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

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Motivation and contents (interest events: neutrinos)

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

- 2 combined scintillators:
  - $\bar{\nu}_e + p \rightarrow e^+ + n \quad (Q = -1.8 \text{ MeV})$
  - $^6\text{Li}-\text{ZnS}$ foil (neutrons capture after thermalization $\sim 64\mu$s)
  - $n + ^6\text{Li} \rightarrow ^3\text{H} + \alpha \quad (Q = 4.8 \text{ MeV})$

ES ($e^+, e^-, p, \ldots$)

NS ($\alpha, n, \ldots$)

$<dt_{\text{NS-ES}} > \sim 64\mu$s

$e^+$

$n$ ($\alpha$ or $^3\text{H}$)

Acquisition window (1.2 ms)
Motivation and contents (Background : BiPo-214)

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

$^{214}$Bi - $^{214}$Po : $\beta^-$ ($T_{1/2}$ = 19.9 mins, $Q$ = 3.27 MeV, $<E>$ = 0.642 MeV)

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

+ radiative

ES ($e^+$, $e^-$, p, ...)

NS ($\alpha$, n, ...)

<dt$_{NS-ES}$> ~ 164 $\mu$s

Acquisition window (1.2 ms)
Charge Integration Method (CI)

\( \alpha \) 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.
1D-Convolutional Neural Network (1D-CNN)

1D-CNN Input

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

1D-CNN Output and performance

Limits and associated bias

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

\[ Q_{\text{long}} = 3500 \text{ samples (87.5} \mu\text{s)} \]

\[ Q_{\text{short}} = 300 \text{ samples (7.5} \mu\text{s)} \]

NS from BiPo-214 (α)

\[ Q_{\text{long}} = 3500 \text{ samples (87.5} \mu\text{s)} \]

\[ Q_{\text{short}} = 300 \text{ samples (7.5} \mu\text{s)} \]

NS from AmBe calib. (n)
(2 layers from source)

\[ \text{CI} = \frac{Q_{\text{long}}}{Q_{\text{short}}} \]

\( (N_{\text{evt}} = 10^4) \)

\[ \alpha_{\text{rej}} \quad \text{ n}_{\text{eff}} \]
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
Backup: Neutron reference dataset choice
Combine CNN and PSD using linear cuts

**Combining CI and CNN:**
- useful for same $\alpha_{\text{rej}}$ point.
- not useful for same $n_{\text{eff}}$ point
  - decrease the neutron events Efficiency.
- gain on $\alpha_{\text{rej}}$ not strong compared to CNN algo alone (at same new $n_{\text{eff}}$).
- combined linear cuts not competitive to CNN alone => required sophisticated cuts.

**Same $\alpha_{\text{rej}}$ point:**

A) $CI$ alone ($CI>1.455$):
- $\alpha_{\text{rej}} = 80 \% \mid n_{\text{eff}} = 84.3 \%$

B) $CI>1.455$ and $CNN$ score $<0.711$:
- $\alpha_{\text{rej}} = 93.3 \% \mid n_{\text{eff}} = 76.7 \%$
  - low decreasing of $n_{\text{eff}}$
  - gain of $\alpha_{\text{rej}} = 2.98$ (compared to CI method alone).