

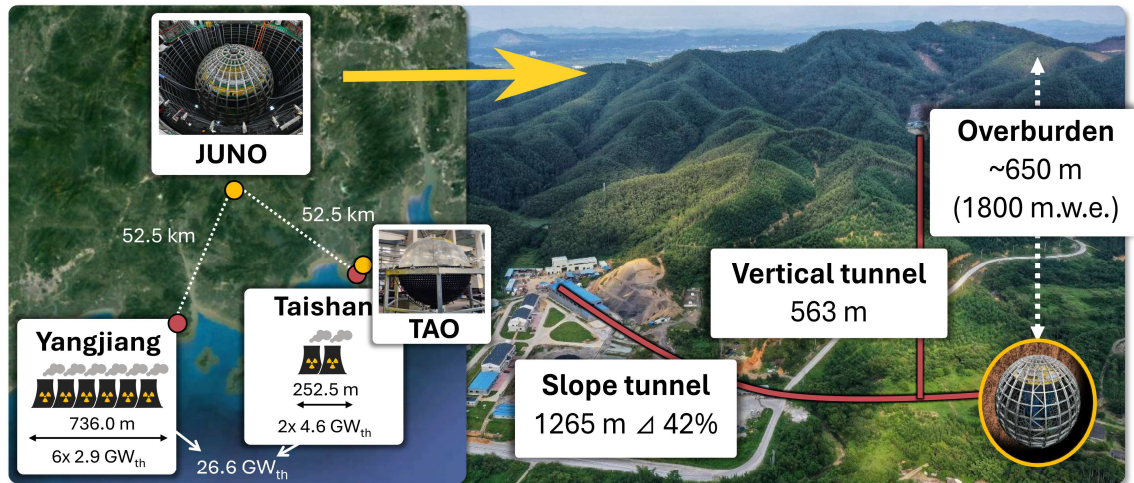
# Omnidirectional Photon Time Projection with Large Liquid Neutrino Detectors

Benda Xu

Department of Engineering  
Center for High Energy Physics  
Tsinghua University

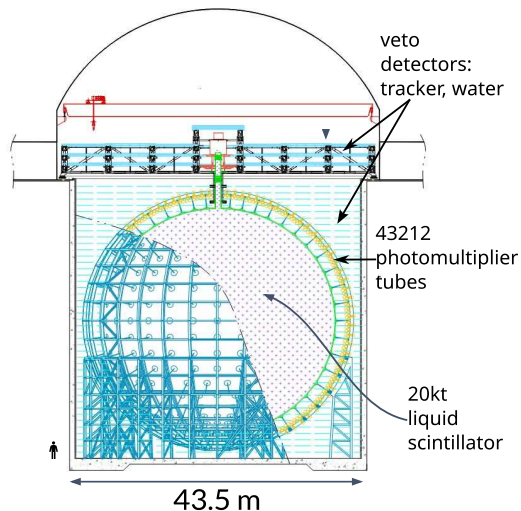
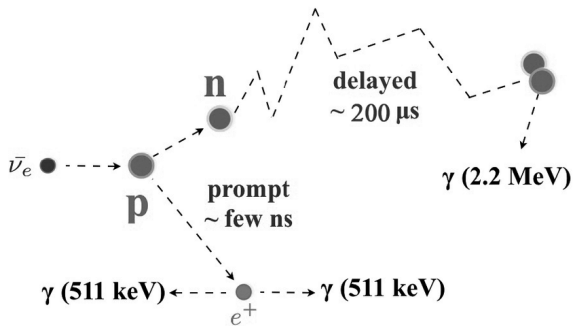
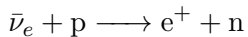
2025-08-28 TAUP, Xichang

# Jiangmen Underground Neutrino Observatory



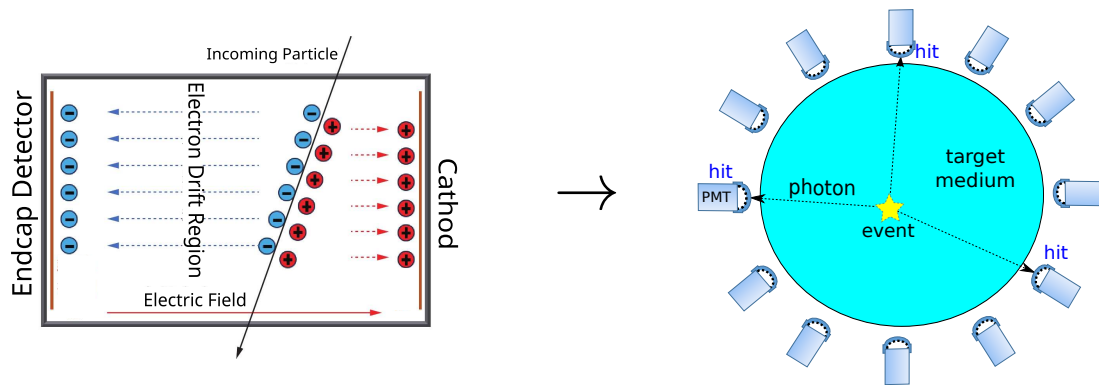
- 52.5 km is the sweet spot for  $\nu$  oscillation.

# $\bar{\nu}$ Inverse Beta Decay



- $e^+/\gamma$  scintillation light are collected by photomultipliers.

# Photon Time Projection at Liquid Scintillation Detectors

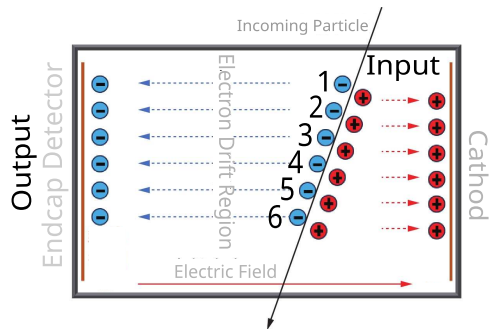


## From drift electrons to omnidirectional photons

- Speed from drift 1 cm/τs to intrinsic 20 000 cm/τs, needing faster readout.
- Photons travel in all directions, needing stronger algorithm and computing.

$$1D \quad \Delta z = v \Delta t \quad \rightarrow \quad \vec{r} = \vec{v} \Delta t \quad 3D$$

# Green's Function Analog for a TPC



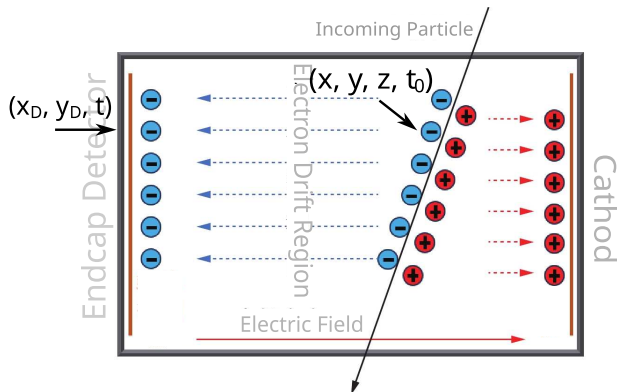
- Linear superposition of outputs.
- $\mathcal{D}_{\text{TPC}}(\cdot)$  is the linear detection operator.
- **linear differential operator** has Green's function.

$$\mathcal{D}_{\text{TPC}}(i_1 + i_2 + i_3 + \dots + i_6) = \mathcal{D}_{\text{TPC}}(i_1) + \mathcal{D}_{\text{TPC}}(i_2) + \dots + \mathcal{D}_{\text{TPC}}(i_6)$$

# The Trivial Green's Function

$$G(x_D, y_D, t; x, y, z, t_0) = \delta(x - x_D)\delta(y - y_D)\delta(z - v(t - t_0))$$

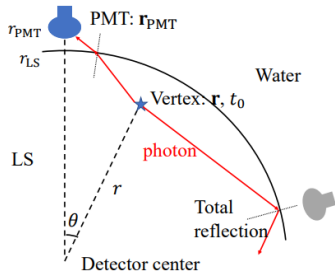
- $\delta(\cdot)$  is the Dirac delta function, in reality replaced with finite-resolution Gaussian.



# Green's Function for Monolithic Liquid Scintillator Detector

$$G(\mathbf{r}_{\text{PMT}}, t; \mathbf{r}, t_0) \xrightarrow{\text{PMT location symmetry}} R(t - t_0; \mathbf{r} - \mathbf{r}_{\text{PMT}}): \text{probe function}$$

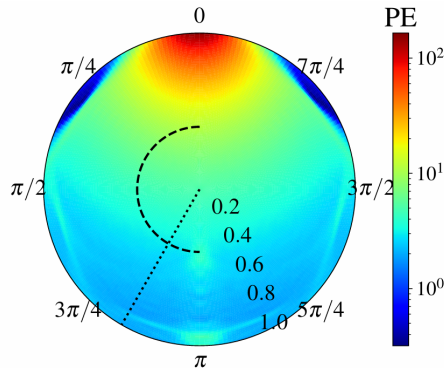
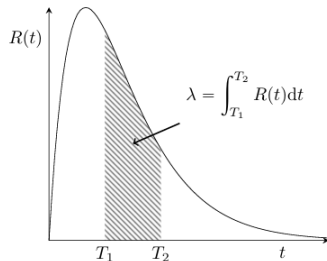
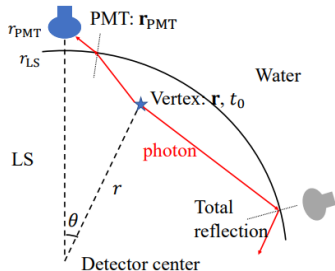
A non-trivial function that exhibits an asymptotic inverse-square dependence.



# Green's Function for Monolithic Liquid Scintillator Detector

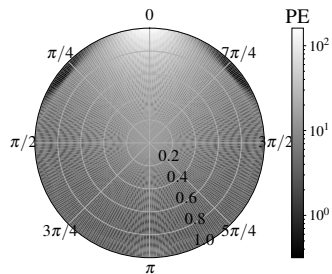
$$G(\mathbf{r}_{\text{PMT}}, t; \mathbf{r}, t_0) \xrightarrow{\text{PMT location symmetry}} R(t - t_0; \mathbf{r} - \mathbf{r}_{\text{PMT}}): \text{probe function}$$

A non-trivial function that exhibits an asymptotic inverse-square dependence.



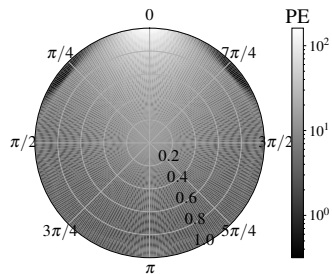


# Characterization of the Probe

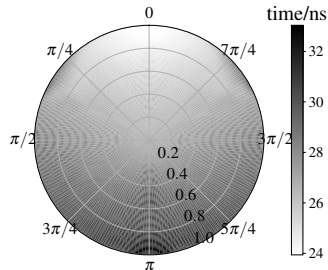


- The deficits at  $\frac{\pi}{4}$  is from the total internal reflection of acrylic-water interface.

# Characterization of the Probe

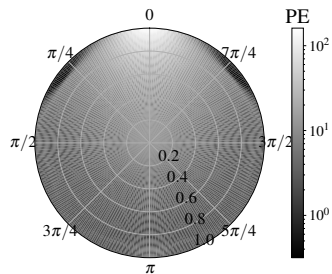


- The deficits at  $\frac{\pi}{4}$  is from the total internal reflection of acrylic-water interface.

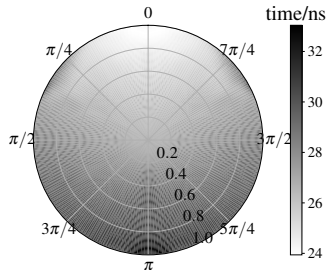


- Photon time of flight from all directions, modified by refraction, reflection and scattering.

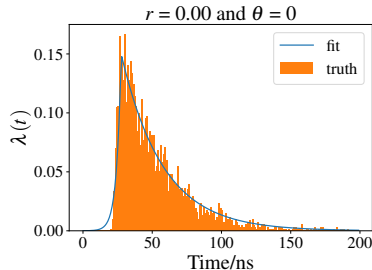
# Characterization of the Probe



- The deficits at  $\pi/4$  is from the total internal reflection of acrylic-water interface.



- Photon time of flight from all directions, modified by refraction, reflection and scattering.



- Shape approximates scintillation time profile.  $\lambda(t) = R(t; \mathbf{r})$  for a specific  $(r, \theta)$ .

# The Quantum Nature of Photon Detection

- A sample of photo-electrons on a PMT is from a **time-dependent poisson process**  $ER_j(t; \vec{r}, t_0)$ , its **intensity function** is superposition of multiple probes.

$$R(t) = \sum_k \left[ R_k^{\text{scintillation}}(t) + R_k^{\text{Cherenkov}}(t) \right] + R^{\text{Dark Count}}(t)$$

## First-Principle Bottom-Up Event Reconstruction

$$\begin{aligned} \mathcal{L}(\{\mathbf{w}_i\} | E, t_0, \mathbf{r}) &= \prod_i p[\mathbf{w}_i | ER_i(t; t_0, \mathbf{r}) + b_i] \quad \leftarrow \text{dark noise} \\ &= \prod_i \sum_j p(\mathbf{w}_i | \mathbf{z}_j) p[\mathbf{z}_j | ER_i(t; t_0, \mathbf{r}) + b_i] \quad \leftarrow \text{total probability} \\ &\quad \leftarrow \text{all PE times (sampled)} \\ &\quad \text{SPE charge spectrum embedded} \end{aligned}$$

Annotations in the diagram:  
 - **waveform**: points to  $\mathbf{w}_i$   
 - **total probability**: points to the product over  $i$   
 - **all PE times (sampled)**: points to the sum over  $j$   
 - **SPE charge spectrum embedded**: points to the overall expression

Chuang Xu, Contribution #260; Novel MCP-PMT response NIM A 1055(2023)168506, NIM A 1066(2024)169626.

# High-Resolution Waveform Analysis for Particle Detection

PEs follow an inhomogeneous Poisson process with intensity  $\lambda\phi(t - t_0)$ .

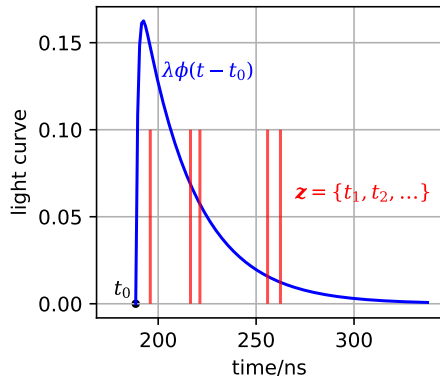


Figure: Sample PEs from Poisson process

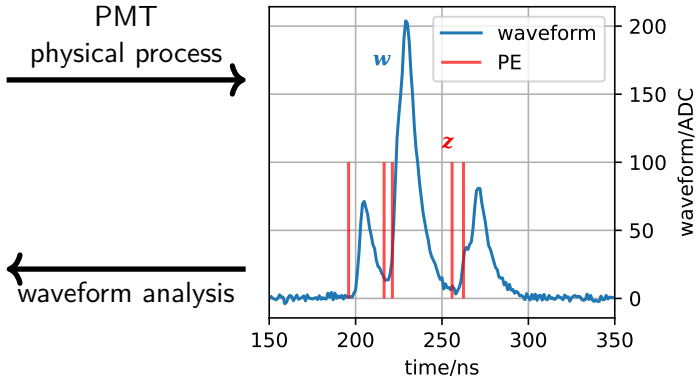


Figure: Convolve PEs into a waveform

Yuyi Wang, Contribution #191; arXiv:2403.03156

# Calibration of the Probe

Neural network as universal functional approximation  $\leftrightarrow$  non-parametric statistics

## Calibration of the detector response

- Time-dependent Poisson point process model as a surrogate to the optical process.
- Its intensity function is statistically learned non-parametrically.

## From generalized linear model (GLM) to generalized additive model (GAM)

$$g(\mathbb{E}[y|\mathbf{x}]) = \beta_0 + \sum_{j=1}^p \beta_j x_j$$

$$\rightarrow g(\mathbb{E}[y|\mathbf{x}]) = \beta_0 + \sum_{j=1}^p f_j(x_j)$$

- $f_j$  are the smooth basis functions.
- Basis are expanded with cartesian products.

# Generalized Additive Model on Histograms

x	y	t	nEV	nPE
...	...	...	...	...

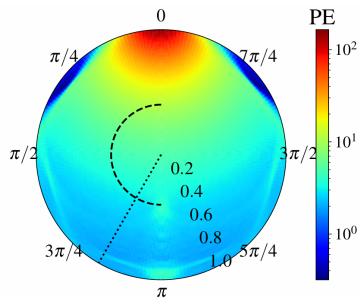
$x$  average  $x$ -coordinate of a bin

$y$  average  $y$ -coordinate of a bin

$t$  central value of a bin

nEV number of events

nPE number of PEs



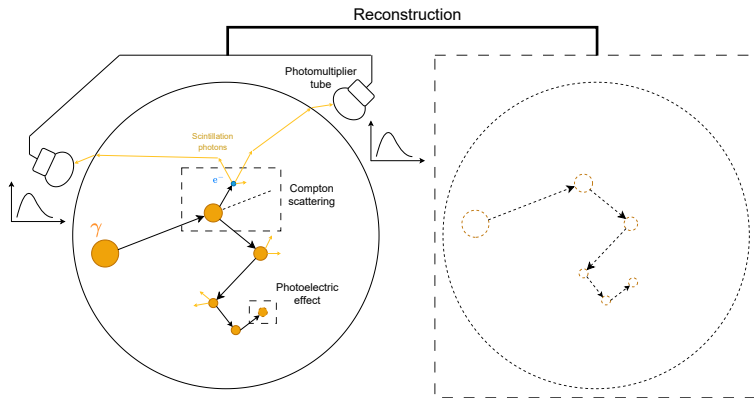
## Regression formula

$$\text{nPE} \sim \pi(\lambda), \log \lambda = \text{te}(x(r, \theta), y(r, \theta), t) + \log(\text{nEV})$$

→ Learn  $R_j(t - t_0; r, \theta)$ , extensible to boosted decision trees and neural networks.

Chuanhui Hao, Contribution #96

# Monolithic Liquid Scintillator as a Compton Camera



- Reconstructed gamma-ray trajectory from Compton and photoelectric electrons.

EPJ C 85, 4 (2025): 438, track effect expected for MeV  $\beta$  at JUNO-TAO



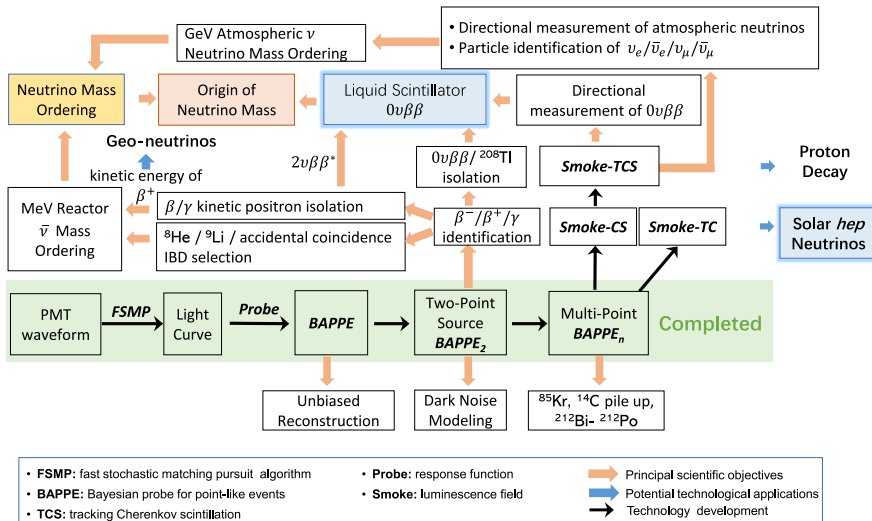
# Summary

- With faster readout and powerful algorithms, large liquid neutrino detectors could gain **omnidirectional photon time projection** tracking capabilities.
- Stochastic model by **classical statistics**, deterministic impulse response by **machine learning** (universal functional approximation).

## Next

- Calibrating the probe by mitigating the effects of PMT dark noise, non-uniform photon detection efficiency, and transit time spread (TTS).
- Promoting cross-experiment collaboration to enhance event reconstruction capabilities for the **DUNE** (LArTPC), **Hyper-K** (water Cherenkov), and **JUNO** (liquid scintillator) neutrino detectors.

# Low and high hanging fruits

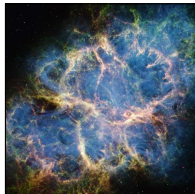


# $\nu$ research enabled by large 20 kt target

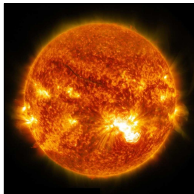
Reactor



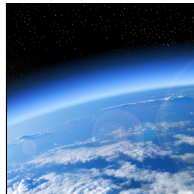
Supernovae



Sun



Atmosphere



Earth Interior



Neutrino source

Expected signal

Energy Region

Reactor

45 evts / day

Supernova burst

$10^4$  evts at 10 kpc

Diffuse supernova background

2-4 evts/ year

Sun  $^8\text{B}$  ( $^7\text{Be}$ )

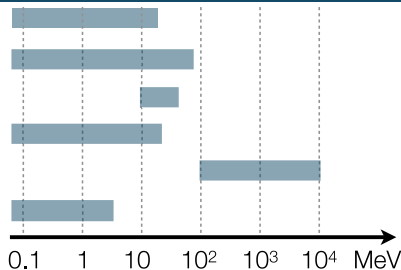
16 (490) / day

Atmosphere

100+ / year

Earth crust & mantle

400 / year



## Cubic Spline

$$f_j(x_j) = \sum_{k=1}^{m_j} \beta_{jk} B_k(x_j) \quad \Rightarrow \quad \mathbf{f}_j = \mathbf{X}_j \boldsymbol{\beta}_j$$

- $\mathbf{X}_j$ :  $n \times m_j$  design matrix
- $\boldsymbol{\beta}_j$ :  $m_j \times 1$  parameter vector

$$\int [f_j''(x_j)]^2 dx_j = \boldsymbol{\beta}_j^T \mathbf{S}_j \boldsymbol{\beta}_j$$

# Ambiguity of direction in 3D

$$\vec{r} = \vec{v}\Delta t.$$

- ① Hardware approach: measure the direction of incoming photon
  - ▶ development of lenses for liquid scintillation and Cherenkov detectors
- ② Solve the inverse problem with machine learning, in light of computational imaging.
  - ▶ extract particle interaction tracks from data analysis.
  - ▶ invertible full probabilistic modeling a.k.a. probabilistic programming

## Super-KamiokaNDE

- time projection

Integration of the intensity function gives a Poisson field.

$$\int R_j(t - t_0; r, \theta) dt = \lambda_j(r, \theta)$$