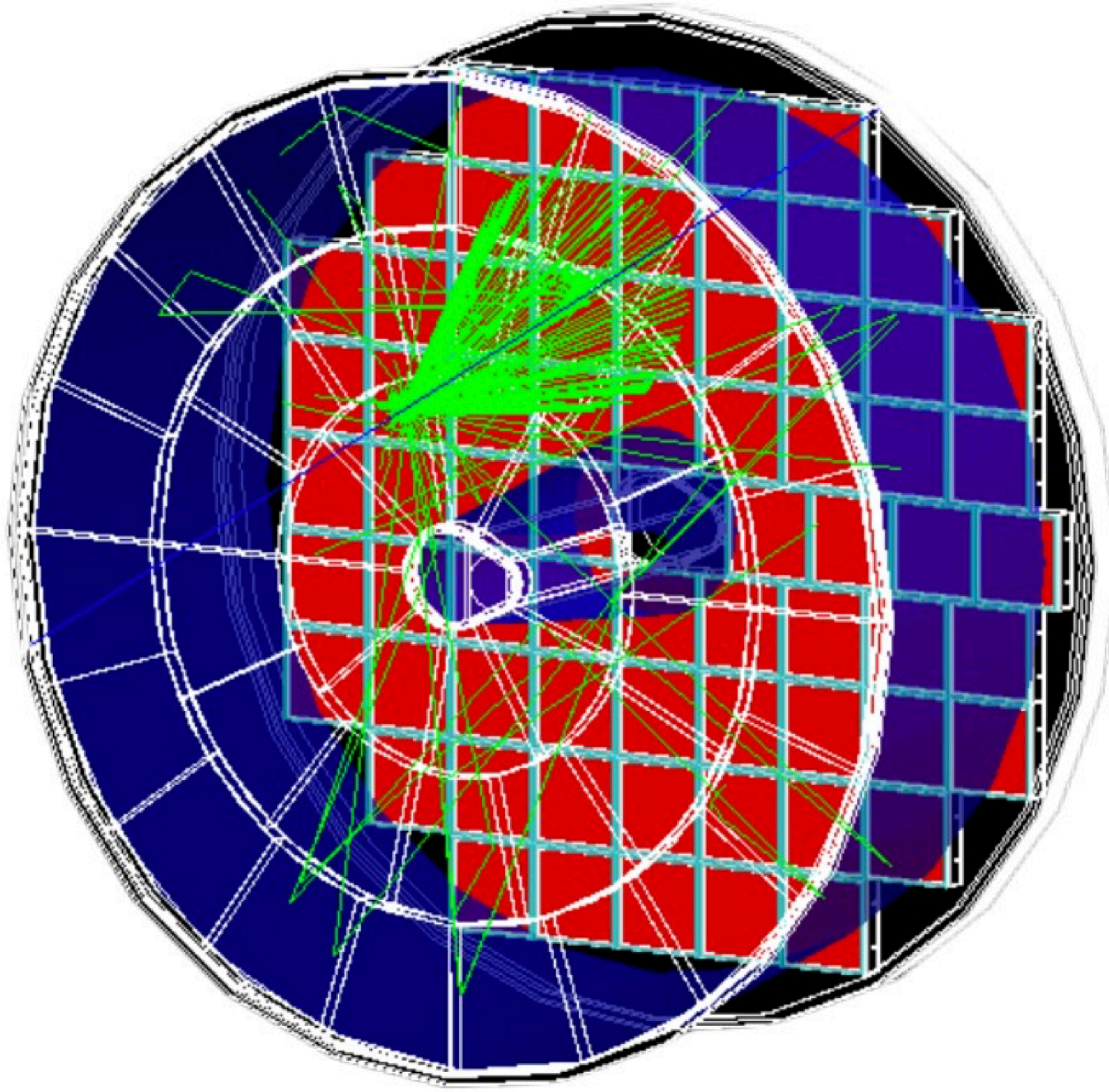
Enhancing PID separation at ePIC using machine learning



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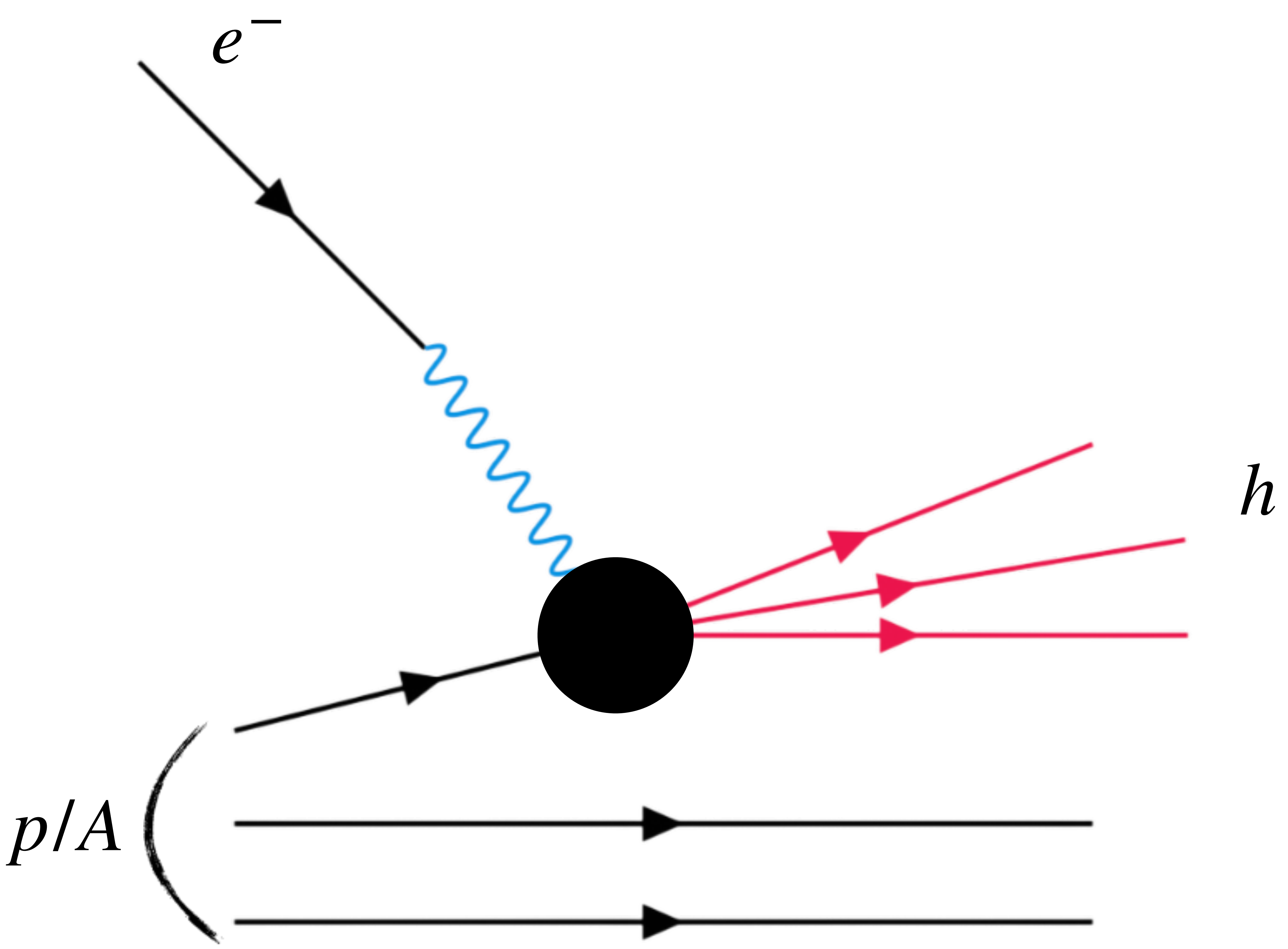
The ePIC Detector at the EIC

pfRICH subsystem in backward region

- **A compact central detector** with several subsystems
- **Hermetic coverage**: $-3.5 < \eta < 3.5$ (tracking, calorimetry, **particle identification**)

Physics Motivations at the EIC



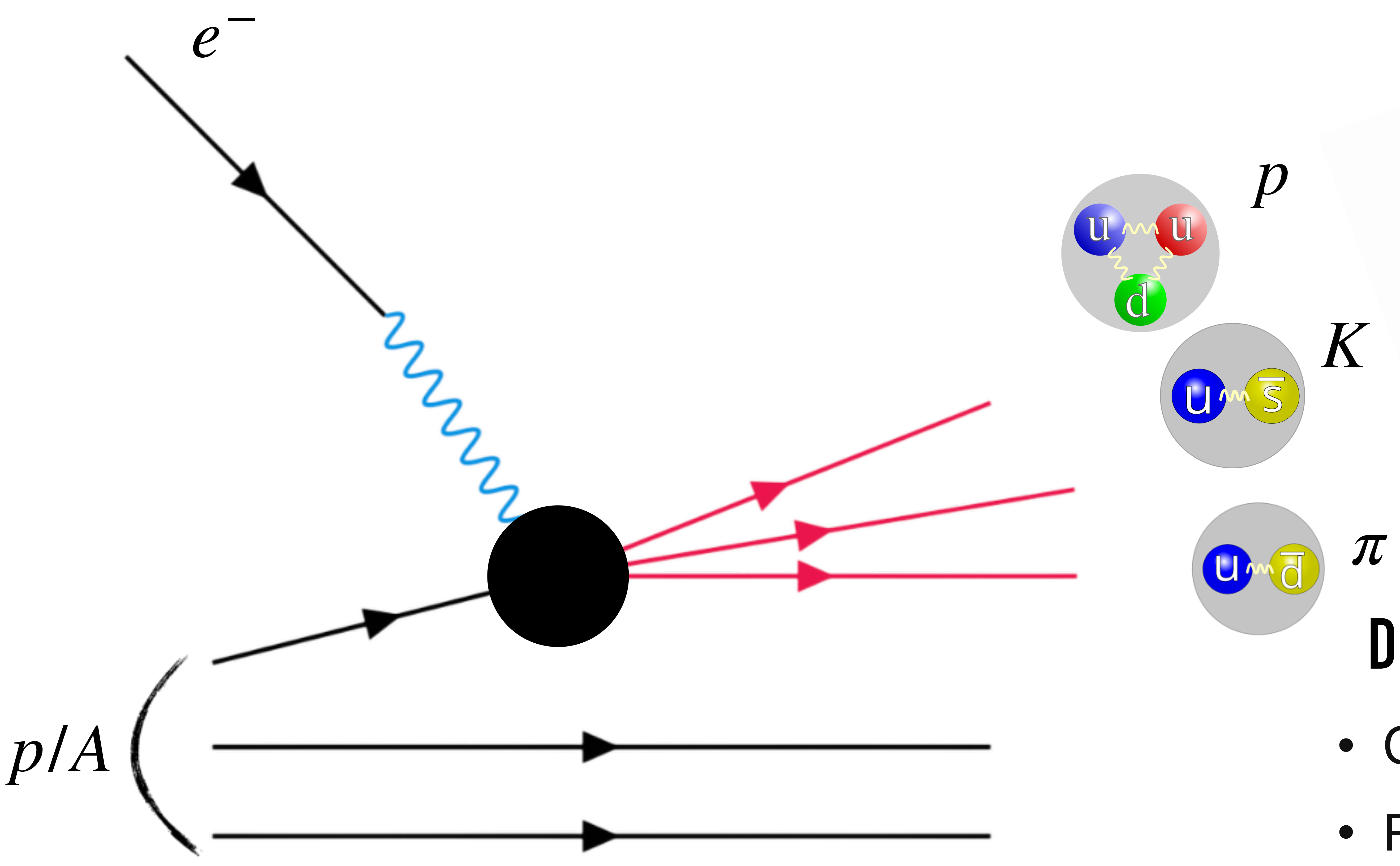
- **Semi-Inclusive Deep Inelastic Scattering**
- Production of hadrons in final-state
- Provide information on:

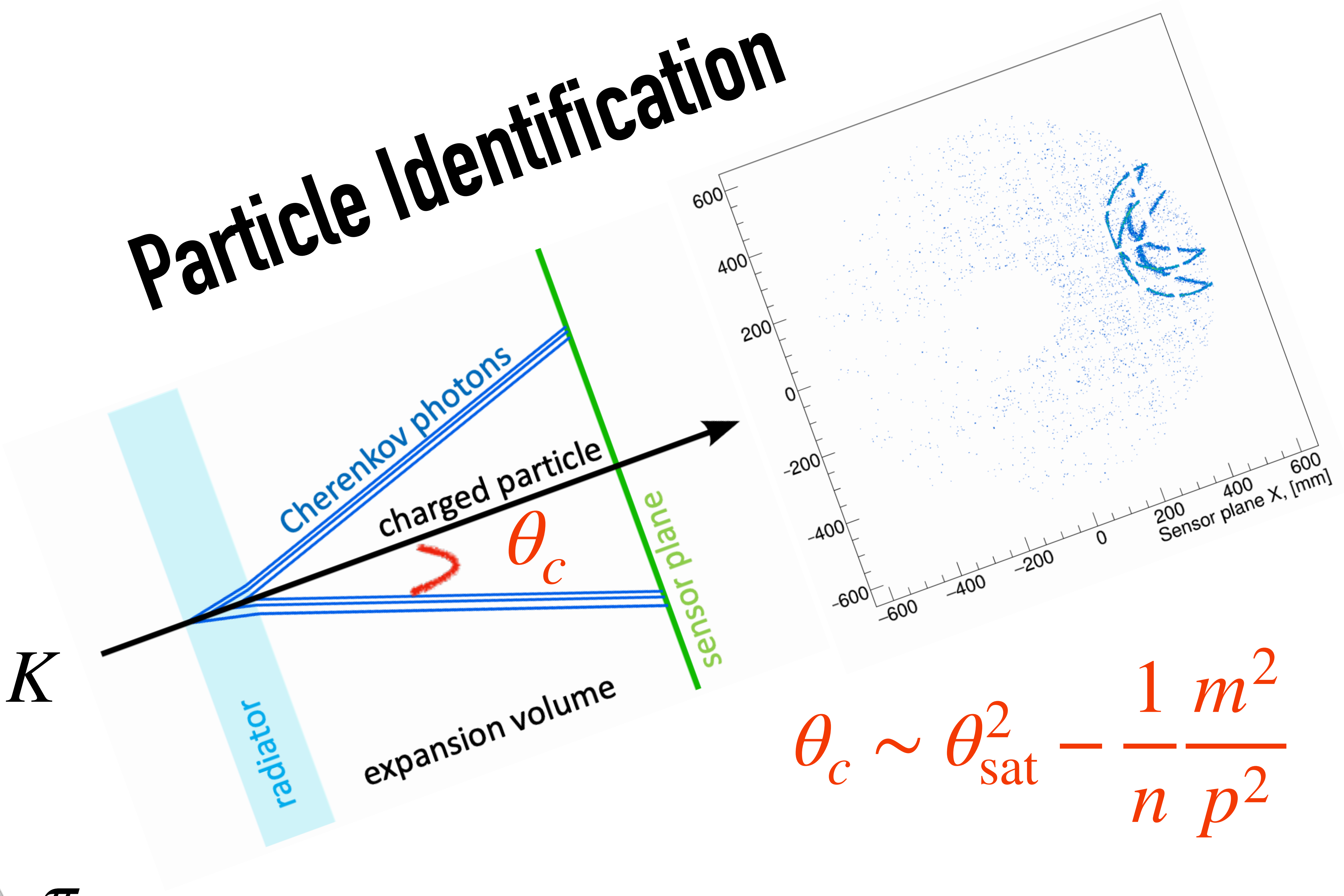
→ the ***fragmentation process (hadronization)***

→ the ***hadronic structure***

Particle Identification detectors are crucial

The pfRICH Concept





$$\theta_c \sim \theta_{\text{sat}}^2 - \frac{1}{n}\frac{m^2}{p^2}$$

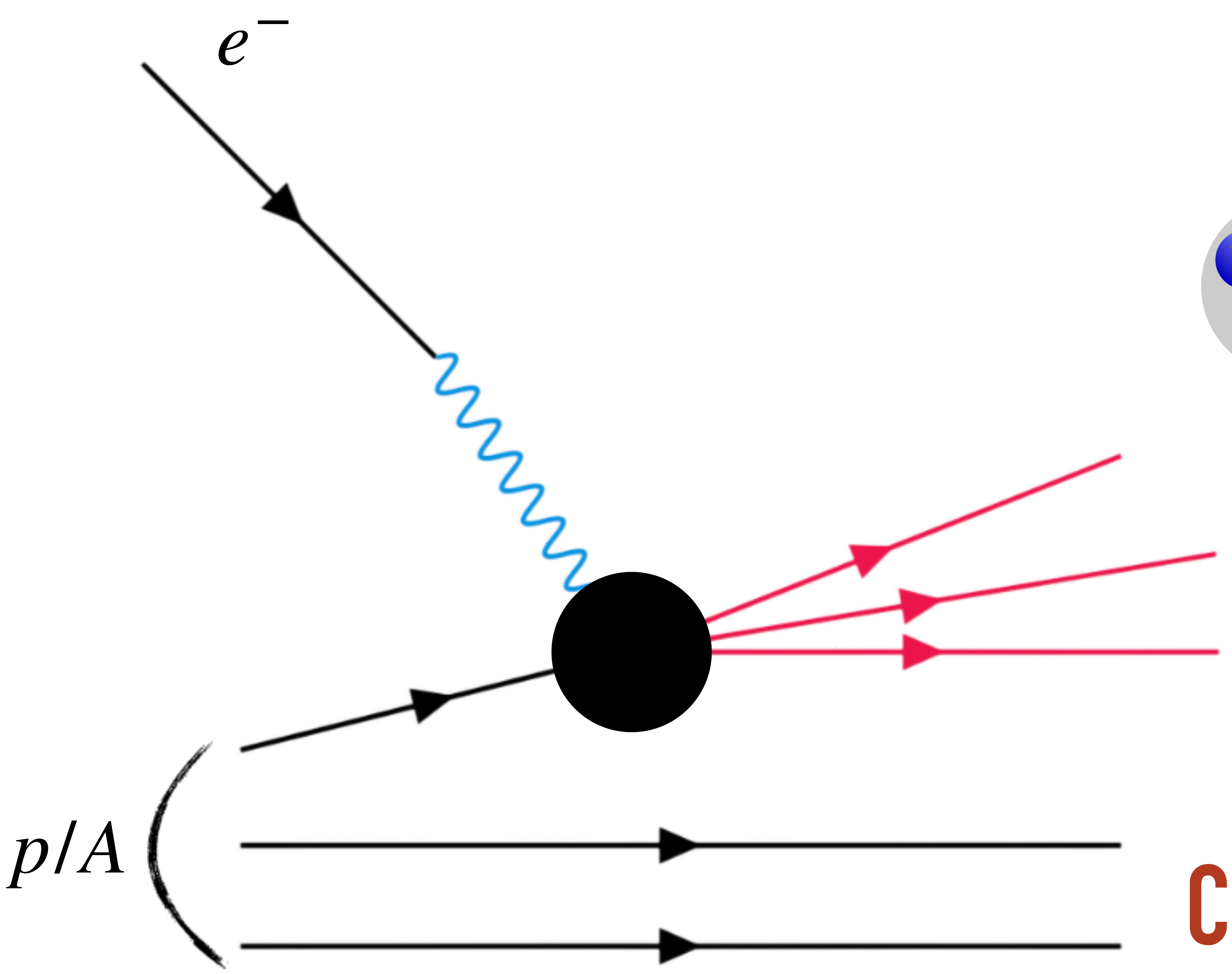
The pfRICH will provide > 3σ π/K separations for momentum up to 7 GeV/c for –3.5 < η < -1.5

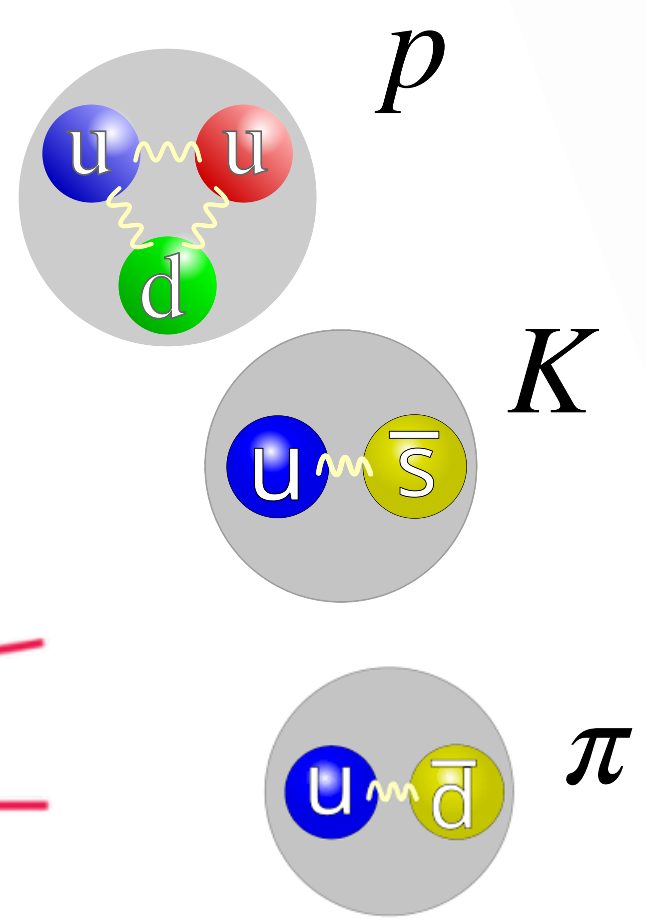
Detection Principle

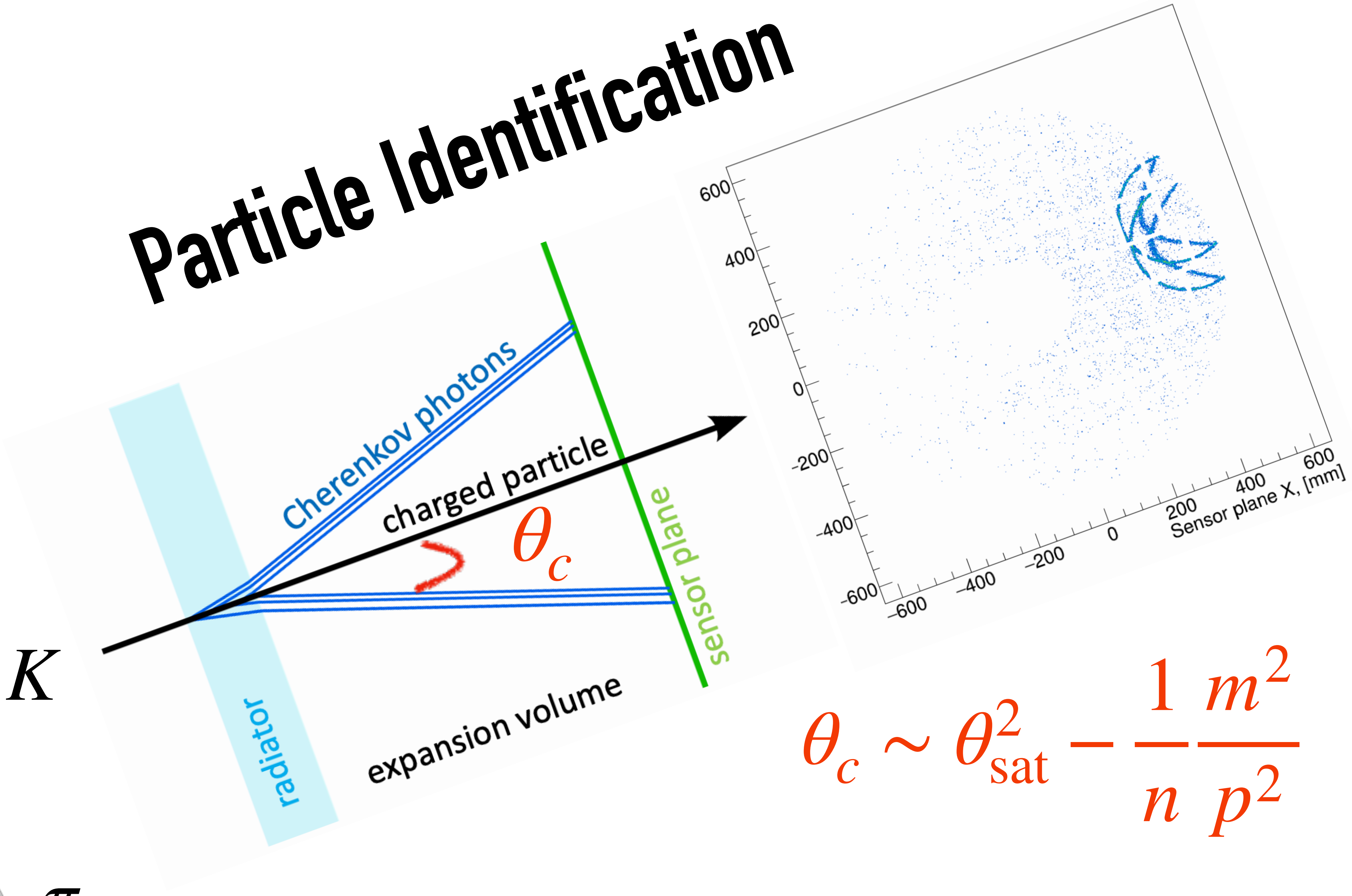
- Charged particle → emits Cherenkov photons at angle θ_c
- Photons project onto photodetectors → form a **ring**

  → **Ring radius** $\propto \tan\theta_c$
- Measuring ring size → deduce θ_c → **particle mass**

The pfRICH Concept



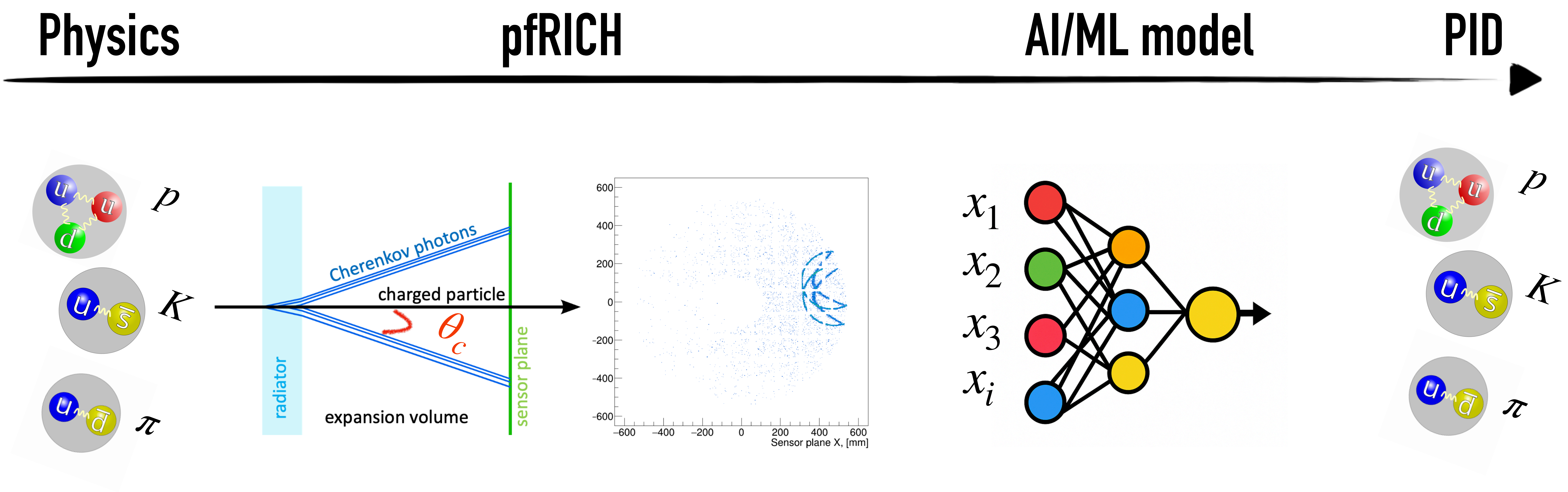




$$\theta_c \sim \theta_{\mathrm{sat}}^2 - \frac{1}{n}\frac{m^2}{p^2}$$

Can we use machine learning to improve particle identification?

The Approach

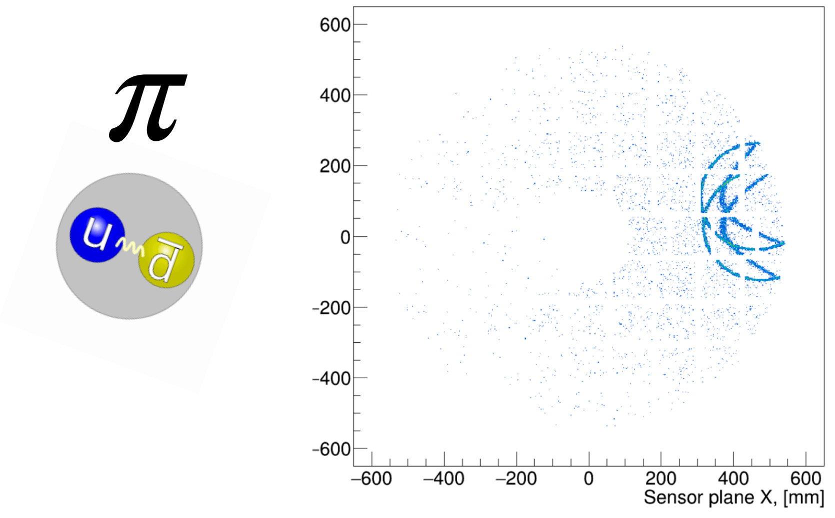


Can we use machine learning to improve particle identification?: Yes!

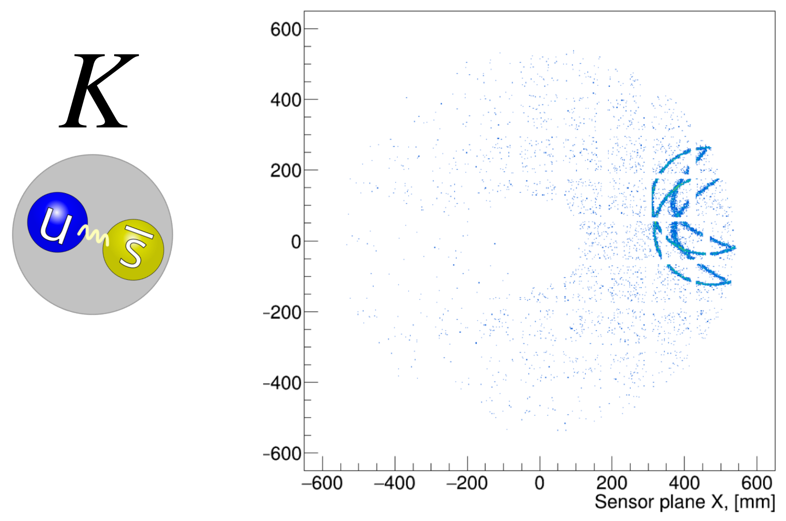
An ideal use case for AI/ML, since the signal is well defined and fully understood

Model Training

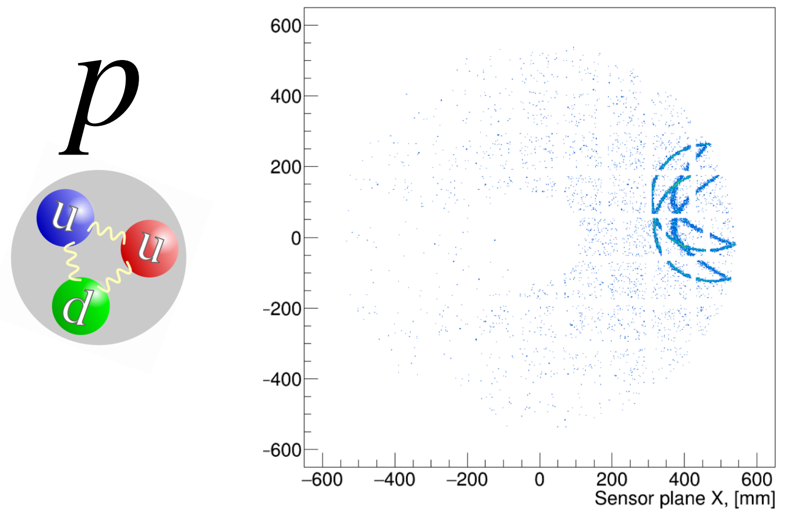
π



K

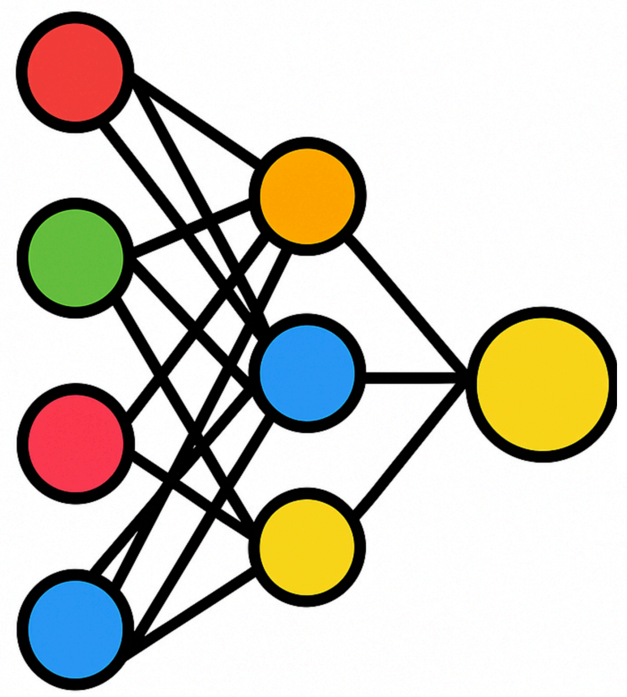


p



Training

x_1
x_2
x_3
x_i



AI/ML model

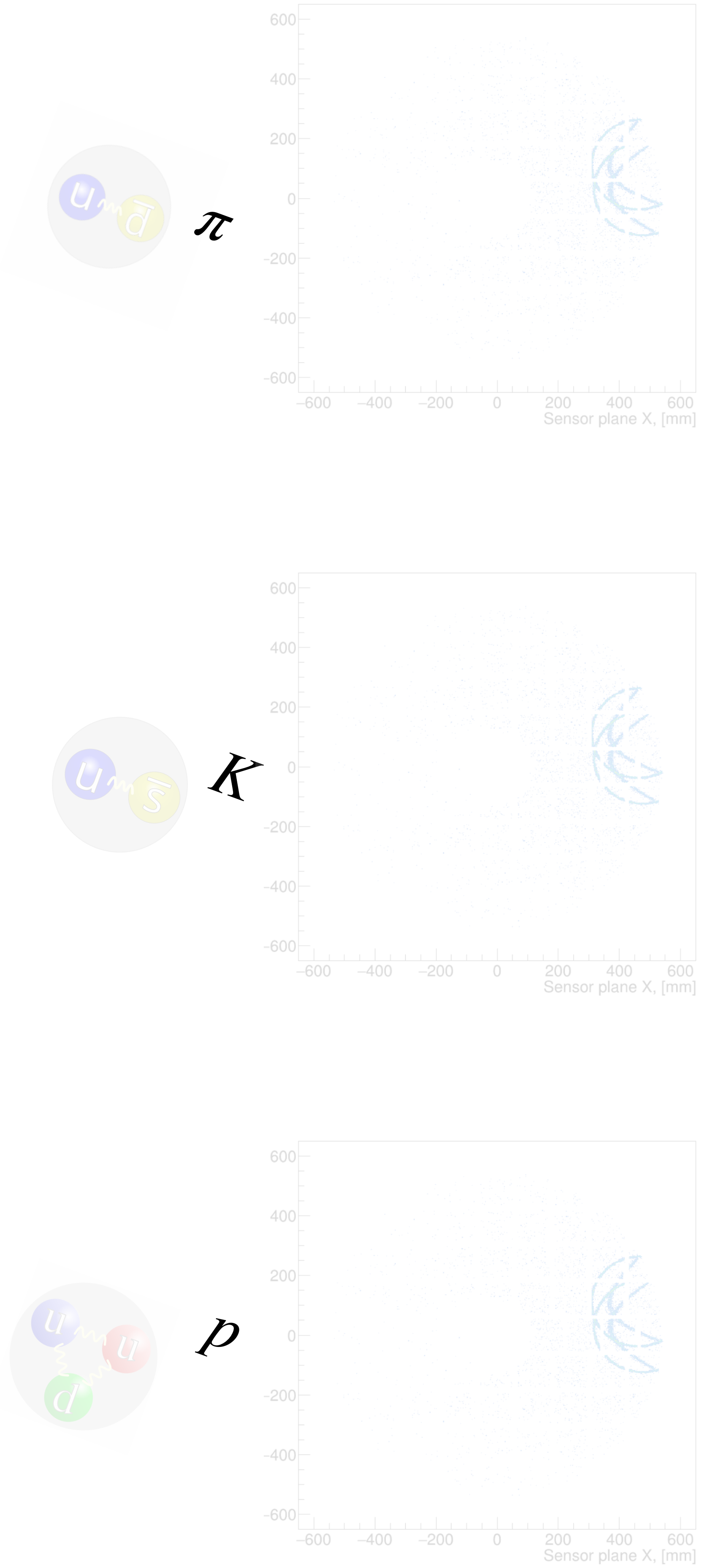
$$f\left(\sum_i w_i x_i + b\right)$$

- Pattern Recognition
- XGBoost - Gradient-boosted

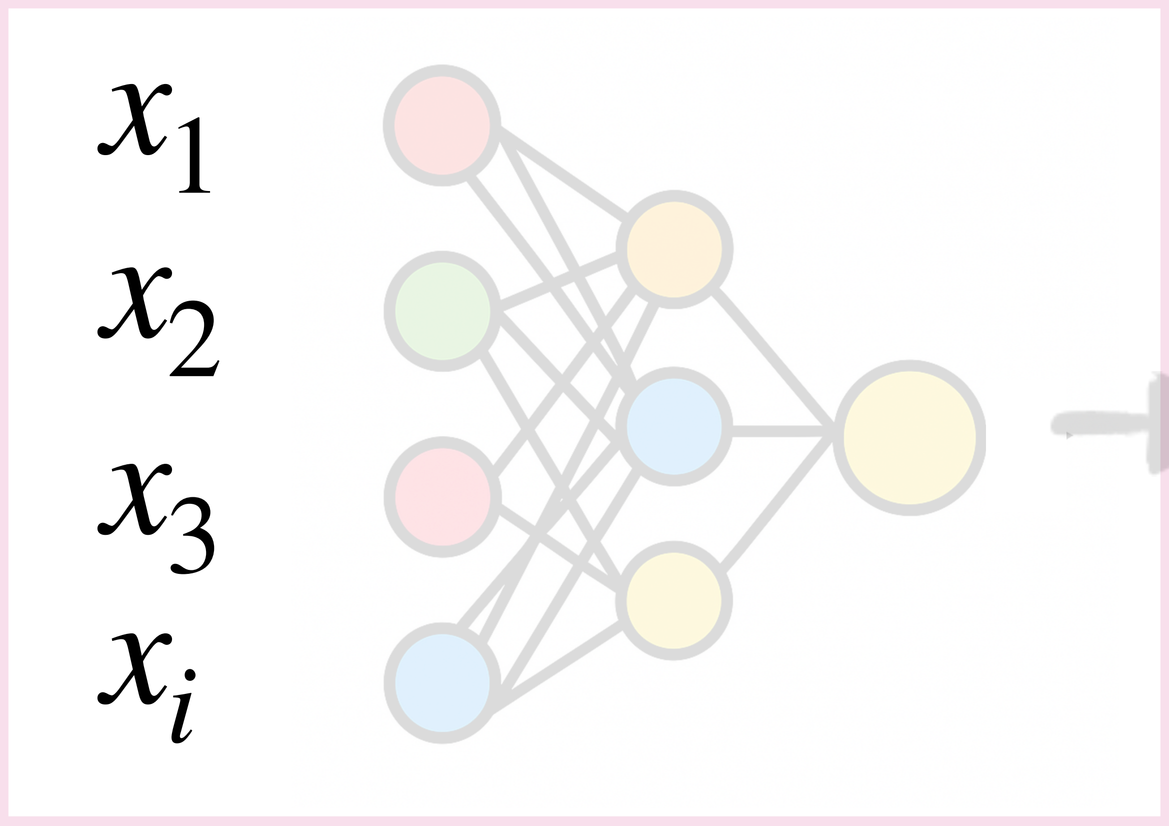
Standalone ePIC pfRICH GEANT4:

- Timing, hits position, momentum …
- More (good) data → better training

Model Inference



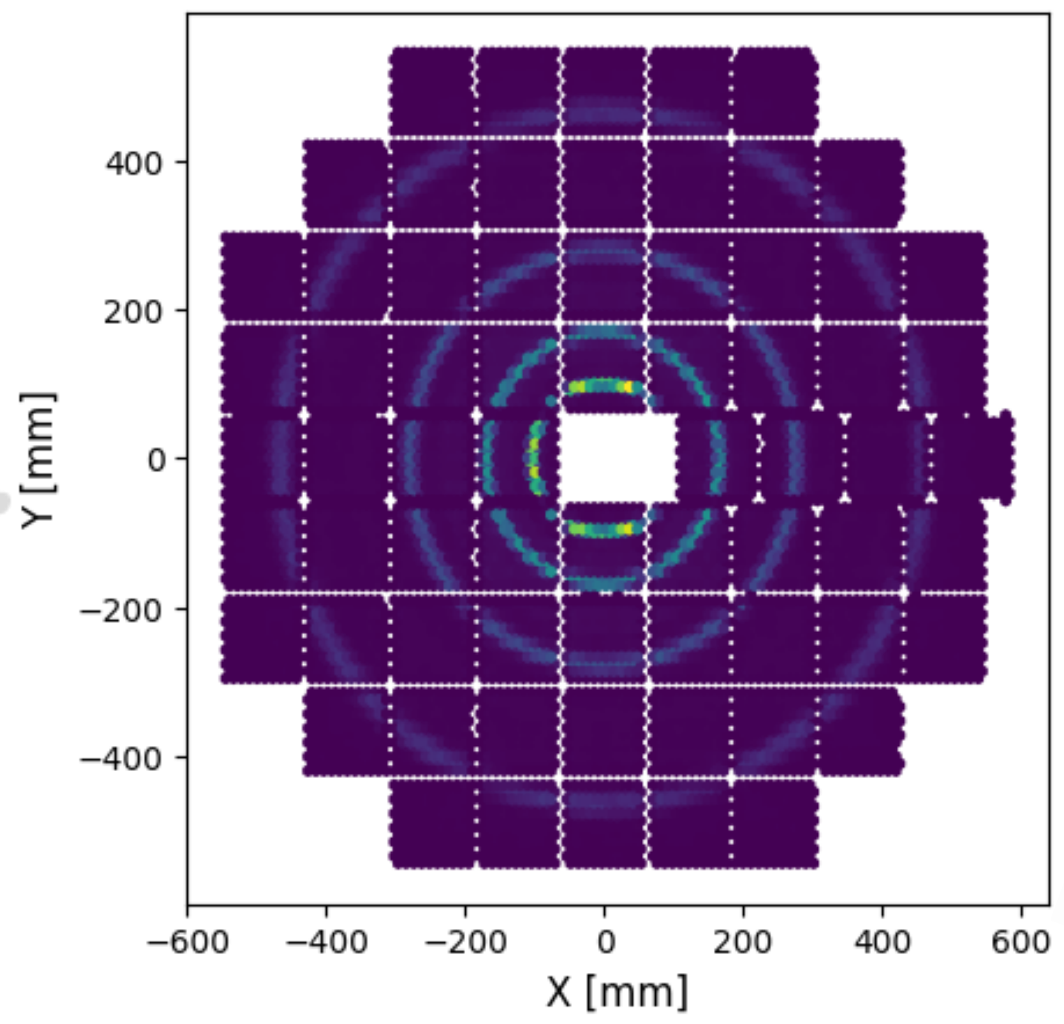
Training

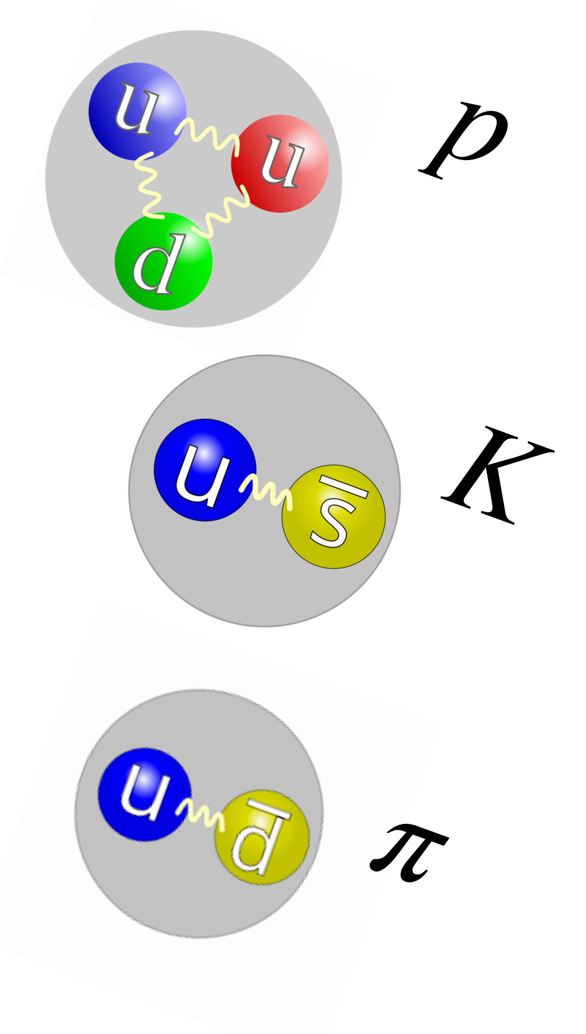


AI/ML model

$$f\left(\sum_i w_i x_i + b\right)$$

Data





Particle Identification

Model Steps

Simulation

→ Generate particle events with Cherenkov photons

Data Preprocessing

→ Convert hit patterns to 64 x 64 images

CNN Encoder

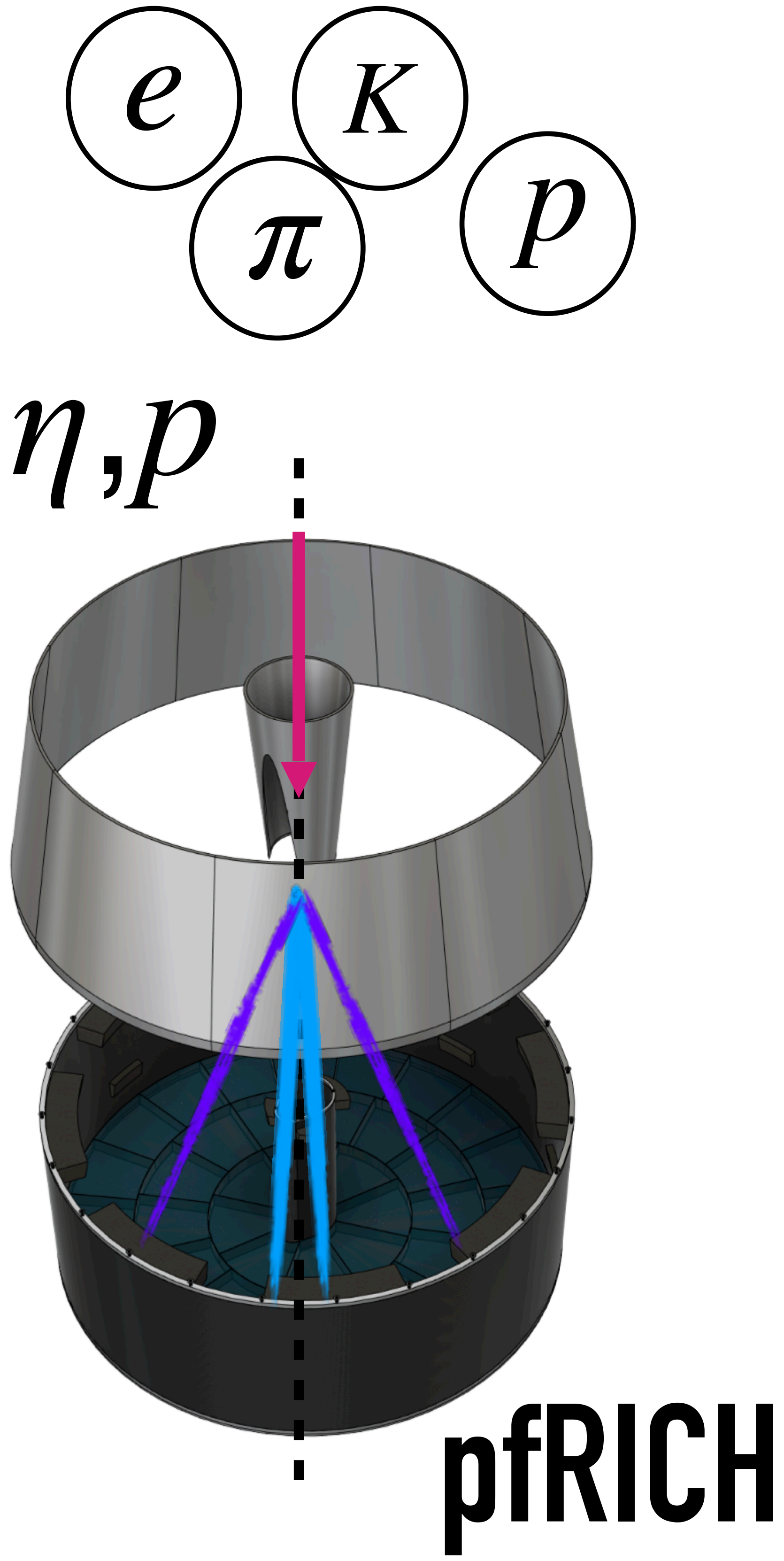
→ Extract spatial features from ring patterns

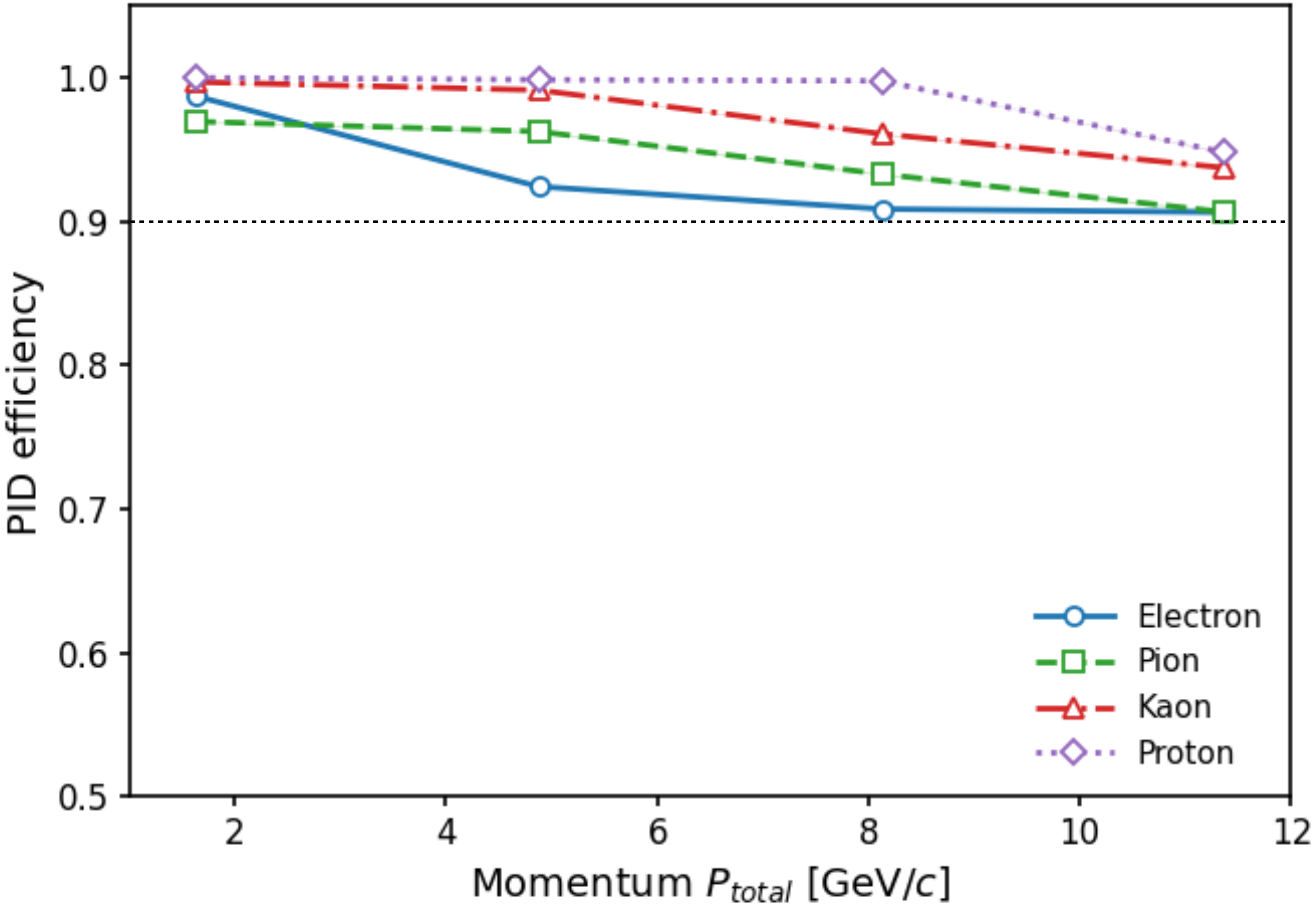
XGBoost Classifier

→ Combine CNN features with kinematics for PID

Hybrid model

Separation Efficiency

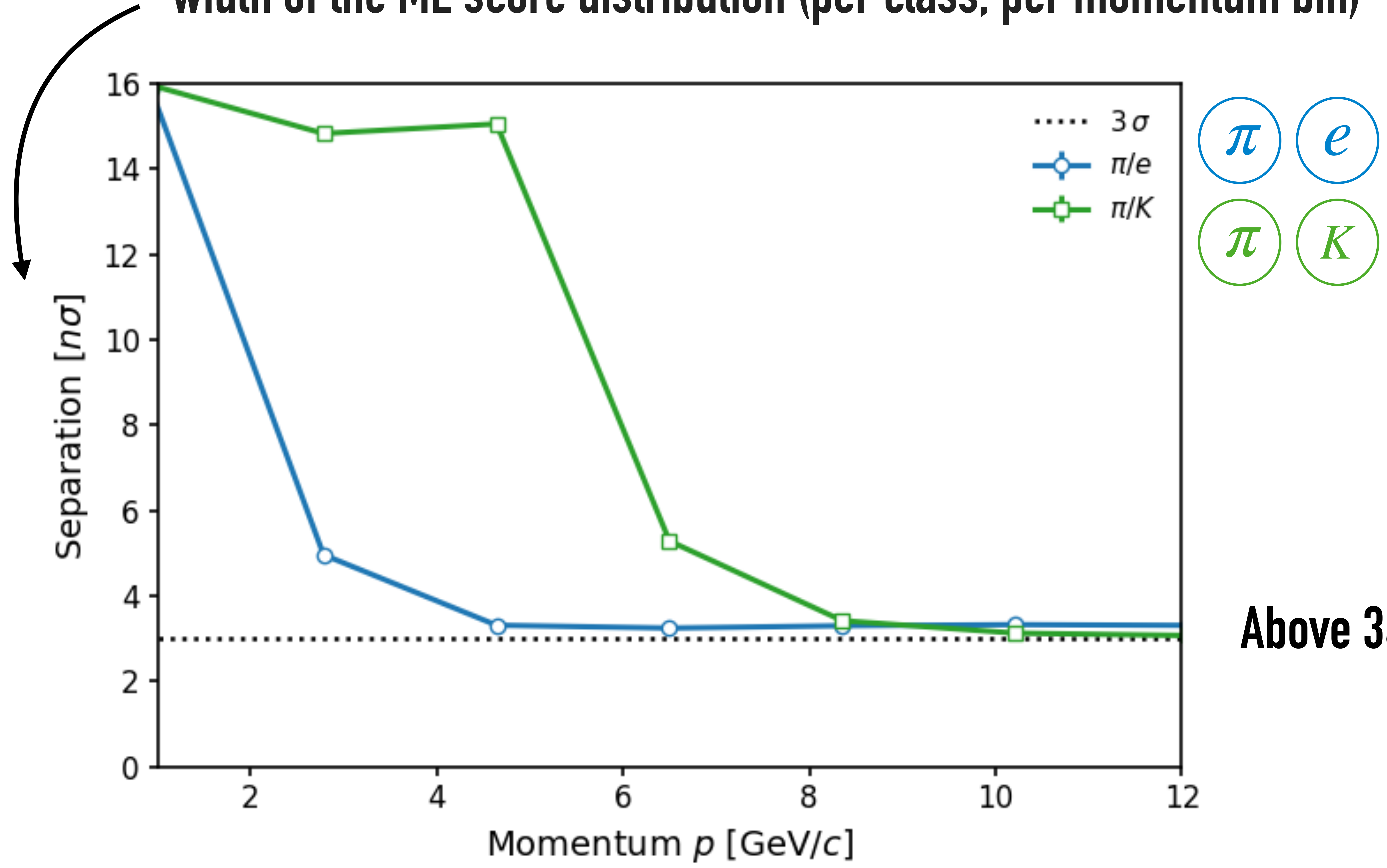




Above 90%

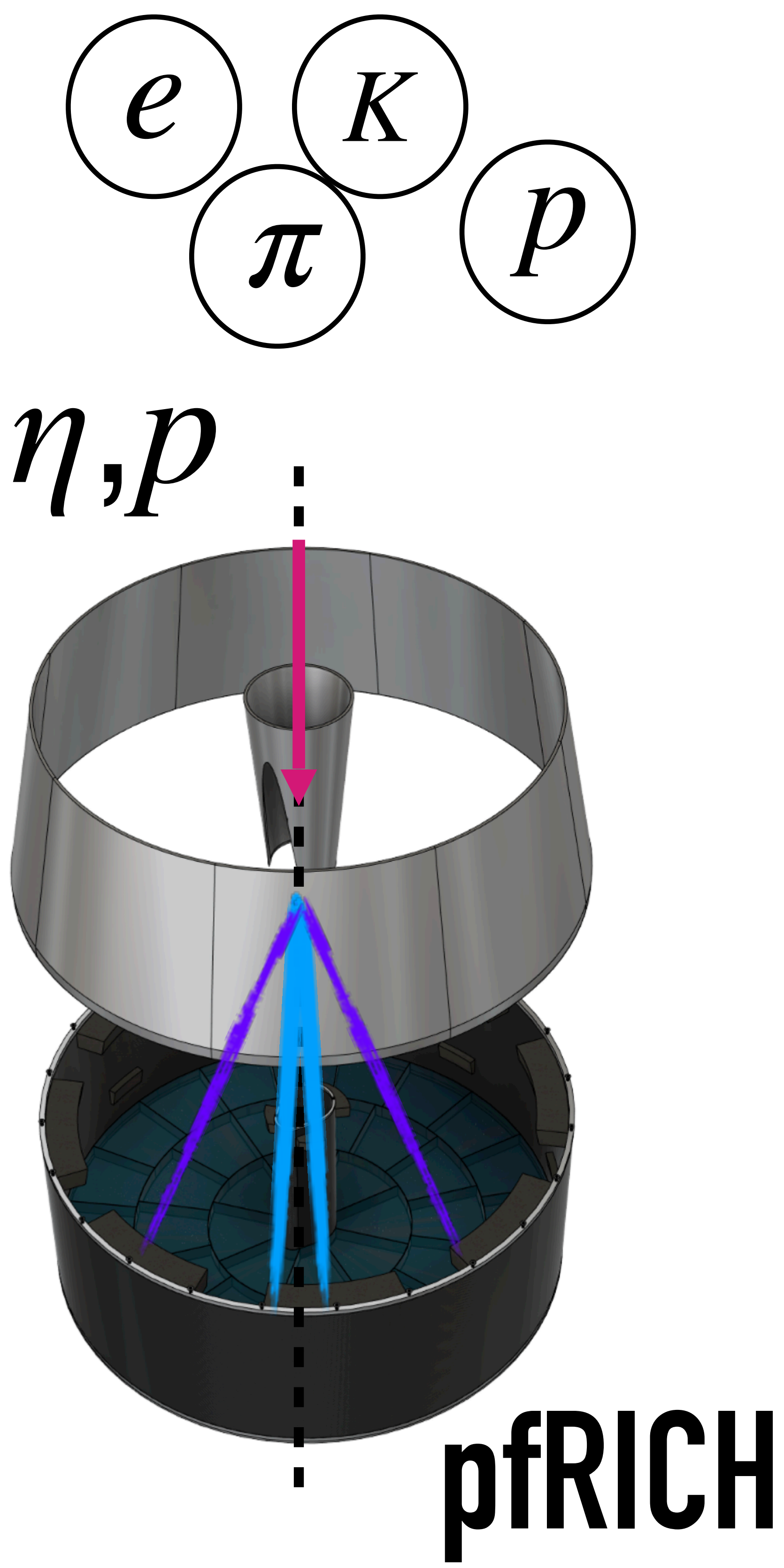
PID Separation

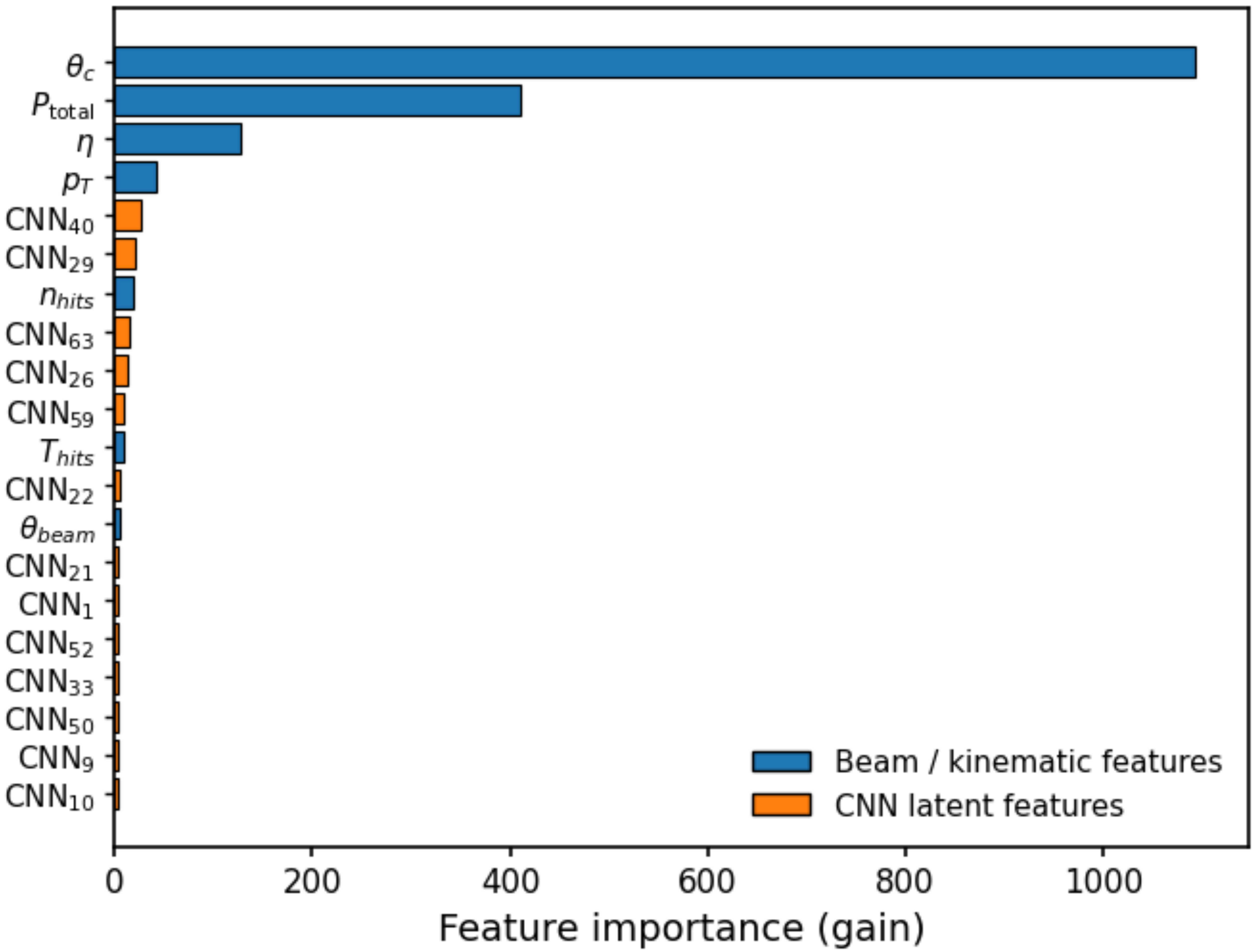
width of the ML score distribution (per class, per momentum bin)



Above 3σ

Feature importance



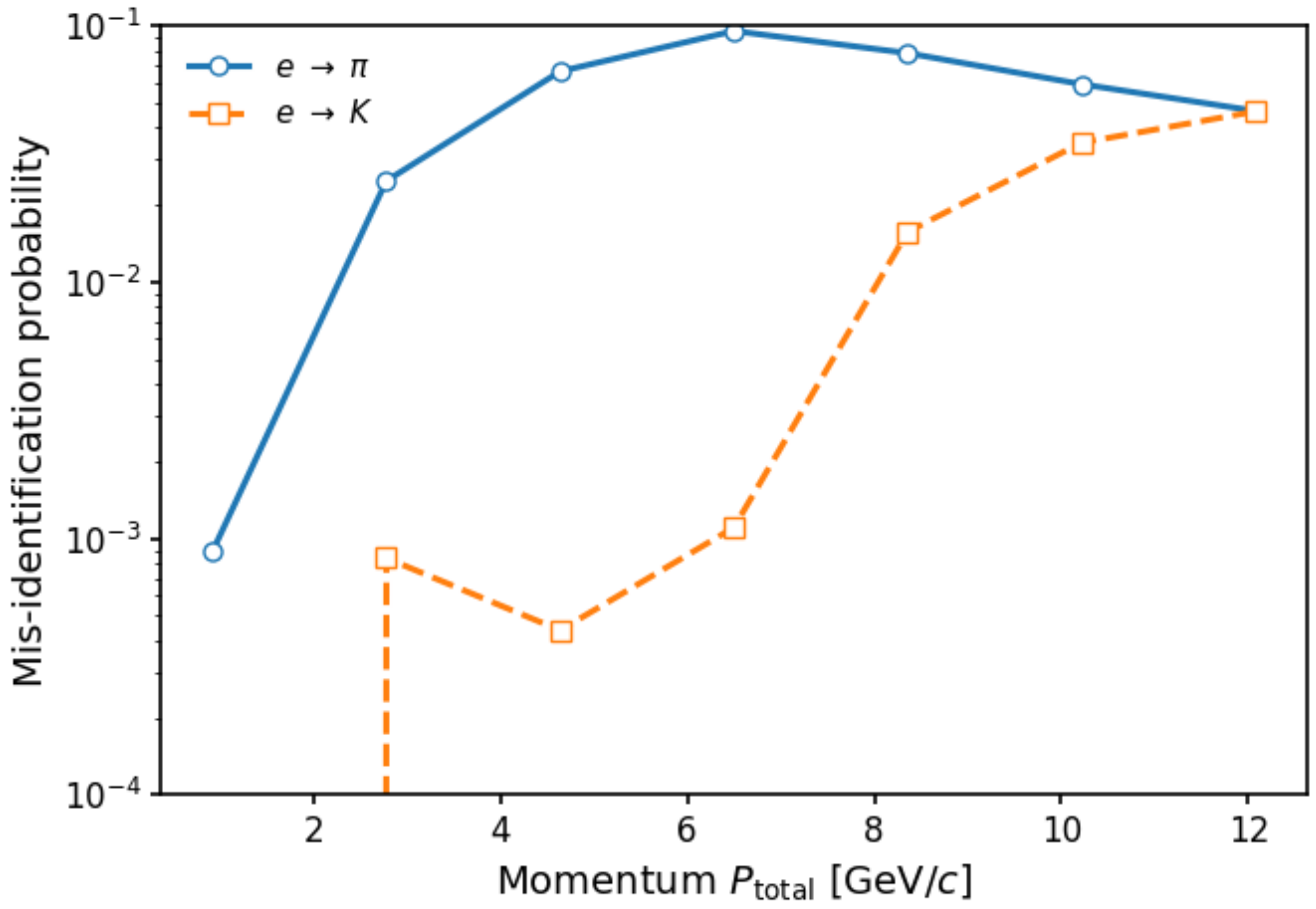


Kinematics info. is dominant

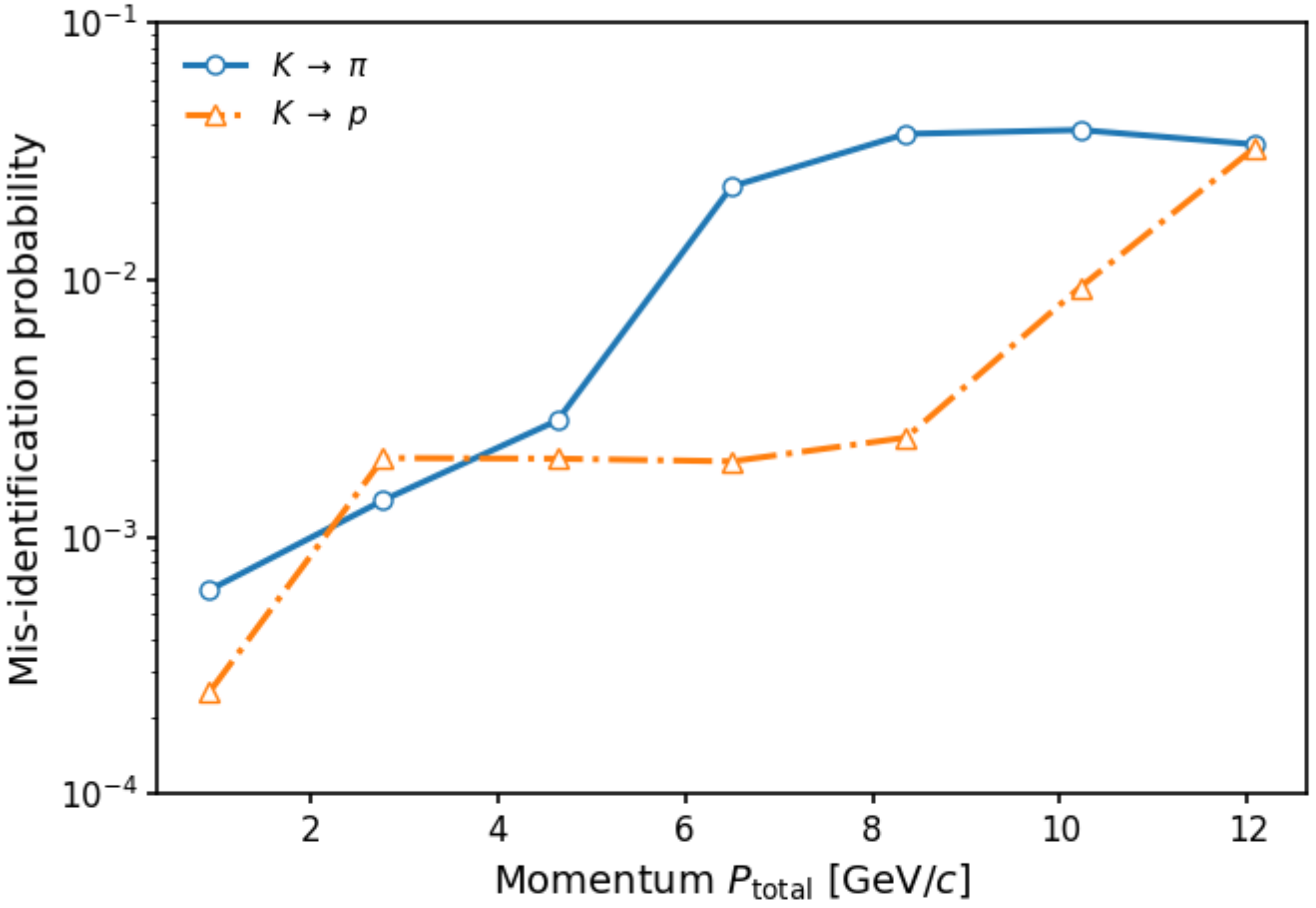
CNN info plays a non-neglieable role

Misidentification

Electron

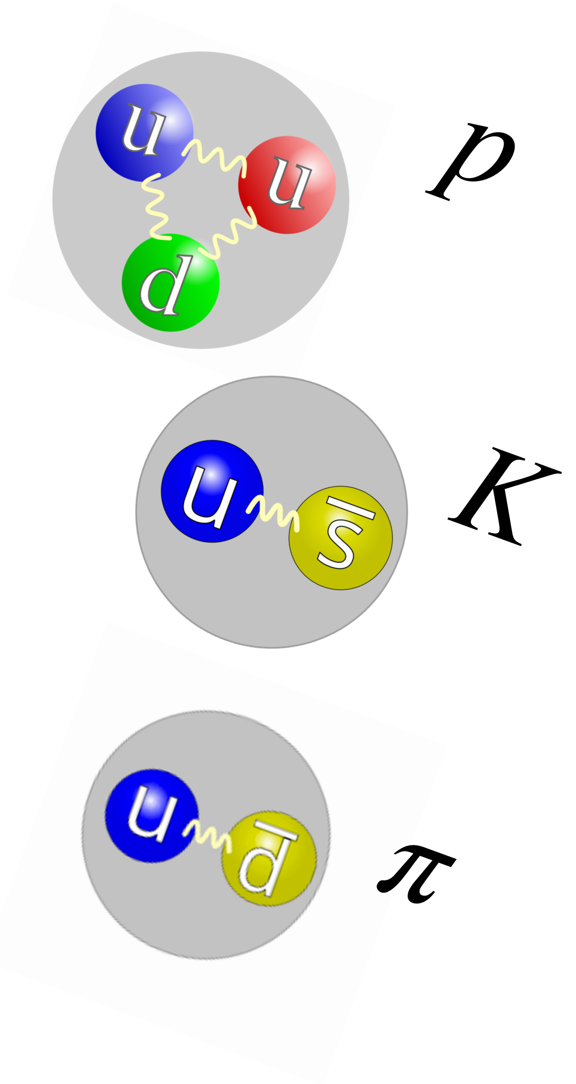


Kaon



Generalize the Approach

Physics | Subsystems | AI/ML model | PID



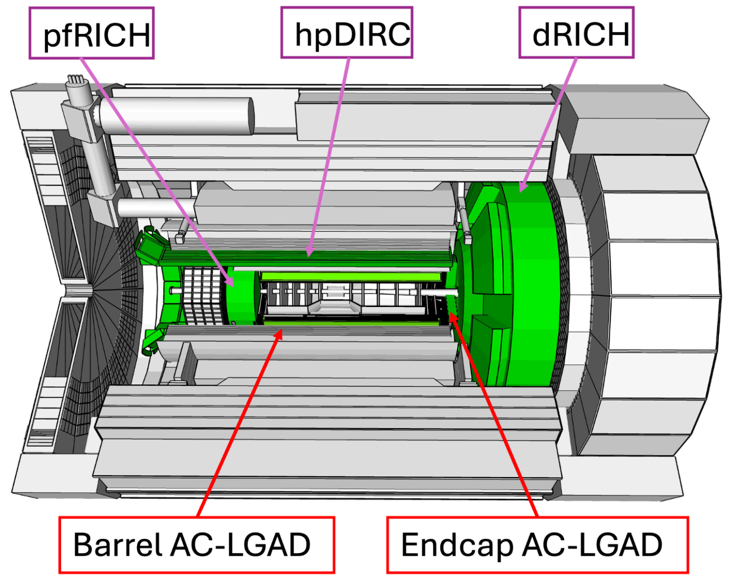
pfRICH

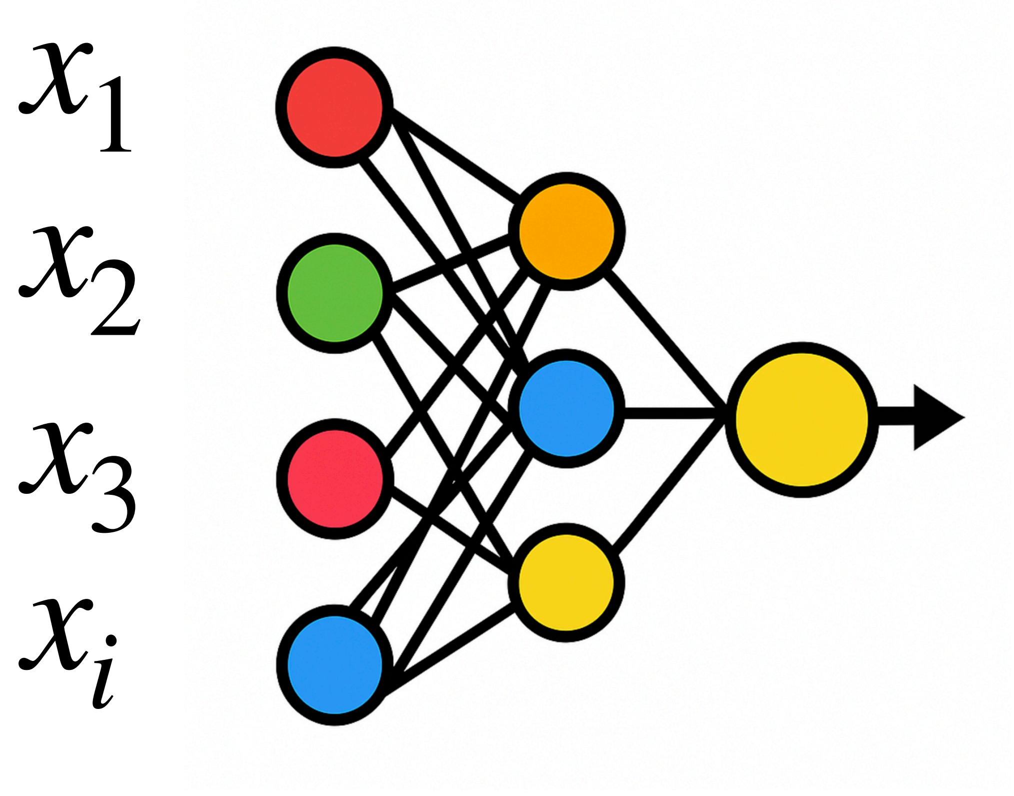
hpDIRC

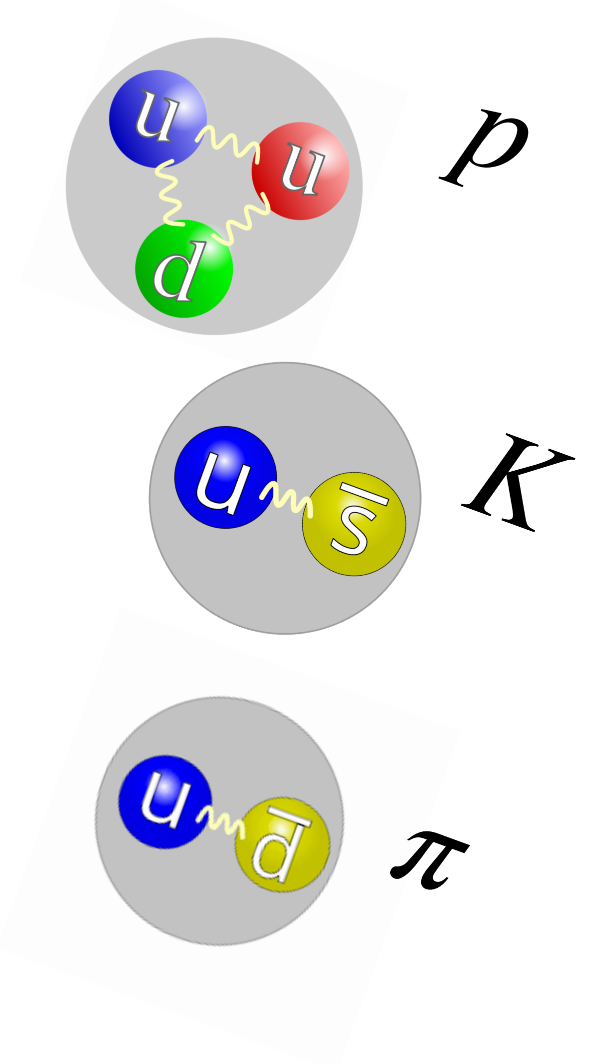
dDRICH

...

ePIC







This method can be extended to <u>all ePIC PID subsystems</u>

Ongoing

The more information available, the better the model will perform

Conclusion

ePIC is a state-of-the-art detector

It requires state-of-the-art computational tools

Detector performance is the best entry point for impactful AI/ML applications

The hybrid ML model for pfRICH is robust

Its integration into the ePIC software is ongoing

The approach is readily extendable to other PID systems