Advanced new tool for background rejection in KamLAND geo-neutrino analysis using machine learning methods

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[Geo-neutrino]

Geo-neutrino : Electron-antineutrinos from natural radioactive decays in the Earth

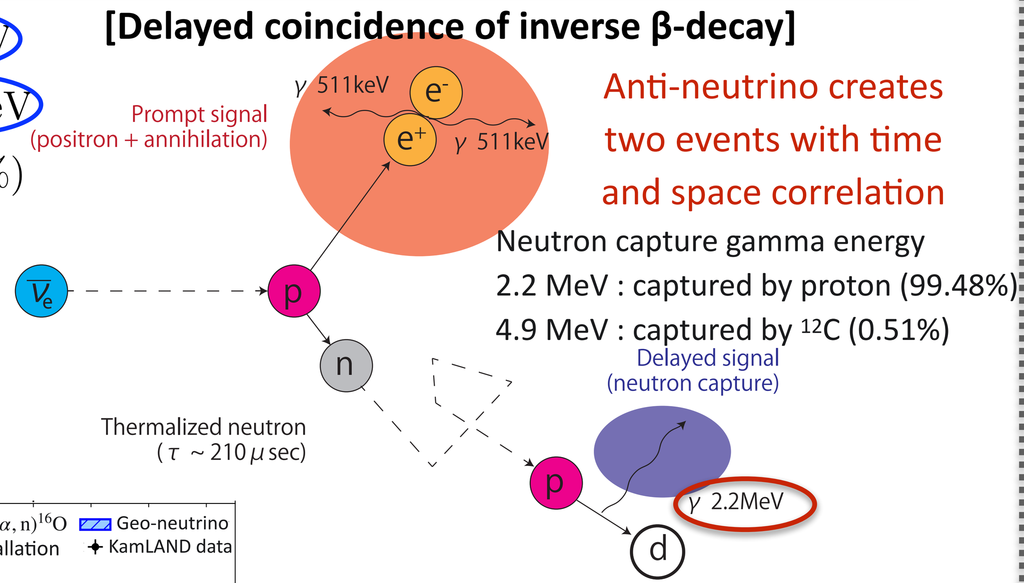
$^{238}U \rightarrow {}^{206}Pb + 8\alpha + 6e^- + 6\bar{\nu}_e + 51.7\,\mathrm{MeV}$

$^{232}Th \rightarrow {}^{208}Pb + 6\alpha + 4e^- + 4\bar{\nu}_e + 42.7\,\mathrm{MeV}$

$^{40}K \rightarrow {}^{40}Ca + e^- + \bar{\nu}_e + 1.311\,\mathrm{MeV}\ (89.28\%)$

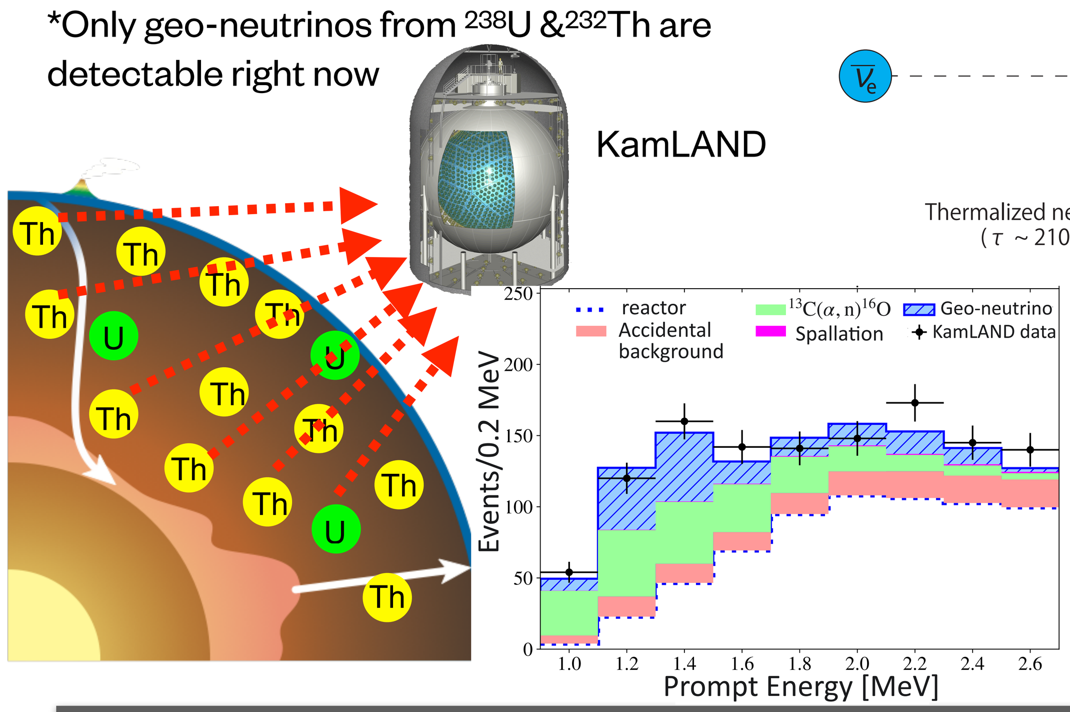
*Only geo-neutrinos from ^{238}U & ^{232}Th are detectable right now

[Delayed coincidence of inverse β-decay]



Anti-neutrino creates two events with time and space correlation

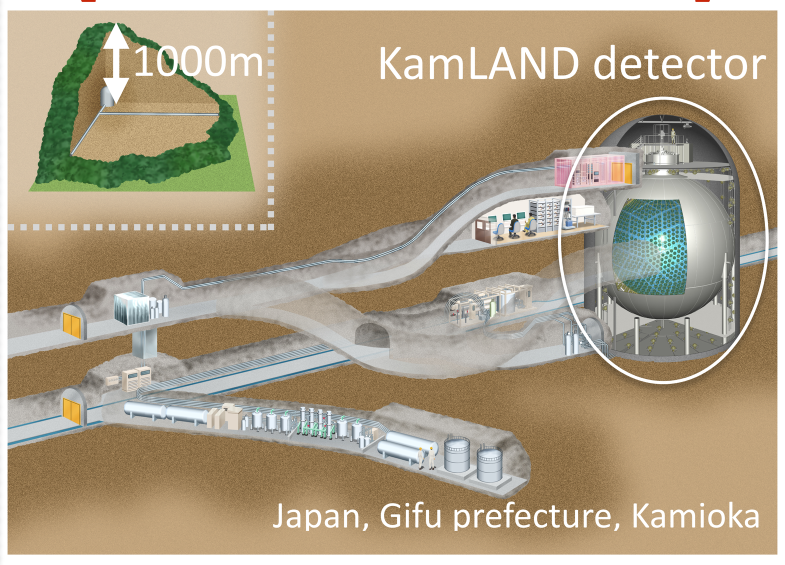
Neutron capture gamma energy
2.2 MeV : captured by proton (99.48%)
4.9 MeV : captured by ^{12}C (0.51%)



Number of geo-nu ∝ amount of U Th radiogenic heat

- **Geo-neutrino is powerful tool to directly measure the amount of radiogenic heat sources**

[KamLAND detector]



Depth: 2700 m.w.e
Muon flux = 1.50×10^{-7} (cm^{-2}s^{-1})

Low background environment
^{238}U: ~ 5.0×10^{-18} g/g
^{232}Th: ~ 1.3×10^{-17} g/g

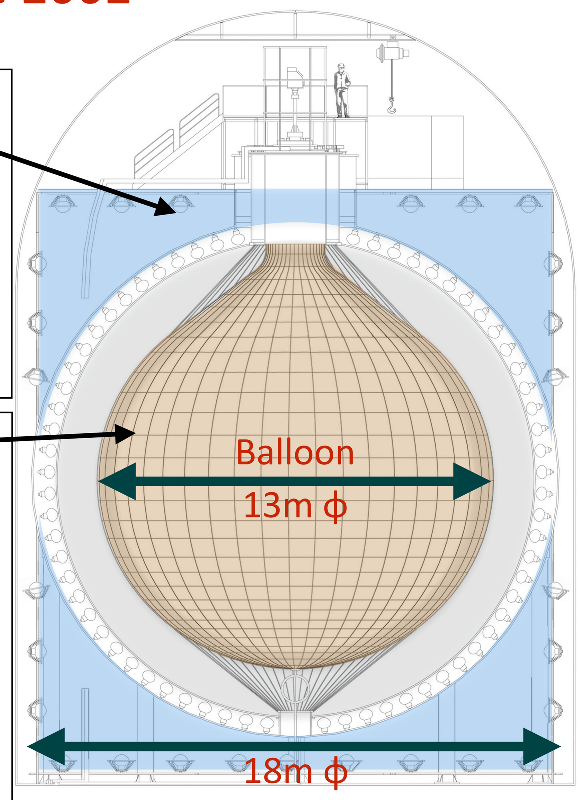
In operation since 2002

Outer detector
- 3.2 kton Pure water
- 20 inch PMTs (#140)

Shielding and active to muon

Inner detector
- 17inch PMT(#1325)
- 20inch PMT(#554)
- Buffer oil
- 1 kton LS in the balloon

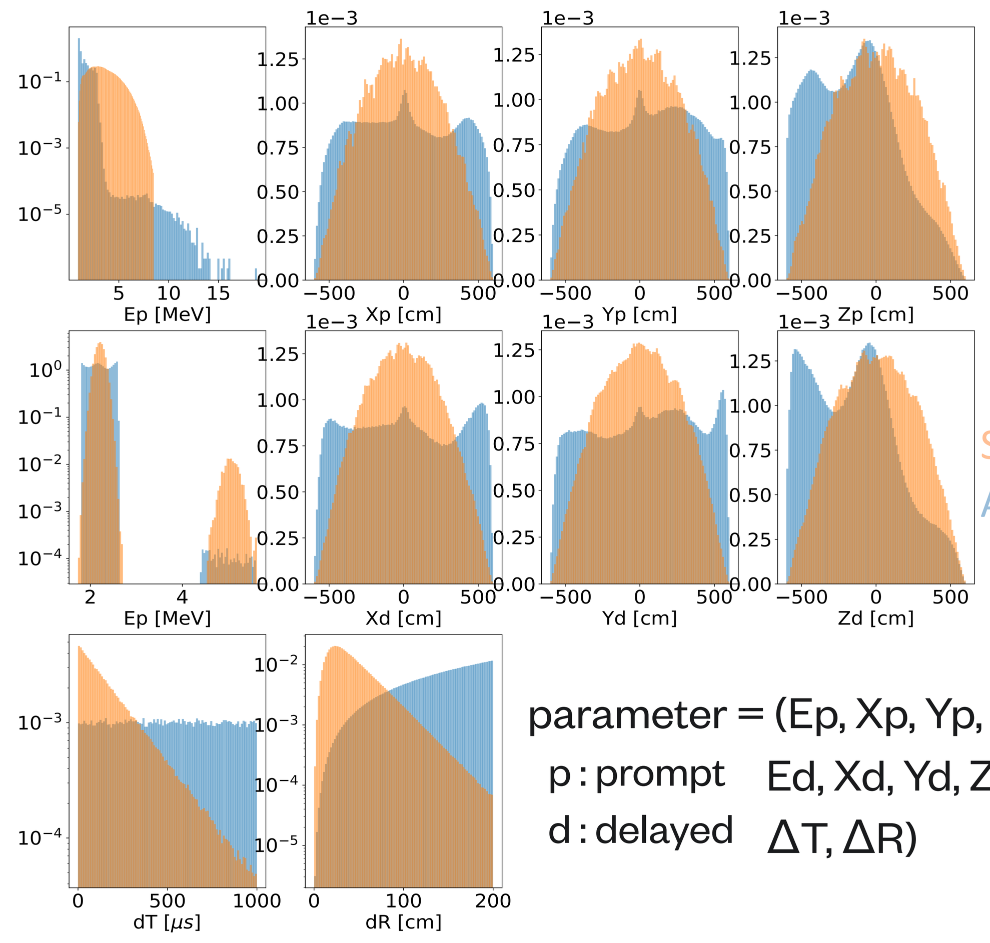
Neutrino detection



[BDT-likelihood selection]

BDT : Boosted Decision Tree

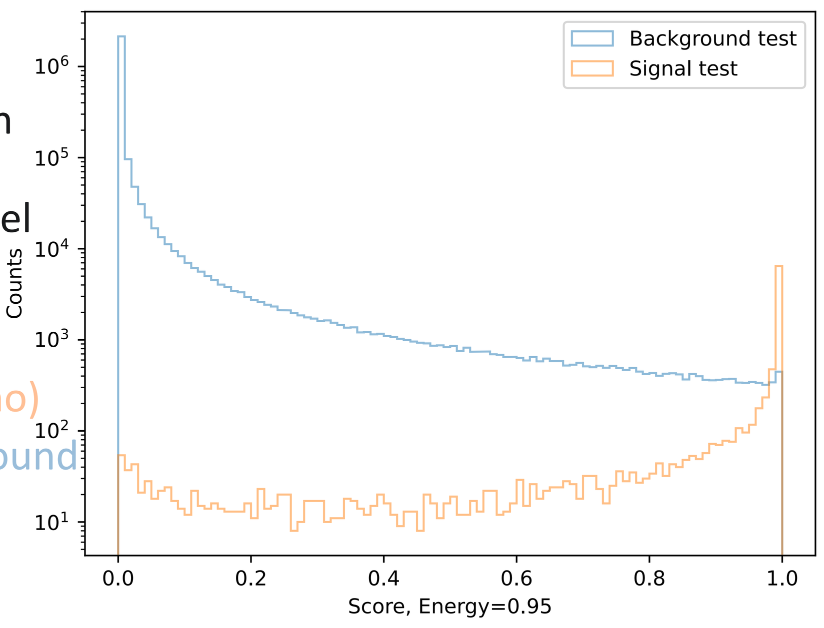
Input parameters



Each data is given a score by the trained BDT model

Signal(anti-neutrino)
Accidental background

Output histogram



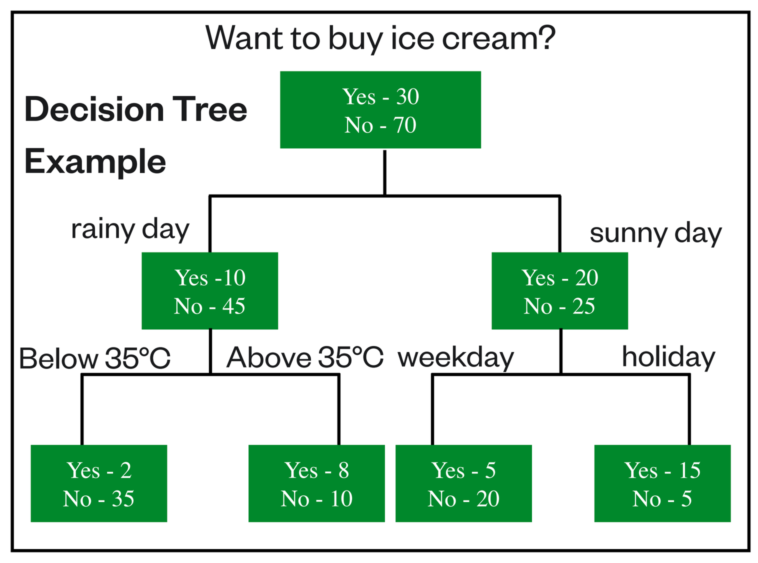
parameter = (Ep, Xp, Yp, Zp, Ed, Xd, Yd, Zd, ΔT, ΔR)
p : prompt
d : delayed

Old likelihood selection
Ep(76 bin), Ed(3 bin), Rp(5 bin), Rd(5 bin), ΔT(1 bin), ΔR(16 bin) → 1200 bin

Improvement points
- Binned analysis → un-binned analysis
- Consider correlations between parameters
- Input parameters taking into account detector asymmetry (R → X,Y,Z)

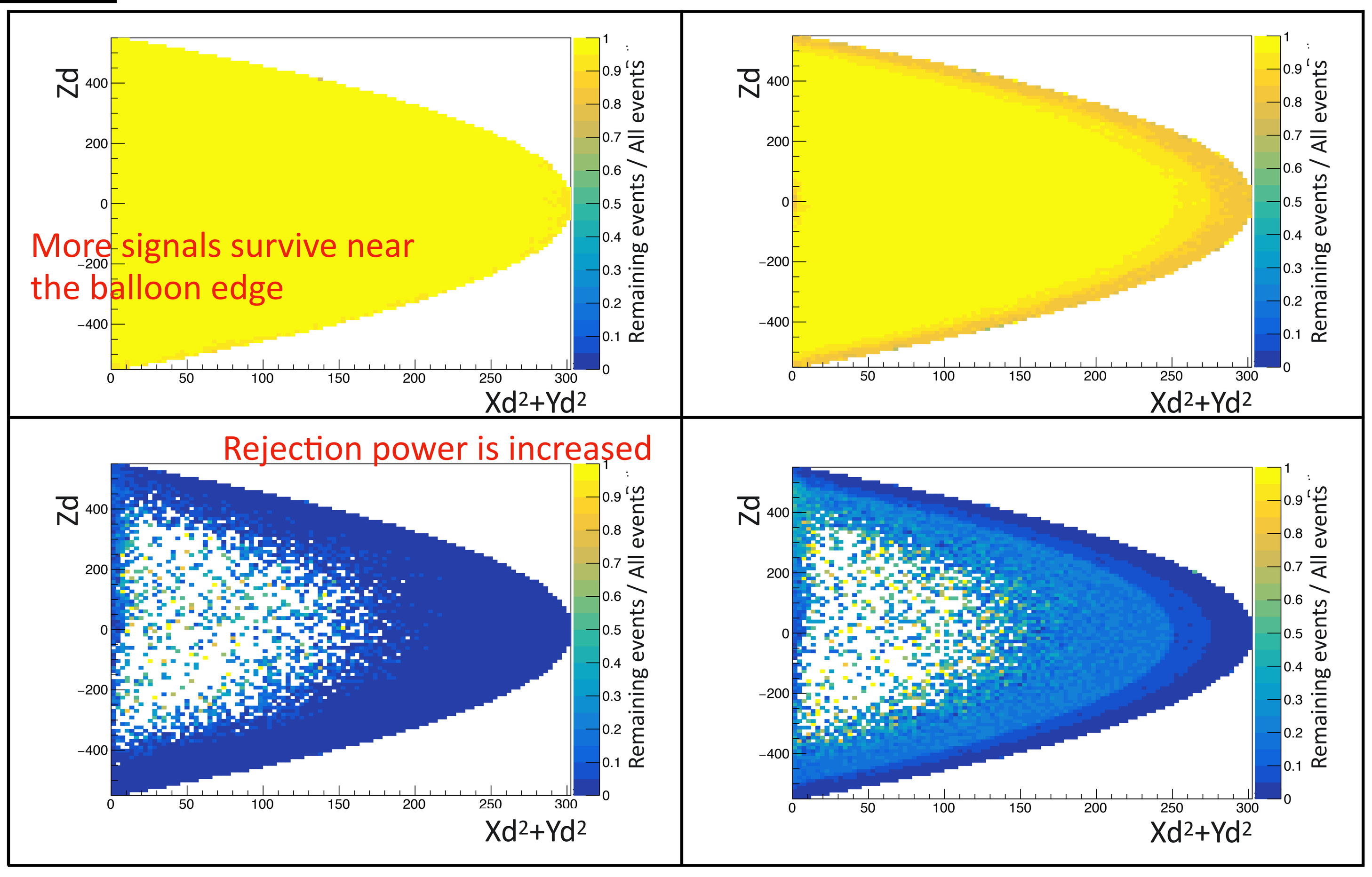
*Training data is generated by simulation(signal) and data-driven(background)
*Hyper-parameters are tuned using optuna

Decision tree :
A decision tree is a model that has a tree-like structure, where each "leaf" represents a question. Data is split based on the conditions of these questions.
(Ex. "leaf" : dT < 200μs , Ed > 2 MeV …)
GBDT (Gradient Boosting Decision-Tree) :
A method to reduce the error (loss) by adding weak learned decision tree. There are several powerful models.
XGBoost (Extreme Gradient Boosting):
Robust and prevents over-learning.

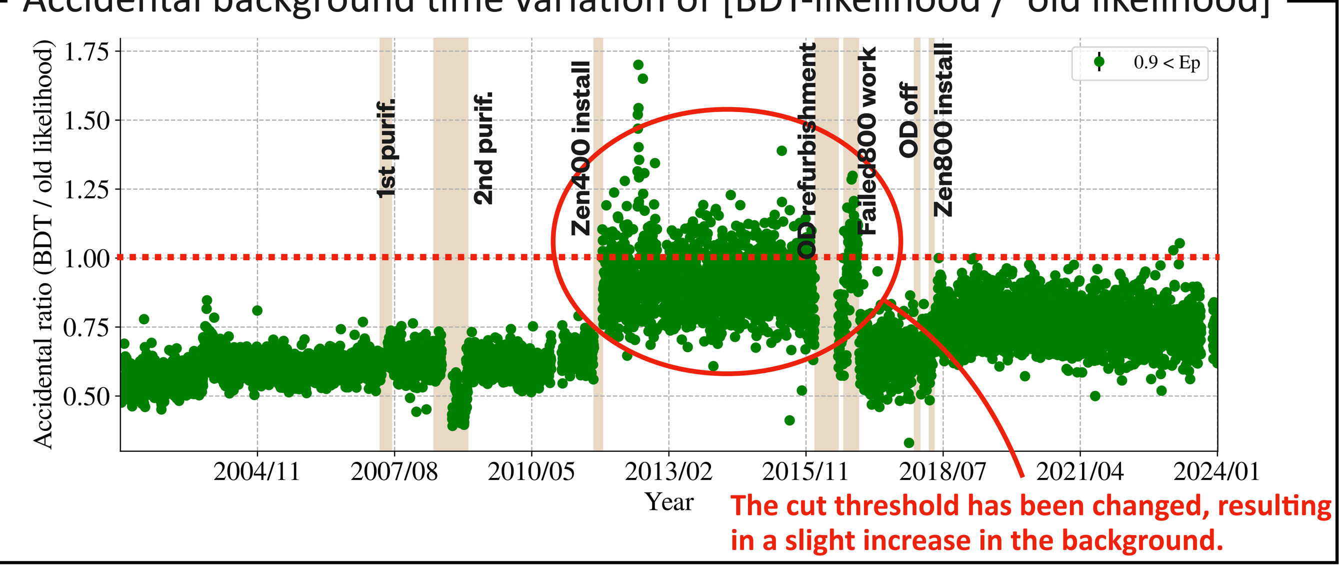


Result

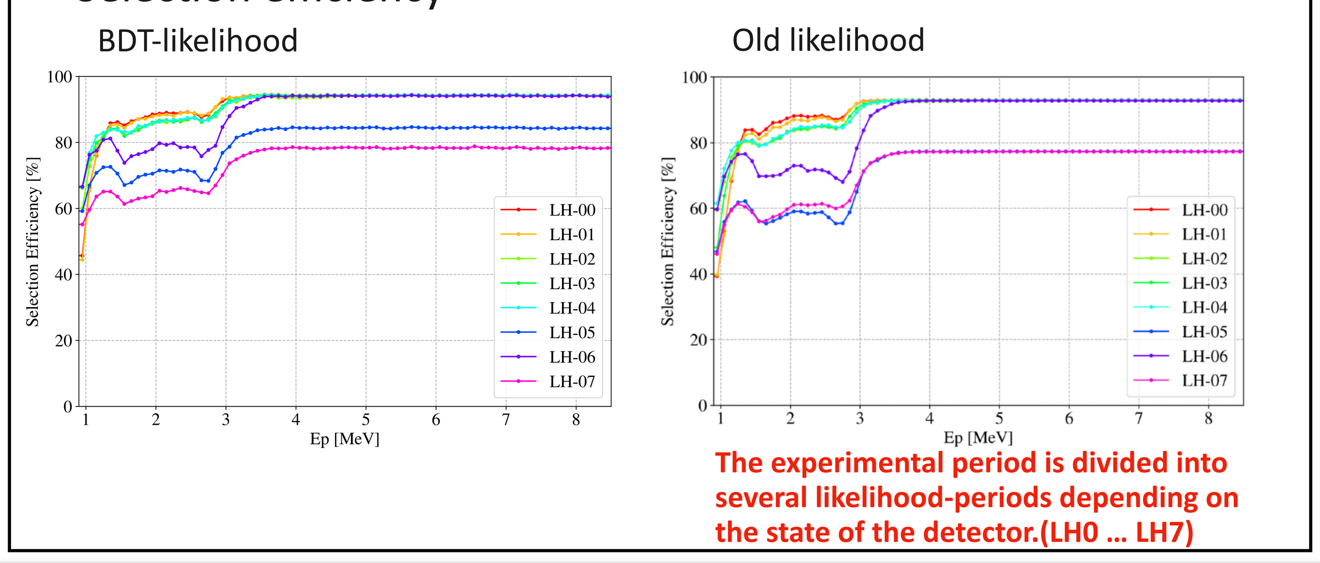
Remaining ratio



Result



Result

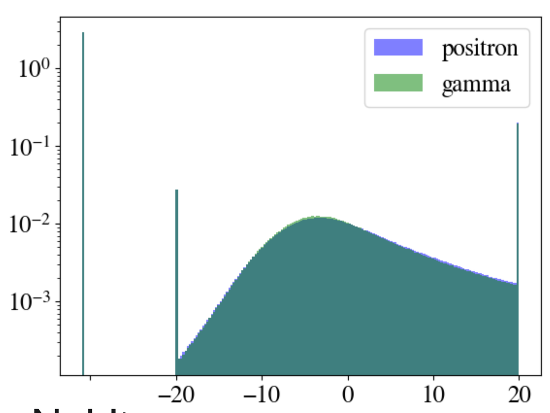


Background : 40% decrease
Signal : 8% increase
Significant improvement in S/N ratio

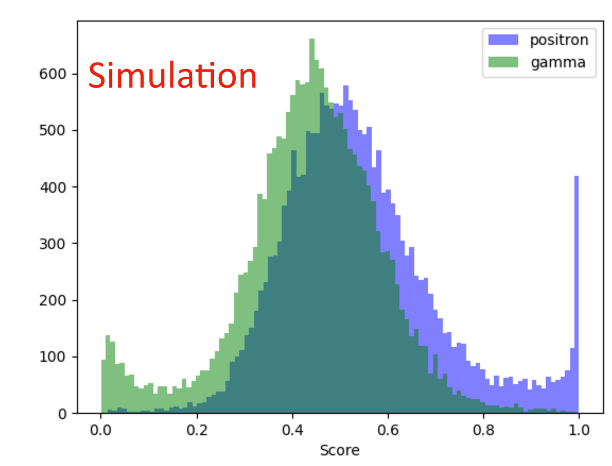
[Particle identification using graph neural network]

- GNN(graph neural network) model
- Training data is created by geant4

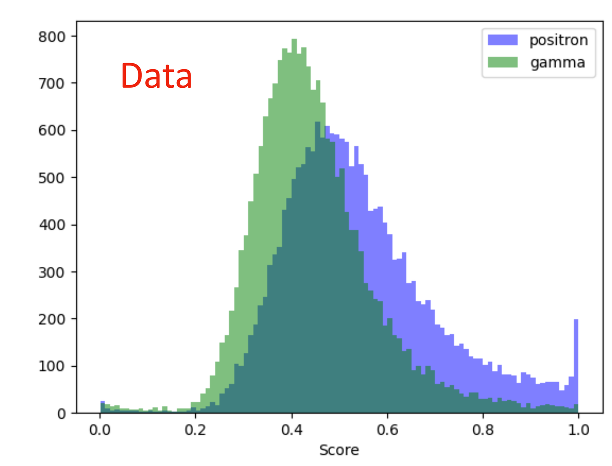
positron(annihilation, ortho-positronium), gamma
Positrons make ortho-positronium at about 50% and lifetime of ortho-positronium is about 3ns in Kam-LS.
Geant4 does not create ortho-positronium, so I made the events using electron and 2γ



Nohit
Time spectrum [ns]

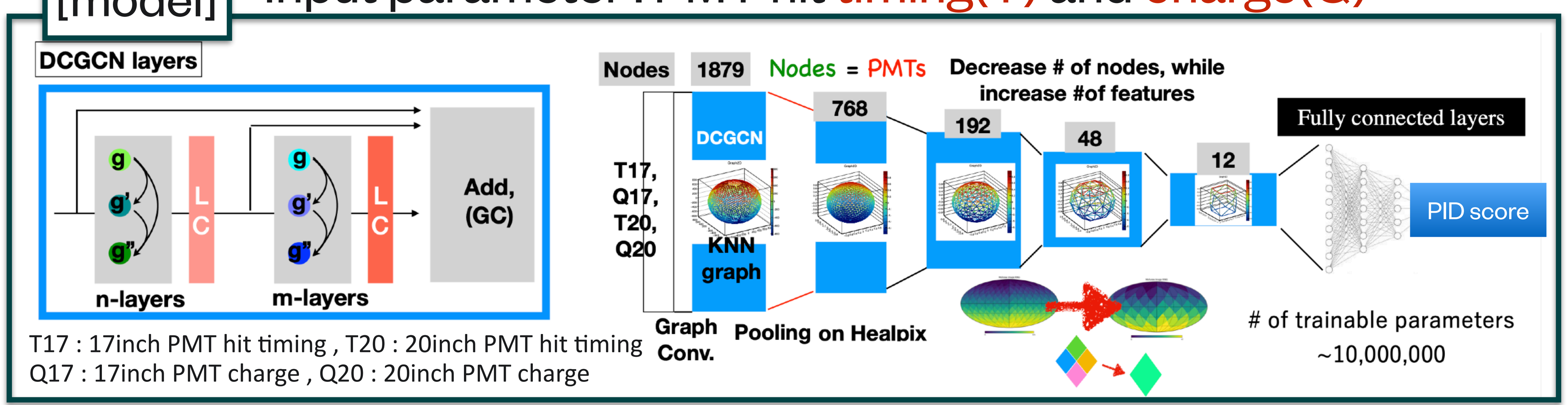


score (simulation data 0.9 - 8.5 MeV)



score (real data)
Positron : ^{11}C positron (1.2 -2.0 MeV)
Gamma : spallation neutron gamma (1.8 - 2.6 MeV)

[model] Input parameter : PMT hit timing(T) and charge(Q)



T17 : 17inch PMT hit timing , T20 : 20inch PMT hit timing
Q17 : 17inch PMT charge , Q20 : 20inch PMT charge

[summary]

* Significant improvements have been achieved by using new tools with Decision Tree
* The use of neural networks showed the feasibility of PID.
* Increased light intensity would improve PID accuracy
* Machine learning may also enable analyses that were previously challenging, such as neutrino directional detection.
* The new analysis using machine learning will be applied to the final data analysis of KamLAND.

Neutrino 2024

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