The 7th International Conference on Particle Physics and Astrophysics (ICPPA-2024)

A Monte Carlo Study of the MPD Performance for Hyperon Selection Using Machine Learning Techniques

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Outline

- **Motivation for the Study of Hyperons**
- **Overview of Multi-Purpose Detector (MPD) – Stage-1**
- **Methods: Topological Cuts (TC) and Machine Learning with ROOT (TMVA)**
- **Study of Hyperon Production:**

$$\Lambda \rightarrow p + \pi^-$$

$$\overline{\Lambda} \rightarrow \overline{p} + \pi^+$$

$$\Xi^- \rightarrow \Lambda + \pi^- \rightarrow p + \pi^- + \pi^-$$

$$\Omega^- \rightarrow \Lambda + K^- \rightarrow p + \pi^- + K^-$$

- **Comparison of TC and MLP Methods Applied to Real Data from BM@N experiment**
- **Summary**

Physics Motivation

➢ **Importance of Hyperons:**

- They have attractive experimental features, making them valuable tools for monitoring detector performance.

➢ **Astrophysical Relevance:**

- Hyperons provide essential signatures of excited and compressed baryonic matter.
- Helps us understand how matter behaves in extreme conditions in neutron stars.

➢ **Quantum Chromodynamics (QCD):**

- Study of hyperons helps to understand strong interactions and QGP.

➢ **Experimental Techniques:**

- Research on hyperons improves experimental methods and data analysis techniques in high-energy physics.

The Goal of This Study

➢ **Improve Selection of hyperons**

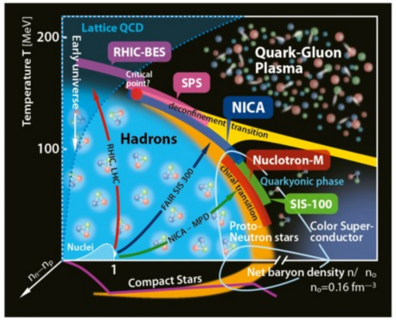
- Improve accuracy and efficiency in identifying strange particles produced in heavy-ion collisions.

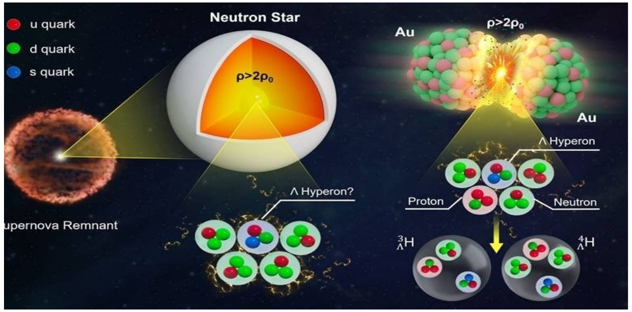
➢ **Use Machine Learning Tools**

- Implement advanced machine learning methods (MLP and BDTD).

➢ **Compare and Evaluate Selection Methods**

- Evaluate machine learning techniques against traditional methods to see which is more effective at reducing background noise.





Data Set

- **Generator:** UrQMD, Min.bias, Bi+Bi @ 9.2 GeV, 100K, 10M and 50M events
- **Detectors:** start version of MPD

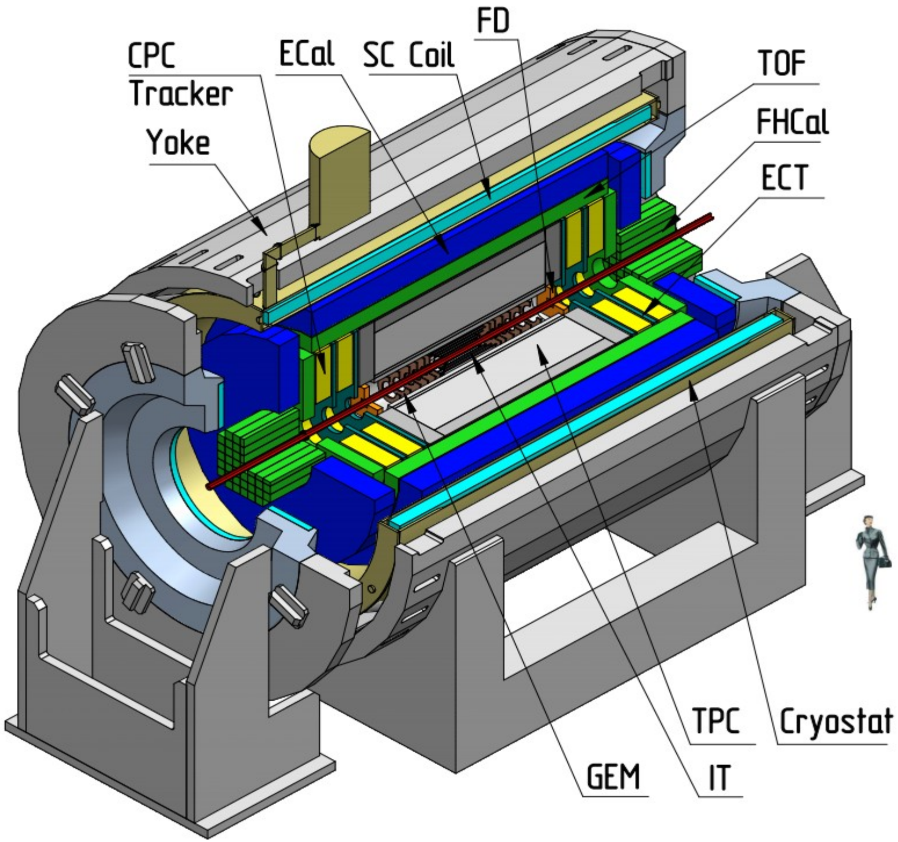
Analysis

- **Track reconstruction:** two-pass Kalman filter with track seeding using outer hits (1st pass) or leftover inner hits (2nd pass)
- **Track acceptance criterion:** $|\eta| < 1.3$, $N_{TPC\ hits} \geq 10$
- **Particle Identification:** dE/dx in TPC & m^2 in TOF
- **Methods:** Topological Cuts (TC) and Machine learning with ROOT (TMVA)

Multi-Purpose Detector: General View

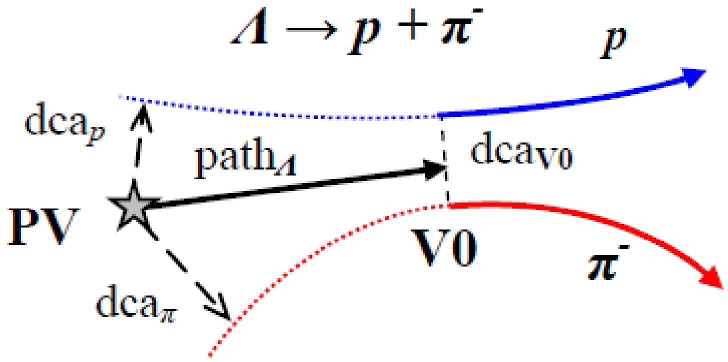
Time-Projection Chamber (TPC): Main tracking detector
Time-Of-Flight (TOF): Particle identification via time-of-flight
Electromagnetic Calorimeter (Ecal): Measurements of photons and electrons
Forward Hadron Calorimeter (FHCal): Measures centrality and event plane
Forward Detector: Provides fast trigger for TOF

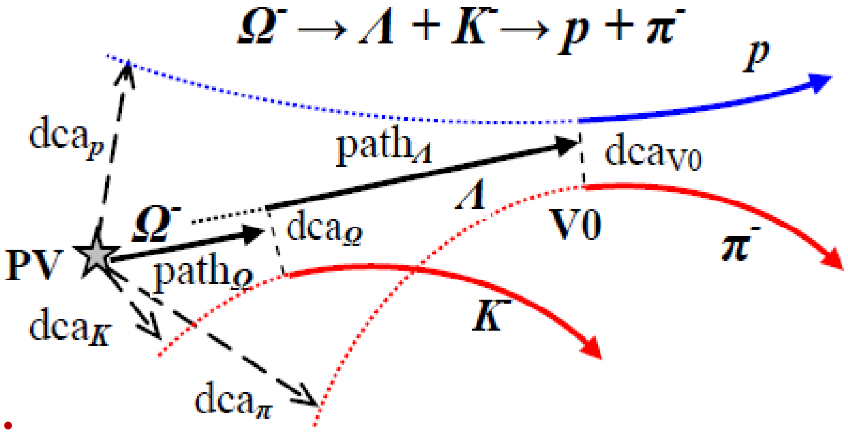
All subdetectors are located inside a superconducting solenoid with nominal field of 0.5 T



http://mpd.jinr.ru/mpd/

Method: Topological Cuts (TC)





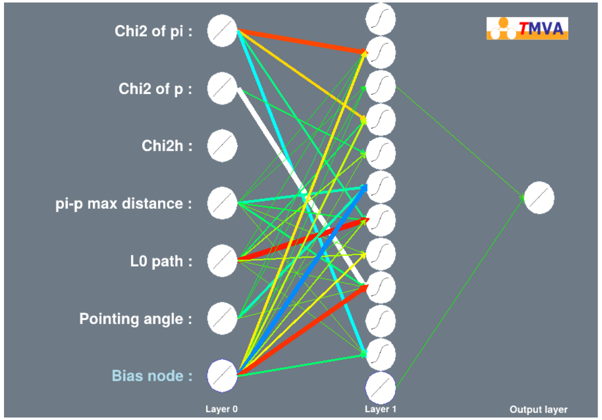
Event topology:

- PV – primary vertex
- V_0 – vertex of hyperon decay
- dca – distance of the closest approach
- path – decay length

Maximization of significance: Significance is defined as **S/√(S+B)**, where **S** and **B** are the total numbers of signal and background combinations inside ±2σ interval around the invariant mass peak position (σ is taken from Gaussian fit of the peak).

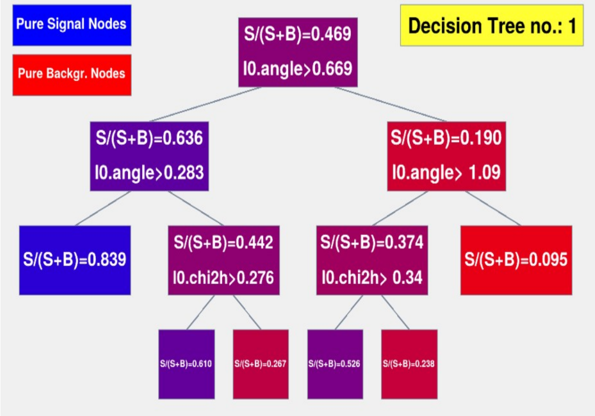
Method: TMVA - MLP

- **TMVA (Tooking for Multivariate Data Analysis):** A framework for machine learning in particle physics.
- **MLP (Multi-Layer Perceptron):** Artificial Neural Network (ANN) structure to perform classification task.
- **Key Parameters:** **NeuronType -** hyperbolic tangent (tanh) activation function, **Ncycles -** 600, **HiddenLayers -** hidden layers set to N+5, where N is the number of input features, **TestRate -** 5% of the data is reserved for testing.



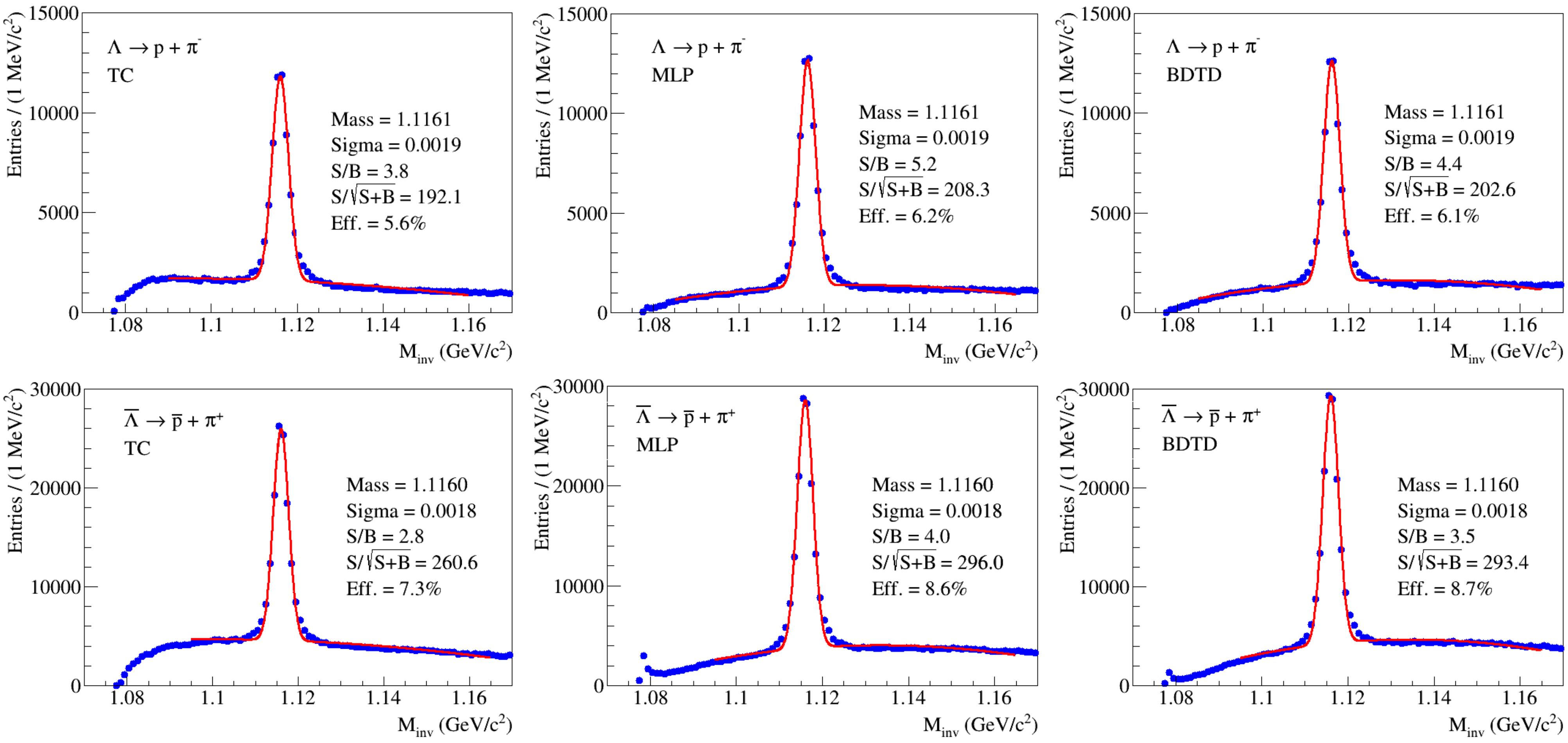
Method: TMVA - BDTD

- **BDTD (Boosted Decision Trees):** An ensemble learning method that combines multiple decision trees.
- **Key Parameters:** **Ntrees** – 400, **MinNodeSize** – Sets a minimum size for terminal nodes (5%), controlling the complexity of the trees.

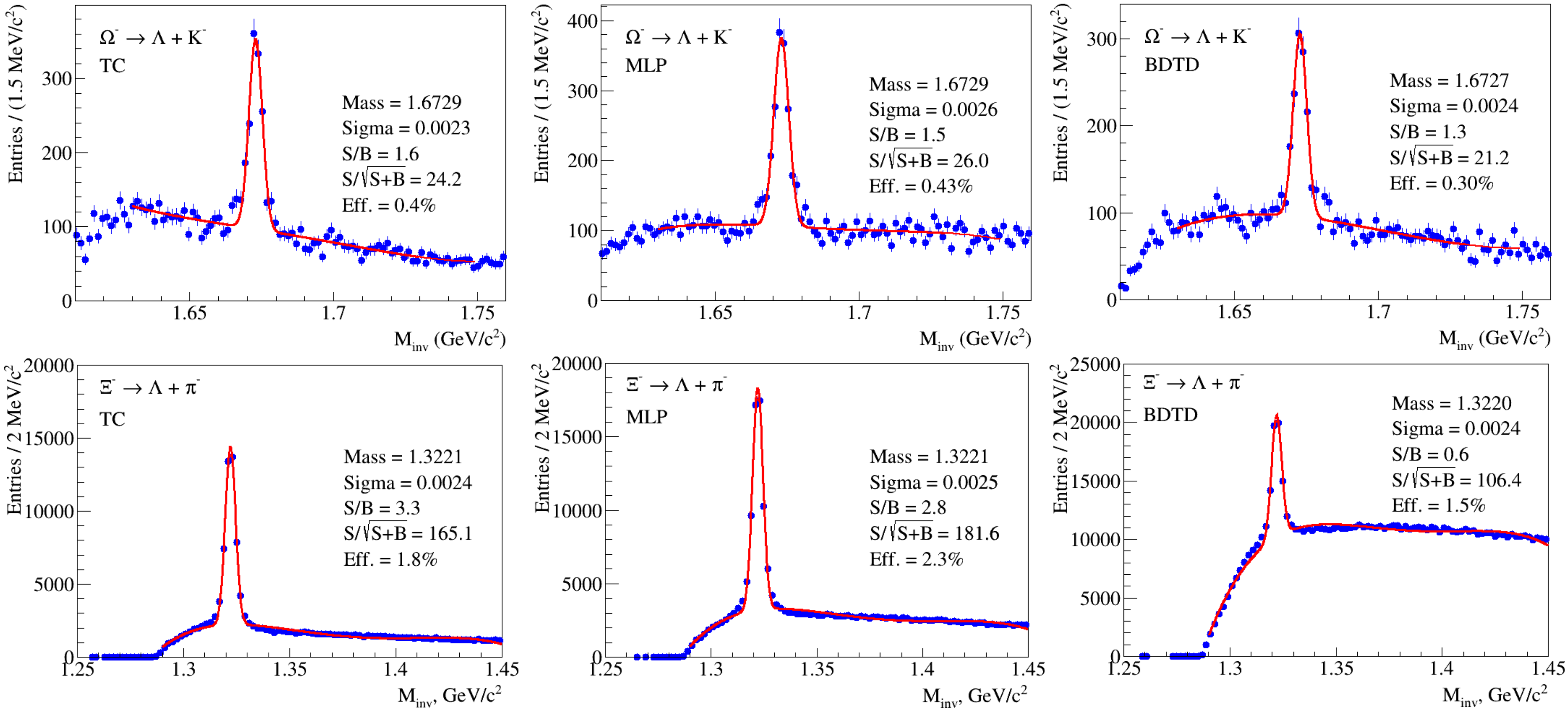


https://root.cern/doc/master/group__tutorial__tmva.html

Λ / $\overline{\Lambda}$ Selection: TC & MLP & BDTD



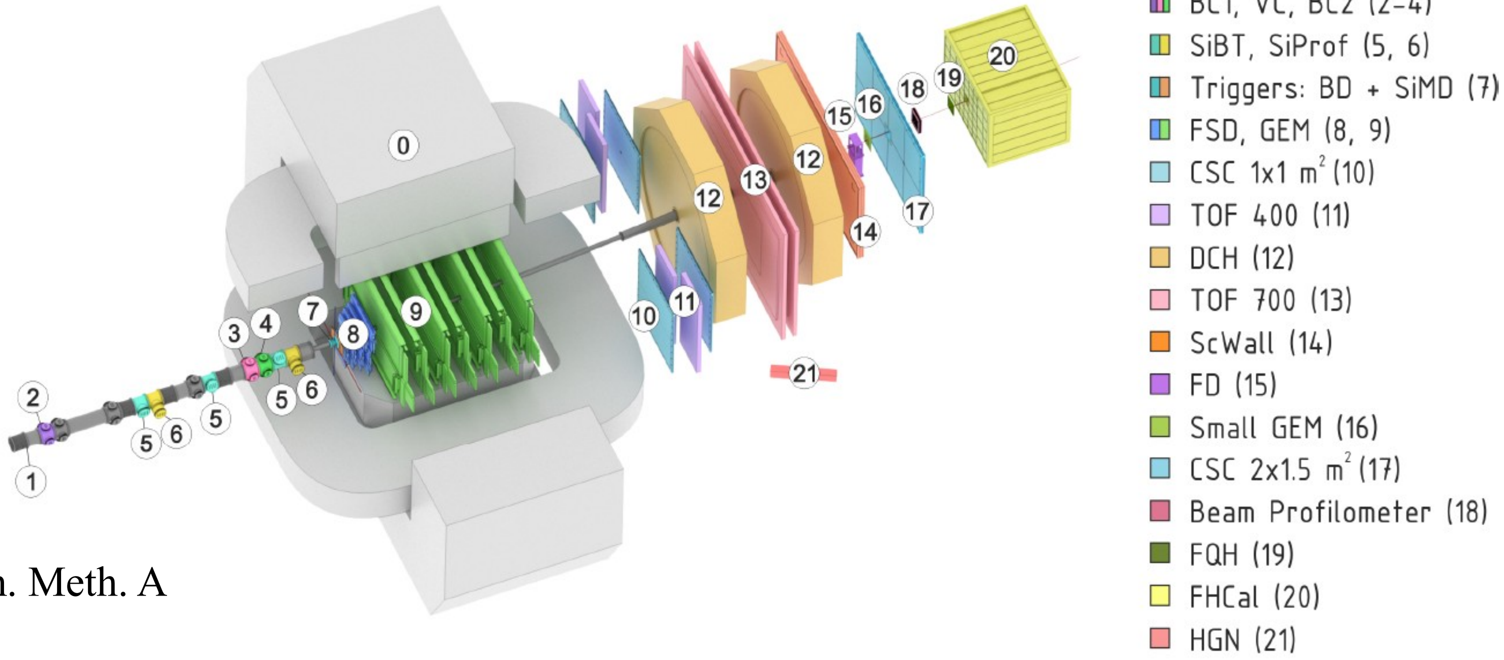
Ω^- / Ξ^- Selection: TC & MLP & BDTD



Configuration of BM@N detector in Xe+CsI run

First physics run with full configuration Dec. 2022 – Jan. 2023
Xe^{124} + CsI interactions, beam kinetic energy 3.8A GeV:

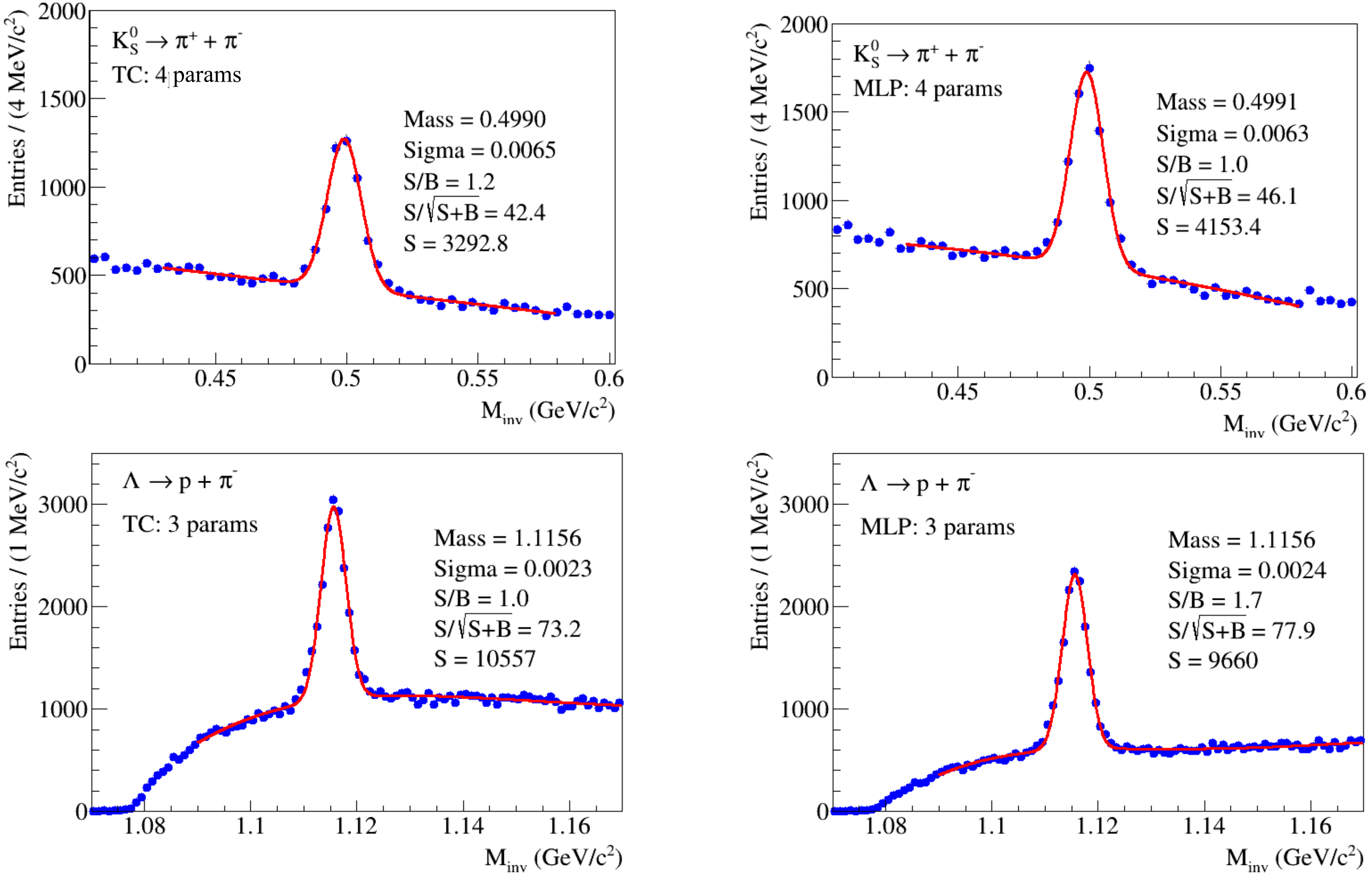
main trigger covers centrality < 70-75% (85% events), min bias trigger (7% events), beam trigger (3% events)
~500M triggers recorded



Detector paper: Nucl. Instrum. Meth. A **1065**, 169532 (2024)

$K^0{}_S$ / Λ Selection: TC vs MLP, Data

Training with MC



Summary

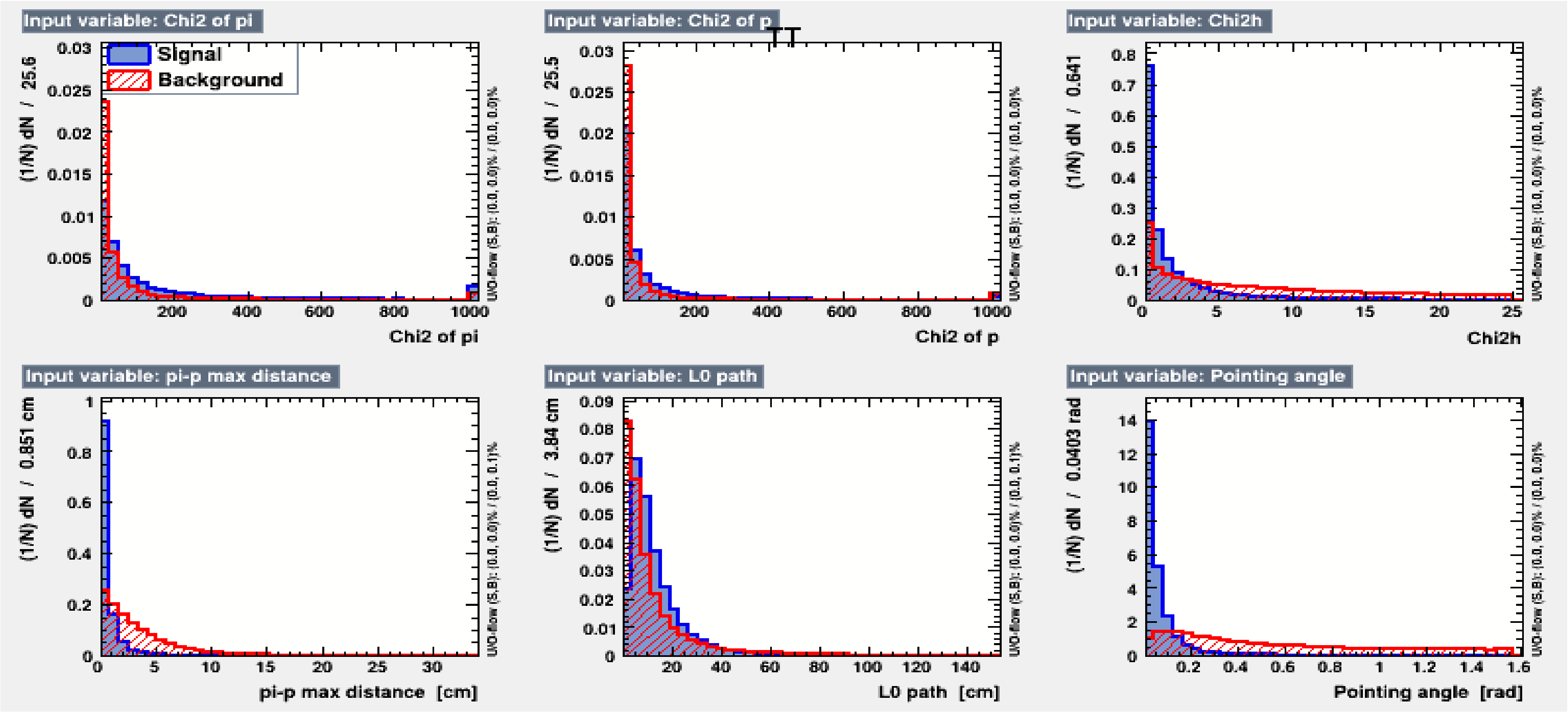
- **Introduction to Machine Learning:** The application of machine learning methods, specifically MLP, improves the quality of identifying strange particles, outperforming traditional methods.

- **Application in Hyperon Selection:** The study successfully demonstrated the application of machine learning techniques in strange particle decay selection, with MLP showing the highest invariant mass peak significance (i.e. highest product of signal efficiency and purity).

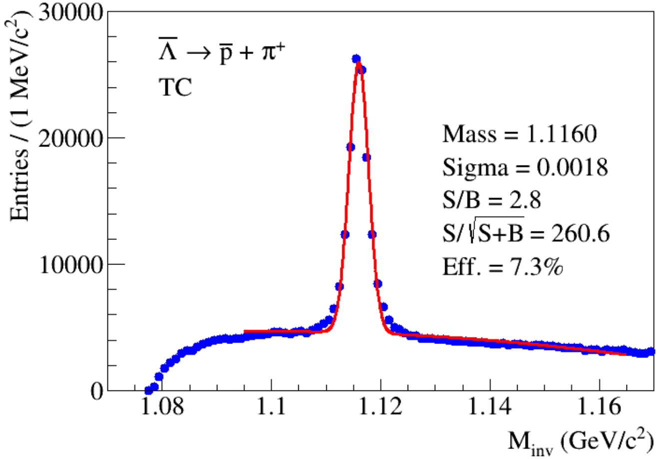
- **Comparison of Different Methods:** Different methods (TC, MLP, BDTD) were compared, highlighting the strengths and weaknesses of each approach.

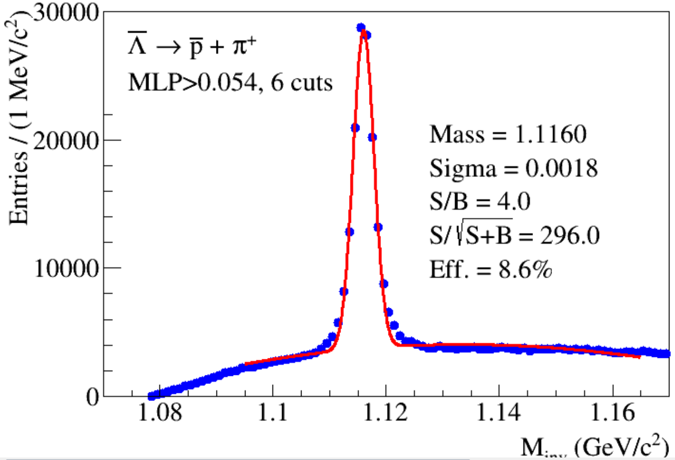
Thank you for your attention!

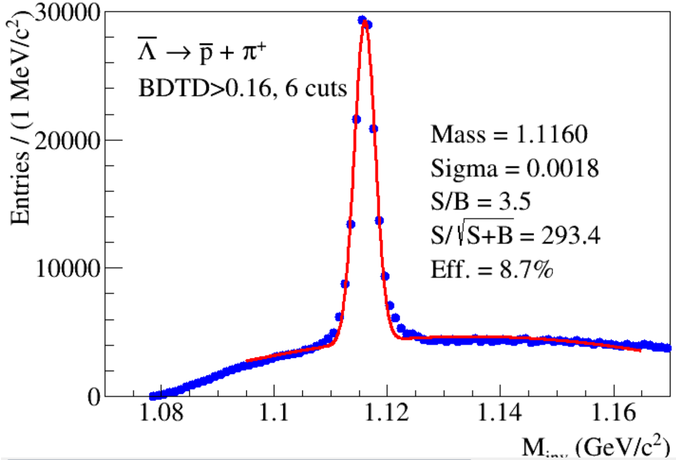
Input Variable

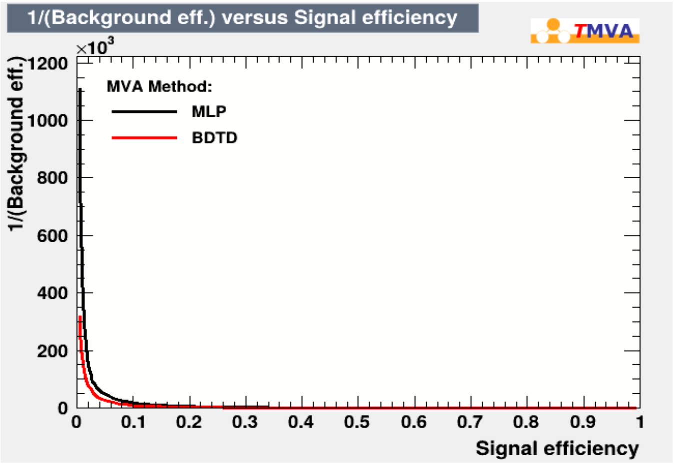


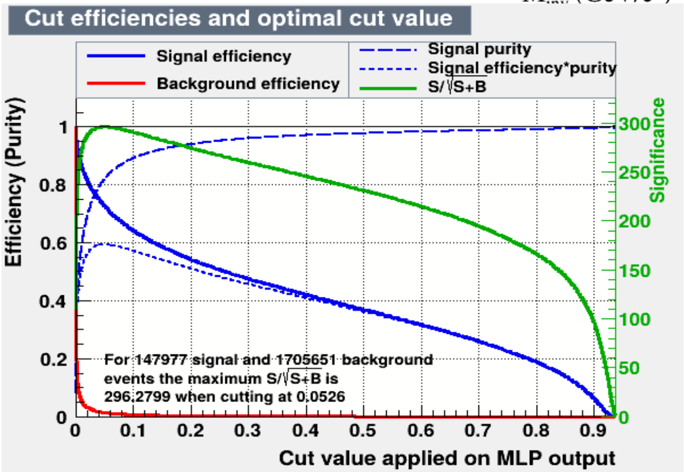
Λ Selection: TC & MLP & BDTD

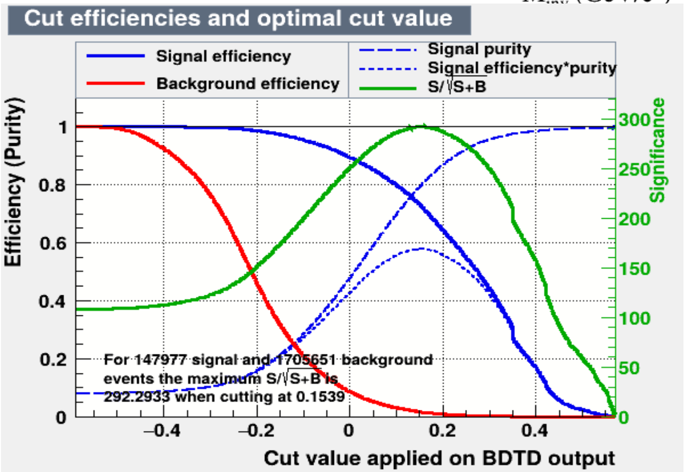




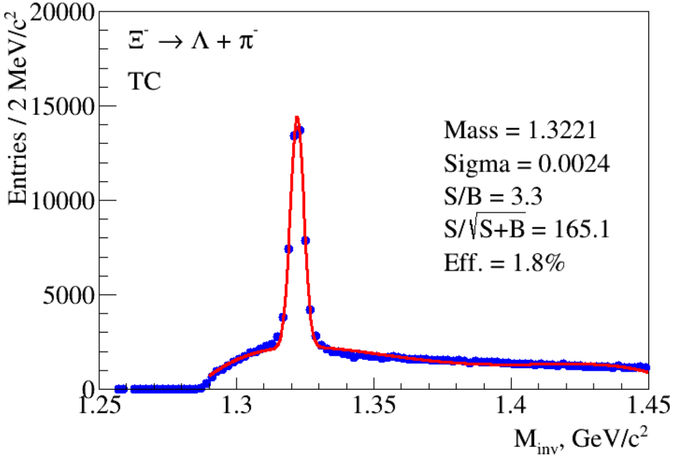


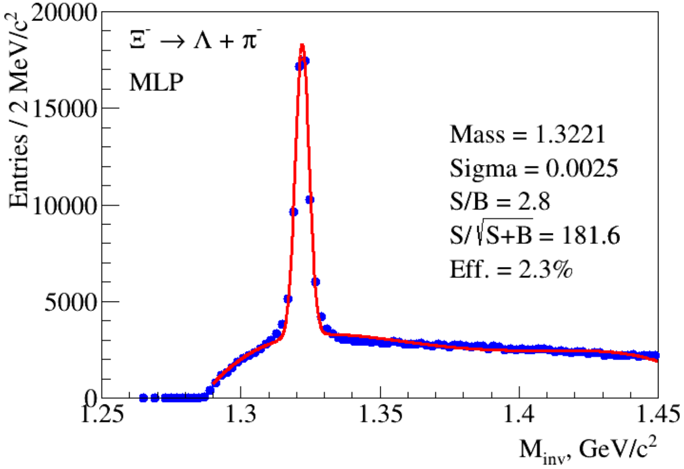


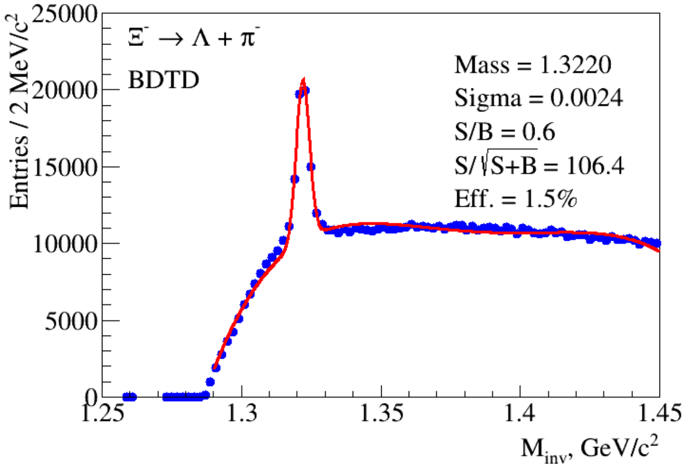


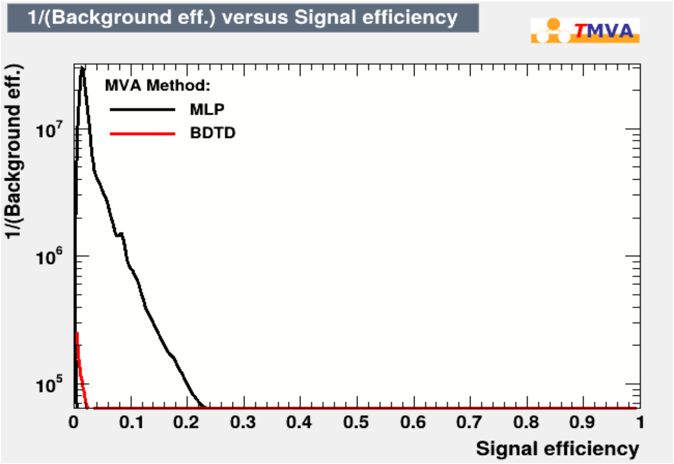


Ξ^- Selection: TC & MLP & BDTD

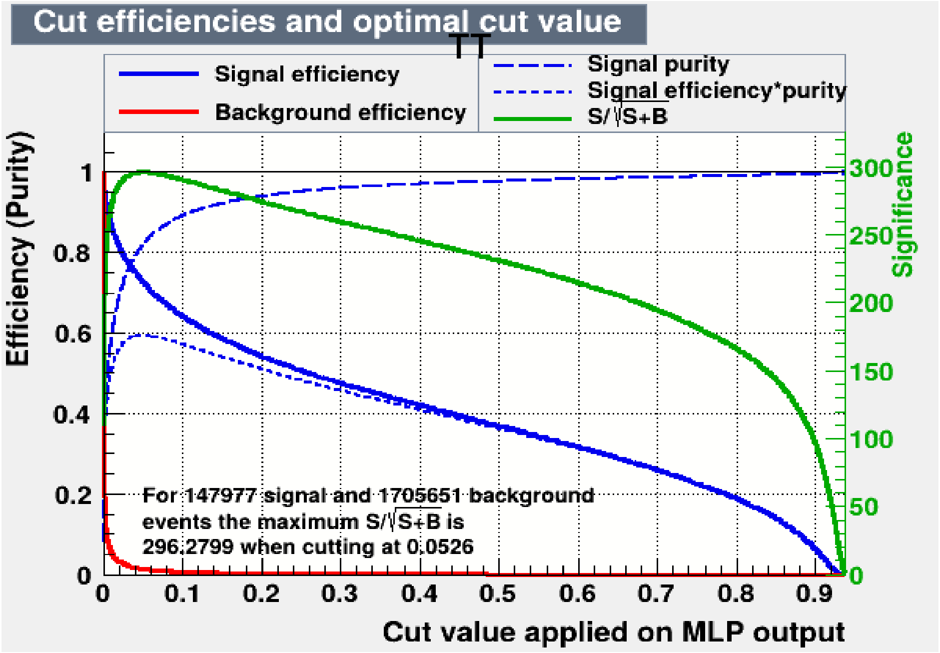


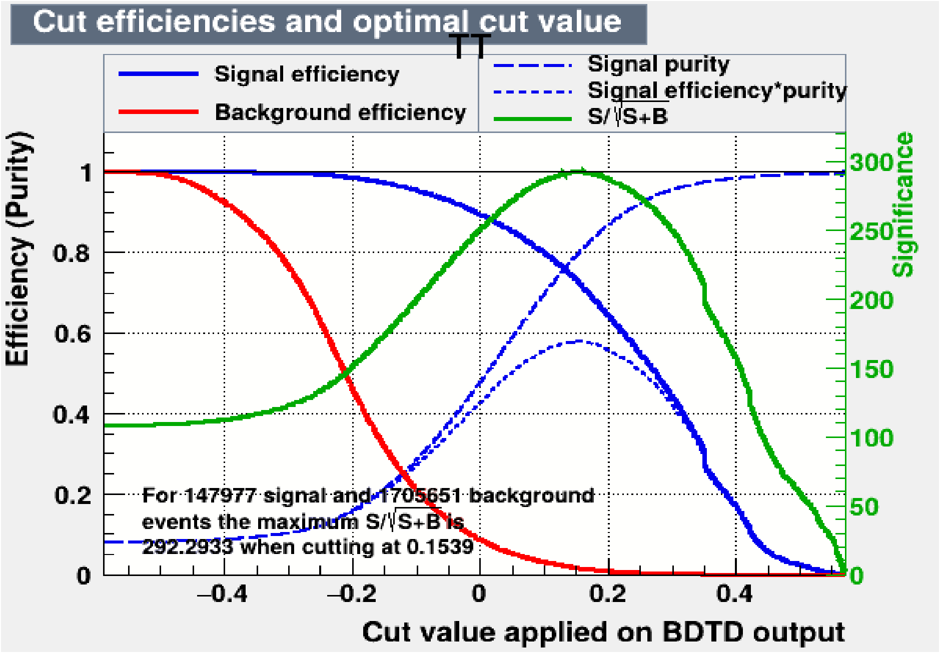






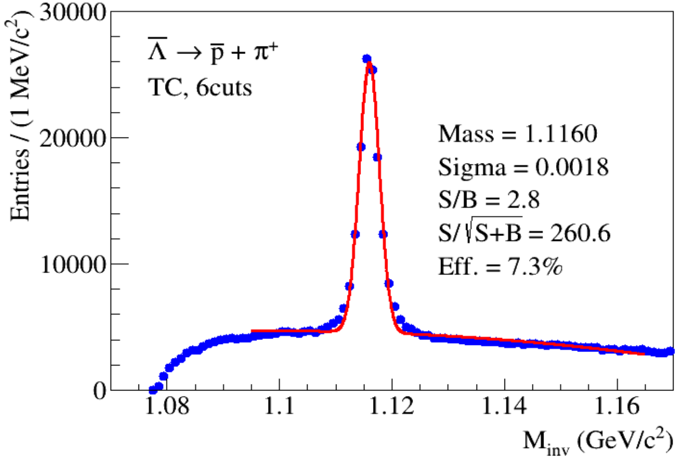
Cut Efficiencies and Optimal Cut Value

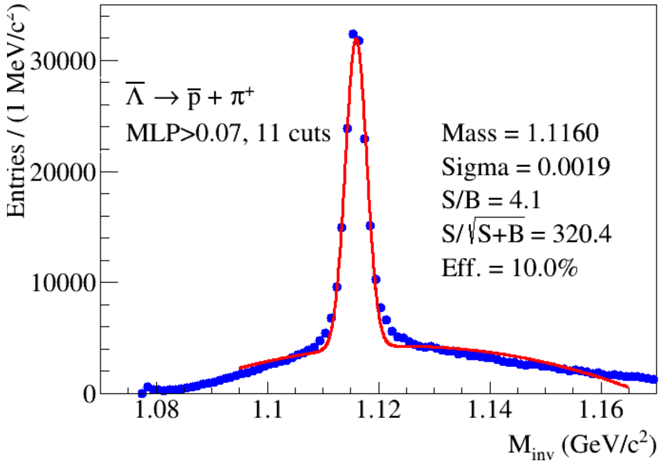


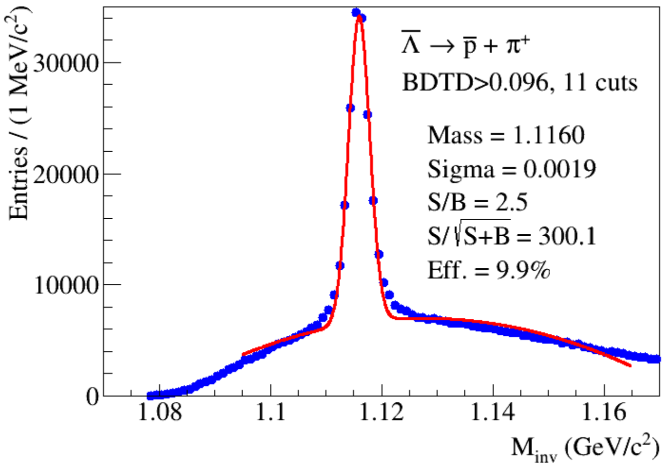


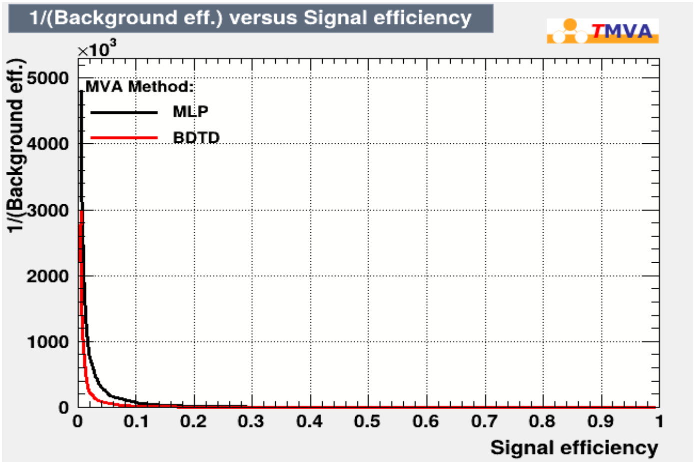
TMVA provides a convenient estimation of signal curves as a functions of the evaluated classifier values.

Λ Selection: TC & MLP & BDTD









- ✓ $X^2_{\pi+}$ > 1.0 – normalized π^+-to-primary vertex impact parameter
- ✓ X^2_{p} > 4.7 – normalized p-to-primary vertex impact parameter
- ✓ X^2_{V0} < 7.5 – X^2 of secondary vertex reconstruction
- ✓ dist $<$ 1.0 – distance of the closest approach
- ✓ Path > 2.4 – lambda decay path
- ✓ angle < 0.09 – lambda momentum and primary-to-secondary vertex vector noncollinearity