Study of the interplay between nuclear charge and energy loss in the FALSTAFF spectrometer

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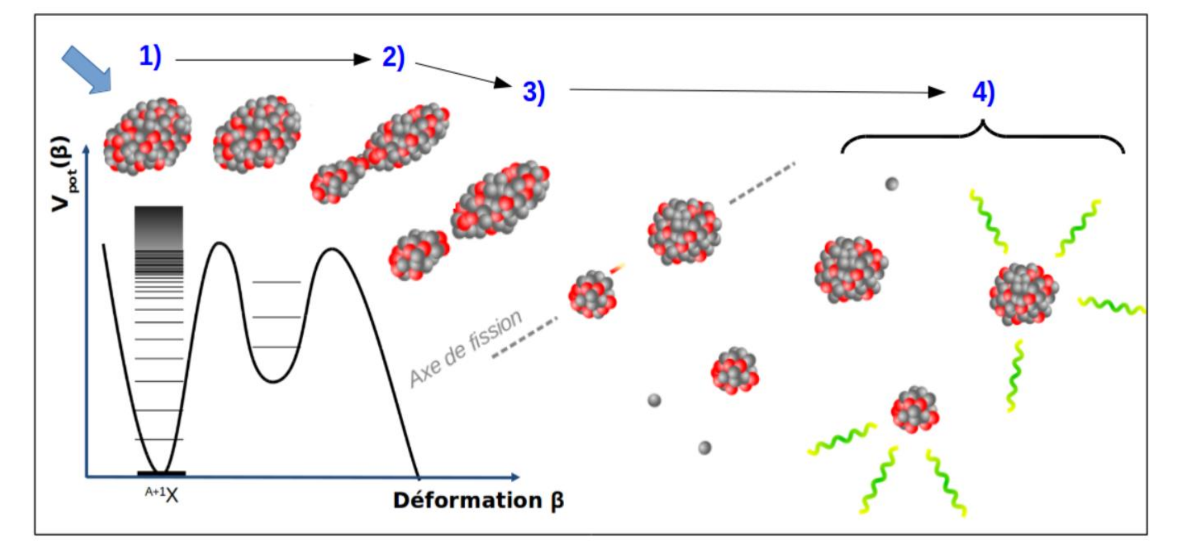
Outline

- Fission
- The FALSTAFF spectrometer
- Machine learning approaches
- Simulated data and preprocessing
- Results
- Conclusions

Fission

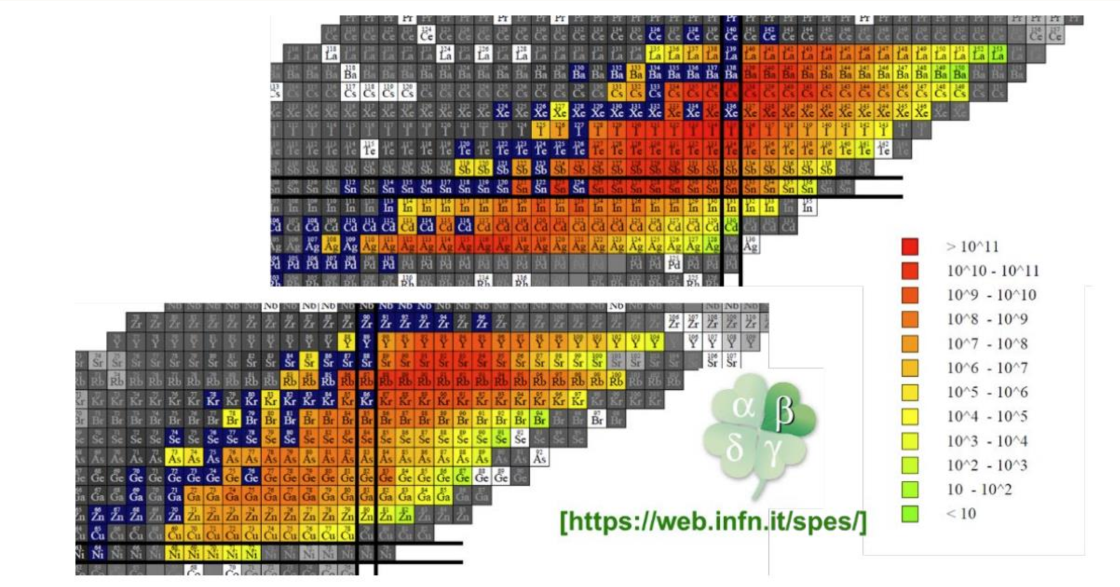
<u>Fission</u> (1938):

- Strong deformation of a heavy nucleus (actinides)
- scission into two lighter ones (stochastic)
- large emission of energy (γ and n)



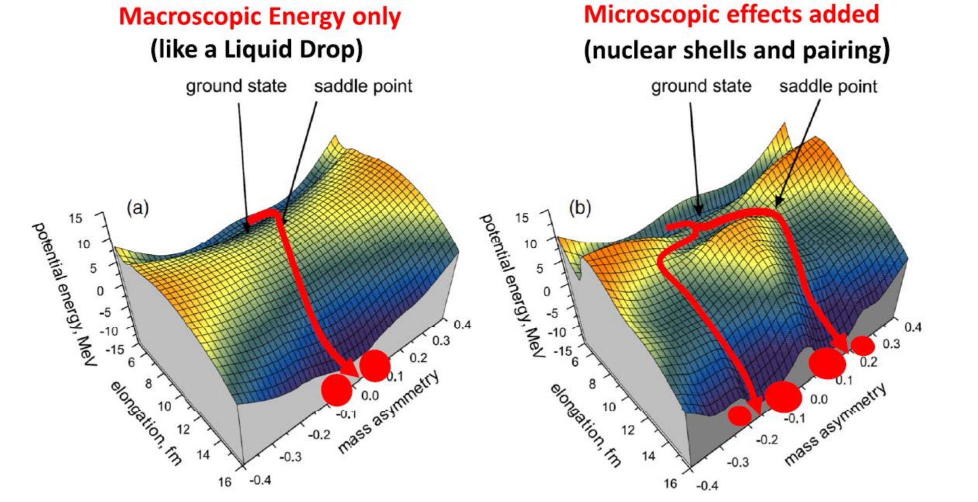
Still an active research field:

- Production of **exotic** nuclei
- **Energy** production in reactors



from
T Marchi et al 2020
J. Phys.: Conf. Ser.
1643 012036

Fission



from [1]
A N Andreyev *et al*
2018 *Rep. Prog. Phys.*
81 016301

Behaviour is sum of **macro-** (Liquid Drop) and **microscopic** effects (Shells)

e.g. : Asymmetric mass distributions (low energy)

Fission plays a role in the **r-process nucleosynthesis**

Neutron captures bring to the formation of actinides ⟶ Low fission barrier

(n,fission) reactions limit the production of super-heavy

Precise fission yields are needed to calculate the **final r-process abundances**

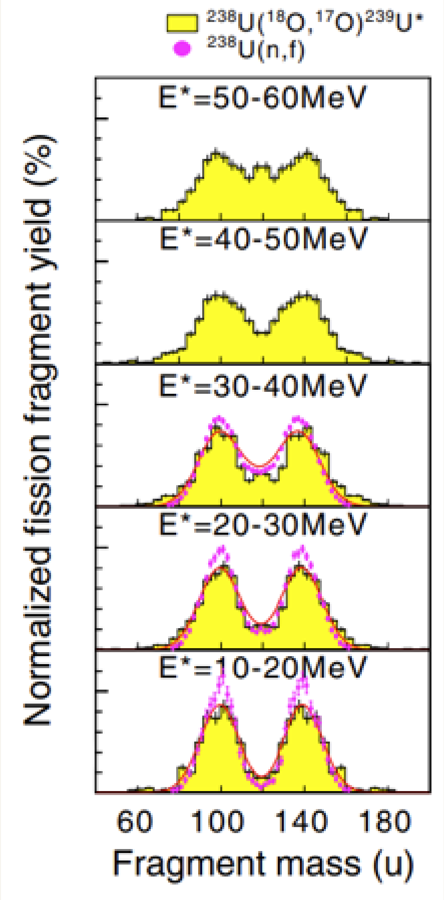
See also [2]
G. Martinez-Pinedo et al.
Progress in Particle and Nuclear Physics 59 (2007) 199–205

To improve models, precise **measurements** are needed

Fission Observables

- **Fission Fragments Mass Distributions (FFMD)**

  Asymmetric distribution in low-energy regime
  Symmetric distribution with higher energy



From [1]
K. Hirose et al.
Phys Rev. Lett.,
119:222501,
2017

Fission Observables

- **Fission Fragments Mass Distributions (FFMD)**

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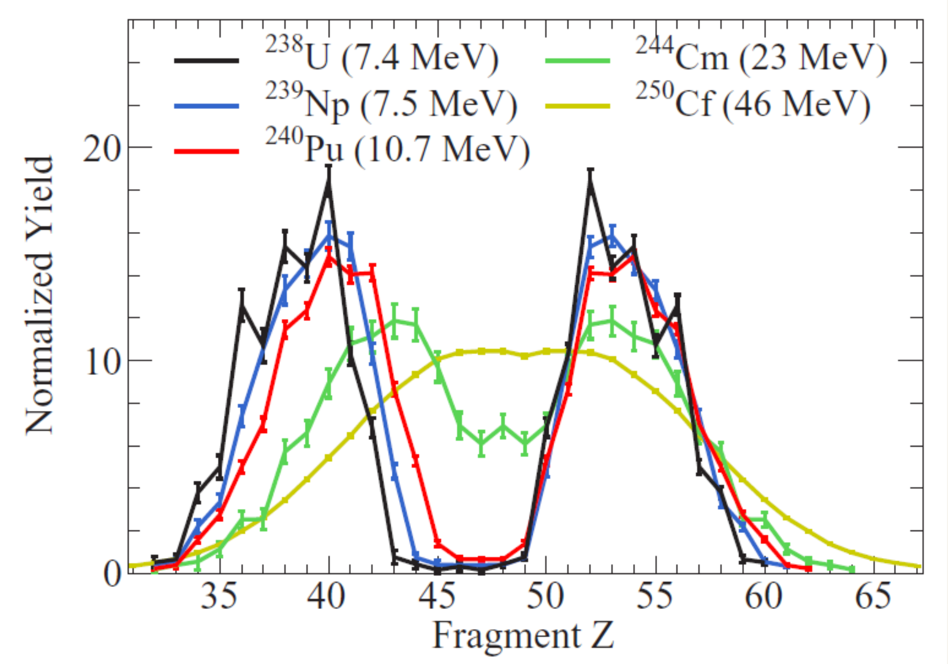
- **Fission Fragments Charge Distributions**

  → **Stability of Z of heavier fragment** [2]



from [3] D. Ramos et al. Phys. Rev. C, 97(5):054612, 2018

[2] K.-H. Schmidt et al. NPA, 665:382, 2000

Fission Observables

- **Fission Fragments Mass Distributions (FFMD)**

  Asymmetric distribution in low-energy regime
  Symmetric distribution with higher energy

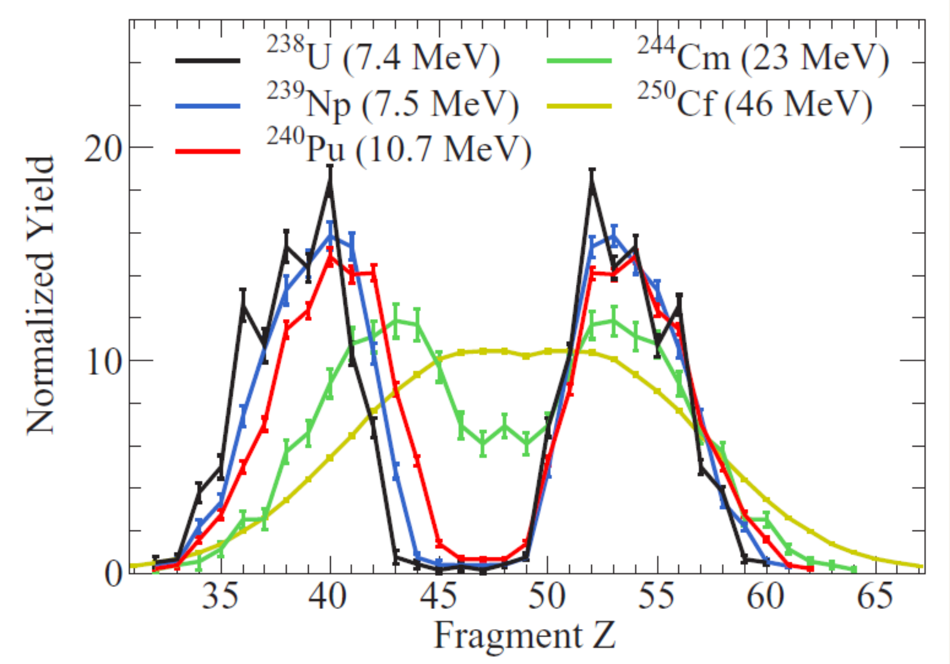
- **Fission Fragments Charge Distributions**

  → **Stability of Z of heavier fragment** [2]

- **Isotopic Fission Fragments Distributions**

  (N,Z) of fragments allow to study the shell effects

  Measured in **inverse kinematics**,
  but not in **n-induced** fission.



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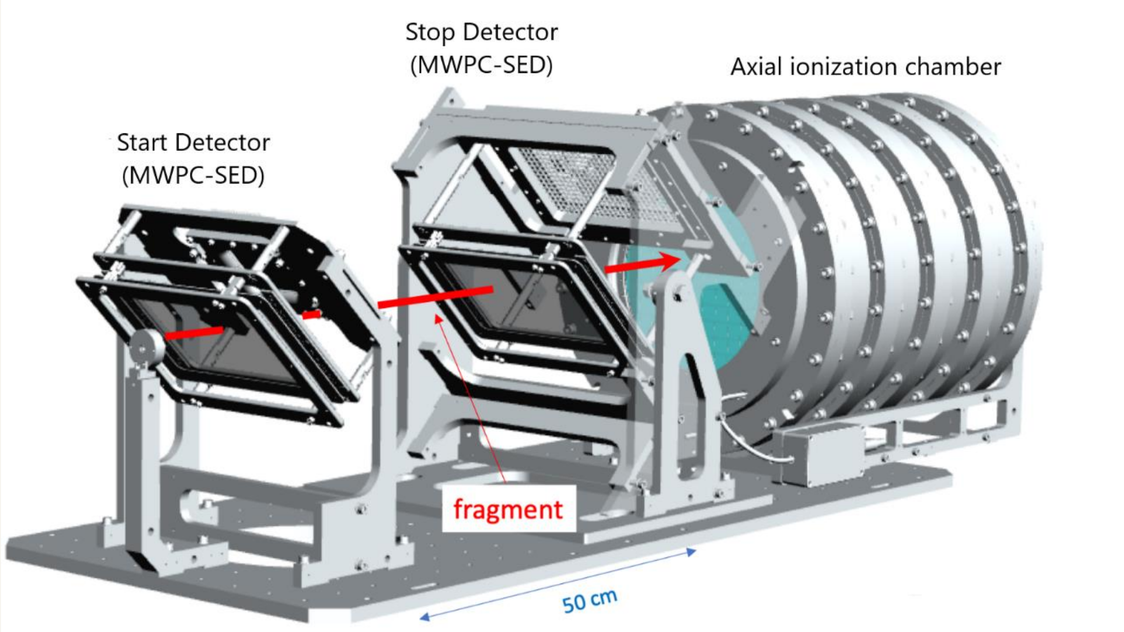
The FALSTAFF spectrometer



[1] D. Dore et al. Nucl. Data Sheet, 2014
[2] D. Doré et al., EPJ Web of Conferences, 2019

Setup for the study of neutron-induced fission at NFS (GANIL-SPIRAL2) [1]

One arm with 2 ToF **SED** detectors (MWPC) and an axial **ionization chamber**

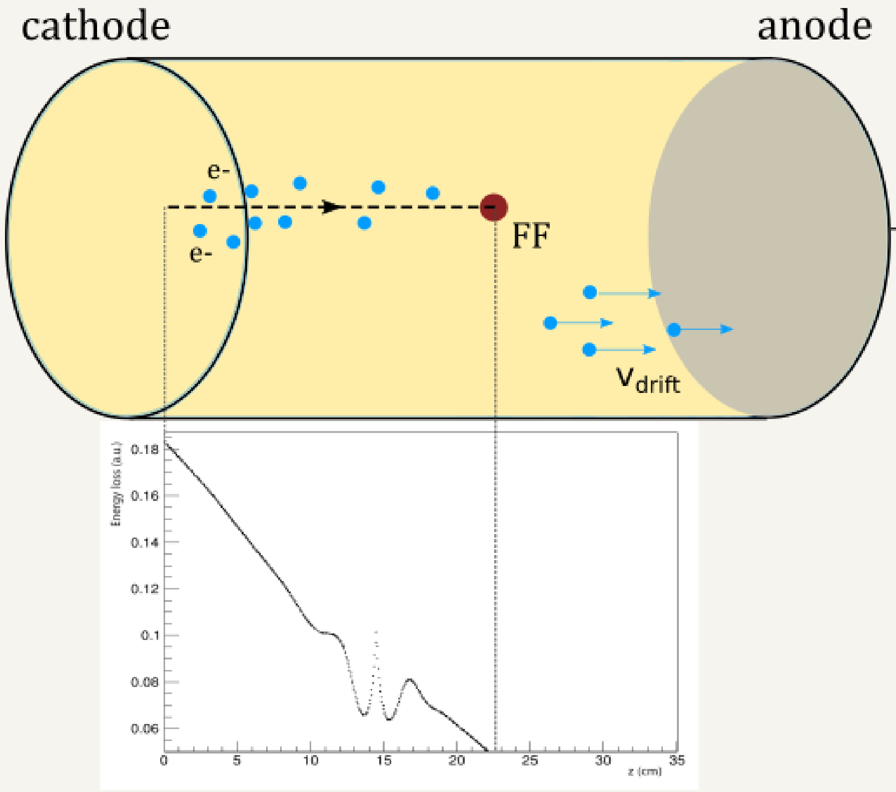
Velocity and **energy** measurement for FFs
⟶ **Mass distribution** [2]

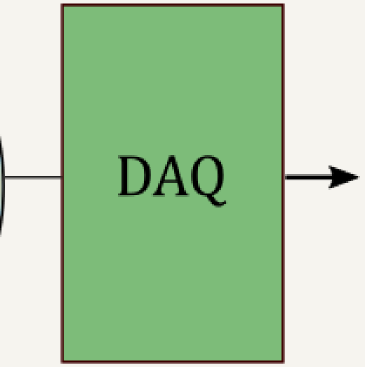
Z distribution?

Ordinary Z-ID methods ($\Delta E - E$) fail at low energy for heavy nuclei (Bragg region)

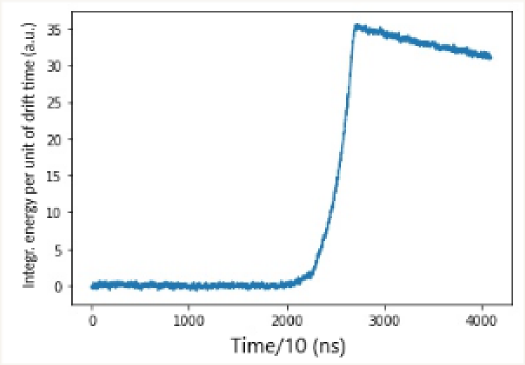
IDEA:
Axial ionization chamber:
Energy loss profile (dependence on Z)

Energy loss profile



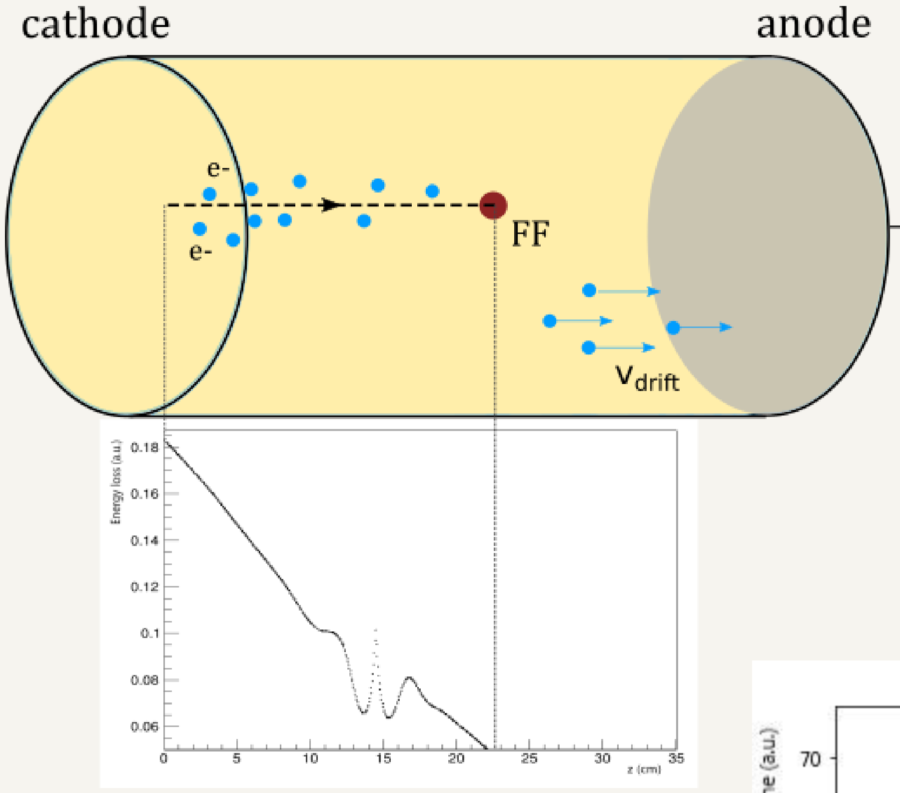


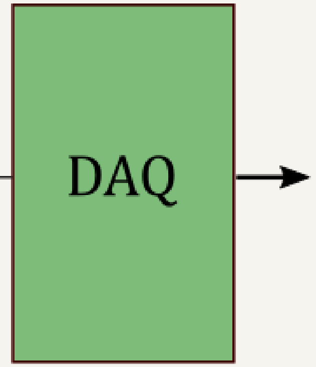
Preamp
integration
$\tau = 120\ \mu s$

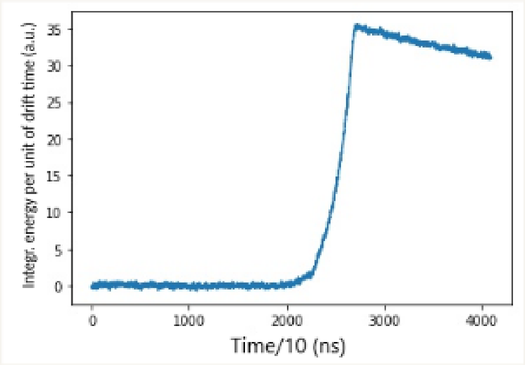


4096-entry array
10 ns sampling time

Energy loss profile







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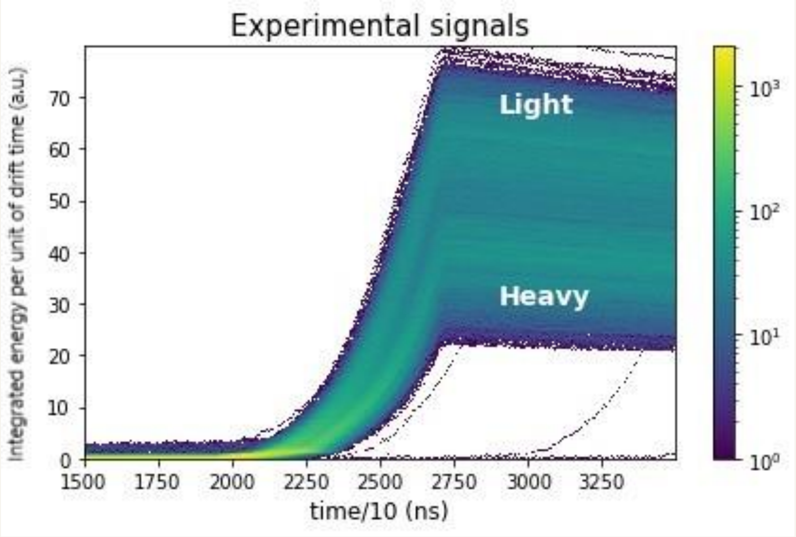
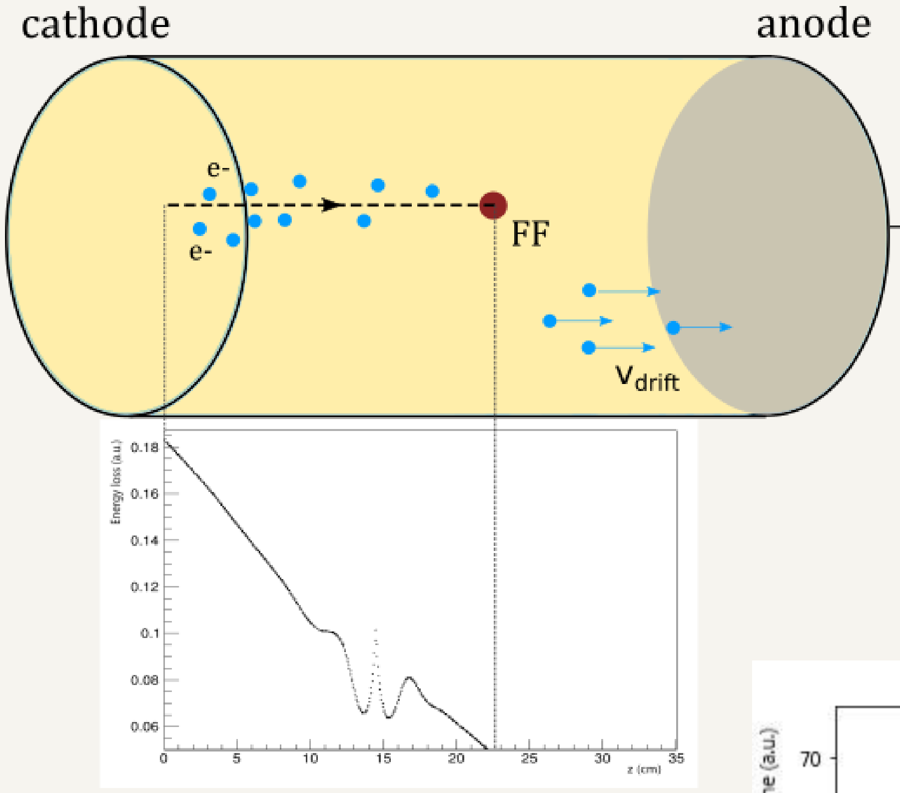
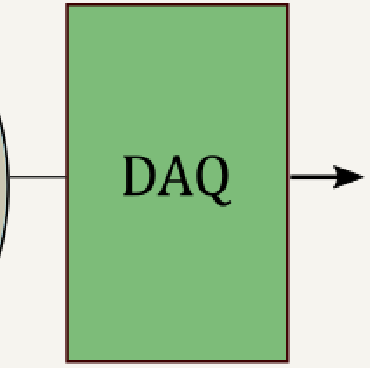
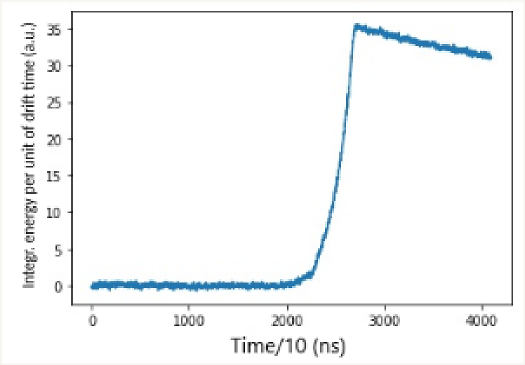


Energy loss profile







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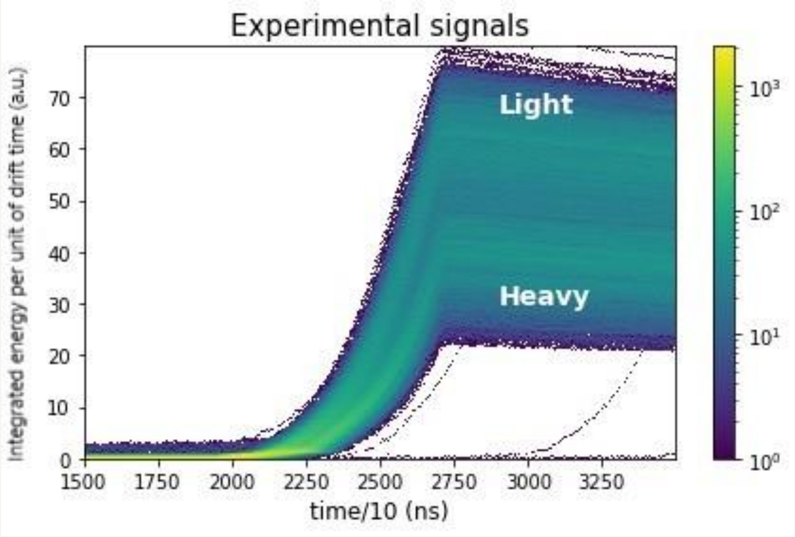
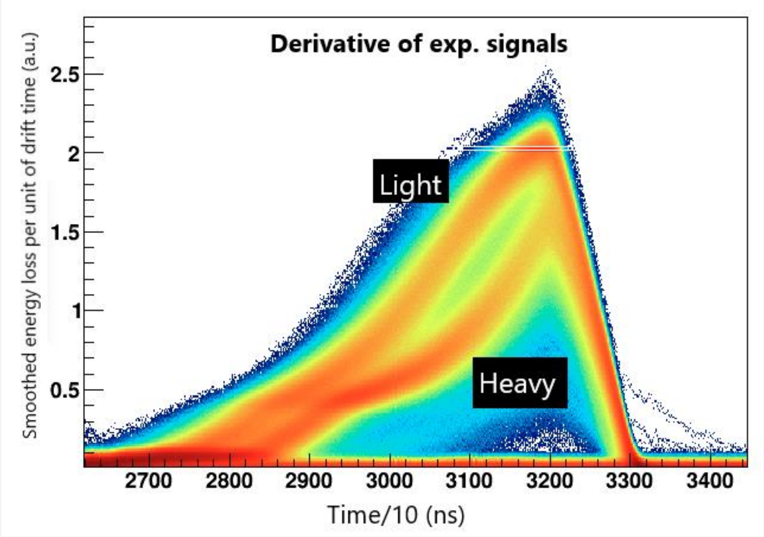
Discrimination between light and heavy fragments

Info on Z in the **shape**



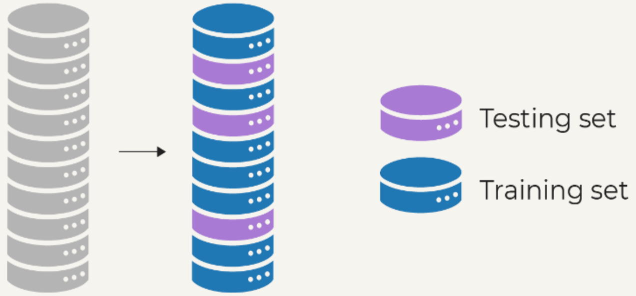


Machine Learning

?

- Generic algorithms that improve through the use of the data

- Train / Test split of the dataset



- Input features – Target

- Frameworks

Supervised

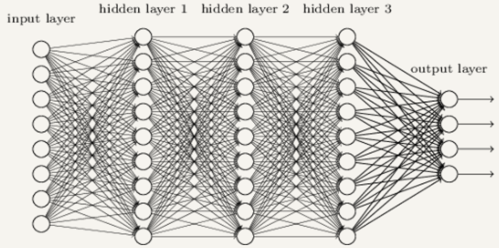
1

0

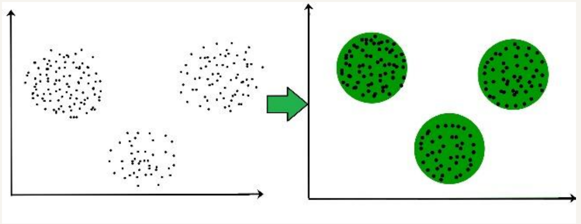
Unsupervised

amazon

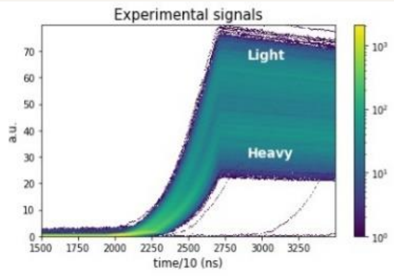
Neural Networks



Clustering



ML approaches

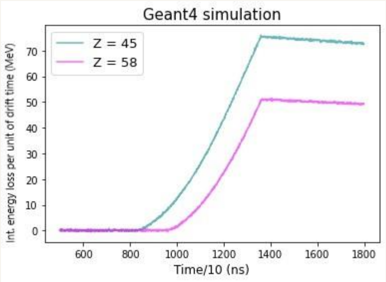


<u>Exp. Data</u>:

Z is not present

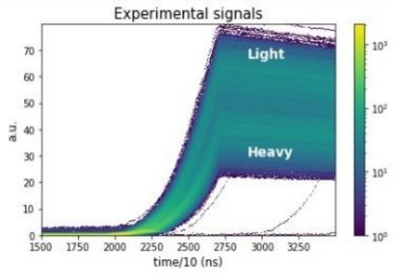
<u>Simulation</u>:

Z is known - **supervised**
Z can be neglected – **unsupervised**



Supervised learning: **Neural Networks**

ML approaches



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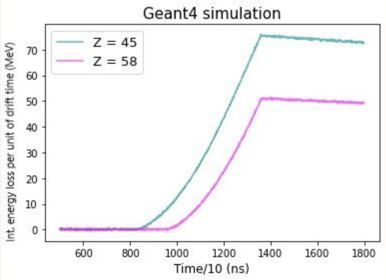

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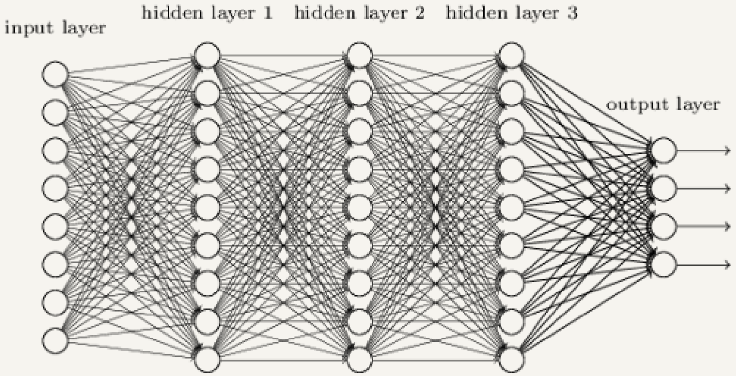
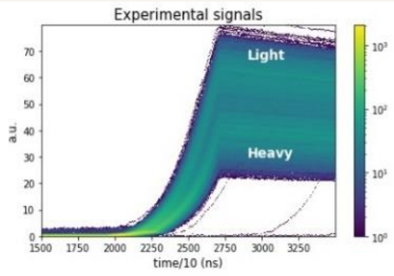


Dense architecture

- Independent inputs
- Fully connected: many parameters, overfitting

ML approaches



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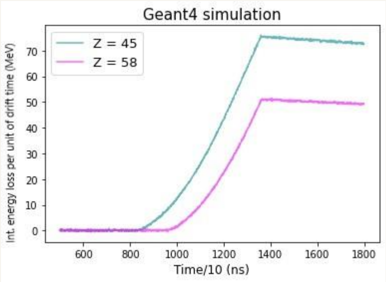

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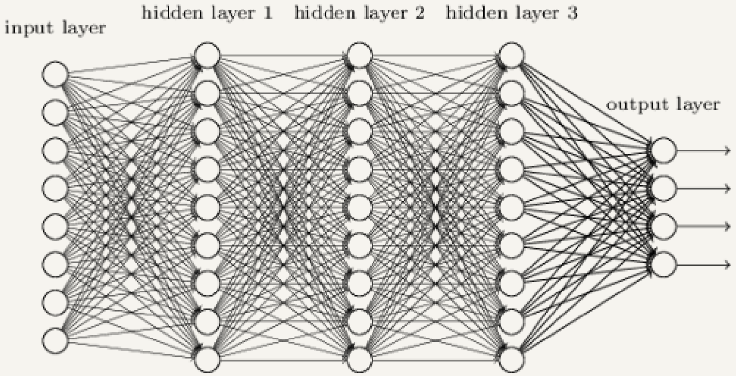

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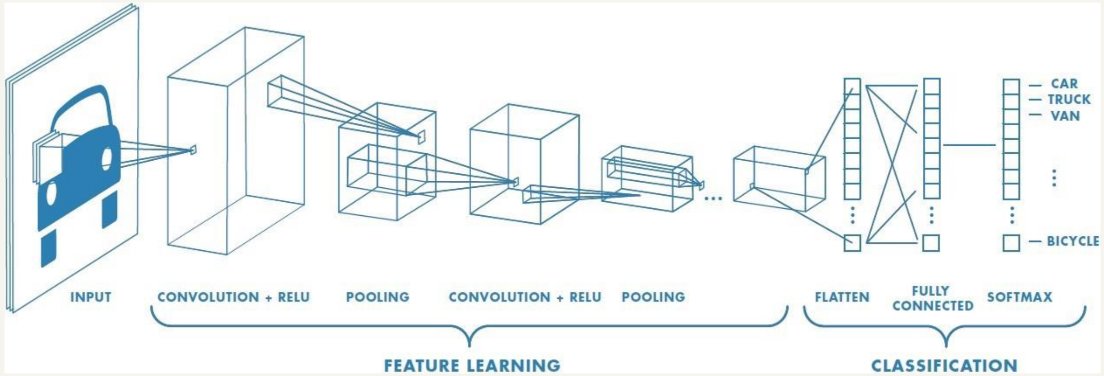


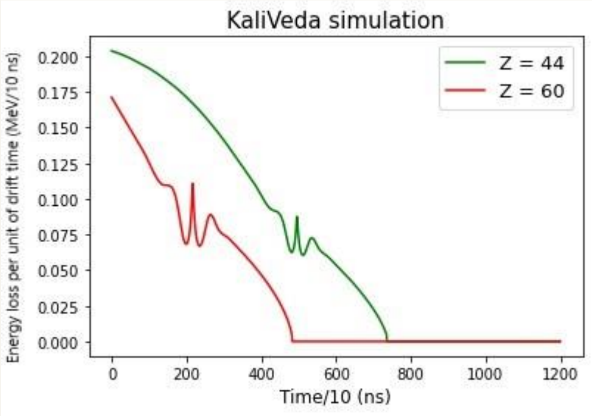
Convolutional architecture
- Position independent filters
- Reasonable number of parameters

Simulated data and preprocessing

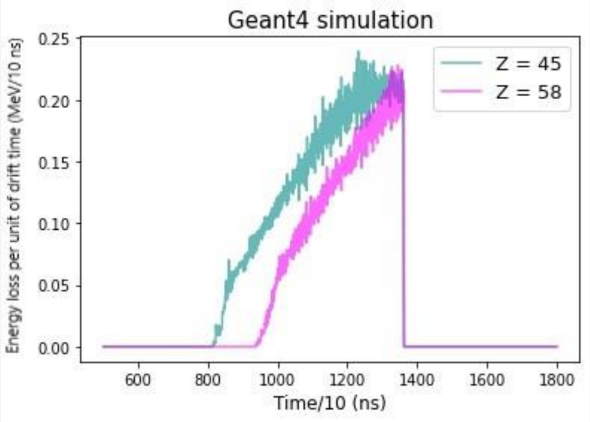
^{252}Cf spontaneous fission simulation

Kaliveda (GEF)

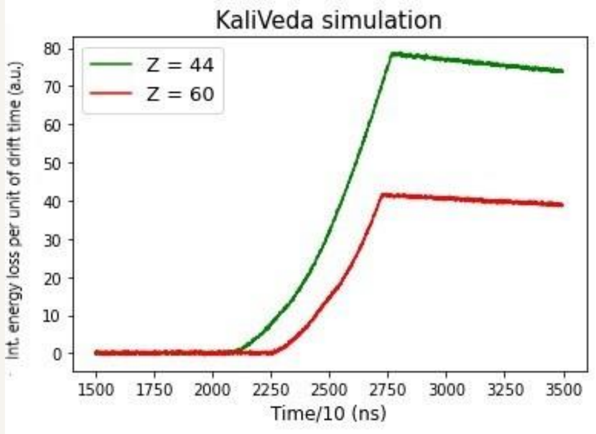
Geant4 (FIFRELIN)



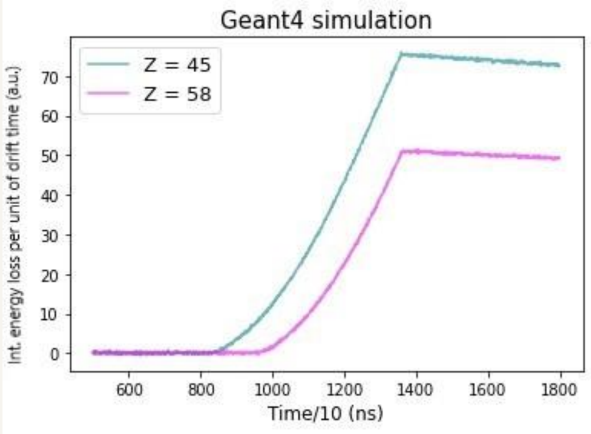
Raw energy loss



Raw energy loss:
Fluctuations due to random interactions



Experimental resolution:
fluctuations and integration



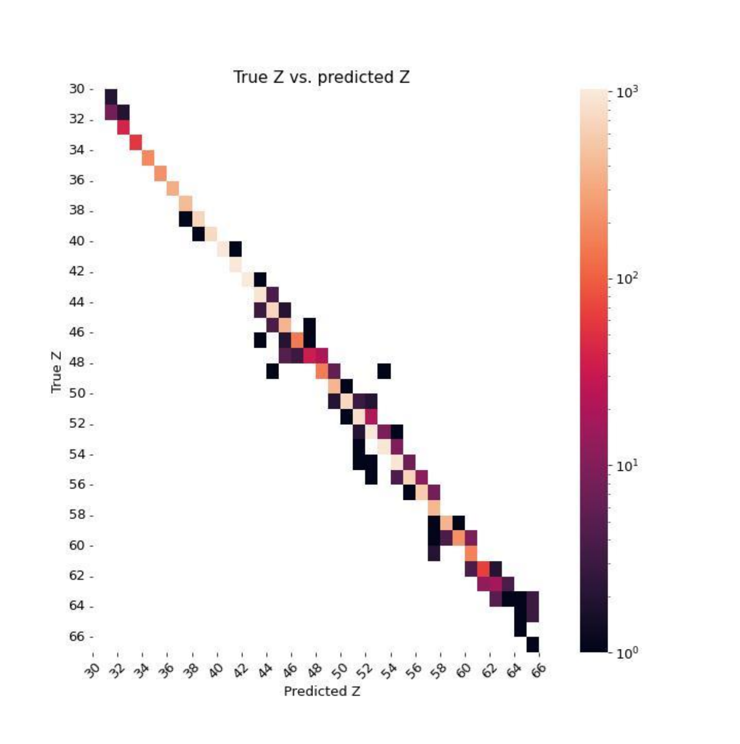
Experimental resolution:
integration

Results – Supervised - Simulation

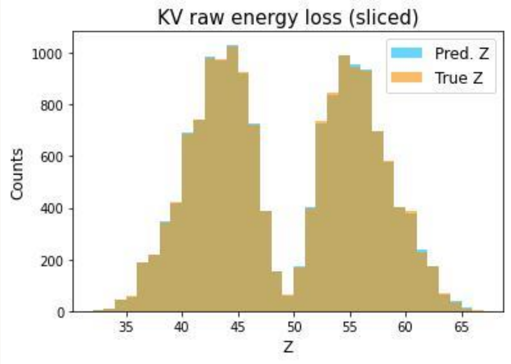
Metrics and graphs are based on the **test set**

- <u>Networks on **raw** signals</u>

Signals have the information needed to **retrieve correctly the *Z*** of the fragments

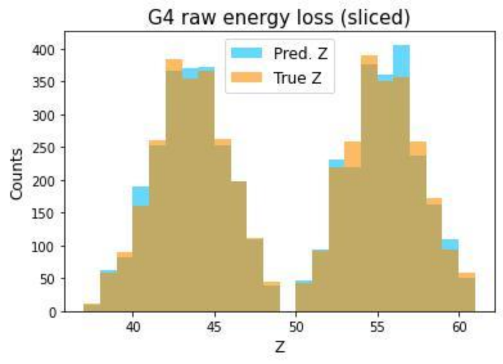


KaliVeda



CNN: 99% accuracy

Geant4

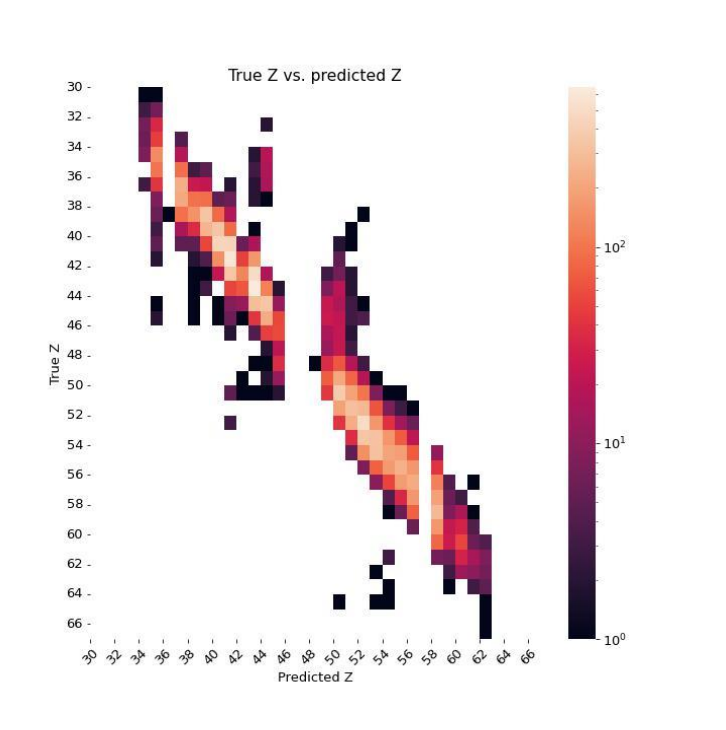


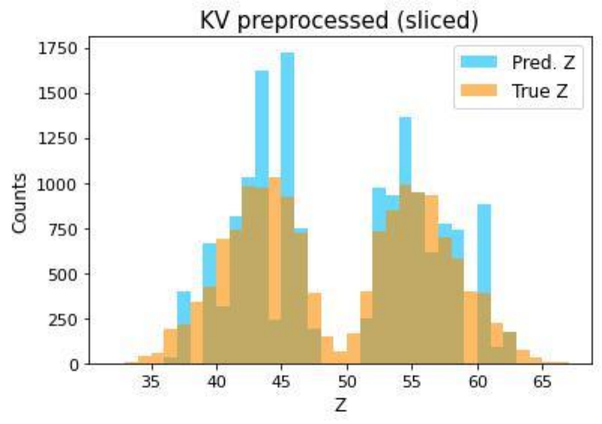
CNN: 83% accuracy

Results – Supervised - Simulation

Metrics and graphs are based on the **test set**

	KaliVeda	Geant4
• Networks on **raw** signals	CNN: 99% accuracy	CNN: 83% accuracy
• Networks on **integrated** signals	CNN: 40% accuracy	CNN: 60% accuracy





The **experimental resolution** worsens the prediction accuracy on signals

Results – Supervised - Simulation

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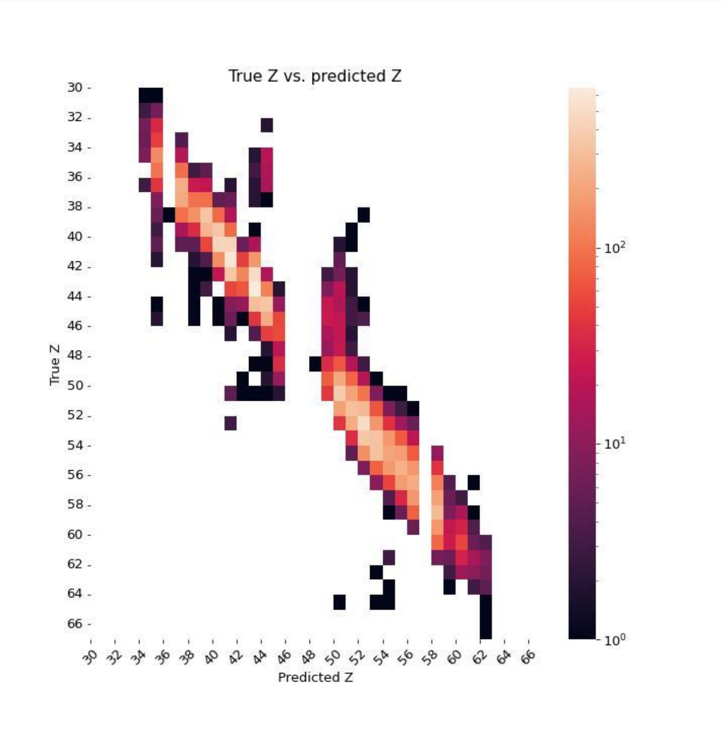

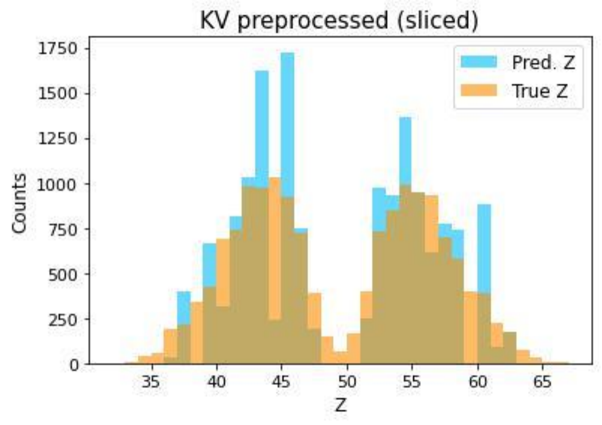

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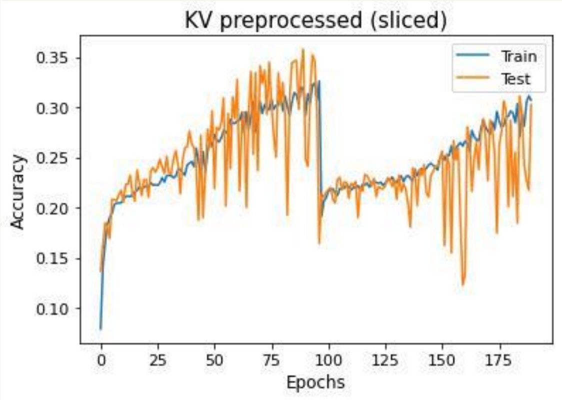


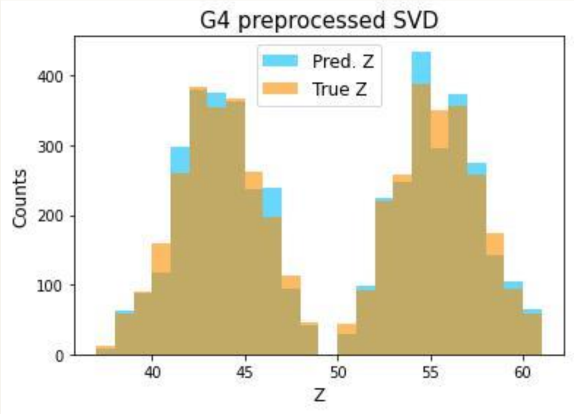
Dense networks show instability in the training: CNNs are preferred

Results – Supervised - Simulation

Metrics and graphs are based on the **test set**

	KaliVeda	Geant4
• Networks on **raw** signals	CNN: 99% accuracy	CNN: 83% accuracy
• Networks on **integrated** signals	CNN: 40% accuracy	CNN: 60% accuracy
• **SVD** dimensionality reduction	CNN: 83% accuracy	CNN: 80% accuracy

Linear algebra operation that keeps only the features that impact more on Z



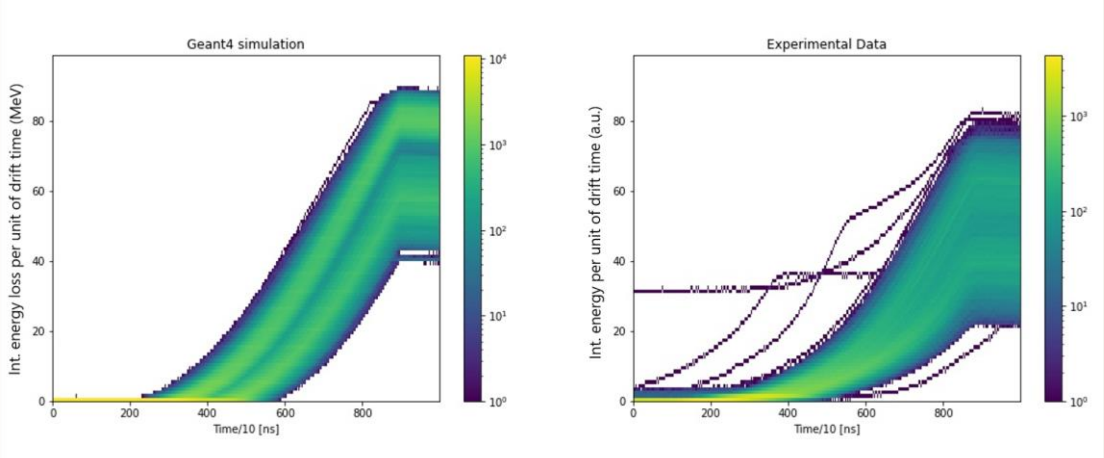
→ Great part of the **initial accuracy is retrieved**

Application to real data

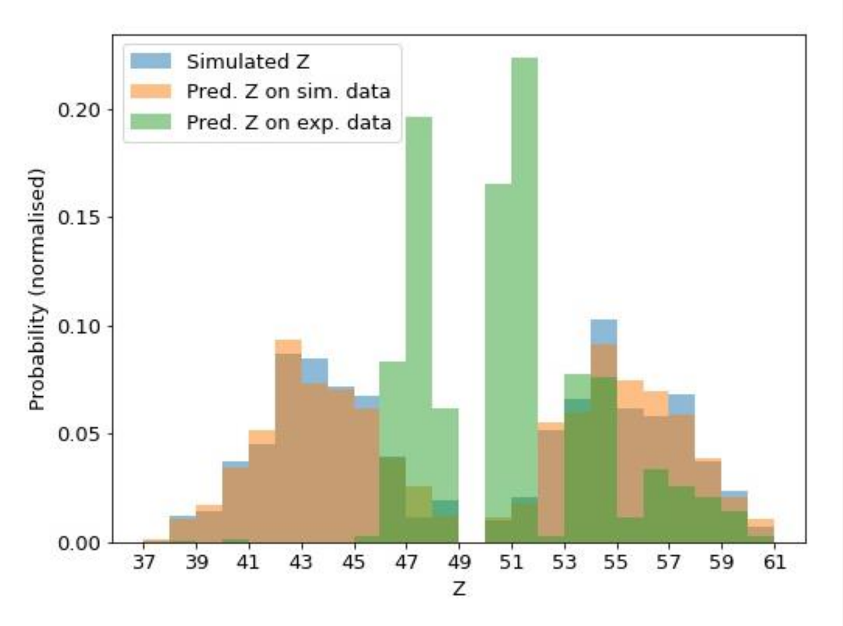
Comparison between Geant4 and real data

Experimental signal not reproduced

Simulated data has different behaviour



Application of CNN on **SVD-reduced exp. data**



<u>Results</u>

Experimental traces **divided** into heavy and light

NO Z identification for real data

Application to real data

Comparison between Geant4 and real data

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Application of CNN on **SVD-reduced exp. data**

<u>Results</u>
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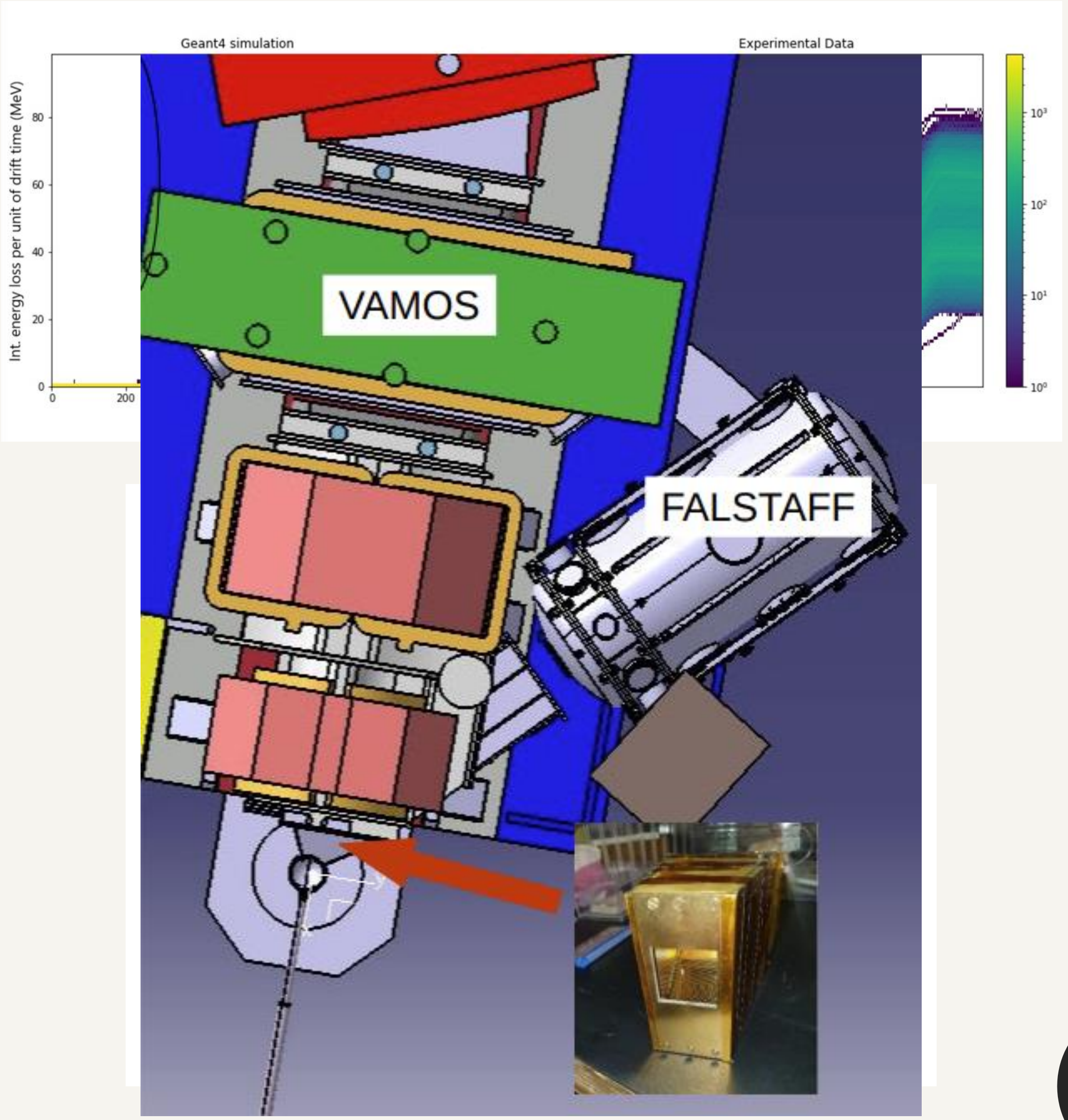
<u>Future steps</u>

Coincident measurement of Z and energy loss profile

FALSTAFF coupled to VAMOS



Conclusions

- Energy loss profiles contain the information to reconstruct the charge

- **CNNs**: powerful and stable tools for our task

- The simulations with the added experimental resolution show that **FALSTAFF can be used for the Z identification**

- Training on real labelled data is needed (experiment ongoing)