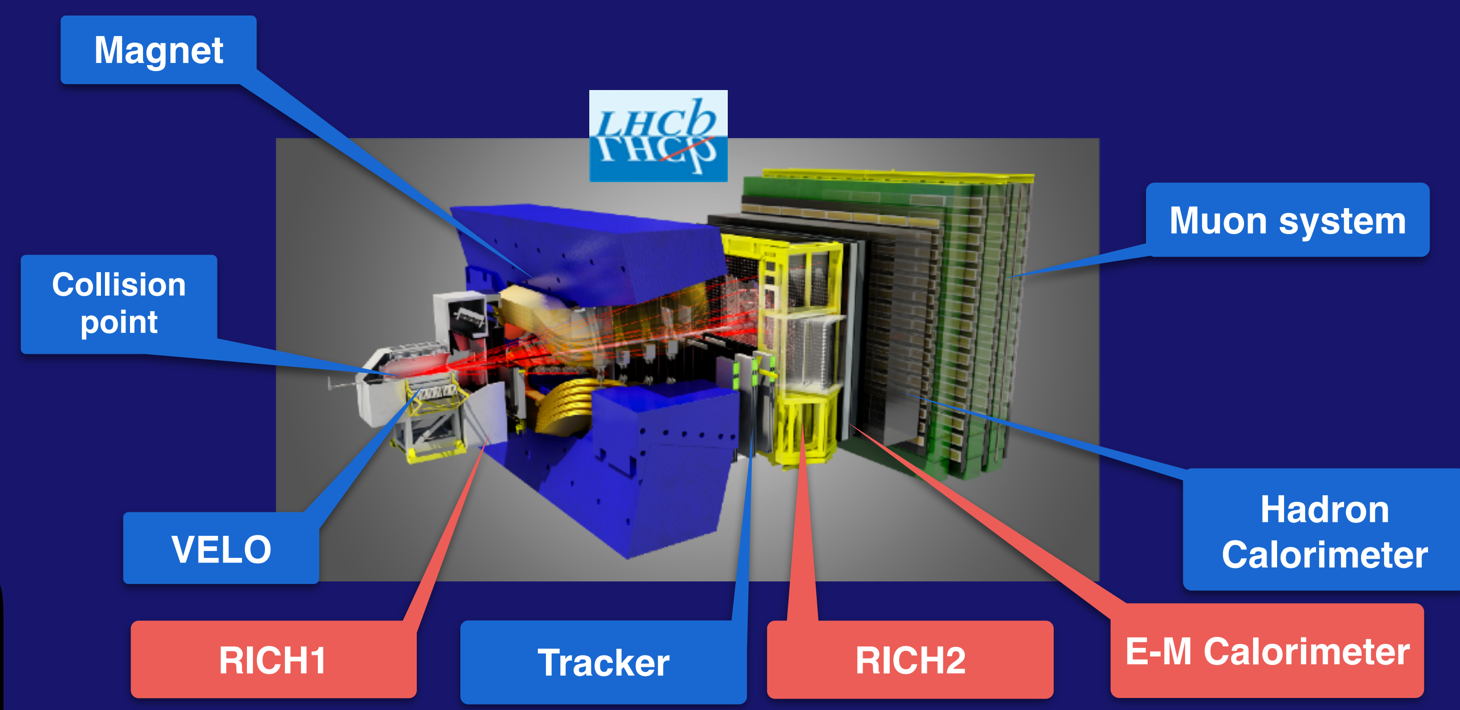
A LHCb Detector Description Using Neural Network Driven Simulation



Context

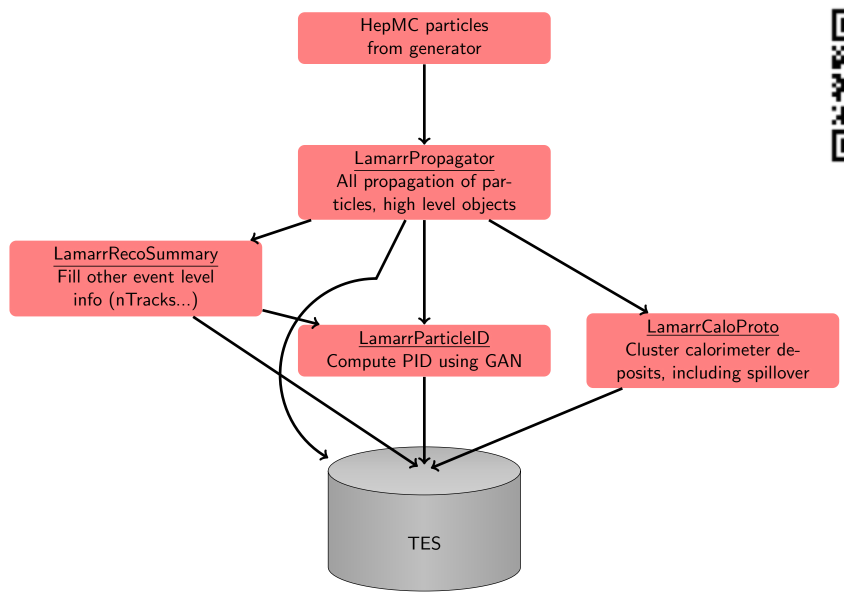
Problem: Simulation takes the major part of computer resources for HEP experiments

- deficiency of resources, need ways to speed up simulation production
- in LHCb: 50% of SIMU resources are taken by RICH, 35% by calorimetry

Approach: Surrogate generative models is a powerful tool which allows significantly speed up and/or improve quality of the simulation for HEP experiments

- LHCb aims to have full detector simulation using parametric model
  - in this presentation: tuning GAN models for RICH and ECAL simulations

Fast Simulation of LHCb High Level Objects (Lamarr)

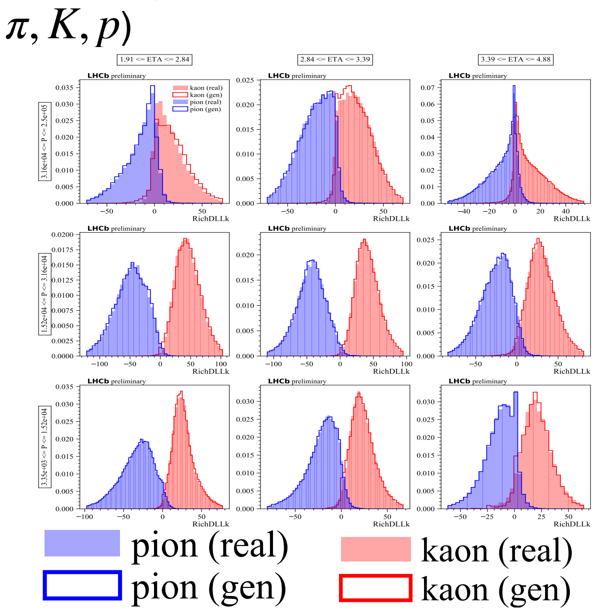


- no GEANT4, mostly parametric
- produces high level physics objects (tracks, clusters, …)

- derive RICH-based particle ID characteristics for tracks :
  - directly from track kinematics (bypassing RICH simulation completely)
  - by using stochastic generative models, GANs
  - train GAN models on detector particle ID calibration samples

Realistic Simulation of the RICH-based Particle Identification

- train generation model (GAN) on collected calibration samples to predict RICH-based particle ID responses for generation-level particles of different types and kinematics
  - (five $3 \rightarrow 5$ GANs for e, μ, π, K, p)



Particle ID characteristics are reproduced reasonably well

- particle ID cuts provides consistent efficiencies for GANs and training calibration samples
  - for the same physics process

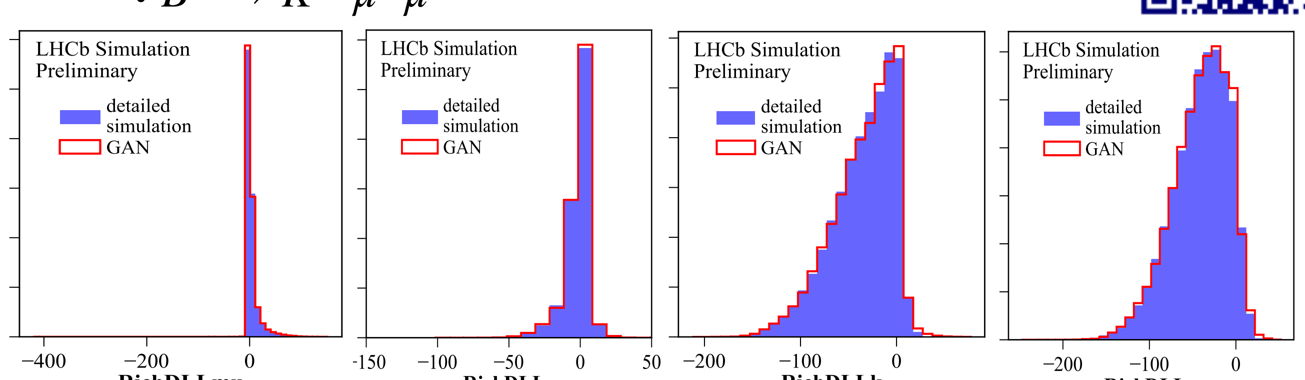
Question:
To which extend we can re-use trained model to data samples with different distribution in physics phase space?

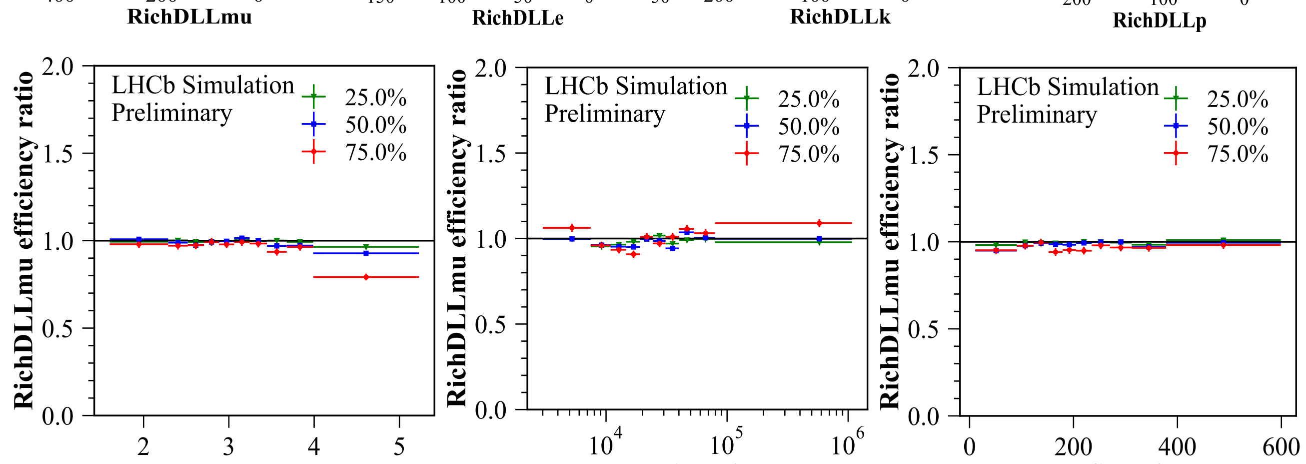
Answer: Generative Model Transfer

- Train GAN for RICH based particle ID on specific calibration samples
- To which extend the trained model is good for different data samples?

Exercise:

- Train GAN for RICH based particle ID variables on muon sampl
  - $B \rightarrow J/\psi(\mu^+\mu^-)X,\ B^\pm \rightarrow J/\psi(\mu^+\mu^-)K^\pm$
- Test GAN on different sample
  - $B^\pm \rightarrow K^{*\pm}\mu^+\mu^-$



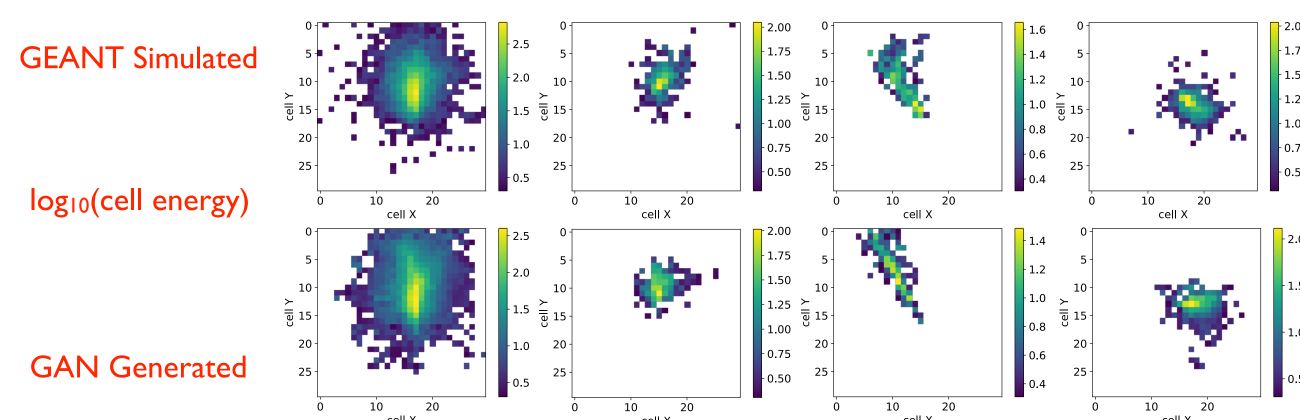


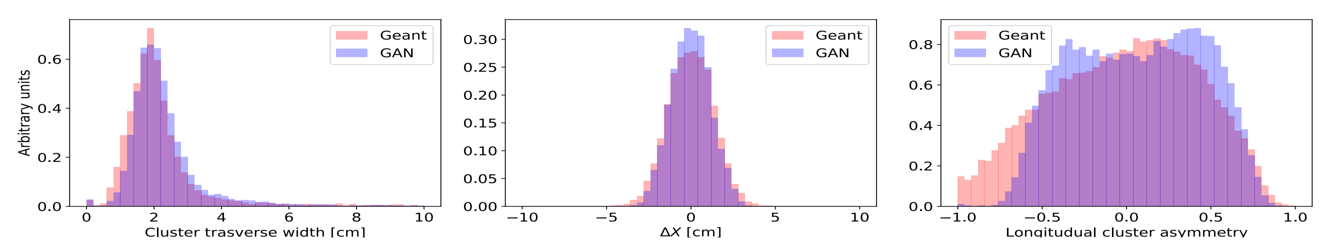
Obtained consistent efficiency: GAN successfully extends to a different physics sample

- generative model transfer is robust and may be used for physics analyses

Fast Simulation of the ECAL Response

- train GAN to generate 30×30 response matrix for particles of different energies, directions and position ($5 \rightarrow 900$ GAN)
- incorporate model into LHCb GEANT4 stack (Gauss)





- some physics distributions are good enough, some are not at all.
- no generative model is ideal. General training procedure is agnostic to underlying physics.
  - however, from the physics perspective, we have specific requirements to the model quality.

Question:
How can we enforce generative model to learn specific physics requirements with higher priority?

Answer: Fine Tune Specific Metrics

- If the target metric is differentiable, may include it directly in the loss
- If the target metric is more complicated and can not be expressed as a computational graph:
  - construct auxiliary surrogate regressor to evaluate target metric for the generated object
  - consider surrogate metric as an object feature
  - train generative model with emphasis on the target feature and the target regressor simultaneously

Illustration: statistic improvement for the non-differentiable property, transverse asymmetry of the ECAL cluster