Towards Reliable Neural Generative Modeling of Detectors

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On behalf of the LHCb collaboration

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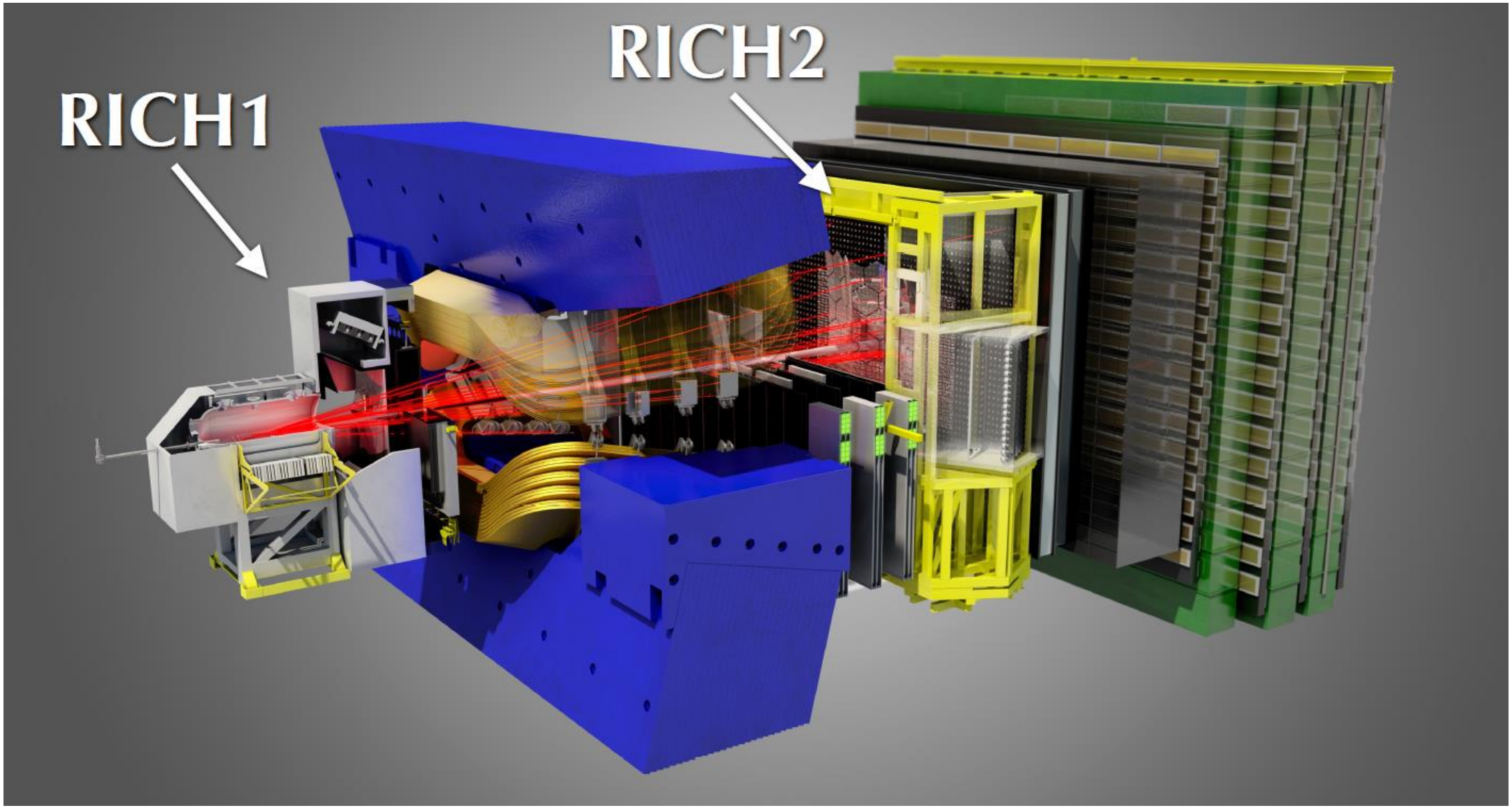
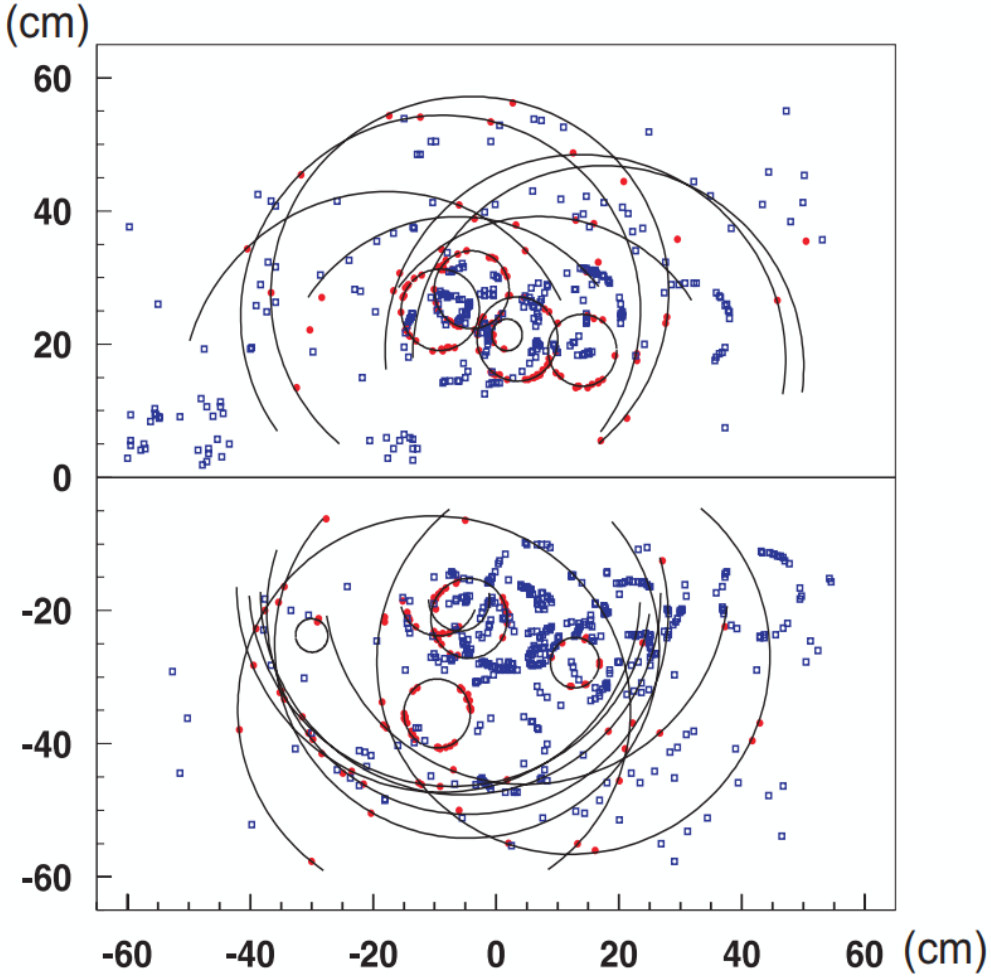
Cherenkov detectors at LHCb



Cherenkov detectors at LHCb

- A particle at a velocity higher than the speed of light in the medium emits Cherenkov photons
- Ring Imaging Cherenkov (**RICH**) detectors make use of the Cherenkov effect to identify particles
- The photons are emitted in a cone whose spread angle is a function of the particle's velocity
- Measuring this angle and momentum allows to constrain the mass of the particle

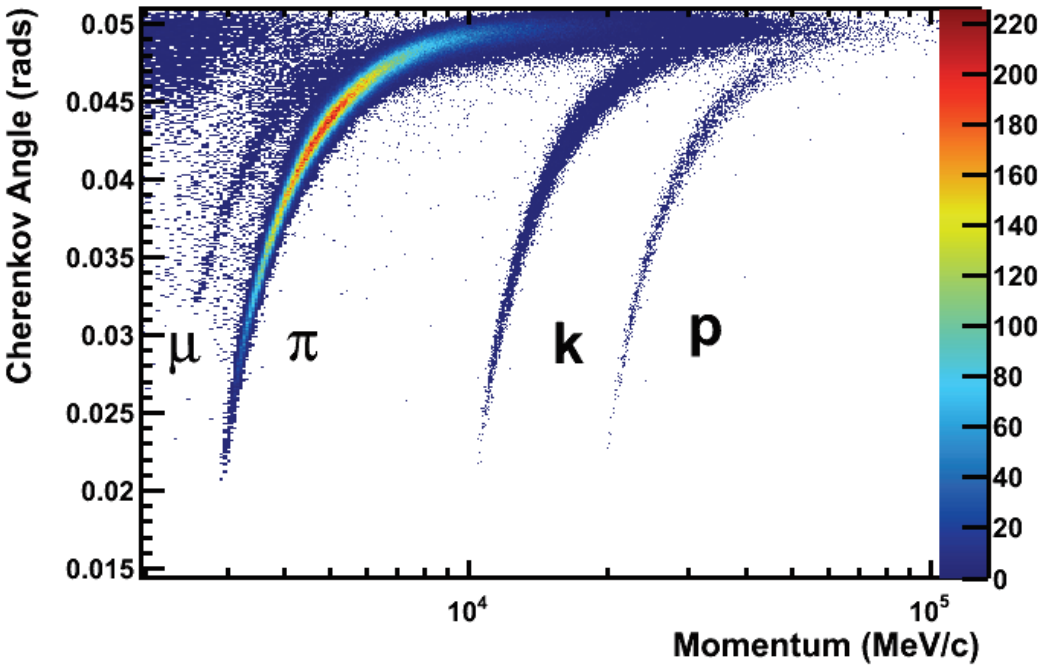


Picture from:
The LHCb Collaboration et al 2008 JINST 3 S08005

Cherenkov detectors at LHCb

- Particle identification (PID) is done with the maximum likelihood method
  - $\mathcal{L}(t_1, \dots, t_N)$ – likelihood to observe a given picture, as a function of all charged particle types (t_i- hypothesized particle type for track i)
  - A hypothesis $(t'_1, \dots, t'_N)$ maximizing $\boldsymbol{\mathcal{L}}$ is searched for
- For each track i, for each x ∈ {K, μ, e, p, below threshold}, quantities DLLx are then calculated as:

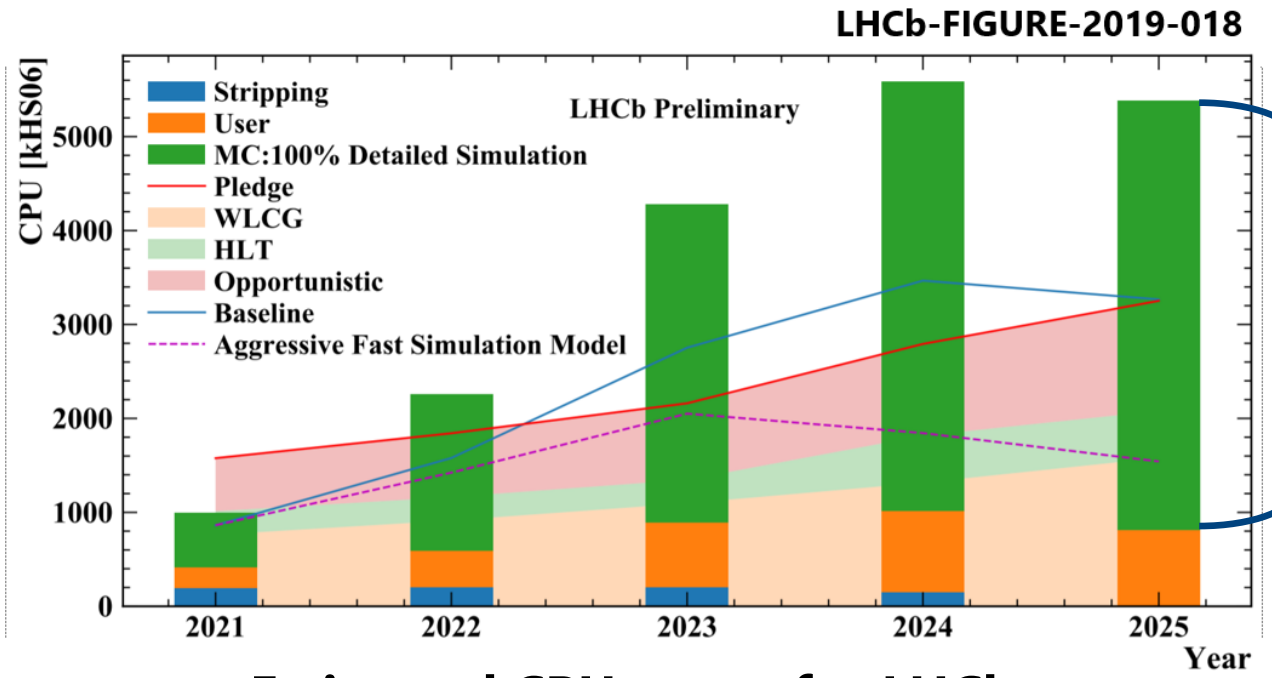
$$DLLx = log\mathcal{L}\left(t_i = x, t_{(-i)} = t'_{(-i)}\right) - log\mathcal{L}(t_i = \pi, t_{(-i)} = t'_{(-i)})$$



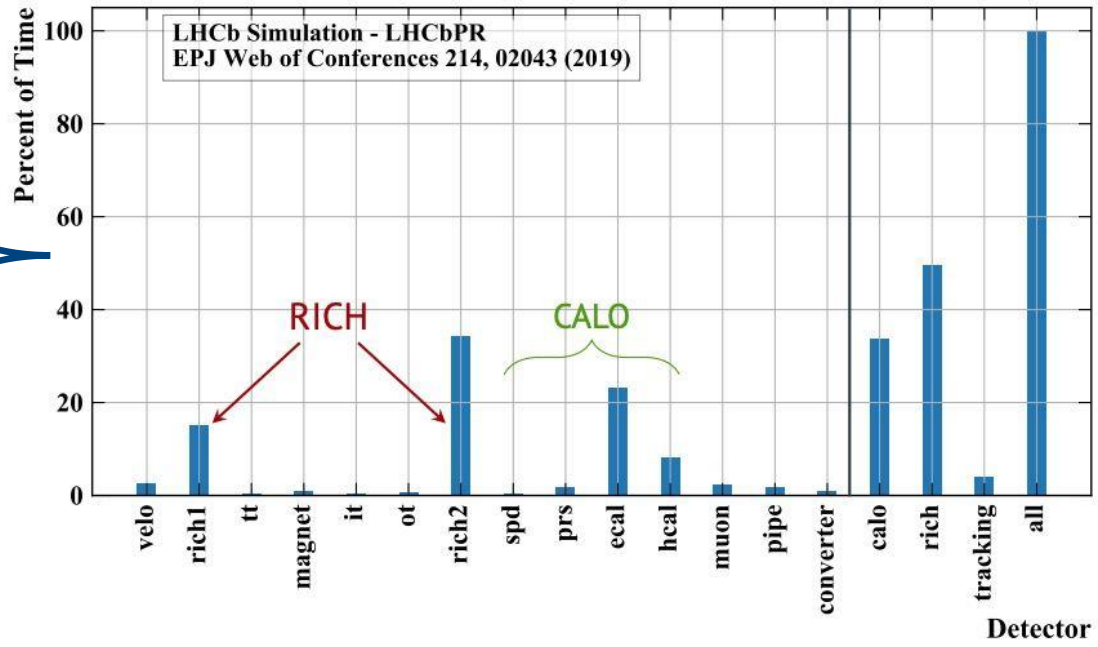
Picture from:
The LHCb RICH Collaboration, Adinolfi, M., Aglieri Rinella, G. et al. Eur. Phys. J. C (2013) 73: 2431

RICH fast simulation problem

- The task of fully simulating a RICH detector is computationally complex
- This problem will get worse with increasing luminosity in Run 3 of the LHC



Estimated CPU usage for LHCb

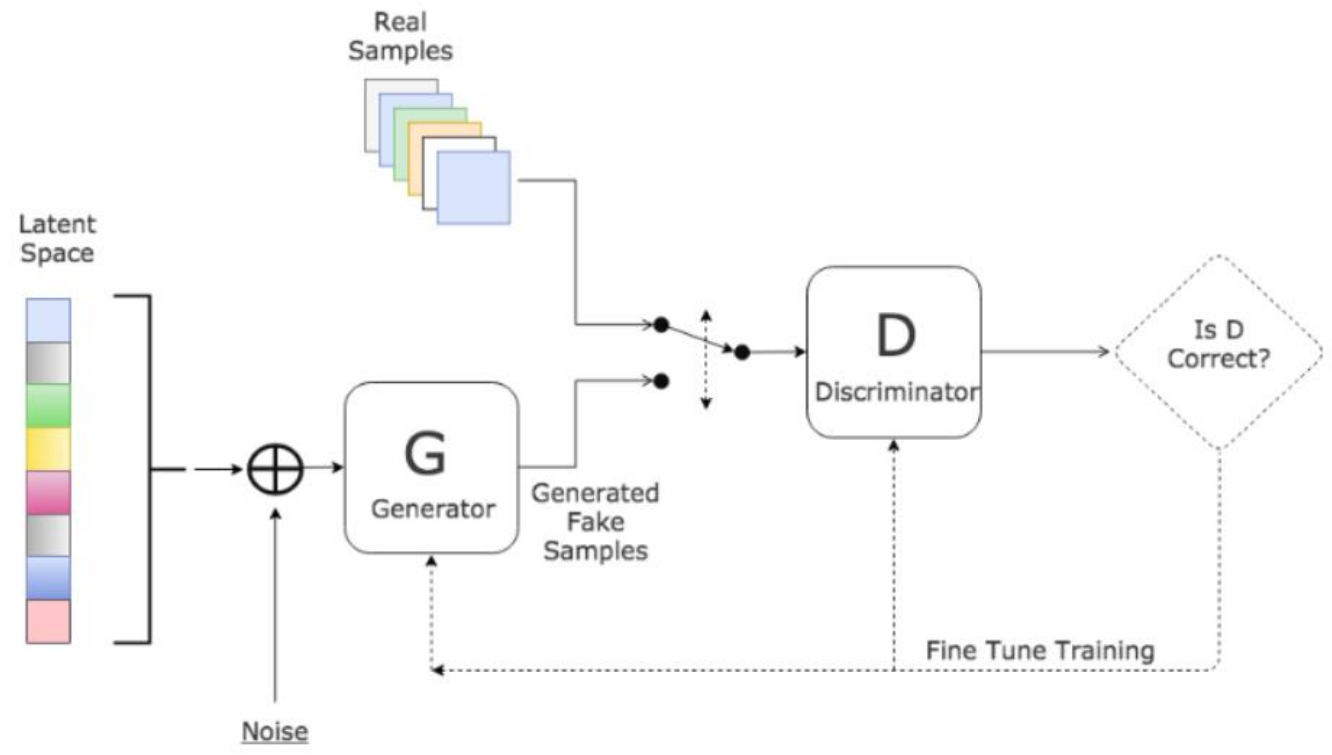


RICH fast simulation problem

- One possible solution is to develop a **data-driven approach** based on generative adversarial neural networks.
- Our global goal:
  - train a **model for fast generation** of PID parameters (RICH DLLs), given particle type and
    track characteristics;
- Current goal:
  - use **simulated data** (MC) to test the generalizability of our model
- Details:
  - Separate model trained for each of the particle types
  - 3 input variables: (P – momentum, η – pseudorapidity, nSPDHits – number of hits in the Scintillating Pad Detector)
  - 5 output variables (RichDLLx, $x \in e, \mu, k, p$, below threshold)

Generative adversarial networks (GANs)

- Two neural networks: **generator**, creates samples, **discriminator**, distinguishes correct samples from those created by generator
- These two neural networks learn to compete with each other in a zero-sum game



Picture from:
Serawork Wallelign. An Intelligent System for Coffee Grading and Disease Identification

Our model architecture (Cramér GAN)

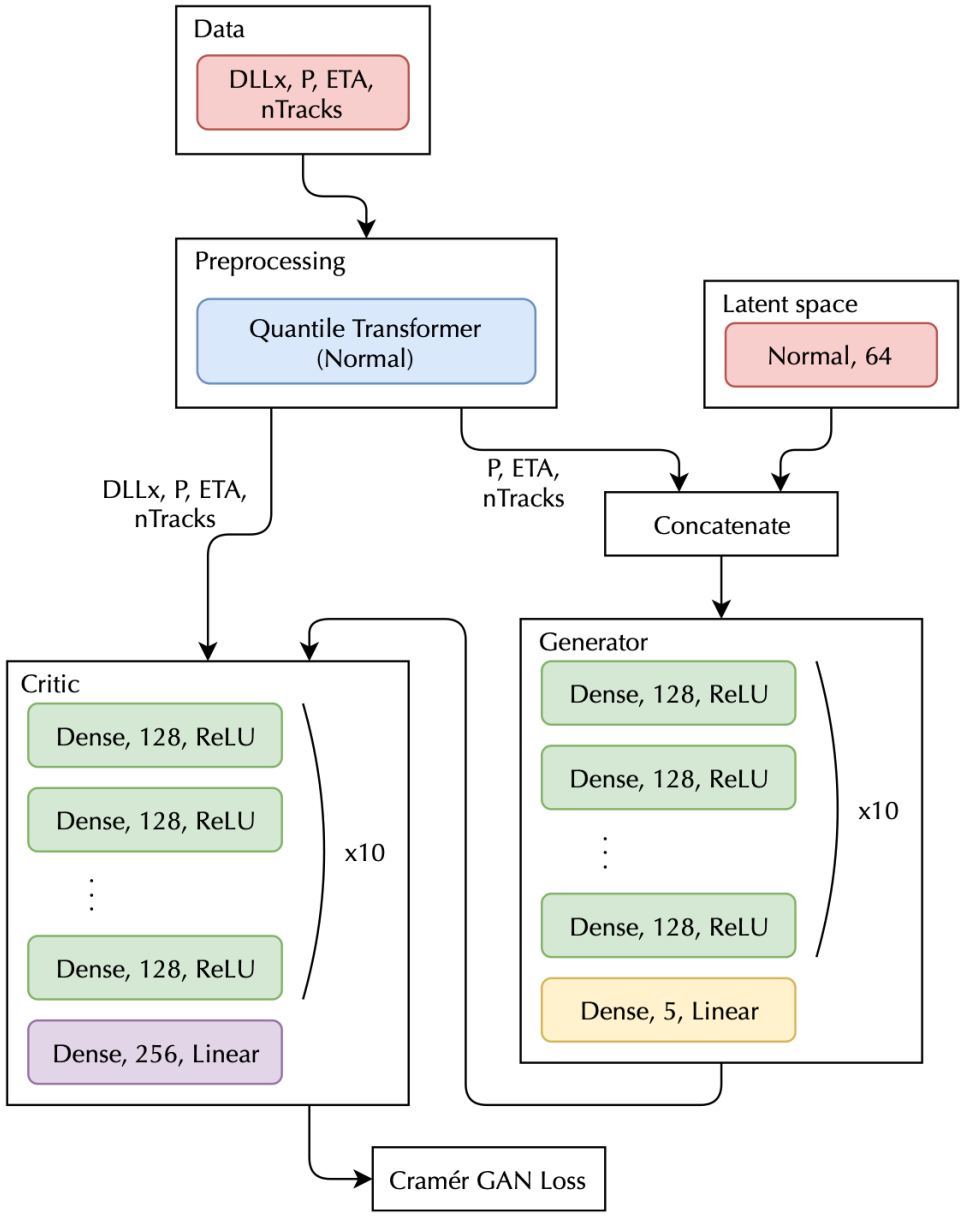
- One of the most common GAN architectures is WGAN-GP due to nice theoretical properties of the Wasserstein distance (arXiv:1704.00028)
- We use Cramér GAN (arXiv:1705.10743) which is one further improvement on top of WGAN, because it gives the best empirical agreement
- Cramér distance between distributions P and Q:

$$l_2^2(P,Q) := \int_{-\infty}^{\infty} (F_P(x) - F_Q(x))^2 \mathrm{d}x$$

F_P and F_Q are CDFs

- This is (1/2 times) the 1-dimensional case of the Energy distance: $X, X' \sim P$ and $Y, Y' \sim Q$

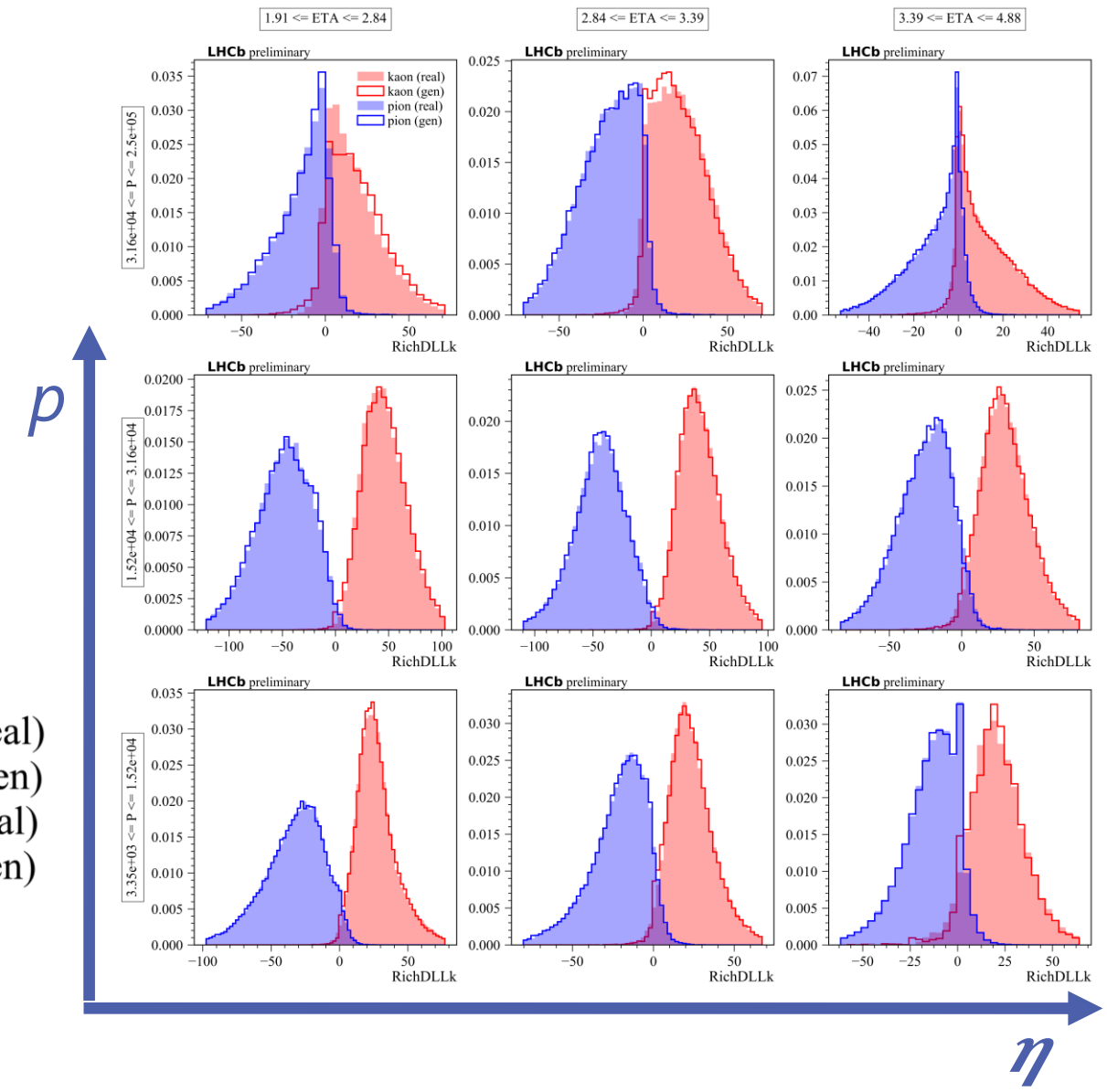
$$\mathcal{E}(X,Y) := 2\,\mathbb{E}\,\|X-Y\|_2 - \mathbb{E}\,\|X-X'\|_2 - \mathbb{E}\,\|Y-Y'\|_2$$

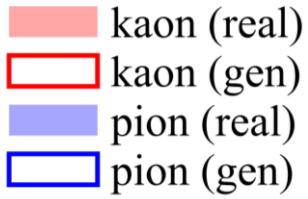


RichDLLk (π vs K)

- Training and testing is performed on real data
- Several clean data samples are selected
- Caveat: the quality metrics only shows the description of particular decays

3x3 bin plot over full P-ETA range





Picture from:
A Maevskiy et al 2020 J. Phys.: Conf. Ser. 1525 012097

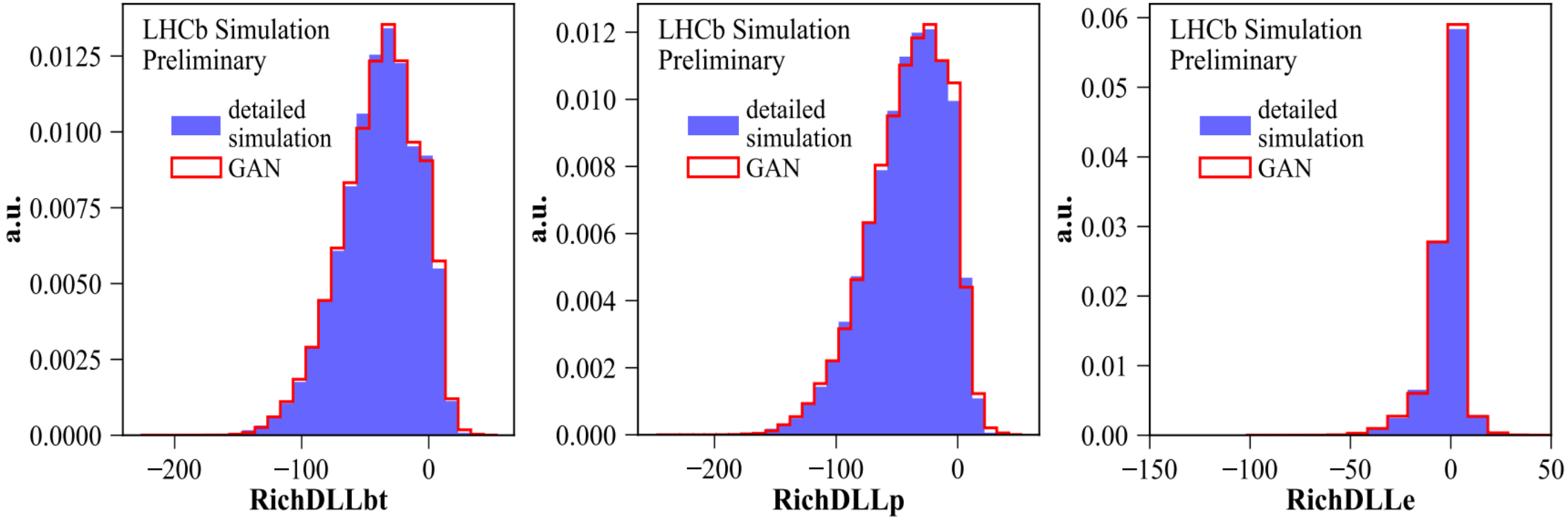
Results on decays into muons

- Training on muons from a mixture of simulated events:
  - Inclusive J/ψ
  - $B^{\pm} \to J/\psi(\mu^{+}\mu^{-})K^{\pm}$

- Evaluating on simulated events for $B^{\pm} \to K^{*\pm}\mu^{+}\mu^{-}$

GAN Simulation Results

- The distributions of DLLx variables for detailed simulation and GAN generated data are in good agreement



- $B^{\pm} \to K^{*\pm}\mu^{+}\mu^{-}$
- But we do not want to compare global distributions, but rather understand how our GANs work in specific cases

Evaluation metric

- We measure the **efficiency** of RichDLLx cuts at various quantiles of the RichDLLx distribution:

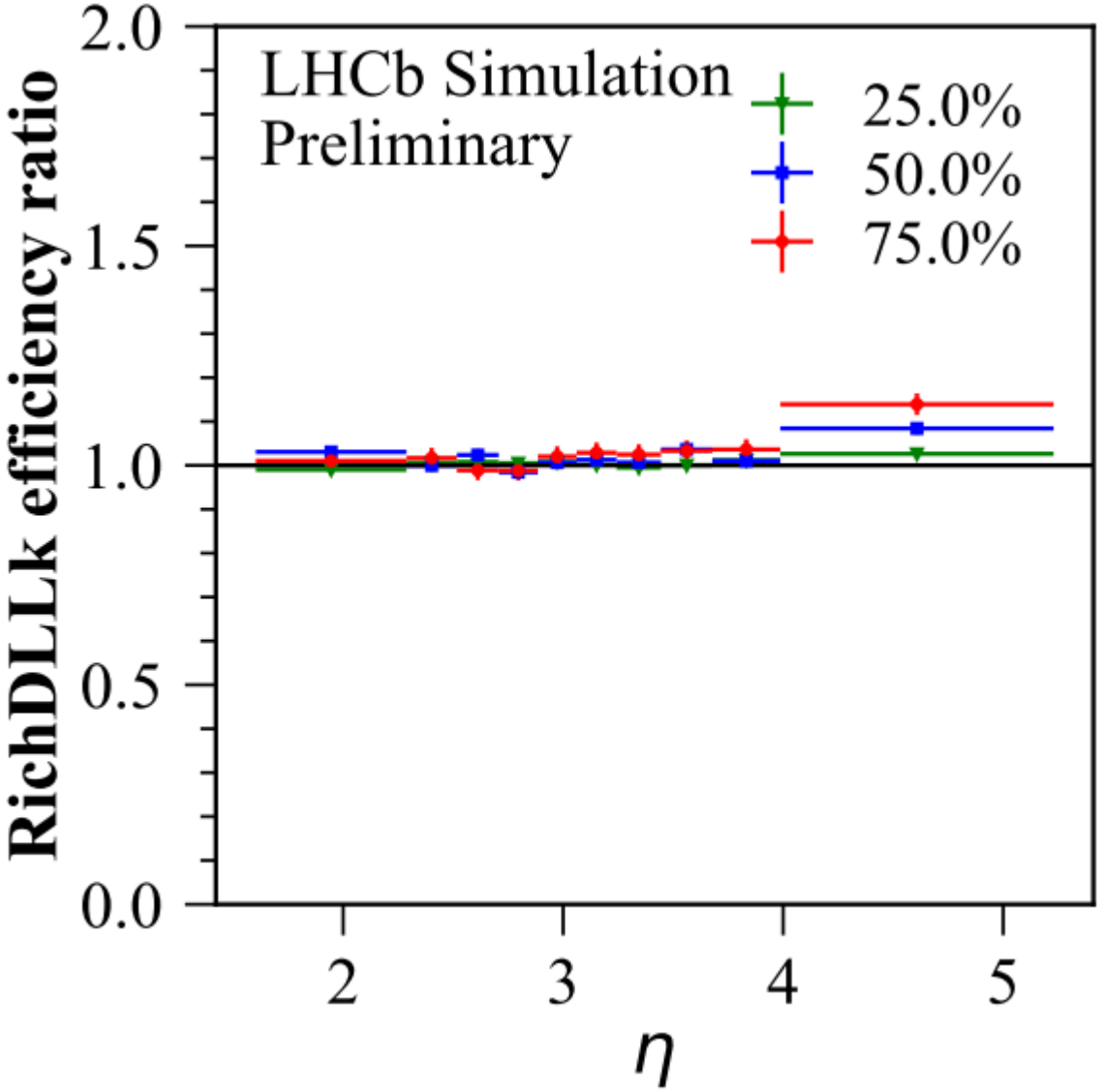
$$\varepsilon = \frac{number\ of\ tracks\ above\ x\%\ threshold}{total\ number\ of\ tracks}$$

- Do this as a function of the input variables:

$$\varepsilon(P, \eta, nSPDHits)$$

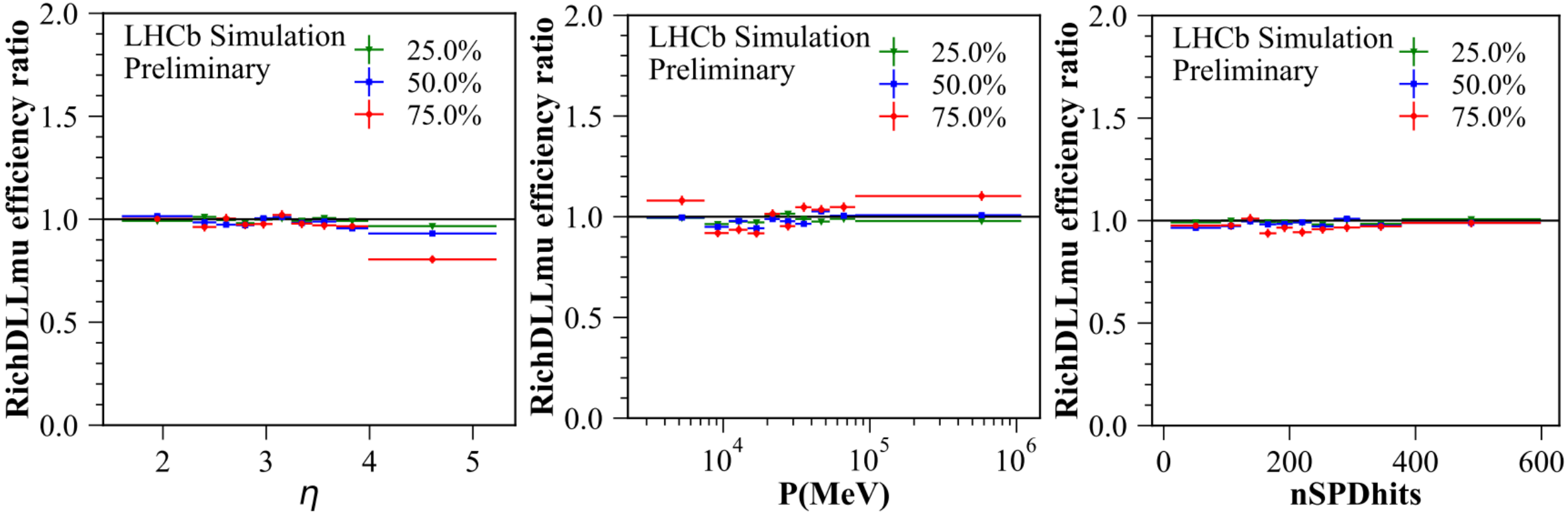
- Calculate the **efficiency ratio** between GAN predictions and simulated events (in bins of a variable):

$$efficiency\ ratio = \frac{\varepsilon_{GAN}}{\varepsilon_{simulated}}$$



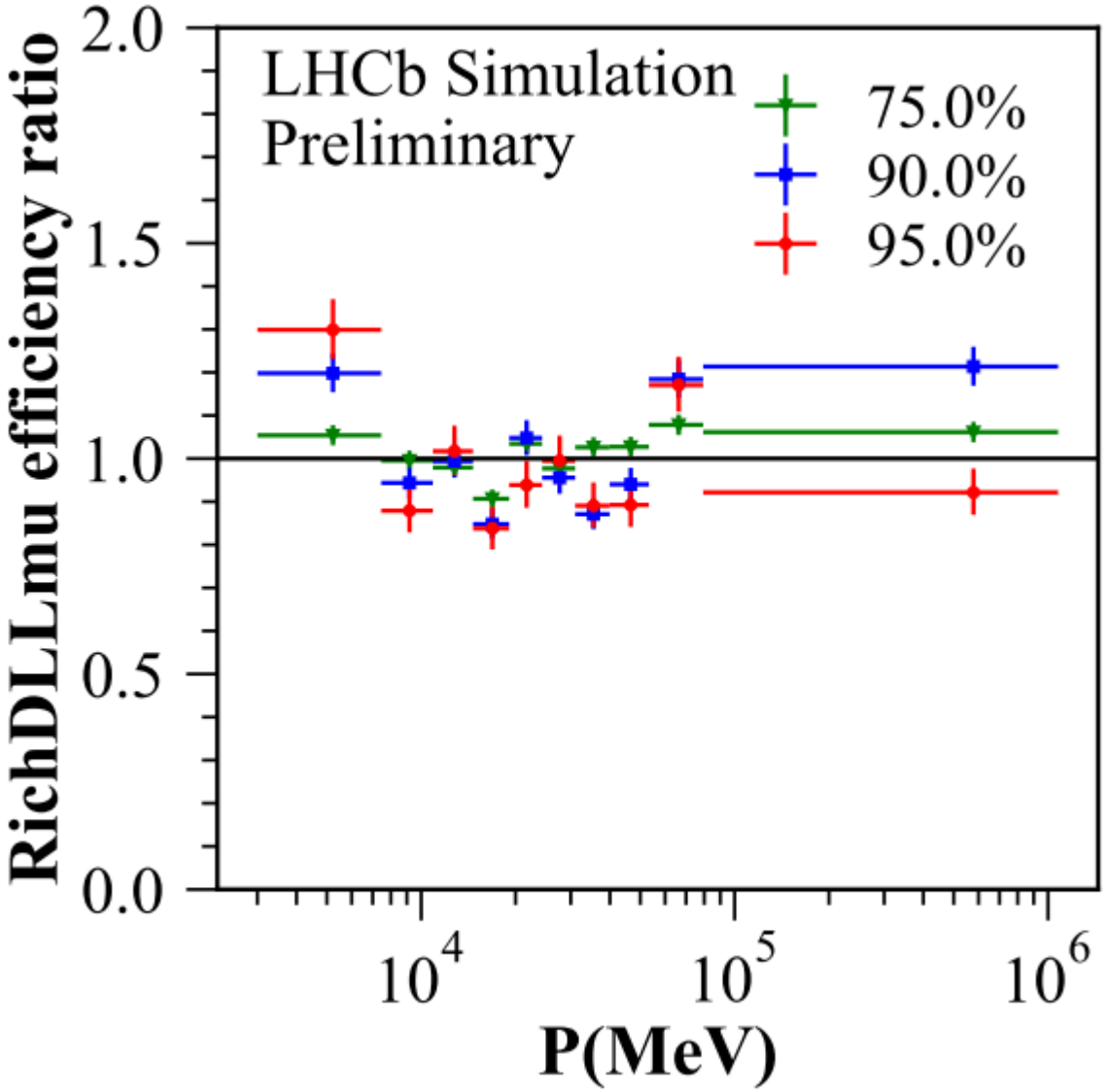
Efficiency Ratio Result (RichDLLmu)

- We trained GAN on simulated data for decays: Inclusive J/ψ and $B^{\pm} \to J/\psi(\mu^{+}\mu^{-})K^{\pm}$
- The ratio of efficiencies between GAN predictions and simulated events for decay $B^{\pm} \to K^{*\pm}\mu^{+}\mu^{-}$ is presented



Tails of distributions

- The quality of agreement degrades on tails of distributions
- We expect the problem to be less pronounced with the growth of training statistics and complexity of the model
- Tail problems affect small amount of events



Conclusion

- The model trained on some decay channels works on other decay channels
- The systematic effects are well under control – we have good efficiency ratios (some tail effects can be seen)
- GAN-based simulation is robust for the kinematic characteristics change
- Our implementation boosts the simulation speed by at least a factor of x100 wrt detailed simulation, depending on the production hardware
- We are working towards neural-network driven description of LHCb detector