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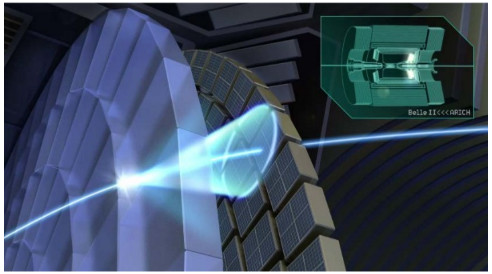


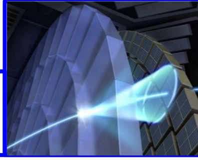
Simulation and reconstruction for Cherenkov detectors

Luka Šantelj,

Jozef Stefan Institute and University of Ljubljana

CEPC 2025

Guangzhou, 5-10 November 2025

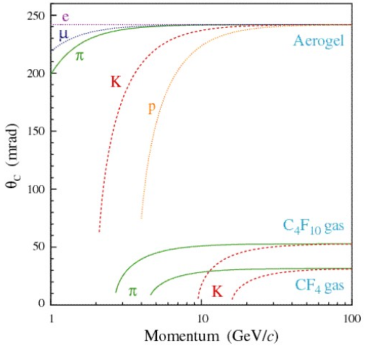


→ from yesterday’s intro talk

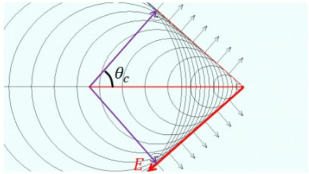
A reminder of Cherenkov detector

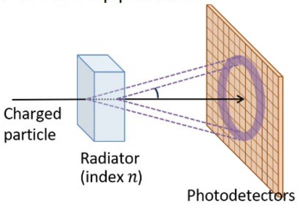
- Cherenkov detector is a powerful tool for charged particle identification, especially for particles with a momentum up to several tens of GeV/c where the ToF is not applicable

LHCb RICH-1 (Aerogel+C_4F_{10} gas radiator)
RICH-2 (CH_4 gas radiator)



2-100 GeV/c





RICH 2025, Kodai Matsuoka

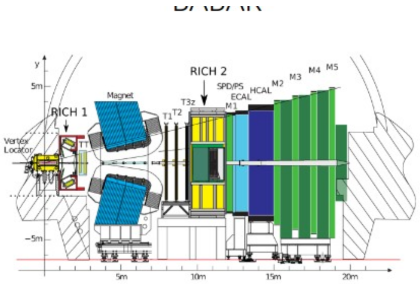
Threshold: $\beta > 1/n$

Cherenkov angle: $\cos\theta_c = \dfrac{1}{n\beta}$

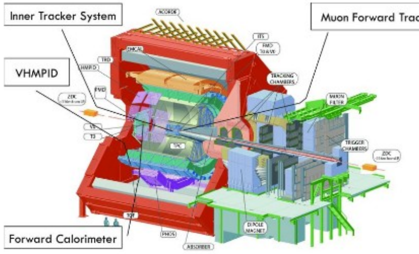
Number of photons: $\dfrac{dN_\gamma}{dE} = \left(\dfrac{\alpha}{\hbar c}\right) Z^2 L \sin^2\theta_C$

Separation power: $N_\sigma \approx \dfrac{|m_1^2 - m_2^2|}{2P^2\sigma[\theta_c(tot)]\sqrt{n^2-1}}$

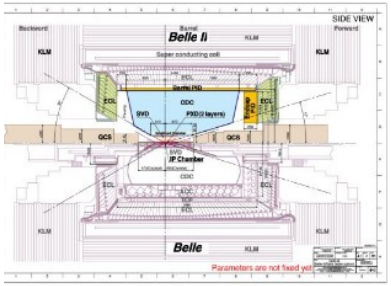
3



LHCb



ALICE 4



BELLE II

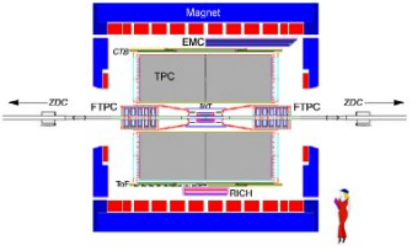
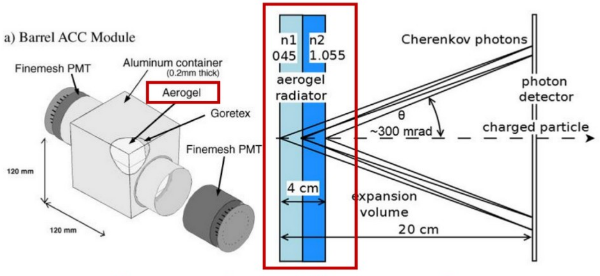


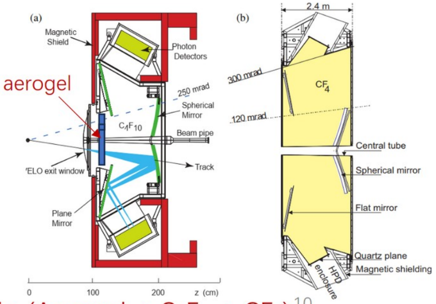
Fig. 2. Cutaway side view of the STAR detector as configured in 2001.

STAR

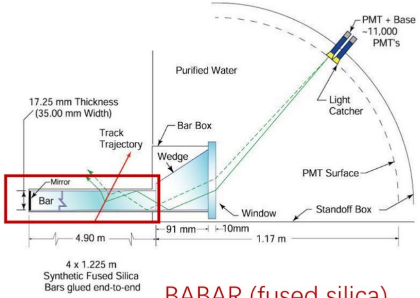
→ several radiator and design geometry options in use



Belle I & Belle II (silica aerogel)



LHCb (Aerogel + C_4F_{10}+ CF_4) 10



BABAR (fused silica)

Outline

- Simulation for RICH detectors
  → use case: Belle II aerogel RICH
- Reconstruction methods – PID likelihoods
  → local (use case: Belle II ARICH)
  → global (use case: LHCb)
- Use of ML/AI for Cherenkov detectors
- Conclusions

Cherenkov detector simulation

→ nominally Cherenkov PID detectors are included in the global Geant4 simulation of experiment

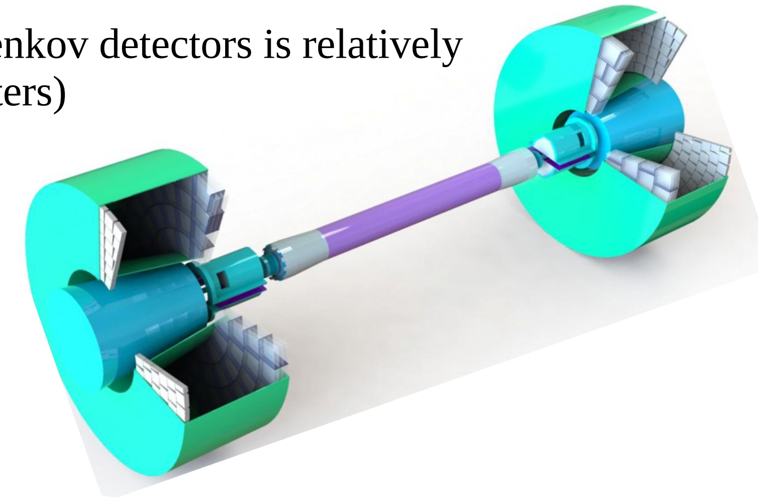
→ Geant4 provides all necessary functionality for simulation of emission and propagation of Cherenkov photons

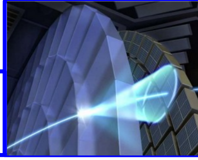
→ detailed description of optical properties of geometry elements is of course required

→ mostly works well out of the box

→ unless enormous amounts of photons propagated, simulation of Cherenkov detectors is relatively lightweight in CPU power compared to other detectors (e.g. calorimeters)

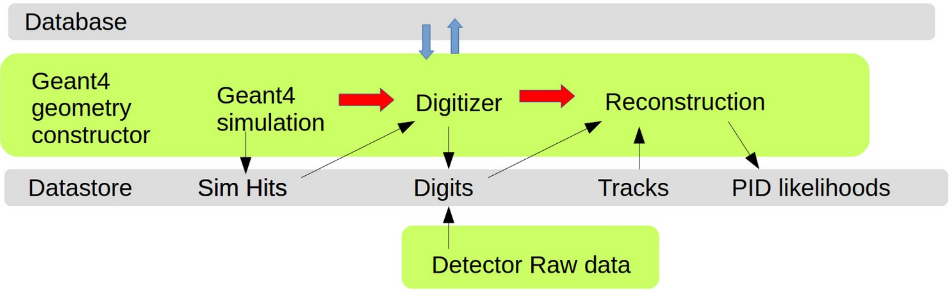
→ optimization trick to consider
since optical photons do not produce secondaries, consider applying photon detector QE curve at the time of photon production!
(avoid propagation of photons which are lost anyway due to QE)

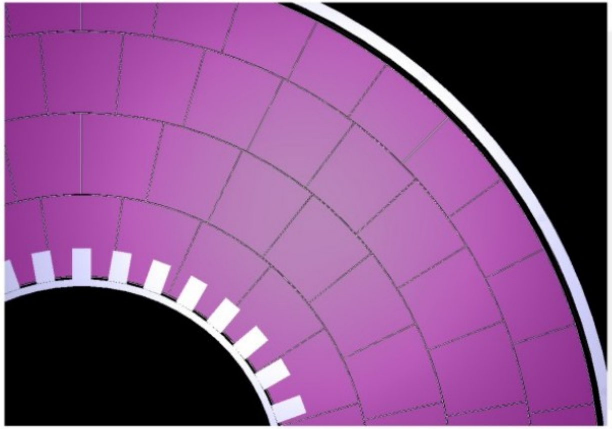


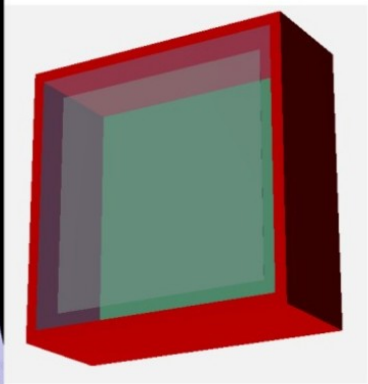


Use case: Geant4 simulation of aerogel RICH @ Belle II

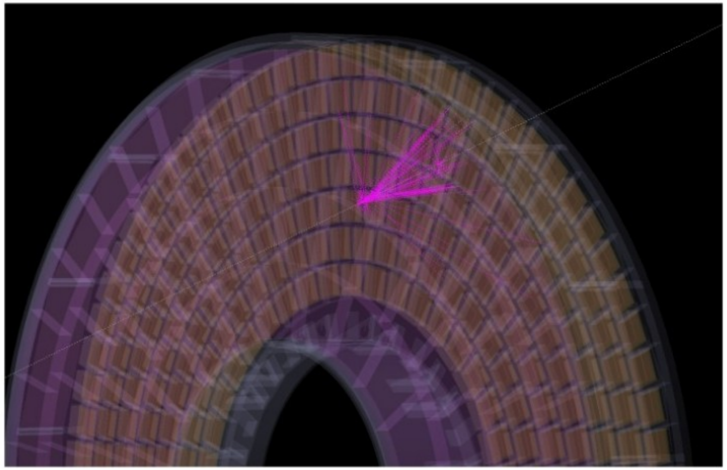
→ general software structure: basic event processing loop

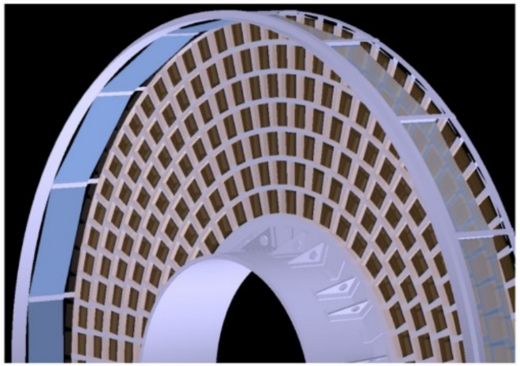


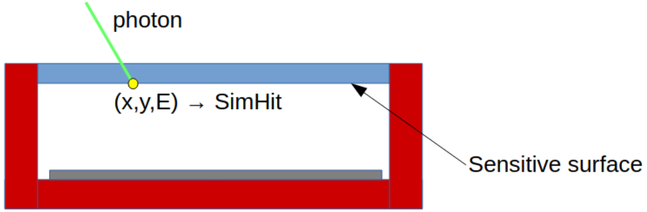


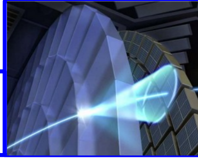


- → detailed geometry description in G4
- → detailed optical properties for aerogel tiles and HAPD quartz window (transmittance vs wavelength etc.)
- → optical processes within HAPD are included, but G4 simulation stops with optical photon being “detected” on the photo-cathode









Digitization

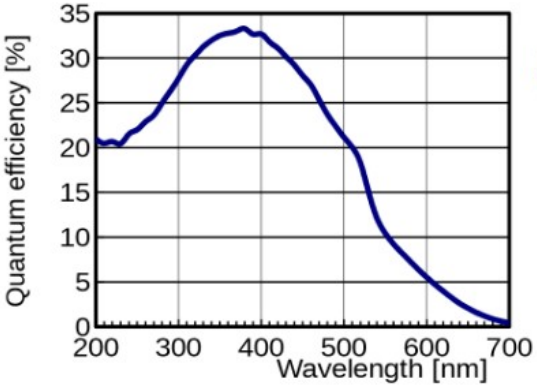
- The digitizer module converts SimHits into Digits, which are used as an input to reconstruction algorithm (Digits ↔ detected photons).

Pixelization SimHit (x,y,E) → APD channel number

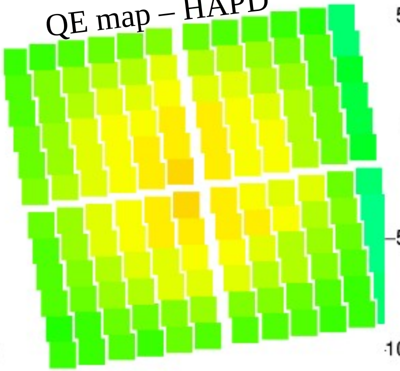
Photocathode QE

- common $QE(\lambda)$ curve shape is used for all HAPDs
- but scaled according to the QE as measured in HAPD QA tests, channel-by-channel for each HAPD.

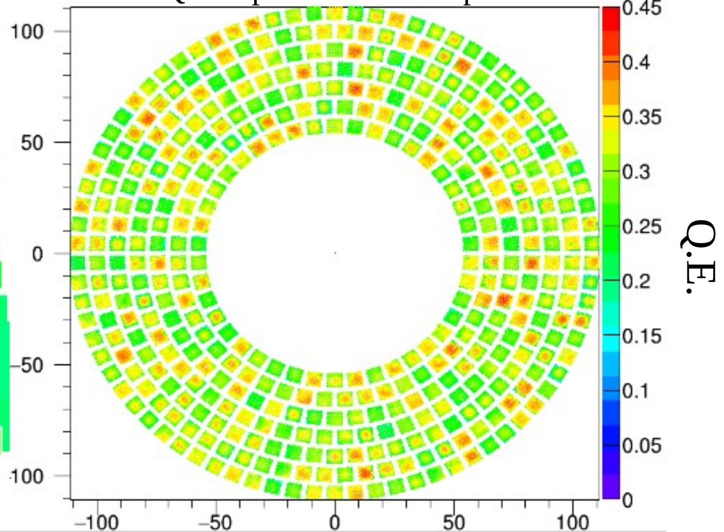
Masking of dead channels (from database)



QE map – HAPD

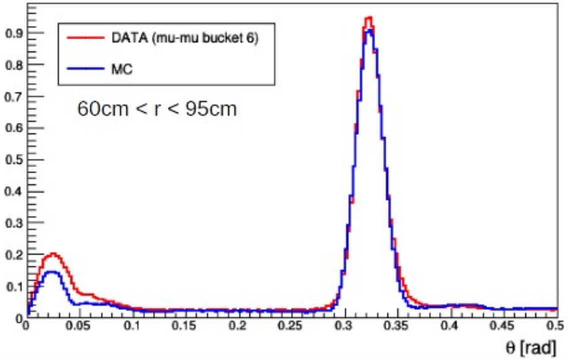


QE map – full detector plane



Cherenkov angle distribution – Data / MC comparison

- Accumulated Cherenkov angle distribution as observed in $\mathbf{e}^+\mathbf{e}^- \to \mu^+\mu^-$ events



DATA

$N_{sig} = 11.38/\mathrm{track}$

$\sigma_c = 12.7\ \mathrm{mrad}$

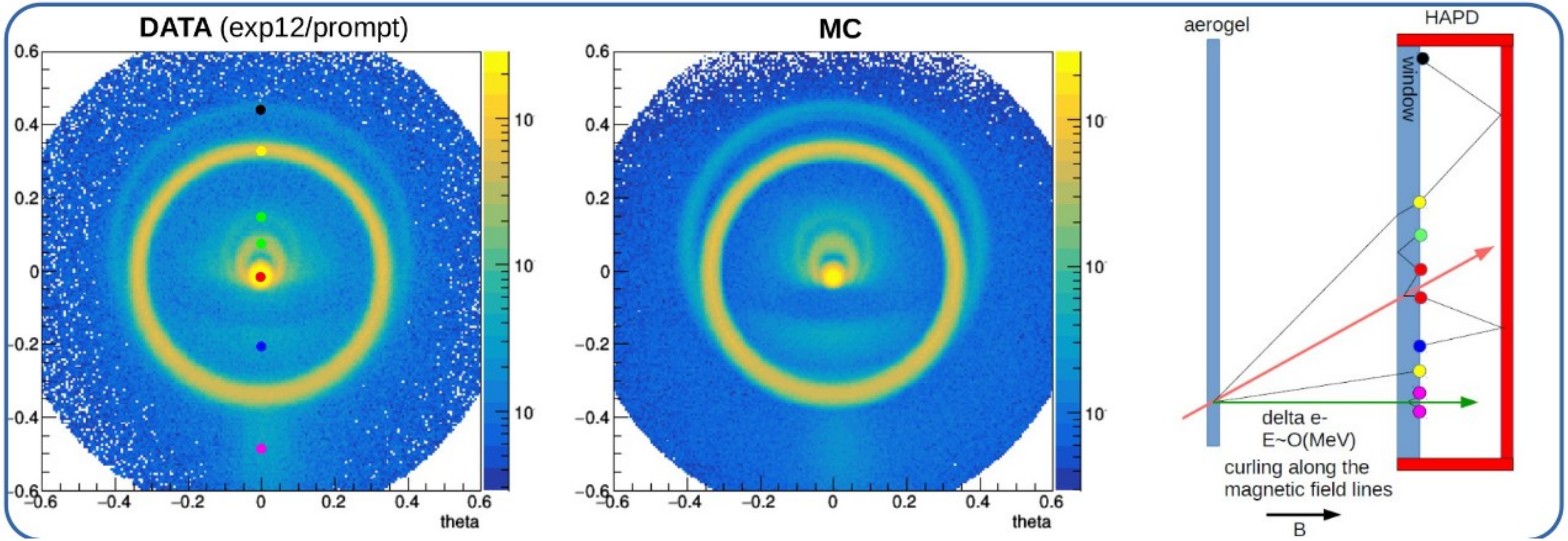
MC

$N_{sig} = 11.27/\mathrm{track}$

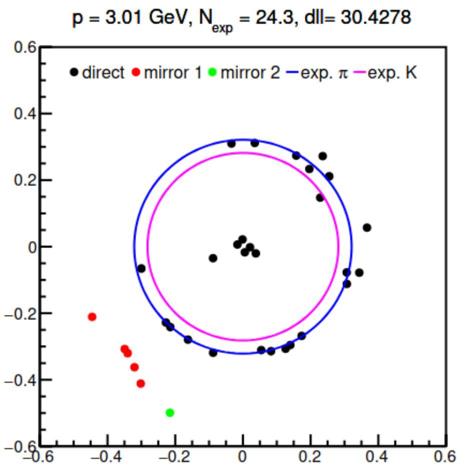
$\sigma_c = 12.75\ \mathrm{mrad}$

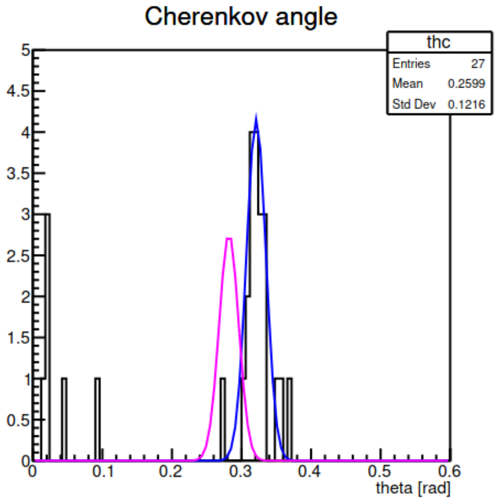
(> 6 GeV/c muons → fully saturated Cherenkov rings)

→ **good DATA/MC agreement !**

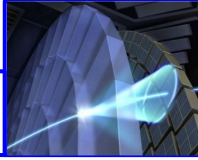


From tracks and Cherenkov photons to PID likelihoods → data reconstruction

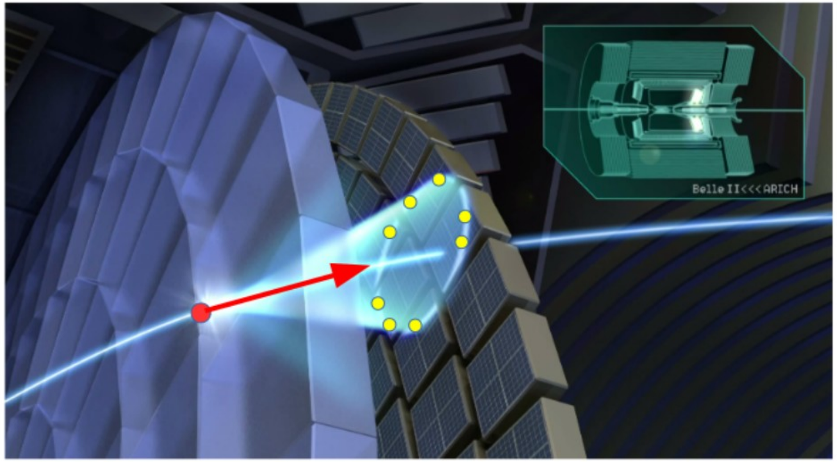




→ for optimal PID performance one needs to go much beyond calculation of mean Cherenkov angle of emitted photons…



PID likelihood evaluation



→ commonly employed when track information (position, direction, momentum) in the radiator is available (from other detector sub-systems)

→ we can base PID on comparison of observed pattern of detected photons with the expected one assuming given track parameters and particle type.

→ evaluate likelihoods for given particle type hypothesis (e.g. e, μ, π, K, p)

Likelihood for particle type h

$$\mathcal{L}^h = \prod_i^{pixels} p_i^h \qquad \text{with} \qquad p_i^h = e^{-n_i^h} \left(\boxed{n_i^h}\right)^{m_i} / \boxed{m_i}!$$

name of the game is evaluation of n_i^h !

probability of observing the observed number of photons on pixel-i

expected number of photons on pixel-i

observed number of photons on pixel-i

Nucl. Instrum. Meth. A, 238:341, 1985

PID likelihood evaluation

→ in case of "binary" photon detection, i.e. pixel is fired for $m_i \geq 1$

$$p_i^h = e^{-n_i^h} \qquad \text{for non-fired pixels}$$

$$p_i^h = 1 - e^{-n_i^h} \qquad \text{for fired pixels}$$

→ evaluating n_i^h for all pixels in the detector might be costly. In low occupancy environment, rewriting the likelihood in the following format can be useful

$$\mathcal{L}^h = \prod_i^{pixels} p_i^h \quad \Longrightarrow \quad \ln \mathcal{L}^h = -N^h + \sum_i^{hit} [n_i^h + \ln(1 - e^{-n_i^h})]$$

total number of fired pixels (hits) expected to be observed $\sum_i^{pixels} n_i^h = N^h$

→ evaluate n_i^h only for fired pixels, but need a method to estimate N^h

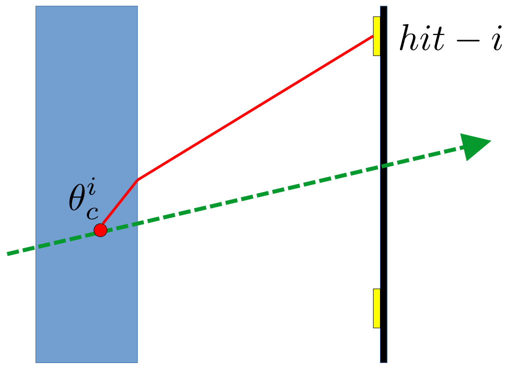
PID likelihood evaluation

Evaluating n_i^h

→ can be done at different levels of sophistication, depending on performance needs, factors limiting the PID performance, computing resources etc.

→ based on detector geometry, track information and hit position, Cherenkov angle $(\theta_c,\phi_c)^i$ for each hit can be reconstructed, assuming photon emission point in the radiator

→ it is a reverse ray-tracing problem, depending on complexity of the geometry and required precision can be solved analytically, semi-analytically (numerically solving analytic relations), or with the use of iterative algorithms



→ finally $n_i^h = \underbrace{n_i^{h,s}(\theta_c^i,\phi_c^i)}_{\text{signal (non-scattered)}} + \underbrace{n_i^{h,b}(\theta_c^i,\phi_c^i)}_{\text{background (scattered, other particles, noise...)}}$

$$n_i^{h,s/b} = \boxed{N^{h,s/b}} \times \boxed{\mathcal{P}^{h,s/b}(\theta_c^i,\phi_c^i)} \times \boxed{d\Omega_i}$$

expected number of "emitted" photons

Cherenkov angle PDF (e.g. Gaussian peak at θ_c^h)

solid angle covered by pixel-i

PID likelihood evaluation

Evaluating N^h

→ can be obtained from expected total number of signal photons to be emitted in the radiator for hypothesis h (scatter and PDE corrected) and average geometrical acceptance for Cherenkov ring.

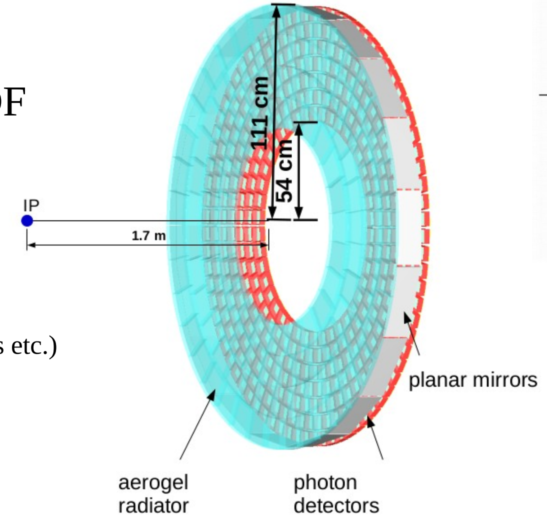
→ or better, ray-tracing “toy simulation” is used to obtain N^h on track-by-track basis.

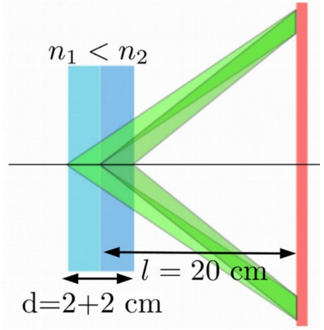
Use case – ARICH @ Belle II

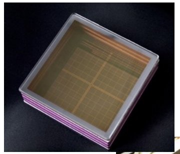
→ instead of evaluating n_i^h in the Cherenkov angle space the PDF is projected from it onto the photo-detector plane

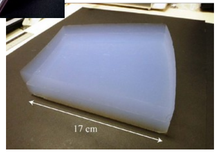
→ this allows for easier inclusion of effects that cannot be easily described in Cherenkov space

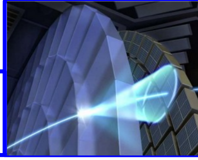
(geometrical acceptance effects, inefficiencies of detectors, internal reflections in photon detectors etc.)





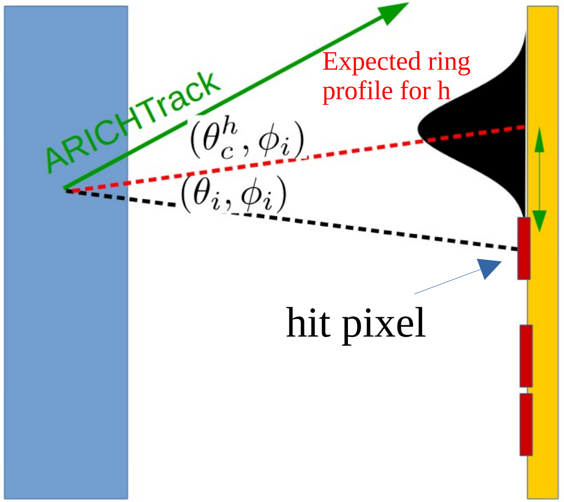






PID likelihood evaluation

→ **implementation of PDF projection to photo-detector plane:**



- first (θ_c^i, ϕ_c^i) are reconstructed, followed by propagation of “toy” photon with $(\boldsymbol{\theta_c^h}, \boldsymbol{\phi_c^i})$ from the assumed emission point in the aerogel to the photo-detector plane

- around the “toy” photon impact point assume Gaussian profile in the radial direction of the expected ring and flat in the azimuthal direction in the x-y space of detector plane

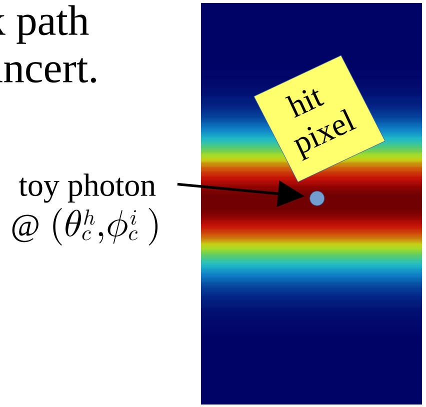
- width of the Gaussian profile is calculated on the track-by-track basis, based on the track path length in aerogel, distance between emission point and photon hit and track parameters uncert.

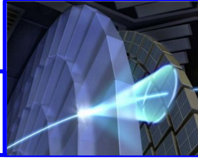
- 2D integral of Gaussian profile over the pixel surface is performed to obtain $n_i^{h,s}$
  (as pixel size is not small compared to Gaussian width)

- nominally background is added in the form $n_i^{h,b} = const. + \mathcal{P}(\theta_c^i; N^h, \mathrm{winHit})$

account for scattered signal photons

particle hit in photon-detector window





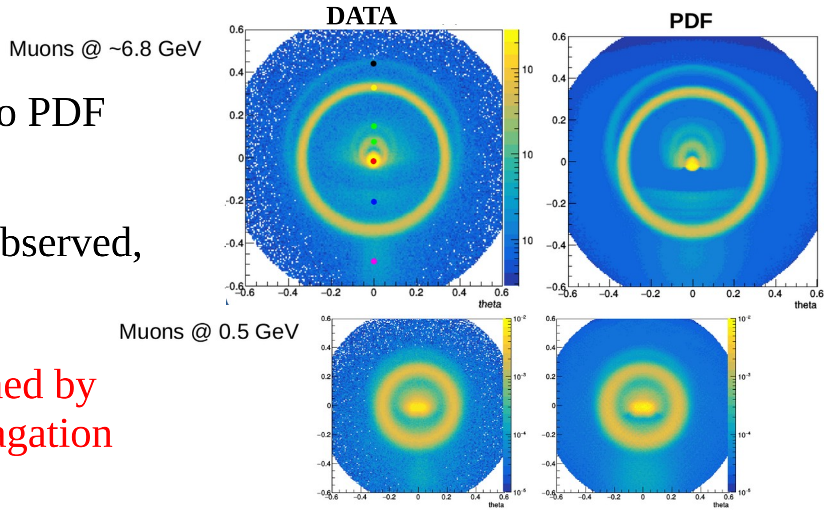
PID likelihood evaluation

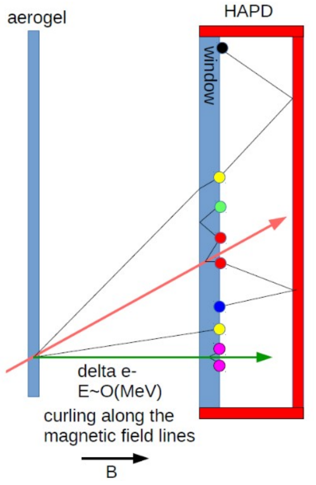
→ in the past few years effort was made to include several additional ring image features to PDF
(cherenkov photons from window, photon reflections…)

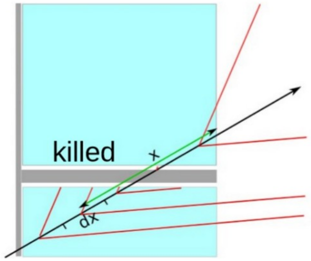
→ only marginal improvements in performance observed, so as default we maintain using original PDF

→ total number of expected photons N^h is obtained by "toy simulation" of photon emission and propagation

- 20 times expected emitted photons are propagated at θ_c^h from 10 points along the track path in aerogel to the photo-detector plane
  (includes: photon loss in gaps between aerogel tiles, pixel-by-pixel Q.E., run based pixel masking)

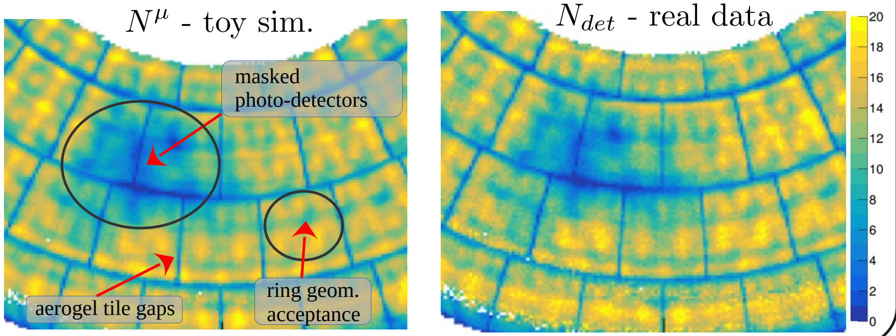






Nucl. Instrum. Meth. A, 876:104–107, 2017
Nucl. Instrum. Meth. A, 952:161800, 2020

Expected / detected number of photons vs. track position
(in e+e−→ $\mu^+\mu^-$)



PID likelihood evaluation

Global likelihoods

Nucl. Instrum. Meth. A, 433:257–261, 1999

→ in cases of non-negligible probability for Cherenkov rings from multiple particles to overlap improved PID performance can be achieved by the use of global likelihood

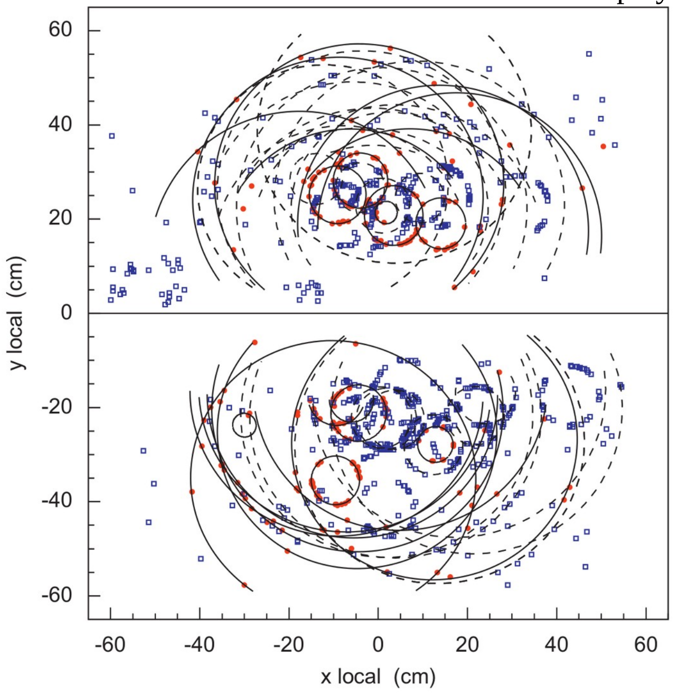
→ here likelihood is not evaluated on track-by-track basis, but for collection of all tracks in an event

→ using similar methods as described $n_i^{\{h\}}$ is calculated summing up contributions from all tracks given their assumed id. hypothesis (here {h} denotes a set of hypotheses for all tracks in an event)

→ set of identities {h} that maximizes $\mathcal{L}^{\{h\}}$ gives the most likely hypothesis for each particle in event

→ in cases where other backgrounds dominate the ring image (not cross-feed from neighboring tracks; e.g. detector noise, photons from secondaries) usage of global likelihood might become unpractical (→ local likelihood with effective background description)

LHCb RICH 1 – simulated event display



PID likelihood evaluation

Use case – LHCb

→ evaluating $\mathcal{L}^{\{h\}}$ for all possible combinations of particle hypothesis in non feasible (~50 tracks | 5 hypotheses)

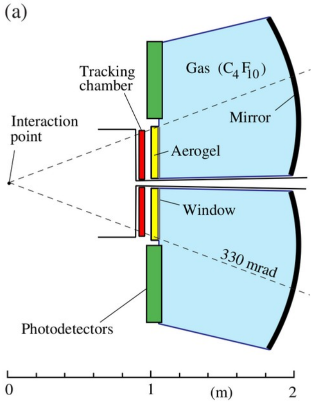
→ start with assuming all particles are pions (most abundant), track-by-track change mass hypothesis and fix it to most likely (max $\mathcal{L}$), iterate until no increase in $\mathcal{L}$ is found.

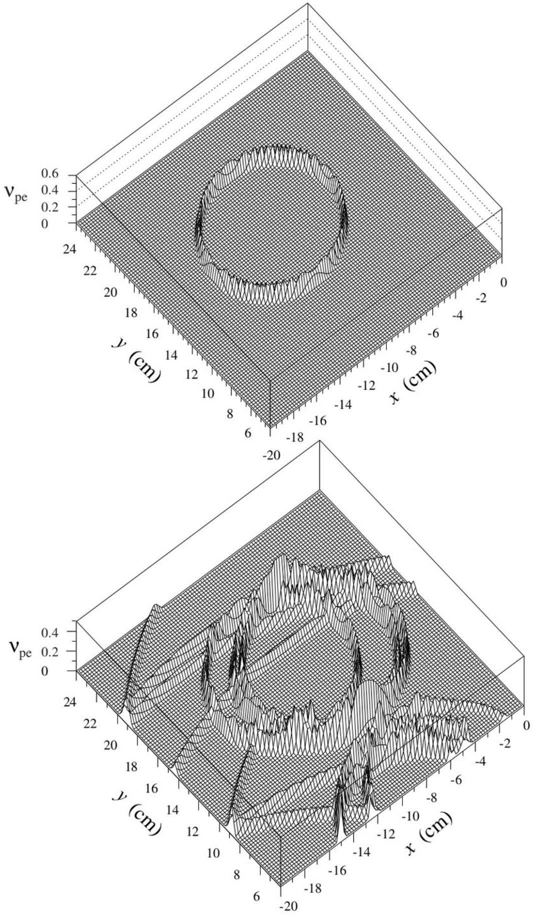
→ typically $2(N_{\mathrm{track}})^2$ likelihood evaluations are needed to obtain max. $\mathcal{L}$, which is manageable.

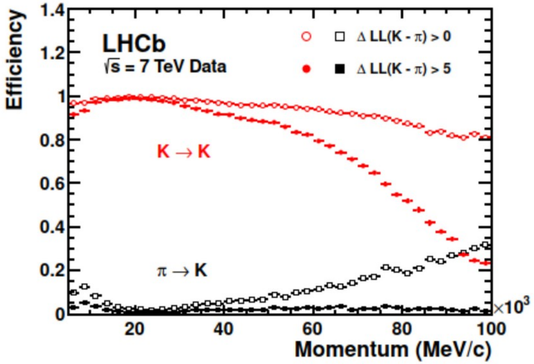
→ particle ID estimators for each track are then Obtained as

e.g. for i-th track, K/pi discrimination:

$$\ln \mathcal{L}^{\{h\}^{max} \Leftarrow K_i} - \ln \mathcal{L}^{\{h\}^{max} \Leftarrow \pi_i}$$







Nucl. Instrum. Meth. A, 433:257–261, 1999

What can Machine Learning methods do for us?

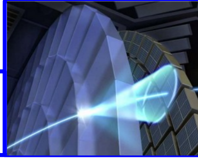
- global PID @ experiments

- pattern recognition / ring reconstruction

- fast simulation and reconstruction (generative AI)

- detector design optimization
  (e.g. E. Cisbani et al 2020 JINST 15 P05009)

- calibration methods
  (e.g. C. Fanelli 2020 JINST 15 C02012)



Global particle identification @ experiments

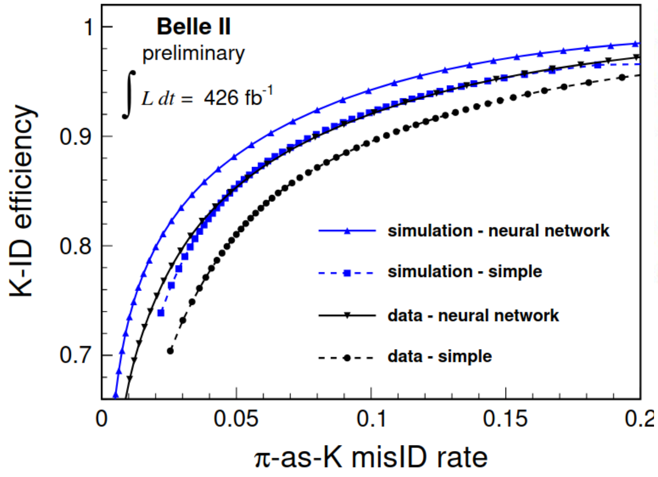
→ traditionally PID is performed using global PID likelihood which is obtained as $\log \mathcal{L}_h = \sum_d \log \mathcal{L}_{h,d}$

sum over sub-detectors

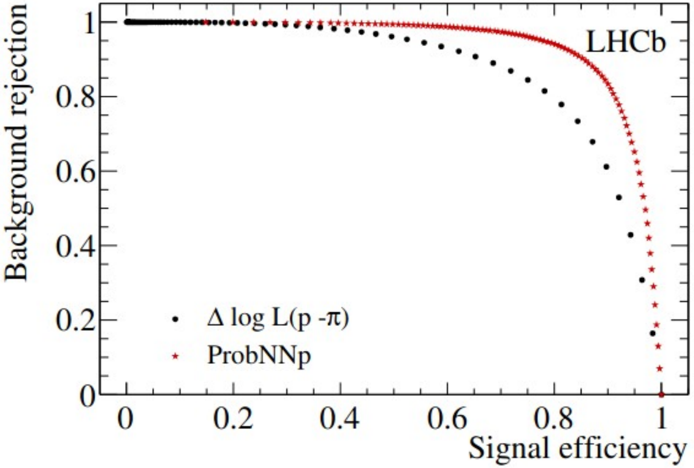
→ **in idealistic case this is end of story**: assuming same particle crosses all sub-detectors and each sub-detector likelihood correctly describes probabilistic processes involved in the generation of detector response upon passage of a particle of a given type

→ in reality: - sub-detector likelihoods are always imperfect/incomplete
- non-trivial correlations between them might exist (e.g. via track information in Cherenkov likelihoods and dE/dx)

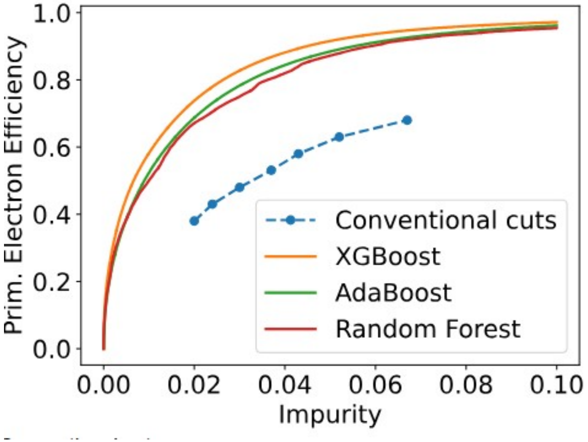
arXiv:2506.04355

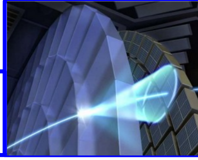


J. Phys.: Conf. Ser. 1085 042038



CBM electron ID / simulation





Machine learning in Cherenkov ring reconstruction

→ in recent years large progress in image classification algorithms: particularly **convolutional neural networks** (CNNs) have proven to excel in image and pattern recognition tasks

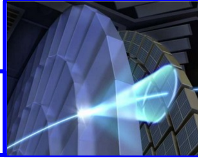
→ PID is essentially classification problem, often with 2D detector images!

→ in its most “radical” form this approach abandons event reconstruction altogether and feeds “raw” images into NN

→ at least at exploratory level several tries can be found in literature

→ there are several challenges in using such approaches (understanding PID systematics, variable experimental conditions etc.)

→ **benefit is speed!** Once NN is trained its application is very fast compared to traditional event reconstruction methods



Machine learning in Cherenkov ring reconstruction

Example: **CNN @ LHCb RICH**

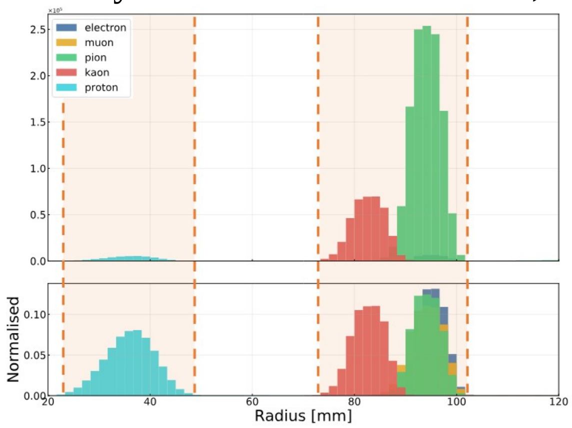
→ around each extrapolated track center radial search of hits is done in selected radius range

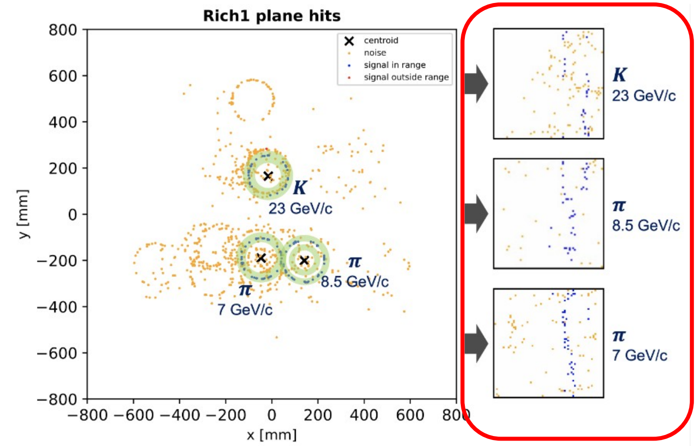
→ hits in this range are polar transformed to obtain 64x64 pixel images (radius, ϕ)

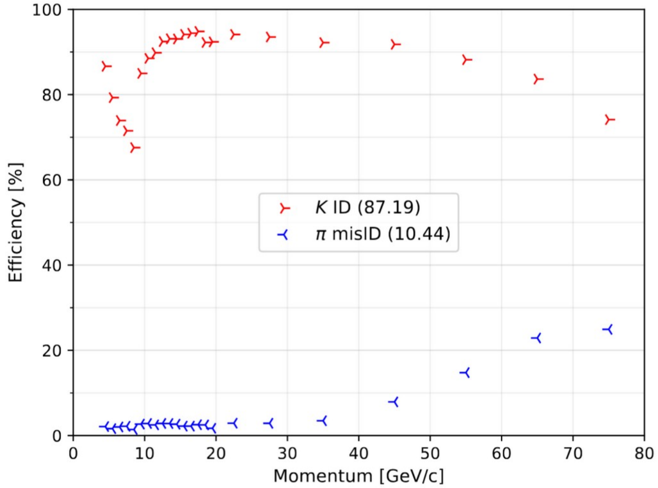
→ CNN is trained on images in 1 GeV/c wide momentum bins

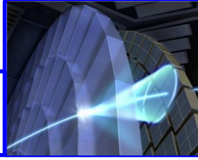
→ up to 50 GeV/c performance close to traditional reconstruction is achieved, but notably worse at momenta above

J. Phys.: Conf. Ser. 2438 012076, 2023









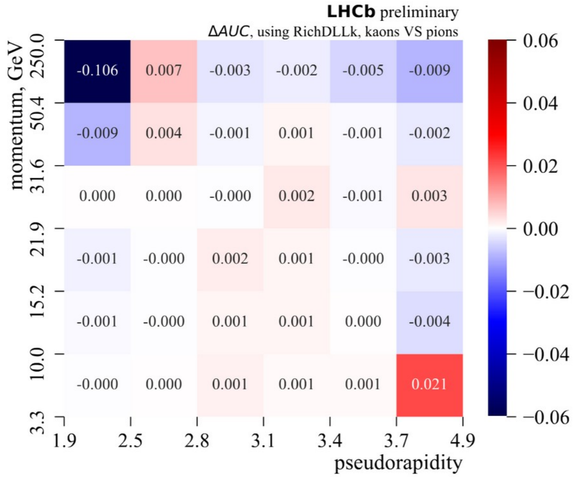
Generative AI

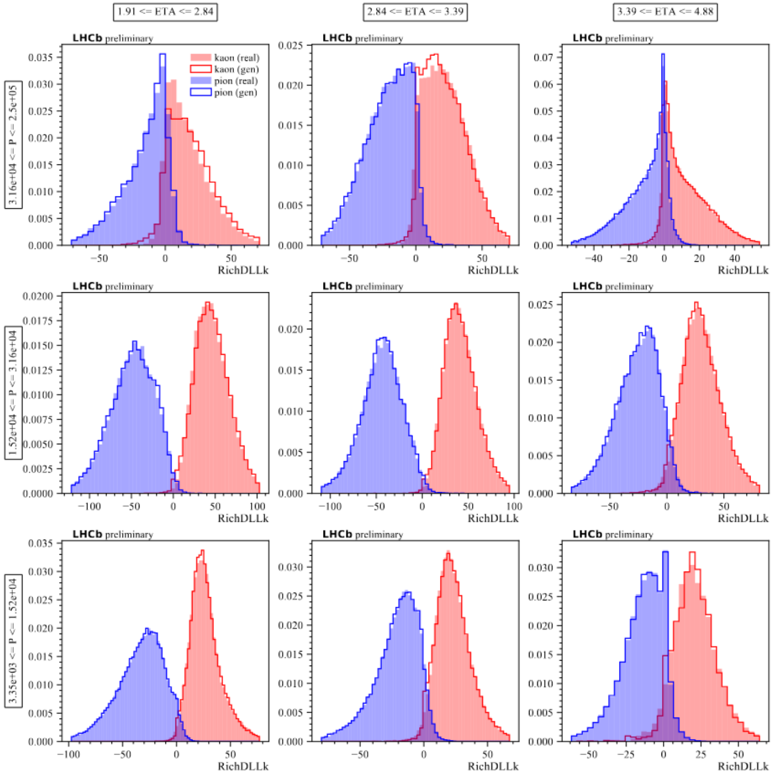
Example: **GANs @ LHCb** J. Phys.: Conf. Ser. 1525 012097, 2020

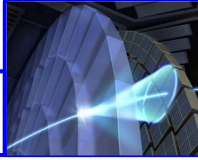
→ goal is to generate PID likelihoods for tracks in an event, based on particle type, momenta, polar angle, and total number of tracks in an event.

→ real data from control samples is used for training (w/ backgrounds sPlot subtracted)

→ obtained differences in AUC between real and generated data of the order 0.1-1%.







Generative AI

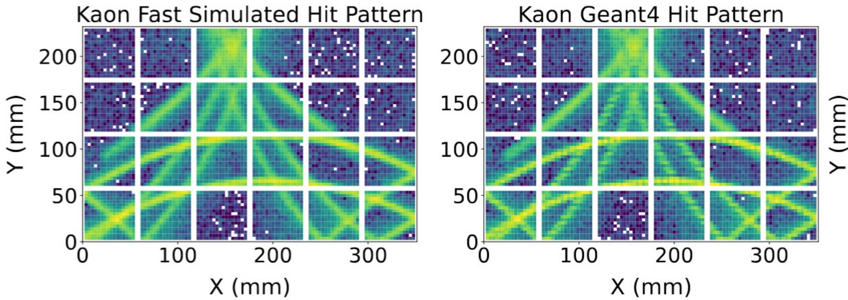
Example: **Deep(er)RICH**

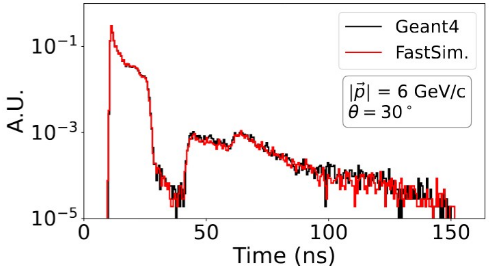
→ extensive work by C. Fanelli et al on GAN models for DIRC-like devices

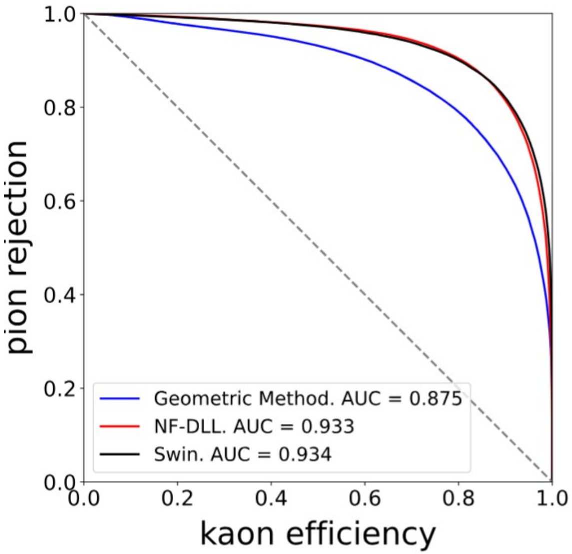
→ general framework with existing adaptations for GlueX DIRC and hpDIRC at EIC

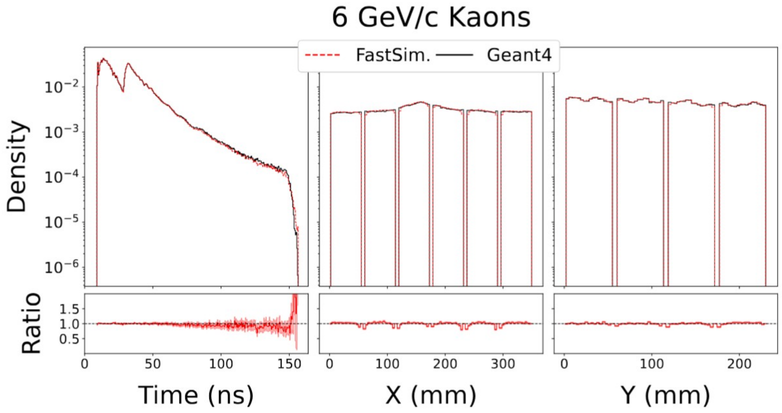
→ used for PID and fast simulation

→ GPU deployment





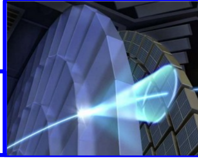




https://arxiv.org/abs/2504.19042

Mach. Learn.: Sci. Technol. 6 015028, 2025

Mach. Learn.: Sci. Technol. 1 (2020) 015010



Conclusions

- Having a reliable detector simulation is critical at all stages of experiment
  → detector design and optimization studies
  → physics impact
  → MC production for physics analyses

- Geant4 out of the box provides good precision for simulation of Cherenkov effects (some manual tunings can easily be done to further increase data/MC agreements)

- Use of involved event reconstruction methods is necessary to exploit the full potential of the installed hardware

- ML/AI methods are entering the game and can be beneficial (if used for right purposes)
  → global PID, fast simulation, …
  → often “forced” usage of ML is seen (e.g. do not use CNN to fit a Gaussian)

Thank you for the attention