

# Machine learning in nuclear and particle physics

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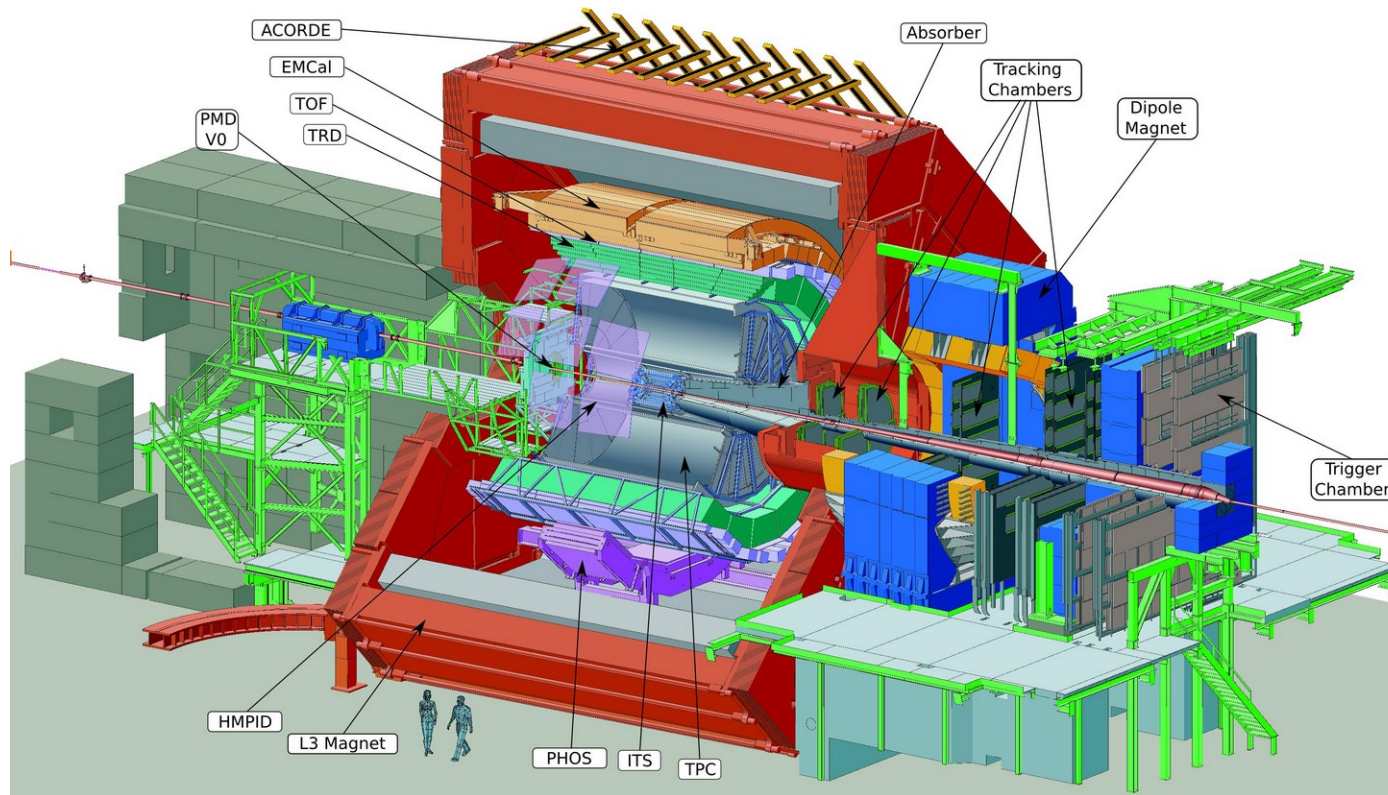
# Outlook

- **ML : particle identification**
- **GNN : particle tracking**
- **CNN : alpha decay in emulsion**
- **GAN : simulate emulsion reaction**
- **Mask R-CNN : hypernuclei finding in emulsion**

# ML for Particle Identification

# Particle identification : Random Forest

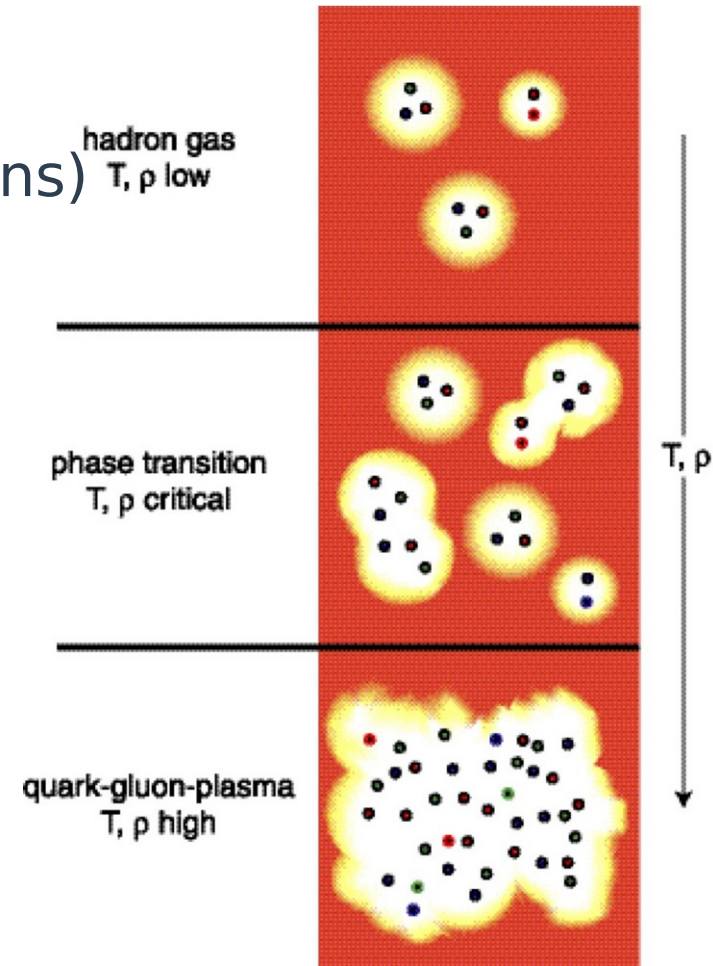
- **ALICE experiment :**
  - PID with TPC and TOF



# Particle identification : Random Forest

## QGP : Quark Gluon Plasma

- Hadron: described QCD (quarks & gluons)
- When heated or compressed
  - Overlap each others
- Quark and gluons move around in relatively large volume
- Phase transition between QGP and hadron gaz.



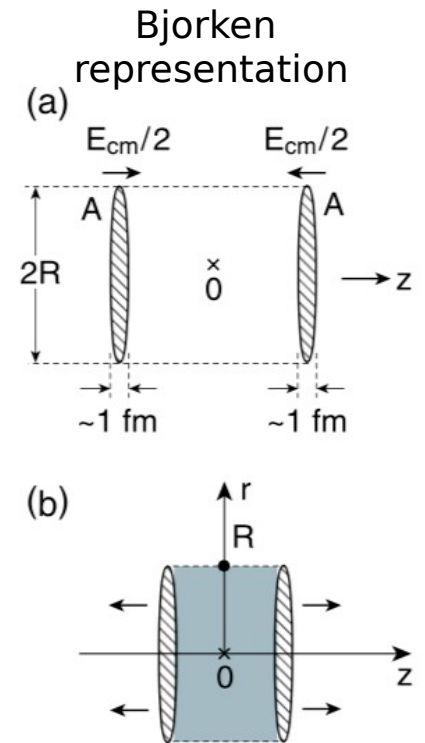
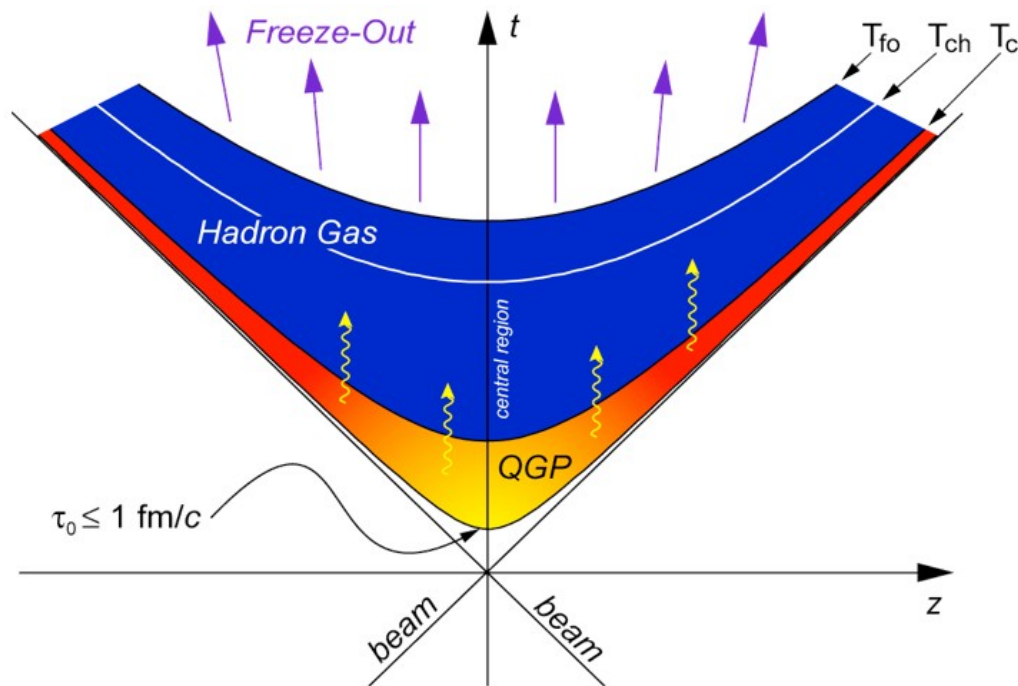
# Particle identification : Random Forest

- Features of the collisions at ALICE :

$$^{208}\text{Pb} + ^{208}\text{Pb} \sqrt{s_{NN}} = 2.76 \text{ TeV}$$

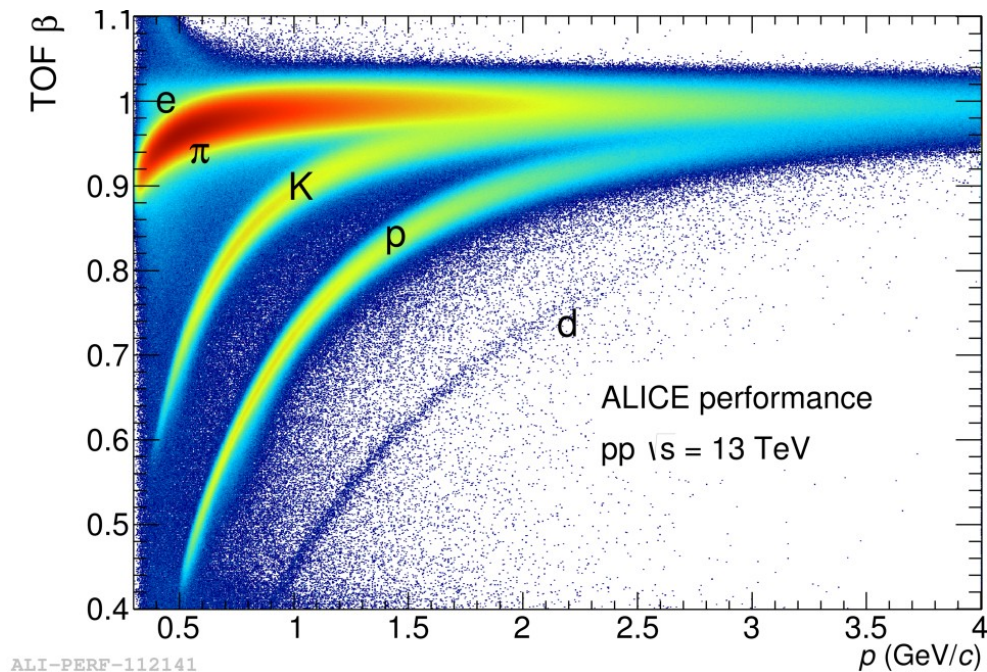
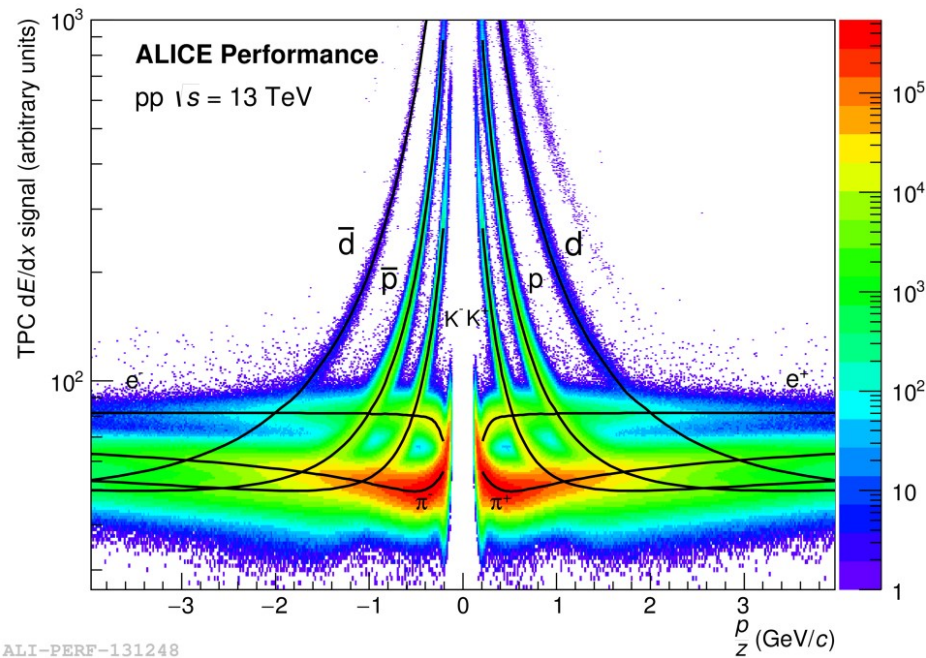
$$p + p \sqrt{s_{NN}} = 7 \text{ TeV}$$

$$p + ^{208}\text{Pb} \sqrt{s_{NN}} = 5.02 \text{ TeV}$$



# Particle identification : Random Forest

- **ALICE experiment :**
  - PID with TPC and TOF



# Particle identification : Random Forest

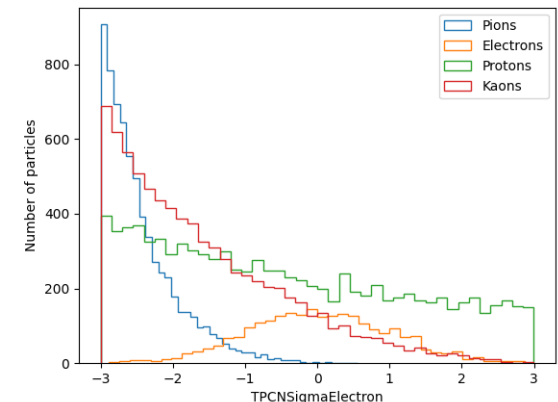
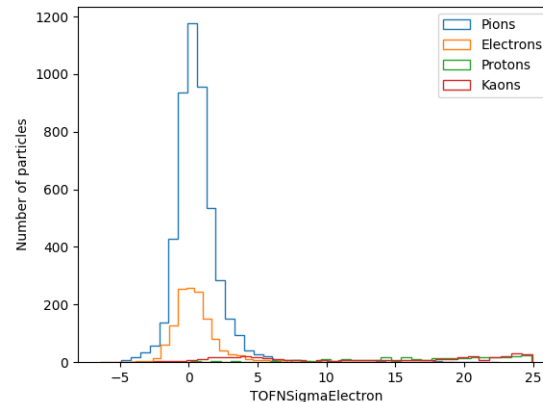
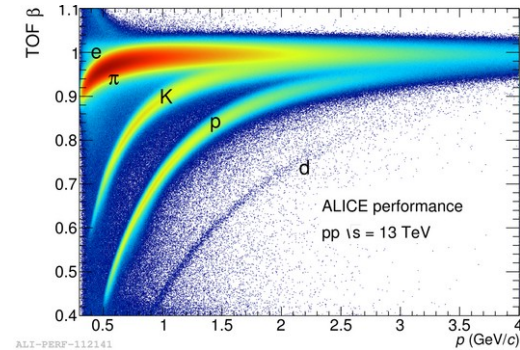
- Models of  $dE/dx$  vs  $p/q$  &  $\beta$  vs  $p/q$

$$\langle -\frac{dE}{dx} \rangle = K z^2 \frac{Z}{A} \frac{1}{\beta^2} \left[ \frac{1}{2} \ln \left( \frac{2 m_e c^2 \beta^2 \gamma^2 W_{max}}{I^2} \right) - \beta^2 - \frac{\delta(\beta \gamma)}{2} \right]$$

$$\beta = \frac{1}{\sqrt{m^2/p^2 + 1}}$$

- Considered features:

- $TOF N \sigma = \frac{TOF^{measured} - \langle TOF^{particle} \rangle}{\sigma_{TOF}}$        $dE/dx N \sigma = \frac{dE/dx^{measured} - \langle dE/dx^{particle} \rangle}{\sigma_{dE/dx}}$
- Multiplicities in detectors
- DCA to primary vertex





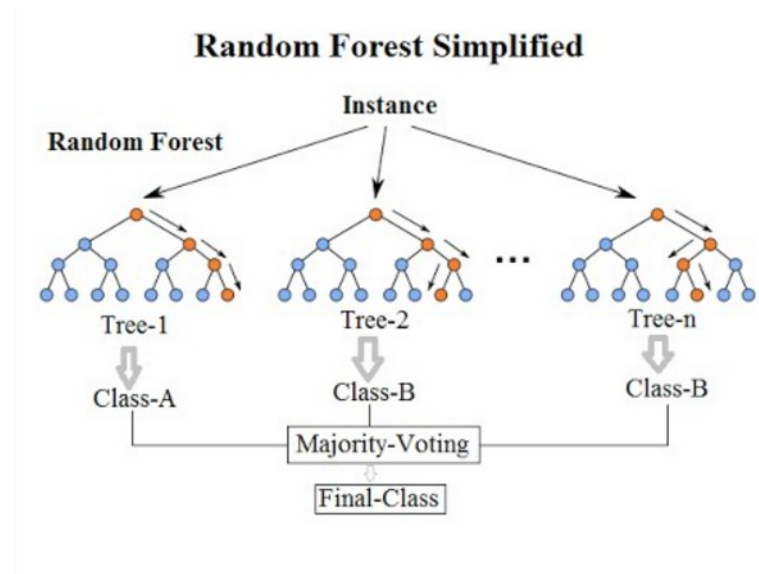
# Particle identification : Random Forest

- **Random Forest :**

- Create Decision Trees :

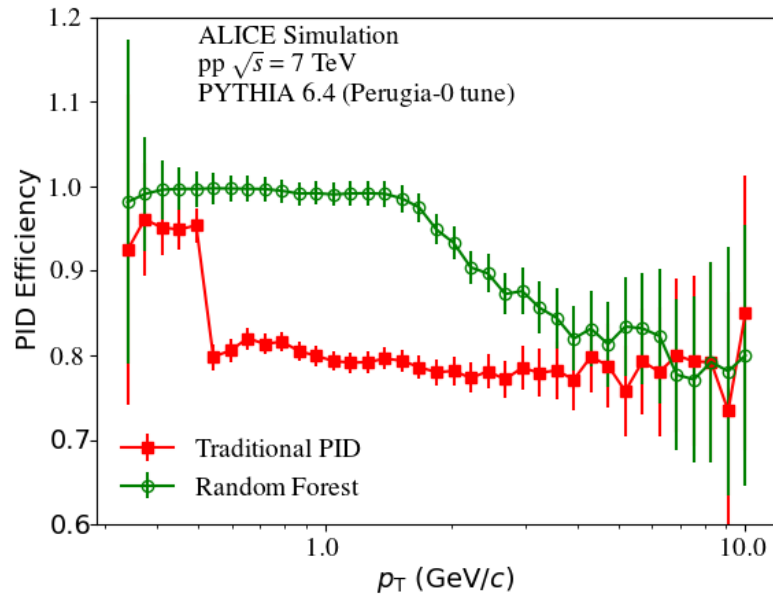
- Each decision tree → optimized on a random subset of features & *only* access to a random set of the training data
    - increases diversity in the forest → more robust prediction

- Final classification → vote

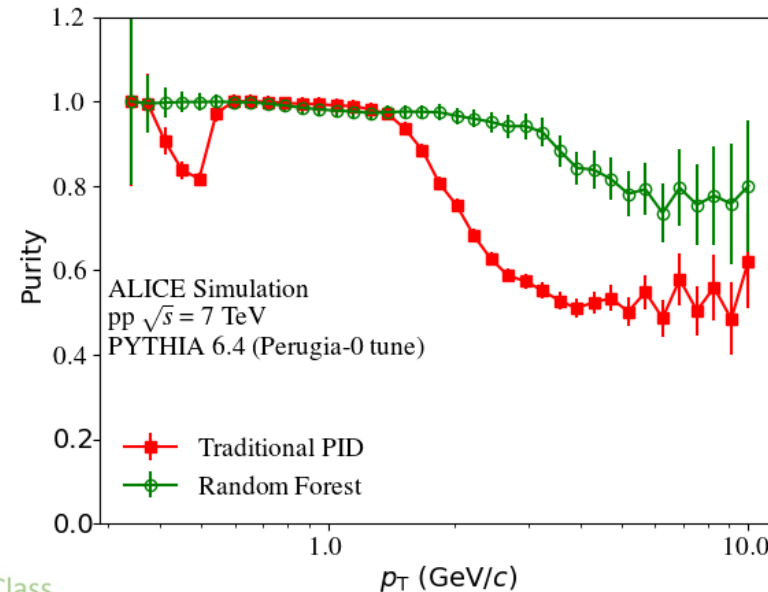


# Particle Identification : Random Forest

## • Results:



Kaon class



$$\text{Efficiency} = \text{TP} / \text{P}$$

		True Class	
		Positive	Negative
Predicted Class	Positive	TP	FP
	Negative	FN	TN

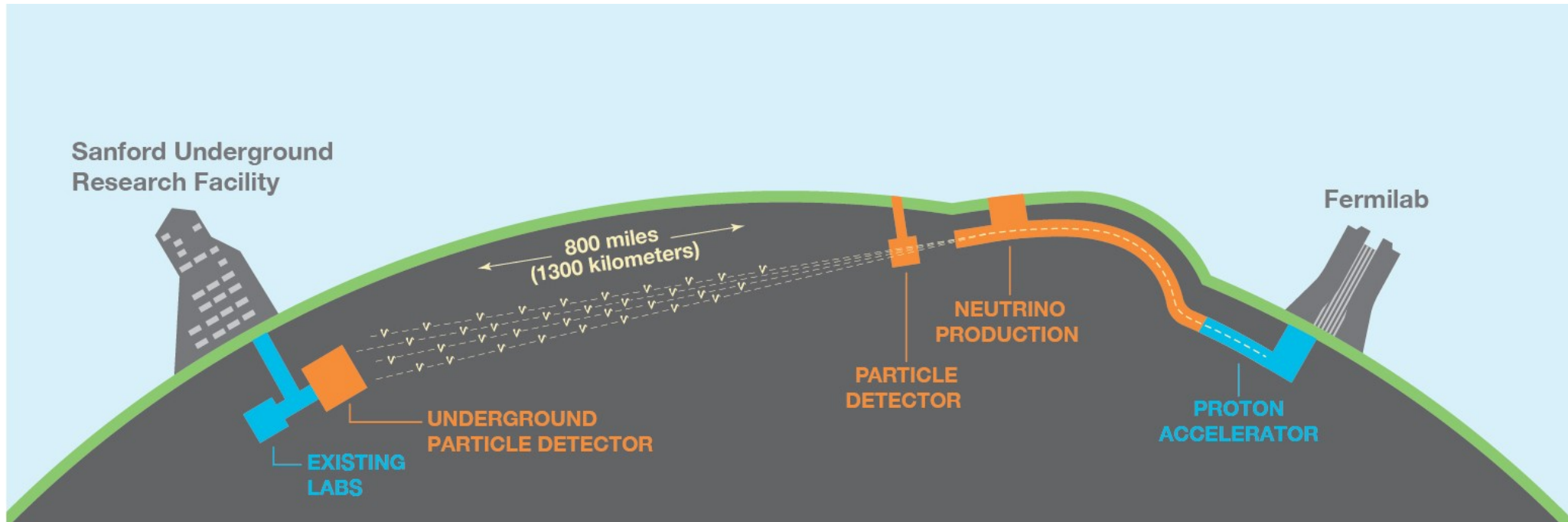
$$\text{Purity} = \text{TP} / (\text{TP} + \text{FP})$$

# DL in Particle Tracking

# Particle tracking : Graph Neural Network

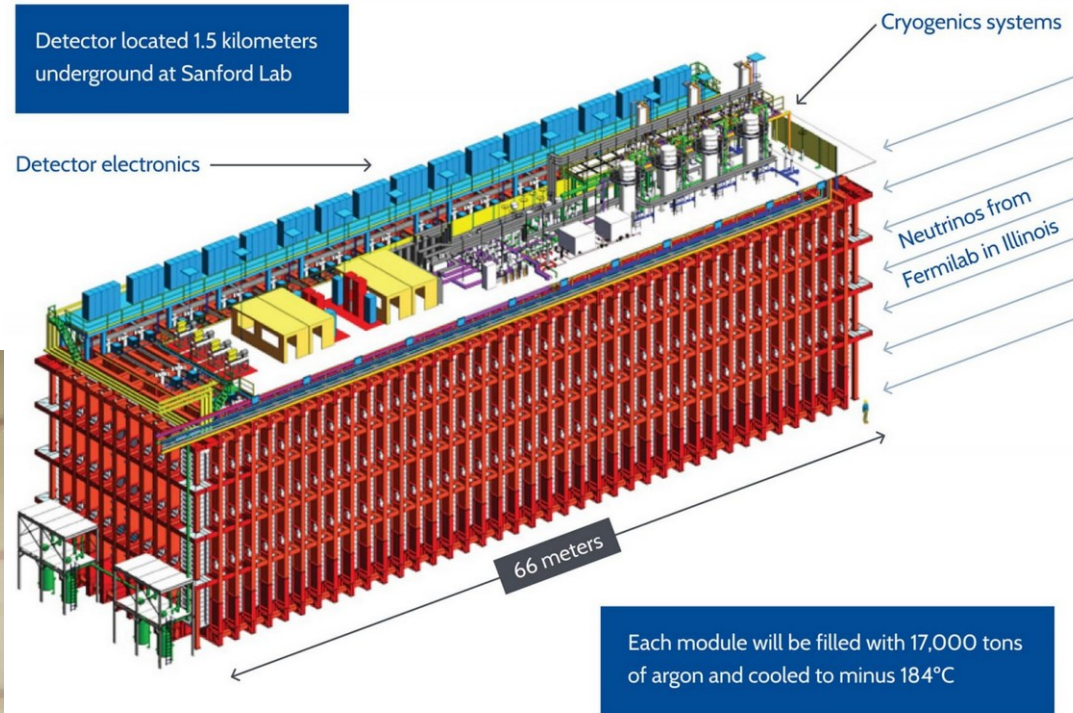
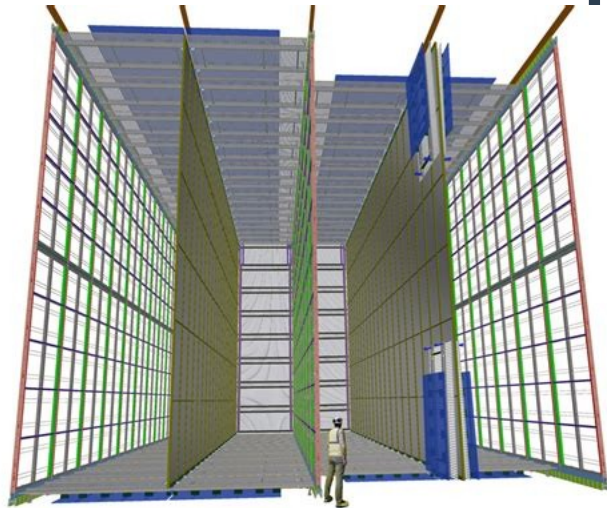
In accelerator-based neutrino oscillation experiments at Fermilab:

Proton beam (120 GeV)  $\rightarrow$   $\pi^+$  beam (10GeV) :  $\pi^+ \rightarrow \mu^+ + \nu_\mu$



# Particle tracking : Graph Neural Network

- The DUNE experiment: Liquid Argon TPC



# Particle tracking : Graph Neural Network

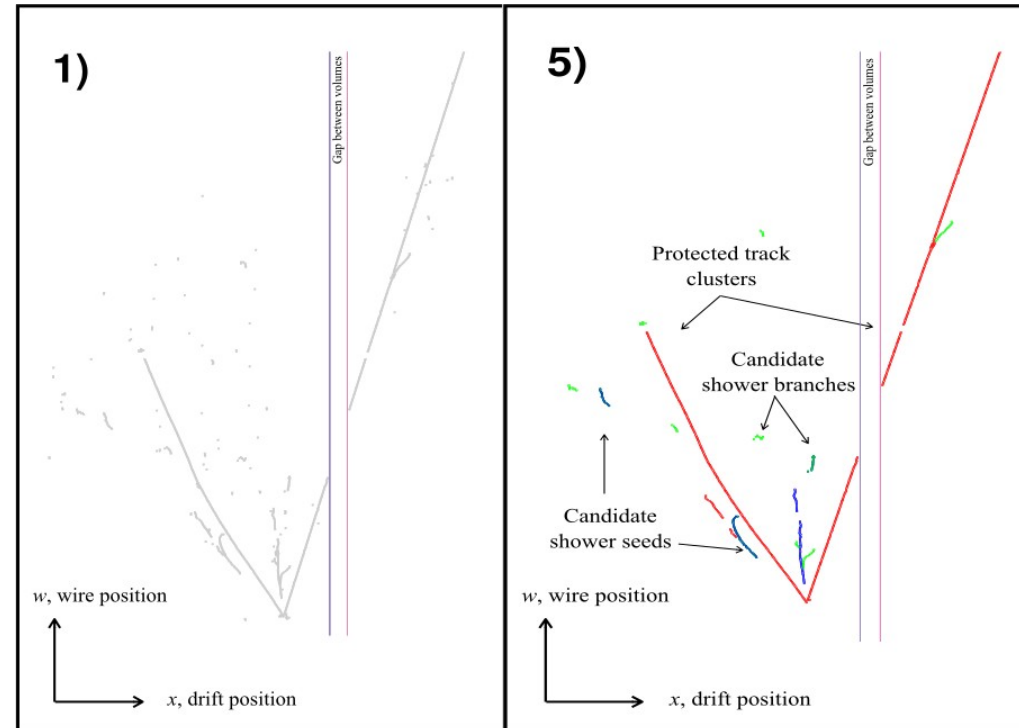
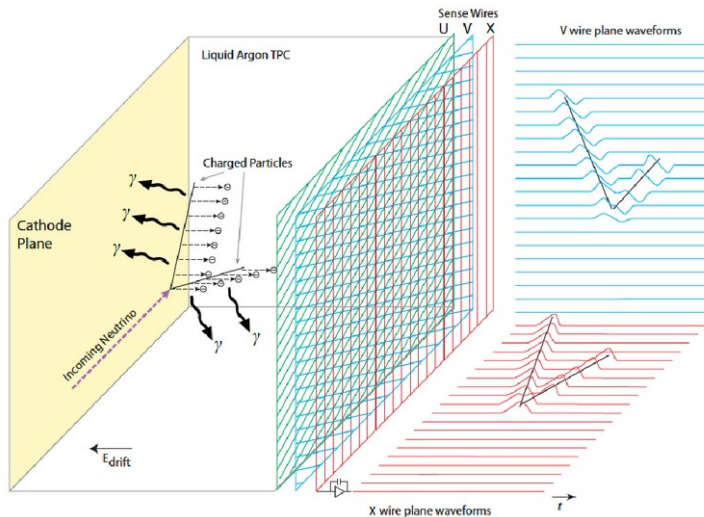
- **Type interaction :**

- Neutrino oscillation  $\nu_\mu / \bar{\nu}_\mu \rightarrow \nu_e / \bar{\nu}_e$  Interact in LArTPC

- Electromagnetic shower :

$$\gamma \rightarrow e^- e^+ \rightarrow \gamma \gamma \rightarrow \dots$$

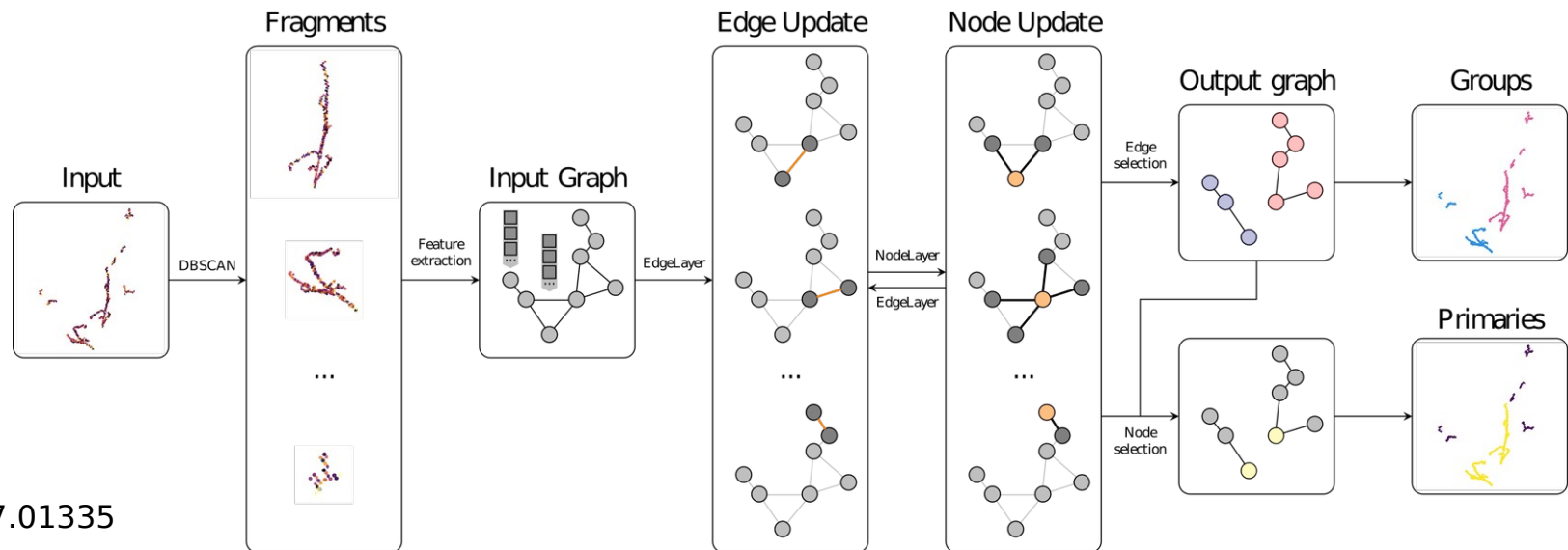
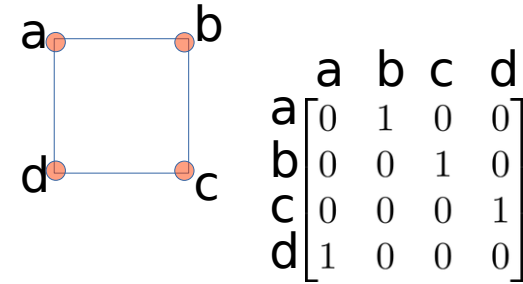
- Tracks ( $p, \pi, \mu$ )



# Particle tracking : Graph Neural Network

- **Graph neural network:**

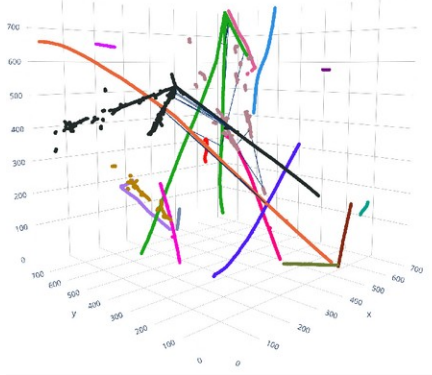
- CNN + network embedding.
  - CNN → receptive field in local spatial features
  - Networks & graph → generalize to arbitrary object
- CNN : conv filter → locality / Graph : adjacency matrix → object relationships



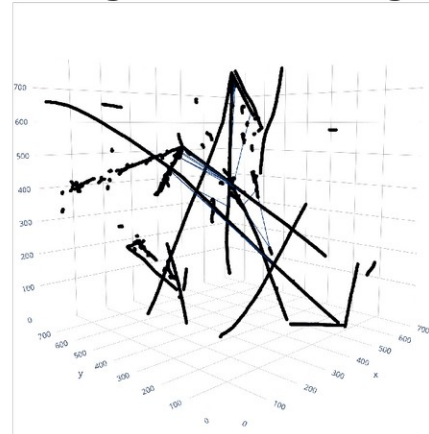
# Particle tracking : GNN

- **Achieved efficiency and purity :  $> 99\%$  !**

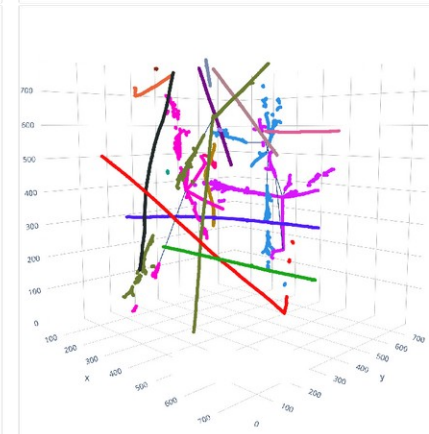
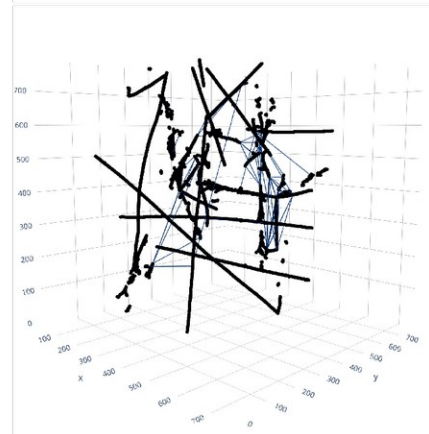
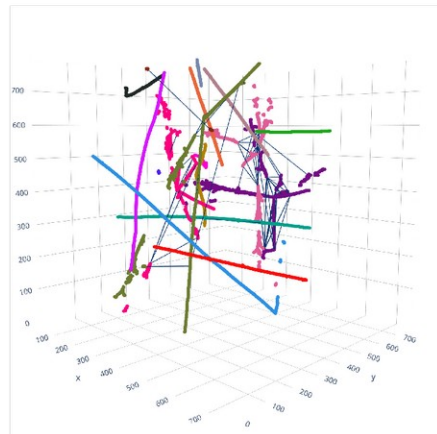
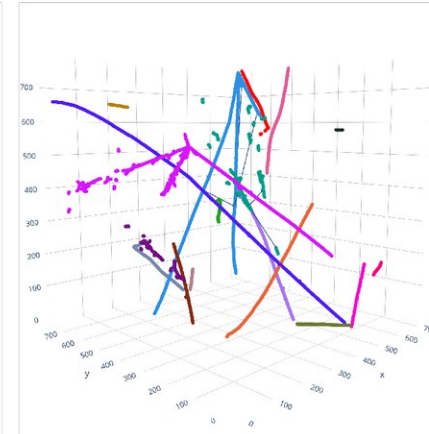
True event



Edge clustering



Classification & edge selection





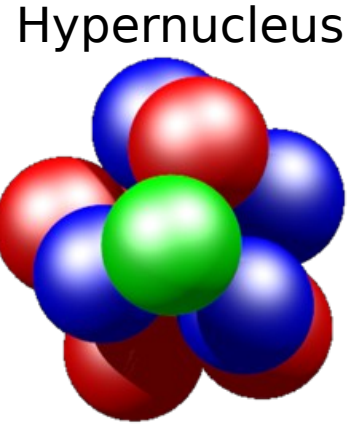
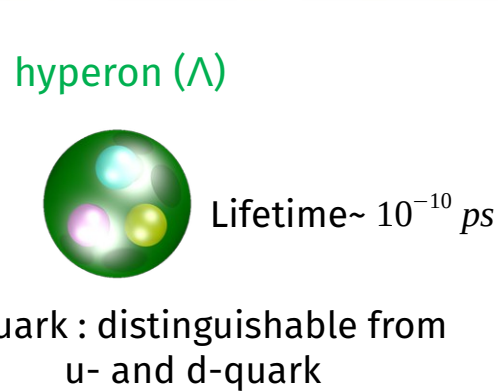
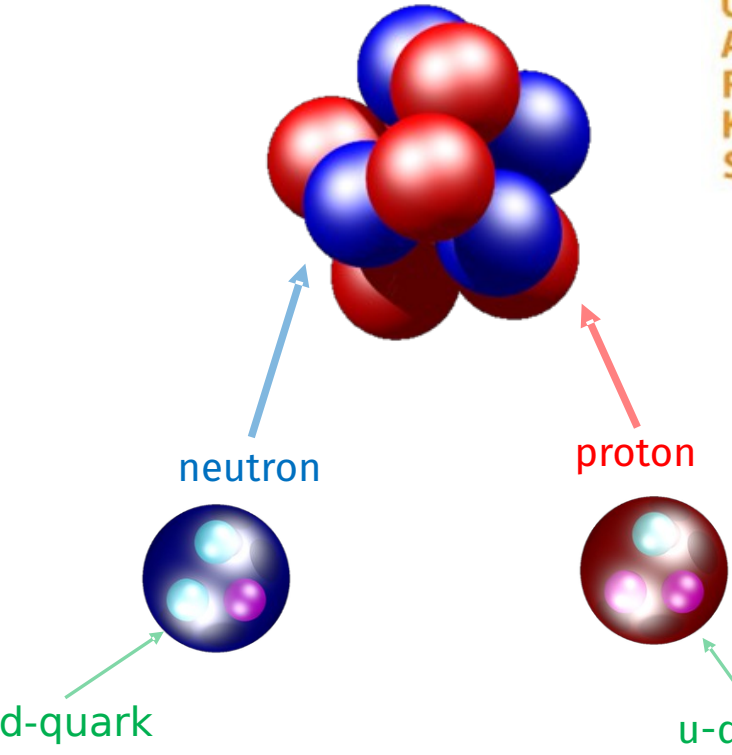
# Particle tracking : GNN

- Hypernuclear study:

QUARKS

<b>UP</b> mass 2,3 MeV/c <sup>2</sup> charge 2/3 spin 1/2 	<b>CHARM</b> 1,275 GeV/c <sup>2</sup> 2/3 1/2 	<b>TOP</b> 173,07 GeV/c <sup>2</sup> 2/3 1/2 
<b>DOWN</b> 4,8 MeV/c <sup>2</sup> -1/3 1/2 	<b>STRANGE</b> 95 MeV/c <sup>2</sup> -1/3 1/2 	<b>BOTTOM</b> 4,18 GeV/c <sup>2</sup> -1/3 1/2 

Hyperon	Quarks	$I(J^P)$	Mass (MeV)
$\Lambda$	uds	0(1/2 <sup>+</sup> )	1115
$\Sigma^+$	uus	1(1/2 <sup>+</sup> )	1189
$\Sigma^0$	uds	1(1/2 <sup>+</sup> )	1193
$\Sigma^-$	dds	1(1/2 <sup>+</sup> )	1197
$\Xi^0$	uss	1/2(1/2 <sup>+</sup> )	1315
$\Xi^-$	dss	1/2(1/2 <sup>+</sup> )	1321
$\Omega^-$	sss	0(3/2 <sup>+</sup> )	1672

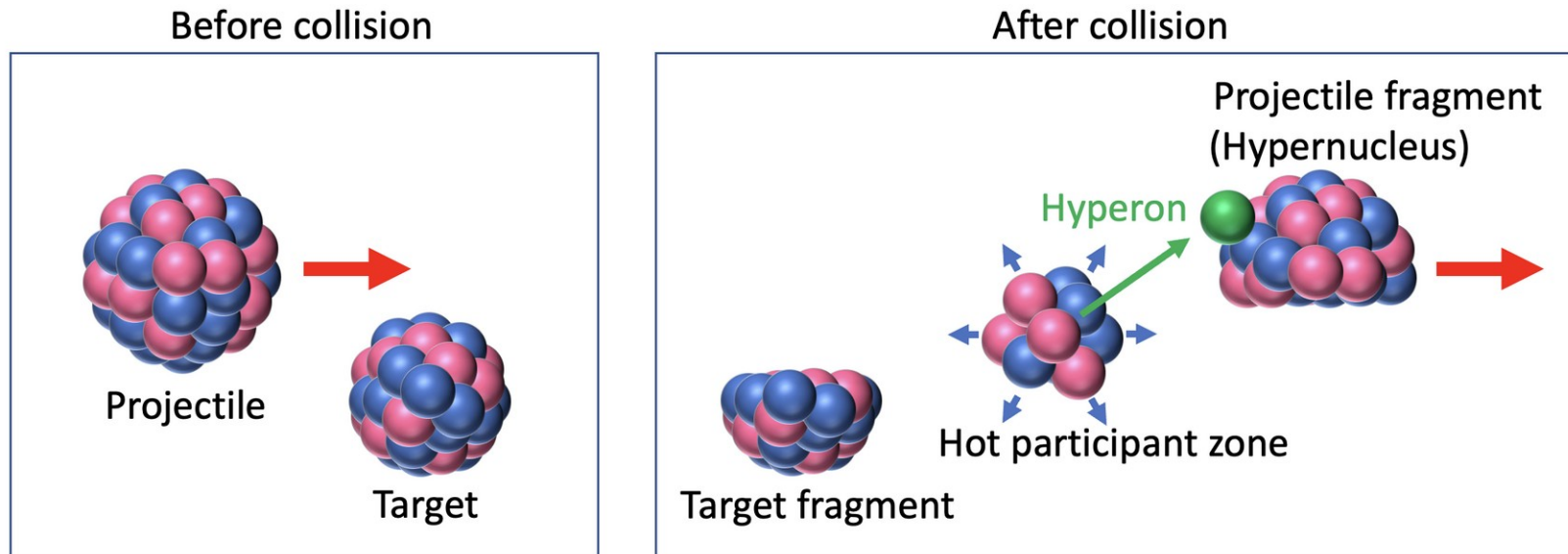


Micro-lab for study Baryon interactions

# Particle tracking : GNN

- **Hypernuclear production in heavy ion collisions:**

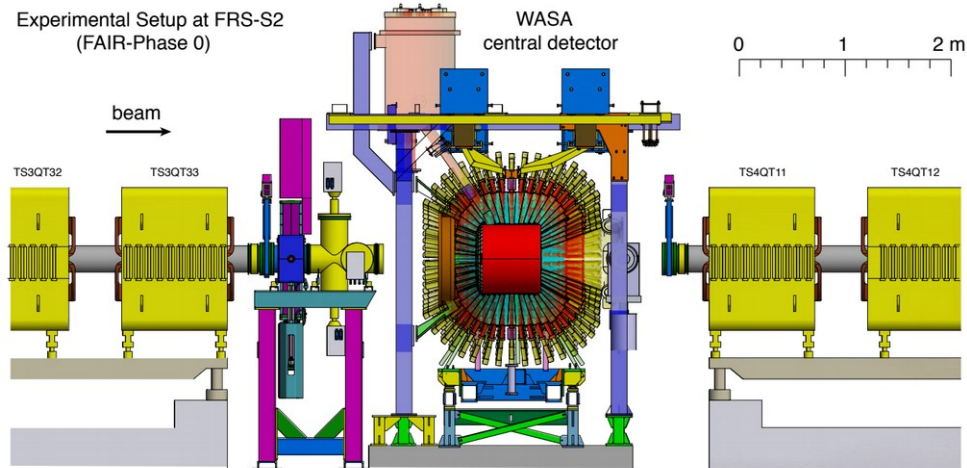
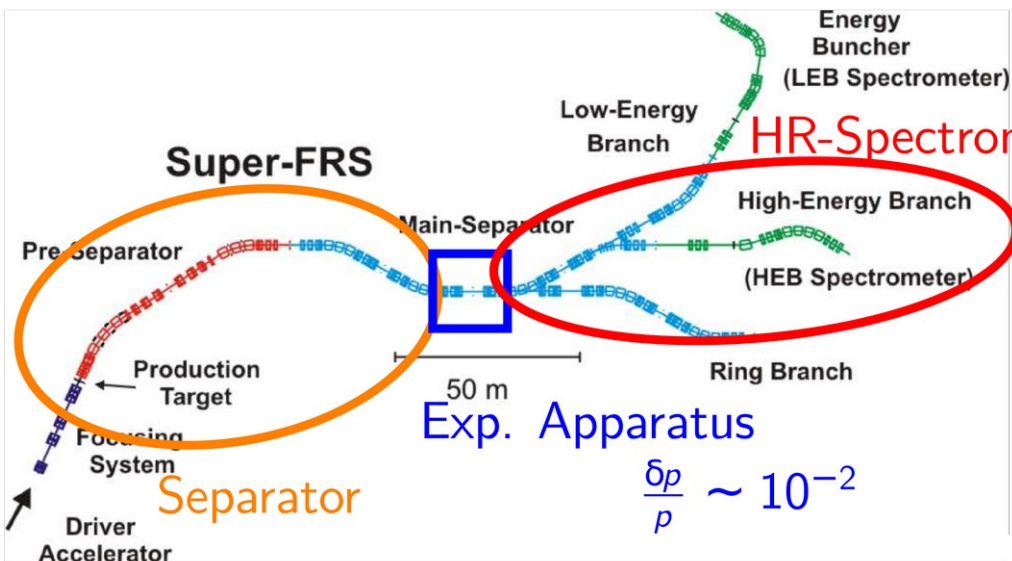
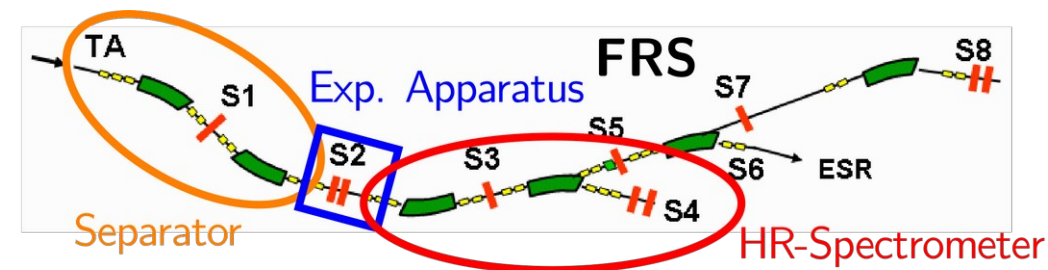
- $NN \rightarrow \Lambda KN$   $E_{th} \sim 1.6$  GeV : Beam  $> E_{th}$  : available at GSI (2 AGeV)



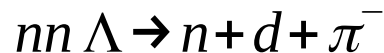
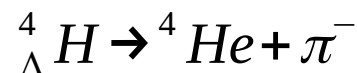
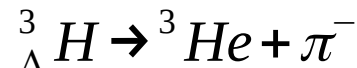
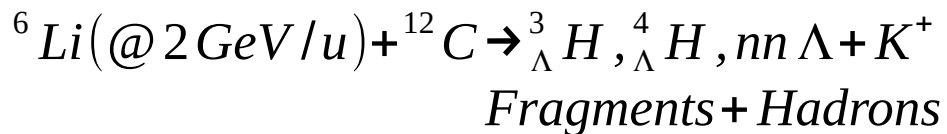
- Coalescence of  $\Lambda$  in spectator fragment
  - same velocity than projectile: Lorentz Boosted
  - study Hypernuclei in flight

# Particle tracking : GNN

- Hypernuclear study our WASA-FRS experiment:

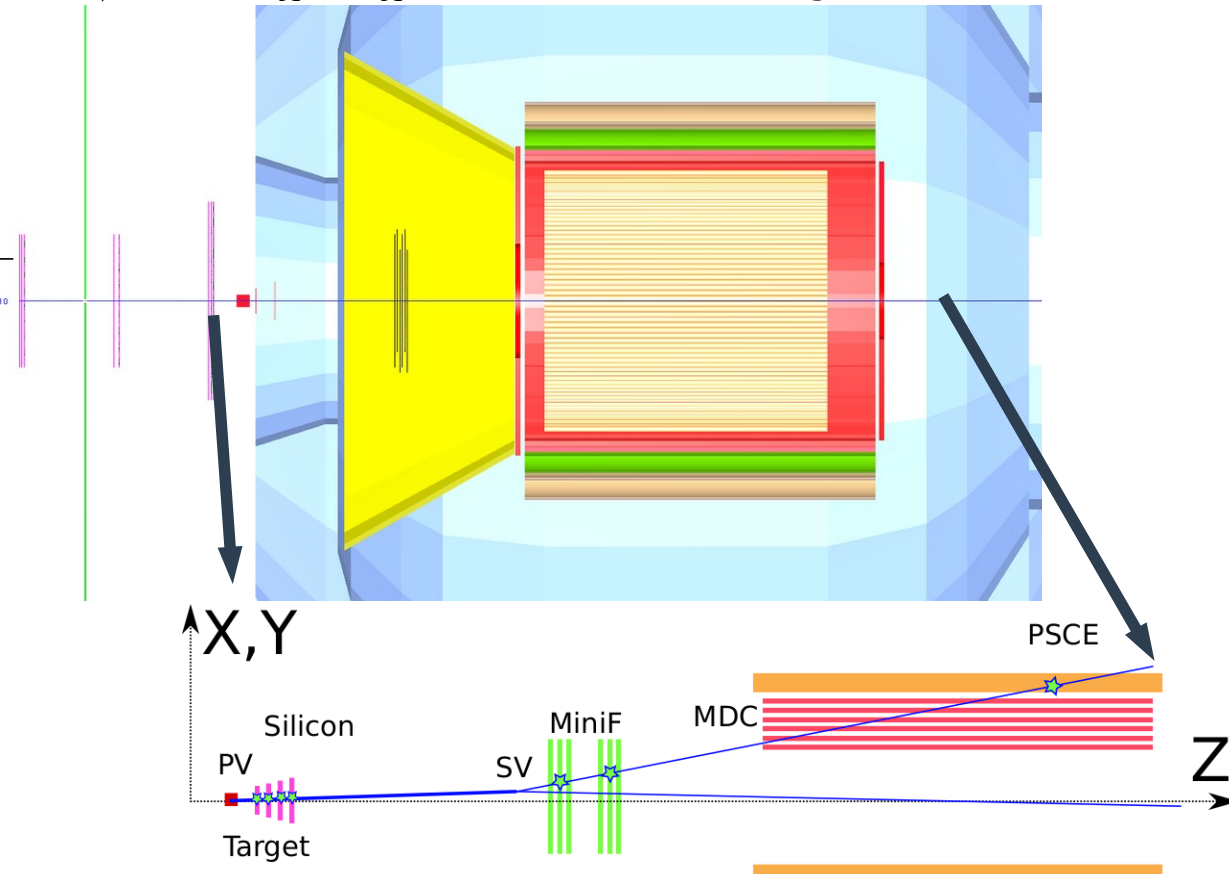
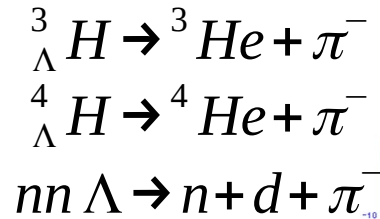
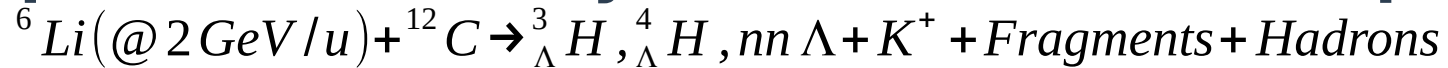


$$\frac{\delta p}{p} \sim 10^{-3}$$



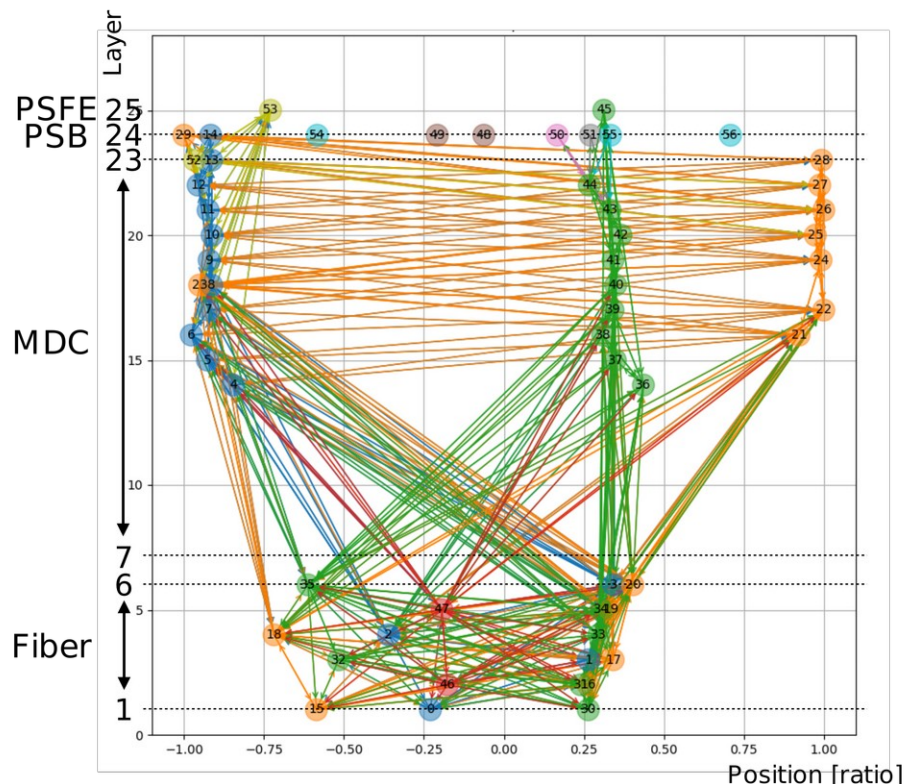
# Particle tracking : GNN

- **Hypernuclear study in our WASA-FRS experiment:**



# Particle tracking : GNN

- Study of Hypernuclei in our WASA-FRS experiment:

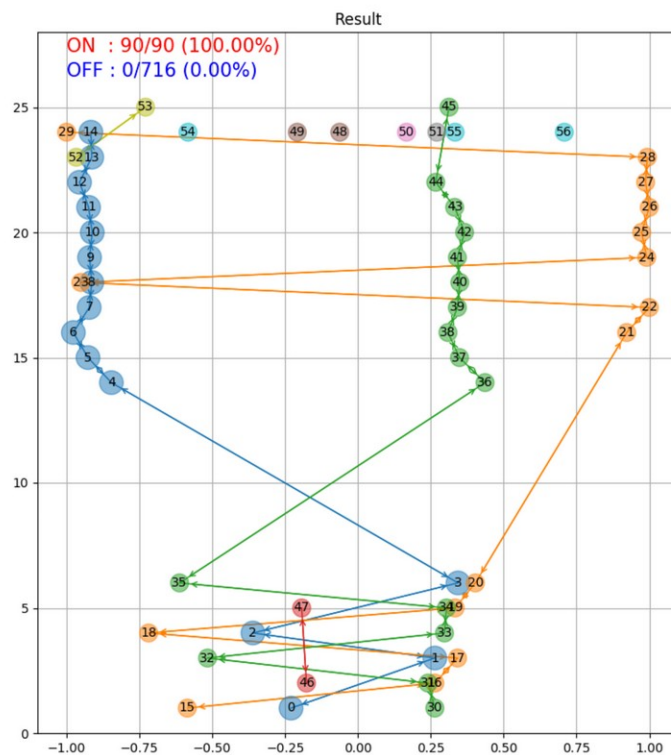


$\pi^-$  (perfect)

98.09 %

$\pi^-$  (valid)

99.92 %



Other (perfect)

97.05 %

Other (valid)

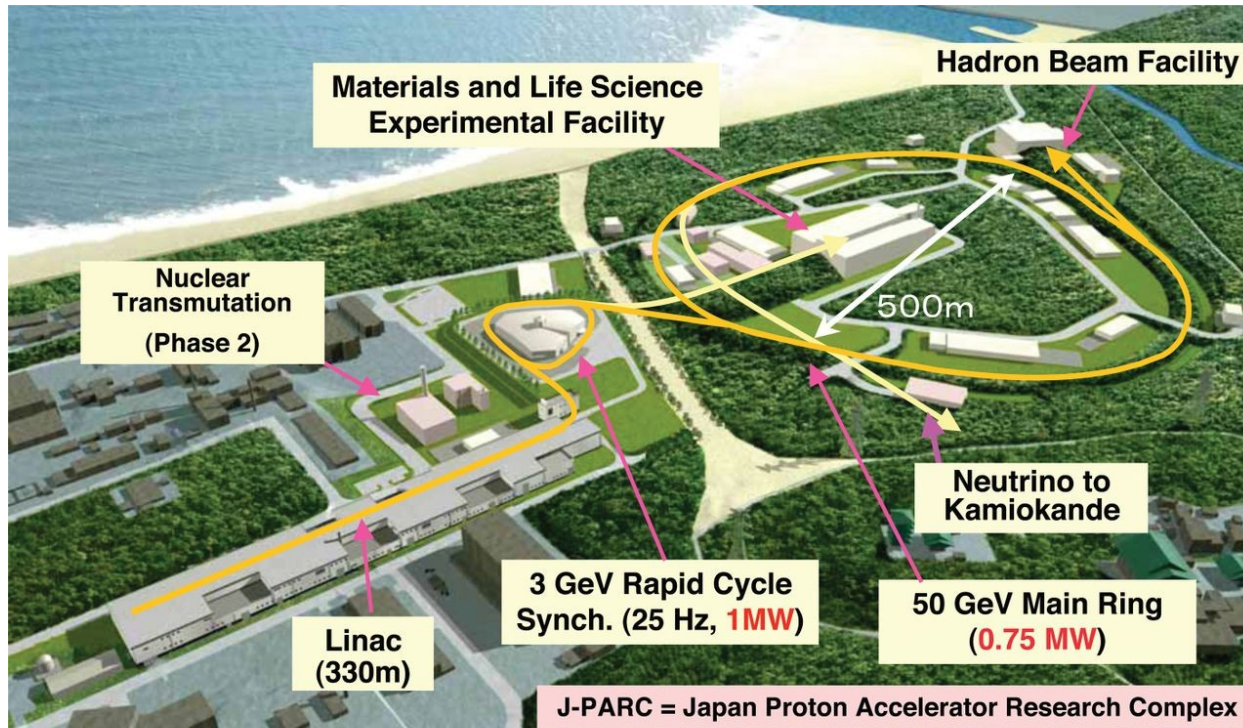
99.07 %

# DL in emulsion analysis

# Finding hypernuclei in emulsion : MaskCNN

- **J-PARC E07 experiment :**

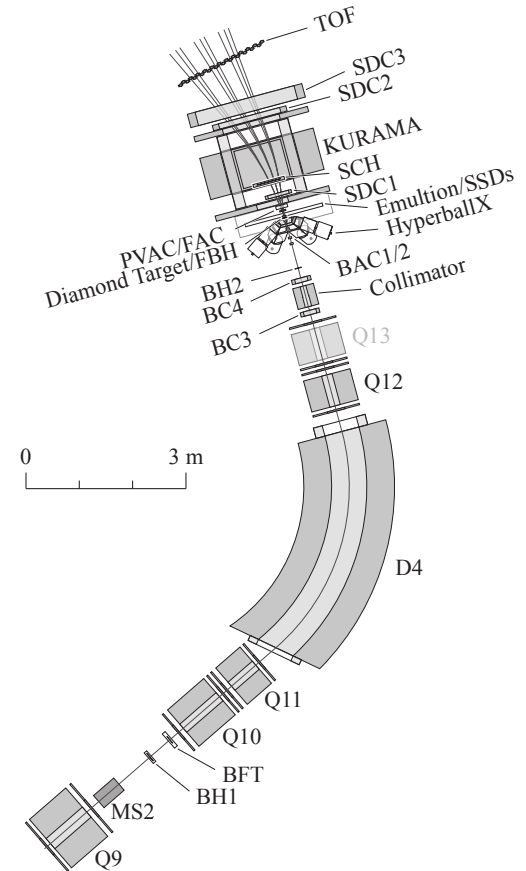
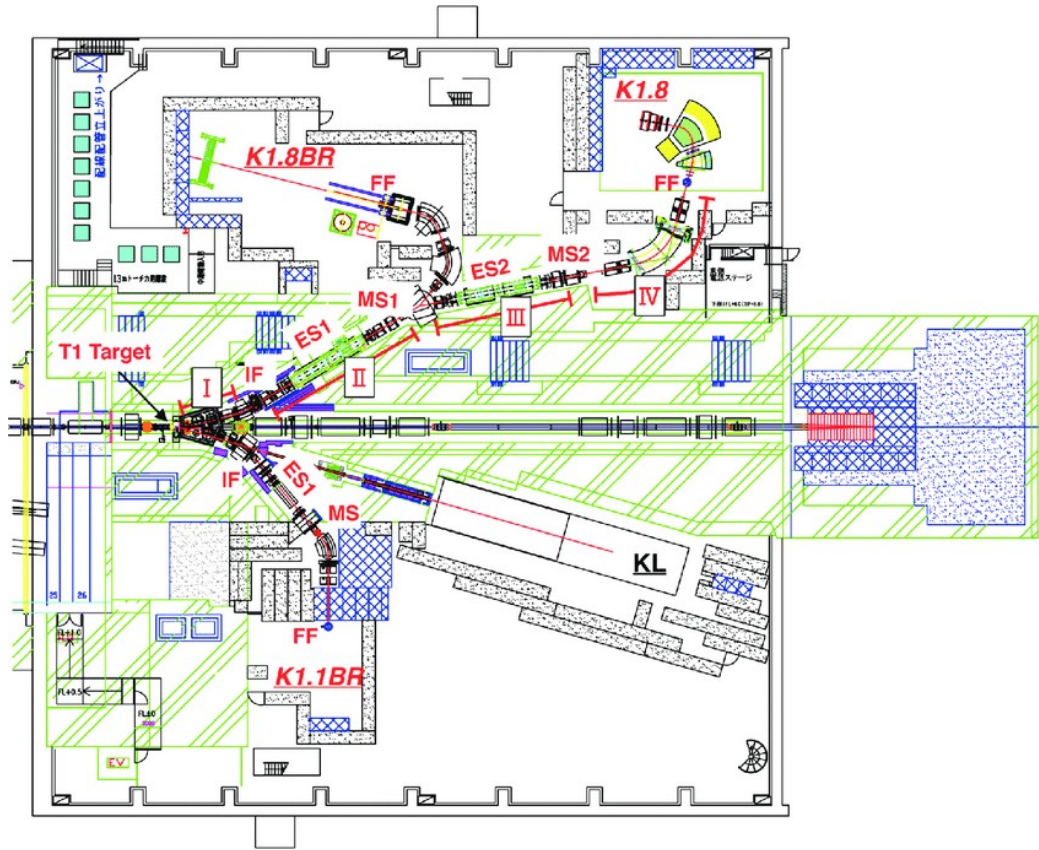
- J-PARC : Japan Proton Accelerator Research Complex



Joint Project between KEK and JAEA

# Finding hypernuclei in emulsion : MaskCNN

- J-PARC E07 experiment : at K1.8 beam line

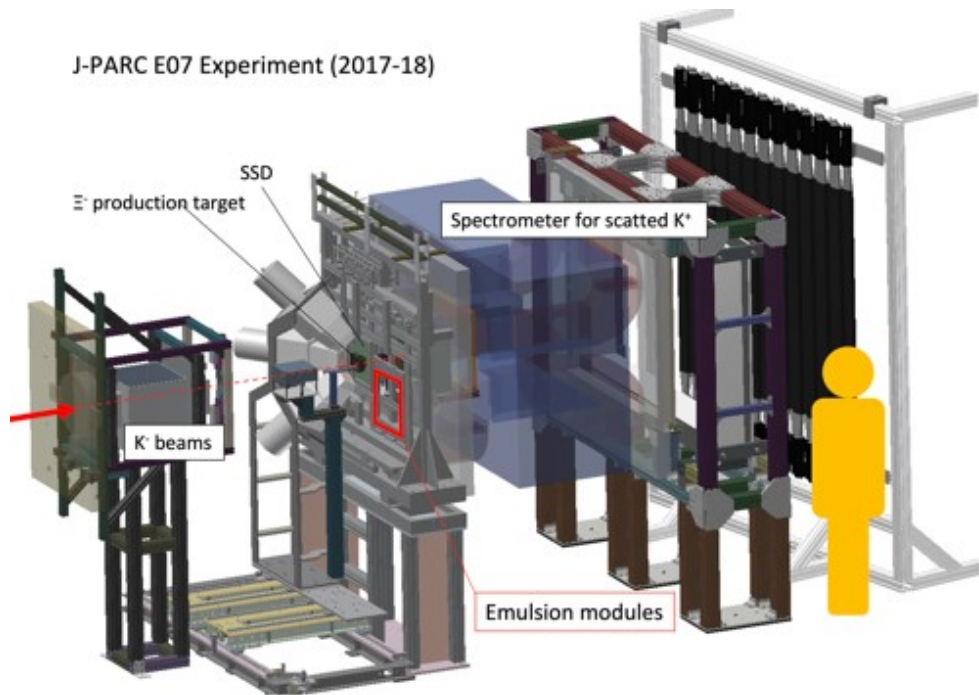




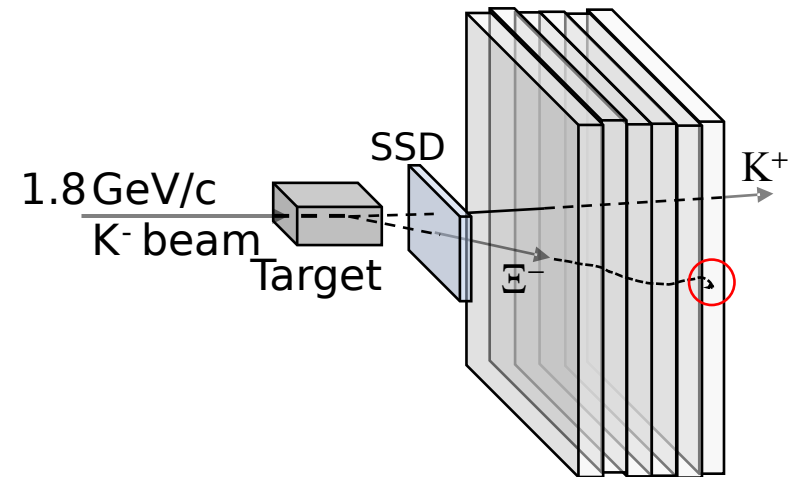
# Finding hypernuclei in emulsion : MaskCNN

- **J-PARC E07 experiment**

- Study of double-strangeness hypernuclei
- **Hybrid methods** : Triggered detectors + nuclear emulsions

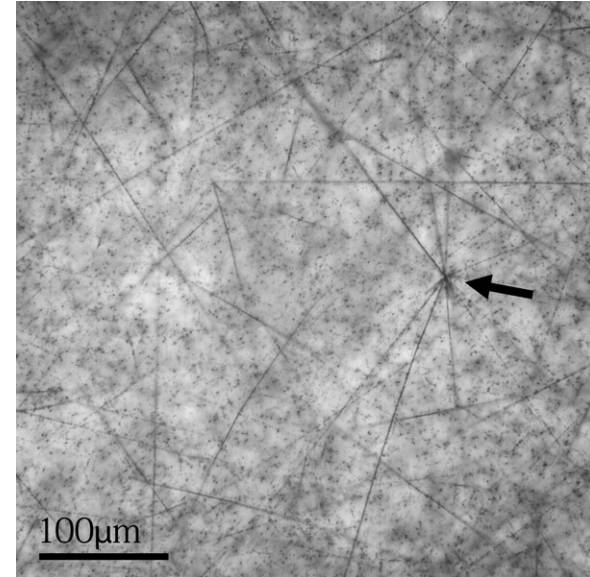
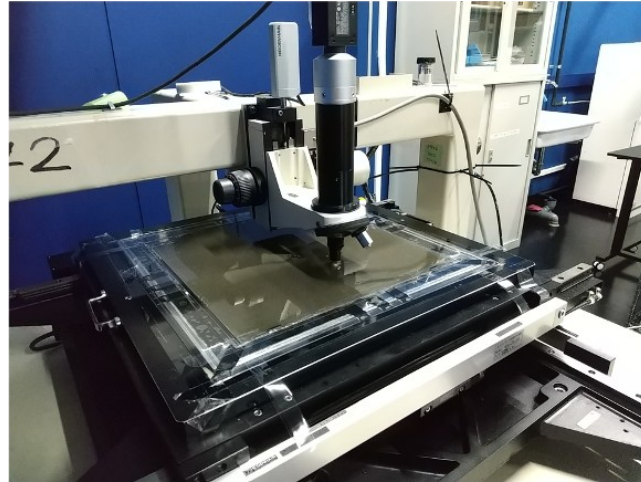


Triggers by the observation of (K-, K+) reactions



# Finding hypernuclei in emulsion : MaskCNN

- Scanning methods :



# Finding hypernuclei in emulsion : MaskCNN

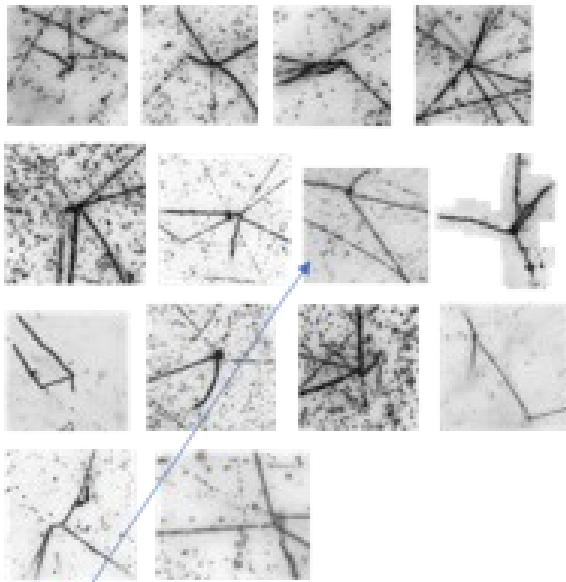
- **Current outcome of E07:**

- Triggered events :  $\Xi^-$  - identified and tracked by detectors + outgoing  $K^+$  → estimation of the position of stopped  $\Xi^-$  in emulsion
- Visual inspections by an optical microscope → around the estimated stop position
- Small portion of emulsion plates analyzed → too much human workload !

# Finding hypernuclei in emulsion : MaskCNN

- **Current outcome of E07:**

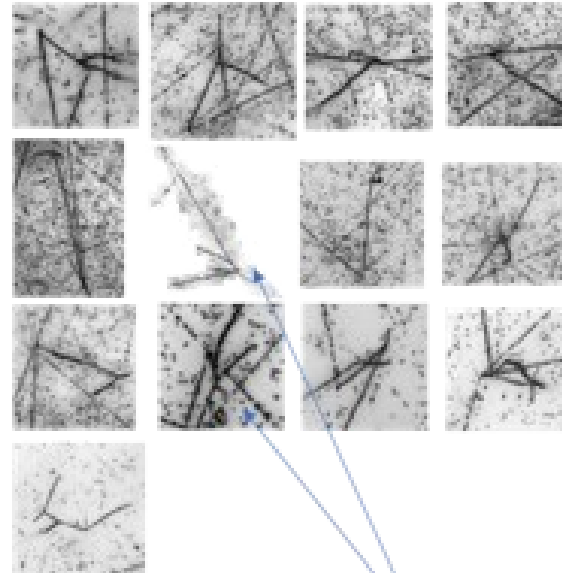
$\Lambda\Lambda$  candidates: 14



$\Lambda\Lambda$ Be

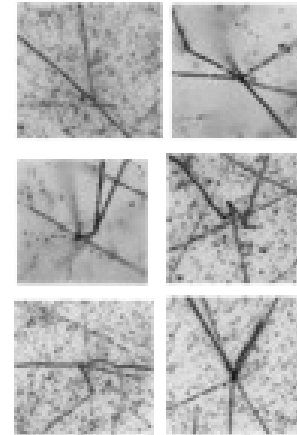
H. Ekawa et al., Prog. Theor. Exp. Phys. 2019, 021D02

Twin  $\Lambda$  events: 13



$^{15}_{\Lambda}\text{C}$

Others: 6



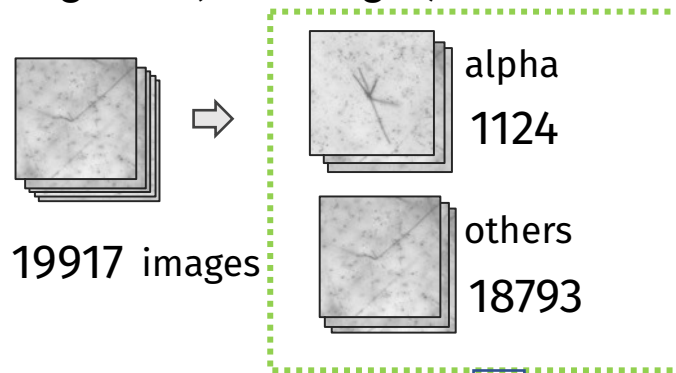
# Finding hypernuclei in emulsion : MaskCNN

- **Still in those 1300 emulsion plates :**
  - K- beam interacted directly with the nuclei of the emulsions
    - produce hypernuclei (single & double)
  - It was proposed to search for hypertriton ( $^3_{\Lambda}\text{H}$ )
  - But : no additional information → need to scan everything !
    - 1.4 billion images / emulsion : 110 TB x 1300 → 140 PB
    - 560 years to analyze this
  - Background :
    - Beam tracks & Nuclear fragmentation : 10000 & 1000 / mm<sup>2</sup>
- **Use of machine learning to find those events !**
  - **To be done in 3 years**

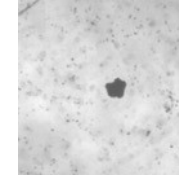
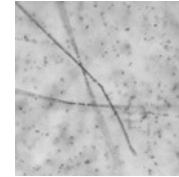
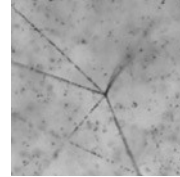
# Finding hypernuclei in emulsion : MaskCNN

## • alpha decay events (calibration) : CNN

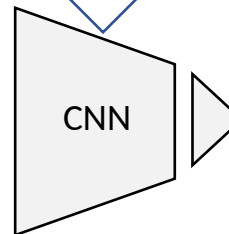
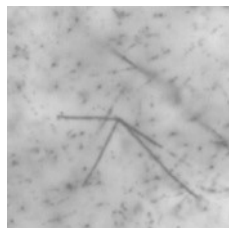
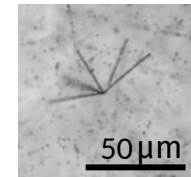
Training data (real images)



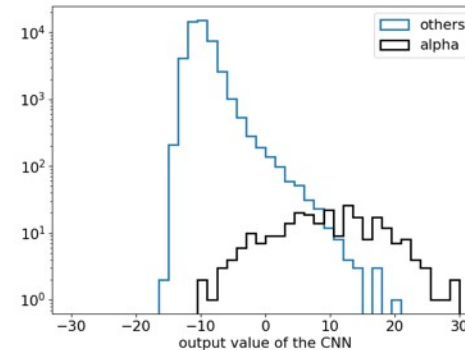
Noise: others



Target



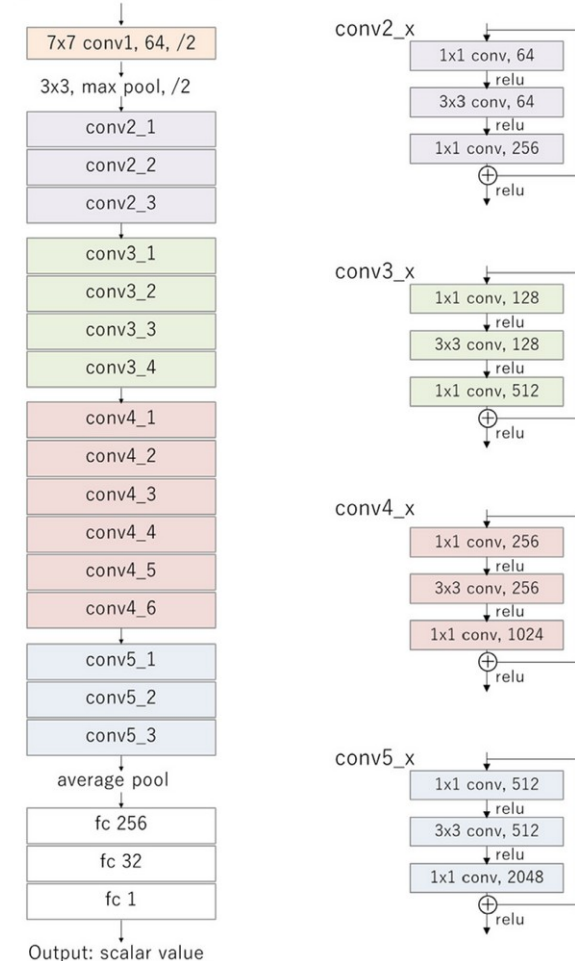
Scalar value



# Finding hypernuclei in emulsion : MaskCNN

- **Alpha decay events:**
  - Spontaneous decay chain of long-lived radioisotopes such as uranium and thorium in the emulsion
  - calibration for density / space homogeneous
- **Convolutional Neural Network**
  - ResNet-50
- **Let have a small digression for some explanations**

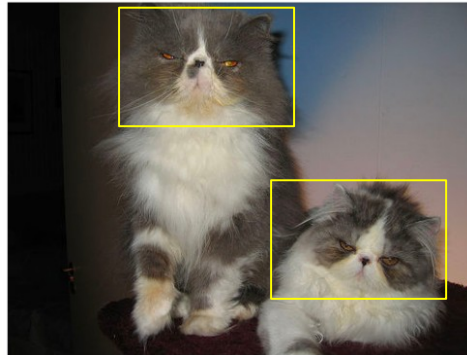
Input: 224x224 3ch image



# Finding hypernuclei in emulsion : MaskCNN

- **What is a CNN :**

- When the structure of data includes “invariance to translation”, a representation meaningful at a certain location can / should be used everywhere



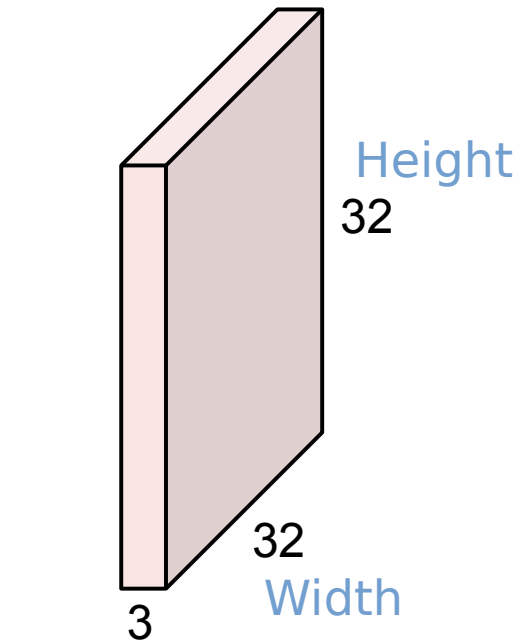
- Convolutional layers build on this idea, that the same “local” transformation is applied everywhere and preserves the signal structure
- 1D Discrete Convolution:  $x \in \mathbb{R}^M, u \in \mathbb{R}^n, \forall i \in [0 \dots M-n+1]: (x * u)_i = \sum_{j=0}^{n-1} x_{i+j} u_j$ 
  - $u$  is called Convolutional kernel of width  $k$
  - Scan across data and multiply by kernel elements



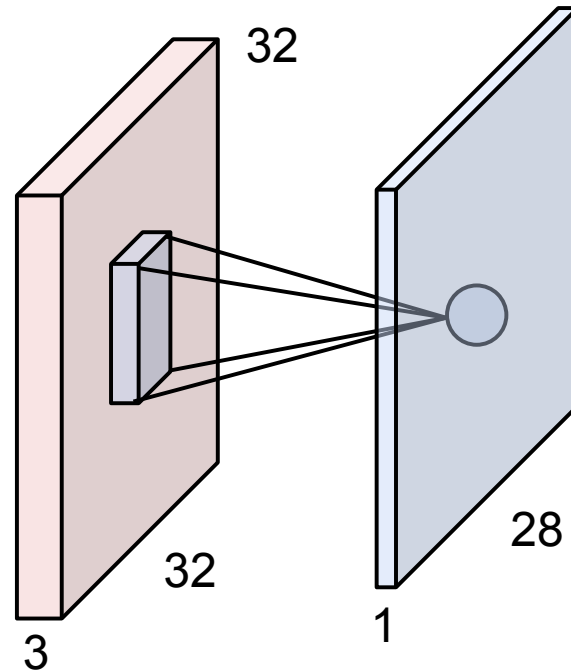
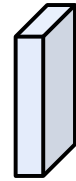
# Finding hypernuclei in emulsion : MaskCNN

- **Convolution Layer: preserve spatial structure**

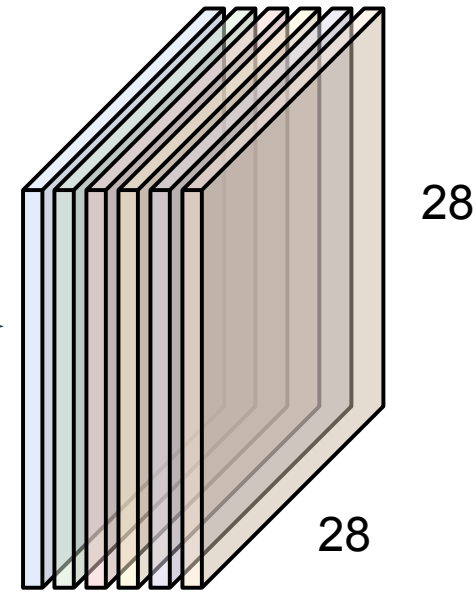
32x32x3 image



5x5x3 filter



activation maps



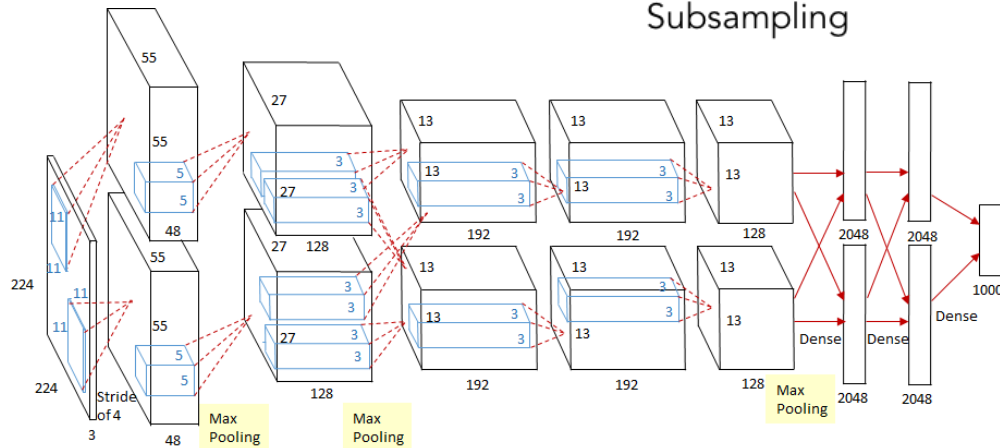
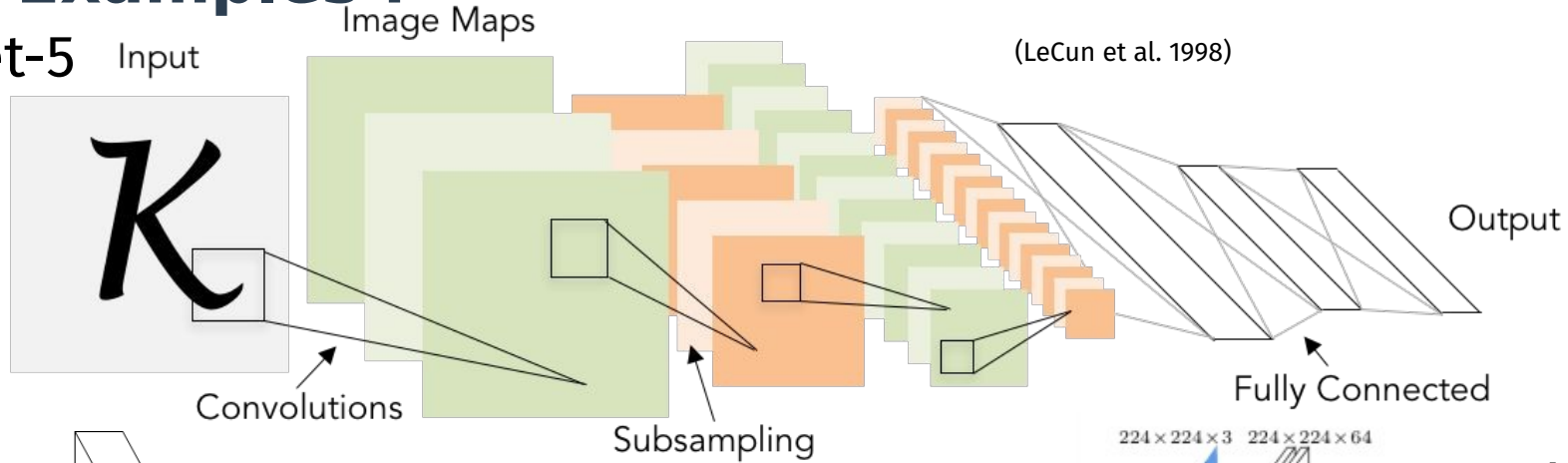
$$(\mathbf{x} * \mathbf{u})_{i,j} = \sum_{c=0}^{C-1} \sum_{n=0}^{h-1} \sum_{m=0}^{w-1} x_{c,n+i,m+j} u_{c,n,m}$$
$$i \times j \in (H-h+1) \times (W-w+1)$$

Each 28x28 (=784) parameters  
Fully Connected Layer :  
32x32x3 x size Hidden (784) → 2.4M

# Finding hypernuclei in emulsion : MaskCNN

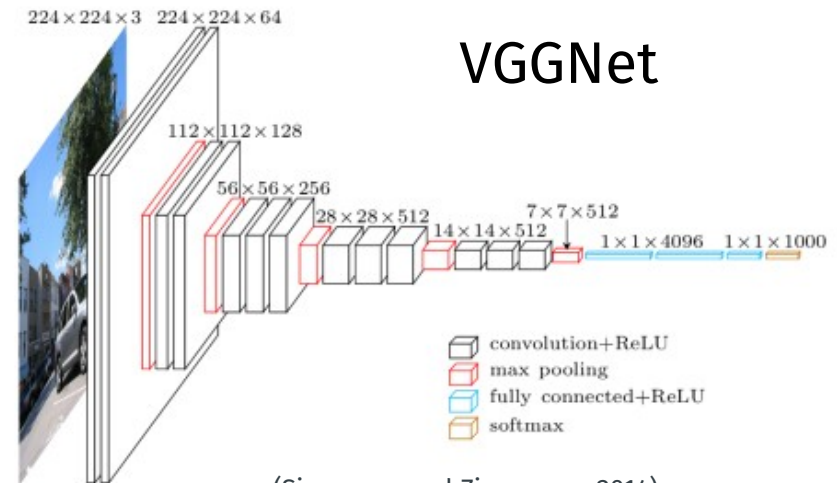
## • Examples :

LeNet-5 Input



AlexNet

(Krizhevsky et al, 2012)

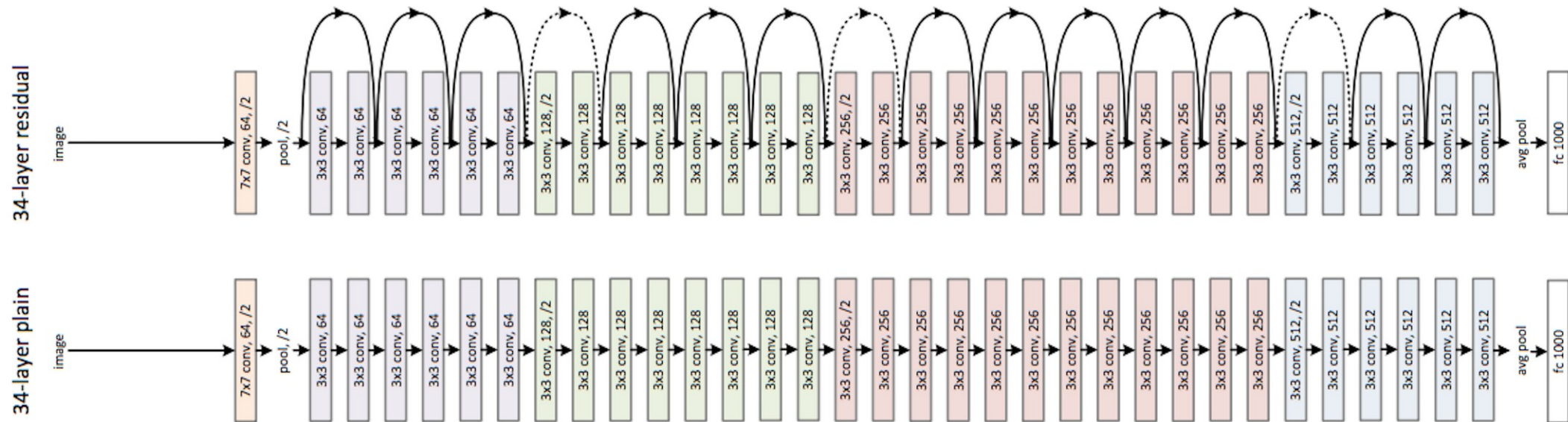


(Simonyan and Zisserman, 2014)

# Finding hypernuclei in emulsion : MaskCNN

- **Back to ResNet:**

- 34 layers :



- Classics : ResNet - 18, -34, -50, 101, 152 (layers)

Params :25M

Params :60M

# Finding hypernuclei in emulsion : MaskCNN

- **CNN classifier : Alpha decay detection**

	Precision	Recall	# of candidates
Conventional method	0.081 +- 0.006	0.788 +- 0.056	2489
CNN classifier	0.547 +- 0.025	0.788	366 +- 18

- **Precision =  $TP / TP + FP$**

- **Recall =  $TP / TP + FN$**

model's ability to detect Positive samples

- **7 times more precision !**

- **Conventional :**

- 2489 out of 46948 events, including 201 true alpha decay

- **CNN classifier:**

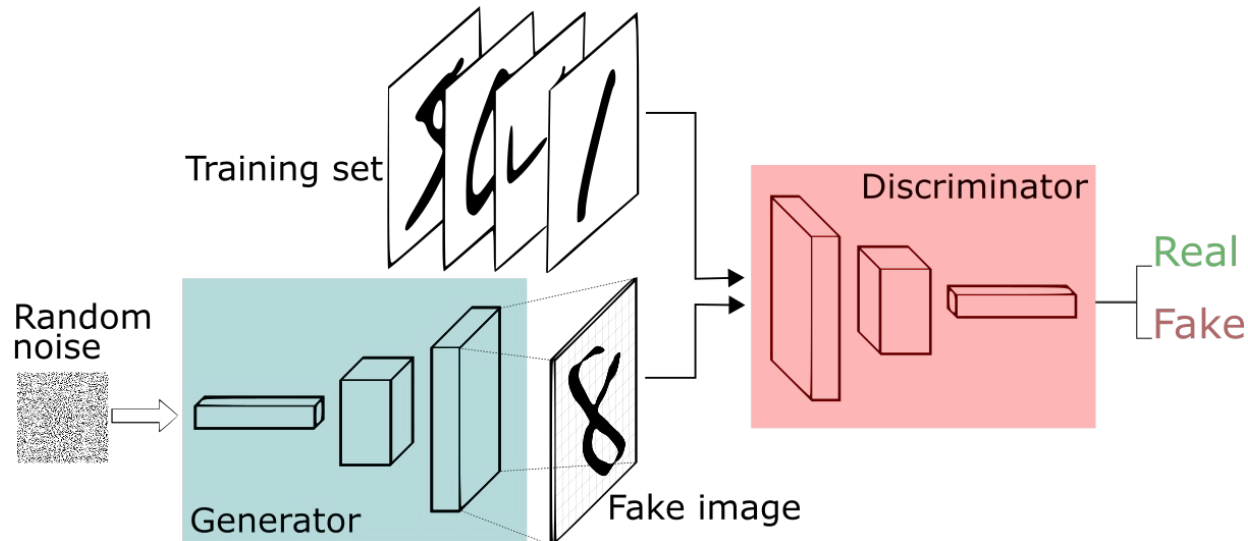
- 350 alpha-decay candidates, including 201 true alpha-decay

# Finding hypernuclei in emulsion : MaskCNN

- **Finding hypertriton :**

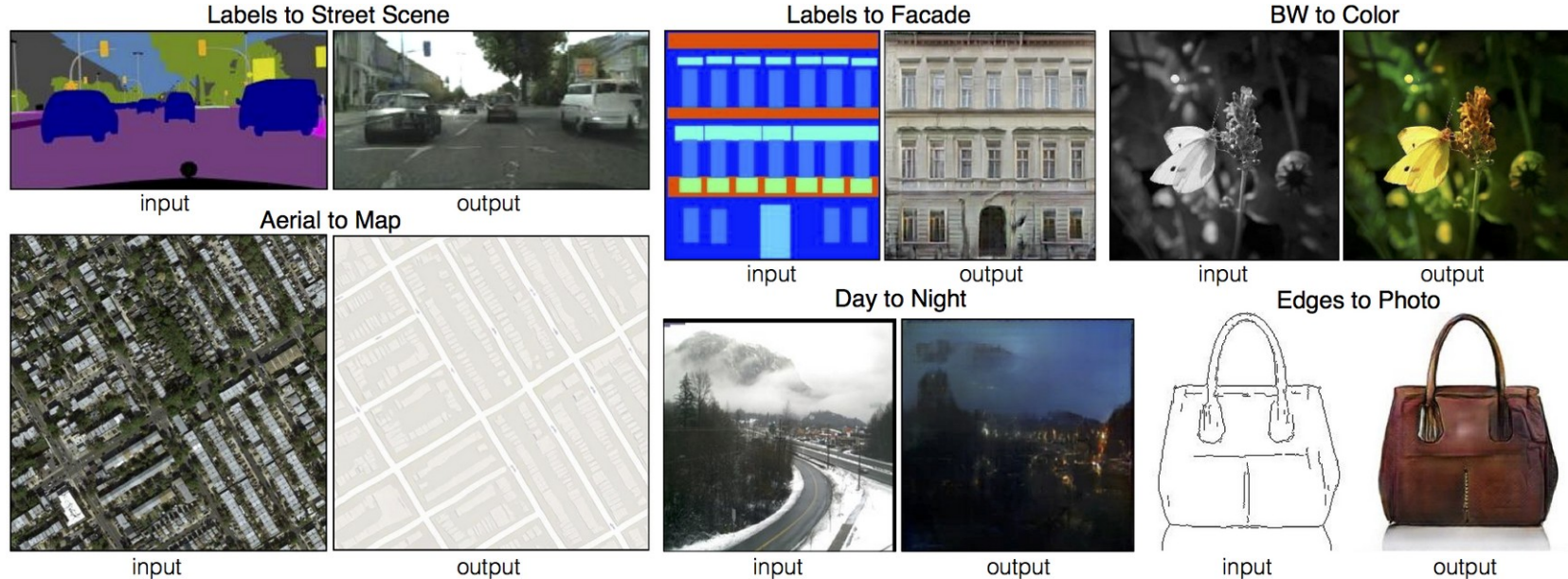
- Needs of training data ! But none has been found  
→ generating event from simulations !
- Problem : how to simulate nuclear emulsion ?!

- **GAN : Generative adversarial networks**



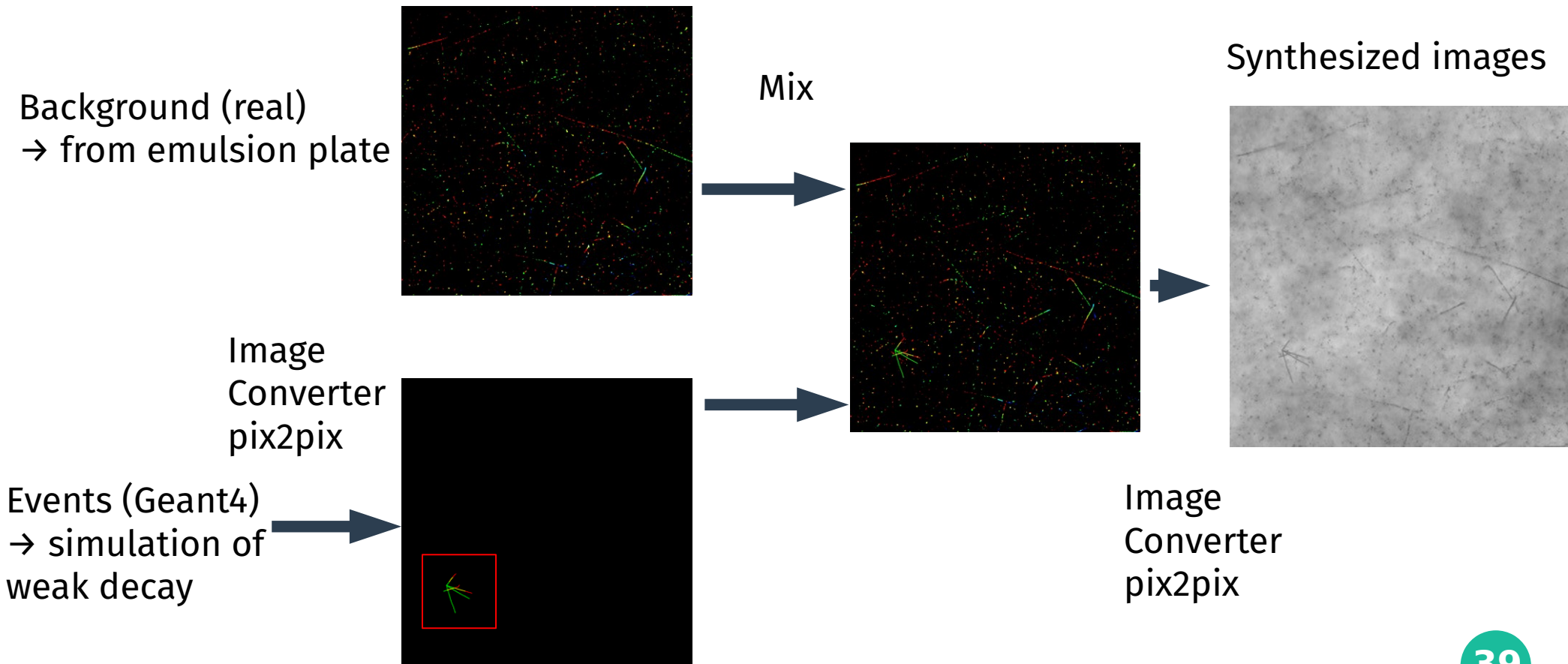
# Finding hypernuclei in emulsion : MaskCNN

- **Simulated hypertriton : GAN + Geant4**
  - pix2pix (Image-to-Image Translation with Conditional Adversarial Nets)



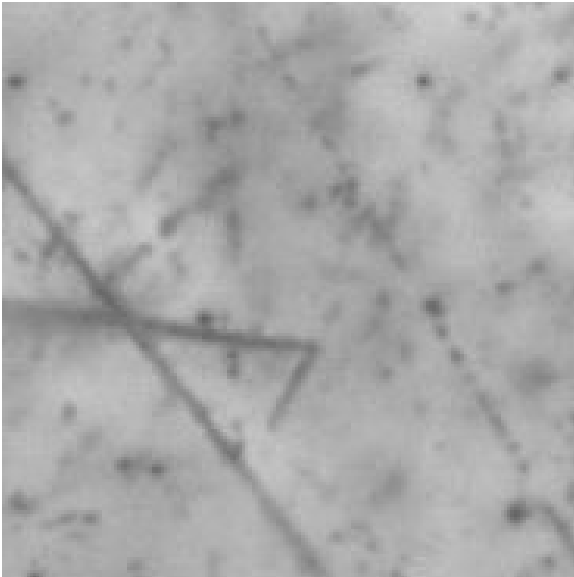
# Finding hypernuclei in emulsion : MaskCNN

- **Simulated emulsion :**

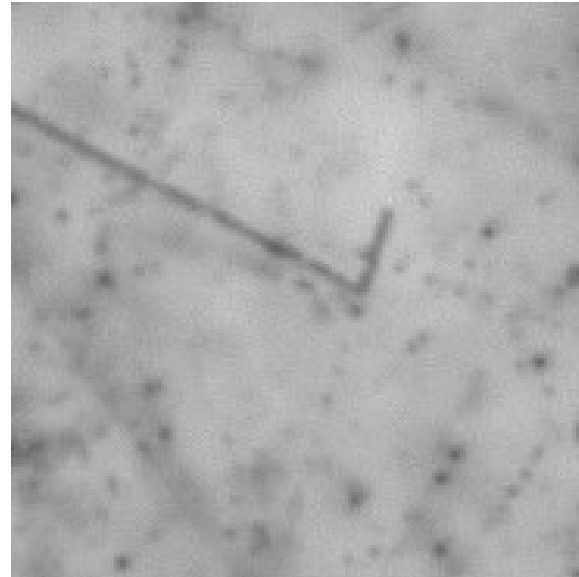


# Finding hypernuclei in emulsion : MaskCNN

- **Simulated event : hypertriton via GAN**



Simulated



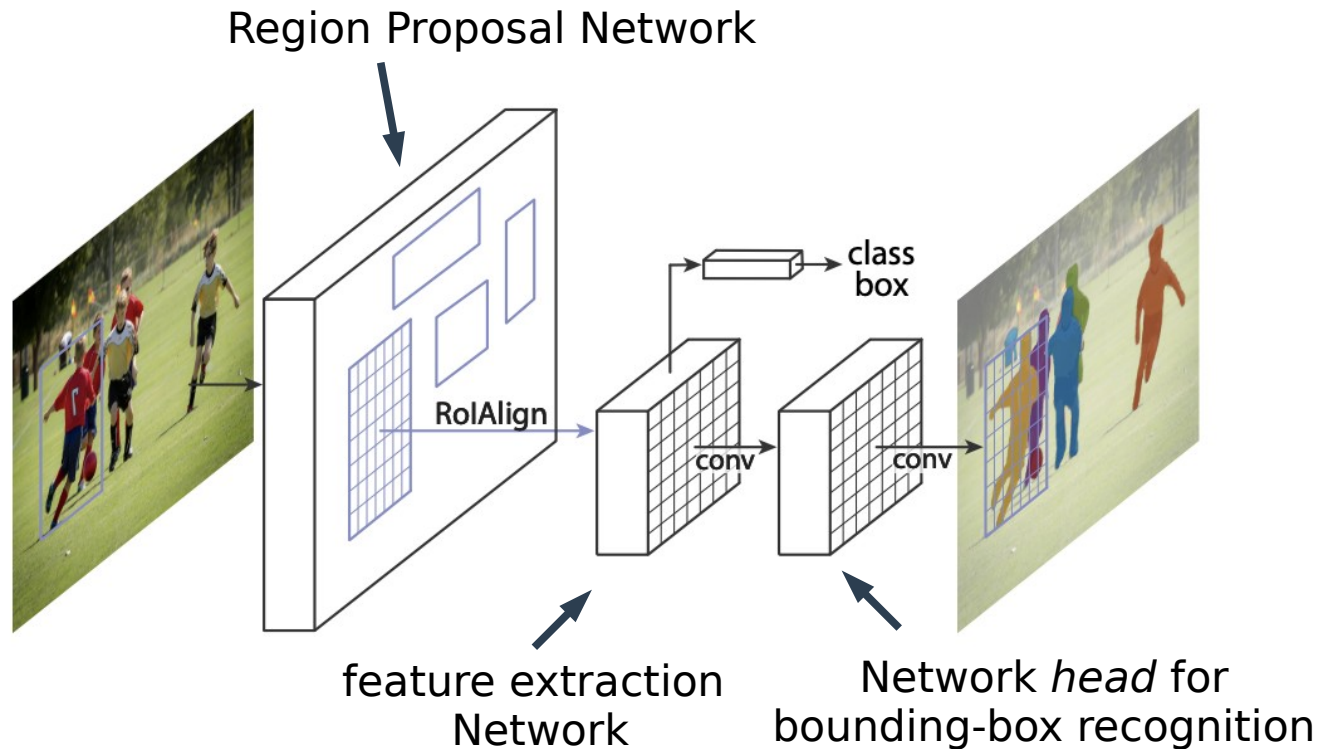
Real

- **hypertriton decay at rest :  ${}^3\text{He} + \pi$  back-to-back**
- **Q-value fixed: length of pion 28 mm of  ${}^3_{\Lambda}\text{H}$  vs 42 mm for  ${}^4_{\Lambda}\text{H}$**



# Finding hypernuclei in emulsion : MaskCNN

- Search for hypertriton-like decay:
  - Mask R-CNN : Instance Segmentation

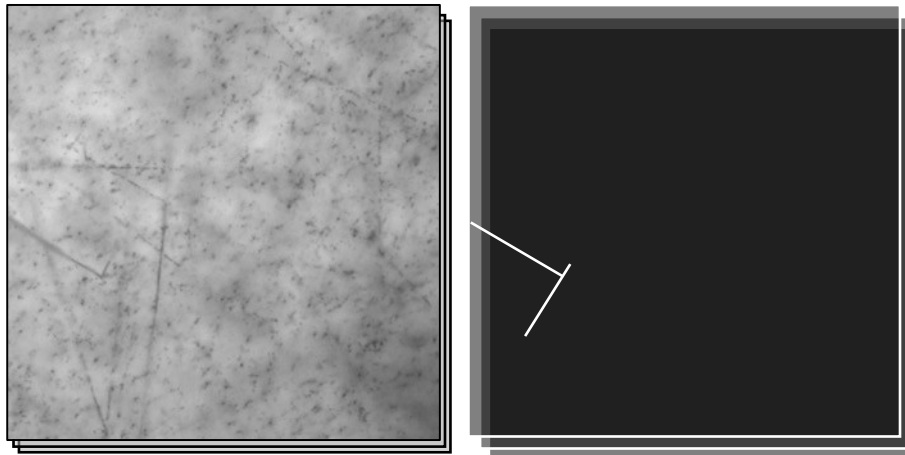


Backbone architecture:  
Networks inside  
Ex: ResNet, ResNeXt,  
Feature Pyramid Network

# Finding hypernuclei in emulsion : MaskCNN

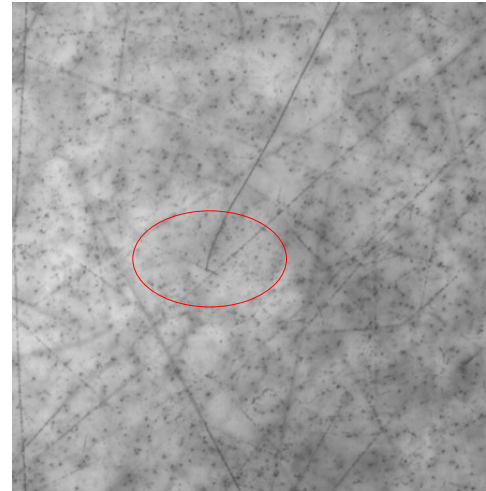
- **Search for hypertriton-like decay:**
  - Training on simulated and generated event
    - “Real” images of simulated emulsion
    - Masks of the instance segmentation of the decay

Simulation

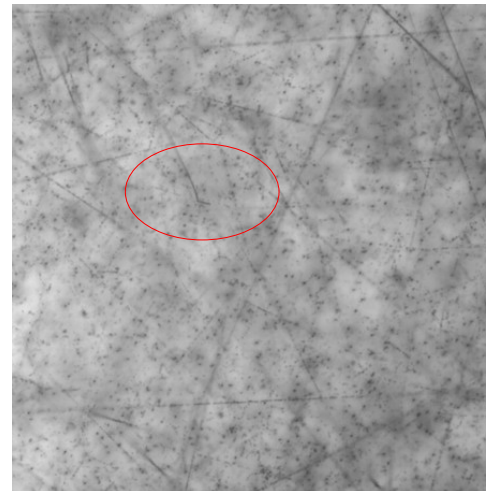
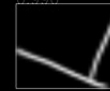


# Finding hypernuclei in emulsion : MaskCNN

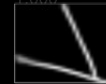
- **Search for hypertriton-like decay:**
  - Training on simulated and generated event → done
  - Analyze the real emulsion images
    - Give us the image and mask - bounding box of what the algorithm found :



Score = 0.996

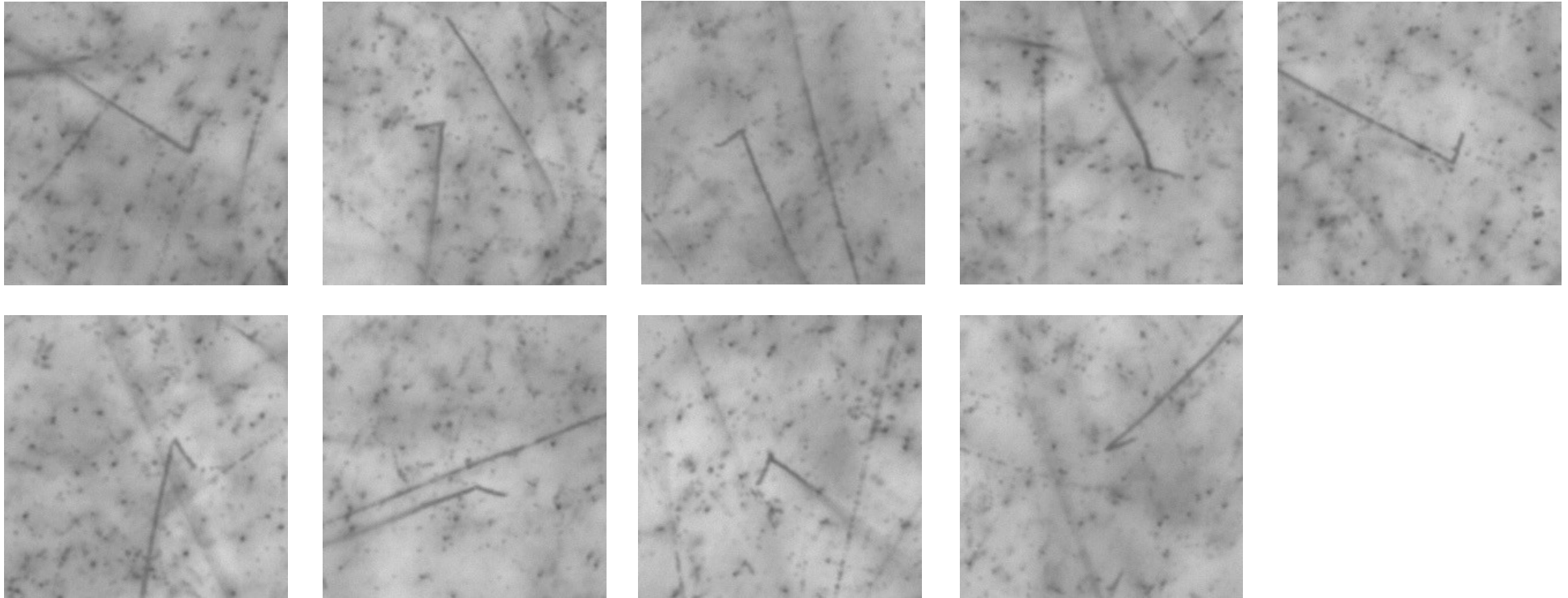


Score = 1.000



# Finding hypernuclei in emulsion : MaskCNN

- Search for hypertriton-like decay:

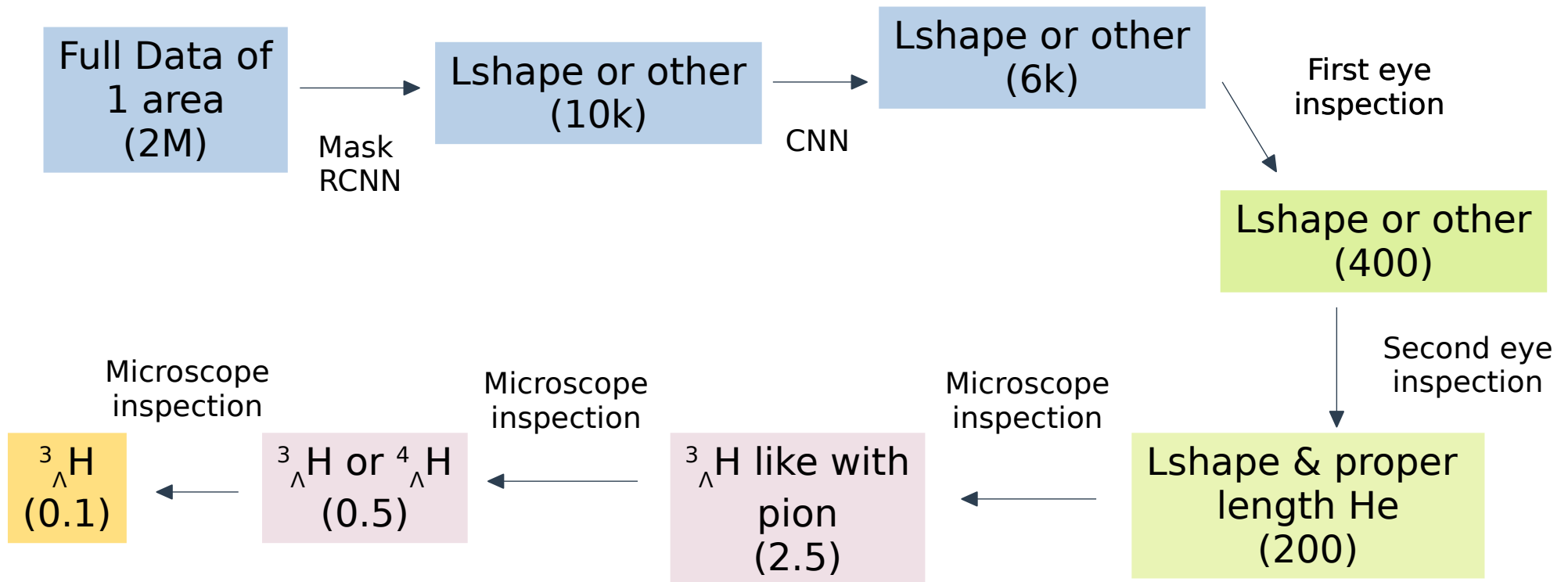


10  $\mu\text{m}$

# Finding hypernuclei in emulsion : MaskCNN

- **The Mask R-CNN is not perfect :**

- Need people to cross check the dataset selected by the NN





**Any questions ?**