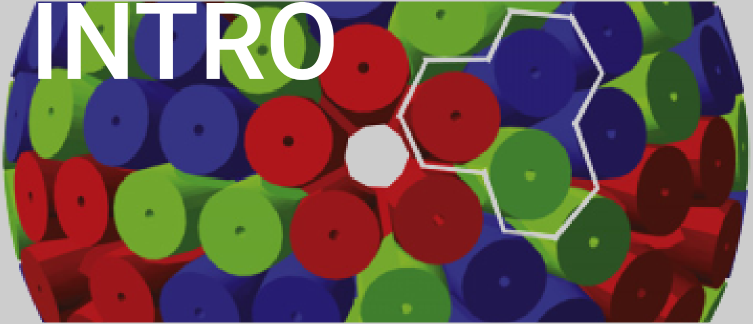
Machine Learning to count interactions in AGATA

Me: Danylo Kovalenko
Taras Shevchenko National University of Kiyv, Kyiv, Ukraine

Supervisor: Joa Ljungvall.
IJCLab, Orsay, France

06.09.2021 - 06.11.2021

INTRO



There is a new age in nuclear structure research, and it requires the new generation of detector systems with unprecendent level of sensitivity and count-rate capabilities.

In AGATA combined:

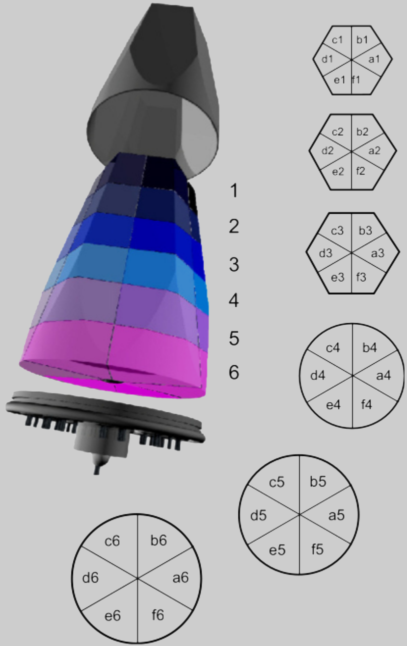
1. Large solid angle
   -> Increase efficency $\left(\varepsilon = \frac{N_{detected}}{N_{emitted}}\right)$

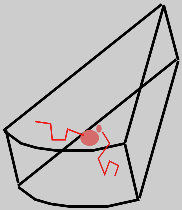
2. Electrically Segmented HPGe detectors and **Gamma-ray “tracking”**
   -> Peak-to-total (Escape supression)

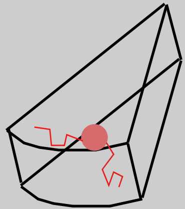
Gamma-ray “tracking” algorithm require:

- Position of interactions -> PSA
- Time of interactions
- Energy deposition

Pulse shape analysis (PSA) can tell more precisely about position of interaction within segment.
But it has the flaw - it can not separate two close interactions and sees one instead.







What the challenge is?

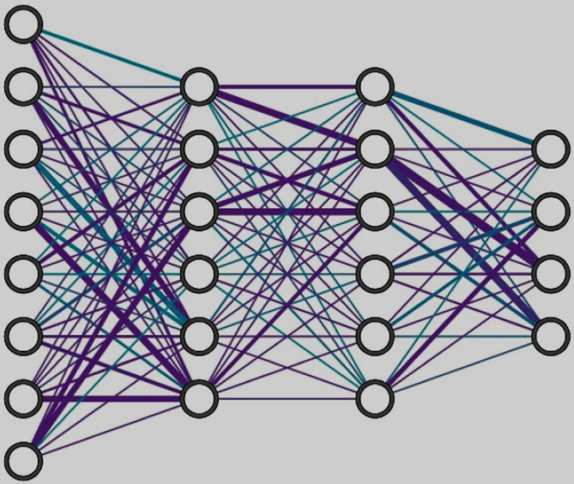
Prediction of number of interactions within segment:

Simulate data with GEANT4

Build and train neural network

Use it in case of real data

Short explanation of deep learning



$$f(\vec{X}, \mathbf{\Omega}) = \vec{\mathbf{Y}}$$

$\vec{X} - input$

$\vec{Y} - output$

The first approach

$$f(\vec{X}, \mathbf{\Omega}) = \vec{\mathbf{Y}}$$

i $\quad \vec{X}_i = [Edep_i, \quad crystal_i, \quad Segment_i] \quad \vec{Y}_i = Y_i$

	edep	crystal	slice_sect	num_of_int
1	61.454	116	5	1
2	236.498	2	14	1
3	379.378	2	24	1
4	264.125	2	23	1
5	1680.0	157	4	3
6	80.0	59	0	1
7	16.929	31	14	1
8	45.961	31	4	2
9	220.426	31	3	3
10	350.442	4	10	1
11	351.887	4	31	1
12	26.857	4	20	1
13	150.814	4	21	1

The second approach

Enegry deposition matrix

$$Edep_{i,j}$$

Cryst x Segm

$$f(\vec{X}, \mathbf{\Omega}) = \vec{\mathbf{Y}}$$

Num. of interactions matrix

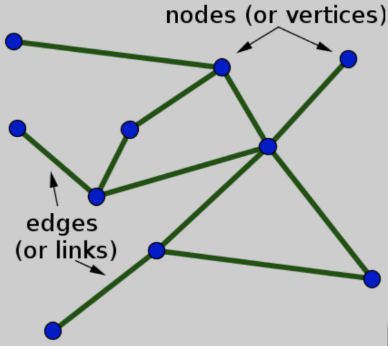
$$NumOfInt_{i,j}$$

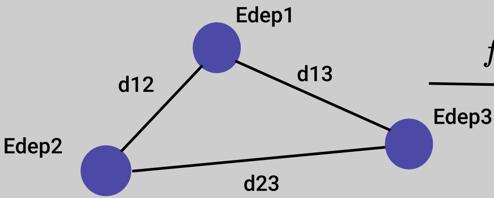
Cryst x Segm

```
Global_array[0][1]

array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])

Global_array[0][1].shape

(165, 56)
```

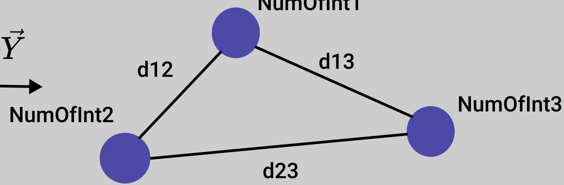
```
Global_array[1][1]

array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])

Global_array[1][1].shape

(165, 56)
```

The third approach





$$f(\vec{X}, \boldsymbol{A}, \boldsymbol{\Omega}) = \vec{Y}$$



$$\vec{X} = [Edep_i] \quad \mathbf{A} = [\mathbf{Distance_{ij}}]$$

The fourth approach

1. Probability distributions inside layers:

$$\Omega$$

Exact meaning

Random value from distributions

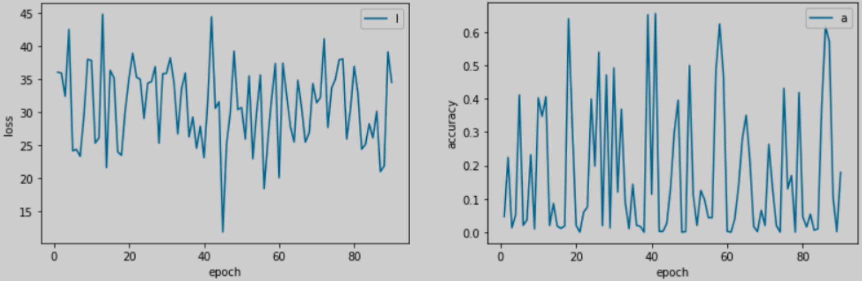
2. Cross-entropy for target and output:

$$\vec{Y} = [P_1, P_2, P_3, \ldots, P_8]$$

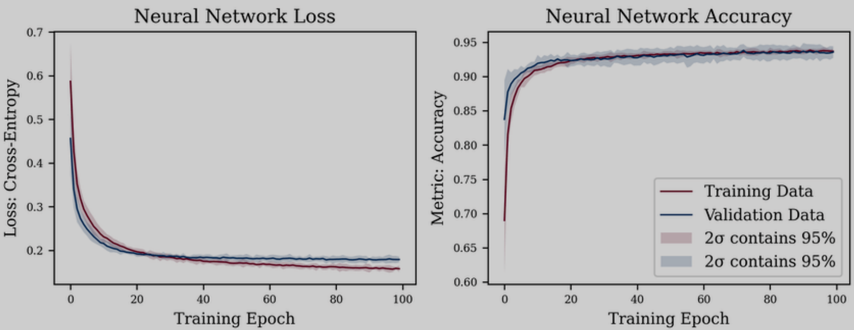
$$\sum P_i = 1$$

P_i -- probability to find “i” number of interactions

Impossibility to train



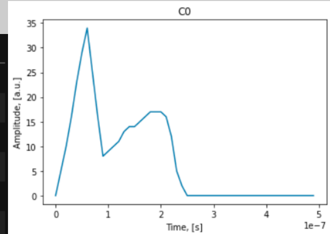
Our result

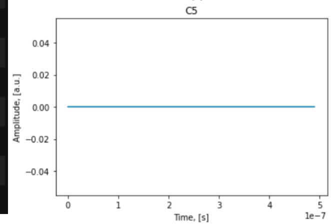


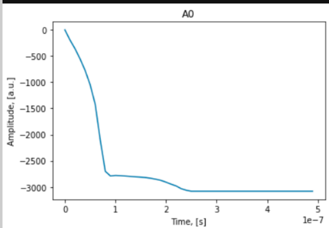
How it should look

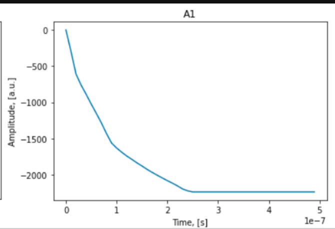
The fifth approach (in process)

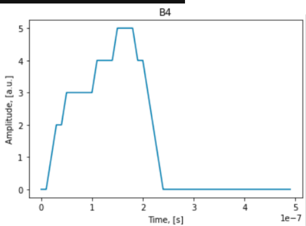
	time	ampl	A0	A1	A2	A3	A4	A5	B0	B1	...	E2	E3	E4	E5	F0	F1	F2	F3	F4	F5
0	0.000000e+00	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	1.000000e-08	235	-192	-296	176	12	1	0	34	11	...	3	1	0	0	-130	37	18	6	1	0
2	2.000000e-08	487	-359	-612	323	25	2	0	71	26	...	6	2	0	0	-248	64	39	12	2	0
3	3.000000e-08	742	-553	-763	378	33	4	0	100	41	...	9	3	0	0	-352	86	54	15	2	0
4	4.000000e-08	1032	-774	-891	413	39	5	1	115	51	...	10	4	1	0	-445	103	71	19	3	0
5	5.000000e-08	1364	-1048	-1026	440	46	6	1	137	60	...	11	5	1	0	-518	119	80	22	3	0
6	6.000000e-08	1759	-1421	-1154	447	51	7	1	157	67	...	13	5	1	0	-432	129	85	24	3	1
7	7.000000e-08	2259	-2106	-1286	435	53	7	1	144	73	...	10	4	1	0	-121	116	77	22	3	1
8	8.000000e-08	2919	-2701	-1432	407	51	6	1	98	66	...	6	3	0	0	140	93	66	19	3	0
9	9.000000e-08	3394	-2789	-1563	381	52	6	1	65	64	...	4	2	0	0	63	74	63	19	3	0
10	1.000000e-07	3433	-2780	-1632	371	55	7	1	71	67	...	5	3	1	0	69	77	67	20	3	0
11	1.100000e-07	3478	-2784	-1690	348	58	7	1	79	71	...	5	3	1	0	74	80	69	21	3	1
12	1.200000e-07	3527	-2791	-1743	327	59	7	1	85	73	...	6	3	1	0	77	84	72	22	4	1











The complexity of fifth approach

1. Each crystal has isolated data storage - the only conection is time.
2. Size of vectors with whole pulse shapes much bigger than sizes of previous input data sets.

That means that computation needs much more time than before. Regardless, with PS we can use all possible information from detector.

Experiment with latest model (in process)

1. Create set of files which contains hyperparameters: learning rate, epochs, batch size.
2. Run model with different files and save the result (list of loss and accuracy) according to it's hyperparameters.
3. Ploting different results in order to find if it changed.
4. Repeat points 1-3 for different models (data formats, sets of layers, sizes of datasets).

Conlusions

Stochastic nature of data (experimental or simulated), as I understand, gives the most weightfull impact on imposibility to train the Neural Network.

But physics tells that there are should be some patterns even if we don’t see it explicitly: directions of scattering and closeness of different events is not completely random.

That is why we use Deep Learning process - to find some implicit connection. And with the increasing complexity, I believe, we will reach the aim.

Thank you for your attention!