PID Techniques and Performance at LHCb in Run 2

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Abstract

One of the most challenging data analysis tasks of modern High Energy Physics experiments is the identification of particles. This paper overviews new approaches to particle identification and demonstrates performance of these approaches. We show the solutions based on Neural Network and Boost Decision Tree models that use observables obtained by sub-detector to solve the problem of charged and neutral particle identification.

Keywords: Particle identification, Neural Network, Boost Decision Tree
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1. Introduction

Particle identification (PID) plays a crucial role in LHCb analyses. The LHCb PID system is composed of Cherenkov detectors, muon chambers and a calorimeter system. Combining information from these subdetectors allows one to recognize long-lived charged and neutral particles [1]. Advanced multivariate techniques can be used to obtain the best PID performance and control systematic uncertainties in a data-driven way. Developed models shows higher performances than the baseline solution. Novel models were developed using environment of the LHCb Run 2. These models show in general good performance and in addition a better efficiency flatness.

2. Charged particles

There are five relatively long-lived types of charged particles that leave tracks at the LHCb detector, namely, electron, muon, pion, kaon, proton. This set of real tracks is complemented by ghost track, which do not correspond to a real particle passed through the detector. The PID algorithm is trained with six possible outcomes thus forming a multi-class problem. Current solution was developed during Run 1 of data taking and is a set of 5 neural networks with one hidden layer trained to distinguish one particle species from the rest [1].

To improve the baseline PID solution performance, several solutions are implemented. Classifier Deep NN combing subdetector responses with deep neural network is trained using Keras library [2]. The winning solution in gradient boosting over decision tree is trained using CatBoost library [3]. In addition, Flat 4d - boosted decision trees classifier with flat dependency of signal efficiency on particle P, P_T, η and $nTracks$ (event multiplicity) observables [4].

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The classifiers are trained using Monte Carlo (MC) sample containing all charged particle types and ghost track candidate. An additional MC samples are used to estimate the classifier performance on real data [1]. This samples are dated from 2016 and contain particles that can be identified purely based on only kinematic properties. The PID performance of each classifier is shown in Fig 1.

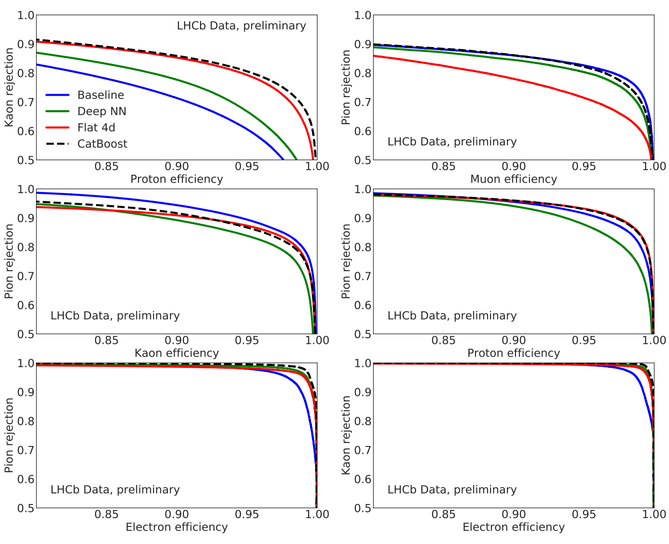

Figure 1: Dependences between background rejection and signal efficiency for six particle pairs.

The PID information strongly depends on the kinematic factors. This correlation leads to a strong dependency of PID efficiency and kinematic variables as shown in Fig 2. Relative to the baseline model, the Flat 4d model has a flatter PID efficiency as a function of the kinematic variables, which reduce systematic uncertainties in the physics result. The classifier achieves non-flatness dependency using a modified loss function [4].

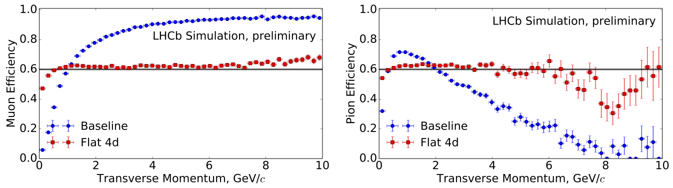

Figure 2: Dependence between Flat 4d model efficiencies and particle transverse momentum for each particle type. The curves correspond to the same global signal efficiency of 60%.

3. Neutral particle

Identification of neutral particles is based on responses in the calorimeter system. The particular problem is to separate prompt photons produced in collisions from photons produced by π^0 decays. The most confusing case is when two photons from the π^0 decay are highly collinear, thus looking similar to a clusters produced by prompt photons.

The baseline model used to separate these responses is based on a 2-layer neural network of TMVA library [5]. The neural network inputs are several aggregated features describing cluster shape in 3×3 ECAL cells area around the cluster seed. Feature set includes the center of gravity of the cluster energy and the second moments of the cluster shape S_{xx}, S_{yy}, S_{xy}. To improve efficiency we use XGBoost model which is a Gradient Boosting over Decision Trees classifier. In this case, inputs are raw energy values in 5×5 ECAL and PS cells around the cell seed.

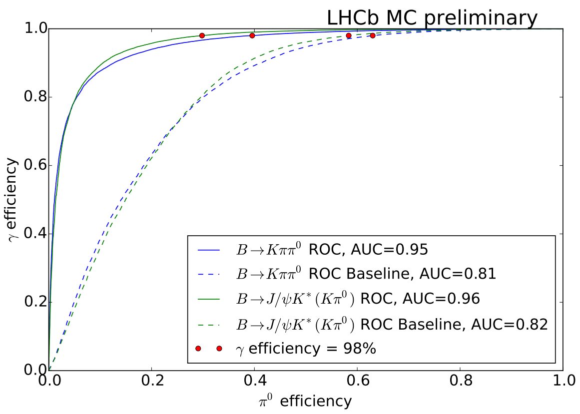

Figure 3: Photon efficiency vs mis-identification curves for the baseline (dashed line) and new method (solid line). Different colors refer to different test samples.

The model is trained using MC samples. Photons and π^0 are obtained from $B^0 \to K\pi\gamma$ and $B^0 \to K\pi\pi^0$ decays respectively. Additional decay channel $B^0 \to J/\psi K^*$ with $K^* \to K\pi^0$ are used as an extra source of π^0 to check the models stability. The performance evaluated on the simulated events show promising results. The obtained quality of γ-π^0 separation is demonstrated in Fig 3.

The uniform dependence of the quality of the model from particles properties is very important for optimal performance. Fig 4 demonstrates that new approach provides flat dependency of quality from transverse energy E_T.

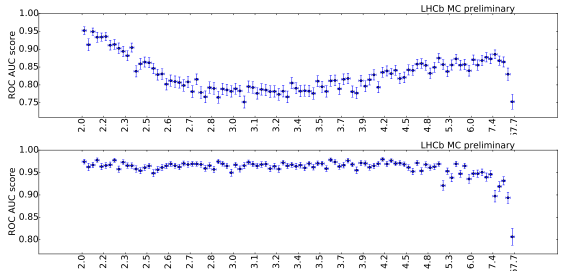

Figure 4: Baseline and XGBoost models quality as function of transverse energy.

4. Conclusion

Advanced machine learning techniques allow to increase particle identification performance both for charged and neutral particles. Combining information from the LHCb tracking system, ring-imaging Cherenkov detectors, electromagnetic and hadron calorimeters, and muon chambers allows to achieve high background rejection for charged particle identification. Applying machine learning approaches to raw energy deposits in the calorimeter provides good prospects for high quality neutral particle identification.

Acknowledgments

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