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A full detector description using neural network driven simulation

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ABSTRACT

The abundance of data arriving in the new runs of the Large Hadron Collider creates tough requirements for the amount of necessary simulated events and thus for the speed of generating such events. Current approaches can suffer from long generation time and lack of important storage resources to preserve the simulated datasets. The development of the new fast generation techniques is thus crucial for the proper functioning of experiments. We present a novel approach to simulate LHCb detector events using generative machine learning algorithms and other statistical tools. The approaches combine the speed and flexibility of neural networks and encapsulates knowledge about the detector in the form of statistical patterns. Whenever possible, the algorithms are trained using real data, which enhances their robustness against differences between real data and simulation. We discuss particularities of neural network detector simulation implementations and corresponding systematic uncertainties.

1. Stability of data driven fastsim models

Generative models trained by using regular ML techniques are widely discussed as a feasible solution to reduce the computational cost of simulation necessary to facilitate HEP experiments. LHCb developed a new framework integrated within the analysis software for mostly parametric really fast simulation of physics events, named Lamarr [1].

Besides other FastSim components, Lamarr particularly uses a GAN-based models to simulate the particle identification (PID) response from the RICH-based PID system [2]. The advantage of the used approach is that the simulator is trained on calibration samples collected during data taking, and thus is not biased by any systematics due to GEANT4 simulation, digitisation etc. The downside of this approach is the training of the model in limited regions of the total phase space which is driven by particular kinematic regions of available calibration data samples. The important question in this situation is to which extent the fast simulation model of predicting PID responses and being trained on data samples in limited phase space would generalise PID predictions to the full phase space.

To illustrate stability of such model [3], we emulate the described situation by using three available simulated calibration samples for muons. Two samples, inclusive $B \to J/\psi(\mu^+\mu^-)X$ and exclusive $B^\pm \to J/\psi(\mu^+\mu^-)K^\pm$ are used to train the model. A sample $B^\pm \to K^{*\pm}\mu^+\mu^-$ is used as a reference to evaluate the quality of the obtained trained model.

Fig. 1 illustrates a consistency in distributions of generated and MC truth PID variables for muons in test sample. The quality metrics for PID variables is however not the distribution of variables by itself, but rather a signal efficiency and fake rates for corresponding PID variables selections. Fig. 2 presents a ratio of the model and MC truth efficiencies at different quantiles of the MC truth distributions and in different regions of kinematic phase space and demonstrates consistency between extrapolated prediction and the one for the reference sample.

2. Surrogate regressors for tuning FastSim models

Another problem for training generative models for use in fast simulation for physics experiments is the quality metrics for generated objects. Regular training approach enforces consistencies of main modes of most pronouncing features of generated objects. However, from physics considerations, the actual quality metrics may be quite

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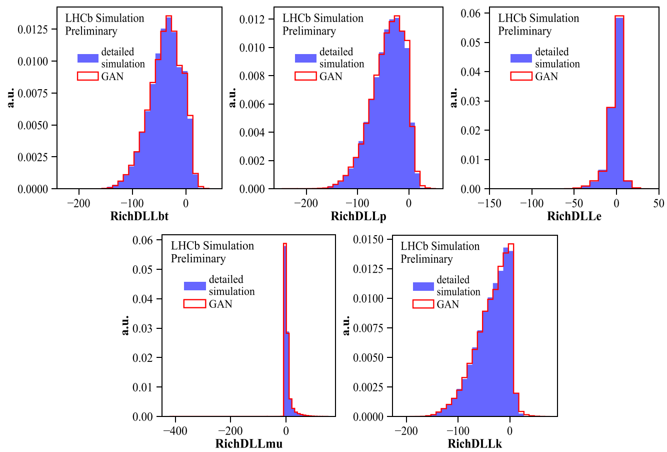

Fig. 1. Distributions of real and generated PID variables for muons from the test decay $B^{\pm} \to K^{*\pm}\mu^{+}\mu^{-}$.

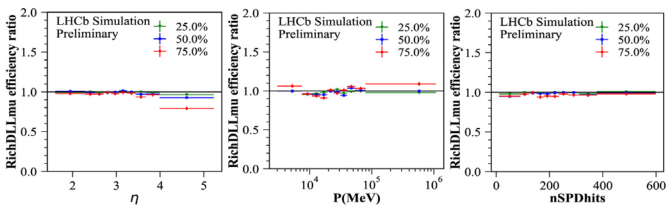

Fig. 2. Dependence of RichDLLmu efficiency ratio on GAN model conditions: momentum (P), pseudorapidity (η), number of hits in the Scintillating Pad Detector (nSPDHits) for the test decays $B^{\pm} \to K^{*\pm}\mu^{+}\mu^{-}$.

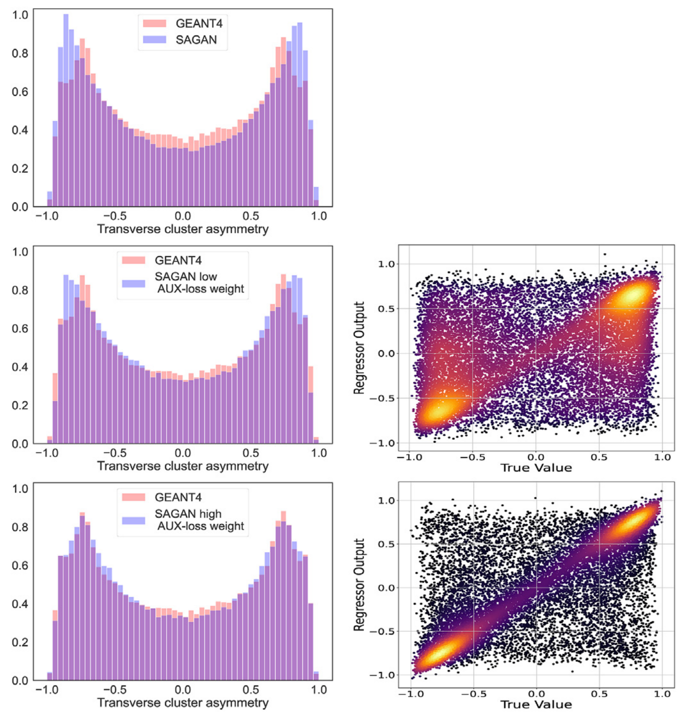

Fig. 3. Improving of the quality of reproducing the "clusterf transverse asymmetry" feature of the generated ECAL clusters. Left column: top — the baseline distributions, middle — the distribution when loosely trained regressor is added to the discriminator, bottom — the distribution when strongly trained regressor is added to the discriminator. Right column: regressor trained quality.

different from those learned by e.g. plain GAN discriminator. If the physics motivated target metrics may be expressed as a computational graph, such metrics may be explicitly added to the discriminator as an extra feature, and therefore be learned during training. Unfortunately, it is often not possible to include metrics of physics quality directly into corresponding discriminator if it is not differentiable. In this case we suggest [4] to substitute such a not differentiable metrics by a differentiable surrogate regressor which reproduces the necessary physics property with some precision. We face this problem when were developing a GAN based model to generate responses for the LHCb electromagnetic calorimeter [5]. Although the primary features of the calorimeter cluster like energy and spatial resolution, cluster size etc are reproduced reasonably well, the "marginal" features which are driven by high level correlations or by tails of distributions do not learn distributions well. The reason is that those "marginal" features are not pronounced well in the discriminator. Thus, the solution is to add these "marginal" but important features to the loss function of the discriminator explicitly. Auxiliary surrogate regressor can facilitate this approach in case of non-trivial metrics.

To demonstrate this approach we consider not differentiable and pretty marginal value of transverse asymmetry of the energy distribution in the energy cluster of the LHCb electromagnetic calorimeter. Fig. 3 illustrates how the addition of the auxiliary surrogate regressor improves the target distribution of generated calorimeter responses. It particularly demonstrates that there is no need for extreme quality of the used regressor to improve the quality of the target metrics.

3. Conclusions

Generative models are proved to be a feasible solution to reduce computing resources necessary to facilitate fast simulation needs for HEP experiments. However, "devil is in details", and different details and minor issues need resolution before using such generative models in production. We demonstrated that models trained on limited set of calibration samples may be reasonably generalised to the bigger physics phase space. Also we demonstrated the approach which allows fine tuning of the generative models to important physics distributions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

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