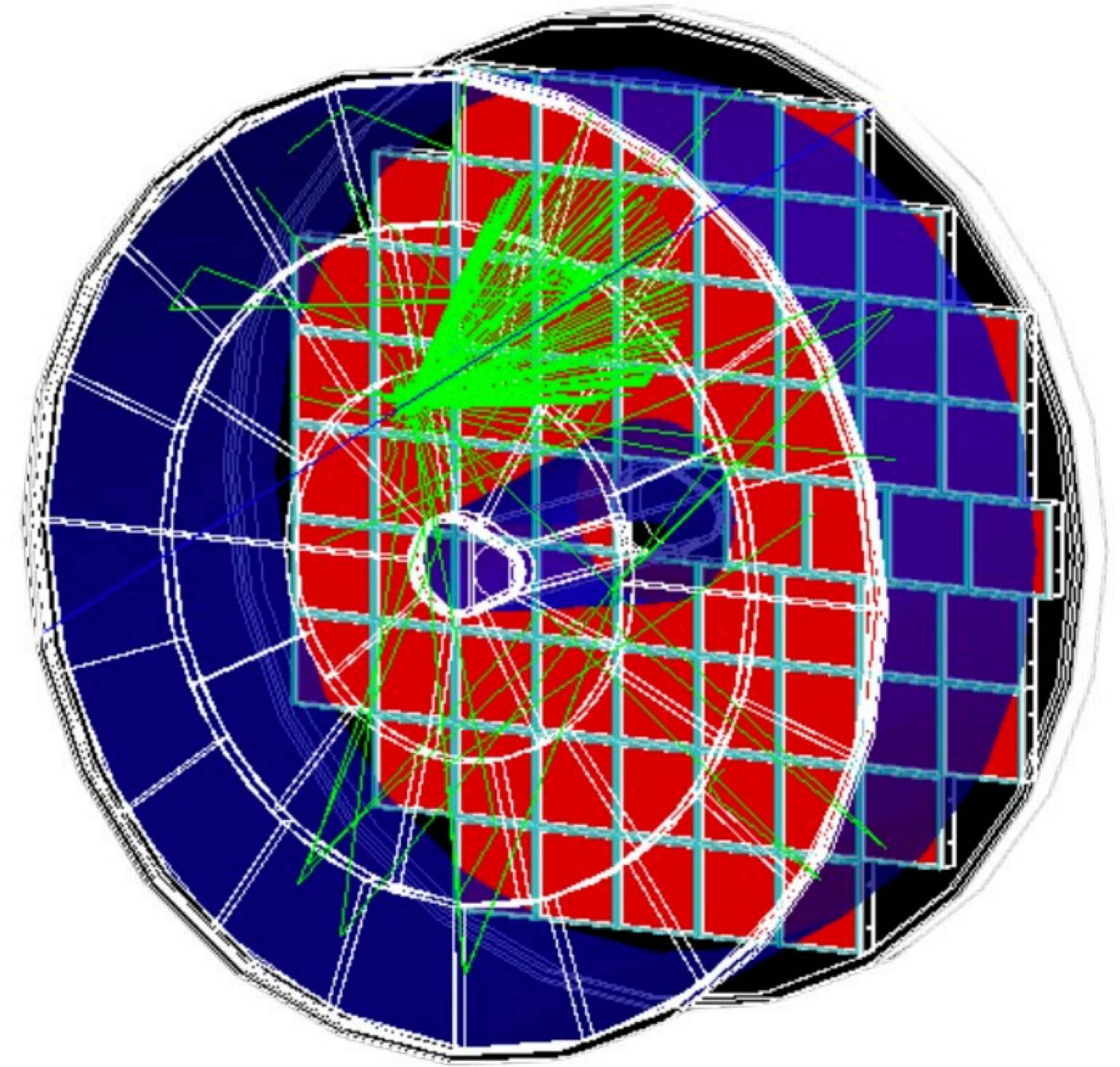


# Machine Learning for the pfRICH Particle Identification subsystem

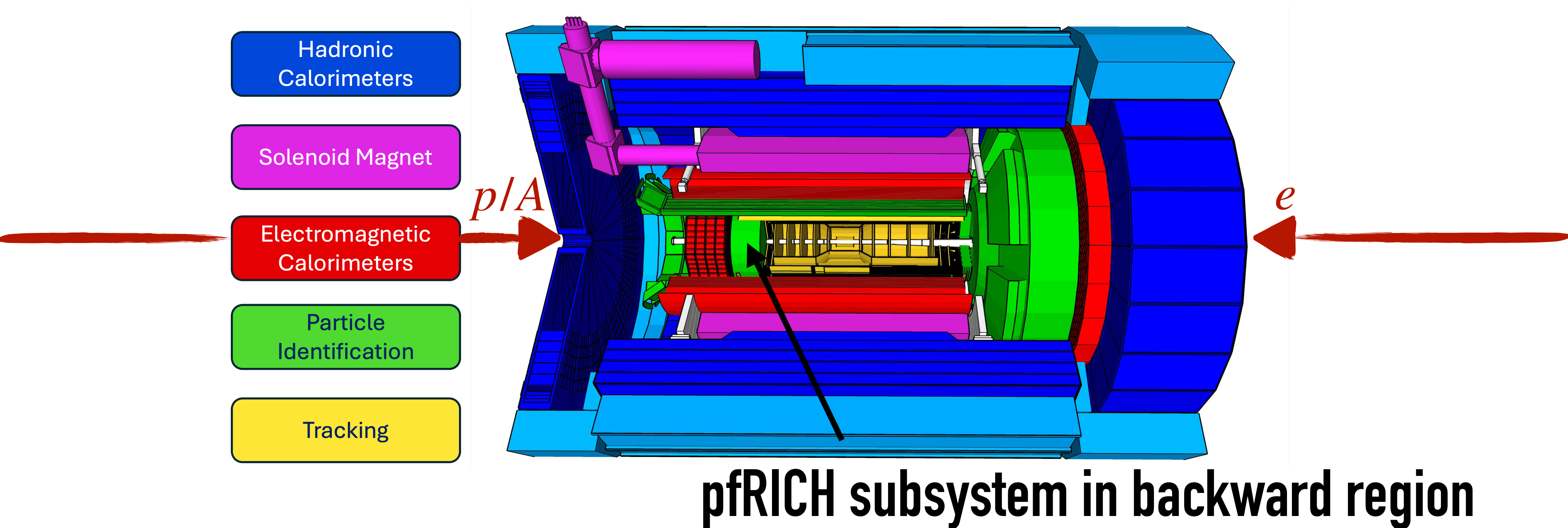
D.H Dongwi, C-J. Naïm and L. Rhode

Artificial Intelligence for the Electron Ion Collider (2025)  
October, 28, 2025



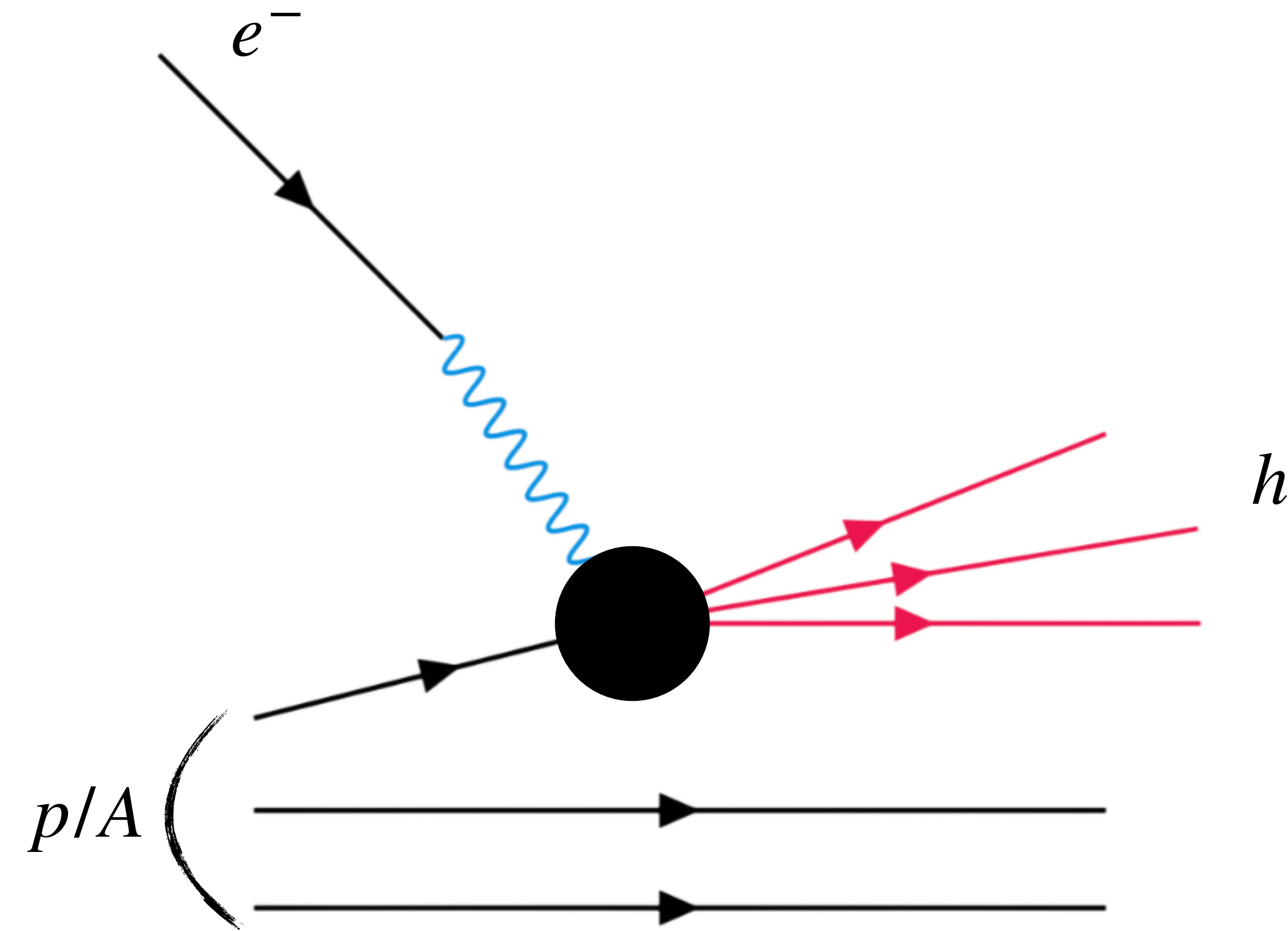


# The ePIC Detector at the EIC



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

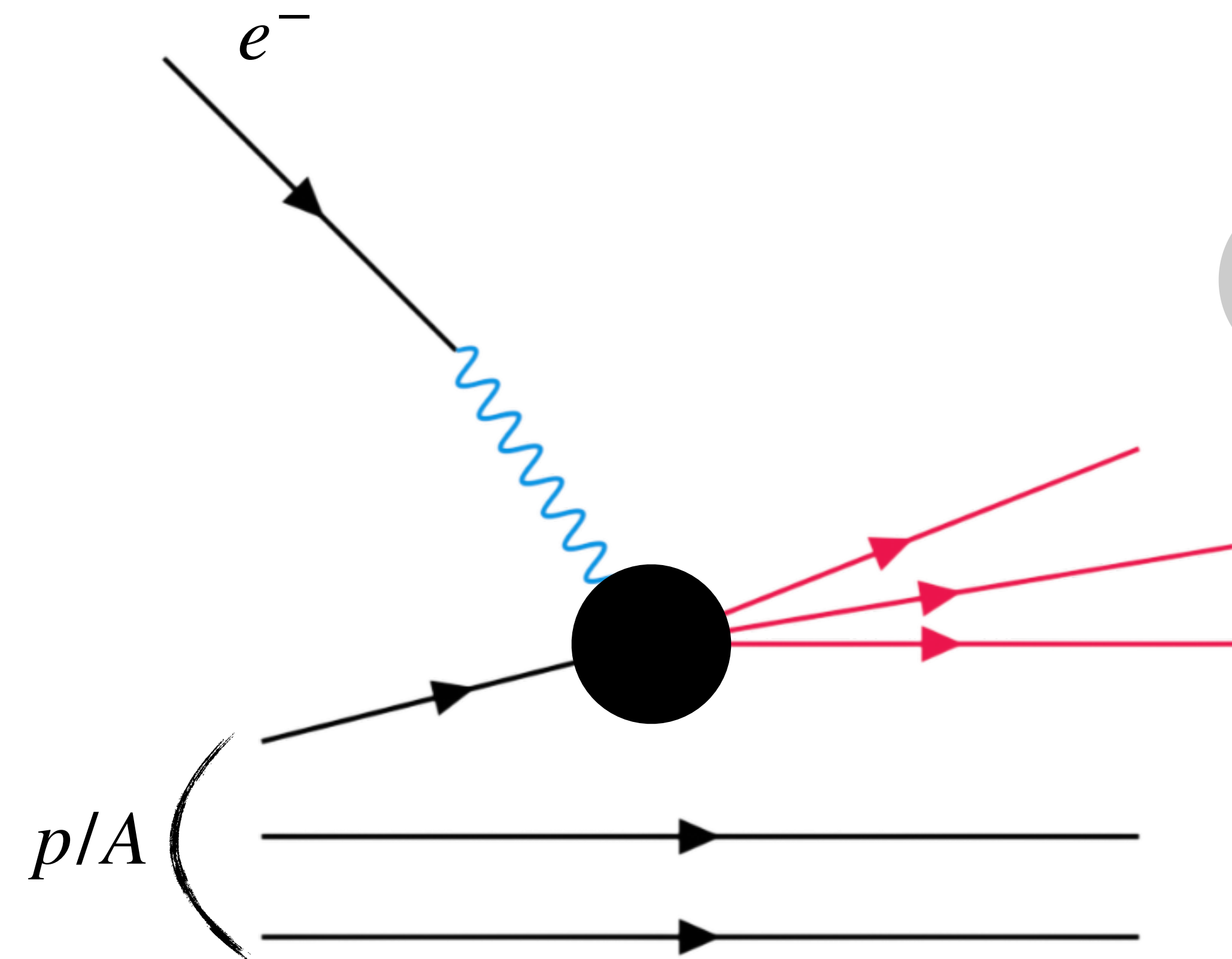
# Physics Motivations at the EIC



- **Semi-Inclusive Deep Inelastic Scattering**
- **Production of hadrons in final-state**
- Provide information on:
  - the *fragmentation process (hadronization)*
  - the *hadronic structure*

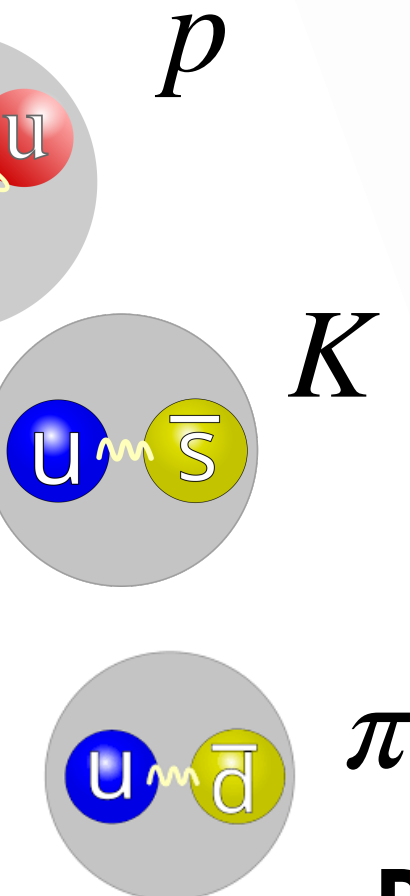
**Particle Identification detectors are crucial**

# The pfRICH Concept



The pfRICH will provide  $> 3\sigma$   $\pi/K$  separations for momentum up to 7 GeV/c for  $-3.5 < \eta < -1.5$

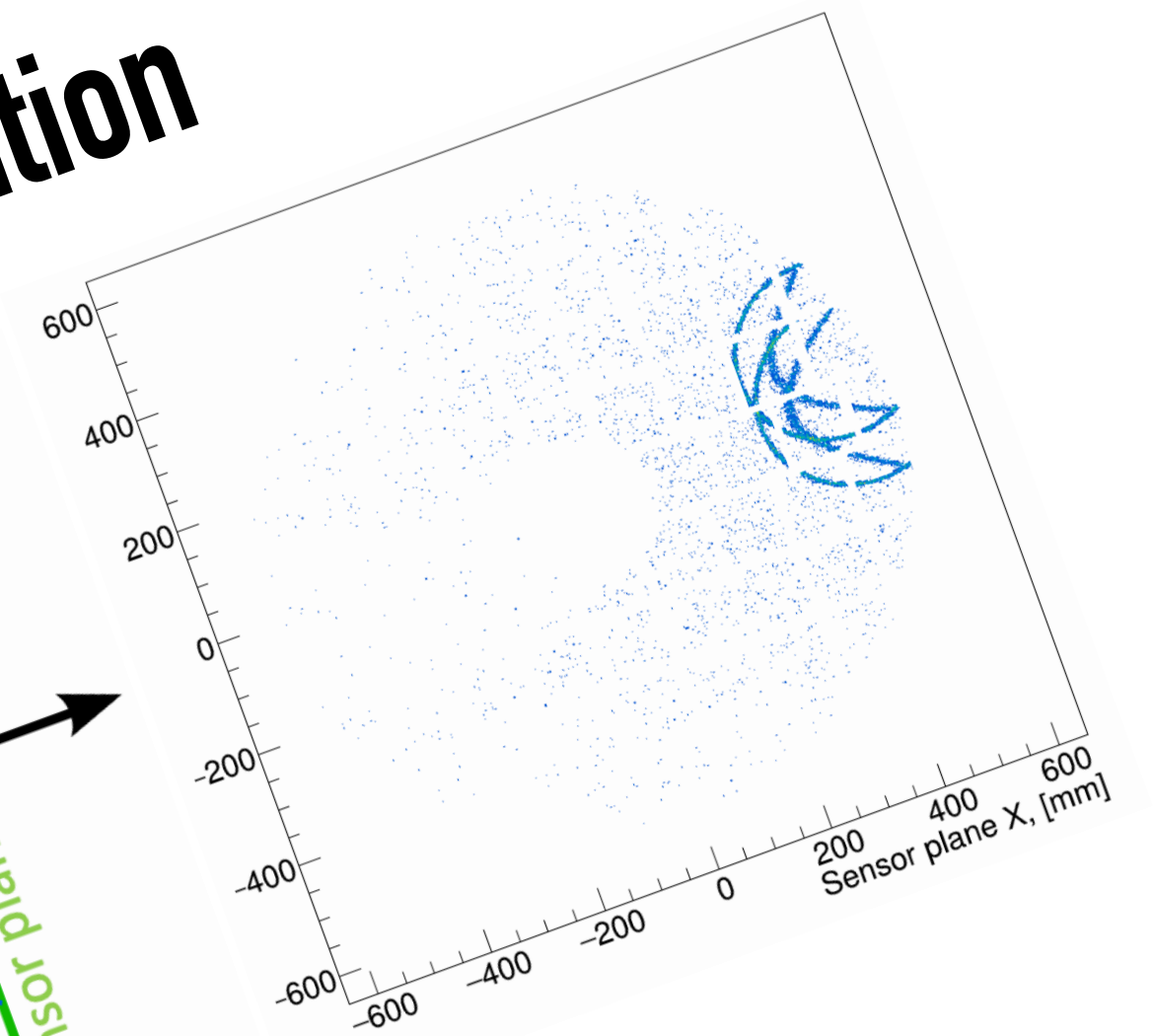
## Particle Identification



## Detection Principle

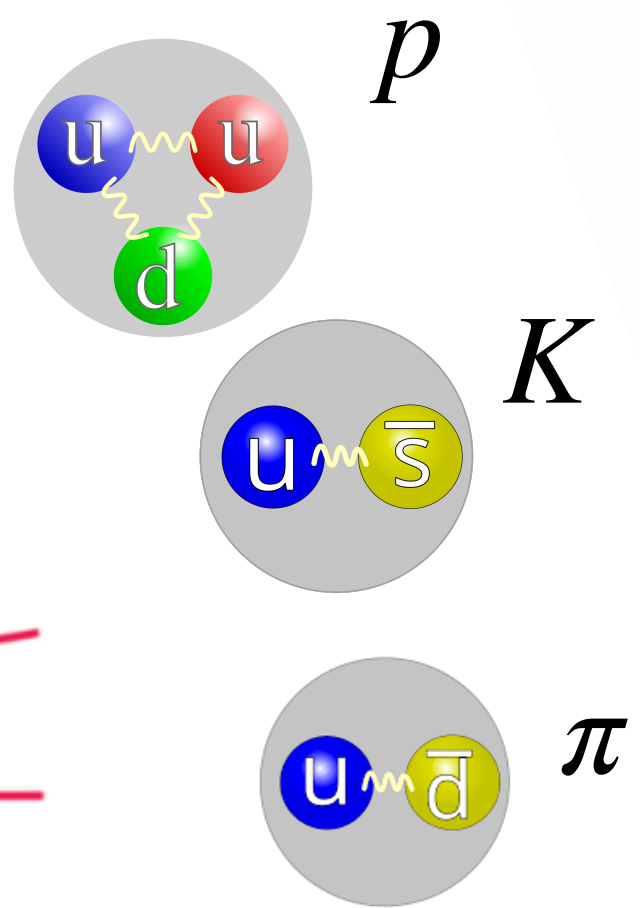
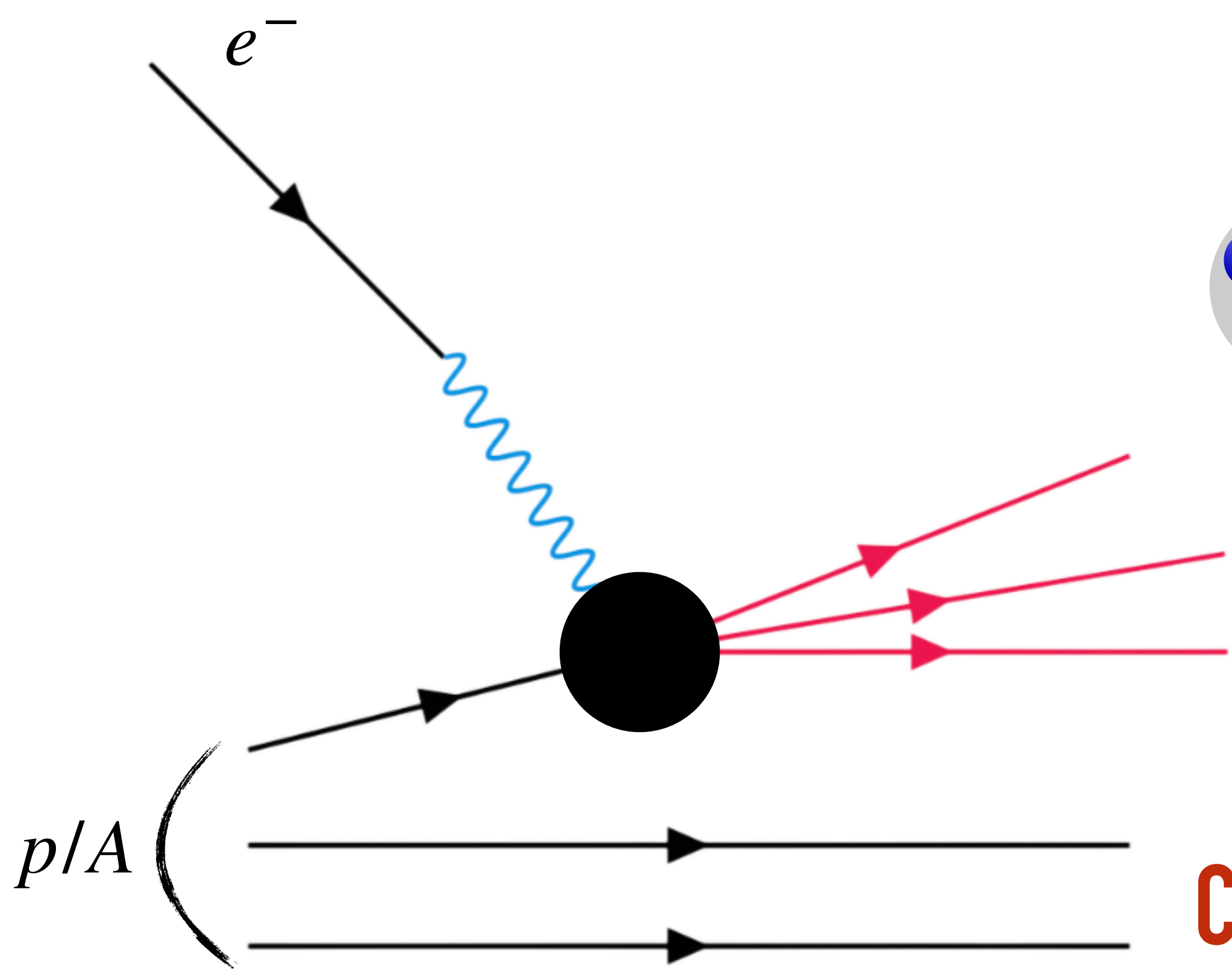
- Charged particle  $\rightarrow$  emits Cherenkov photons at angle  $\theta_c$
- Photons project onto photodetectors  $\rightarrow$  form a **ring**  
 $\rightarrow$  Ring radius  $\propto \tan \theta_c$
- Measuring ring size  $\rightarrow$  deduce  $\theta_c \rightarrow$  **particle mass**

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

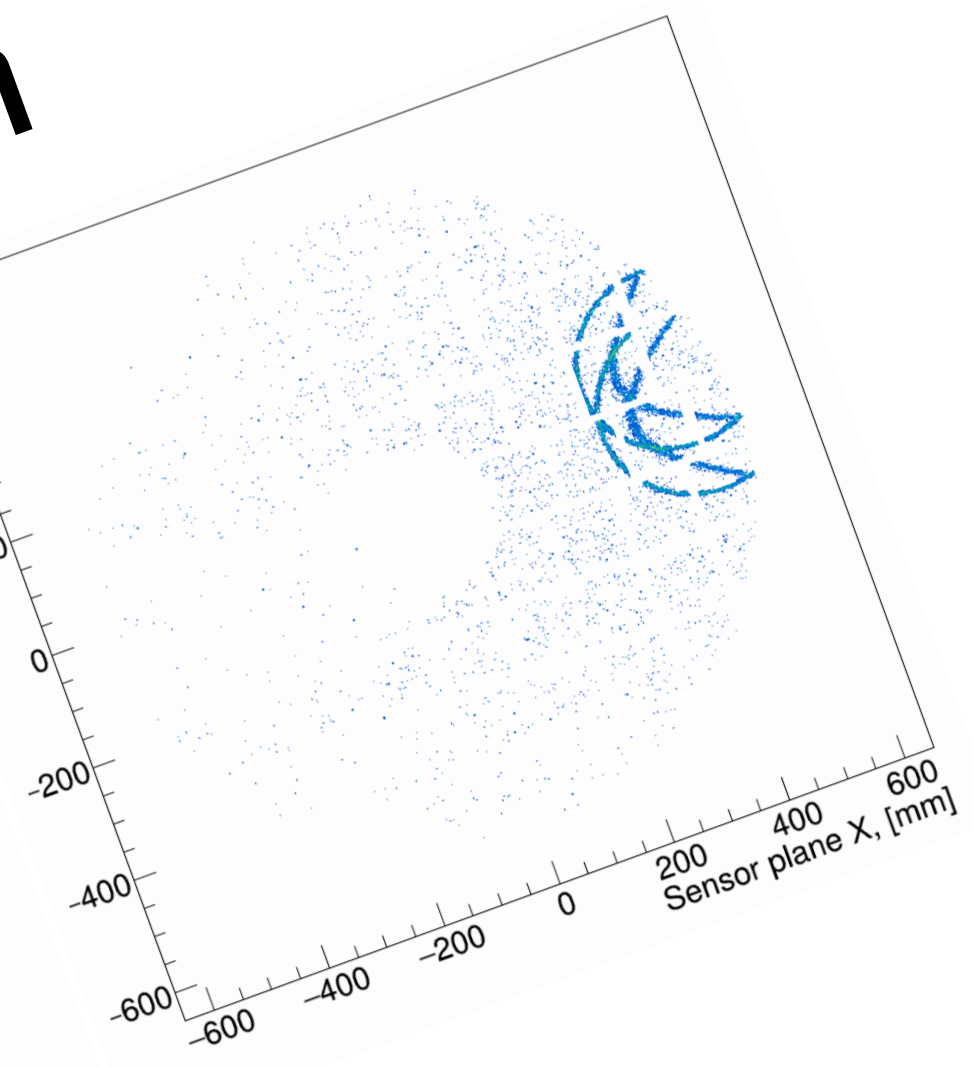
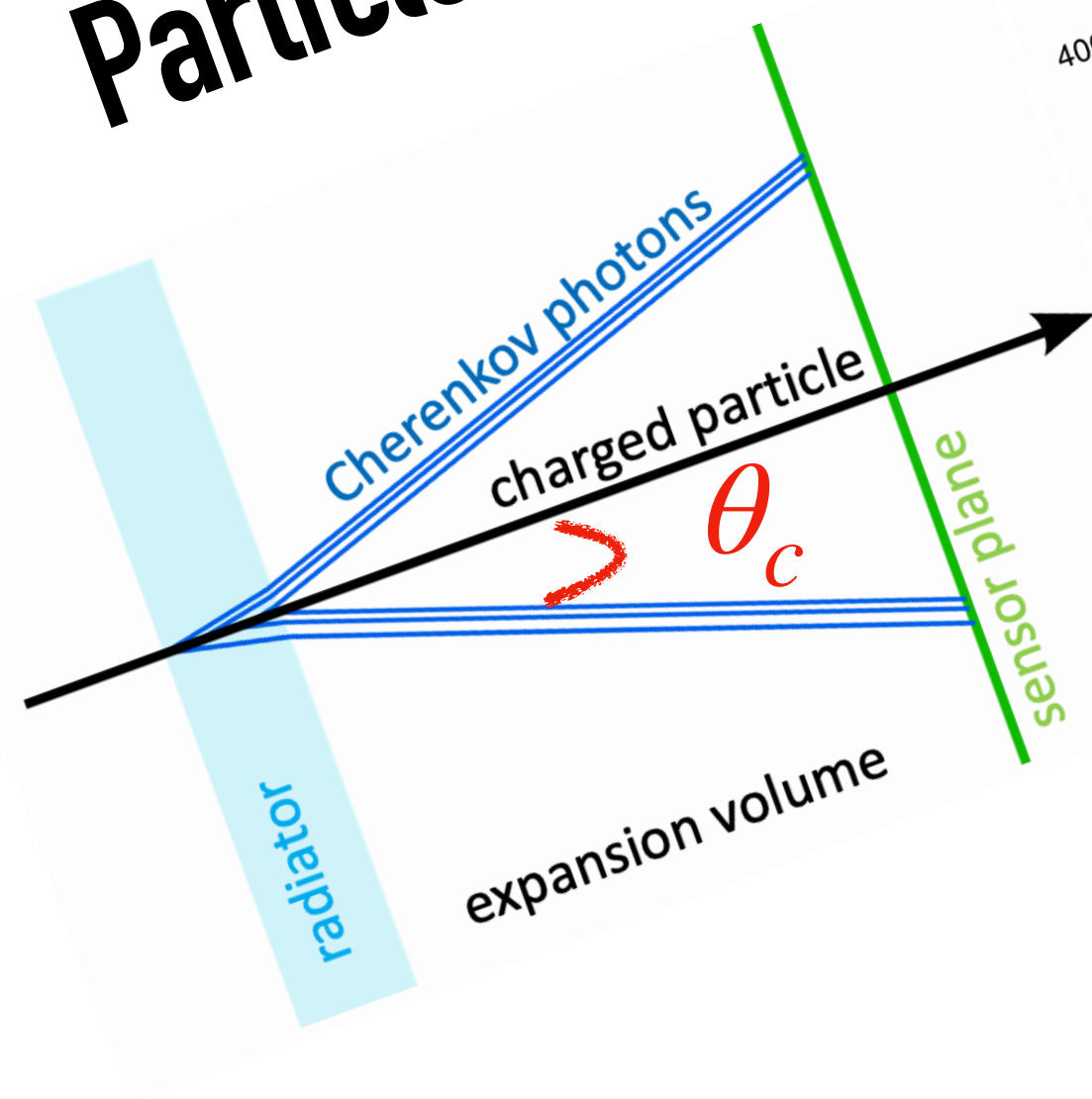




# The pfRICH Concept

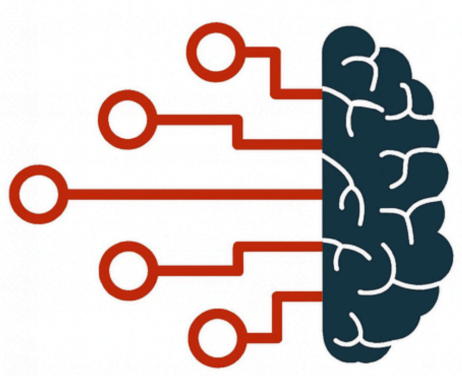


## Particle Identification



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

Can we use machine learning to improve particle identification?



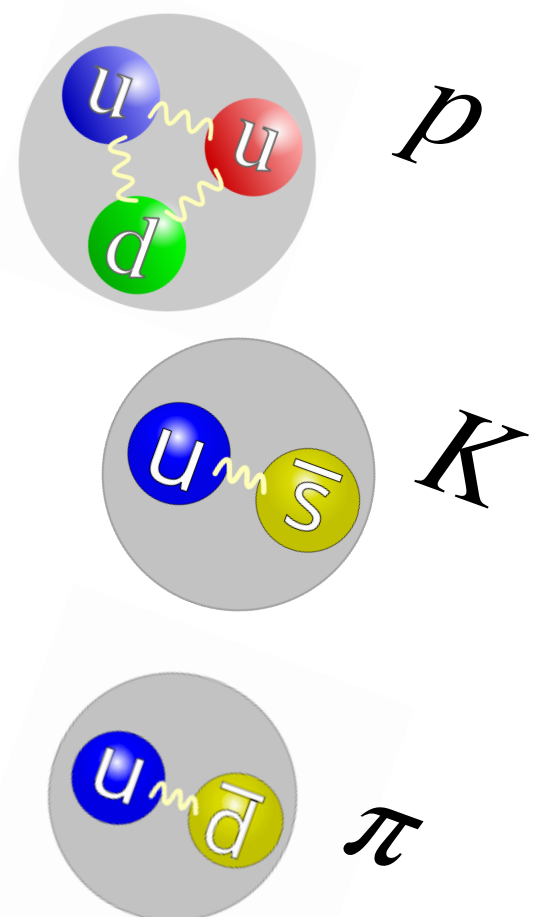
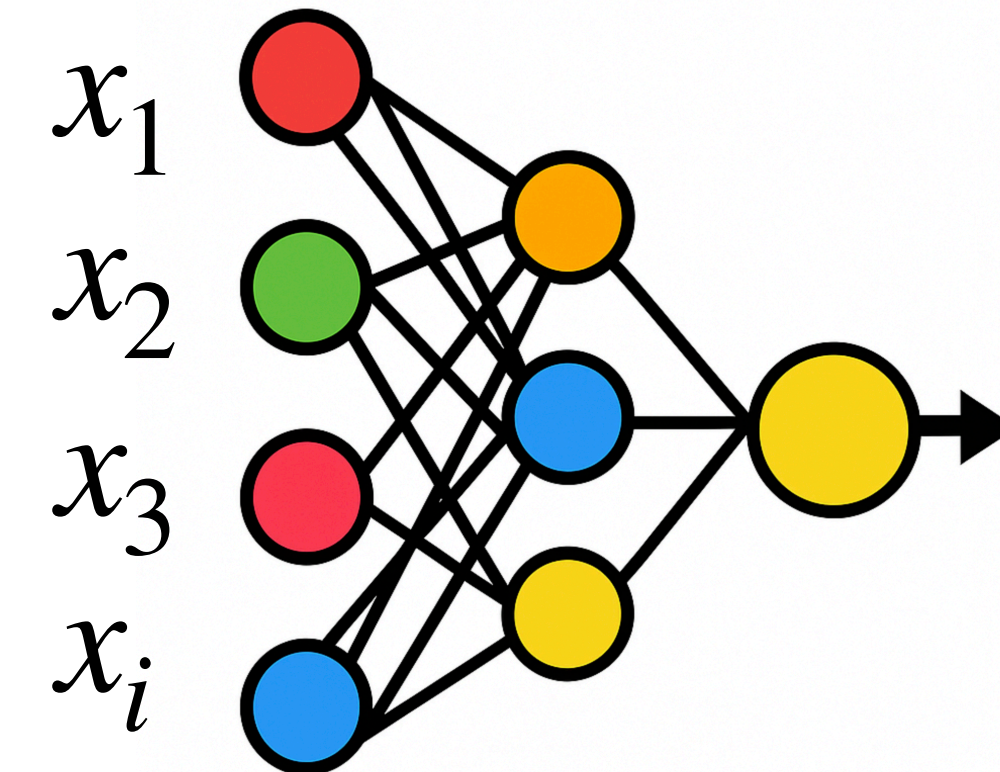
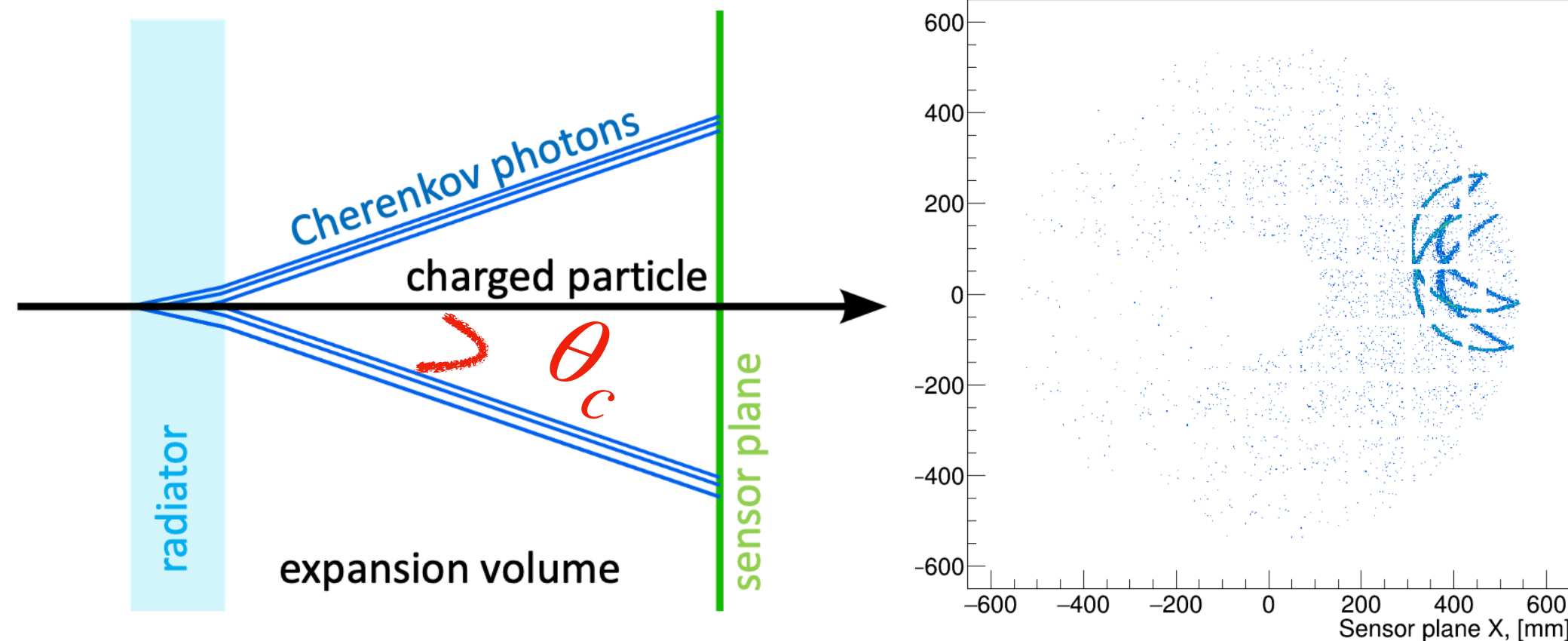
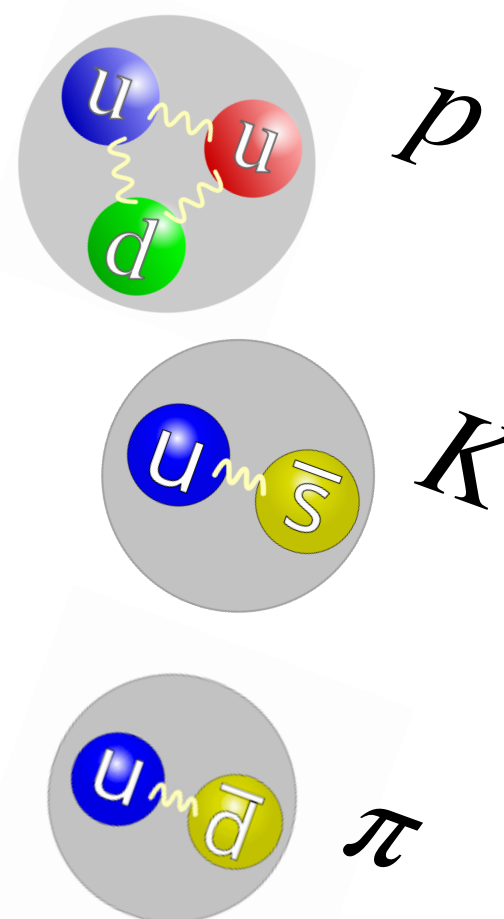
# The Approach

Physics

pfRICH

AI/ML model

PID

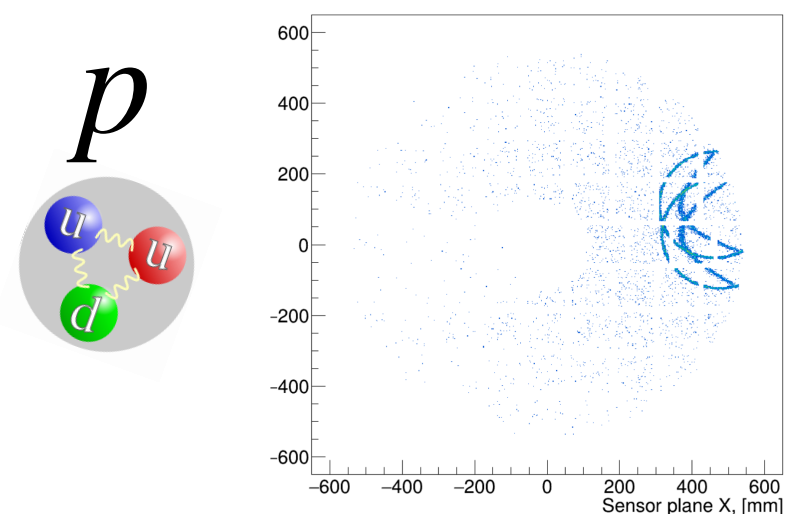
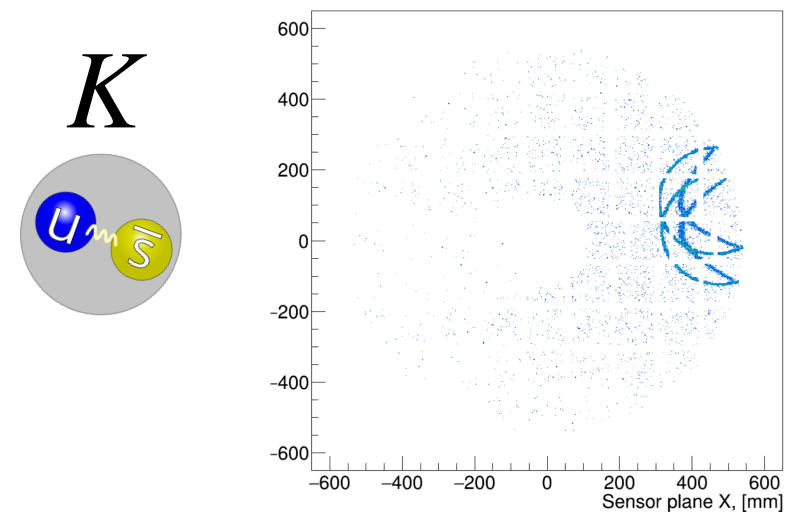
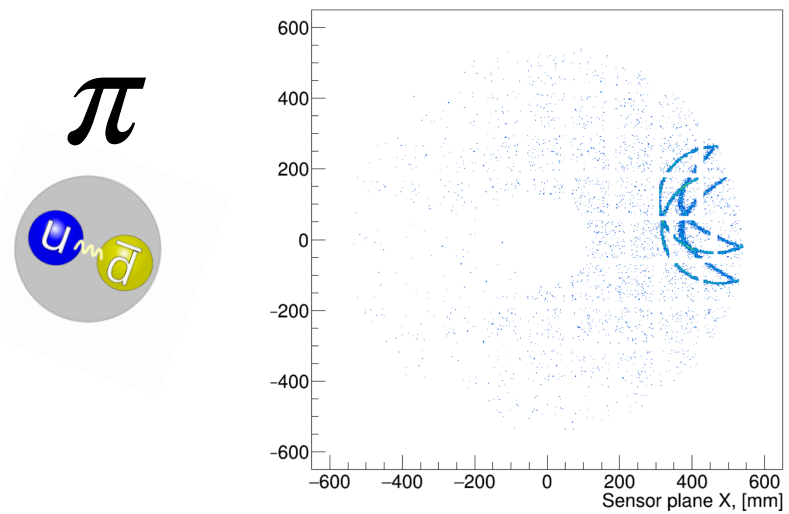


Can we use machine learning to improve particle identification?: Yes!

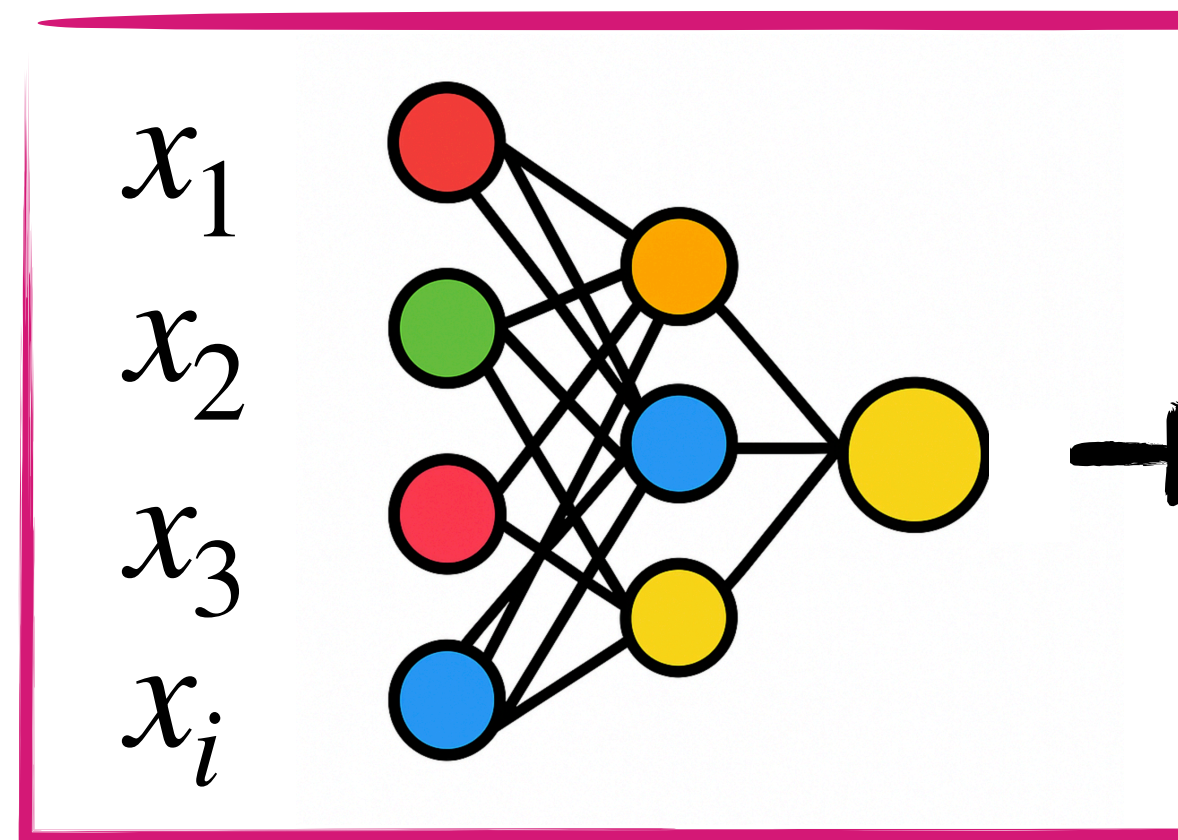
An ideal use case for AI/ML, since the signal is well defined and fully understood



# Model Training



Training



AI/ML model

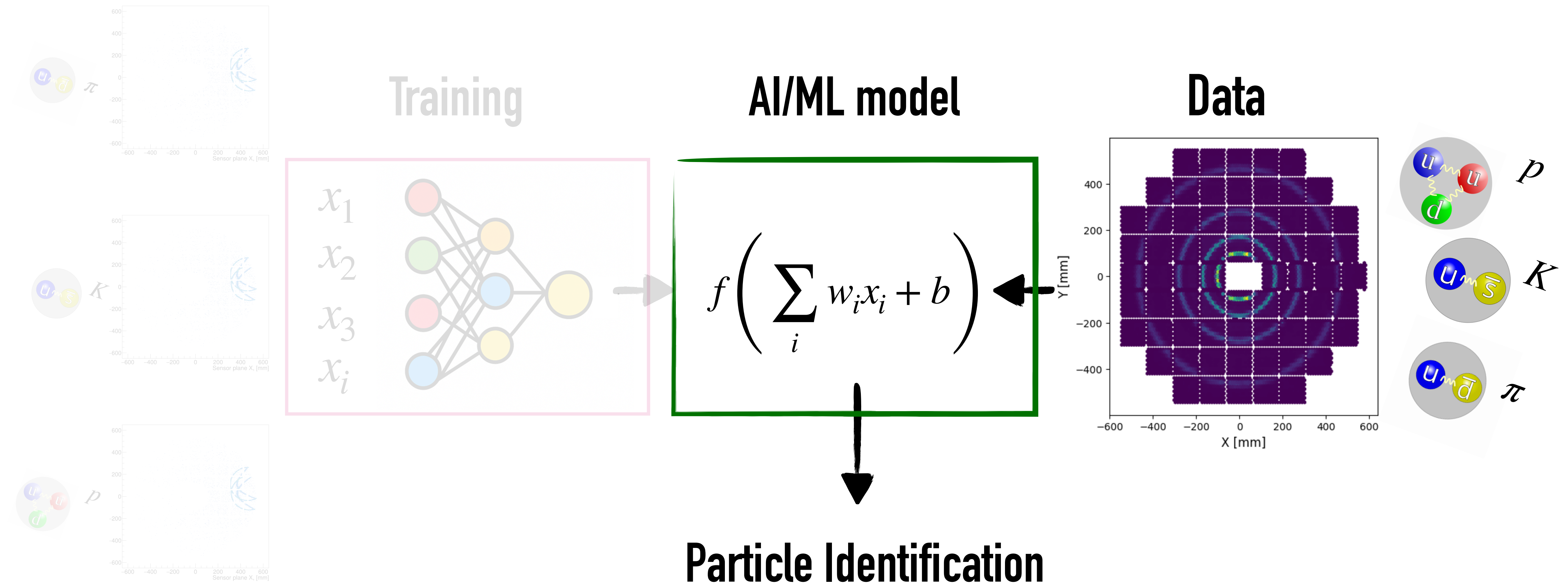
$$f\left(\sum_i w_i x_i + b\right)$$

**XGBoost**  
**Gradient-boosted hybrid**  
**Diffusion model (ongoing)**

**Standalone ePIC pfRICH GEANT4:**

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

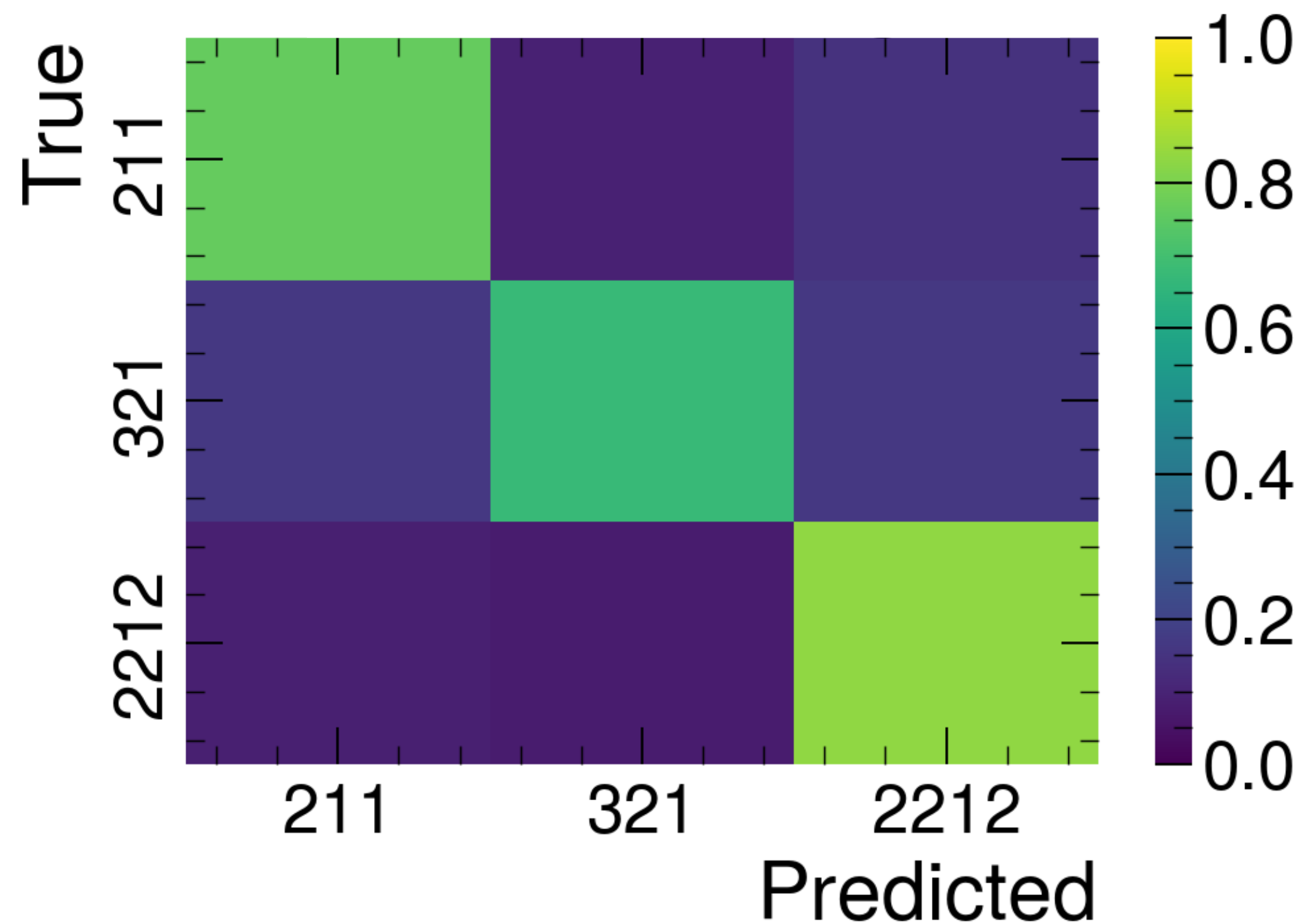
# Model Inference



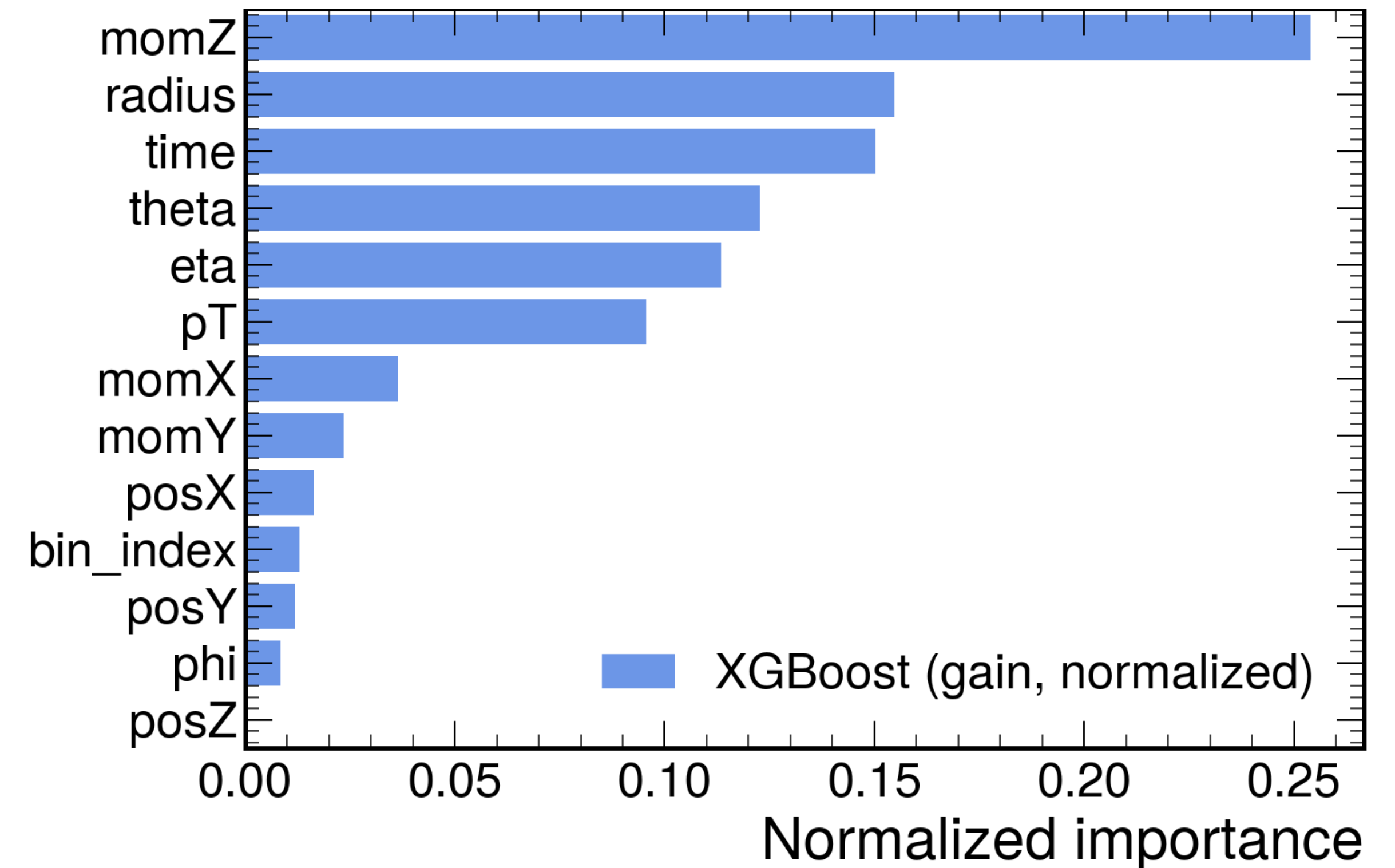


# Results

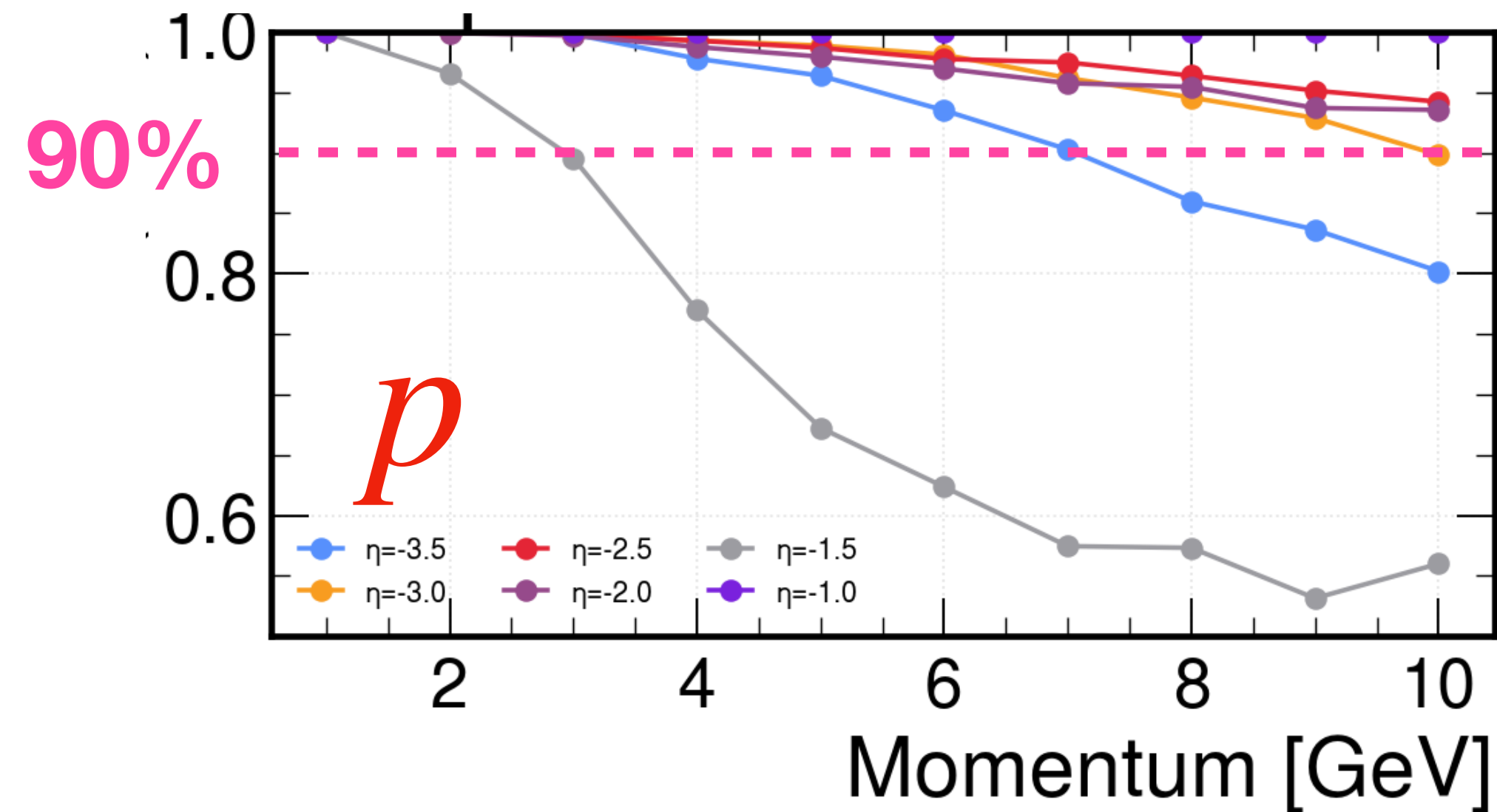
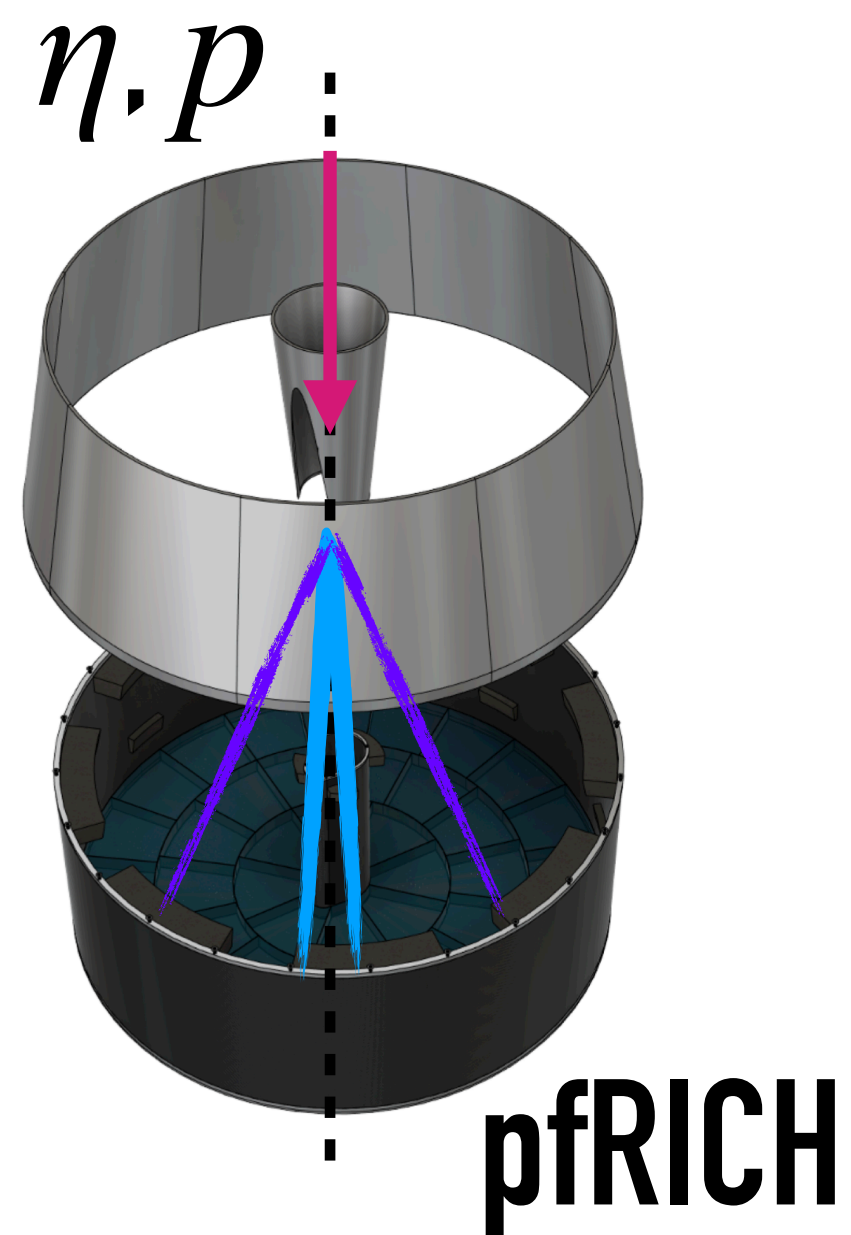
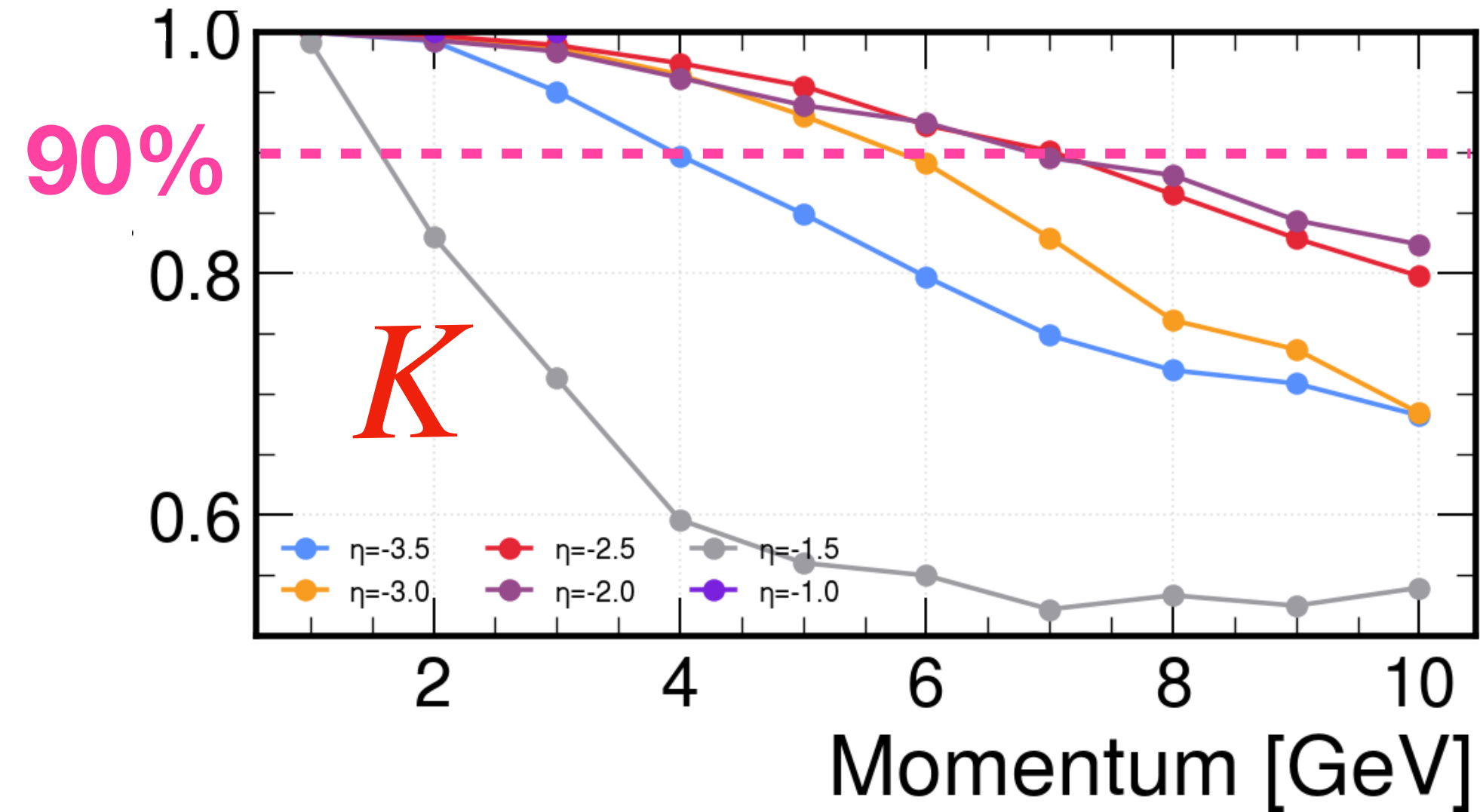
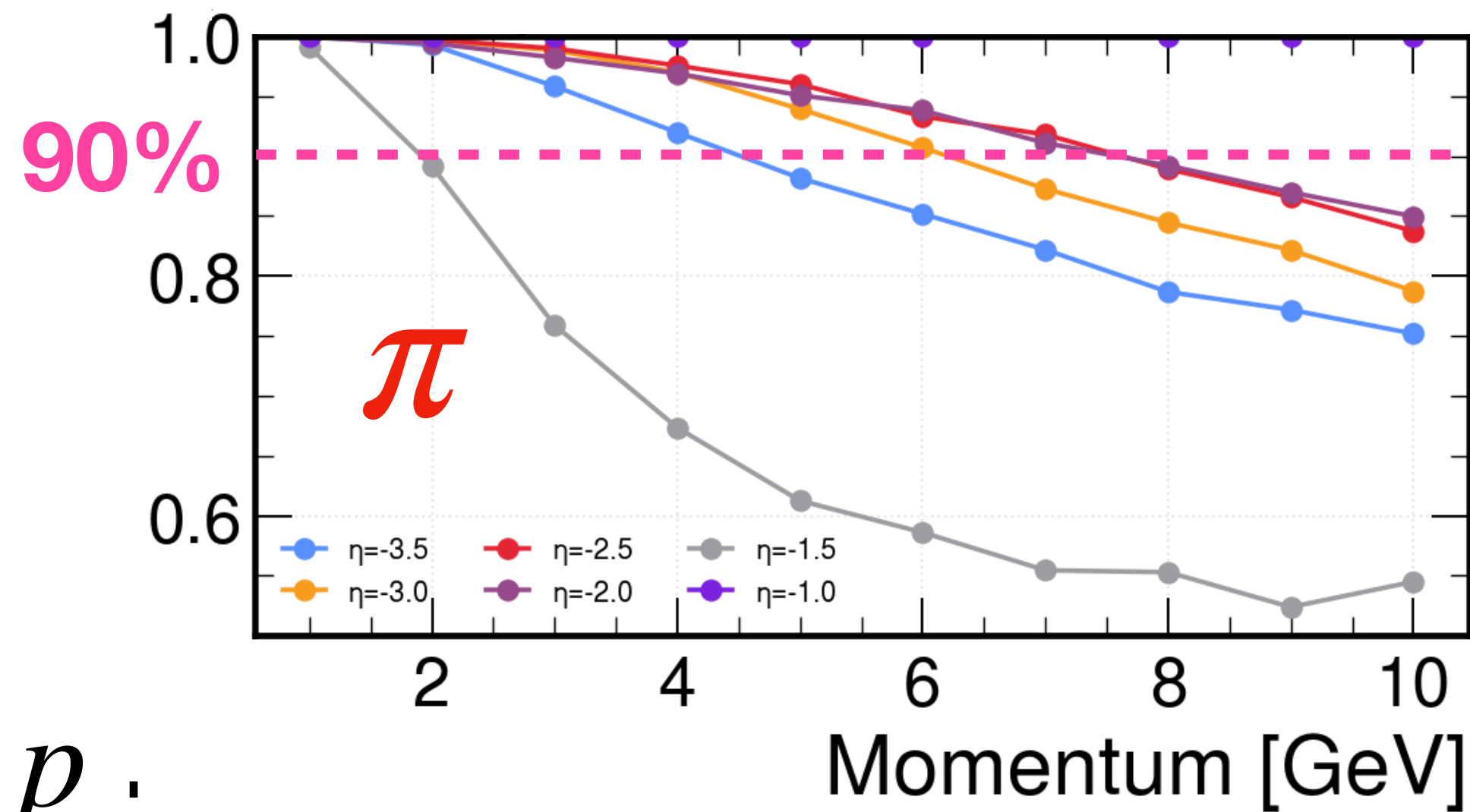
## Confusion matrix



## Feature importance



# Separation Efficiency



**Promising results!**



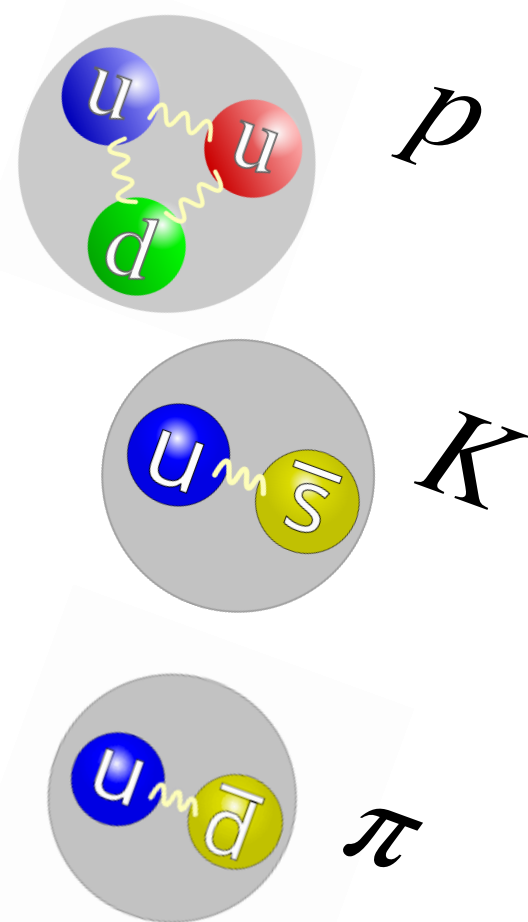
# Generalize the Approach

Physics

Subsystems

AI/ML model

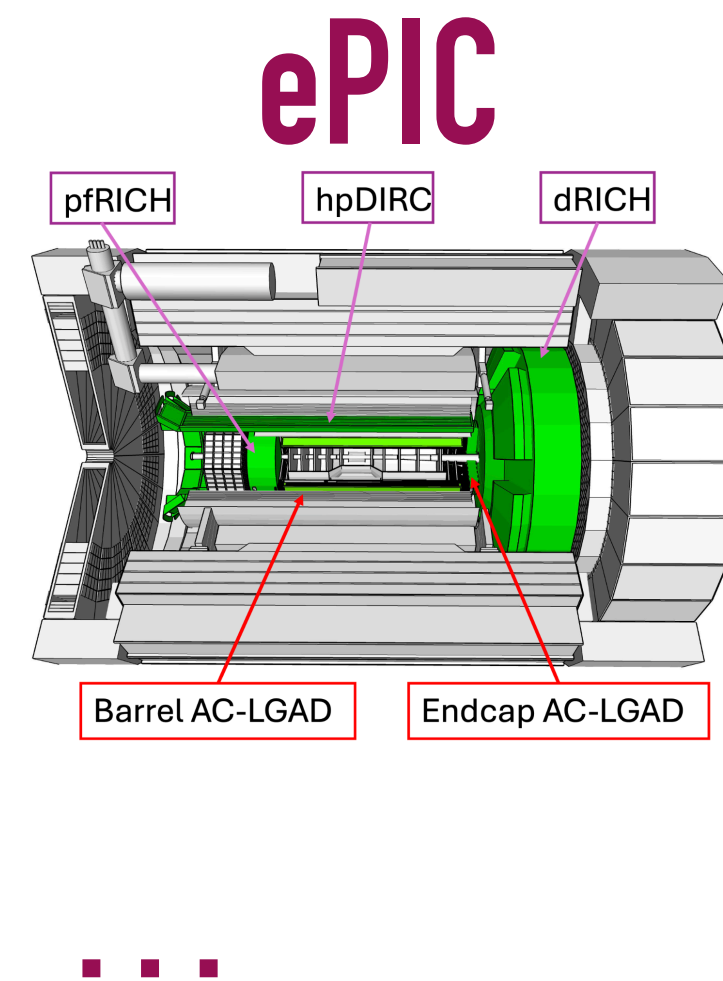
PID



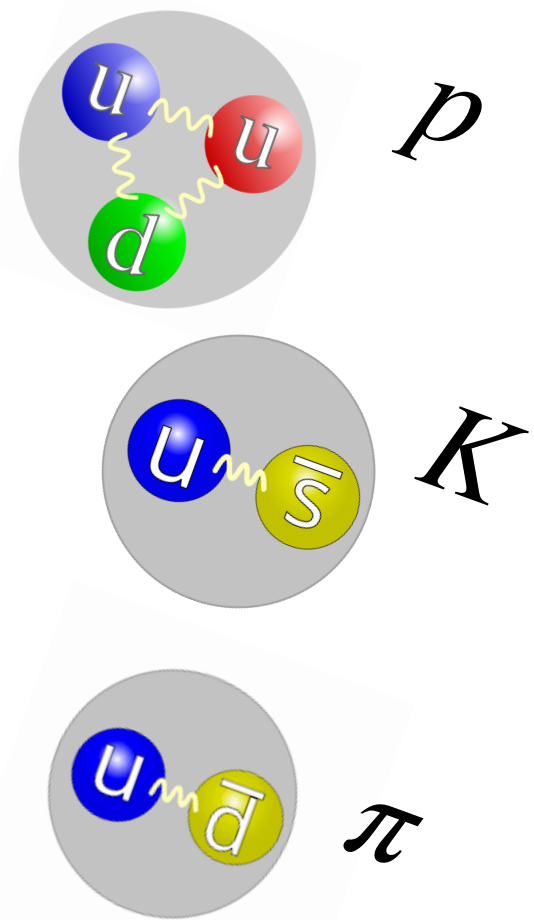
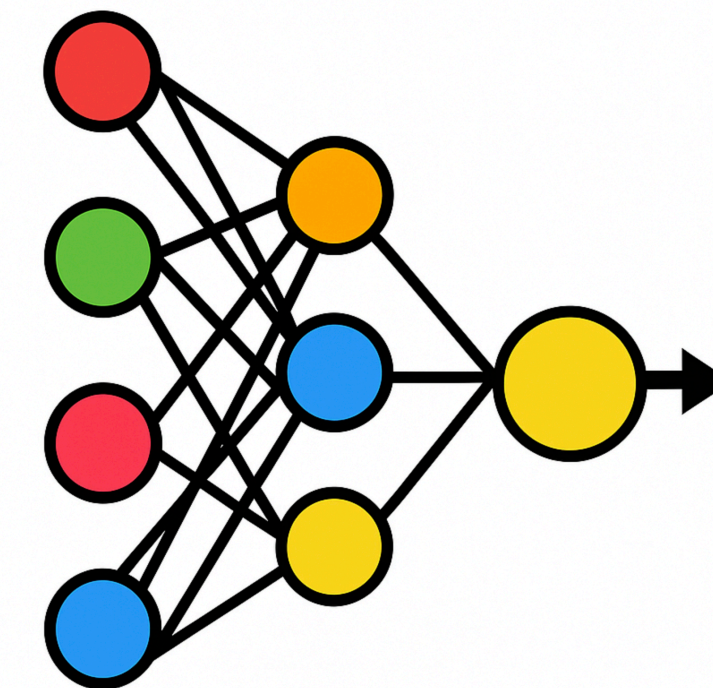
pfRICH

hpDIRC

dDRICH



$x_1$   
 $x_2$   
 $x_3$   
 $x_i$



This method can be extended to all ePIC PID subsystems

The more information available, the better the model will perform

# Conclusion

- **Promising separation** observed — clear distinction between particle species
- Overall, a solid step toward robust and reliable particle identification
- AI/ML methods can be generalized to all ePIC subsystems **See Dmitry's talk**

## Next steps:

- Optimize PID parameters + diffusion model (work in progress)
- Use data produced using NVIDIA OptiX and GDML-based detector geometries
- Generate true SIDIS events within the ePIC software **See Gabor's talk**

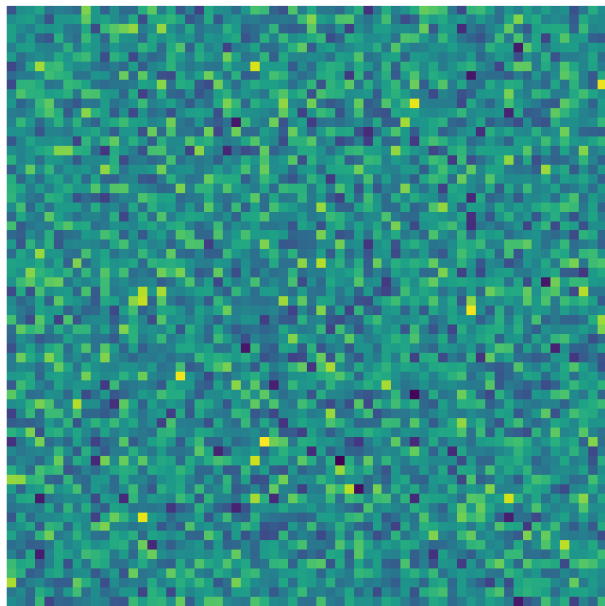




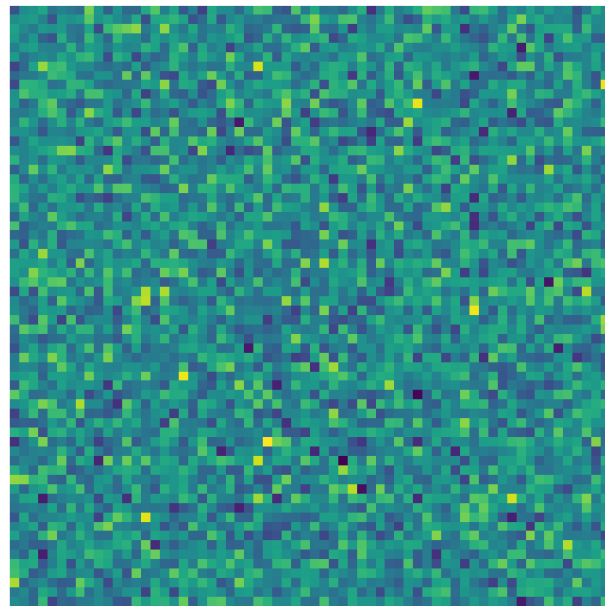
# Backup Slides

## Diffusion model (work ongoing)

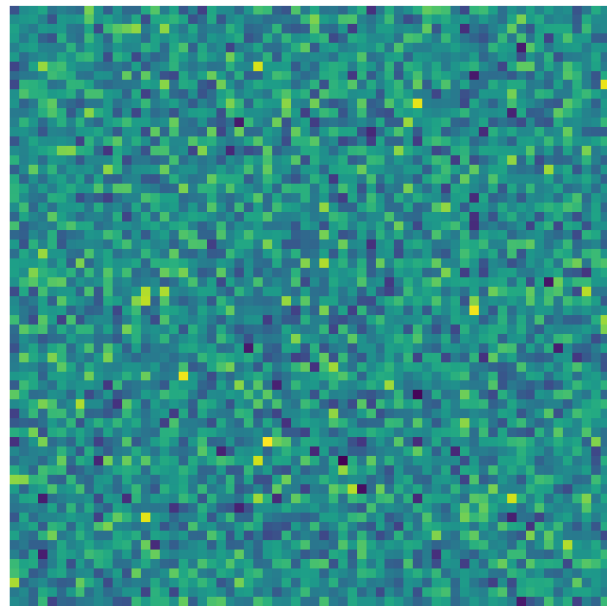
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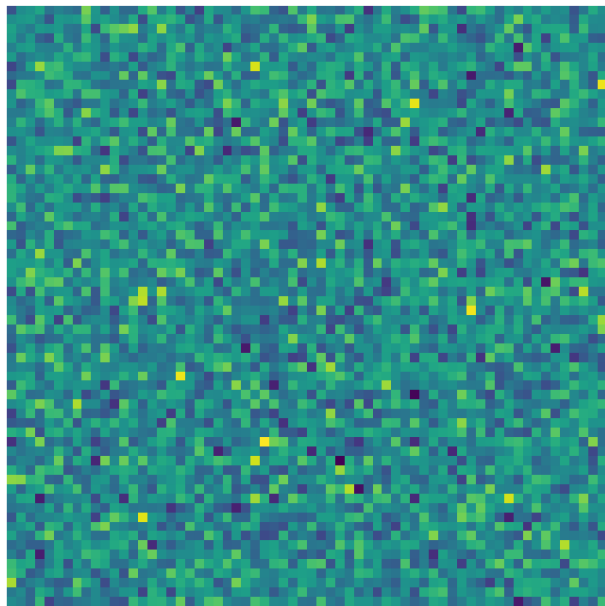
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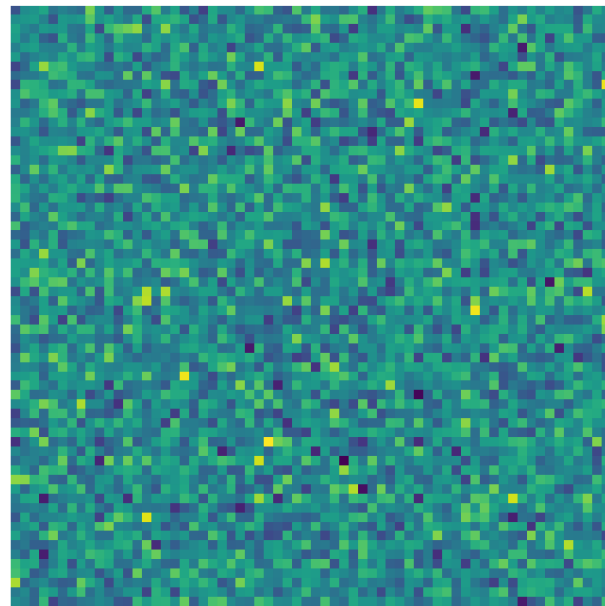
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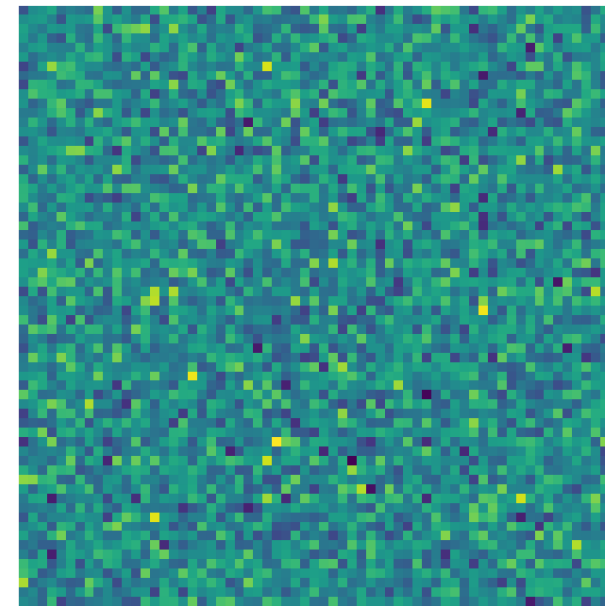
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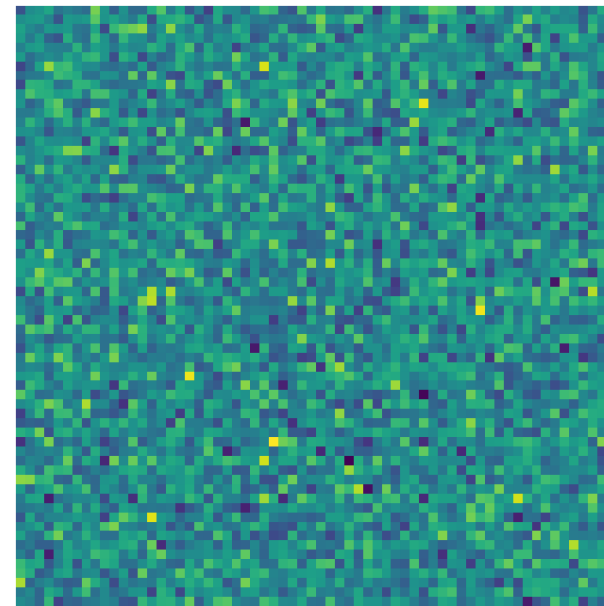
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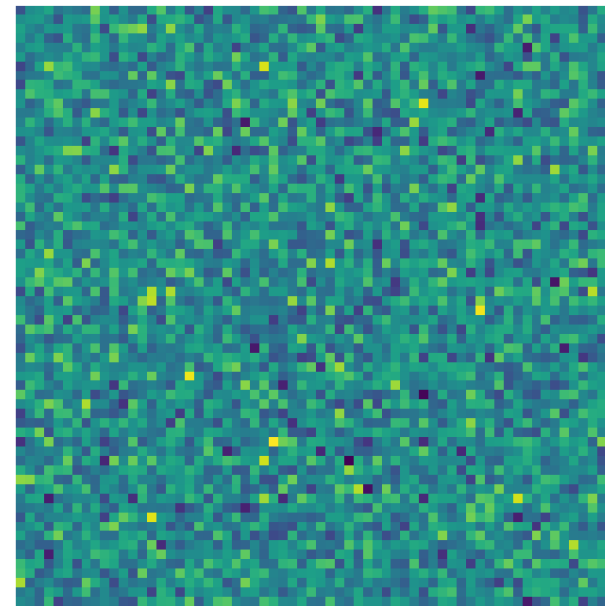
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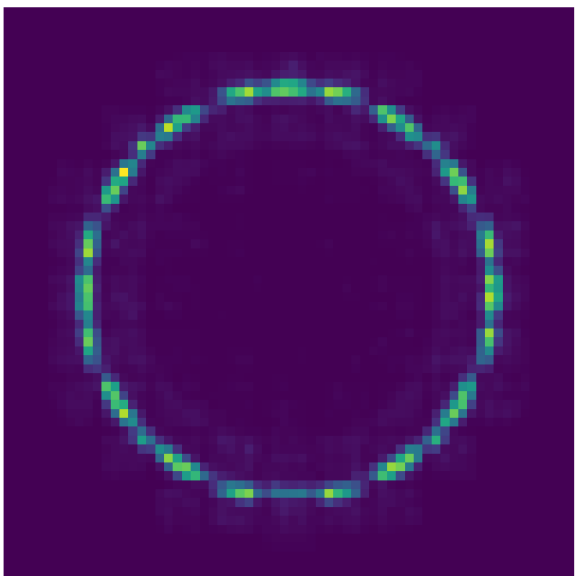
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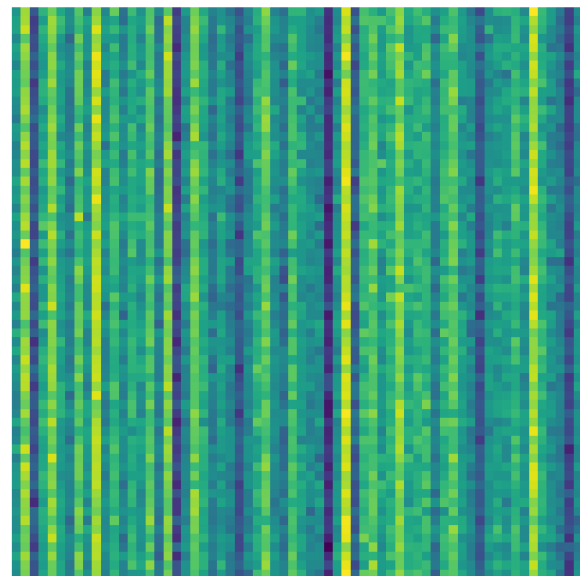
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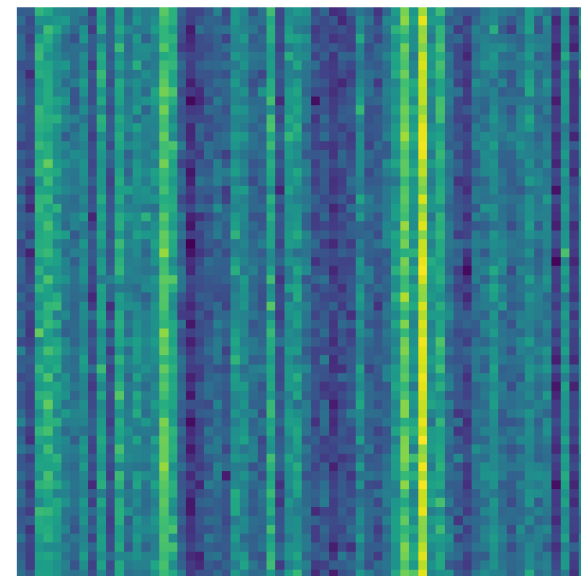
Original



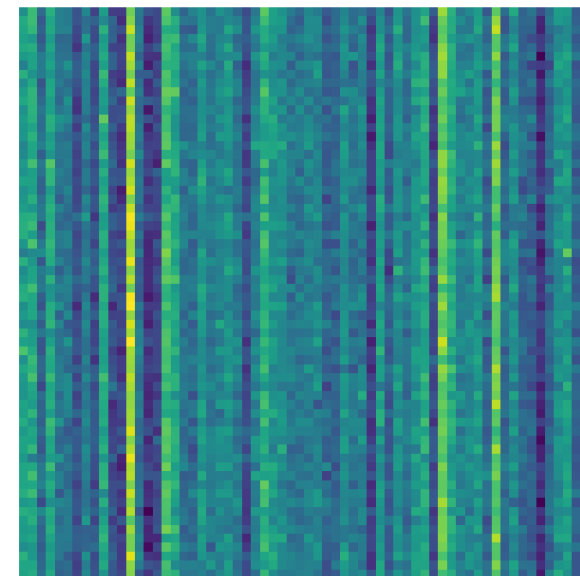
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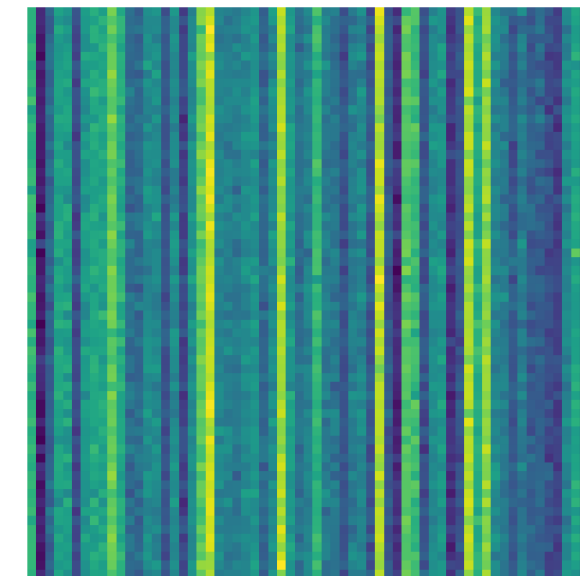
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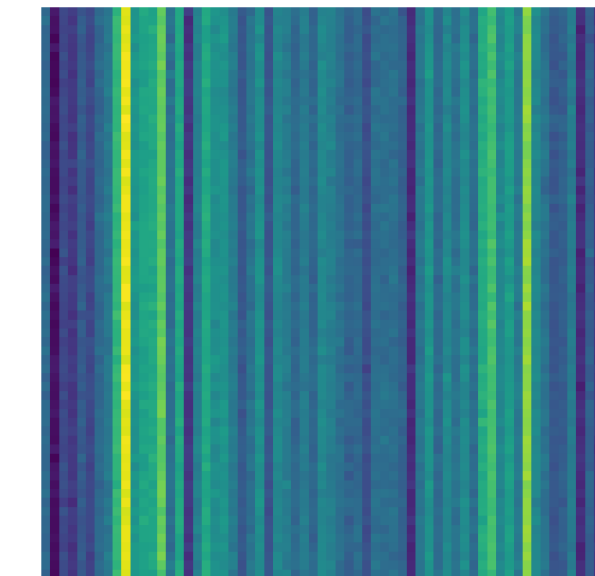
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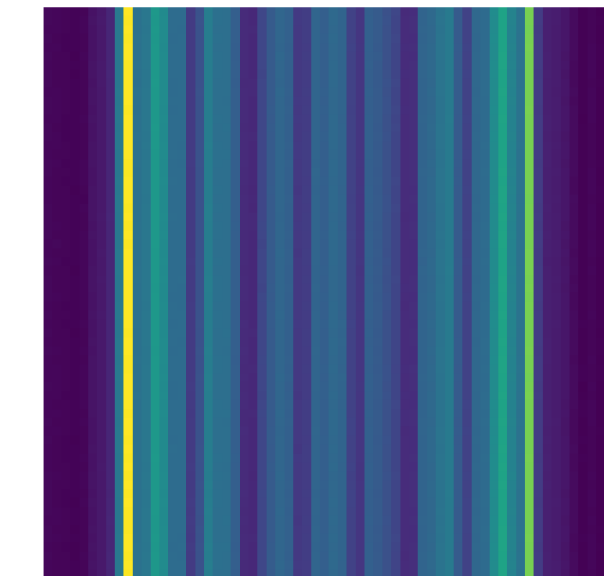
Denoised t=300



Denoised t=100



Denoised t=0



Final Denoised

