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

Question:

To which extend we can re-use RICH PID trained model for 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:

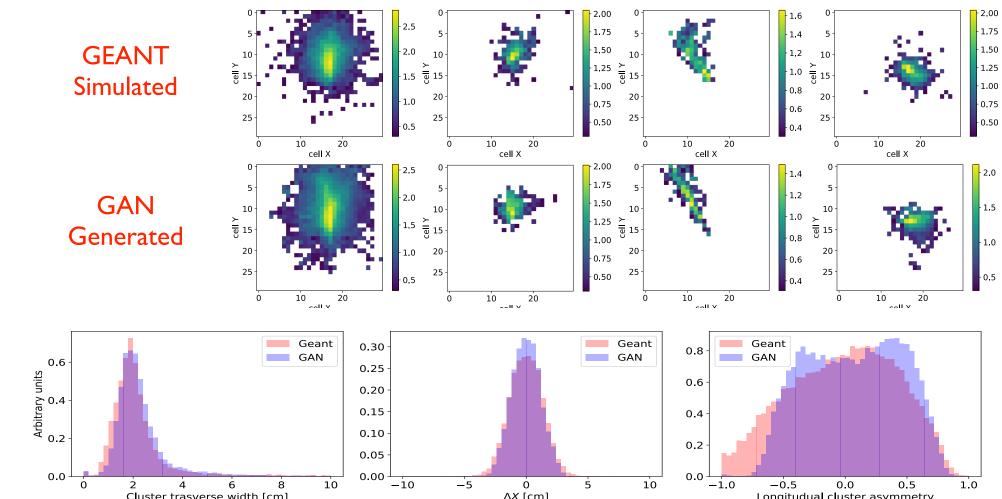
Train GAN for RICH based particle ID variables on muon samples $B \to J/\psi(\mu^+\mu^-)X,~B^\pm \to J/\psi(\mu^+\mu^-)K^\pm$

$$B \to J/\psi(\mu^+\mu^-)X, \ B^{\pm} \to J/\psi(\mu^+\mu^-)K^{\pm}$$

Test GAN on different sample

$$B^{\pm} \rightarrow K^{*\pm} \mu^+ \mu^-$$





Question:

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

Answer: Auxiliary surrogates to fine tune specific metrics

