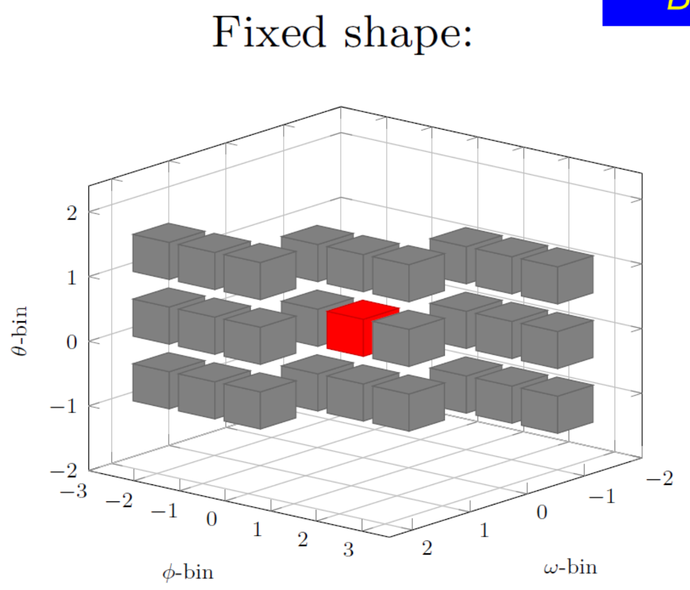
Peak finding in 3D hough space -> < ϕ>, <pt>, < θ>

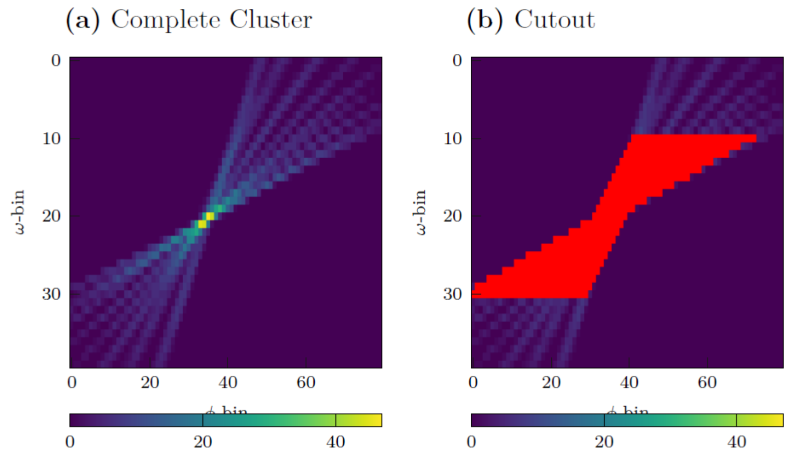
Hough Clustering in 3 Dimensions

- Original algorithm „DBScan" (S. Skambraks):
  - fill Hough space from all track segments (TS)
  - find all isolated clusters in Hough space (set of adjustable parameters)
  - association of Hough curves to clusters by means of „confusion matrix"
  - finally do peak finding and determine < ϕ>, <pt>, < θ>

  problem for implementation at the first trigger level (FPGA):
  cluster finding not deterministic: size and execution time not fixed

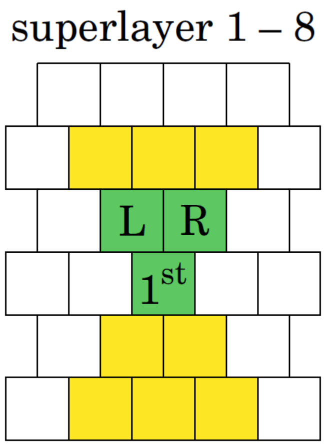
- New cluster finding algorithm (S. Hiesl):
  - fill cells in Hough space from all TS
  - find maximum cell in Hough space (w(cell) > w_{min})
  - store associated track segments within fixed cluster shape
  - select unique TS in each superlayer (maximum cell weight / shortest DT)
  - determine < ϕ>, <pt>, < θ>
  - clear all Hough cells around maximum cell (-> butterfly cut)
  - iterate *n* times



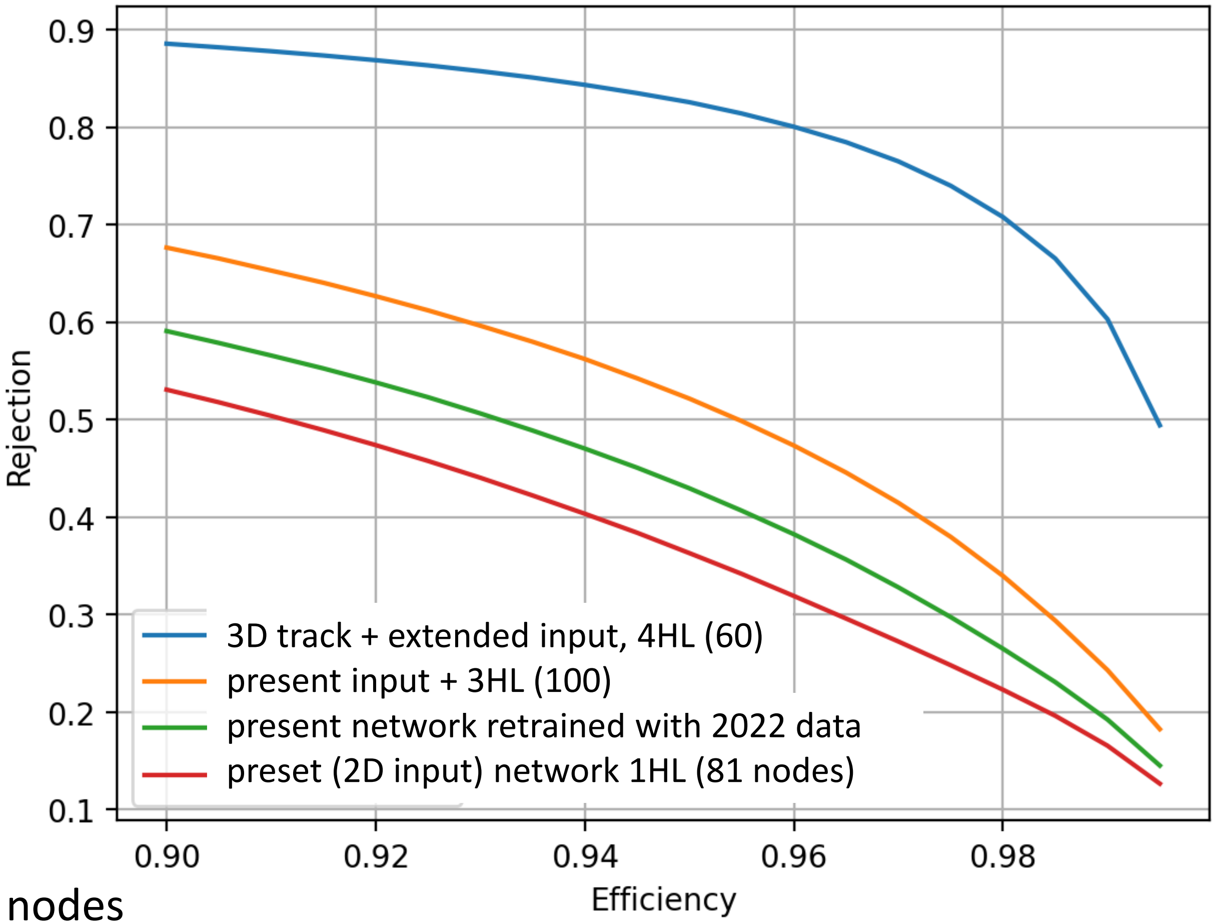


Simon Hiesl (MPI & LMU)

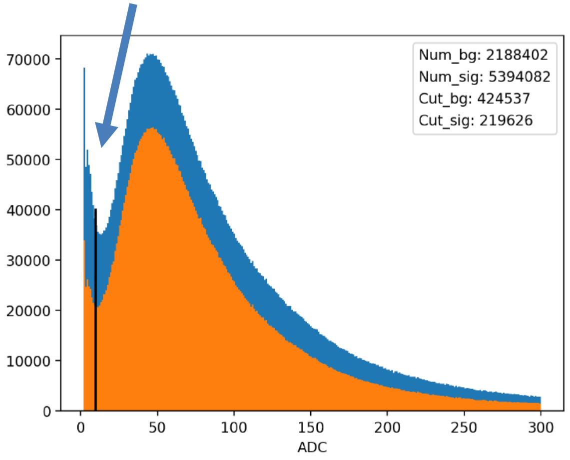
Expected Performance of Upgrade



Extended inputs to network
- „standard“ priority wire (Δϕ, α, DT)
- plus entire wire pattern in TS
  (10 additional binary inputs per TS)
- with condition: ADC count > min
  (remove bg from electronic
  cross-talk & synchr. photons)



electronic cross-talk &
synchrotron photons



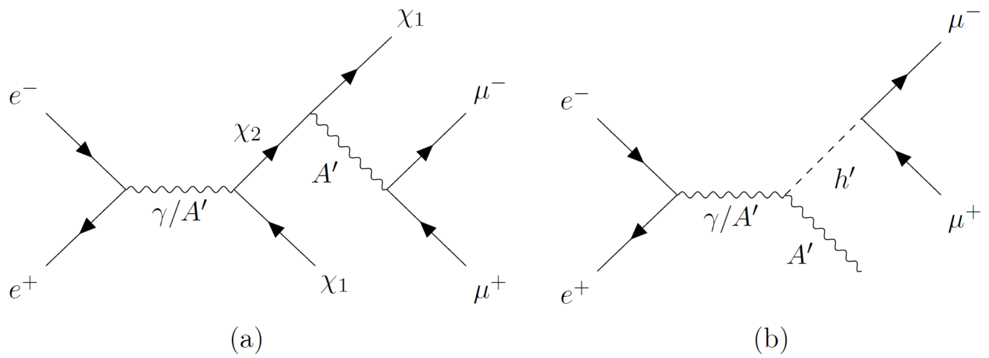
Multi-hidden-layer network
(„deep learning“)

- Several architectures investigated
- „optimal“ configuration with 4 hidden layers and fewer (!) nodes when using 3D track model (easier to implement in HW)

Timo Forsthofer
(MPP & LMU)

How to Trigger on Feebly Interacting Neutral Particles

Example: Inelastic Dark Matter production
DM particles expected to be quite long-lived

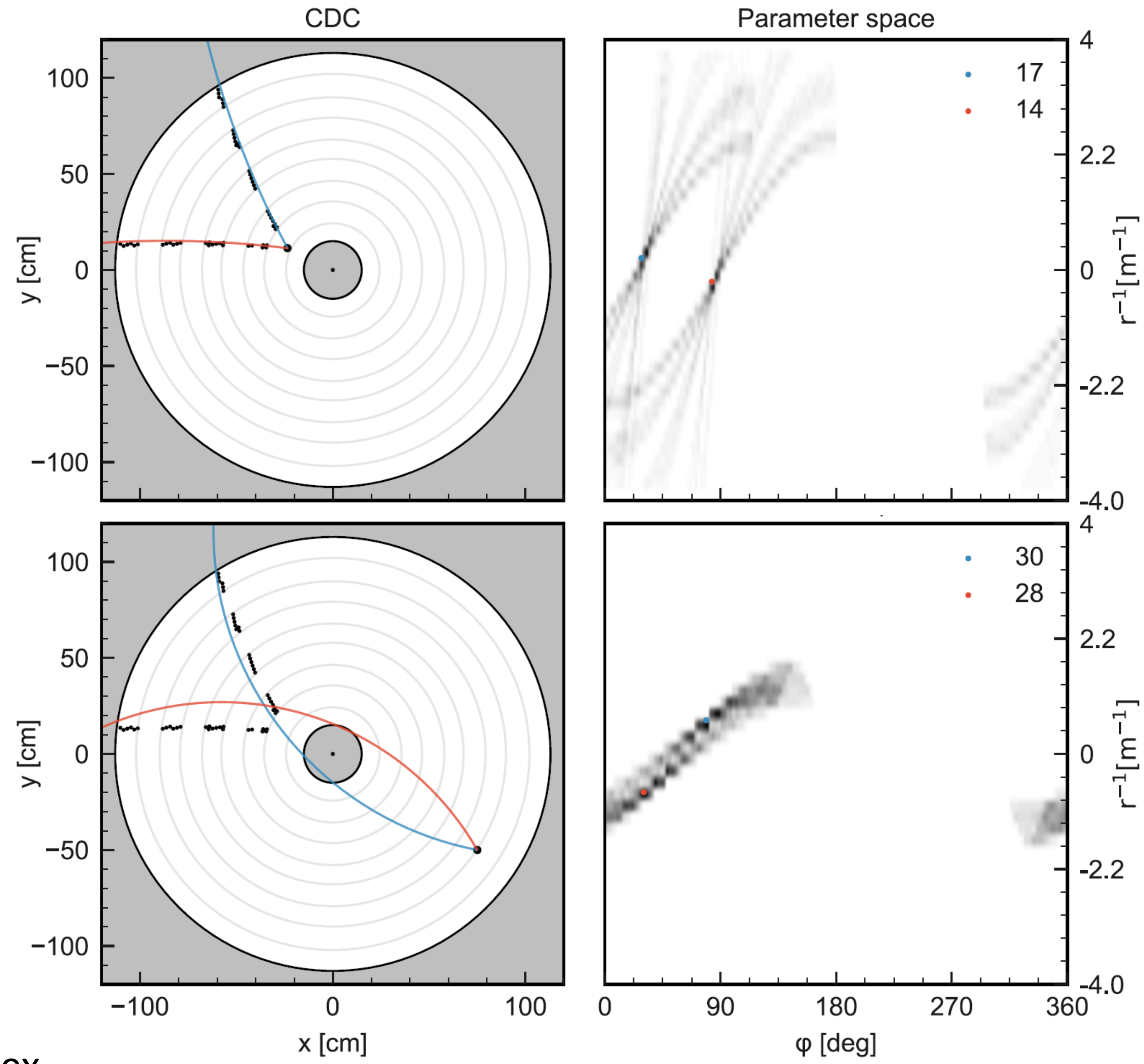


Basic idea:

Divide the CDC axial wire planes into a set of „Macro Cells“, serving as origins for the Hough transforms

FPGA:
-> execute all Hough transforms with origins in each of the Macro cells in parallel (typically of O(100))

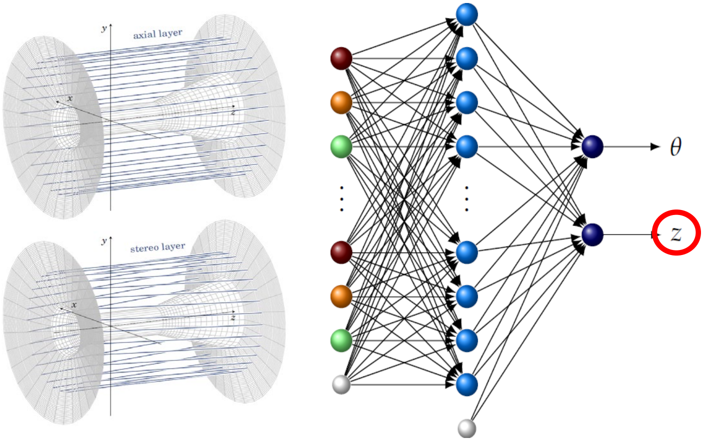
-> use neural networks to determine shape of correct vertex



E. Schmidt (MPP & LMU)

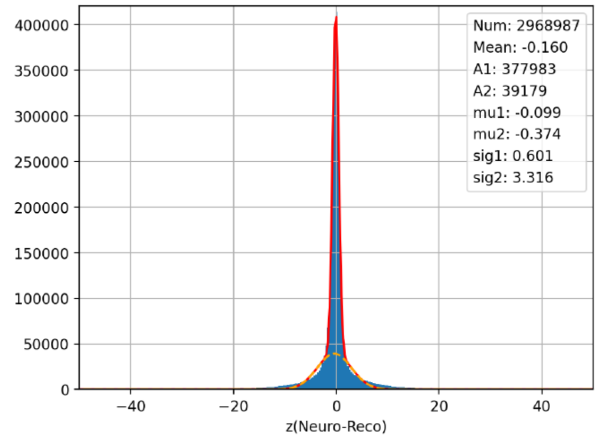
Summary and Conclusions

First Level-1 Neural Network Track Trigger in HEP, operational @Belle II since Jan. 2021



- Neural z-Trigger: „working horse“ for Belle II track trigger system
- New feature: **Minimum Bias Single Track Trigger (STT)**
  - excellent performance even under severe background conditions
  - however, “Feed-down” and “Fakes” need attention with rising luminosity

- Upgrade: More powerful FPGA boards now available (Virtex UltraScale 7 XCV
  - track finding via optimized 3D Hough cluster algorithm (novel method!)
  - additional inputs from all wires within the TSs (136 inputs total)
    (coarse analog thresholds for CDC wire signals to suppress background)
  - deep-learning neural network architectures (4 x 60 hidden nodes)
  - superior performance both in resolution and background suppression

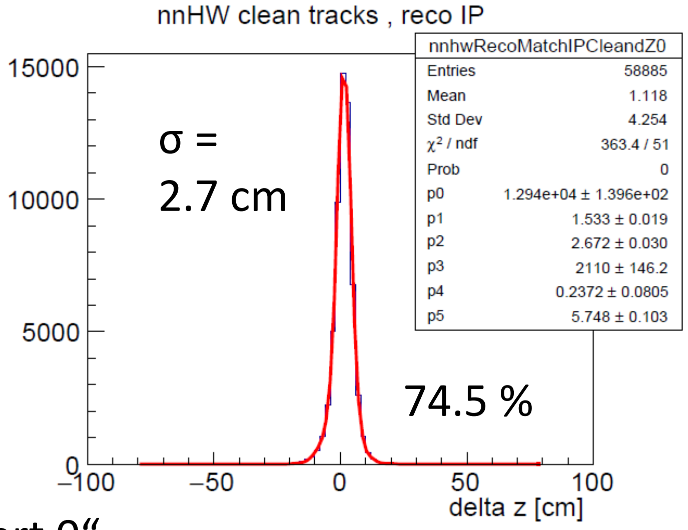


- Commissioning by summer 2024, launch planned for the fall 2024 data taking

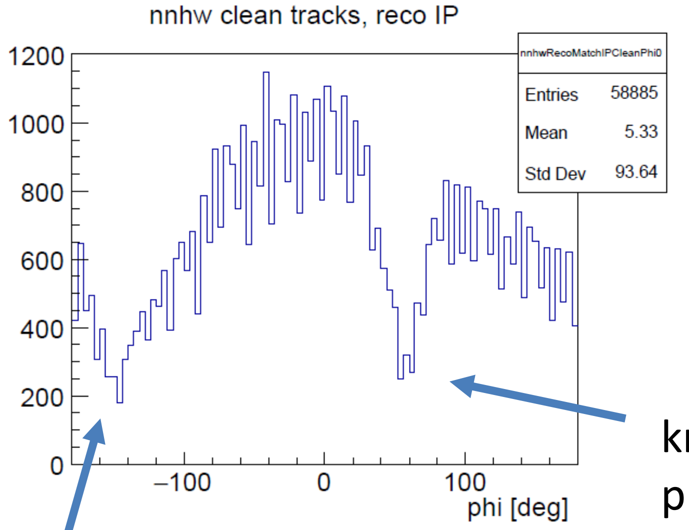
- Neural **Displaced Vertex Trigger** on the horizon, aiming at long-lived new particles, commissioning planned end of 2024

BACKUP

z-Resolution for „Clean“ IP Tracks („Expert 0“)

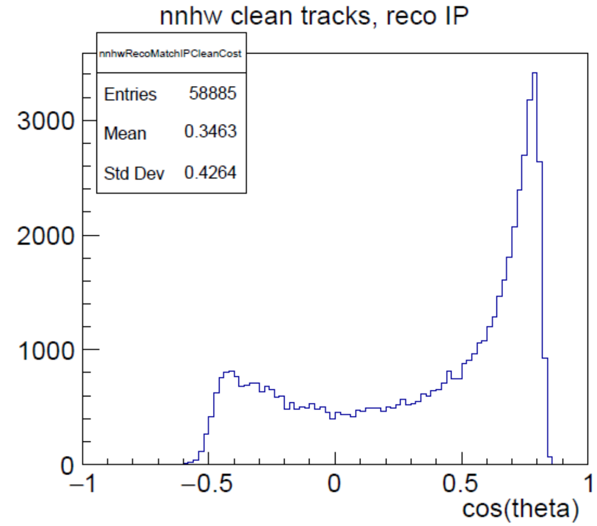


„expert 0“



known problem

new CDC inefficiency



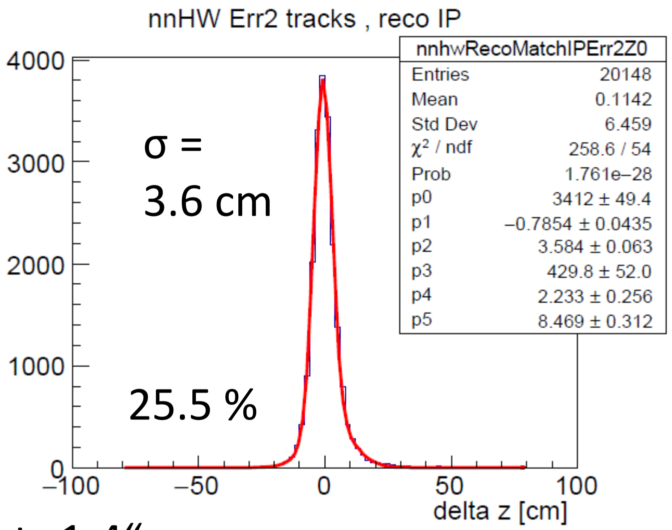
Gaussian fits to neuro tracks associated with reco tracks from IP (|z|<1 cm, d < 1.5cm)

Central Gauss: σ = 2.7 cm

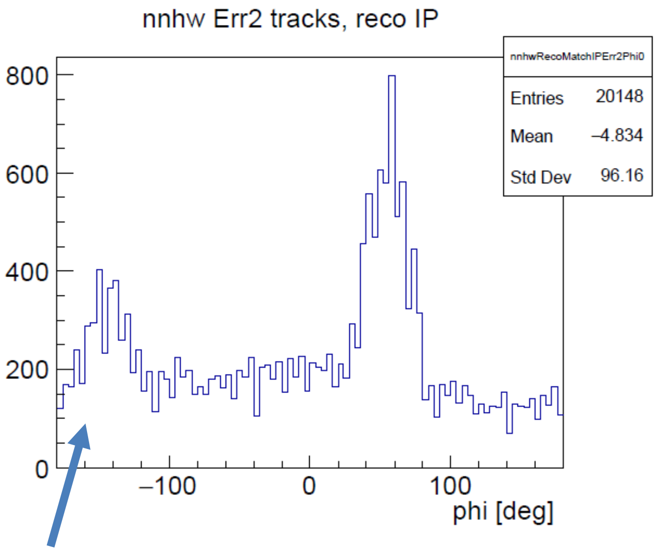
2nd Gauss: σ = 5.7 cm (14.1 %)

Exp 24, runs 790 - 890, New FW   STT active, zcutTrig = 20 cm   19/03/2022 50

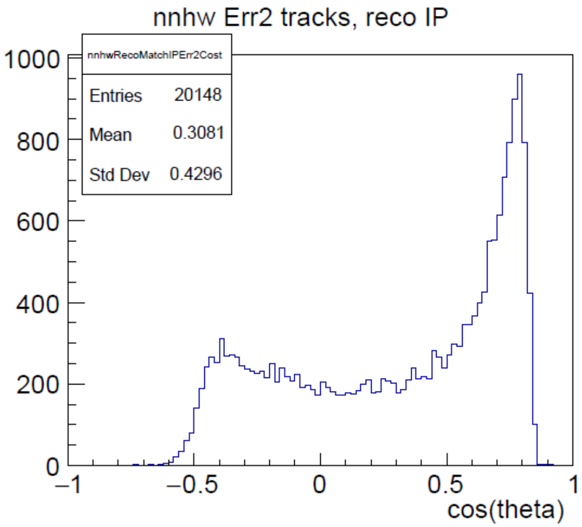
z-Resolution for IP Tracks („Experts 1-4“)



„experts 1-4“



new CDC inefficiency



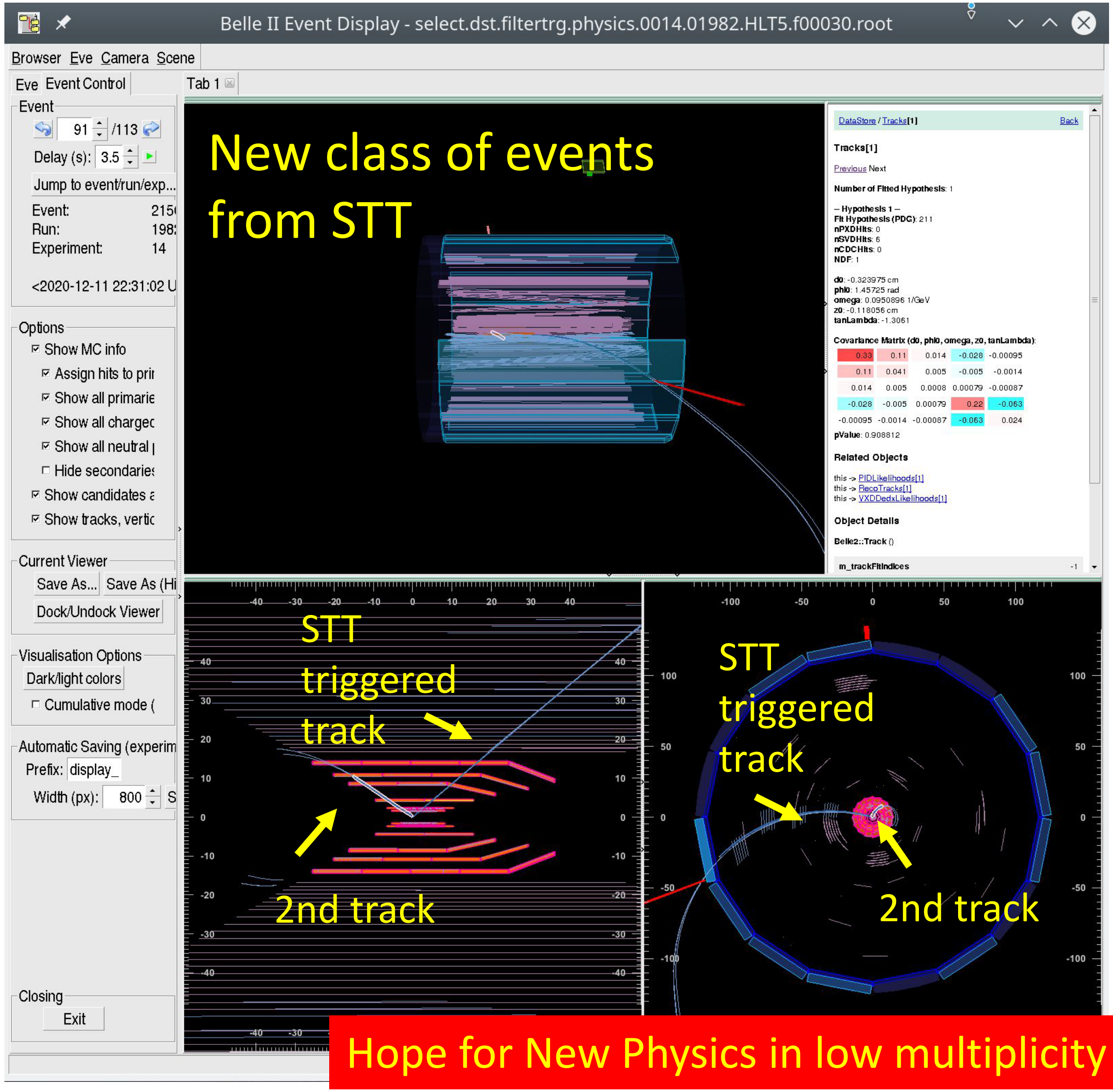
Gaussian fits to neuro tracks associated with reco tracks from IP (|z|<1 cm, d < 1.5cm)

Central Gauss: σ = 3.6 cm

2nd Gauss: σ = 8.5 cm (11.2 %)

Exp 24, runs 790 - 890, New FW   STT active, zcutTrig = 20 cm   19/03/2022 51

STT Triggers ONLY



2nd track
reconstructed
only in PXD/SVD

Caution:

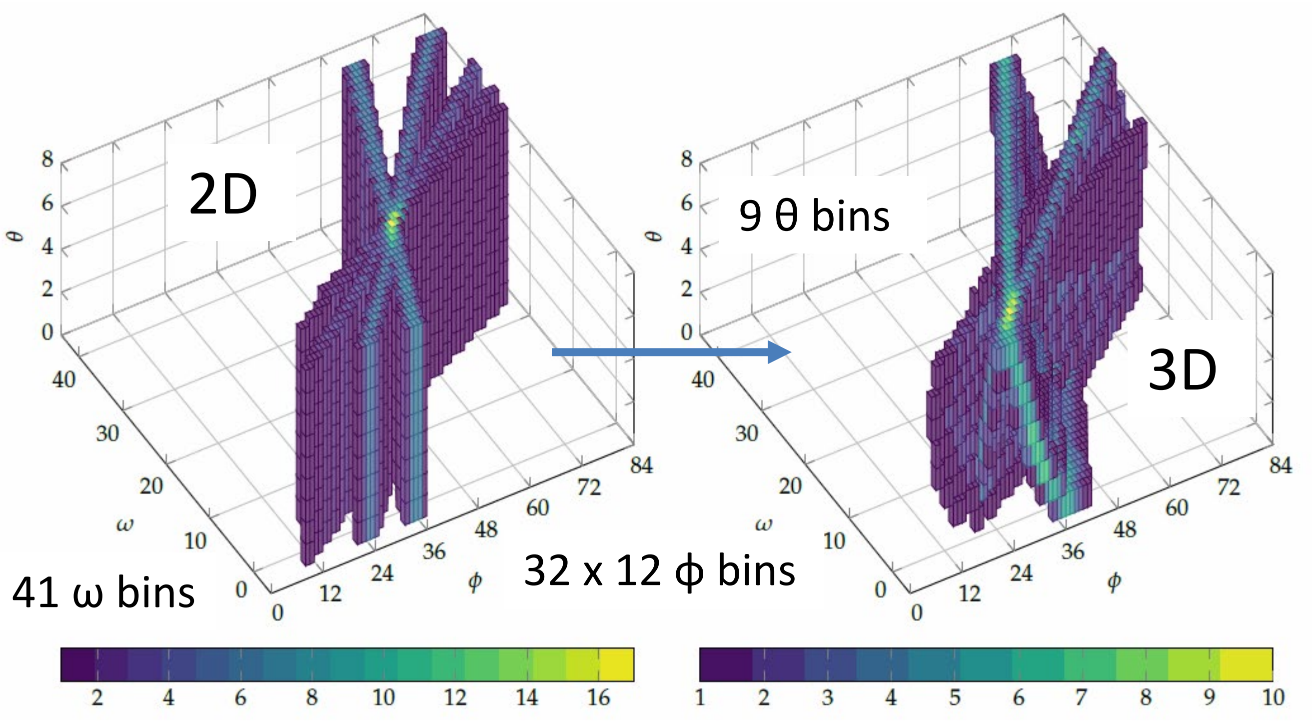
efficiency of STT not easy to calculate from data since no other orthogonal trigger (e.g. ECL) available

Hope for New Physics in low multiplicity final states ?

3D Hough Track Finding

- Extend traditional 2D (ω=1/p_T ,ϕ=azimuth angle) Hough space by a third dimension, the (binned) polar angle θ
- For track finding use axial and stereo track segments (->3D)
- Peak finding in 3D Hough space

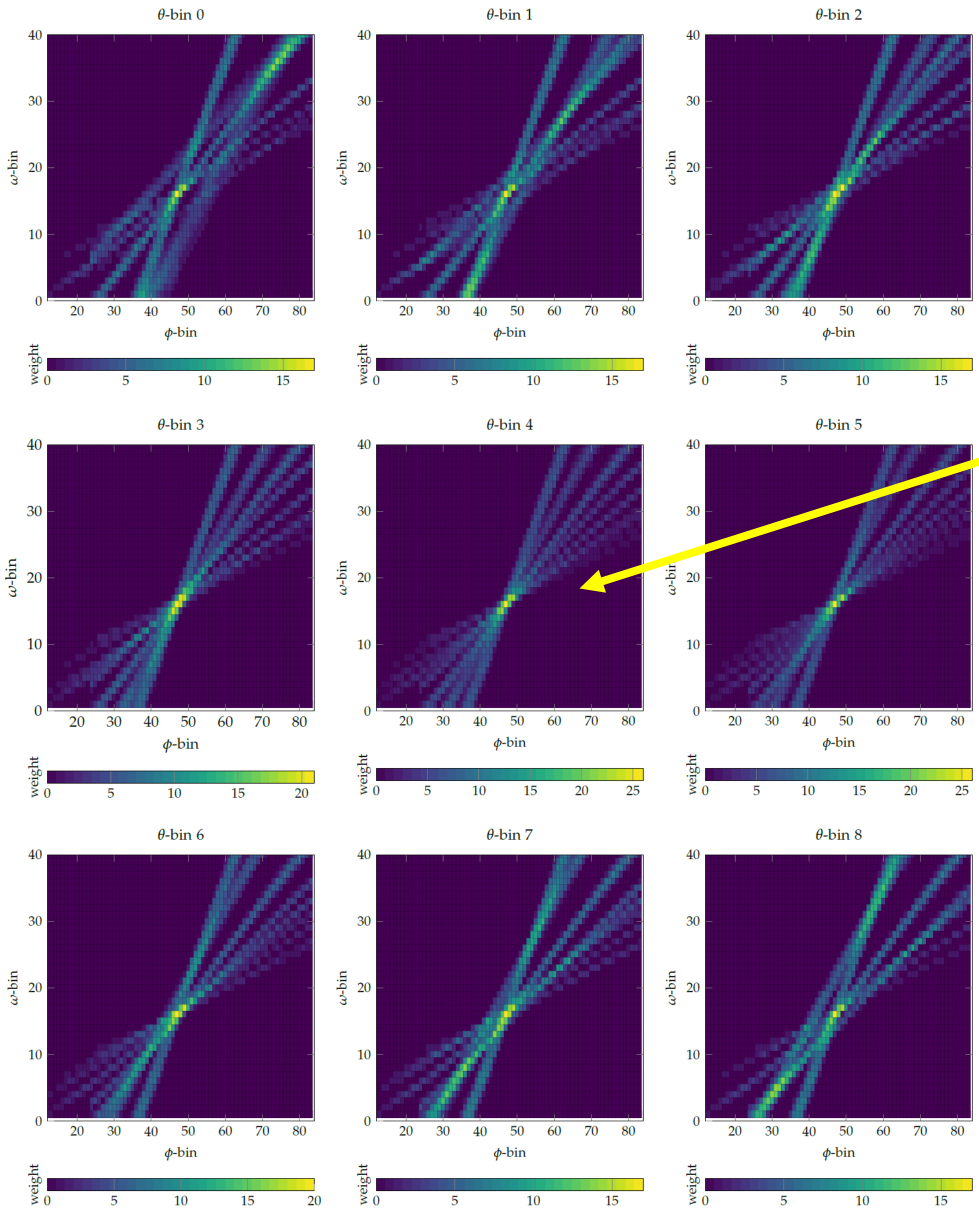
Sebastian Skambraks (LMU)

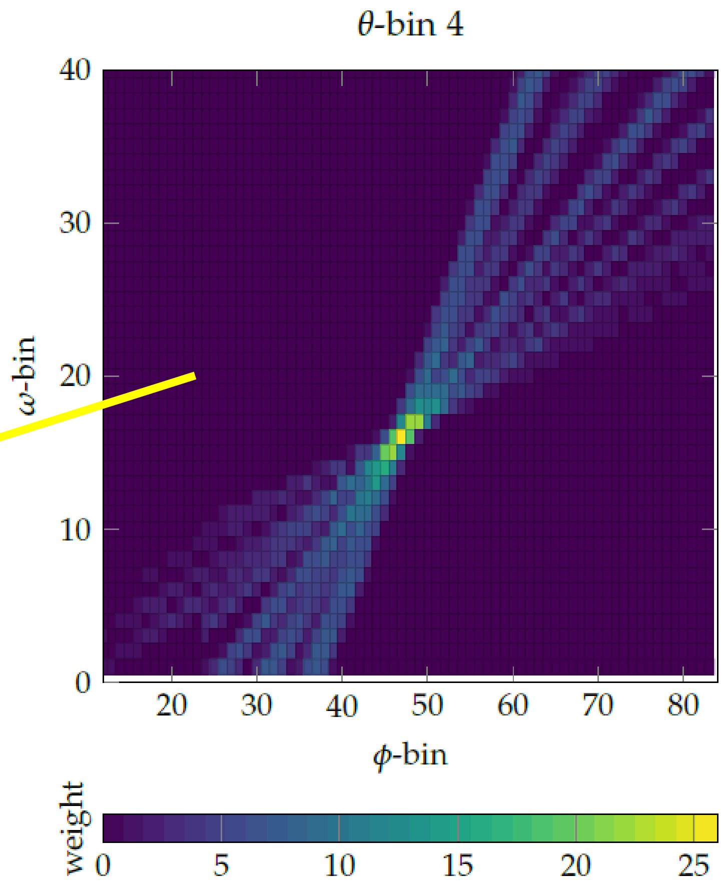


Main advantages:

- more TS (9 vs 5)
  -> suppress fakes
- No need to choose STS by min drift time
  -> find „correct" STS
- Force track model to originate from IP
  -> suppress candiates
  far from IP
- 3D track candidates come with θ estimate,
  -> improve z resolution

Example of 3D Hough Map



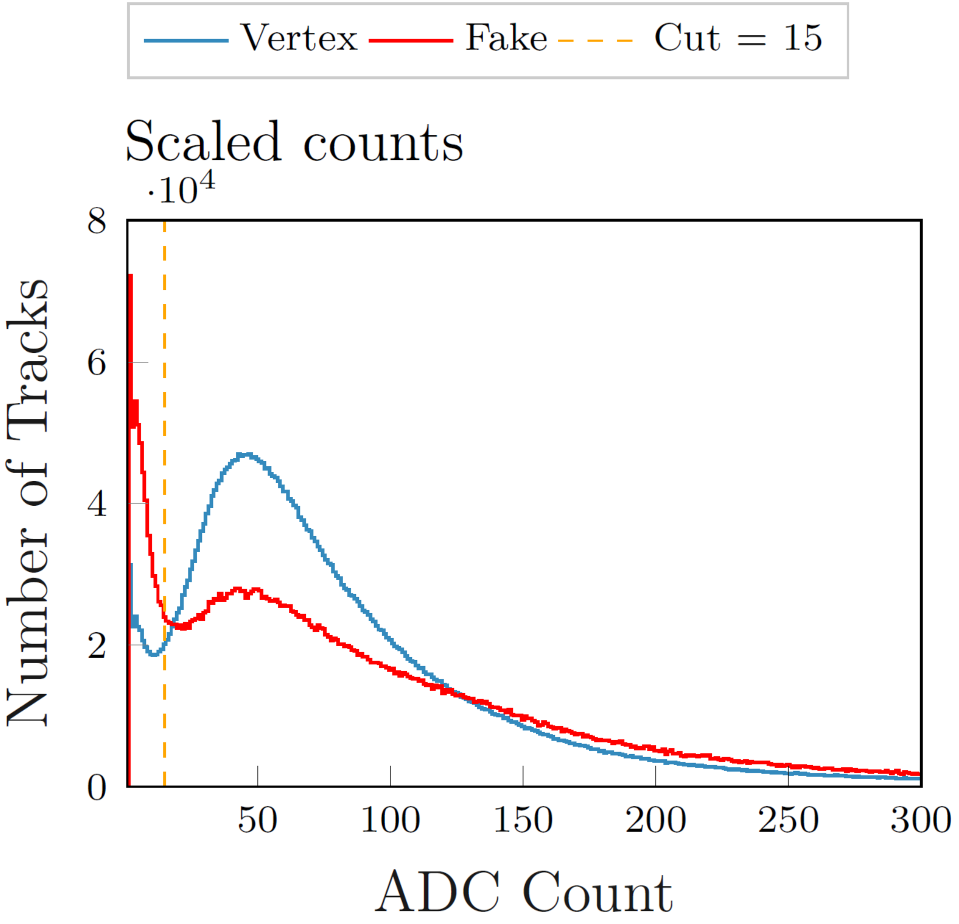


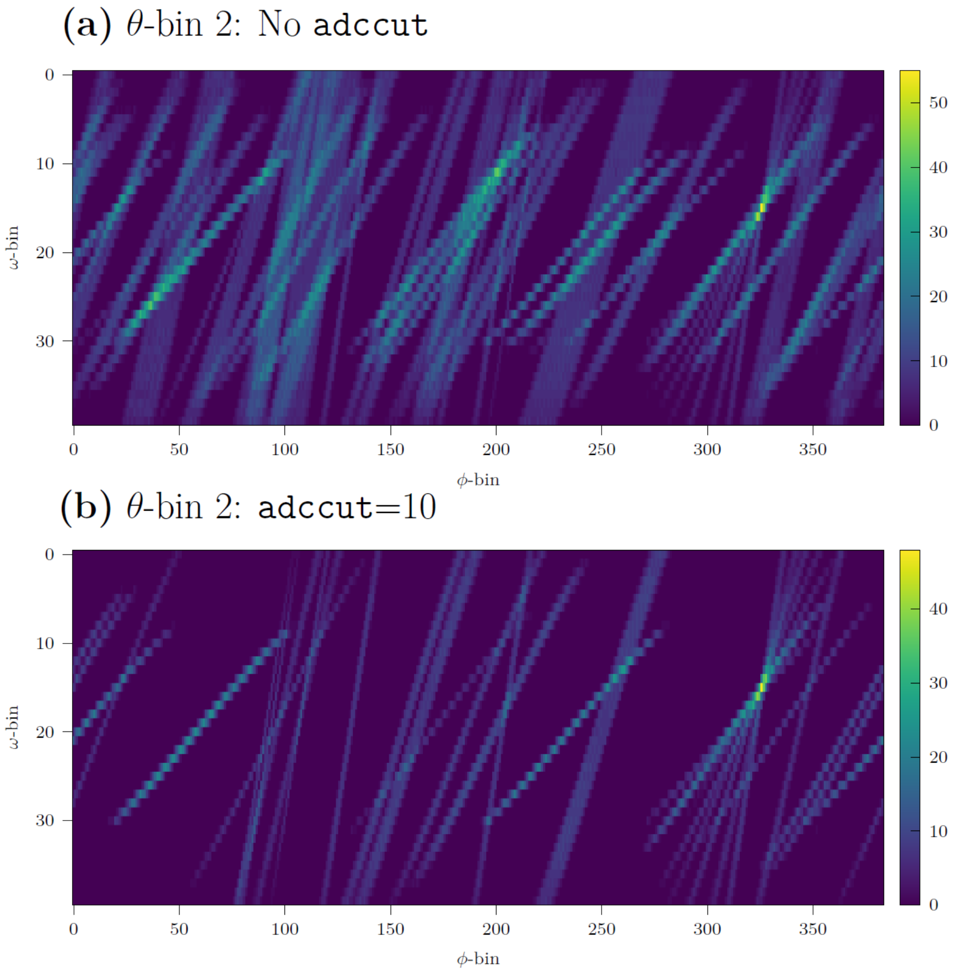
Stacked view for illustration only, cluster finding is done in 3D

Simon Hiesl (MPI & LMU)

Real Data Analysis

- Very high backgrounds were observed in the last experiment (due to high luminosity)
- The Hough spaces contain a lot of background track segments





$\Longrightarrow$ Reduction of noise using a cut on the ADC count

Simon Hiesl (MPI & LMU)

Efficiency on Real Single Track Events

Simon Hiesl (MPI & LMU)

- Hit to cluster relation:
  - All hits in a cluster are considered
  - The largest weight distribution for each SL is used
- Cut on the number of axial and stereo SL hits (for background reduction)

Efficiency for single track events: Cut at $\pm 10\,\mathrm{cm}$

`adccut`	Efficiency 3D	Efficiency 2D
No Count	94.1%	94.0%
10 Counts	96.3%	95.3%

Fake-Rate for all found tracks:

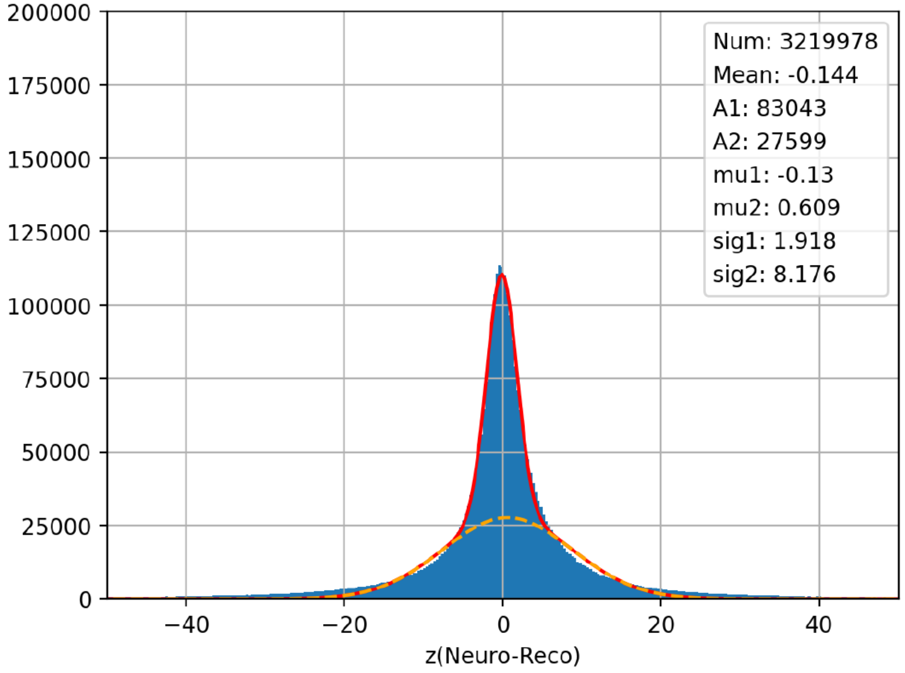
`adccut`	Fake-Rate 3D	Fake-Rate 2D
No Count	13.1%	31.6%
10 Counts	5.8%	13.5%

But: Neural network not trained for 3D candidates at the moment (see presentation by Timo Forsthofer)

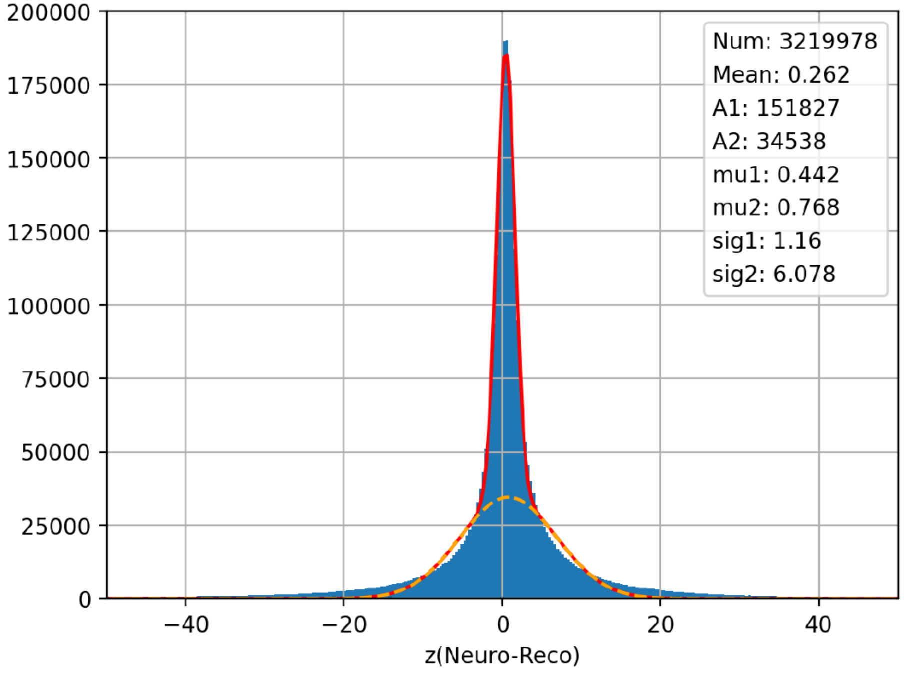
Deep Learning Architectures

- New, more powerful FPGAs allow for bigger networks
- Three or four hidden layers beneficial for resolution
- More hidden layers better than more nodes per layer

Timo Forsthofer
(MPP & LMU)



1HL with 81 Nodes

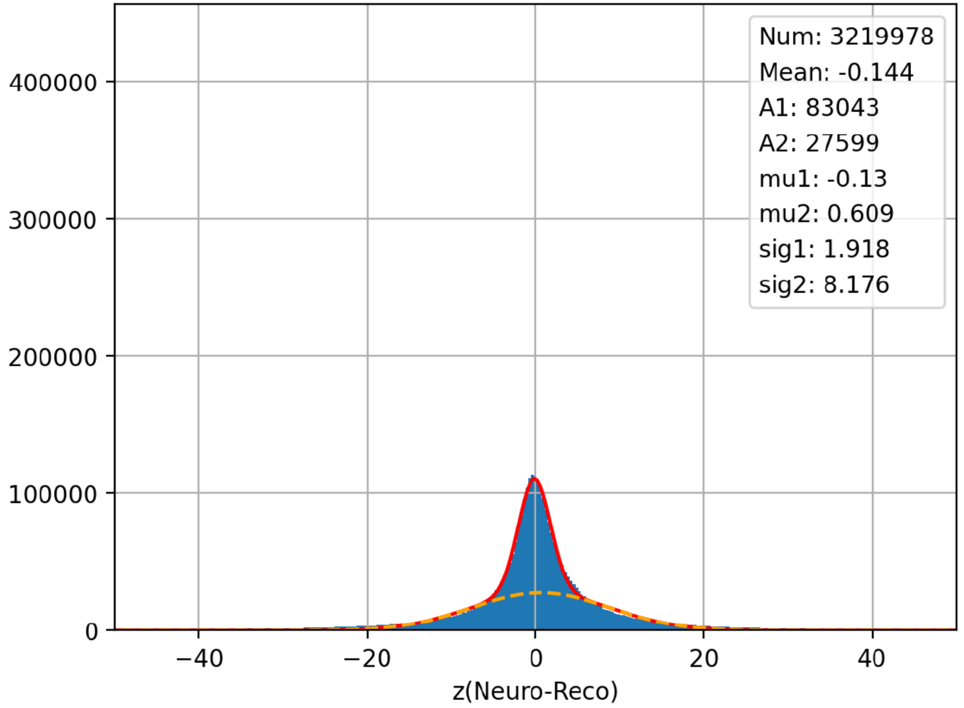


4HL with 100 Nodes per HL

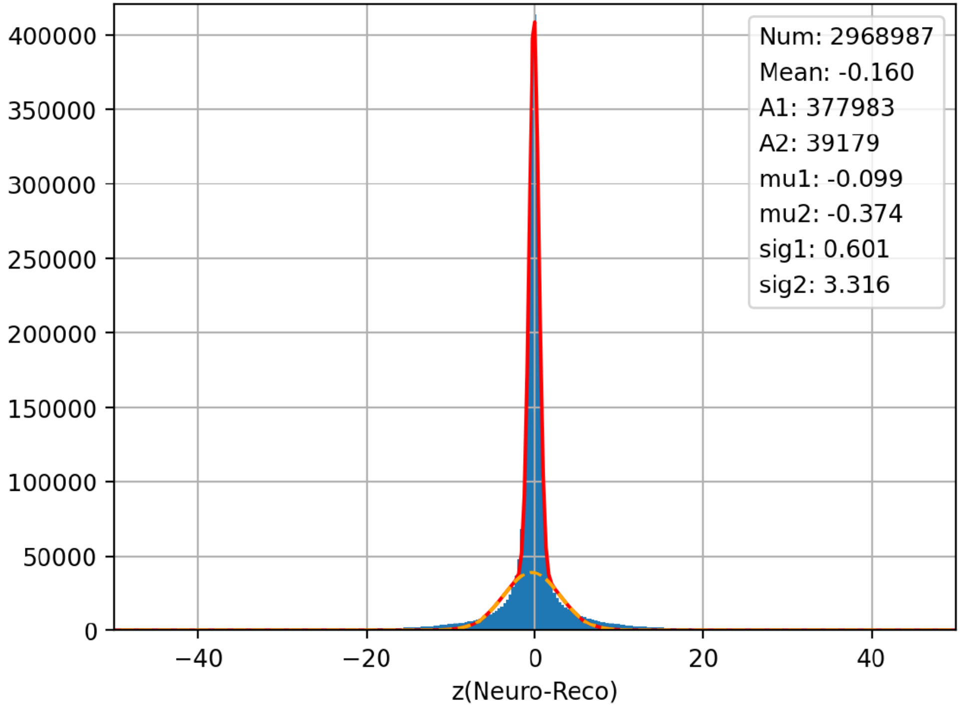
Final Performance Evaluation

Timo Forsthofer
(MPP & LMU)

- Combination of all advances leads to increase in accuracy by almost a factor of three
- z-Cut can be reduced from 15cm to under 10cm



Present Network Architecture

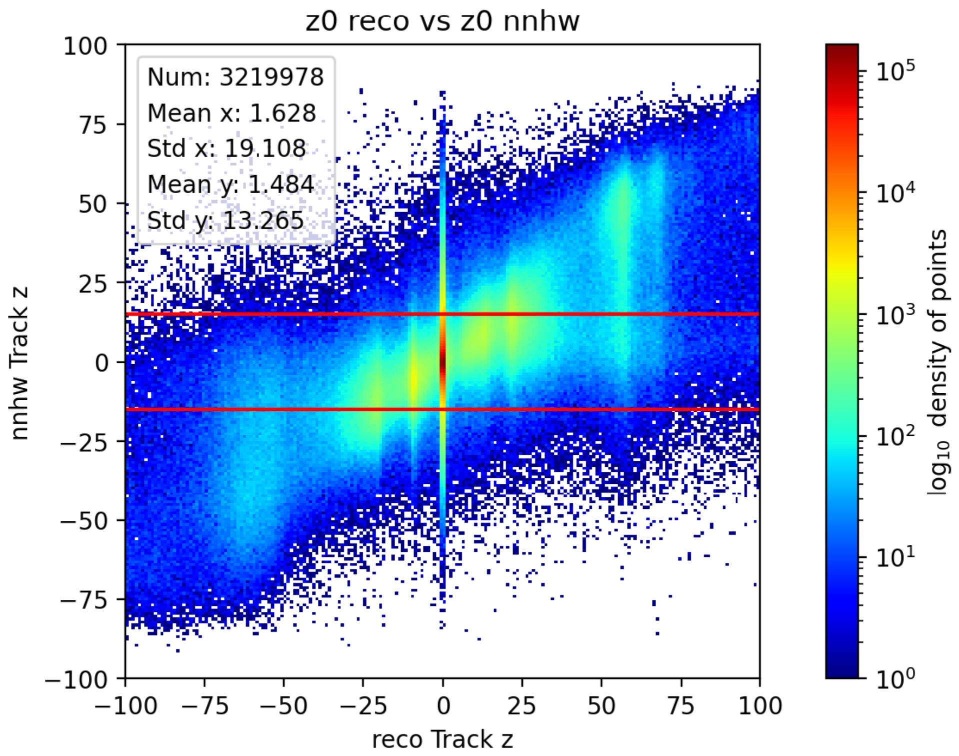


Deep Neural Network with Extended Input, ADC-cut and 3D-Input

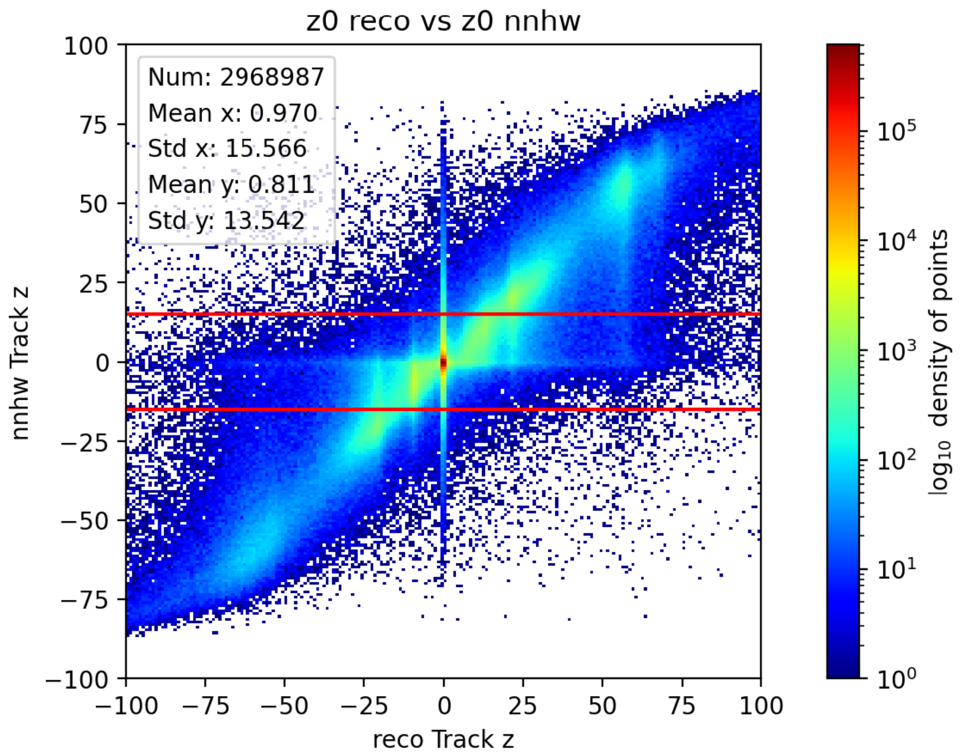
Final Performance Evaluation

Timo Forsthofer
(MPP & LMU)

- Especially extended input helpful in reducing Feed-Up and Feed-Down



Present Network Architecture



Deep Neural Network with Extended Input, ADC-cut and 3D-Input