Unfolding methods is AlCap

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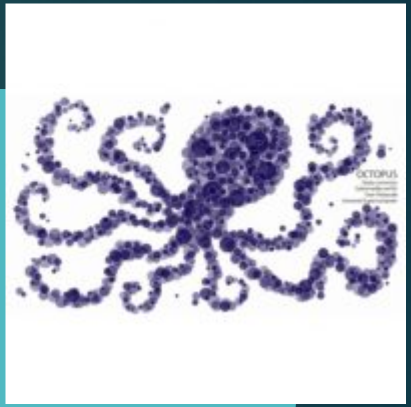
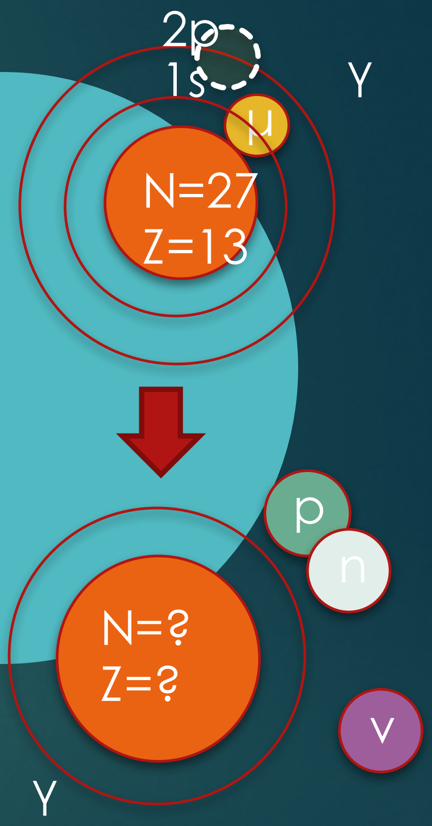
山中研合同年末発表会 12月28日 11:40-12:00

Contents



Short Introduction



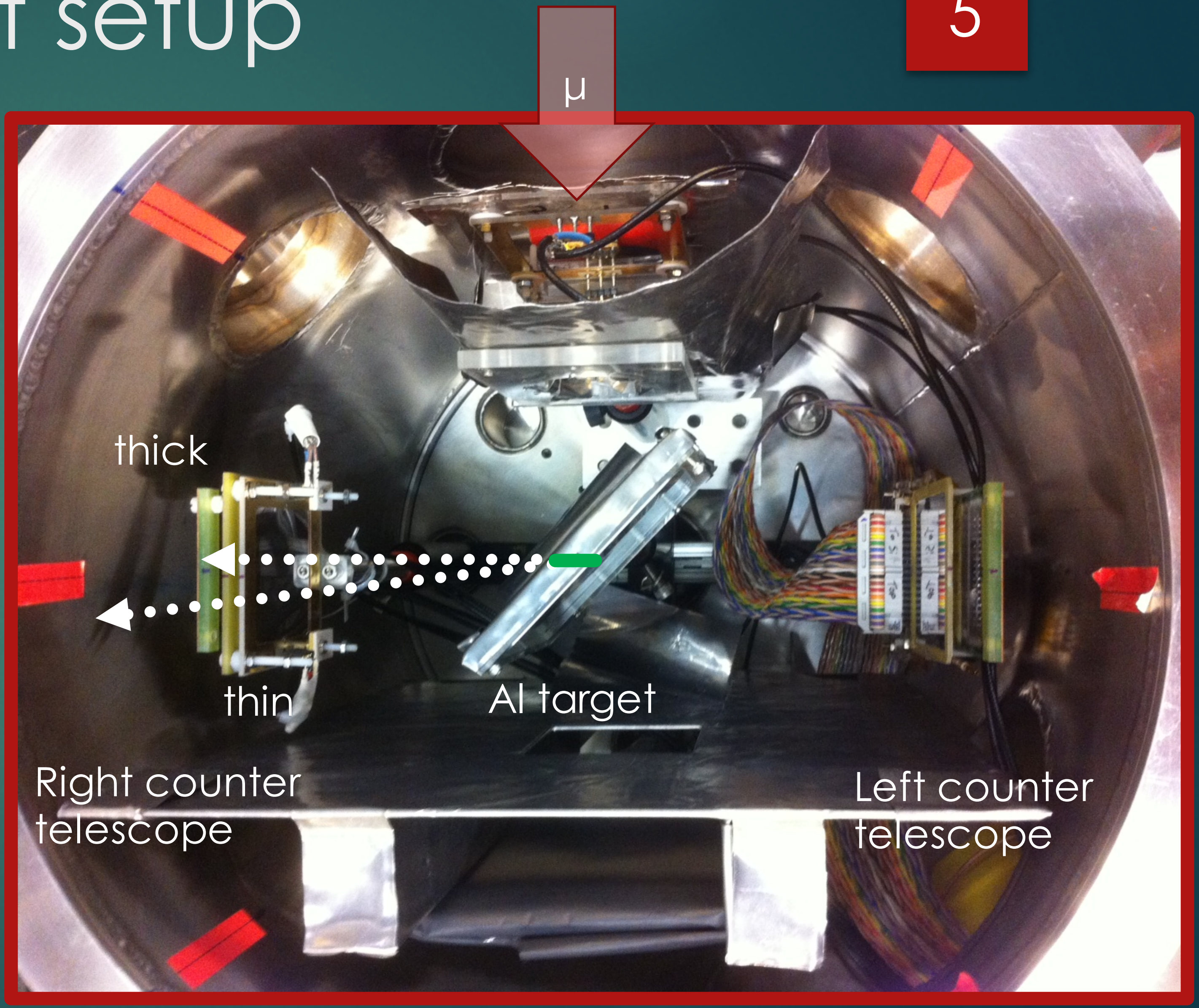
- The R2015 run of AlCap measured the charged particle emission rate and energy spectrum after muon nuclear capture in aluminium.
- E < 40MeV for aluminium, and titanium has never been measured before. (A. Wyttenbach, 1978 doi:10.1016/0375-9474(78)90218-X)
- Muons interact weakly with the protons in the nuclei emitting neutrons and muon neutrinos, $\mu + p \rightarrow n + \boldsymbol{\nu}_{\mu}$.
- Precompound nuclei may also be created that has some probability to emit protons (and/or other charged particles) to return to a stable nuclear configuration (P E Hodgson 1987 Rep. Prog. Phys. 50 1171)

Motivations for and difficulty of unfolding

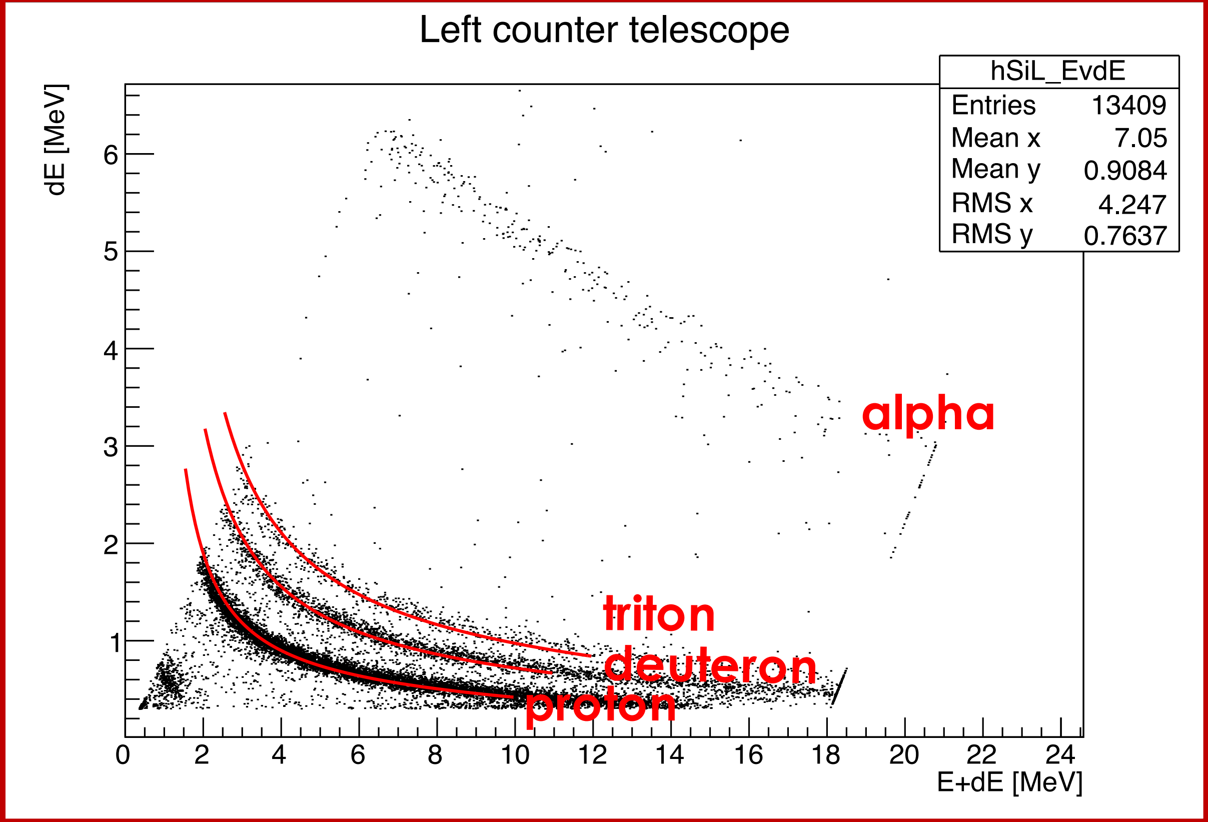
- To reveal the **true energy** of particles before detector effects, e.g. due to finite detector resolution, unknown energy loss.
- To compare the result between two different experiments. Different experiments have different detector responses so unfolding is necessary.
- However, unfolding is difficult and ill-posed (solutions may not exist, unstable and is not unique).
- The opposite to unfolding is forward-folding which is to fit the data with a smeared theoretical spectrum, which is considerable easier.
- For AlCap and muon-conversion experiments like COMET/Mu2E the proton emission results were used in the design of the detectors.
- It is also possible to use protons for normalization in addition to looking at the K-alpha muon x-ray count <u>if the rates are known for Al</u>.

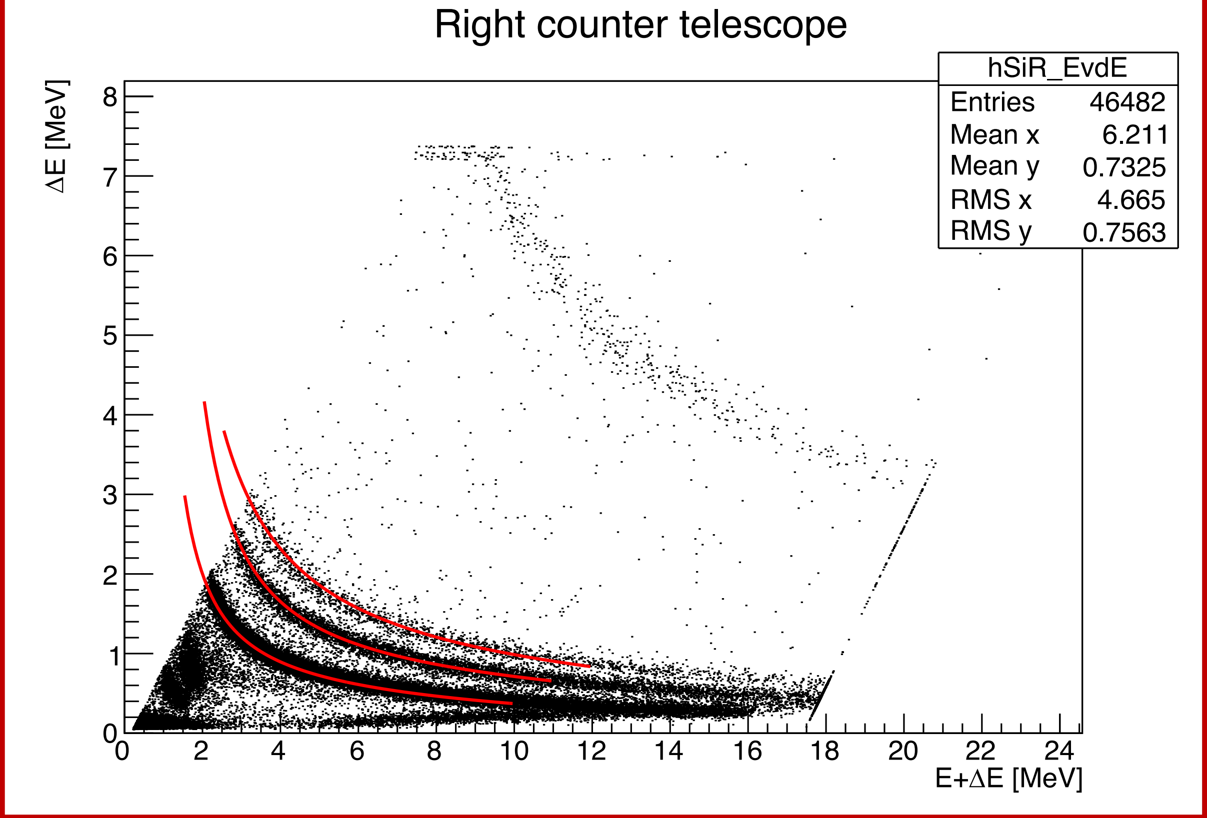
AlCap experiment setup

- Charged particles, neutrons and gammas are emitted from the target (Al, Si, Ti) after nuclear muon capture
- These particles lose energy (unknown amount) when passing through the 100micron target.
- Charged particles that reach the counter telescopes deposit the remaining energies.
- References: arXiv:1501.04880



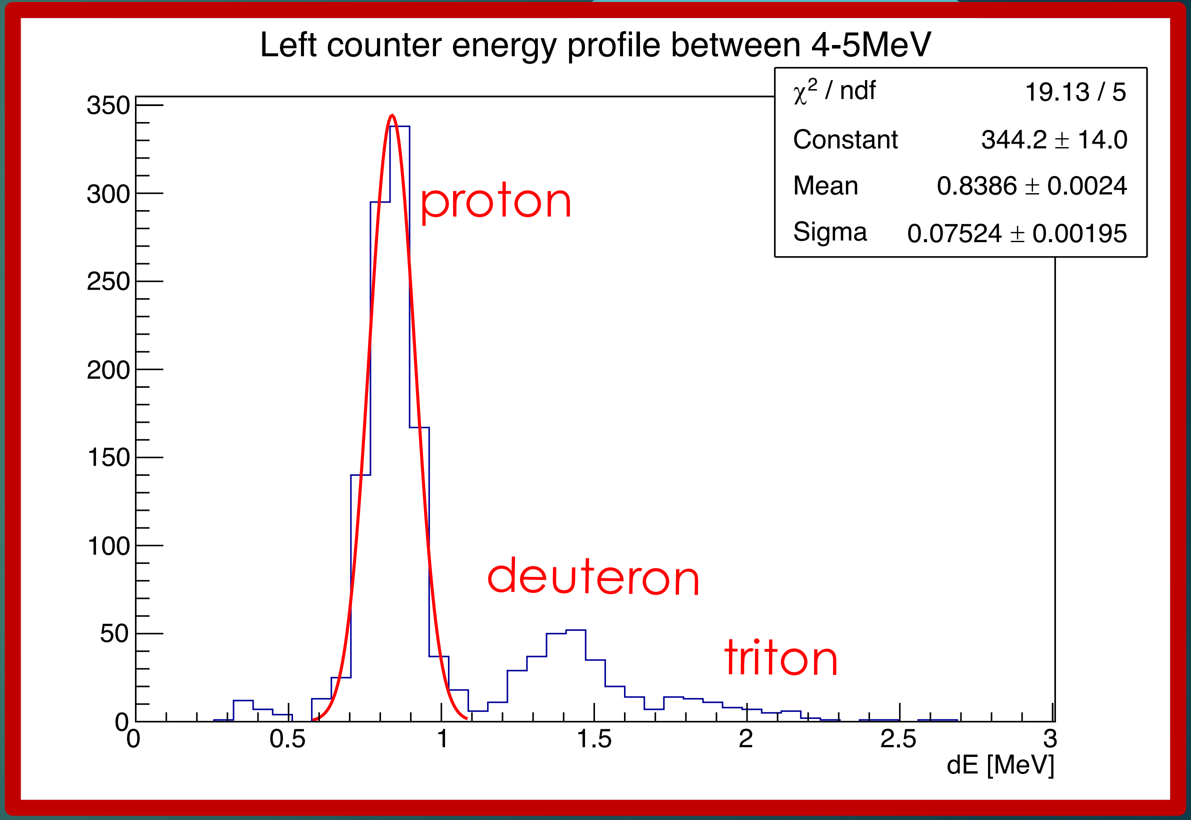
Charged particle identification





Likelihood probability method

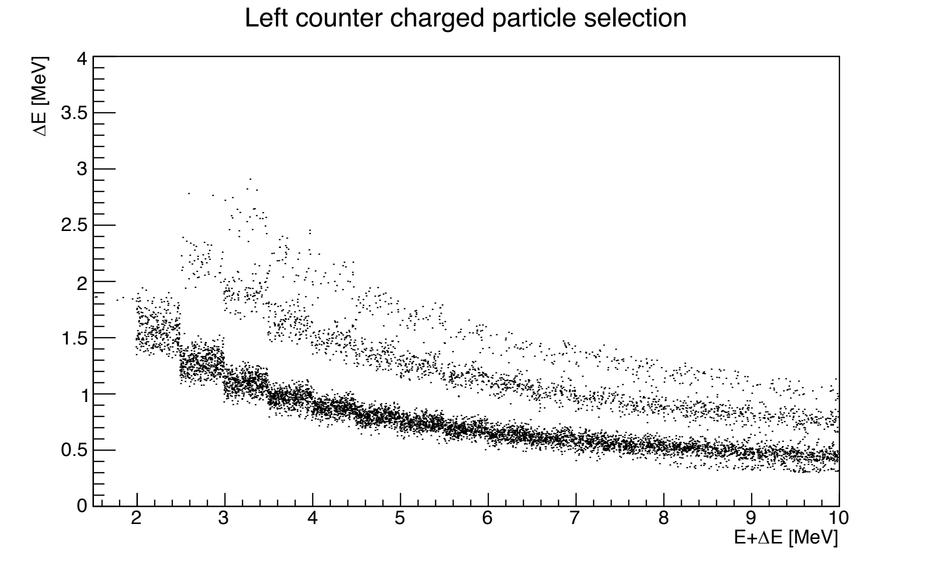
- From the previous slide, we had compared the data with Monte Carlo truth (which were the red lines labelled with particle names)
- We can use a <u>Gaussian</u> model to fit the data for every energy bin and select particles that lie within <u>3σ</u> to be classified as one of the charged particles. σ is determined from the counter telescope energy resolution.

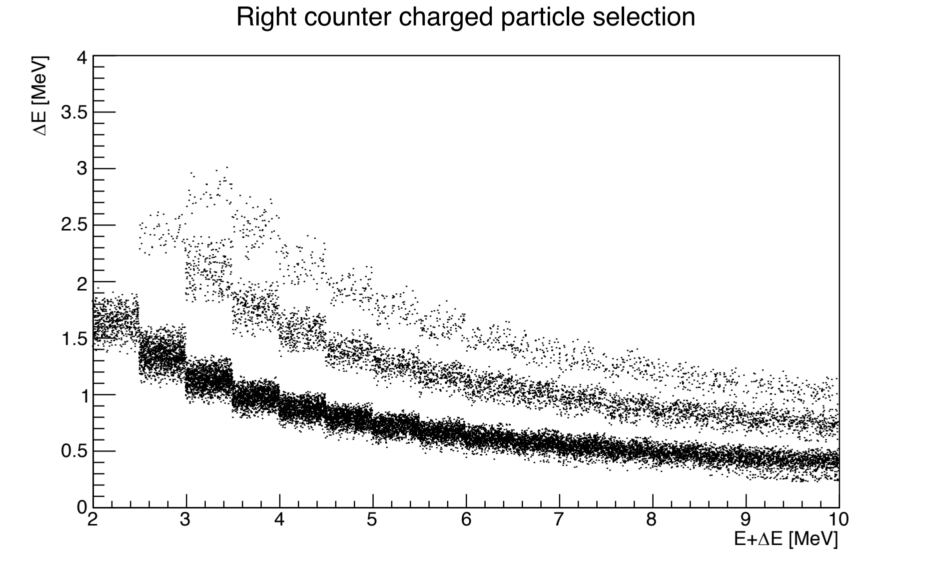


Y-projection of the ΔE-E plot, or energy deposit in the thin Silicon detector

LLP cut selection results

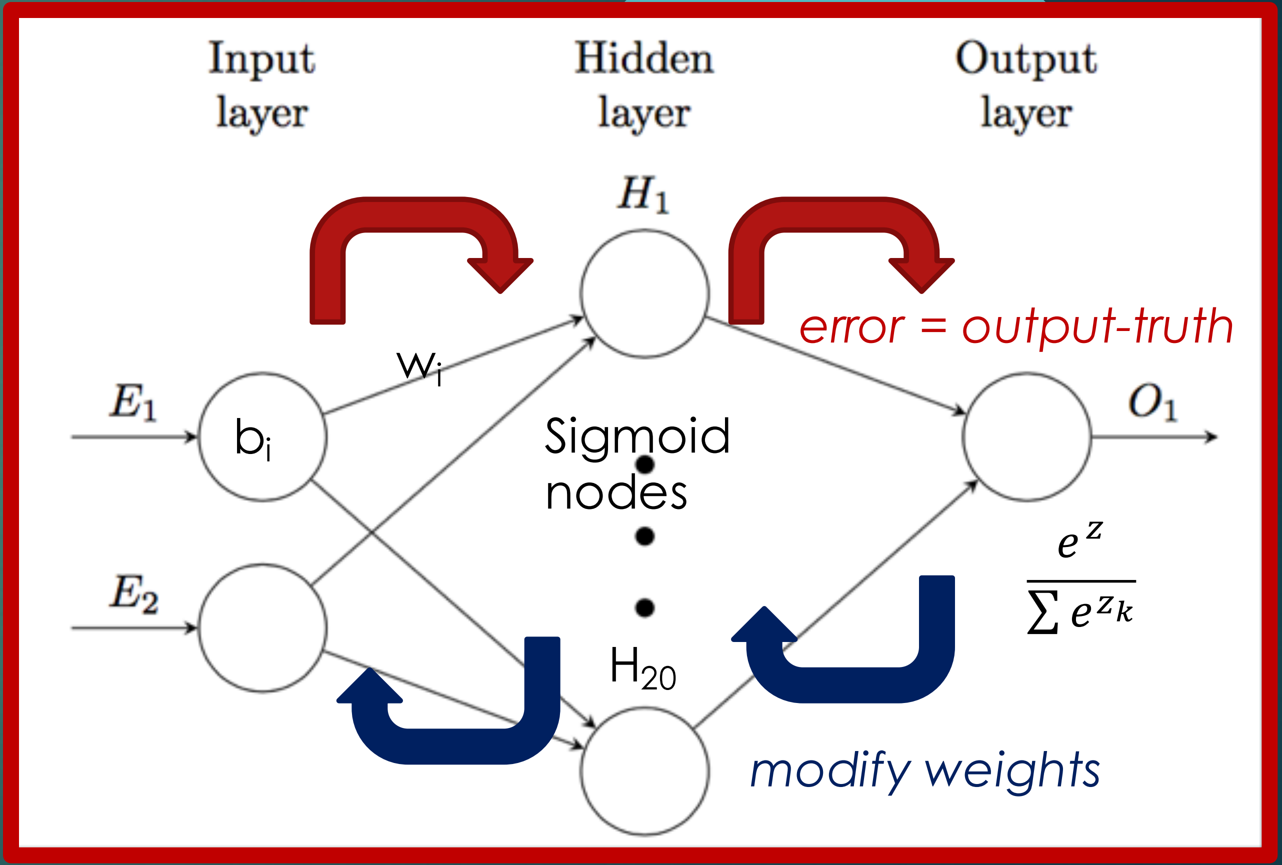
- Energy bin size of 500keV is used. This is convenient later for unfolding.
- The LLP method is applied on all three charged particle types: protons, deuterons and tritons separately.
- Only energies less than 10MeV is not used due to particles not stopping in the thick Silicon detector.
- Those particle do not fit in the dE/dx curve.
- The upper limit of this technique at about 10MeV is set by punch through particles.





Artificial neural network architecture for classification

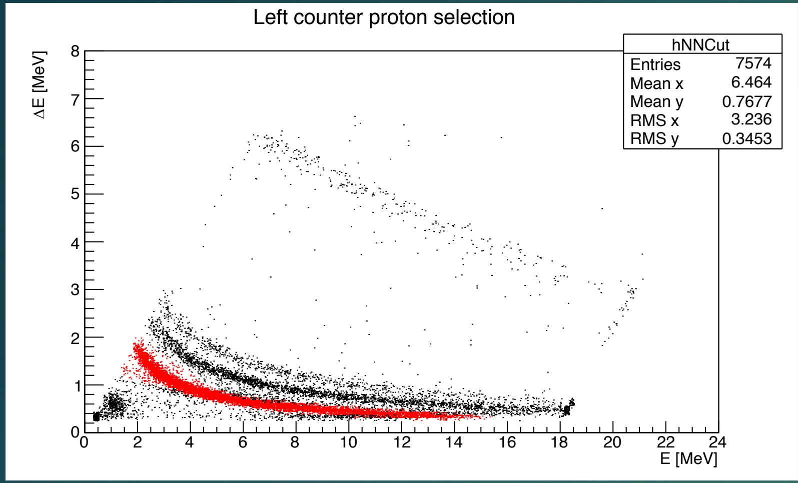
- Input layer consists of two nodes, thin detector energy deposit, E_1 and thick detector energy deposit, E_2.
- Hidden layer consists of 20 nodes.
- Output layer is a softmax node used for classification of signal and background. It outputs a probability value between 0 and 1.
- Training is done on all types of particles that may exist which is the background and the signal would be the charged particle we want to classify.

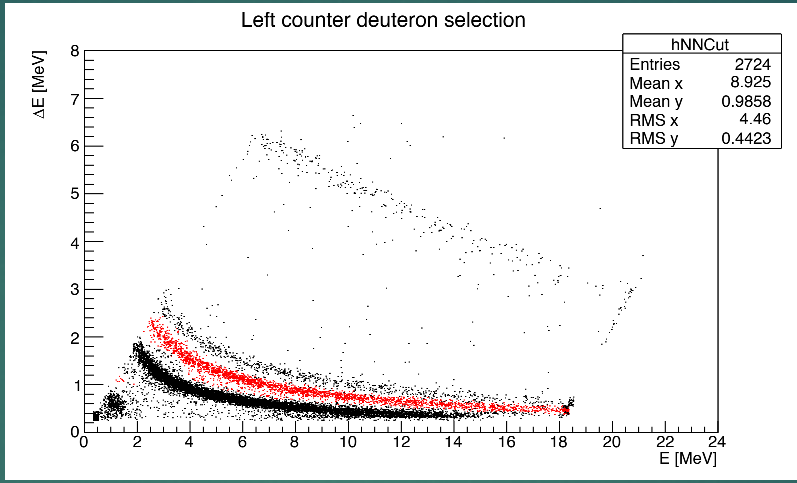


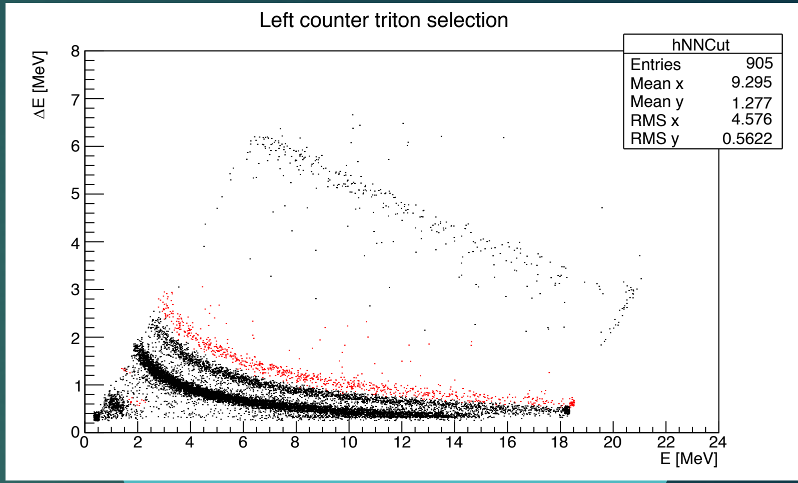
(Dis)Advantages of neural networks in AlCap

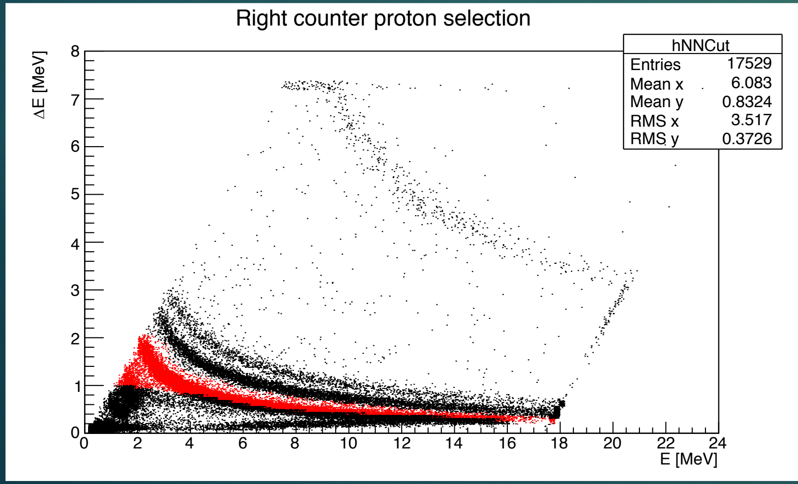
- [Good] Compared to the cut selection, this technique offers a chance to automate the particle ID process and recover higher energy particles beyond 10MeV where it was not possible to be done using the LLP cut method.
- [Not so convenient] Unlike the cut selection method, it is necessary to model all the noise and particles that can be detected by the counter telescopes for good identification.

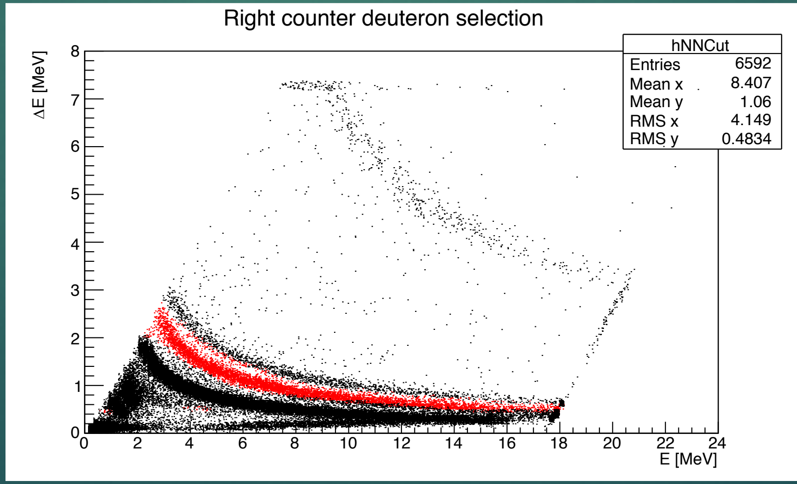
Classification results

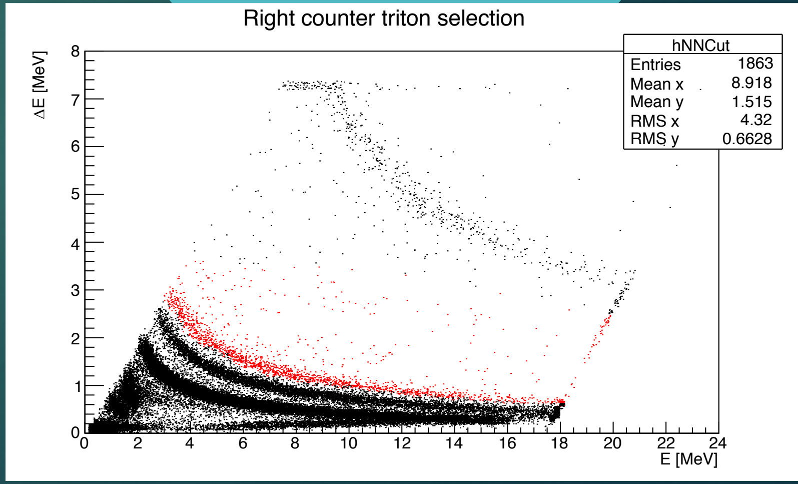












Bayesian inference

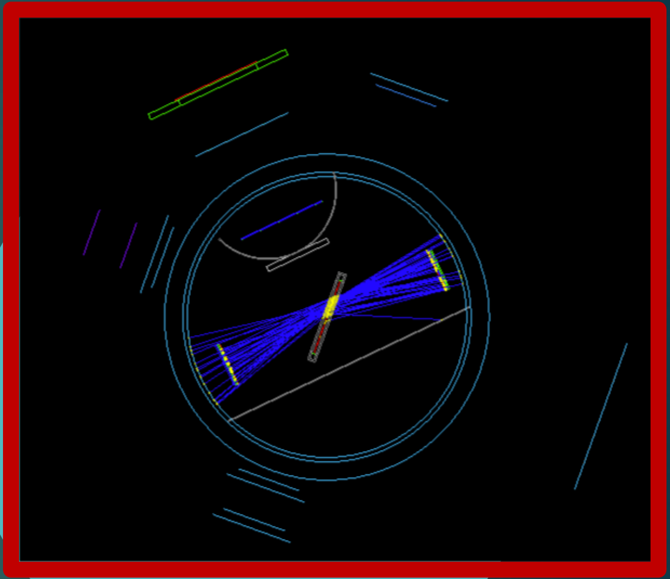
- Based on a priori knowledge of the experiment, usually from Monte Carlo it is possible to use Bayesian probability inference methods to ascertain the cause C_i from measurement of the event E_i.

$$P(C_i|E_i) = \frac{P(E_i|C_i)P(C_i)}{P(E_i)}$$

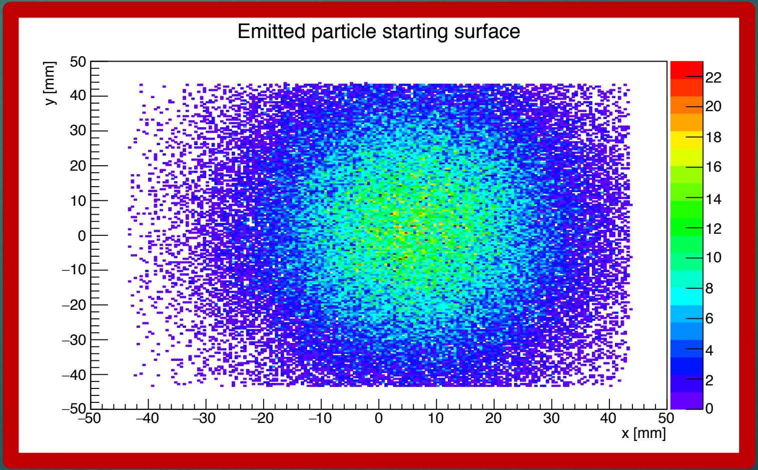
- The <u>probability</u> of the <u>truth</u> cause C_i if E_i <u>data</u> is measured is thus determined by the Bayesian formula above.
- For AlCap, a Monte Carlo simulation provides the truth data which can then be used to produce a <u>response matrix</u> that relates the truth and measured data by a particle counter telescope.
- However, it is also the difficulty of this technique as it is sensitive to variations in the Monte Carlo initial run conditions and setup.
- Unfolding in ROOT: RooUnfold (arXiv:1105.1160)

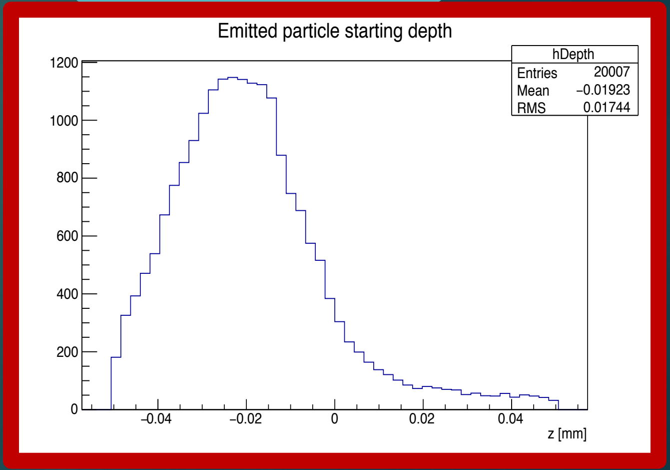
Muon stopping distribution

- The muon beam profile hitting the Aluminium target has been measured by a 14-strip silicon detector (both horizontally and vertically)
- The muon beam energy was inferred both from beam measurement of punch-through muons using a 14-strip silicon + thick silicon and the muon stopped and punch through energies.
- However, it is only possible to use Monte Carlo to infer the muon stopping depth in the 100micron target.



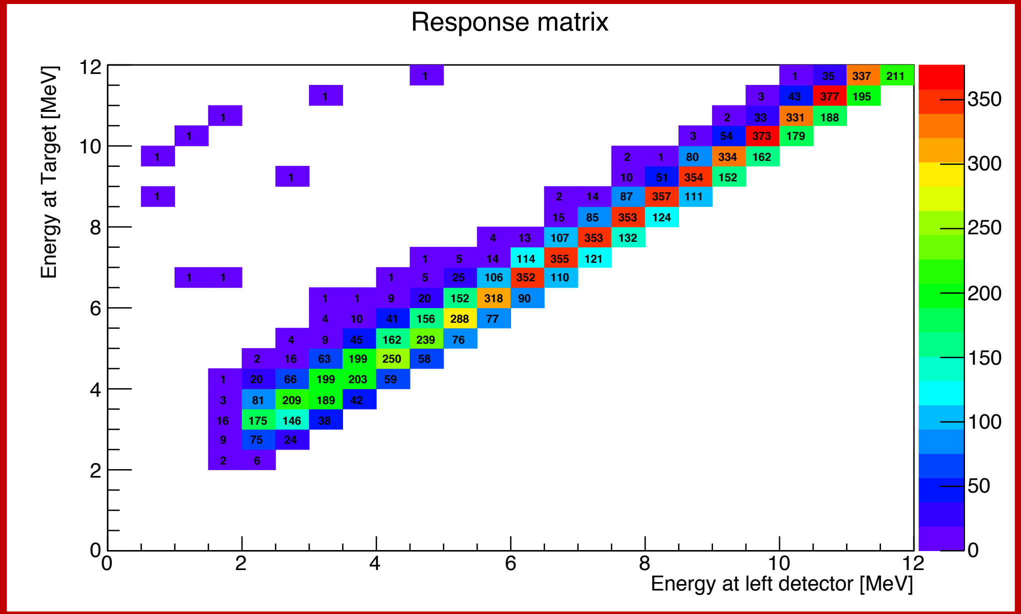
A stopping distribution is estimated starting with a muon with energy 1.39MeV with spread of 0.122MeV.



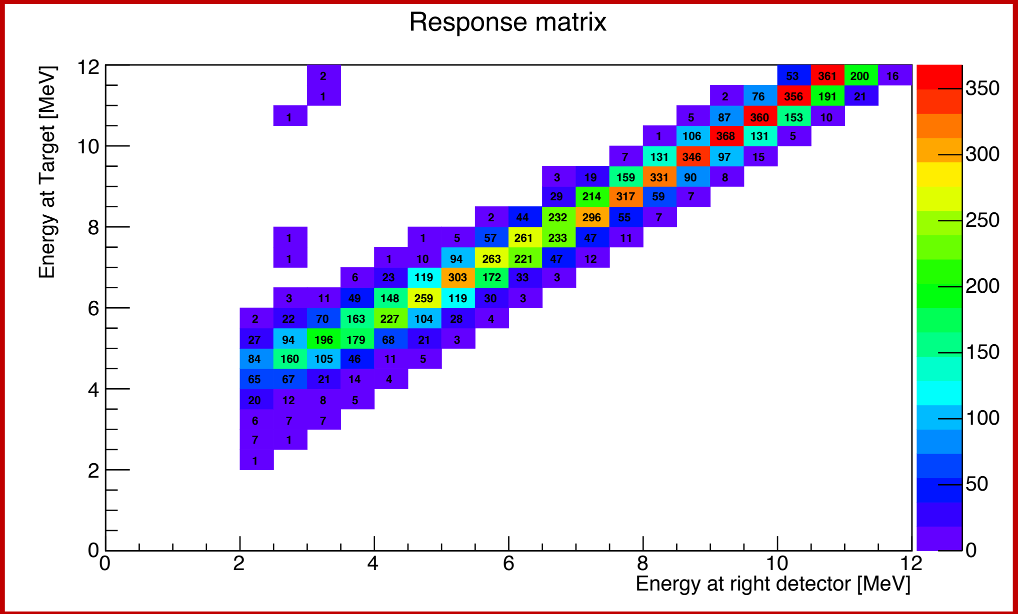


Response matrices

- Essentially this matrix relates the truth energy (energy of the charged particles at creation) and the measured energy at the detector.
- Starting particle energy is <u>unknown</u> so to reduce bias, a uniform distribution between 0 to 12 MeV is used.
- This is then used to unfold the measured data to obtain the charged particle energy spectrum at creation.

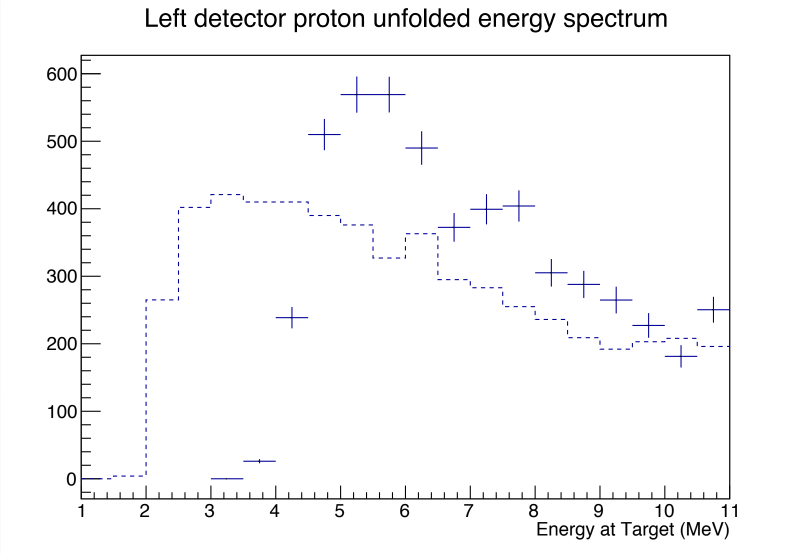


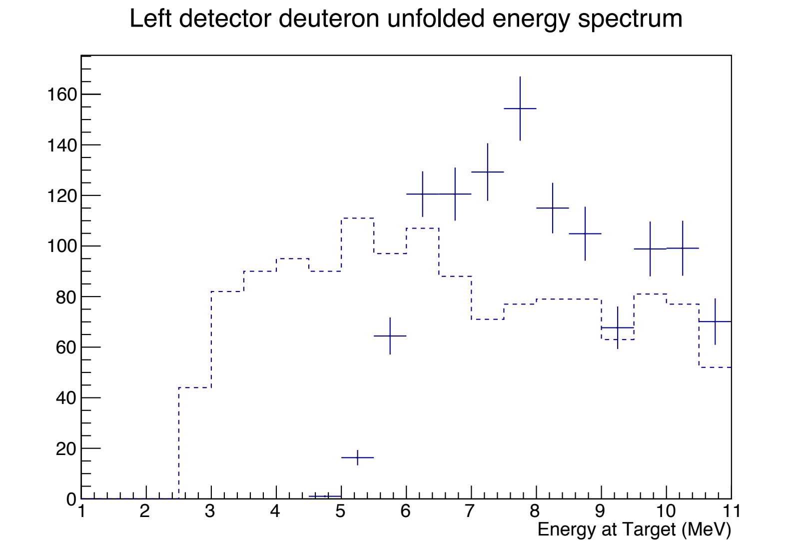
Left

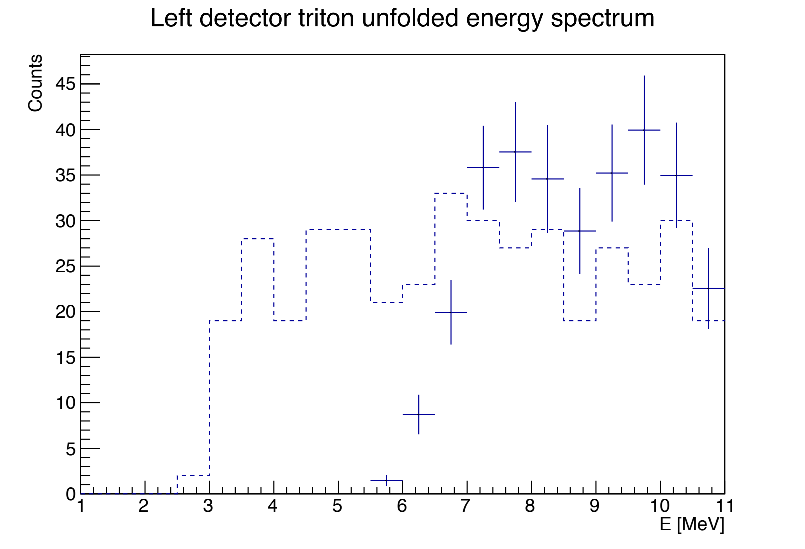


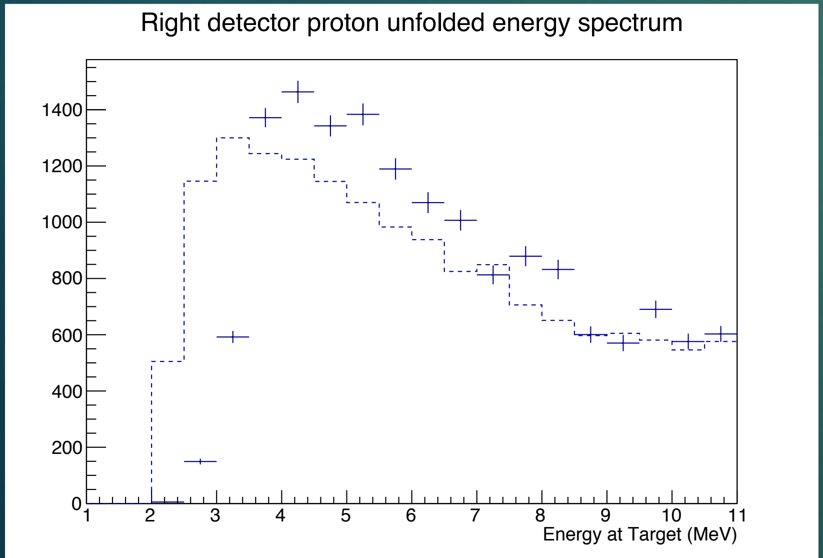
Right

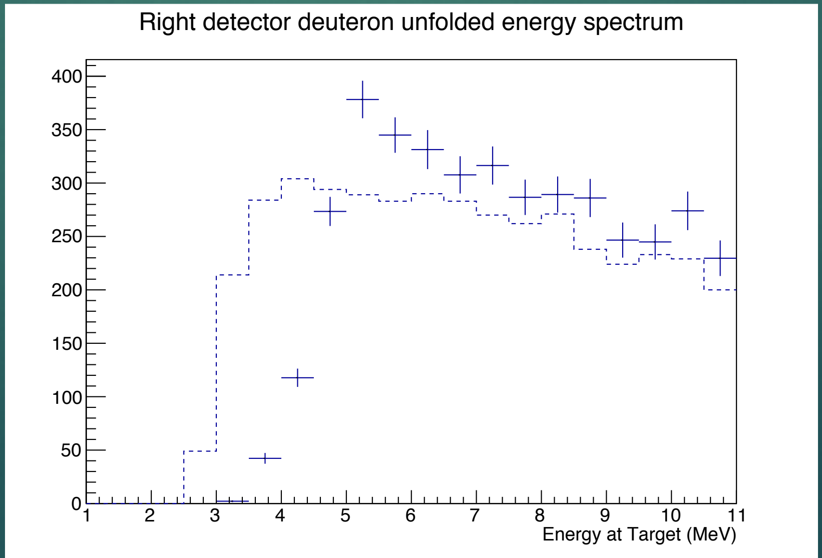
Bayesian unfolding results

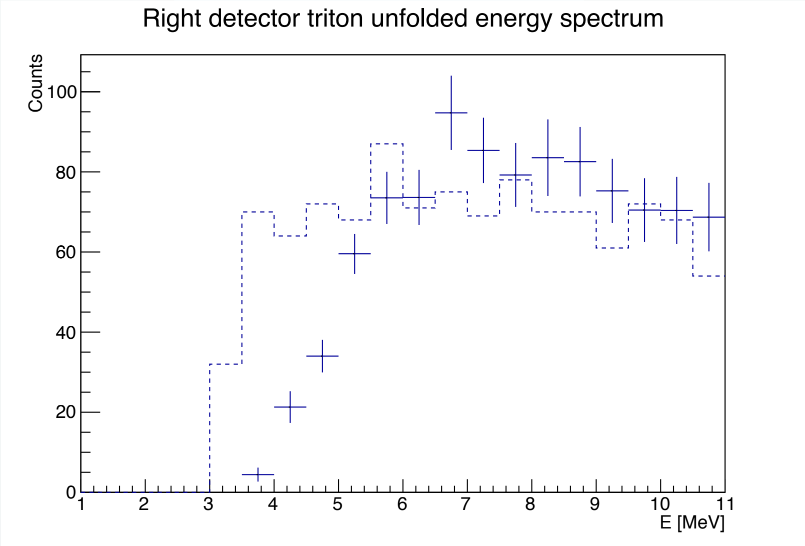






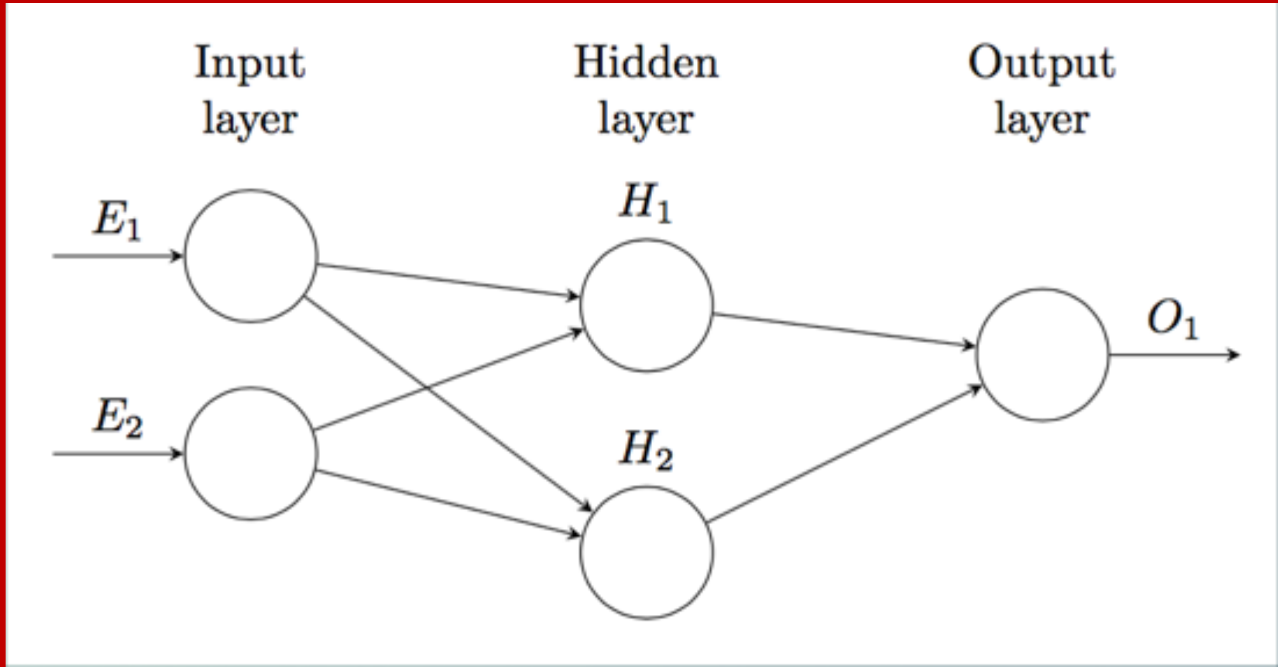




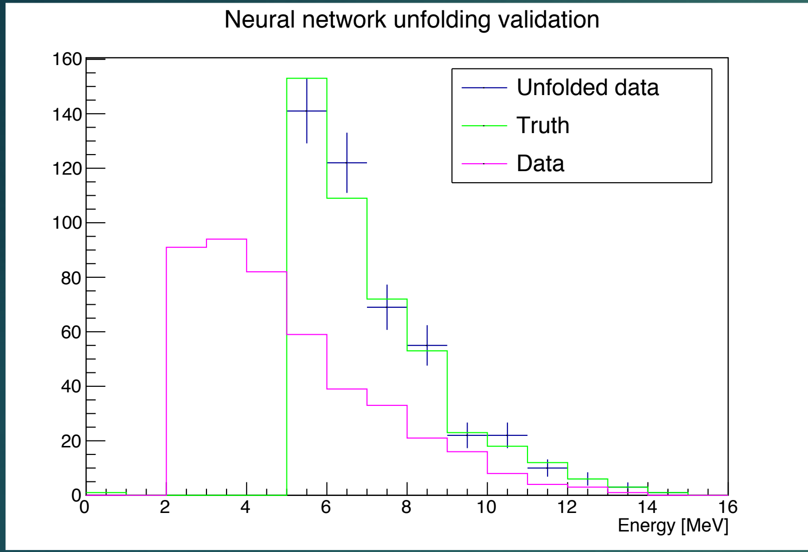


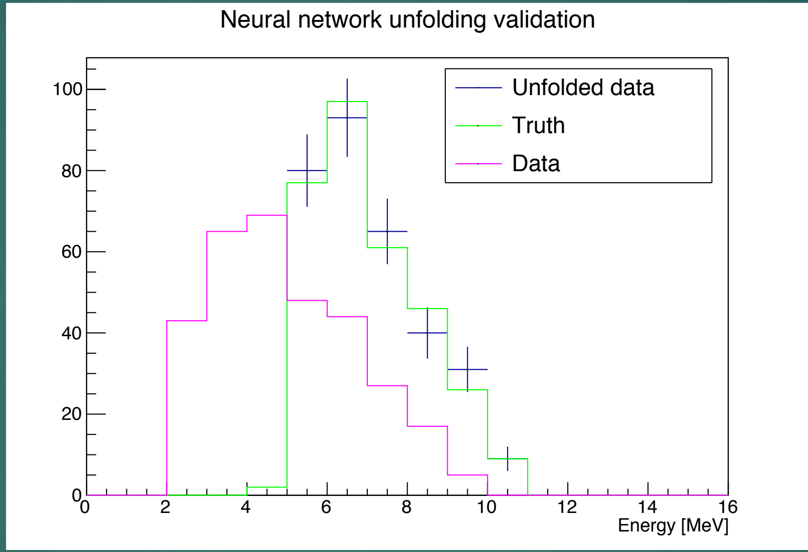
Artificial neural network unfolding

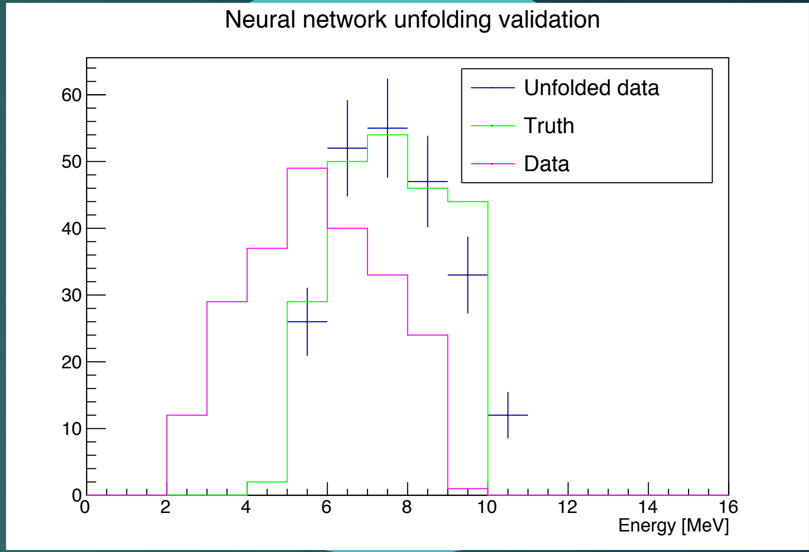
- The architecture used is not the same as for classification. There is still only one hidden layer but it only consists of two nodes. The output node is also not a softmax node, but outputs the unfolded energy.
- This network is trained on each charged particle separately.
- Similar to the Bayesian inference method, this is also sensitive to variations in the Monte Carlo.



Neural network unfolding verification with Monte Carlo







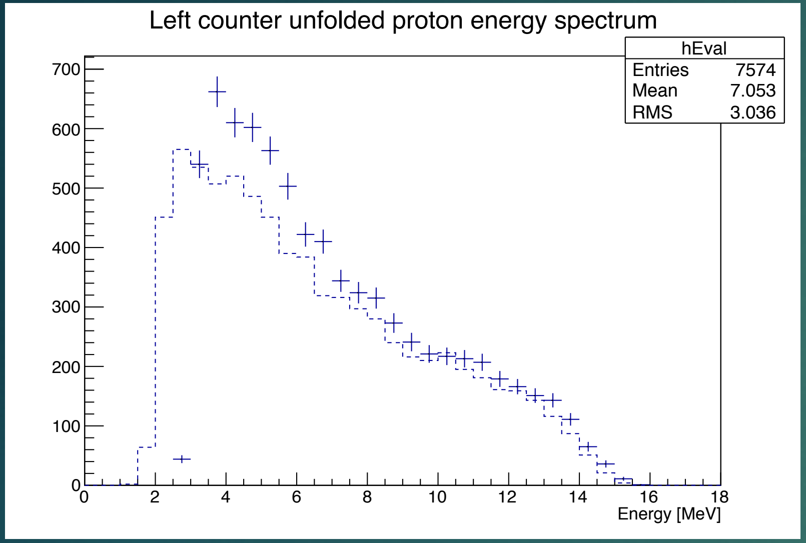
Exponential with
decay constant, ƛ=2

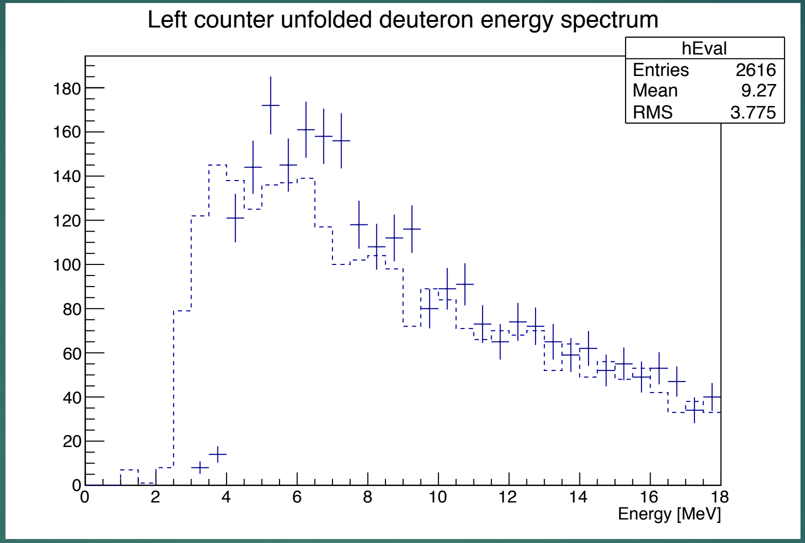
Gaussian with
Mean μ=6 and sigma σ=2

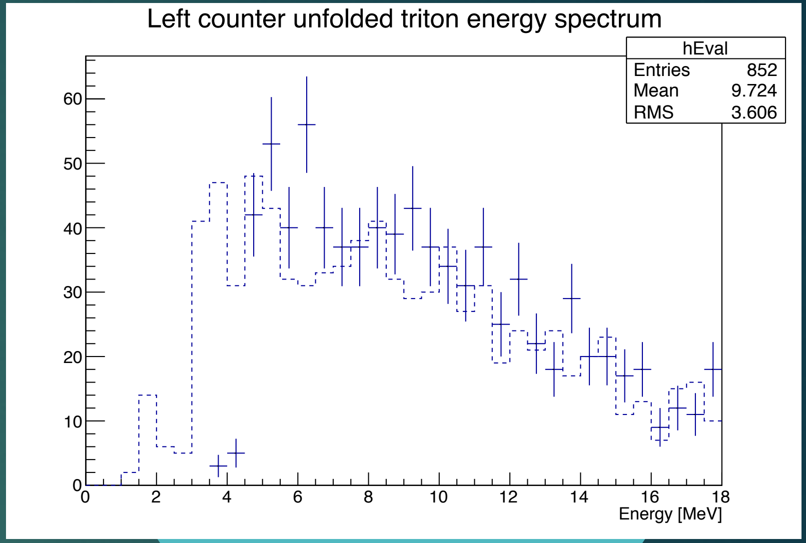
Uniform distribution
0 to 10 MeV

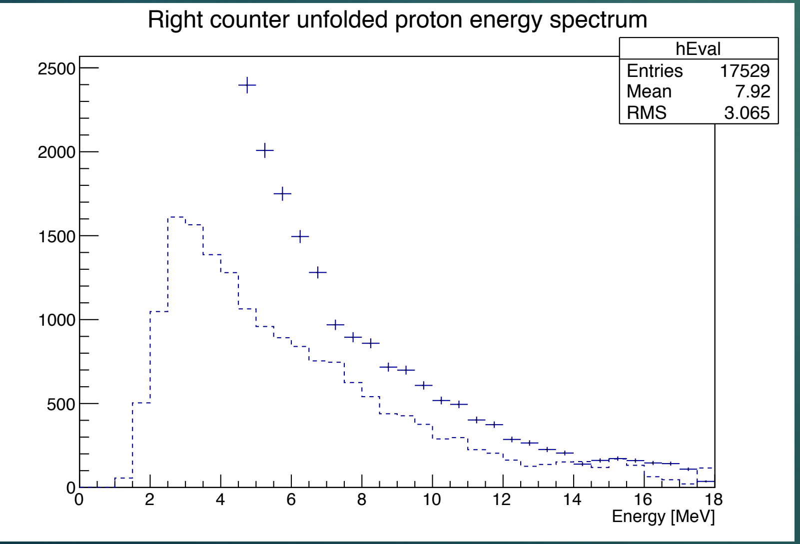
Measured protons with the above distribution on the left counter telescope

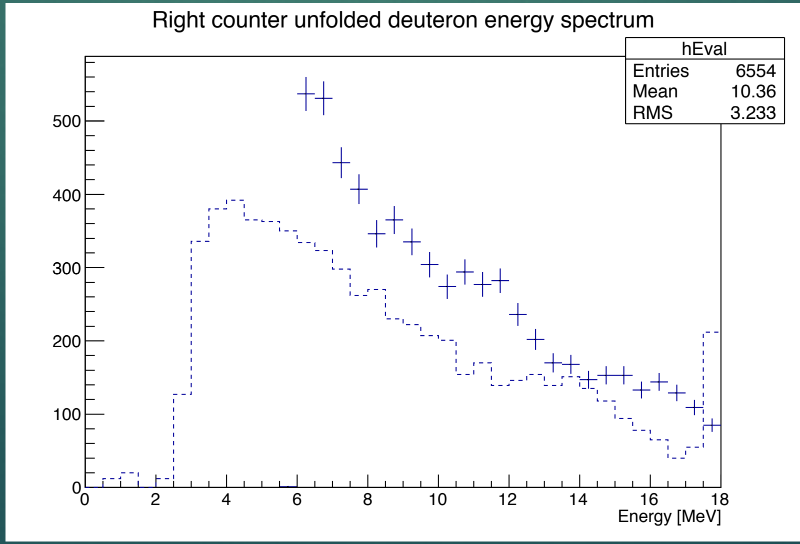
Neural network unfolding results

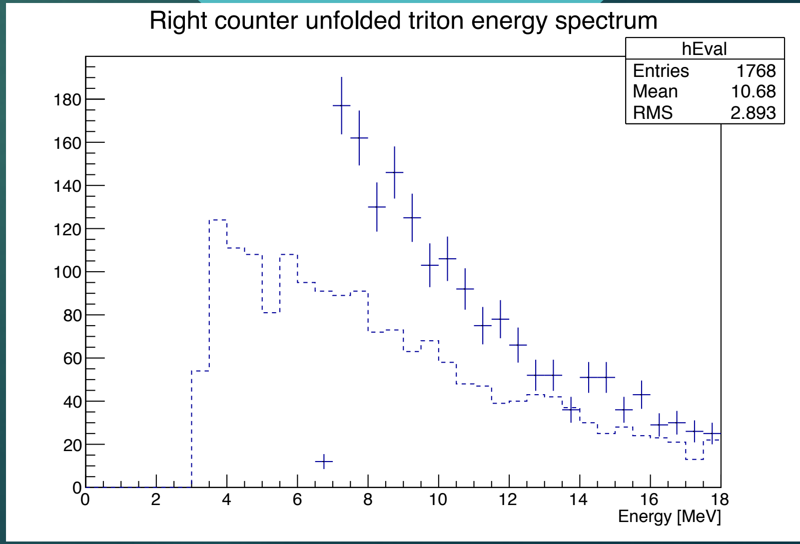












Preliminary results

- Total number of captured muons is $(6.36 \pm 0.10) \times 10^7$ and this is used as the normalization factor.
- Charged particles emitted between 2 to 10 MeV using the Bayesian method
- The value for protons is comparable to the previous R2013 result.
- Systematic errors are now being quantified. This includes detector nonlinearity, noise, etc.

Charged Particle	Measured by right det. [%]	Measured by left det. [%]
Proton	1.714 ± 0.031	0.577 ± 0.013
Deuteron	0.449 ± 0.010	0.132 ± 0.004
Triton	0.111 ± 0.004	0.0339 ± 0.002

Summary

- Two techniques for charged particle identification and cut selection were discussed.
  - Gaussian based likelihood probability cut
  - Artificial neural network classifier
- Two techniques for unfolding for the true charged particle emission spectrum was also discussed.
  - Bayesian inference
  - Artificial neural network regressor
- Preliminary results of charged particles emitted per captured muon was shown.

Backup

- Gaussian probabilities