MPD Cross-PWG Meeting 20 December 2022

Possible application areas of machine learning techniques at MPD.

Alexander Zinchenko

Disclaimer

- Based on common-sense considerations (not on expert view)

Outline

- TPC fast digitizer
- TPC cluster finder
- Track reconstruction
- Application of machine learning for PID
- Signal extraction (background suppression)
- Summary / outlook

Application of Machine Learning at MPD – first look


Proceedings of the VIII International Conference "Distributed Computing and Grid-technologies in Science and Education" (GRID 2018), Dubna, Moscow region, Russia, September 10 - 14, 2018

POSSIBLE APPLICATION AREAS OF MACHINE LEARNING TECHNIQUES AT MPD/NICA EXPERIMENT AND EVALUATION OF THEIR IMPLEMENTATION PROSPECTS IN DISTRIBUTED COMPUTING ENVIRONMENT

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At present, the accelerator complex NICA is being built at JINR (Dubna). It is intended for performing experiments to study interactions of relativistic nuclei and polarized particles (protons and deuterons). One of the experimental facilities MPD (MultiPurpose Detector) was designed to investigate nucleus-nucleus, proton-nucleus and proton-proton interactions.
During the preparation of the physics research program, the production of a large volume of simulated data is required, including high-multiplicity events of heavy-ion interactions with high energy. Realistic modelling of the detector response for such events can be significantly accelerated with a use of generative models.
A selection of rare physics processes traditionally uses machine learning based approaches.
For the high luminosity accelerator operation for the proton-proton interaction research program it will be necessary to develop high-level trigger algorithms and methods, based on machine learning techniques.
During the data taking, the tasks of the fast and efficient processing and storage of large amounts of experimental data will become more and more important, requiring involvement of distributed computing resources.
In this work these problems are considered in connection to the MPD/NICA experimental program preparation.

Keywords: machine learning, generative models, multivariate analysis, heavy-ion collisions

615

Simulation of TPC and EMC response using generative models

Multivariate analysis for dilepton and open charm selection

+

Track reconstruction

Particle identification

Hyperon selection

TPC fast digitizer

HSE team

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THE EUROPEAN PHYSICAL JOURNAL C

Regular Article - Experimental Physics

Simulating the time projection chamber responses at the MPD detector using generative adversarial networks

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Abstract High energy physics experiments rely heavily on the detailed detector simulation models in many tasks. Running these detailed models typically requires a notable amount of the computing time available to the experiments. In this work, we demonstrate a new approach to speed up the simulation of the Time Projection Chamber tracker of the MPD experiment at the NICA accelerator complex. Our method is based on a Generative Adversarial Network – a deep learning technique allowing for implicit estimation of the population distribution for a given set of objects. This approach lets us learn and then sample from the distribution of raw detector responses, conditioned on the parameters of the charged particle tracks. To evaluate the quality of the proposed model, we integrate a prototype into the MPD software stack and demonstrate that it produces high-quality events similar to the detailed simulator, with a speed-up of at least an order of magnitude. The prototype is trained on the responses from the inner part of the detector and, once expanded to the full detector, should be ready for use in physics tasks.

1 Introduction

Computer simulations of high-energy physics experiments play a crucial role in a variety of relevant tasks, including detector geometry optimization [1,2], selecting best analysis strategies [3,4], and testing the Standard Model (SM) predictions and searching for new phenomena beyond the SM [5,6]. For a typical experimental data analysis, the number of simulated events usually translates directly to the uncertainty of the final physics result. The amount of computational resources spent on the simulations usually takes a notable fraction of the total computing capabilities of an experiment and is comparable with that spent on the real data processing [7,8]. Therefore, faster approaches to event generation and simulation are in great demand for the existing and future high energy physics experiments.

The MPD detector is one of the two experiments at the NICA accelerator complex – a new heavy ion accelerator facility being constructed at the Joint Institute for Nuclear Research and located in Dubna, Russia [9,10]. The complex is designed to study the properties of dense baryonic matter. For the tracking, MPD utilizes a time projection chamber (TPC) in the central barrel [11]. TPC simulation is very CPU-intensive [12], and hence a fast simulation approach for TPC is highly desirable.

A typical approach to constructing models for fast simulation of particle physics detectors is to use a simplified detector geometry and a simplified model of the interaction of particles with matter [13]. This approach is justified for subsystems with a flat sensitive volume, such as silicon trackers, that measure the two-dimensional coordinate of a passing particle. For systems with a large volume, such as calorimeters or TPC-based trackers, this approach makes it difficult to achieve a reasonable compromise between accuracy and simulation speed.

Another fast simulation approach is an analytical parameterization of the detector responses, as can be seen in shower shape parameterizations for calorimeters [14]. This approach can significantly speed up the calorimeter simulation, but it makes it difficult to achieve high quality simulated data. A common solution for calorimeters is also to use the so-called "frozen showers" [13] when detailed simulated system responses are stored as a response library for subsequent reuse.

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Generative Adversarial Networks for the fast simulation of the Time Projection Chamber responses at the MPD detector

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Abstract. The detailed detector simulation models are vital for the successful operation of modern high-energy physics experiments. In most cases, such detailed models require a significant amount of computing resources to run. Often this may not be afforded and less resource-intensive approaches are desired. In this work, we demonstrate the applicability of Generative Adversarial Networks (GAN) as the basis for such fast-simulation models for the case of the Time Projection Chamber (TPC) at the MPD detector at the NICA accelerator complex. Our prototype GAN-based model of TPC works more than an order of magnitude faster compared to the detailed simulation without any noticeable drop in the quality of the high-level reconstruction characteristics for the generated data. Approaches with direct and indirect quality metrics optimization are compared.

1. Introduction

Simulation of particle detectors is inevitable in the High Energy Physics (HEP) experiments. For a typical HEP data analysis, the limited size of simulated data samples often contributes directly to the uncertainty in the final result. Since the number of simulated events that one can afford to produce is constrained by the computational efficiency of the simulation algorithms, faster algorithms are always desired [1].

Computational efficiency of the detailed simulation is often limited by the fine granularity of the physics simulation steps being performed. Therefore, a speed-up may be achieved by aggregating a sequence of such steps with a single estimate of the probability distribution for the last step output parameters, conditioned by the first step inputs. An important requirement for such a probability distribution estimate is that it should allow for efficient sampling. Generative Adversarial Networks (GANs) [2] are a good candidate for such a parametric estimate since they only require a forward pass through a neural network to generate new samples. In this work, we demonstrate an application of GANs for building a fast-simulation model of the Time Projection Chamber (TPC) detector at the MPD experiment at the NICA accelerator complex [3].

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Generative Surrogates for Fast Simulation: TPC Case

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Abstract

Simulation of High Energy Physics experiments is widely used, necessary for both detector and physics studies. Detailed Monte-Carlo simulation algorithms are often limited due to the computational complexity of such methods, and therefore faster approaches are desired. Generative Adversarial Networks (GANs) are well suited for aggregating a number of detailed simulation steps into a surrogate probability density estimator readily available for fast sampling. In this work, we demonstrate the power of the GAN-based fast simulation model on the use case of simulating the response for the Time Projection Chamber (TPC) in the MPD experiment at the NICA accelerator complex. We show that our model can generate high-fidelity TPC responses, while accelerating the TPC simulation by at least an order of magnitude. We describe alternative representation approaches for this problem and also outline the roadmap for the deployment of our method into the software stack of the experiment.

Keywords: fast simulation, time projection chamber, generative adversarial network

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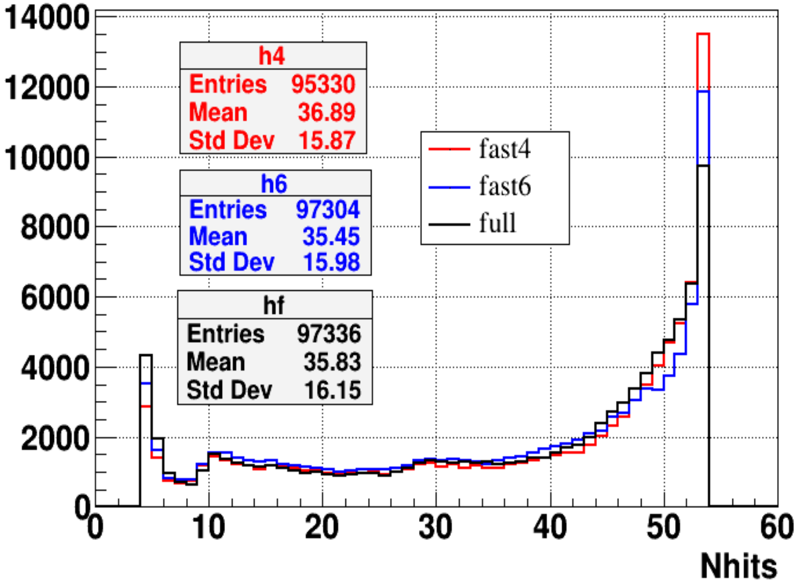
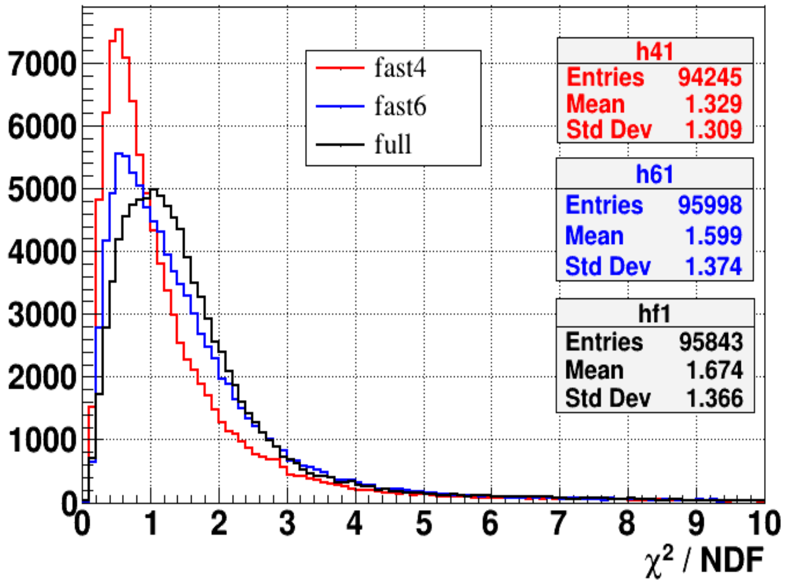
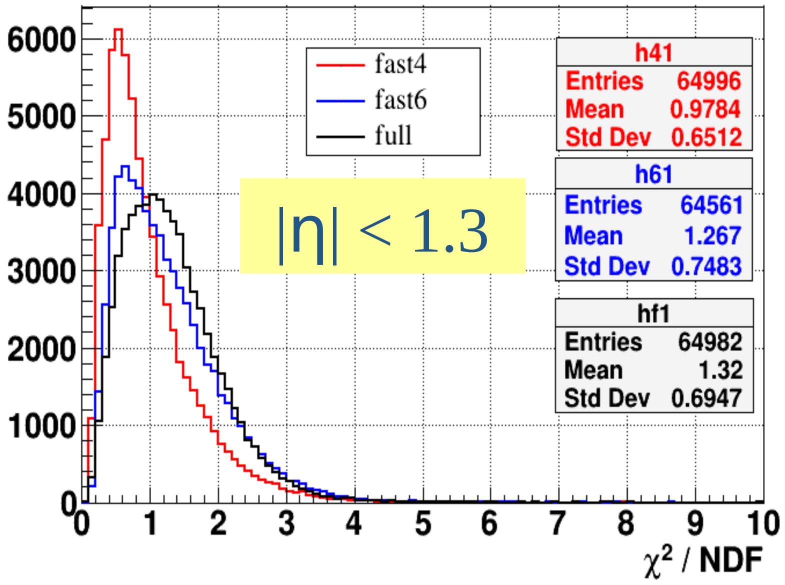
Preprint submitted to Nuclear Instruments and Methods in Physics Research A July 12, 2022

TPC fast digitizer







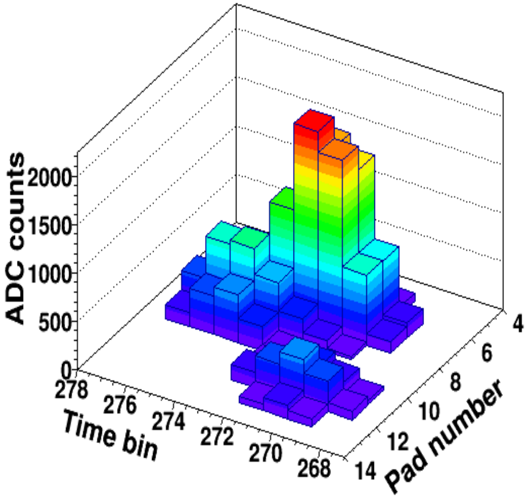
Future steps:

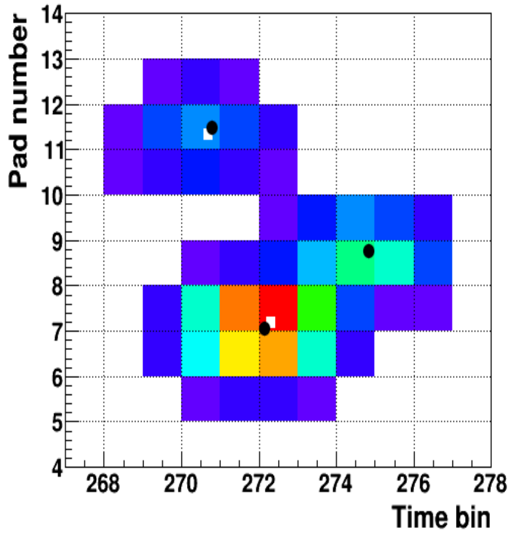
- ❑ Add the 7th input track parameter;
- ❑ Generate signals for 3 (2) neighbor padrows (to account for correlations)

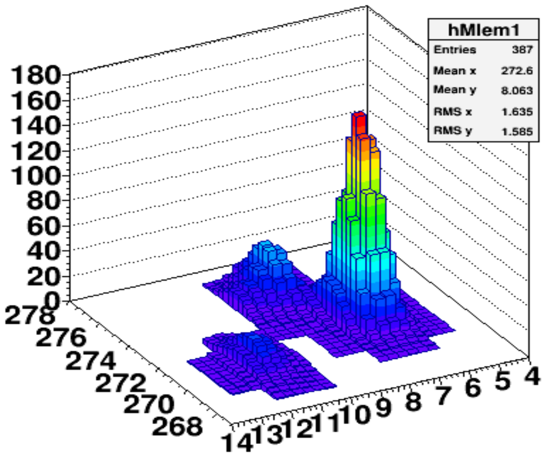
TPC cluster finder

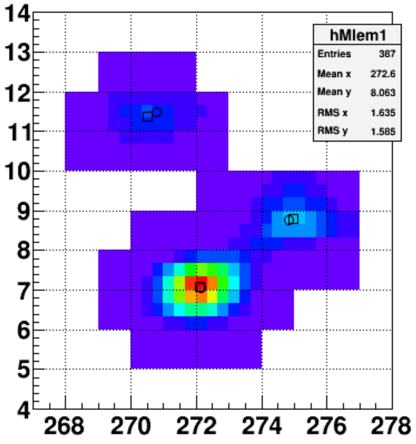
Tasks: Two-track separation (for femtoscopy) and cluster charge determination (for *dE/dx* identification)

Fresh ideas are welcome (Machine Learning?) - simple use case: selection of one-track clusters (currently is based on the number of local maxima in the cluster)

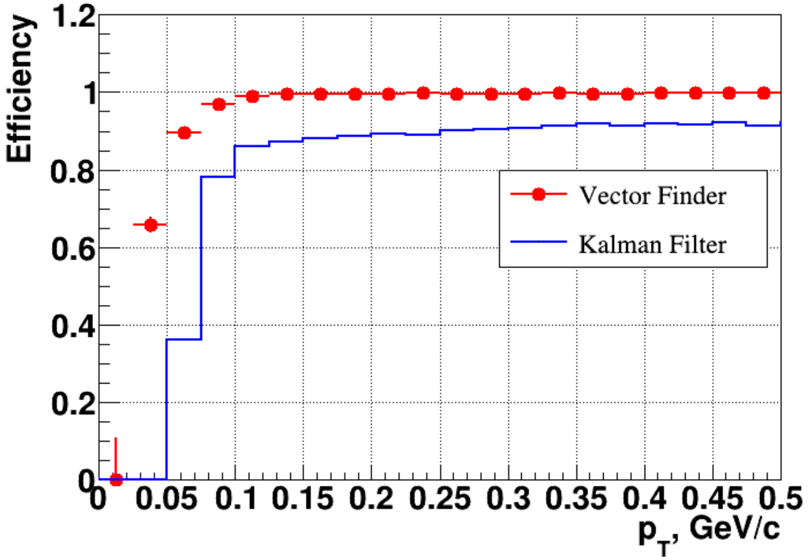


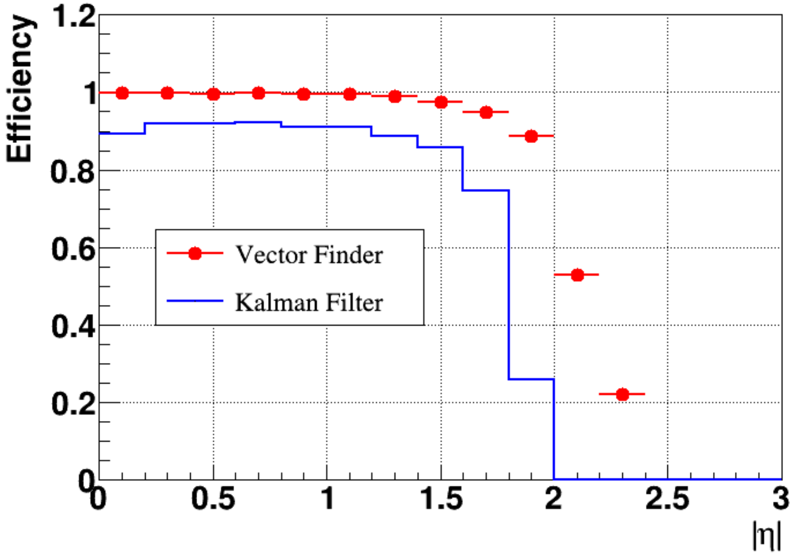


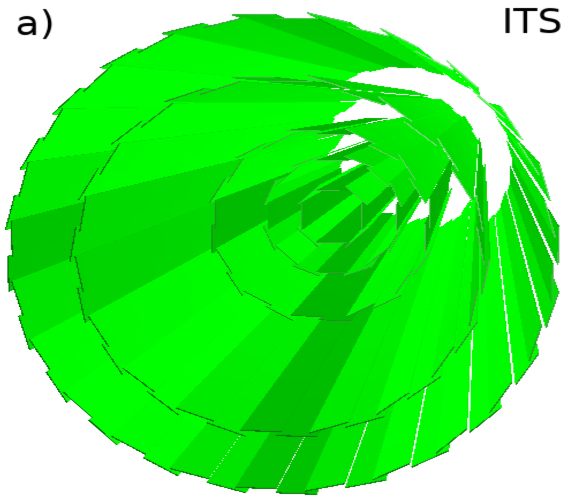




Track reconstruction: Vector Finder toolkit for ITS

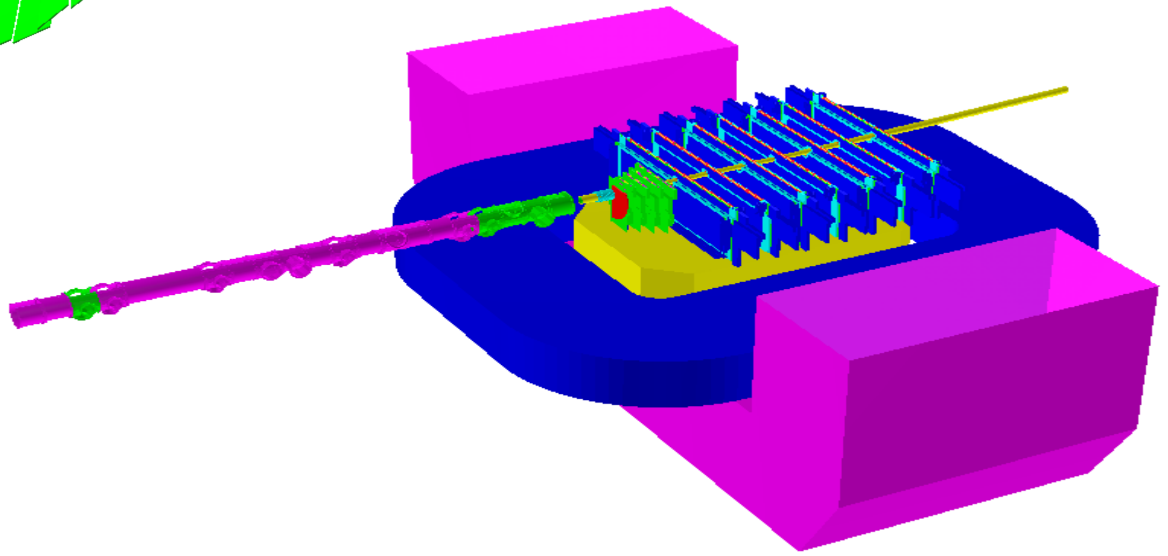




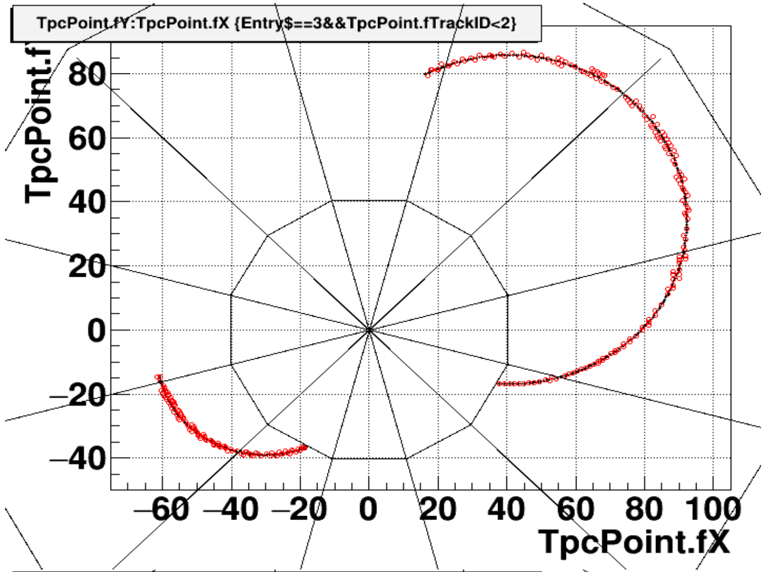


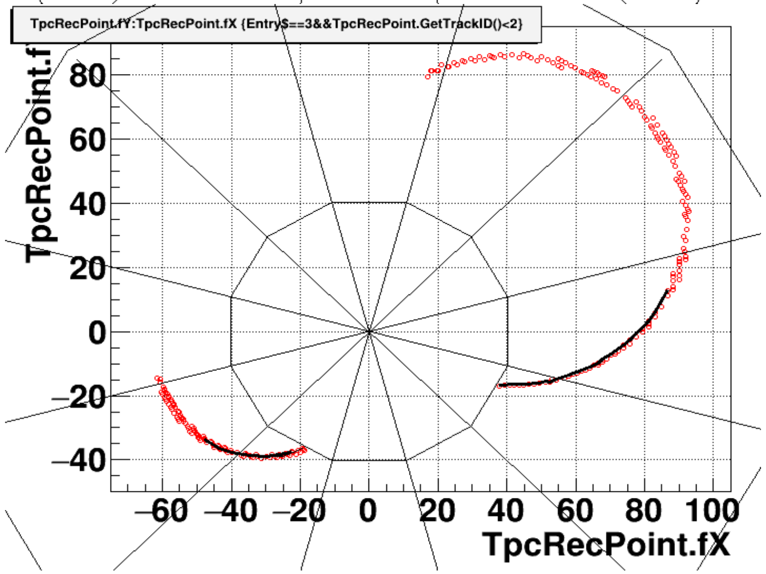
D. Zinchenko

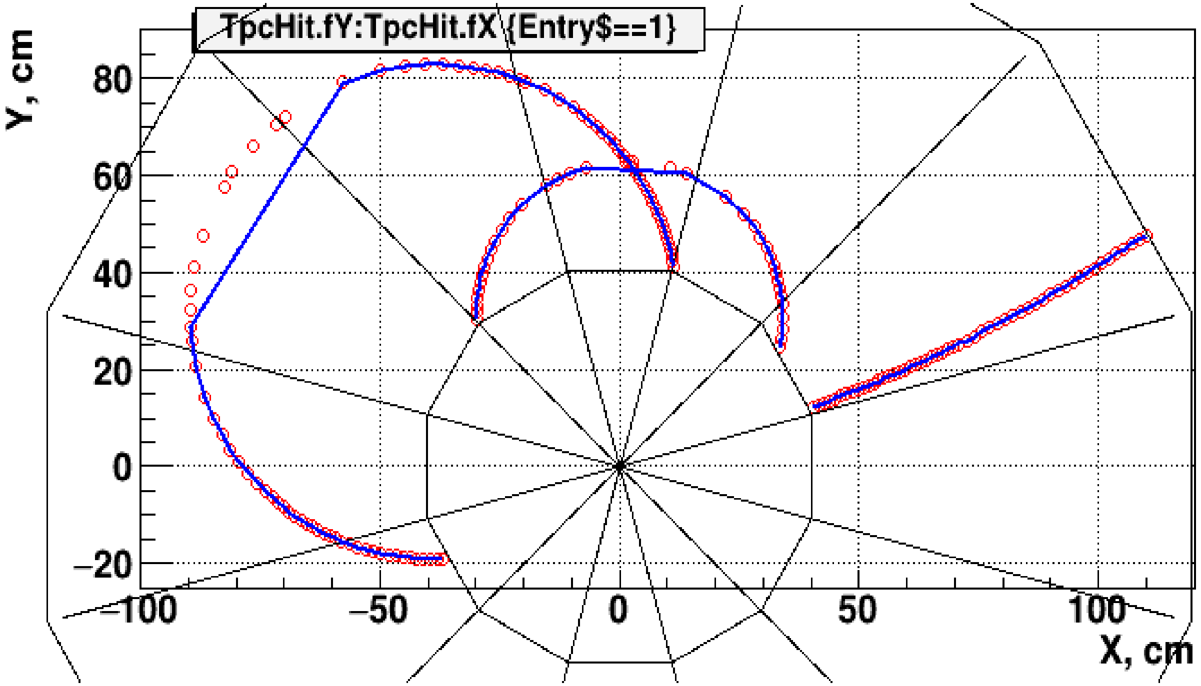
BM@N inner tracker:
VF with ML plugins



Track reconstruction: low-pT tracks







I. Tserruya,
S. Rode

Required some changes of the Kalman filter main engine.

Some additional modifications might be necessary for realistic clusters.
Contingent on TPC response simulation for large crossing angles.
Not clear if it is possible on a short time scale.

ML PID for TOF Matched TPC Tracks

X Collaboration Meeting of the MPD Experiment at the NICA Facility

Machine learning for particle identification

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Alexey Aparin[1], Alexander Mudrokh[1], Vladimir Popoyan[2], Grigorii Tolkachev[3]

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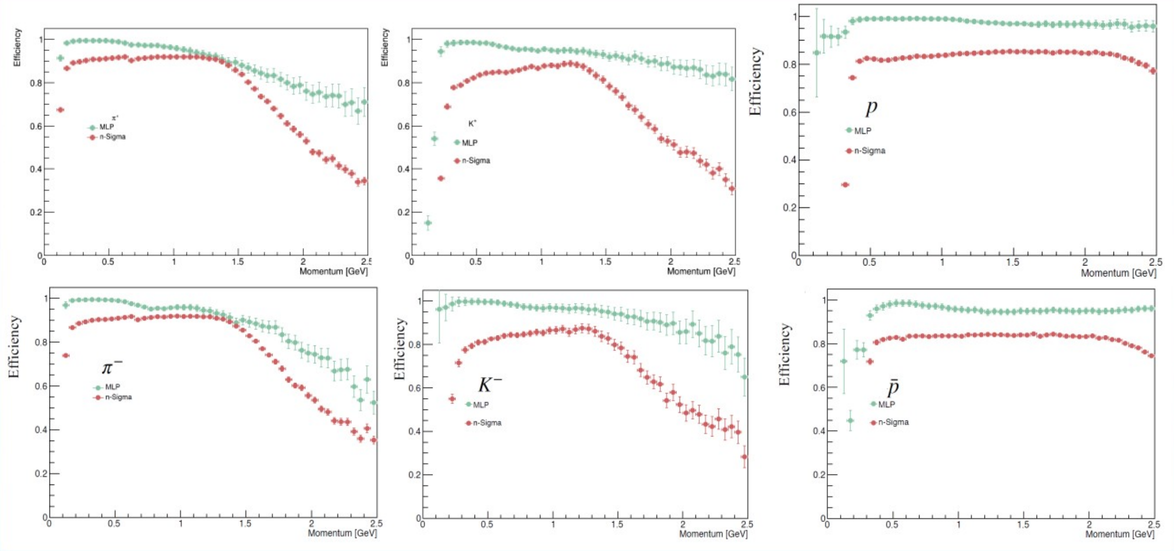
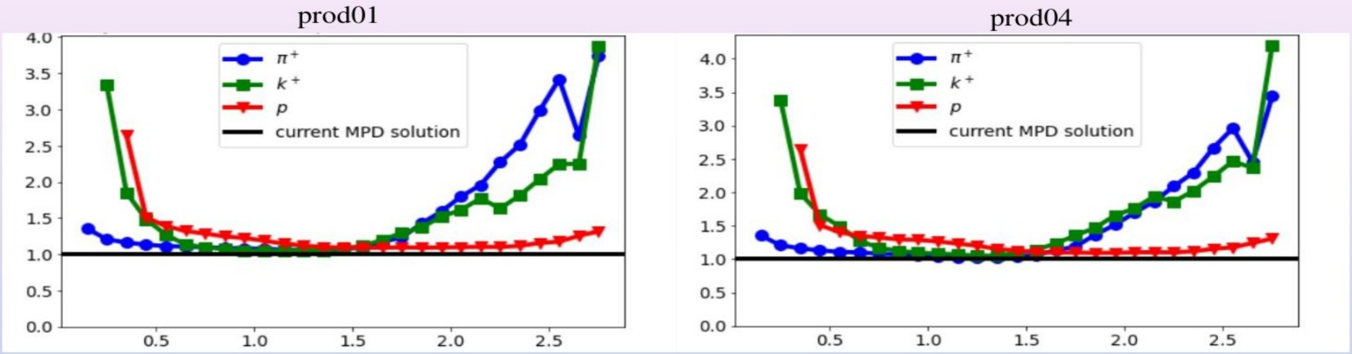
Dubna
10 November 2022

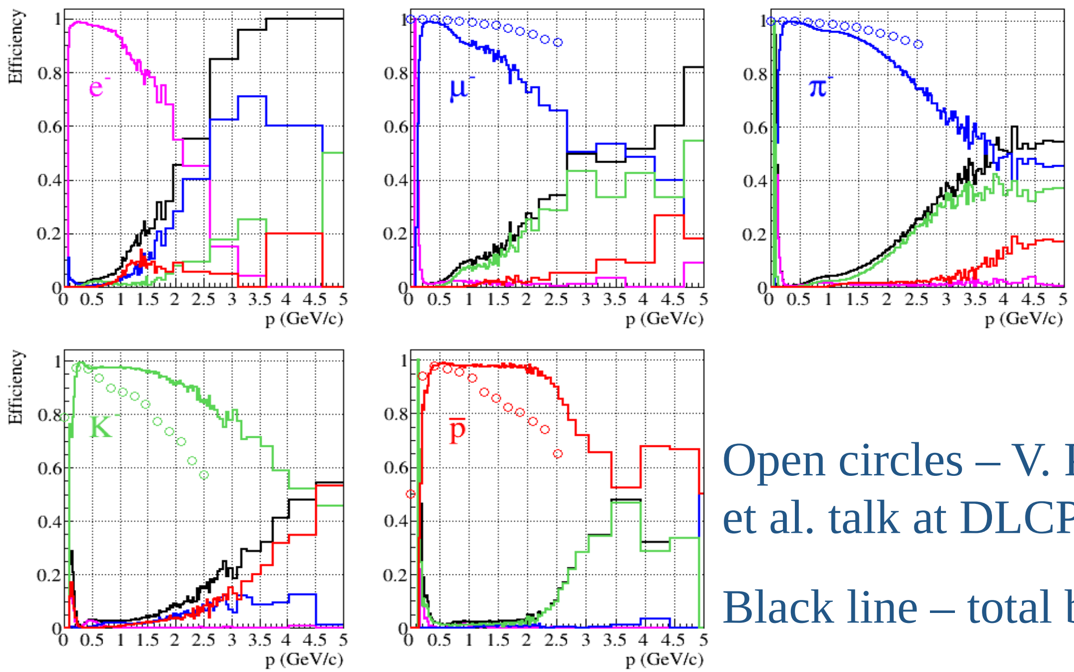
Comparison MLP with n-sigma method



Efficiency ratio of CatBoost and n-sigma method



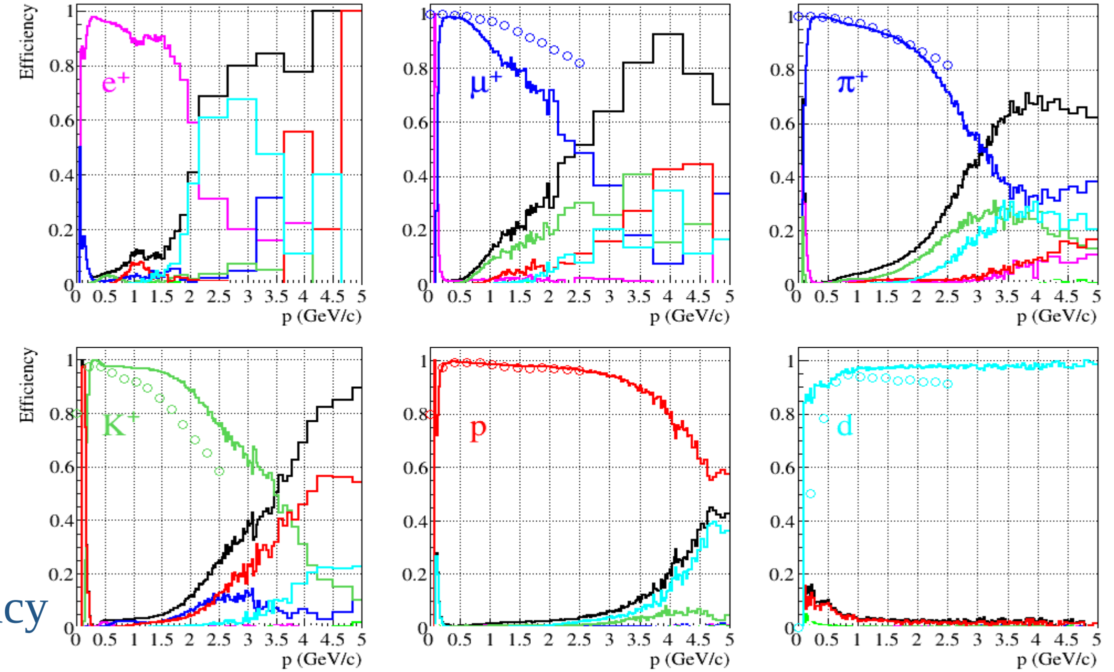
TMVA PID for TOF Matched TPC Tracks



I. Rufanov

Open circles – V. Papoyan et al. talk at DLCP-2022

Black line – total background efficiency



- Input data: MPDROOT simulation of PHQMD min. bias BiBi collisions at 9.2 GeV
- TMVA method: Neural Networks with Multilayer Perceptrons (MLP)
- Track classification variables: Q, momentum, dE/dx, TOF, N of hits, pseudorapidity and DCA
- Currently, muons and pions are considered as a same classification case

Plans: find out the reason of low-momentum miss-classification; separate muon and pion sclassification cases; choose optimal set of variables for classification (include azimuthal angle)

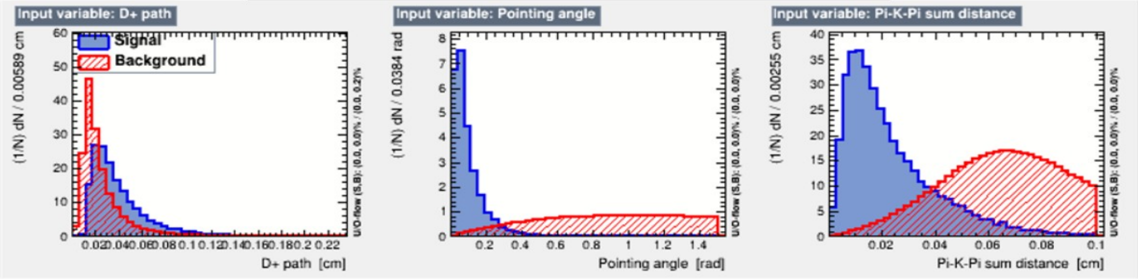
Open charm reconstruction and selection in ITS

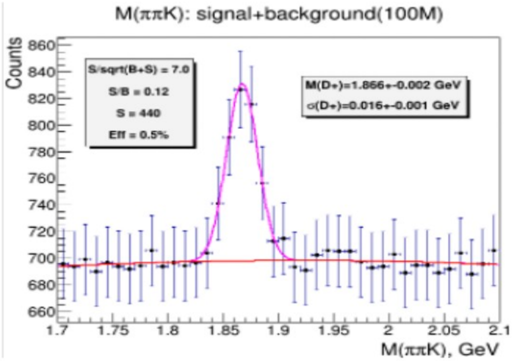
WP1 - Simulations

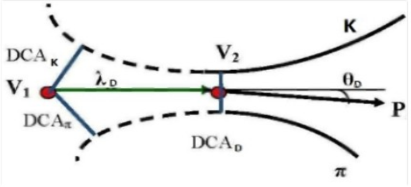
MPD - ITS

D⁺ and D⁰ reconstruction using KF

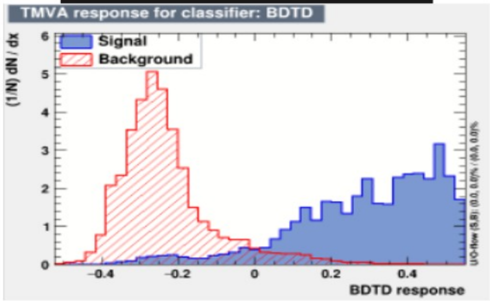
TC: dca(π), dca(K), dca(πK), λ(D), θ(D) cuts

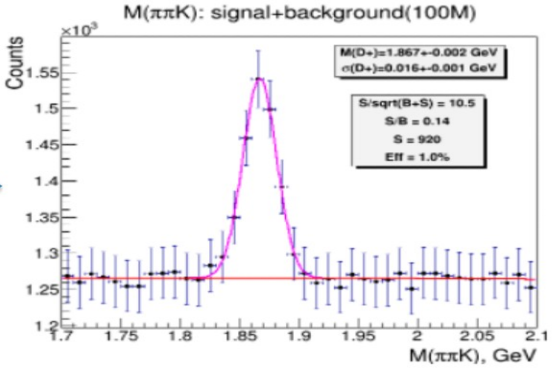






MVA: BDT classifier cuts



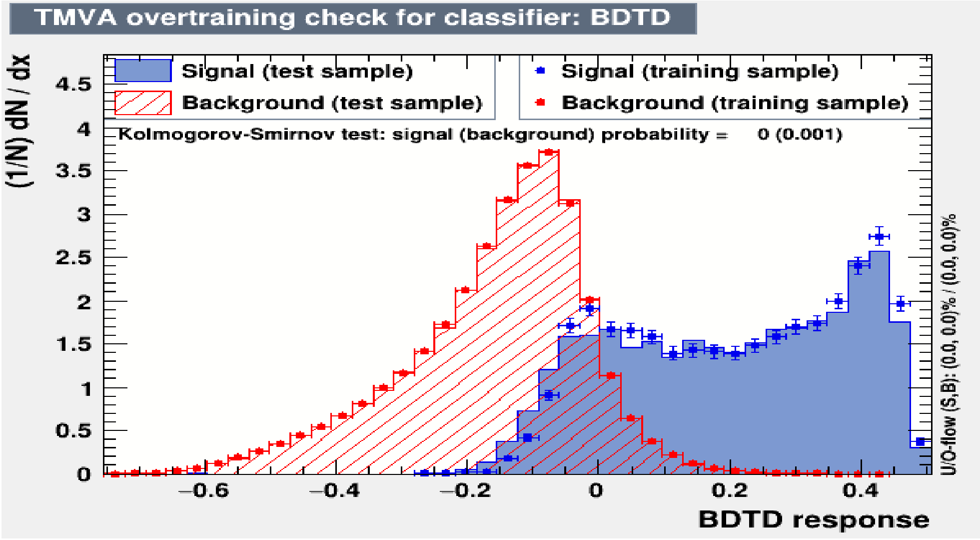


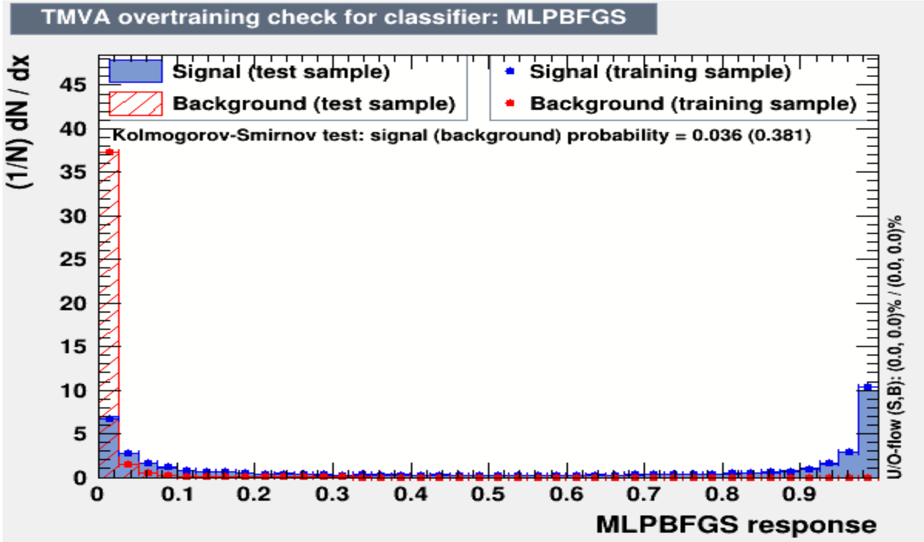
Particle	D⁰		D⁺	
Method	TC	MVA	TC	MVA
Efficiency, %	0.80	0.85	0.50	1.0
Significance	5.3	5.5	7.0	10.5
S/B(2σ) ratio	0.10	0.10	0.12	0.14

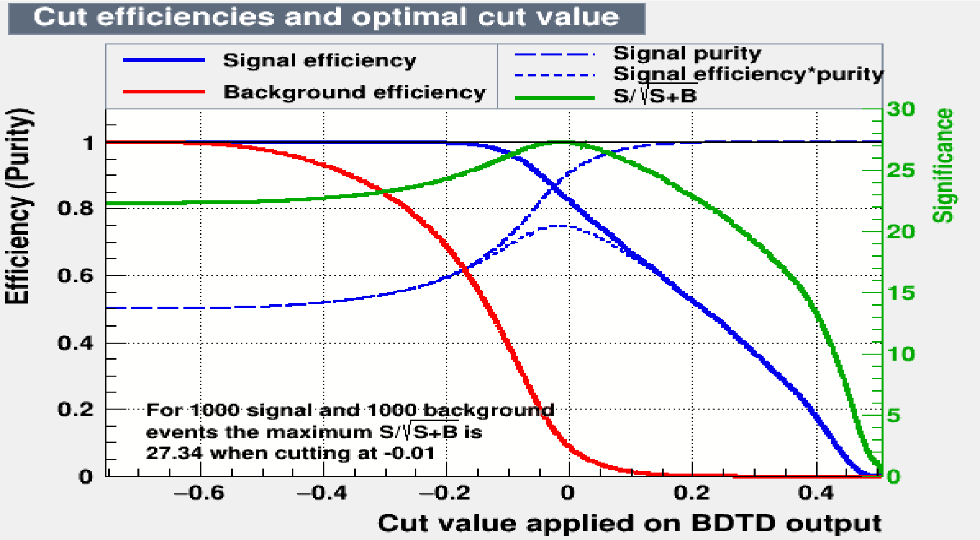
Using the topological cuts allows to reconstruct D⁰ and D⁺ decays with an efficiency of 0.8% and 0.5% respectively. Using the optimal BDT cut allows to reconstruct D⁰ and D⁺ with an efficiency of 0.85% and 1.0% respectively.

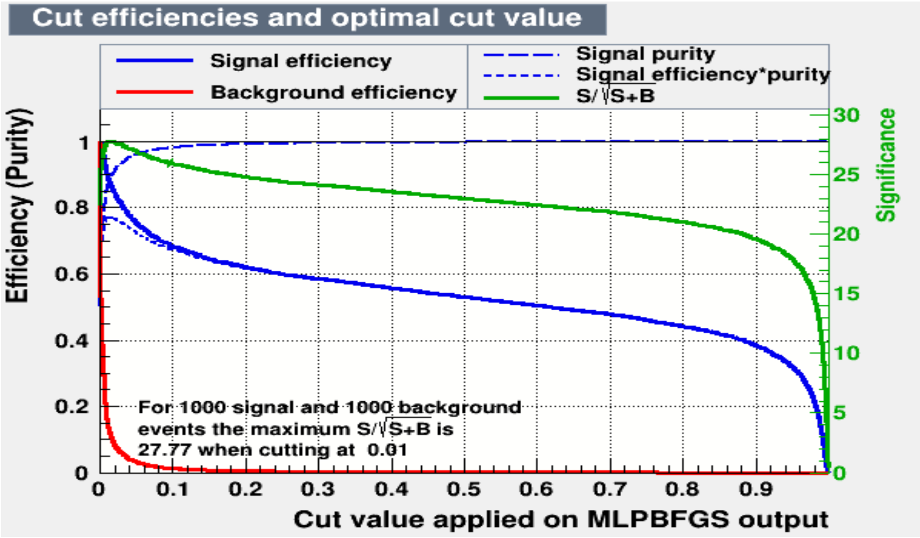
A. I. Zinchenko, S. N. Igolkin, V. P. Kondratiev & Yu. A. Murin" NICA-MPD Vertex Tracking Detector Identification Capability for Reconstructing Strange and Charmed Particle Decays". Physics of Particles and Nuclei Letters , volume 17, pages 856–870 (2020)

TMVA package: network performance





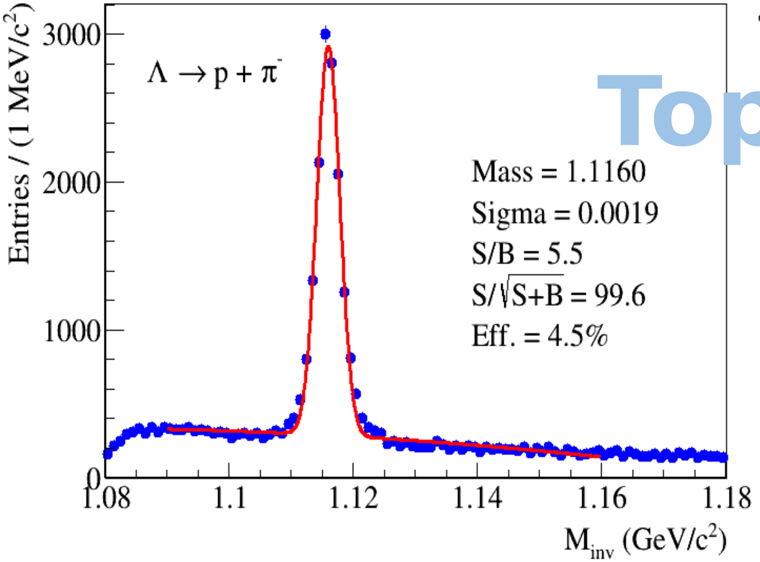


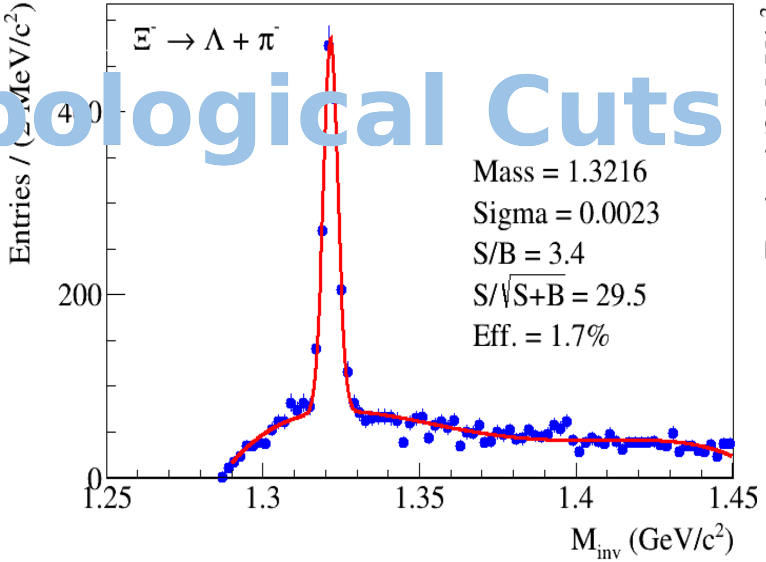


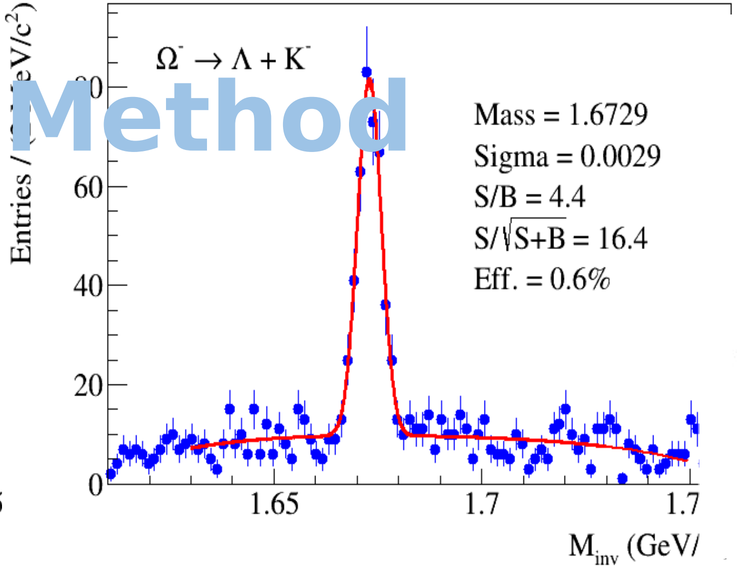
Hyperon reconstruction: TC vs TMVA

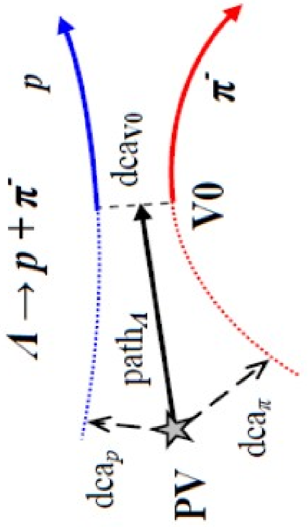
V. Vasendina

Topological Cuts Method

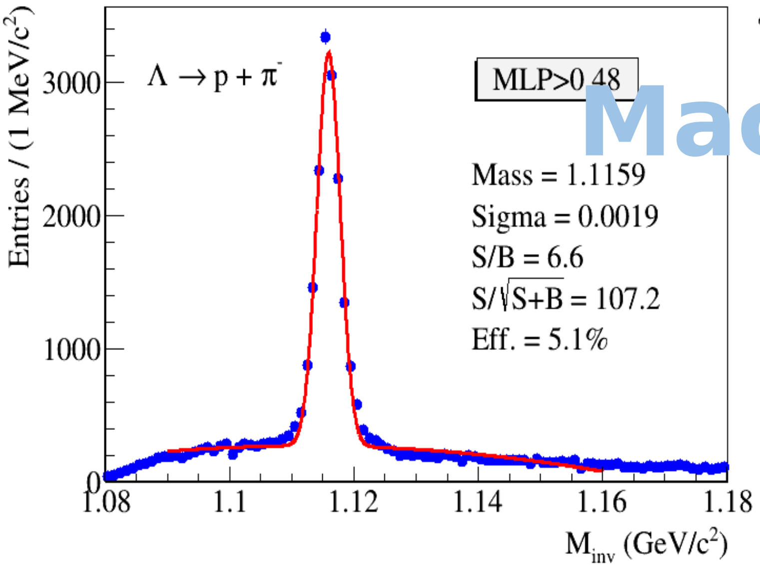


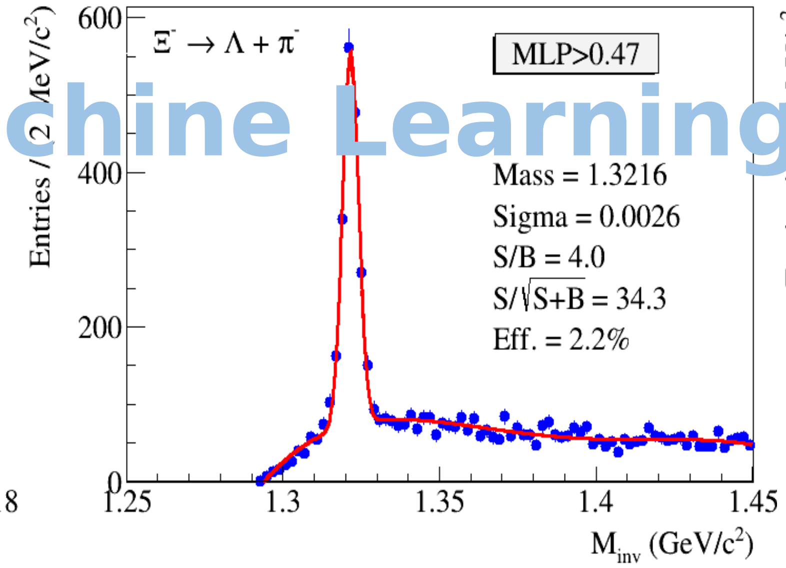


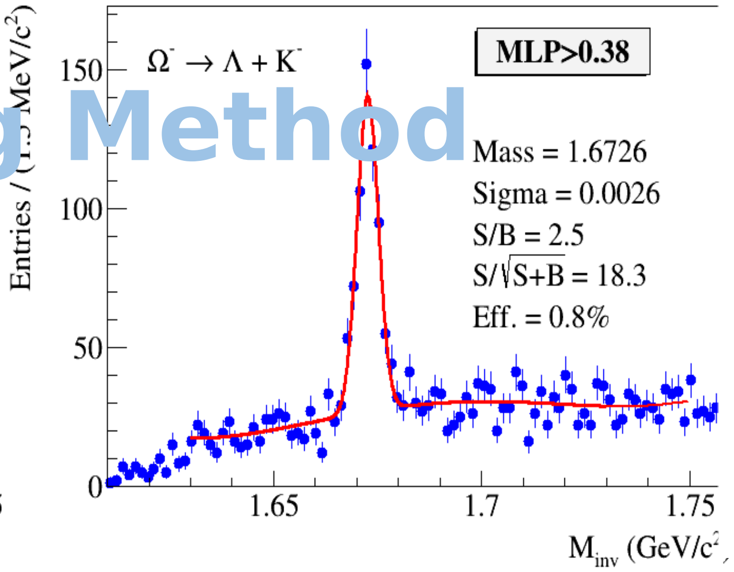


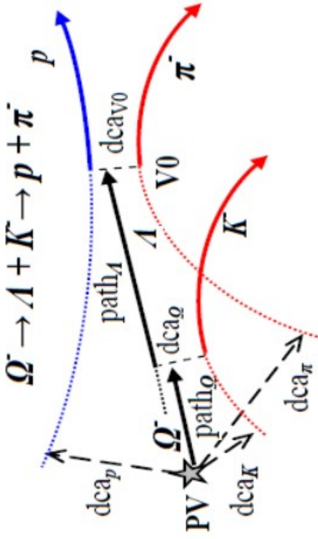


Machine Learning Method









Summary / Outlook

- There are several areas at MPD where machine learning approaches can be applied;
- They can help to improve some results and / or optimize some reconstruction and analysis procedures;
- The task of training of ML models for real data is an issue to keep in mind.