



Muon/Pion Identification Based on Machine Learning Algorithm at BESIII

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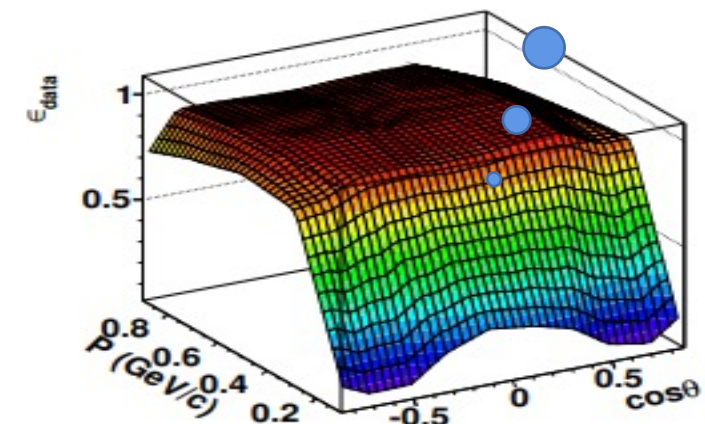
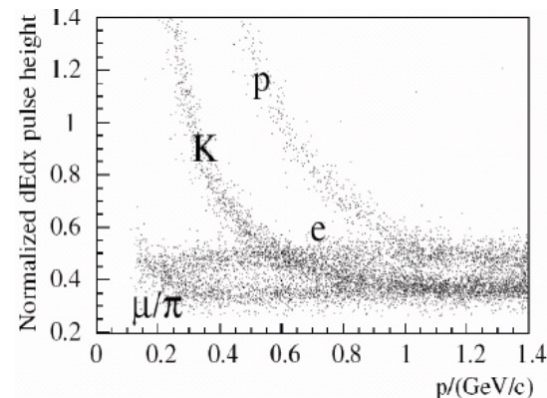
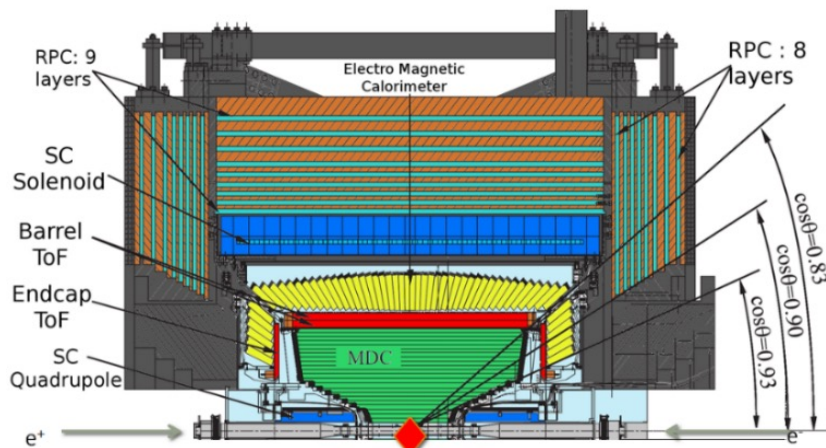
INTRODUCTION



INTRODUCTION

- Particle identification (PID) is one of the most important and commonly used tools for the physics analysis in collider physics experiments.
- For BESIII experiment, traditional methods like the maximum likelihood method are difficult to improve due to the intrinsic correlations between input variables.
 - Especially for very challenging problem: muon/pion separation

Great room for improvement at certain regions



- ❑ The muon discrimination efficiency w.r.t. momentum and $\cos\theta$ by traditional PID software.

INTRODUCTION

- In recent decades, The data-driven machine learning (ML) has provided a powerful toolbox.
 - ML based techniques have been rapidly developed and have shown successful applications in HEP experiments .
 - ML have developed rapidly and achieved outstanding results in the field of particle identification. (Hot topic)
 - One of the obvious advantages of applying ML to PID is its capability of combing many correlated variables to solve the most difficult problems for traditional methods
 - Previous studies show that the gradient boosting decision tree (typically BDT) has superior performance
- Targeting at the muon/pion identification problem at the BESIII experiment, we have developed a new PID algorithm based on the BDT algorithm.
 - Further improving the performance of traditional PID algorithms and exploring its physical potential

METHODOLOGY

METHODOLOGY

★ In order to fully explore the PID performance of the detector. Using advanced BDT (XGBoost) , develop a novel muon/pion PID algorithm. **(Challenging)**

01 Configuration

- Based on a data-driven approach, BDT is used as a key technical approach.
- Selected hyper-parameters:
 - **max_depth**: 8
 - **n_estimators**: 300

02 Systematic errors

- Systematic error :
$$\Delta\varepsilon = \frac{\varepsilon(\text{Data}) - \varepsilon(\text{MC})}{\varepsilon(\text{MC})} \quad (\varepsilon : \text{PID efficiency})$$
- Through detailed cross-validation to evaluate deviations :
 - **Different decay processes**
 - **MC/data**



DATA SAMPLE & FEATURE SELECTION

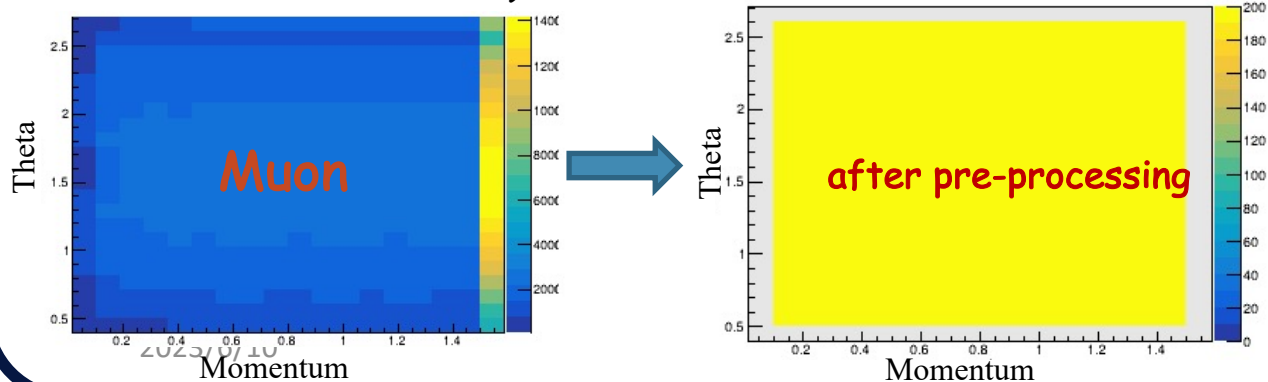
DATA SAMPLE

Based on the substantial amount of high-quality Monte Carlo simulation (MC)/real data samples from BESIII, relying on its mature offline software system (BOSS).

Train sample

- Single muon/pion MC samples
- High purity and well distribution (Pre-processing)

- Make sure the distribution of p and $\cos \theta$ is flattened to avoid bias
- $0.1 \text{ GeV}/c < p < 1.5 \text{ GeV}/c, -0.88 < \cos \theta < 0.88$ (bin numbers :16*20)



Cross-validation sample

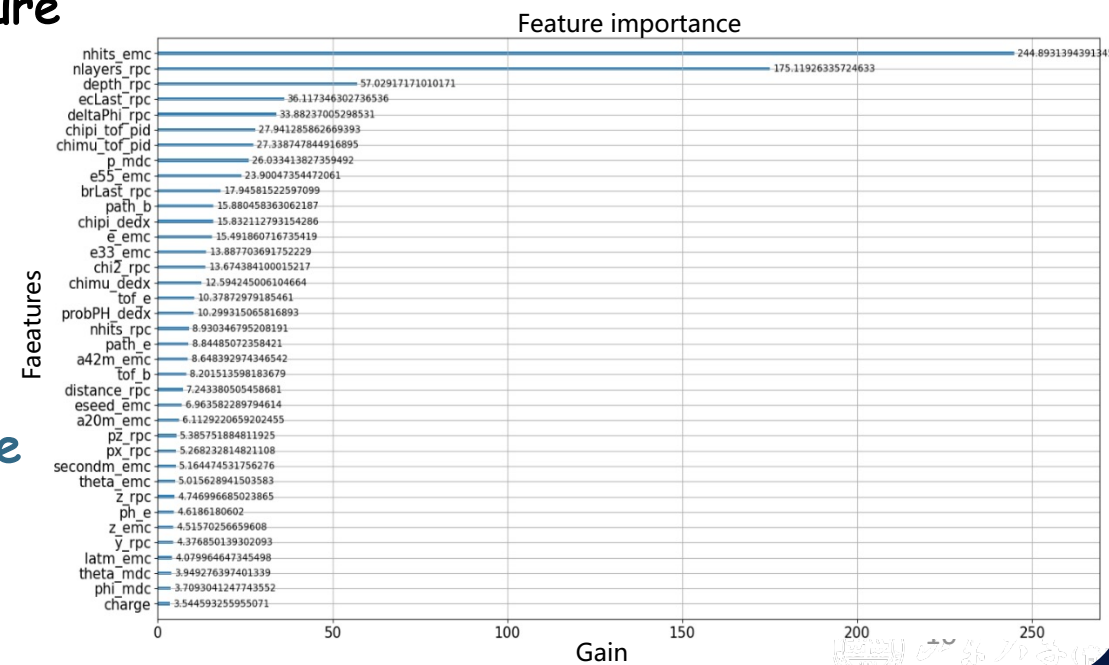
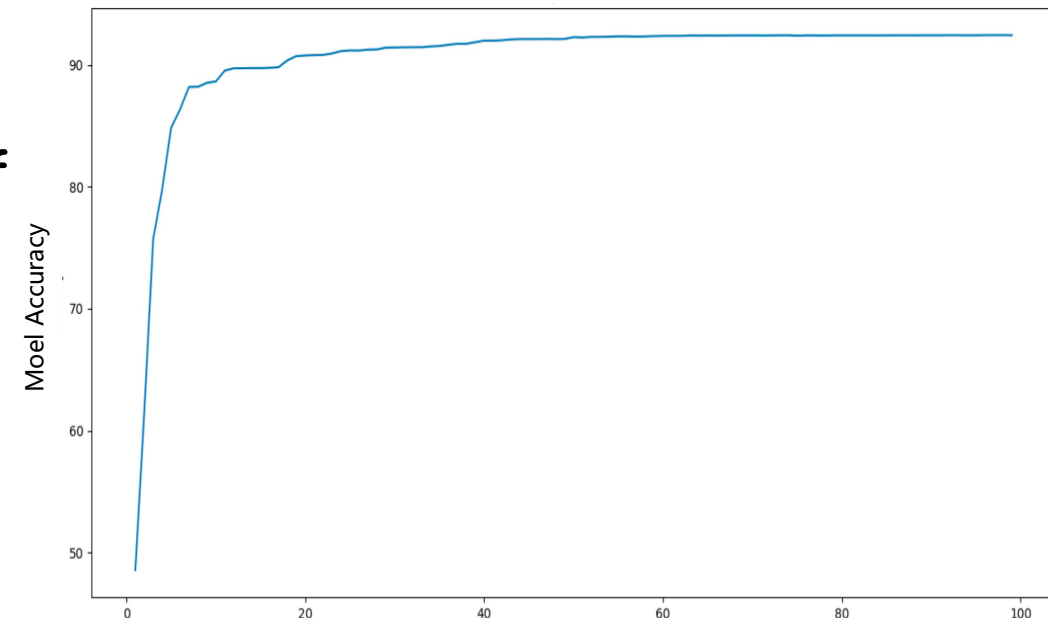


The purity (P) of the μ/π samples : $\frac{N_{\text{sample pure}}}{N_{\text{sample}}}$

- Different decay processes:
 - $\psi (2s) \rightarrow \pi^+ \pi^- J/\psi \rightarrow \pi^+ \pi^- \mu^+ \mu^-$ (P = 99.13%)
 - $J/\psi \rightarrow \pi^+ \pi^- \pi^0 \rightarrow \pi^+ \pi^- \gamma \gamma$ (P = 99.37%)
 - $J/\psi \rightarrow \gamma \mu^+ \mu^-$ (P = 97.97%)
- MC/data:
 - $J/\psi \rightarrow \pi^+ \pi^- \pi^0 \rightarrow \pi^+ \pi^- \gamma \gamma$ (P = 99.37%)
 - $J/\psi \rightarrow \gamma \mu^+ \mu^-$ (P = 97.97%)

FEATURE SELECTION

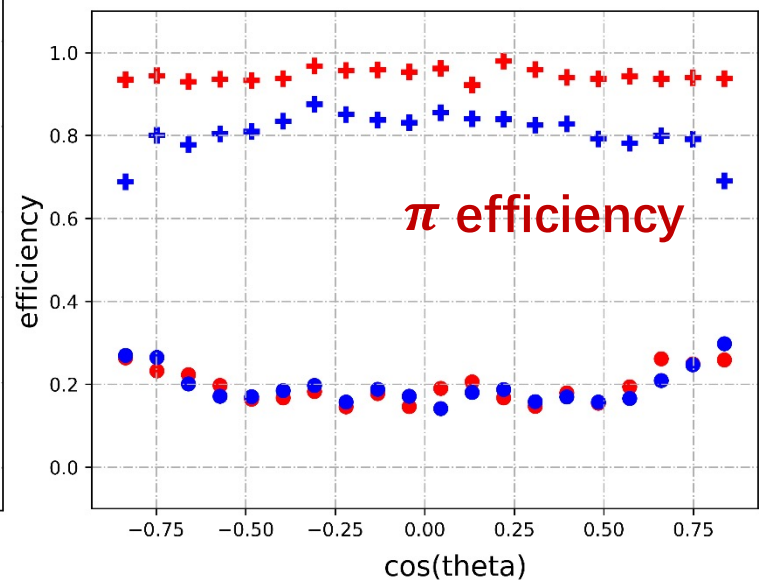
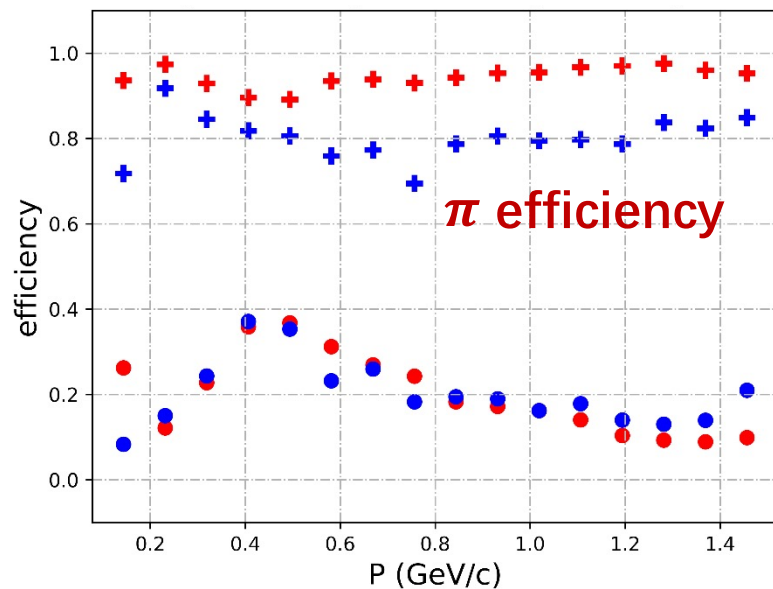
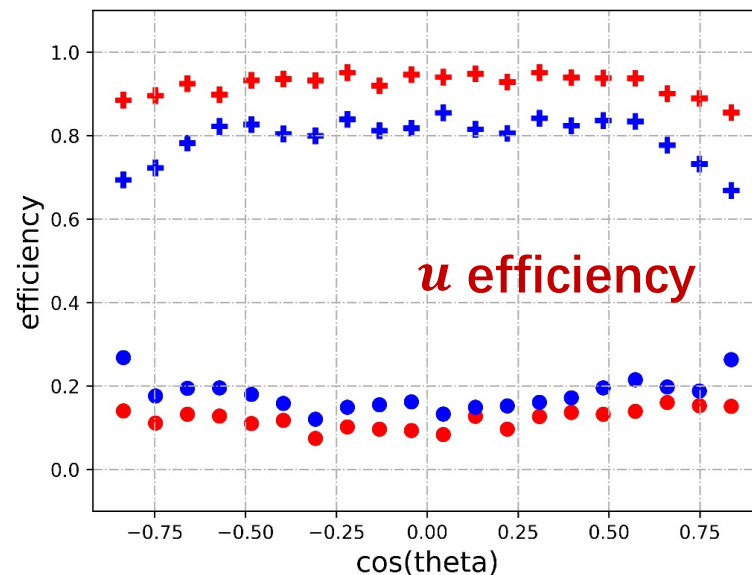
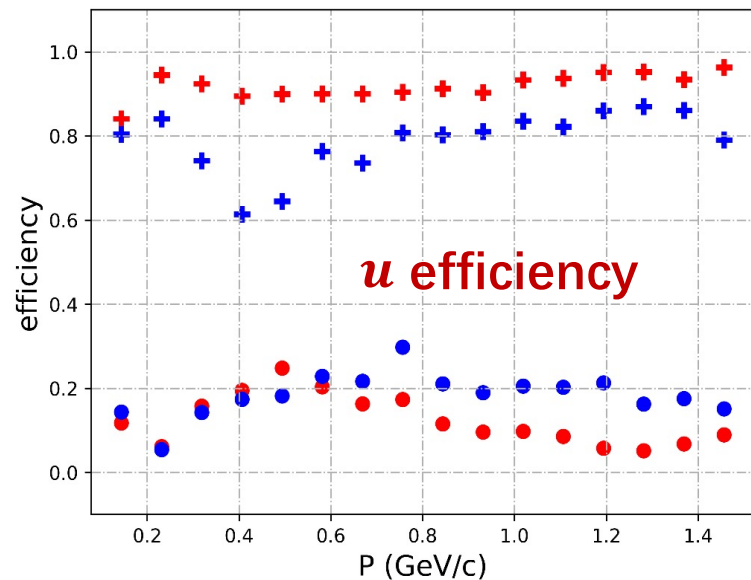
- To extract effective features from a large amount of interrelated sub-detectors information.
- First model trained with all 108 features.
 - Contain MDC, dE/dX, TOF, EMC, MUC information
 - Based on XGBoost (as baseline)
- Features are then selected according to feature importance.
 - Eliminate redundant features to reduce training time
 - Eliminate features that have large MC/Data deviation to suppress systematical error
- Eliminate strongly-correlated features, **37 features are kept**



PERFORMANCE ANALYSIS



Comparison with traditional PID algorithm



Signal efficiency
 + XGboost model + Traditional PID algorithm

Background efficiency
 ● XGboost model ● Traditional PID algorithm



➤ *Signal efficiency :*

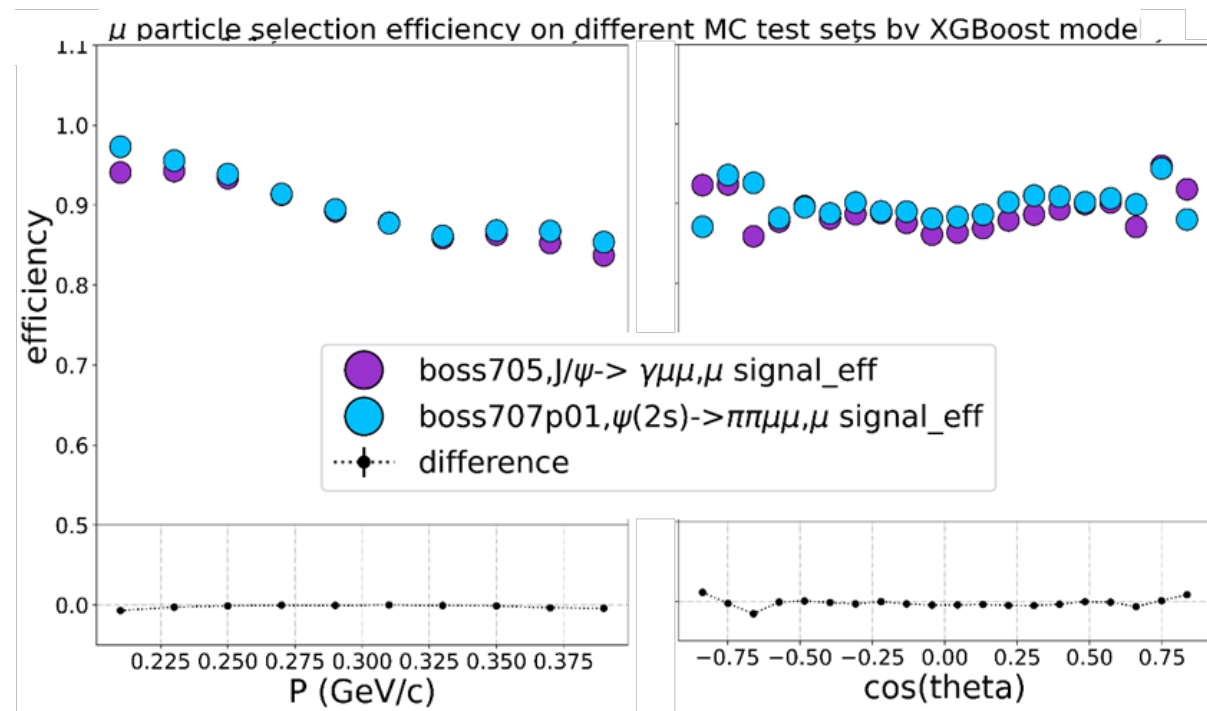
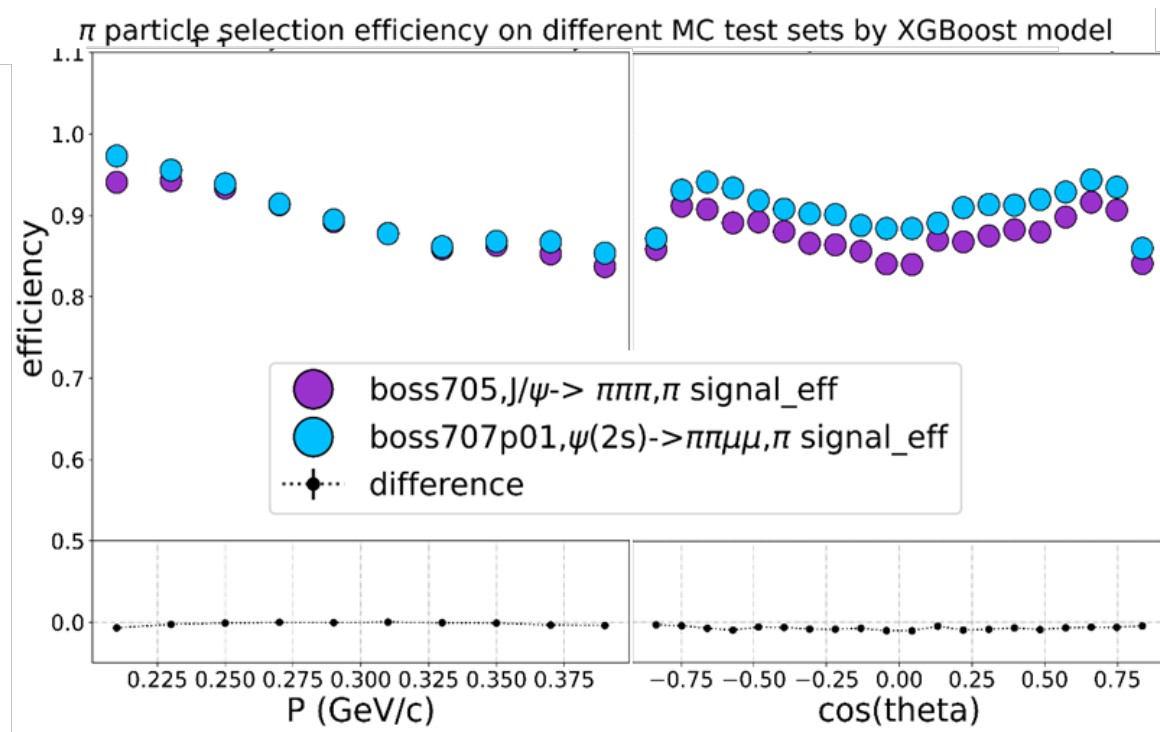
$$\frac{\text{The number of signal selected correctly}}{\text{The total number of signal}}$$

➤ *Background efficiency :*

$$\frac{\text{The number of background misidentified as signal}}{\text{The total number of background}}$$

Cross validation between different decay processes

- To check generalization ability
- To estimate the deviations **different decay channels**



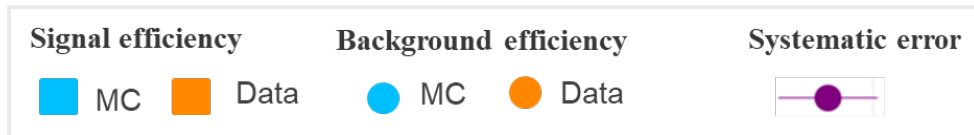
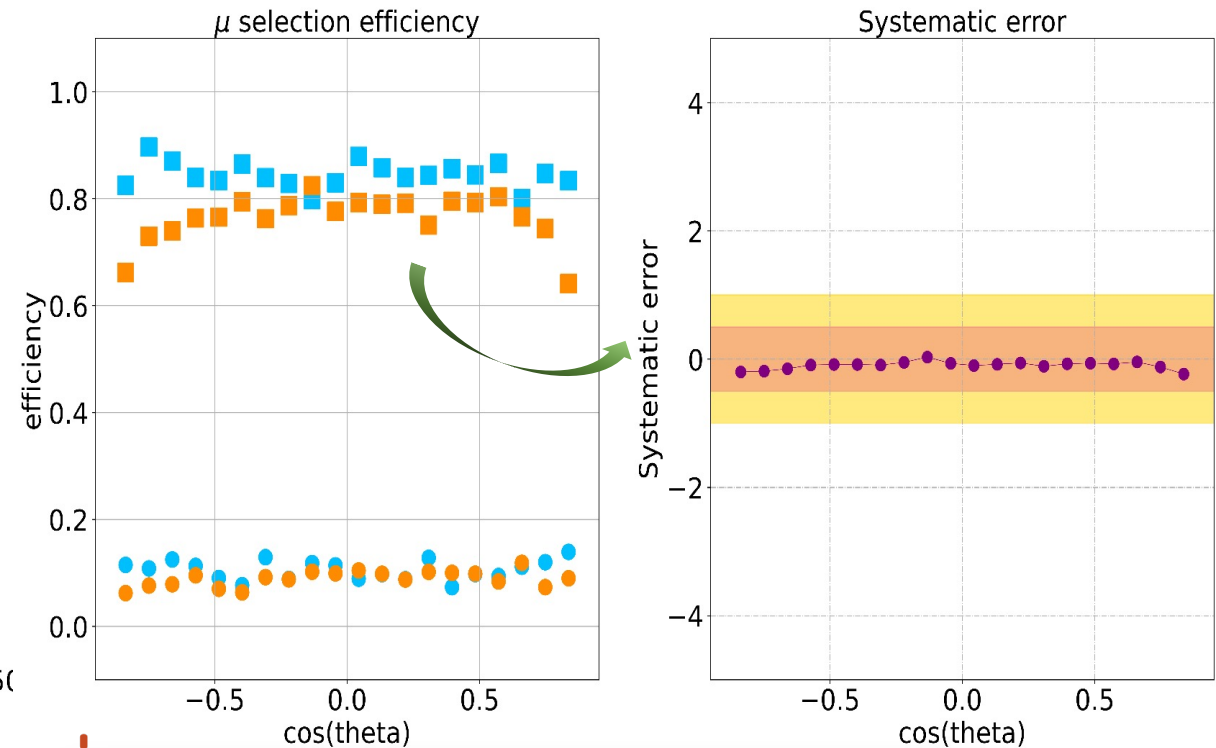
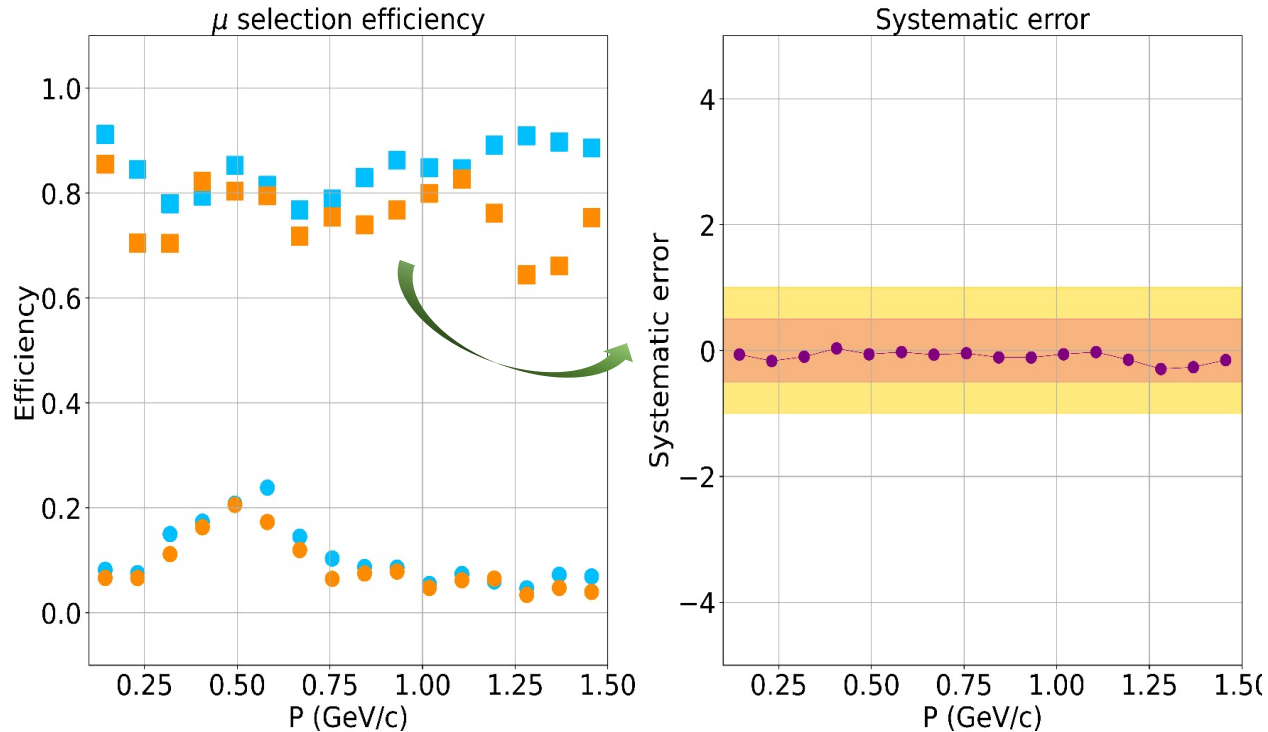
Cross validation between MC and Data

MC/data:

$J/\psi \rightarrow \pi^+\pi^-\pi^0 \rightarrow \pi^+\pi^-\gamma\gamma$ (P = 99.37%)

$J/\psi \rightarrow \gamma \mu^+\mu^-$ (P = 97.97%)

- To estimate **systematical error**



Systematic error :

$$\Delta\varepsilon = \frac{\varepsilon(\text{Data}) - \varepsilon(\text{MC})}{\varepsilon(\text{MC})} \quad (\varepsilon : \text{PID efficiency})$$

BOSS Integration

To make the algorithm available to analyzers, a BOSS package is developed

- For easy-to-use, the package is integrated with BESIII Event Data Model
- Based on C-API of XGBoost, and provided similar interface with PID package
- Pre-trained model is integrated, and made transparent to users

Will make available to public
once validated

```
#include "DeepParticleID/DeepParticleID.h"

StatusCode AnalysisAlg::execute() {
    // .....
    DeepParticleID* Deeppid = new DeepParticleID(XGBoost);
    Deeppid->calculate(*itTrk);
    float prob_mu = Deeppid->prob(0);
    float prob_pi = Deeppid->prob(1);
    if (prob_mu > prob_pi) {
        //.....
    }

    //.....
}
```

GlobalPID Algorithms Based on Machine Learning at STCF

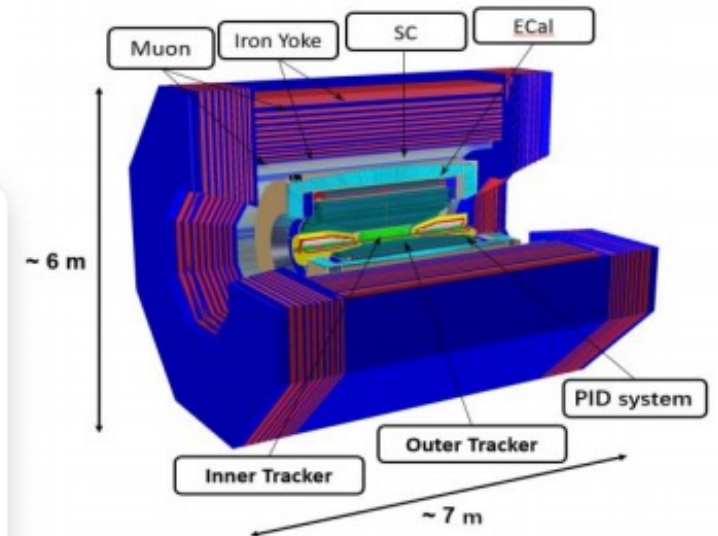
GlobalPID Algorithm

超级陶粲装置 (STCF)

- The Super Tau Charm Facility (STCF), with a luminosity greater than $0.5 \times 10^{35} \text{ cm}^{-2} \text{ s}^{-1}$ and a center-of-mass energy range of 2-7 GeV, is an important option for China's future accelerator-based particle physics large-scale scientific facility.
- The development and research of the **Global Particle Identification (GlobalPID) software algorithm** is crucial for achieving the future physics objectives of the STCF experiment.
 - PID software is an important component of The STCF offline software system (OSCAR).
- Building on the experience gained from particle identification work in the early stages of BESIII, the STCF experiment will utilize advanced ML techniques to innovate and develop the GlobalPID algorithm.
 - By integrating all sub-detector information
 - To fully exploit the PID performance of the detector
 - Needed to facilitate the progress of physics analysis work

Physics Objectives

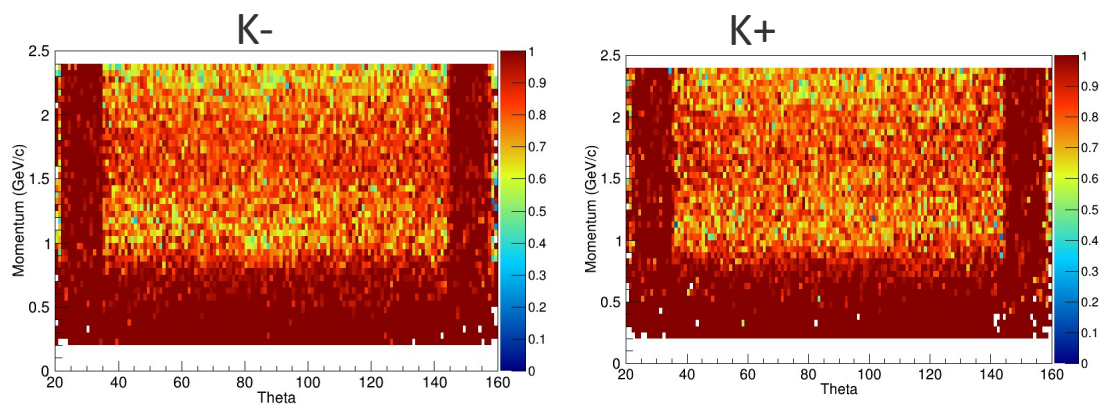
- Searching for new exotic hadronic states
- Studying flavor physics and CP violation physics
- Searching for new physics beyond the standard model at the forefront of high precision



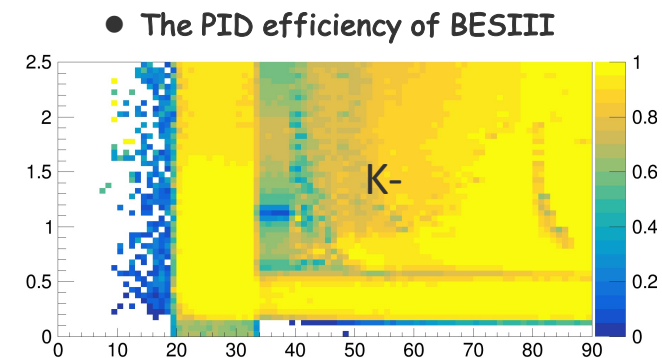
GlobalPID Algorithm

超级陶粲装置 (STCF)

- Based on OSCAR simulation and reconstruction results, [Tracker/dEdx/RICH/DTOF/ECAL/MUD](#) information have been collected. (Full list of variables please see backup slides)
 - 50000 tracks for each type ($e^\pm, \mu^\pm, \pi^\pm, K^\pm, p^\pm$)
 - MC single charged track using ParticleGun
 - $p \in (0.2, 2.4) \text{ GeV}/c, \theta \in (20^\circ, 160^\circ), \text{phi} = 0^\circ$
- ML model (based on XGBoost) is trained and optimized to discriminate (e, μ, π, k, P)
- Preliminary results have been obtained. The model and GlobalPID algorithm have been integrated into OSCAR software and is available for analysis and research.



X-axis: Theta (20, 160, 140bins)
Y-axis: Momentum (0, 2.5, 50bins)
Color gradient :Efficiency (0,1)



performance needs to be further validated !!

SUMMARY



SUMMARY

- ✓ A muon/pion identification algorithm based on machine learning model (XGBoost) is developed based on the high quality data samples at BESIII and has been integrated into the BOSS.
- ✓ Performance analysis shows XGBoost model provides obviously higher discrimination power than traditional methods.
- ✓ Detailed cross-validation was conducted and an evaluation method for the systematic error of the machine learning model was provided, which can be used by BESIII physics analysts.
 - Evaluate deviations between different decay processes
 - Evaluate deviations between MC/data
- ✓ Developed a ML-based GlobalPID algorithm for future STCF experiments.
 - Algorithm framework is established
 - Integrated into OSCAR software
 - Global PID algorithm has preliminary results

THANKS



Backup



● π^\pm selection: $J/\psi \rightarrow \pi^+ \pi^- \pi^0 \rightarrow \pi^+ \pi^- \gamma\gamma$

◆ Good charge Track Selection:

- $|V_z| < 10.0$ cm
- $|R_{xy}| < 1.0$ cm
- $|\cos\theta| < 0.93$
- $N_{\text{good charge}}=2$, total charge=0

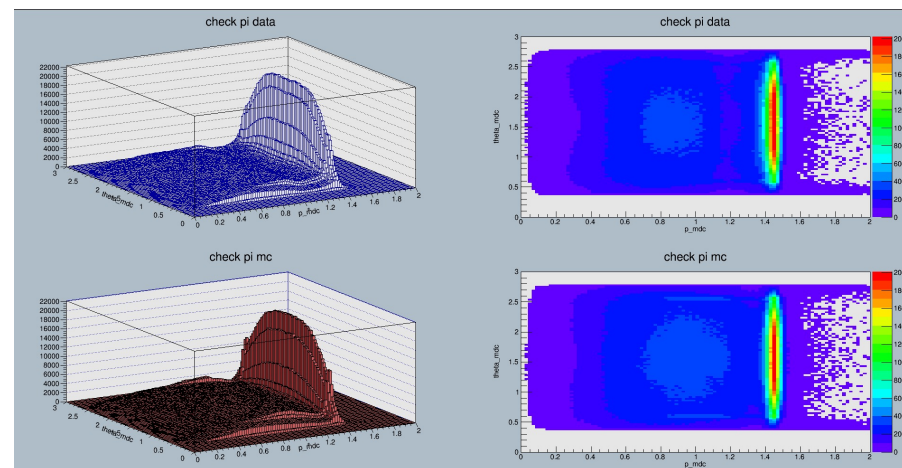
◆ Good photon Selection:

- $E_\gamma > 25\text{MeV}$ for barrel EMC ($|\cos\theta| < 0.8$) or
- $E_\gamma > 50\text{MeV}$ for endcap ($0.86 < |\cos\theta| < 0.92$)
- Time spent in emc: $0 < t < 700\text{ns}$
- $\theta_\gamma, \text{charge} \geq 10$ (degree)
- $N_\gamma = 2$

◆ 4C Kinematic fit:

- $|m_{\gamma\gamma} - 0.135| < 0.015$ GeV
- $\chi^2(\gamma\gamma\pi\pi) < \chi^2(\gamma\gamma KK)$, $\chi^2(\gamma\gamma\pi\pi) < 100$

◆ Only one track is used as PID, which needs to meet $\text{prob}(\pi) > \text{prob}(k)$ 、 $\text{prob}(\pi) > \text{prob}(p)$ and $E/P < 0.8$. And keep another track information.





Backup 2

● μ^\pm selection: $e^+ e^- \rightarrow J/\psi \rightarrow \gamma \mu^+ \mu^-$

◆ Charge track selection:

✓ $N_{\text{charge}}=2$

◆ Good photon selection:

✓ Time spent in emc: $0 < t < 700\text{ns}$

✓ $E_\gamma > 25\text{MeV}$ for barrel EMC ($|\cos\theta| < 0.8$) or

✓ $E_\gamma > 50\text{MeV}$ for endcap ($0.86 < |\cos\theta| < 0.92$)

✓ $N_\gamma > 0$

◆ randomly selected one of the charged traces and compared its momentum with another traces:

✓ If the momentum of the track is within (1.5, 1.8) GeV, further selection cuts include:

• $|V_z| < 10.0\text{ cm}$

• $|R_{xy}| < 1.0\text{ cm}$

• $|\cos\theta| < 0.8$

• The energy deposited in the EMC is within (0.05, 0.27) GeV

• The depth in MUC of the track is greater than 40 cm

• $\text{prob}(\mu) > 0.001 \ \&\& \ \text{prob}(\mu) > \text{prob}(k) \ \&\& \ \text{prob}(\mu) > \text{prob}(e)$

✓ If the momentum of the track is less than 1.5 GeV, further selection cuts include:

• $|V_z| < 10.0\text{ cm}$

• $|R_{xy}| < 1.0\text{ cm}$

• $|\cos\theta| < 0.93$

• Energy deposited in the EMC within (0.03, 0.22) GeV

• $\text{prob}(\mu) > 0.001 \ \&\& \ \text{prob}(\mu) > \text{prob}(k) \ \&\& \ \text{prob}(\mu) > \text{prob}(e)$

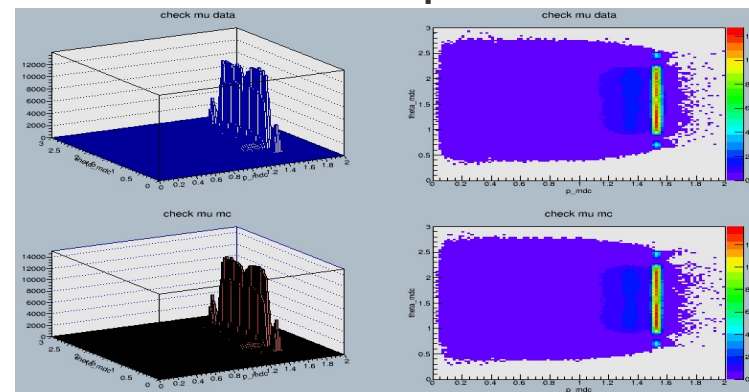
✓ The angle between the photon and the missing momentum is less than 10° .

✓ 4C Kinematic fit:

• The combination with the smallest χ^2 is chosen as the best combination (select good photon)

◆ Saving that track information without any cut conditions

◆ Repeat the three and four steps for the other track in this event





● *37 features*

- **MDC:** 'p_mdc', 'theta_mdc', 'phi_mdc', 'charge'
- **dE/dX:** 'chimu_dedx', 'chipi_dedx', 'probPH_dedx',
- **TOF_B:** 'tof_b', 'path_b'
- **TOF_E:** 'tof_e', 'path_e', 'ph_e'
- **TOF:** 'chimu_tof', 'chipi_tof'
- **EMC:** 'nhits_emc', 'z_emc', 'theta_emc', 'e_emc', 'eseed_emc', 'e33_emc', 'e55_emc', 'secondm_emc', 'latm_emc', 'a20m_emc', 'a42m_emc'
- **MUC:** 'brLast_rpc', 'ecLast_rpc', 'nhits_rpc', 'nlayers_rpc', 'depth_rpc', 'chi2_rpc', 'y_rpc', 'z_rpc', 'px_rpc', 'pz_rpc', 'distance_rpc', 'deltaPhi_rpc'





● $\psi(2s) \rightarrow \pi^+ \pi^- J/\psi \rightarrow \pi^+ \pi^- \mu^+ \mu^-$

➤ Good charge Track Selection:

$|V_z| < 10.0 \text{ cm}$

$|R_{xy}| < 1.0 \text{ cm}$

$|\cos\theta| < 0.93$

charge every good charge track = ± 1

$N_{\text{good charge track}} = 4, \text{ total charge} = 0$

➤ Candidates for π :

✓ The momentum of the charged track is required to less than 1 GeV

➤ Candidates for μ :

✓ The momentum of the charged track is required to greater than 1 GeV

✓ The energy deposited in the EMC of the charged track is less than 0.6 GeV

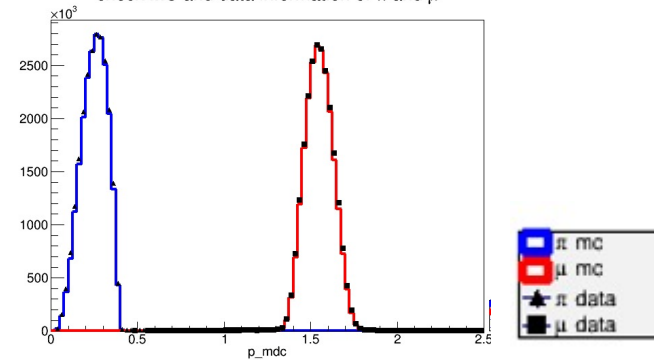
➤ There must be two charged muon candidates, which one is plus and one is minus

➤ There must be two charged pion candidates, which one is plus and one is minus

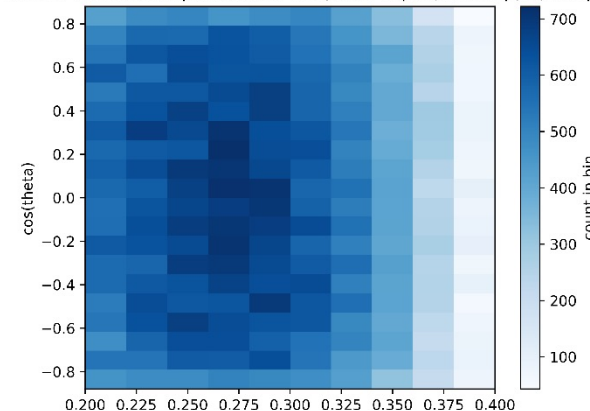
➤ 4C Kinematic fit:

Four momentum constrained kinematic fit is performed and the χ^2 is less than 200.

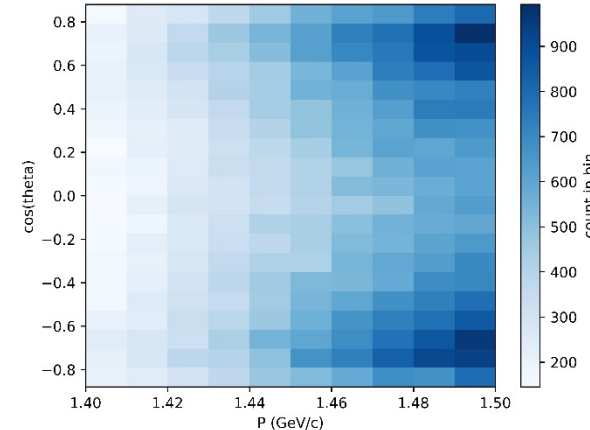
check MC and data information of π and μ



The number of π mc samples in each bin (boss707p01, π from $\psi(2s) \rightarrow \pi\pi\mu\mu$)



The number of μ mc samples in each bin (boss707p01, μ from $\psi(2s) \rightarrow \pi\pi\mu\mu$)





| 名称 | 特征量信息 | 说明 | 名称 | 特征量信息 | 说明 |
|-----------------------|---|---|-----------------|--|--|
| ReconstructinParticle | 'charge' 'mom_x' 'mom_y' 'mom_z' | 重建粒子的电荷 粒子在xyz方向上的动量 | MUDTrack | 'theta' 'phi' 'hitNum' 'RPCHitNum' 'PSHitNum' 'maxHit' 'maxHitLayer' | 在极方向上的夹角 在xy平面上的夹角 在u子探测器里的击中数 在电阻板室 (RPC) 中的击中 在塑料闪烁体探测器上的击中 有最大击中数所在层的击中数 有最多击中数目的层数 |
| RecRICHLikelihood | 'likelihood_e' 'likelihood_mu' 'likelihood_k' 'likelihood_pi' 'likelihood_p' | 该粒子假设为电子的可能性 该粒子假设为muon的可能性 该粒子假设为kaon的可能性 该粒子假设为kaon的可能性 该粒子假设为proton的可能性 | DTOFpid(未来增加使用) | 'logL_e' 'logL_mu' 'logL_pi' 'logL_k' 'logL_p' | 粒子分别在五种粒子假设下的可能性 |
| TrackerRecTrack | 'helixPar_d0' 'helixPar_phi' 'helixPar_cpa' 'helixPar_z0' 'helixPar_tanl' | 螺旋线五参数: 螺旋线上在x-y平面内与参考点的距离最小的一个点 (p0) 与参考点的距离 x-y平面上圆心与参考点的连线方位角 径迹横动量倒数, 符号与带电径迹的电荷符号相同 x-y平面上螺旋线上到参考点最近的点的z坐标(p0的z坐标) 螺旋线倾斜度 (pz/pt) | | | |
| DEDX | 'dEdXsepE/MU/PI/K/P' | 基于五种粒子假设下的chi2值 | | | |
| RecECALShower | 'numHits' 'energy' 'eSeed' 'e3x3' 'e5x5' 'position_x' 'position_y' 'position_z' 'secondMoment' 'LateralMoment' 'ZernikeMoment{2,0}' 'ZernikeMoment{4,2}' | 在ECAL里的击中数目 重建粒子的能量 种子的能量 3*3晶体内的能量沉积 5*5晶体内的能量沉积 Shower的x坐标 Shower的y坐标 Shower的z坐标 二阶矩阵 横向矩阵 Zernike2*0矩阵 Zernike4*2矩阵 | | | |

