Development of innovative methods for a fission trigger construction

B. Pertille[1], **M. Lebois**[1,2], M. Mehdi[1], S. Oberstedt[3], J.Guillot[1], D. Thisse[4],

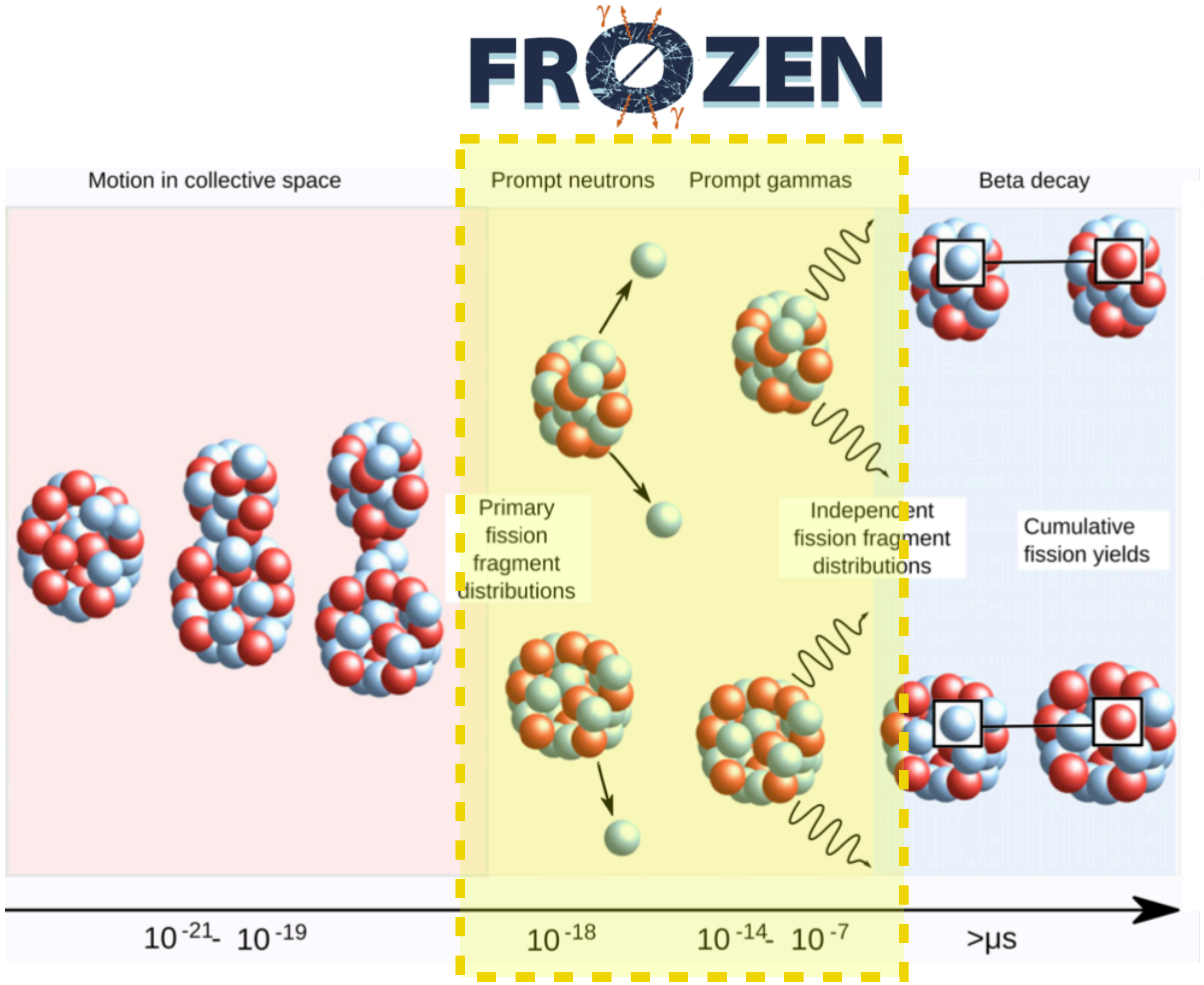
1 Université Paris-Saclay, CNRS/IN2P3, IJC Laboratory, France
2 Institut Universitaire de France.
[3] JRC Geel
[4] CEA Paris-Saclay

CONTENTS:

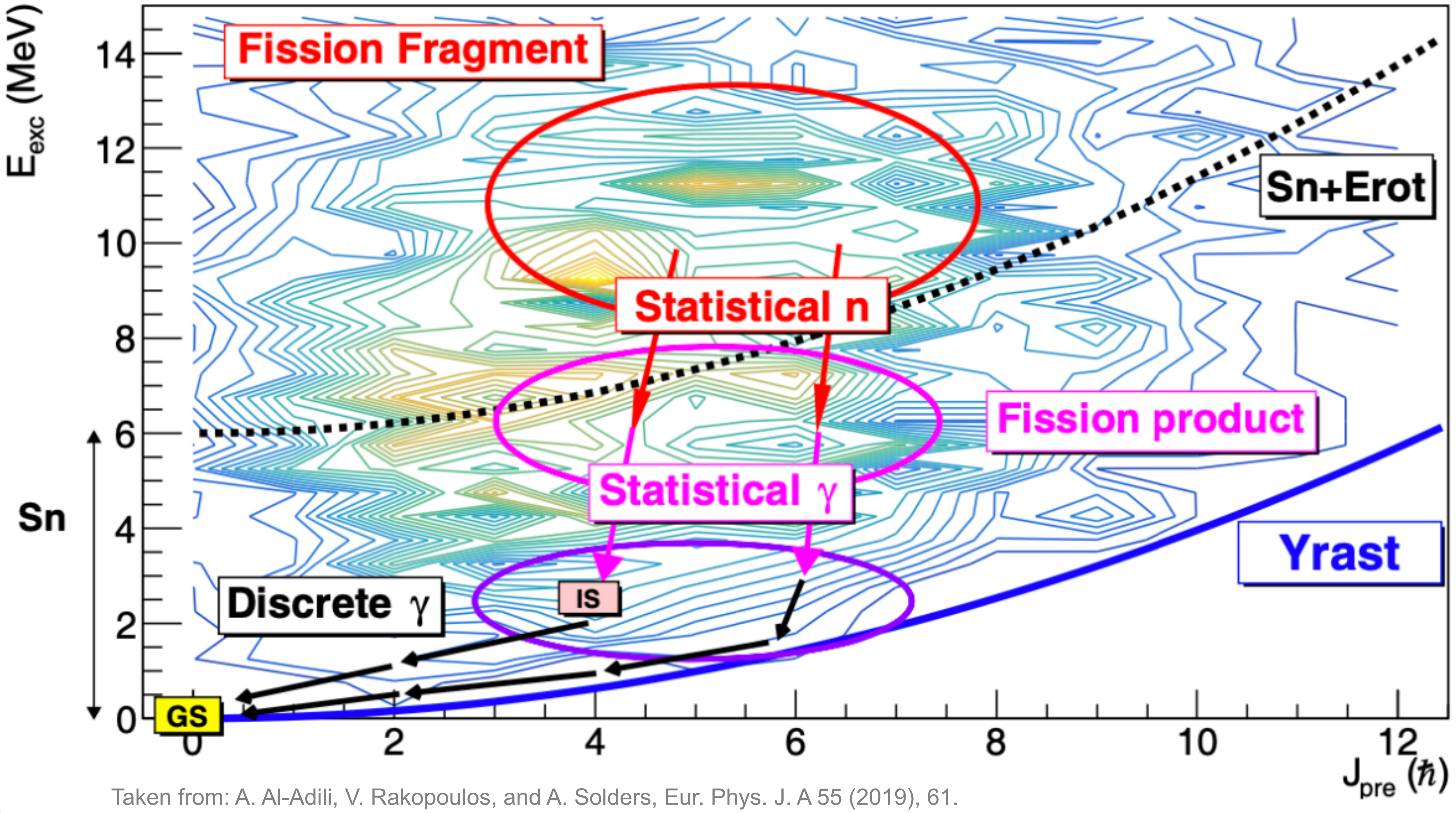
- Fission fragments de-excitation
- N-SI-125 experiment with ν-Ball2
- Fission tag with dFGIC
- Neural Networks for fission triggering

CONTENTS:

Nuclear fission



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

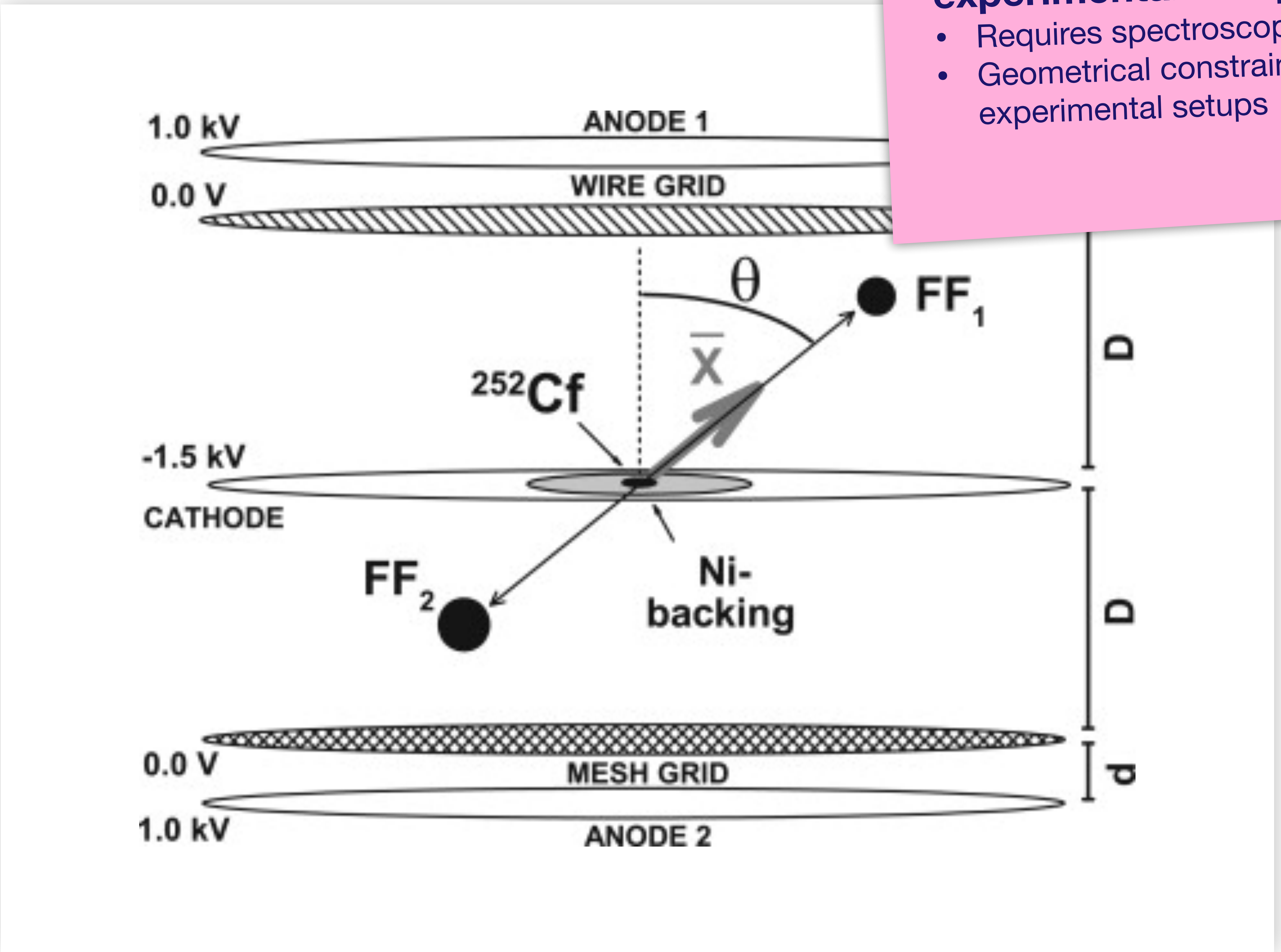


Taken from: A. Al-Adili, V. Rakopoulos, and A. Solders, Eur. Phys. J. A 55 (2019), 61.

Fission Tagging

Dedicated detector:

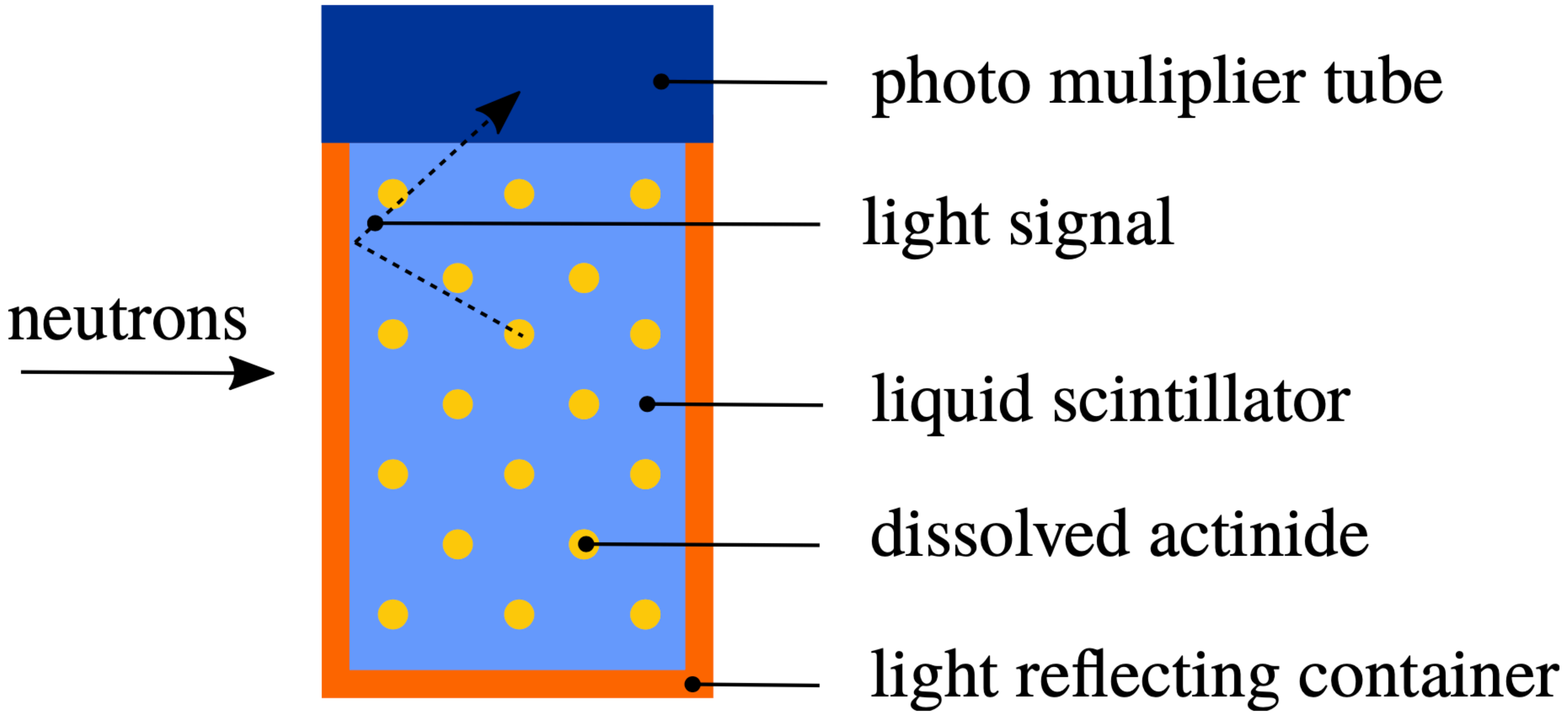
…such as an ionisation chamber



Taken from: L. Bardelli et al., Nucl. Instrum. Methods Phys. Res. A, vol. 654, pp. 272-278, 2011.

It is NOT suitable for all experimental setups:
- Requires spectroscopic target
- Geometrical constraints experimental setups

…such as an active target



PhD thesis: Dennis Wilmsen. Nuclear structure studies with neutron-induced reactions : fission fragments in the N=50-60 region, a fission tagger for FIPPS, and production of the isomer Pt-195m. Physics [physics]. Normandie Université, 2017. English. <NNT : 2017NORMC269>. <tel-01768580>

Fission Tagging

Dedicated detector:

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Taken from: L. Bardelli

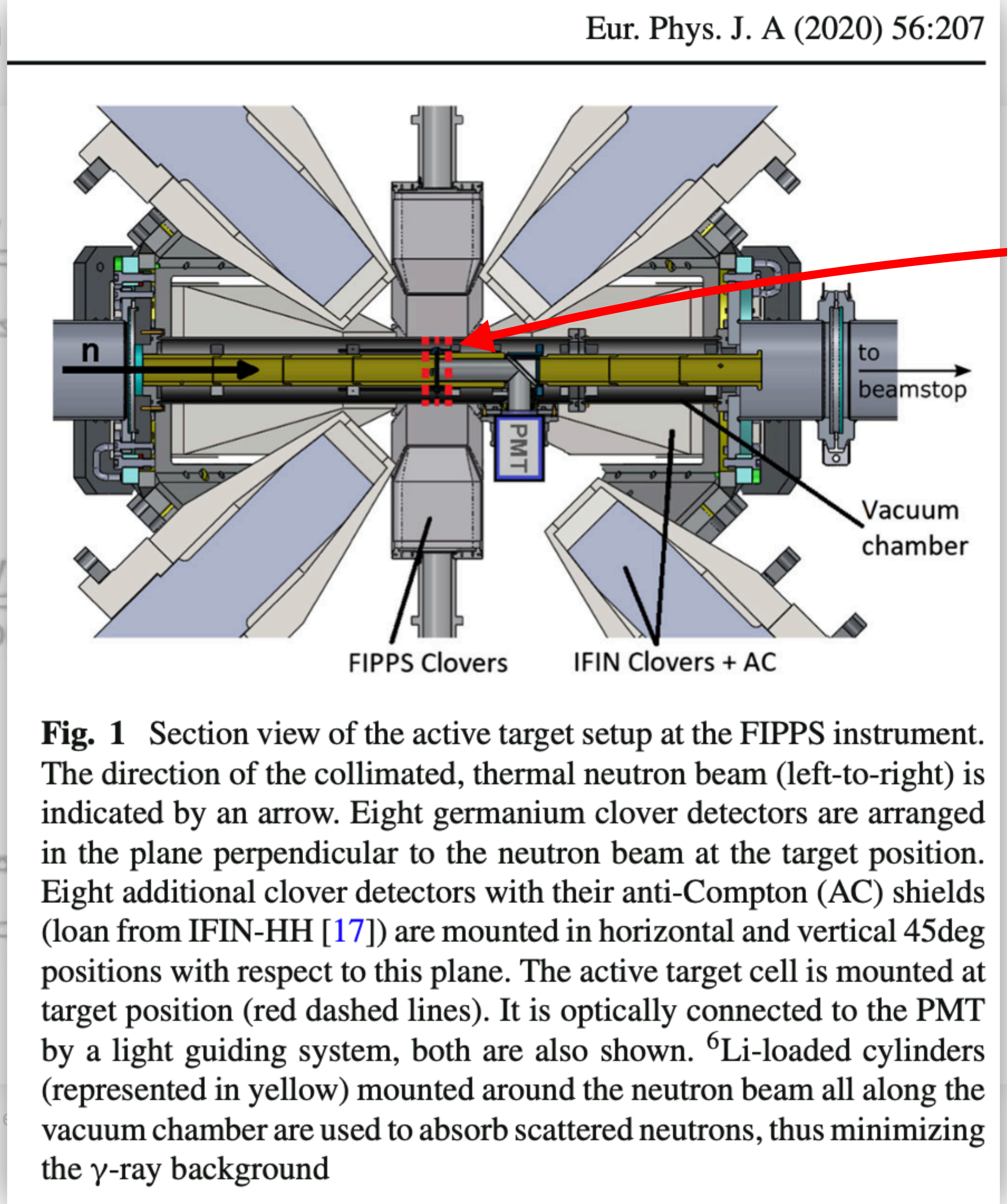
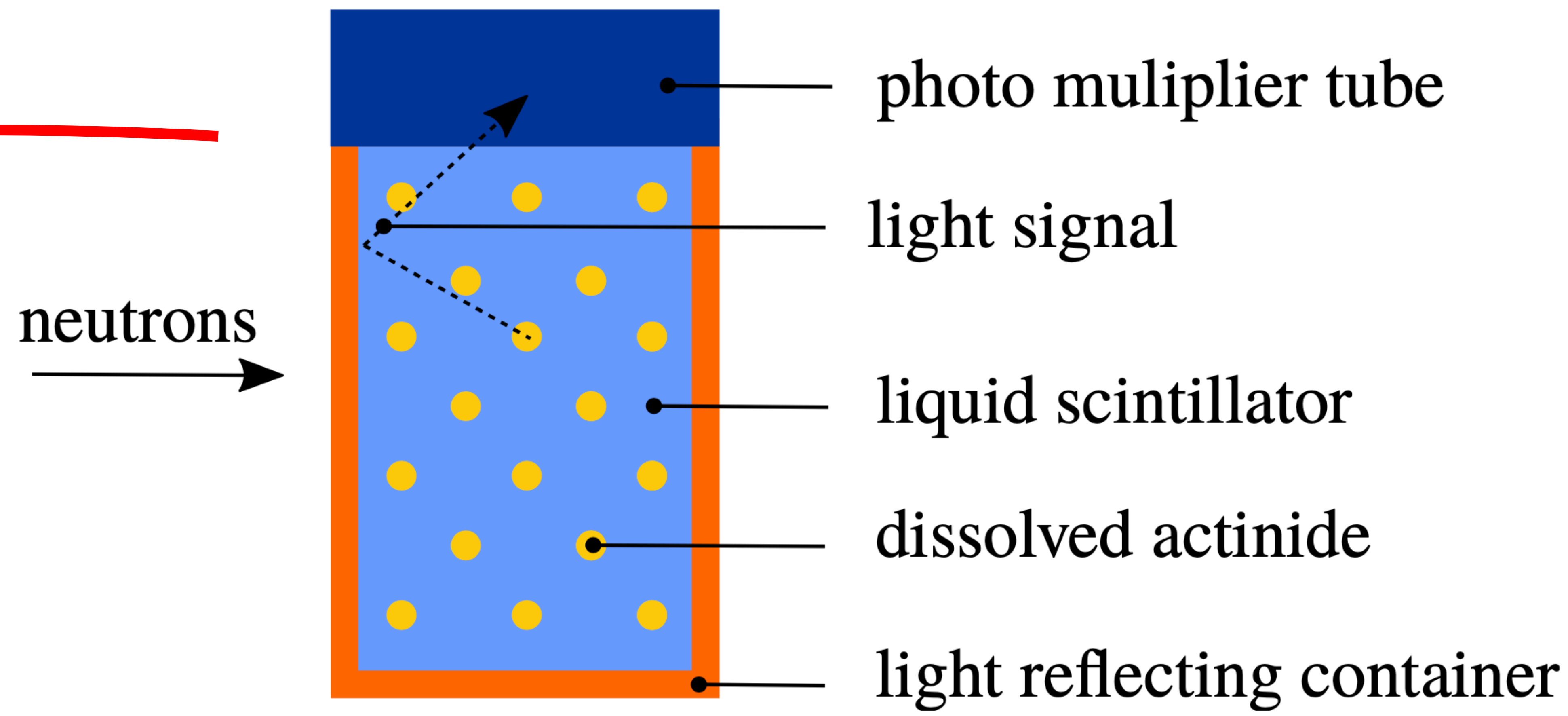


Fig. 1 Section view of the active target setup at the FIPPS instrument. The direction of the collimated, thermal neutron beam (left-to-right) is indicated by an arrow. Eight germanium clover detectors are arranged in the plane perpendicular to the neutron beam at the target position. Eight additional clover detectors with their anti-Compton (AC) shields (loan from IFIN-HH [17]) are mounted in horizontal and vertical 45deg positions with respect to this plane. The active target cell is mounted at target position (red dashed lines). It is optically connected to the PMT by a light guiding system, both are also shown. ^{6}Li-loaded cylinders (represented in yellow) mounted around the neutron beam all along the vacuum chamber are used to absorb scattered neutrons, thus minimizing the γ-ray background

…such as an active target



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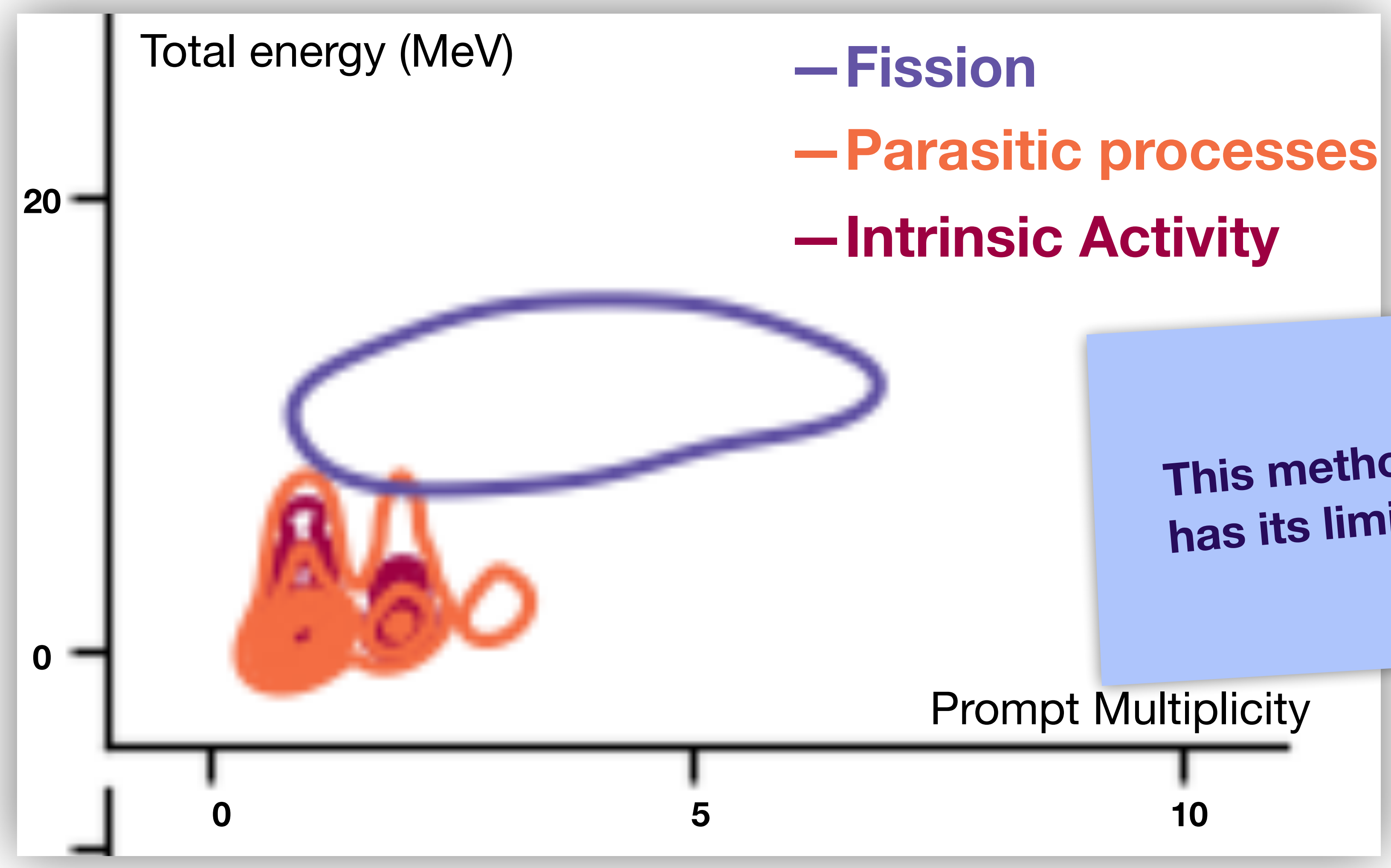
Fission tagging efficiency of 97.8 (25)% for $^{233,235}U$
This fission tag gives a gain in statistics up to a factor of 10

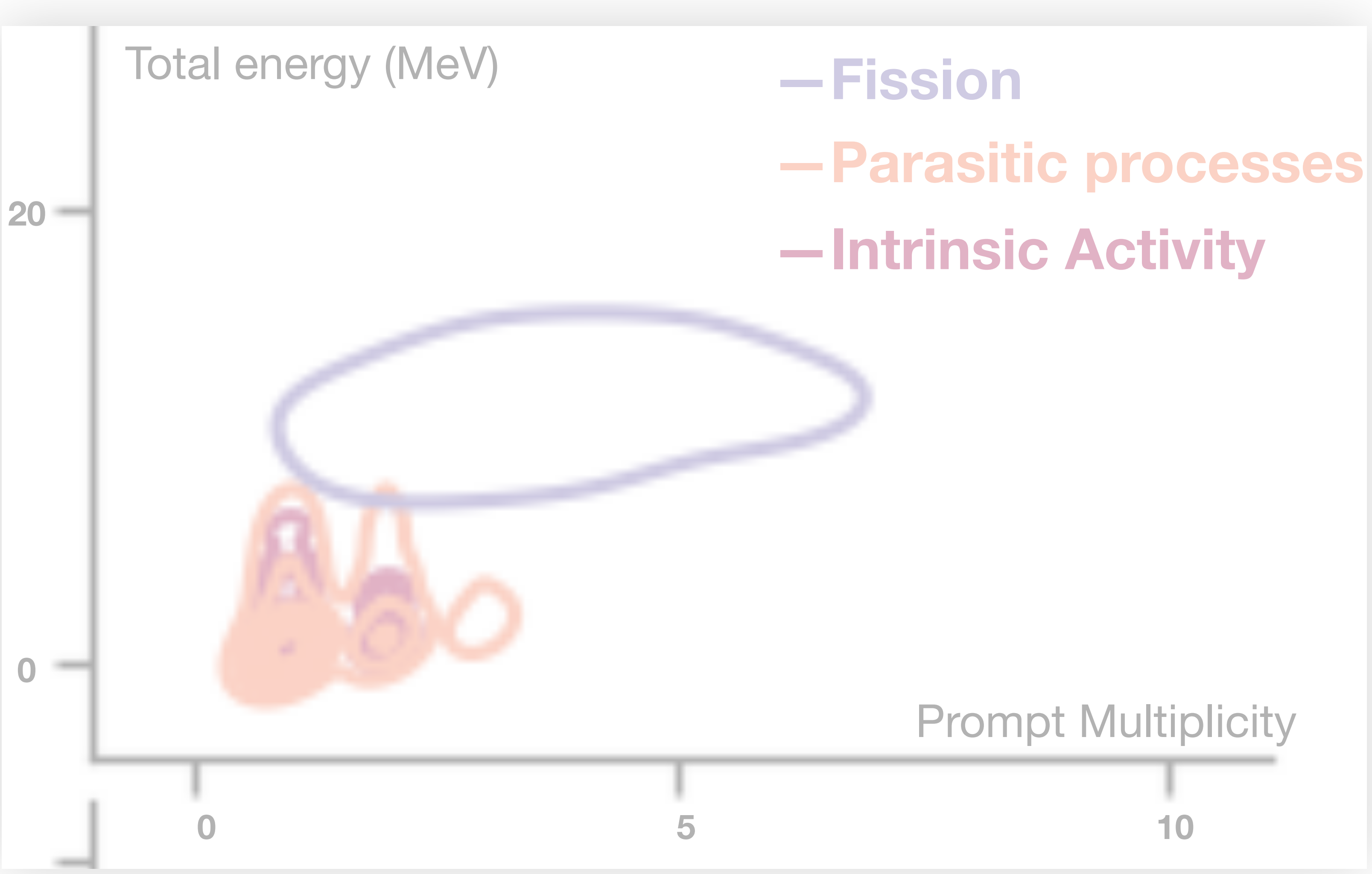
Constraints:
- Suitable for dissolvable actinides;
- Target mass density.

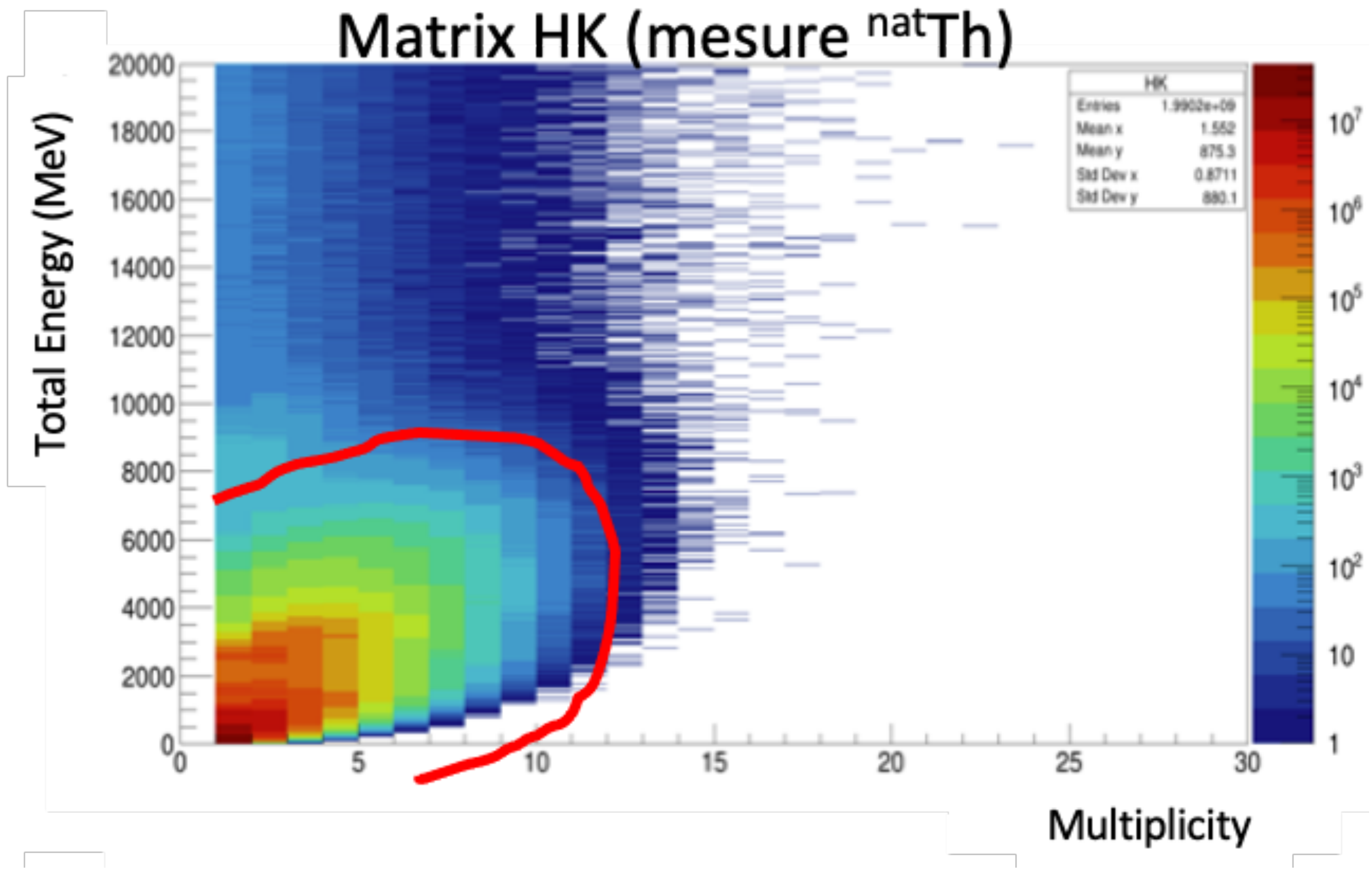
Calorimetry for fission event recognition



This method also has its limitations…

Calorimetry for fission event recognition





D. Thisse, Paris-Saclay, PhD thesis (2021)

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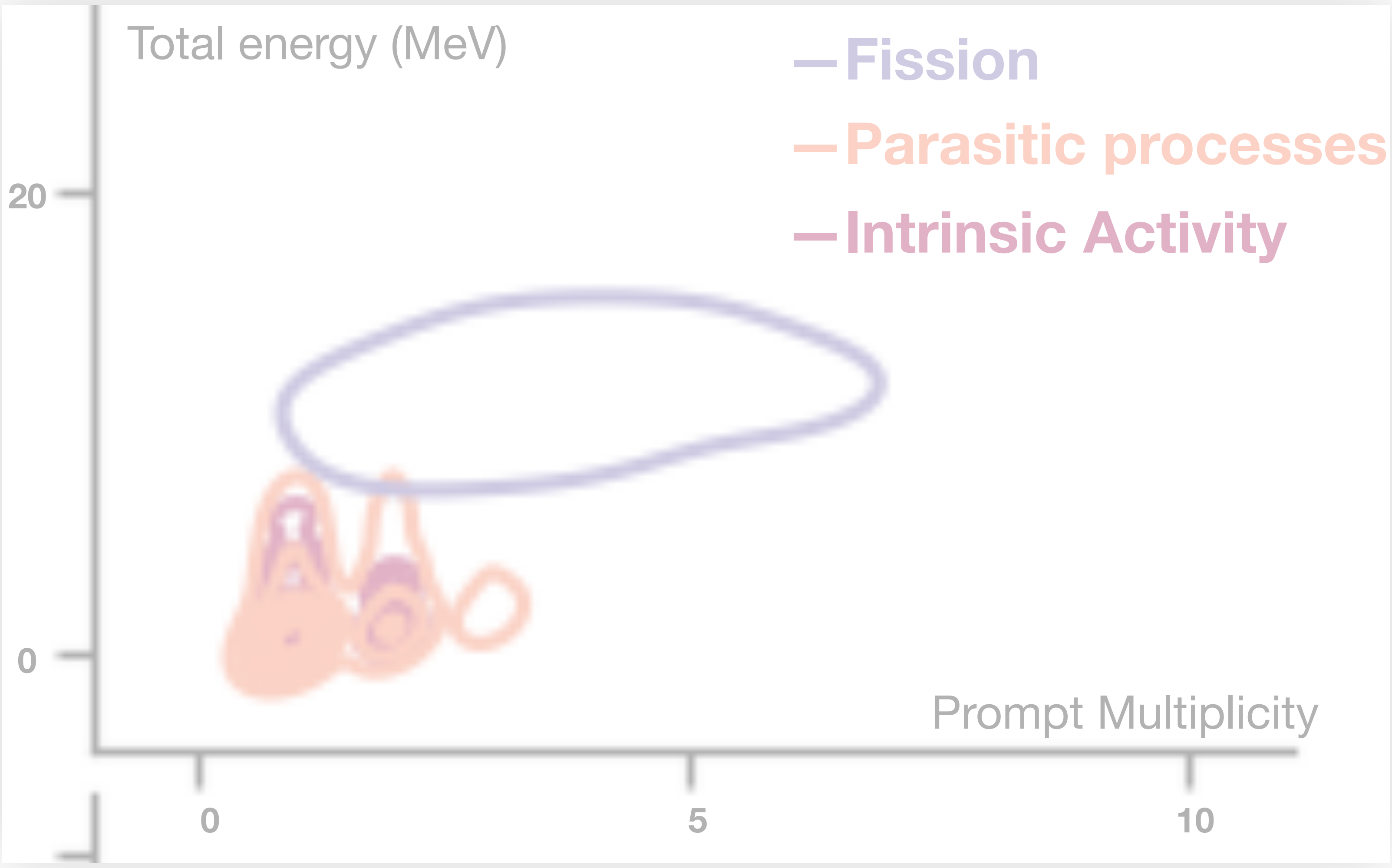

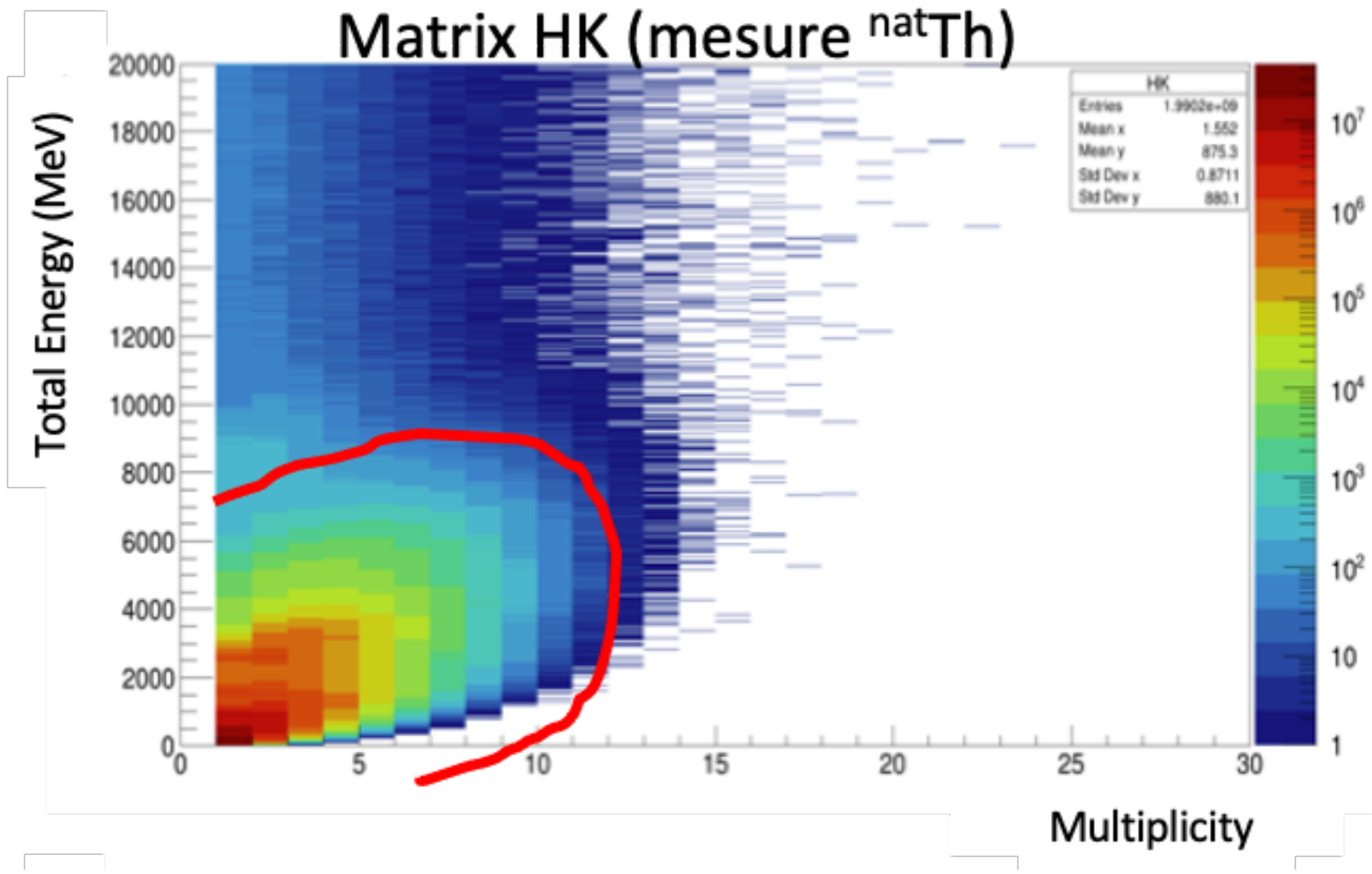

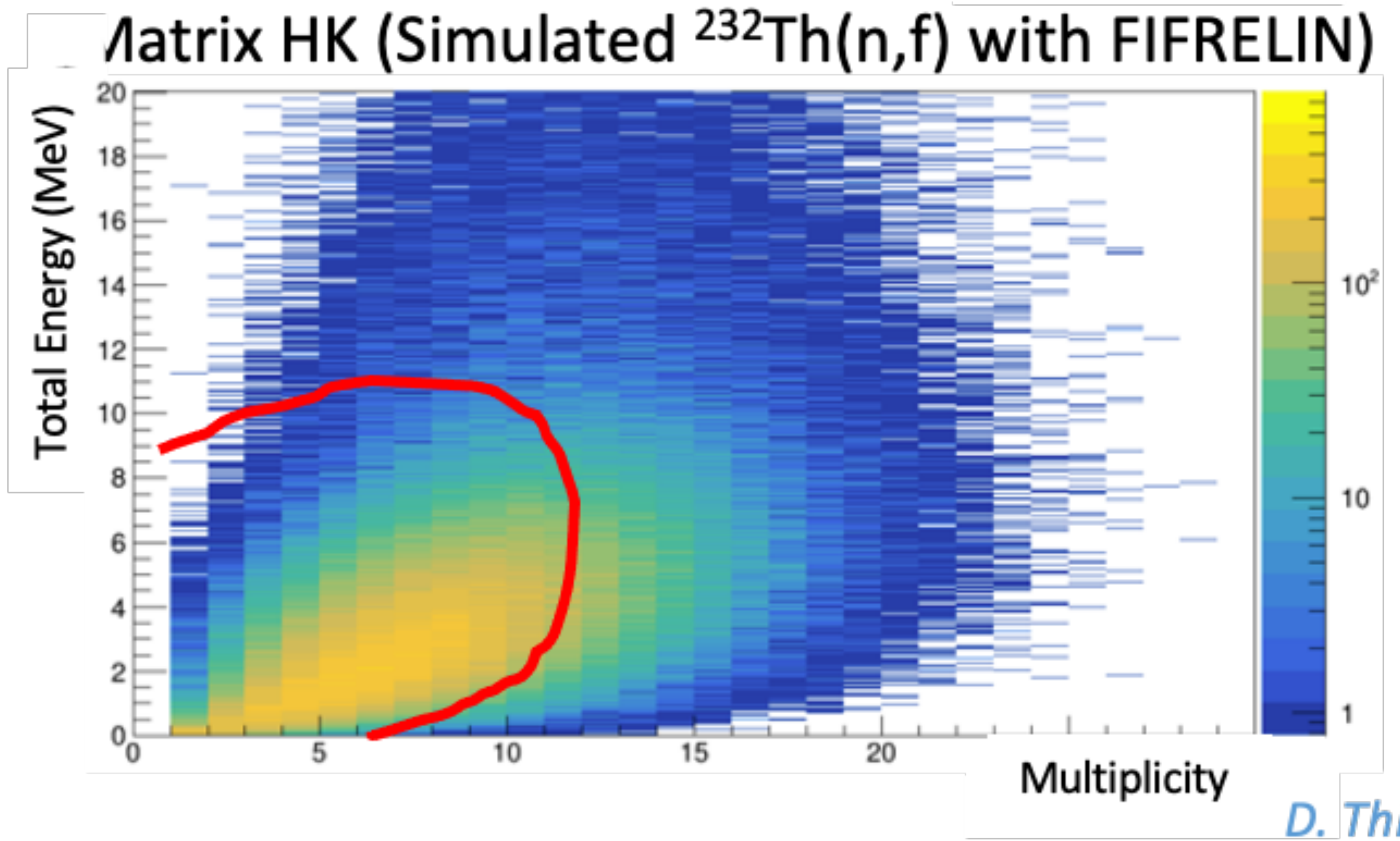

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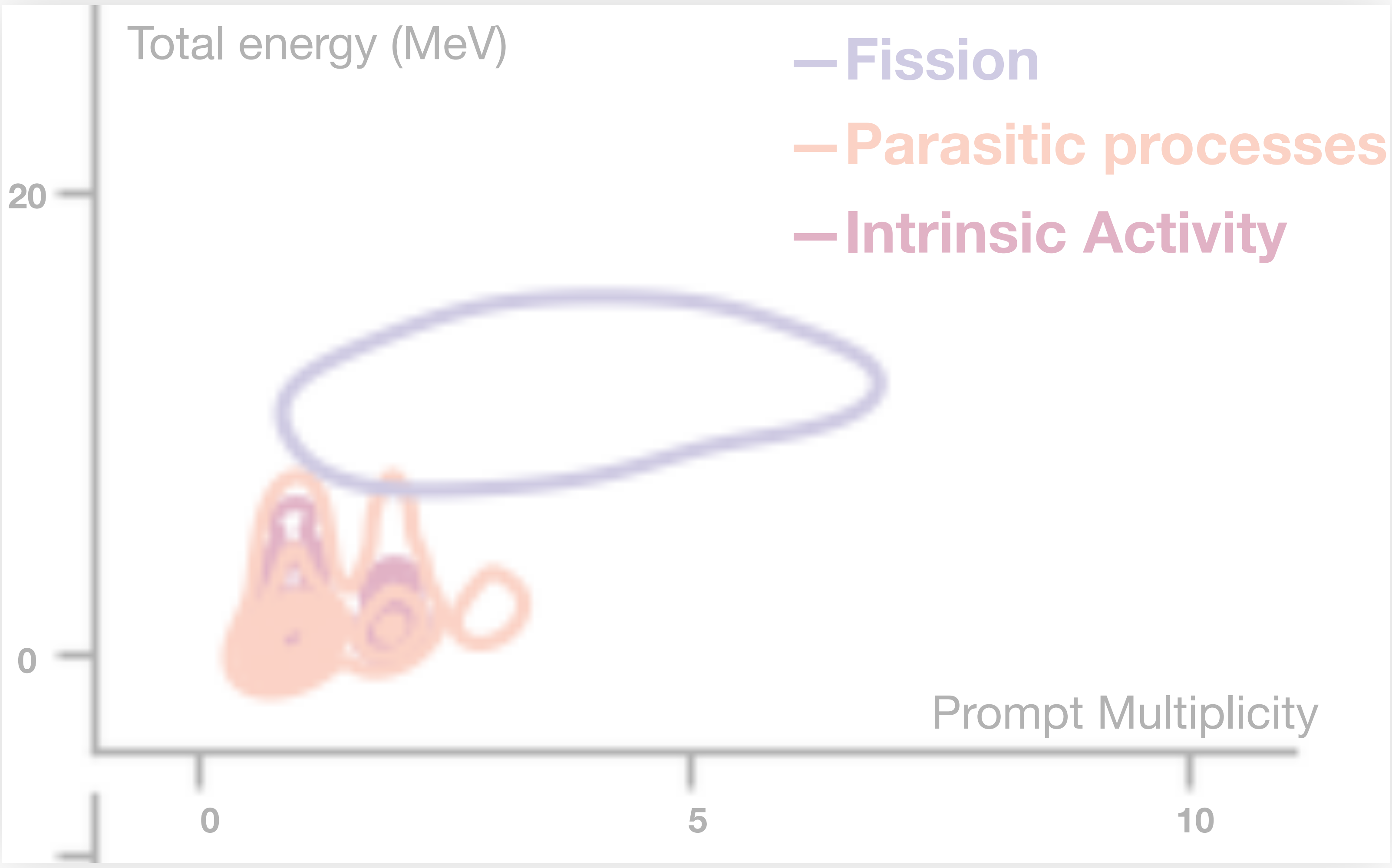

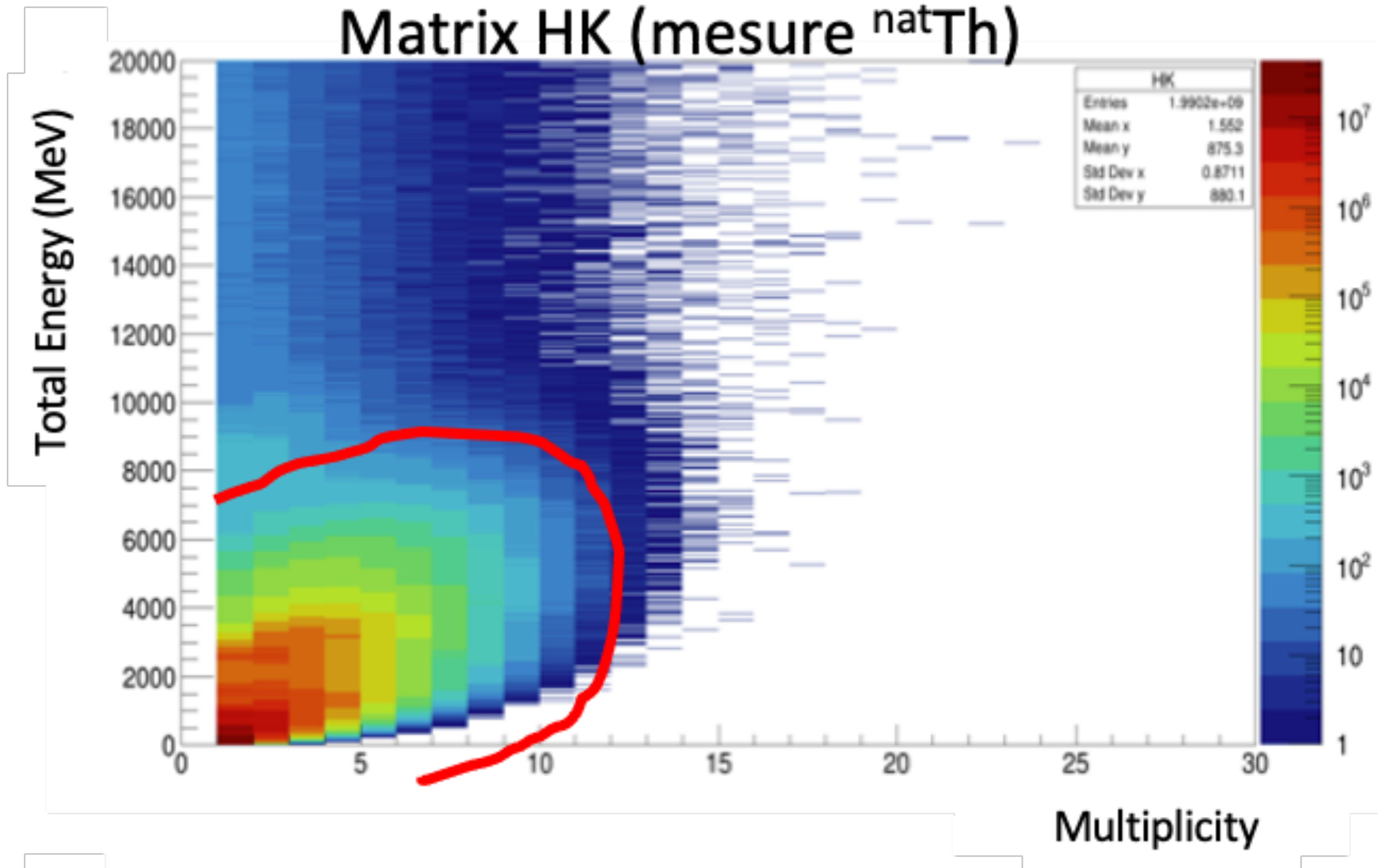

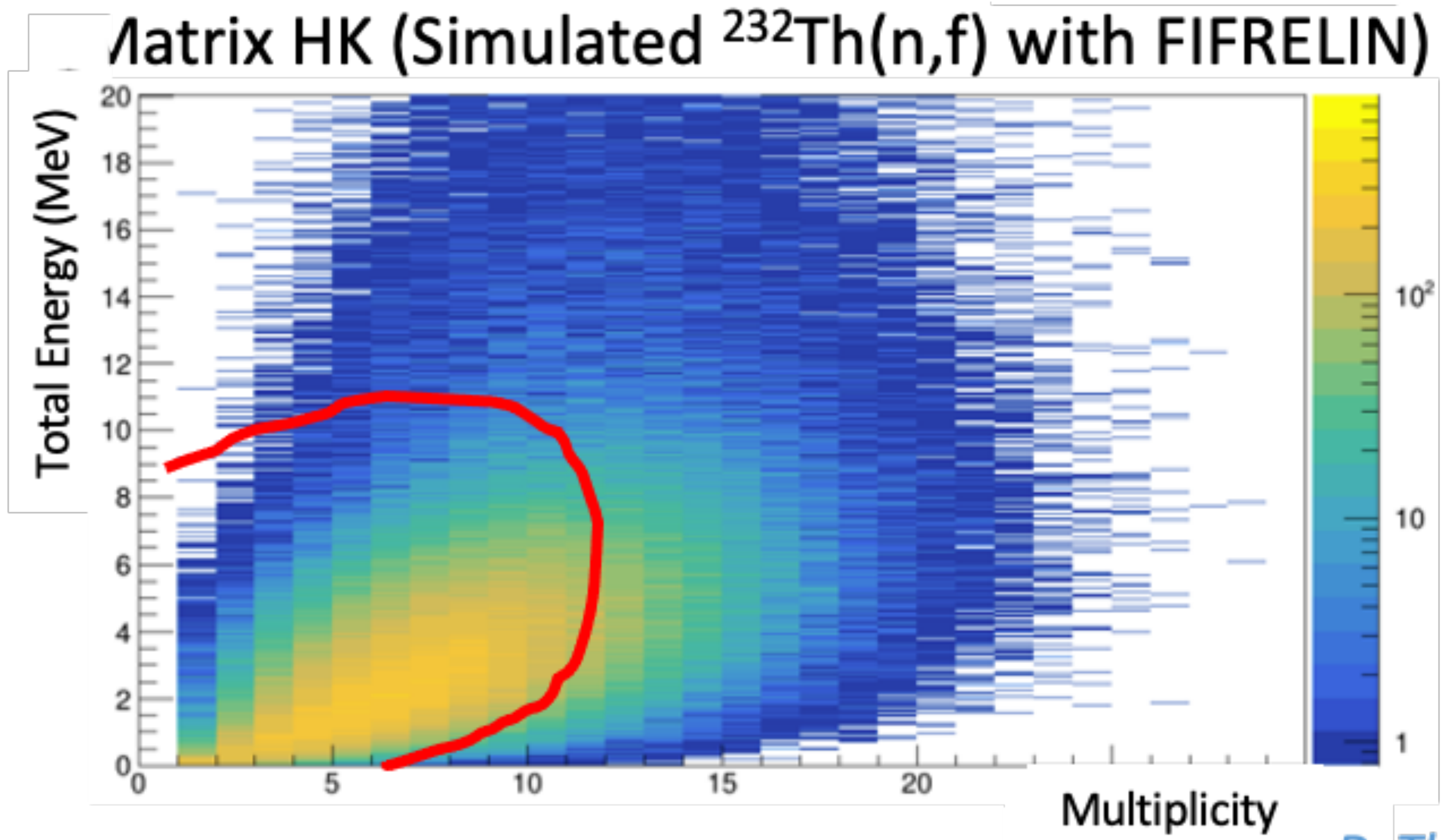

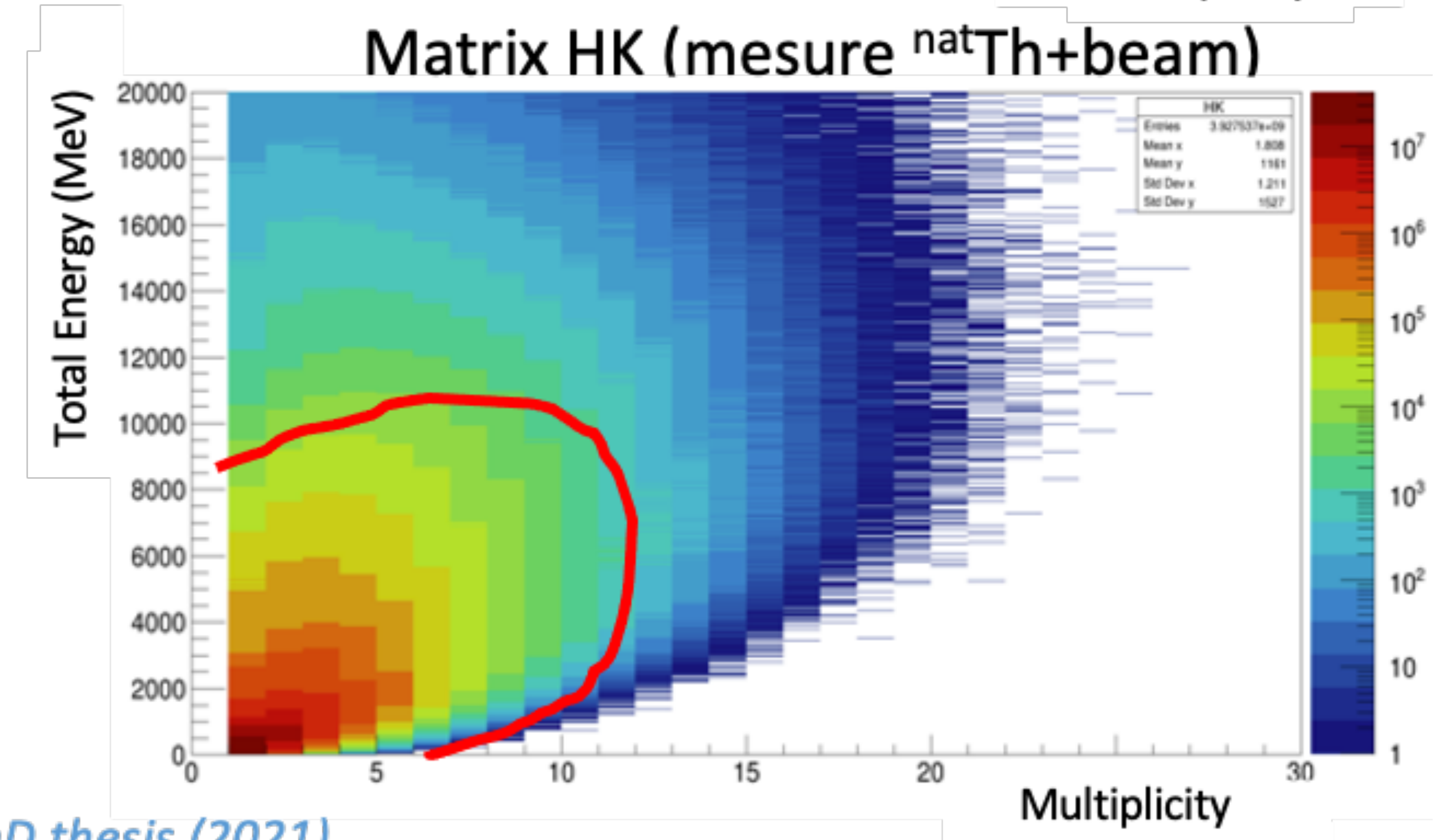

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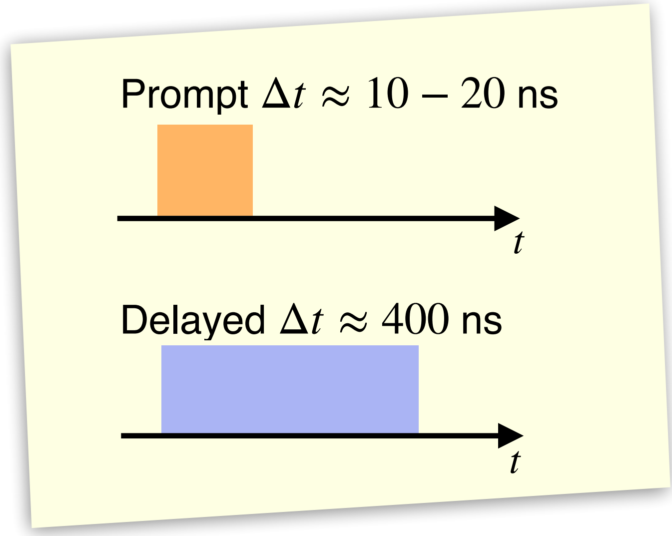
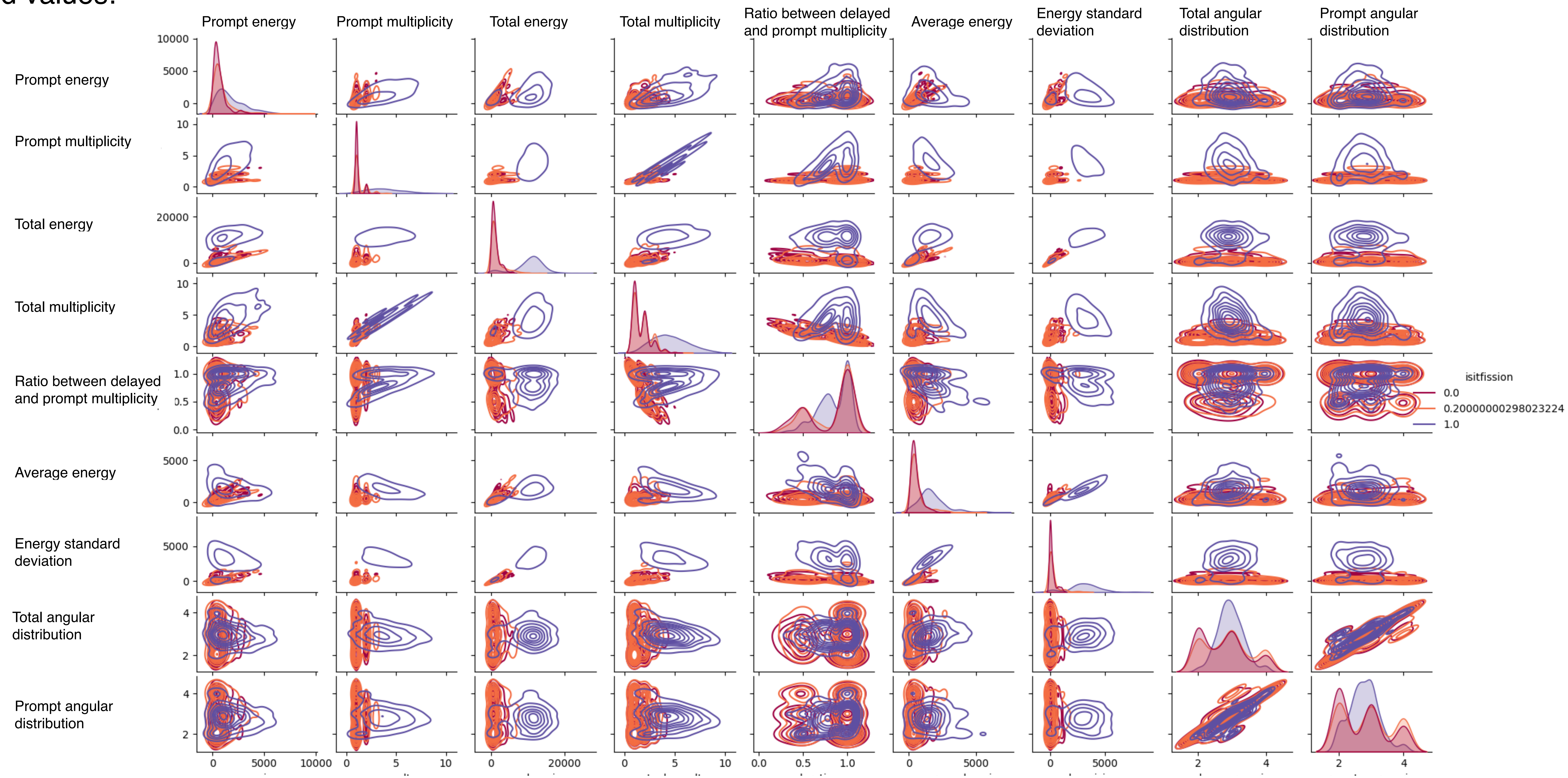
Fission event recognition

Measured values:





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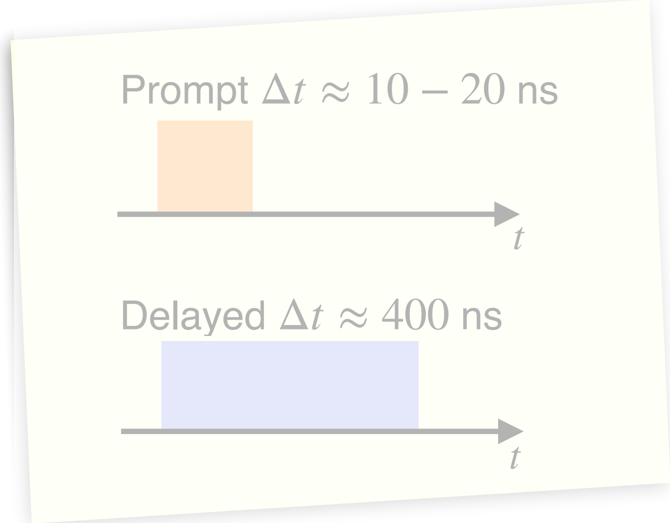
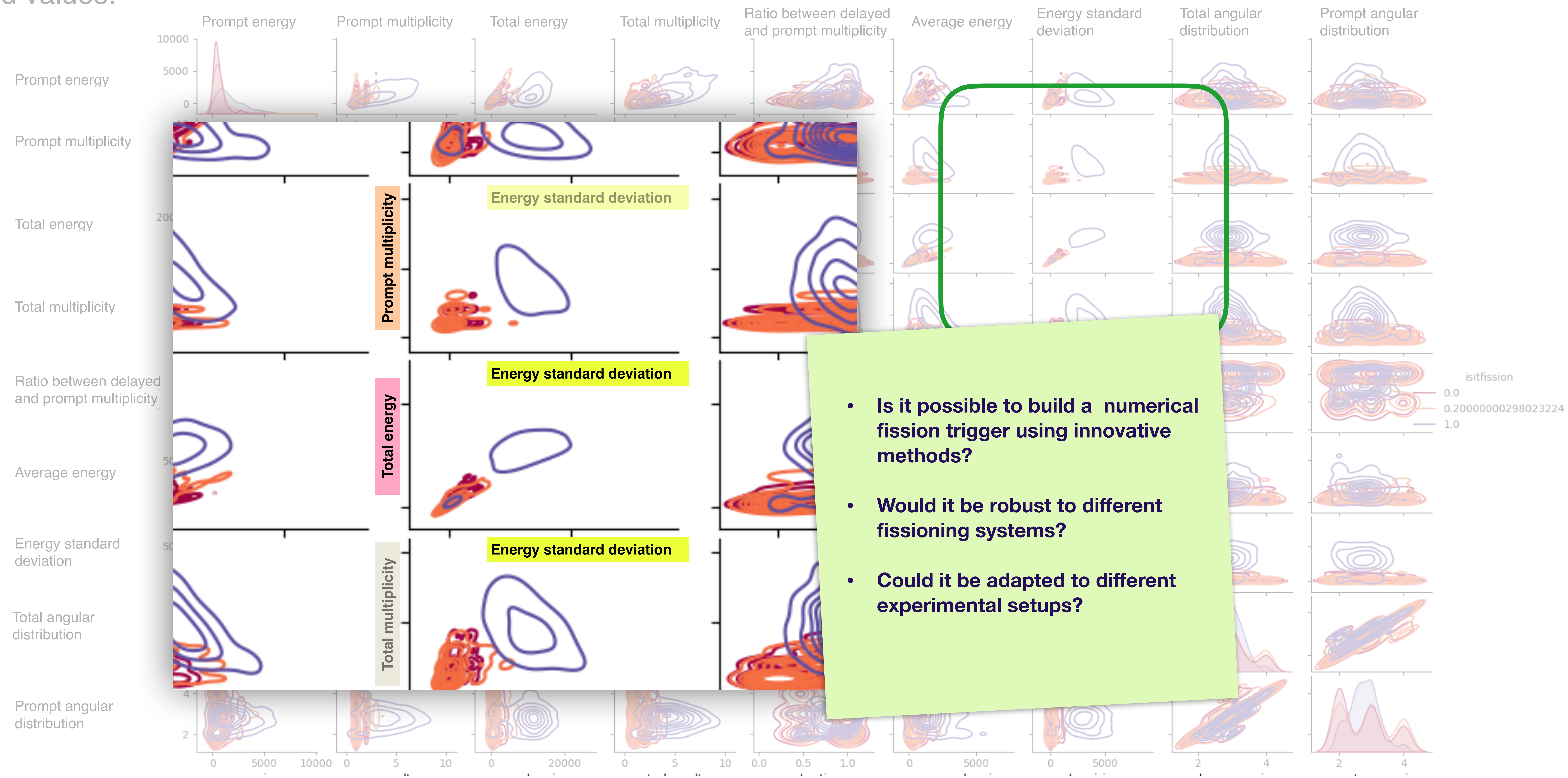




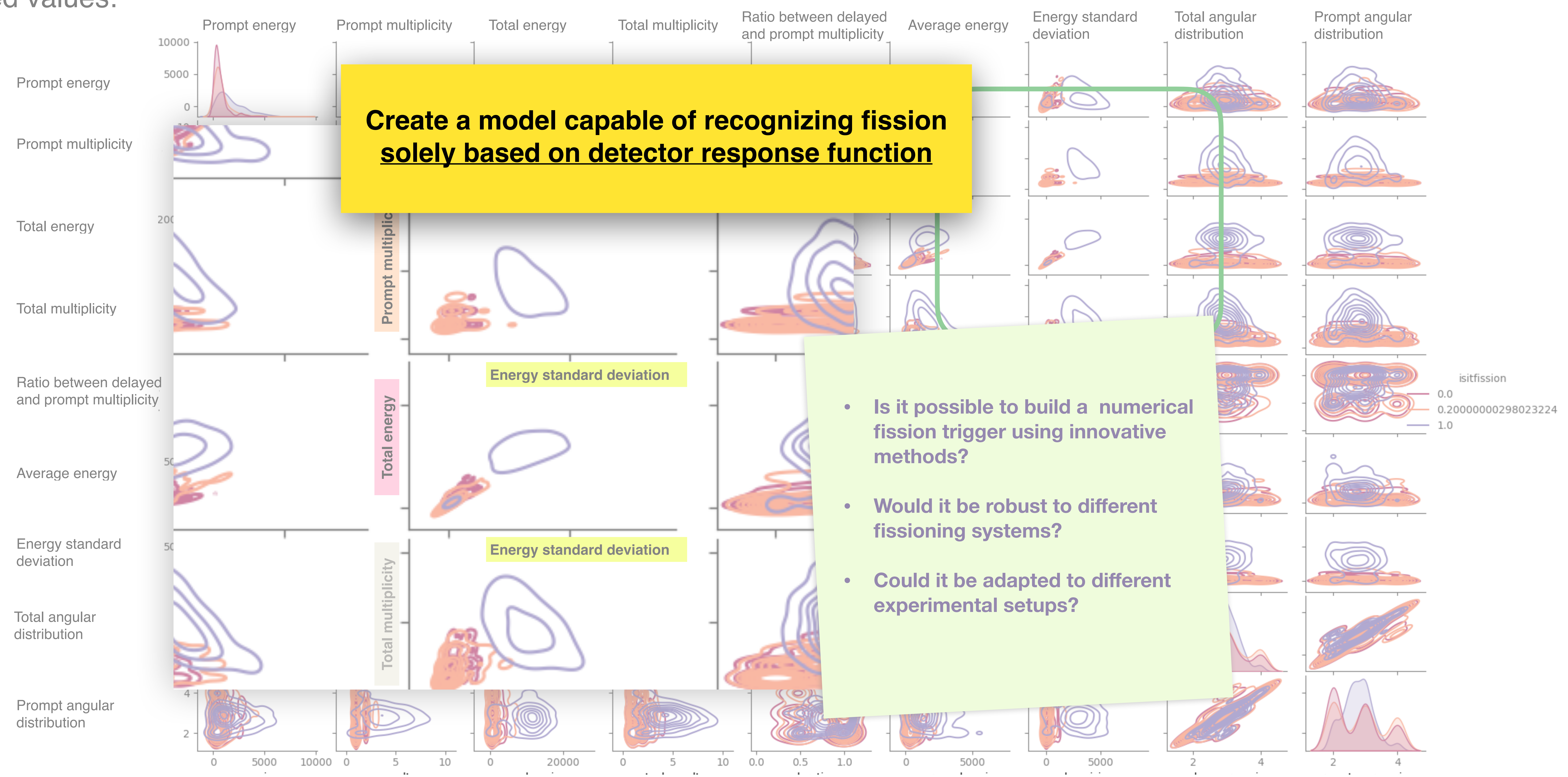
- **Is it possible to build a numerical fission trigger using innovative methods?**
- **Would it be robust to different fissioning systems?**
- **Could it be adapted to different experimental setups?**

Fission event recognition

Measured values:

Prompt $\Delta t \approx 10 - 20$ ns

Delayed $\Delta t \approx 400$ ns



Create a model capable of recognizing fission solely based on detector response function

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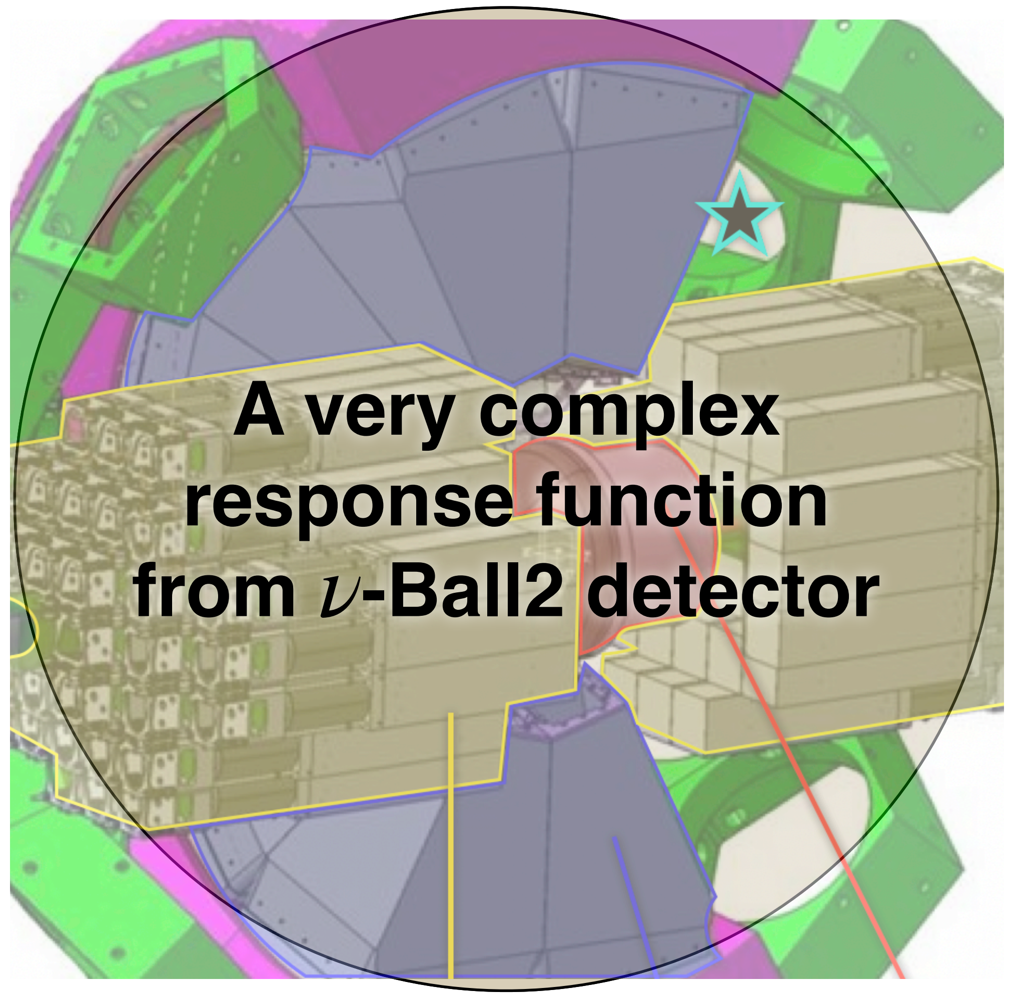
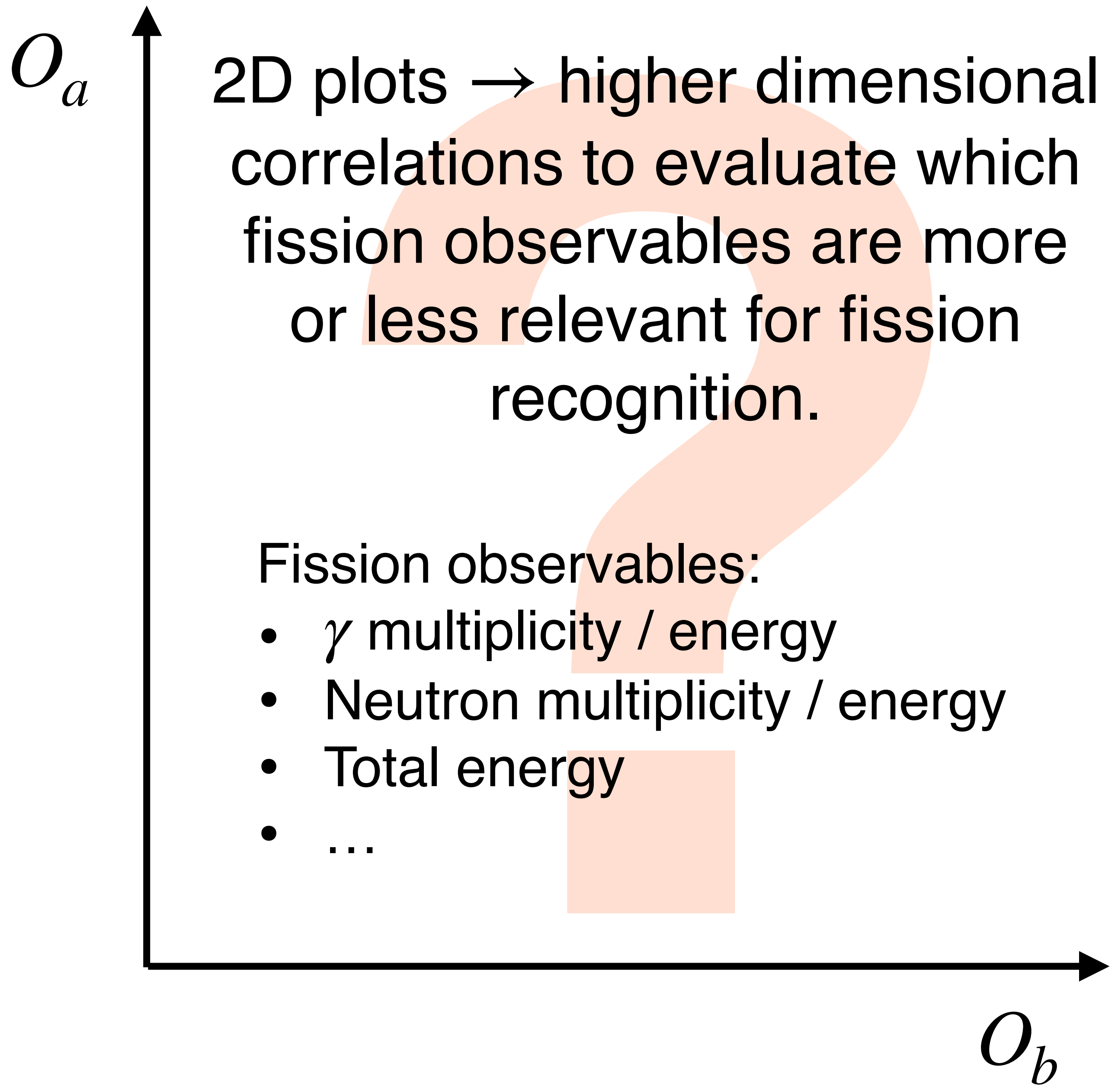
Fission trigger based on ν-Ball2 response function



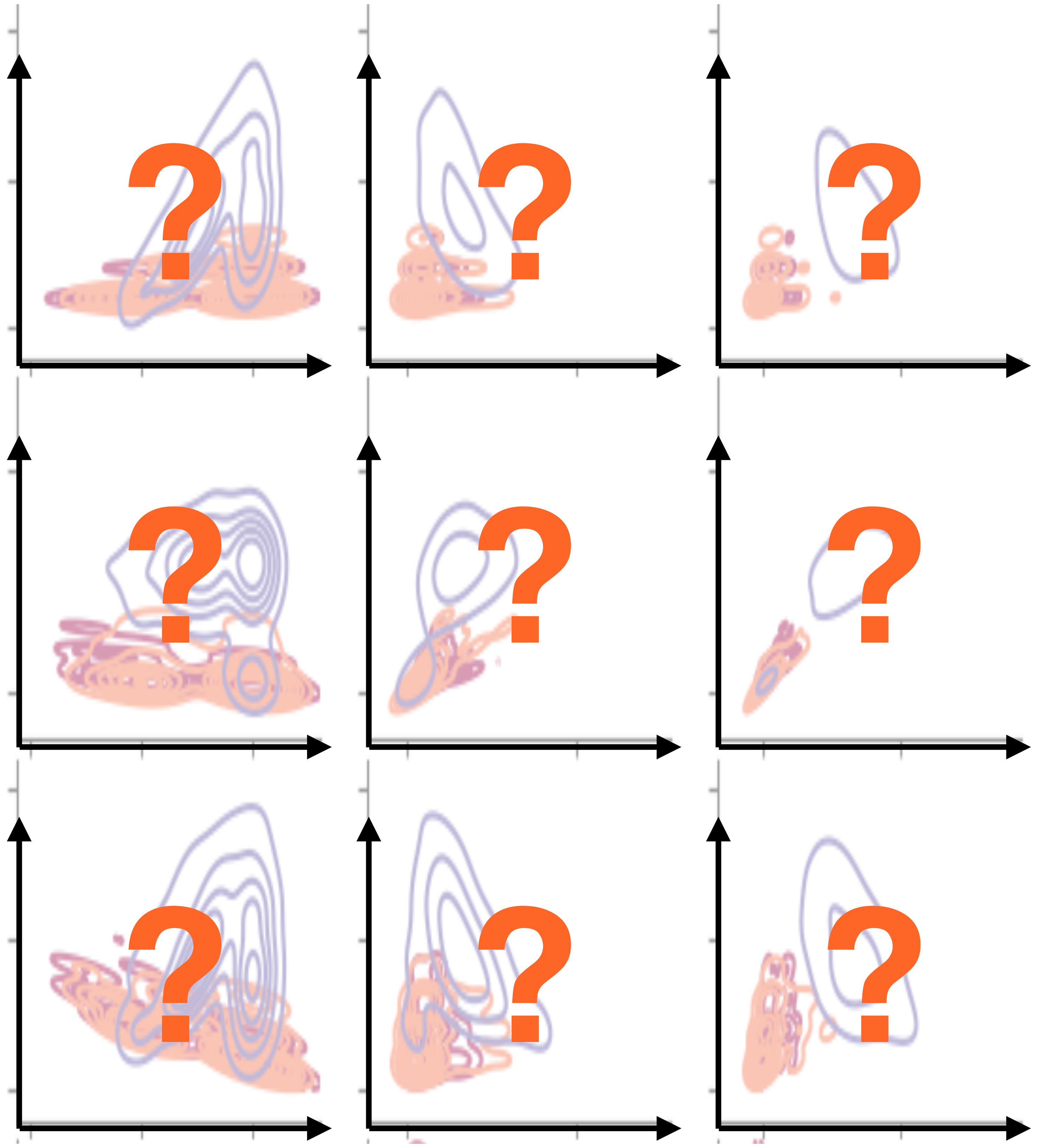
Fission tag

Create a model capable of recognizing fission <u>solely based on detector response function</u>



2D plots → higher dimensional correlations to evaluate which fission observables are more or less relevant for fission recognition.

Fission observables:
- γ multiplicity / energy
- Neutron multiplicity / energy
- Total energy
- …



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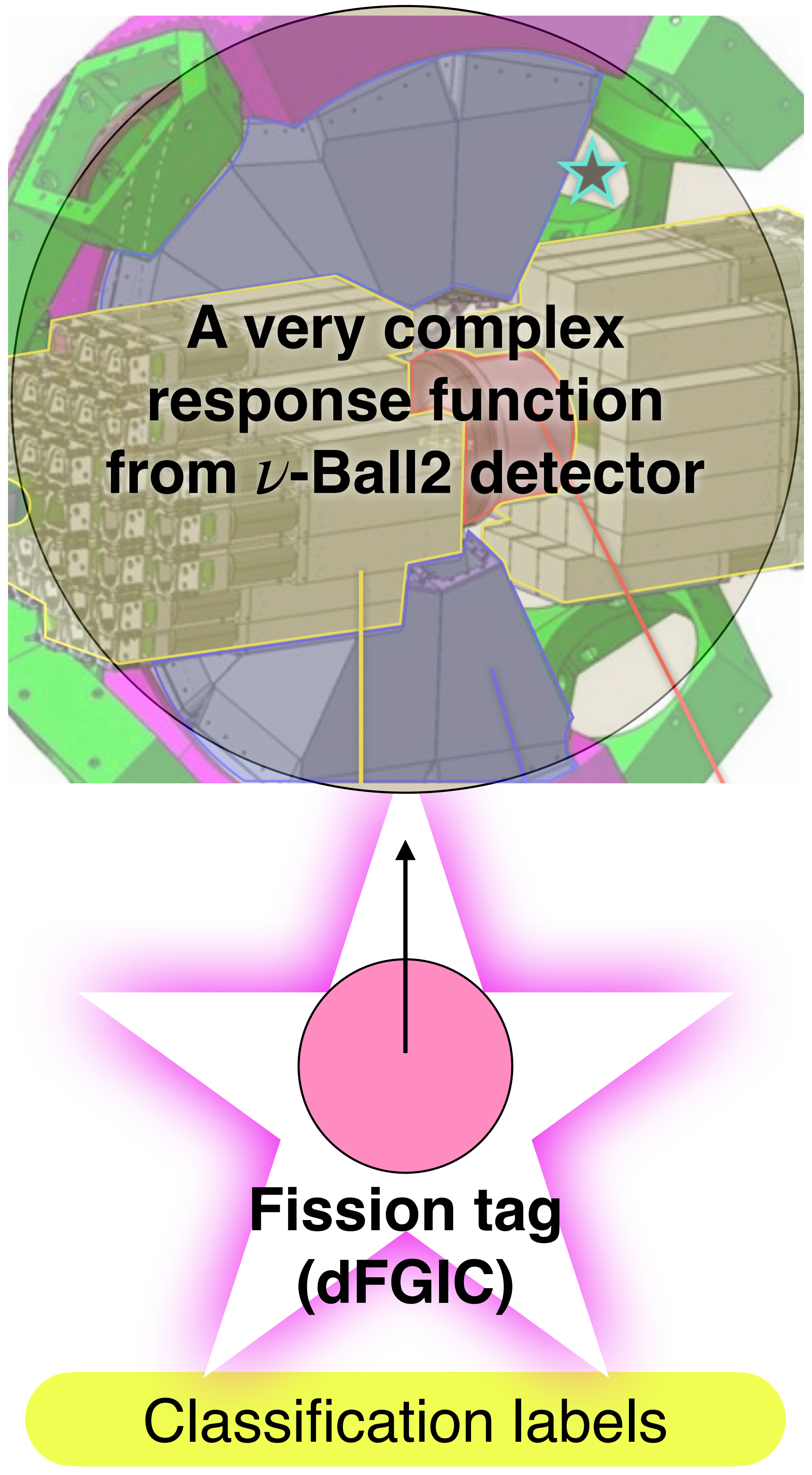

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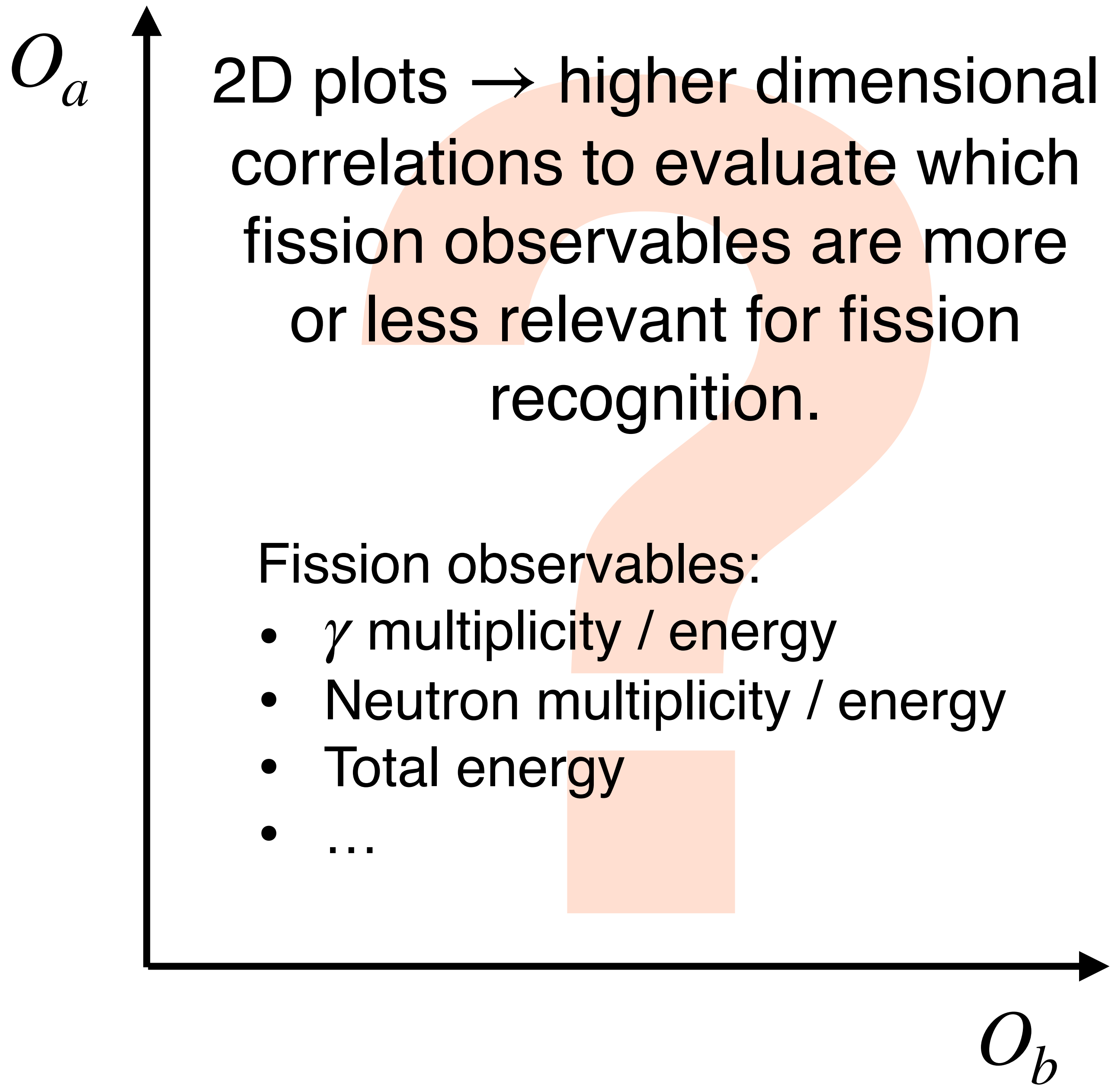

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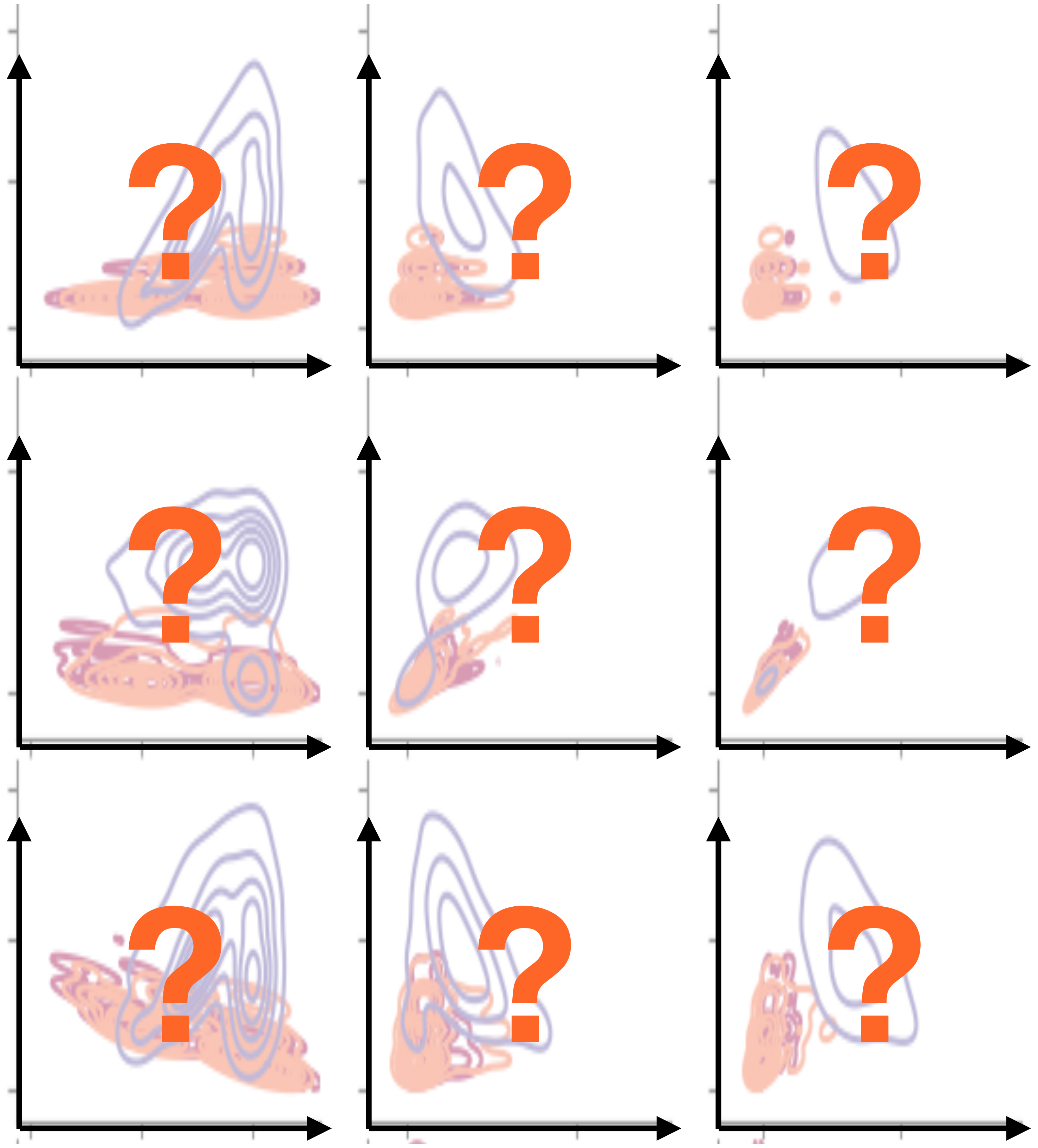

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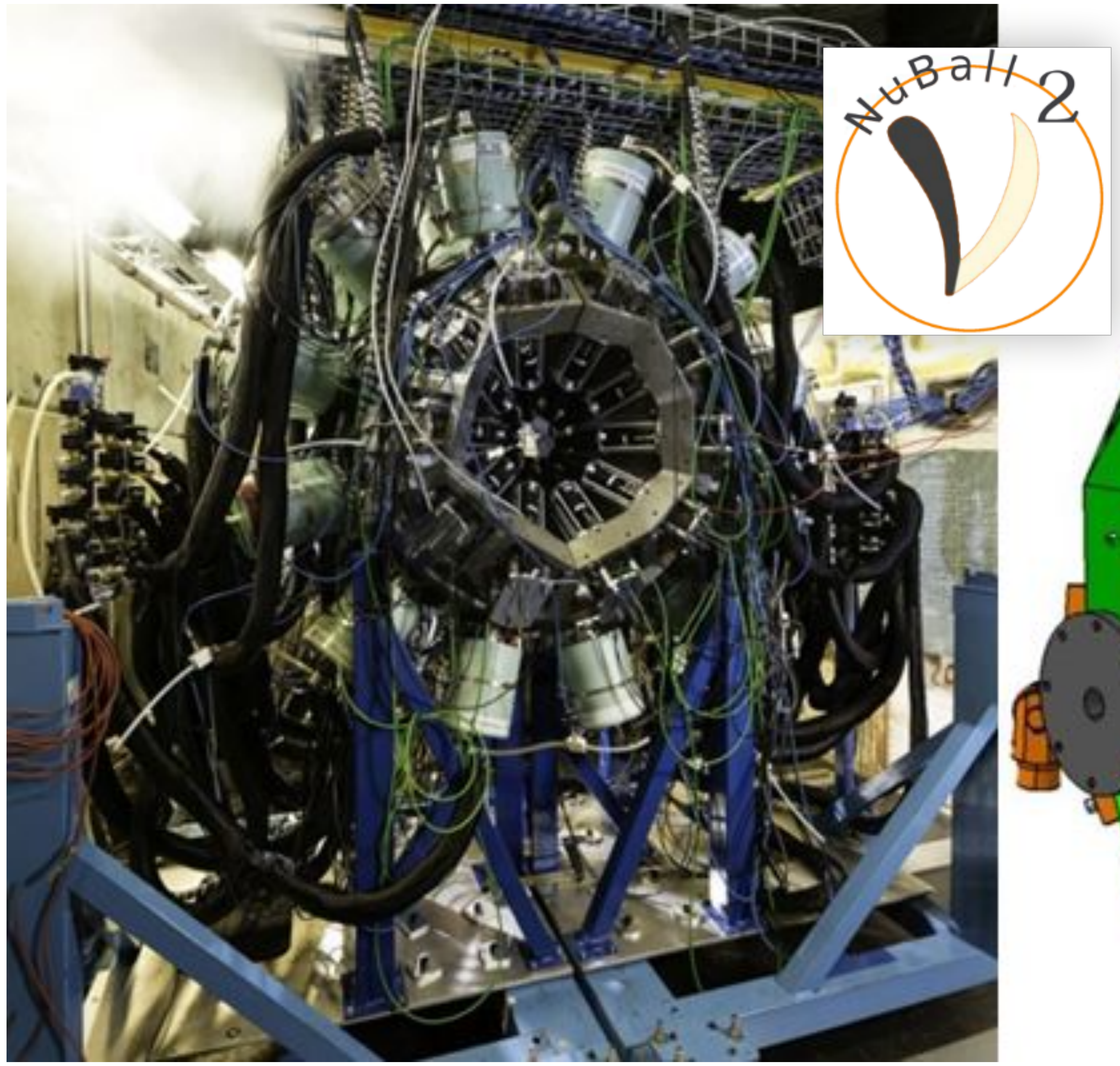
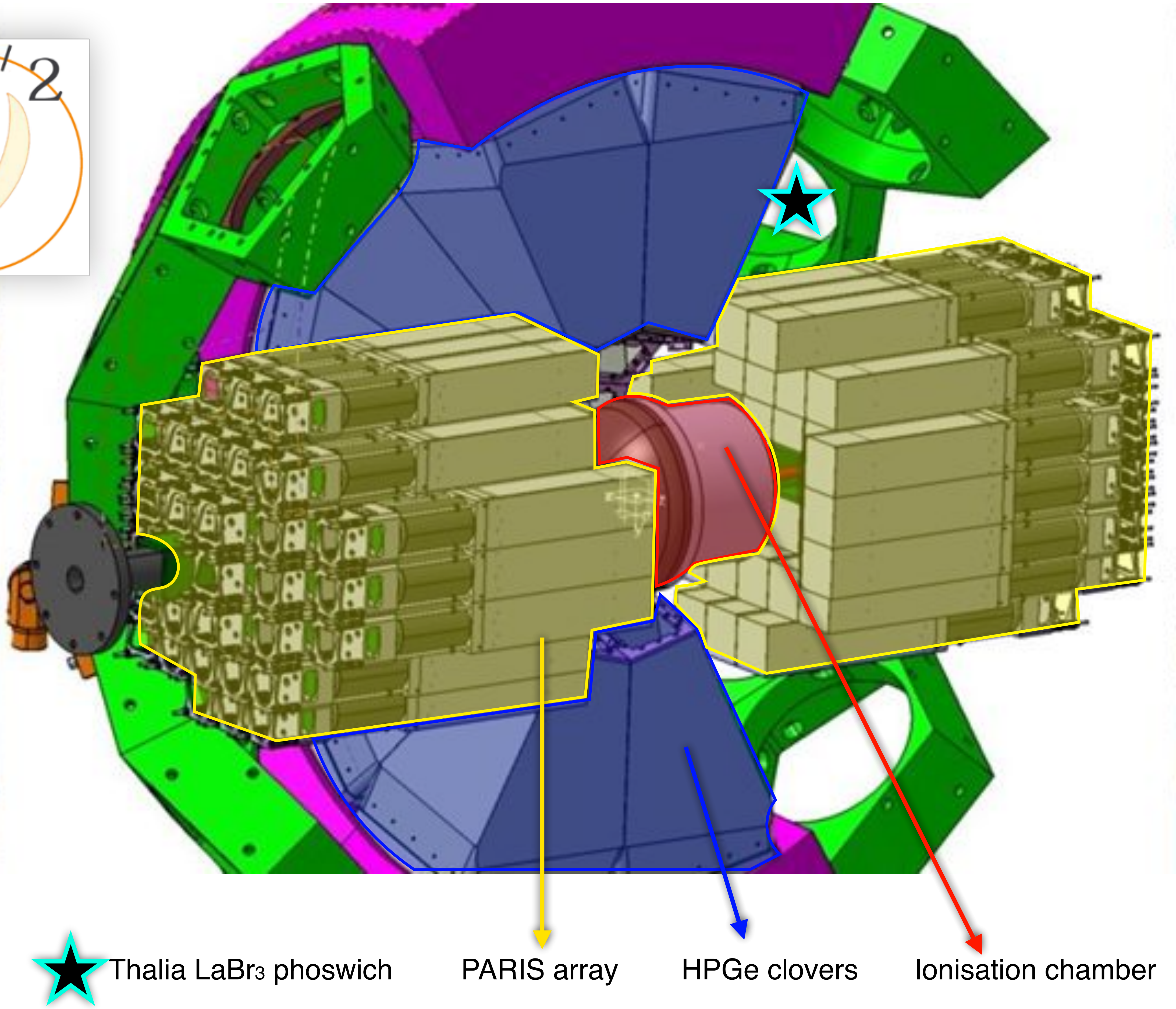
The N-SI-125 experiment setup



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
70 phoswhiches La(Ce)Br_3:NaI

Thalia LaBr3

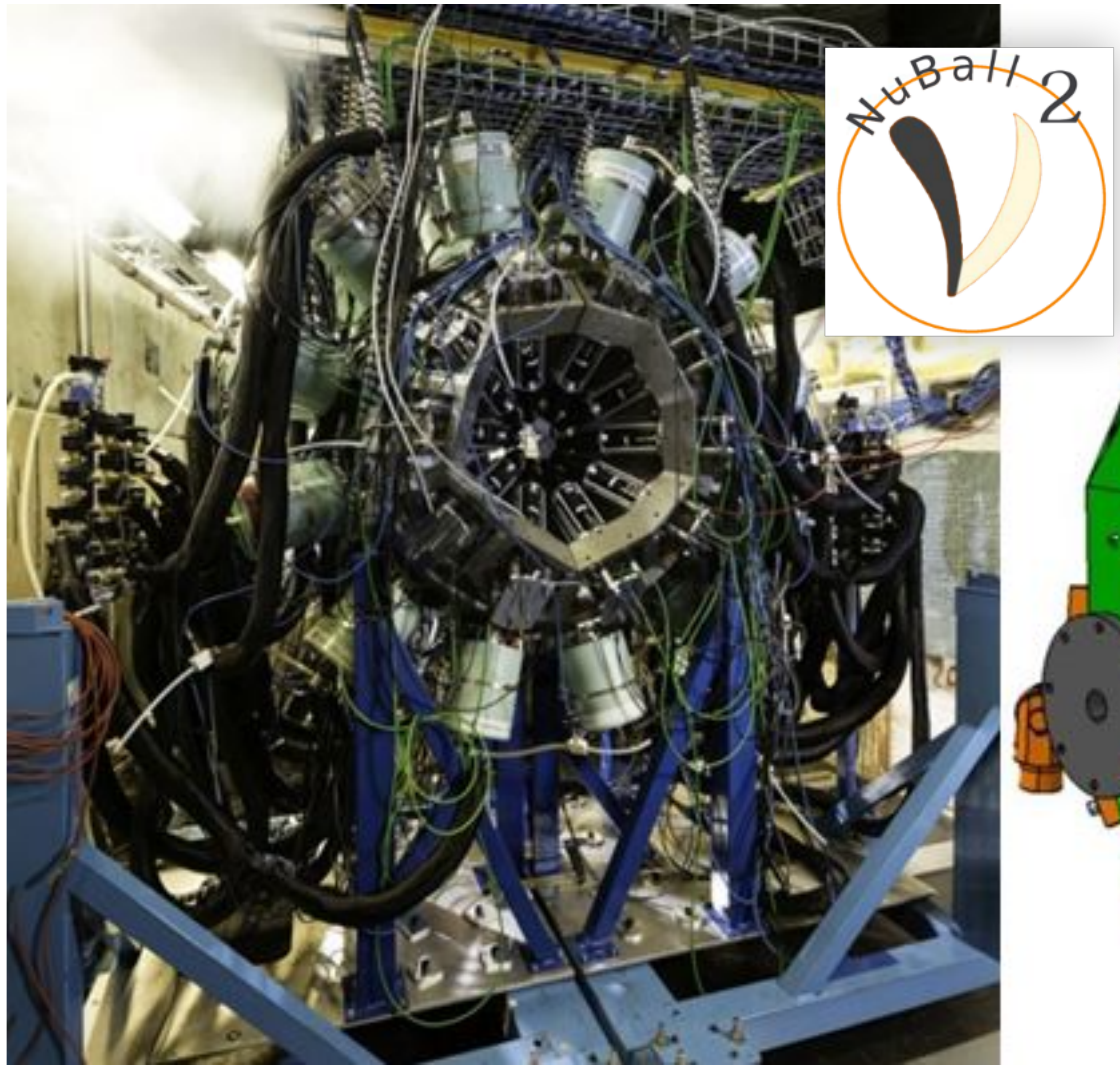
Neutron detection
energy and multiplicity

PARIS array
Thalia LaBr3
Exploratory

Fission fragments detection

Ionisation chamber

The N-SI-125 experiment setup



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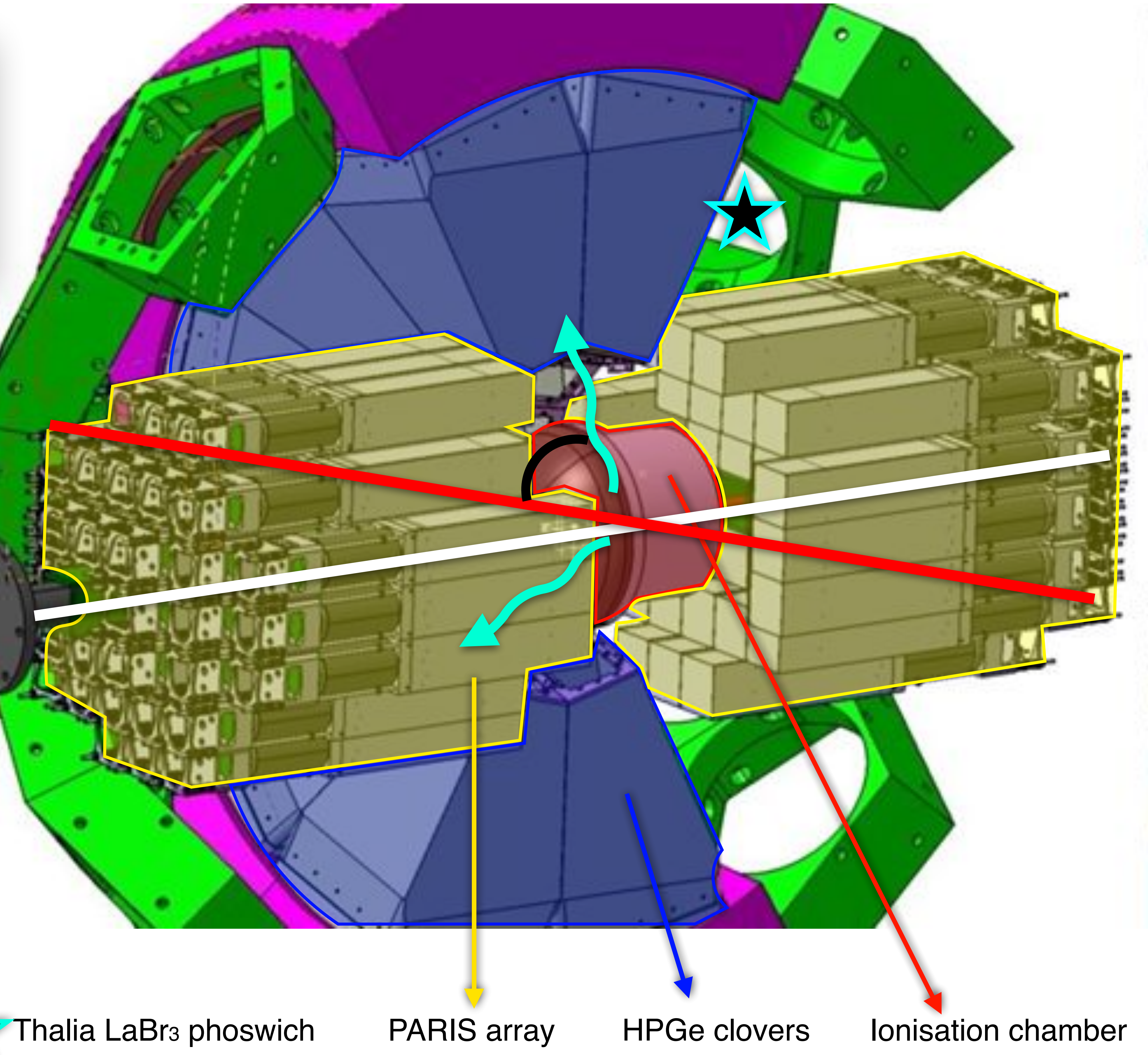

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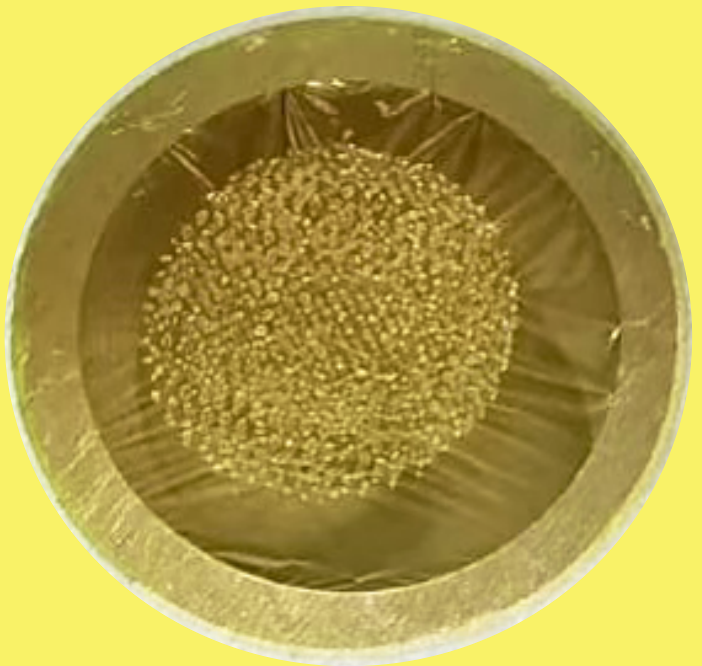
Taken from: https://alt

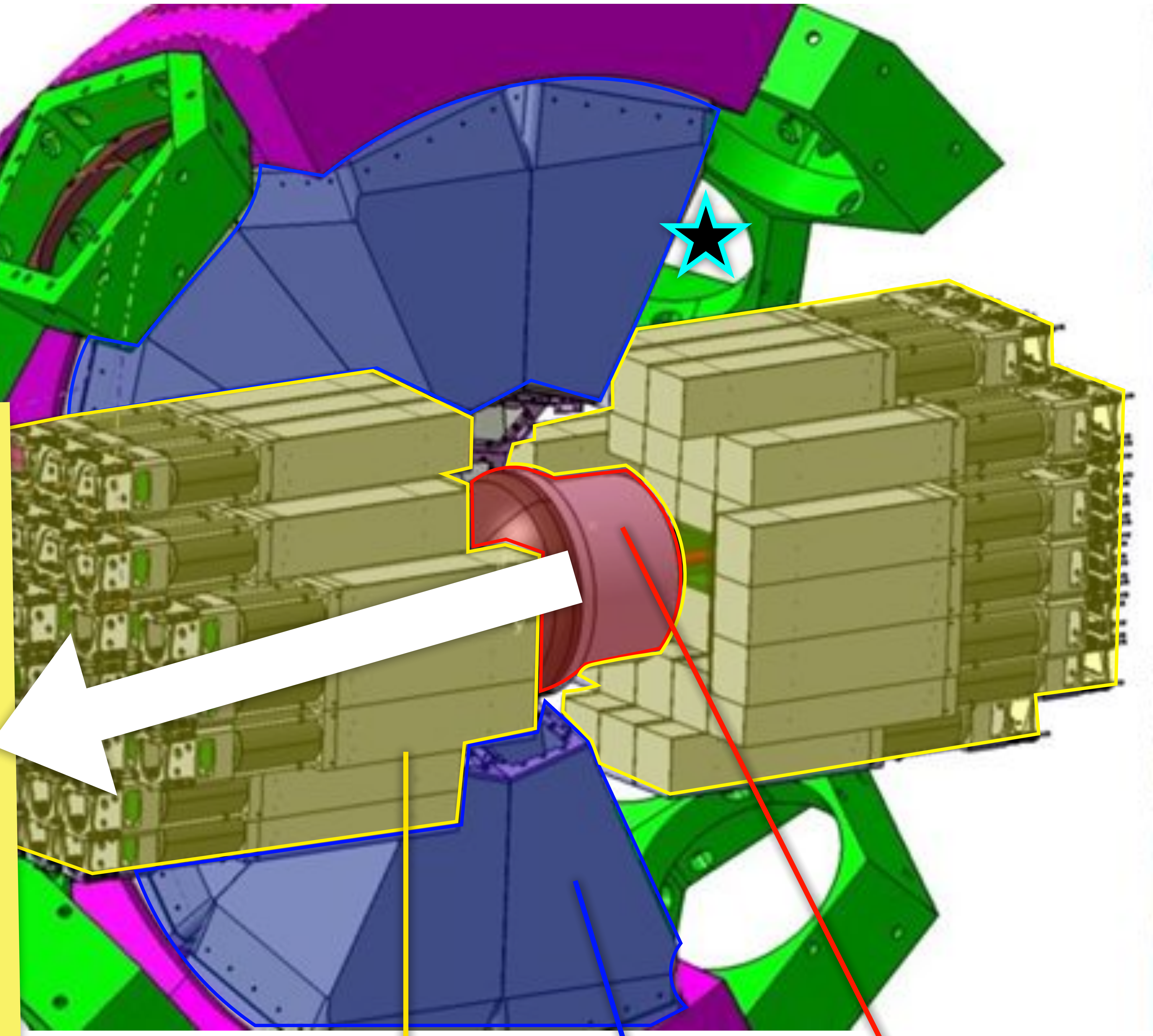


^{252}Cf source

$96.9\,\%$ α decay
$3.1\,\%$ fission

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

- Al ring $\varnothing_{out} = 40$ mm , $\varnothing_{in} = 30$ mm
- PI foil $36\,\mu g/cm^2$ + Au $52\,\mu g/cm^2$



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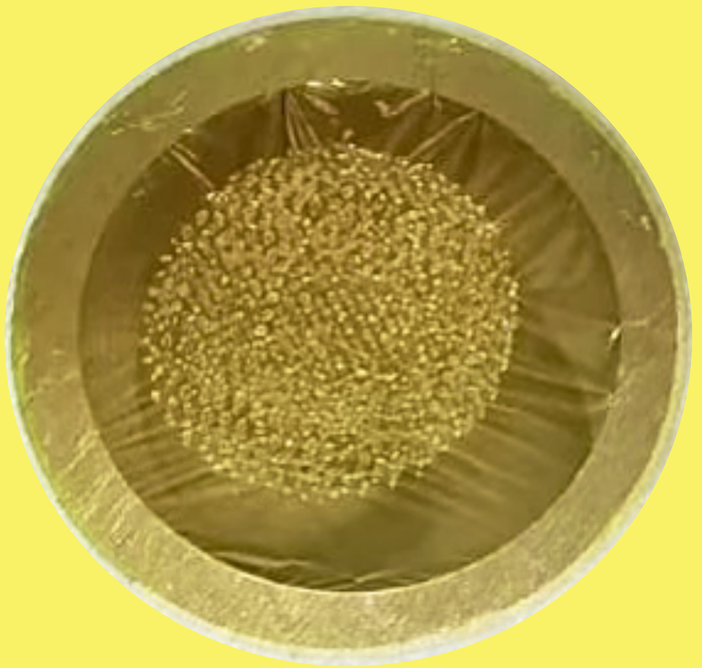

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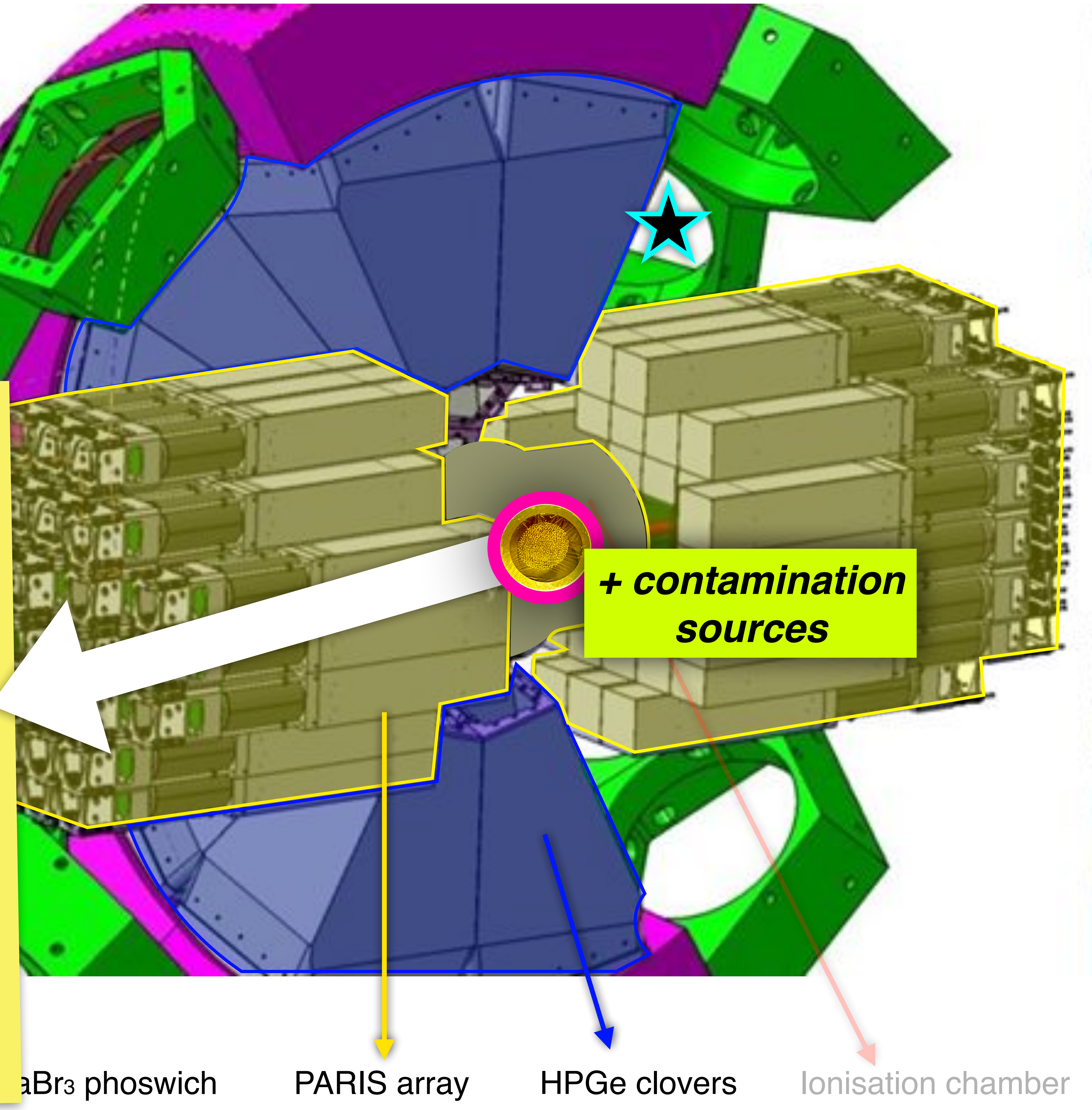

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Neutron detection
energy and multiplicity

PARIS array

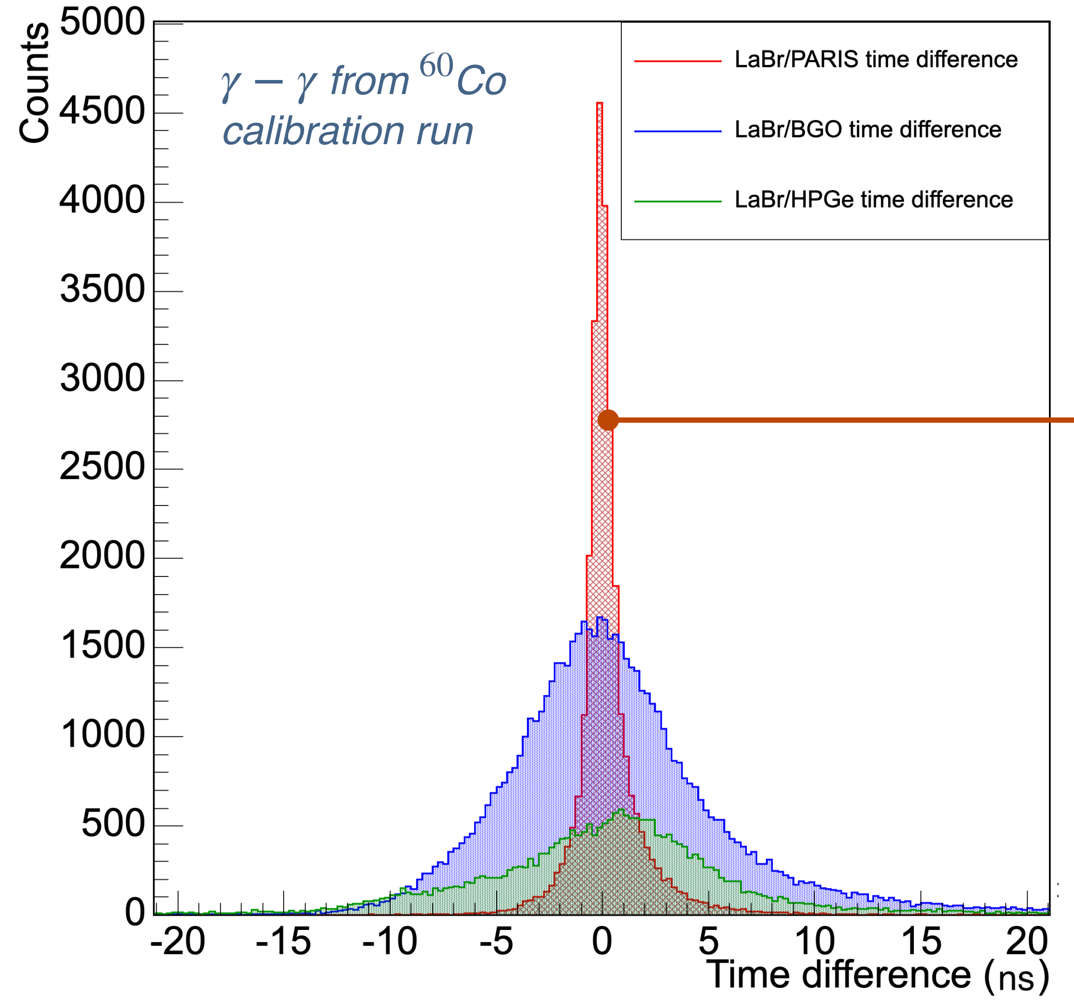
Thalia LaBr3

Exploratory

Fission fragments detection

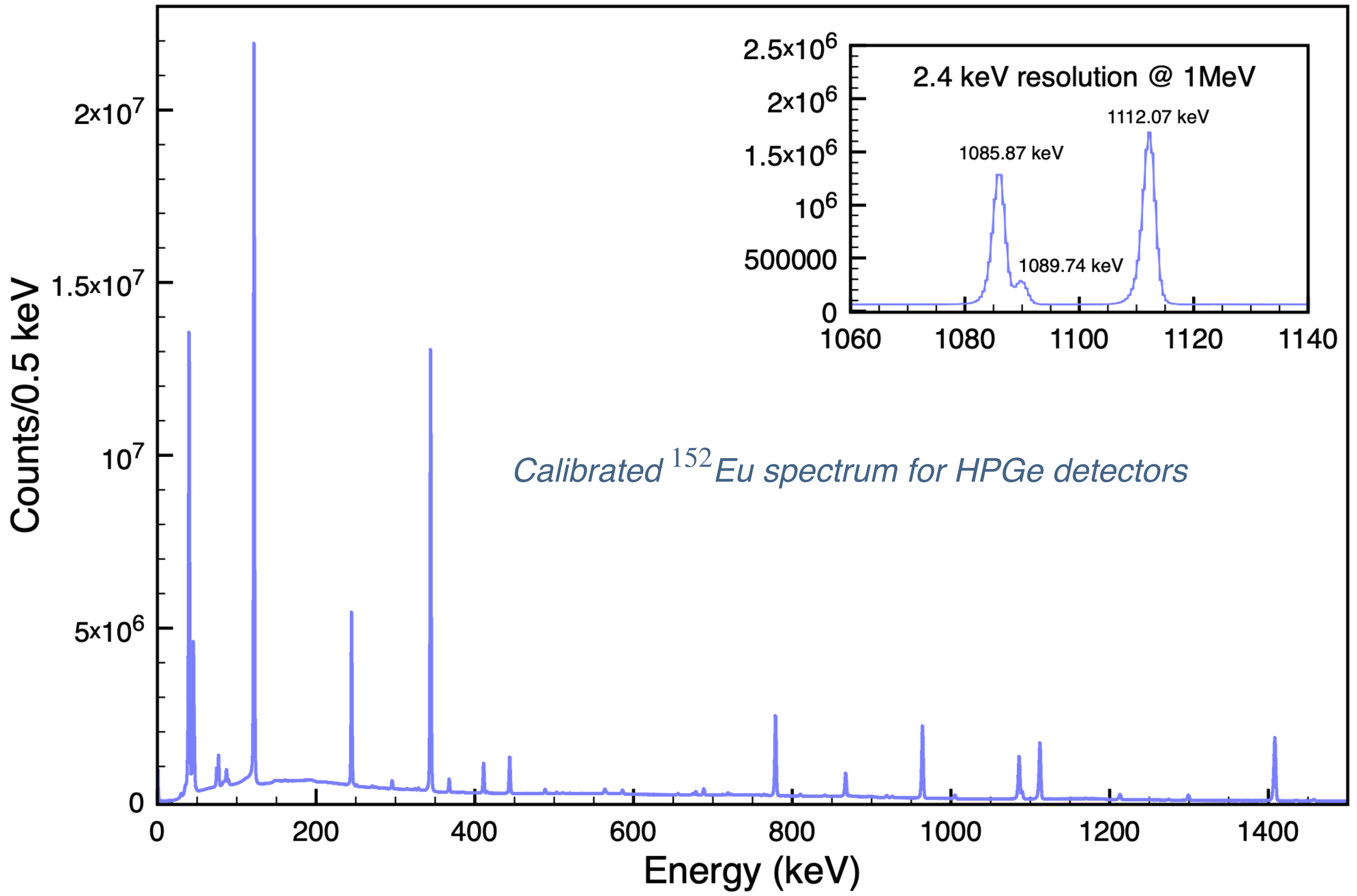
Ionisation chamber

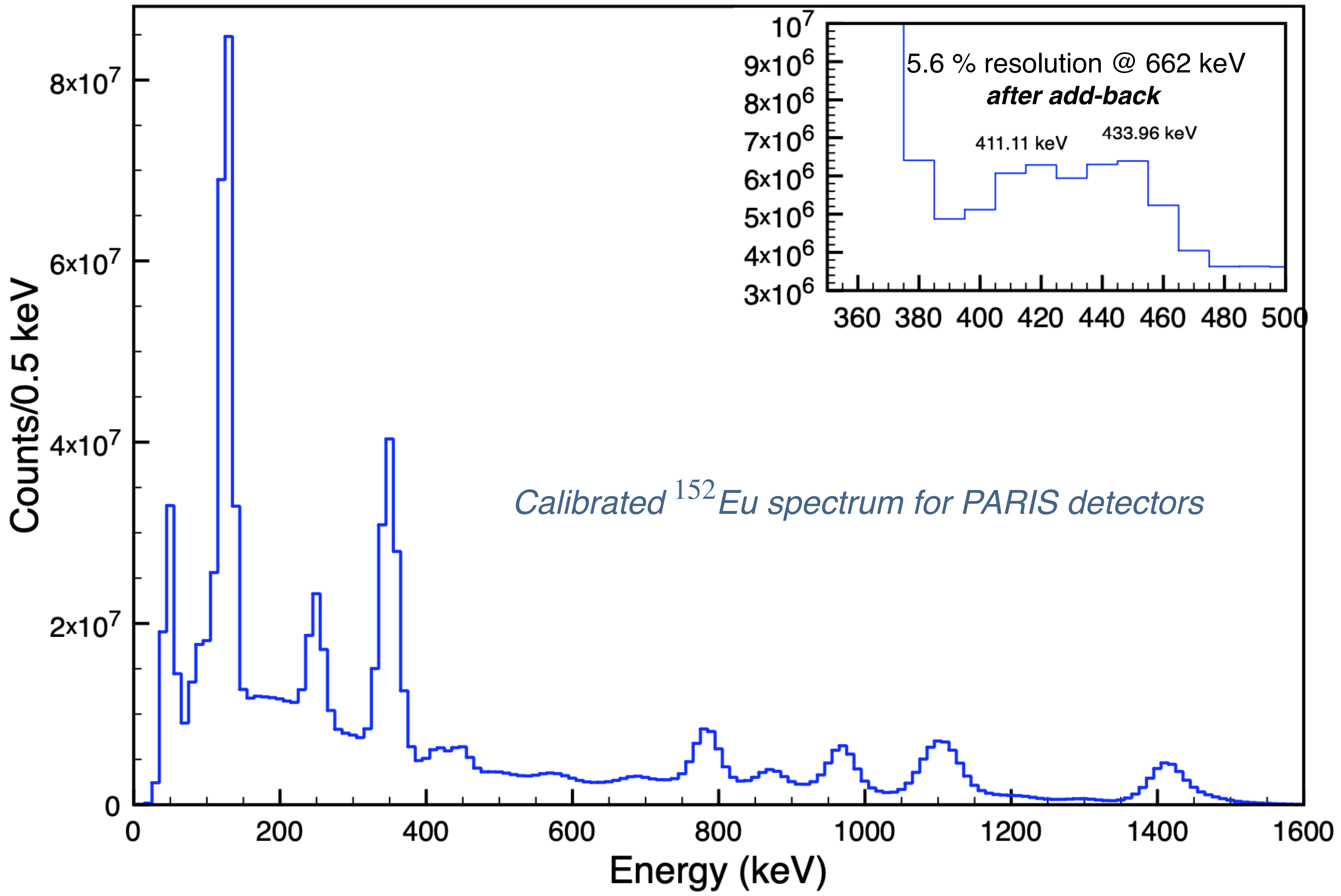
Time alignment and Energy calibration of ν-Ball2



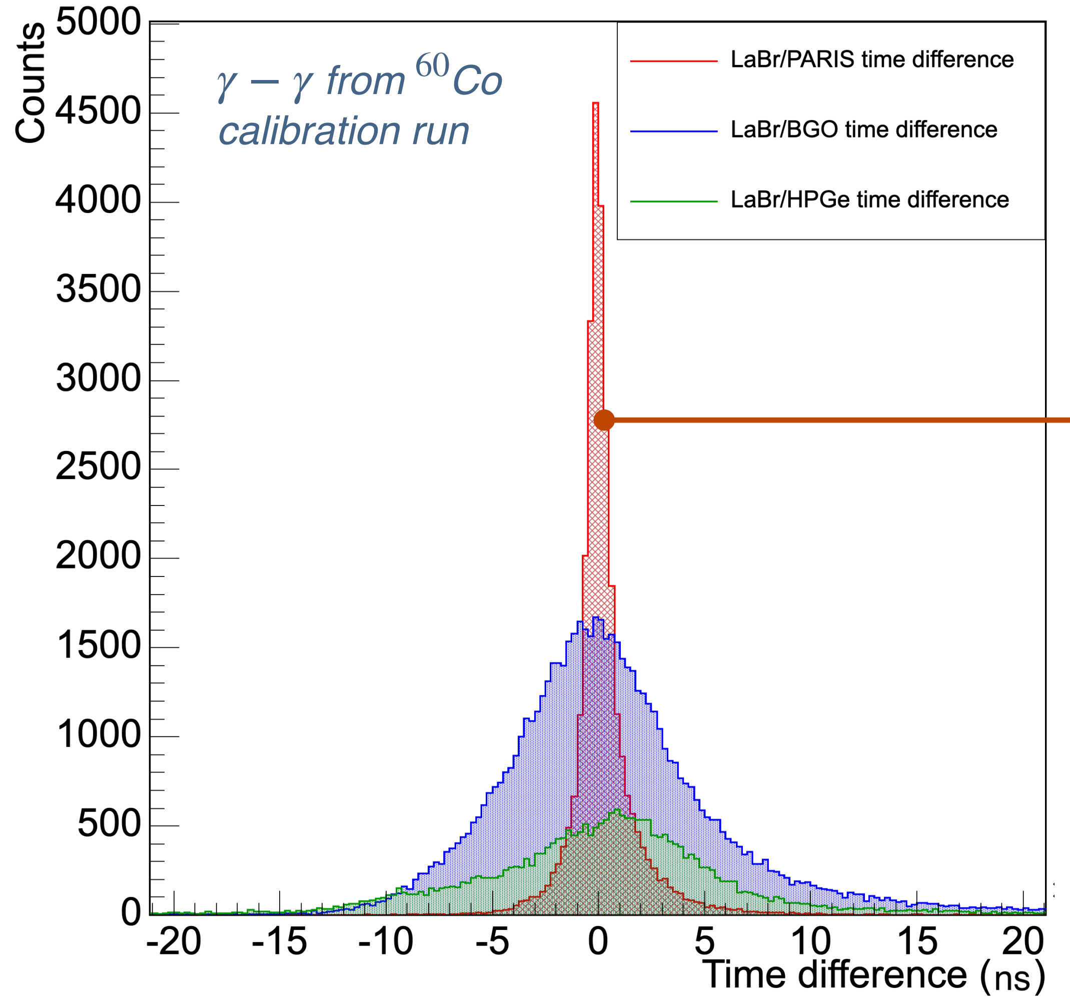
Time resolution PARIS 1.2 ns
($LaBr_3$:NaI and $CeBr_3$:NaI)

Align ν-Ball2 detectors in time using pure $LaBr_3$ as a reference.





Time alignment and Energy calibration of ν-Ball2



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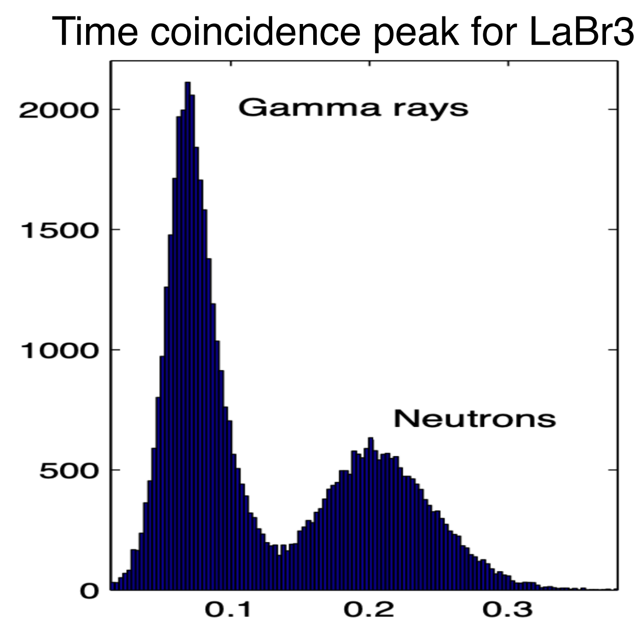
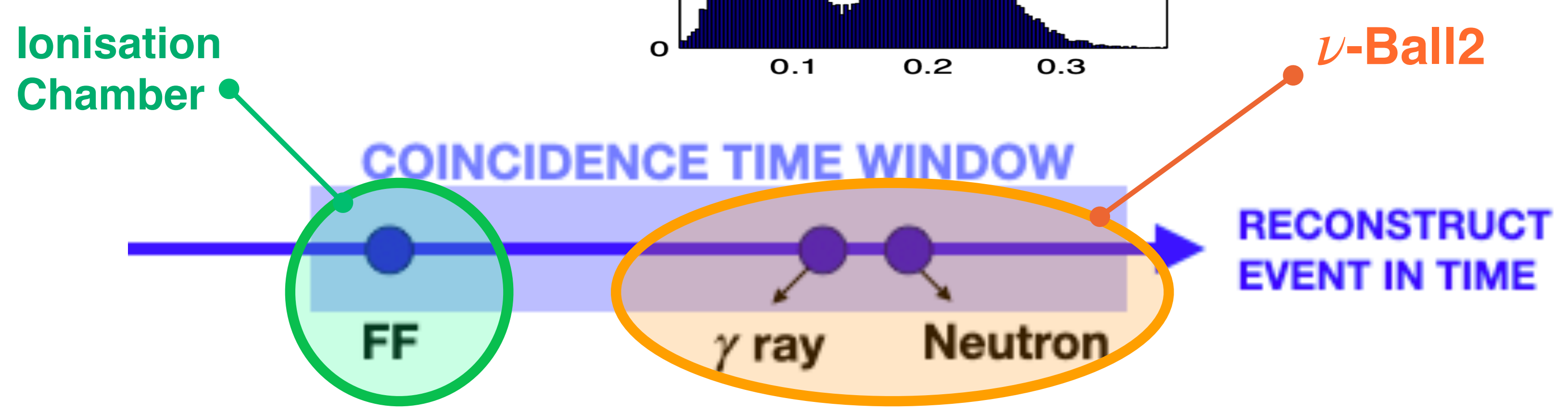
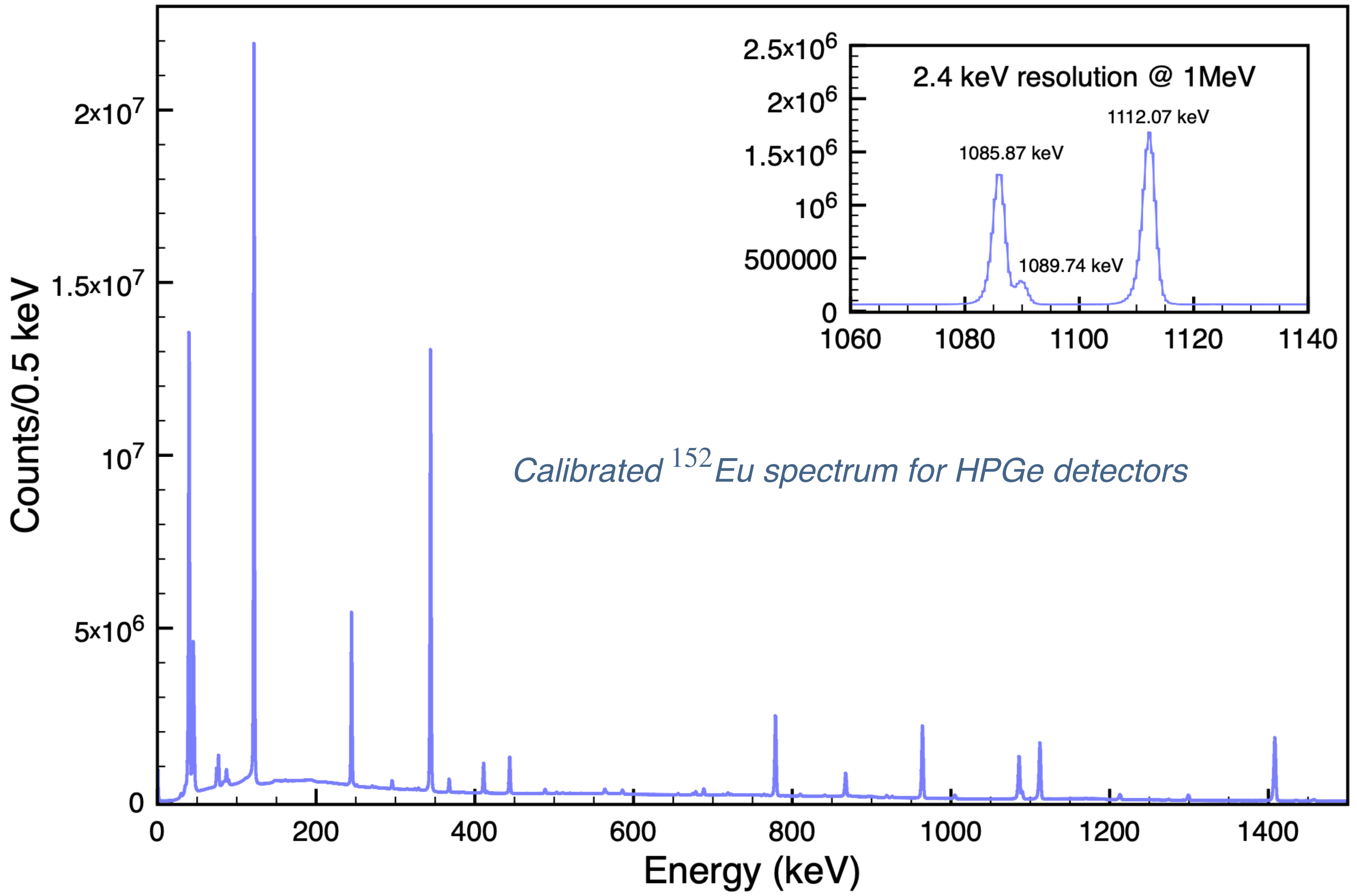
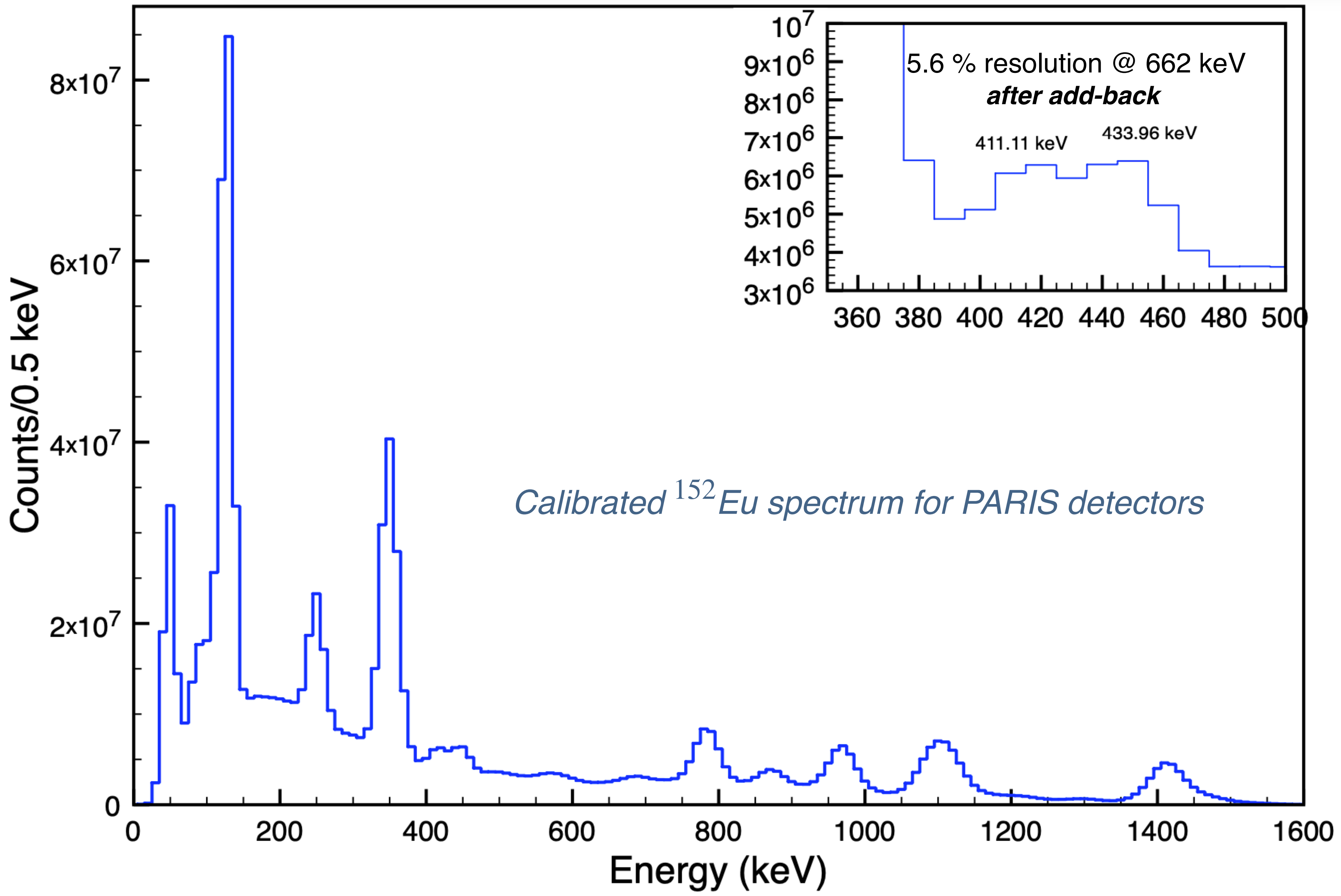


Expect a clear n/γ separation due to TOF







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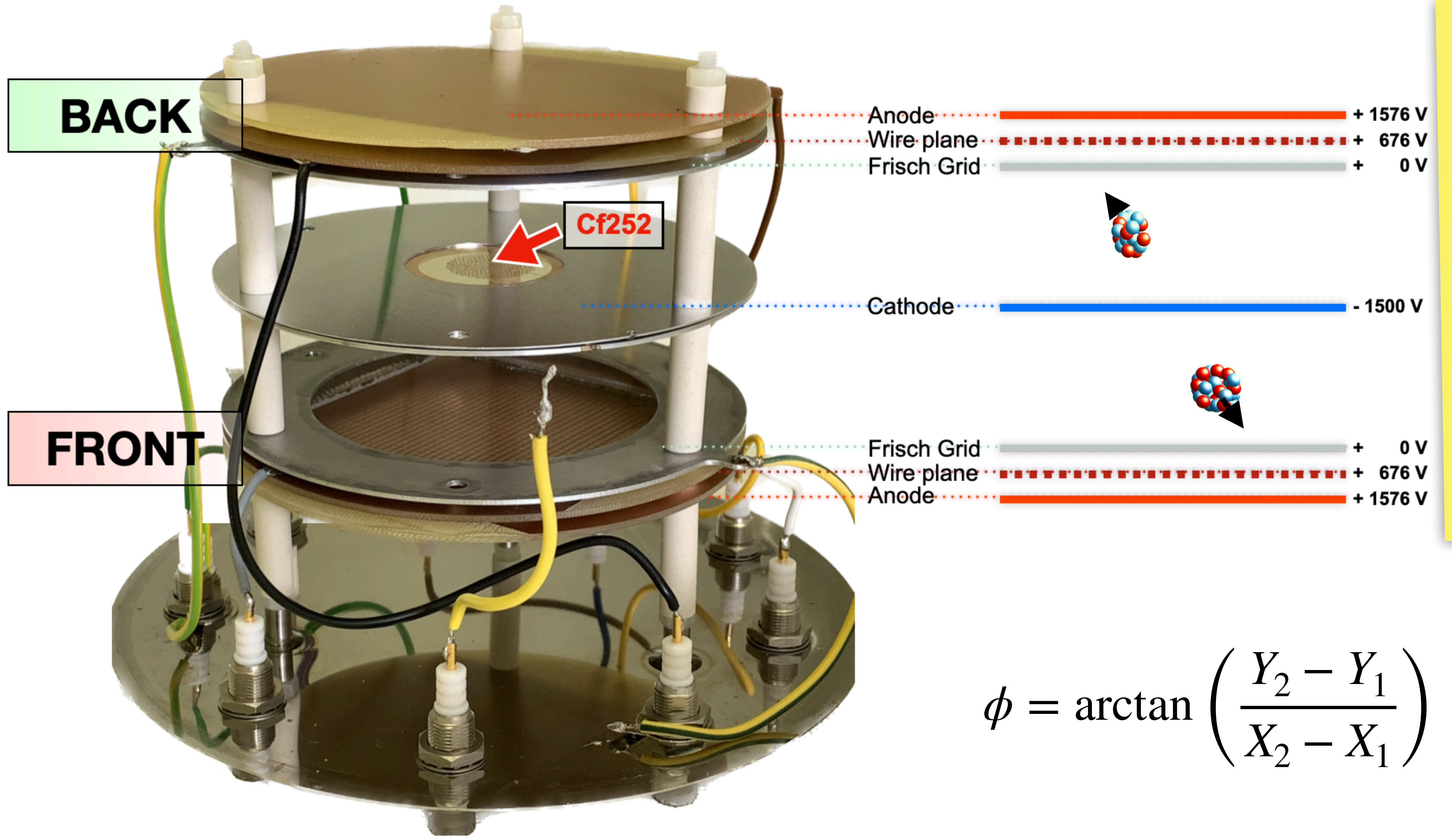
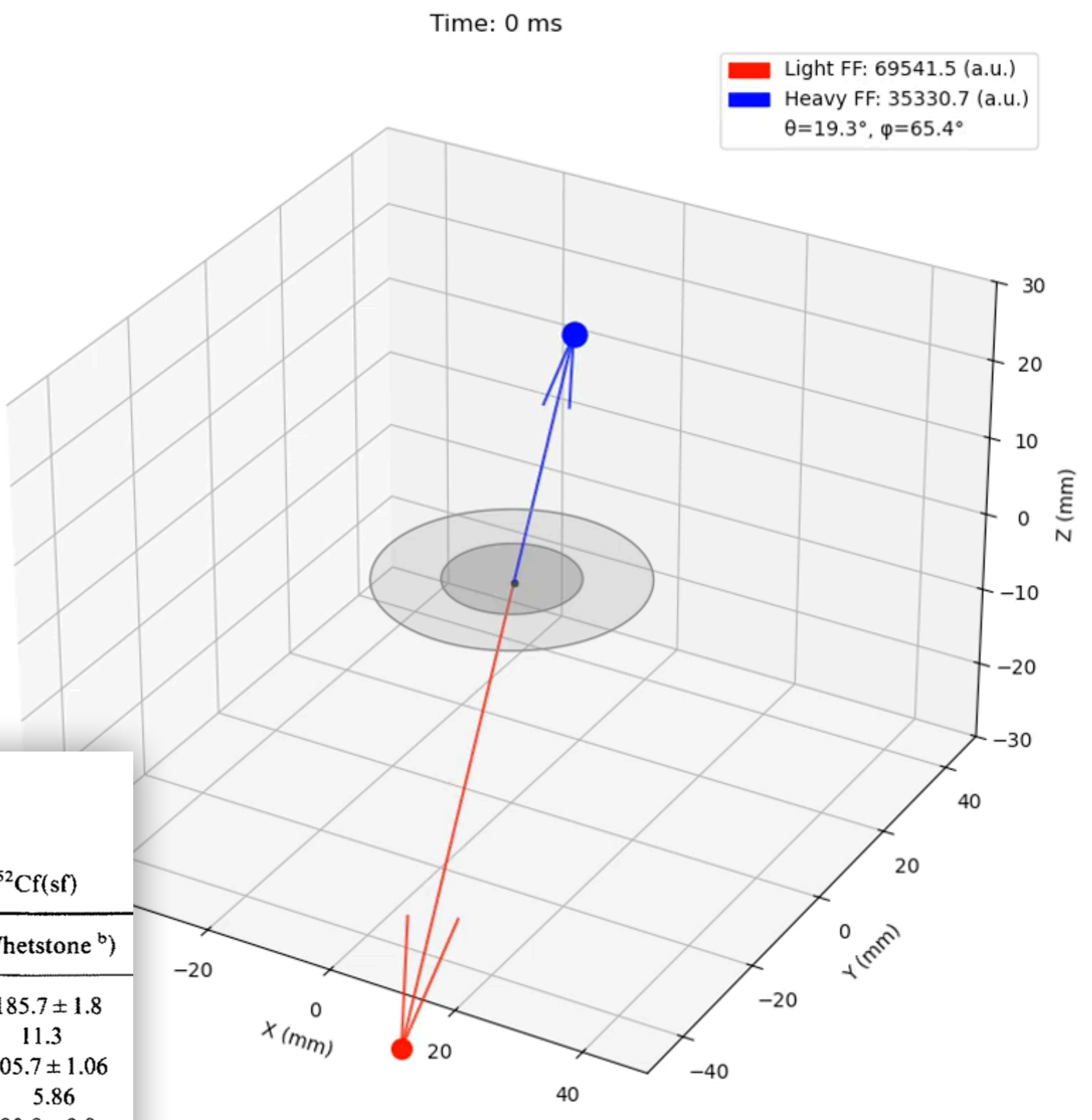
Event reconstruction (dFGIC)

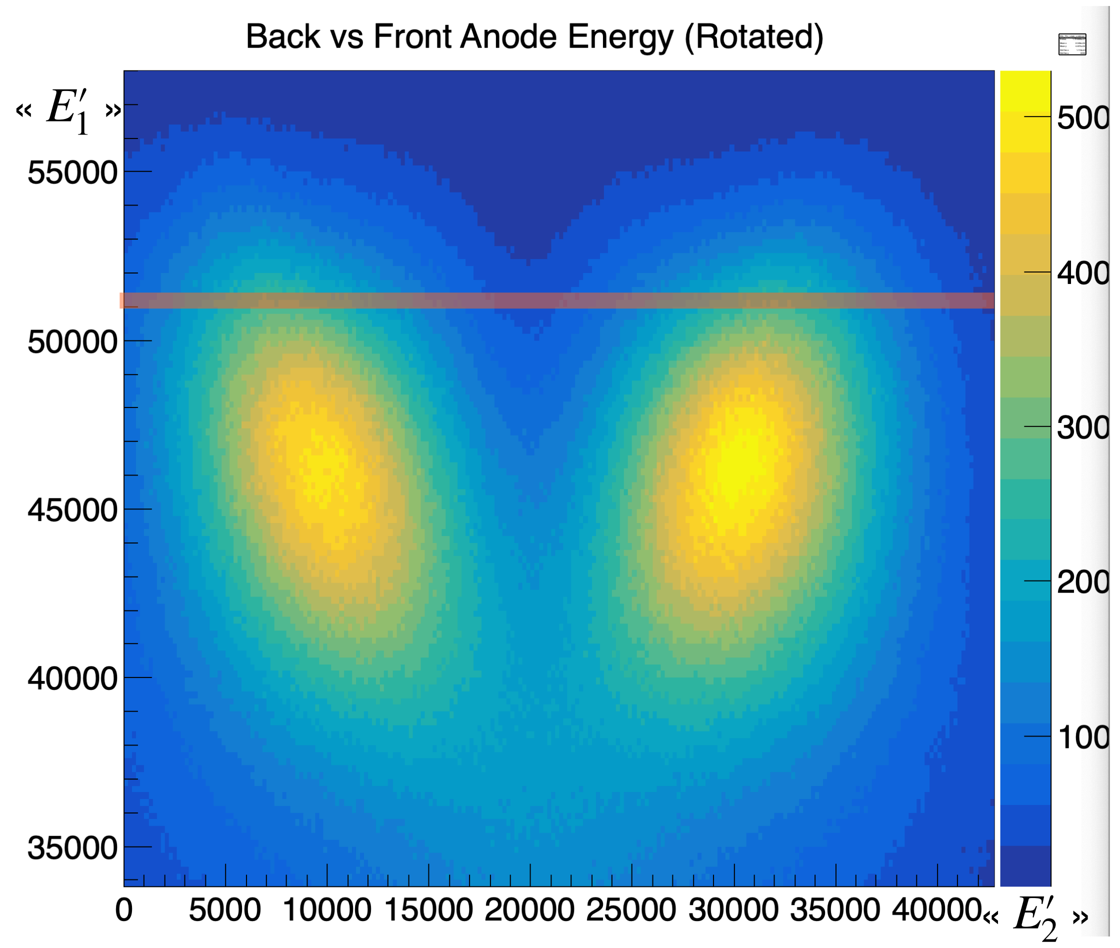


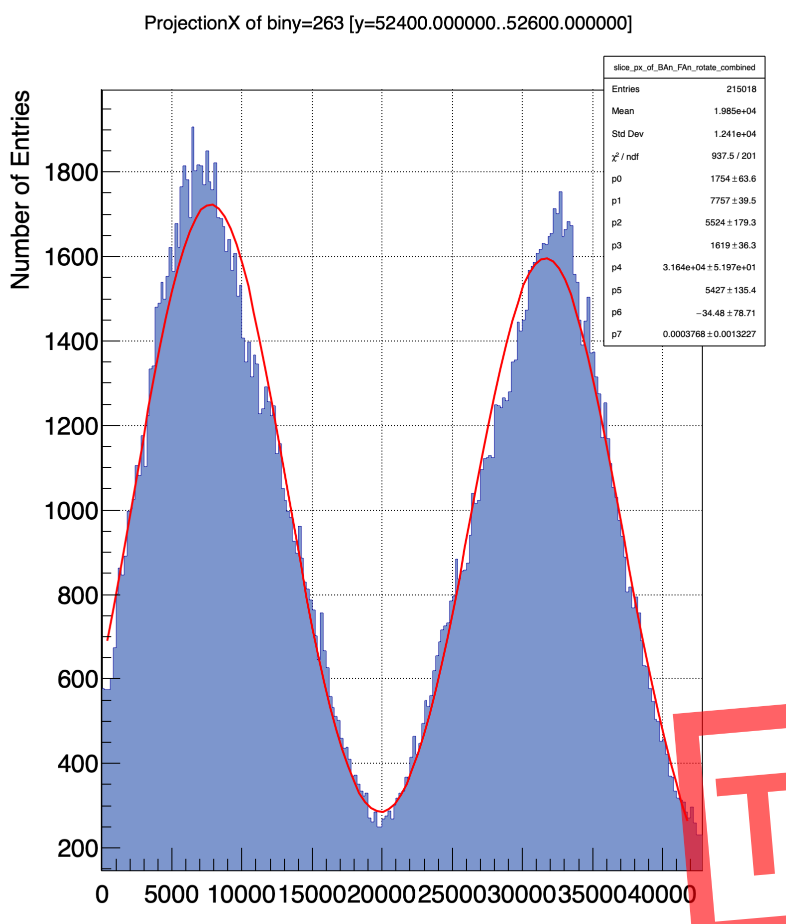
Fission event reconstruction:

Event i : $\left\{ \begin{array}{l} \textit{timestamp}; \\ \text{« } E_1 \text{ », « } E_2 \text{ »} \\ \theta_1,\ \theta_2,\ \phi \\ R_1,\ R_2 \end{array} \right.$

$$\phi = \arctan\left(\frac{Y_2 - Y_1}{X_2 - X_1}\right) \qquad \cos\theta_{1,2} = \frac{\bar{z}_{1,2}}{\bar{r}_{1,2}} = \frac{\nu\left(\bar{t}_{\theta_{max}} - \bar{t}_{1,2}\right)}{\bar{r}_{1,2}}$$







G. Barreau et al. / $^{252}Cf(sf)$

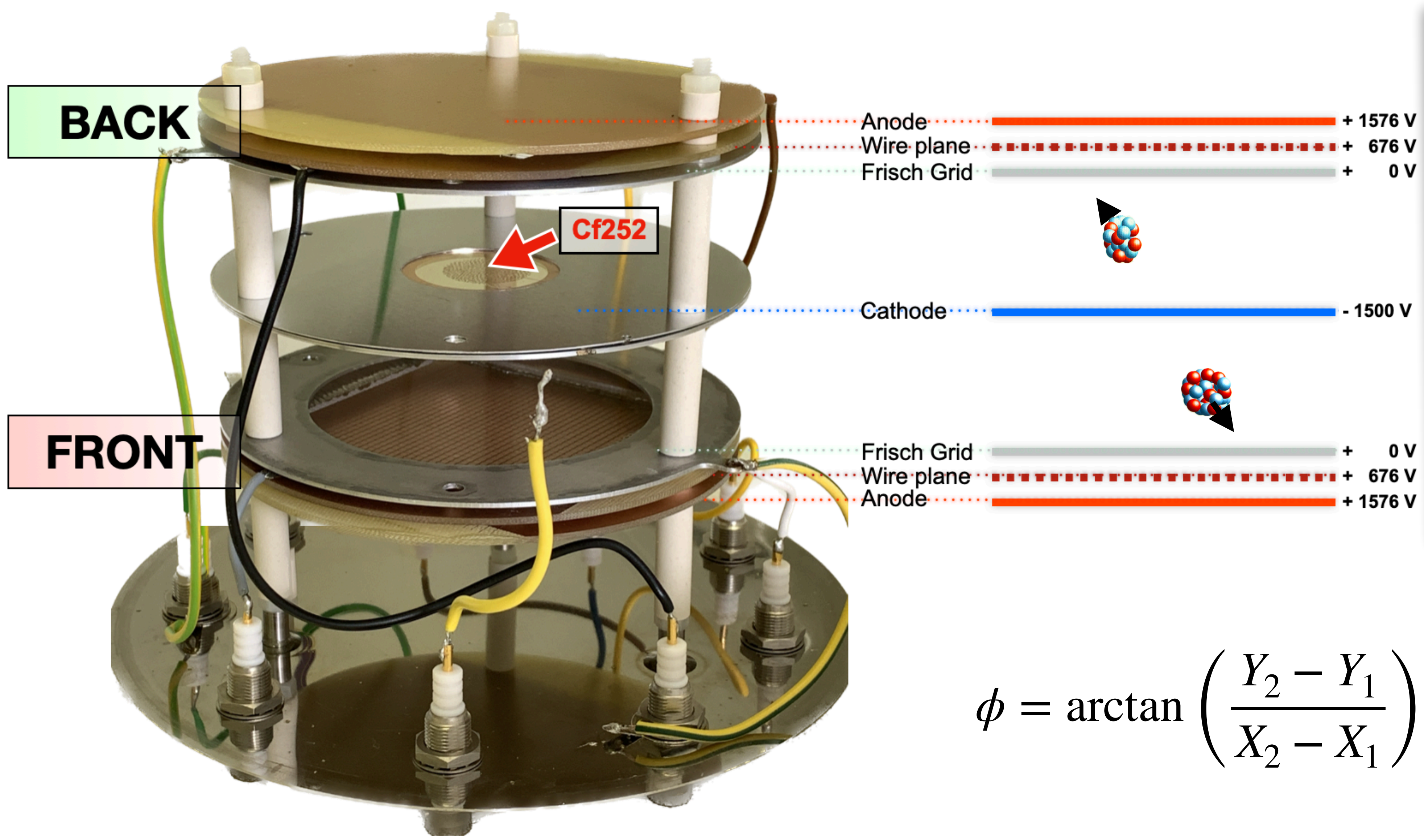
TABLE 1

Mean values, rms widths and other relevant quantities for ^{252}Cf(sf)

	This work	Schmitt *et al.* [a]	Whetstone [b]
$\langle E_K \rangle$ [MeV]	185.8 ± 1.0	185.5 ± 1.2	185.7 ± 1.8
σ_{E_K} [MeV]	12.1	12.0	11.3
$\langle E_L \rangle$ [MeV]	105.5 ± 0.6	106.2 ± 0.7	105.7 ± 1.06
σ_{E_L} [MeV]	6.3		5.86
$\langle E_H \rangle$ [MeV]	80.3 ± 0.4	80.3 ± 0.5	80.0 ± 0.8
σ_{E_H} [MeV]	8.8		8.53

TO DO

Event reconstruction (dFGIC)



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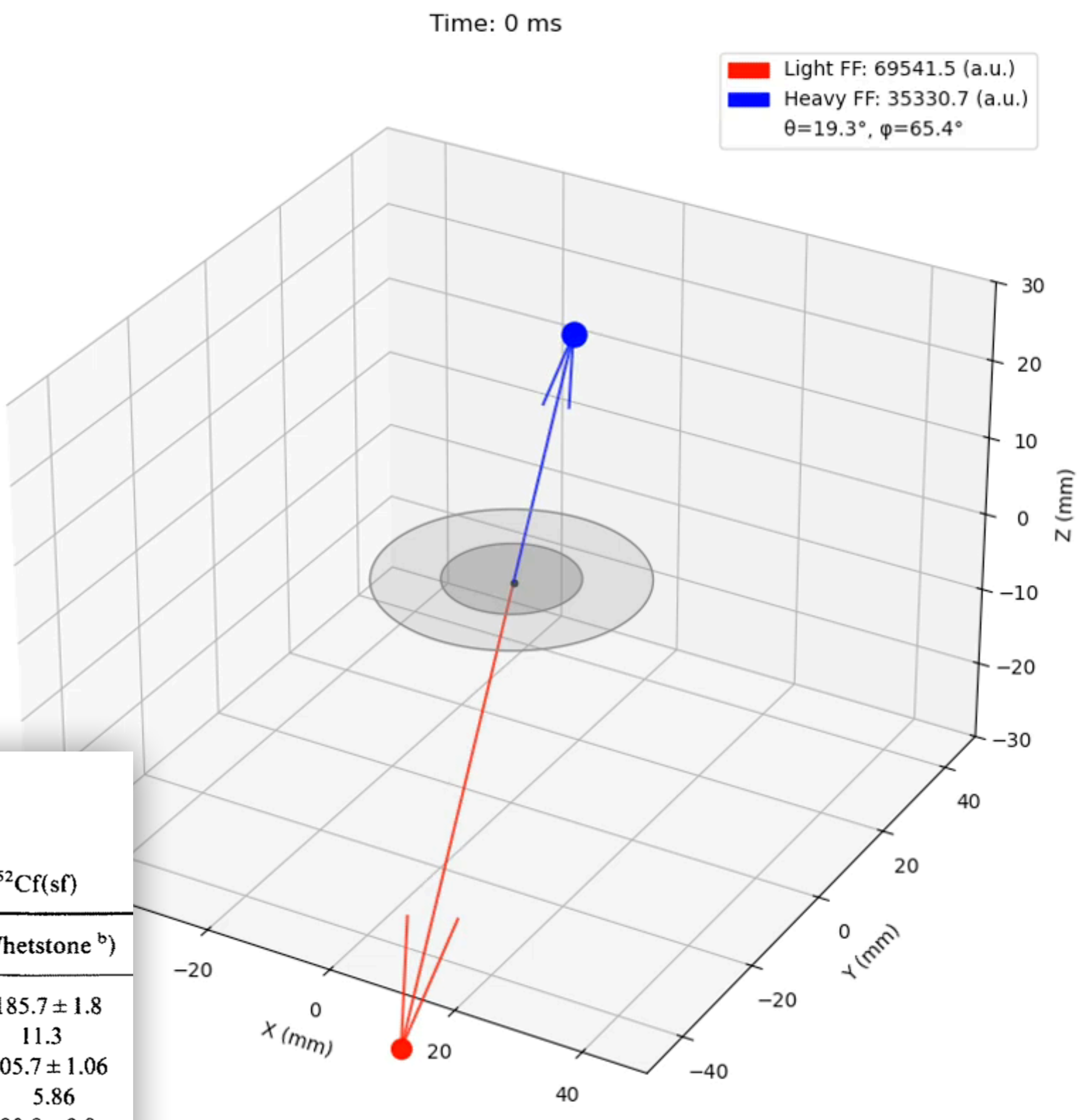
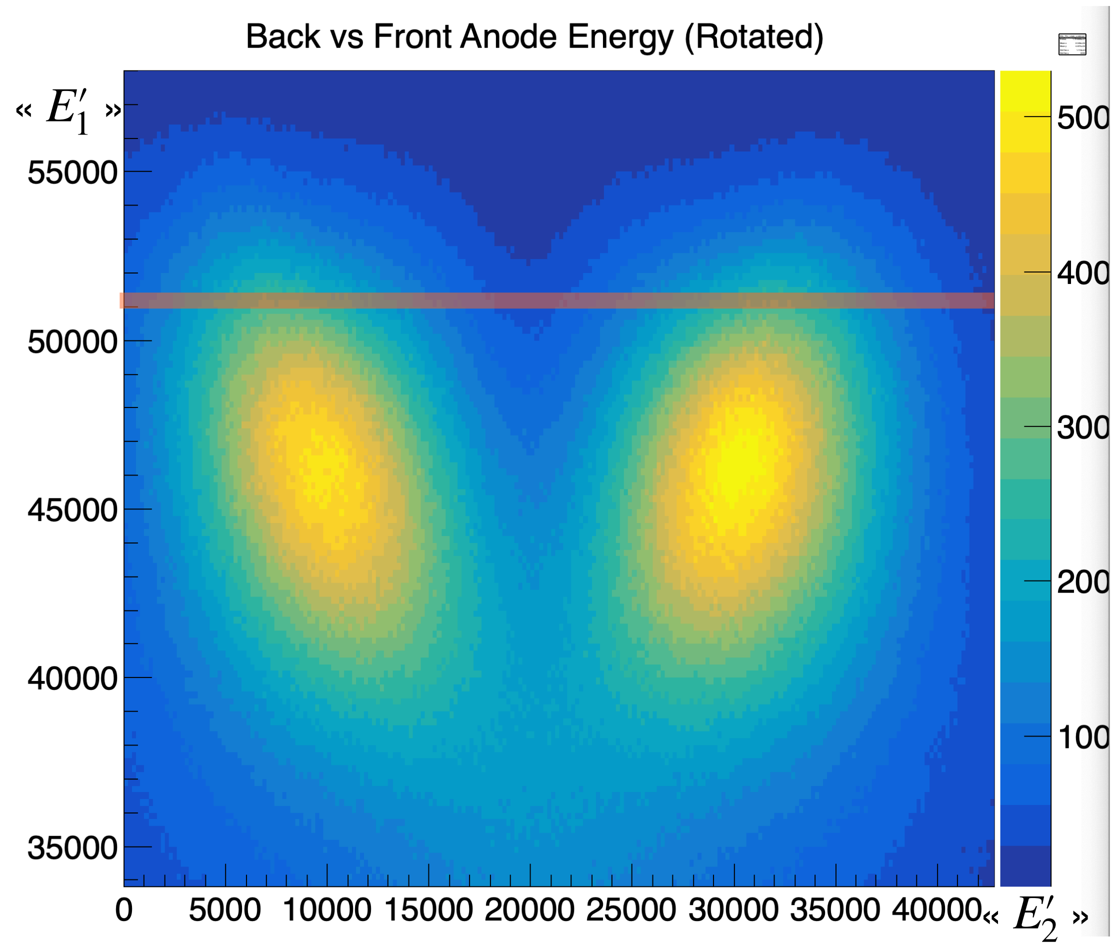
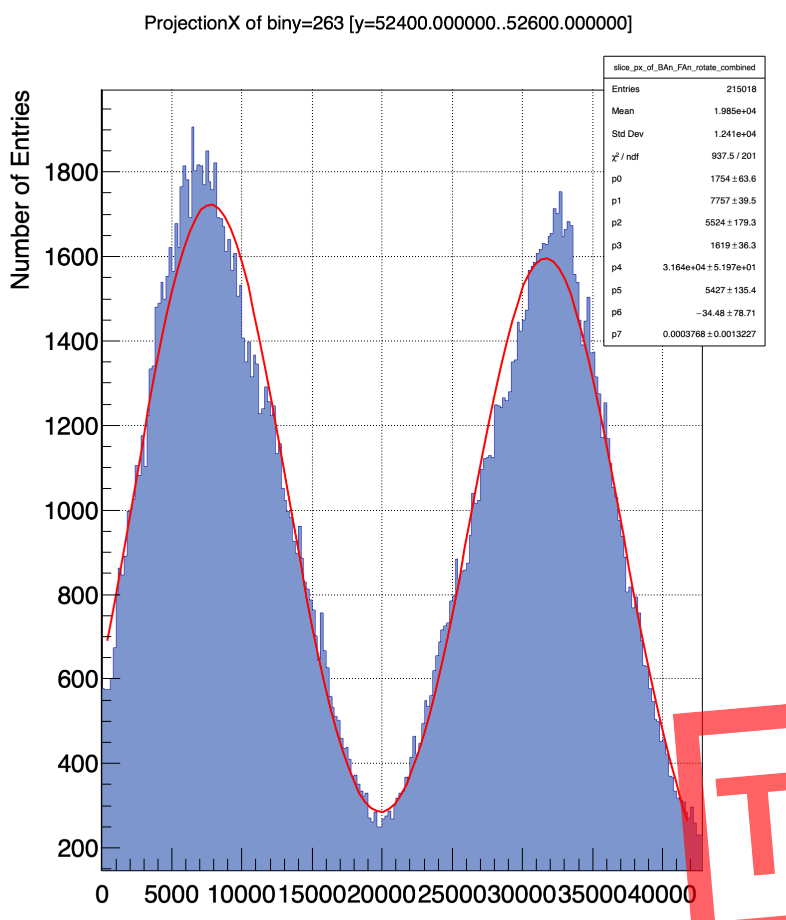






G. Barreau et al. / $^{252}Cf(sf)$

TABLE 1

Mean values, rms widths and other relevant quantities for ^{252}Cf(sf)

	This work	Schmitt *et al.* [a]	Whetstone [b]
$\langle E_K \rangle$ [MeV]	185.8 ± 1.0	185.5 ± 1.2	185.7 ± 1.8
σ_{E_K} [MeV]	12.1	12.0	11.3
$\langle E_L \rangle$ [MeV]	105.5 ± 0.6	106.2 ± 0.7	105.7 ± 1.06
σ_{E_L} [MeV]	6.3		5.86
$\langle E_H \rangle$ [MeV]	80.3 ± 0.4	80.3 ± 0.5	80.0 ± 0.8
σ_{E_H} [MeV]	8.8		8.53

TO DO

Waveform analysis

Waveform analysis through most frequently used methods

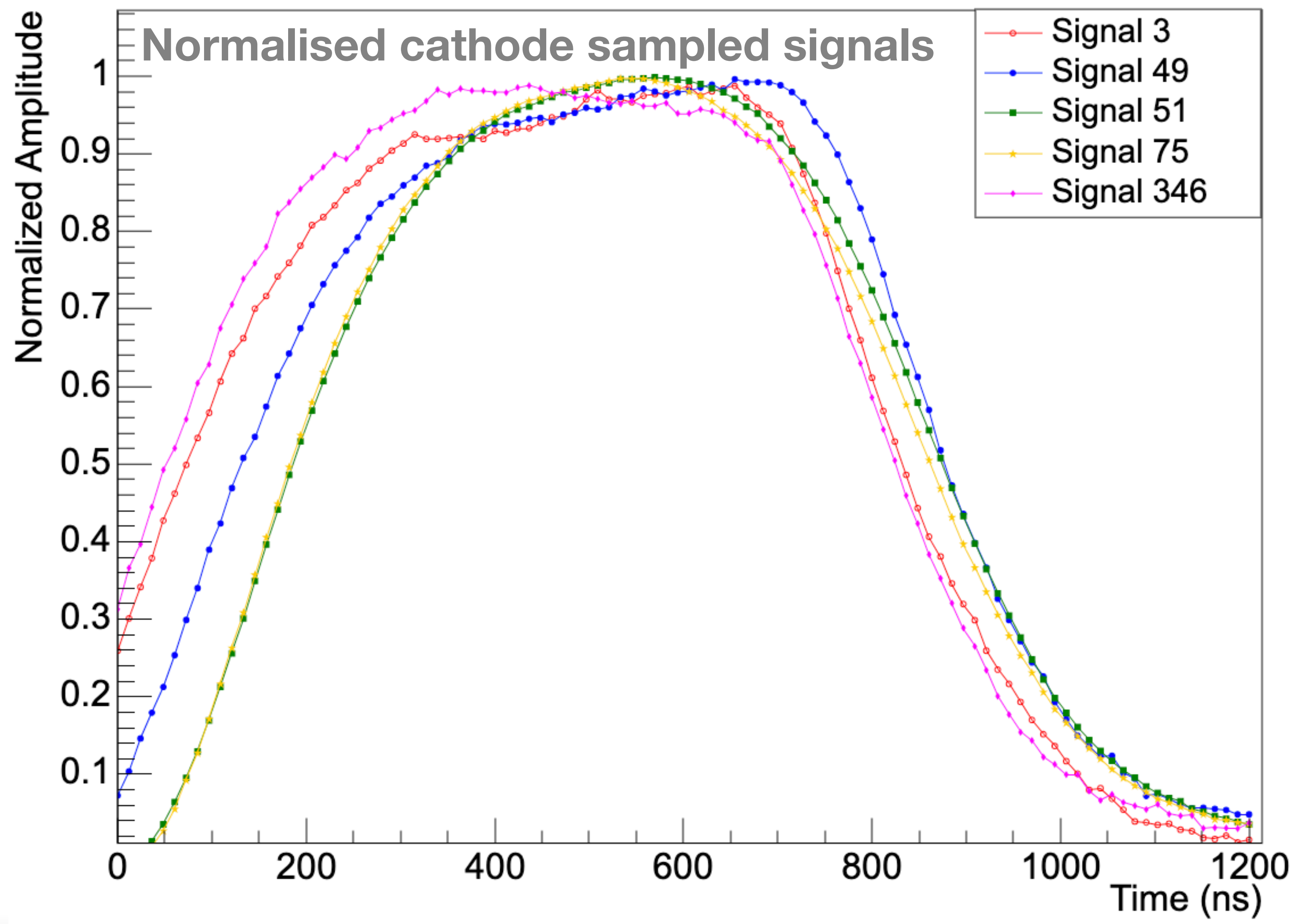
- Moving average algorithm;
- RC filter;
- Signal baseline correction;

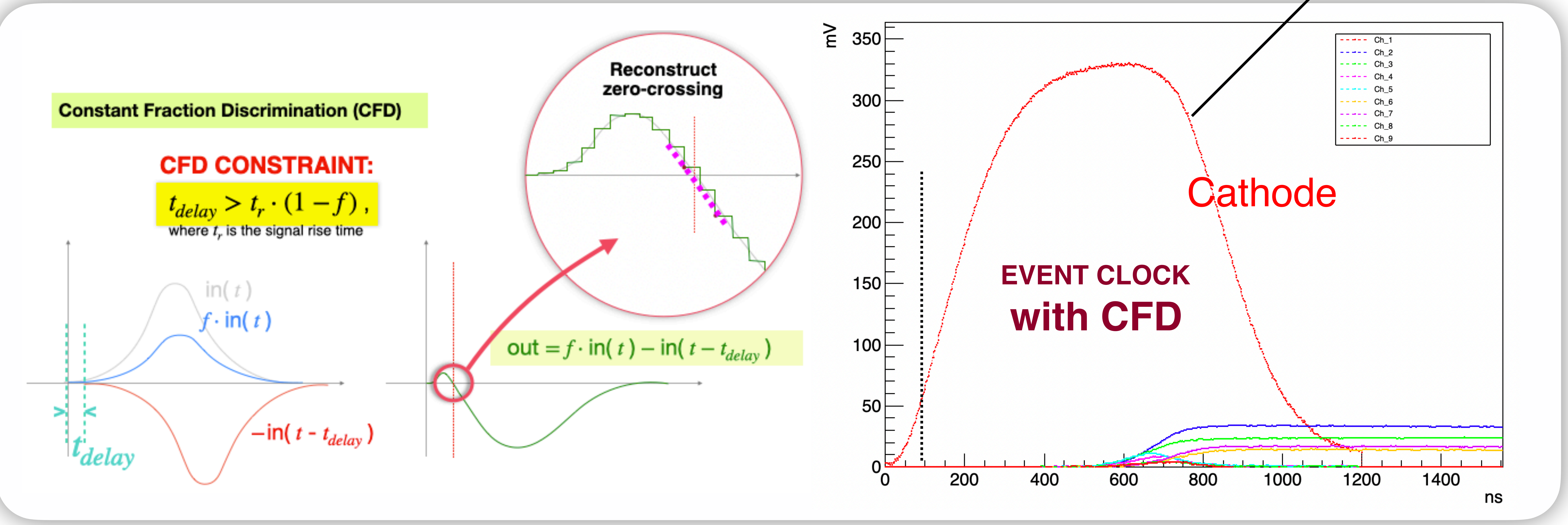
→ BOTH TIME AND « ENERGY MEASUREMENTS

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

→ « ENERGY » MEASUREMENTS

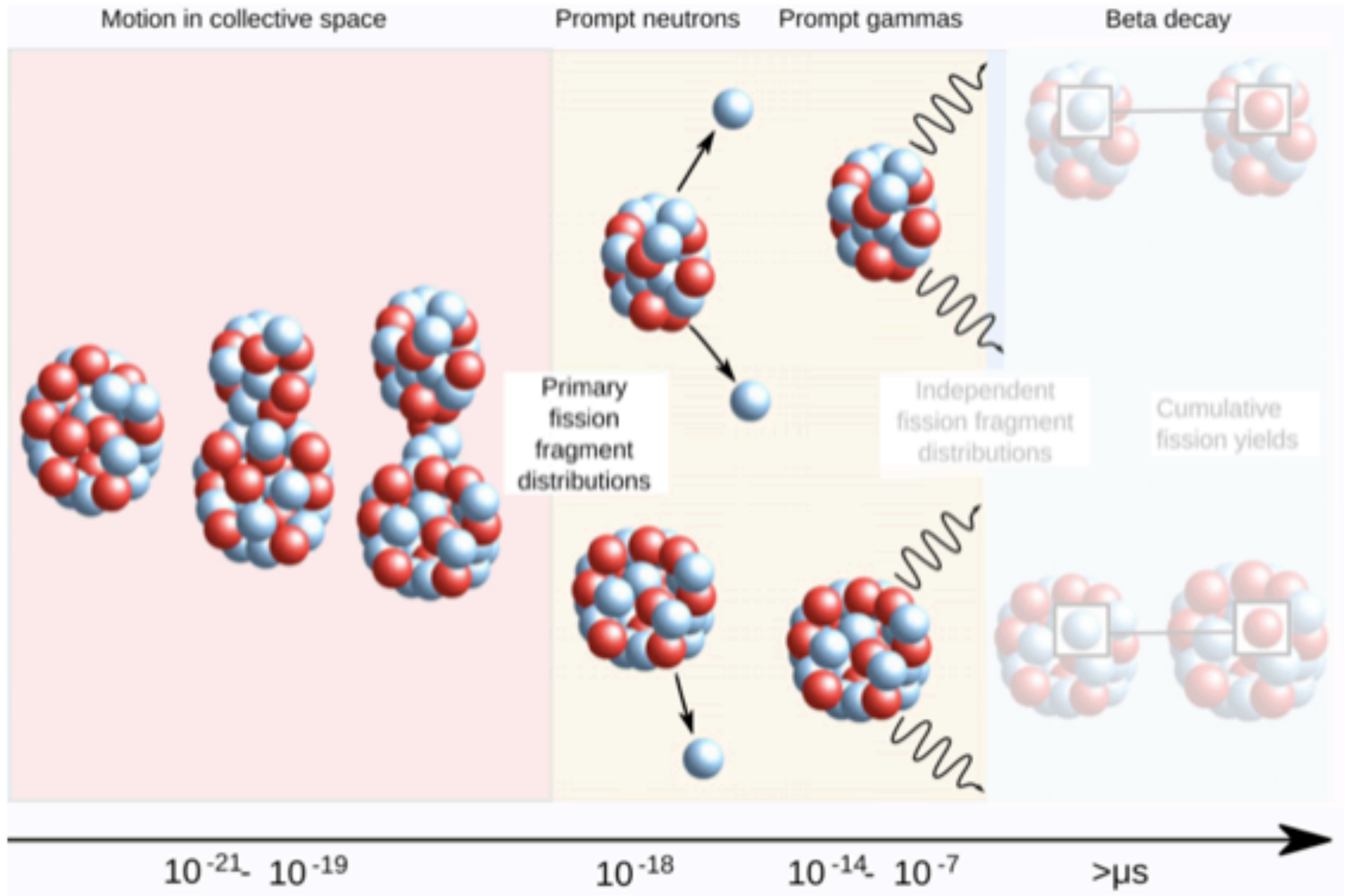
- Constant Fraction Discrimination (CFD) **TIME MEASUREMENTS**

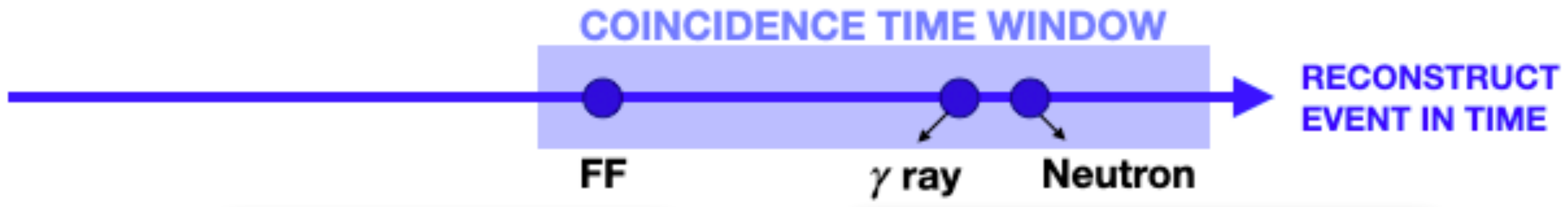




CFD* on cathode signals requires ~15000 FLOP per signal

Event reconstruction





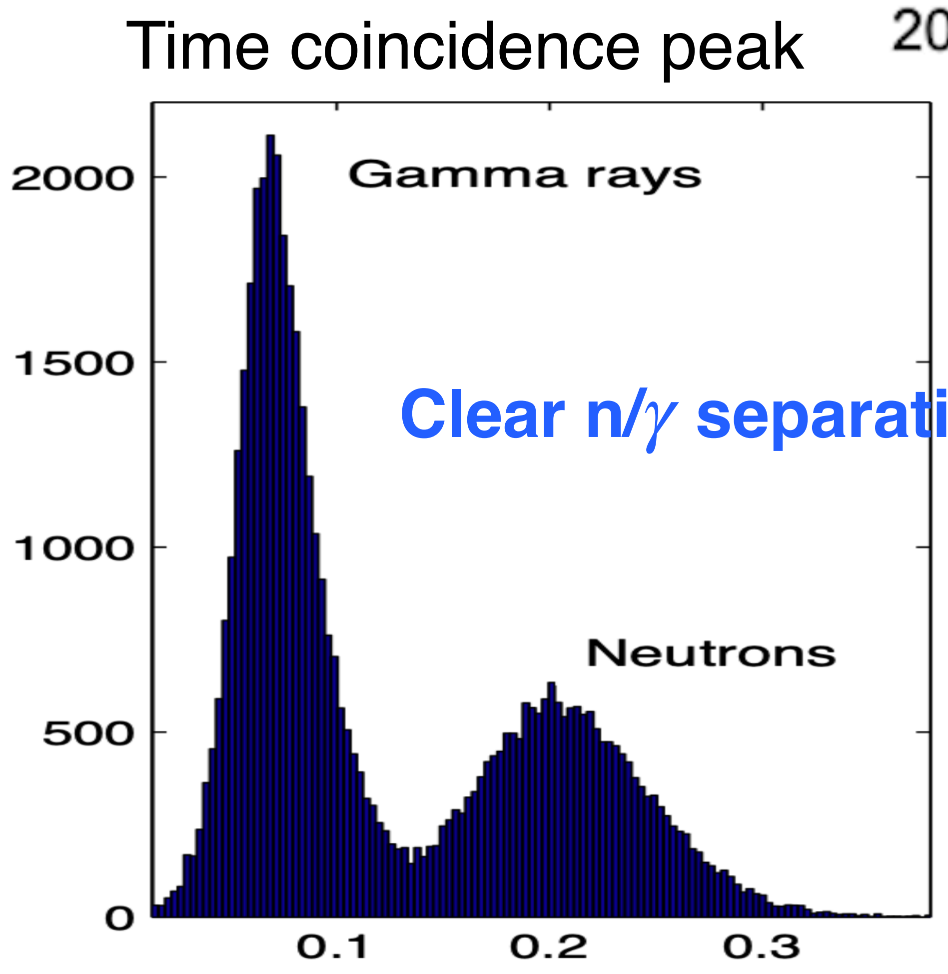
Cathode signal IC (fission trigger)

$LaBr_3$ scintillator (coincidence detector)

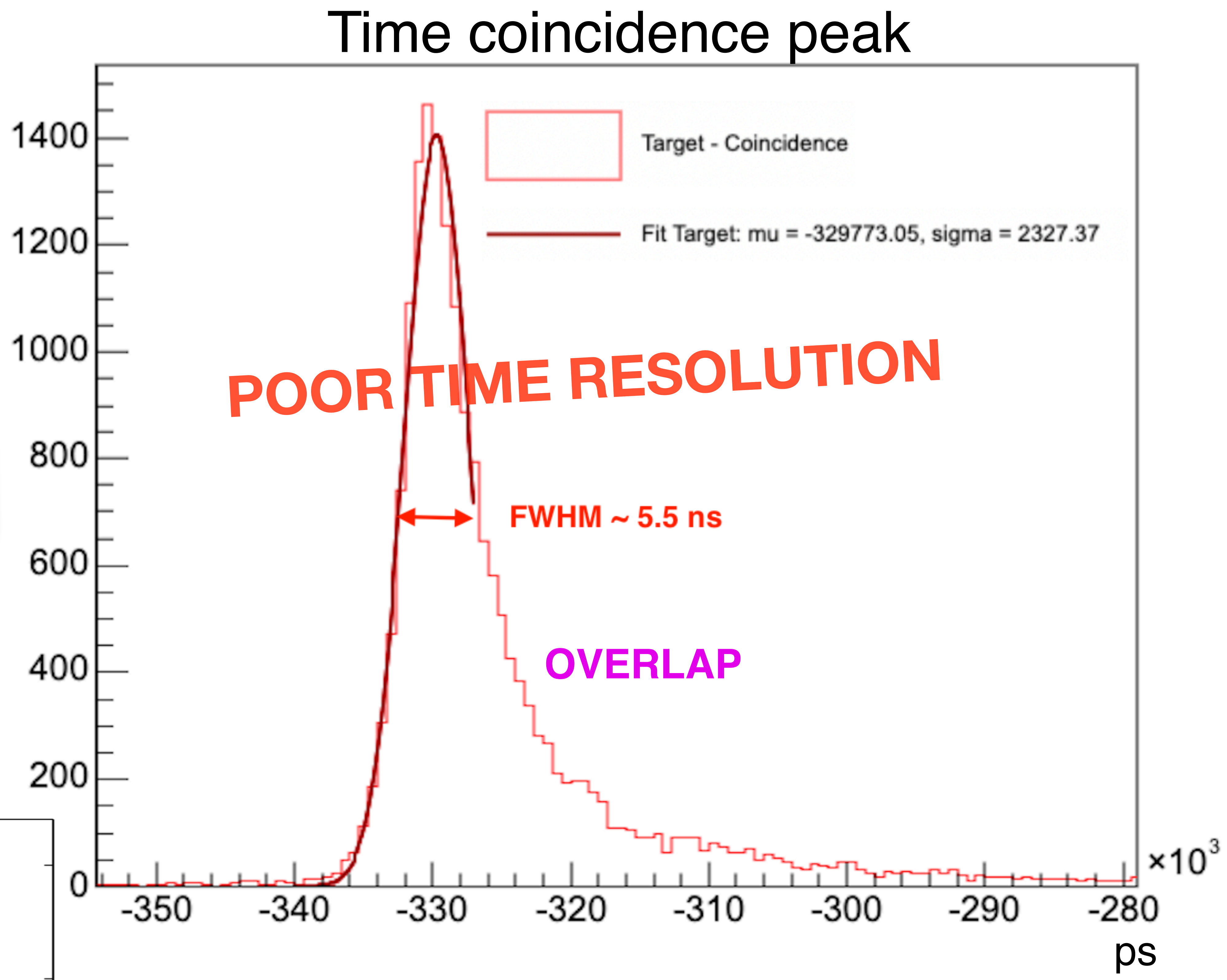
CFD on cathode signals requires ~15000 FLOP per signal

Triggering of signal can be optimised to 1-2% of signal rise time.

Cathode rise time ~300 ns

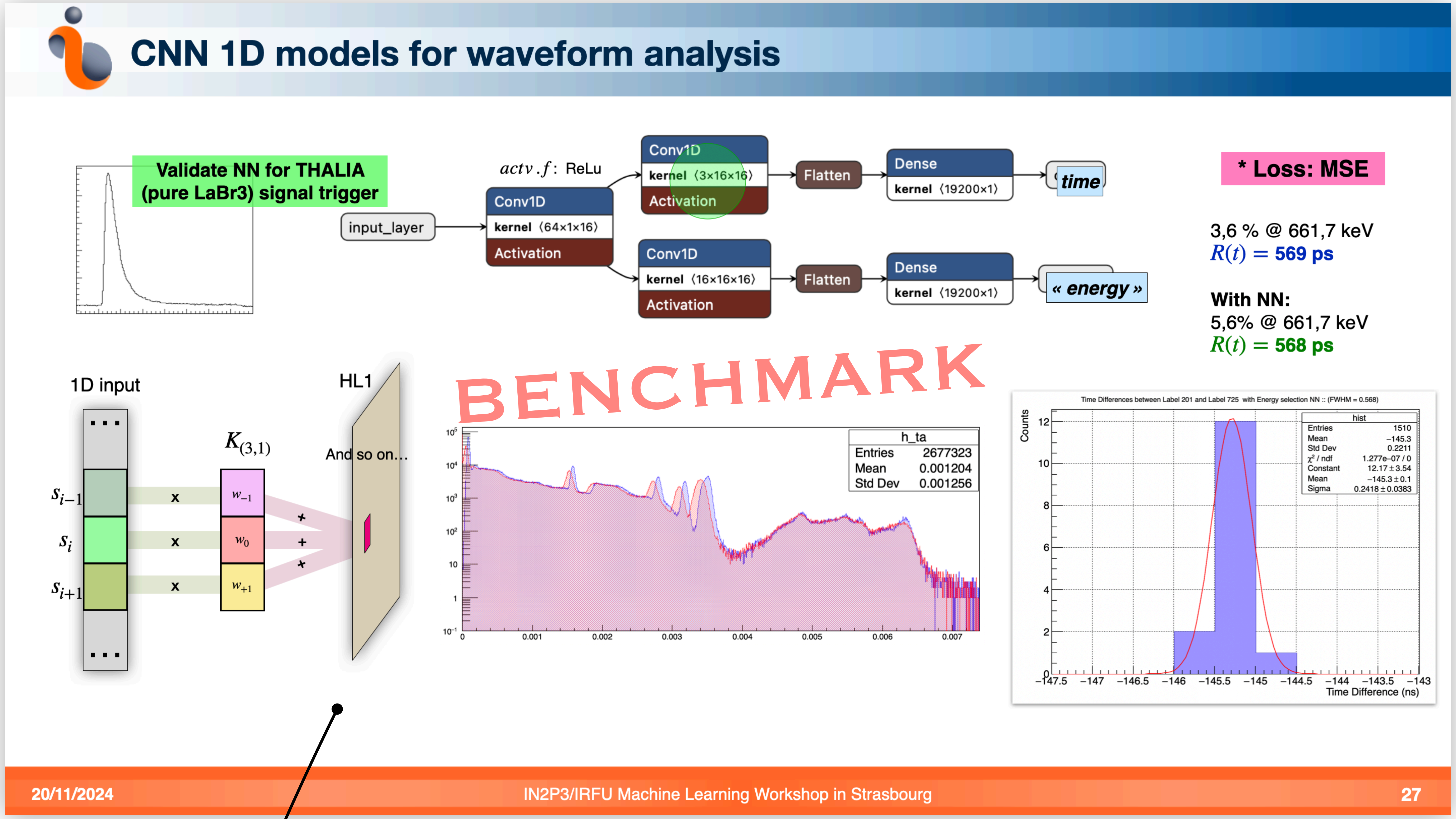


Clear n/γ separation due to TOF



1.Time resolution is not sufficient to separate n/γ
2. Expect to obtain a resolution down to 3 ns

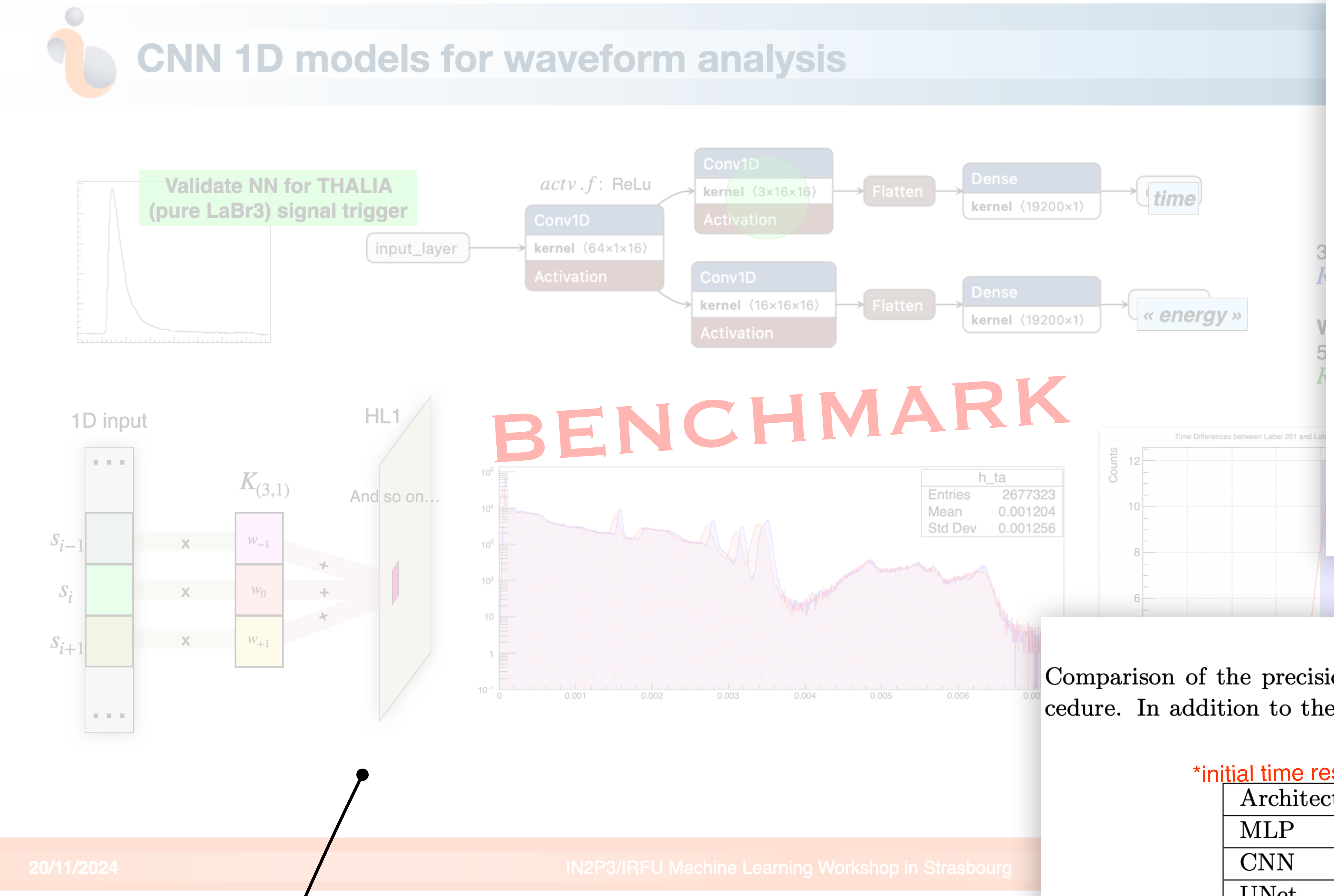
Regression model for signal triggering

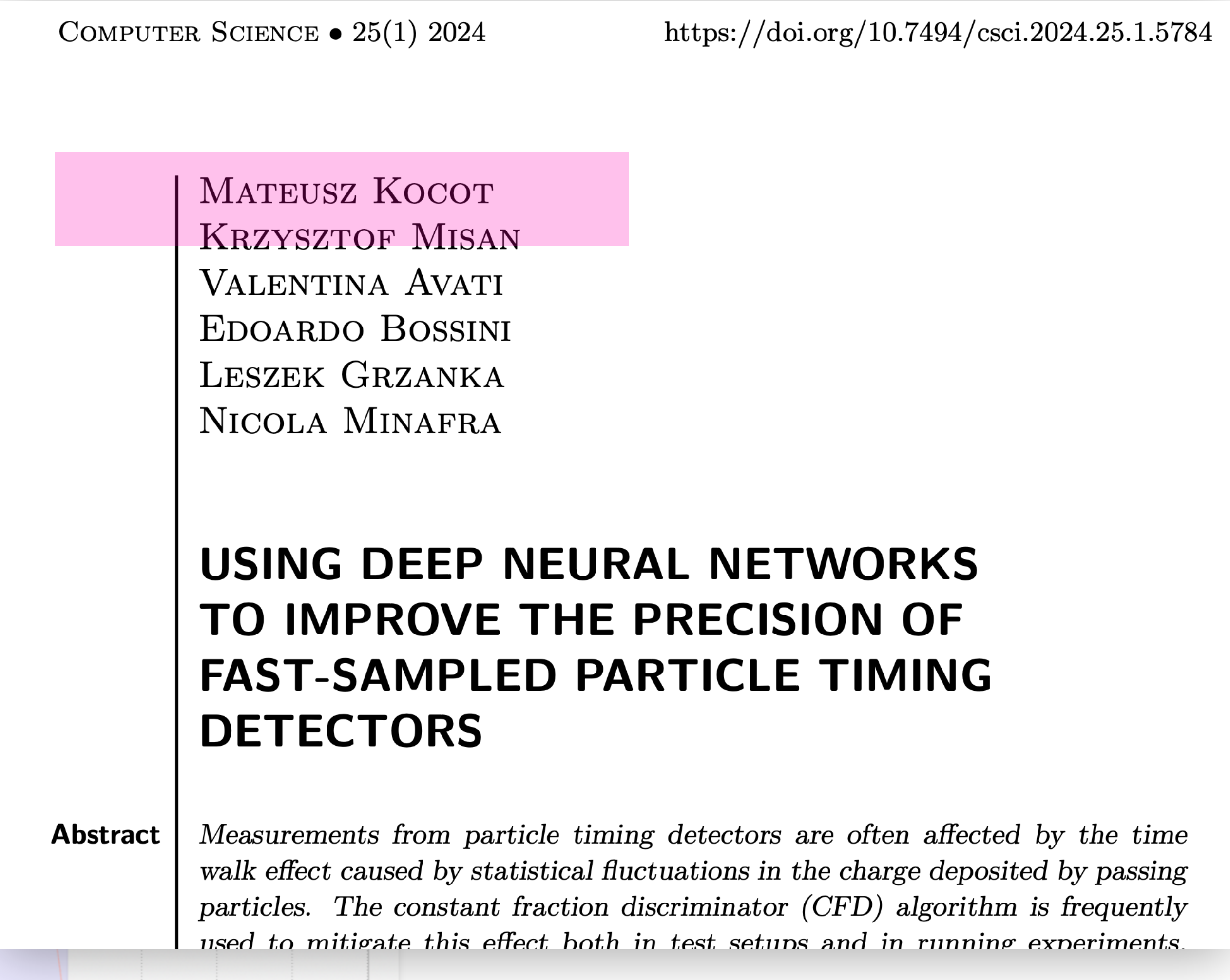


CNN 1D regression model **successfully predicted the signal triggering** for benchmark pure $LaBr_3$ detector without degrading time resolution.

<u>However</u>, model did **not** generalise well for cathode signals and required **more** operations than CFD algorithm.

Regression model for signal triggering





Computer Science • 25(1) 2024 https://doi.org/10.7494/csci.2024.25.1.5784

Mateusz Kocot
Krzysztof Misan
Valentina Avati
Edoardo Bossini
Leszek Grzanka
Nicola Minafra

USING DEEP NEURAL NETWORKS TO IMPROVE THE PRECISION OF FAST-SAMPLED PARTICLE TIMING DETECTORS

Abstract *Measurements from particle timing detectors are often affected by the time walk effect caused by statistical fluctuations in the charge deposited by passing particles. The constant fraction discriminator (CFD) algorithm is frequently used to mitigate this effect both in test setups and in running experiments.*

Table 1

Comparison of the precisions achieved by the optimal models in the cross-validation procedure. In addition to the cross-validation scores, the number of parameters used by each network is reported, too

*initial time resolution (with CFD) 73.3 ps

Architecture	Mean [ps]	Std [ps]	Parameter count
MLP	63.90	0.85	2737
CNN	62.83	1.34	36,865
UNet	60.71	1.19	456,965

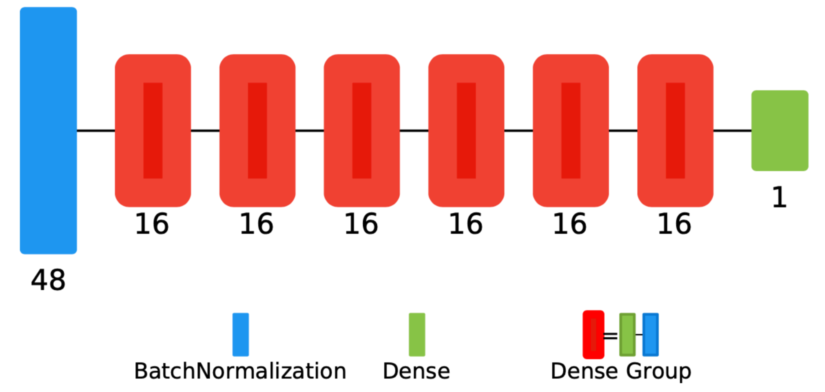


Figure 8. Optimal MLP model [3]

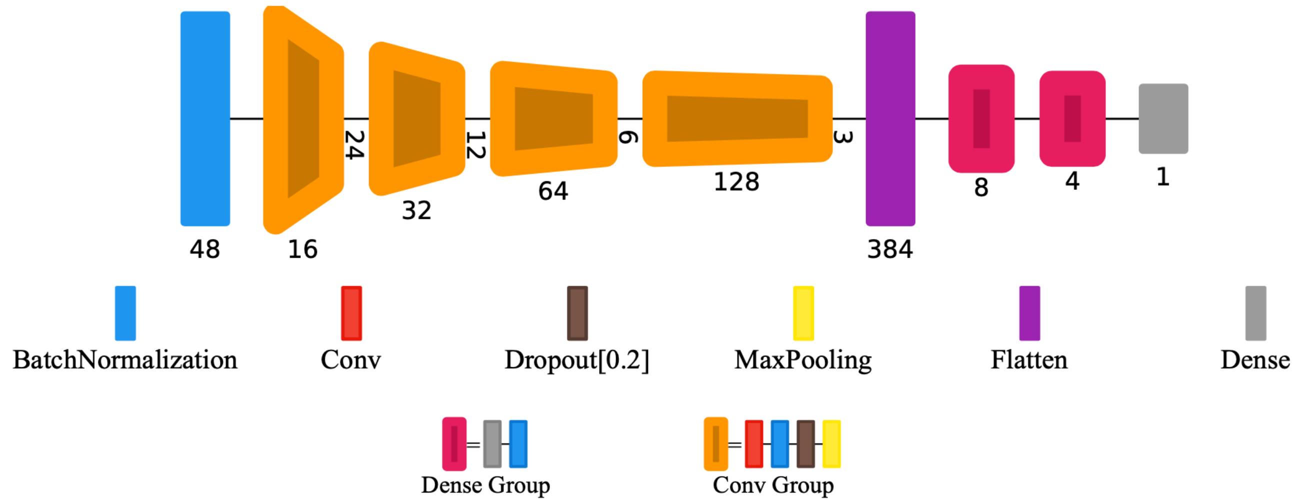


Figure 9. Optimal CNN model [3]

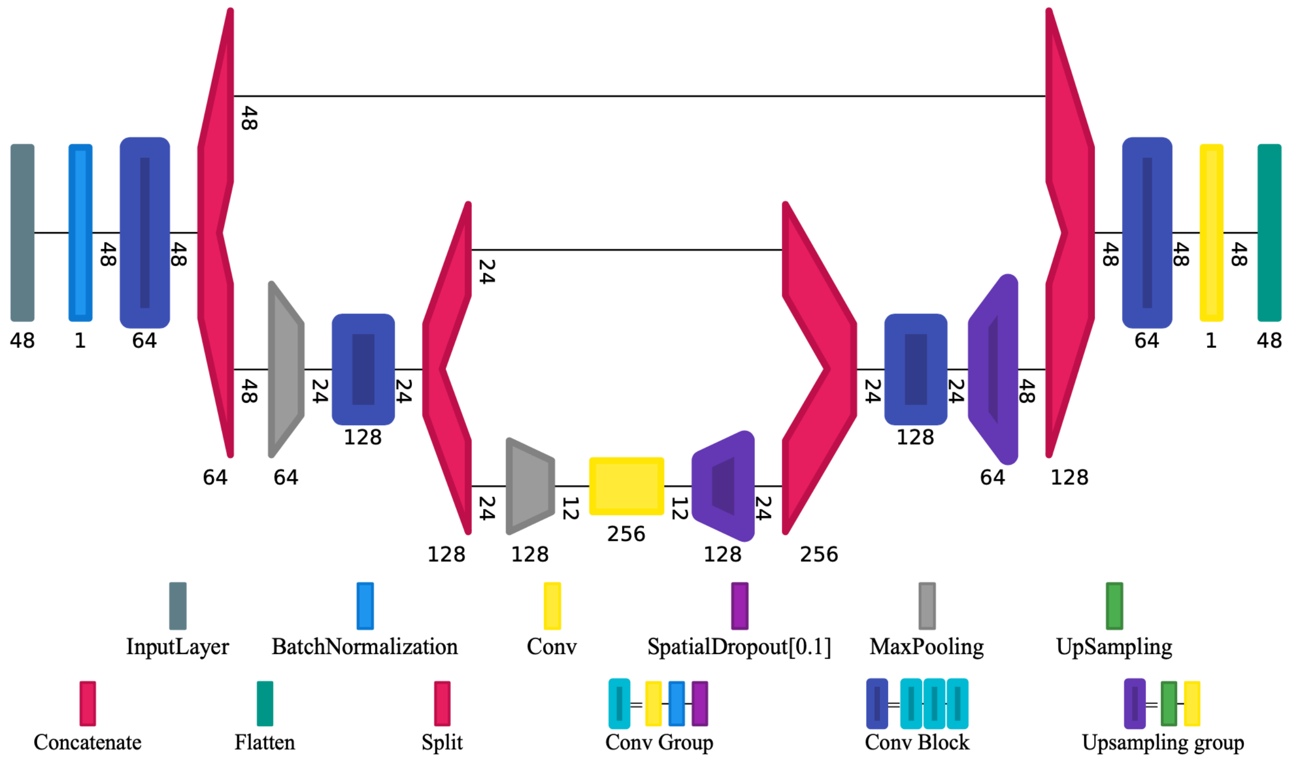


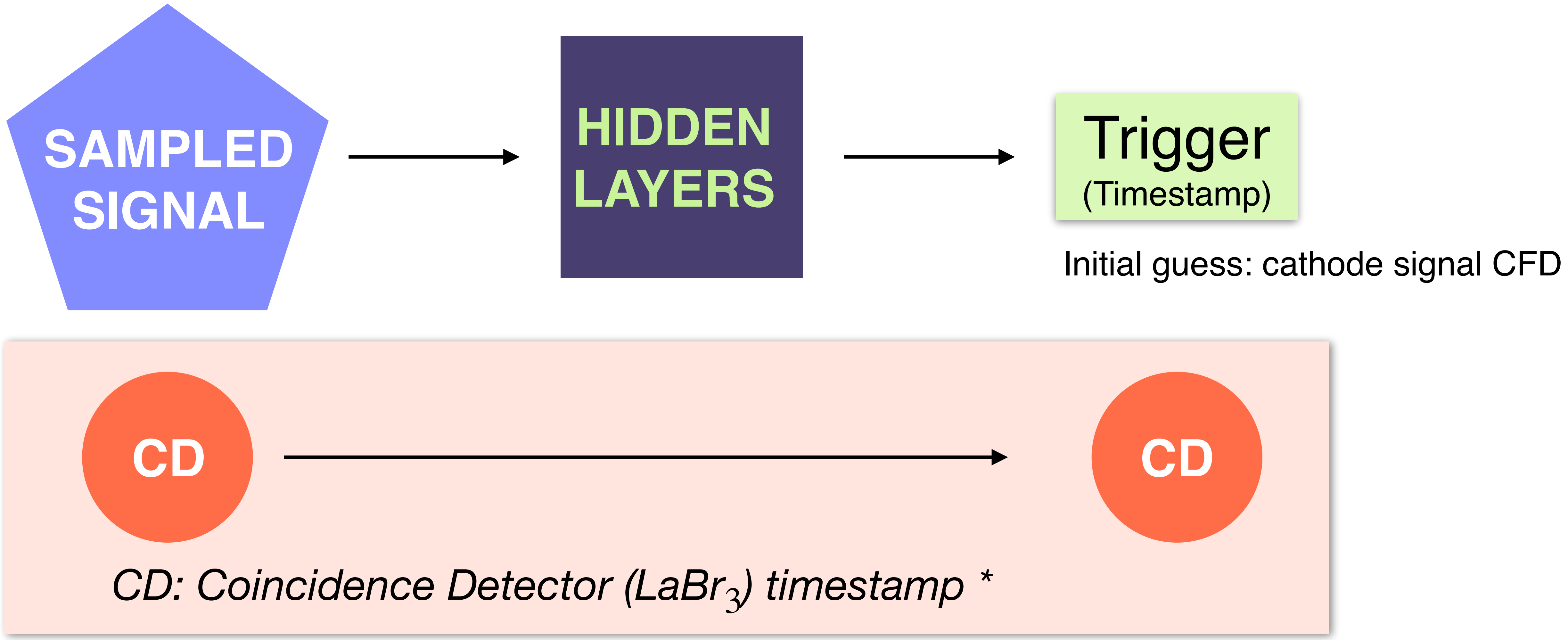
Figure 10. Optimal UNet model [3]

M. Kocot also uses MSE loss function

CNN 1D regression model **successfully predicted the signal triggering** for benchmark pure $LaBr_3$ detector without degrading time resolution.

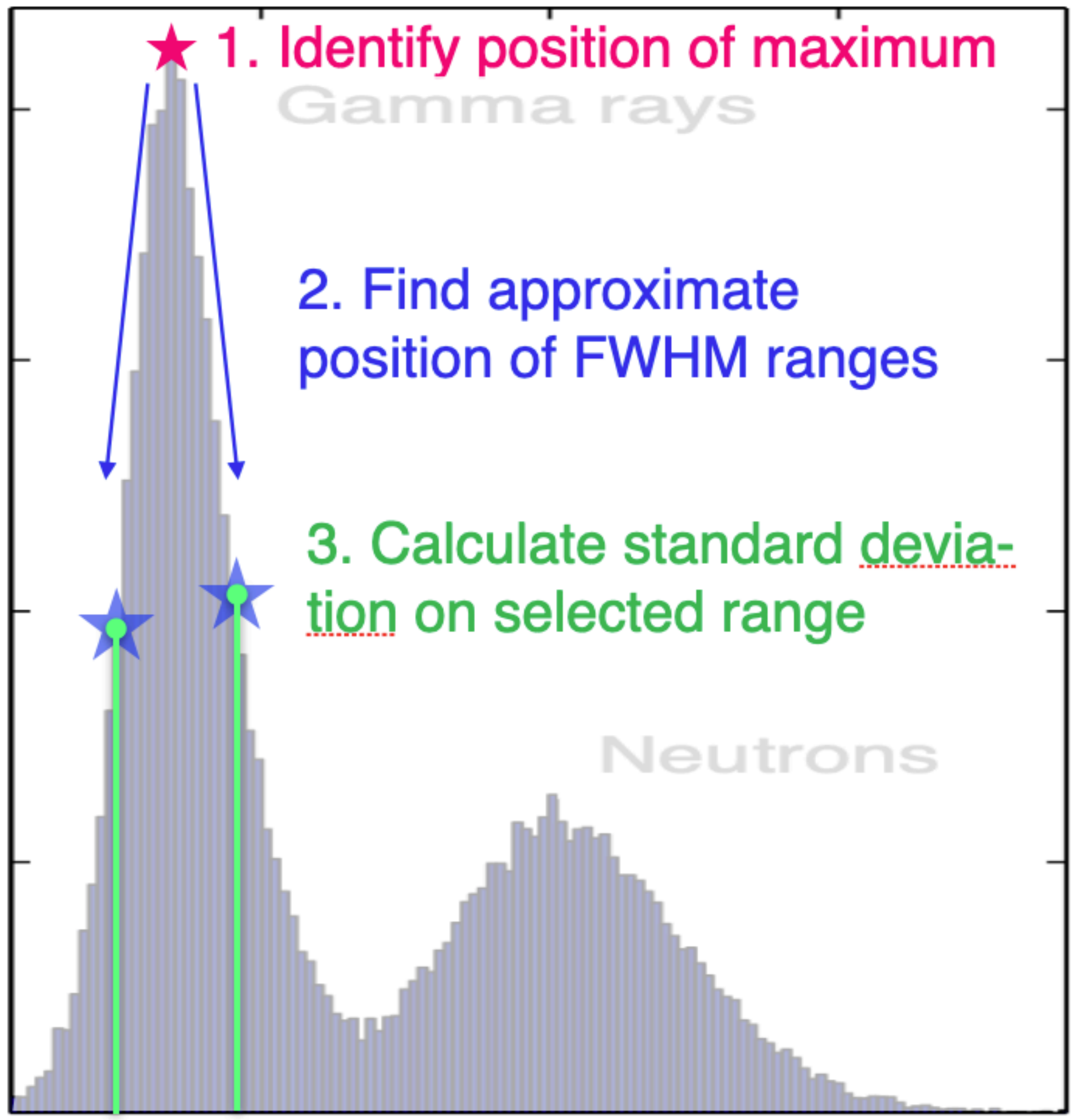
<u>However</u>, model did **not** generalise well for cathode signals and required **more** operations than CFD algorithm.

Loss function for time resolution improvement



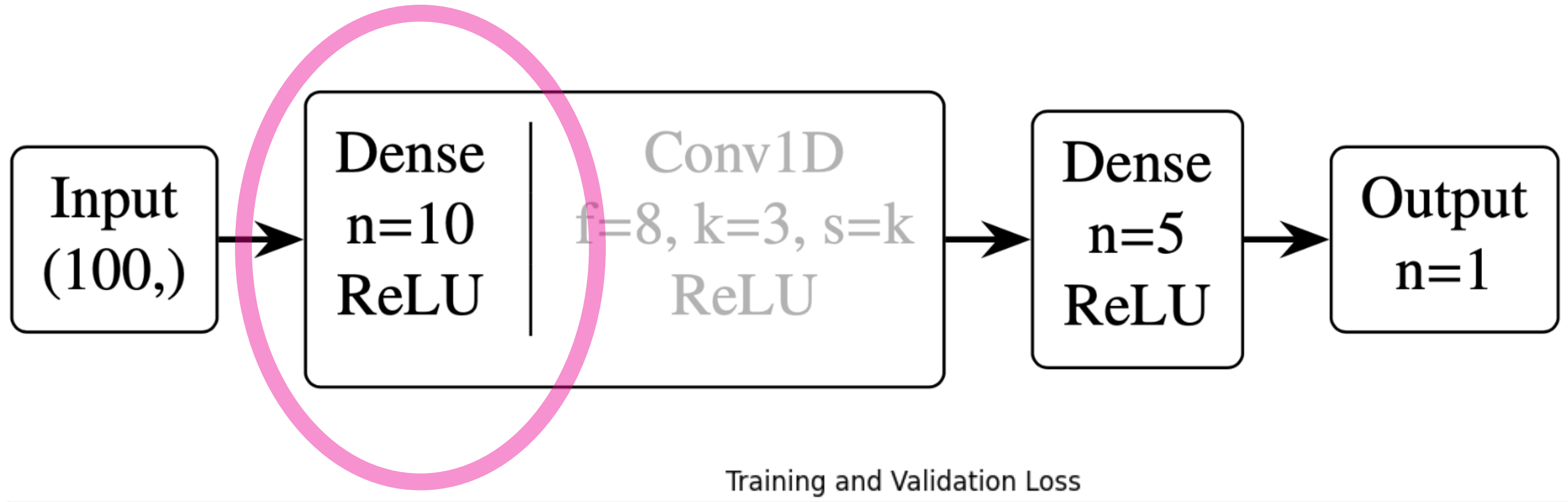
NO CONNECTION BETWEEN CD NEURON AND ANY OTHER LAYER IN NN ARCHITECTURE.

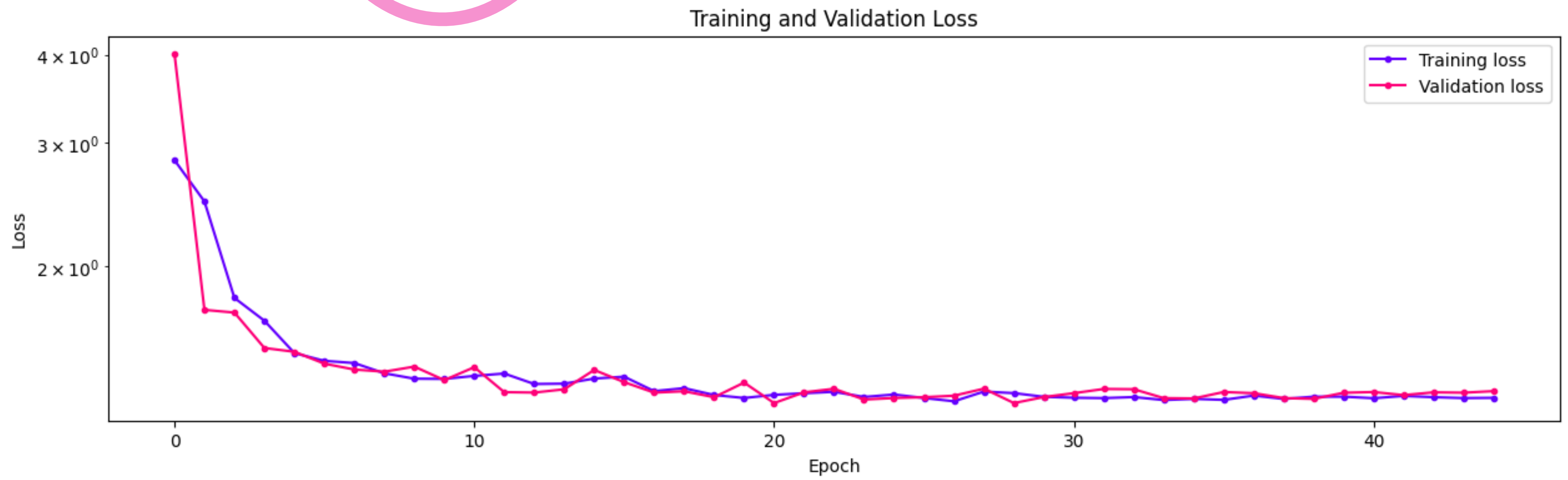
USED ONLY FOR LOSS ESTIMATION.

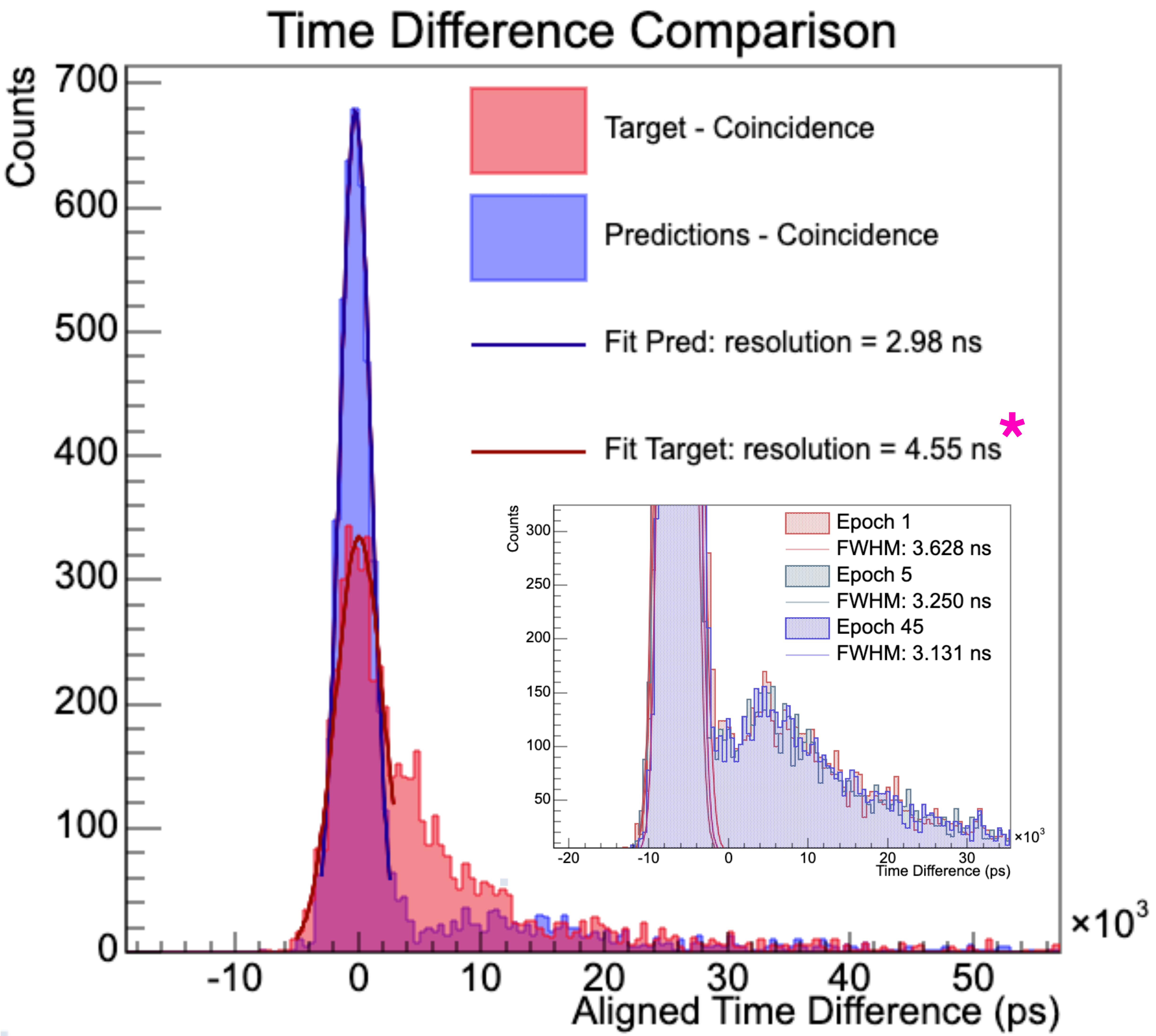


By batch

Final Model







The model can be loaded in c++ script with Tensorflow API and it was directly implemented in our raw data conversion code to ROOT format, replacing the CFD algorithm.

Our final model has **1065 parameters** and requires 2110 FLOP per signal entry, with **total FLOP 2910 per signal.**

The total number of operations already takes into account signal downsampling (600 + 100 FLOP) and rescaling (100 FLOP).

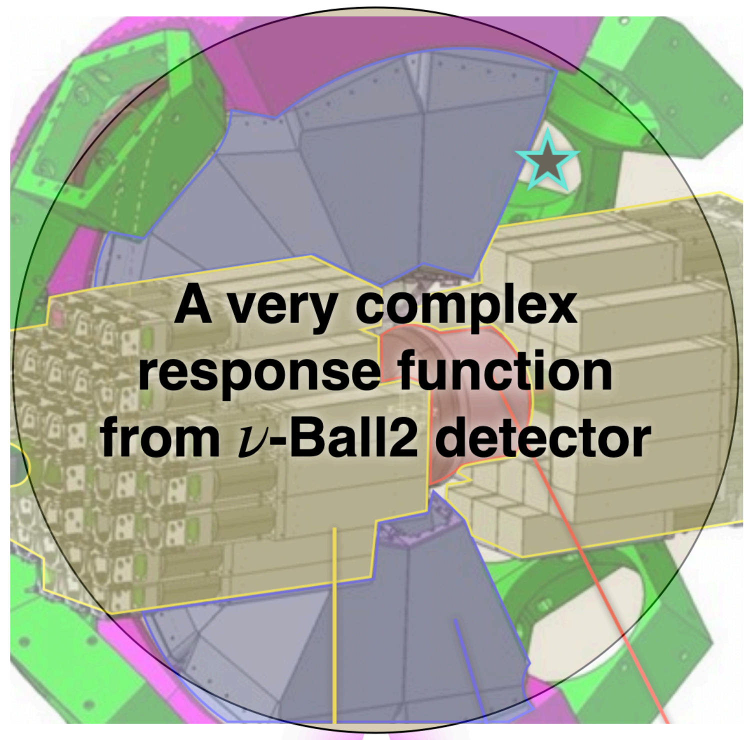
This represents a computational cost 5 times smaller than CFD algorithm with a time resolution at least 34% better * .

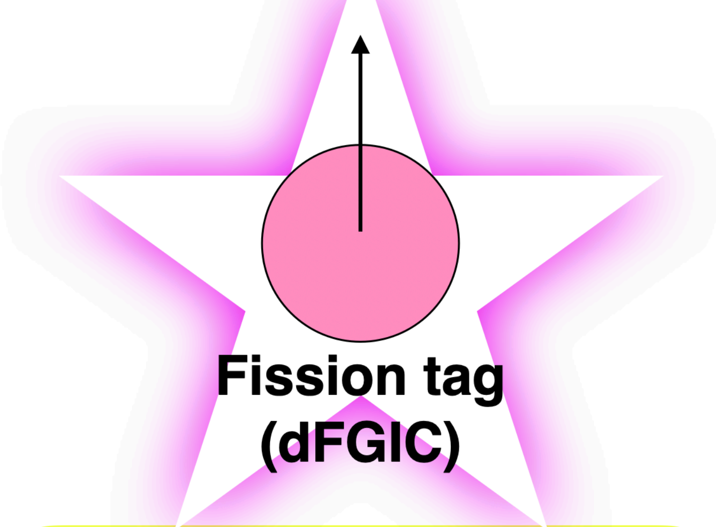
CONTENTS:

- Fission fragments de-excitation
- N-SI-125 experiment with ν-Ball2
- Fission tag with dFGIC
- **Neural Networks for fission triggering**

Fission trigger based on ν-Ball2 response function

Create a model capable of recognizing fission
solely based on detector response function





Classification labels

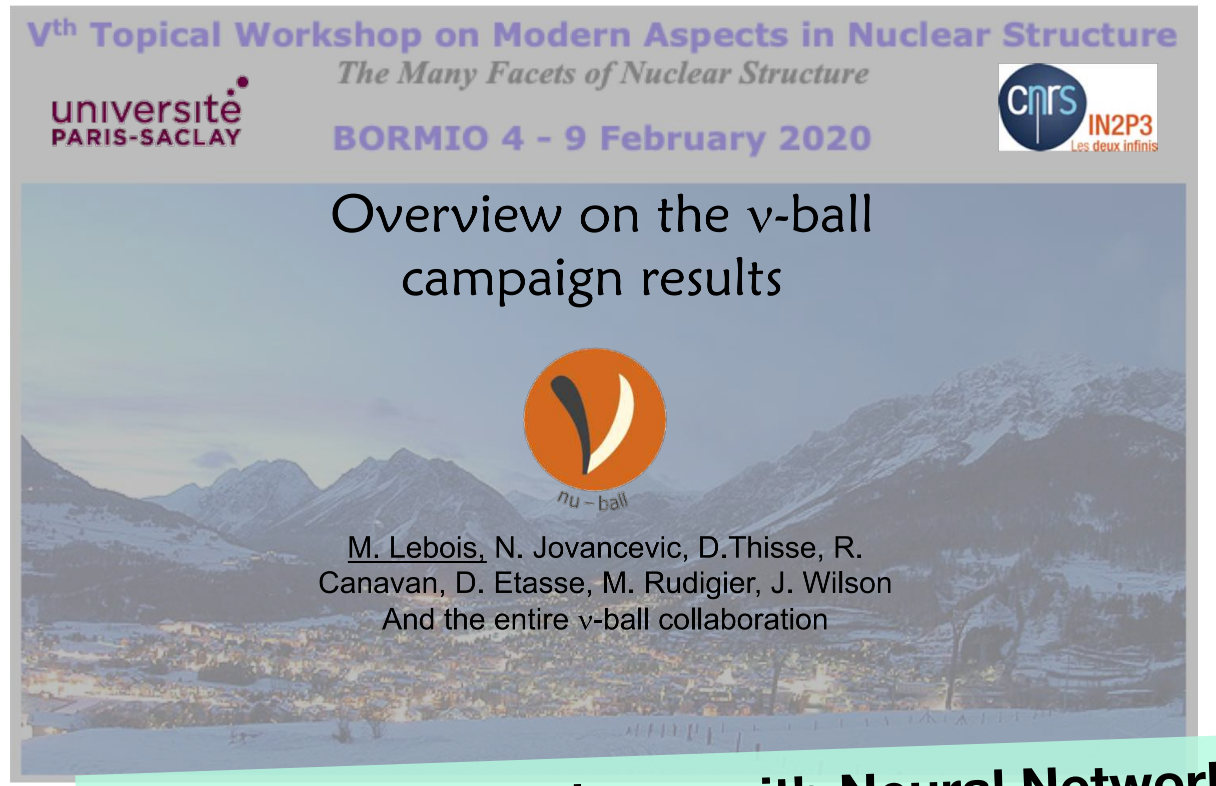
O_a

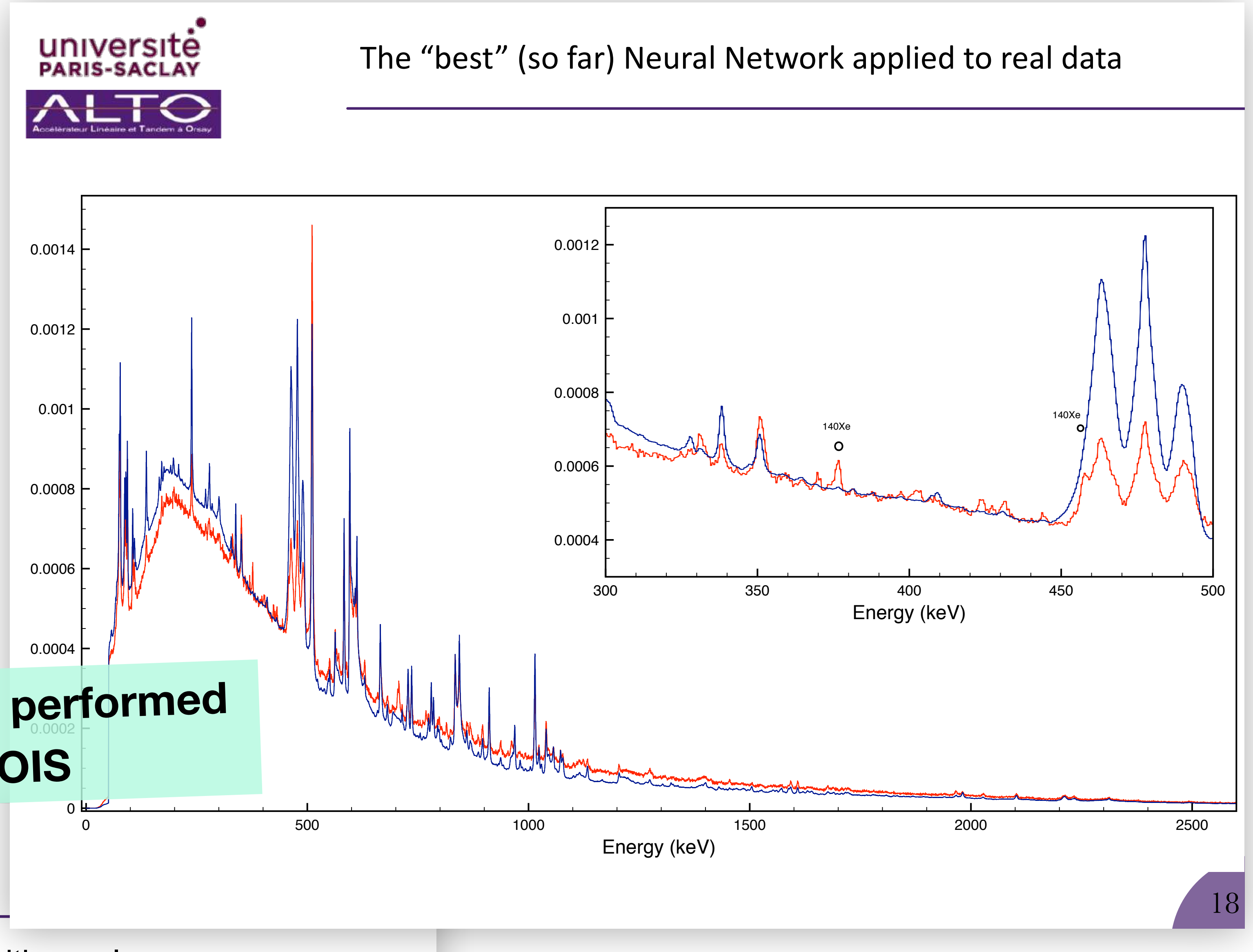
2D plots → higher dimensional correlations to evaluate which fission observables are more or less relevant for fission recognition.

Measured values:

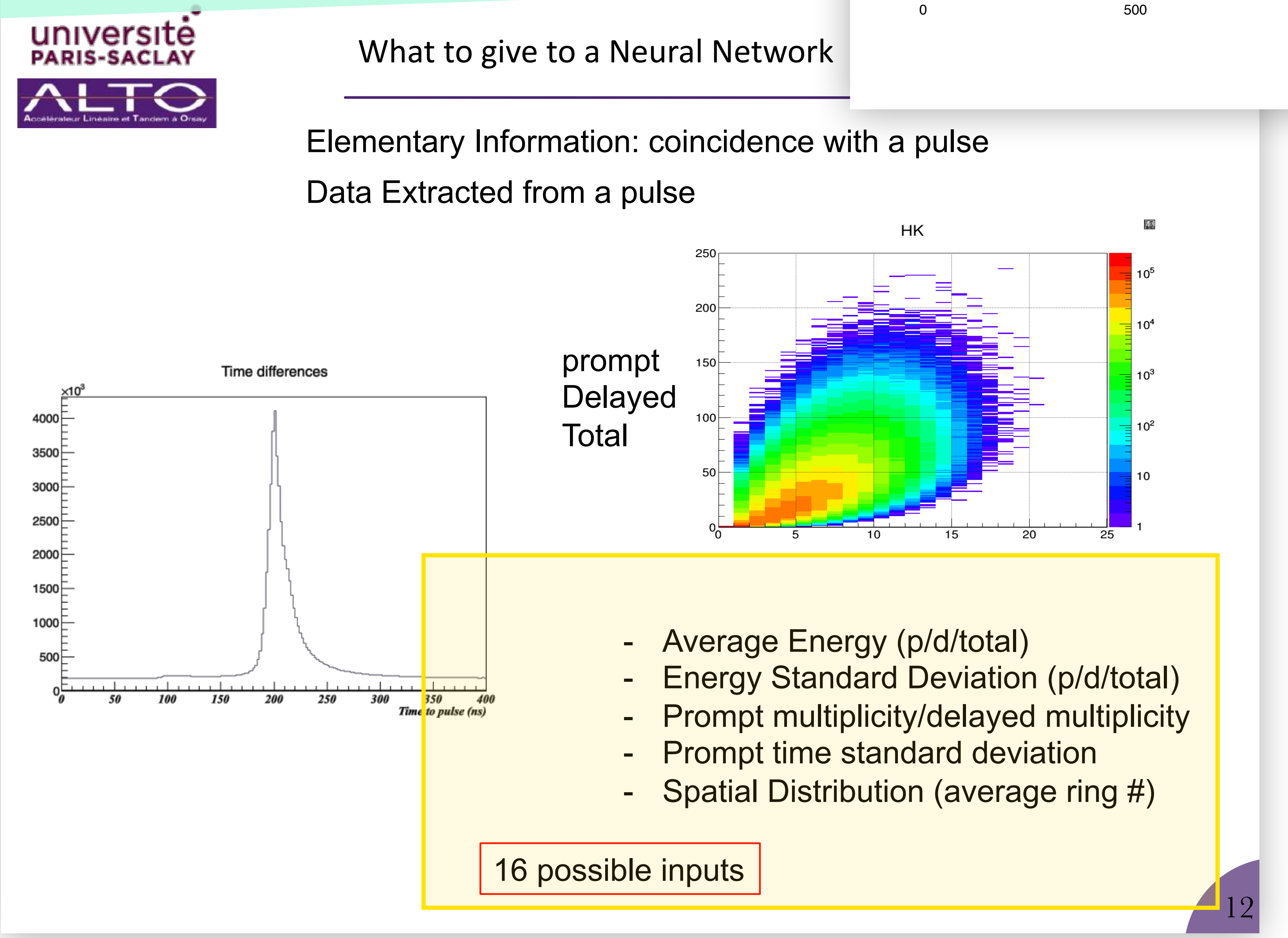
- **γ multiplicity / energy**
- **Neutron multiplicity / energy**
- **Total energy**
- **…**

O_b



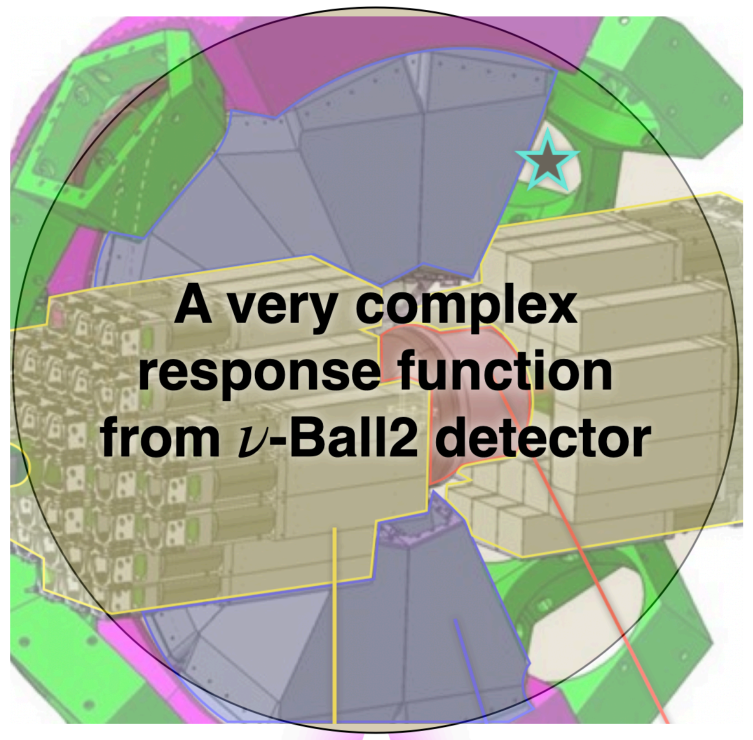


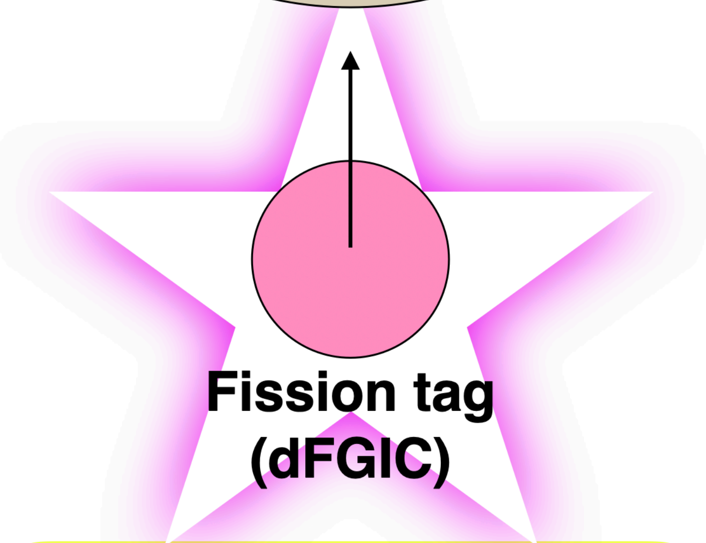
Tests for fission trigger with Neural Networks performed on ν-Ball campaign results by M. LEBOIS



Fission trigger based on ν-Ball2 response function

Create a model capable of recognizing fission
<u>solely based on detector response function</u>



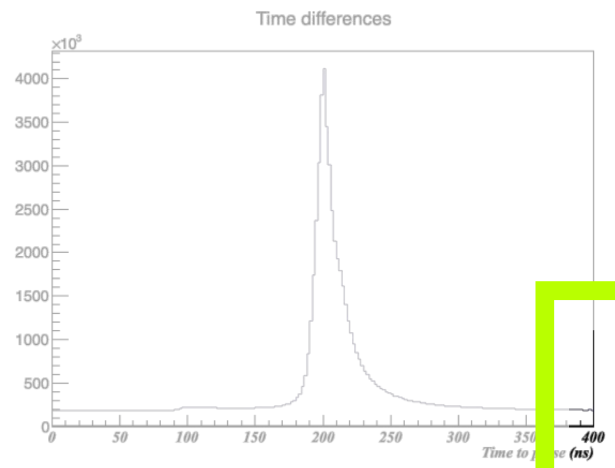


Classification labels

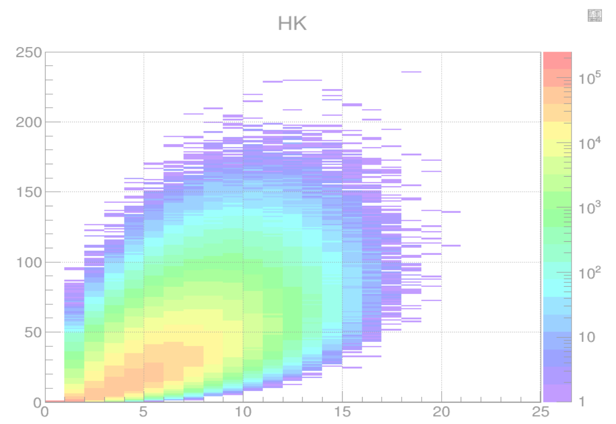
What to give to a Neural Network

Elementary Information: coincidence with a pulse

Data Extracted from a pulse



prompt
Delayed
Total



- Average Energy (p/d/total)
- Energy Standard Deviation (p/d/total)
- Prompt multiplicity/delayed multiplicity
- Prompt time standard deviation
- Spatial Distribution (average ring #)

16 possible inputs

Current state:

Building final dataset by reconstructing « Hit » events measured values.
Boolean classification label « *is fission* » given by ionisation chamber output

Additional input, compared to ν-Ball:
with ν-Ball2 it is possible to detect **neutrons** and discriminate them from γ-rays

Clear fission tag by dFGIC (ionisation chamber)

Hundreds of millions of fission events available for training and validation
(Even though we expect to train model with around 10^4 events)

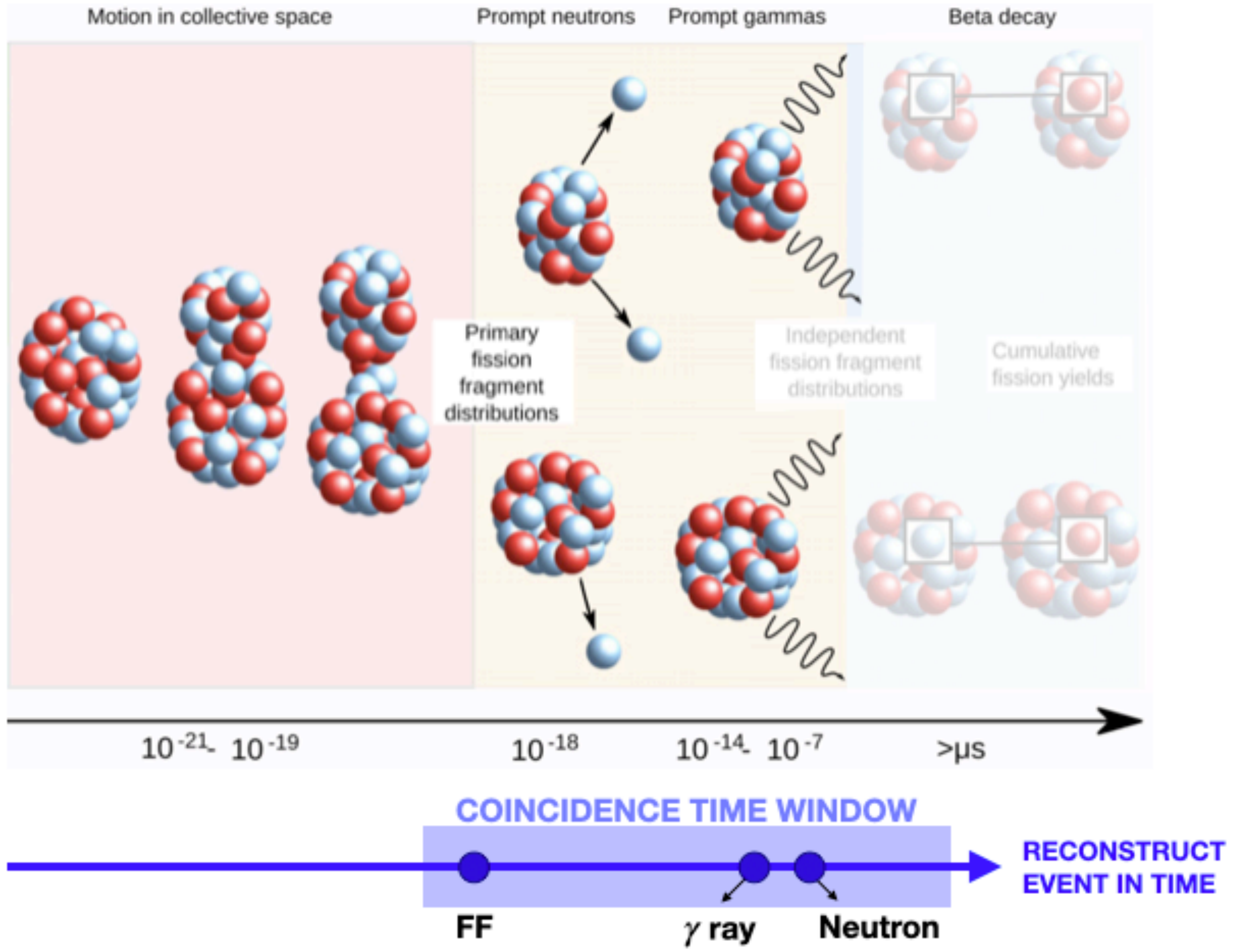
Model architecture:
Input layer with « Hit » measured values
One or two hidden layer (MLP / FCNN) with no more than 3 times the input size
Single output neuron with « is fission » or « is not fission » boolean classification

BACKUP SLIDES

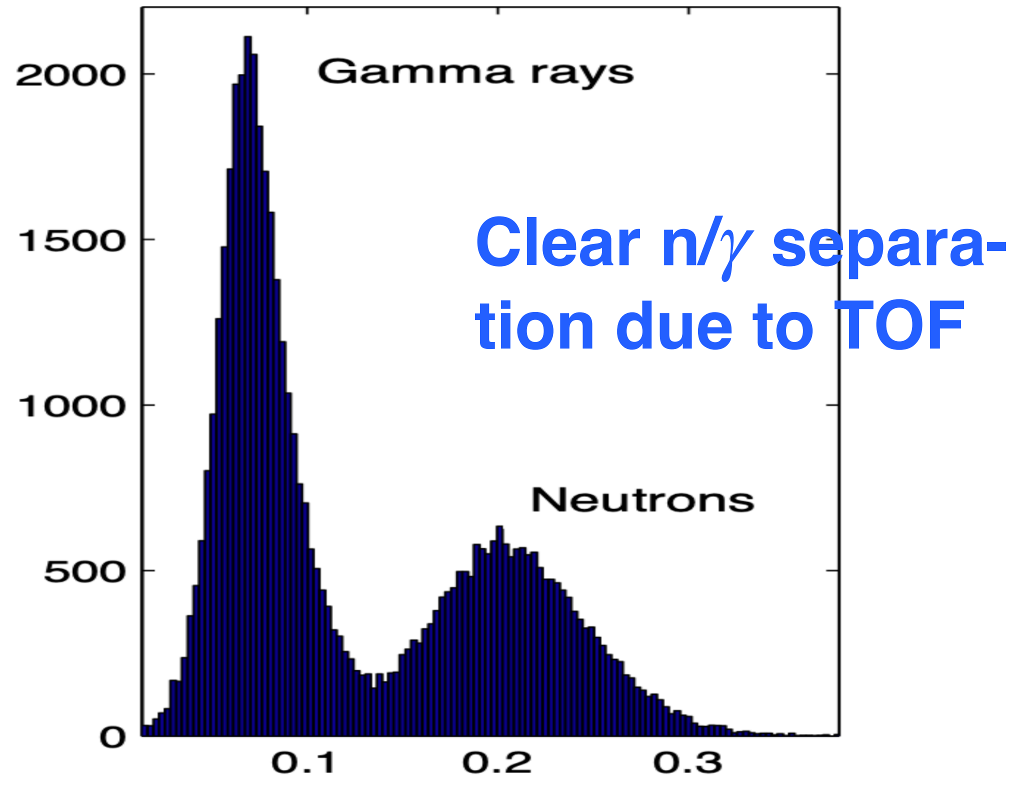
BACKUP SLIDES

BACKUP SLIDES

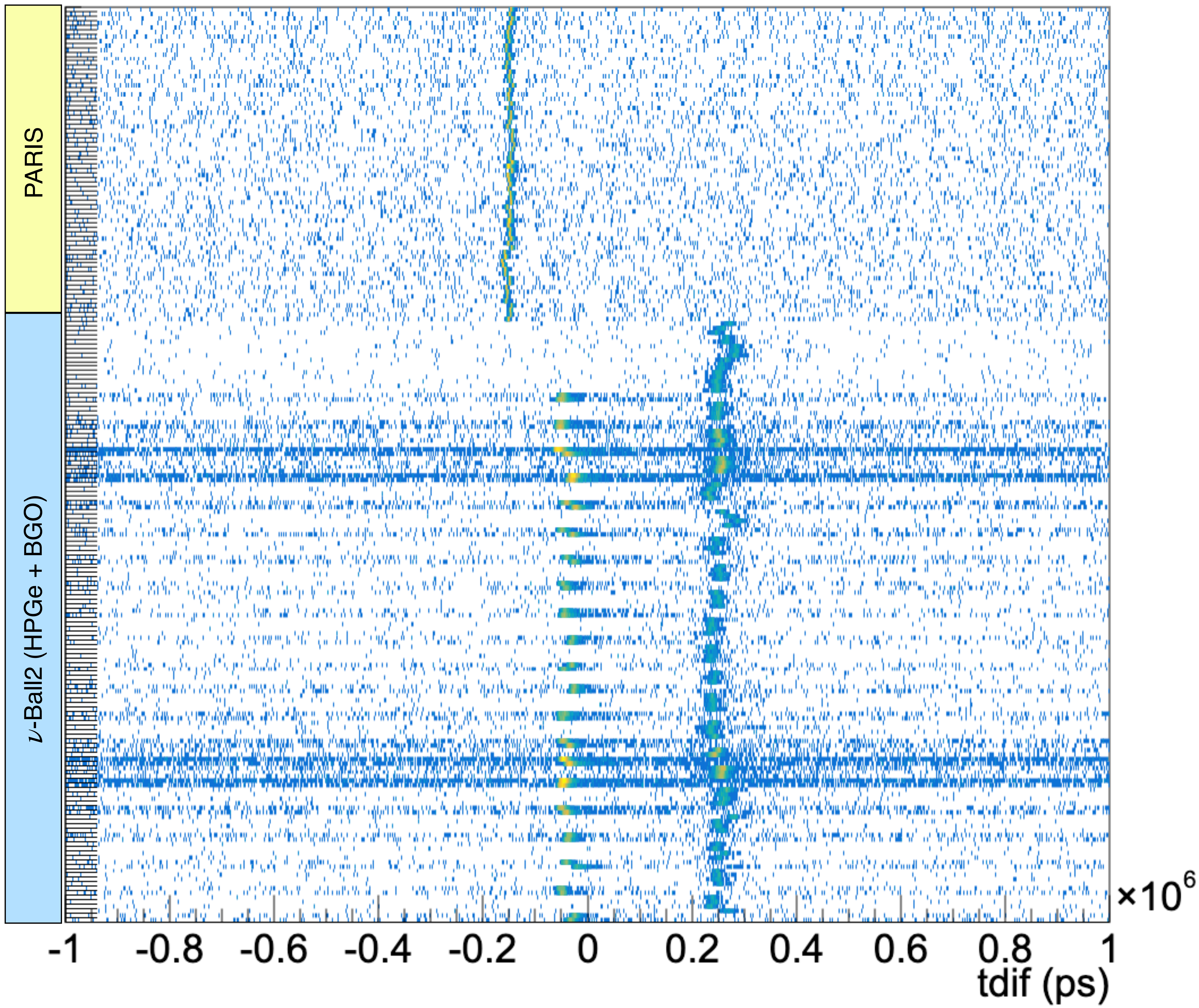
Event reconstruction



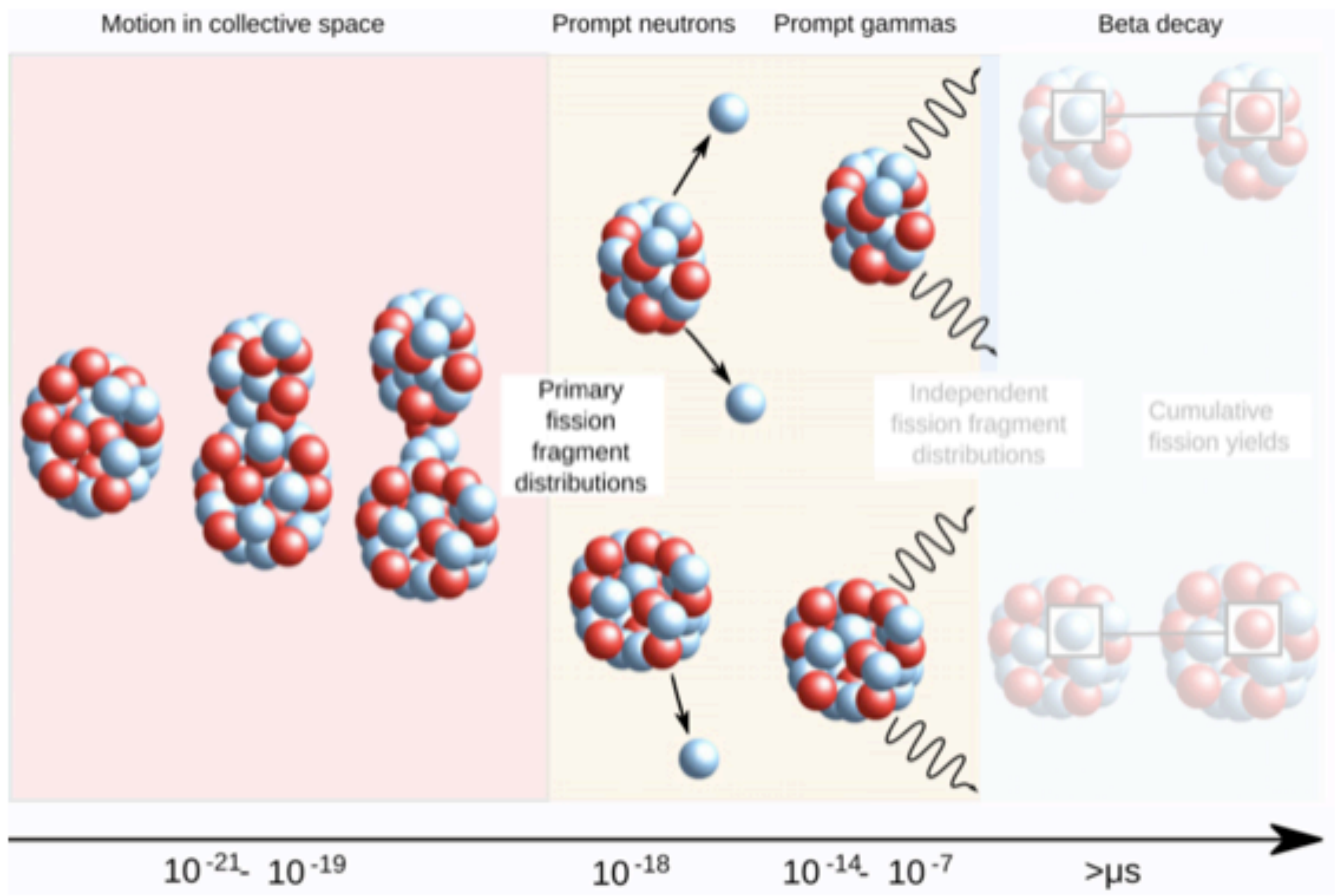
Time coincidence peak for LaBr3

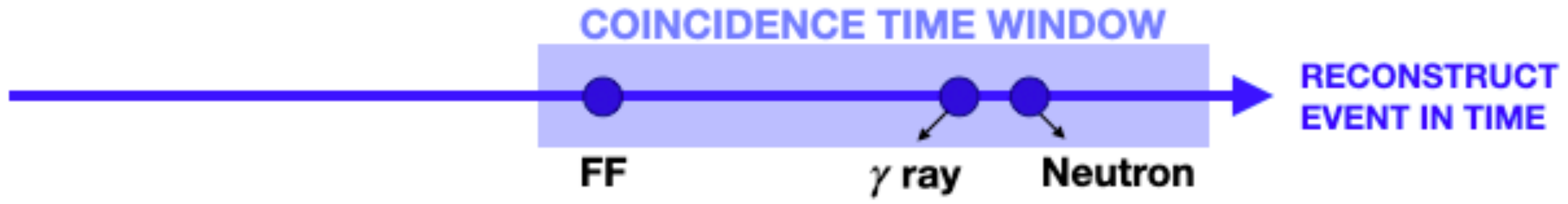


Align ν-Ball2 detectors in time using pure $LaBr_3$ as a reference.

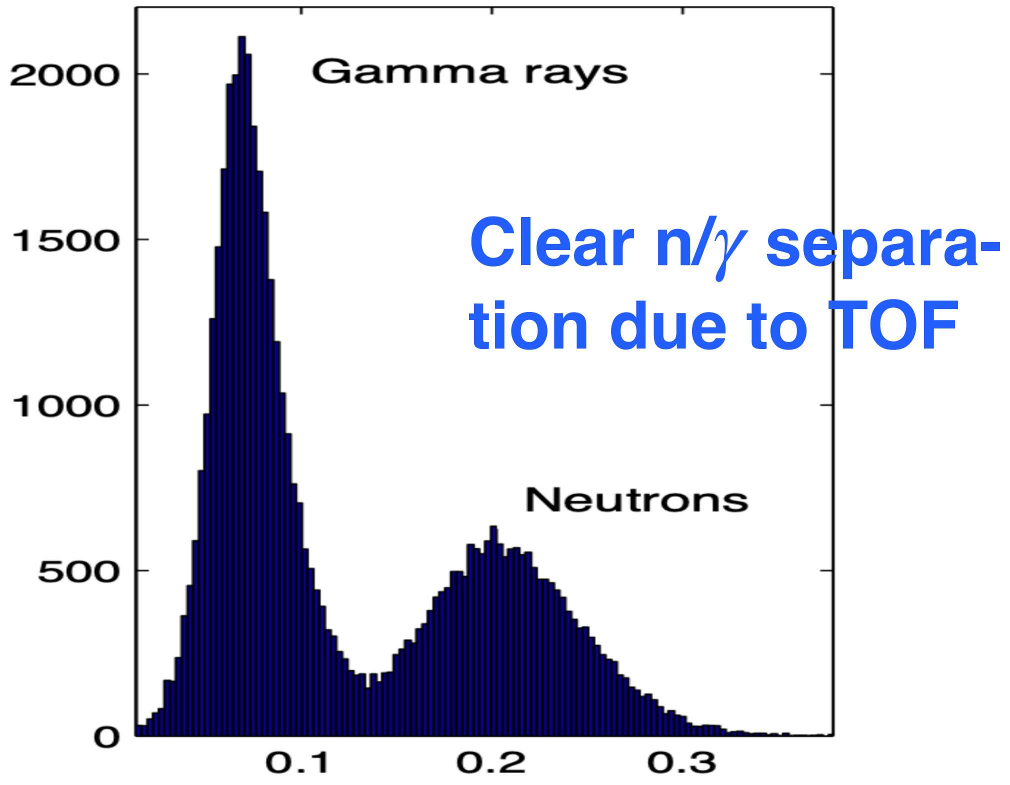


Event reconstruction





Time coincidence peak for LaBr3



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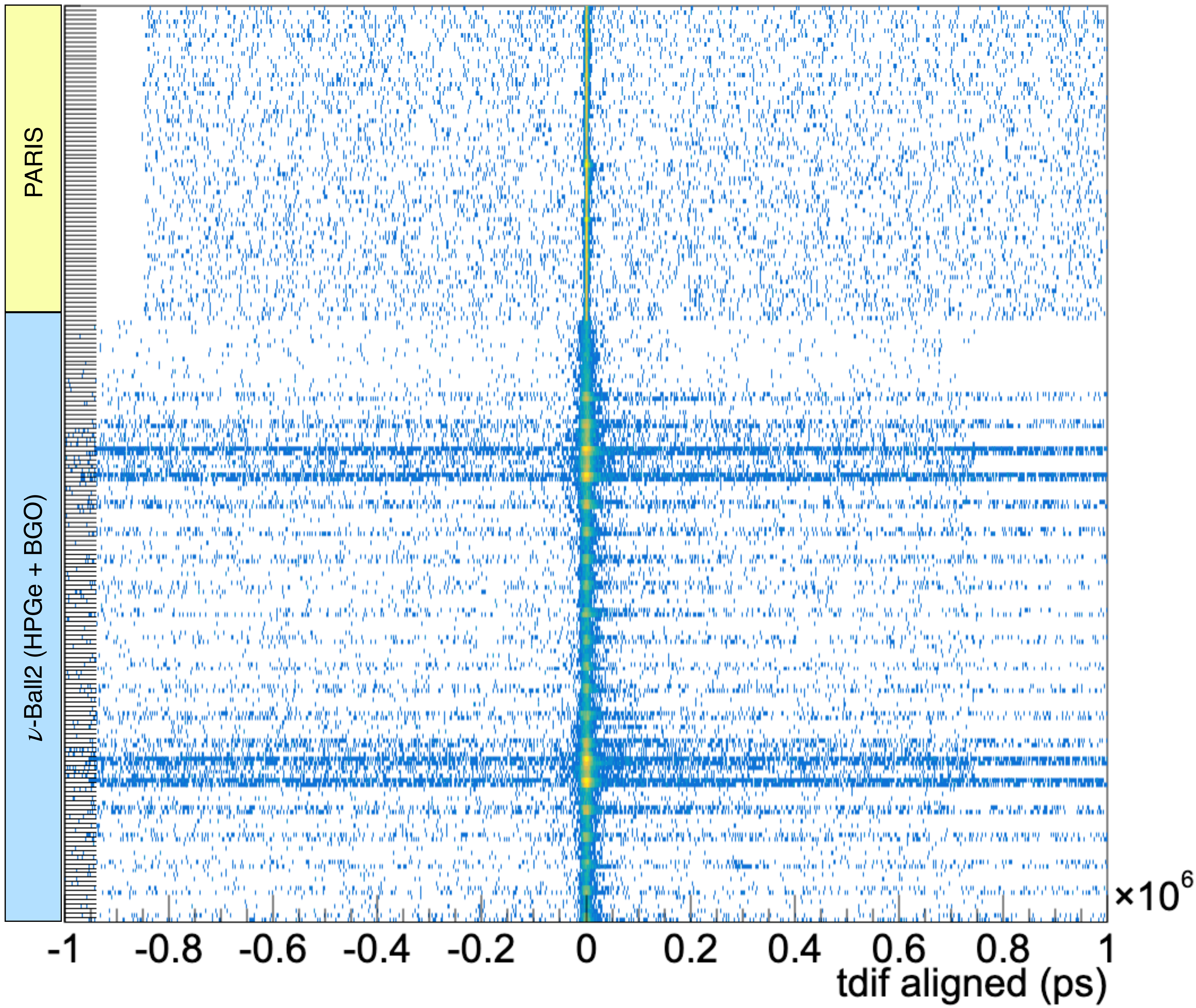
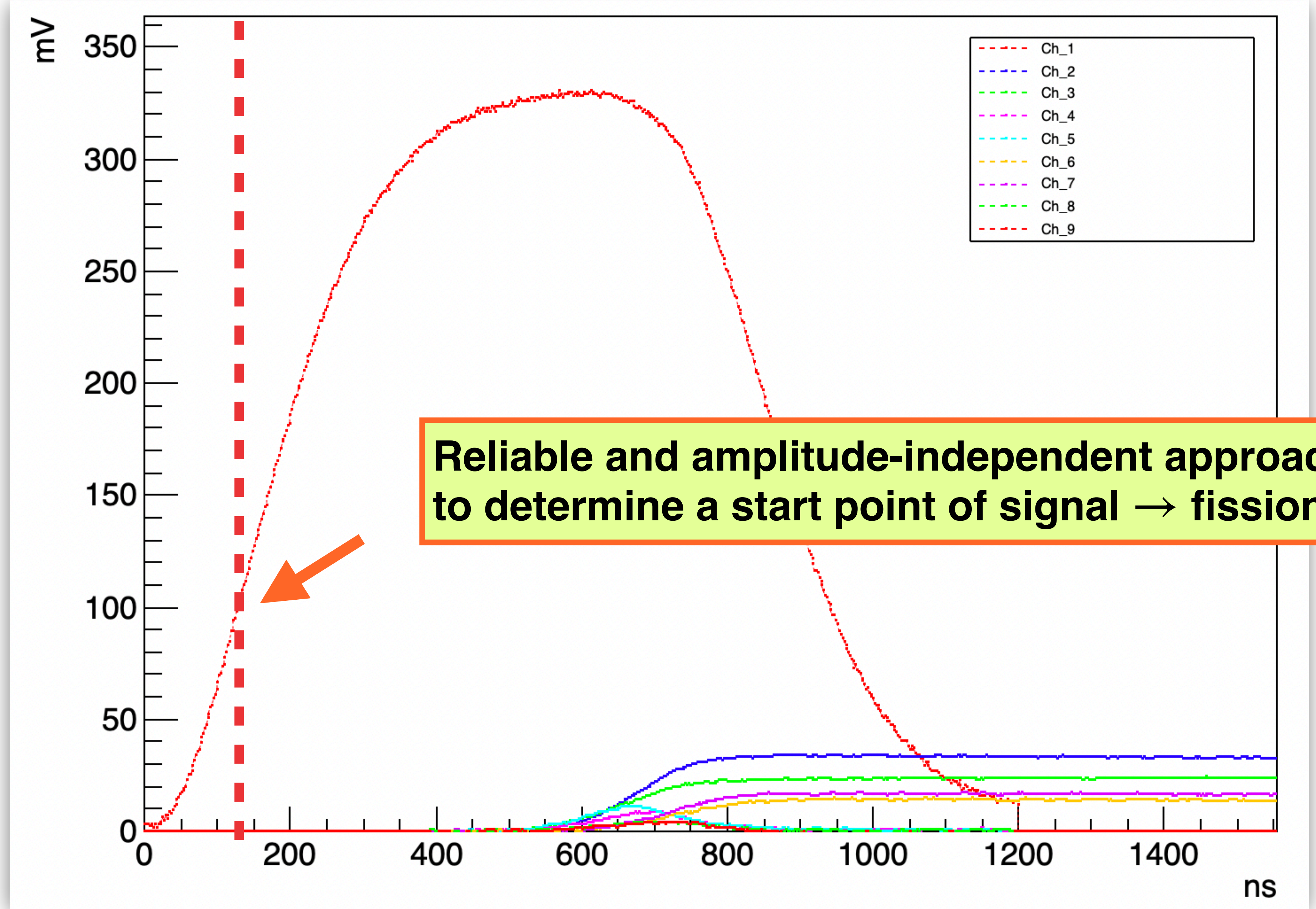


Constant Fraction Discrimination (CFD)

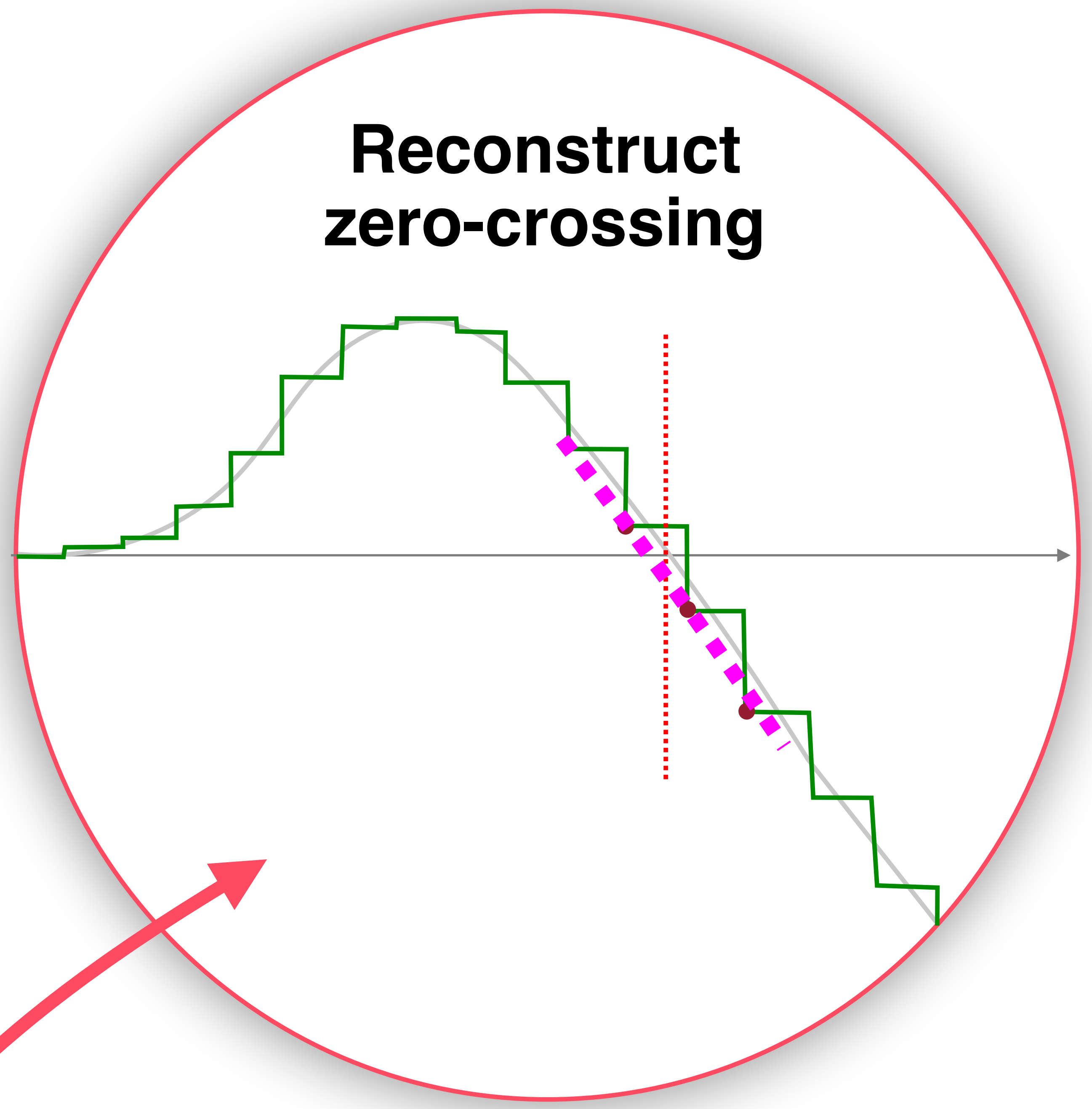


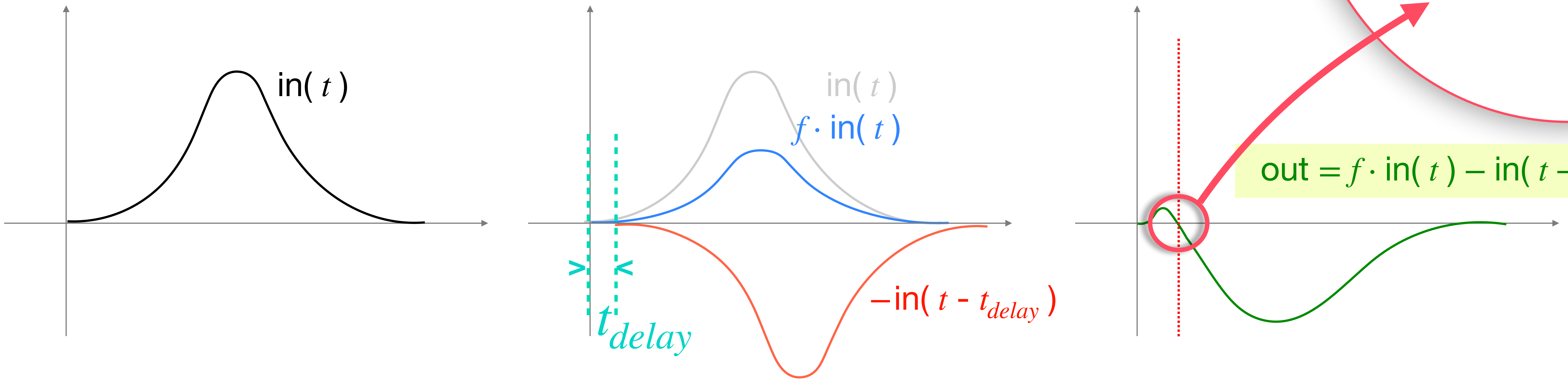
Reliable and amplitude-independent approach to determine a start point of signal → fission event

CFD CONSTRAINT:

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

where t_r is the signal rise time

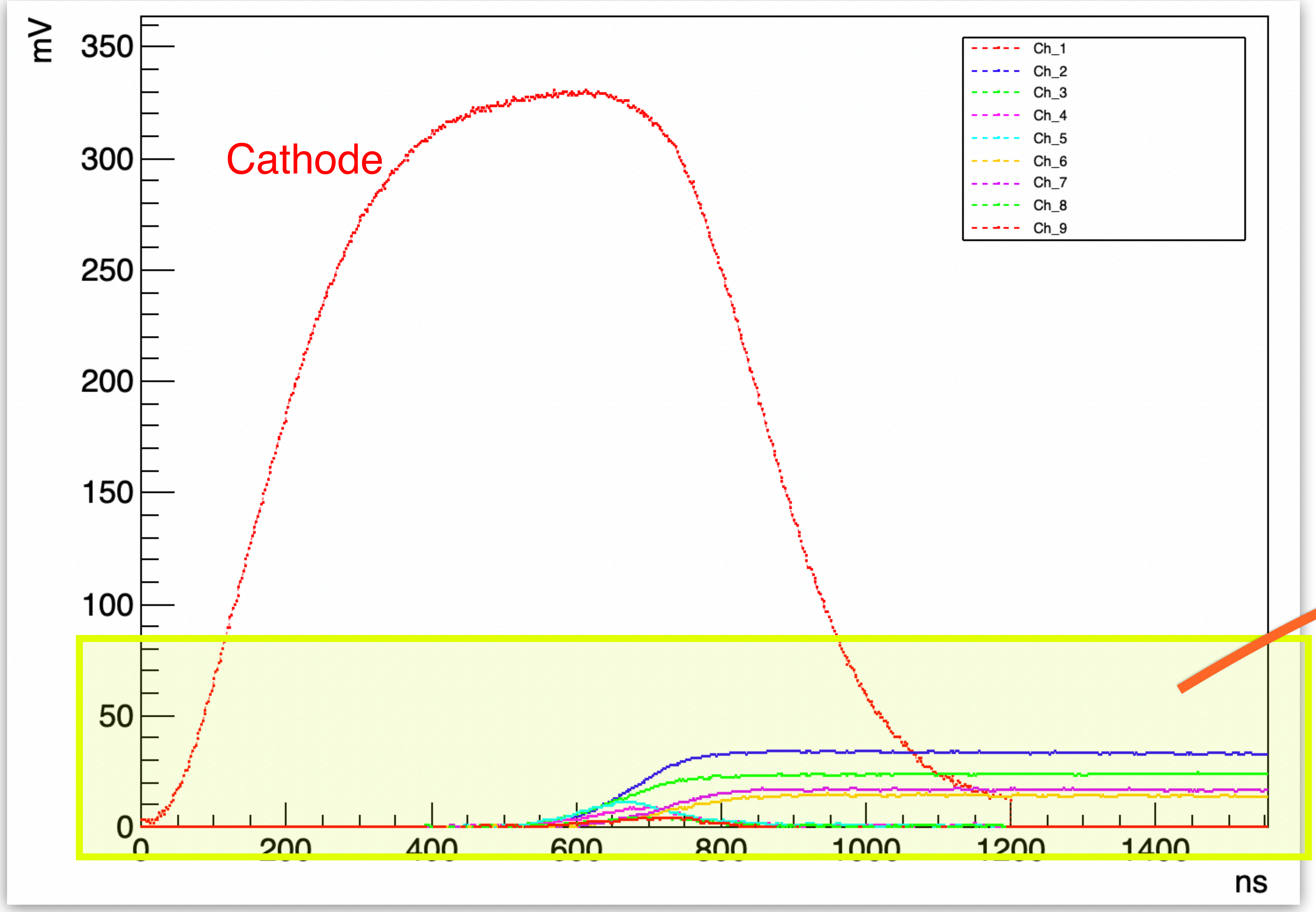


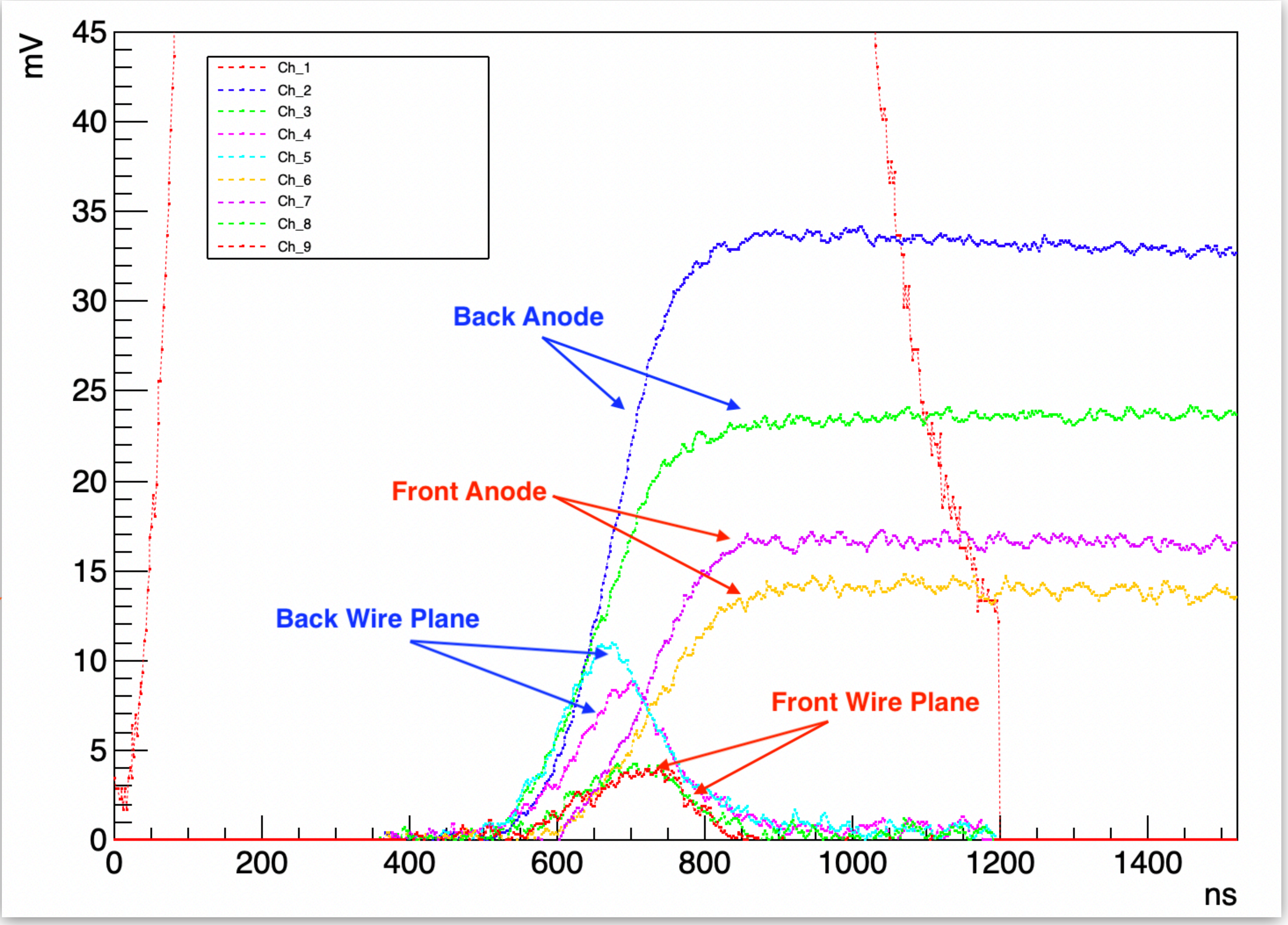


$\text{out} = f \cdot \text{in}(t) - \text{in}(t - t_{delay})$

Double Frisch-Grid Ionisation Chamber (dFGIC)

Ionisation chamber signals sampled every 2ns





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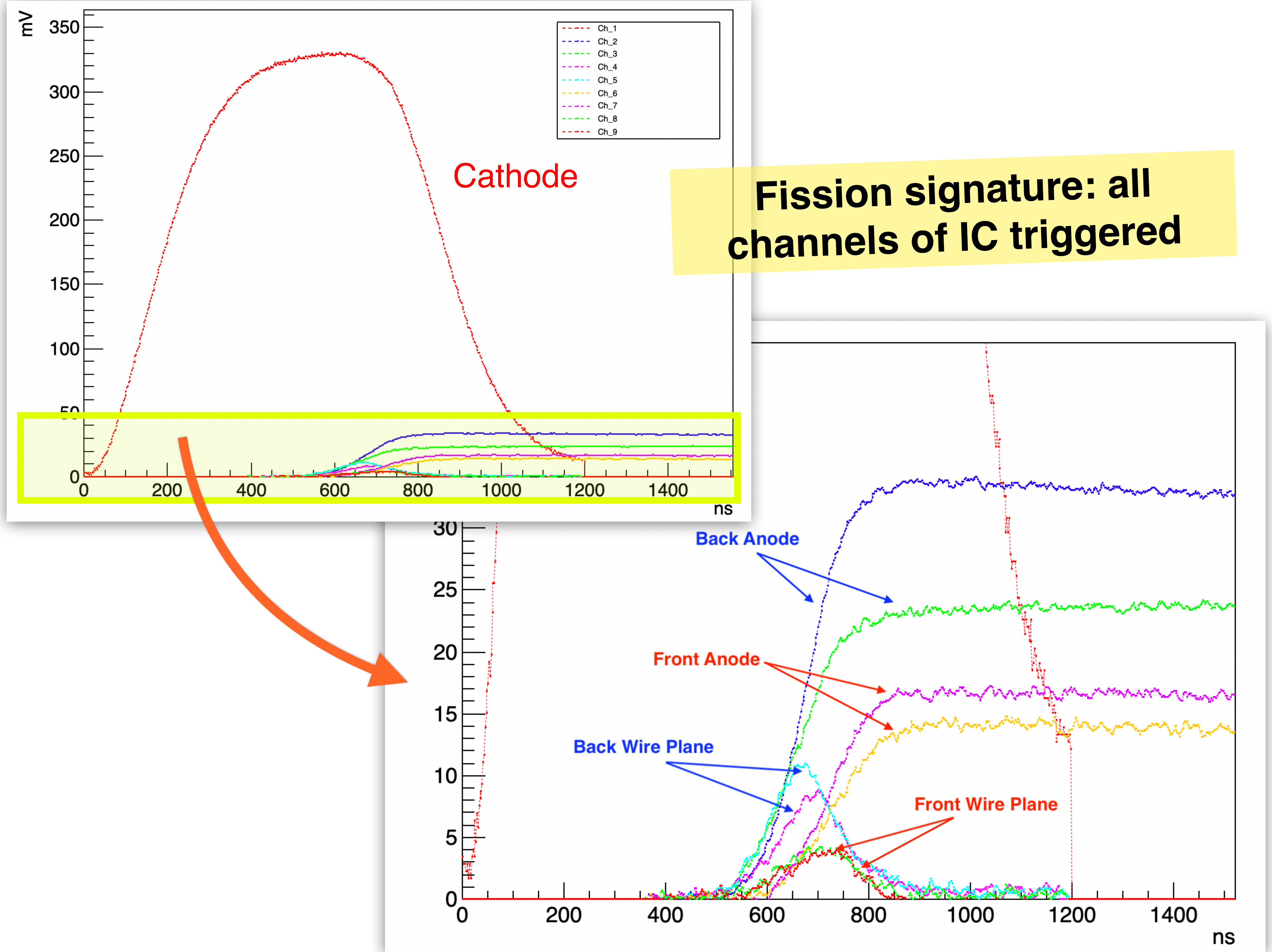
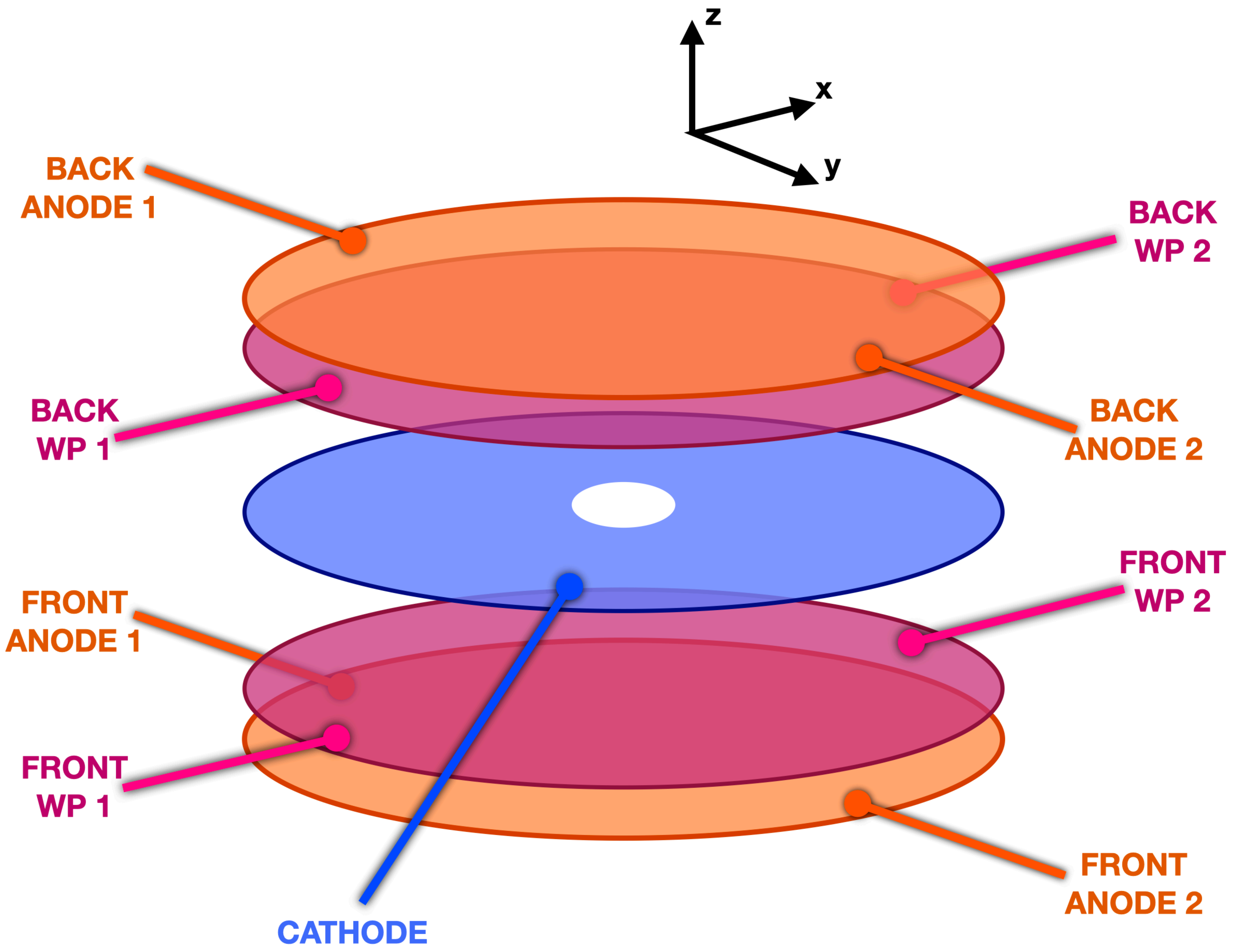


Fission signature: all channels of IC triggered



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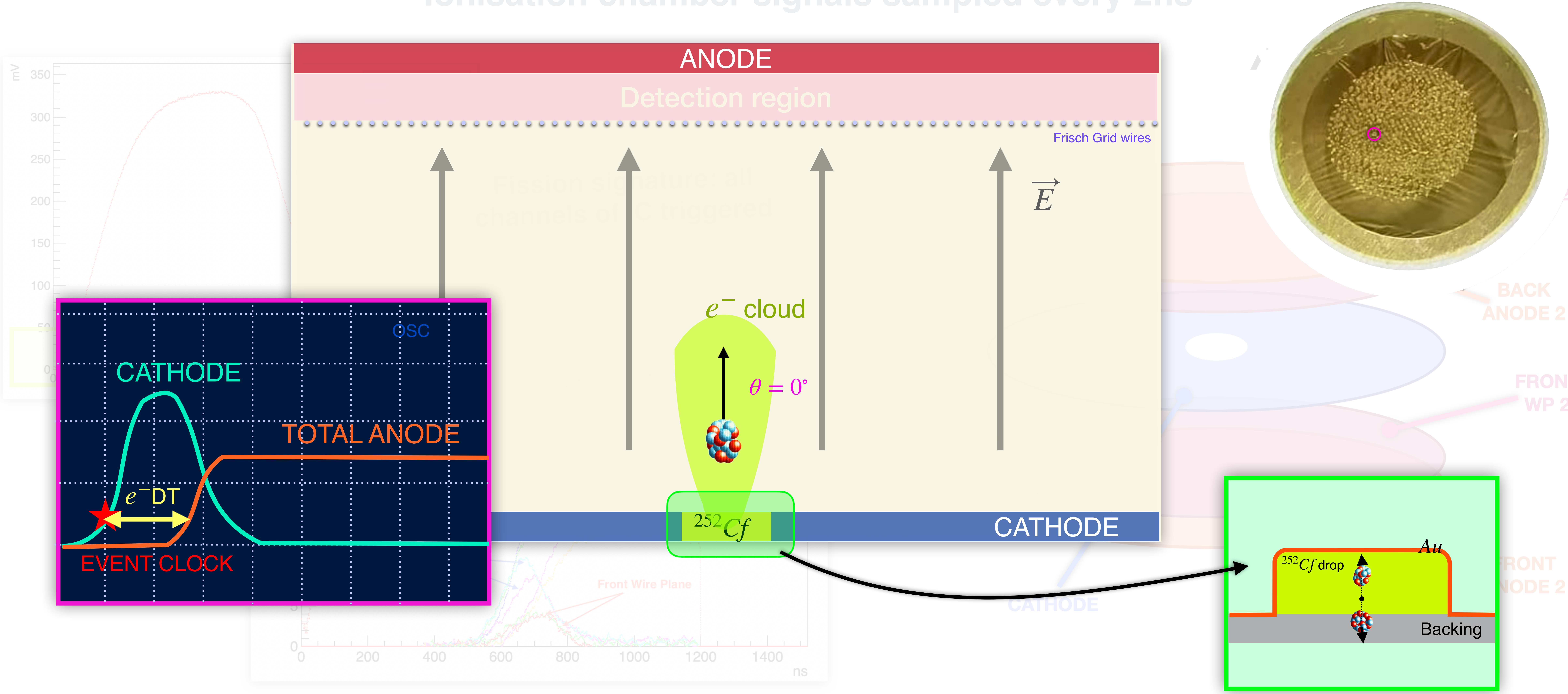

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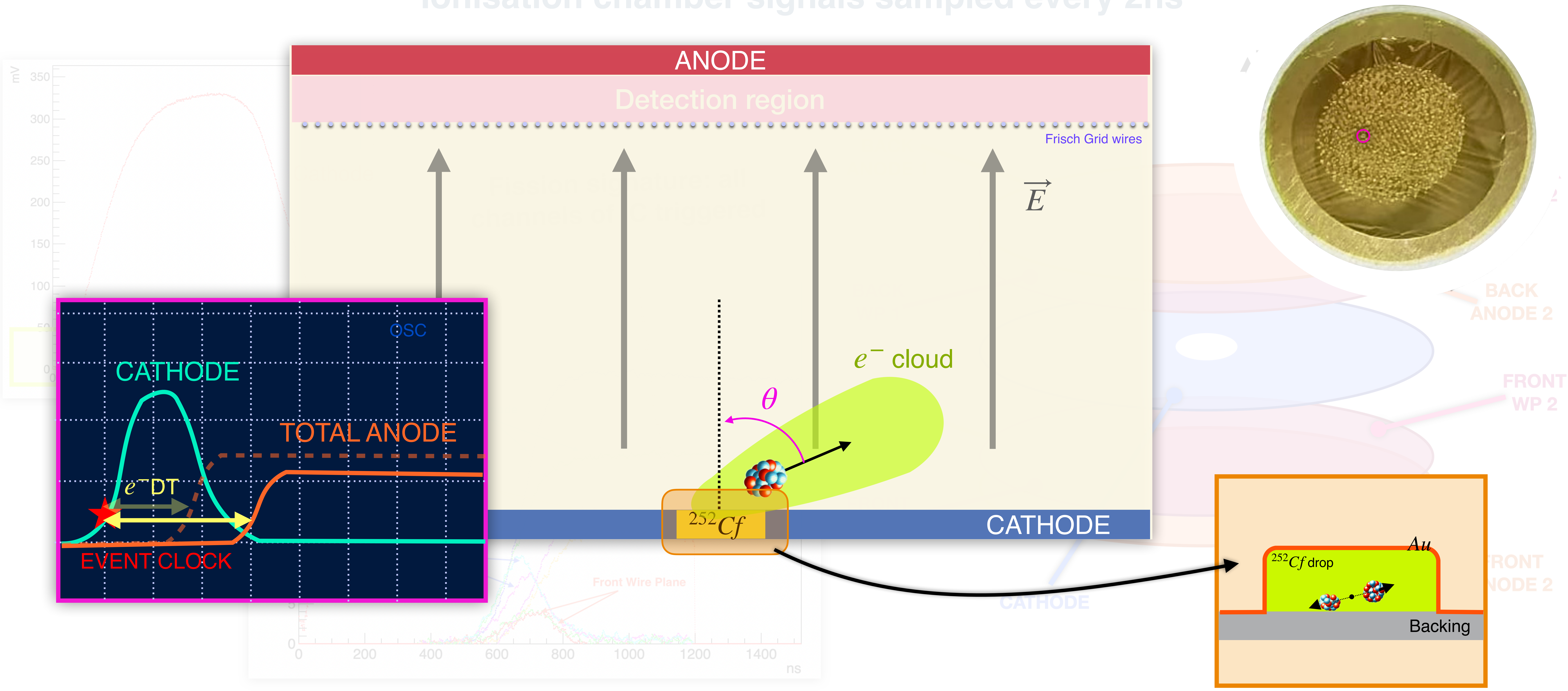

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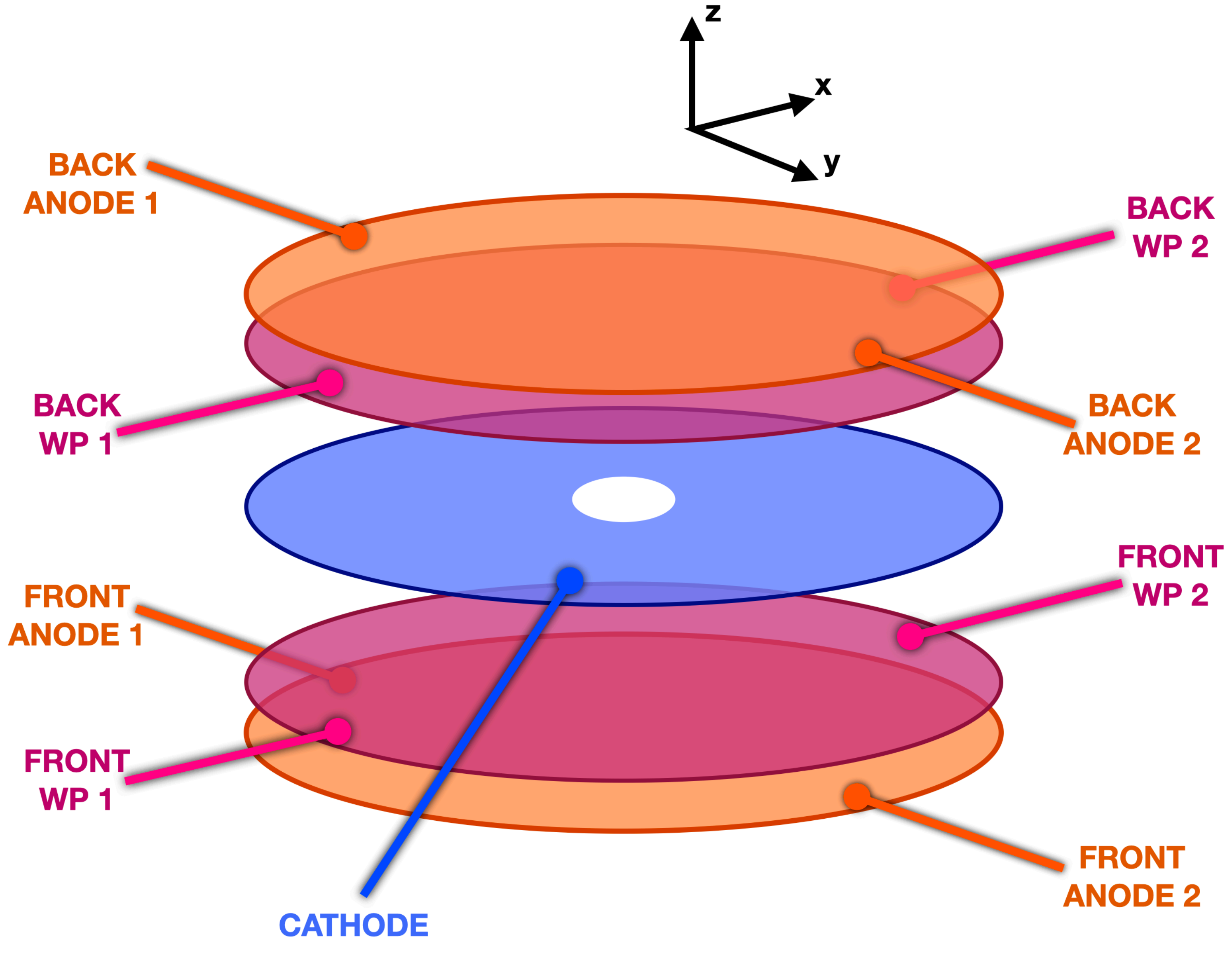
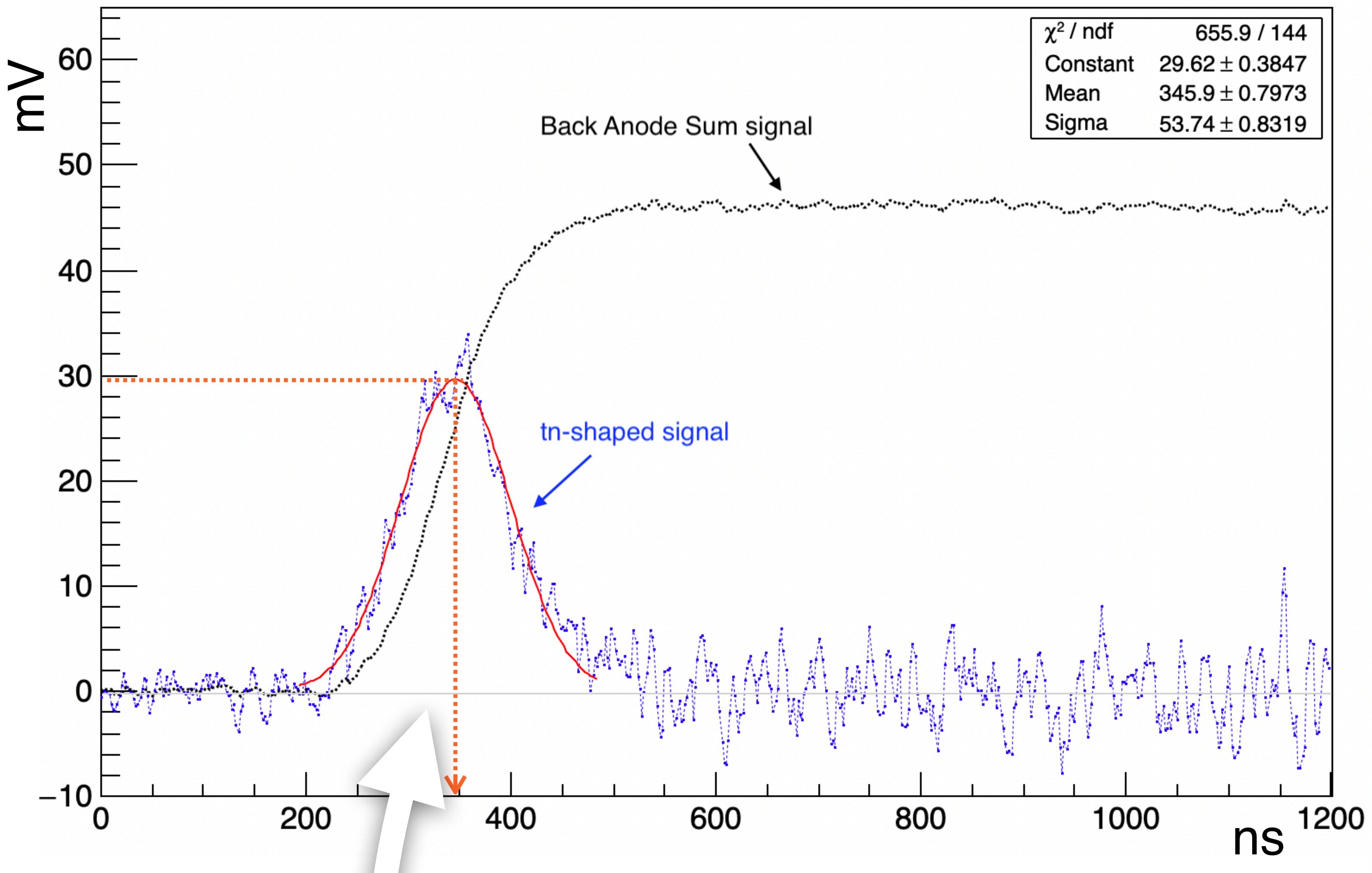


$$\bar{x} = k_x \frac{P_1 - P_2}{P_1 + P_2}, \quad \bar{y} = k_y \frac{A_1 - A_2}{A_1 + A_2}$$



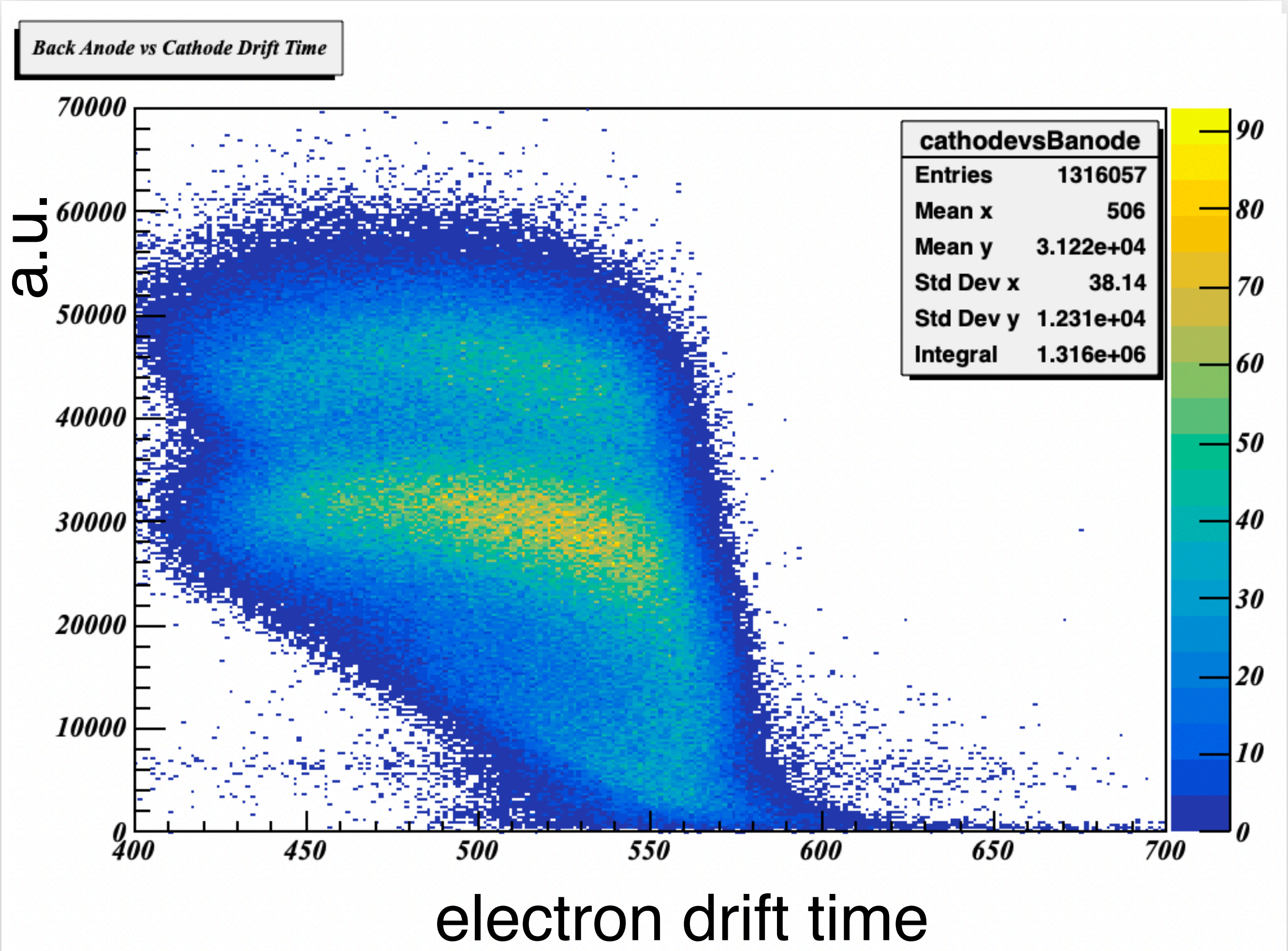
$$\bar{z} = v_d \cdot (\bar{t}_{(0^\circ,0^\circ)} - \bar{t}_{(\theta_x^\circ,\theta_y^\circ)})$$

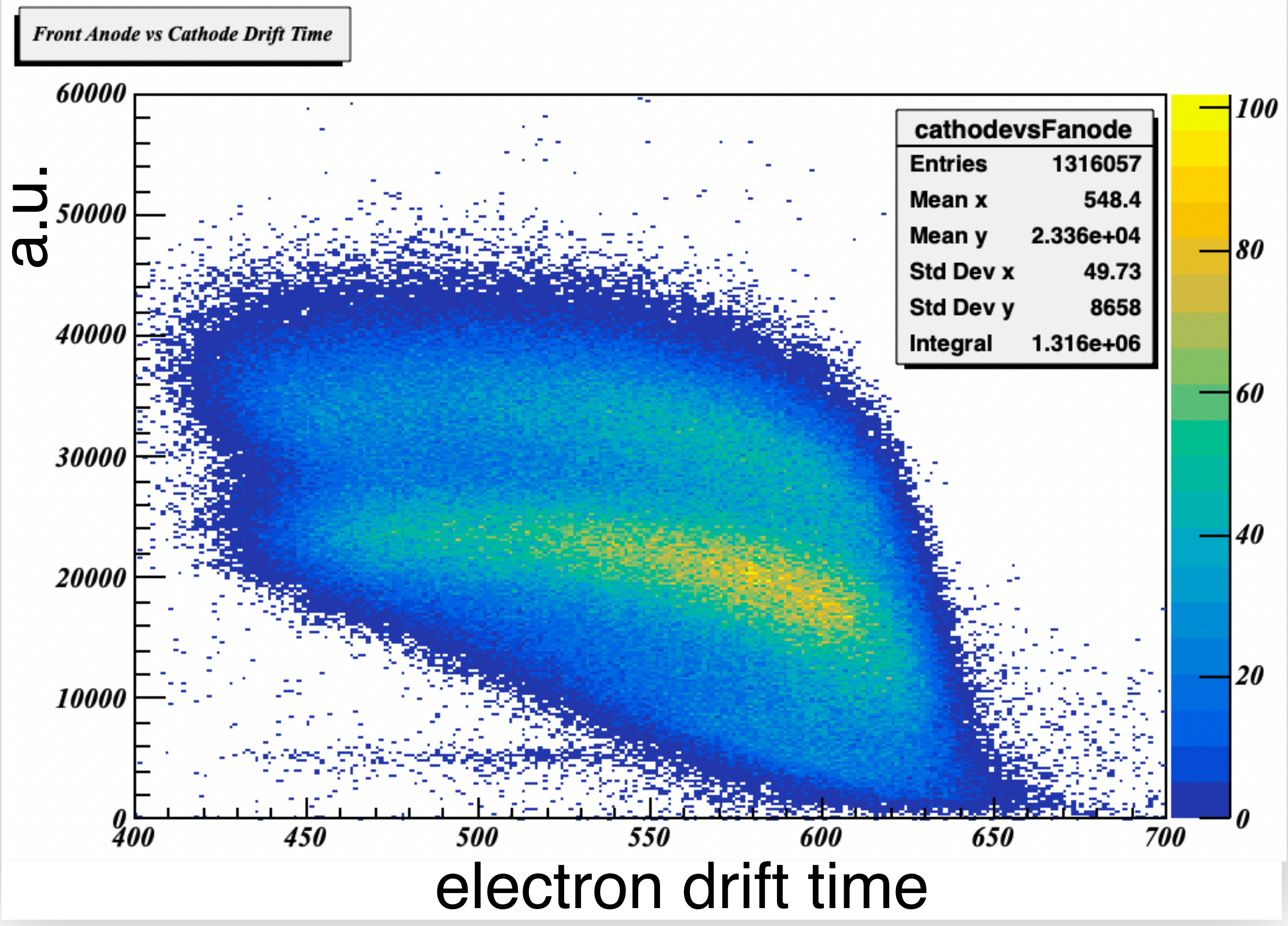
average electron drift time

Electron drift velocity

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

Energy vs. Electron drift time





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.

Waveform analysis through most frequently used methods

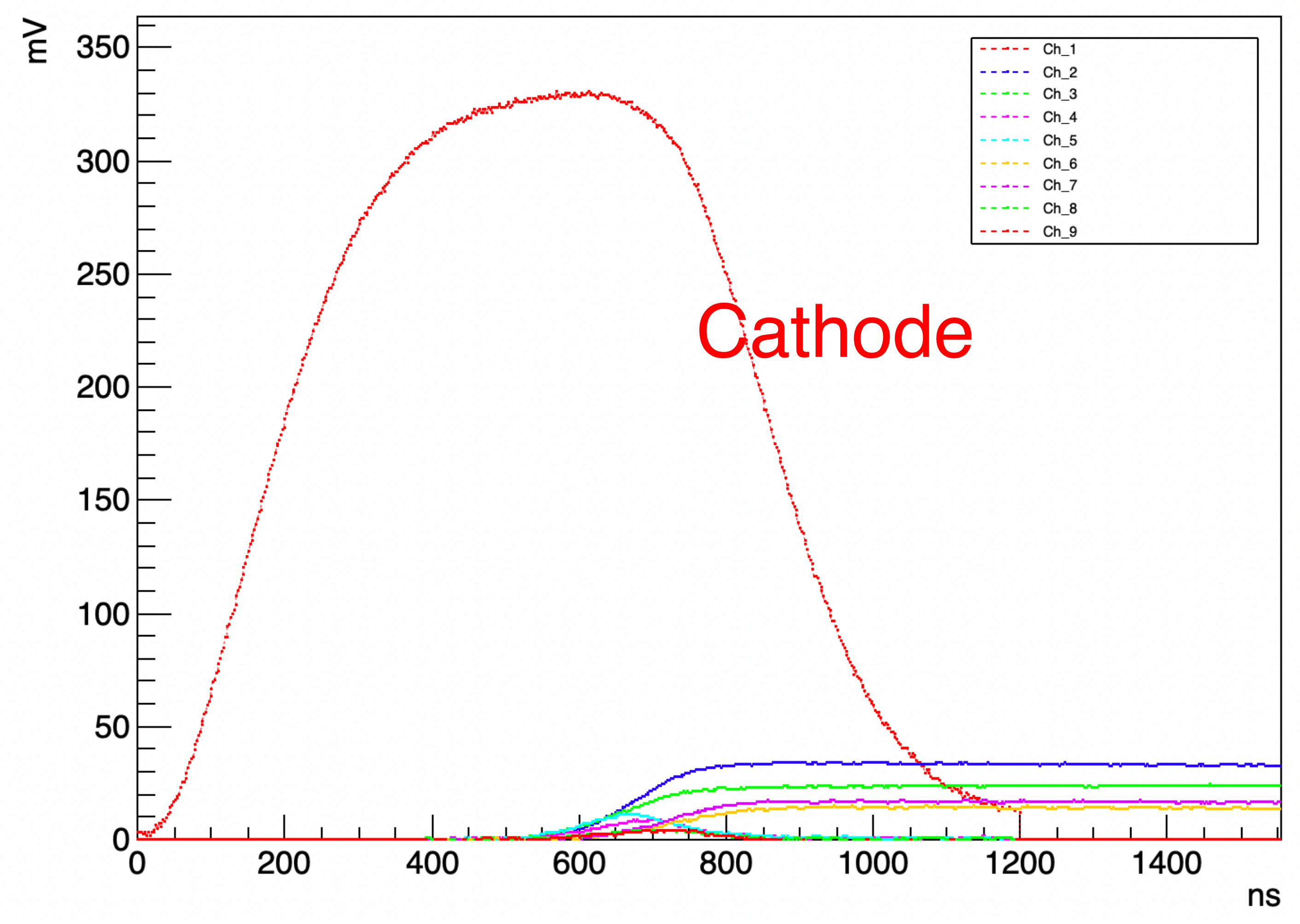
- Moving average algorithm;
- RC filter;
- Signal baseline correction;

→ 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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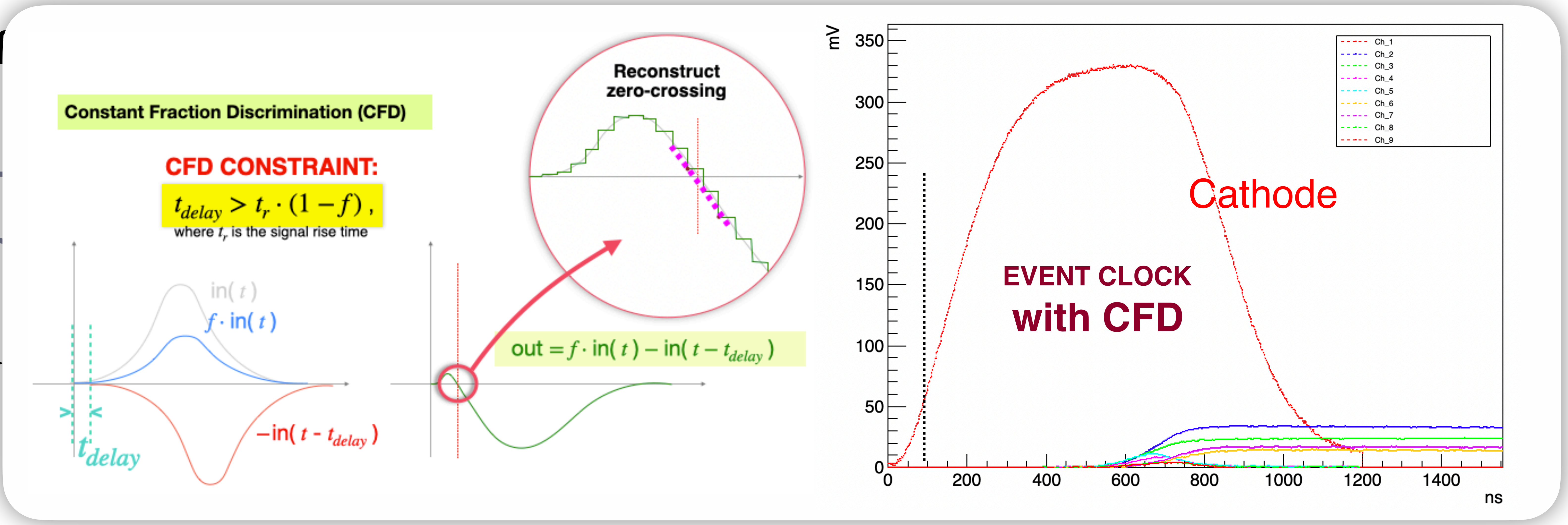
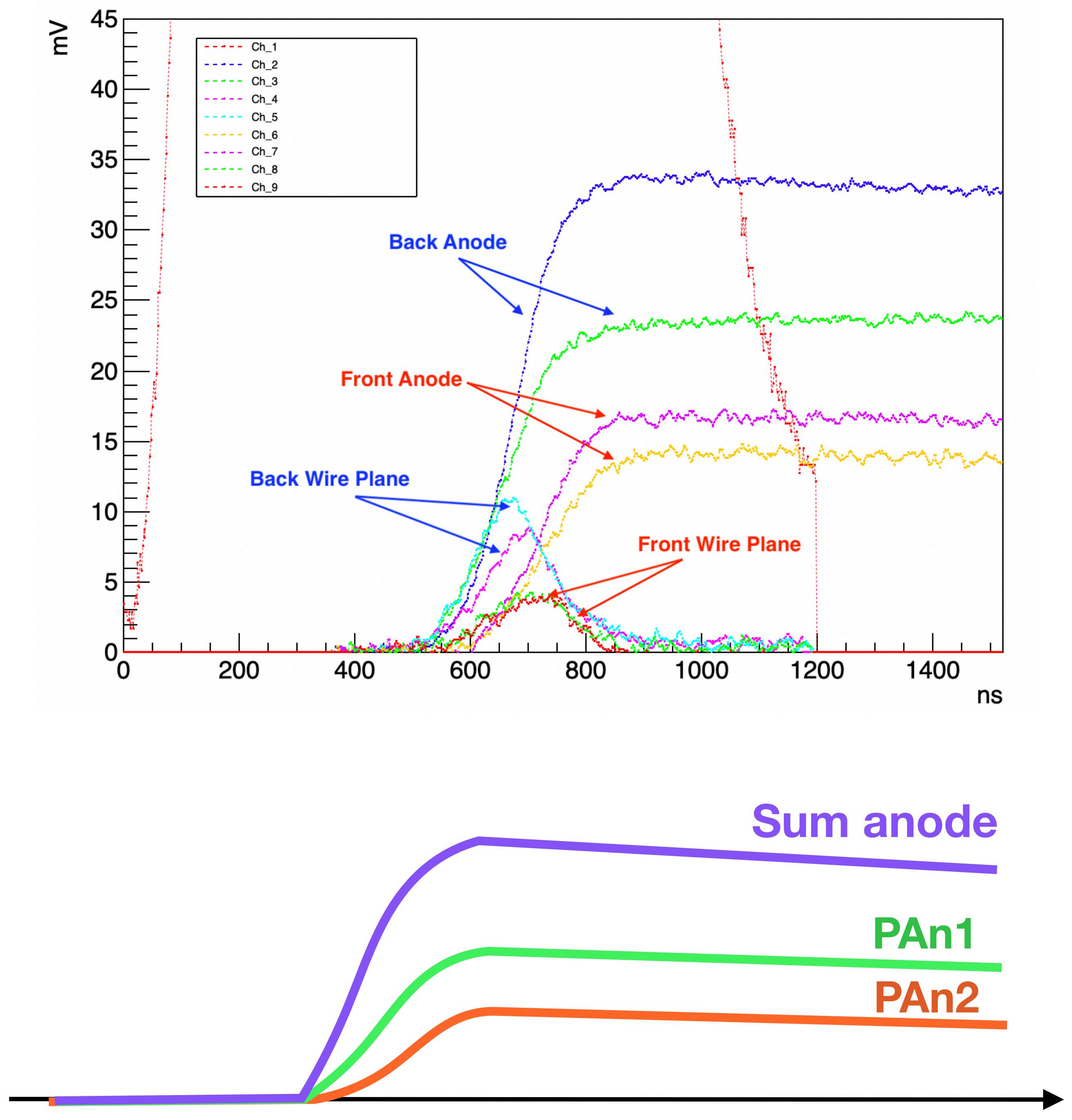
BOTH T
MEASU



Waveform analysis

Waveform analysis through most frequently used methods

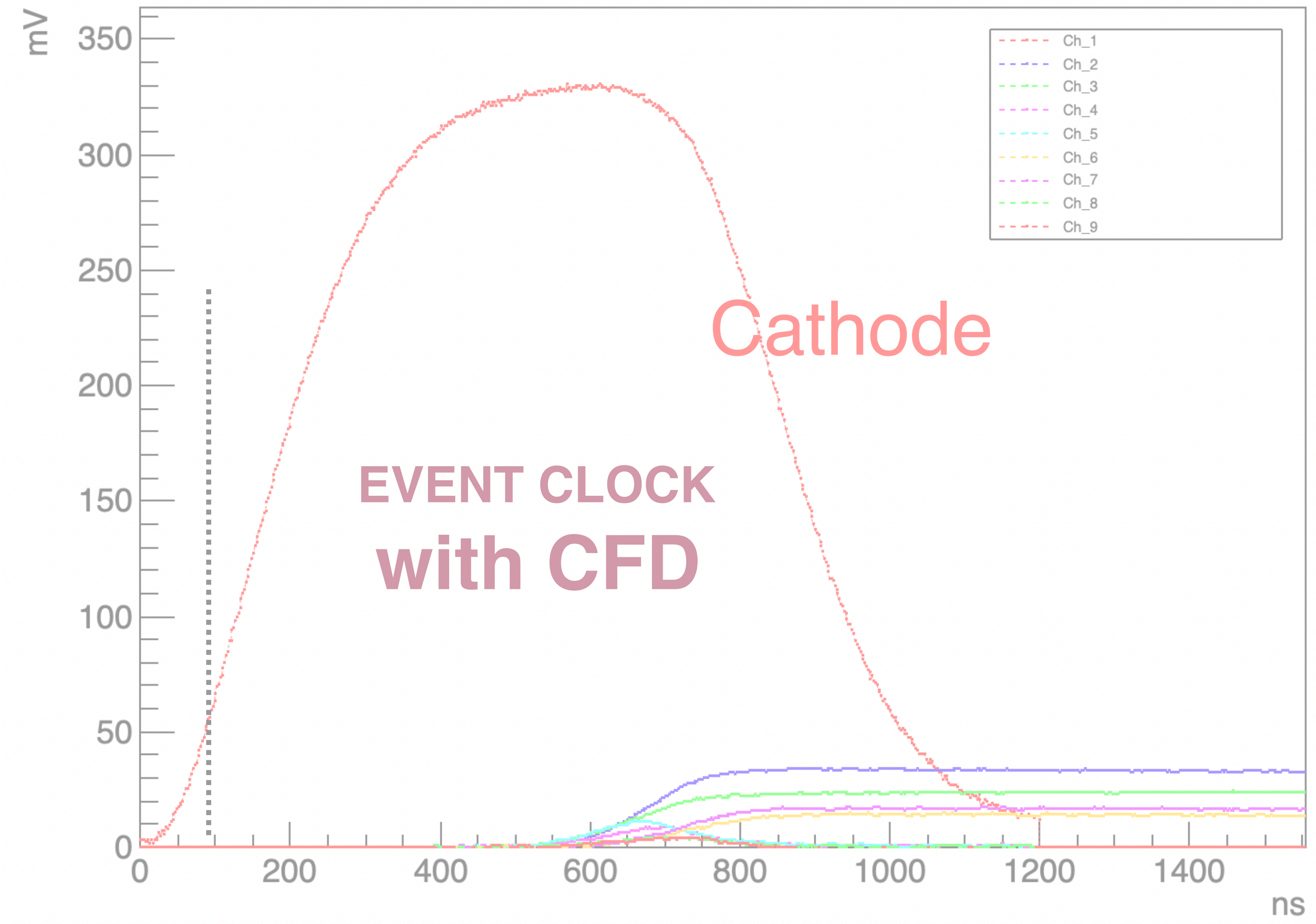


- Perform CFD in all anode signals
- Select first anode signal output for each side as reference. Align and sum samples for both sides

I TIME AND « ENERGY
SUREMENTS

« ENERGY » MEASUREMENTS

TIME MEASUREMENTS



Waveform analysis

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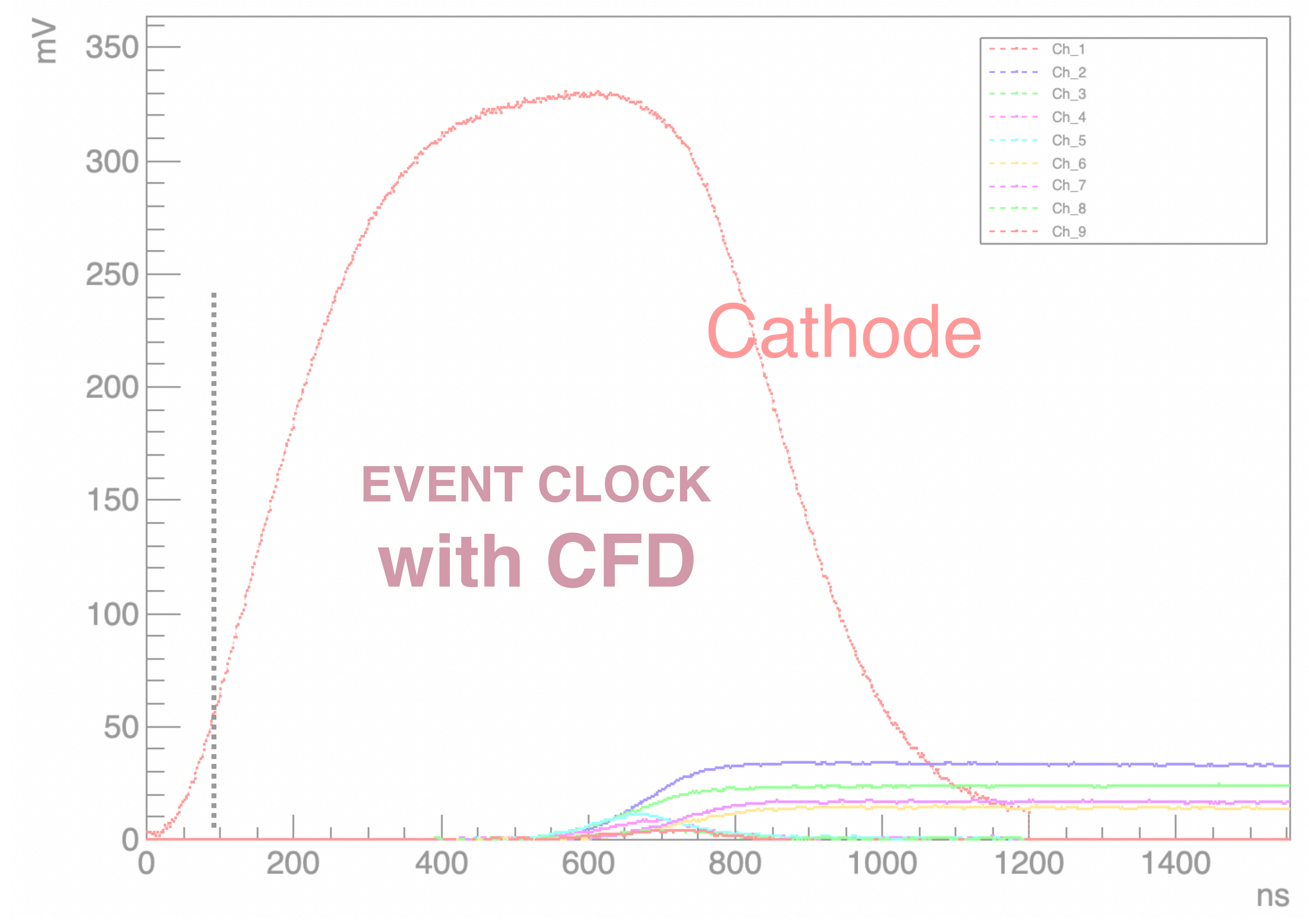
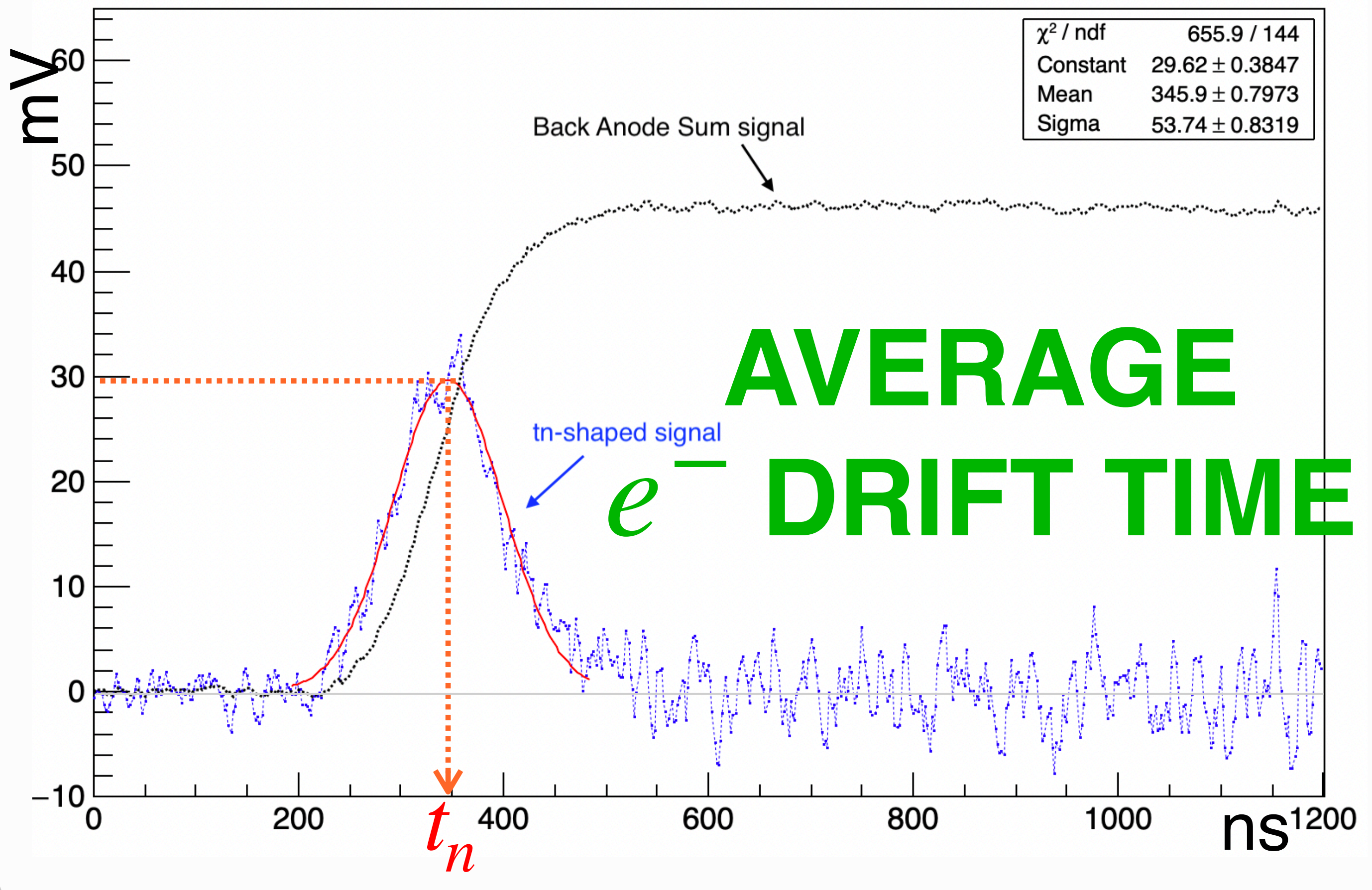
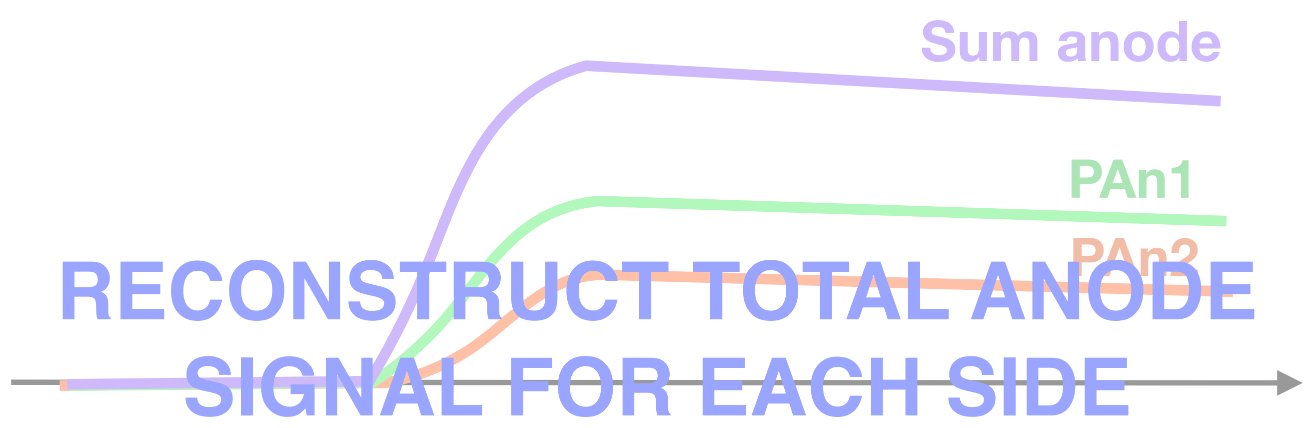


$$t_n = \frac{1}{Q_{max}} \cdot \sum_{k=k_0}^{k_0+n} (q_{k+1} - q_k)(k - k_0) \cdot \frac{1}{f_s}$$

e.g. Waveform analysis for average electron drift time calculation:



RECONSTRUCT TOTAL ANODE SIGNAL FOR EACH SIDE



- Perform CFD in all anode signals
- Select first anode signal output for each side as reference. Align and sum samples for both sides

Waveform analysis

Waveform analysis through most frequently used methods

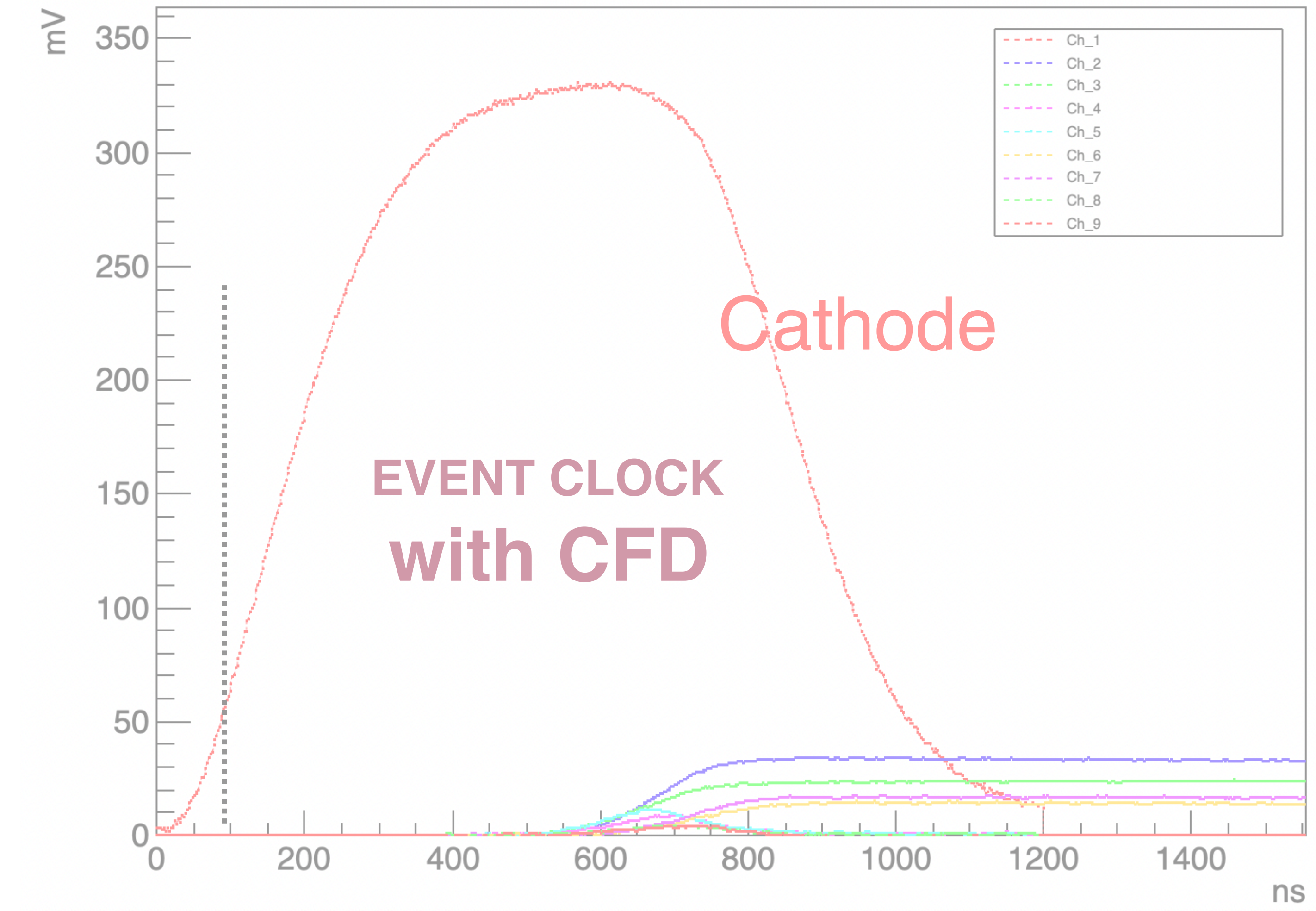
- Moving average algorithm;
- RC filter;
- Signal baseline correction;

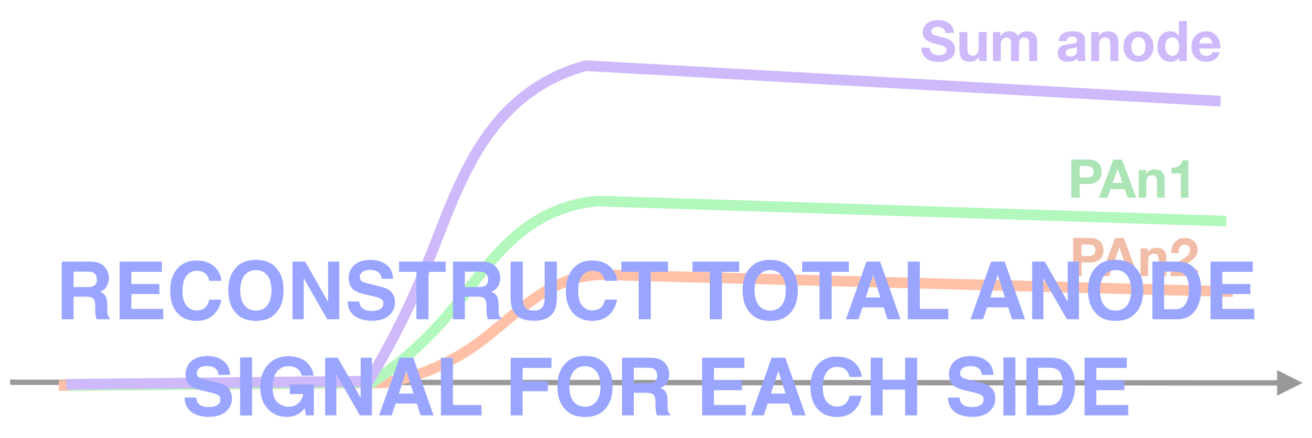
→ **BOTH TIME AND « ENERGY MEASUREMENTS**

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

→ **« ENERGY » MEASUREMENTS**

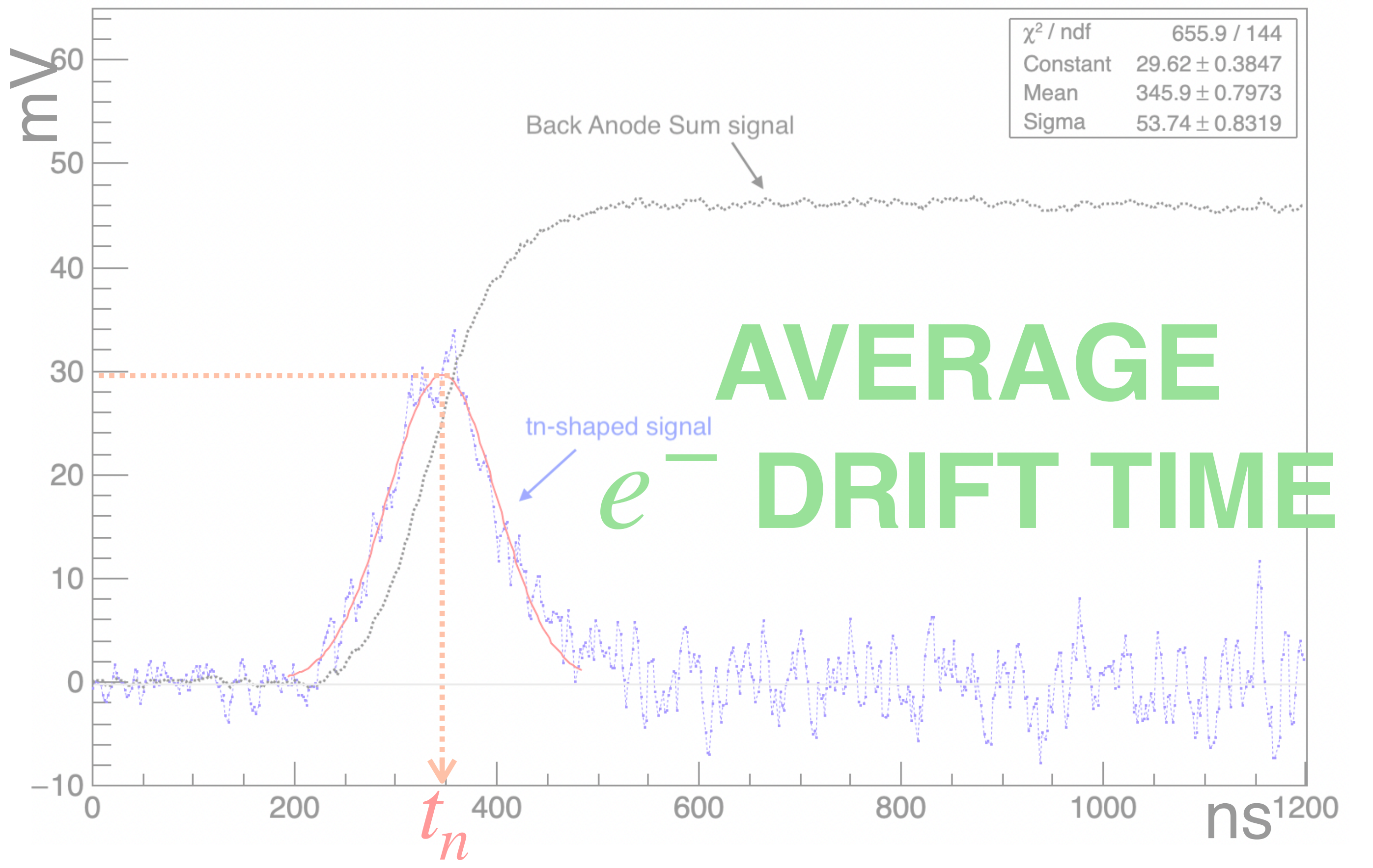
- Constant Fraction Discrimination (CFD) **TIME MEASUREMENTS**

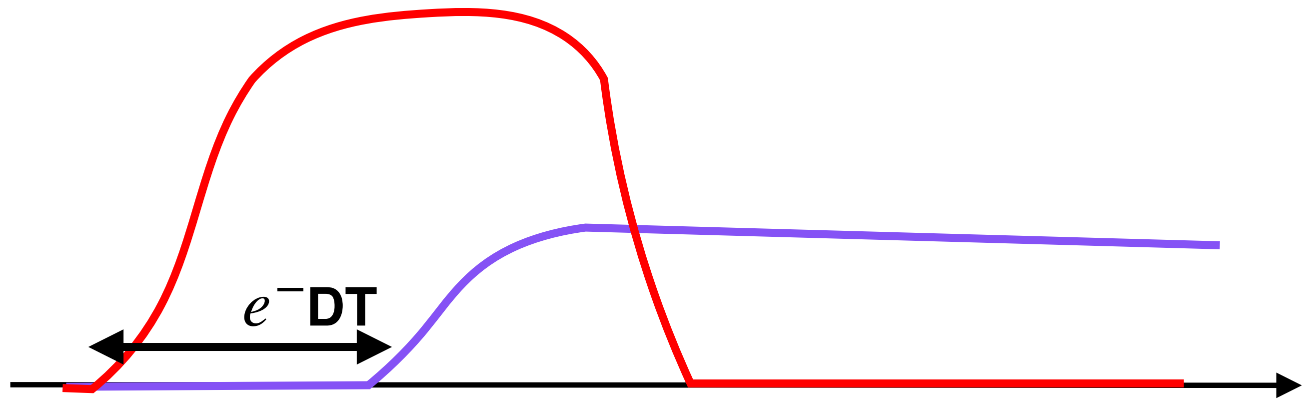




- Perform CFD in all anode signals
- Select first anode signal output for each side as reference. Align and sum samples for both sides

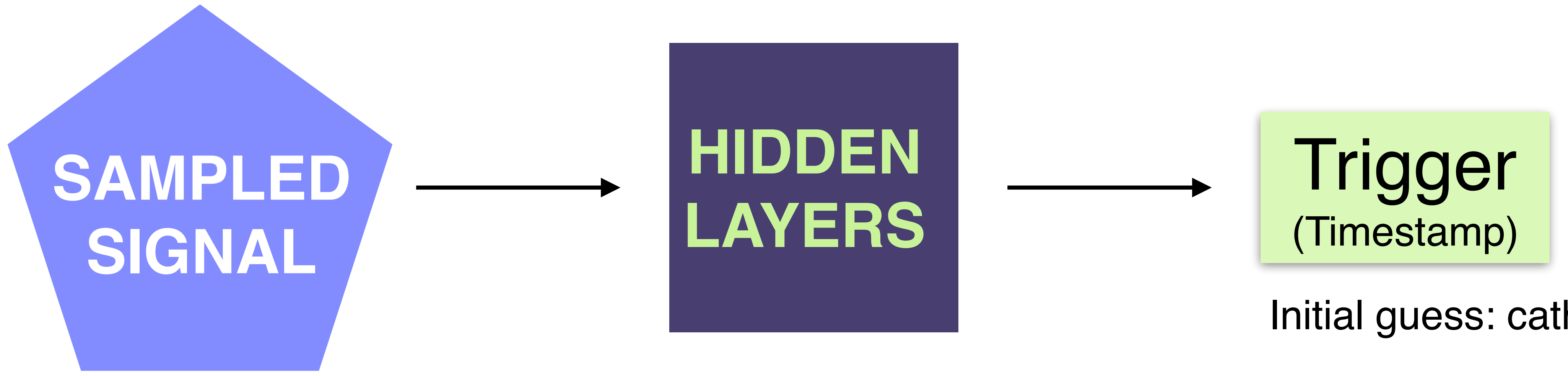
e.g. Waveform analysis for average electron drift time calculation:



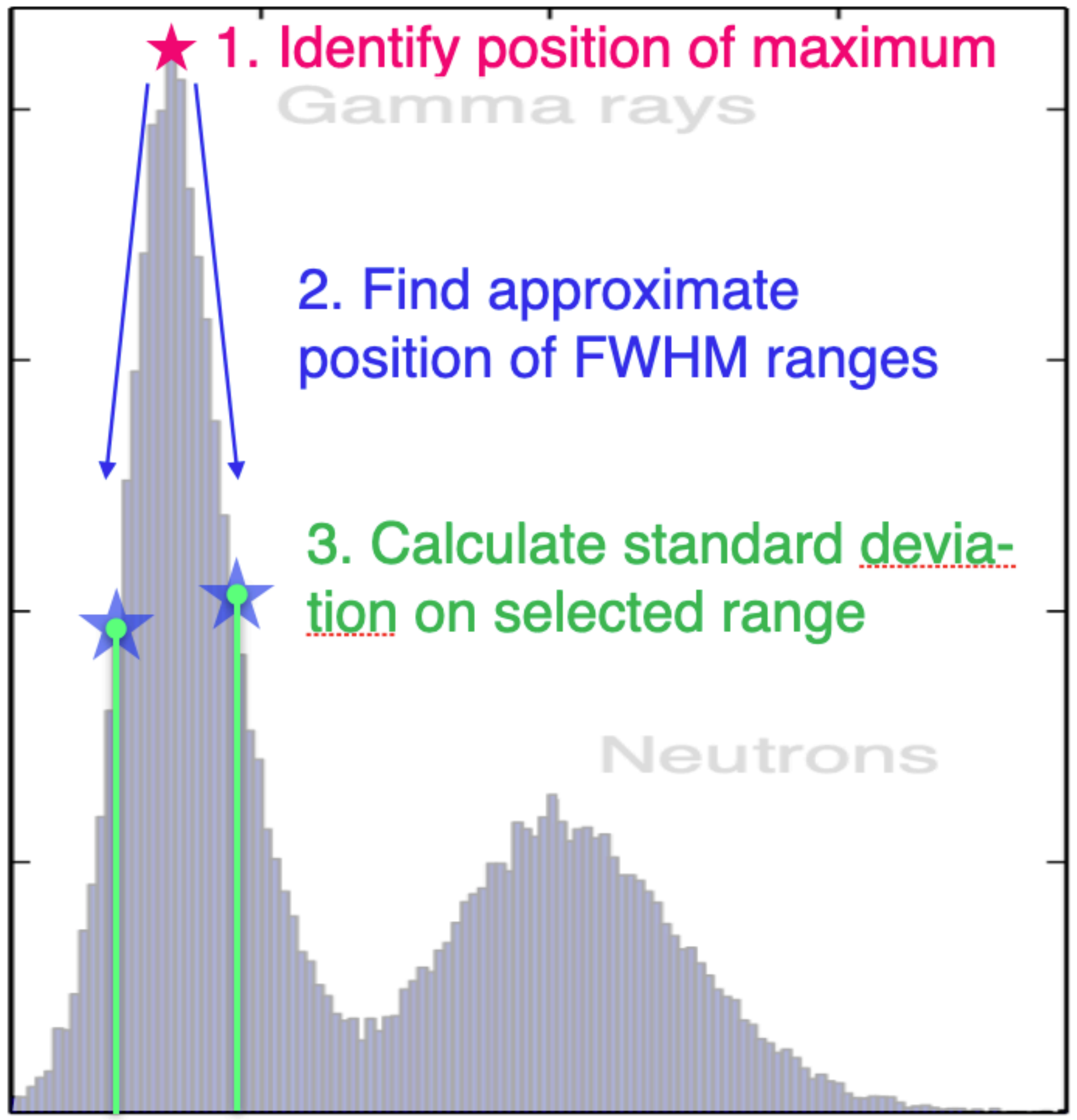


- e^- drift time is the time difference between cathode and sum anode calculated timestamps (with CFD)
- Apply shaping filters to measure « energy » for all channels

Loss function for time resolution improvement

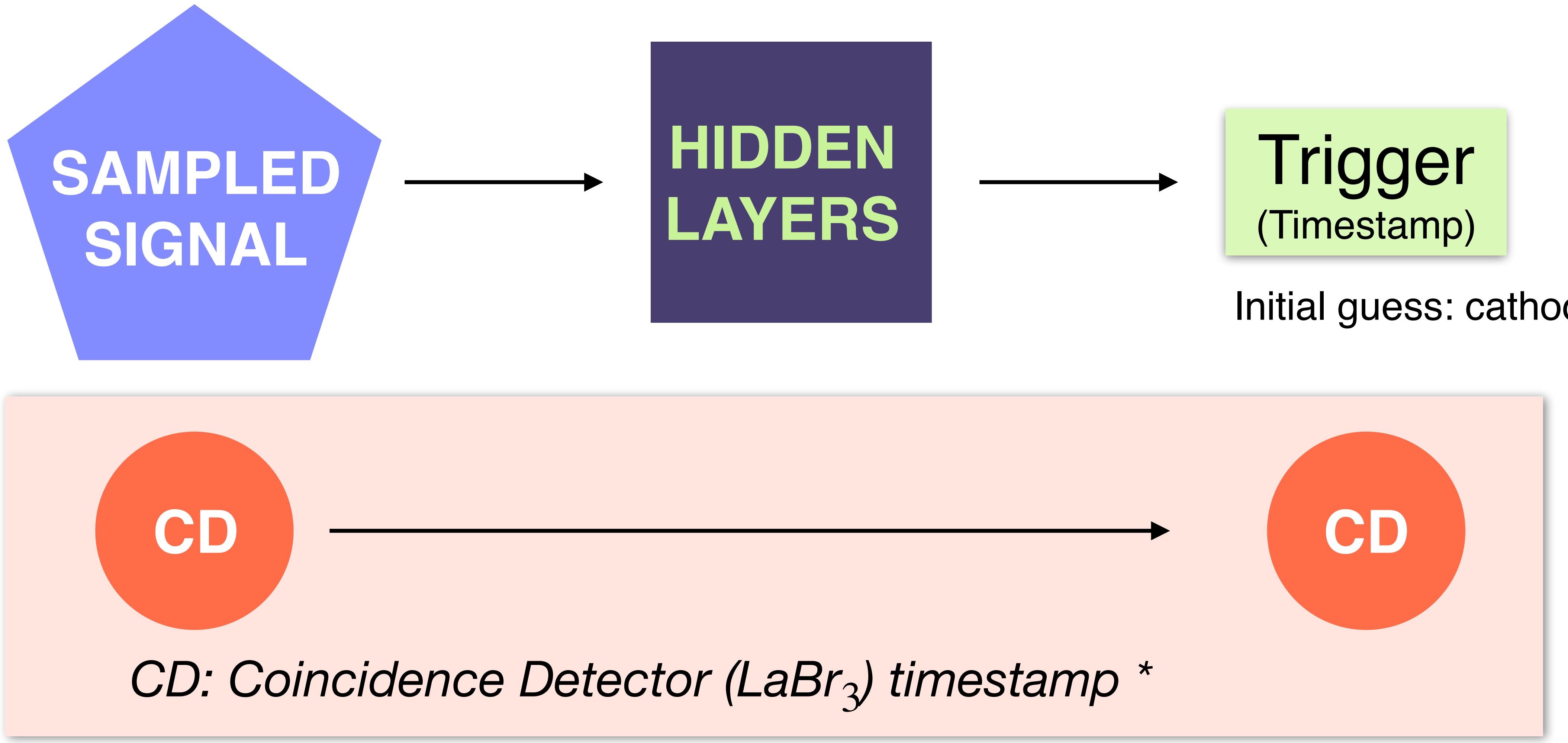


Initial guess: cathode signal CFD



By batch

Loss function for time resolution improvement

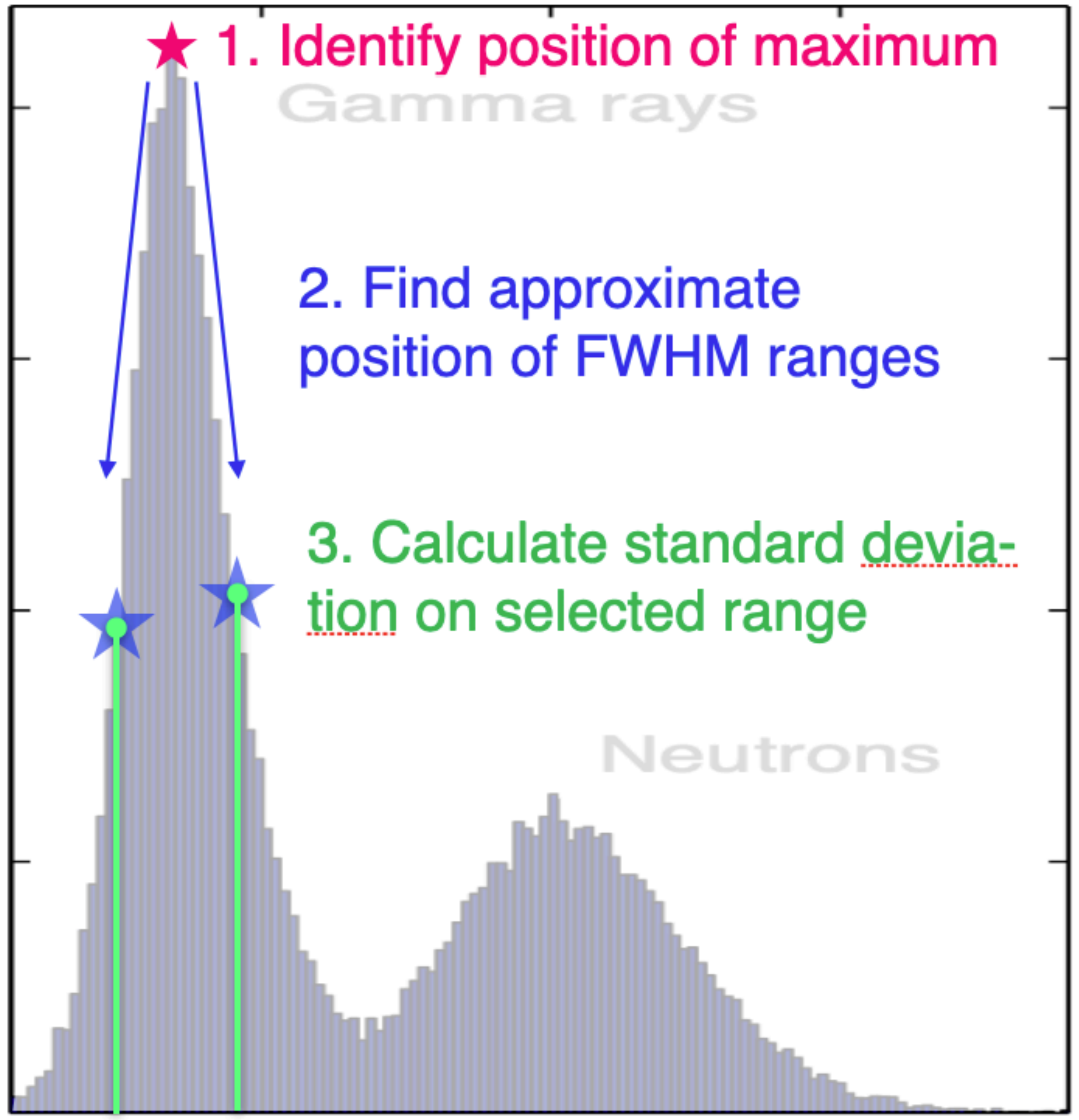


Initial guess: cathode signal CFD

CD: Coincidence Detector ($LaBr_3$) timestamp *

NO CONNECTION BETWEEN CD NEURON AND ANY OTHER LAYER IN NN ARCHITECTURE.

USED ONLY FOR LOSS ESTIMATION.



By batch

Layer complexity

CFD on cathode signals requires ~15000 FLOP per signal

3.1.1. Fully connected neural network (FCNN)

$$\text{FLOP}_{\text{FCNN}} = 2 \times L_{in} \times L_{out} + b \qquad (1)$$

3.1.2. Convolutional neural network (CNN) - one dimension

$$\text{FLOP}_{\text{CNN}} = 2 \times L_{in} \times L_{out} \times F \times K + b \qquad (2)$$

$$L_{out} = \left\lfloor \frac{L_{in} - K + 2P}{S} \right\rfloor + 1 \qquad (3)$$

Where F is the number of filters and K is the kernel size, P is the padding option, S is the stride, and b is the bias term.

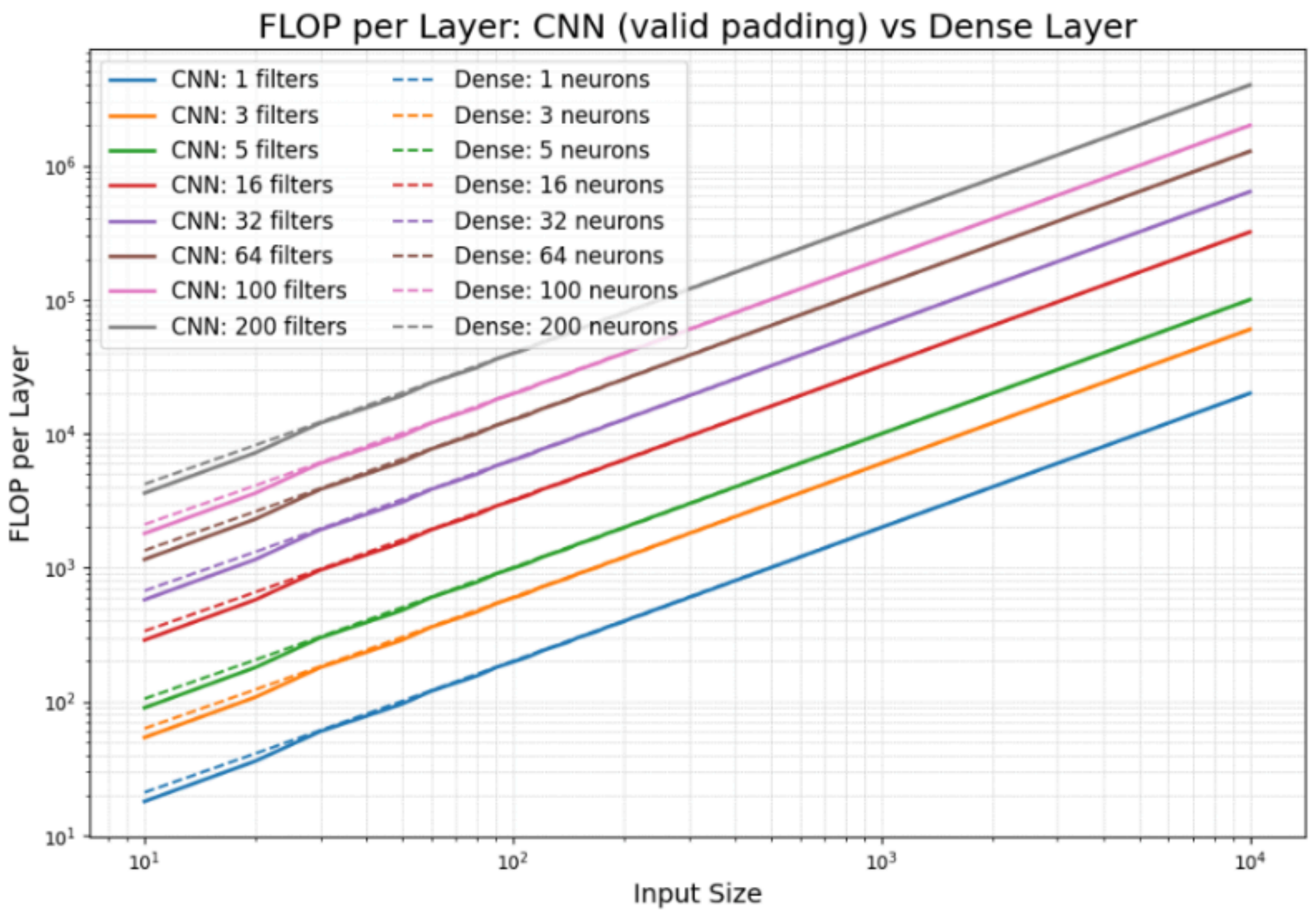


Figure 5: Comparison of total computational cost (FLOP) per layer for 1D convolutional layers (CNN) and fully connected (dense) layers as a function of input size. Fluctuations in convolutional model comes from valid padding (or no padding), not recommended if border information is crucial. Solid lines represent CNNs, and dashed lines represent dense layers. Both axes are on logarithmic scales.

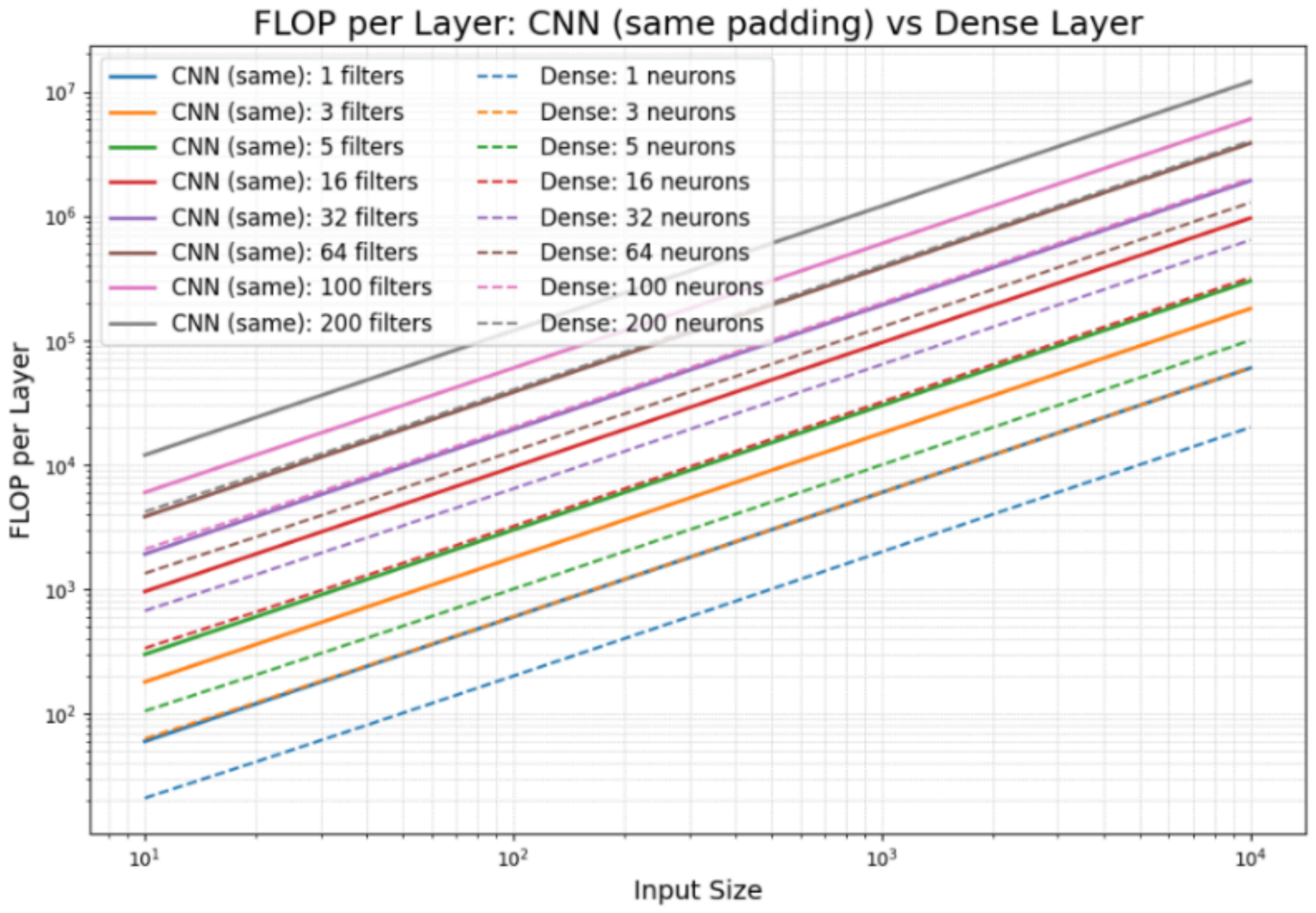


Figure 6: Comparison of total computational cost (FLOP) per layer for 1D convolutional layers (CNN) and fully connected (dense) layers as a function of input size. Case for layers designed with "same" padding, which preserves border information. In this situation, convolutional layers conserve their dimensions, hence the higher complexity.

Layer complexity

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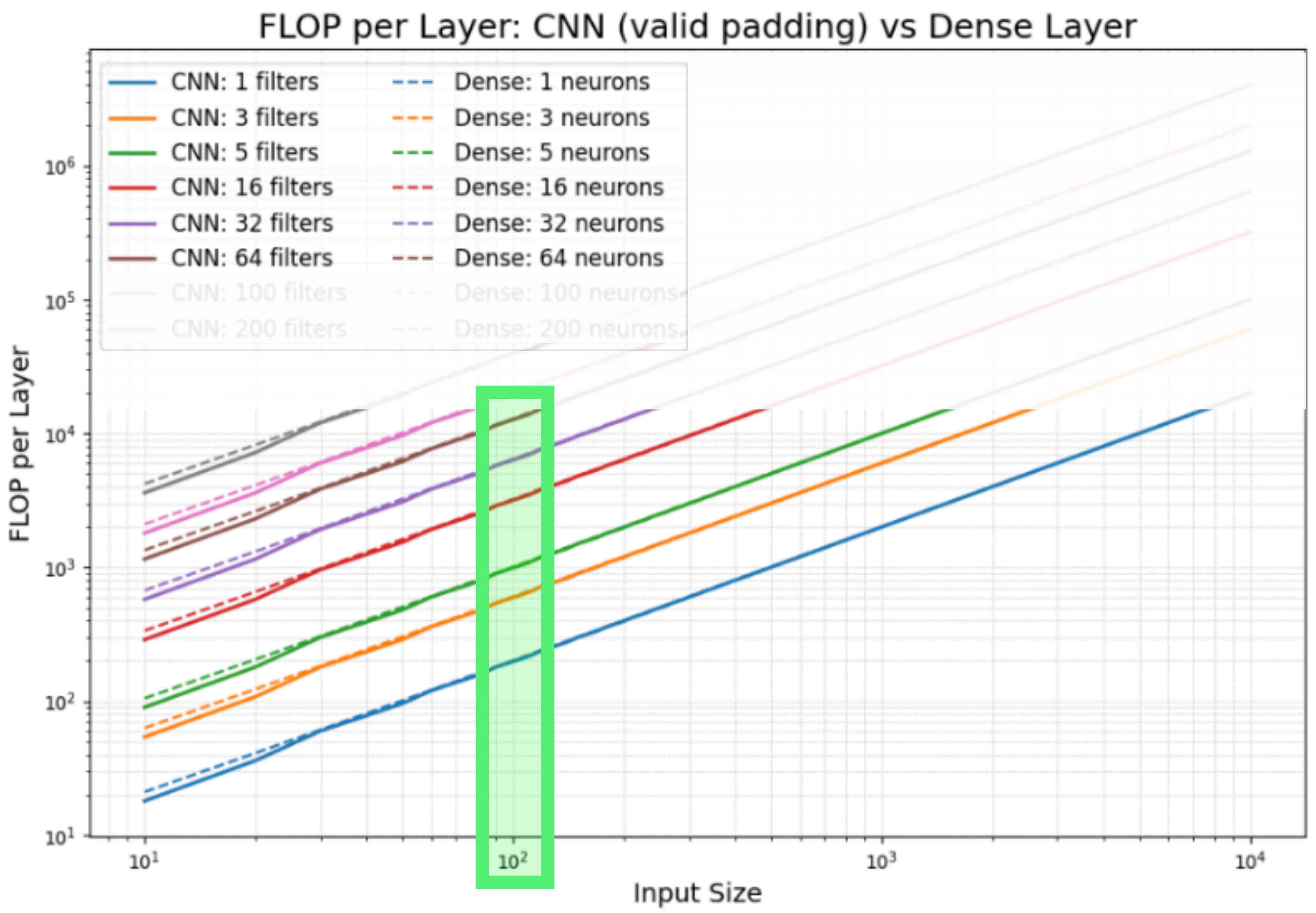

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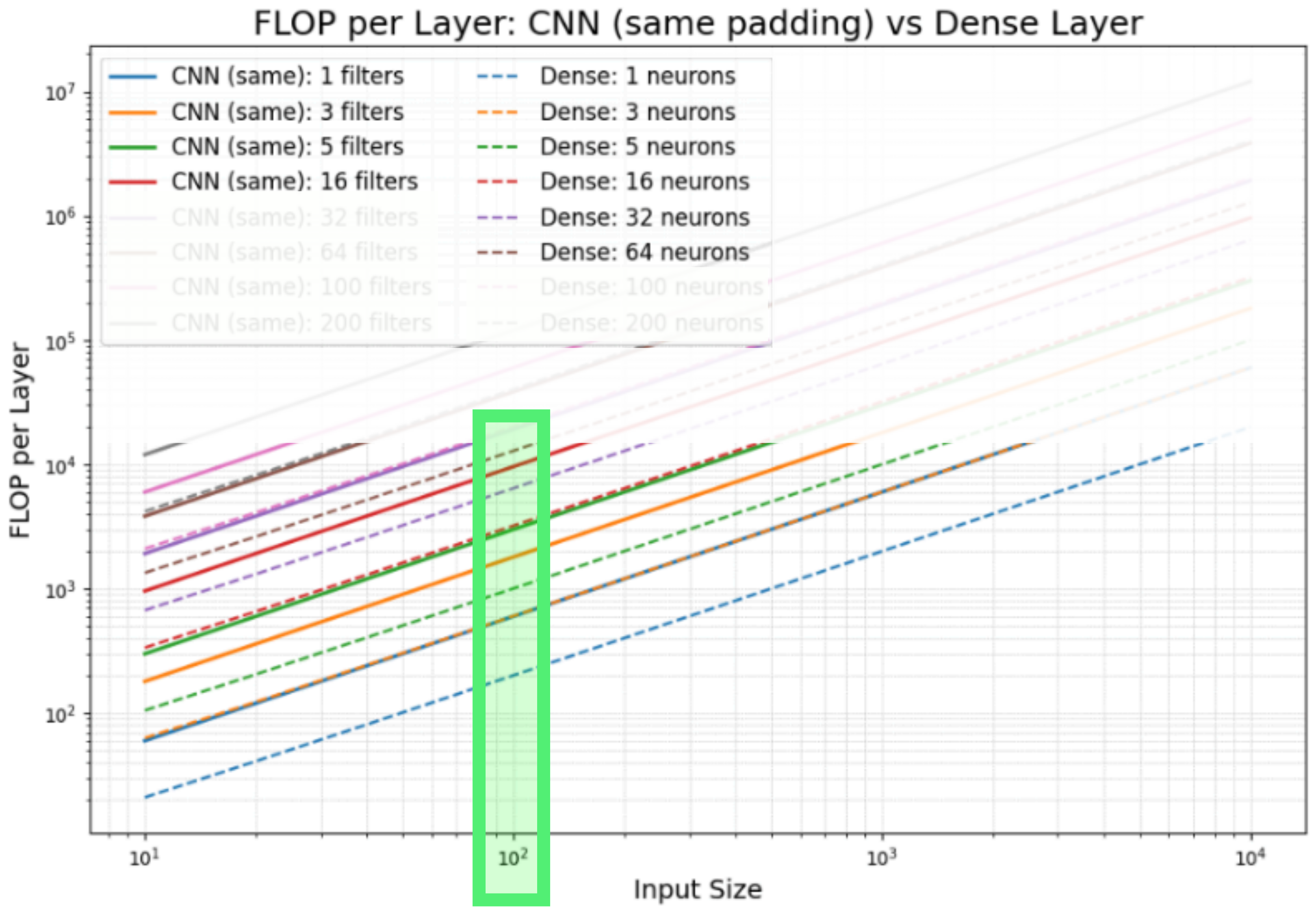

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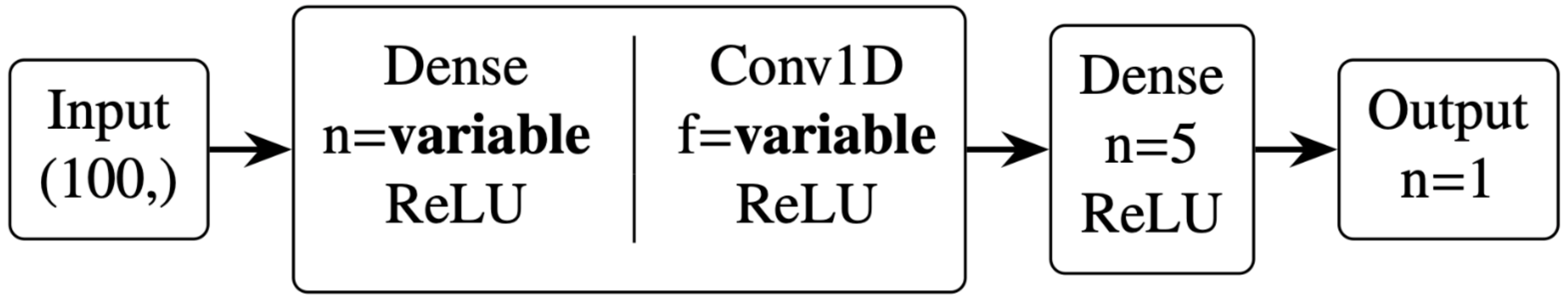
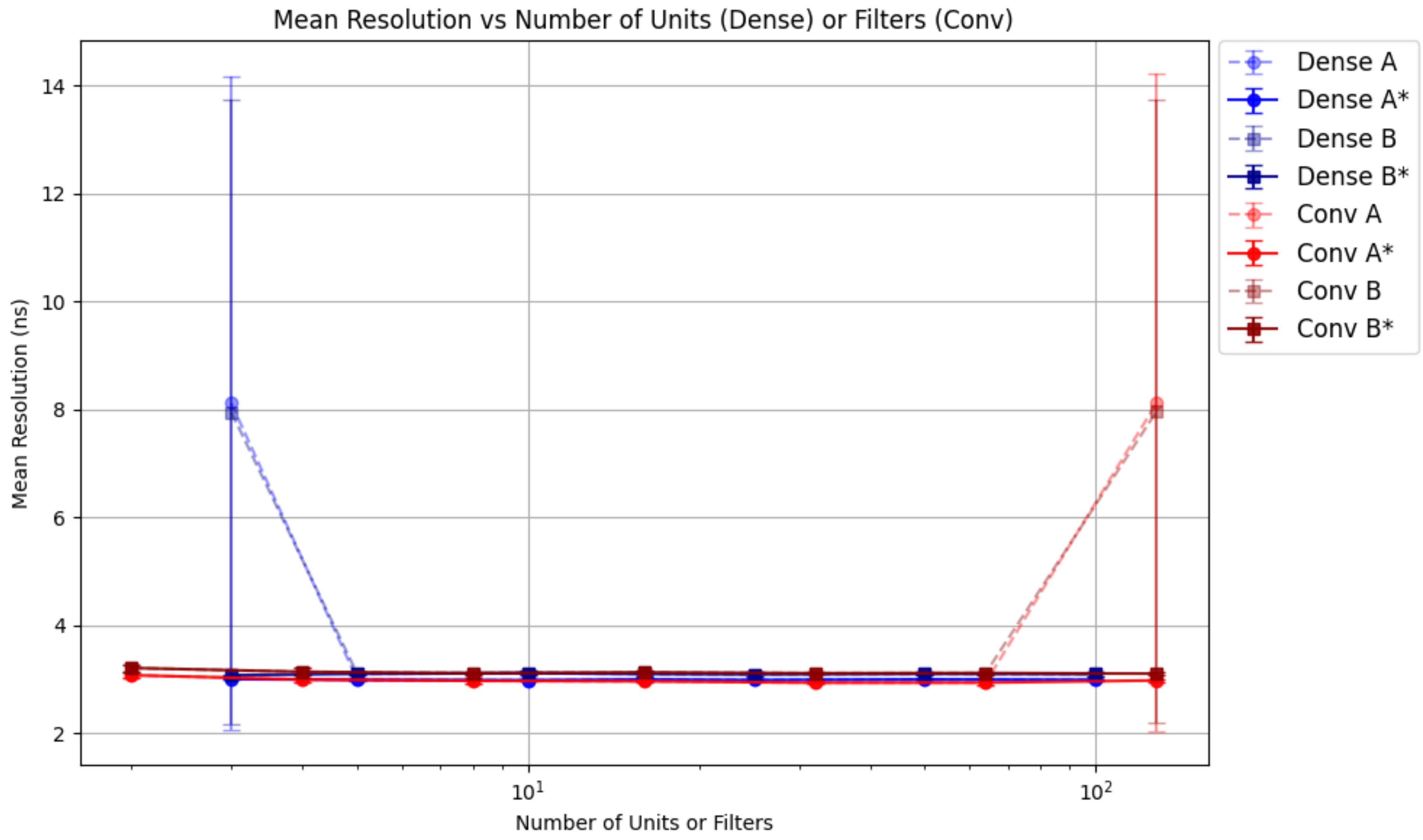
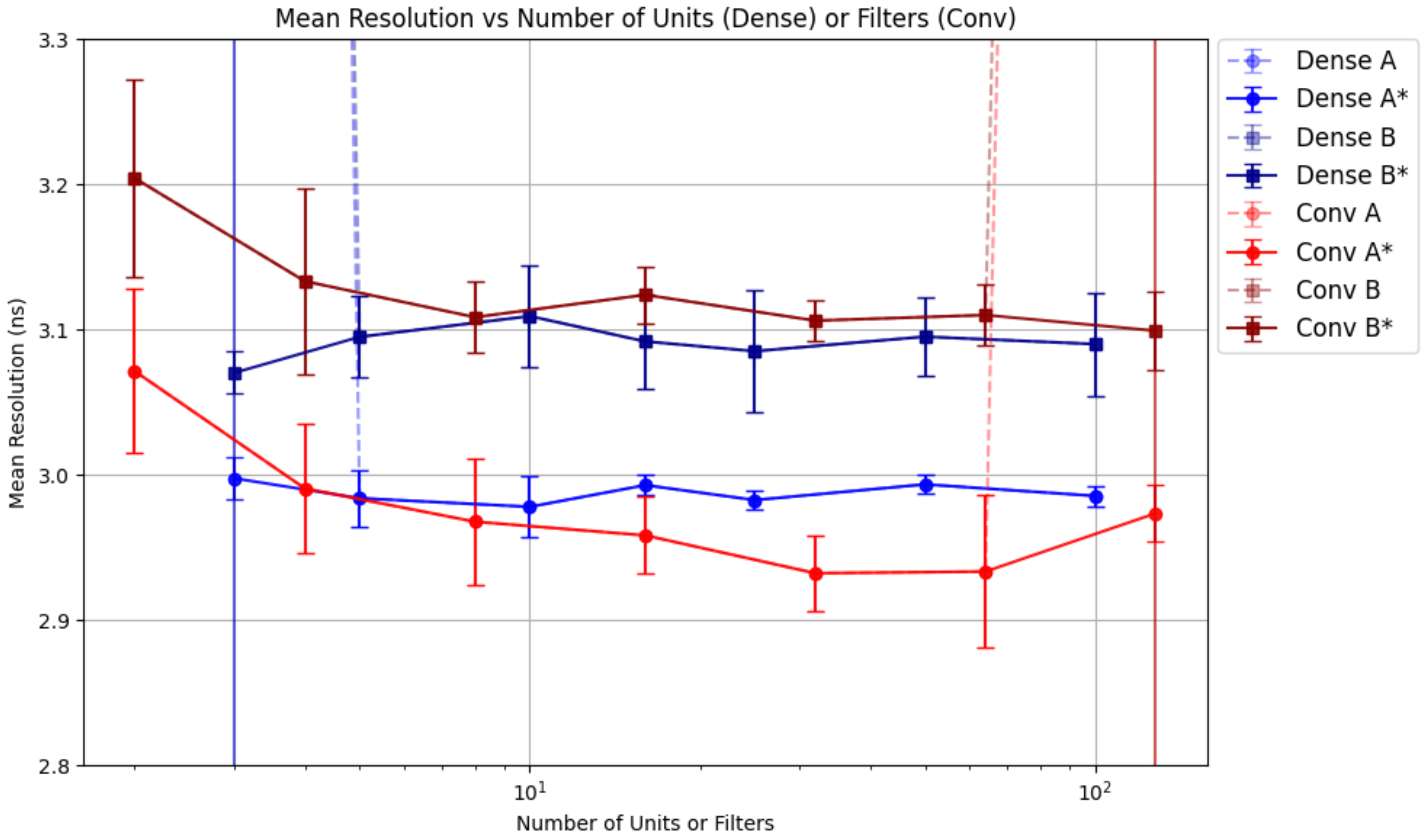
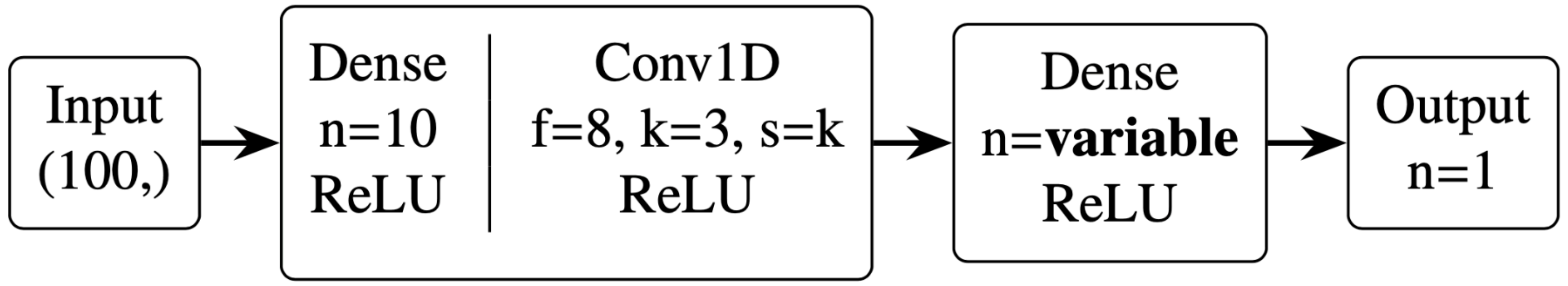
Model tuning - first hidden layer

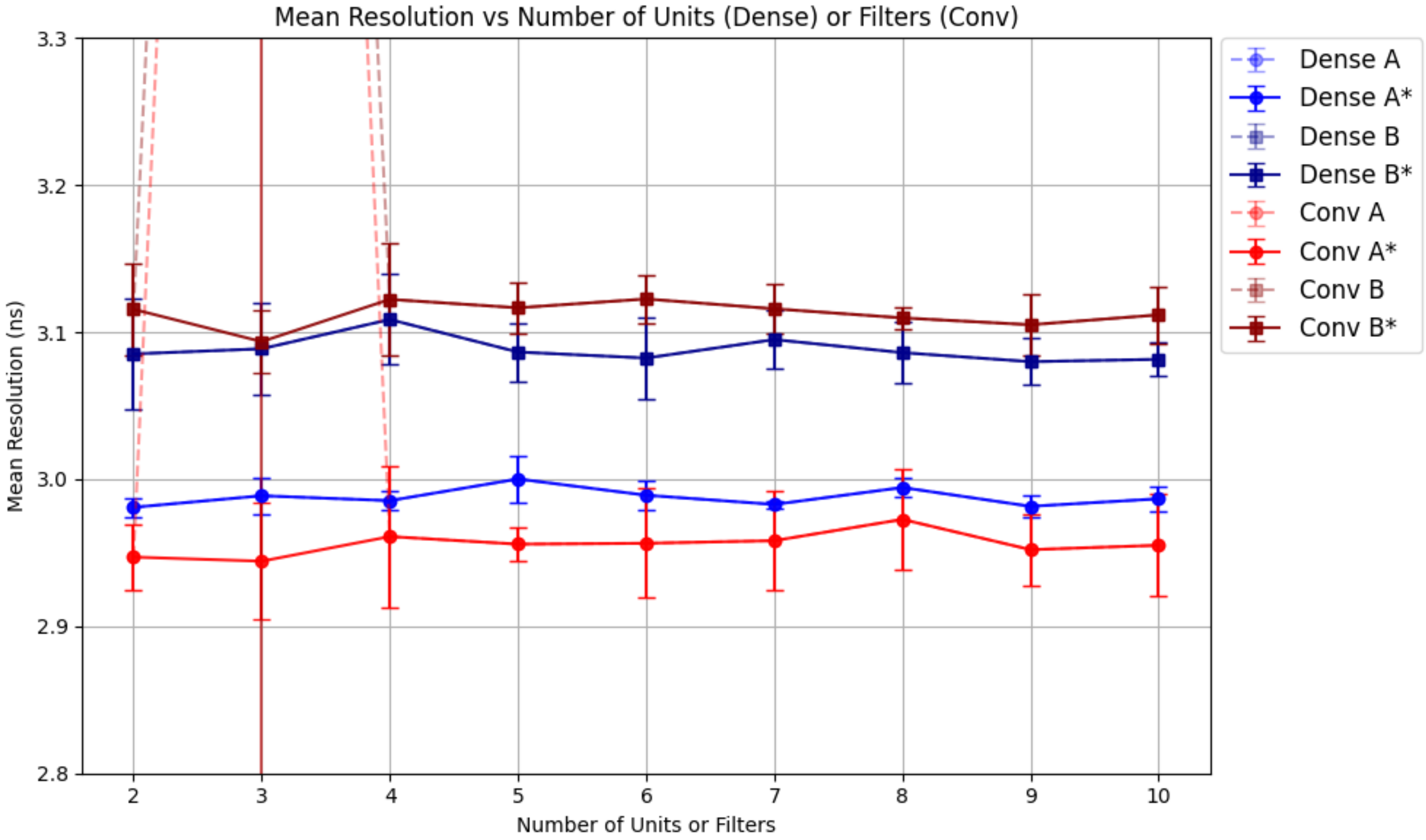




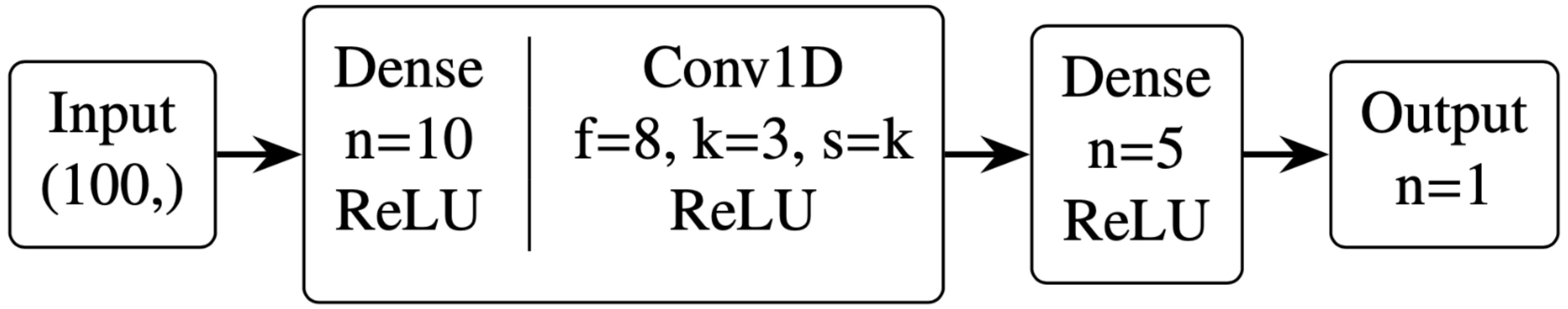


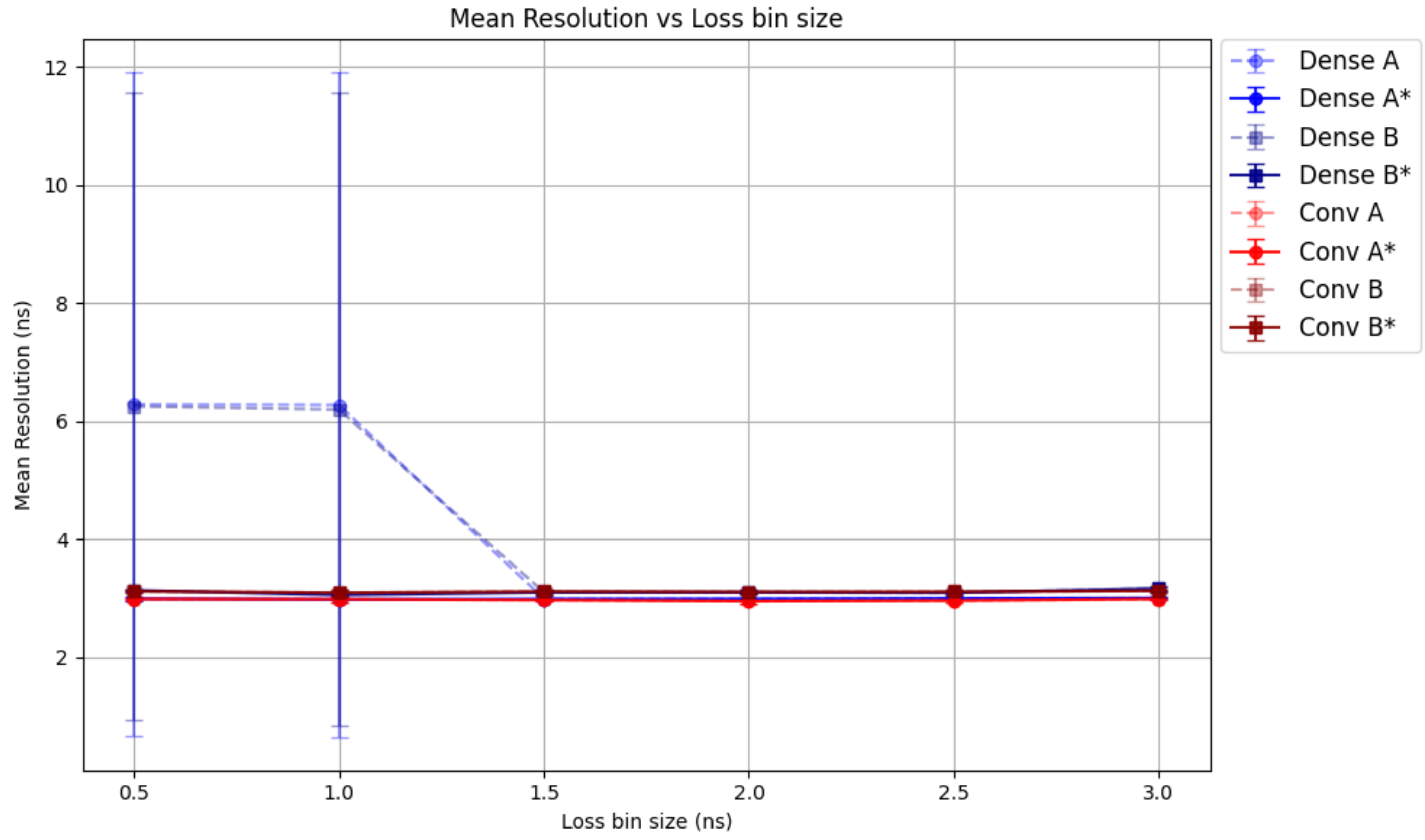
Model tuning - second hidden layer

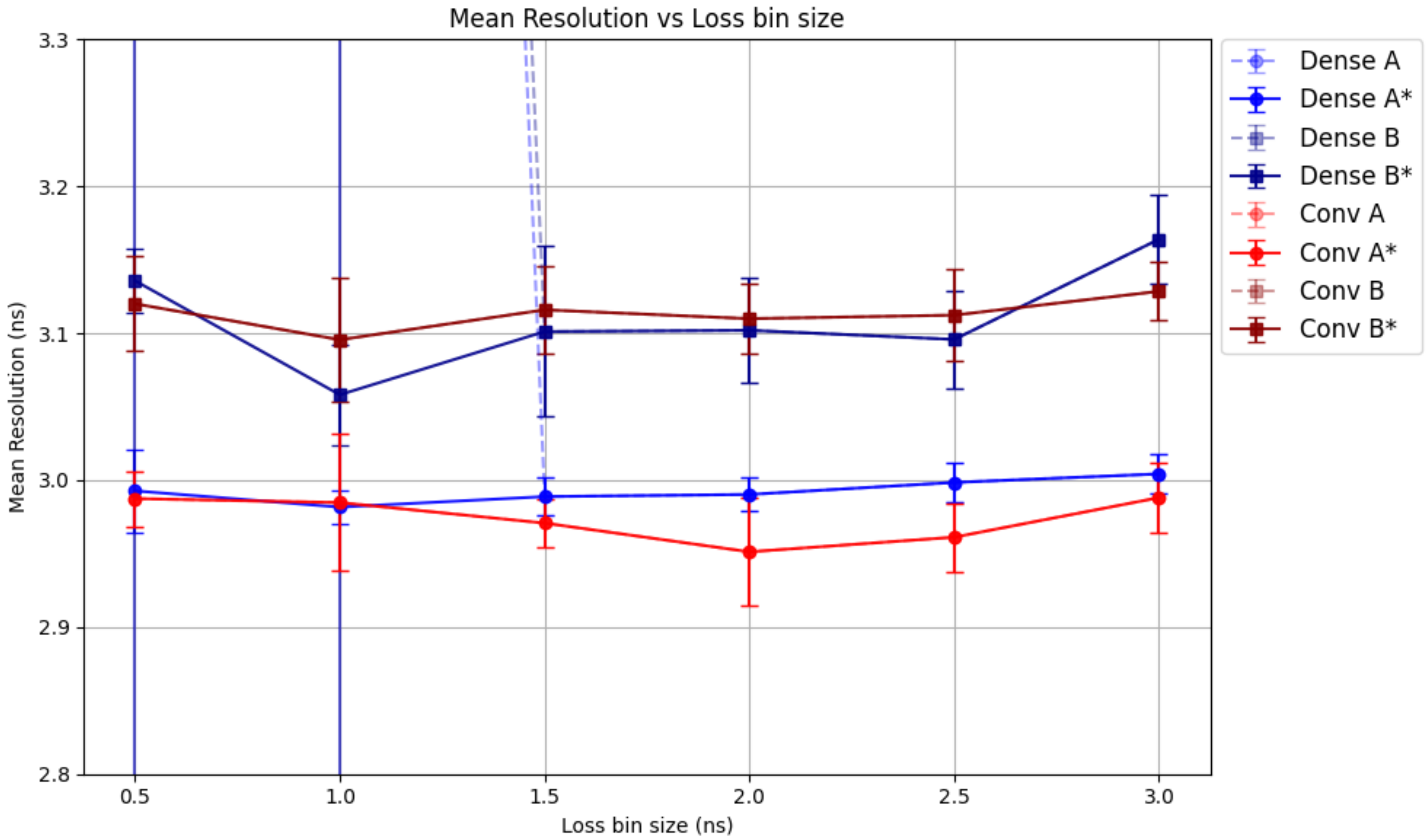


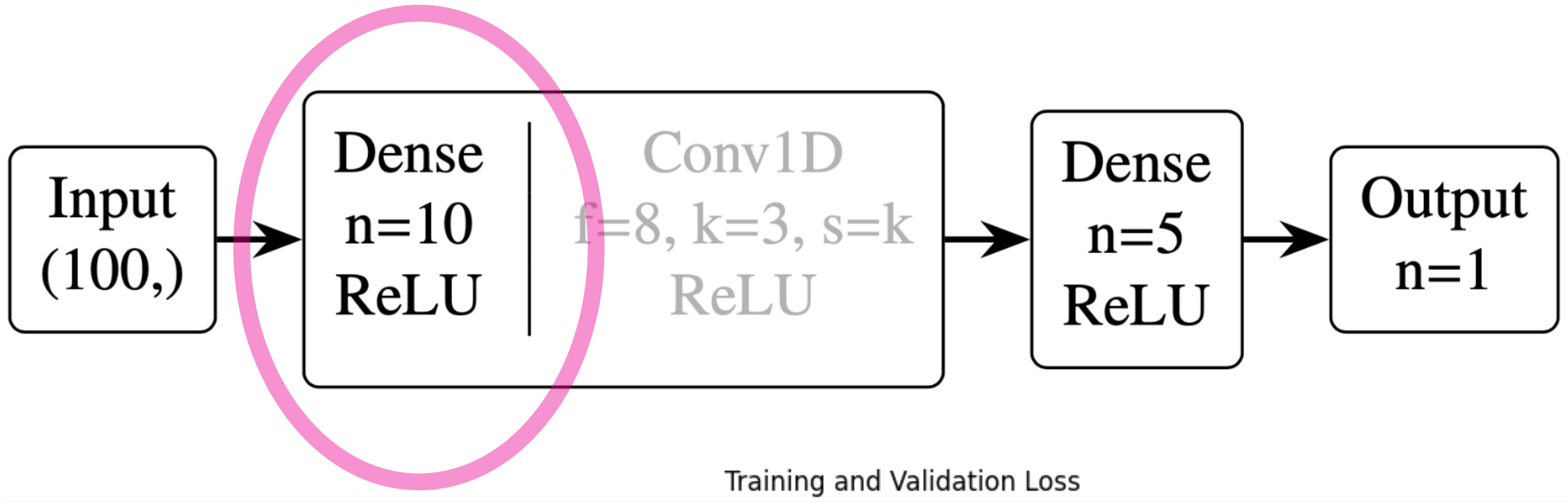


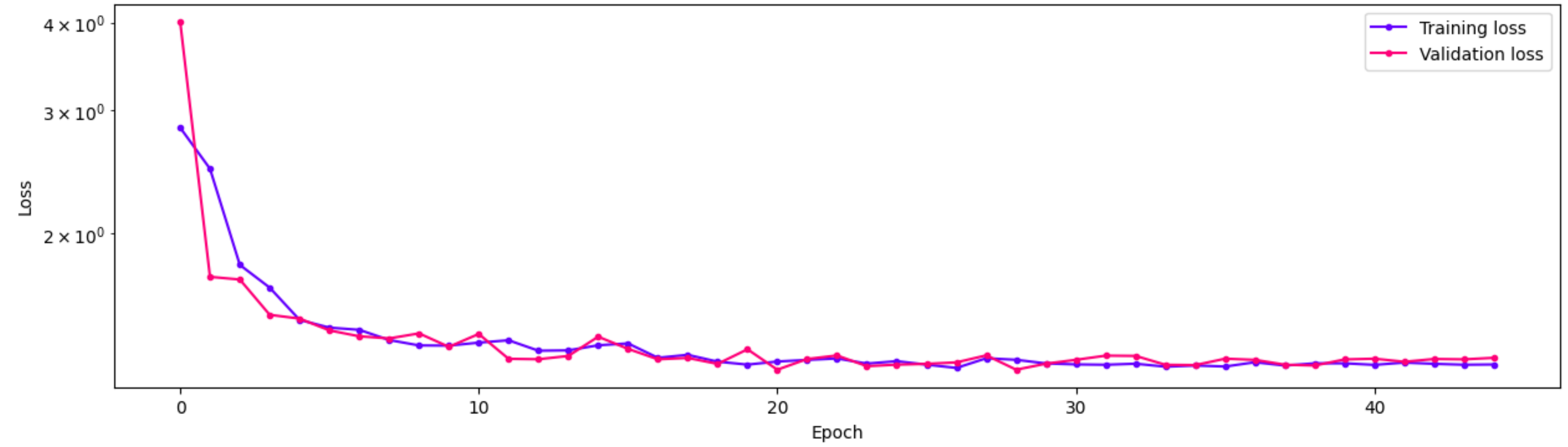
Model tuning - loss function bin size











The model can be loaded in c++ script with Tensorflow API and it was directly implemented in our raw data conversion code to ROOT format, replacing the CFD algorithm.

Our final model has **1065 parameters** and requires 2110 FLOP per signal entry, with **total FLOP 2910 per signal.**

The total number of operations already takes into account signal downsampling (600 + 100 FLOP) and rescaling (100 FLOP).

This represents a computational cost 5 times smaller than CFD algorithm with a time resolution at least 34% better * .