Kalman-Based Reconstruction in the EIC ZDC

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Motivations

- **Goal:** reconstruct neutral particles (neutron, photons) in the ZDC

  - Physics case: $\Lambda^0 \rightarrow n + \pi^0 \rightarrow n + \gamma\gamma$

  - Assess detector performances, prior to further tuning of the geometry

- **Challenge:**

  - only calorimetric information (position along x,y and energy deposits)

  - possible multi-particle overlap

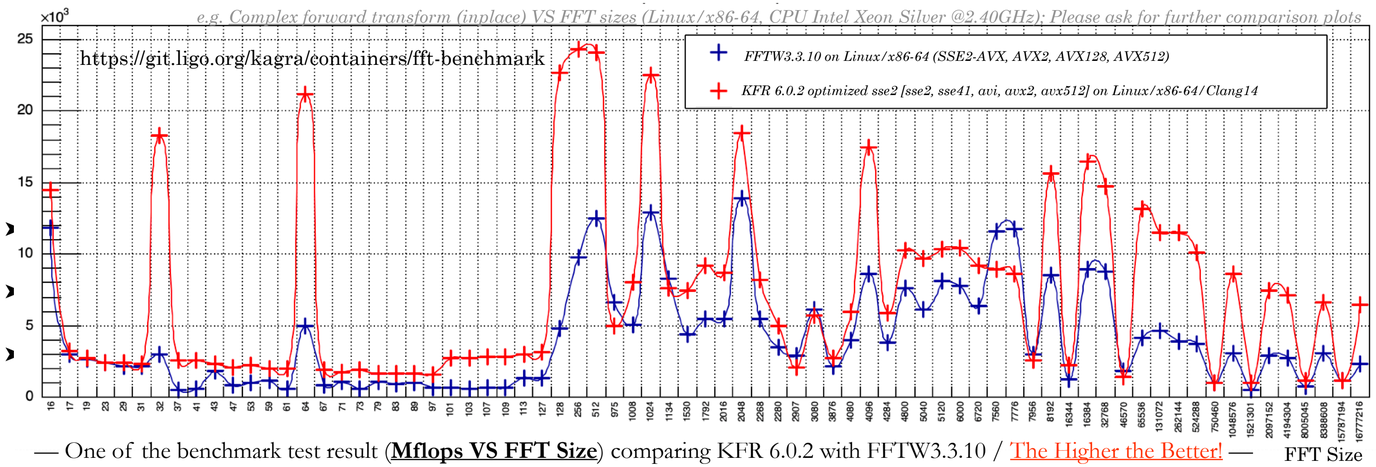
  - noise possibly underestimated

My group's interest:

- Explode and elaborate AI technics based on our past expertise either in pure AI (or Astrophysics)
- Streaming readout & DAQ (Echelon 0-1) for event filtering; ZDC detector for study of meson structure

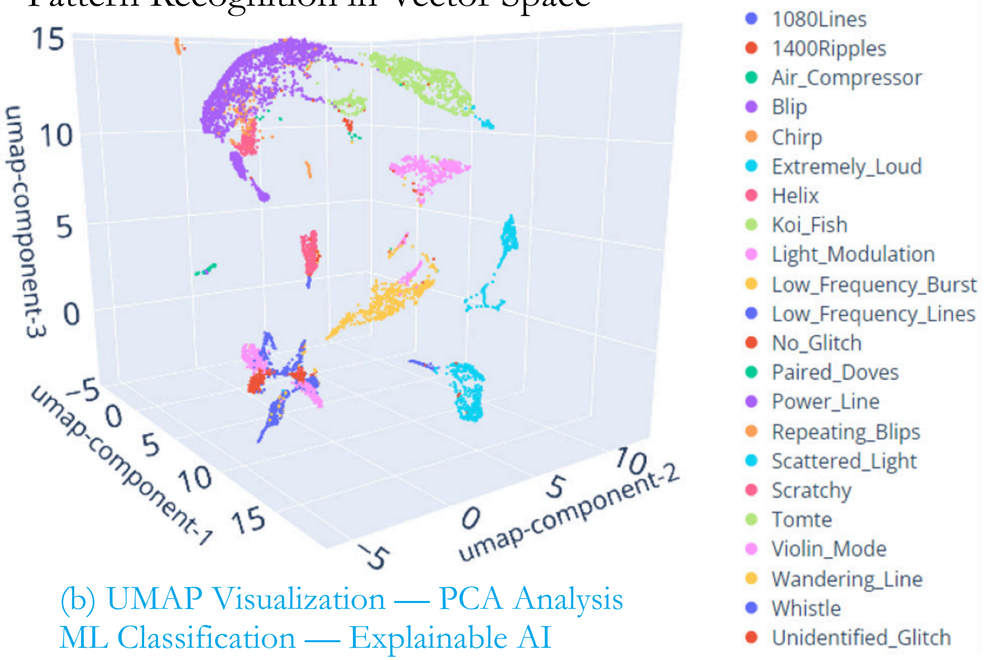
Introduction

Tokyo City University: "Data Science" Laboratory



(a) Optimization (in red) & Benchmarking of Signal Transformation (FFT) — Extending Python/C++ ROOT Framework toward Multidimensional Tensors / TimeSeries Analysis at CERN
arXiv:2503.14292v1 [astro-ph.IM] - ACAT2024 Invited Talk.

Pattern Recognition in Vector Space



(b) UMAP Visualization — PCA Analysis
ML Classification — Explainable AI
https://nature.com/articles/s41598-022-13329-4 [Scientific Reports]

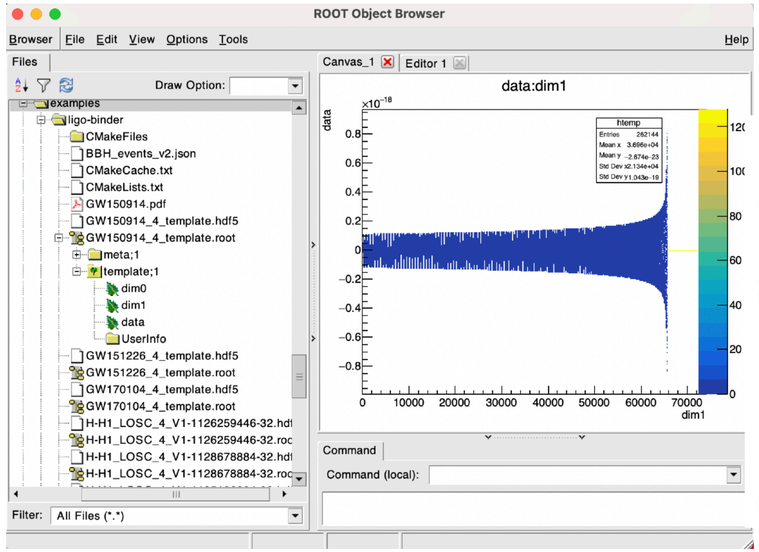
conda-forge

https://github.com/hep-packaging-coordination
dedicated HEP initiative aiming to compile all sort of arch. and machines (powerpc, aarch64, window, macos etc.)

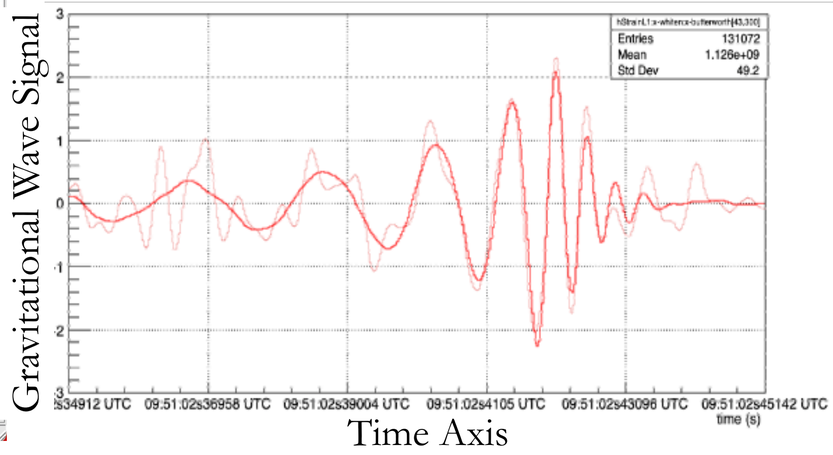
HEP Forge * (no link with http://hepforge.org)

https://github.com/hep-forge
http://anaconda.org/hep-forge
repository with no strict requirements to publish (linux only, AMD64/ARM64)

(c) Coordination & Maintenance of the HEP Packaging Software on Conda Repositories
(pre-compiled software installation & legacy support)

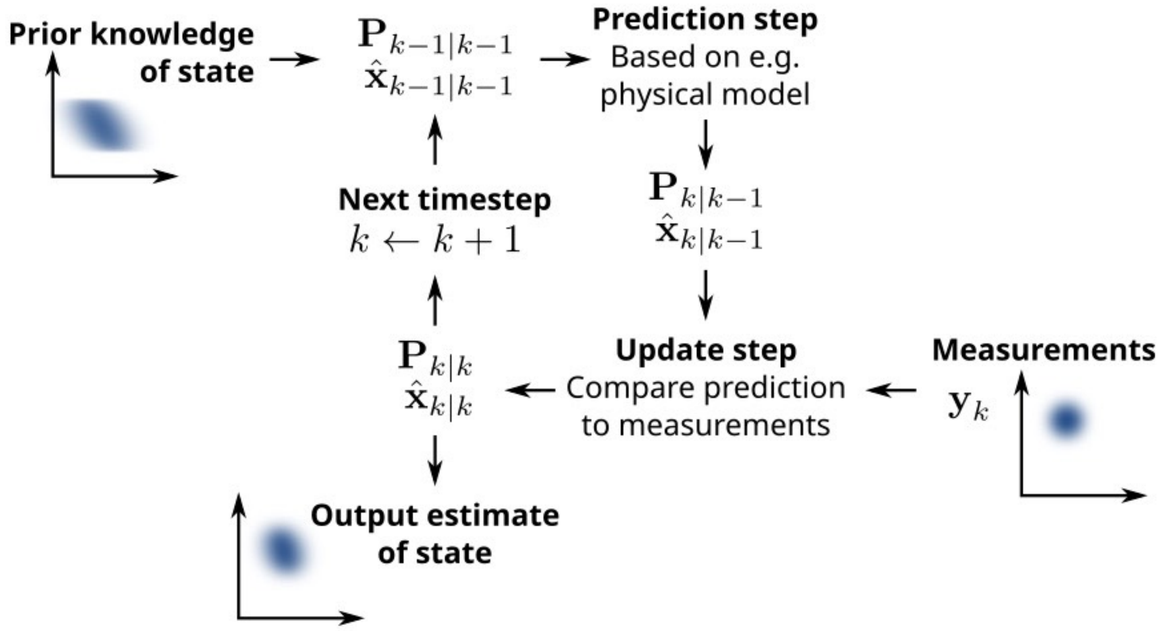


(d) First Gravitational Wave Extraction using ROOT Experimental Signal Processing (e) + **Kalman Filtering** https://link.aps.org/doi/10.1103/jpr4-m3ck



Traditional Kalman example

Ballistic model



Developed by Rudolf Kalman in 1960.
First use in Apollo guidance computer.

Equations of Kalman

$$\hat{\mathbf{x}}_{k|k-1} = F_{k-1}\,\hat{\mathbf{x}}_{k-1|k-1},$$
$$P_{k|k-1} = F_{k-1}\,P_{k-1|k-1}\,F_{k-1}^{T} + Q_{k-1}$$

$\mathbf{w}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$ (process noise)

$\mathbf{v}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{R})$ (Measurement noise)

From State Space → To Observing (Measurement) Space

$$\mathbf{x}_{k+1} = F_k\,\mathbf{x}_k + \mathbf{w}_k$$

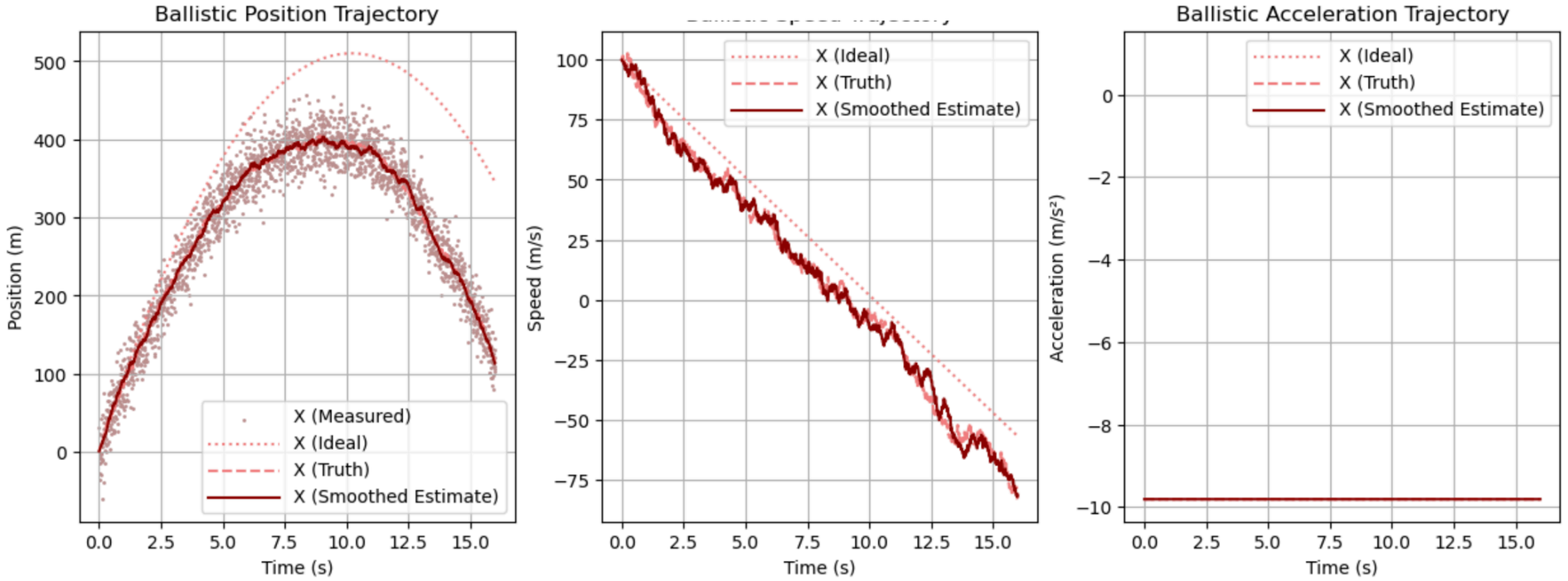
$$\mathbf{z}_k = H\,\mathbf{x}_k + \mathbf{v}_k,$$

Traditional Ballistic Model

- Simple model for practical introduction of the concept (constant acceleration)

$$x(t) = \frac{1}{2}gt^2 + v_0 t + x_0 \longrightarrow \mathbf{x} = [z,\ \dot{z},\ \ddot{z}]^\top \text{ (state vector)}$$

$$F = \begin{pmatrix} 1 & \Delta t & 0 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{pmatrix}, \quad H = \begin{pmatrix} 1 & 0 & 0 \end{pmatrix} \longrightarrow z \text{ (measurement vector)}$$



- Noise model ? Process noise VS Measurement Noise. (See next slide)

Transition from Ballistic Model to ZDC

By analogy

	Projectile model (toy)	**ZDC EIC**
System dynamics	Ballistic trajectory	Track position / angle
(Physics induced-) Process noise	Friction, wind	EM shower, stochastic fluctuation
Measurement noise	GPS or Camera uncertainty	Detector resolution (per slice); position and energy deposit

Transition to ZDC Reconstruction

Why Kalman Here?

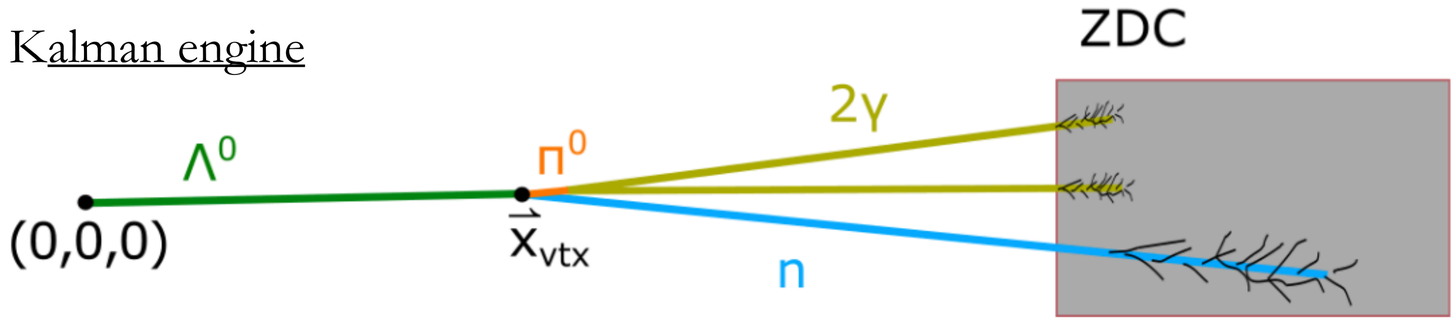
- **Detector Characteristics**
  - layered calorimeter → natural discretization along z
  - 4D information available: (x, y, "z", E)

- **It naturally handles**
  - sequential layers (ZDC sampling): transition matrix (k → k+1)
  - process noise (fluctuating showers)
  - partial information

- One Kalman component per track, but one Kalman engine

$$\mathbf{A} = \mathrm{diag}(\mathbf{A}_1, \ldots, \mathbf{A}_N),$$

- **Track reconstruction engine:**
  - Linear Kalman Filter
  - Extended Kalman Filter (non linear) for including energy deposit (later)
  - Unscented Kalman Filter for non-linear noise distribution.



(Taken from: SJ Paul *et al.*)

- Rauch-Tung-Striebel smoother for taking into account a backward pass on the measurement

Kalman Filter per Component

One Component = One Candidate Track

$\mathbf{w}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$ (process noise)

$\mathbf{v}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{R})$ (Measurement noise)

- **State Definition:**

$$\mathbf{x}_k = (x_k,\ y_k,\ t_{x,k},\ t_{y,k})^T, \qquad \mathbf{x}_{k+1} = F_k\,\mathbf{x}_k + \mathbf{w}_k, \qquad F_k = \begin{pmatrix} 1 & 0 & \Delta z_k & 0 \\ 0 & 1 & 0 & \Delta z_k \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

$$\mathbf{z}_k = H\,\mathbf{x}_k + \mathbf{v}_k, \qquad H = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

- **Measurement :** traditional clustering, possibility for machine learning (Kalman is still flexible)

$$\mathbf{z}_k = \begin{pmatrix} x_k \\ y_k \end{pmatrix}, \qquad R_k^{(0)} = \begin{pmatrix} \sigma_{x,k}^2 & \sigma_{xy,k} \\ \sigma_{xy,k} & \sigma_{y,k}^2 \end{pmatrix} \text{, with} \qquad x_k = \frac{\sum_{i\in\mathcal{H}_j^{(k)}} E_i\,x_i}{\sum_{i\in\mathcal{H}_j^{(k)}} E_i}, \qquad y_k = \frac{\sum_{i\in\mathcal{H}_j^{(k)}} E_i\,y_i}{\sum_{i\in\mathcal{H}_j^{(k)}} E_i}$$

$+\Delta E_k$

- **Noise Modeling**
  - Process noise (Q) accounts for shower fluctuations & scattering
    Q to be determined with CWNA model by calculating $t_x(z_k + \Delta z_k)$
    R. Frühwirth, "App. of Kalman filtering to track and vertex fitting", Nucl. Instrument. Meth. A 262, 444 (1987)

$$\frac{dt_x}{dz} = \eta_x(z), \qquad \langle \eta_x(z)\,\eta_x(z')\rangle = \sigma_t^2\,\delta(z-z')$$

(stochastic diffusion: σ_t^2 ~ strength diffusion of the shower axis; typically including Molière radius+radiation length for spread of the EM & hadronic showers

  - Measurement noise (R) depends on cluster spread, detector granularity & energy deposition
    Detector characteristics ~ position & energy resolutions

Vertex Reconstruction for assessing precision

Performance and detector reconstruction

Backward extrapolation of reconstructed tracks to find common intersection along z

Method:

- Pairwise closest approach from gamma and neutron
- χ^2 minimization
- Weighted intersection using uncertainties from Kalman filter (P_k)

Resolution considerations and advantages of Kalman

- Limited by angular resolution, shower fluctuations, detector segmentation
- Assess detector performance on the fly
  comparing generated vs reconstructed information
- Compute pull distribution for each track, using covariance matrix P_k:
  any deviation ~ badly conditioned (R,Q) noise

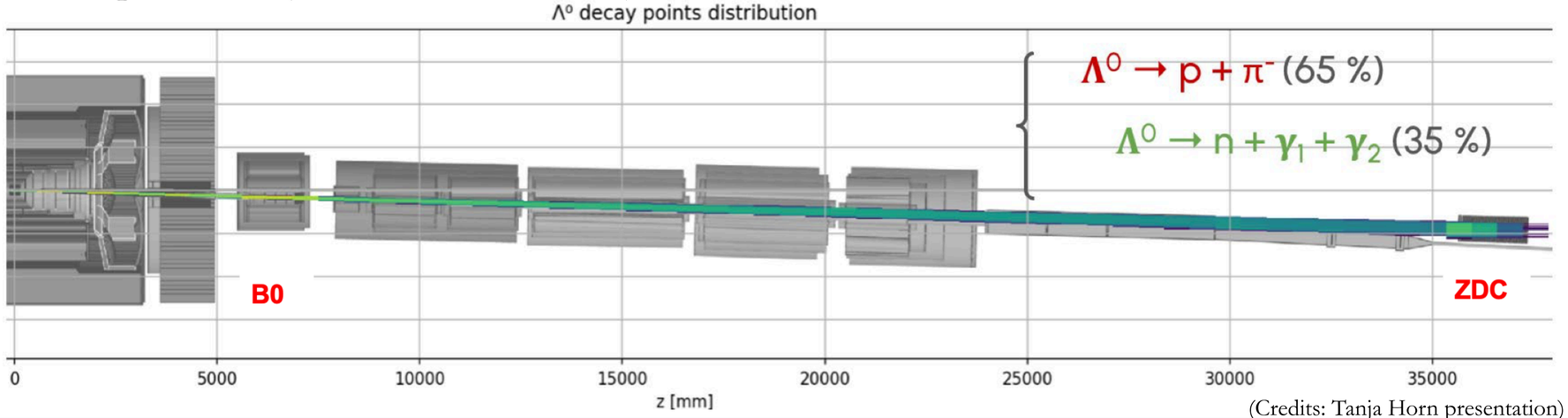
Step 5 — Physics Reconstruction

π^0 or Λ^0 reconstruction

- extrapolate reconstructed directions backward;
- **π^0 reconstruction**
  - combine γ_1 and γ_2 directions
  - invariant mass constraint

$$m^2_{\gamma\gamma} = 2\,E_{\gamma_1} E_{\gamma_2} (1 - \cos\theta_{\gamma\gamma})$$

- **Λ^0 reconstruction:** width of the Λ_0 peak is a direct figure of merit, coupled with angular resolution of the three neutral tracks, the energy resolution of the calorimeter, and the vertex resolution.
  - combine neutron + π^0;
  - reconstruct vertex position (wrt. z_{vtx} resolution)



(Credits: Tanja Horn presentation)

Summary

Kalman filtering is a swift and adaptable approach for describing a system's dynamic from differential equations.

1. **3D Clustering:** Separate particles are created.
2. **Layer Integration:** Measurements are incorporated into the layers.
3. **One Kalman per Component:** Trajectories are calculated for each component.
4. **Backward Extrapolation:** Vertex positions are determined.
5. **Combine Particles:** The particles are combined to obtain physics observables.

Extensions:

- **Incorporating Energy E:** Energy is included in the state vector x_k.
- **Detailed Model Study:** A comprehensive study of the electromagnetic and neutron showers is conducted.
- **Testing Systematics:** Systematics are tested using the resulting covariance matrix, chi2, and by changing the detector design on-the-fly.
- **Dynamic energy reconstruction:** implementing Longo–Sestili model for describing more precisely the energy deposit VS. nuclear interaction length.

Extension (for fun):

- **Neural Networks for Clustering:** Neural networks are used for clustering.
- **Comparison with Traditional Graph Neural Networks (GNN)**