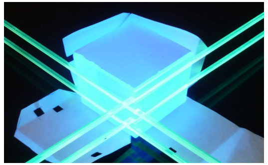

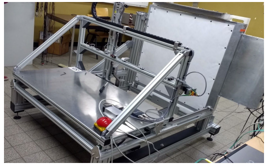

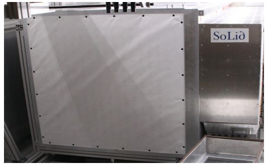

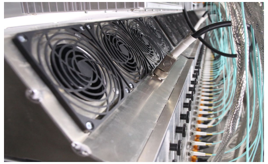

SoLiđ

cnrs

lpc caen
Laboratoire de physique corpusculaire

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Pulse Shape Discrimination using convolutional Neural Network (CNN) for the SoLid experiment

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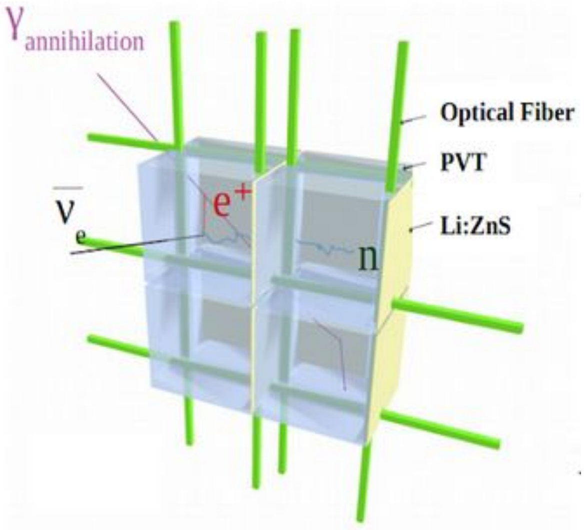
XIX International Workshop on Neutrino Telescopes

Motivation and contents (interest events : neutrinos)

SoLid

Class 1 : Inverse Beta Decay (IBD) events as interest ones.



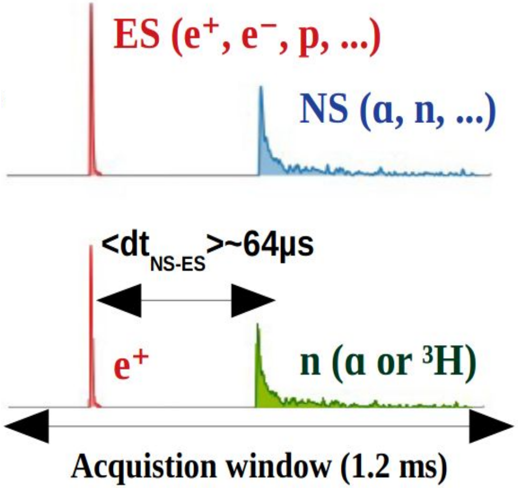
2 combined scintillators :

→ PVT as protons fixed target

$$\bar{\nu}_e + p \to e^+ + n \quad (Q = -1,8\,\mathrm{MeV})$$

→ ^{6}Li-ZnS foil (neutrons capture after thermalization ~64μs)

$$n + {}^6\mathrm{Li} \to {}^3\mathrm{H} + \alpha \quad (Q = 4,8\,\mathrm{MeV})$$



Motivation and contents (Background : BiPo-214)

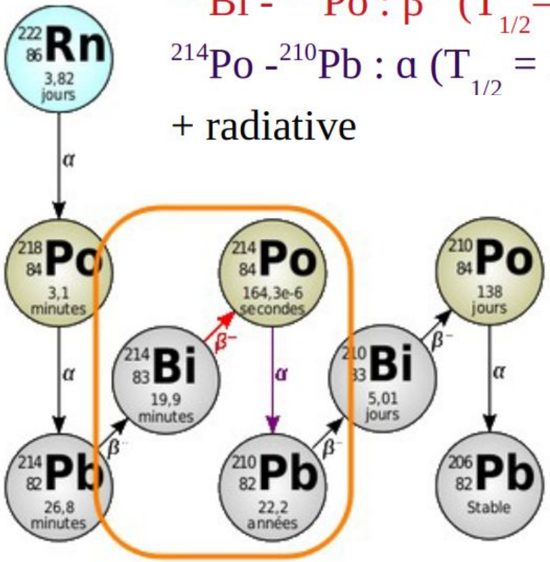
SoLid

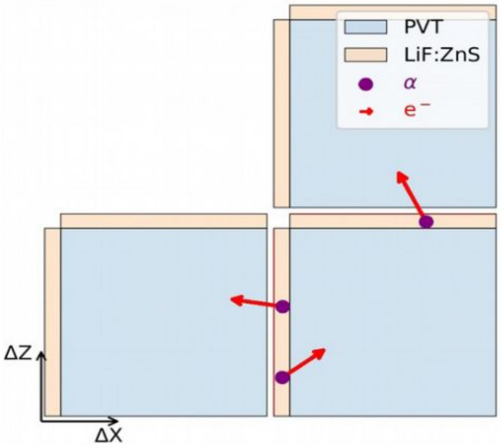
Class 2 : BiPo-214 decay from ^{238}U radioactive chain as background.

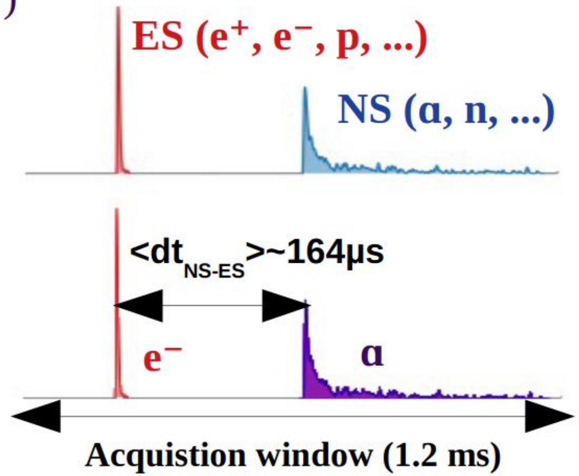
^{214}Bi - ^{214}Po : β^- ($T_{1/2}$=19.9mins, Q=3,27MeV, <E>=0.642MeV)

^{214}Po - ^{210}Pb : α ($T_{1/2}$ = 164.3µs, Q = 7.833 MeV, <E>=7.7MeV)

+ radiative

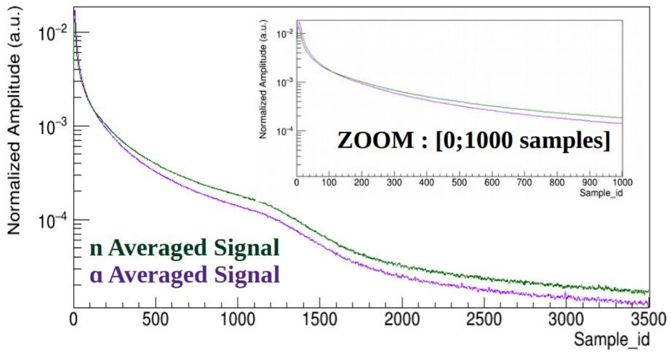






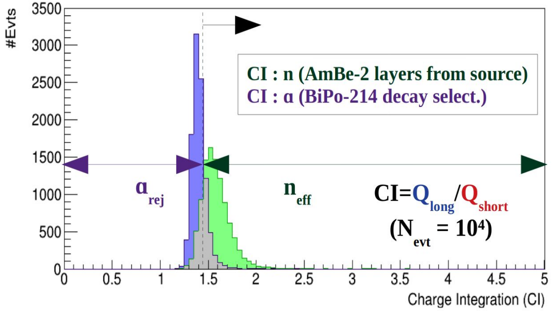
Charge Integration Method (CI)

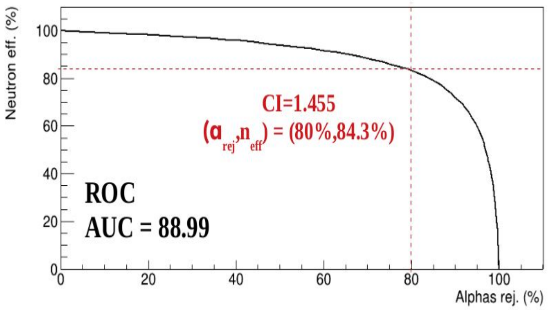
α and n average signals



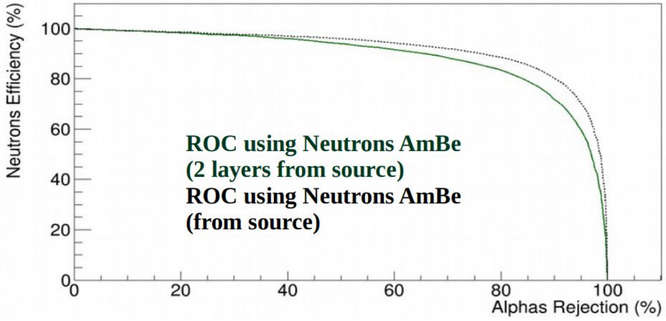
-> Sum of active channels signal by evts
-> Sum over evts on resp. pure ref. datasets
-> Normalization to integral (3500 samples)
-> Obvious differences are observed.

Computation and performances





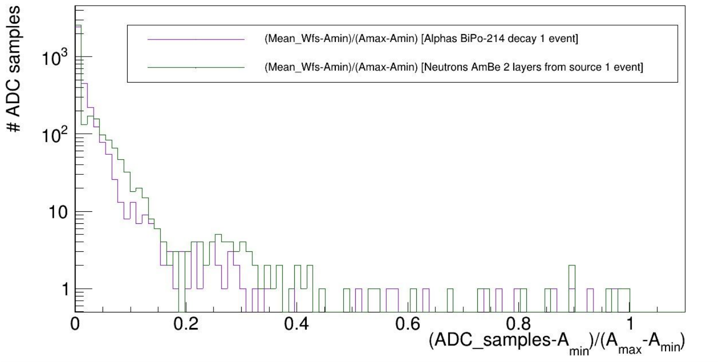
Limits and associated bias



1D-Convolutional Neural Network (1D-CNN)

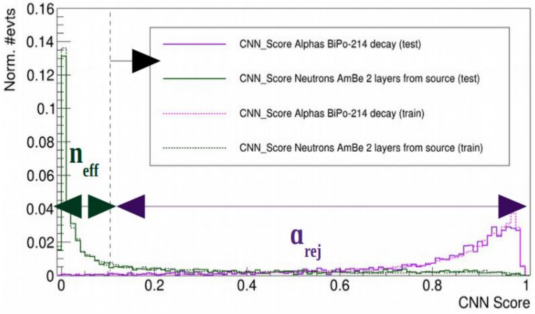
SoLid

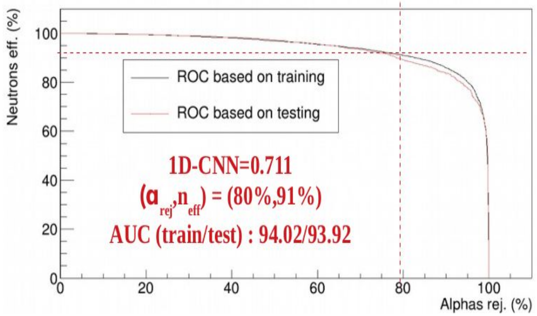
1D-CNN Input



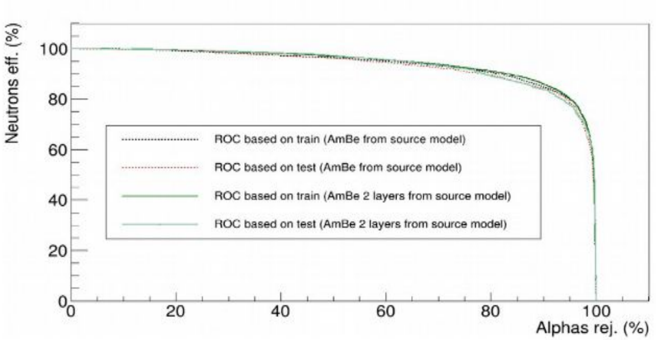
-> taking ADC value at each sample (ADC_value)
-> subtracting those by Amin => ADC_Value-Amin
-> normalizing (ADC_value-Amin) by (Amax-Amin)

1D-CNN Output and performance





Limits and associated biais



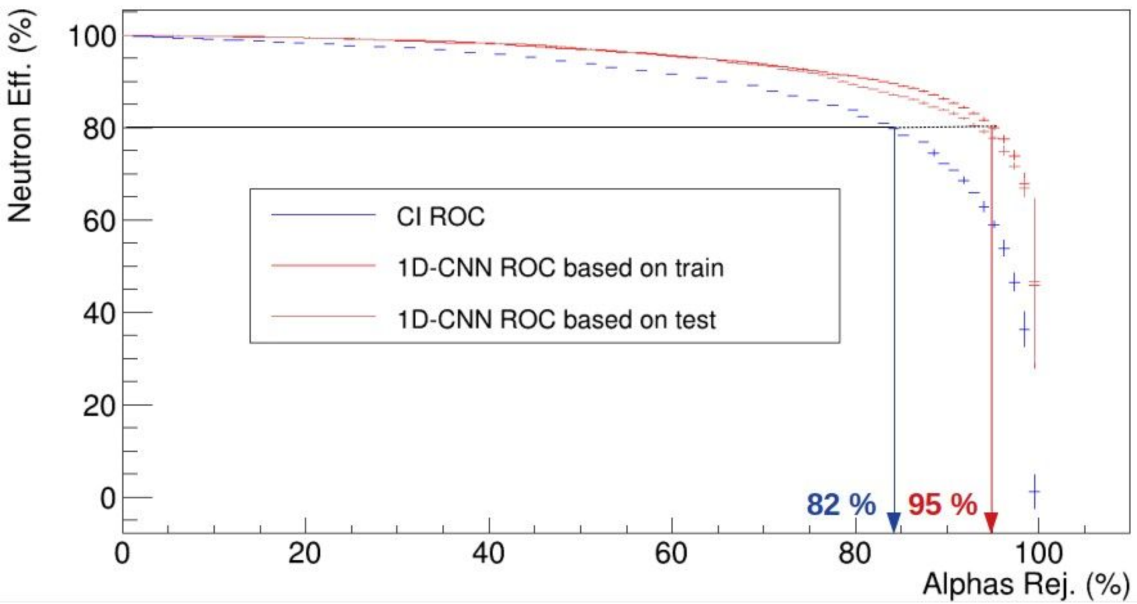
PSD methods : Comparison and summary

SoLid

- At same neutron eff (80%) 1D-CNN is more performant than CI : gain of 3.6 on alpha rejection (1-0.82/1-0.95)

- dependencies on baseline variation/jitter effects removed

- Modern Machine Learning are useful tools to improve background rejection



Backup : Compute CI on NS

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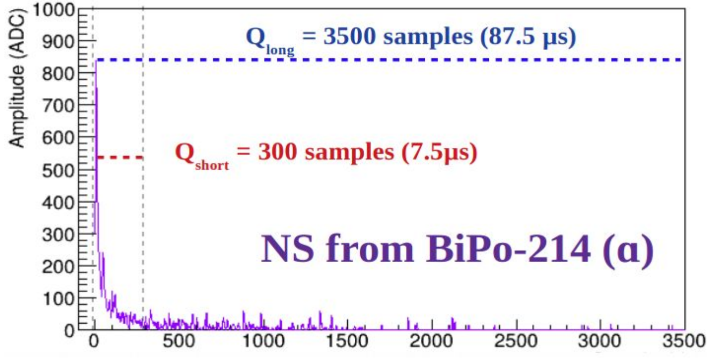
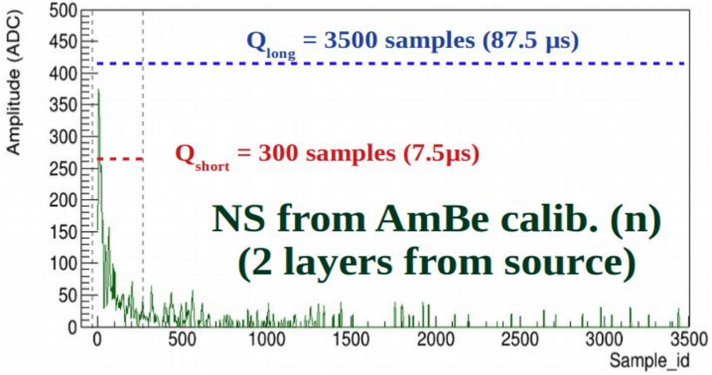
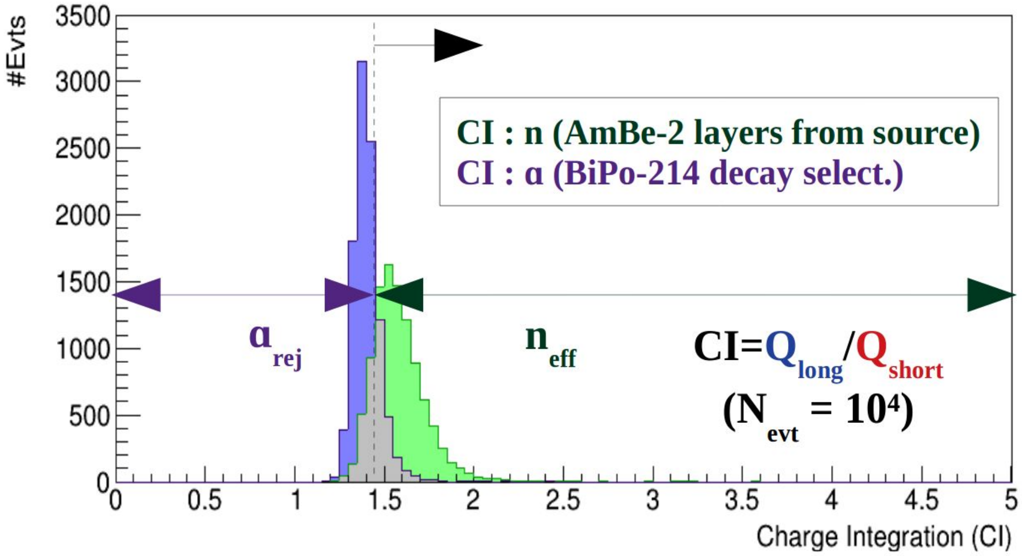


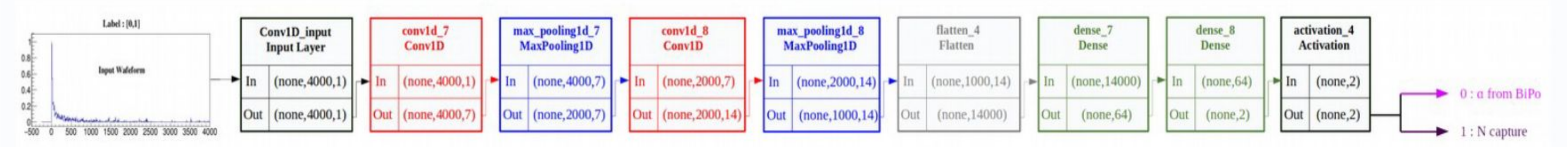




Backup : Method, optimization, accuracy

SoLid

1D-CNN algorithm :



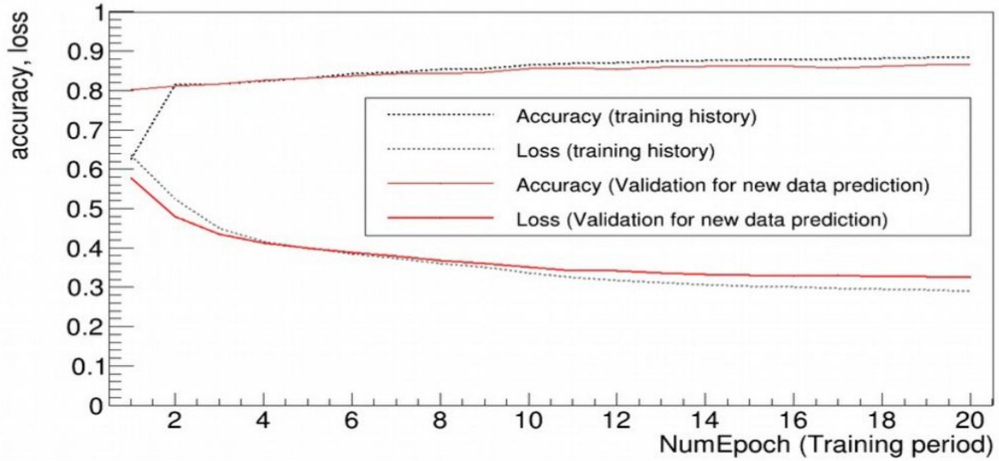
Train and test :

Train/Test over 10000 evts
Train over 80 % of evts
Test over 20% of evts

Optimization method :

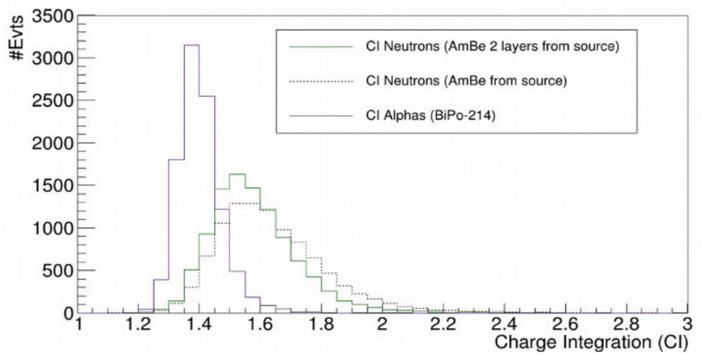
Model used : Adam optimiser
loss function : categorical entropy

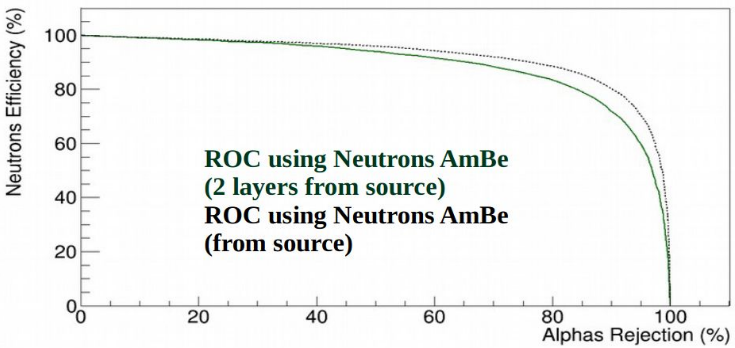
Accuracy and stability :

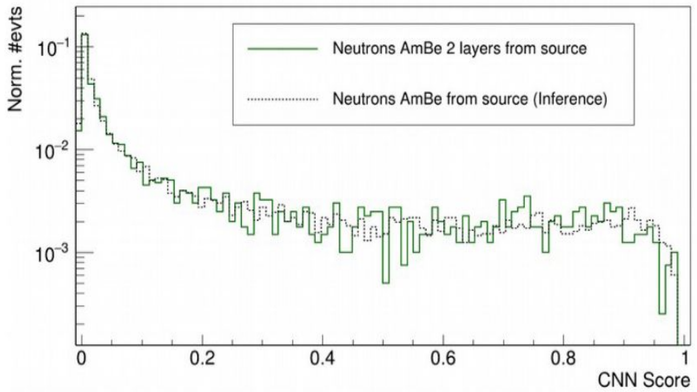


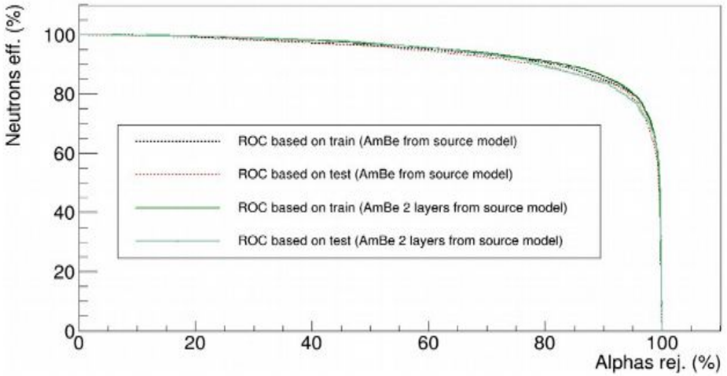
Backup : Neutron reference dataset choice

SoLid



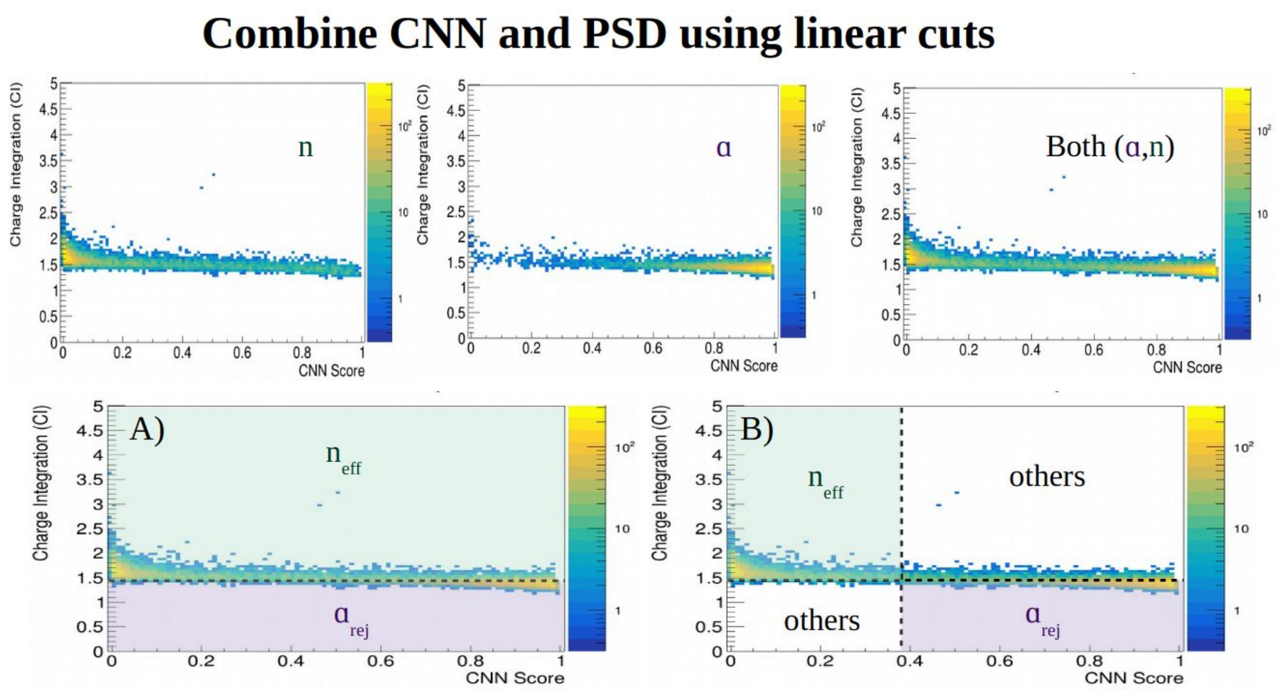






Backup : Complementarity CI and 1D-CNN

SoLid



Combining CI and CNN :

→ useful for same $α_{rej}$ point.

→ not useful for same n_{eff} point

  → decrease the neutron events Efficiency.

  → gain on $α_{rej}$ not strong compared to CNN algo alone (at same new n_{eff}).

→ combined linear cuts not competitive to CNN alone => required sophisticated cuts.

Same $α_{rej}$ point :

A) CI alone (CI>1.455) :

$α_{rej}$ = 80 % | n_{eff} = 84.3 %

B) CI>1.455 and CNN score<0.711 :

$α_{rej}$ = 93.3 % | n_{eff} = 76.7 %

→ low decreasing of n_{eff}

→ gain of $α_{rej}$ = 2.98 (compared to CI method alone).