中国科学院高能物理研究所
Institute of High Energy Physics
Chinese Academy of Sciences

江门中微子实验
Jiangmen Underground Neutrino Observatory

Deep Learning-Based ^{14}C Pile-Up Identification in the JUNO Experiment

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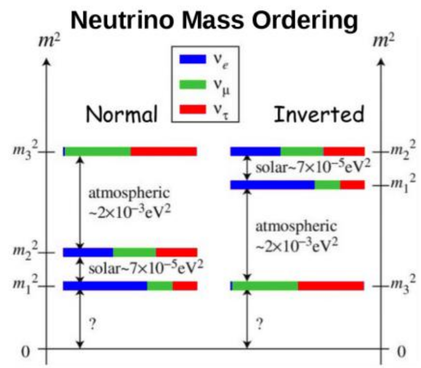
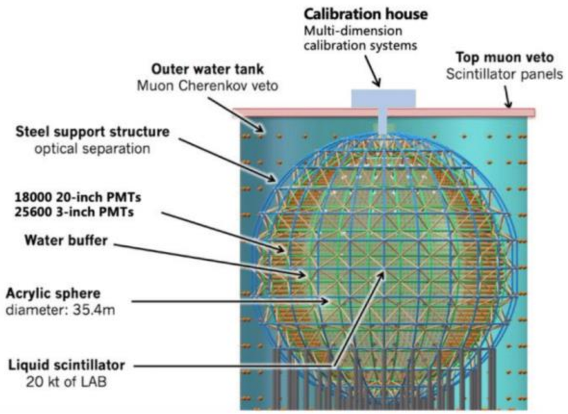
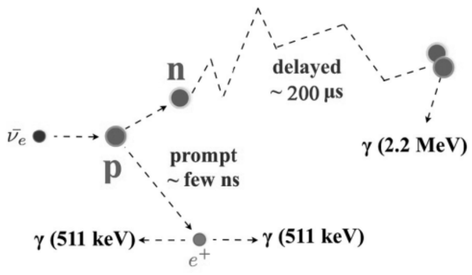
Motivation

- The neutrino mass ordering (NMO) measurement is one of the most important topics in neutrino physics
- Jiangmen Underground Neutrino Observatory (JUNO)
  - Large liquid scintillator detector (20kt)
  - NMO sensitivity: 3σ (reactors only) with ~6 years using inverse beta decay (IBD)
  - The energy resolution of e^+ is vital
- The ^{14}C (β decay) from the LS could pile up with e^+ which will deteriorate the energy resolution, need to be studied carefully

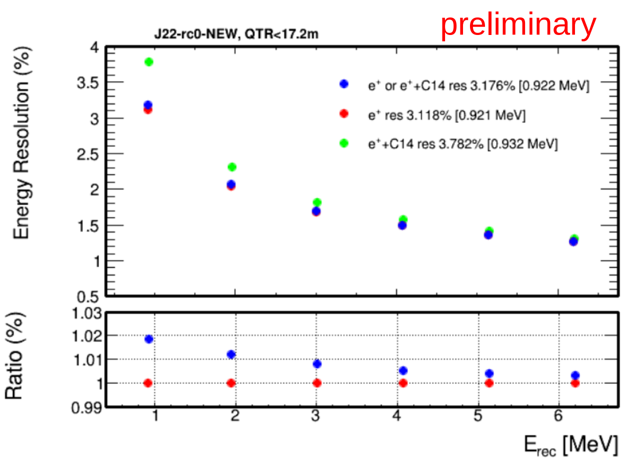


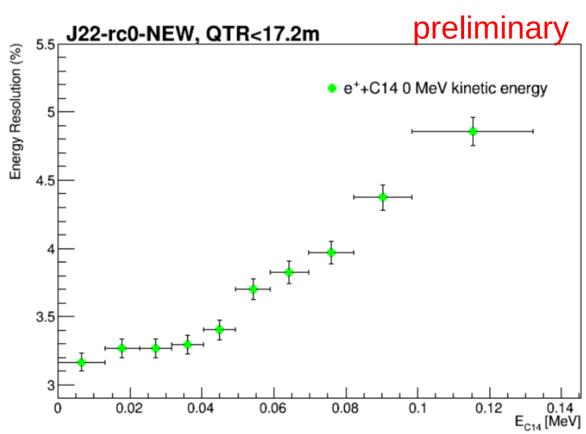


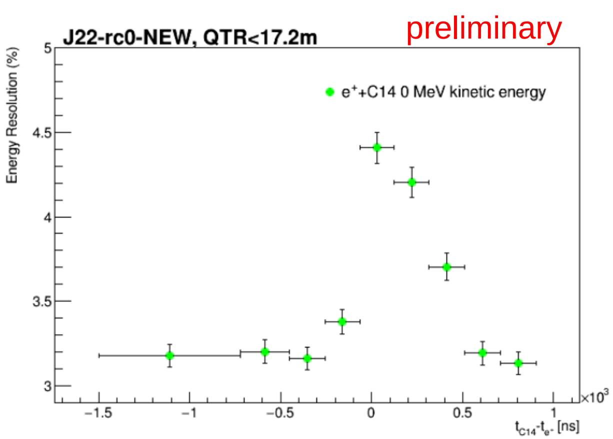


^{14}C pile-up effects

- The default β decay rate from ^{14}C is 40k Hz for the JUNO liquid scintillator
- There is ~7% that a e^{+} could pile up with ^{14}C decay



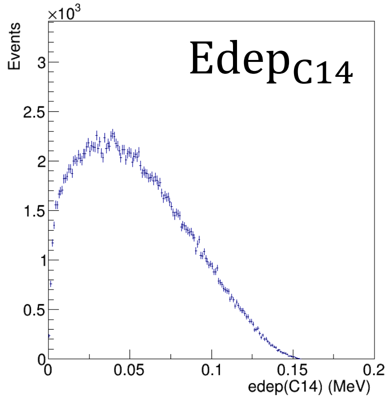




- To mitigate the effect
  - The first step is efficiently identifying the pile-up events (this study)
  - Then multi-site reconstruction should be developed to reconstruct the energy of e^{+} for the pile-up event correctly

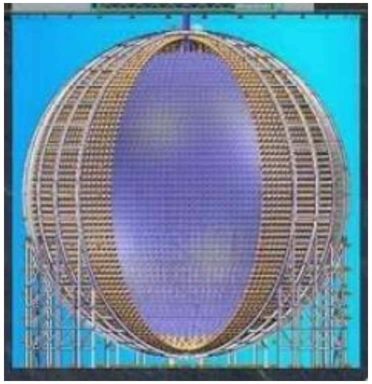
Dataset

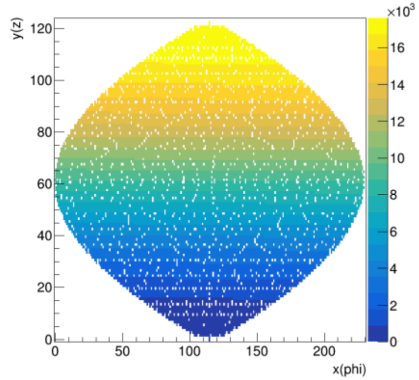
- Produced using JUNO offline software (J22.1.0-rc0)
- Including Geant4 detector simulation, electronics simulation, waveform reconstruction, and event reconstruction
- Samples:
  - Pure e^{+} and $e^{+} + {}^{14}C$ pile-up events
  - kinetic energy of e^{+} : 0~5MeV, 0MeV, 1MeV, 2MeV, 3MeV, 4MeV, 5MeV



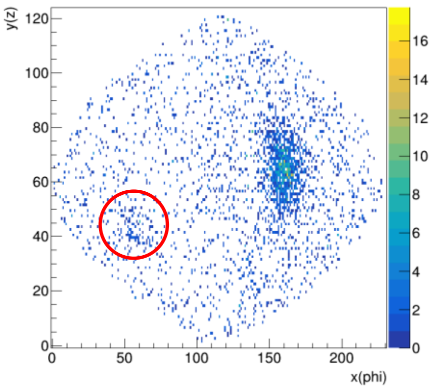
Methodology (2D CNN)

- Similar to the computer vision problem:
  - Data are presented as images with 2 channels:
    - Each PMT is mapped to a pixel
    - Channel 1: total reconstructed charge
    - Channel 2: reconstructed first hit time
  - Exploit a convolutional neural network-based model to distinguish the pile-up

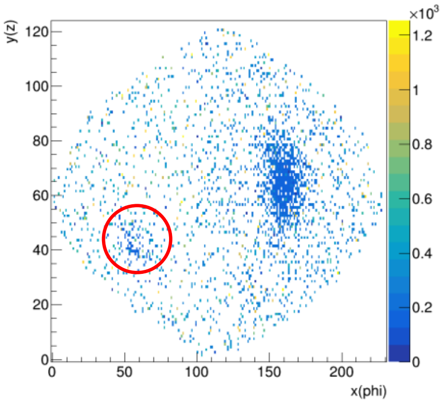




PMT id ⟺ pixel



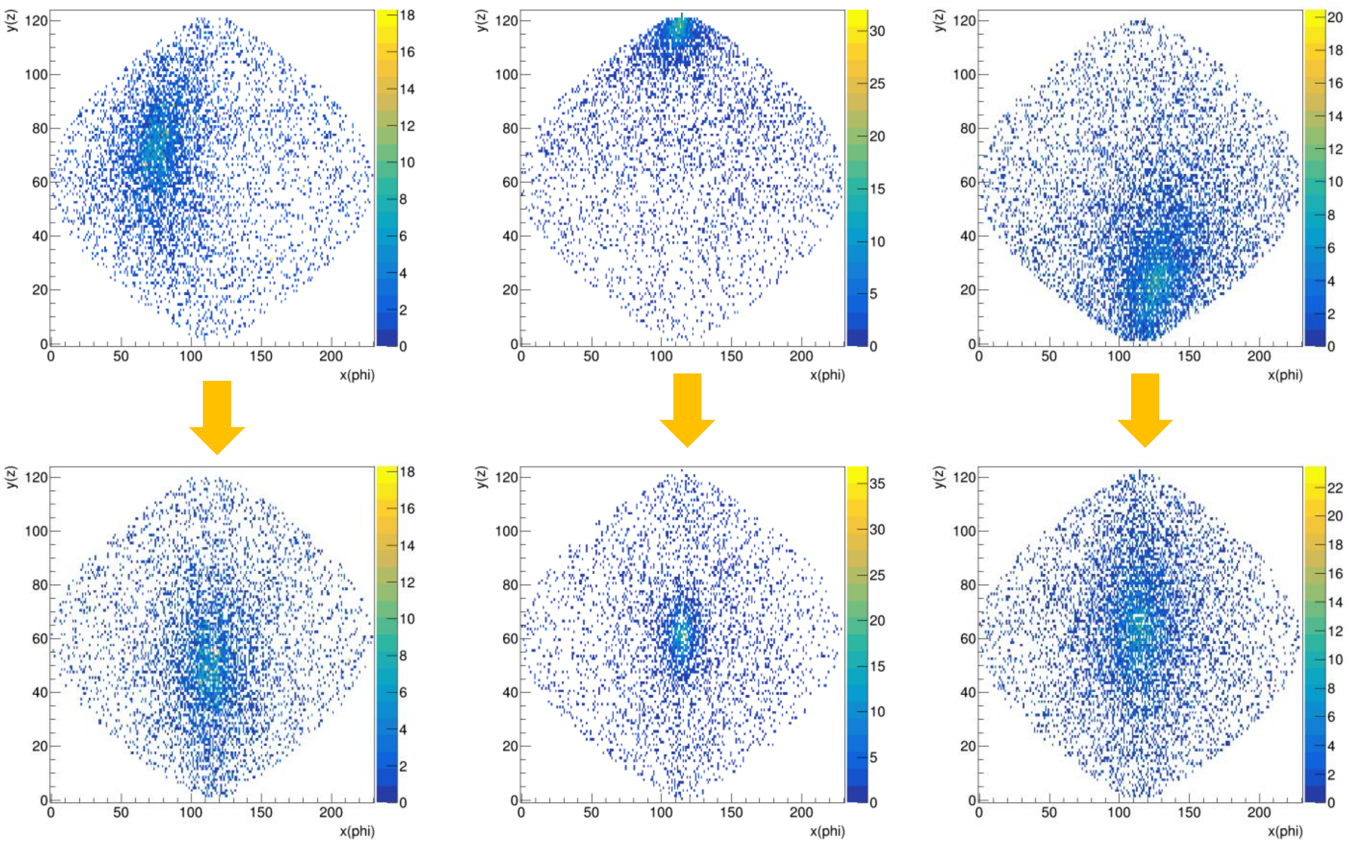
Charge by PMTs



First hit time by PMTs

Rotation of the data

- To help ML training, rotating the reconstructed position to the X axis

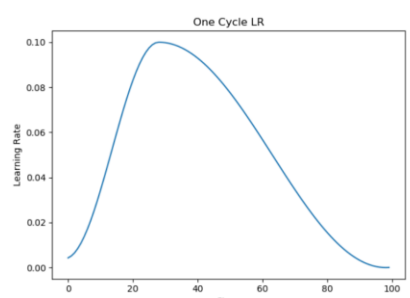


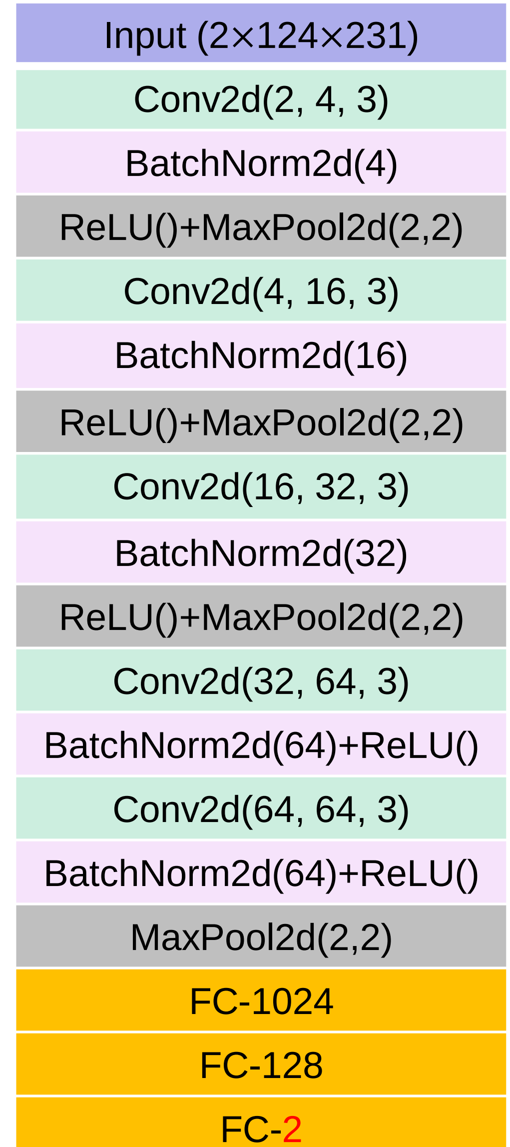
Charge by PMTs

Charge by PMTs, After rotation

Model

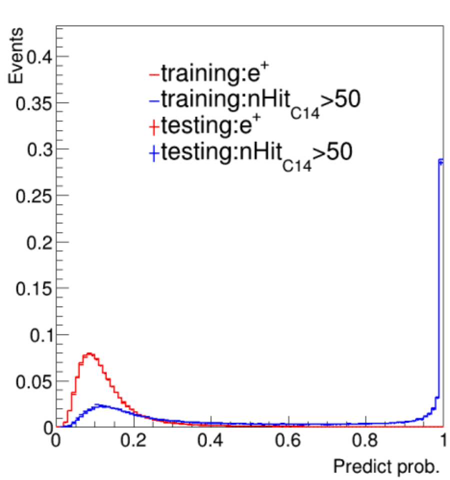
- Convolutional neural network-based
- Input data:
  - 124*231 2D array with 2 channels:
    - Total charge channel is scaled by 5
    - First hit time channel is scaled by 100
- Output:
  - 2 values (imply the probability of 2 categories)
- Categories of data:
  - Category 0: pure 0~5 MeV e^+, ~160k training data
  - Category 1: 0~5 MeV e^+ with $nHit_{C14}$ > 50, ~90k training data
- Loss: nn.CrossEntropyLoss()
- Optimizer: Adam
- LR Scheduler: OneCycleLR

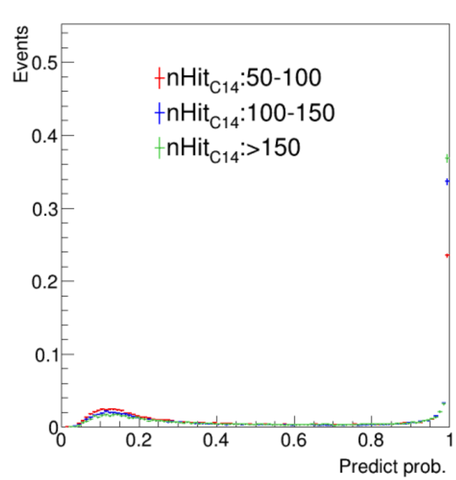


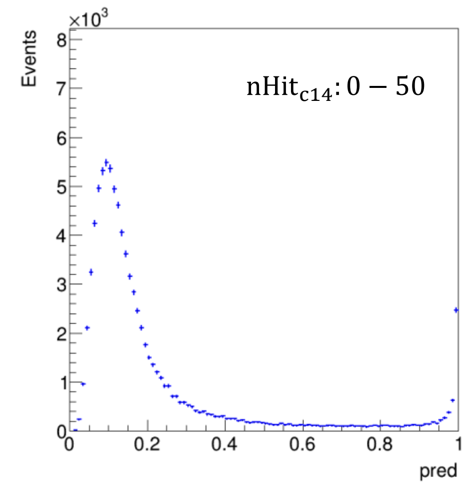


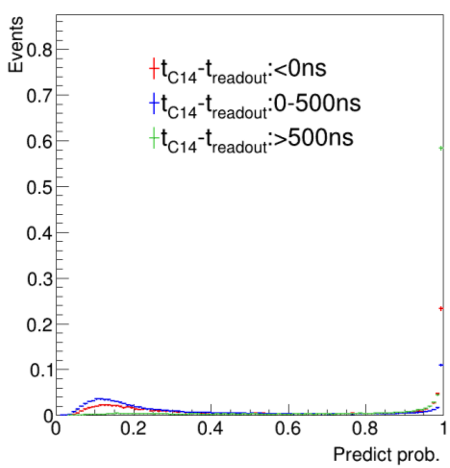
Performance

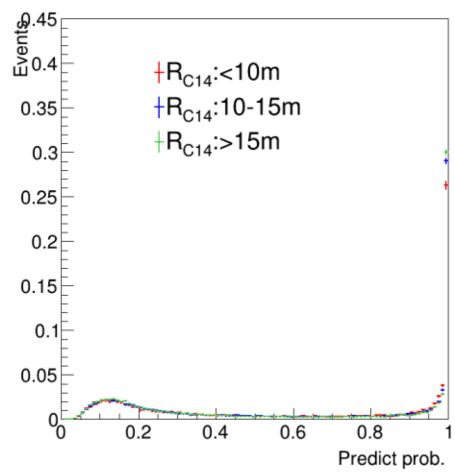
- Training and testing: 0~5 MeV e^+ samples





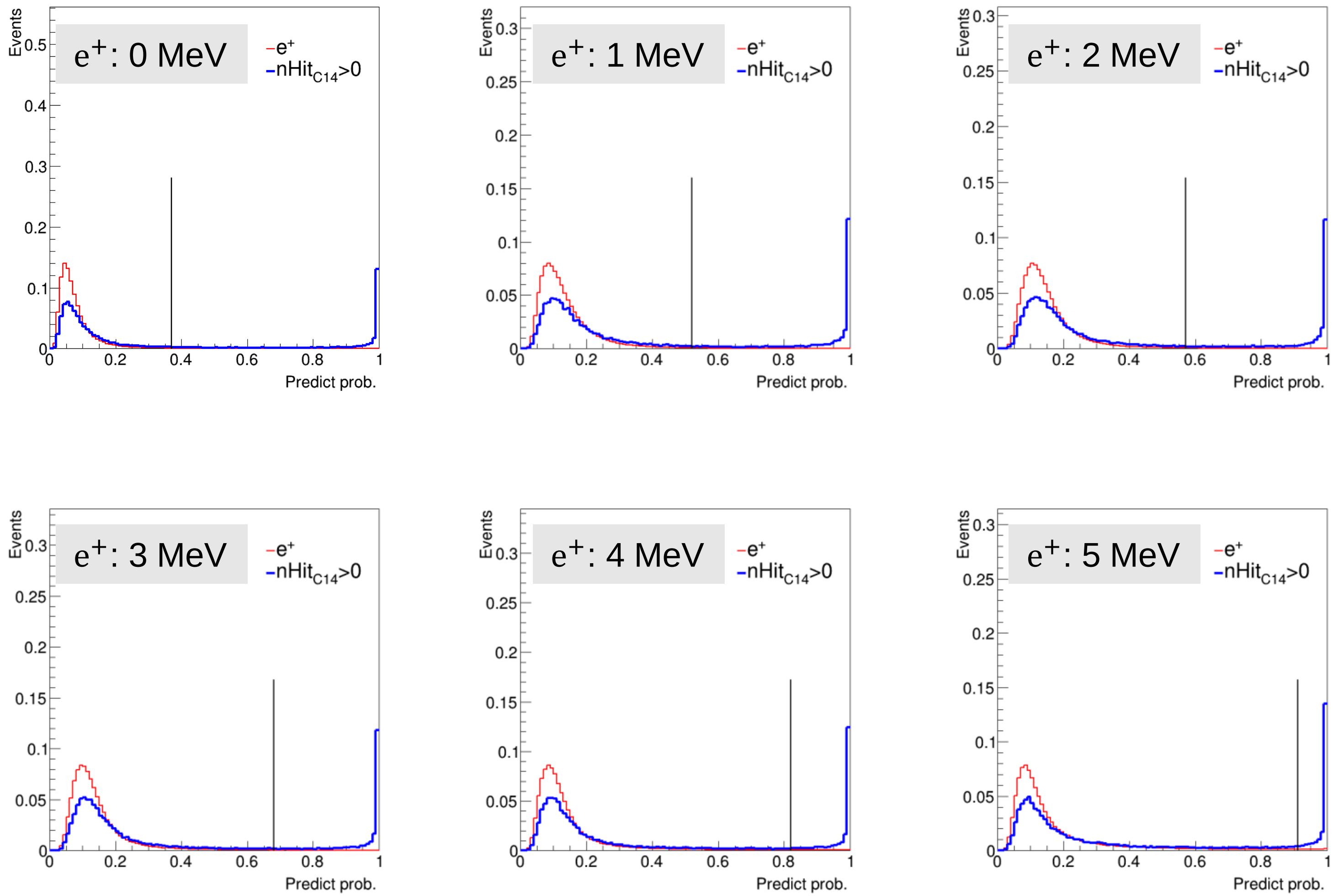






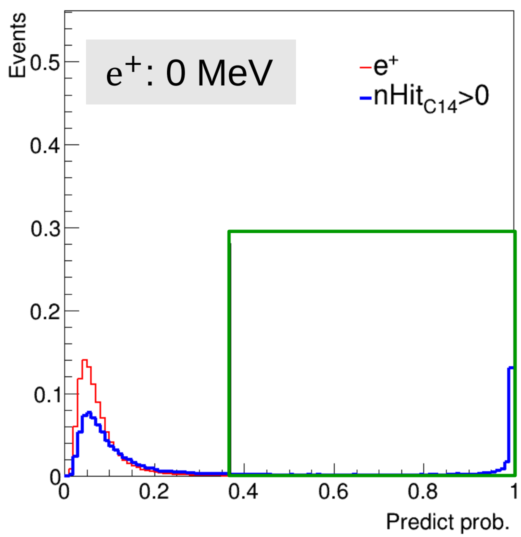
Performance

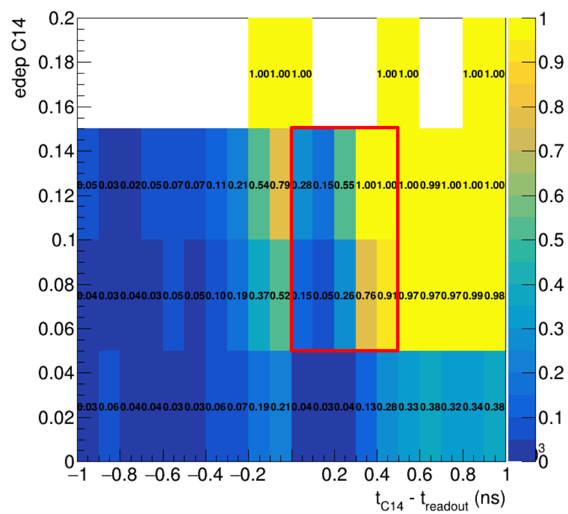
- Testing : 0, 1, 2, 3, 4, 5 MeV e^+ samples

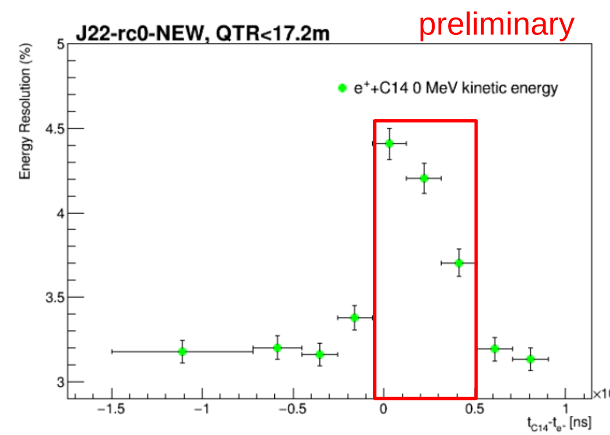


Performance for 0 MeV e^+

- Check the pile-up identificantion efficiency when 99% of e^+ is kept



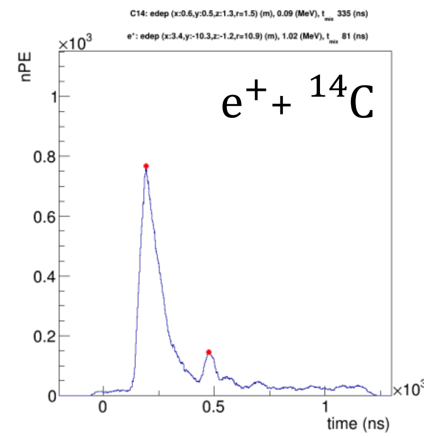


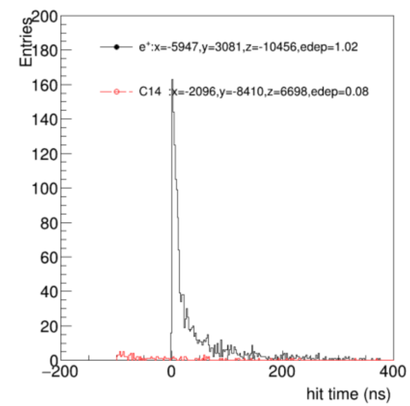


- High identification efficiency for late mixed ^{14}C
- For some crucial regions, the efficiency need to be improved

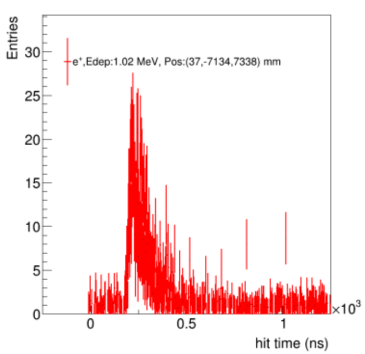
Using the distribution of hit time

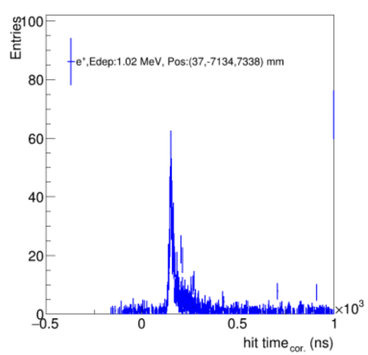
- The 2D projection dispersed the $^{14}\mathrm{C}$ information
- The $^{14}\mathrm{C}$ information will be more concentrated using 1D distribution
- Try the ML method with hit time distributions as input:
  - Original hit time
  - The time-of-fly corrected hit time





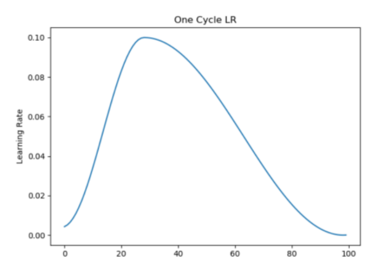
detsim, $^{14}\mathrm{C}$ corrected tof with e^+ vertex





Model (1D)

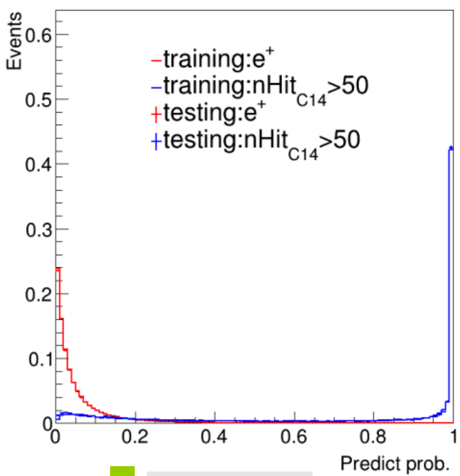
- Convolutional neural network-based
- Input data:
  - 1500 1D array with 2 channels:
    - Original hit time channel: from -250 ns to 1250 ns, scaled by 10
    - Tof corrected hit time channel: from -500 ns to 1000 ns, scaled by 50
- Output:
  - 2 values (imply the probability of 2 categories)
- Categories of data:
  - Category 0: pure 0~5 MeV e^{+}, ~160k training data
  - Category 1: 0~5 MeV e^{+} with $nHit_{C14} > 50$, ~90k training data
- Loss: nn.CrossEntropyLoss()
- Optimizer: Adam
- LR Scheduler: OneCycleLR

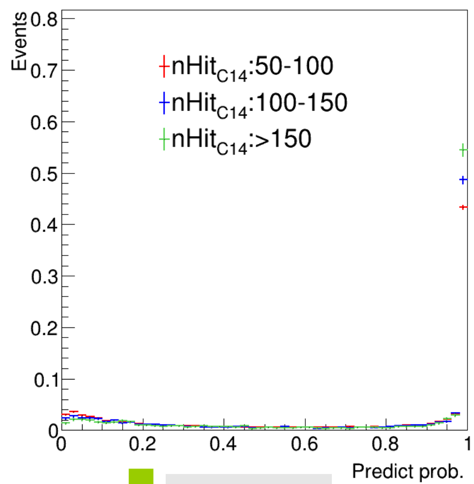


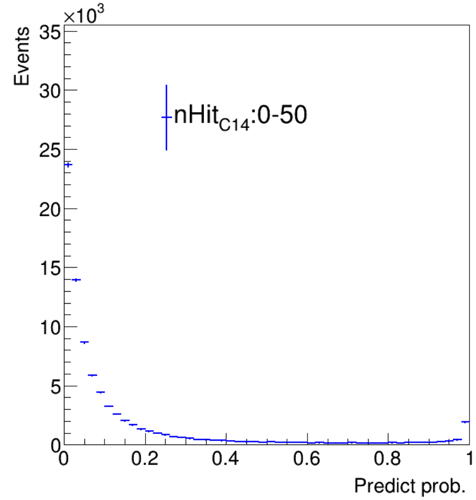
- Input (2×1500)
- Conv1d(2, 4, 3)
- BatchNorm1d(4)
- ReLU()+MaxPool1d(2)
- Conv1d(4, 16, 3)
- BatchNorm1d(16)
- ReLU()+MaxPool1d(2)
- Conv1d(16, 32, 3)
- BatchNorm1d(32)
- ReLU()+MaxPool1d(2)
- Conv1d(32, 64, 3)
- BatchNorm1d(64)+ReLU()
- Conv1d(64, 64, 3)
- BatchNorm1d(64)+ReLU()
- MaxPool1d(2)
- FC-1024
- FC-128
- FC-2

Performance

- Training and testing: 0~5 MeV e^+ (or $\mathrm{nHit}_{\mathrm{C14}} > 50$)samples

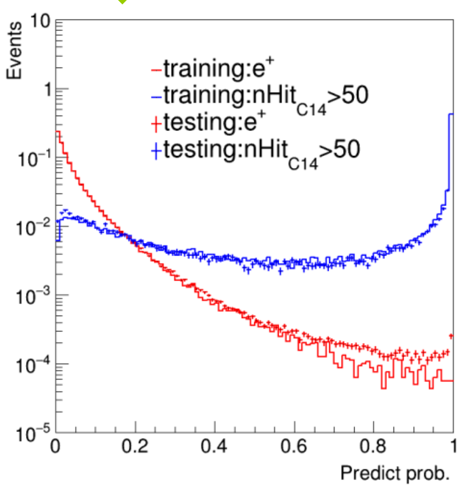


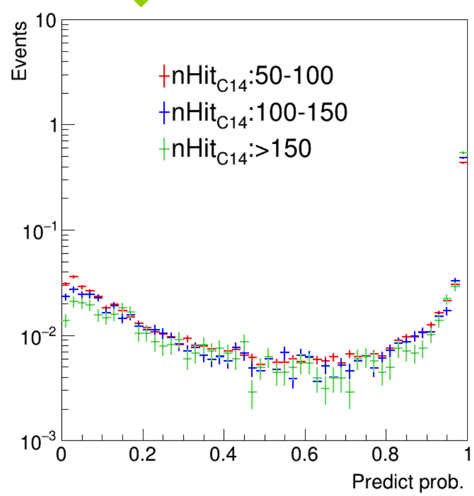




Log scale

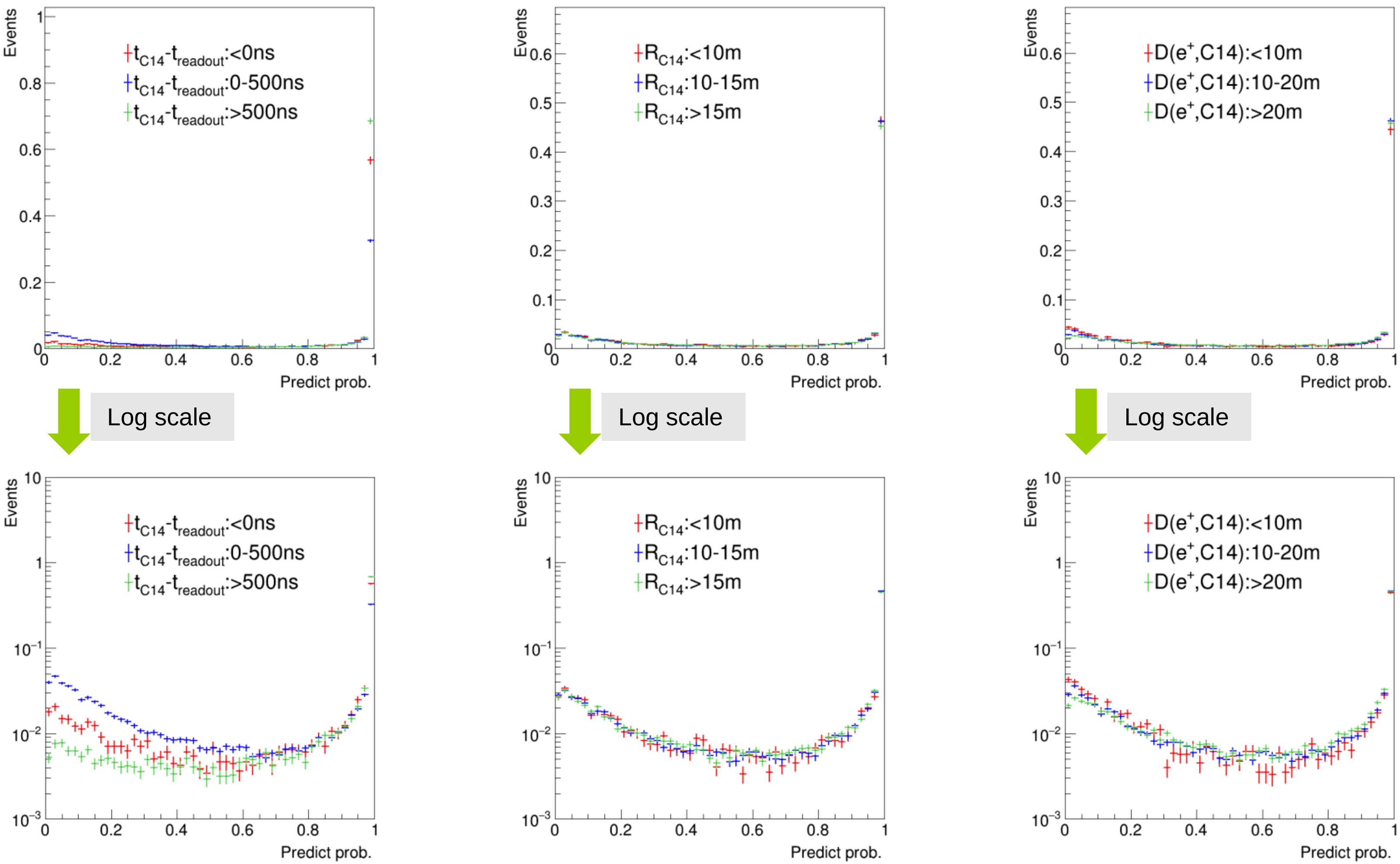
Log scale





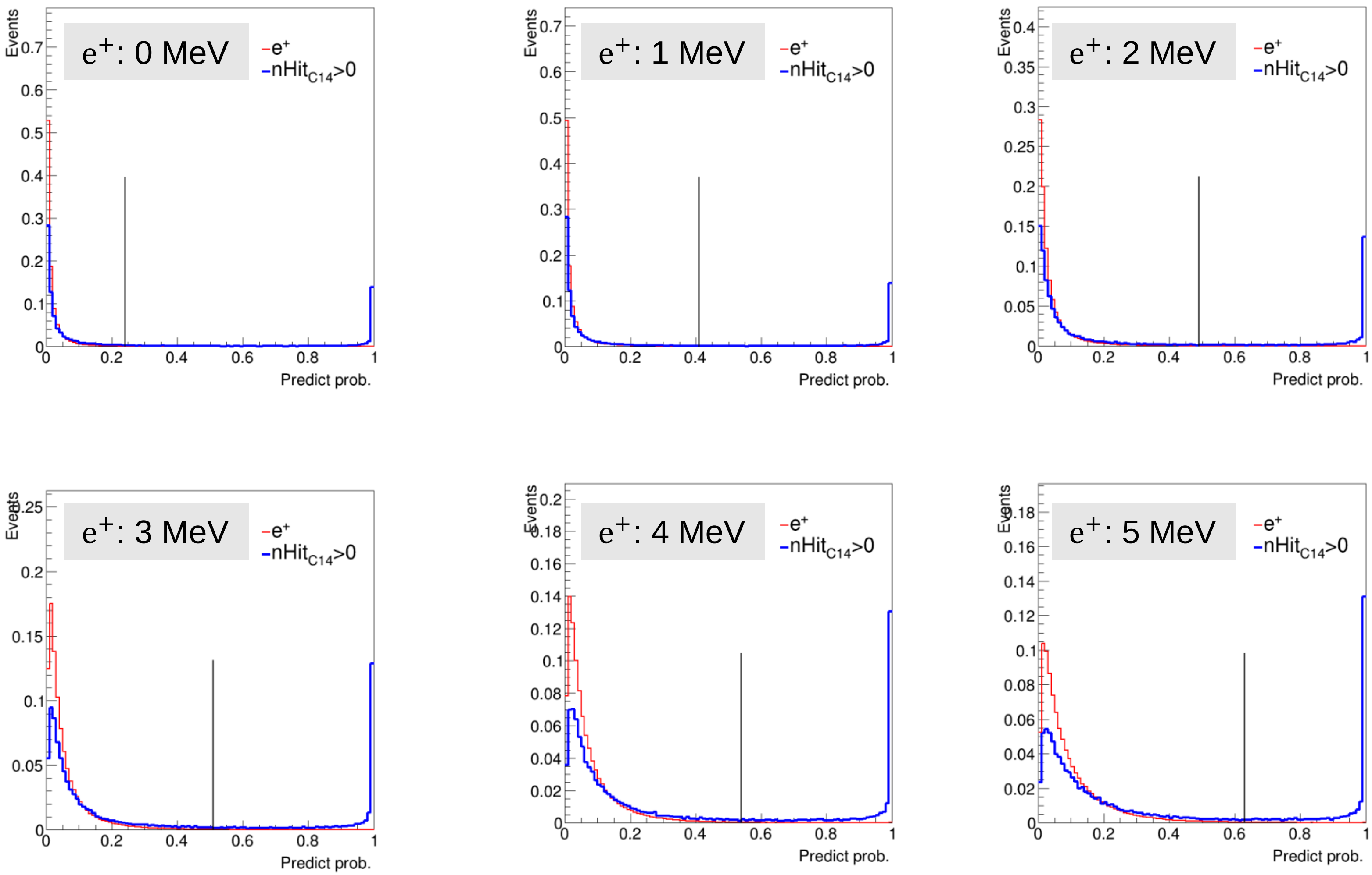
Performance

- Training and testing: 0~5 MeV e^{+} with $nHit_{C14} > 50$



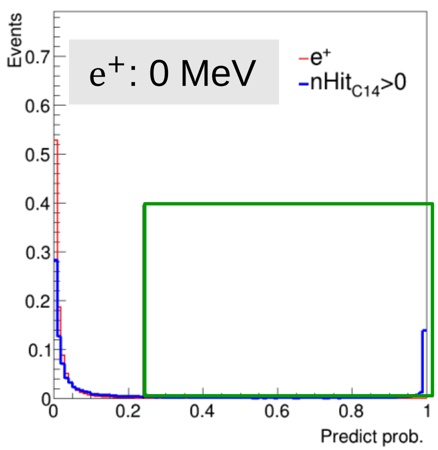
Performance

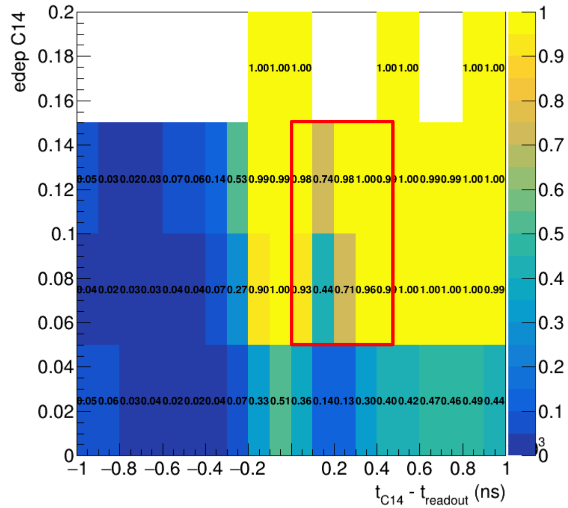
- Testing : 0, 1, 2, 3, 4, 5 MeV e^+ samples



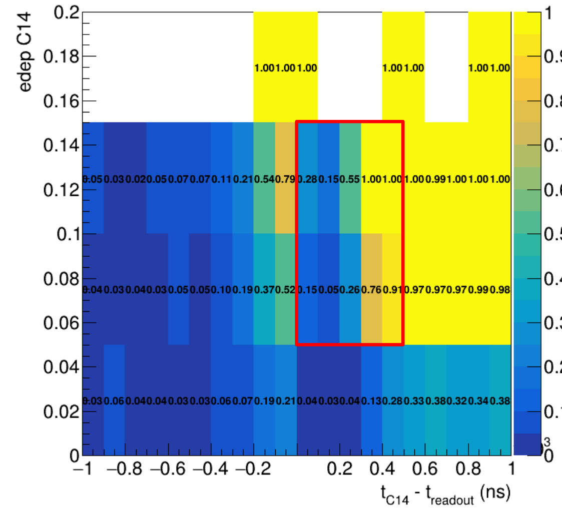
Performance for 0 MeV e^+

- Check the pile-up identificantion efficiency when 99% of e^+ is kept





1D CNN

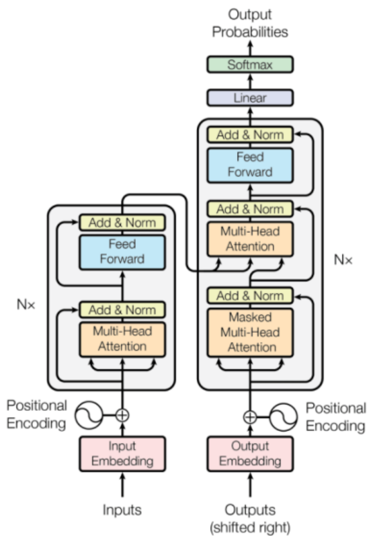


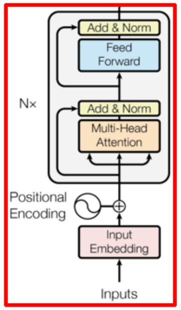
2D CNN

- High identification efficiency
- Much better for crucial regions

Transformer model

- The Transformer has gained significant attention and popularity, particularly in NLP tasks (e.g. ChatGPT)
- To apply the transformer for this study, one can treat the 1D distribution as a sequence of words
- Same input as 1D CNN model
- Using the encoder part of the Transformer model

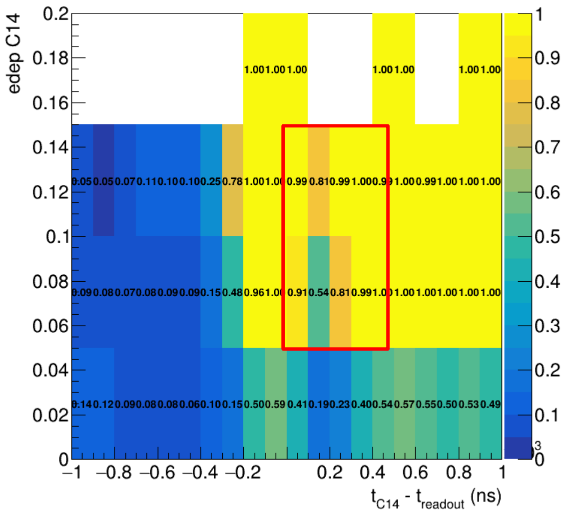




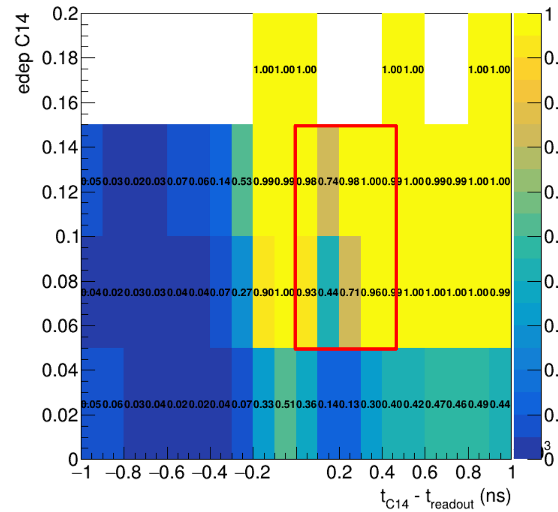
Input (2×1500)
Conv1d(2, 32, 1)
BatchNorm1d(32)
PositionalEncoding(32)
2*TransformerEncoderLayer (32,8,2048,0.1)
torch.mean(dim=0)
FC-1024
ReLU()
FC-128
ReLU()
FC-2

Performance for 0 MeV e^+

- Check the pile-up identificantion efficiency when 99% of e^+ is kept



Transformer



1D CNN

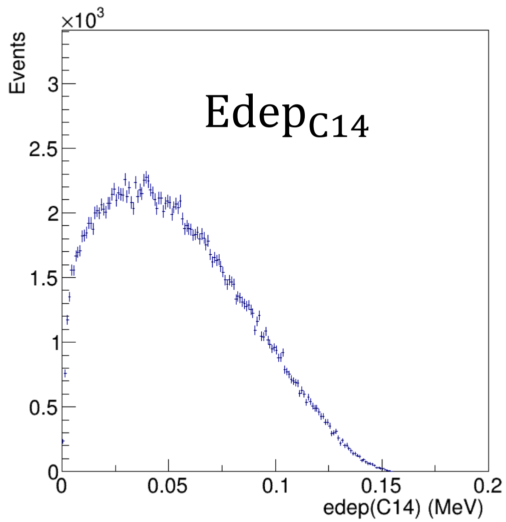
- High identification efficiency
- A bit improved for crucial regions

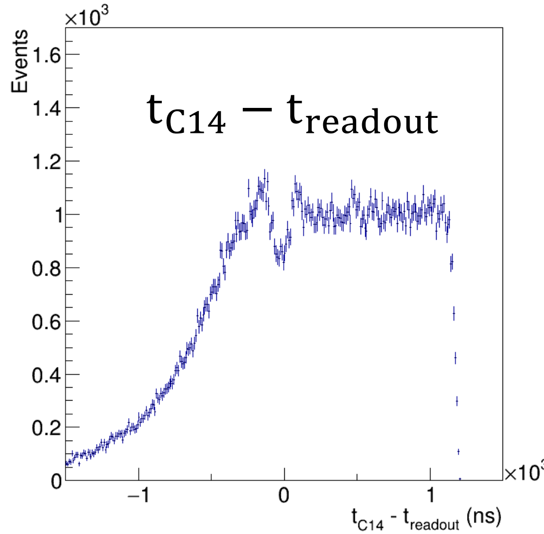
Summary

- The energy resolution of e^+ is key for the JUNO experiment
- The pile up from $^{14}\mathrm{C}$ will deteriorate the energy resolution
- To mitigate this effect, the identification of pile-up events is the first step
- Different ML-based methods are used for the $^{14}\mathrm{C}$ pile-up identification. Including the 2D CNN, 1D CNN, and Transformer model
- The 1D distribution seems to have a better concentration of $^{14}\mathrm{C}$ hits and it outperforms the 2D model
- The results from the 1D CNN and Transformer model are similar. Slightly better performance is achieved by the Transformer model

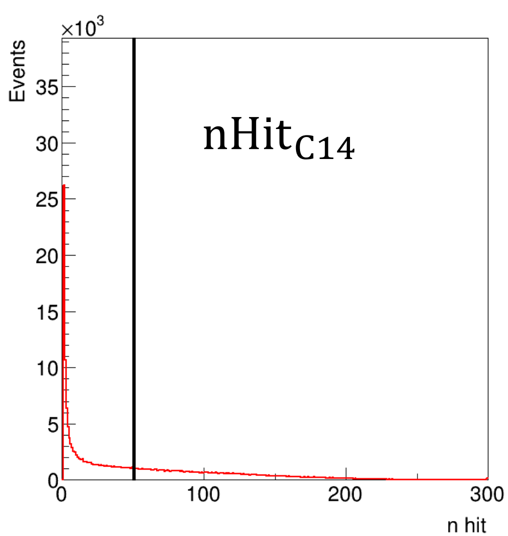
Back up

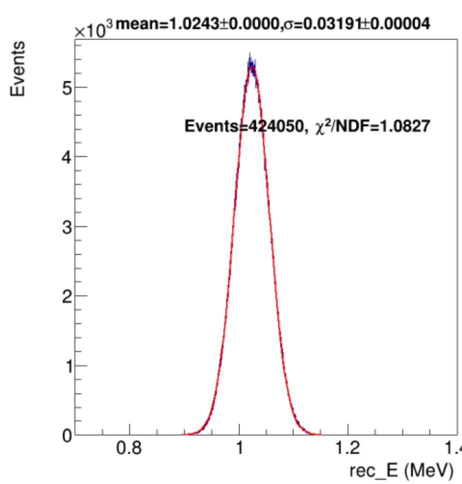
Some checks



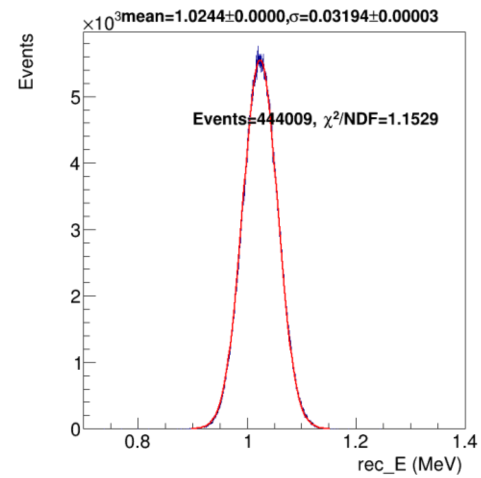


- $\mathrm{t_{readout} = t_{trigger} - 100\ ns}$
- $\mathrm{t_{C14}}$ is mixing time of $^{14}\mathrm{C}$ at electronic simulation



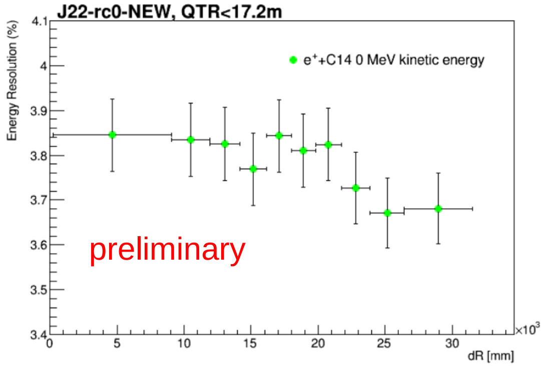


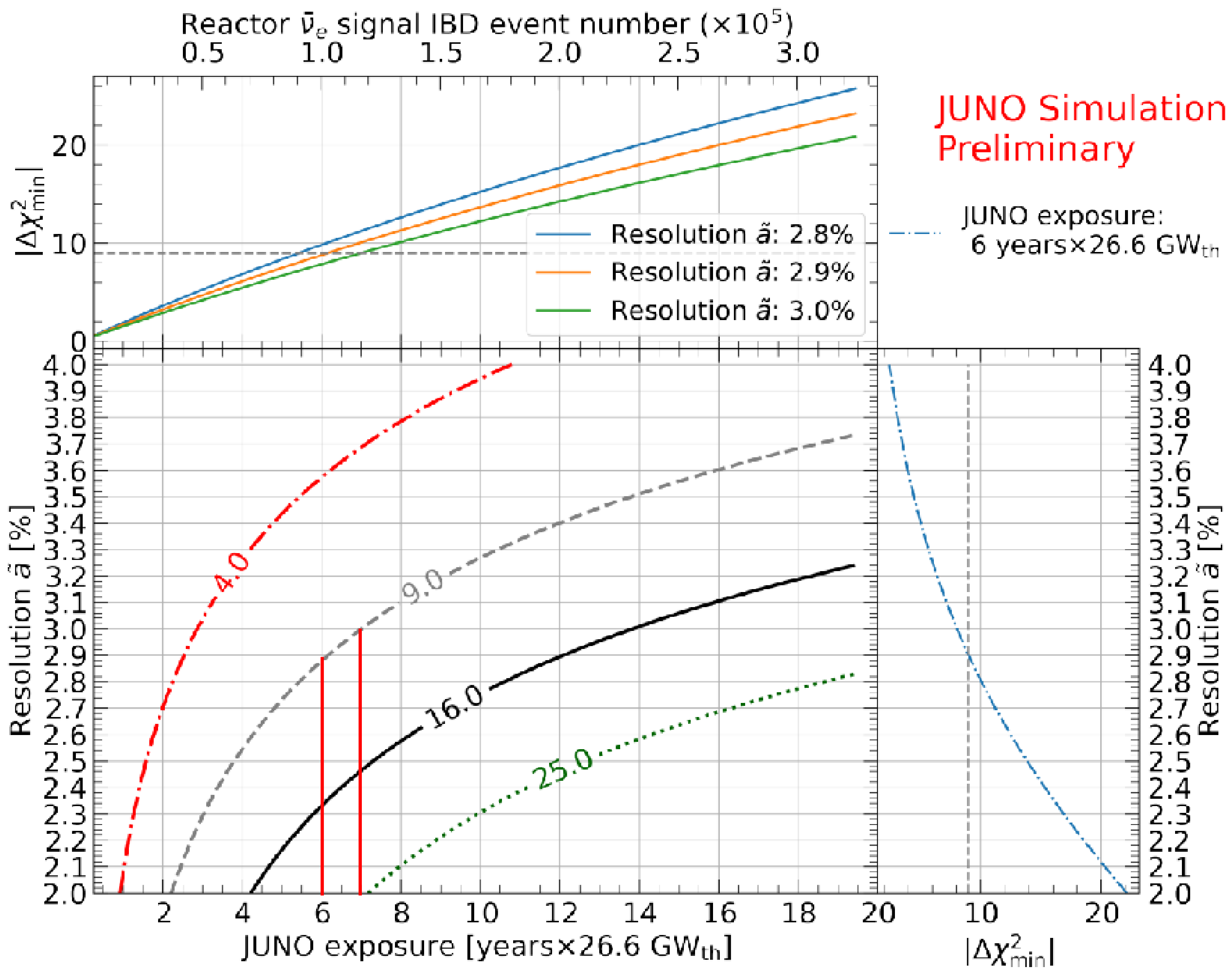
0MeV $\mathrm{e^+}$



0MeV $\mathrm{e^+}$ with $\mathrm{nHit_{C14}}$ <50 pile-up:
0.094% relatively increase in $\sigma_{recE}^{e^+}$

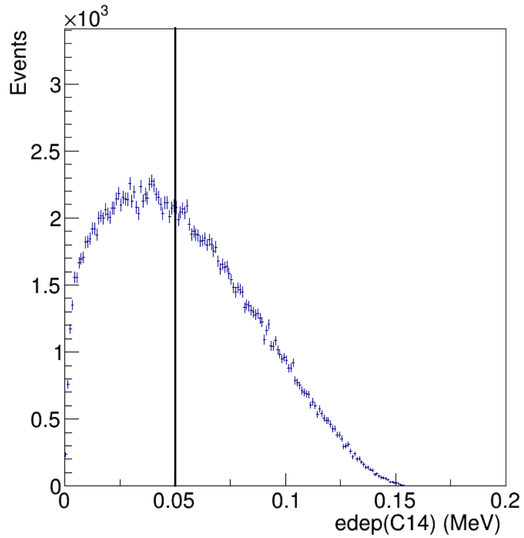
Energy resolution

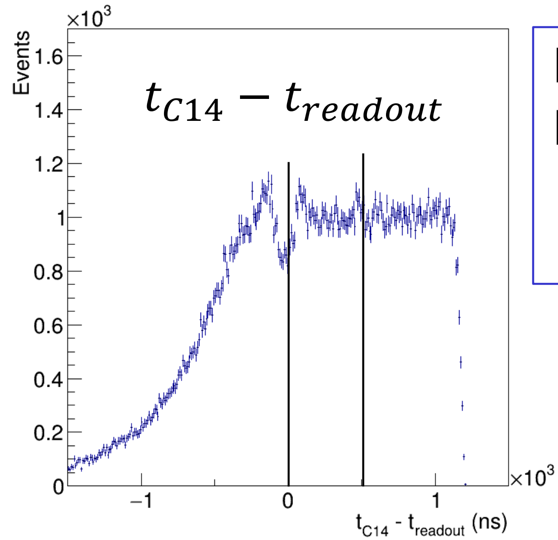




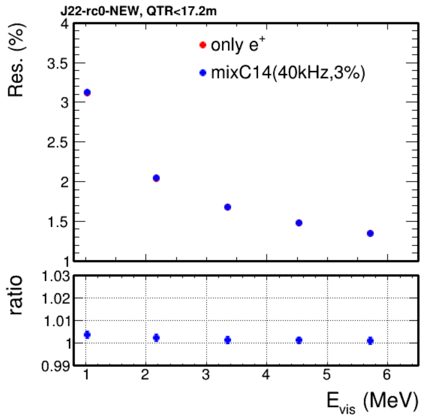
Reactor $\bar{\nu}_e$ signal IBD event number ($\times 10^5$)
JUNO Simulation Preliminary
Resolution $\tilde{a}$: 2.8%
Resolution $\tilde{a}$: 2.9%
Resolution $\tilde{a}$: 3.0%
JUNO exposure: 6 years×26.6 GW_{th}
$|\Delta\chi^2_{min}|$
Resolution $\tilde{a}$ [%]
4.0
9.0
16.0
25.0
JUNO exposure [years×26.6 GW_{th}]

Some checks

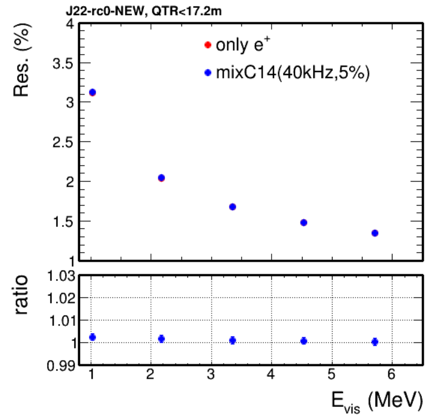




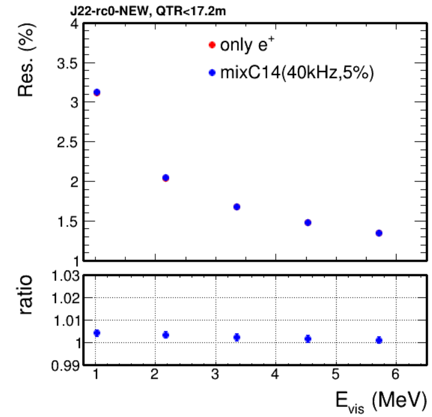
- $t_{readout} = t_{trigger} - 100\ ns$
- t_{e^+} (t_{C14}) is mixing time of e^+ (C14) at electronic simulation



Remove: C14 edep > 0.05 MeV

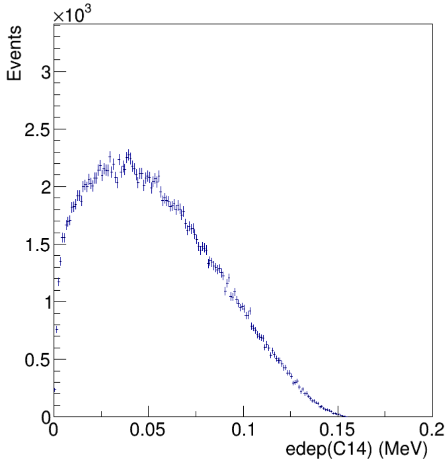


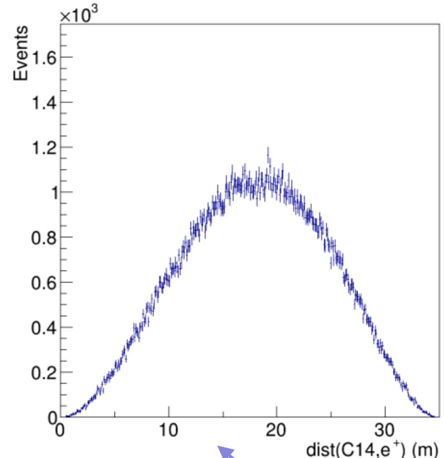
Remove: $0 < t_{C14} - t_{readout} < 500$ ns

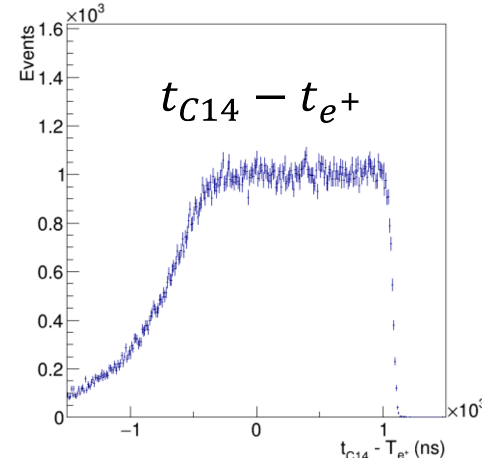


Remove: $0 < t_{C14} - t_{readout} < 400$ ns

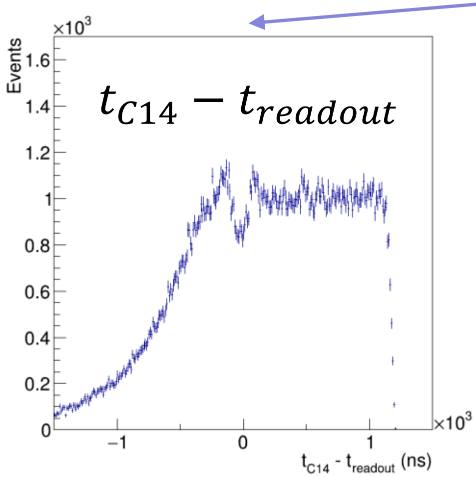
Check some distributions

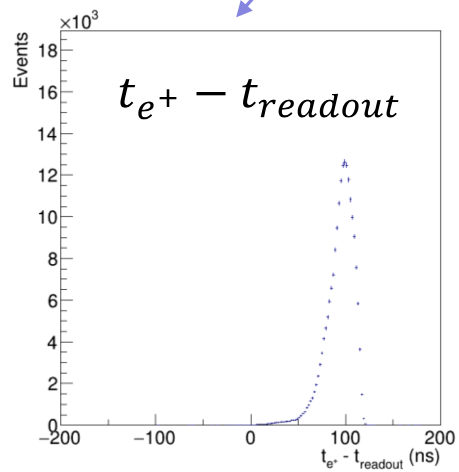






For readouts contain hits from C14





- ☐ $t_{readout} = t_{trigger} - 100\ ns$
- ☐ t_{e^+} (t_{C14}) is mixing time of e^+ (C14) in elecsim

Consistent check

From Jiang Wei

```
mean=1.024267+-0.000049,res=3.114843+-0.003420%
mean=2.166115+-0.000068,res=2.039844+-0.002248%
mean=3.344596+-0.000086,res=1.676845+-0.001869%
mean=4.526019+-0.000104,res=1.479079+-0.001663%
mean=5.709060+-0.000120,res=1.348178+-0.001523%
mean=6.892424+-0.000135,res=1.249835+-0.001399%
```

```
$cat kRes.txt
1.022   1.0237  4.73756e-05     3.12226 0.00332645
1.272   1.29543 5.19471e-05     2.70515 0.00287844
1.522   1.58186 5.6613e-05      2.41311 0.00258356
1.772   1.87269 6.10666e-05     2.20053 0.00233683
2.022   2.16547 6.5629e-05      2.04571 0.00218312
2.522   2.75394 7.4585e-05      1.82824 0.00196065
3.022   3.34385 8.35146e-05     1.68182 0.00181166
3.522   3.93441 9.18545e-05     1.56753 0.00169285
4.022   4.52529 0.000100289     1.4837  0.0016076
4.522   5.11651 0.000109387     1.41126 0.00154548
5.022   5.70821 0.000116527     1.35426 0.00147221
5.522   6.29978 0.000126754     1.30376 0.00145339
6.022   6.89163 0.000132877     1.2562  0.00139152
7.522   8.66789 0.000172012     1.15688 0.00141377
9.022   10.4452 0.000190706     1.07738 0.00129446
12.022  14.0028 0.000256328     0.966111        0.00126794
jiangw@[09:28:30]:/scratchfs/juno/jiangw/Time_Grid/8/e+
```

- Checked the energy resolutions for 0,1,2,3,4,5 MeV e^+, they are consistent with Wei results within statistic error

Dataset

- detsim, produced by Wei Jiang:
  - e^+:root://junoeos01.ihep.ac.cn//eos/juno/valprod/valprod0/J22.1.0-rc0-NEW/e+/e+_Uniform/(0~5MeV, 0MeV, 1MeV, 2MeV, …)
  - C14:root://junoeos01.ihep.ac.cn//eos/juno/valprod/valprod0/J22.1.0-rc0-NEW/C14/C14_Uniform
- elecsim:

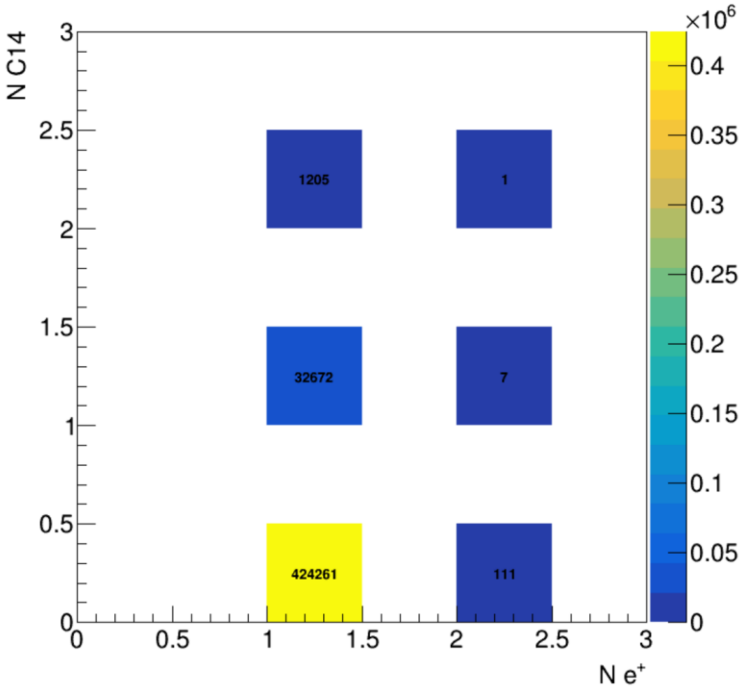
```
source /cvmfs/juno.ihep.ac.cn/centos7_amd64_gcc830/Pre-Release/J22.1.0-rc0/setup.sh
python $TUTORIALROOT/share/tut_det2elec.py --evtmax -1 --seed 0 --loglevel Fatal  --input IBD:root://junoeos01.ihep.ac.cn//eos/juno/valprod/valp
rod0/J22.1.0-rc0-NEW/e+/e+_Uniform//0MeV/detsim/root/detsim-0.root --input C14:root://junoeos01.ihep.ac.cn//eos/juno/valprod/valprod0/J22.1.0-rc
0-NEW/C14/C14_Uniform/detsim/root//detsim-0.root --rate IBD:100 --rate C14:40000 --loop IBD:0 --loop C14:1 --output /cefs/higgs/wxfang/JUNO/C14M
ixing/elec//elec_0.root --user-output /cefs/higgs/wxfang/JUNO/C14Mixing/elec//elecUSER_0.root --nHitsThreshold 500 --Trigger_FiredPmtNum 200
```

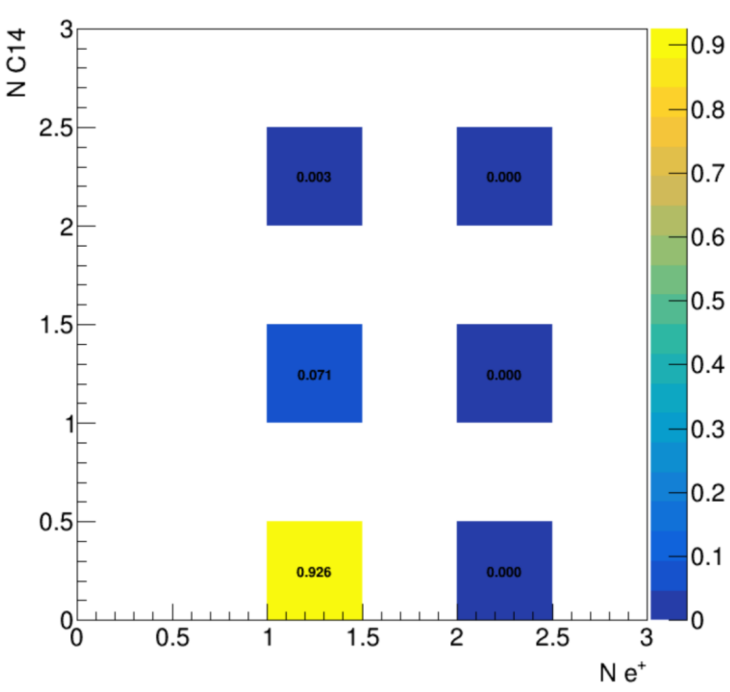
- calib:

```
source /junofs/users/jiangw/J22.1.0-rc0/bashrc
python $TUTORIALROOT/share/tut_elec2calib.py --evtmax -1 --enableElecTruth --input /cefs/higgs/wxfang/JUNO/C14Mixing/elec//elec_3556.root --outp
ut /cefs/higgs/wxfang/JUNO/C14Mixing/calib//calib_3556.root --user-output /cefs/higgs/wxfang/JUNO/C14Mixing/calib//calibUSER_3556.root
```

- rec:

```
source /junofs/users/jiangw/J22.1.0-rc0/bashrc
python ${TUTORIALROOT}/share/tut_calib2rec.py --evtmax -1 --gdml --method energy-point --enableQTimePdf --enableUseEkMap --enableLTSPEs --enable
TimeInfo --SignalWindowL 420 --enableSPMTInfo --RecMapPath /scratchfs/juno/jiangw/J22-rc0-PDF-NEW/recMap --input /cefs/higgs/wxfang/JUNO/C14Mixi
ng/calib//calib_3709.root --output /cefs/higgs/wxfang/JUNO/C14Mixing/rec//rec_3709.root --user-output /cefs/higgs/wxfang/JUNO/C14Mixing/rec//rec
USER_3709.root --elec yes
```


N C14
3
2.5
2
1.5
1
0.5
0
0
0.5
1
1.5
2
2.5
3
N e+
1205
1
32672
7
424261
111
×10^6
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0


N C14
3
2.5
2
1.5
1
0.5
0
0
0.5
1
1.5
2
2.5
3
N e+
0.003
0.000
0.071
0.000
0.926
0.000
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0