Cherenkov Detectors Fast Simulations Using Neural Networks

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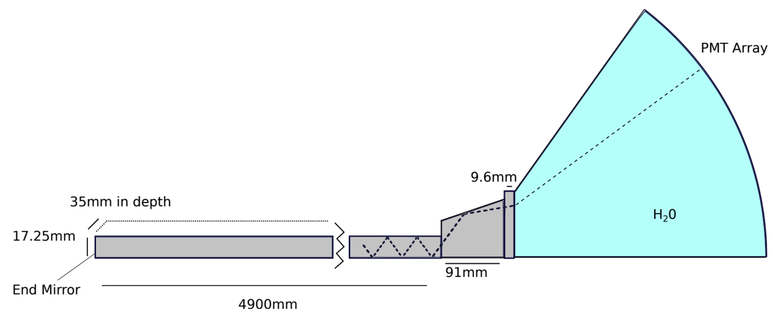
Need a faster simulation?

A typical Cherenkov detector simulation is quite slow: propagating the Cherenkov photons through the media requires expensive calculations. This is particularly important since during LHC era one needs **a lot of** simulated events. **We thus need a better, faster way to have reliably simulated events.**

In this work, we concentrate on simulating the Detector of Internally Reflected Cherenkov light (DIRC) of BaBar and SuperB. We simulate tracks sampling from flat in pseudorapidity [-1.6, 1.6] and Gaussian in energy (mean 6 GeV, with 2 GeV).

We use a fastDIRC simulation [1] to produce a reasonable detector response. This simulator uses Kernel Density Estimation (10000 times faster than Geant4 already).

The approach is extendable to other types of Cherenkov detectors subject to training set of full simulation.



Schematic diagram of one BABAR box that contains 12 fused-silica bars (each 17.25 mm thick, 35 mm wide, and 4.9 m long) and wedges. BABAR used a large tank filled with purified water to transport photons from the fused-silica wedges to the PMT array. Drawing not to scale. Figure from [1].

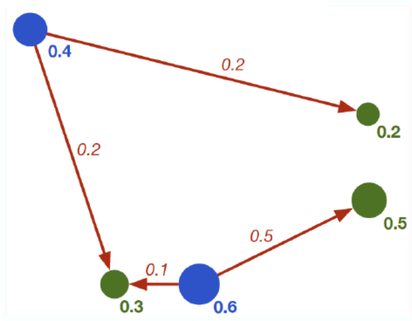
Generative neural nets are here to help!

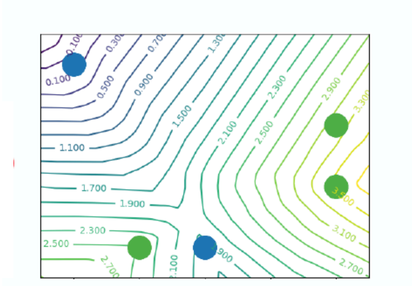
Generative adversarial neural nets (GANs) provide a rule to connect input observables with distributions of output ones [2].

In order to train a GAN, we minimize a Wasserstein distance, also called Earth-Mover Distance:

- Interpret one distribution as target, one as earth heap
- Distance of distribution = effort to move earth heap to target (mass x distance)

$$D_W = \underbrace{\min_{\gamma \in \prod(P_x, P_{\hat{x}})}}_{\text{optimal transport plan}} \underbrace{\mathbb{E}_{(x,\hat{x})\sim\gamma}}_{\text{mass}} \underbrace{\|x - \hat{x}\|_2}_{\text{distance}}$$





Which in fact can be proxied like:

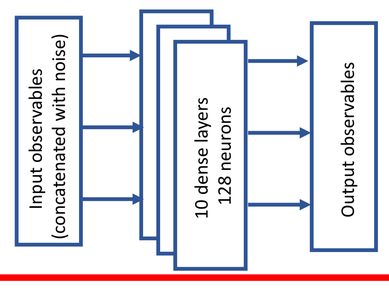
$$D_W = \max_{C \in \mathrm{Lip}_1} -\mathbb{E}_{P_x} C(x) + \mathbb{E}_{P_{\hat{x}}} C(\hat{x})$$

$$\mathrm{Lip}_k : \|C'\|_2 \leq k$$

expectation value

generator replaced by critic

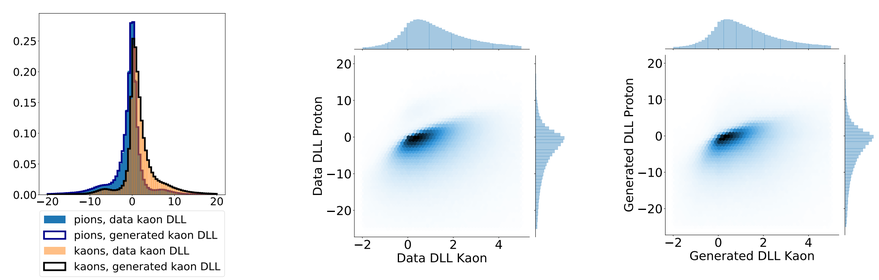
Final generator configuration is very simple, which still provides a high performance:



Log-Likelihood prediction

Unlike other approaches (see for example, [2]), we **predict high level observables after reconstruction**, effectively bypassing a generation of detector responses. This allows to save generation time and simplify the detector complexity at the expense of reconstruction dependence. In our case, we use delta log-likelihoods, a set of functions associated to particle probabilities.

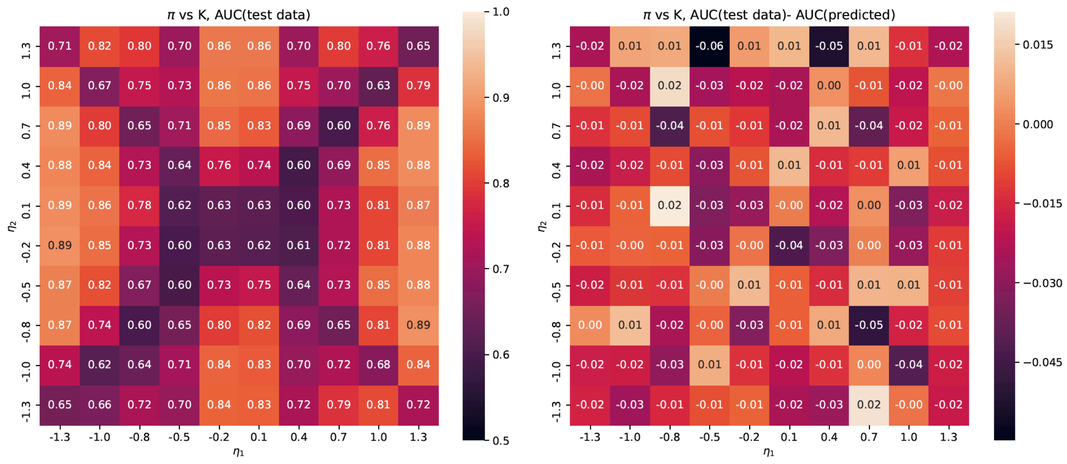
We construct a neural network that takes type of signal particle and its kinematic observables and a distance to the closest adjacent particle.



An example of 1D projection (left) and 2D projections to log-likelihood observables for data (center) and generated (right) pions and kaons.

Closest Particle Influence

One of the main possible problem of high level observables generation is their interaction with other particles. We take the influence into account by adding an information about the kinematics of the closest particle to a generator.



Separation power between kaons and pions measured in area under curve scores (AUC score). Left is the actual simulation, right is the difference with our simulation. The statistical uncertainty is around 0.01.

Take Home Message

The generative neural network **can be used** to simulate detector response also for high-level features.

The precision is at the **percent level,** however, more training data can be taken to improve it.

Currently, the method is faster than any other fast simulation method. The speed improvement with respect to full simulation in GEANT is $8*10^4$ times on a single CPU core. The batch generation on GPU produces up to 1M tracks per second.

References:
[1] John Hardin, Mike Williams FastDIRC: a fast Monte Carlo and reconstruction algorithm for DIRC detectors JINST 11 (2016) no.10, P10007
[2] Ian J. Goodfellow et al, Generative Adversarial Networks arXiv:1406.2661.
[3] Michela Paganini , Luke de Oliveira, Benjamin Nachman Phys.Rev. D97 (2018) no.1, 014021.

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