



FB23



# Multi-neutron detection based on machine learning

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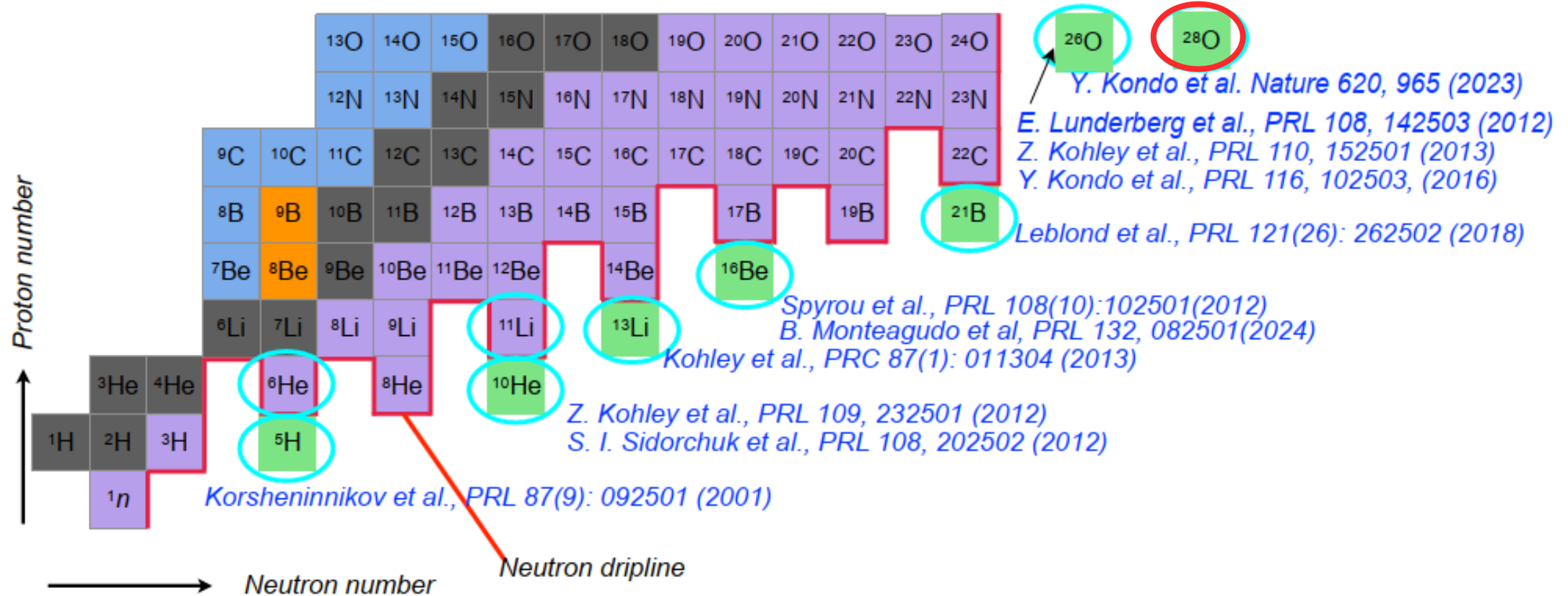
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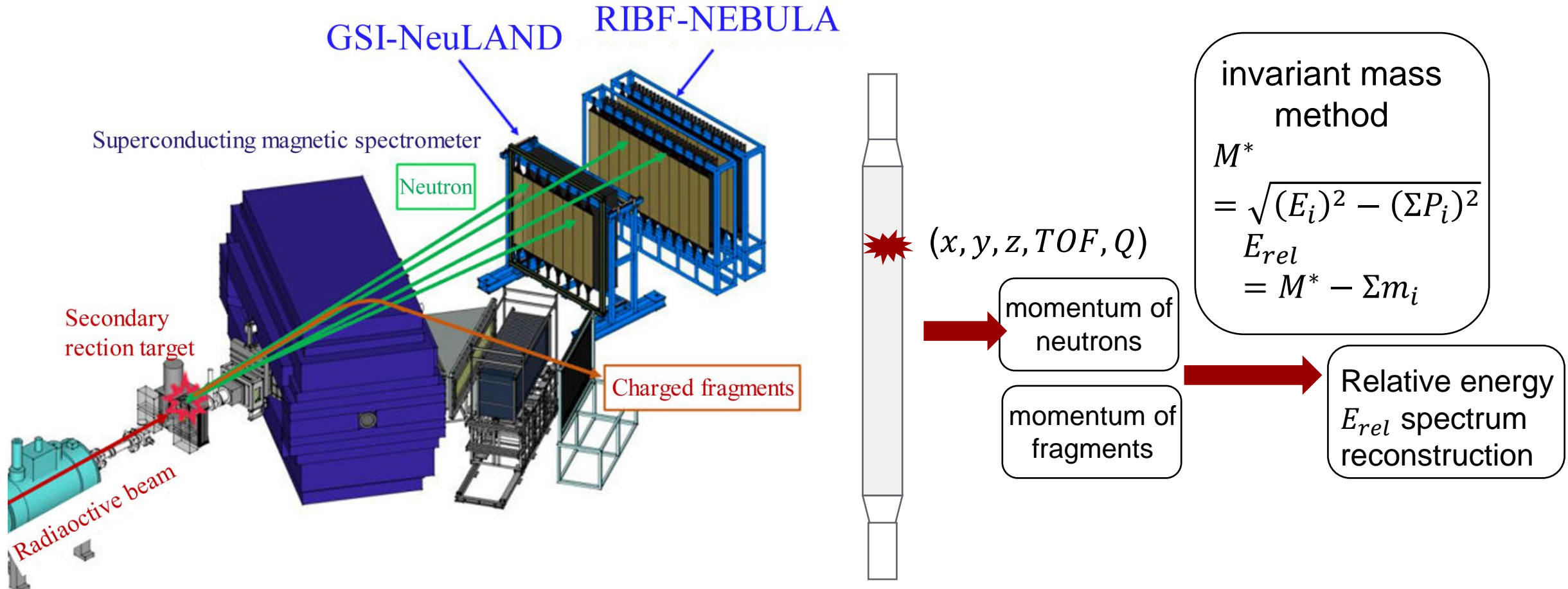
2024.09.26

- Background
- Method – exclusion of crosstalk using DNN
- Result – comparing traditional and machine learning algorithms
- Summary

# Background

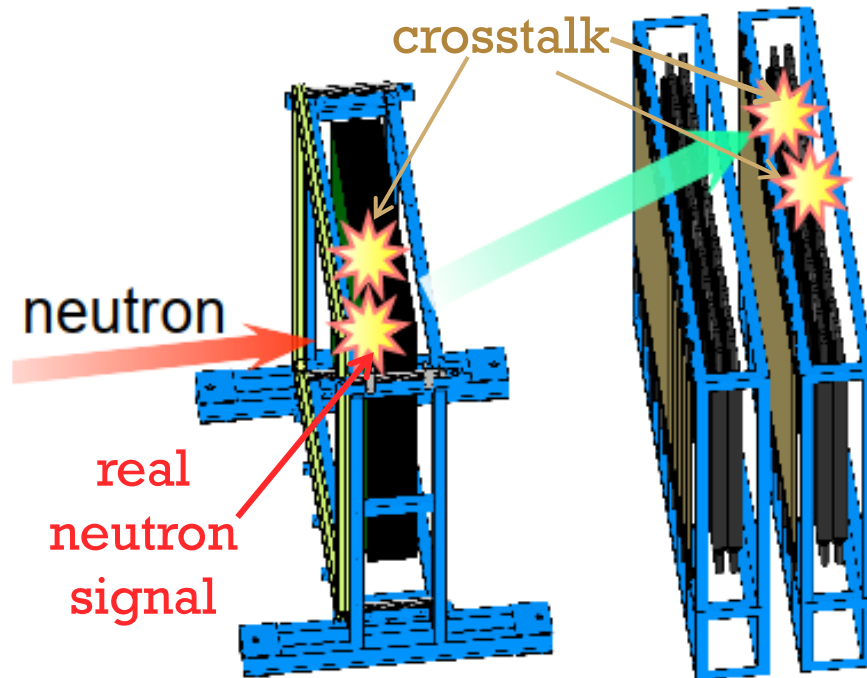


# Multi-neutron detection experiment



Typical layout of experiment at RIBF, RIKEN.

HUANG S, YANG Z, MARQUÉS F, et al. Few-Body Systems, 2021, 62(4): 102

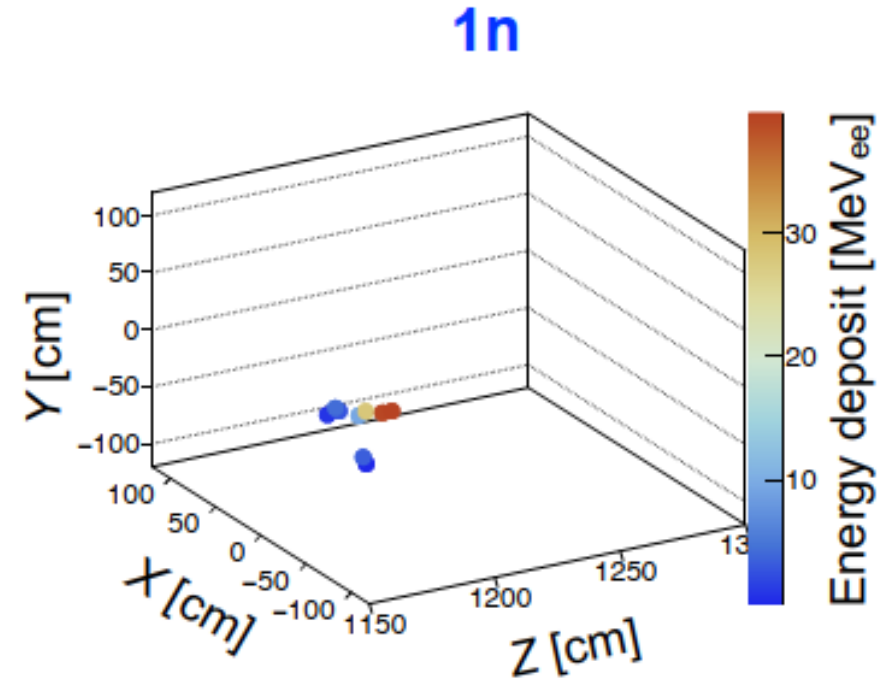
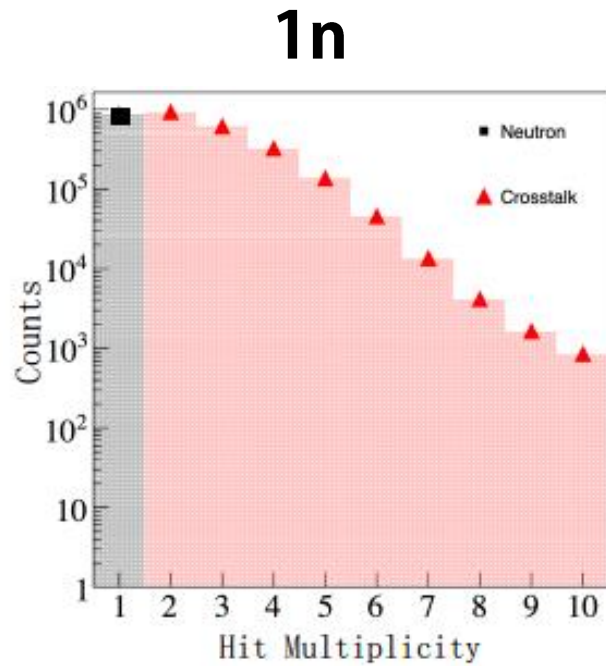


The secondary charged particles  
gamma rays  
scattered neutrons

↓  
crosstalk

The challenges of multi-neutron detection:  
low detection efficiency of neutrons  
large number of crosstalk signals, real neutron signal will inevitably be excluded

Data from Geant4 simulation

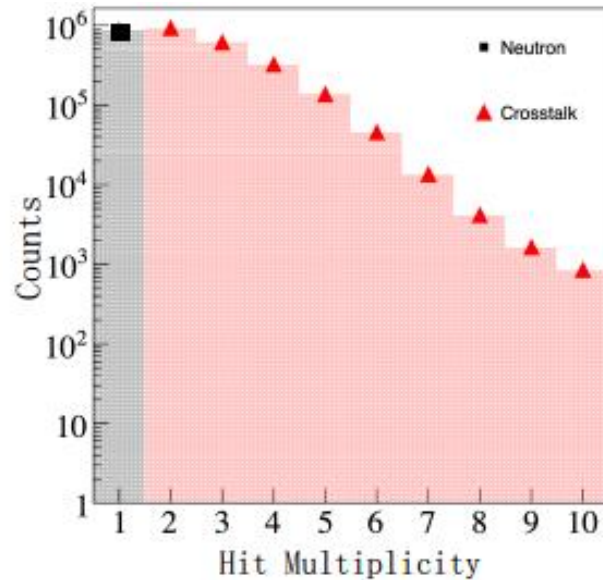


**a single neutron can also generate a large number of crosstalk**

**directly select the first signal?**

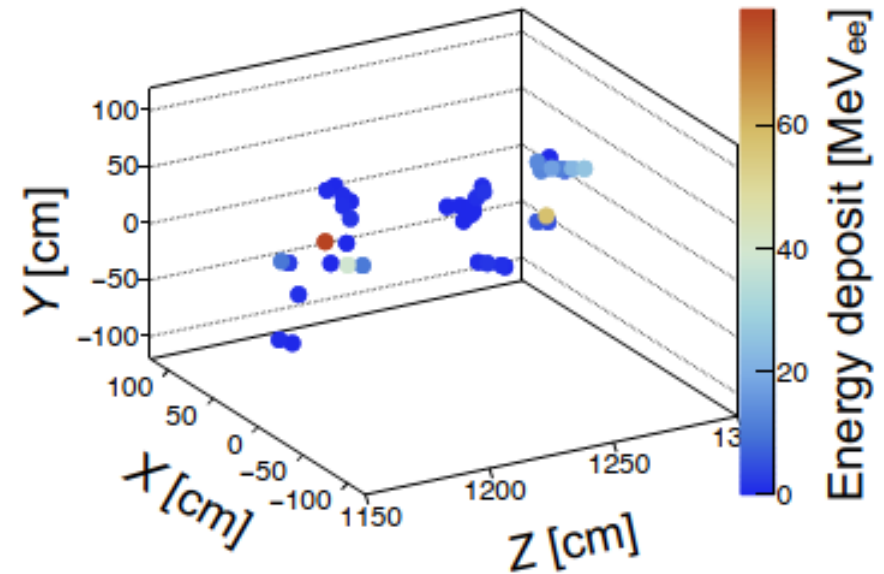
Data from Geant4 simulation

1n



a single neutron can also generate a large number of crosstalk

4n

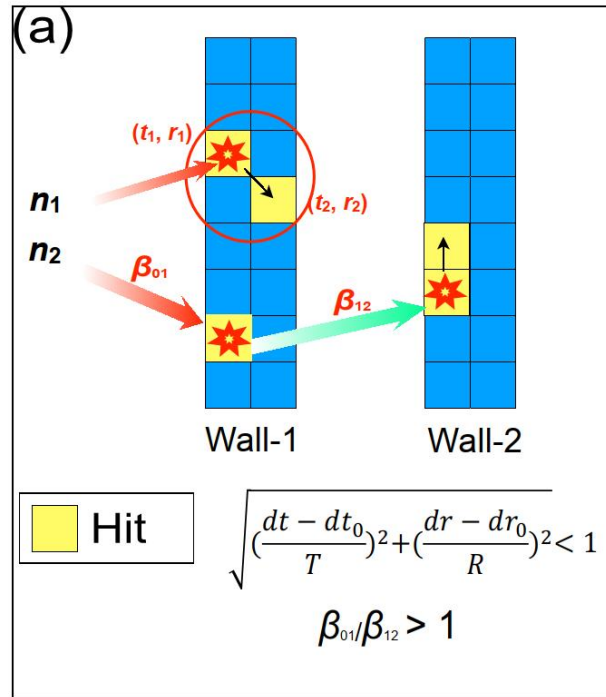


directly select the first signal?

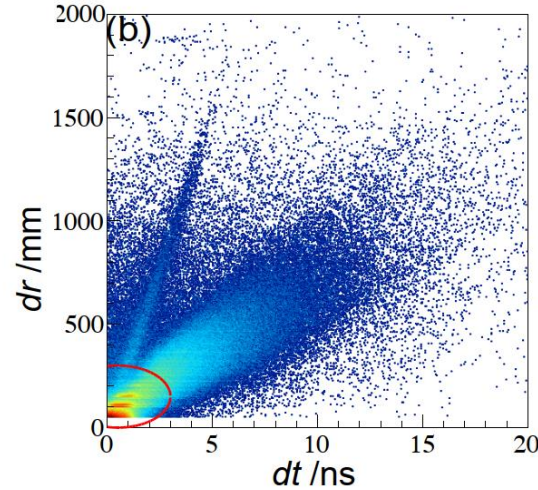
not applicable to the case of multiple neutron events, timing of signals is very complicated



## high crosstalk rejection

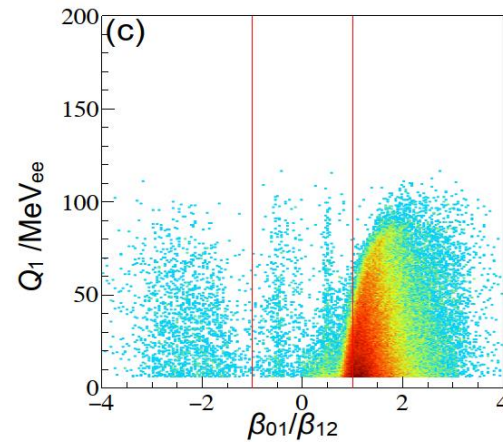


1n



Crosstalk signals can be divided into two types

The first type  
caused by the secondary particles near  
the initial signal of the neutron detectors  
**time and space correlation**



The second type  
generated by reaction of scattered neutrons  
velocity should decrease compared to incident  
neutrons.  
**kinematic condition**

Kondo et al., *Nuclear Instruments and Methods in Physics Research Section B* 463: 173-178 (2020)

S. W. Huang et al., *Few-Body Systems* 62(4): 1-7 (2021)



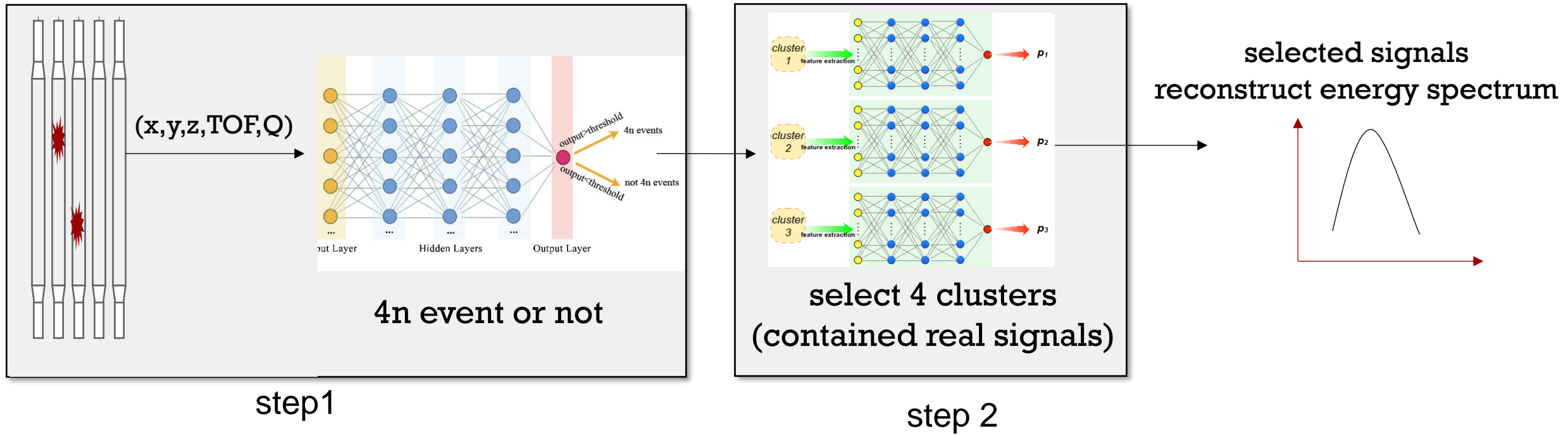
- Background
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- **predicting fission fragment yield distribution.** WANG Z A, PEI J, LIU Y, QIANG Y., PRL 123: 122501 (2019)
- **predicting nuclear mass.** Niu Z M, Liang H Z., PRC 06(2): L021303 (2022)
- **predicting ground state energy.** Knöll et al., PLB 839: 137781 (2023)
- **particle identification in plastic scintillators.**  
Doucet et al., Nucl. Instrum. Methods Phys. Res., Sect. A 954, 161201 (2020)
- **particle identification in AT-TPC tracks.**  
Kuchera et al., Nucl. Instrum. Methods Phys. Res., Sect. A 940: 156-167 (2019)



C.A. Douma et al, Nucl. Instrum. Methods Phys. Res., Sect. A 990, 164951 (2020)

# Deep Neural Network



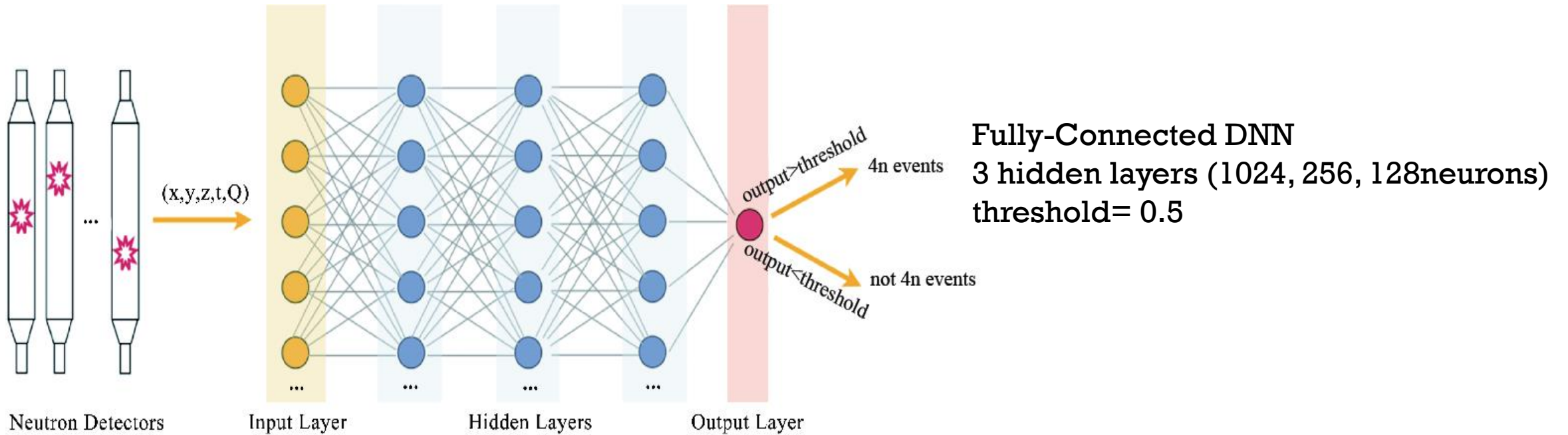
Two-step deep neural network (DNN).

(1) Neutron multiplicity determination

(2) Neutron selection

Training/validation set (1 million events) + test set  
from Geant4 simulation

# Machine learning algorithm – step 1

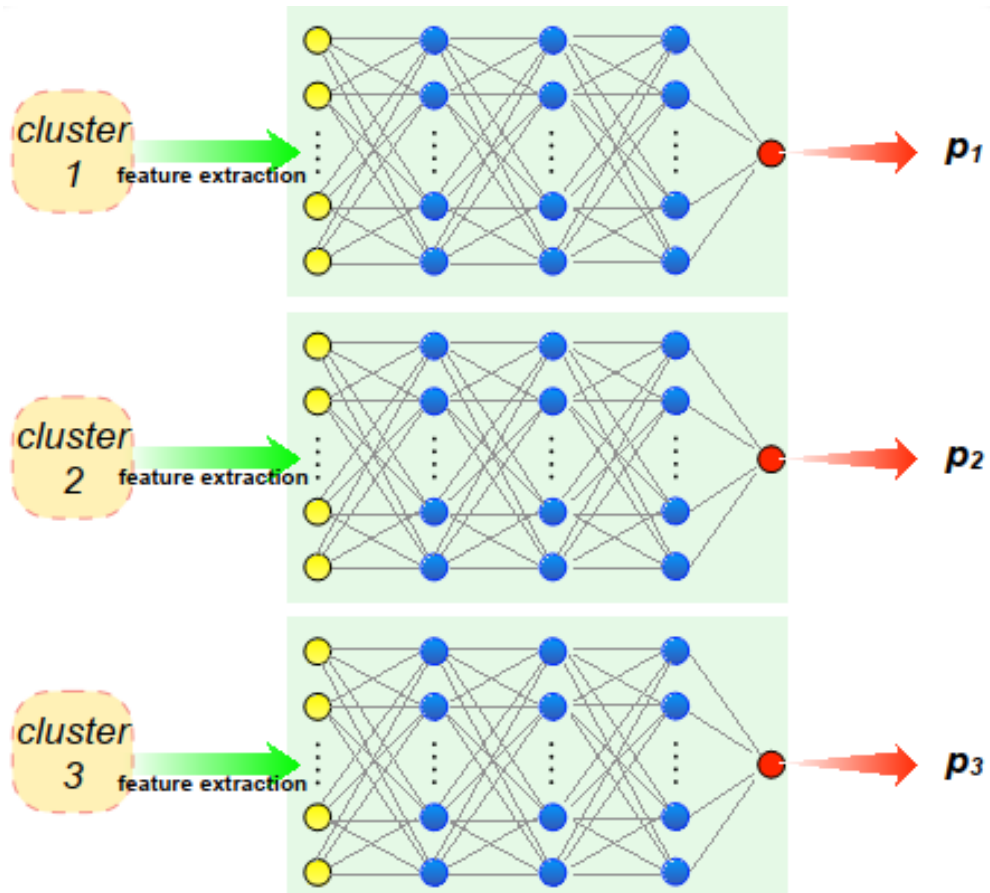


## The principle of first step DNN

Input: Information recorded by the neutron detector  
(X, Y, Z, TOF, Q...)

Output: value between 0 (not 4n) and 1 (4n)

# Machine learning algorithm – step 2



$p_1$  14 input layer features  
12 hidden layers(200 neurons per layer)

Training Set: Number of reacted neutron equals object neutron  
Feature: information of a single cluster (X,Y,Z,TOF,Q...)  
Label: 0 or 1 (i.e. whether the cluster contains real signal)

To pick out the cluster where the real neutron is, each cluster is fed into the model and the predicted value  $p$  is obtained. Sort all the output value to select them.

The principle of second step DNN

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# Result: 2n channel

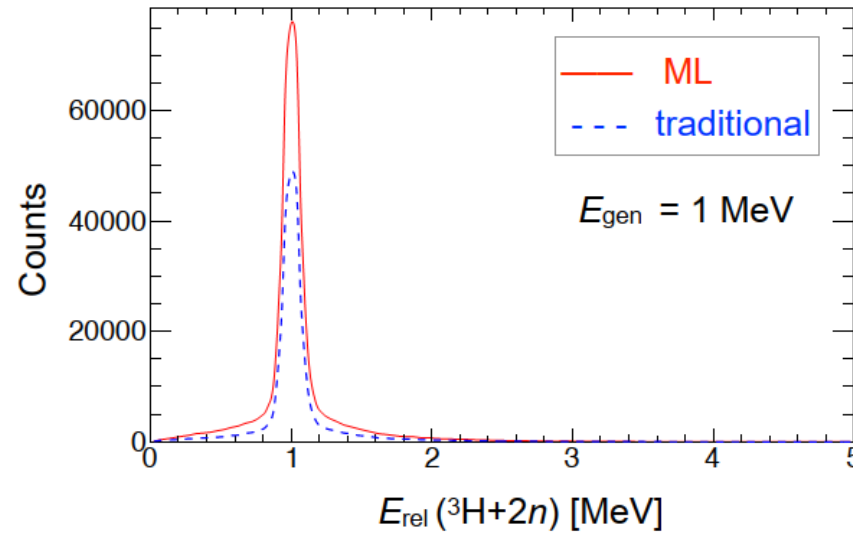
Define:

crosstalk exclusion rate  $r_1$

$$r_1 = \frac{\text{eliminated crosstalk events}}{\text{initial crosstalk events}}$$

multi n misclassification rate  $r_2$

$$r_2 = \frac{\text{misclassified as } 2n \text{ events}}{\text{total } 2n \text{ events}}$$



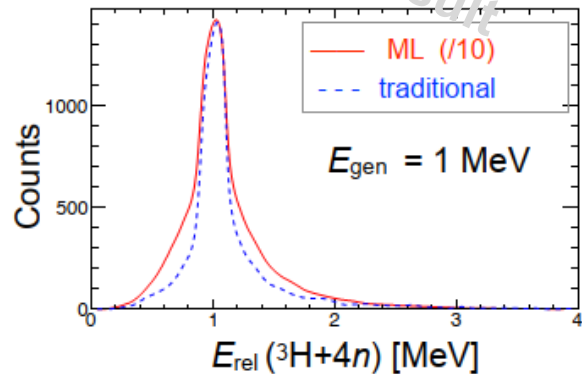
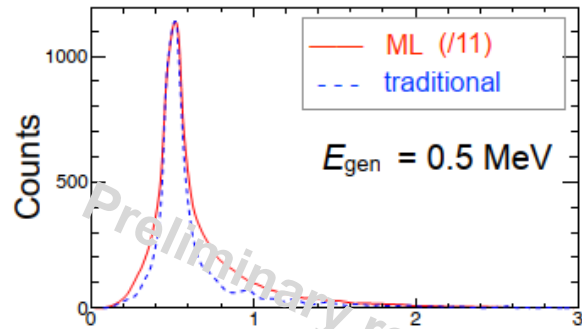
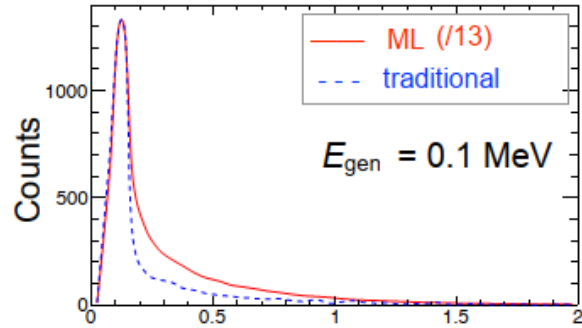
$$M^* = \sqrt{(E_i)^2 - (\sum P_i)^2}$$

$$E_{rel} = M^* - \sum m_i$$

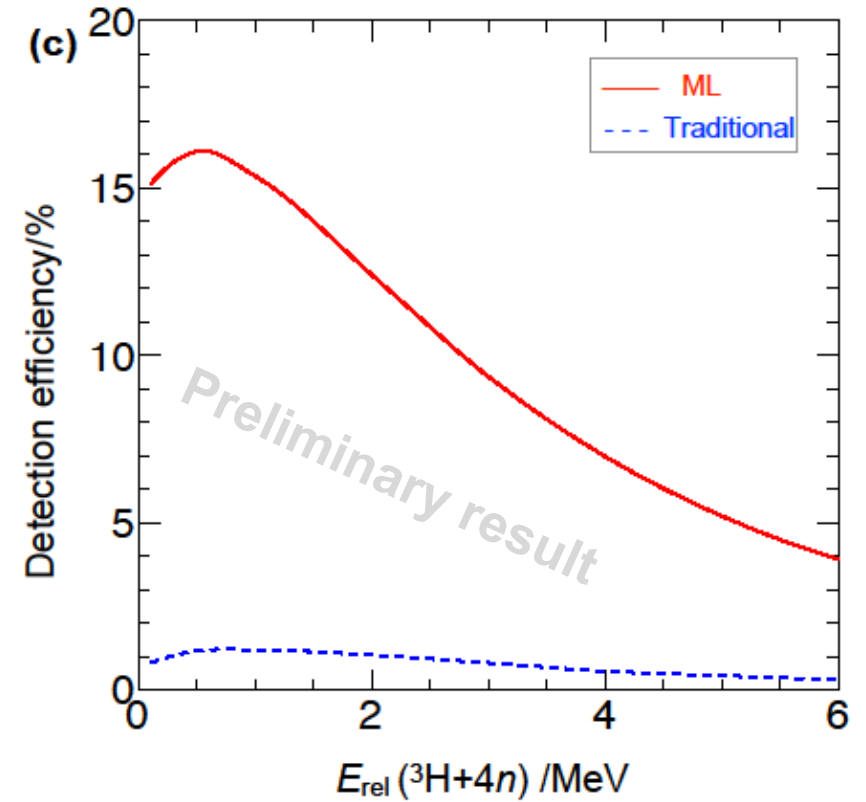
I%	$r_1$	$r_2$
traditional	98.43	3.83
ML	99.40	1.33

$E_{rel}$  peak position  
Detection efficiency  
Energy resolution

# Result: 4n efficiency

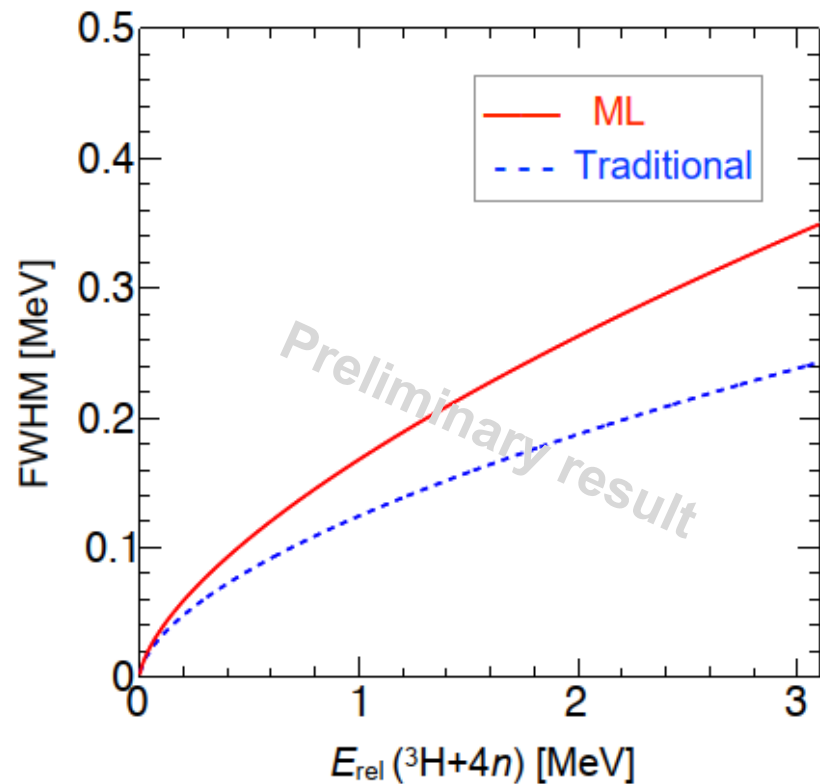
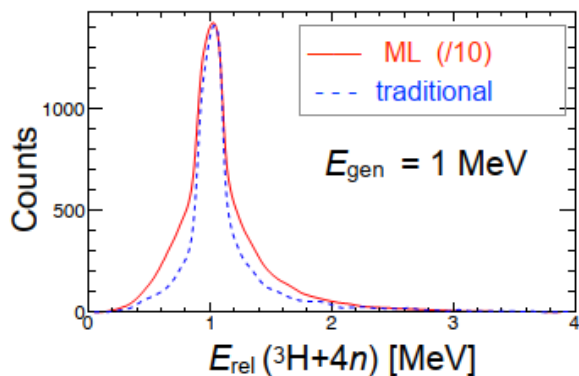
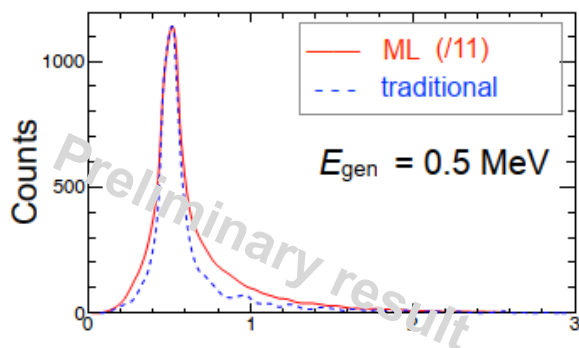
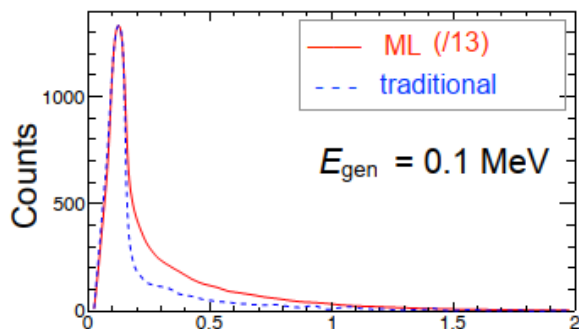


$I/\%$	$r_1$	$r_2$
traditional	99.53	18.34
ML	99.69	13.75



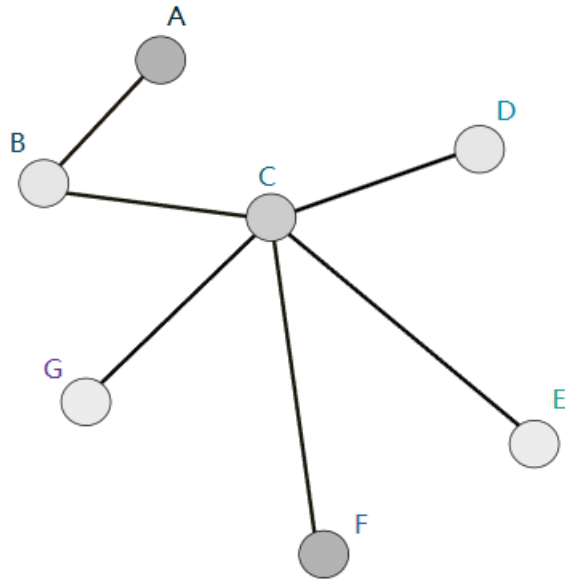
Machine learning algorithm improves the efficiency significantly

# Result: 4n resolution

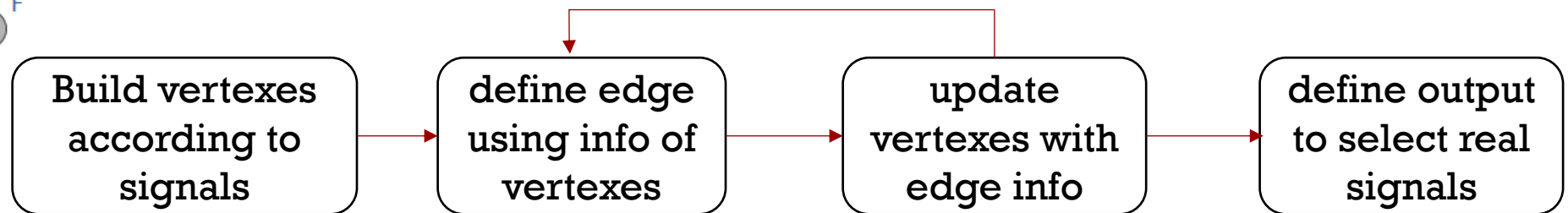


Energy resolution of ML algorithm will be slightly worse

correlation between different clusters of signals (missing in DNN)



- vertex: represent the information of each detector
- edge: information about correlation of two signals (such as  $\beta$ )
- adapted from Particle-net in high energy physics



Huilin Qu et al., Phys. Rev. D 101: 056019 (2020)

A neural network-based multi-neutron identification algorithm is developed, which significantly improves the four-neutron efficiency (>10 times) compared with the traditional algorithm.

We are now trying to use graph neural network (GNN) and other methods to develop multi-neutron identification algorithm, hoping to further improve the results by introducing correlations between clusters.

We will continue to explore and optimize algorithms for **the high-efficiency and high-resolution multi-neutron spectrometer** under construction, and apply them to multi-neutron detection.