











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

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Motivation and contents (interest events : neutrinos) Solid

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



2 combined scintillators :

 \rightarrow PVT as protons fixed target

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

 \rightarrow ⁶Li-ZnS foil (neutrons capture after thermalization ~64µs)

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

ES (e⁺, e⁻, p, ...) NS (a, n, ...) <dt_{NS-ES}>~64µs



Motivation and contents (Background : BiPo-214) SoLid

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



Charge Integration Method (CI)

SoLid



 α and n average signals

Computation and performances



Limits and associated bias



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

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

0.16

SoLid

1D-CNN Input



(%) #evi 100 0.14 eff. CNN Score Alphas BiPo-214 decay (test Norm. Neutrons 0.12 ROC based on training Score Neutrons AmBe 2 layers from source (test 80 0.1 ROC based on testing CNN Score Alphas BiPo-214 decay (train) 0.08 CNN Score Neutrons AmBe 2 layers from source (train) n 1D-CNN=0.711 0.06 $(a_{rai}, n_{rai}) = (80\%, 91\%)$ 0.04 20 AUC (train/test) : 94.02/93.92 a 0.02 rei 00 0.2 0.4 0.6 0.8 20 40 60 80 100 **CNN Score** Alphas rej. (%) Limits and associated biais 100

1D-CNN Output and performance

Neutrons eff. (%) 80 ROC based on train (AmBe from source model 60 ROC based on test (AmBe from source model) ROC based on train (AmBe 2 lavers from source model) 40 ROC based on test (AmBe 2 lavers from source model 20 00 20 40 60 80 100 Alphas rej. (%)

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

PSD methods : Comparison and summary

- 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



SoLid

Backup : Compute CI on NS

SoLid





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

Charge Integration (CI) n (CI) 4.5 Both (a,n) n C 3.5 Integr Charge 2.5 0.5 0.2 0.4 0.6 0.8 0.2 0.4 0.6 0.8 0.6 0.8 0.4 **CNN Score CNN Score CNN Score** 5 Charge Integration (CI) Charge Integration (CI) A) B) 4.5 4.5 n_{eff} 10² 10² n_{eff} others 3.5 3.5 3 2.5 10 2.5 10 others a 0.5 0.5 rei rei 00 00 0.2 0.2 0.4 0.6 0.4 0.6 0.8 0.8 **CNN Score CNN Score**

Combine CNN and PSD using linear cuts

Combining CI and CNN :

- \rightarrow useful for same a_{rei} point.
- \rightarrow not useful for same n_{off} 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.

 $\begin{array}{l} \underline{Same \ a}_{rej} \ \underline{point :} \\ A) \ CI \ alone \ (CI > 1.455) : \\ a_{rej} = 80 \ \% \ \mid n_{eff} = 84.3 \ \% \end{array}$

B) CI>1.455 and CNN score<0.711 : $a_{rej} = 93.3 \% | n_{eff} = 76.7 \%$ \rightarrow low decreasing of n_{eff} \rightarrow gain of $a_{rej} = 2.98$ (compared to

CI method alone).