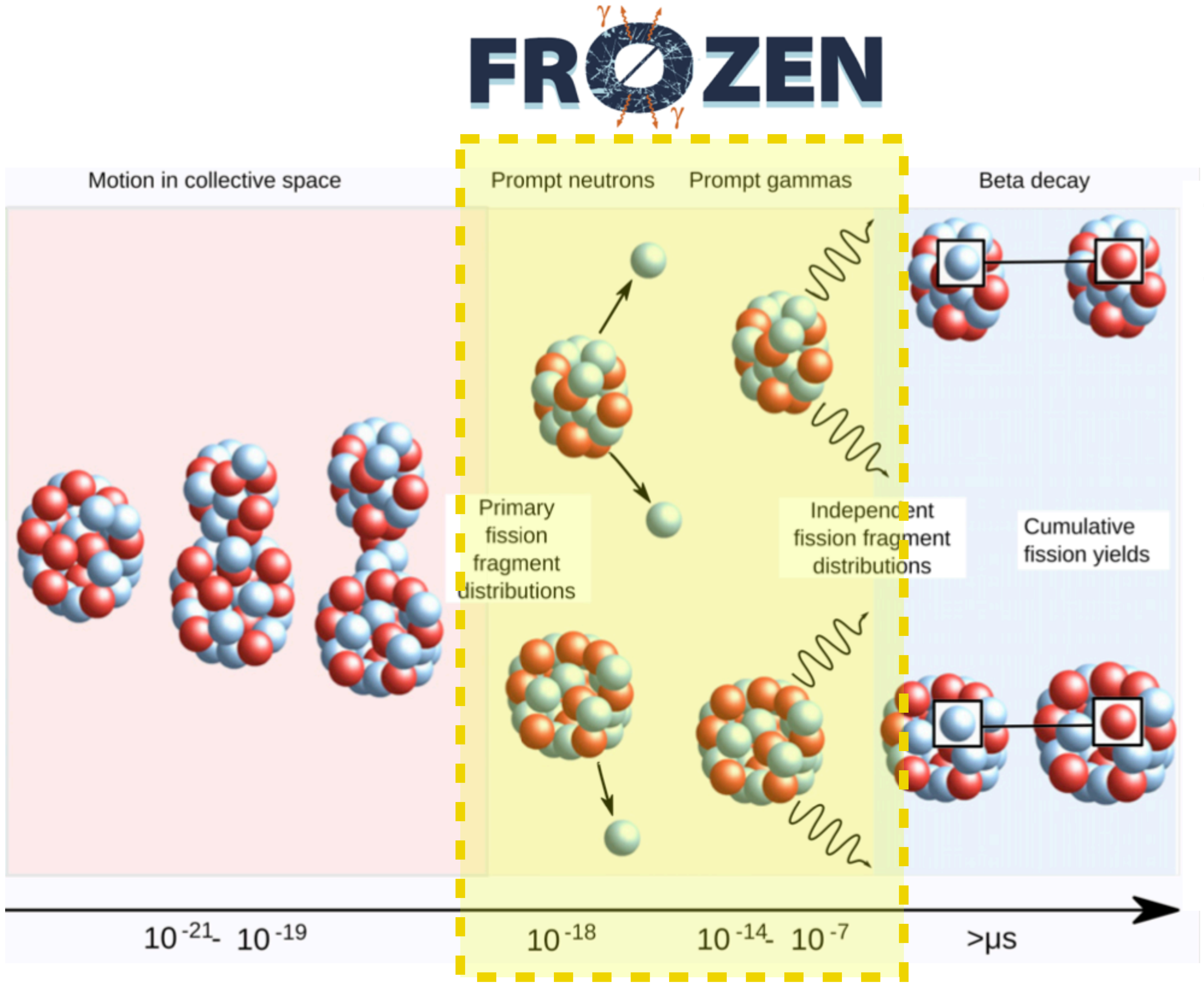
Characterization of the de-excitation path of fission fragments during the spontaneous fission of 252Cf

N-SI-125 data analysis status

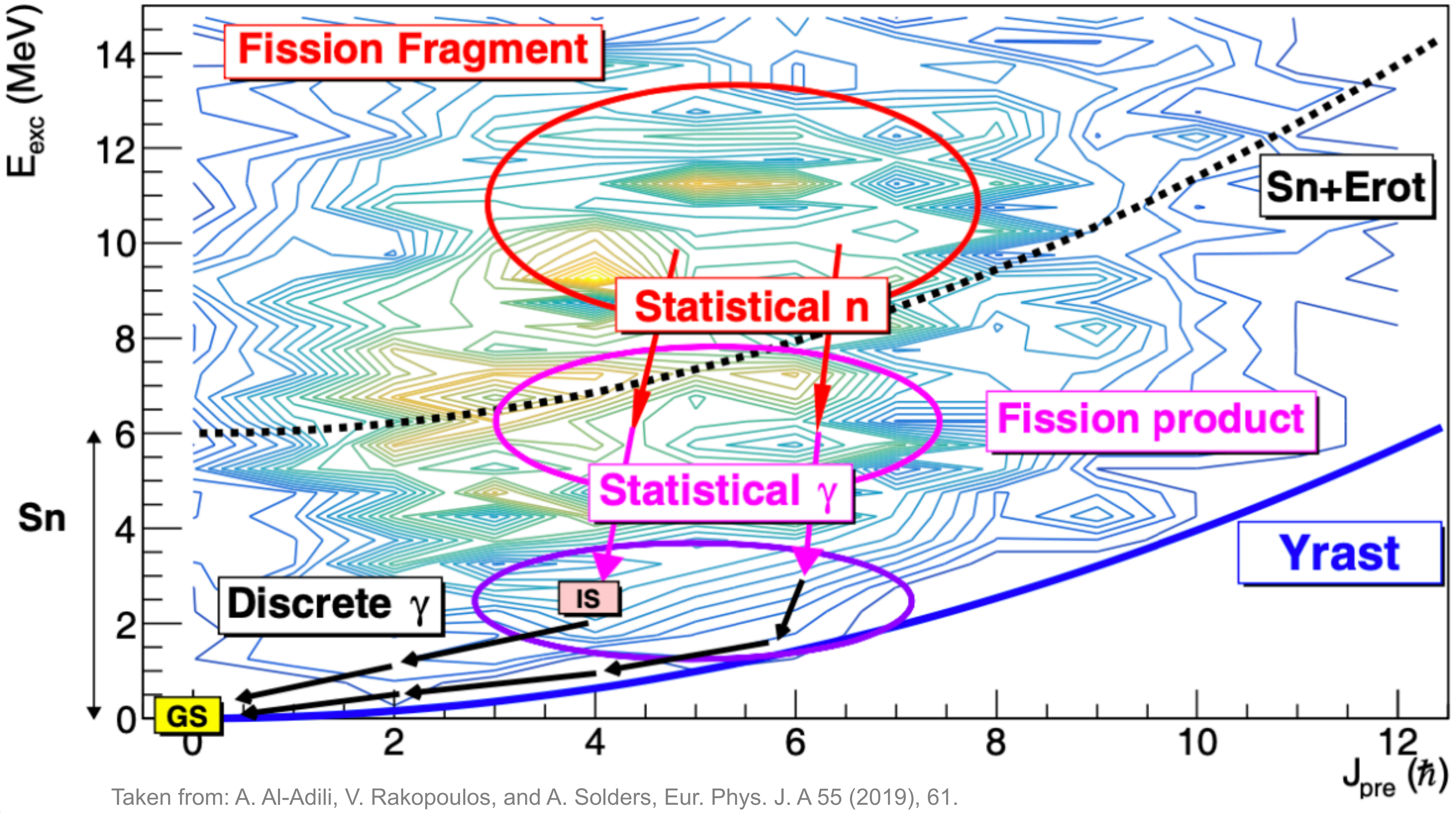
B. Pertille[a], M. Lebois[a], M. Mehdi[a], S. Oberstedt[b], J. Guillot[a], D. Thisse[c], A. Göök[b] et al.

[a] - Université Paris-Saclay, CNRS/IN2P3, IJC Laboratory, Orsay, France
[b] - European Commission, Belgium
[c] - Atomic Energy Commission (CEA), France

Physics motivation for the FRØZEN project

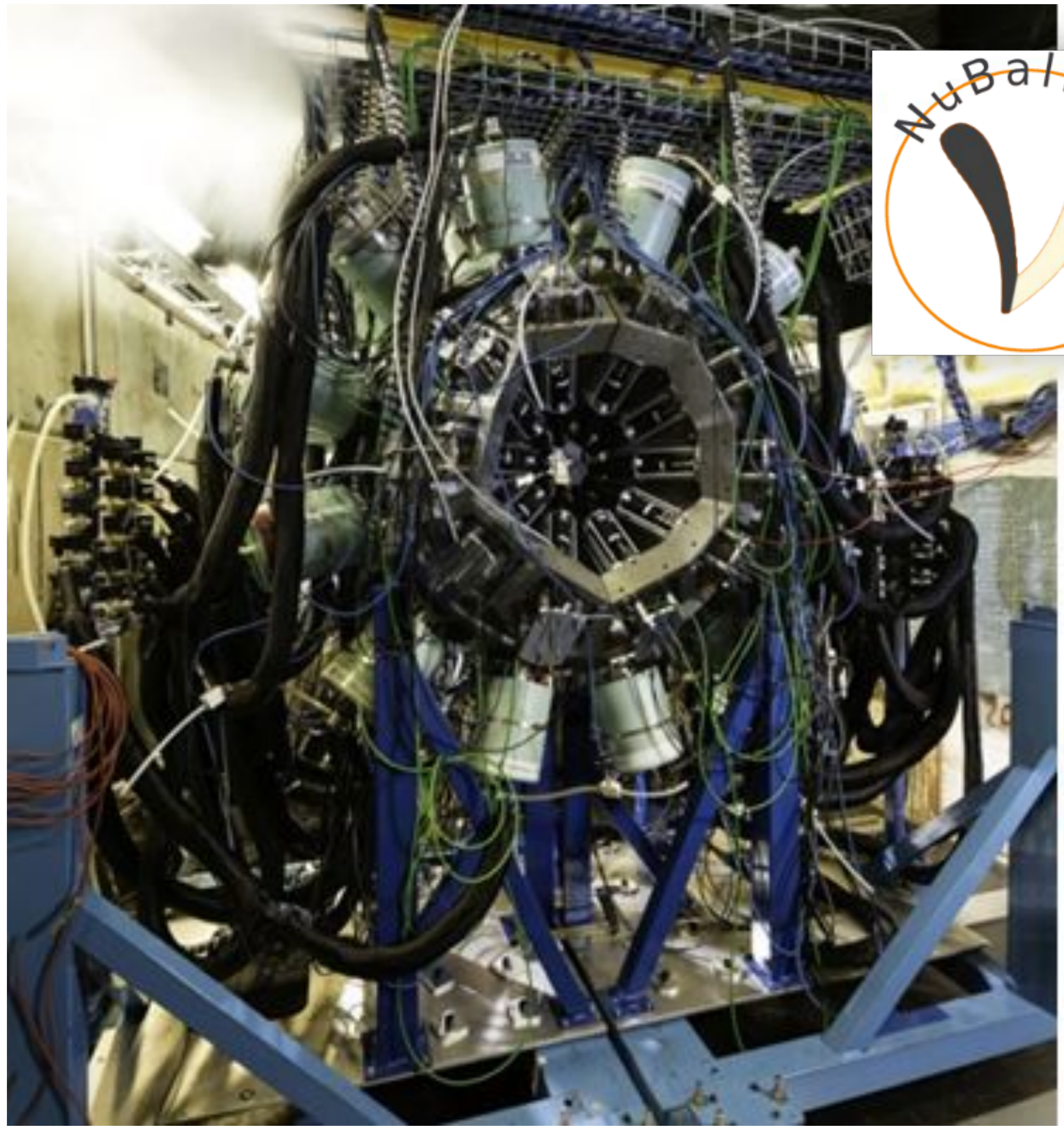


Adapted from: M. Bender, *et al*. Future of nuclear fission theory. Journal of Physics G: Nuclear and Particle Physics, 47(11):113002, oct 2020.

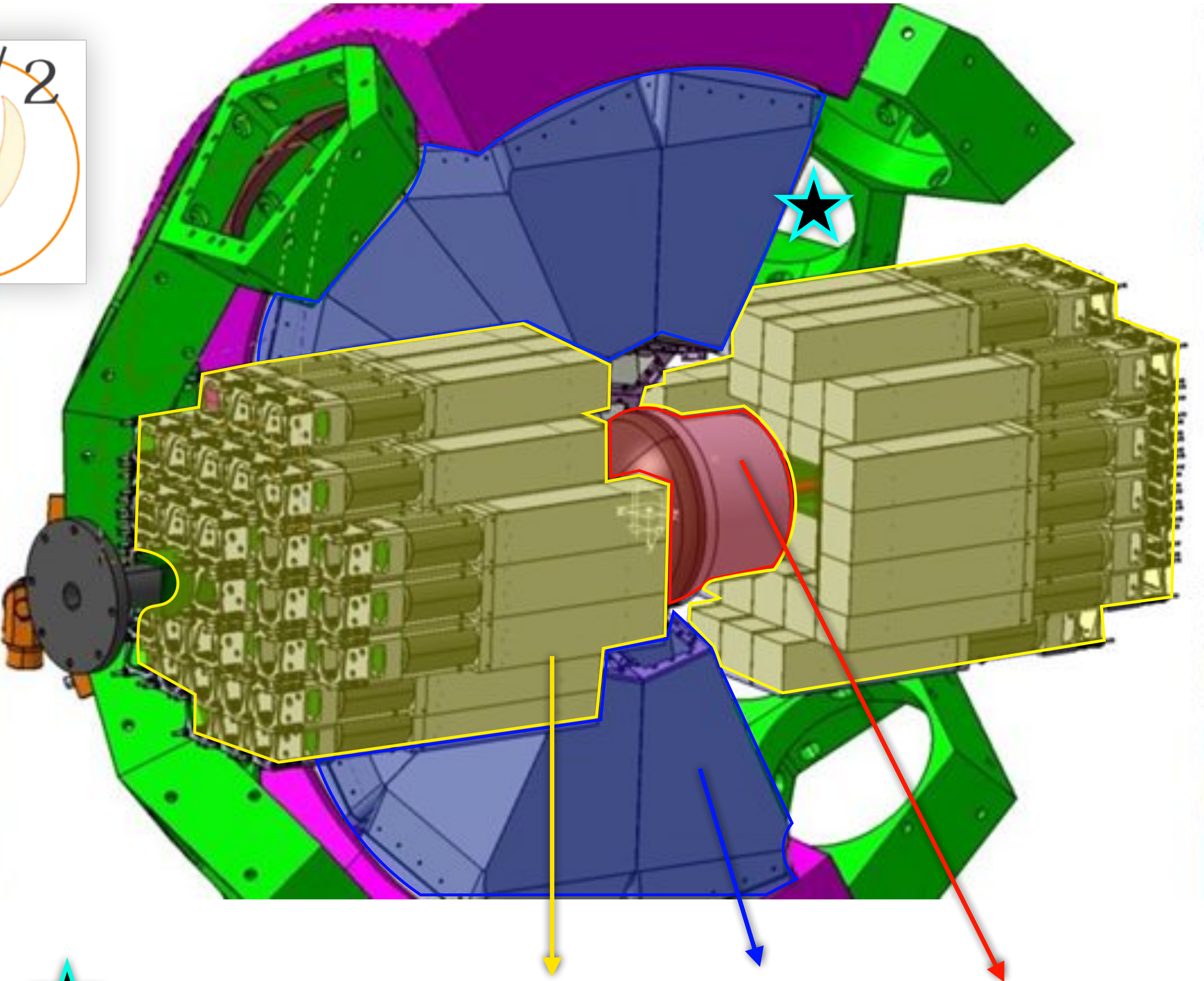


Taken from: A. Al-Adili, V. Rakopoulos, and A. Solders, Eur. Phys. J. A 55 (2019), 61.

The N-SI-125 experiment setup



Taken from: https://alto.ijclab.in2p3.fr/en/nu-ball2-online-scientific-workshop-2/



ALTO
Accélérateur Linéaire auprès du Tandem d'Orsay

Gamma detection
energy and multiplicity

24 High-Purity Germanium clovers (HPGe)

PARIS array
72 phoswhiches La(Ce)Br_3:NaI

Thalia LaBr3

Neutron detection
energy and multiplicity

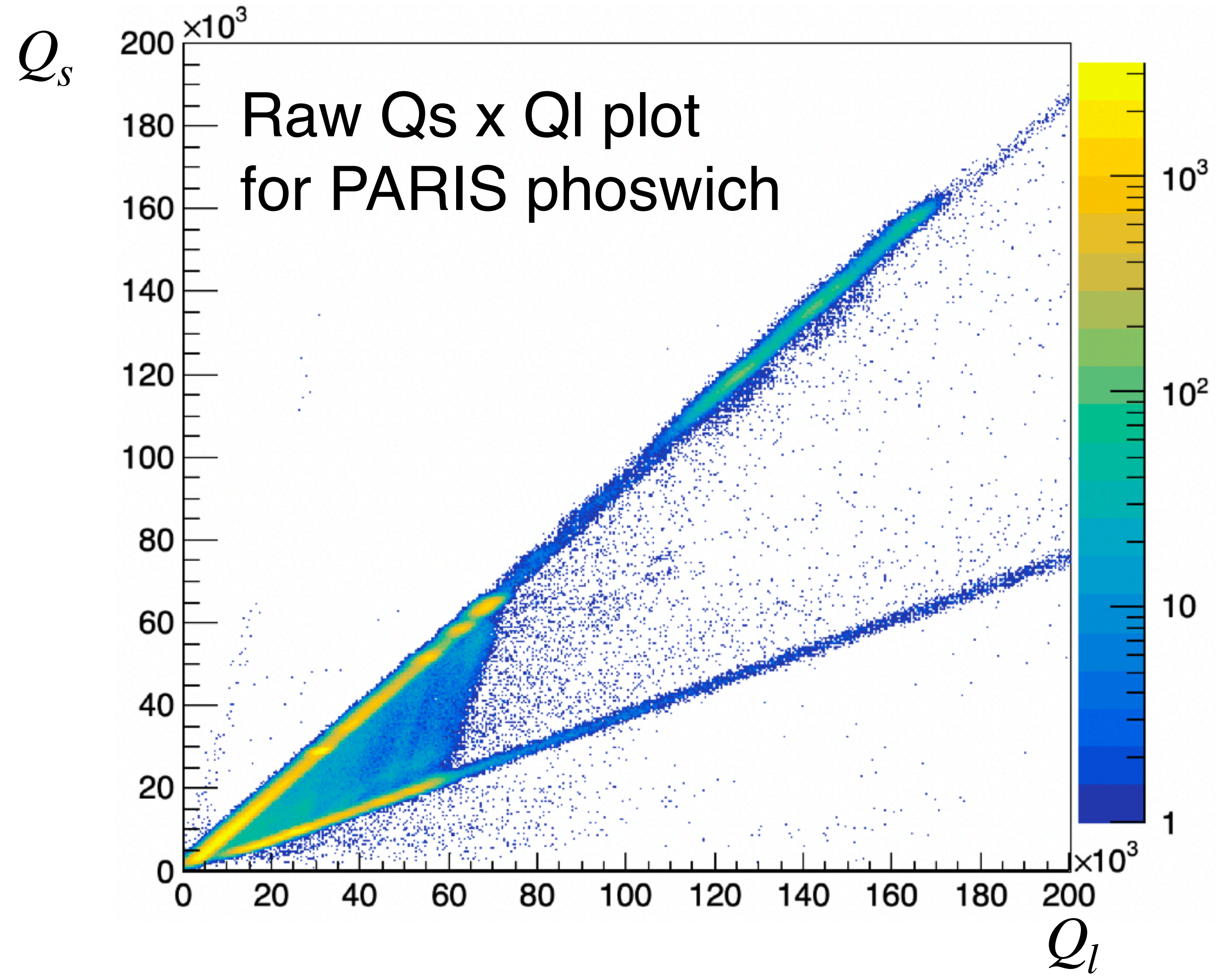
PARIS array

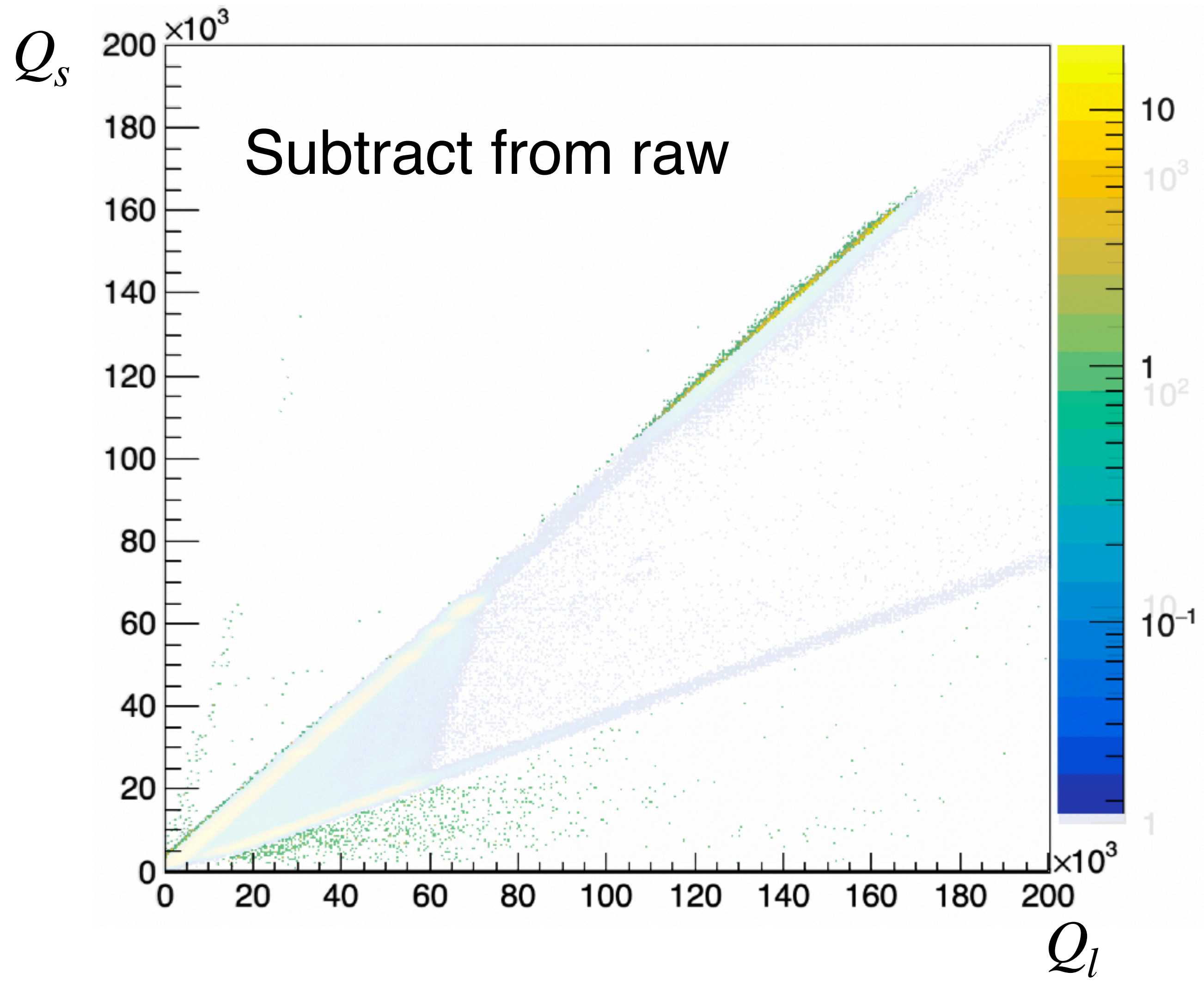
Thalia LaBr3

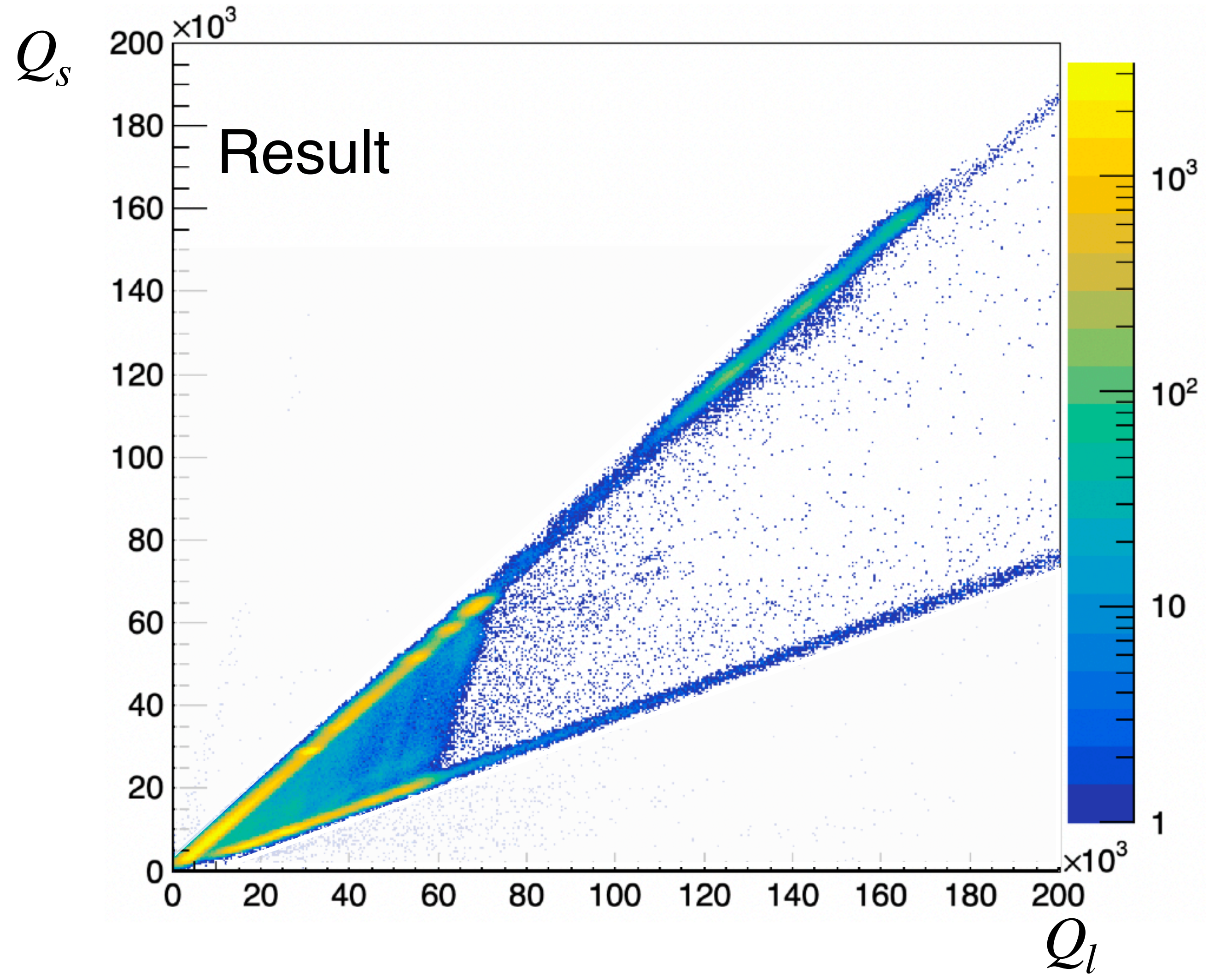
Fission fragments detection

Ionisation chamber

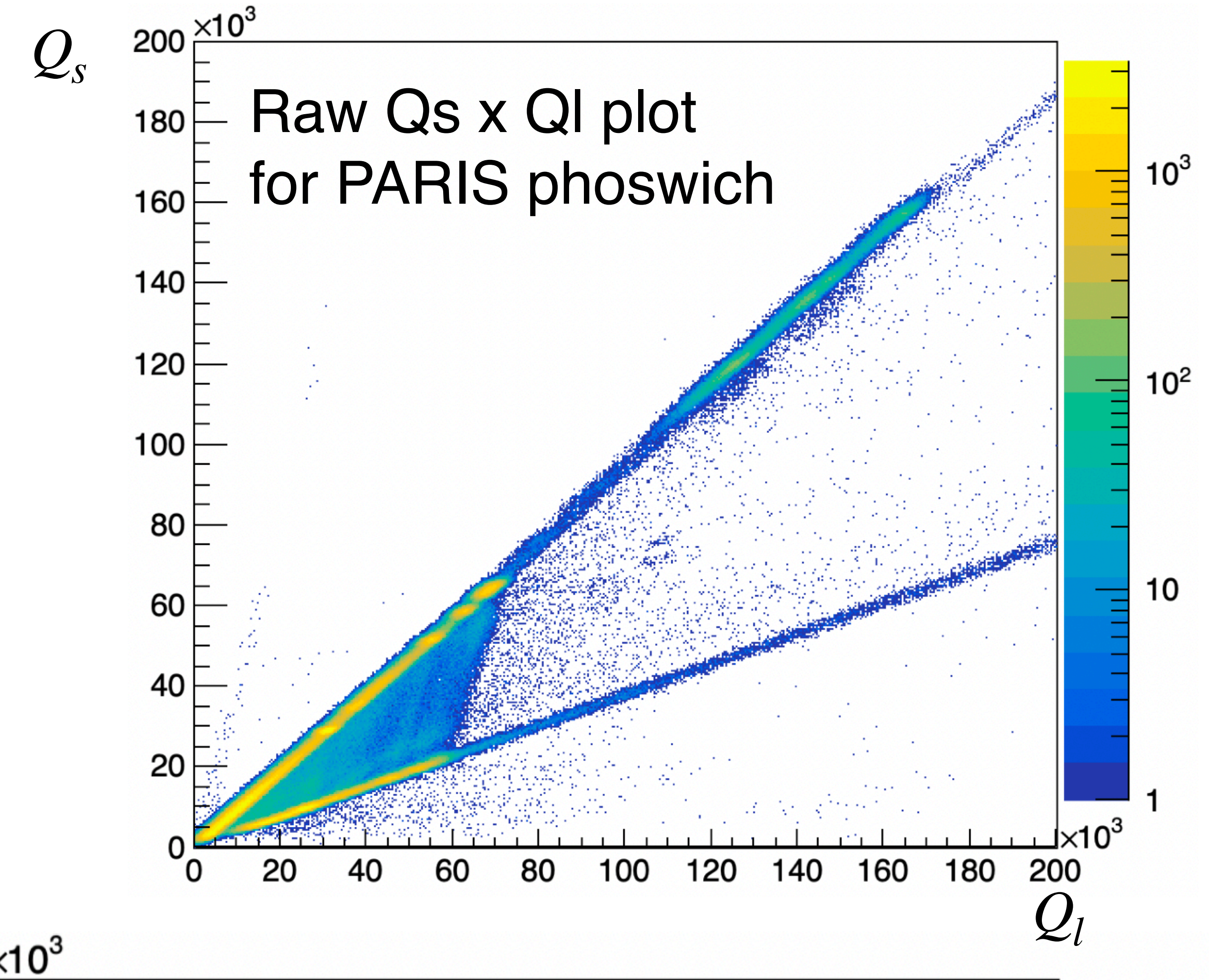
PARIS array


Raw Qs x Ql plot
for PARIS phoswich
Q_s
Q_l


Subtract from raw
Q_s
Q_l


Result
Q_s
Q_l

PARIS array



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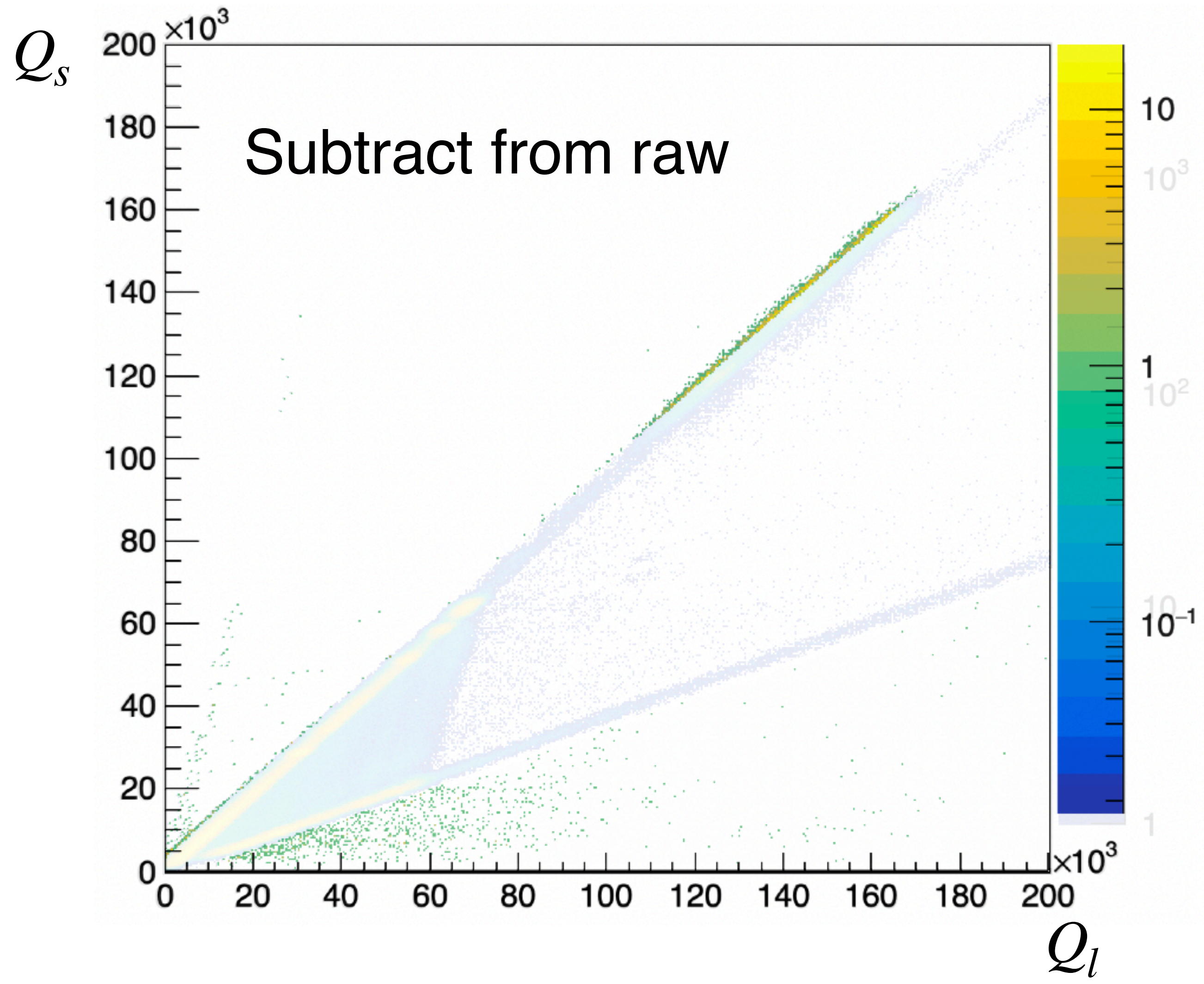

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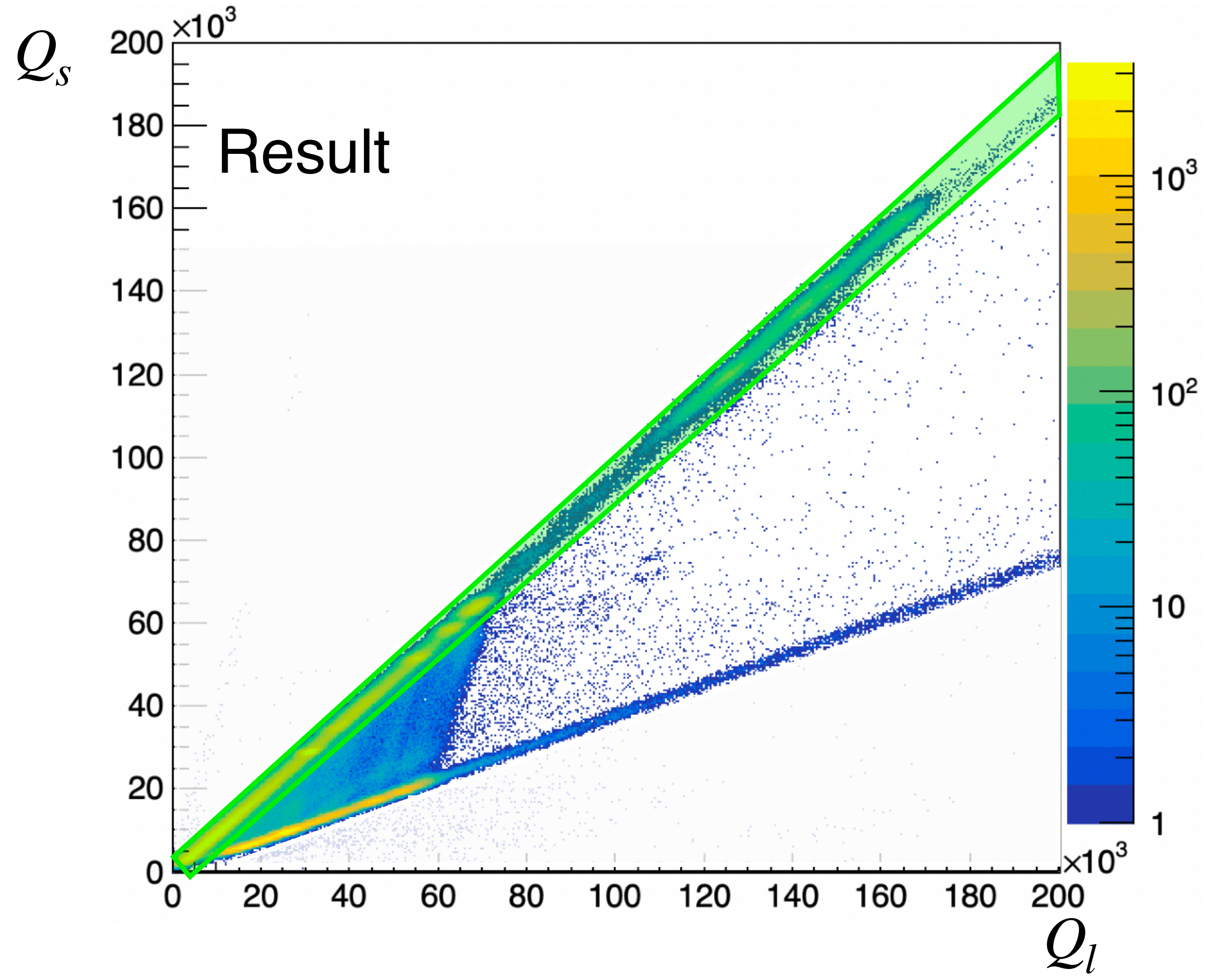
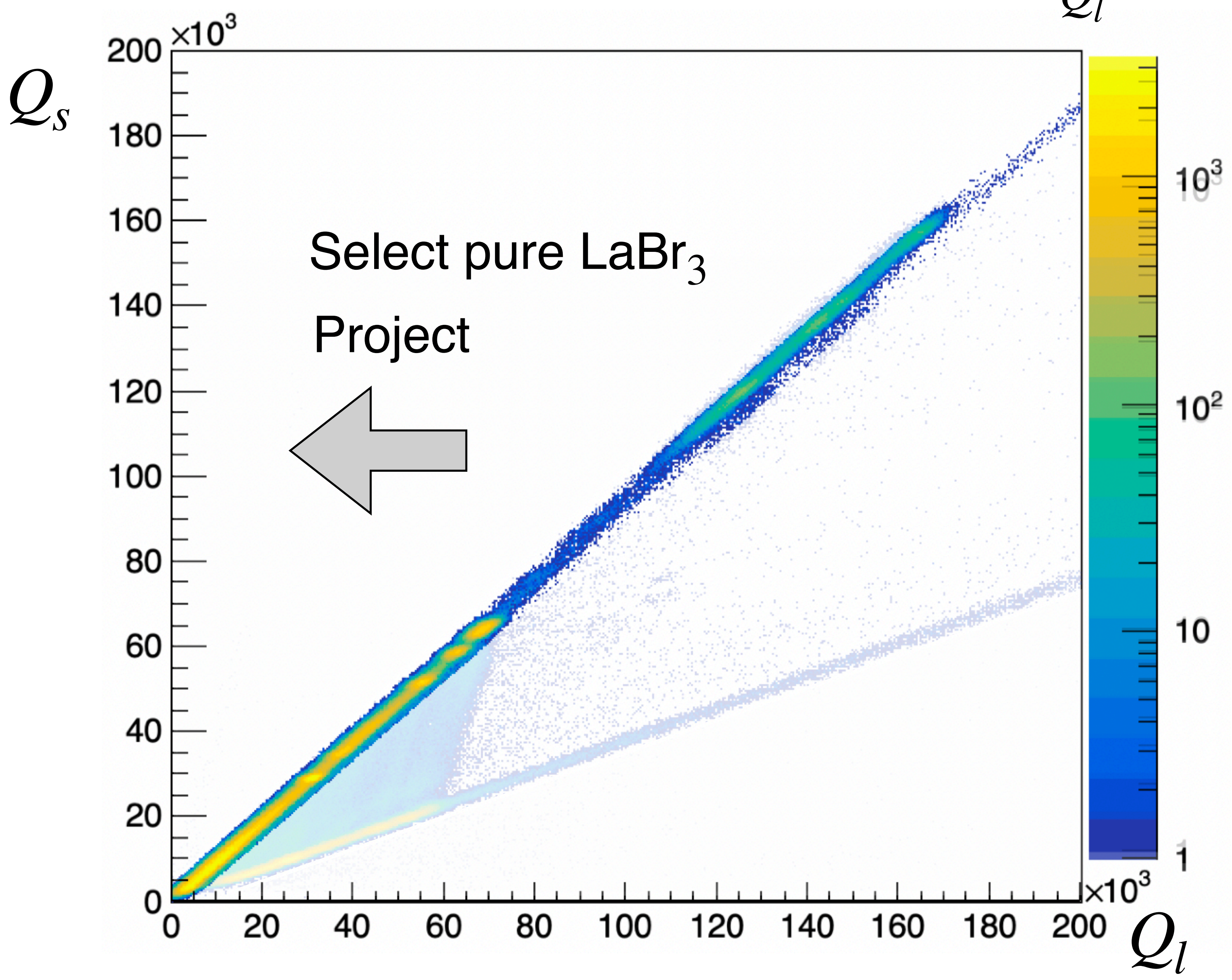
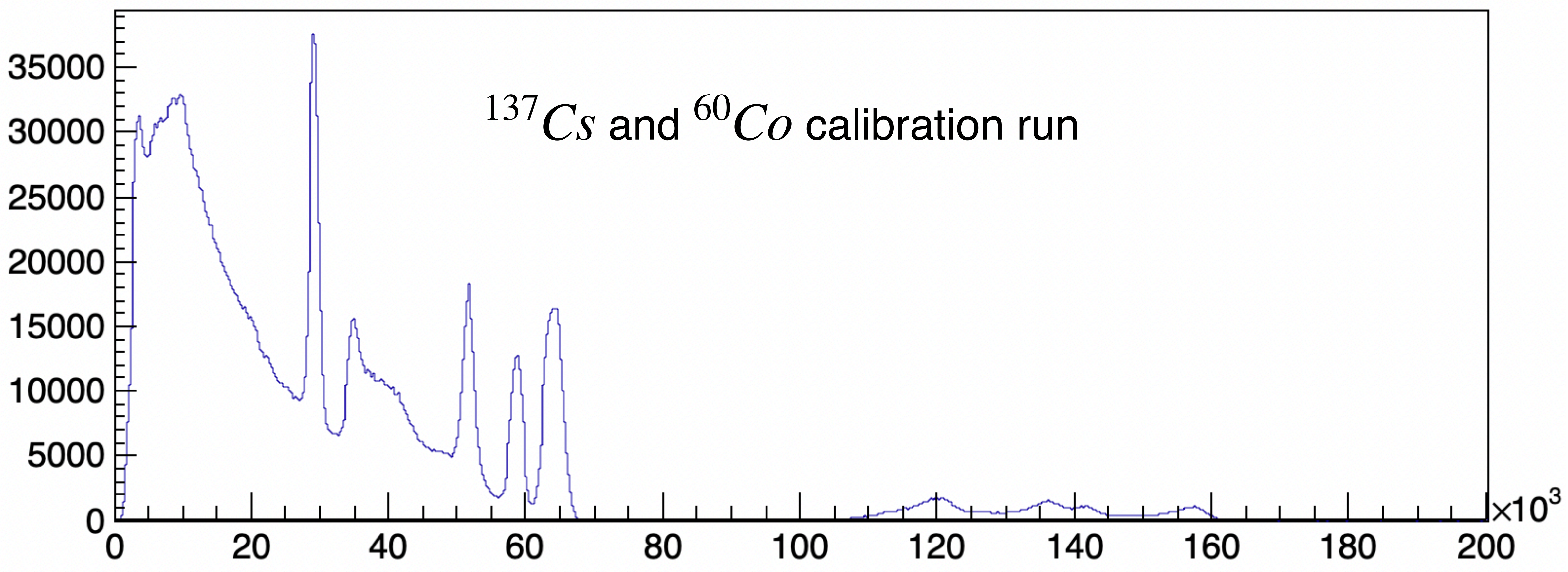


Result
Q_s
Q_l

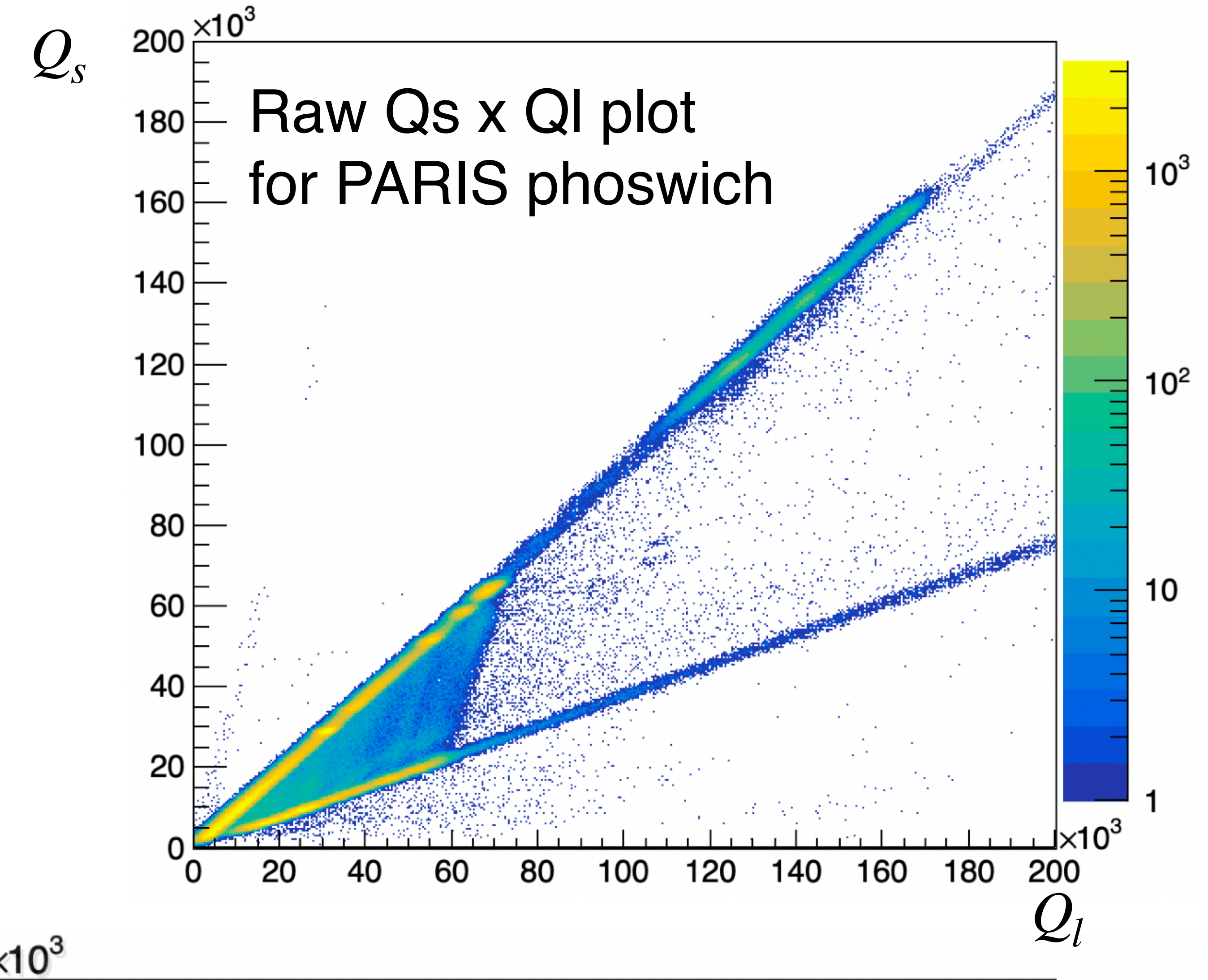


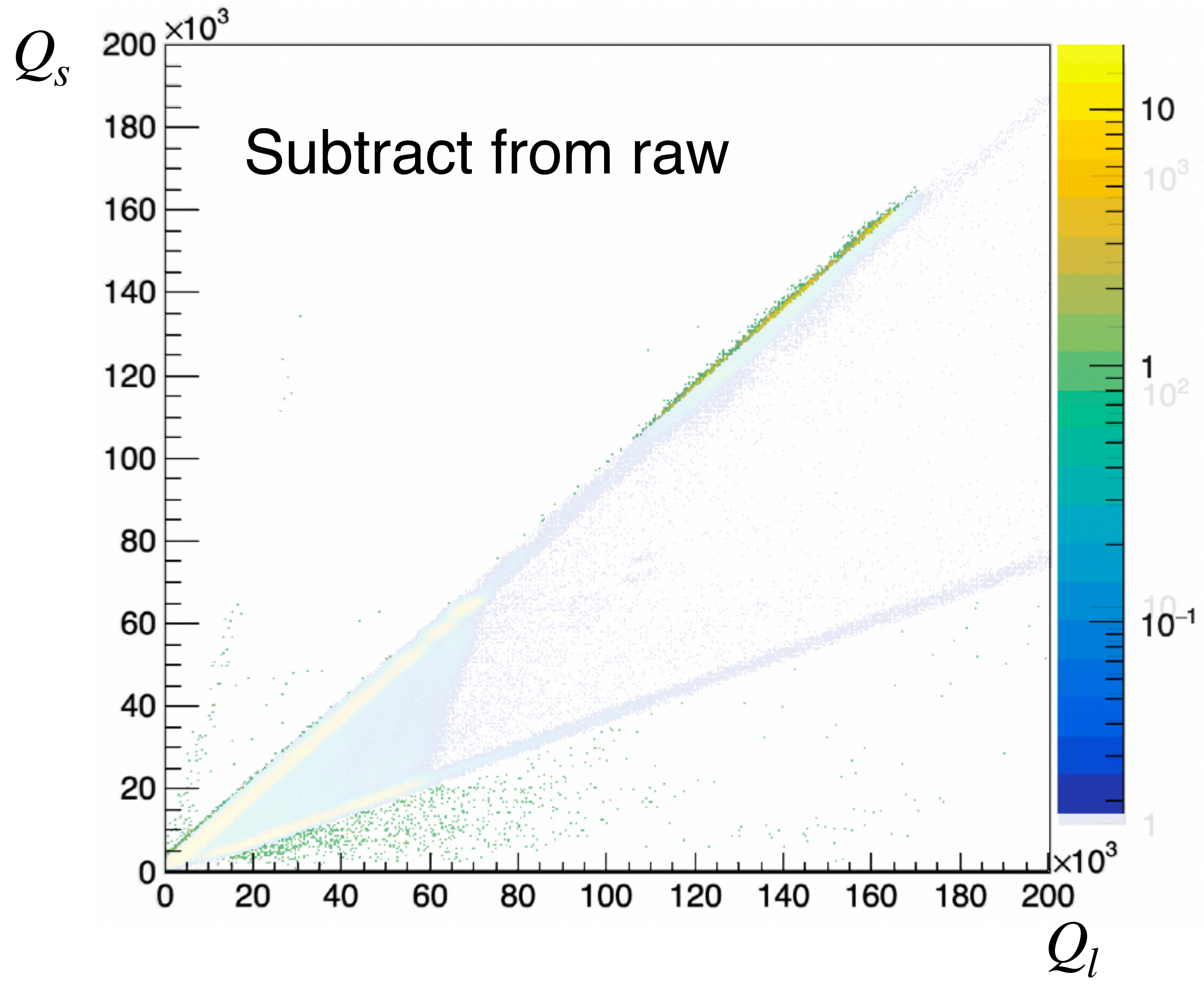
Select pure $LaBr_3$
Project
Q_s
Q_l

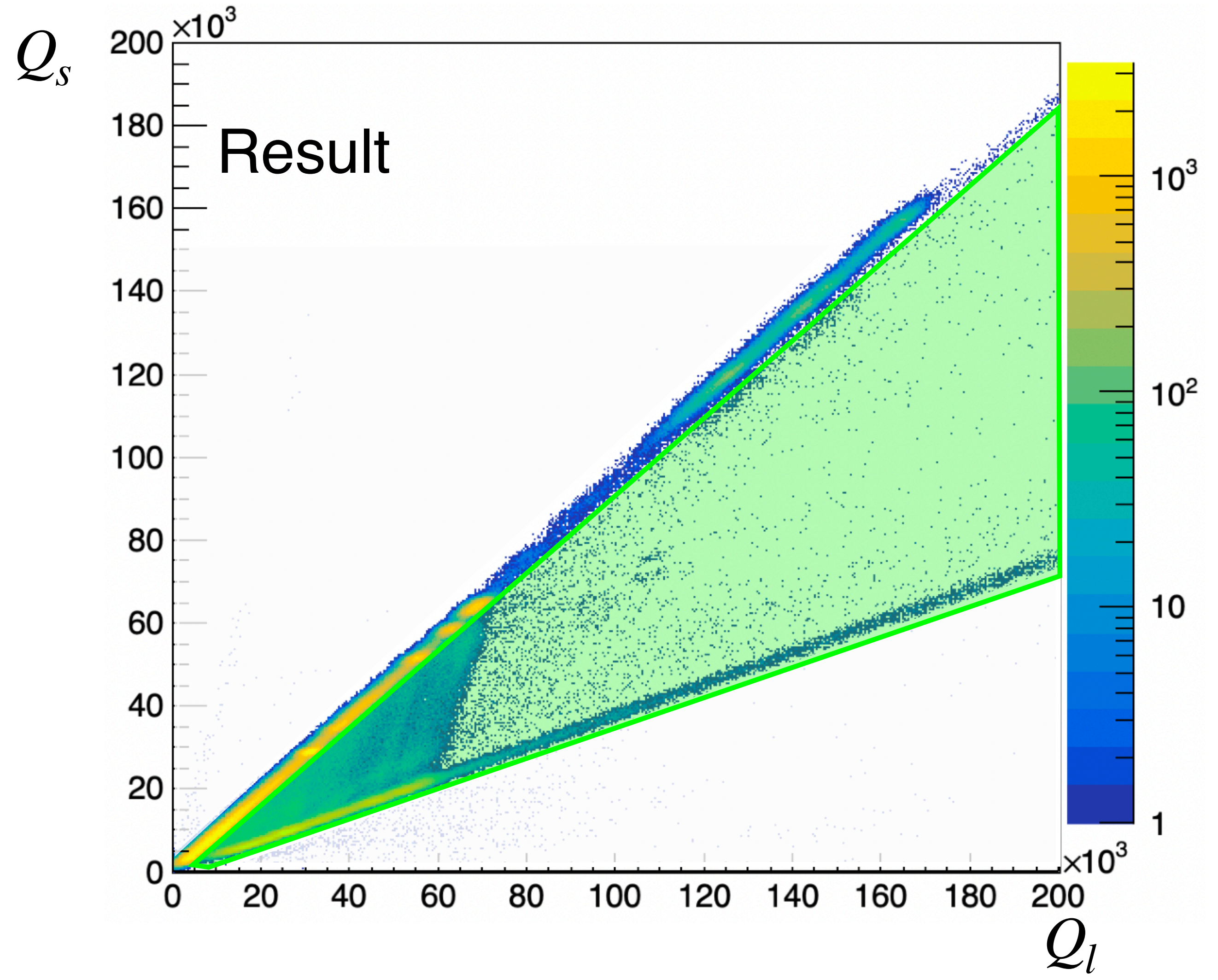


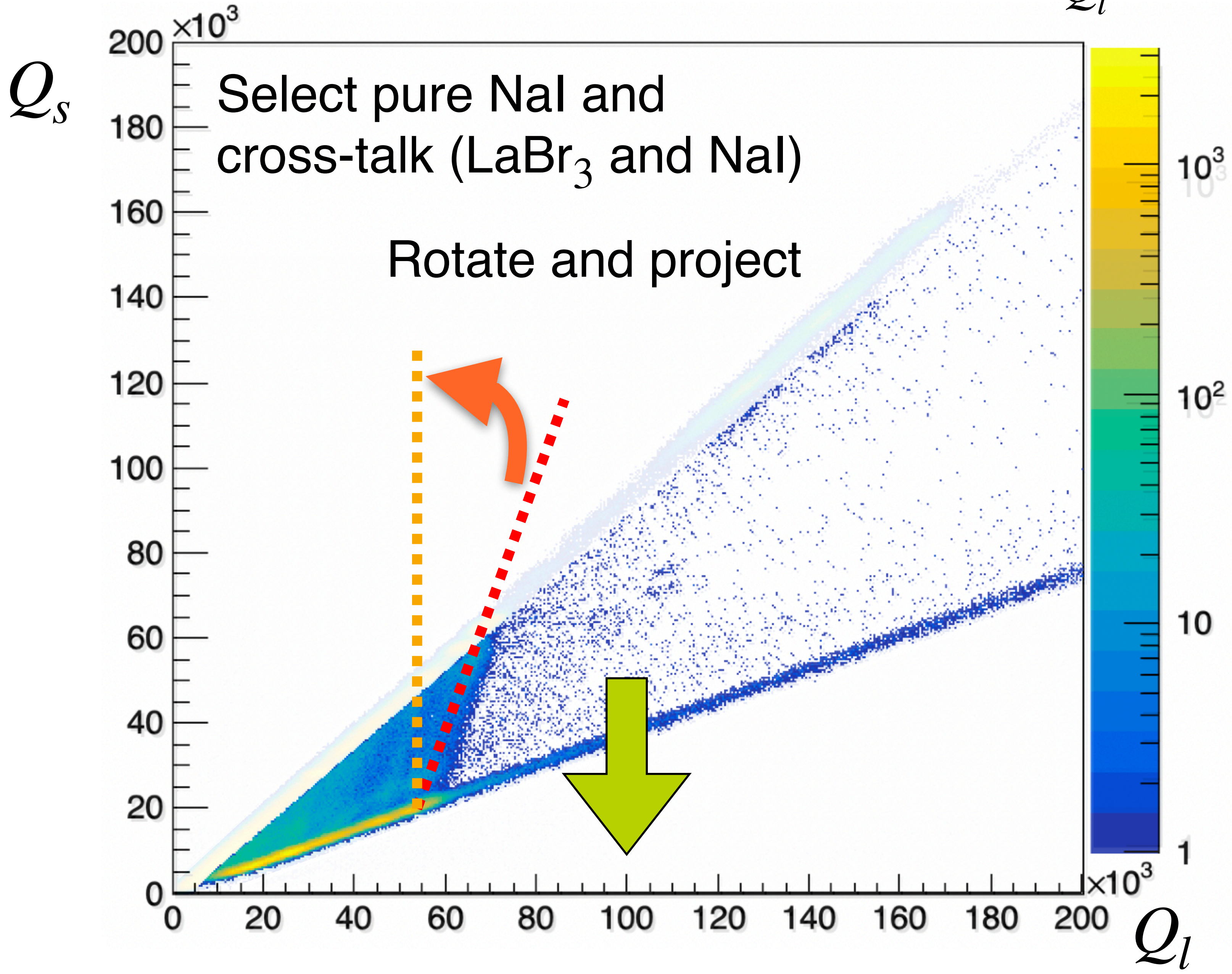
^{137}Cs and ^{60}Co calibration run

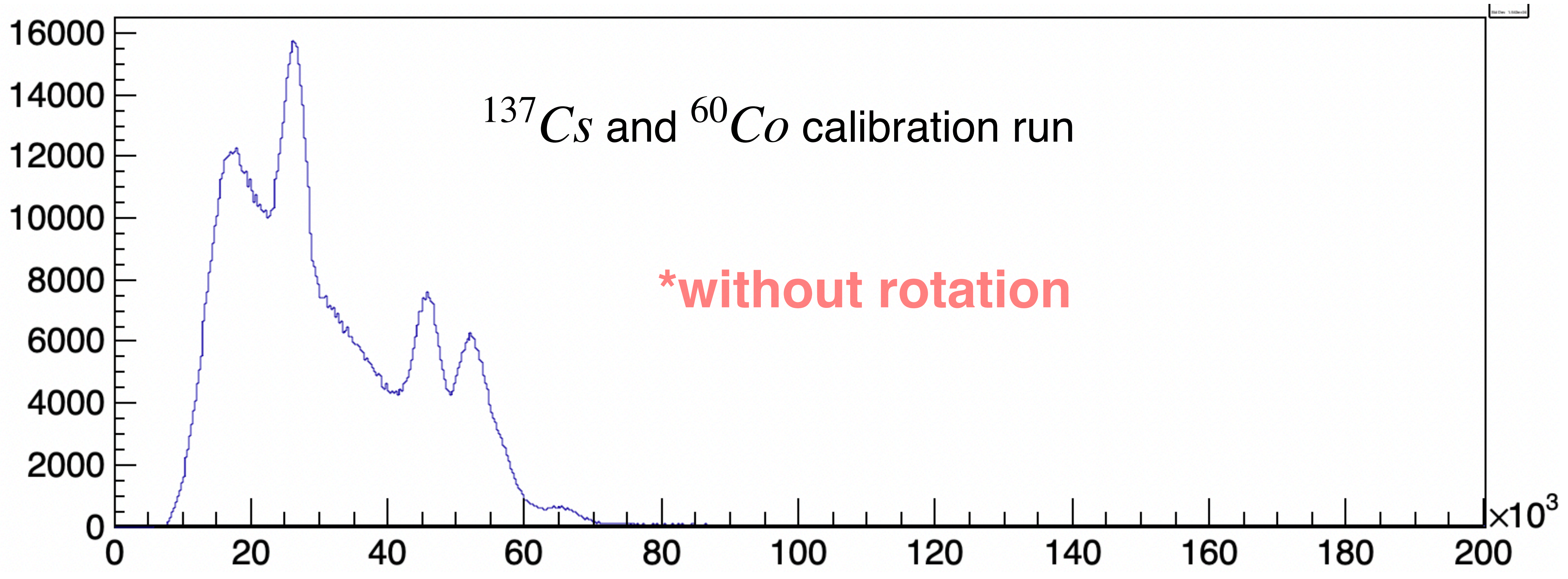
PARIS array


Raw Qs x Ql plot
for PARIS phoswich
Q_s
Q_l
×10³


Subtract from raw
Q_s
Q_l
×10³


Result
Q_s
Q_l
×10³


Select pure NaI and
cross-talk (LaBr3 and NaI)
Rotate and project
Q_s
Q_l
×10³


^{137}Cs and ^{60}Co calibration run
*without rotation
×10³

Calibration is ongoing…

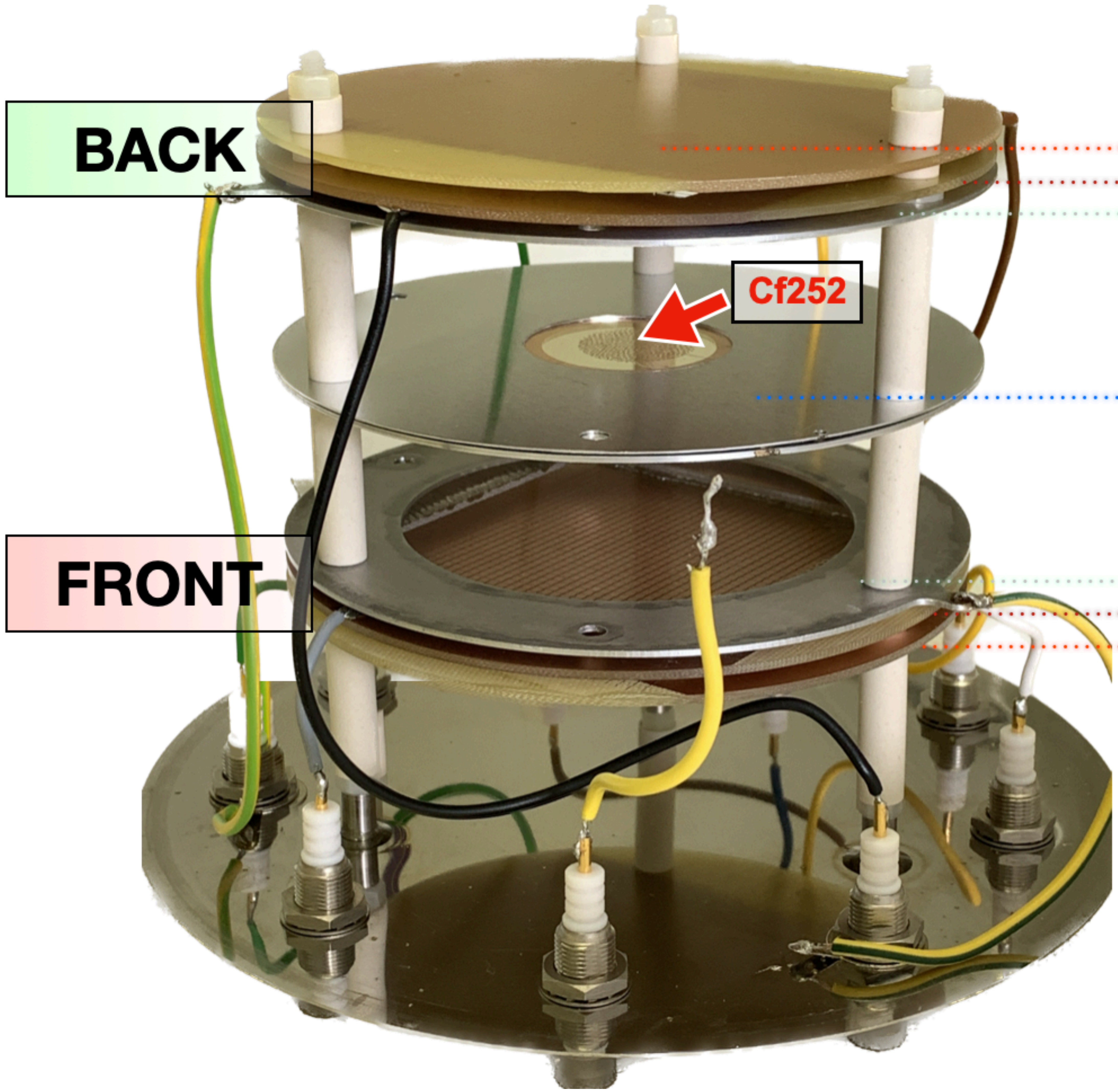
24 HPGe clovers => 96 channels

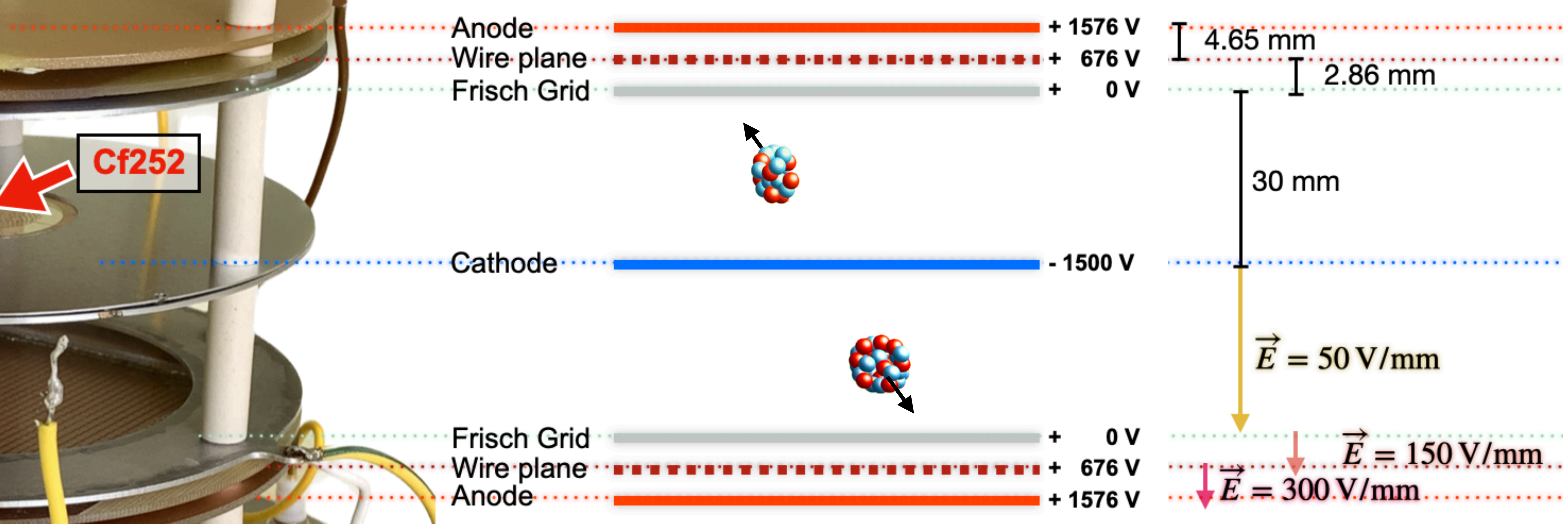
PARIS array
72 phoswhiches $La(Ce)Br_3:NaI$

More than 200 channels

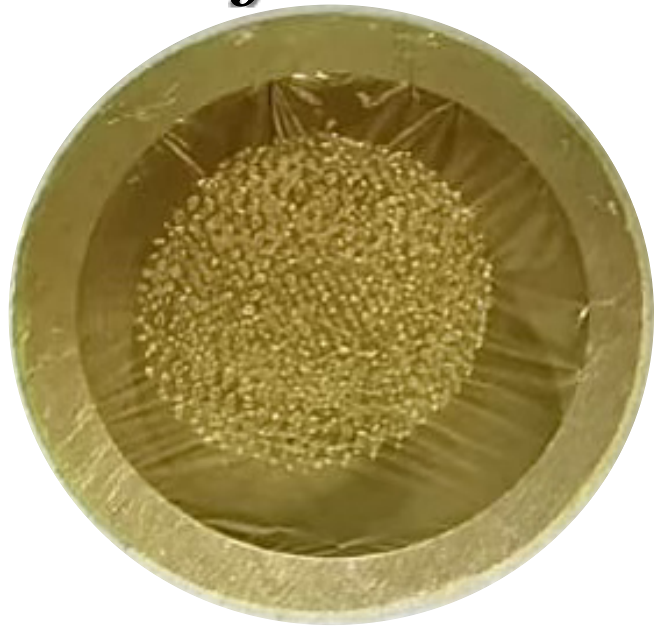
Calibration with ^{152}Eu, ^{60}Co, ^{137}Cs and *AmBe*

Double Frisch-Grid Ionisation Chamber (dFGIC)





^{252}Cf source



96.9 % α decay
3.1 % fission

~330 fissions $\cdot\ s^{-1}$

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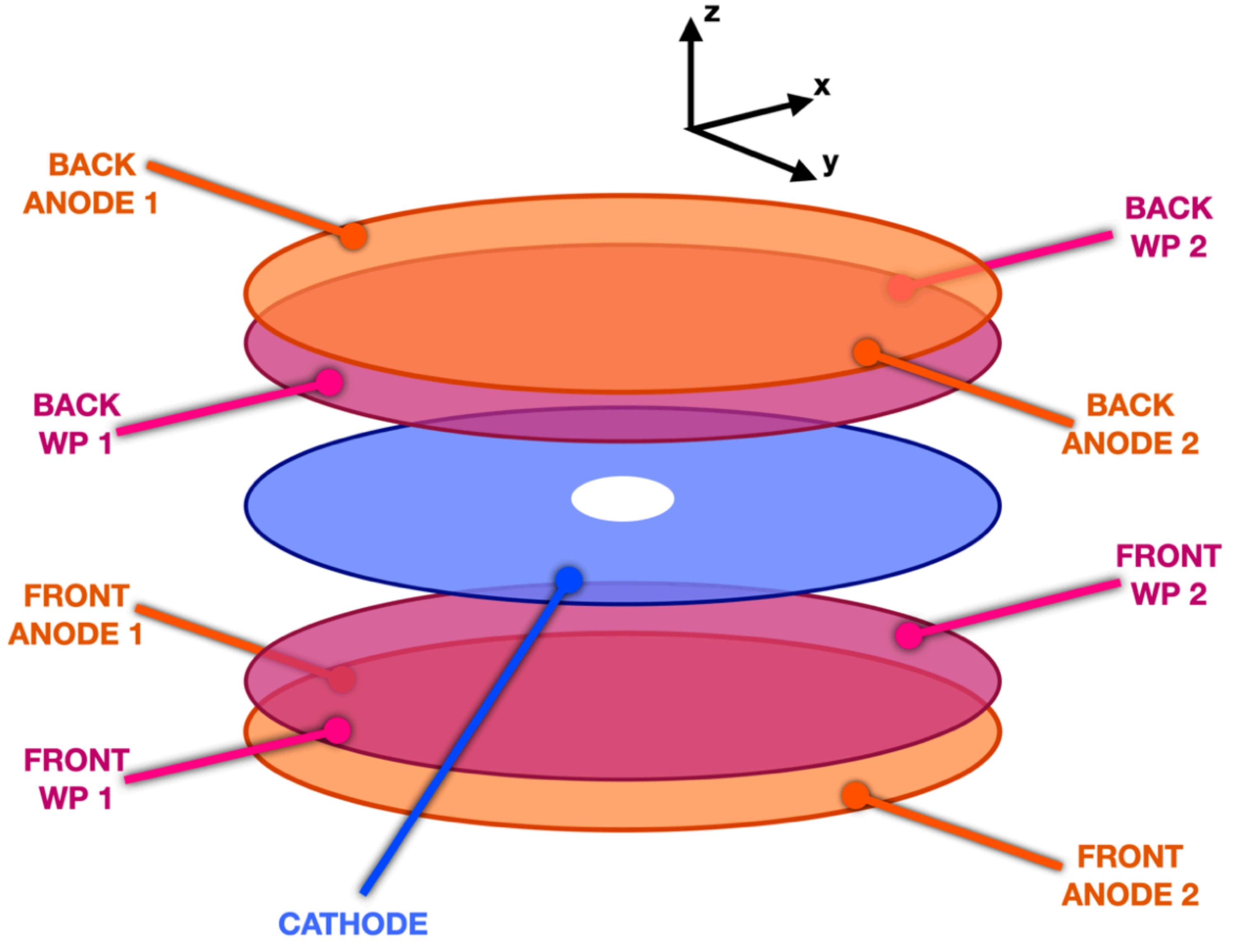

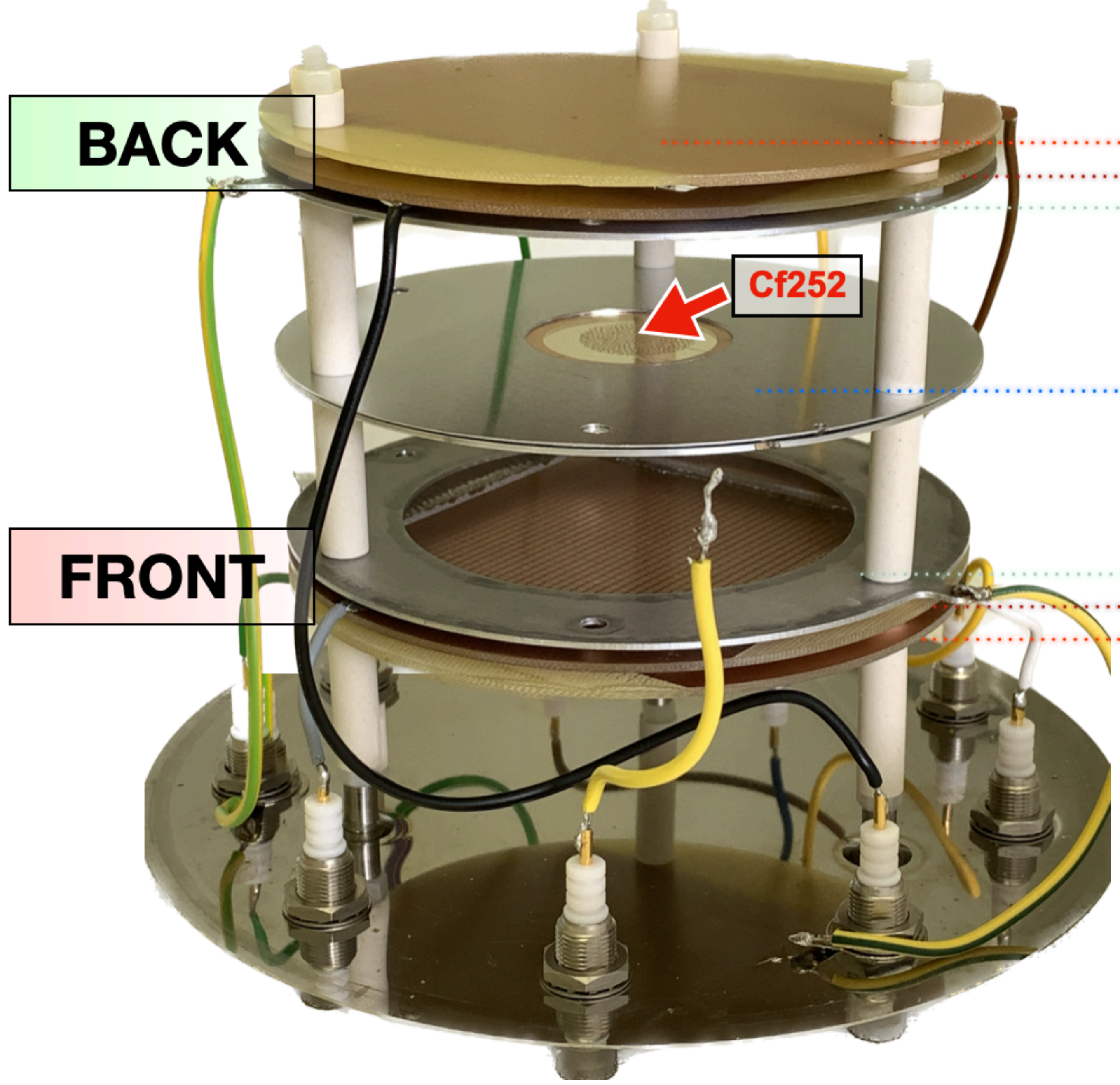

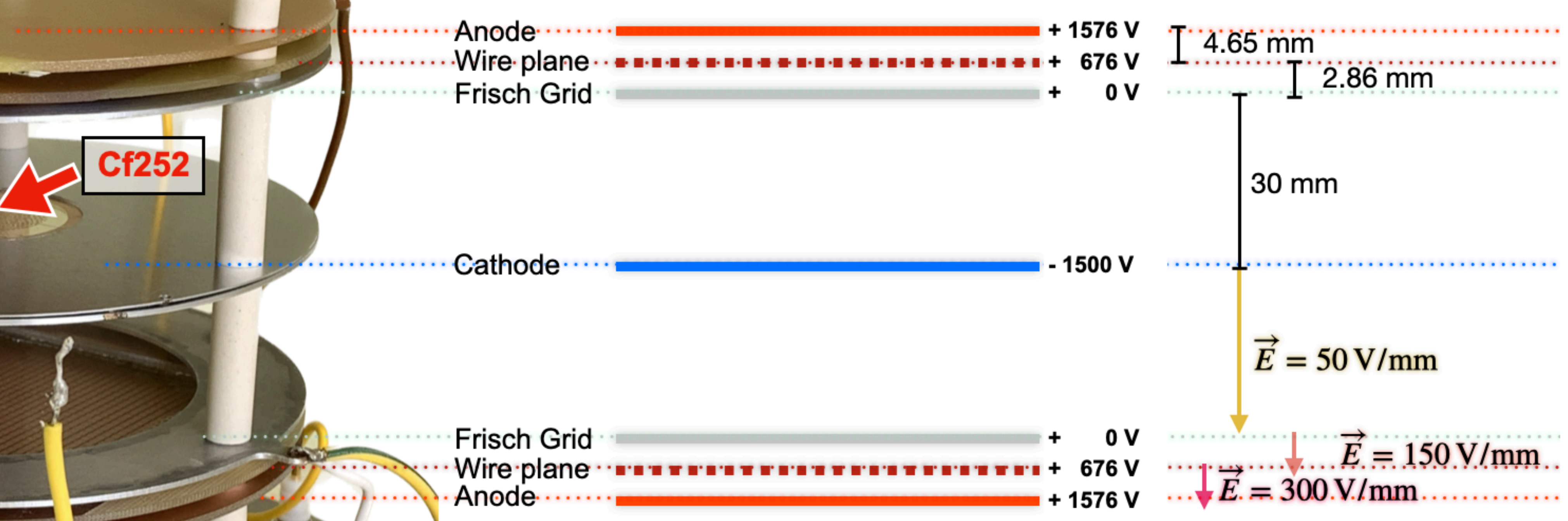

$$\bar{x} = k_x \frac{P_1 - P_2}{P_1 + P_2}, \quad \bar{y} = k_y \frac{A_1 - A_2}{A_1 + A_2}$$

calibration constants

$$\bar{z} = v_d \cdot (\bar{t}_{(0^\circ,0^\circ)} - \bar{t}_{(\theta_x^\circ,\theta_y^\circ)})$$

average electron drift time

electron drift velocity

Adapted from: A. Göök, *et al.* A position-sensitive twin ionization chamber for fission fragment and prompt neutron correlation experiments. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, 830:366–374, 2016.

CFD for a reliable cathode signal trigger: start of our fission event

CFD* CONSTRAINT:

$$t_{delay} > t_r \cdot (1 - f)\,,$$

where t_r is the signal rise time

The average electron drift time is the maxima of the resulting wave form of the anode sum signal shaped using the following equation:

$$t_n = \frac{1}{Q_{max}} \cdot \sum_{k=k_0}^{k_0+n} (q_{k+1} - q_k)(k - k_0) \cdot \frac{1}{f_s}$$

* CFD: Constant Fraction Discrimination

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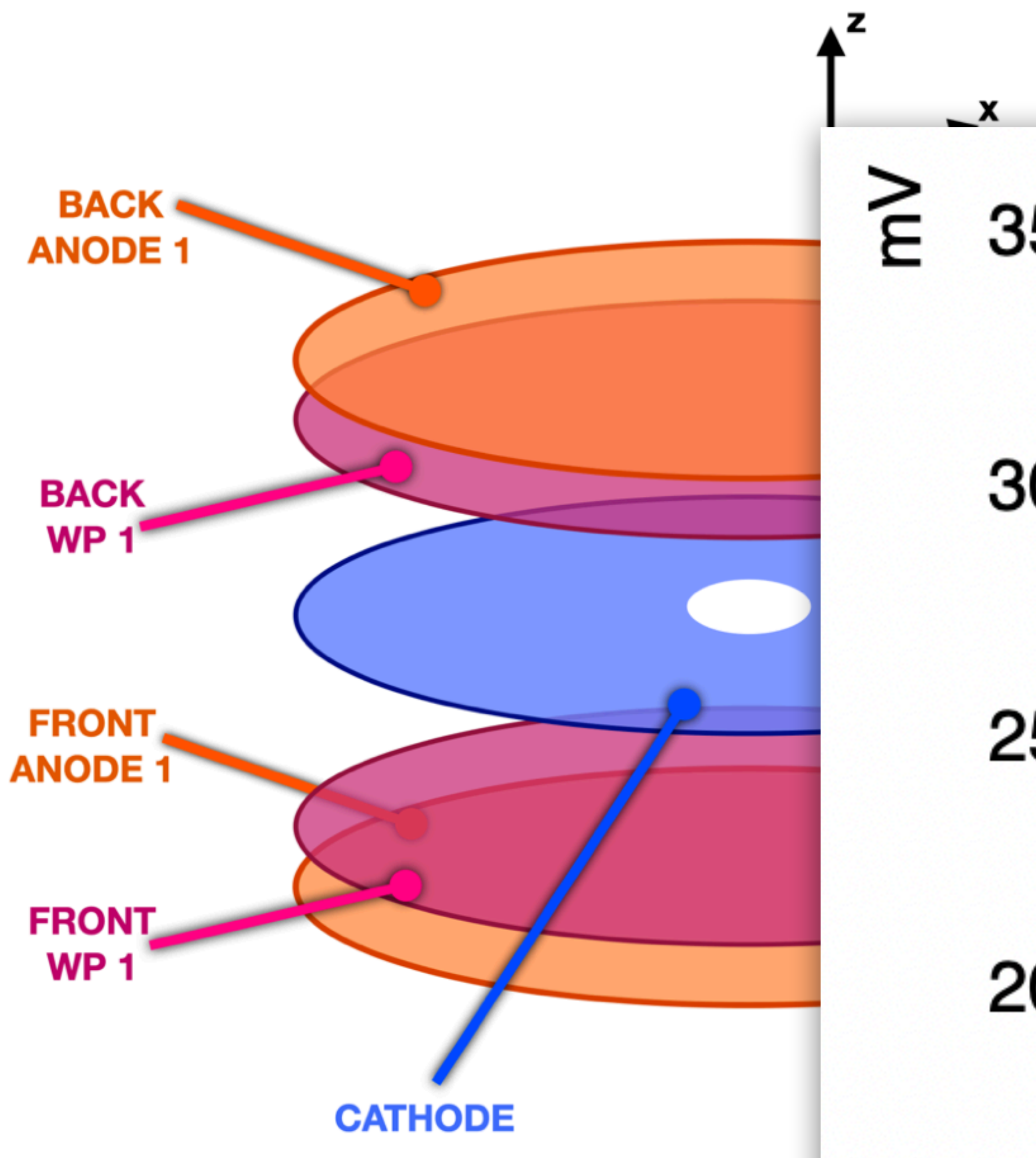
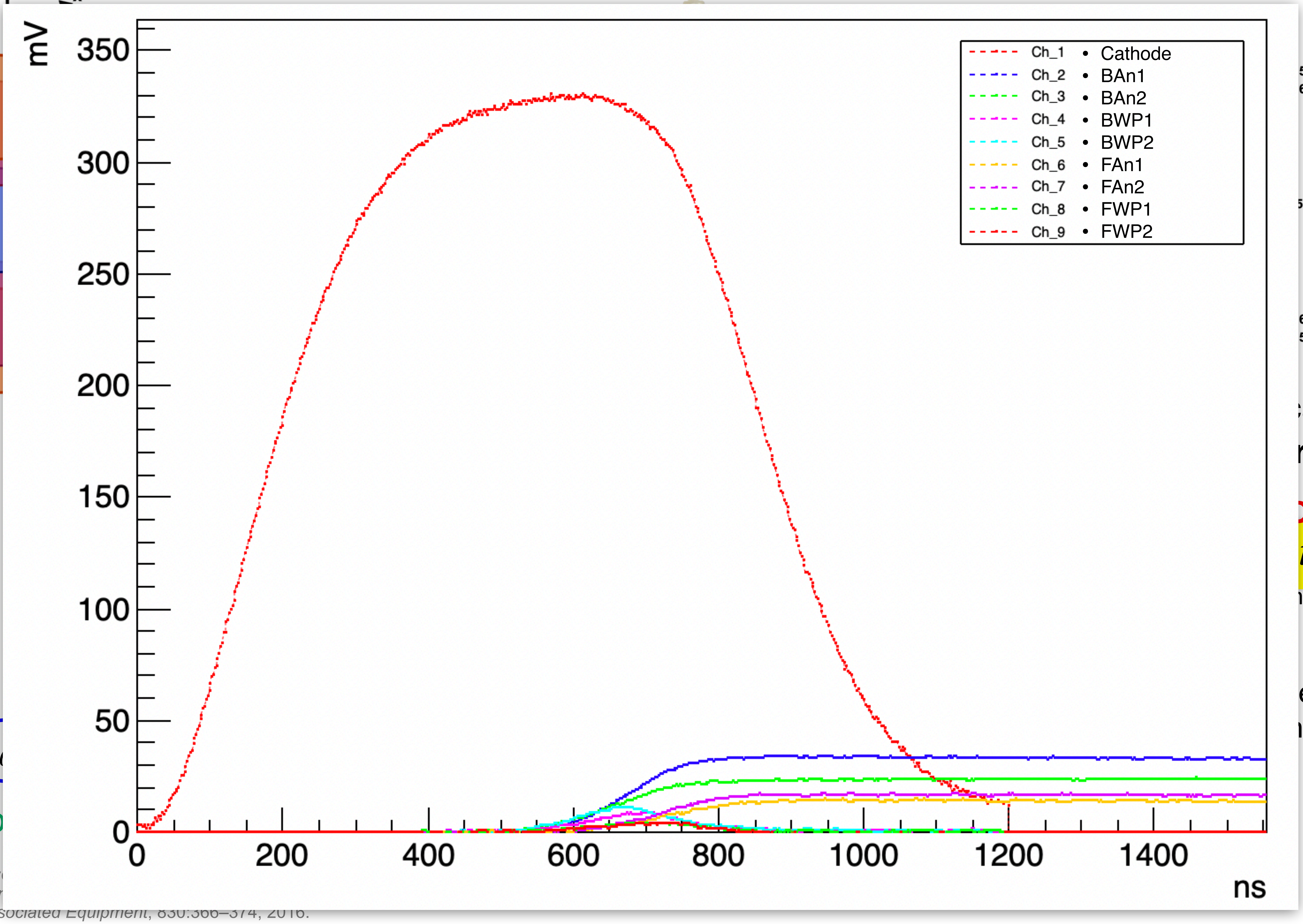


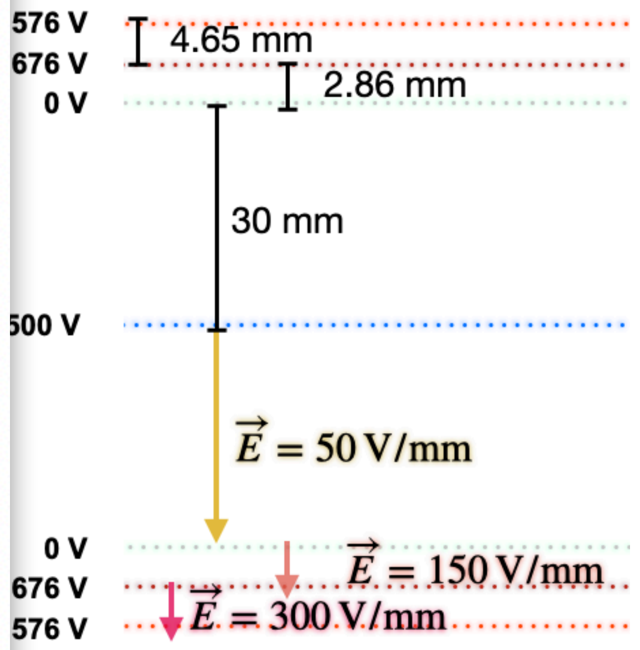
$\bar{x} = k_x \frac{P_1 - P_2}{P_1 + P_2}, \quad \bar{y}$

calibration

$\bar{z} = v_d \cdot (\bar{t}_{(0°,0°)} - \bar{t}_{(}$

electro





athode signal trigger:
r fission event

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$t_r \cdot (1 - f)$,

ne signal rise time

e

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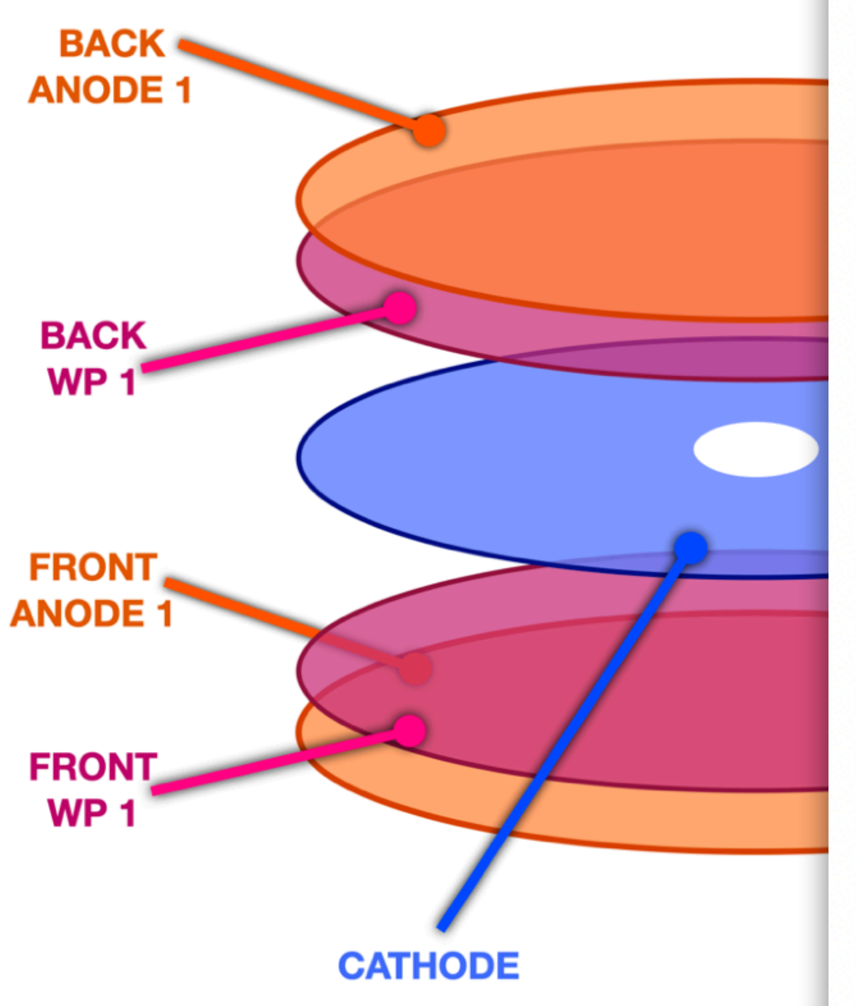

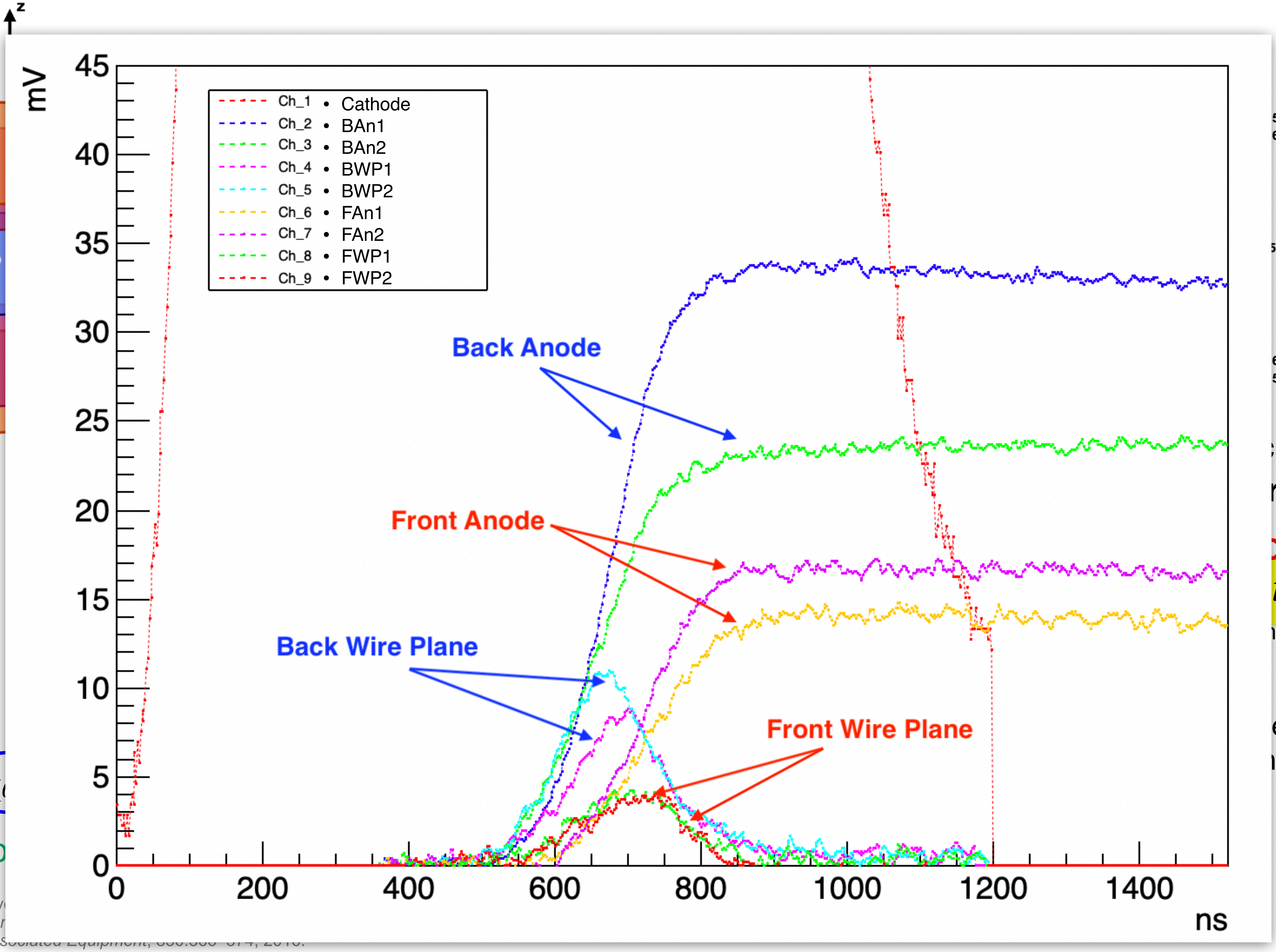

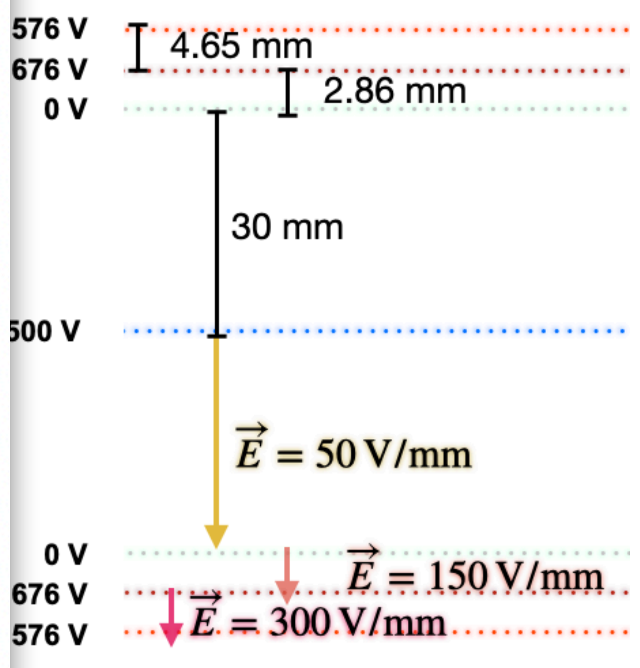

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Trace analysis

Trace analysis through most frequently used methods

- Moving average algorithm;
- RC filter;
- Signal baseline correction;

→ **BOTH TIME AND ENERGY MEASUREMENTS**

- CR-RC and CR-RC4 shaping filters;
- Trapezoidal shaping filter;
- Signal integration (deposited charge)

→ **« ENERGY » MEASUREMENTS**

- Constant Fraction Discrimination (CFD) **TIME MEASUREMENTS**

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How do we know if the method works?

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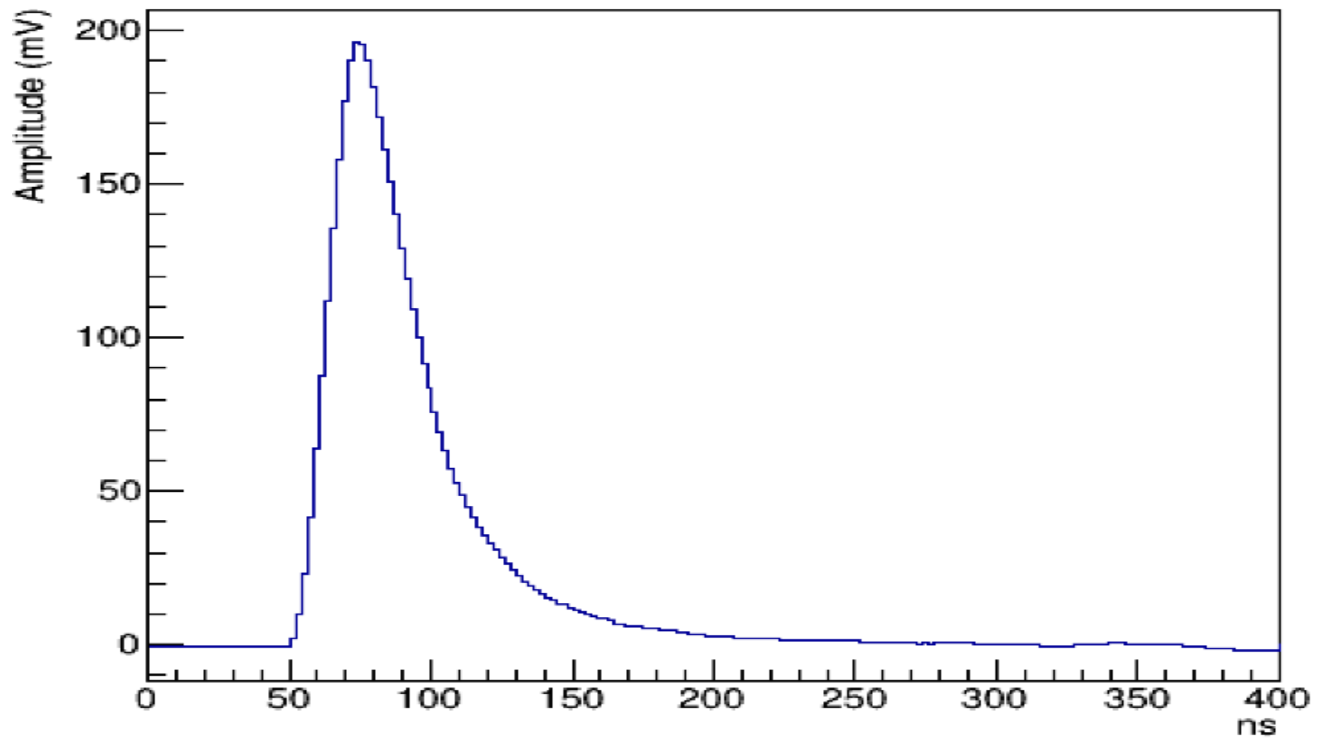
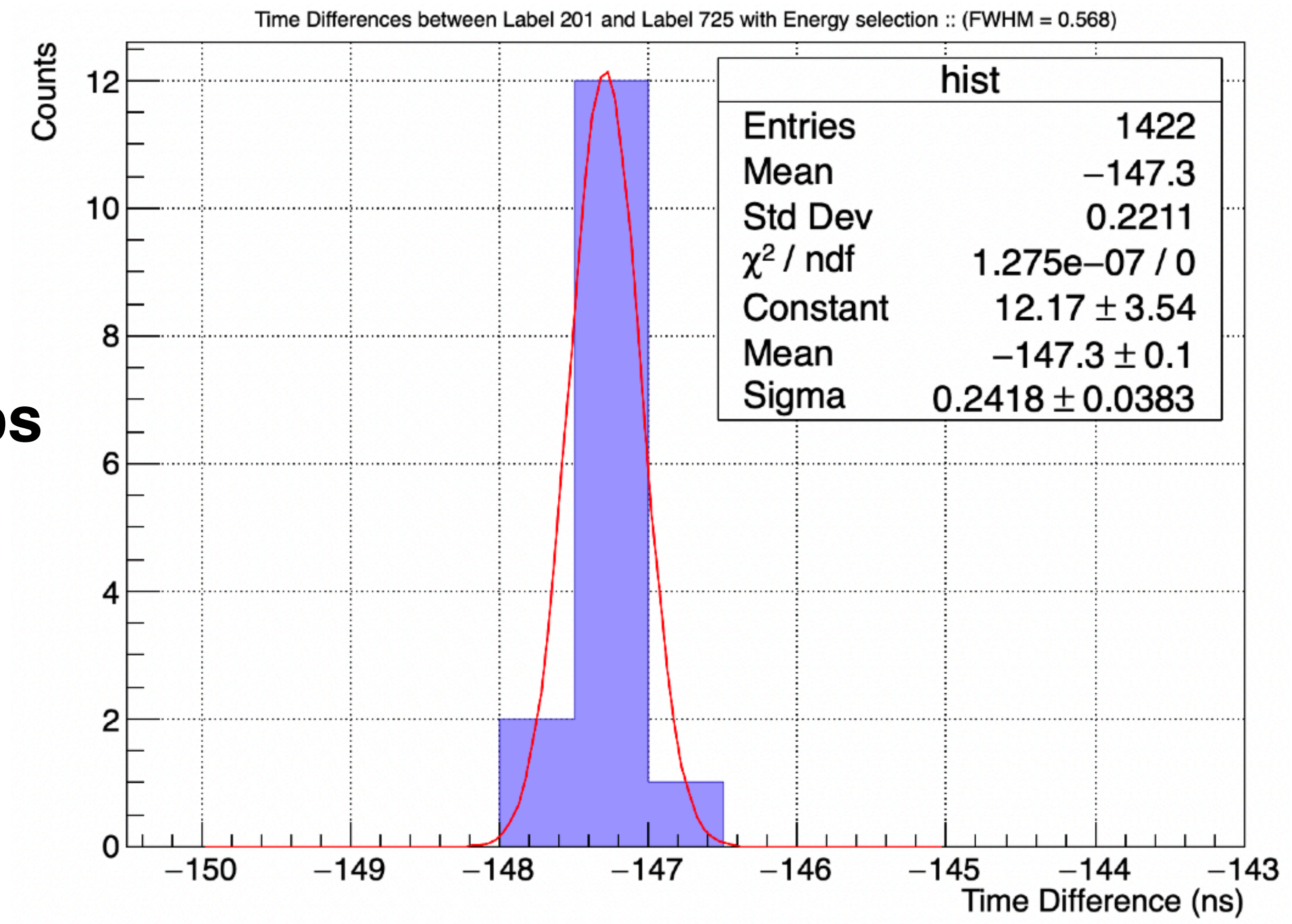
THALIA $LaBr_3$ data stored as a trace:



~31.7 keV @ 1170 keV

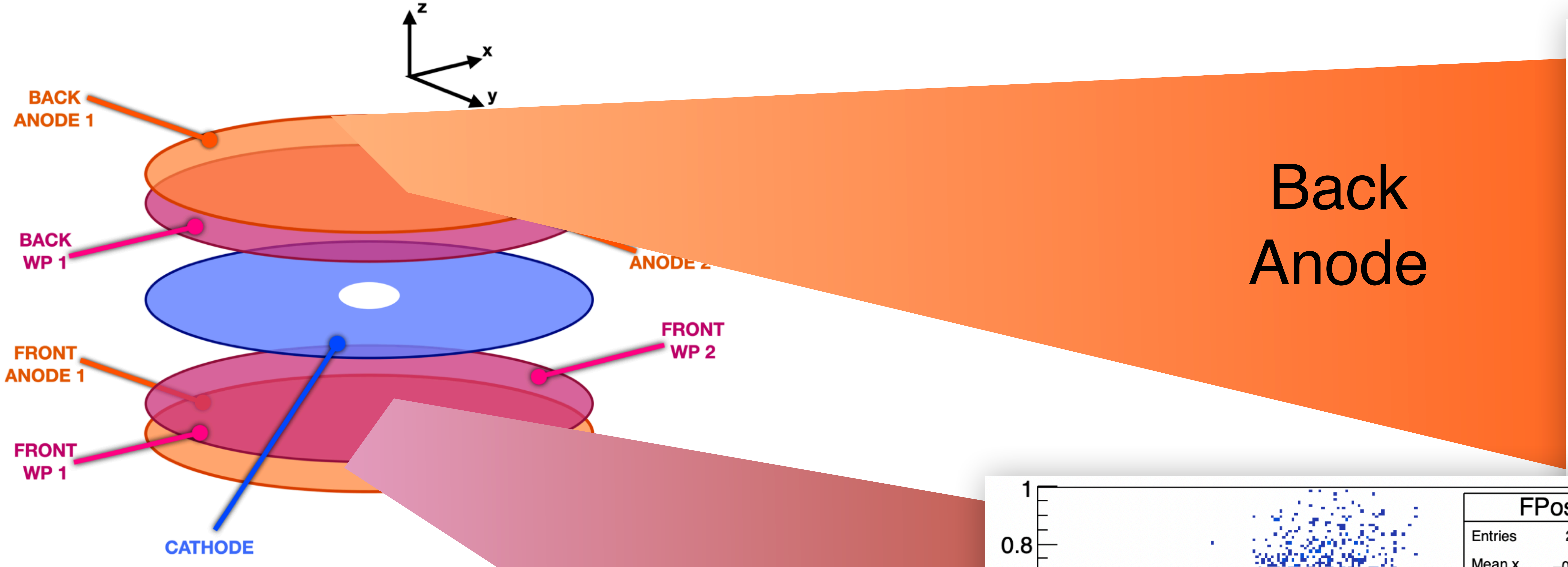
Time resolution of ~570 ps

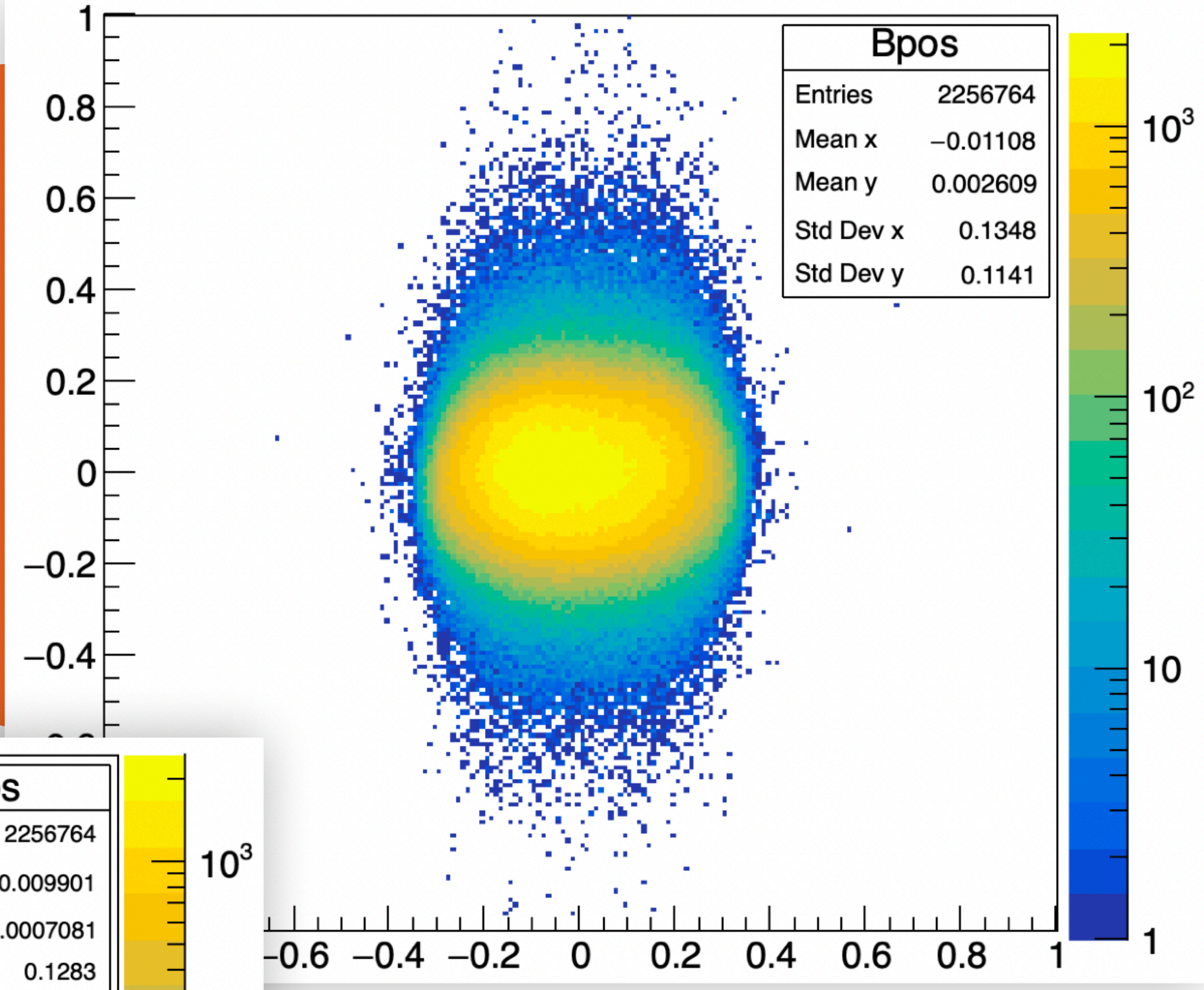
* with gamma energy selection: 1170 & 1330 peaks on ^{60}Co calibration run

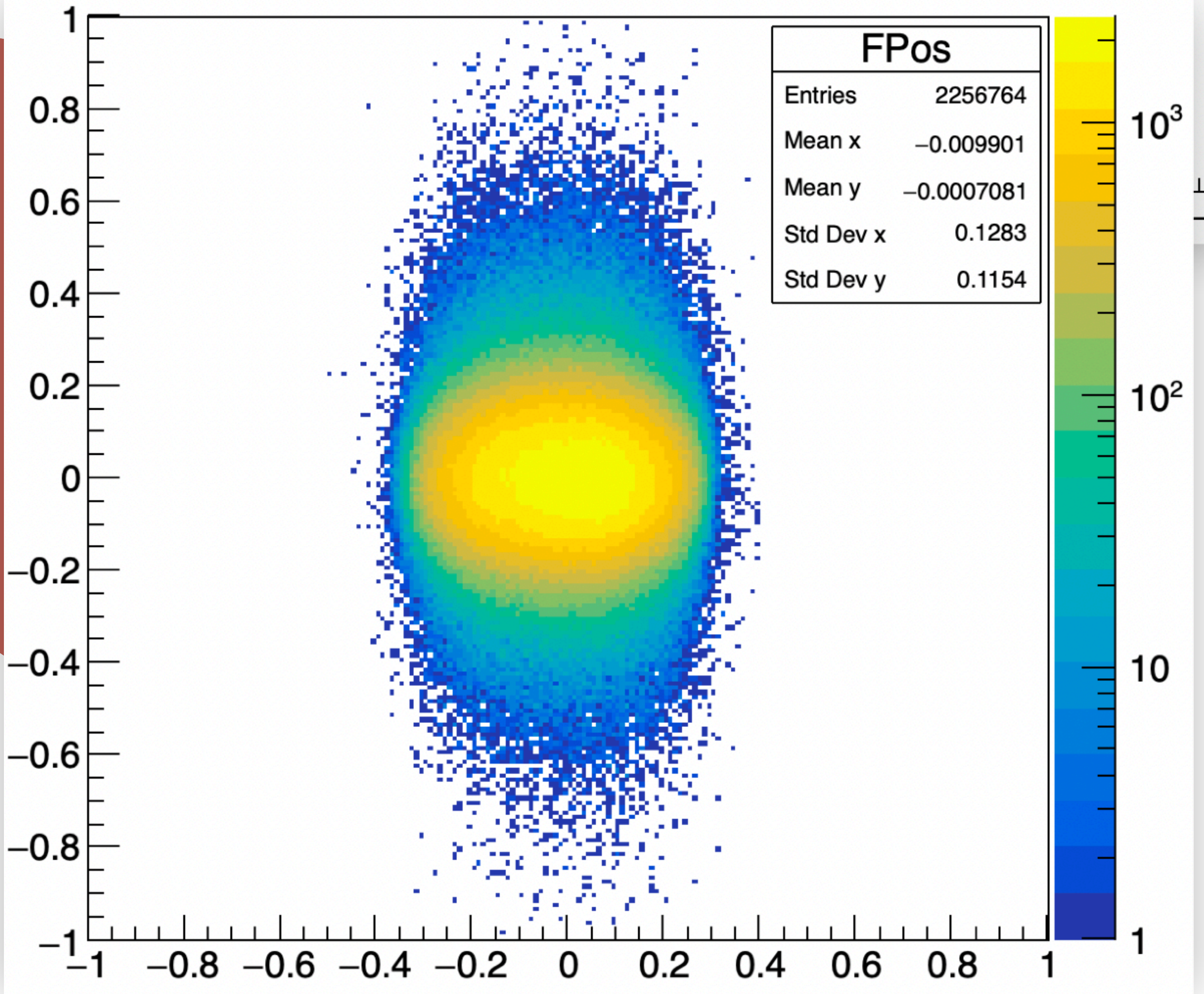


How do we know if the method works?

By evaluating the results obtained from a well-known detector => $LaBr_3$







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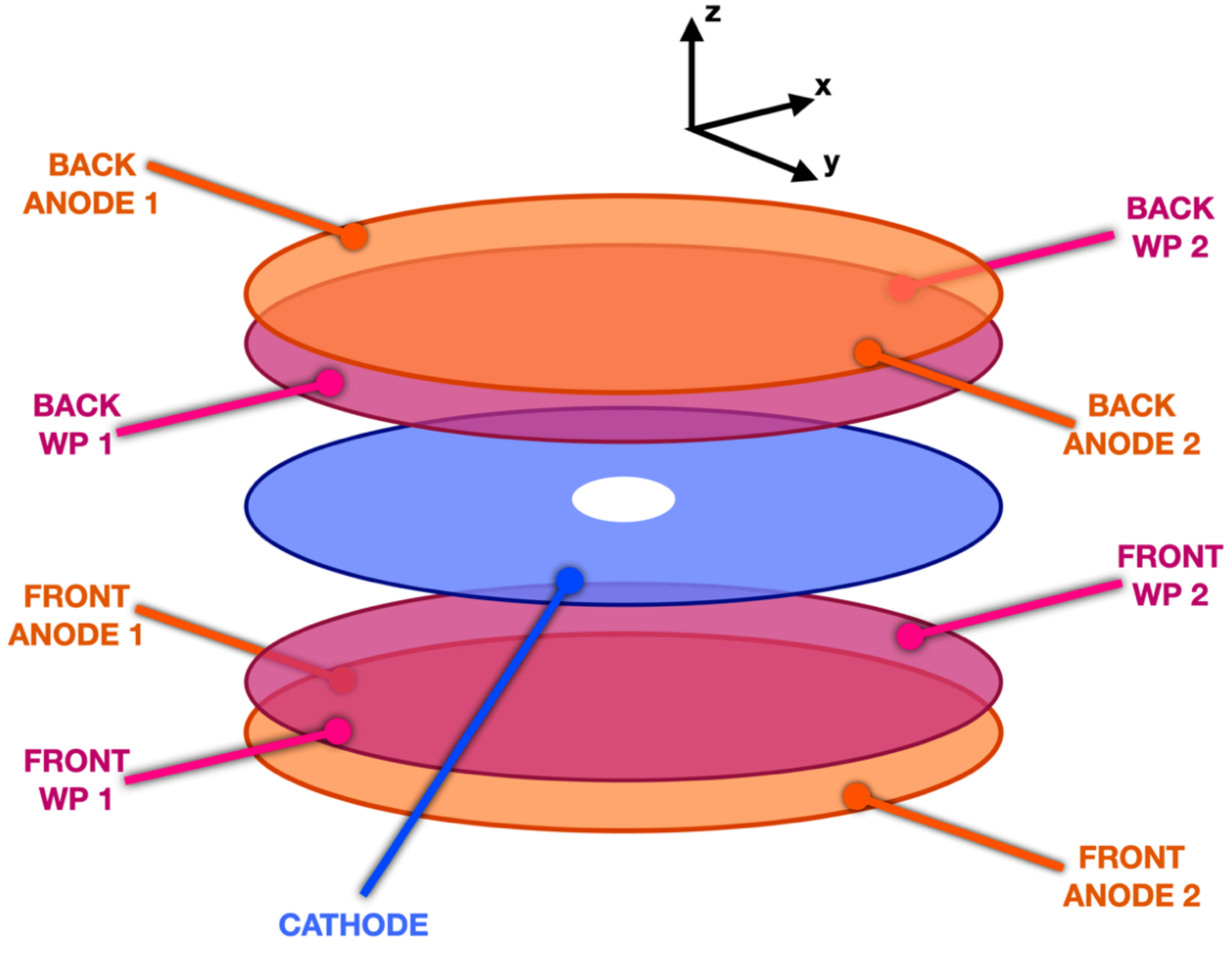

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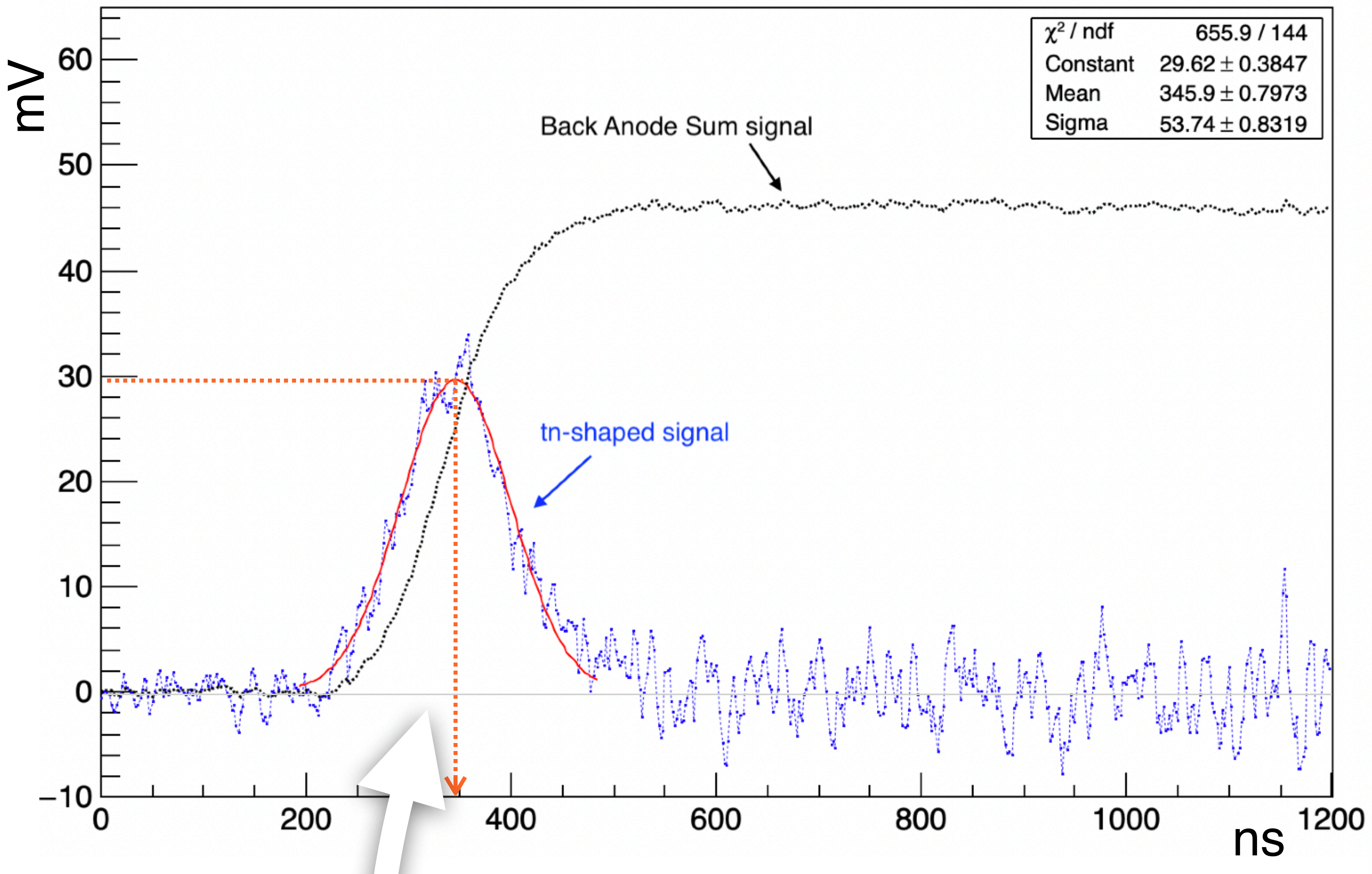

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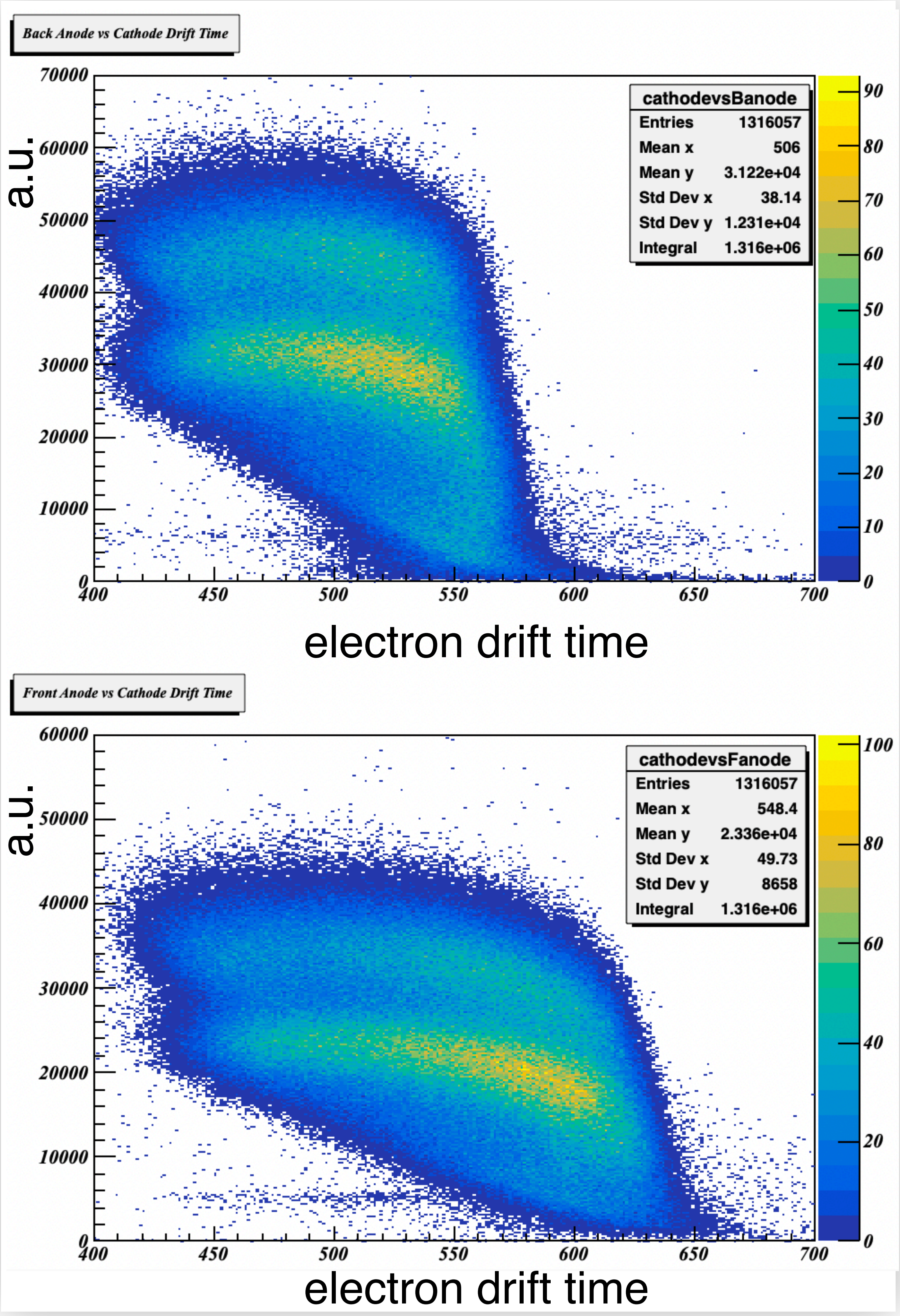
Energy vs. Electron drift time



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TIME CONSUMING

Trace analysis takes **~2s per 1k fission events**

3 weeks of data acquisition -> 600M events

300 h or 13 days to process the traces

=> yes, we are working with an optimized multi-threading algorithm

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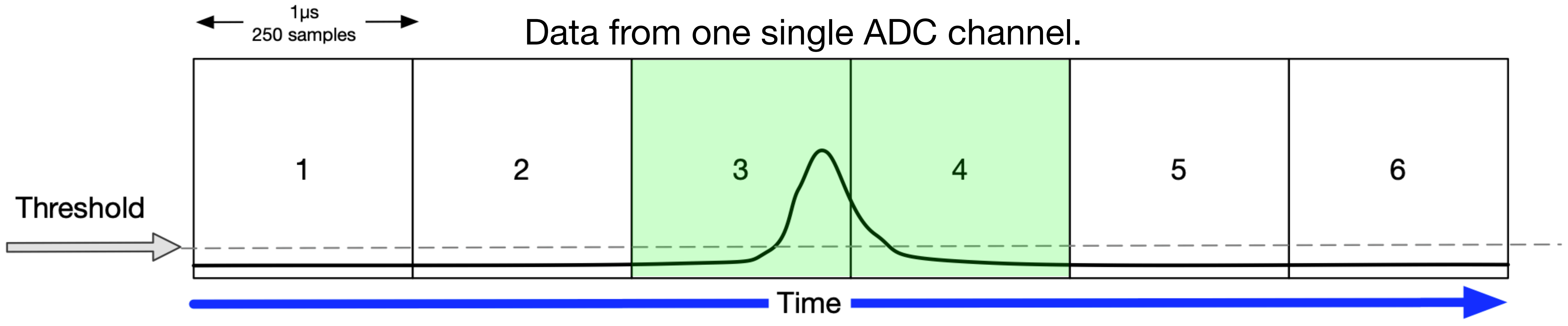
An example…

Streaming readout data acquisition

Taken from: A. Boehnlein et al. Rev. Mod. Phys. 94, 031003 (2022)



Adapted from: Streaming mode Data Acquitiion at Jefferson Lab

A virtual trigger based on an unsupervised hierarchical cluster algorithm selects the relevant data to reconstruct the physics event

Neural Networks

Supervised vs. unsupervised learning

Regression vs. classification model

Hyperparameters

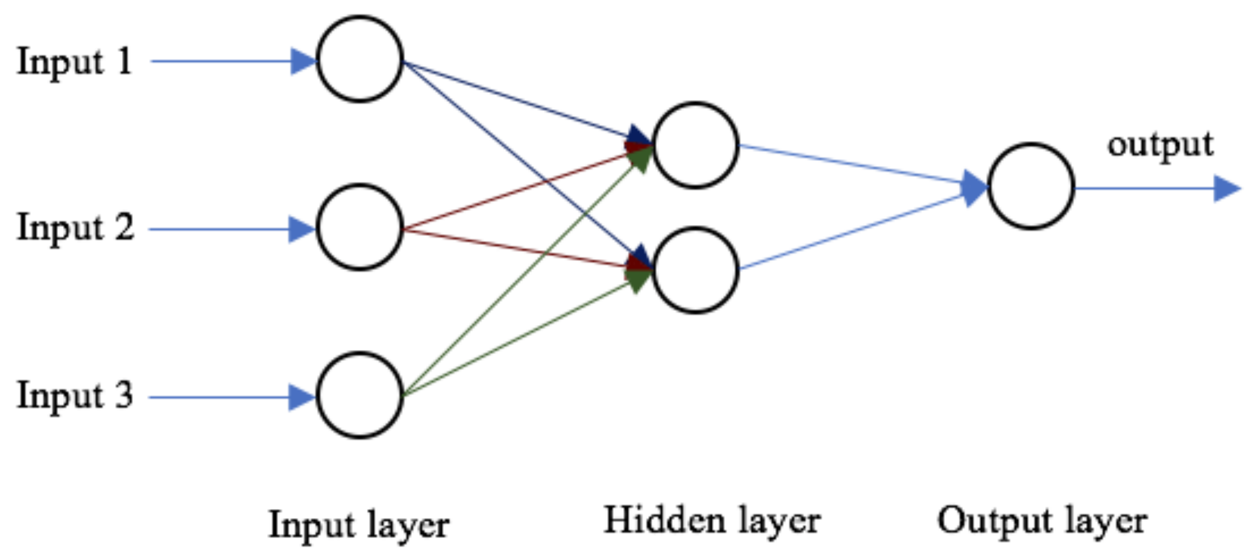
- Activation function
- Batch size
- Epochs
- Learning rate
- Loss function
- Number of hidden layers
- Number of neurons per layer

Parameters

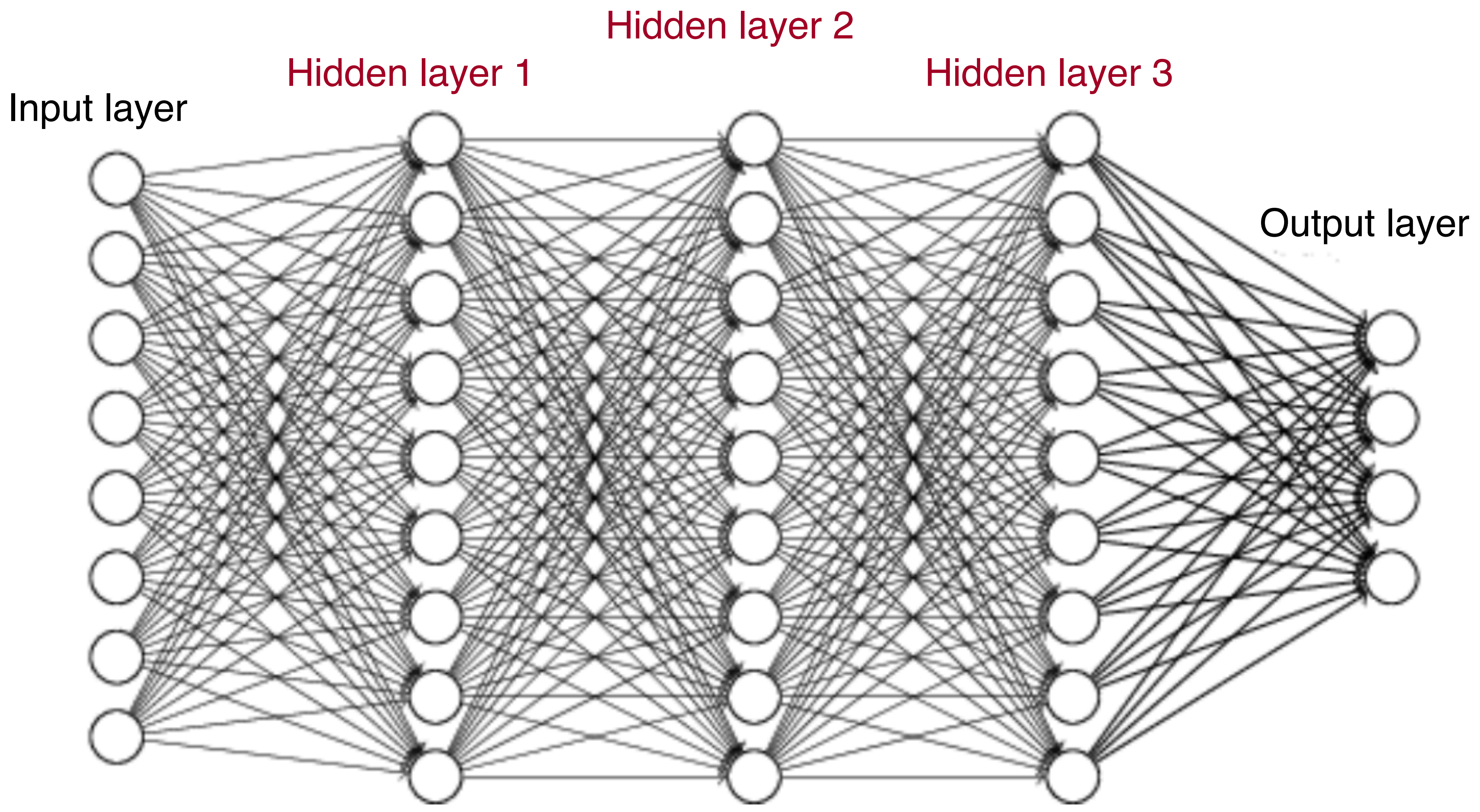
- Weights and biases

$$Y = \sum_i (weight_i \cdot input_i) + bias$$

Fully Connected Neural Networks (**FCNN**)



Taken from: A. Said and F. Sayed Ibrahim. Comparative study of segmentation techniques for detection of tumors based on mri brain images. *International Journal of Biochemistry and Biotechnology*, 8:10, 09 2017



Taken from: https://math.stackexchange.com/q/2048722

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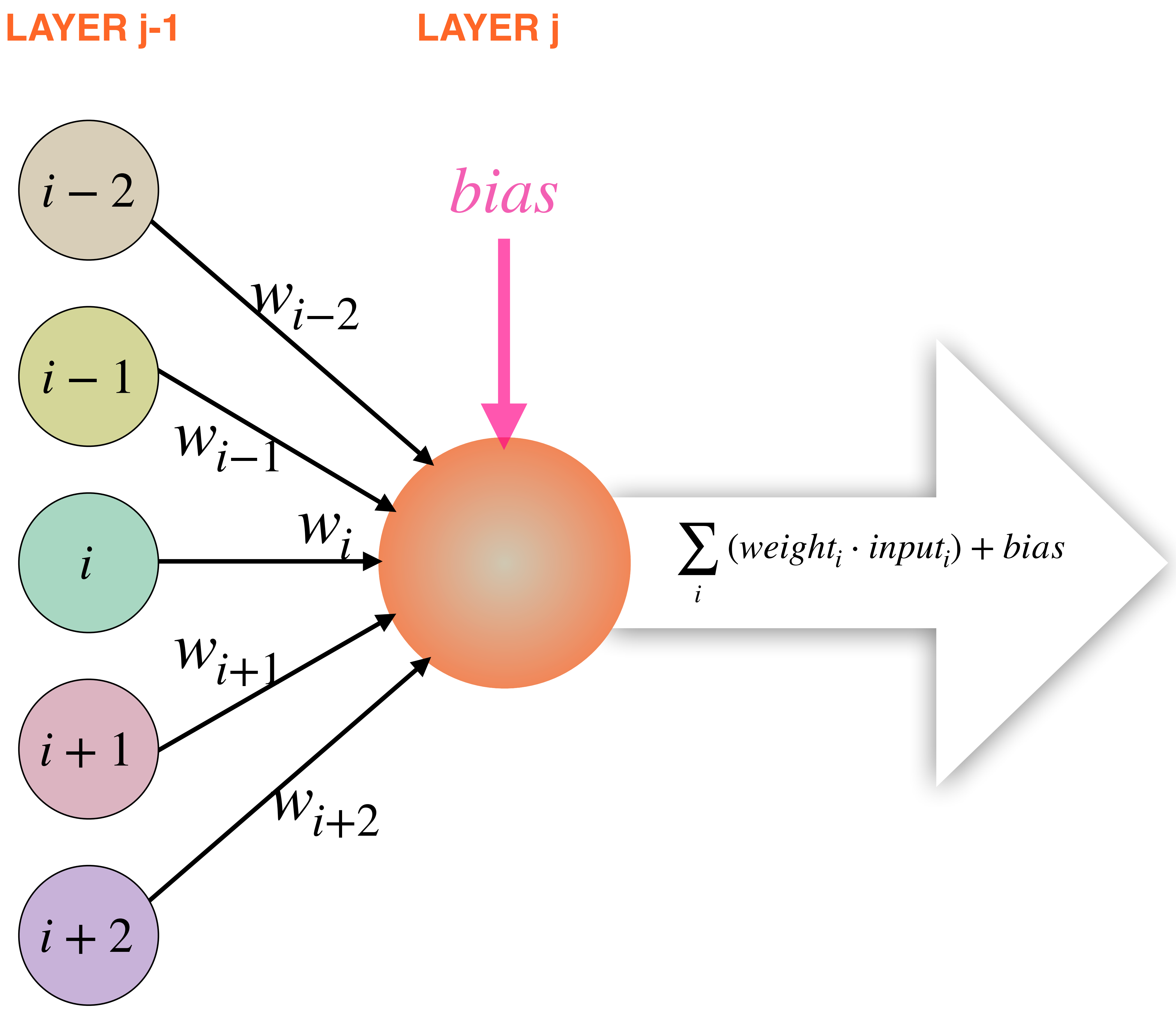
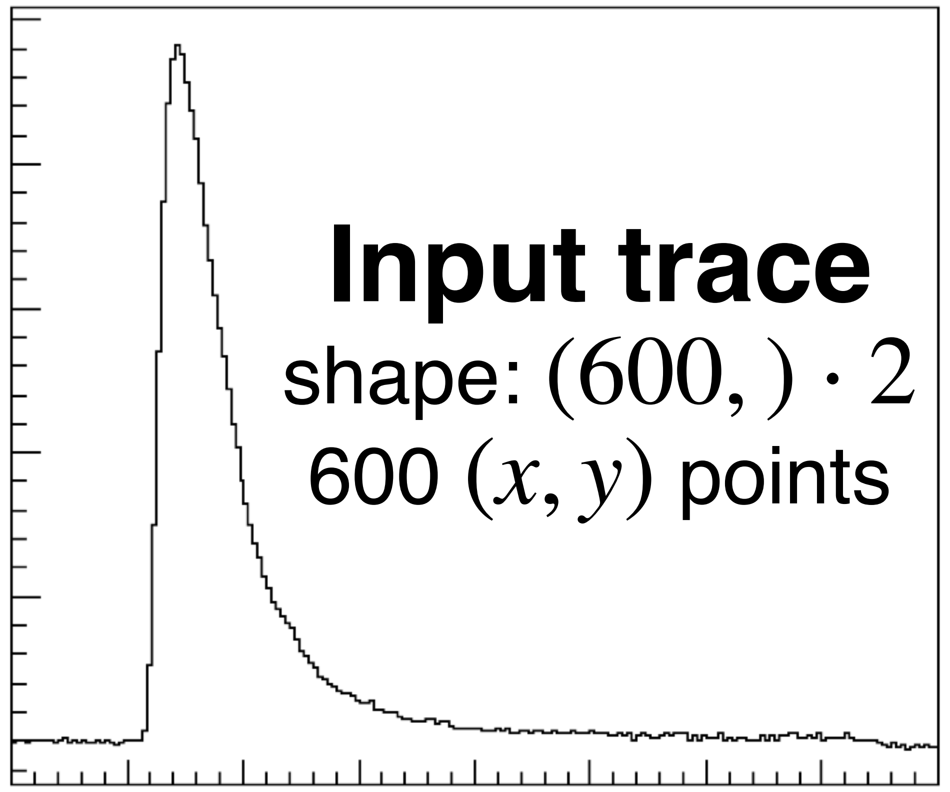


FCNN models for trace analysis



Input trace
shape: $(600,) \cdot 2$
600 (x, y) points

→ FCNN →

Hidden layer 1
shape: $(600,)$

$actv.f$: ReLu or sigmoid

→ FCNN →

Hidden layer 2
shape: $(600,)$

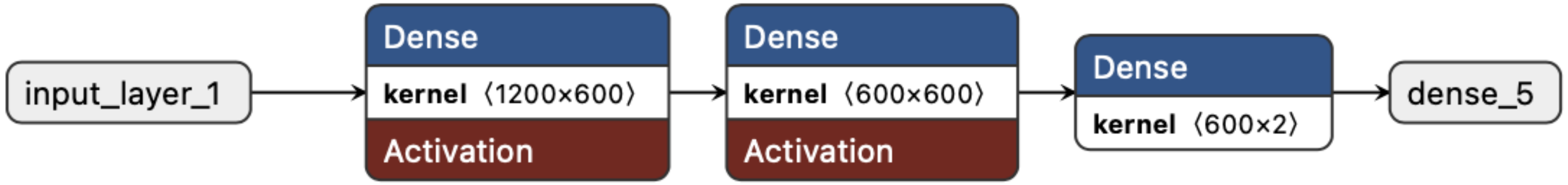
$actv.f$: ReLu or sigmoid

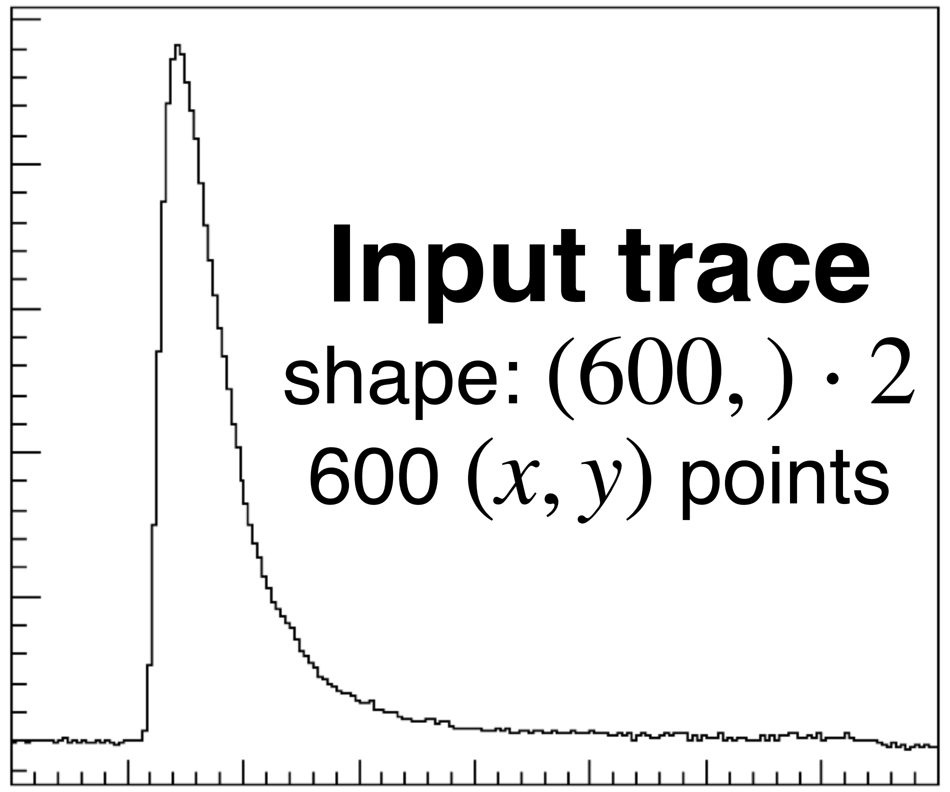
→ FCNN →

Outputs:
shape: $(2,)$

(« energy », « time »)

FCNN models for trace analysis





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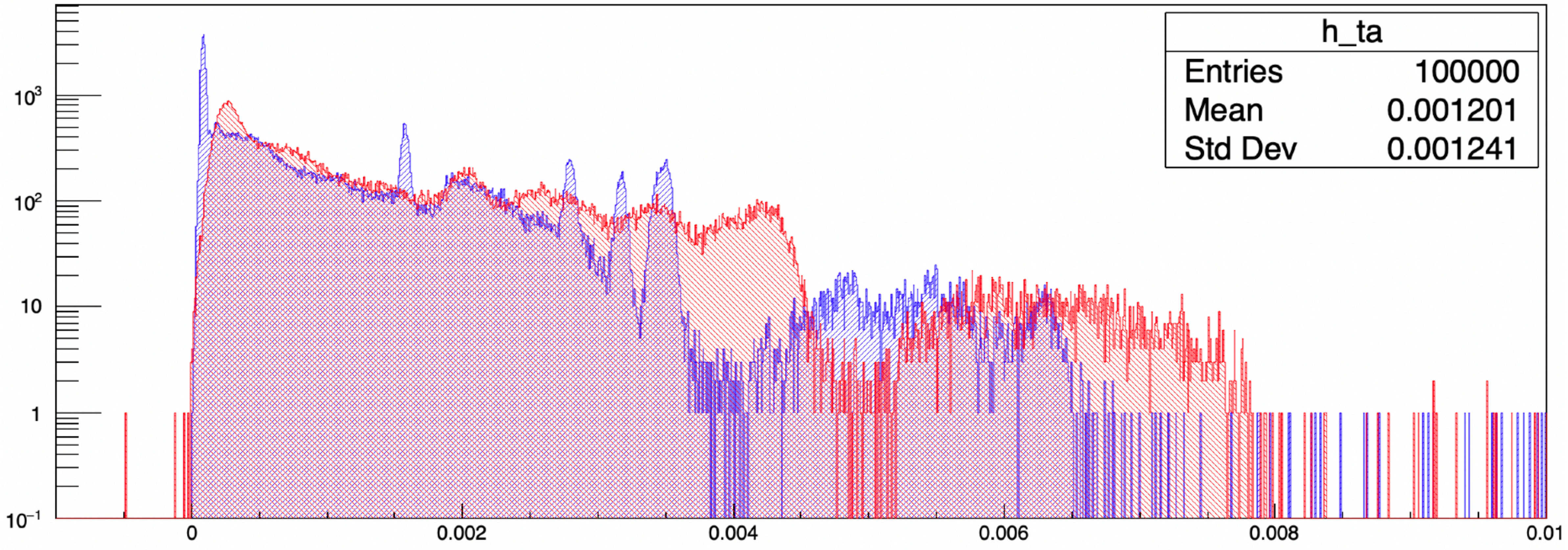
FCNN

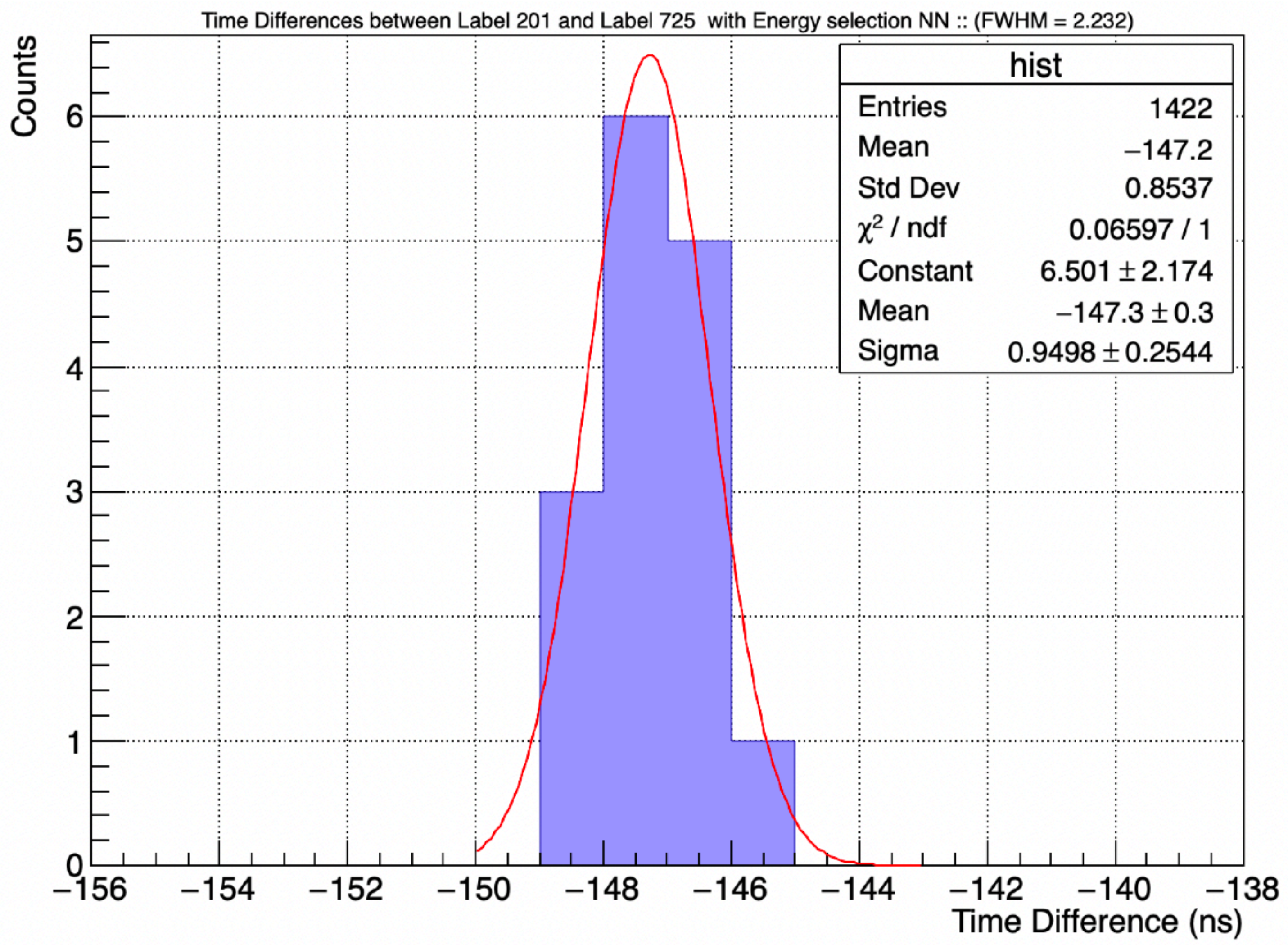
Hidden layer 2
shape: $(600,)$
$actv.f$: ReLu or sigmoid

FCNN

Outputs:
shape: $(2,)$
(« energy », « time »)

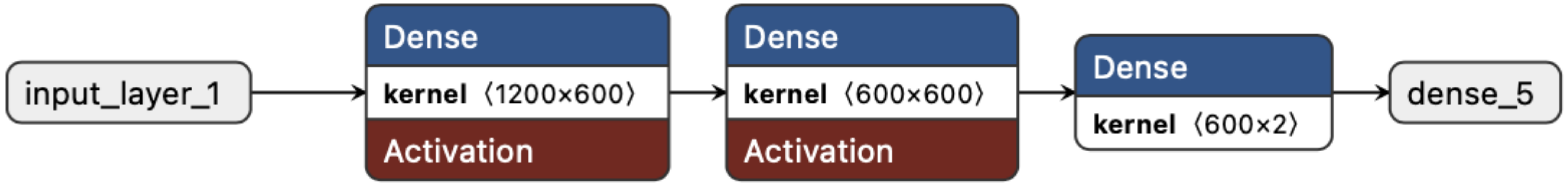
Prediction takes ~ 80s for 1M traces
-> should be able to perform much faster in C++/C

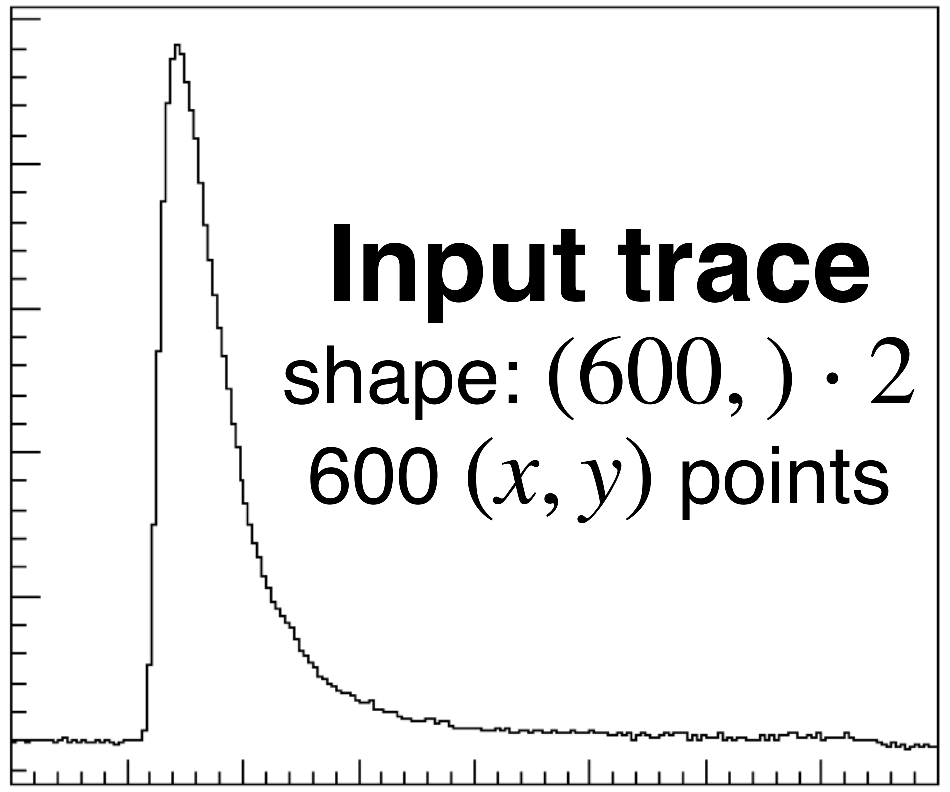




$R(t) =$ **2232 ps**

FCNN models for trace analysis





Input trace
shape: $(600,)\cdot 2$
600 (x, y) points

FCNN

Hidden layer 1
shape: $(600,)$
$actv.f$: ReLu or sigmoid

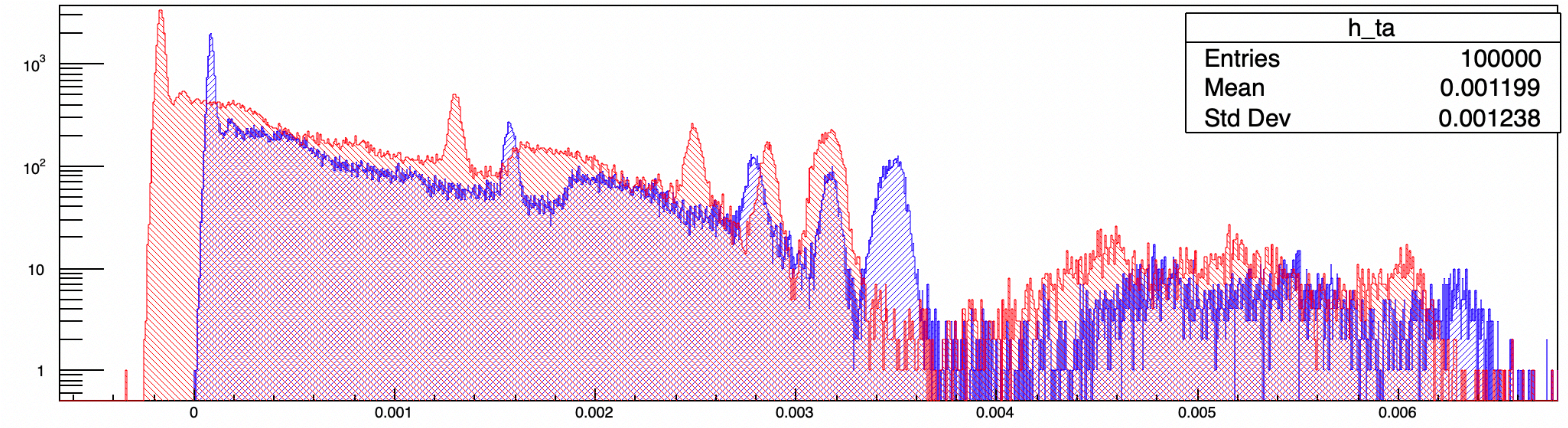
FCNN

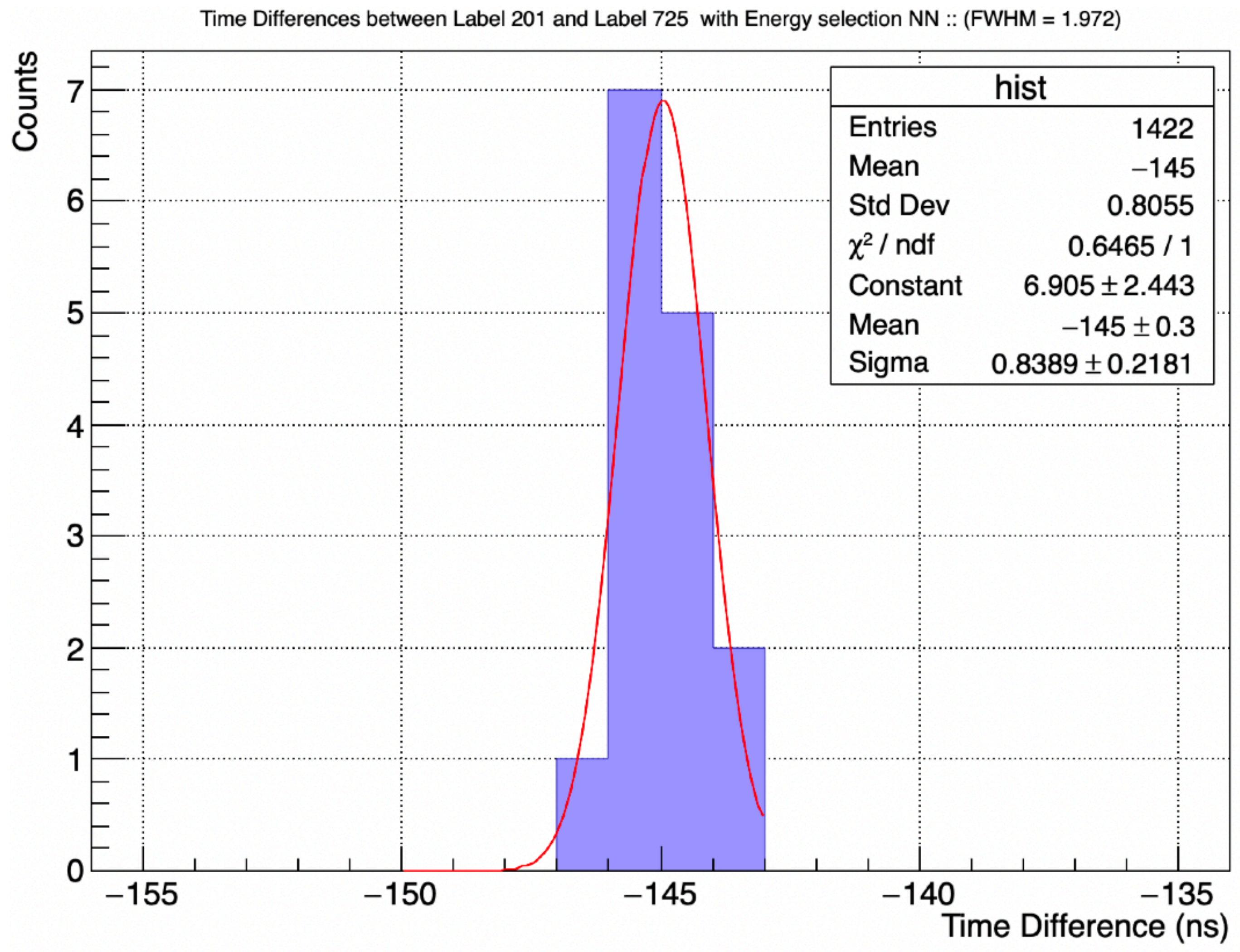
Hidden layer 2
shape: $(600,)$
$actv.f$: ReLu or sigmoid

FCNN

Outputs:
shape: $(2,)$
(« energy », « time »)

Prediction takes ~ 80s for 1M traces
-> should be able to perform much faster in C++/C

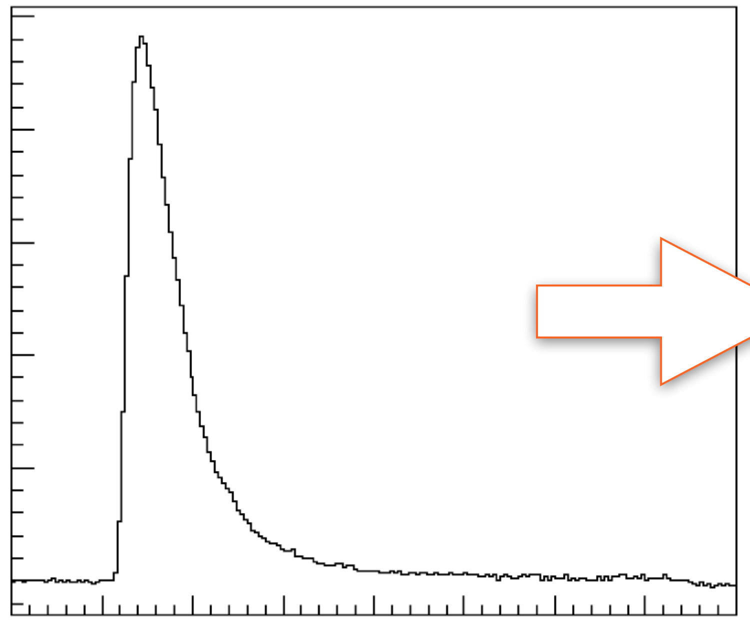


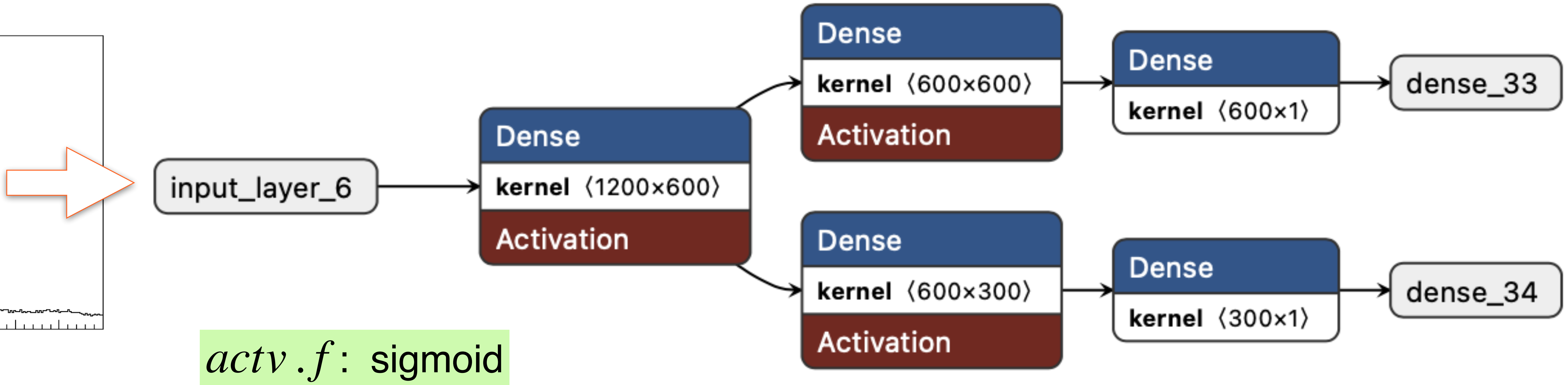


31.7 keV @ 1170 keV
$R(t)$ = 569 ps

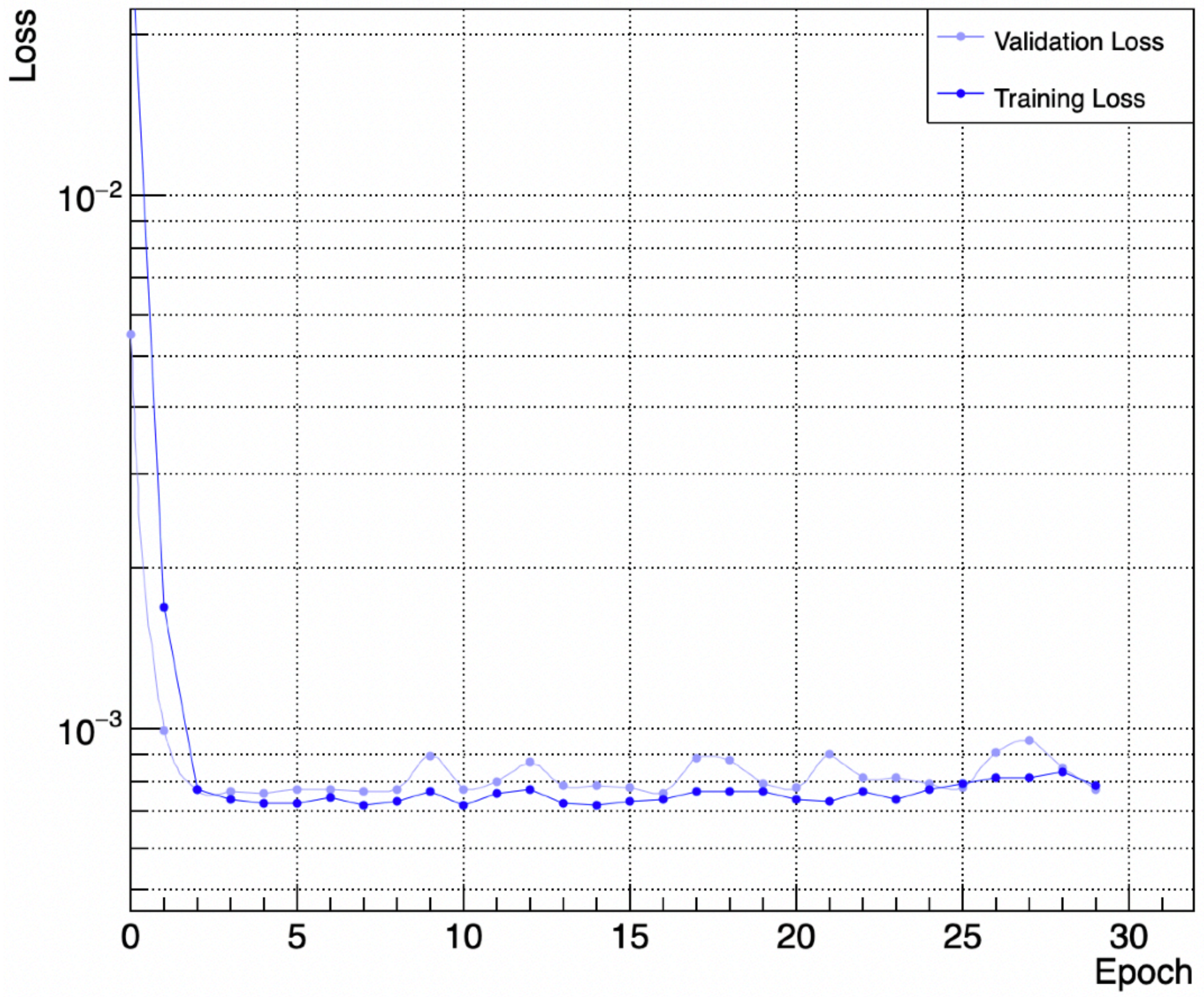
With NN:
37 keV @ 1170 keV
$R(t)$ = **1970 ps**

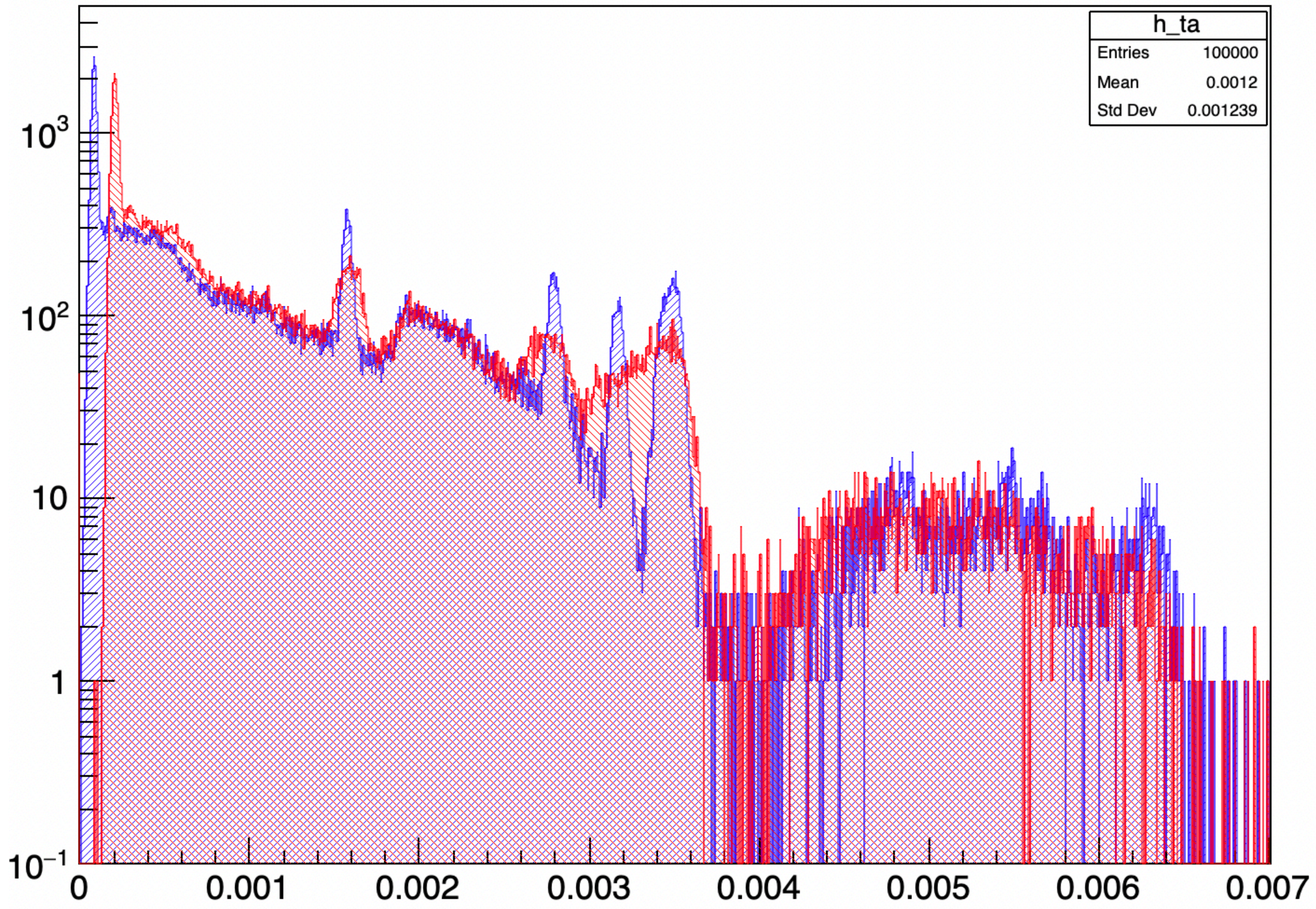
FCNN models for trace analysis

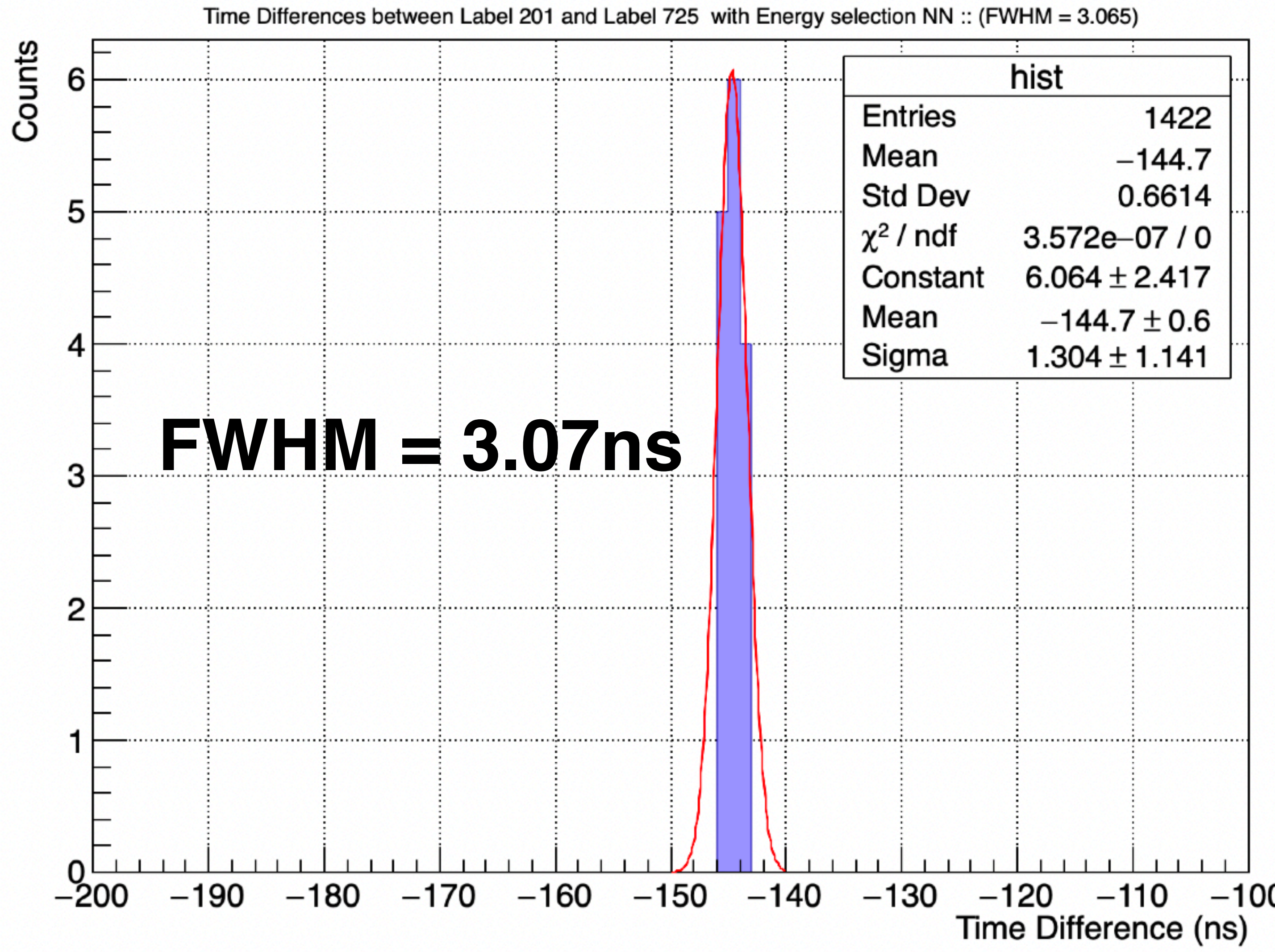




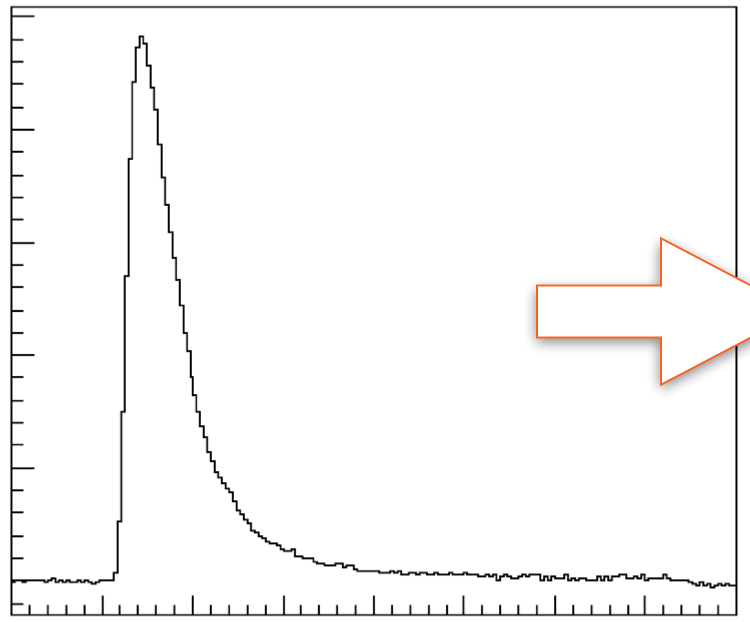
$actv.f$: sigmoid

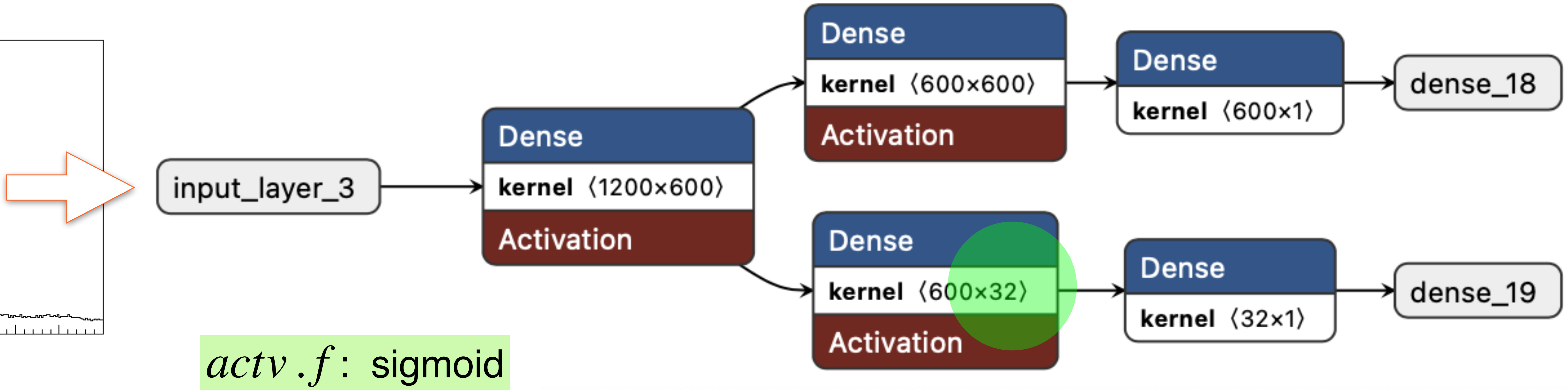




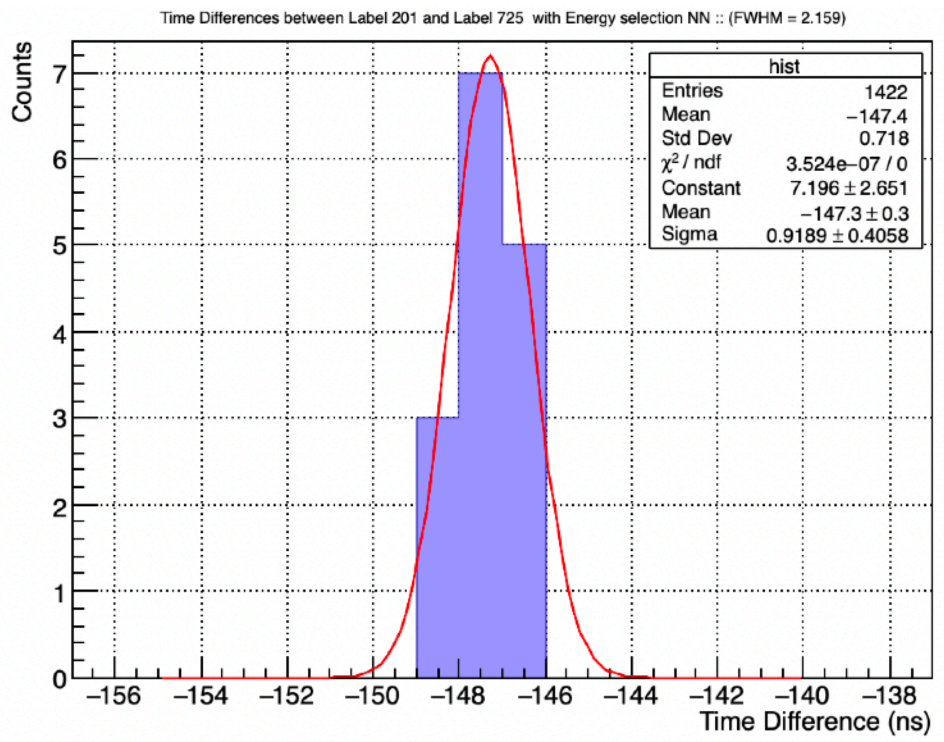


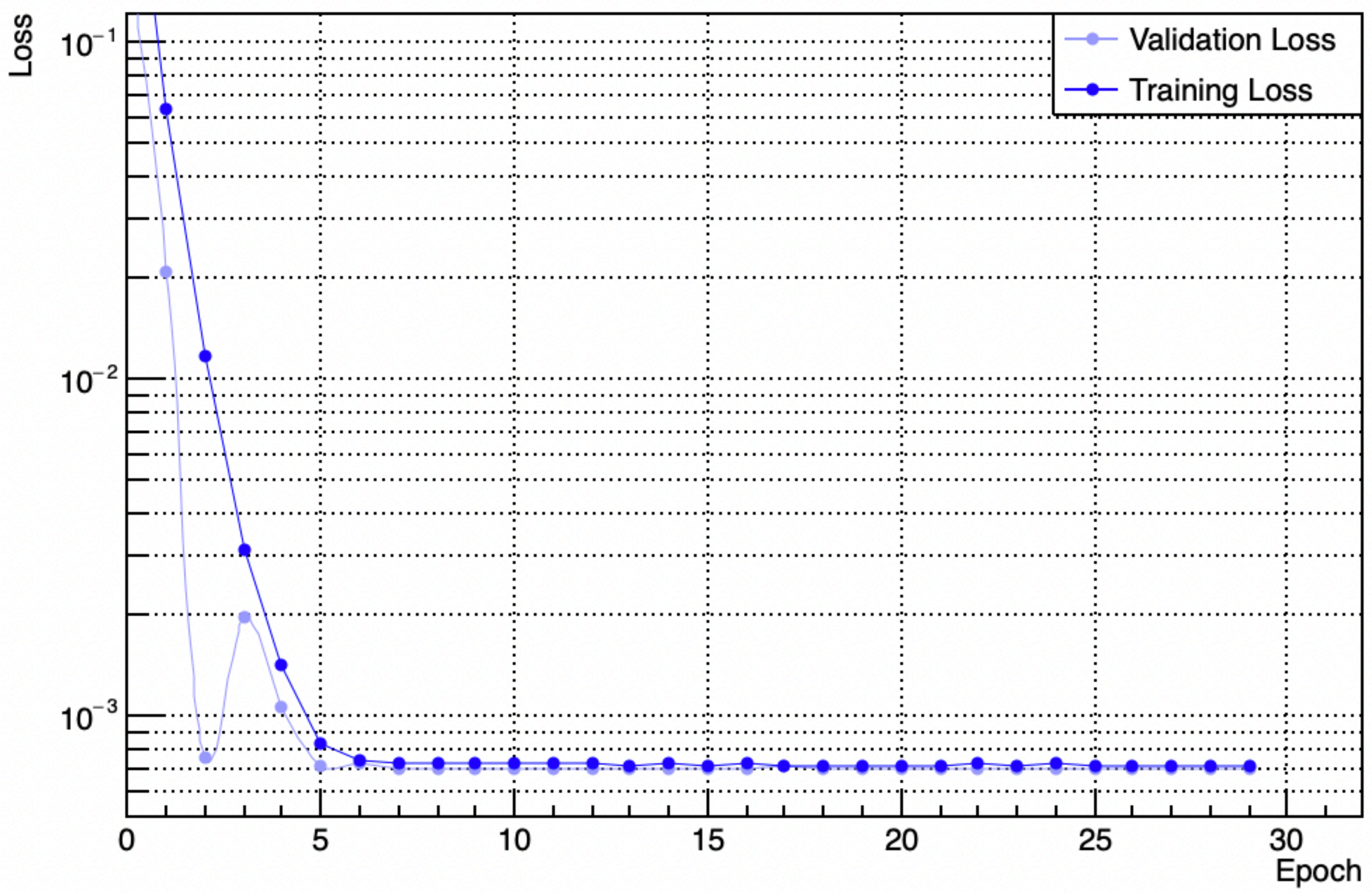
FCNN models for trace analysis

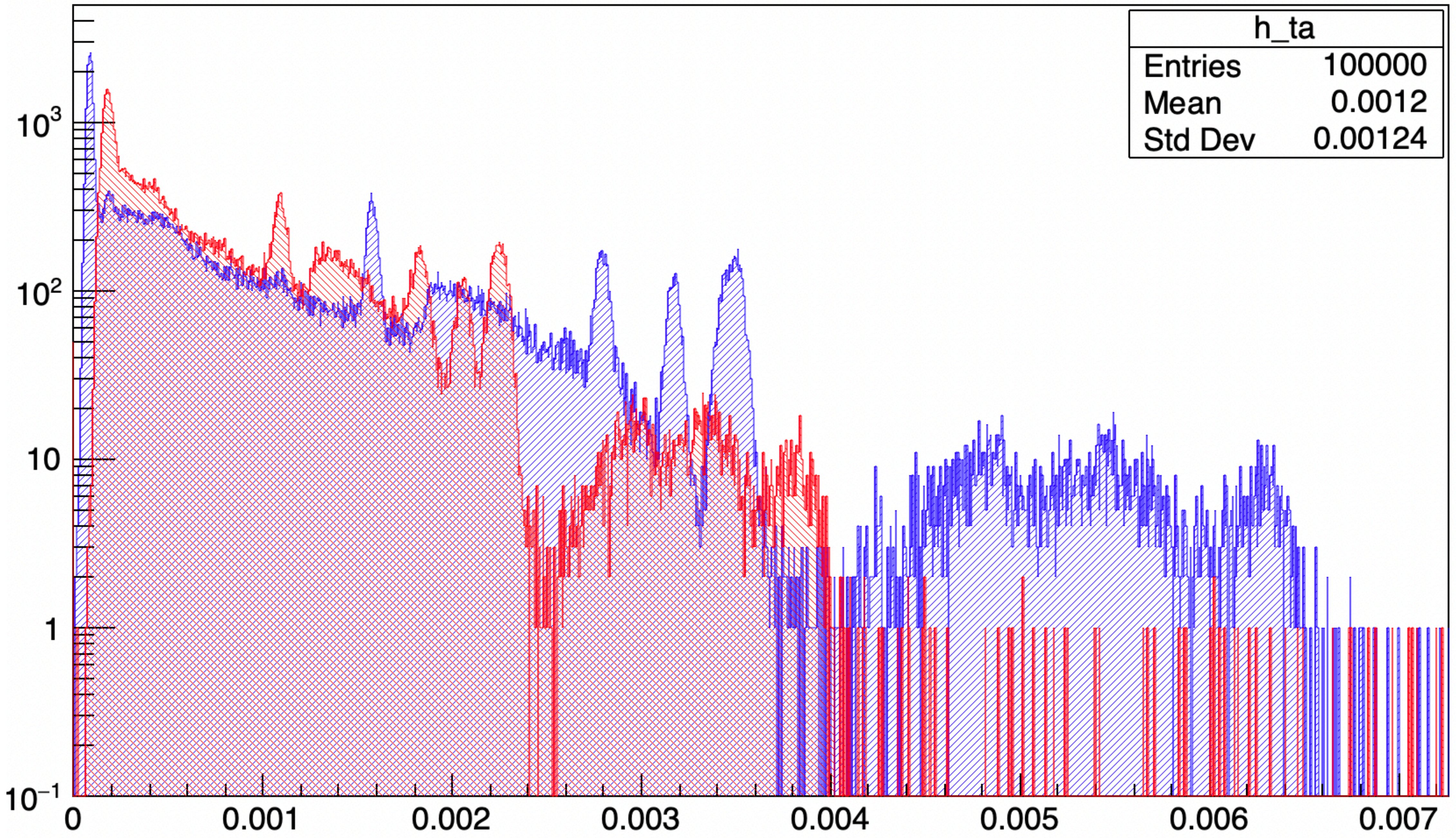




$actv.f:$ sigmoid







31.7 keV @ 1170 keV
$R(t) = 569$ ps

With NN:
59.6 keV @ 1170 keV
$R(t) = 2158$ ps

Neural Networks

Supervised vs. unsupervised learning

Regression vs. classification model

Hyperparameters

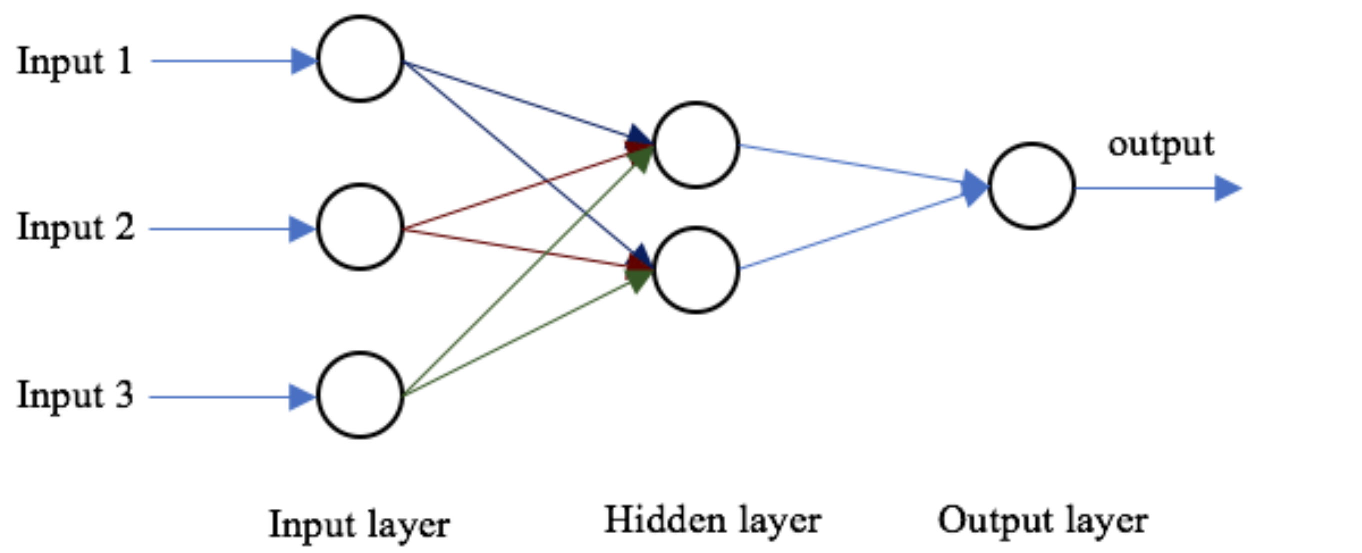
- Activation function
- Batch size
- Epochs
- Learning rate
- Loss function
- Number of hidden layers
- Number of neurons per layer

Parameters

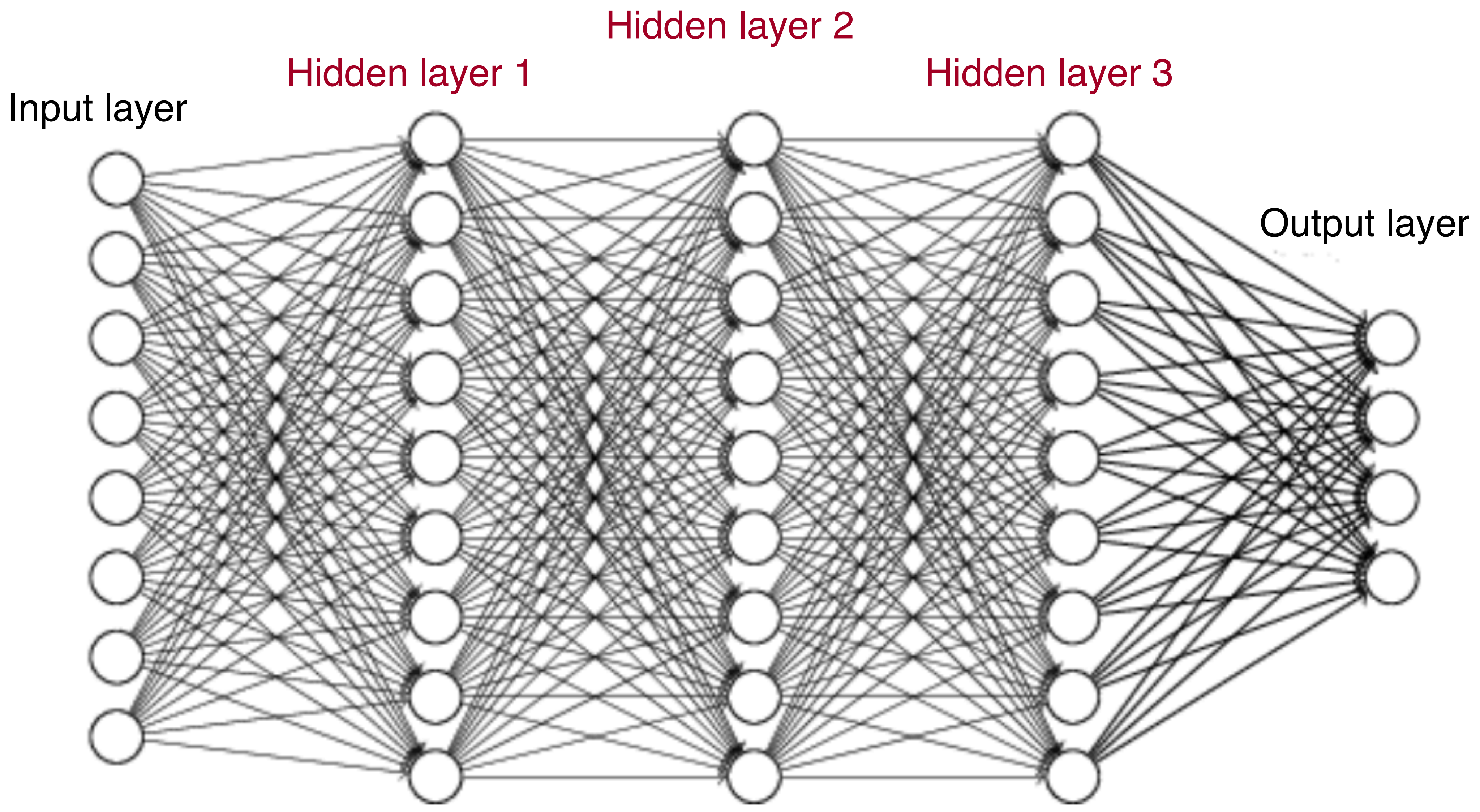
- Weights and biases

$$Y = \sum_i (weight_i \cdot input_i) + bias$$

Fully Connected Neural Networks (**FCNN**)



Taken from: A. Said and F. Sayed Ibrahim. Comparative study of segmentation techniques for detection of tumors based on mri brain images. *International Journal of Biochemistry and Biotechnology*, 8:10, 09 2017



Taken from: https://math.stackexchange.com/q/2048722

Neural Networks

Supervised vs. unsupervised learning

Regression vs. classification model

Hyperparameters

- Activation function
- Batch size
- Epochs
- Learning rate
- Loss function
- Number of hidden layers
- Number of neurons per layer

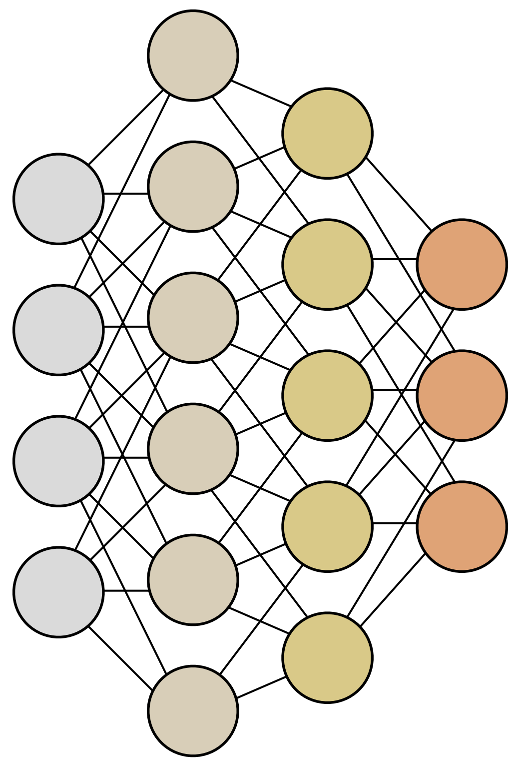
Parameters

- Weights and biases

simple NN

$$Y = \sum_i (weight_i \cdot input_i) + bias$$

NN

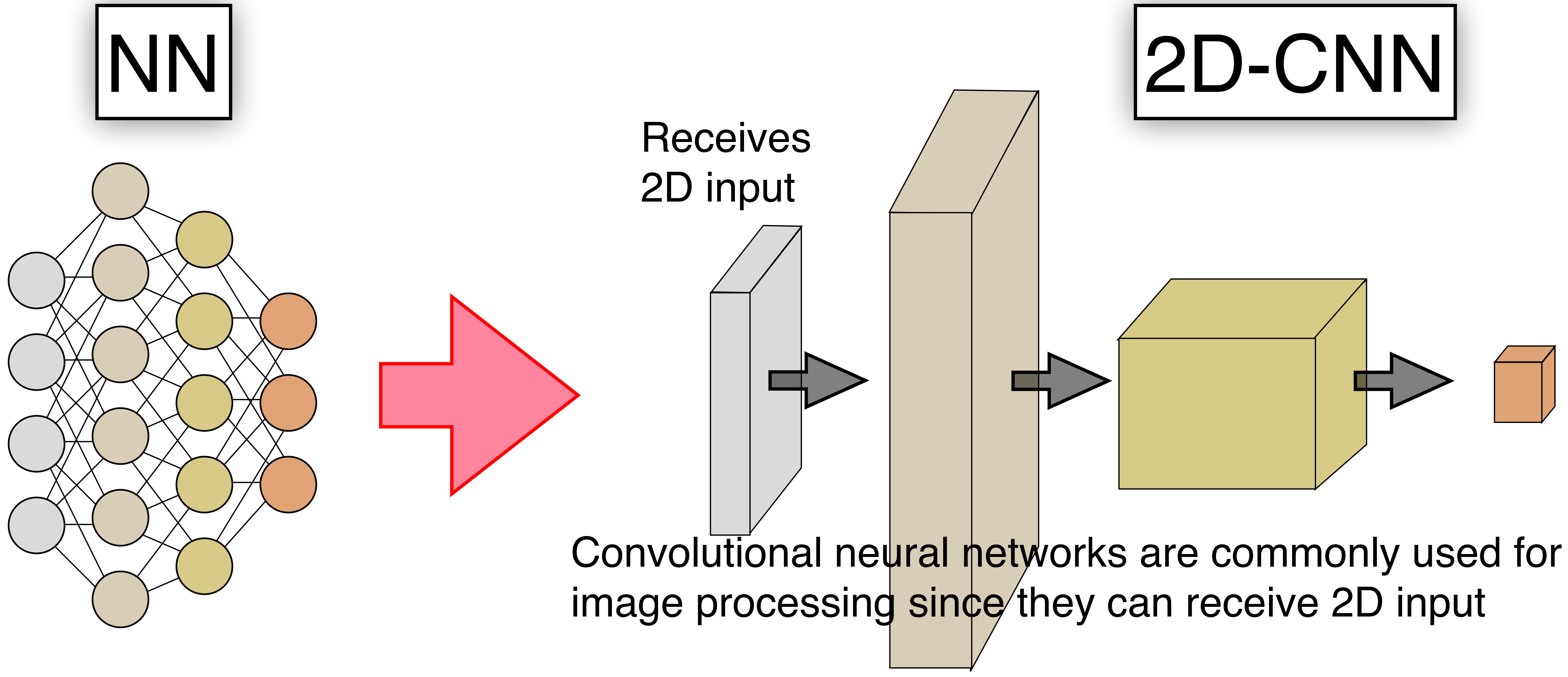


Supervised vs. unsupervised learning

Regression vs. classification model

Hyperparameters

- Activation function
- Batch size
- Epochs
- Learning rate
- Loss function
- Number of hidd
- Number of neur



$$Y_{i,j,k} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \sum_{c=0}^{C-1} (X_{i+m,j+n,c} \cdot W_{m,n,c,k}) + bias_k$$

Parameters

Weights and biases

$$Y = \sum_i (weight_i \cdot input_i) + bias$$

Neural Networks

Supervised vs. unsupervised learning

Regression vs. classification model

Hyperparameters

- Activation function
- Batch size
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- Number of neur…

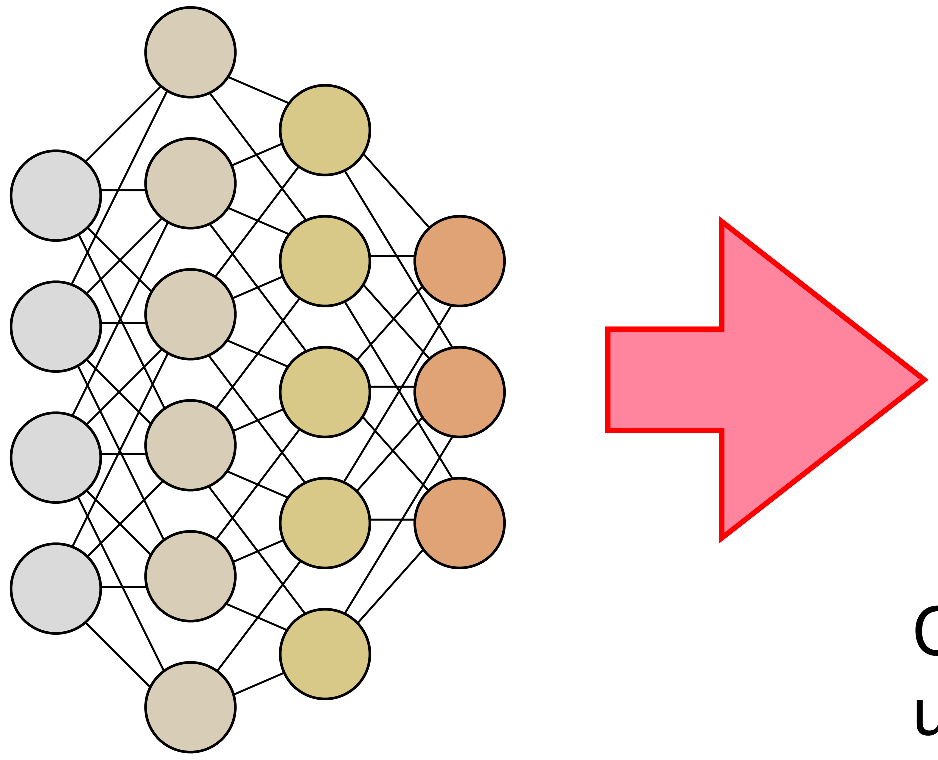
Parameters

- Weights and biases

$$Y = \sum_i (weight_i \cdot input_i) + bias$$

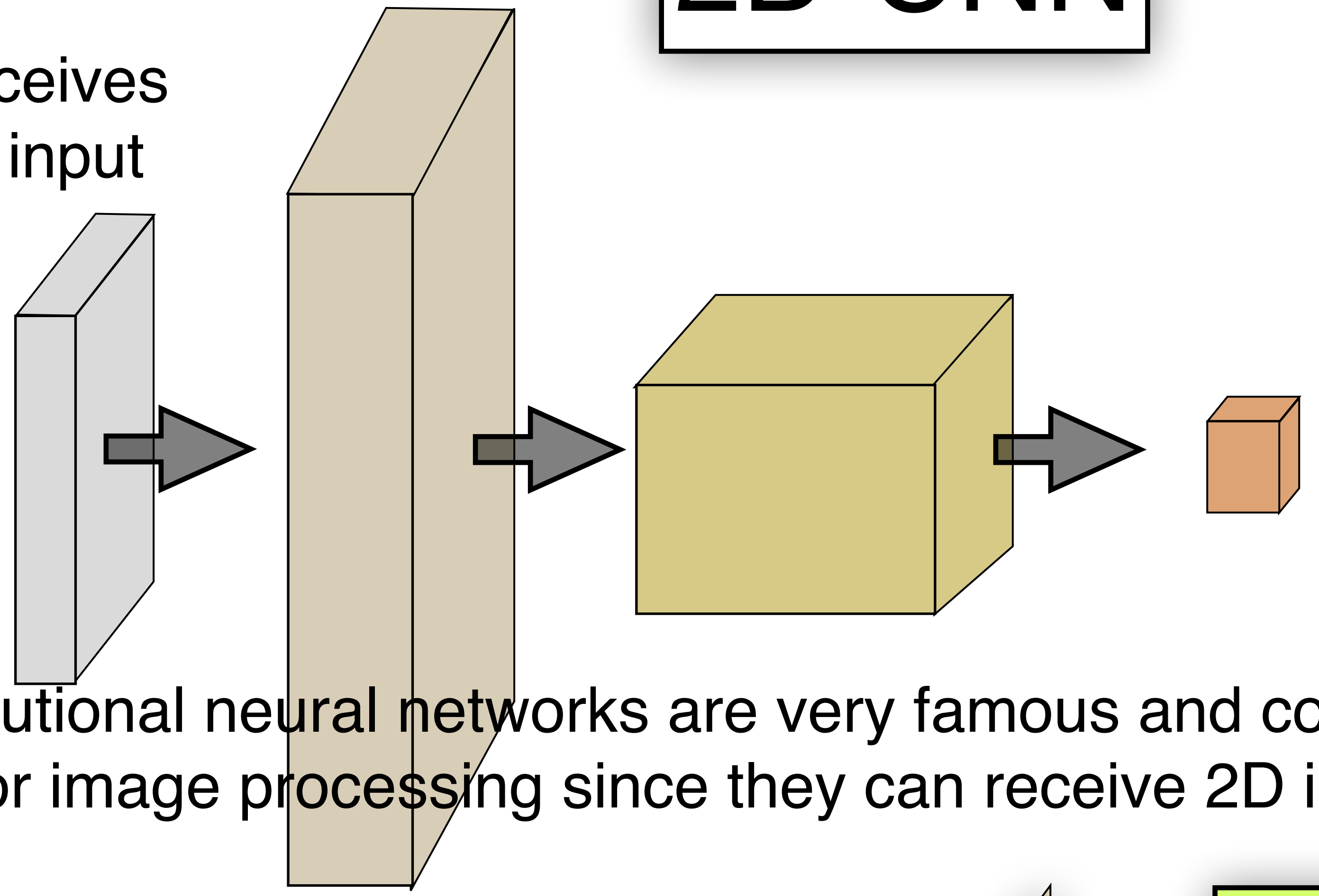
$$Y_{i,j,k} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \sum_{c=0}^{C-1} (X_{i+m,j+n,c} \cdot W_{m,n,c,k}) + bias_k$$

NN



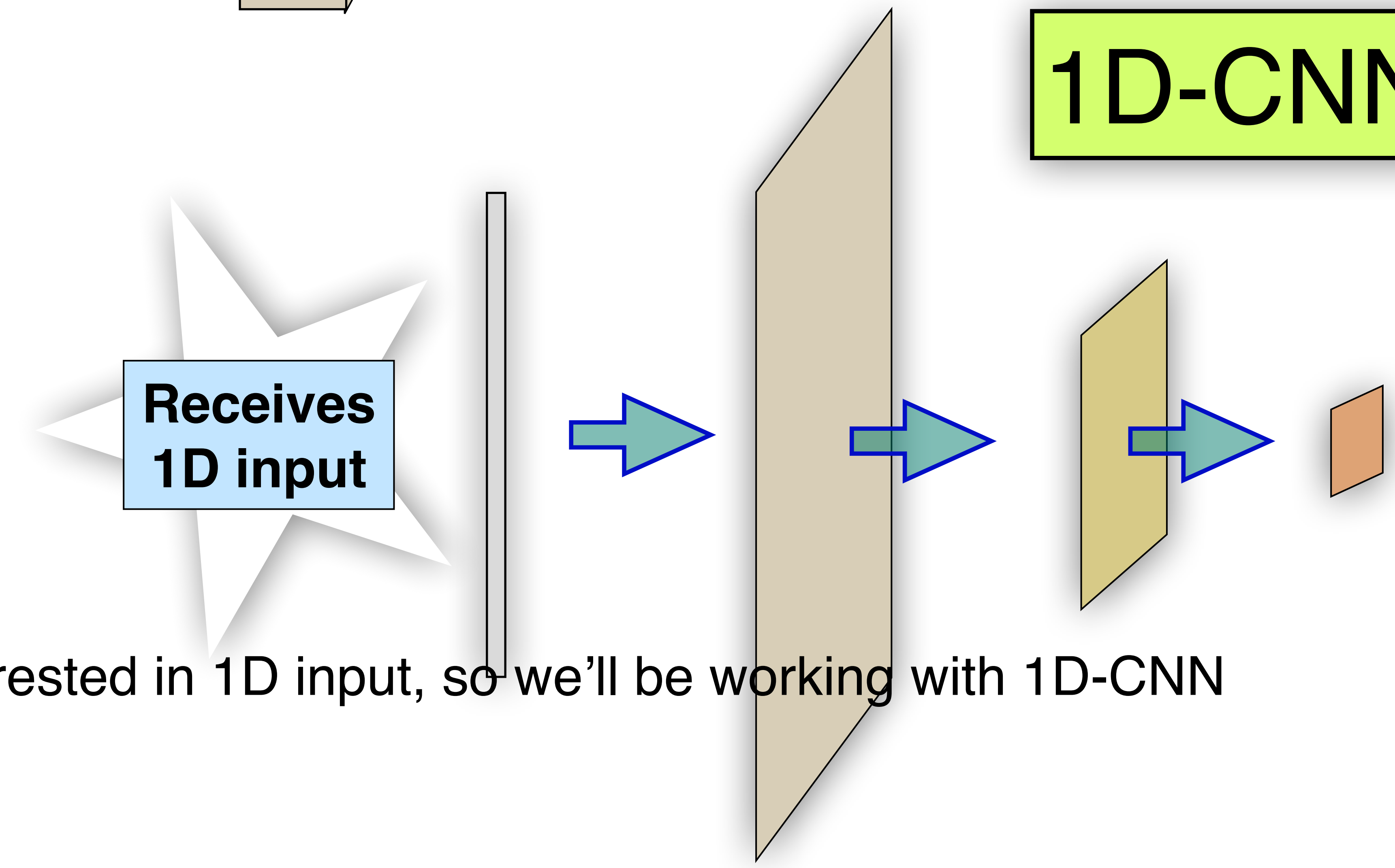
2D-CNN

Receives 2D input



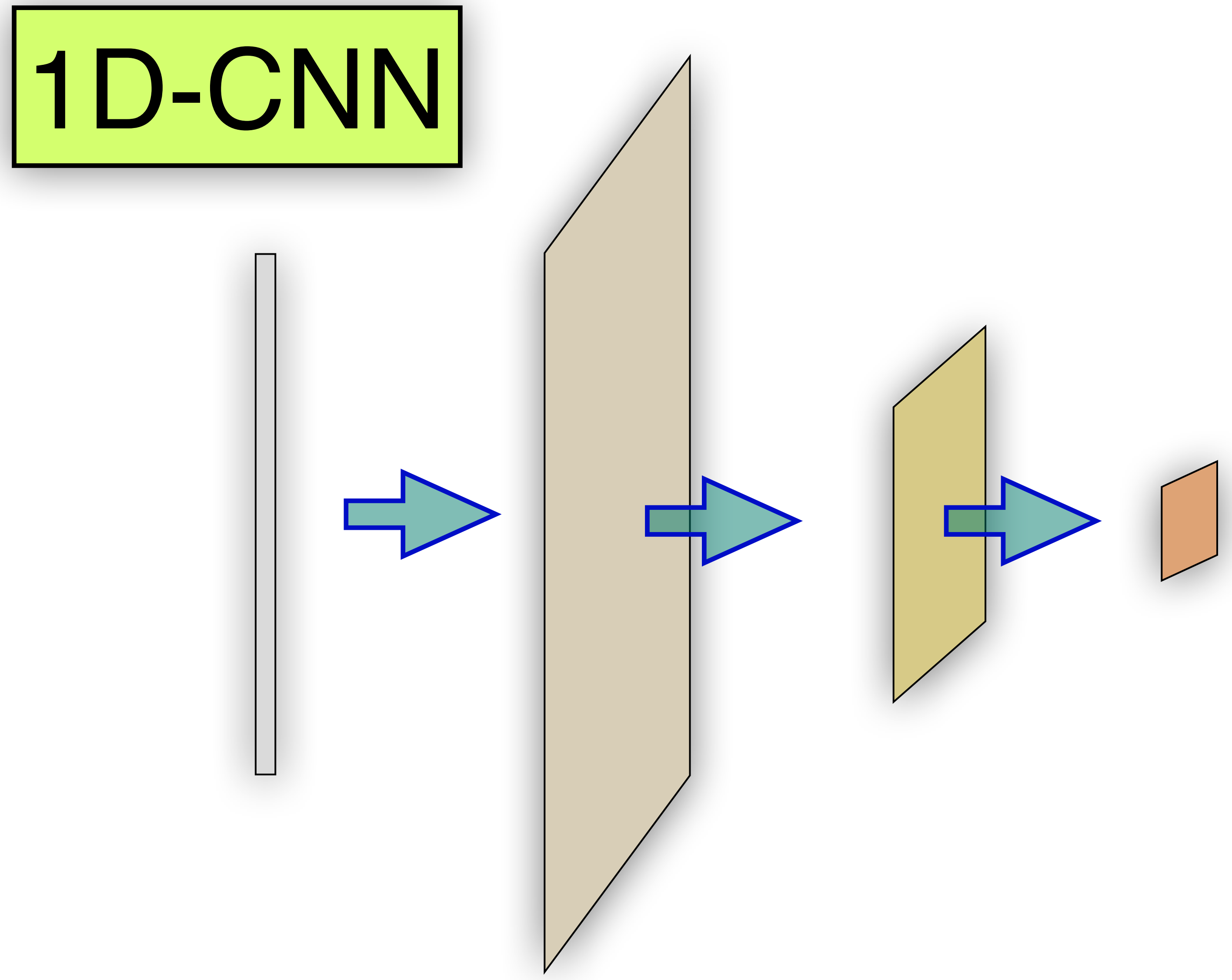
Convolutional neural networks are very famous and commonly used for image processing since they can receive 2D input

1D-CNN



We are interested in 1D input, so we'll be working with 1D-CNN

Neural Networks



Parameters

Weights and biases

$$Y_{i,j,k} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \sum_{c=0}^{C-1} (X_{i+m,j+n,c} \cdot W_{m,n,c,k}) + bias_k$$

Kernel size vs. filters

Neural Networks

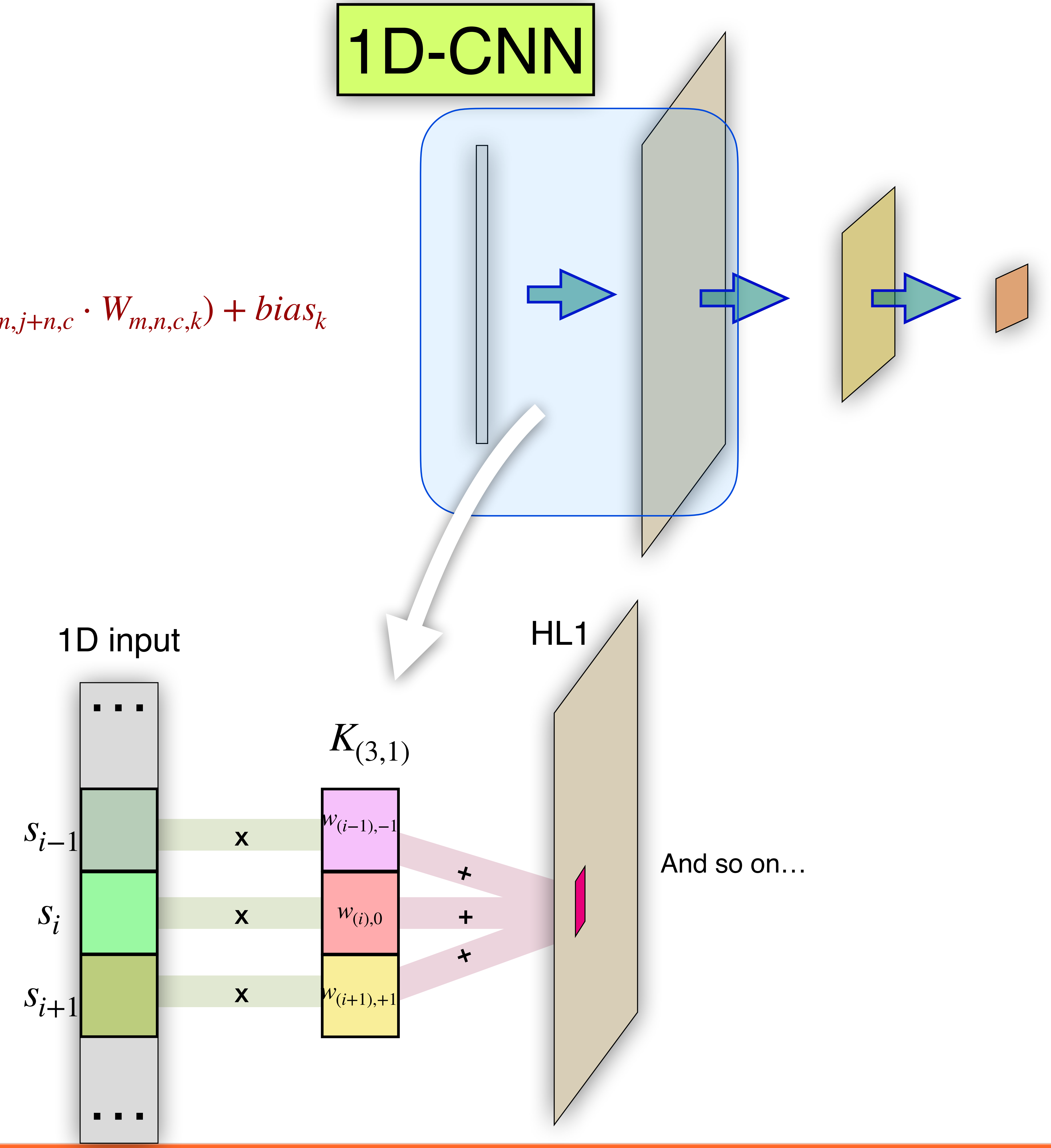
Parameters

Weights and biases

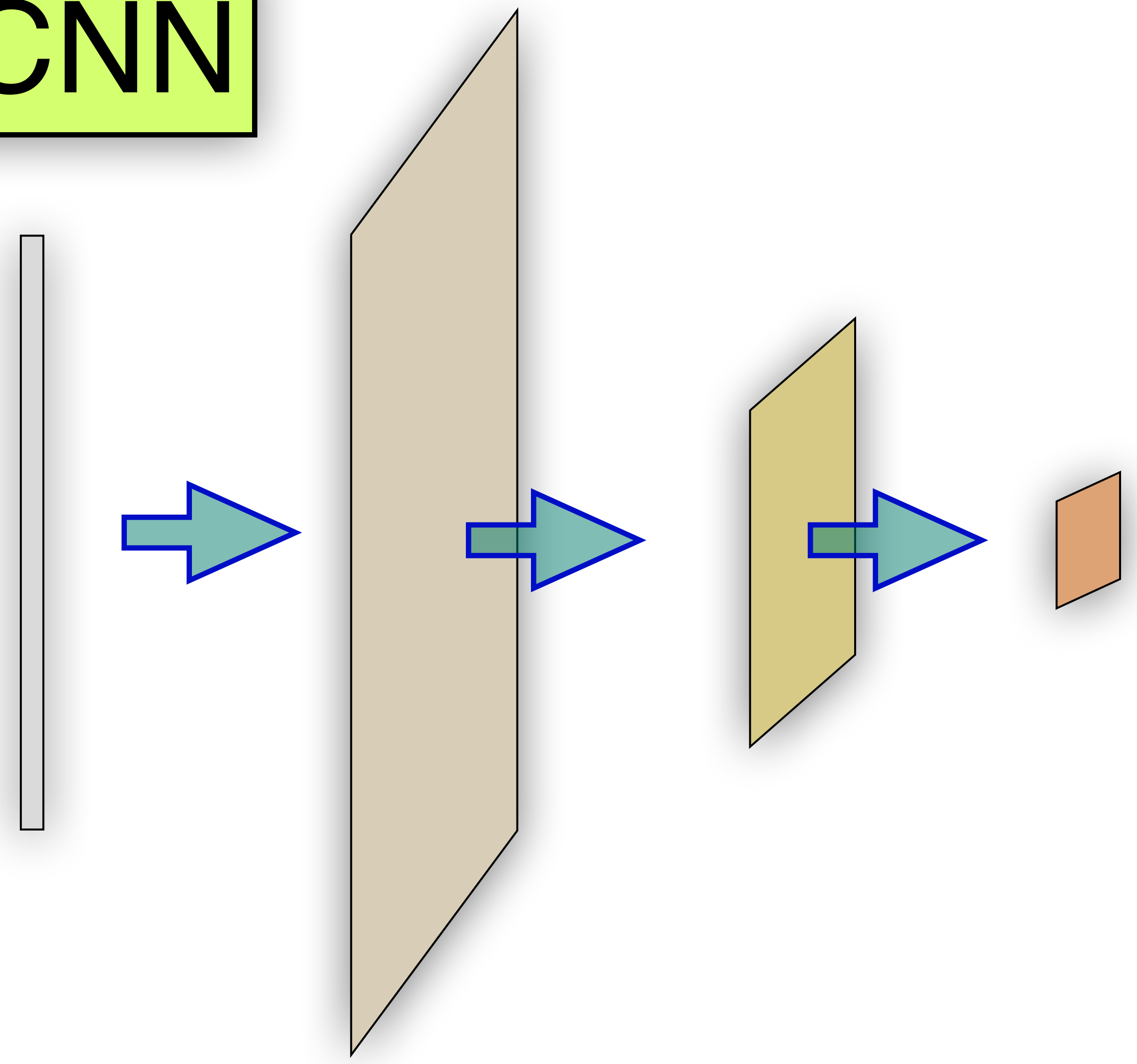
$$Y_{i,j,k} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \sum_{c=0}^{C-1} (X_{i+m,j+n,c} \cdot W_{m,n,c,k}) + bias_k$$

Kernel size vs. filters

- **Kernel size** $K_{(n,m)}$
- Number of filters



1D-CNN



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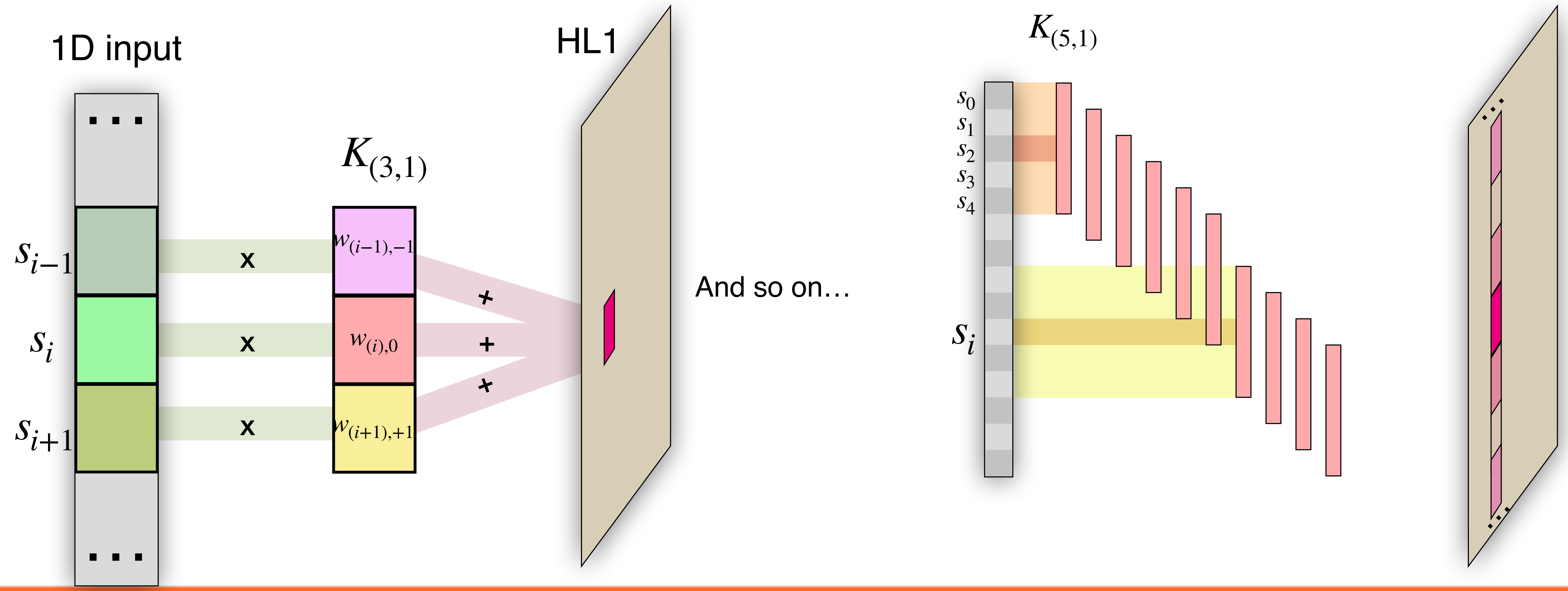

Neural Networks

Parameters

Weights and biases

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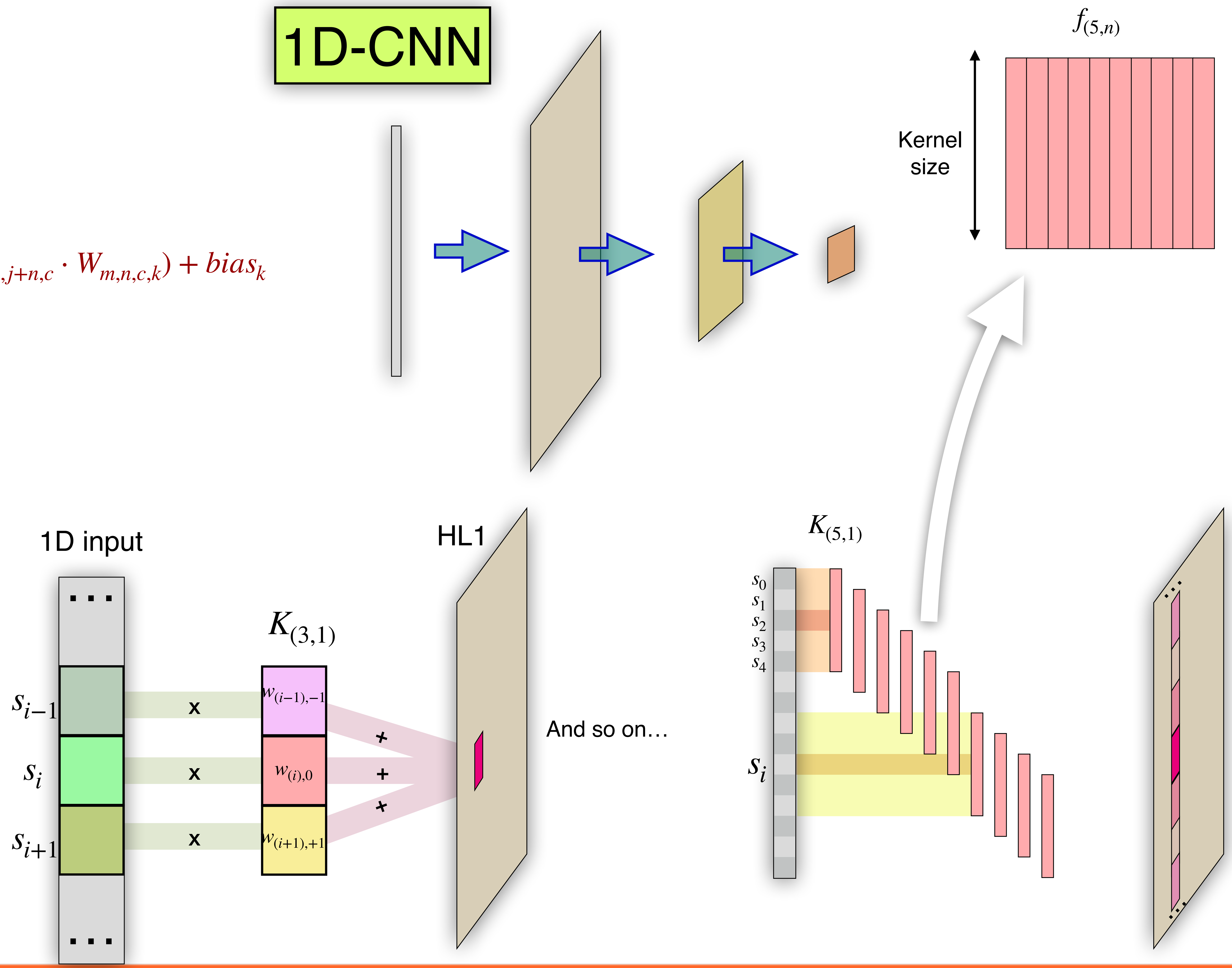


1D-CNN

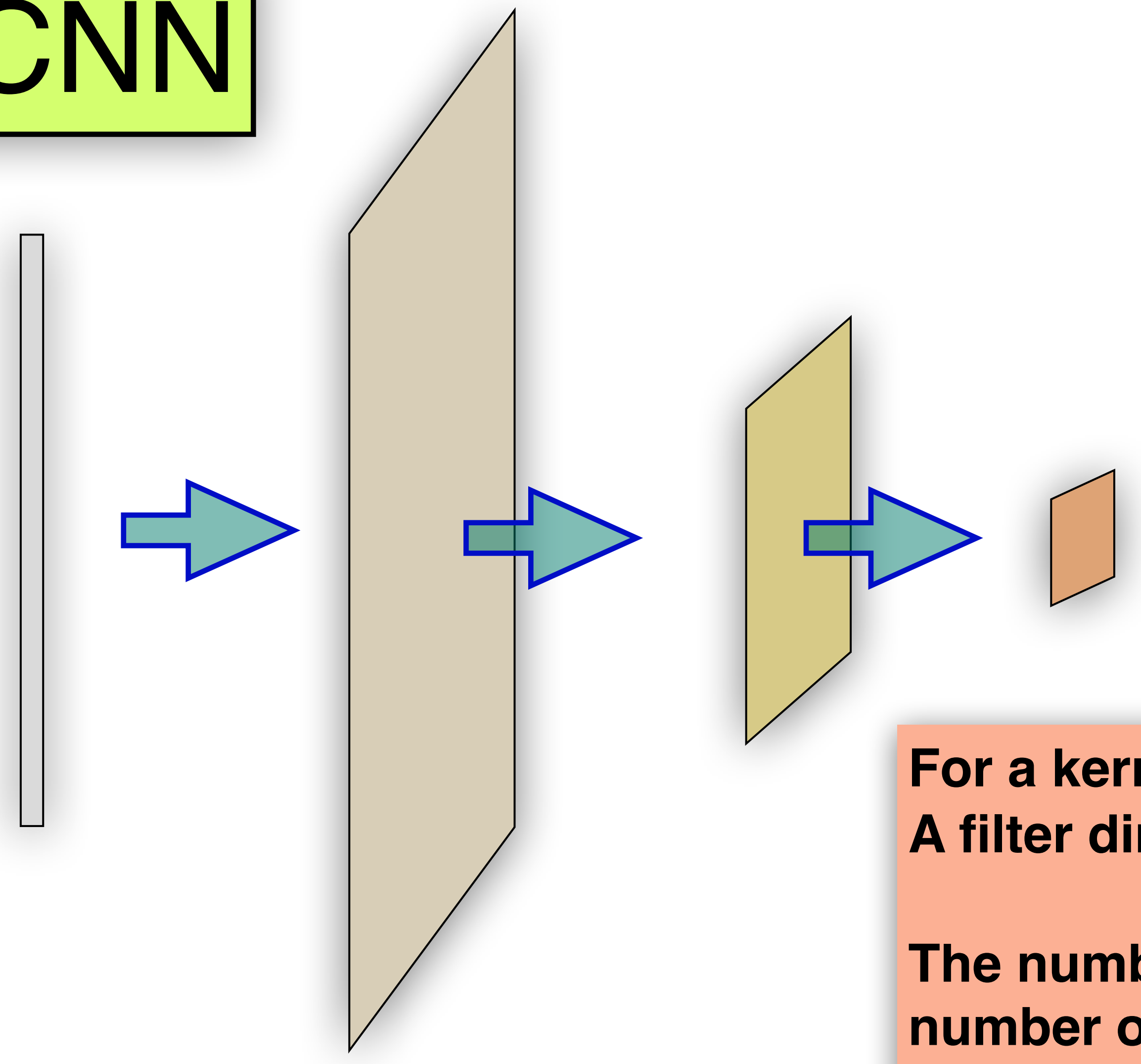
Parameters

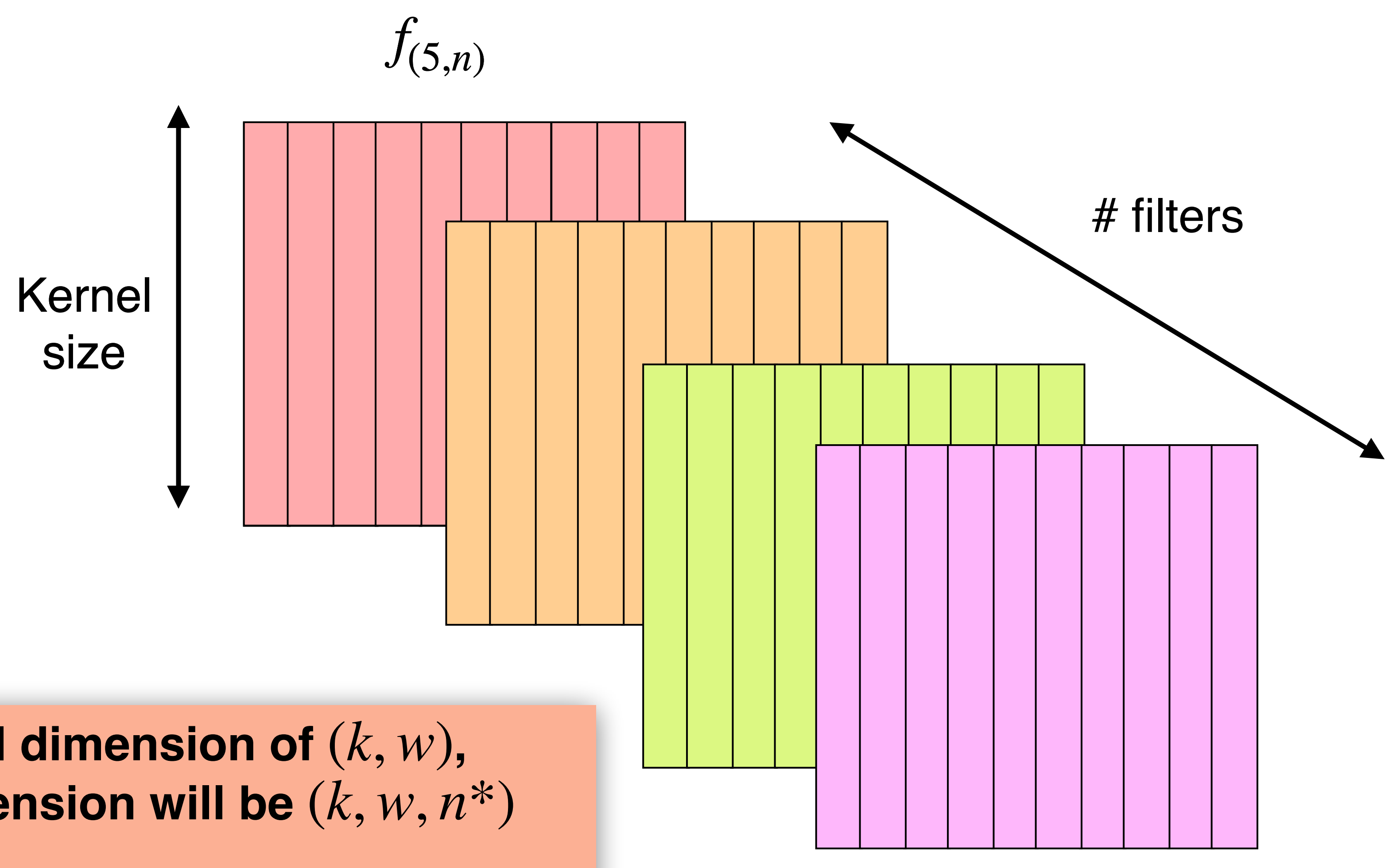
Weights and biases

$$Y_{i,j,k} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \sum_{c=0}^{C-1} (X_{i+m,j+n,c} \cdot W_{m,n,c,k}) + bias_k$$

Kernel size vs. filters

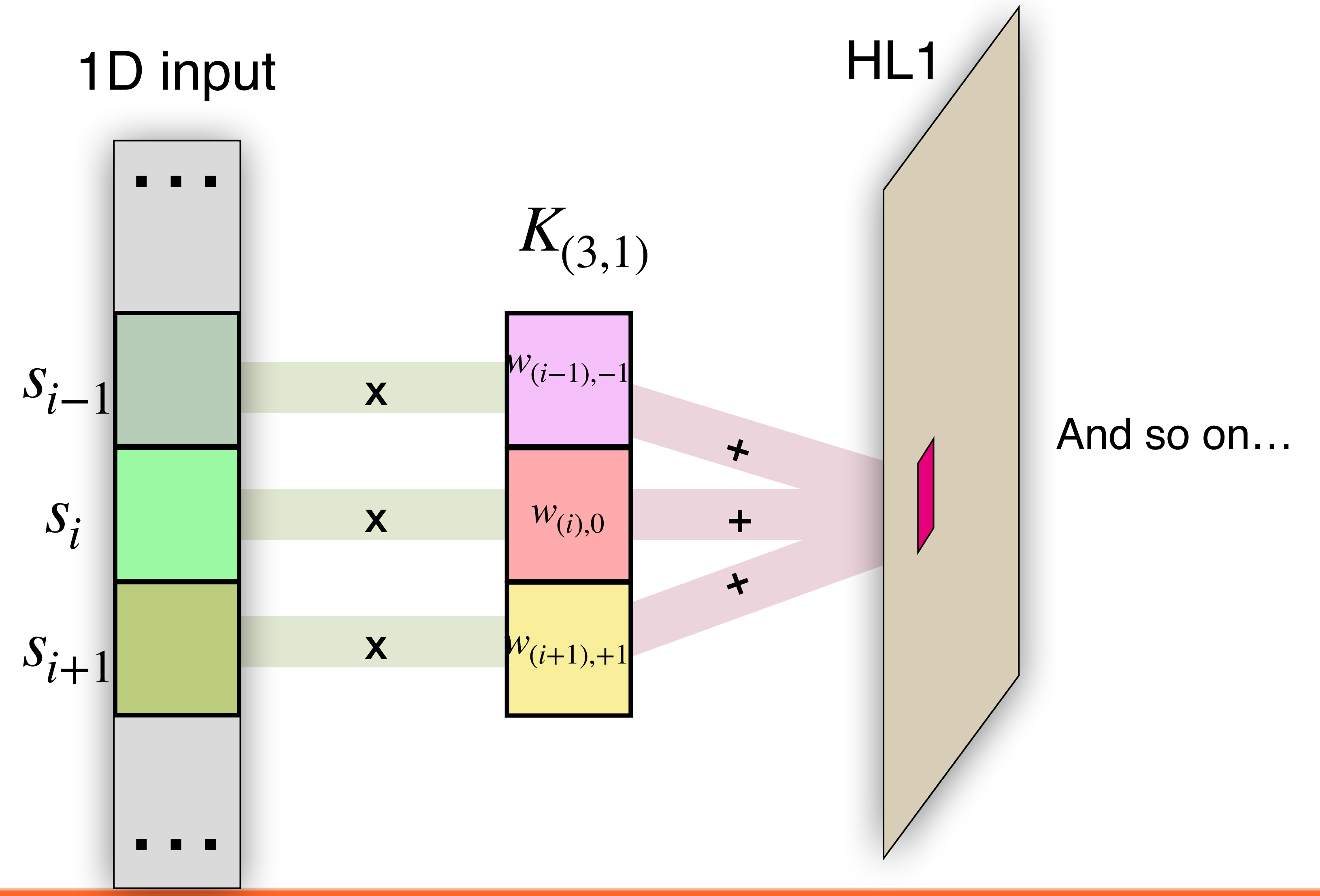
- Kernel size $K_{(n,m)}$
- **Number of filters**

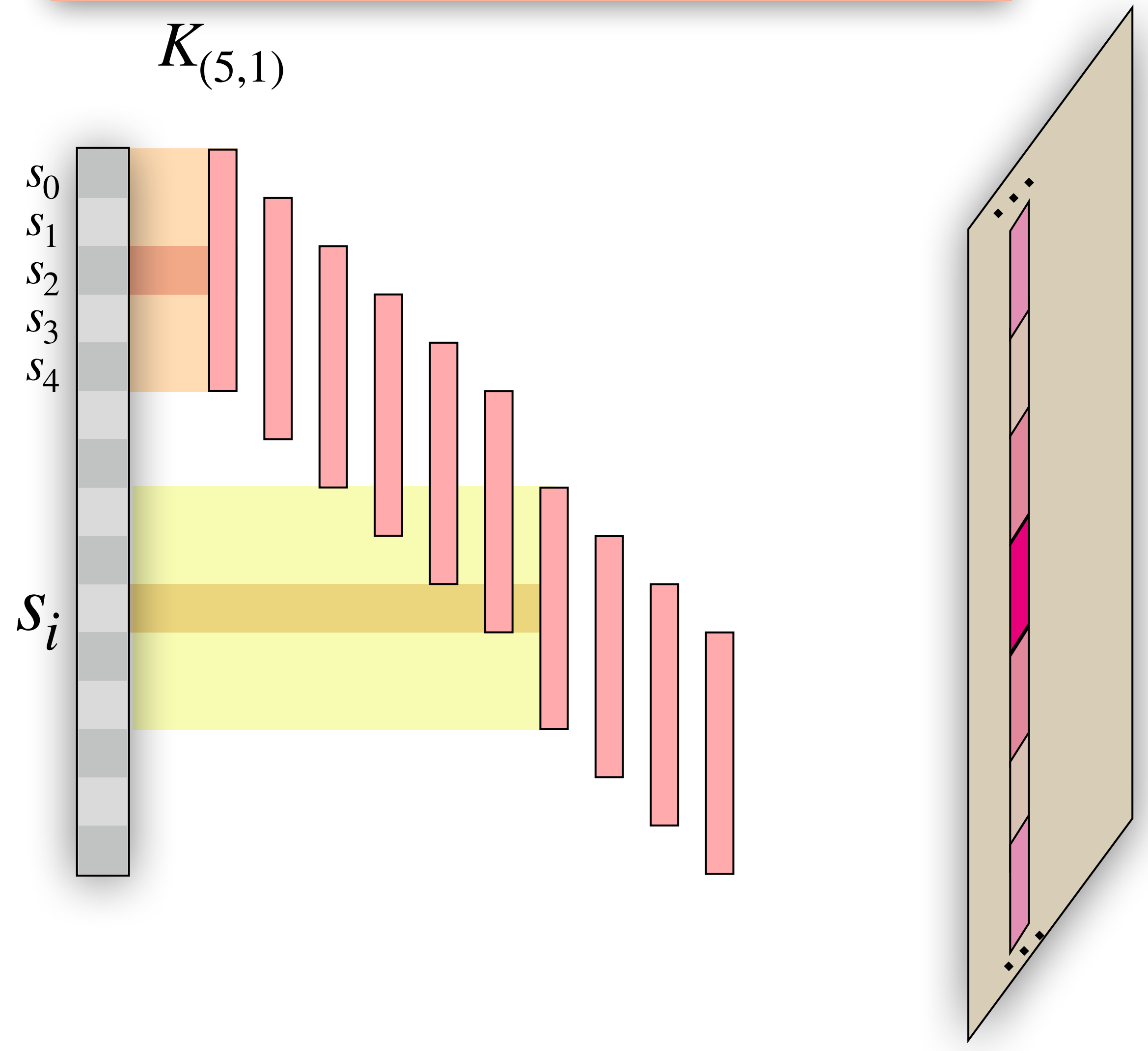




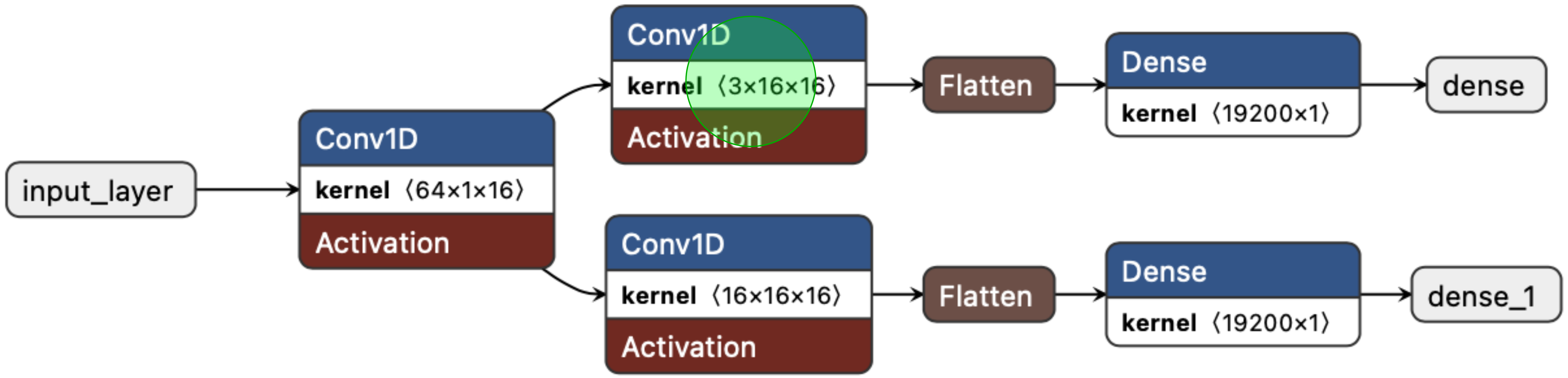
For a kernel dimension of (k, w),
A filter dimension will be (k, w, n^*)

The number of filters is related to the number of features one wants to extract from the input data

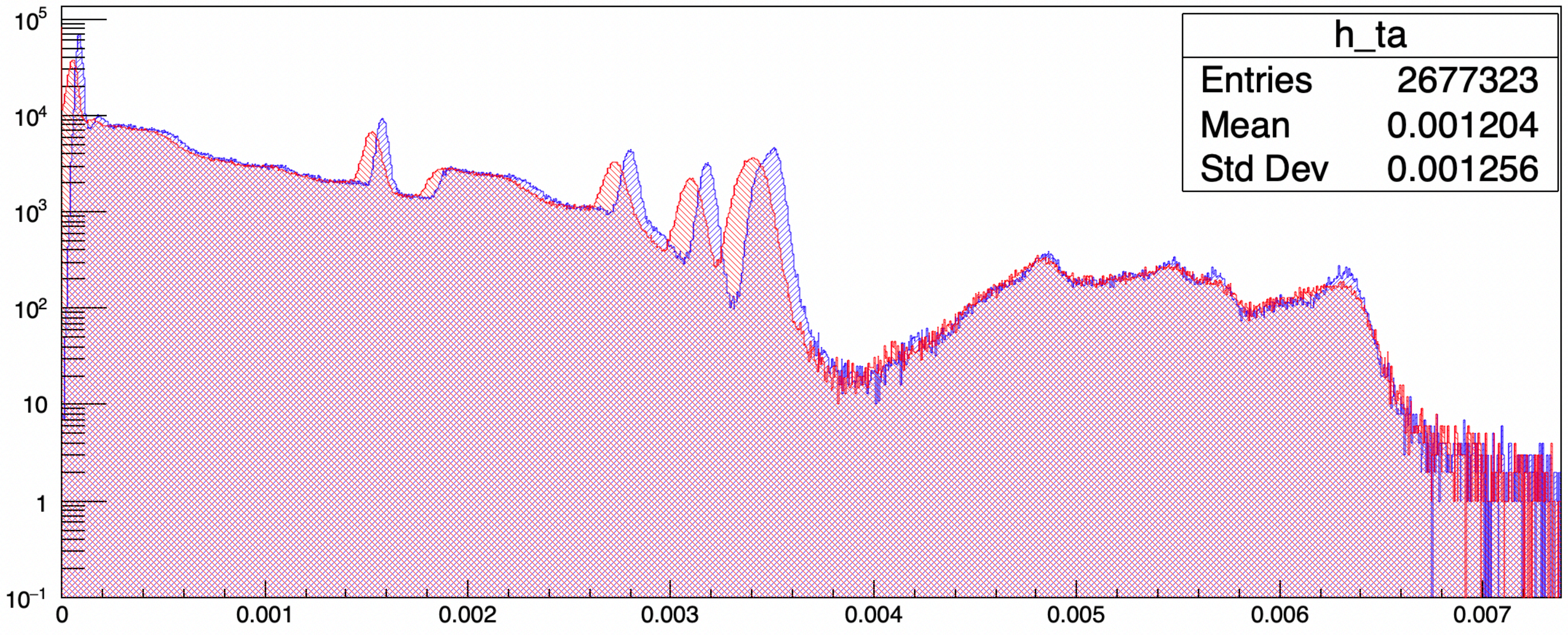


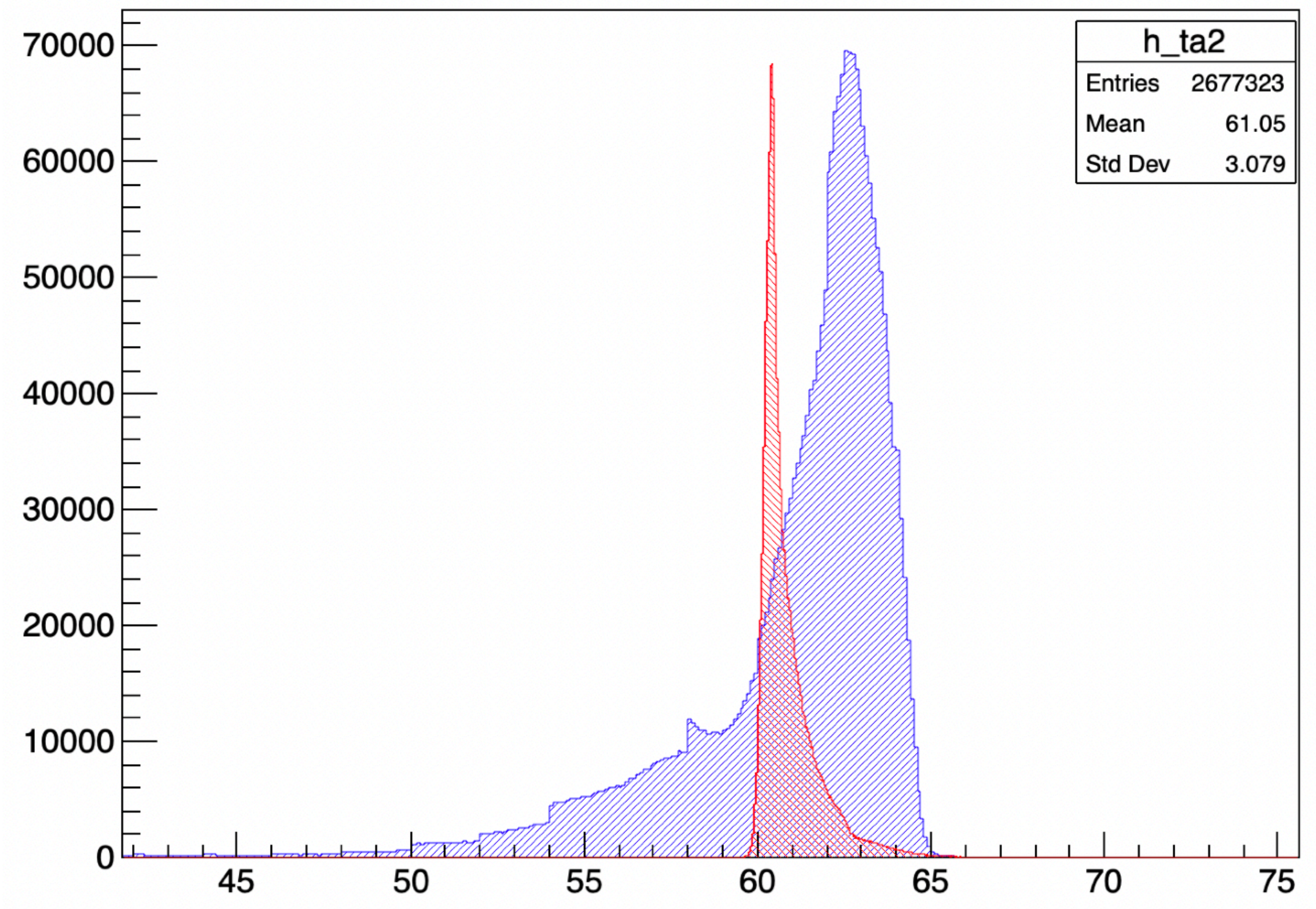


CNN 1D models for trace analysis



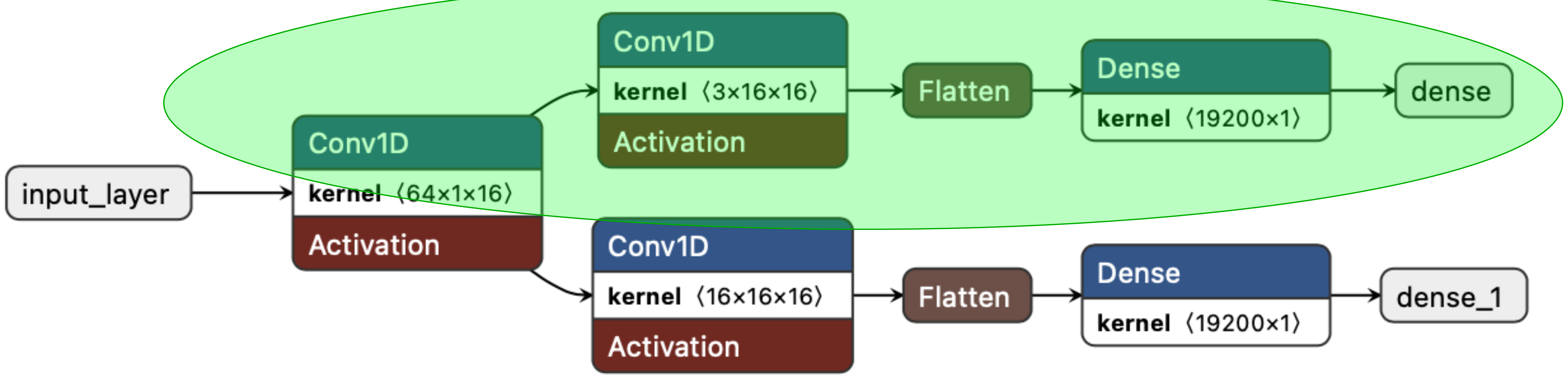
$actv.f:$ ReLu





CNN 1D models for trace analysis

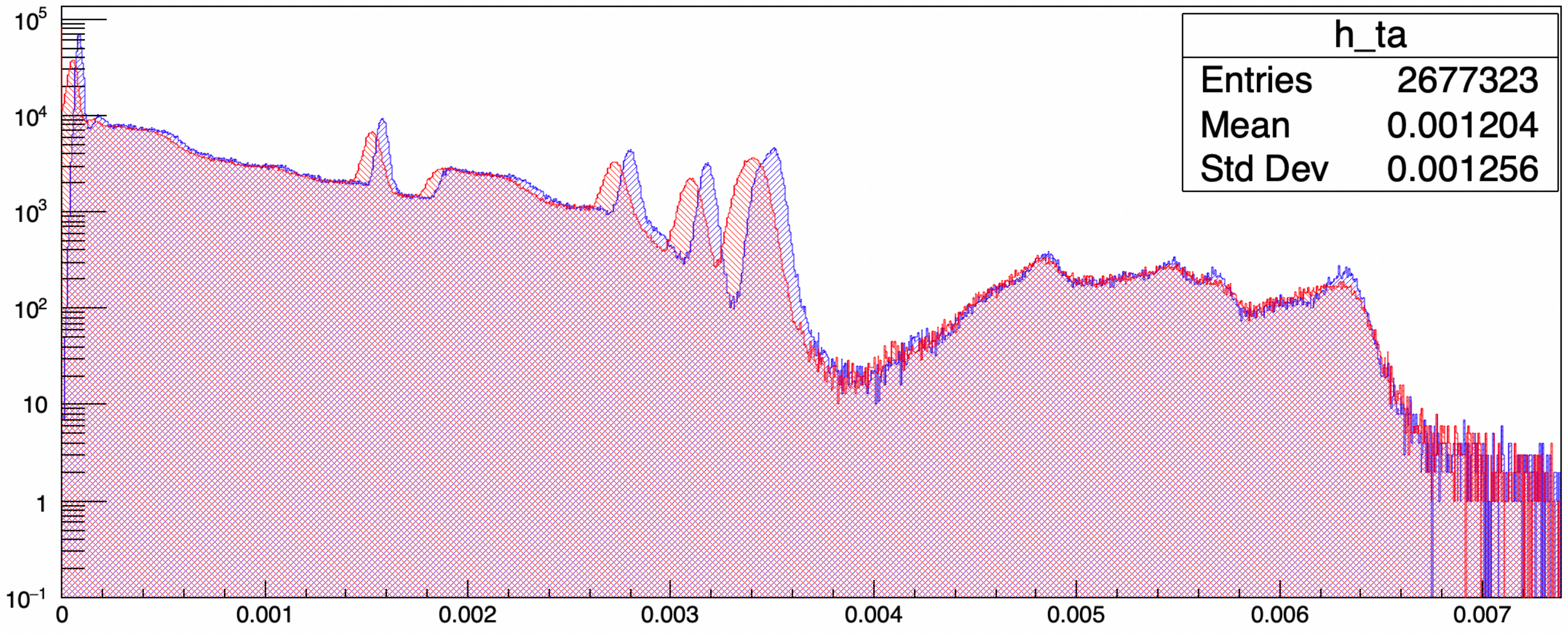
Best time result for kernel size close to signal rise time (size 3 -> 6 ns)

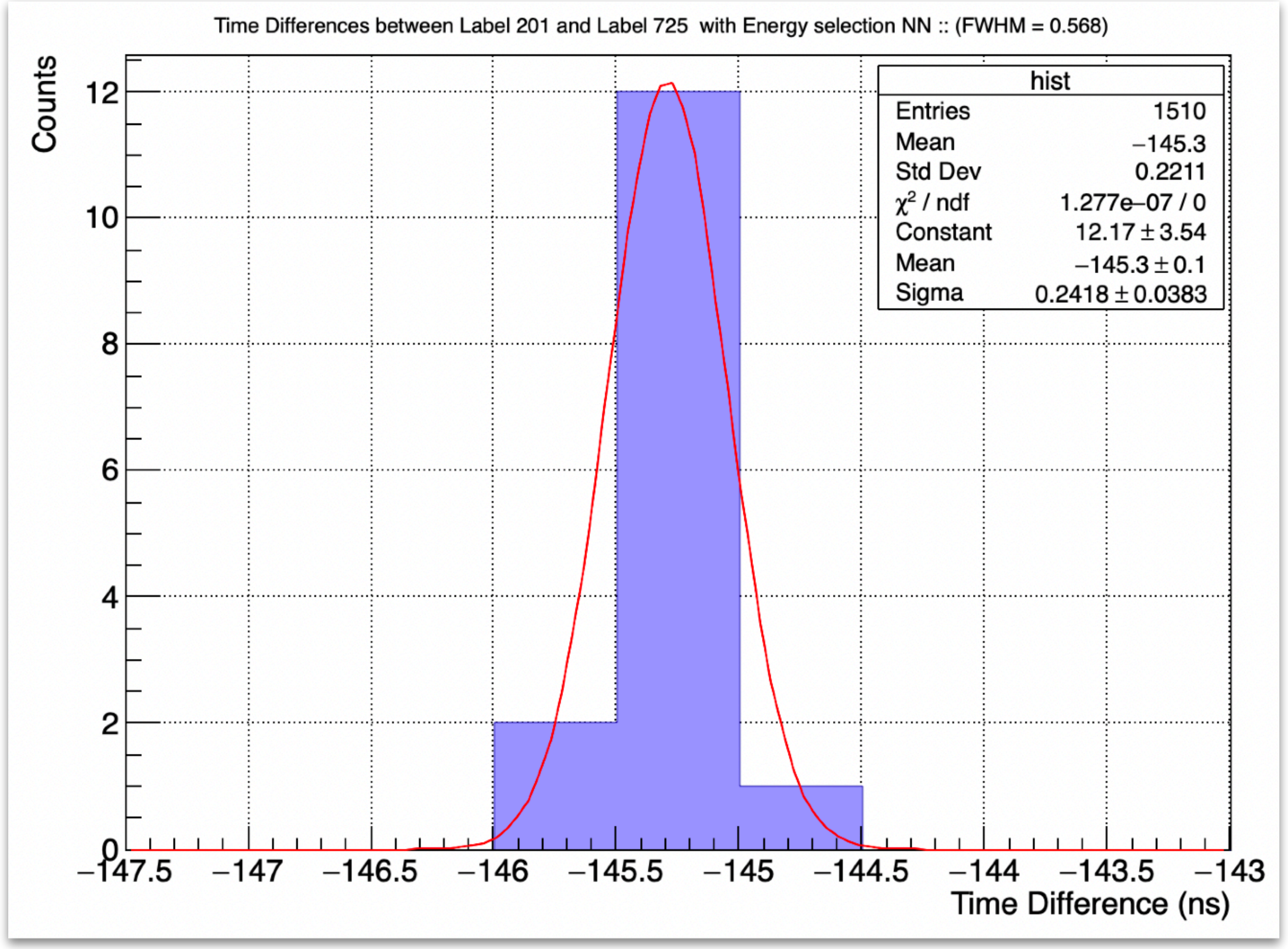


31.7 keV @ 1170 keV
$R(t)$ = 569 ps

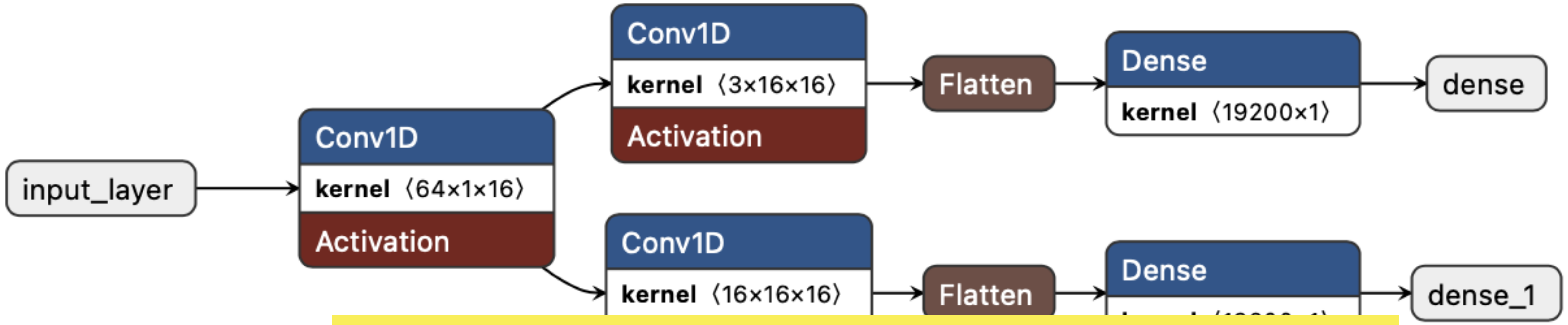
With NN:
46.4 keV @ 1170 keV
$R(t)$ = 568 ps

$actv.f$: ReLu





CNN 1D models for trace analysis

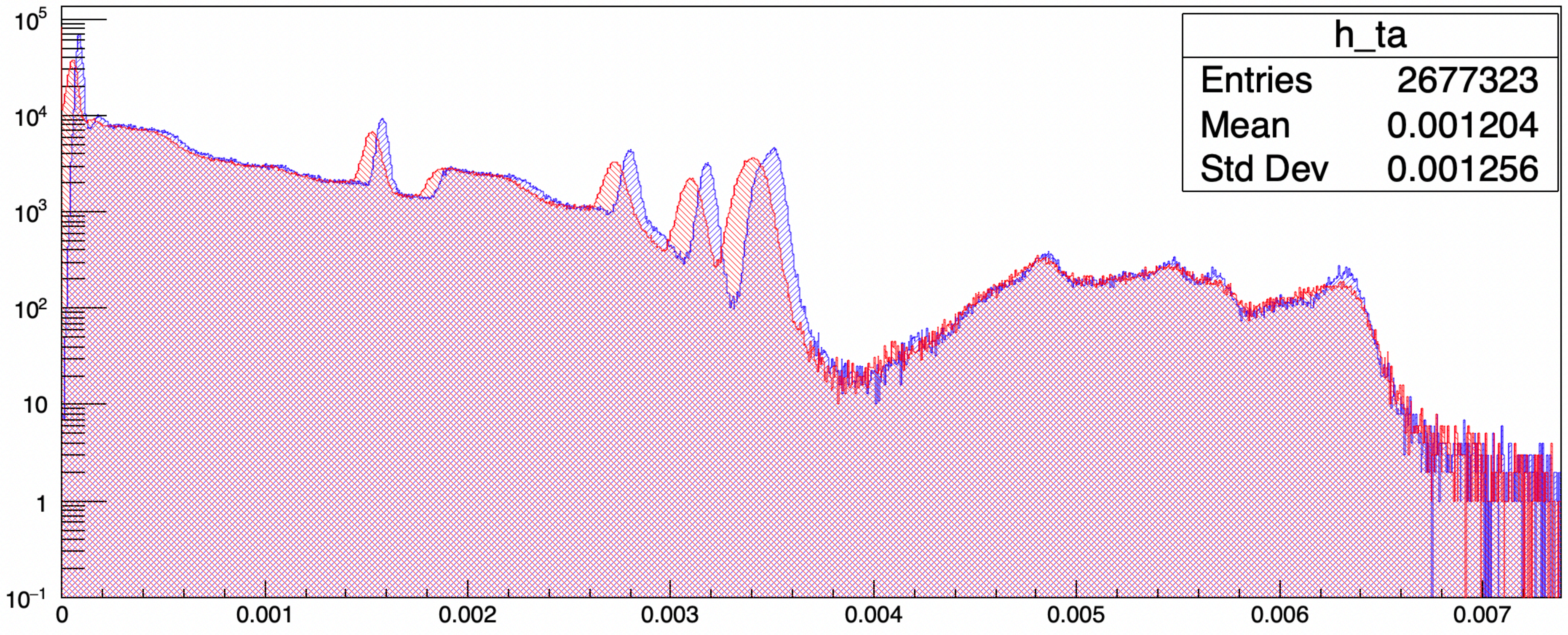


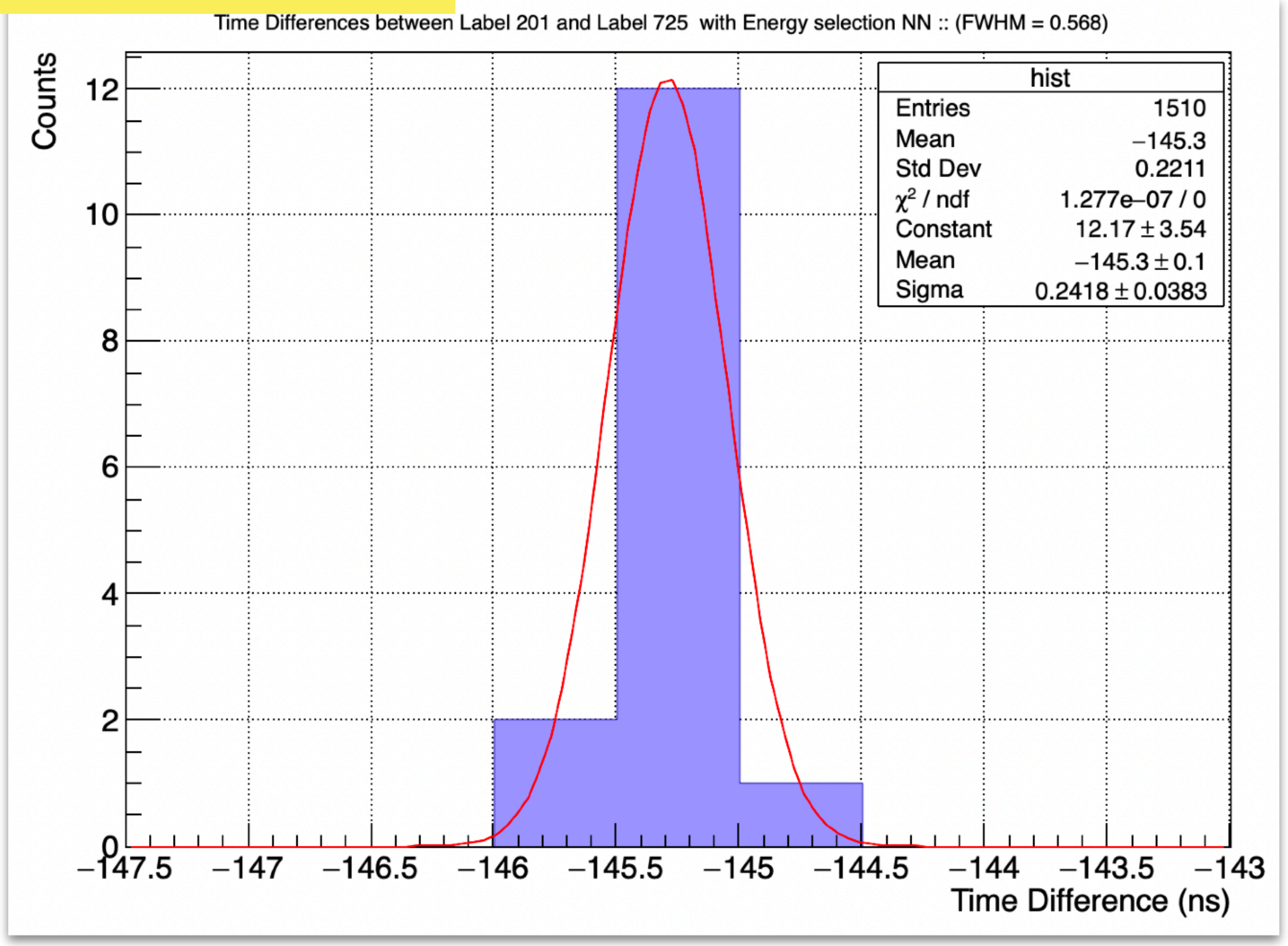
31.7 keV @ 1170 keV
$R(t)$ = 569 ps

With NN:
46.4 keV @ 1170 keV
$R(t)$ = **568 ps**

$actv.f$: ReLu

Newt step: new CNN or FCNN model with sigmoid activation function for « energy » value prediction





Perspectives

Short term

- Converge for a more robust NN model for trace analysis
- Implement the model for dFGIC adapting the hyperparameters
- Detailed evaluation of computational costs
  - Prediction time
  - Number and complexity of operations …
- ν-Ball2 finish calibration and get resolutions/efficiencies

Long term

- Develop new AI algorithms for fission trigger based on ν-Ball2 response function
- Evaluate the correlation between fission observables such as energy and multiplicity of neutrons and gammas for fission recognition

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CFD CONSTRAINT:

$$t_{delay} > t_r \cdot (1 - f) \,,$$

where t_r is the signal rise time