EVENT RECONSTRUCTION IN JUNO

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(on behalf of JUNO)
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OUTLINE

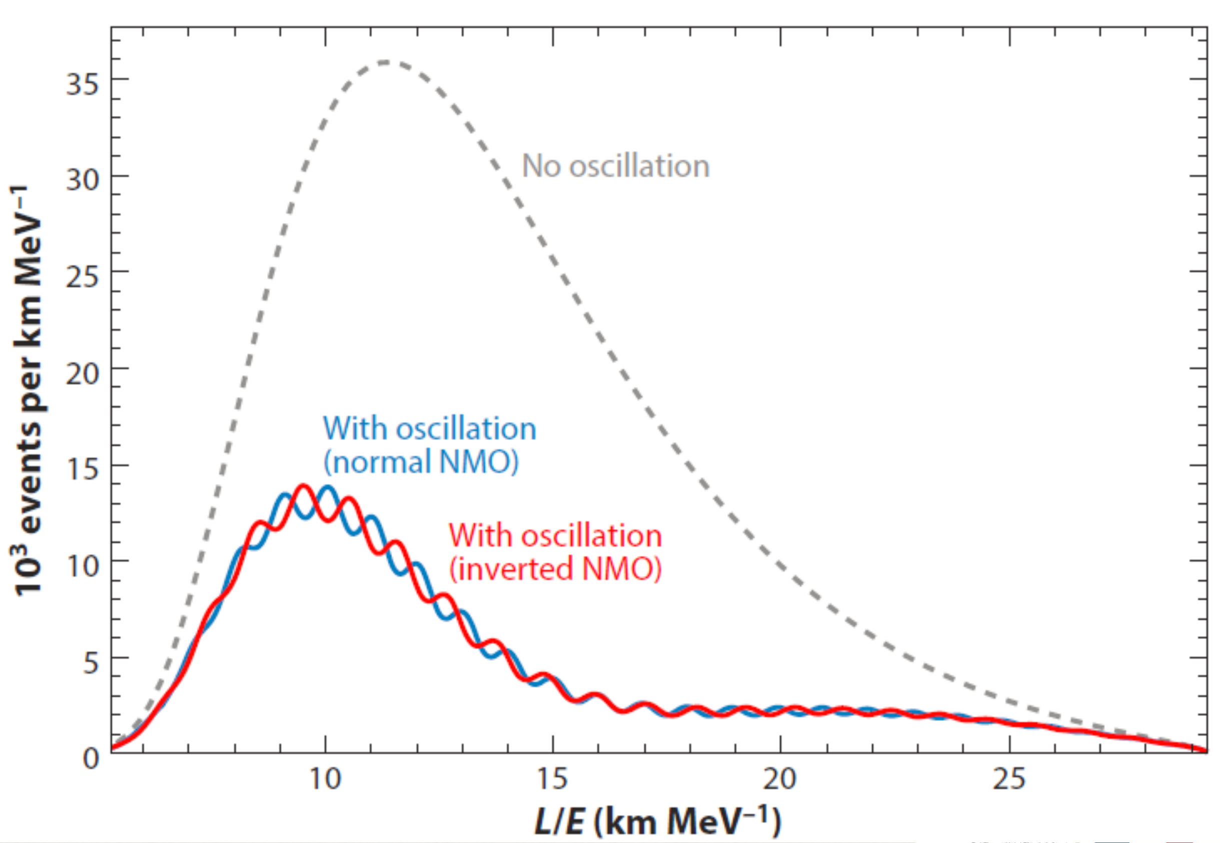
- Introduction of JUNO
- Traditional methods
  - Vertex reconstruction
  - Energy reconstruction
- Machine Learning based methods
  - Inputs,Models etc
- Summary

*Disclaimer:
all studies based on Monte Carlo Simulation;
many studies still on-going;
mainly focusing on the methods

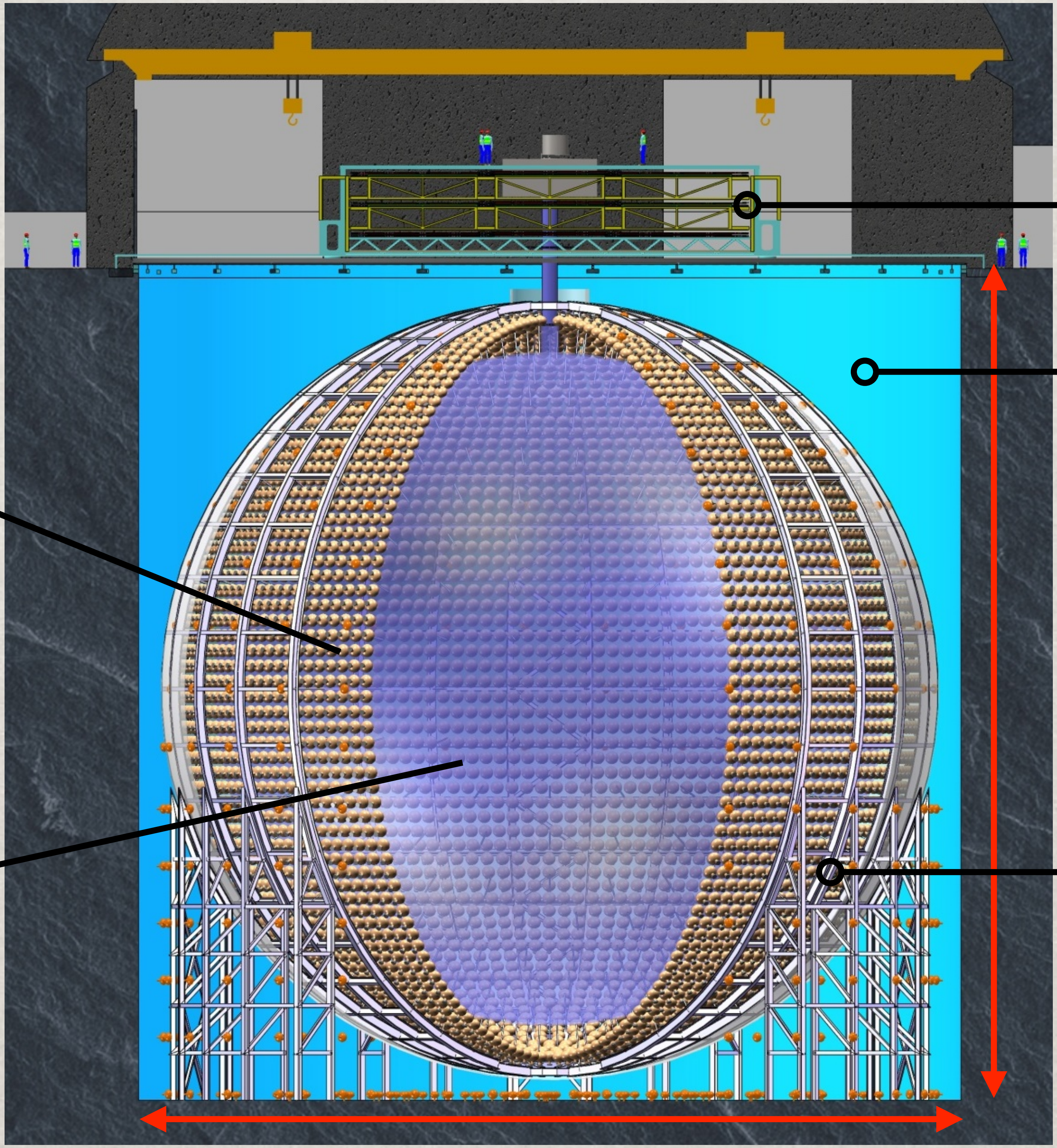
JUNO

- Jiangmen Underground Neutrino Observatory(JUNO):
  - Determine the neutrino mass ordering
  - Measure neutrino oscillation parameters to sub-percent level
  - SuperNova, Solar, Atm. Geo. etc

	DETECTOR TARGET MASS	ENERGY RESOLUTION
KamLAND	1000 t	6%/√E
D. Chooz	8+22 t	8%/√E
RENO	16 t	8%/√E
Daya Bay	20 t	8%/√E
Borexino	300 t	5%/√E
JUNO	**20000 t**	**3%/√E**



DETECTOR



Top Tracker

Water Pool

Depth: 44m

ϕ: 43.5m

Central Detector*

~17,612 20" PMTs

+ ~25,600 3" PMTs

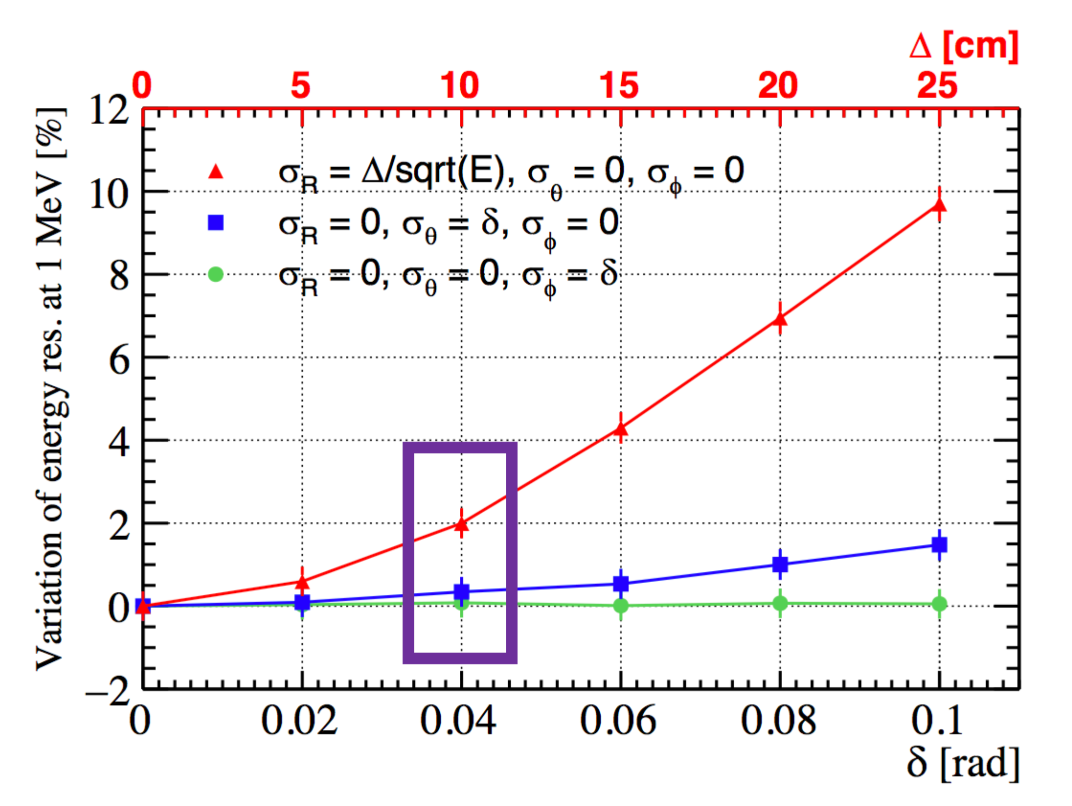
+ ~75% coverage

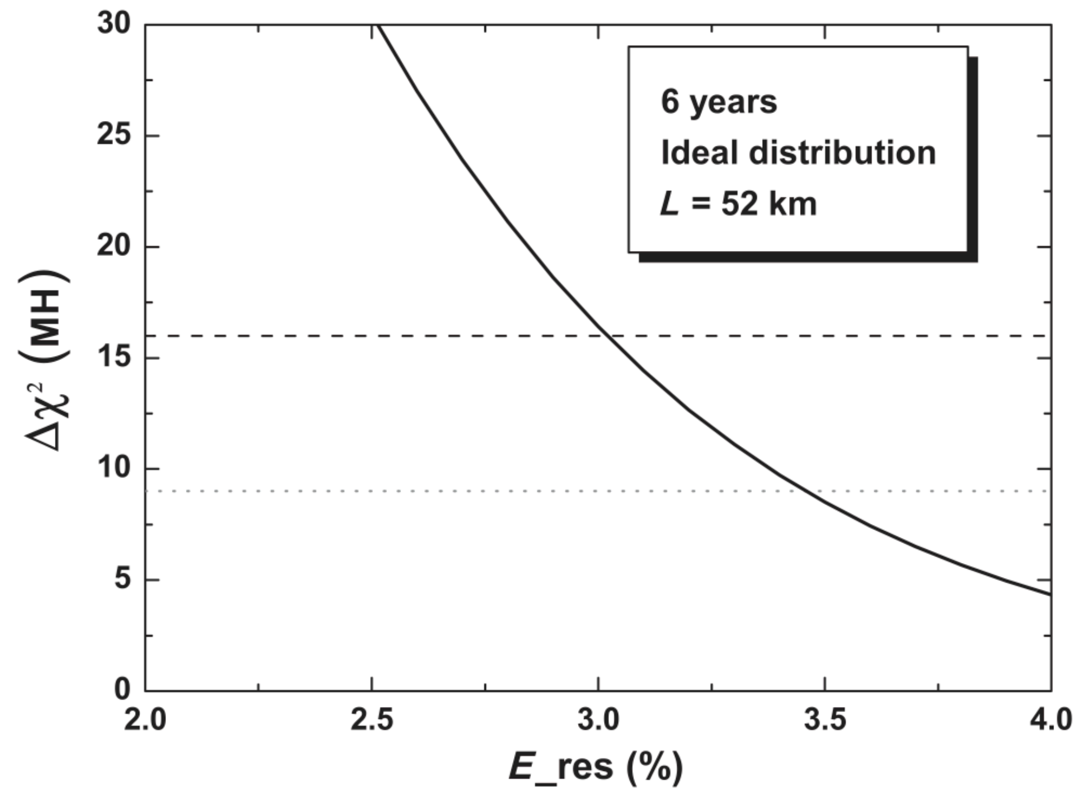
Liquid Scintillator
20kton

Central Detector*
Acrylic sphere
Stainless steel truss

RECO. FOR REACTOR $\bar{\nu}$

- Particles deposit energy in Liquid Scintillator —> emitting photons —> detected by PMTs
- Charge and time of PMTs —> vertex & energy
- Importance: crucial for physics sensitivity





TRADITIONAL METHODS

Vertex Reco.

Nucl.Sci.Tech. 32 (2021) 5, 49

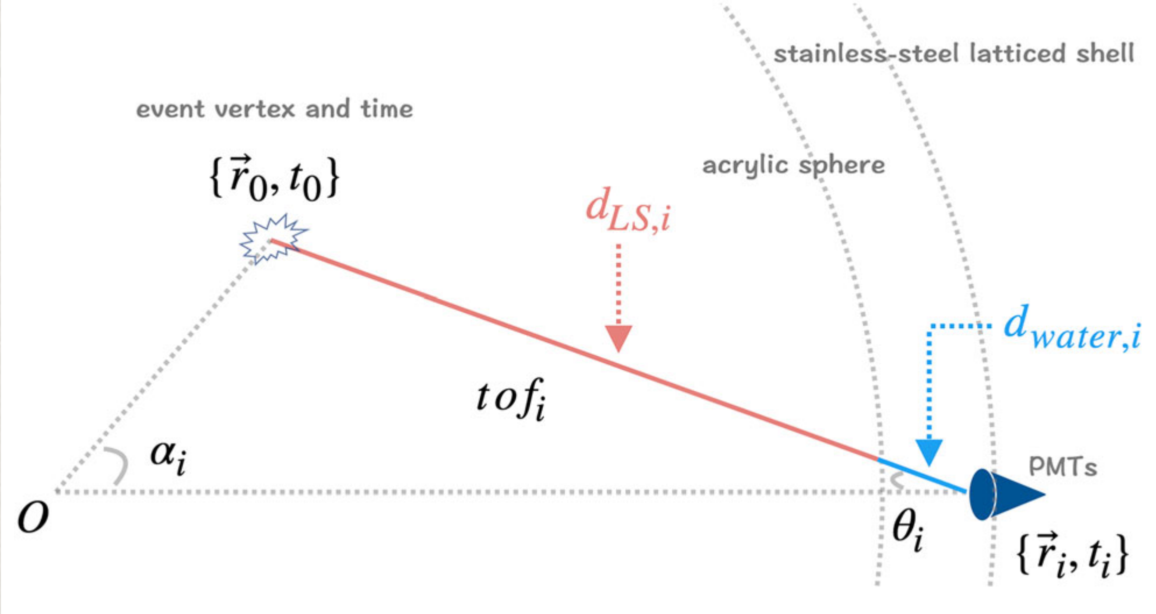
Methods	PMT info.	pros&cons	Usage
Charge Center	charge	simple and fast less accurate	initial value
Peak Time Fitter	time	simple more accurate	more accurate initial value
Time Likelihood	time	complex and most accurate	final value

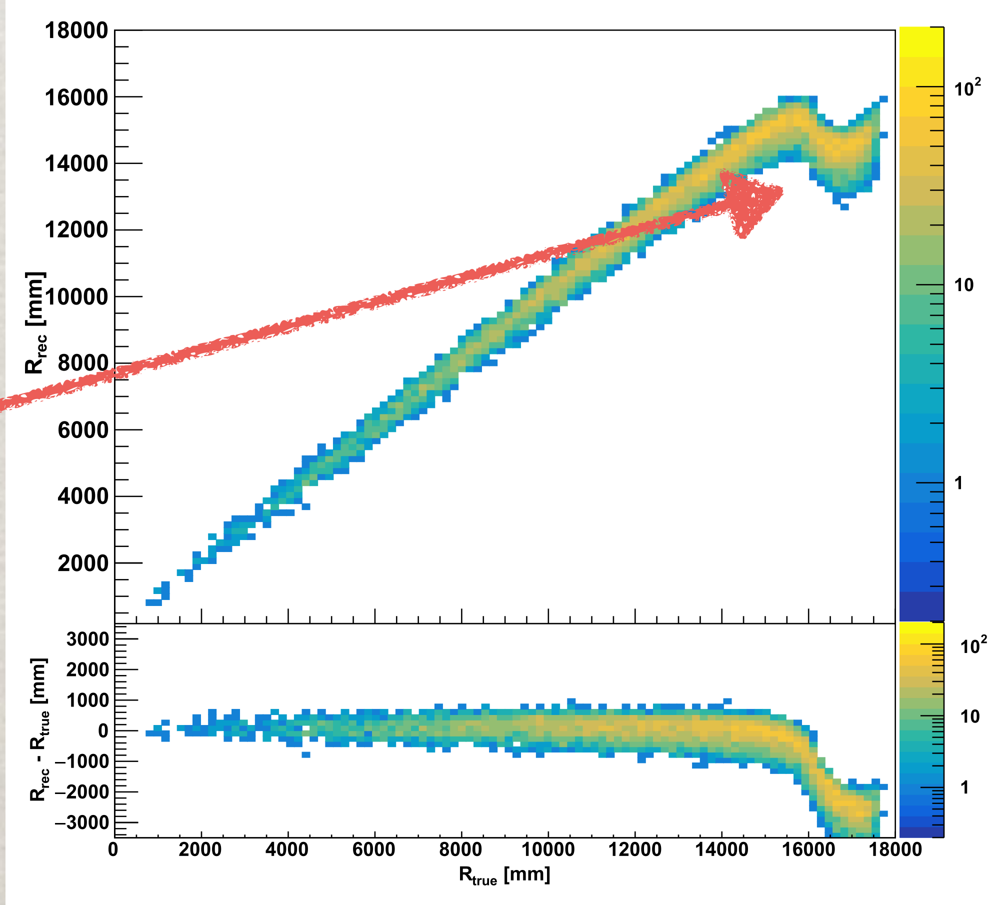
Charge Center

- Charge weighted average position of fired PMTs

$$\vec{r}_0 = a \cdot \frac{\sum_i q_i \cdot \vec{r}_i}{\sum_i q_i},$$

- Large bias near the edge due to photon leakage





Peak Time Fitter

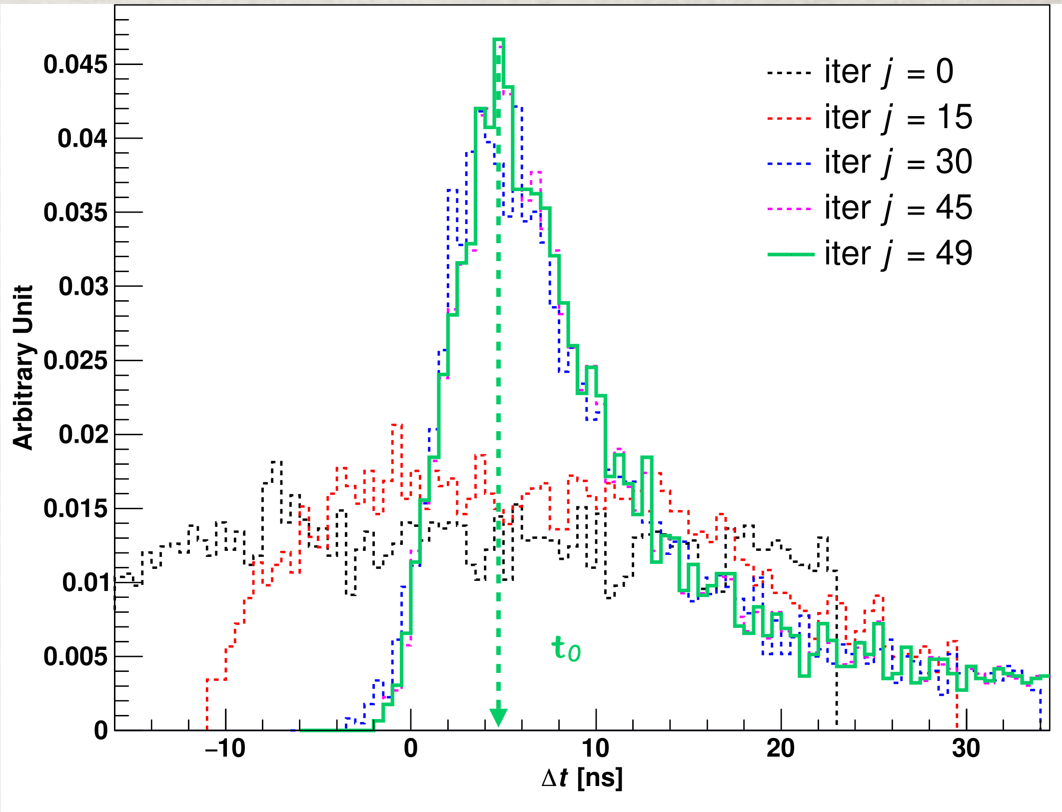
- Define "residual time"

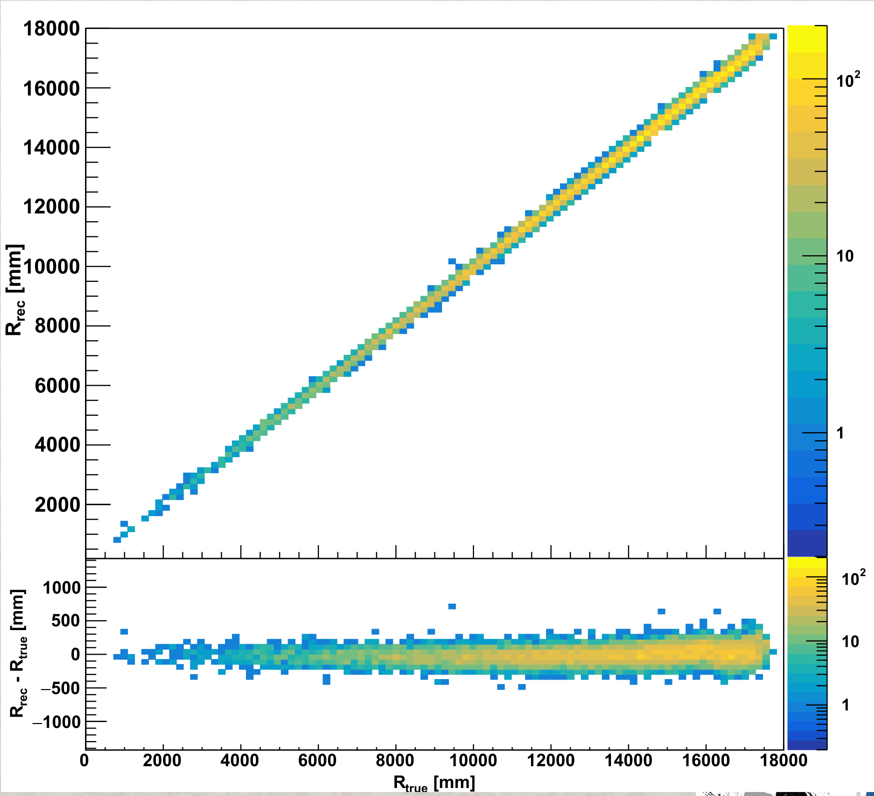
$$\Delta t_i(j) = t_i - \mathrm{tof}_i(j), \quad \text{j-th iteration}$$

- Apply correction to the vertex

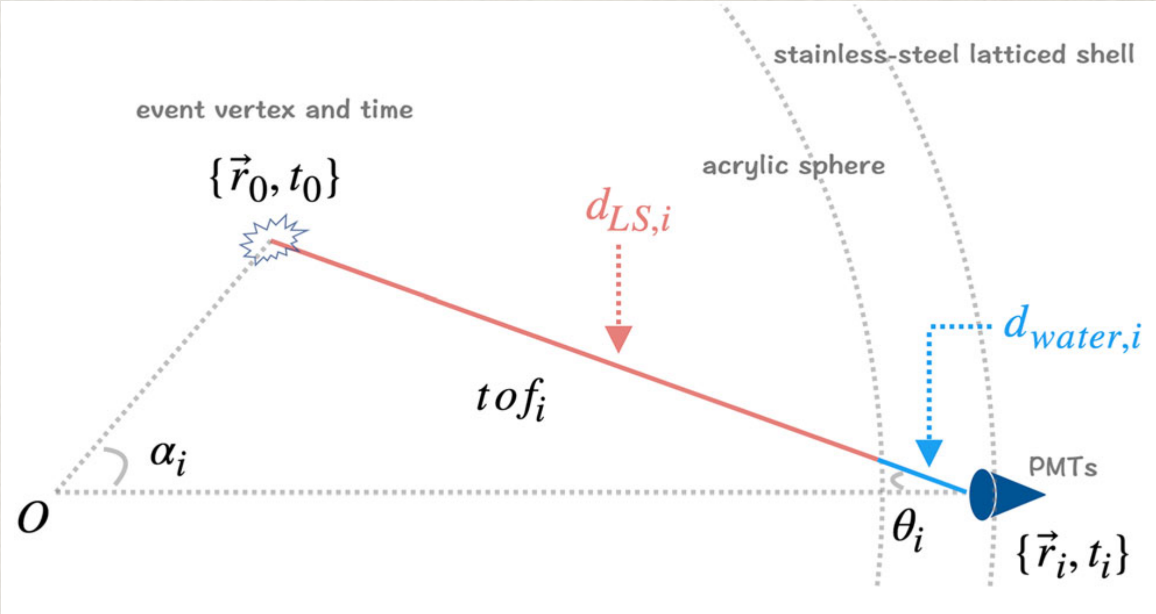
$$\vec{\delta}[\vec{r}(j)] = \frac{\sum_i \left(\frac{\Delta t_i(j) - \Delta t^{\mathrm{peak}}(j)}{\mathrm{tof}_i(j)}\right) \cdot (\vec{r}_0(j) - \vec{r}_i)}{N^{\mathrm{peak}}(j)},$$

- Iterate until Δt shape converges





Time Likelihood

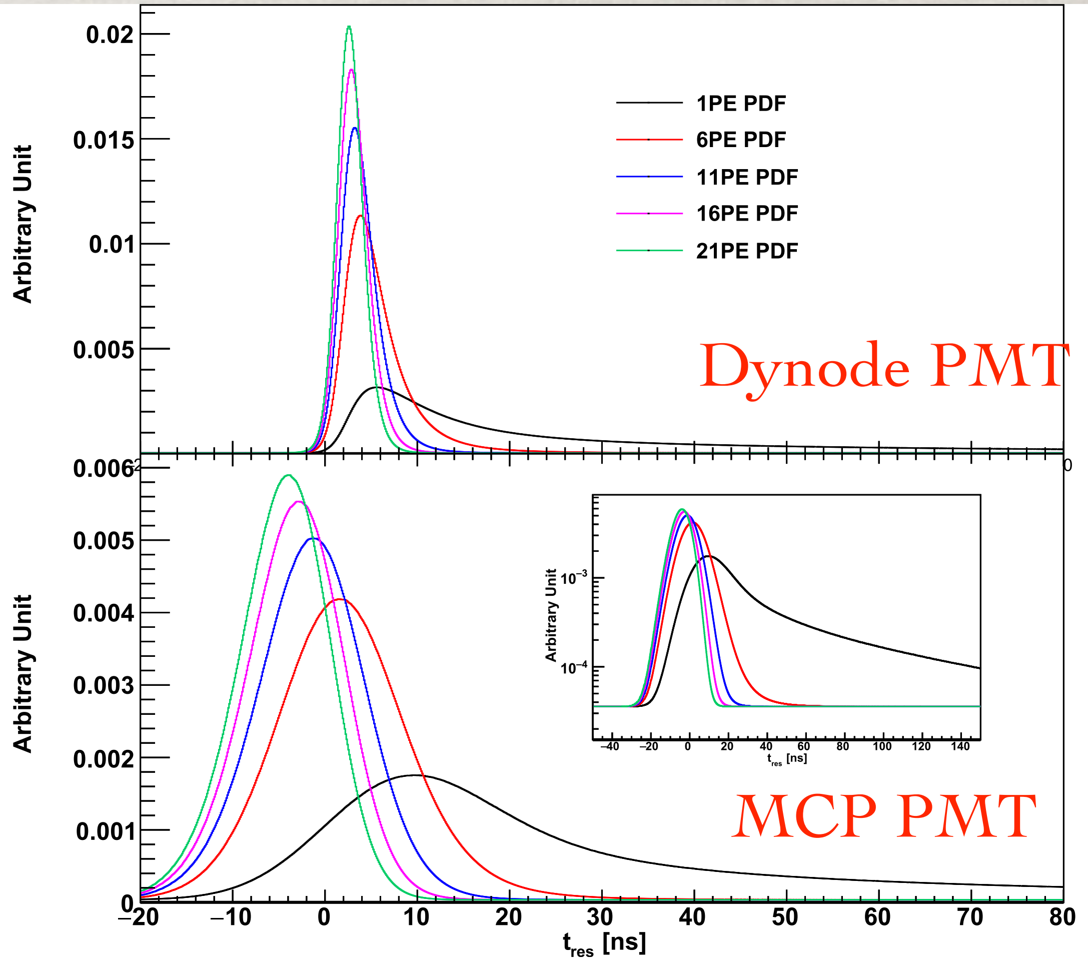


- Define residual time

$$t^i_{\rm res}(\vec{r}_0, t_0) = t_i - {\rm tof}_i - t_0,$$

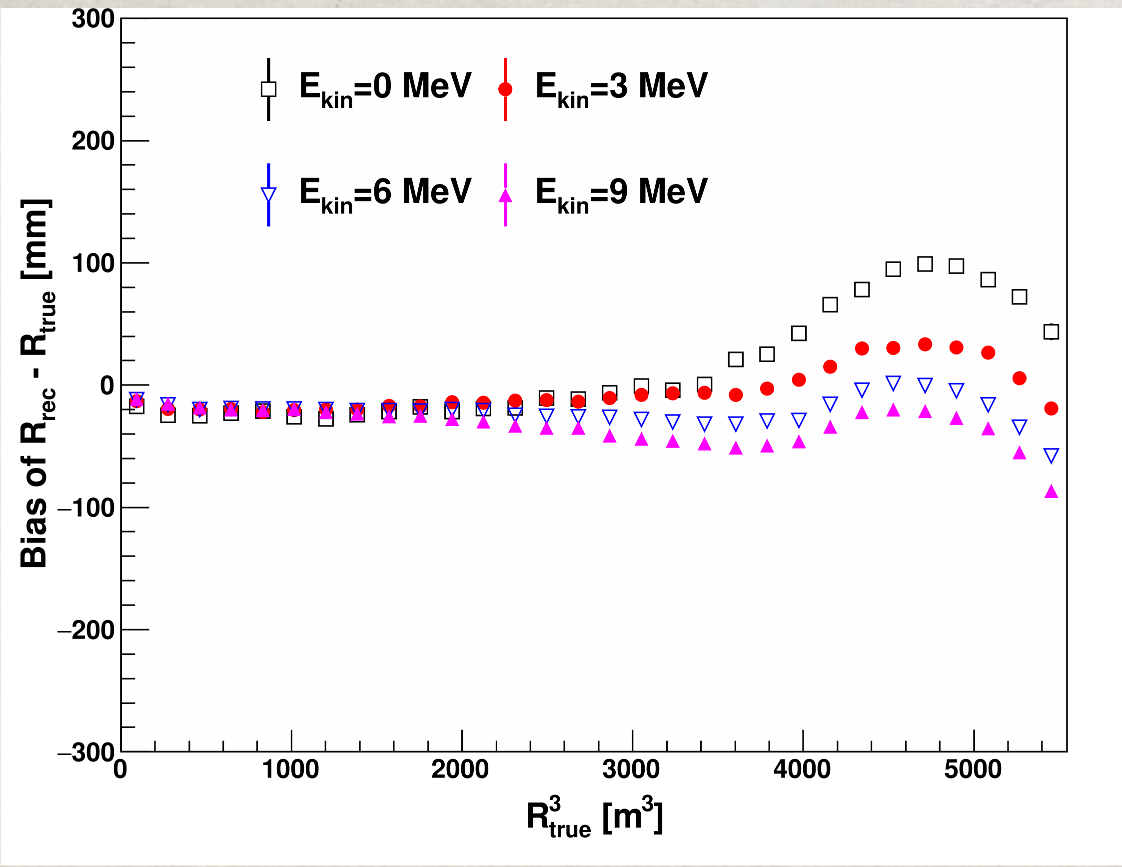
- Construct pdf $p(t_{res})$
- Minimize likelihood function

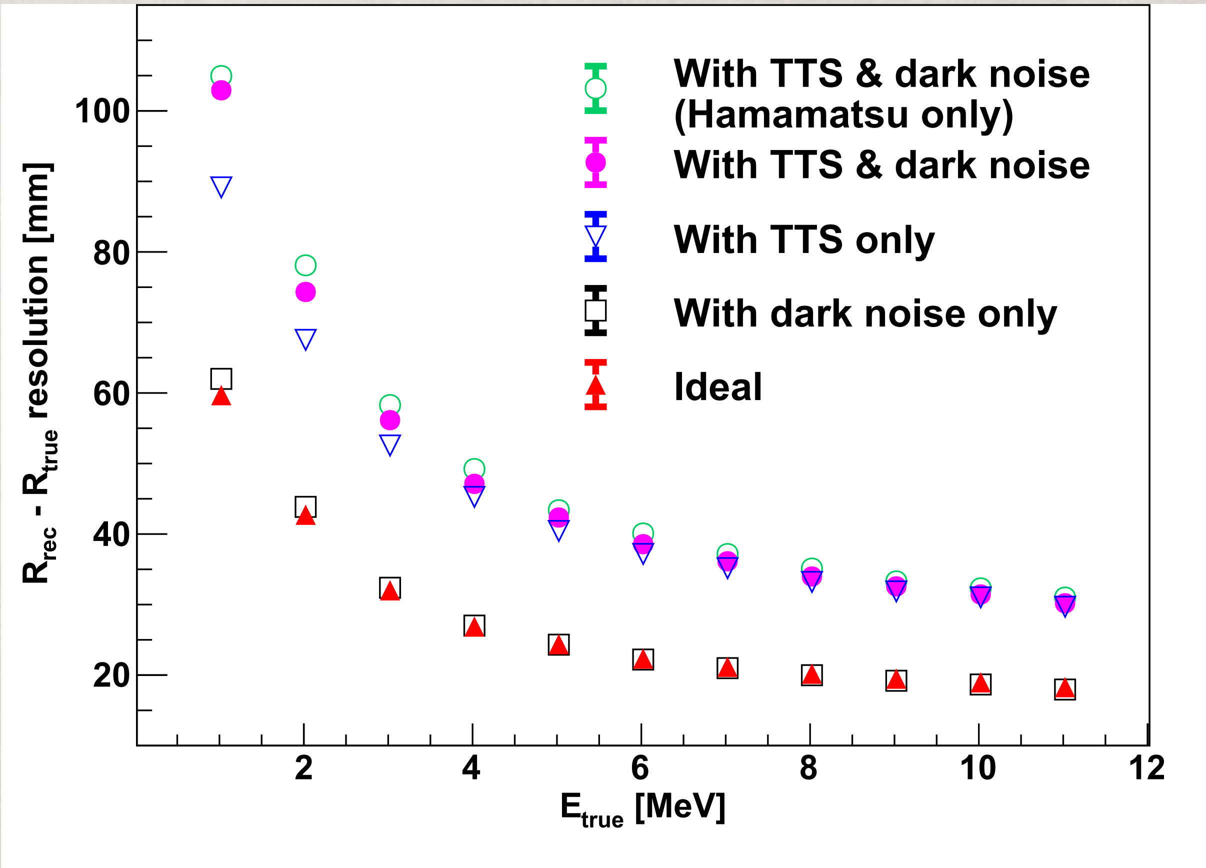
$$\mathcal{L}(\vec{r}_0, t_0) = -\ln\left(\prod_i p(t^i_{\rm res})\right).$$



PERFORMANCE

- Bias near the detector edge
- PMT Transit Time Spread(TTS) is the dominant factor





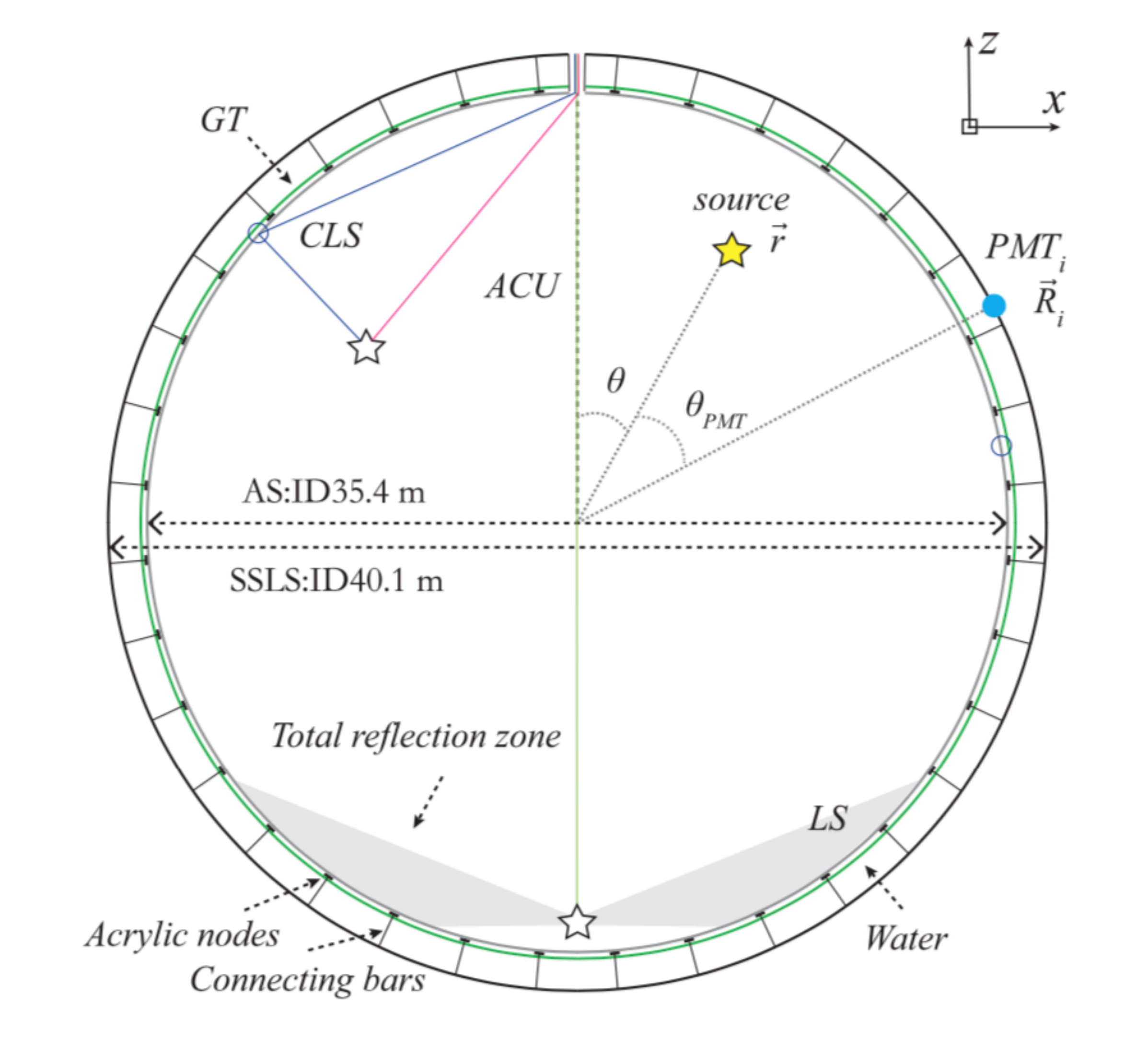
Energy Reco.

NIMA 1001 (2021) 165287

- Simple total PE method: E ~ total PE
- Maximum likelihood method*
  - optical model independent
  - calibration data driven
  - taking into account differences among PMTs
- Main factors for energy resolution:
  - photon statistics
  - energy non-uniformity*
  - PMT dark noise

METHOD PRINCIPLE

- Step1: use calibration data to construct the expected number of PhotoElectron $\hat{\mu}(r, \theta, \theta_{PMT})$ for PMTs
- Step2: maximize the likelihood function



$$\mathcal{L}(\{k_i\}|r, \theta, \phi, E_{vis}) = \prod_i \mathcal{L}(k_i|r, \theta, \phi, E_{vis}) = \prod_i \frac{e^{-\mu_i} \cdot \mu_i^{k_i}}{k_i}$$

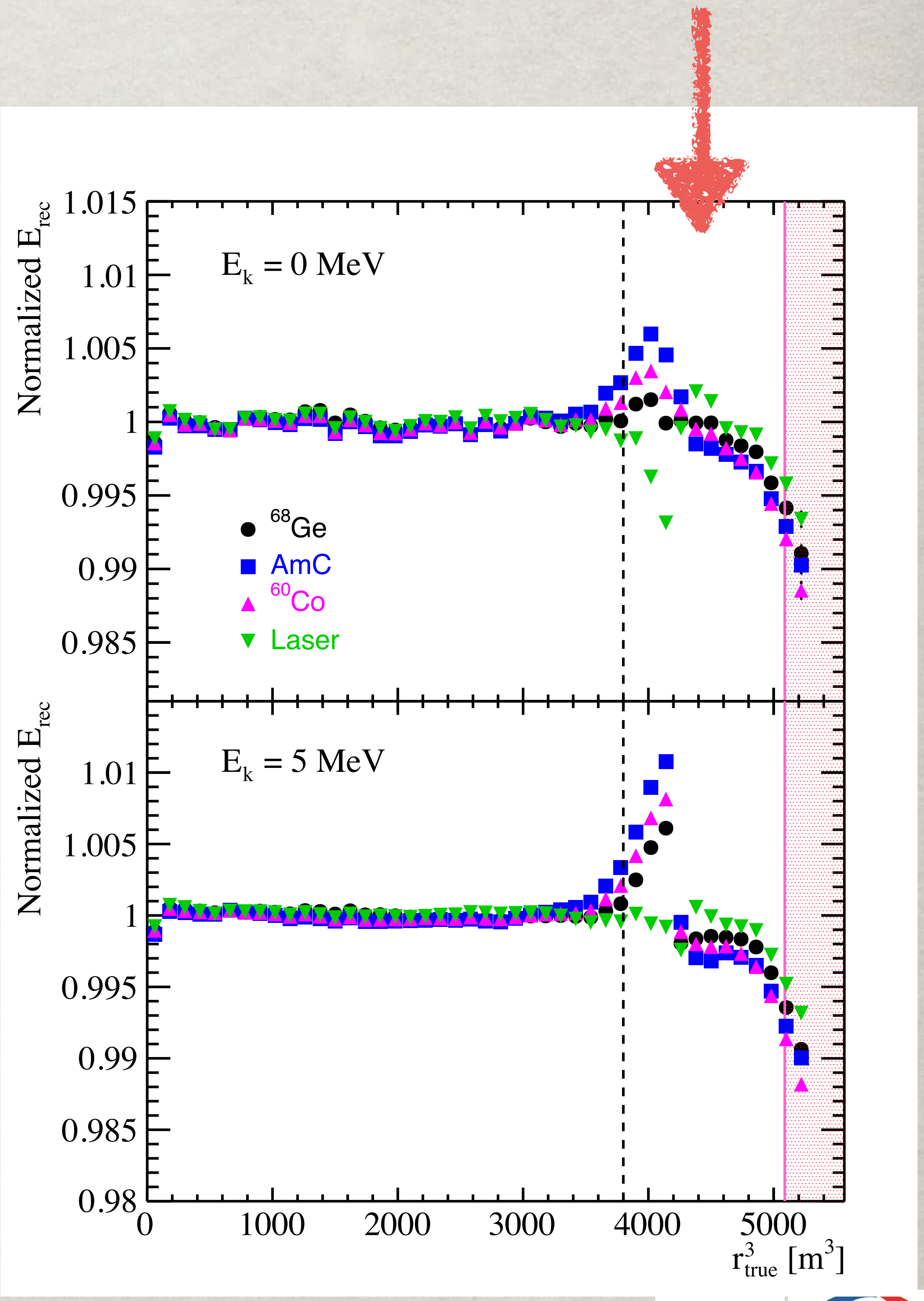
$$\mu_i = E_{vis} \cdot \hat{\mu}_i$$

*{k_i} — detected PE for PMTs
E_{vis} — visible energy

SOURCE CHOICE

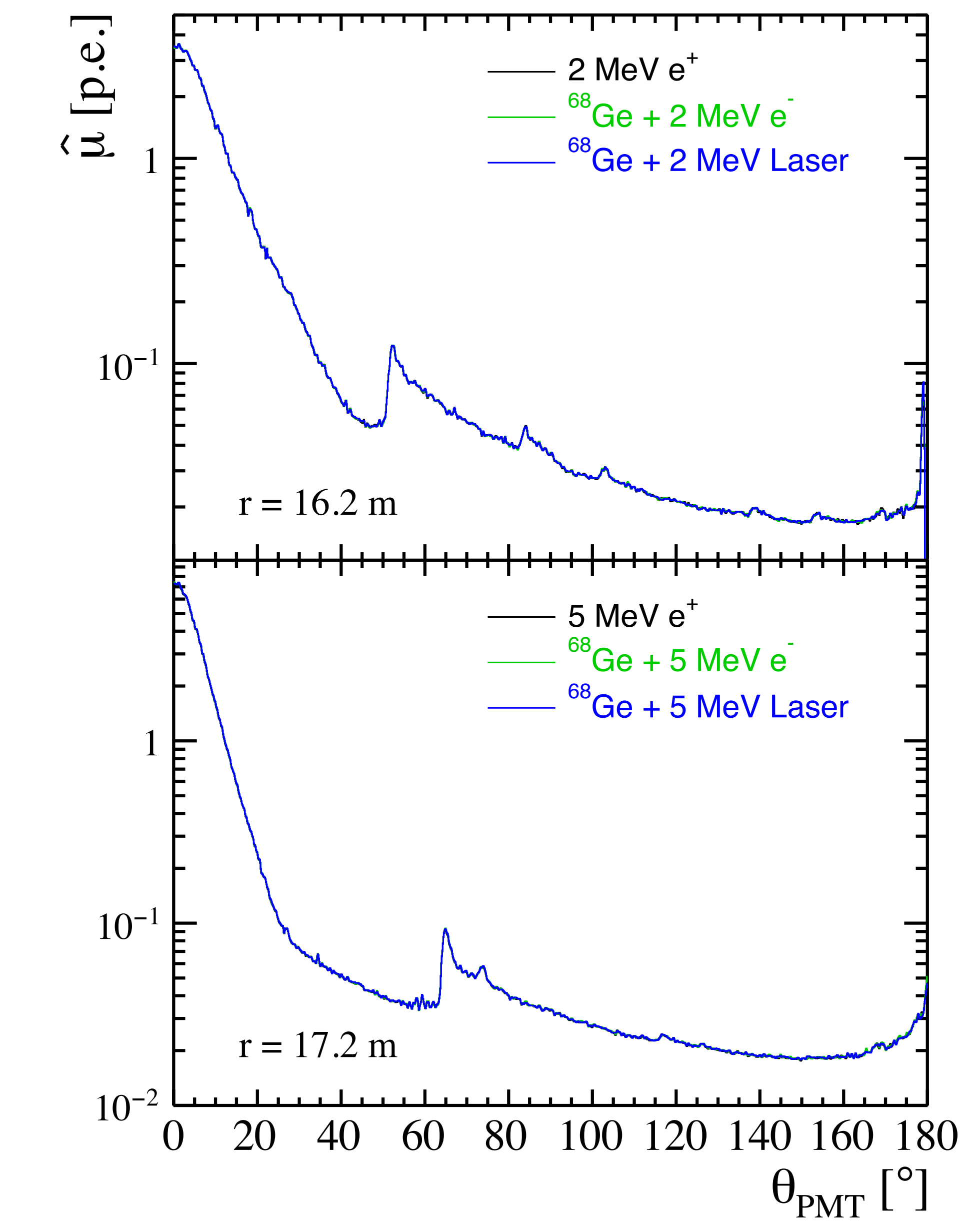
Source	Type	Energy [MeV]
^{68}Ge	γ	2×0.511
^{60}Co	γ	$1.173 + 1.333$
AmC	(n,H)γ	2.22
Laser	op	1

- Obvious energy non-uniformity in the total reflection region
- Laser(^{68}Ge) is better at high(low) energy



COMBINED SOURCE

- Energy deposition of positron in LS
  - kinetic part: point-like
  - annihilation part: ball-like
- Use combined source Laser+^{68}Ge to mimic positron



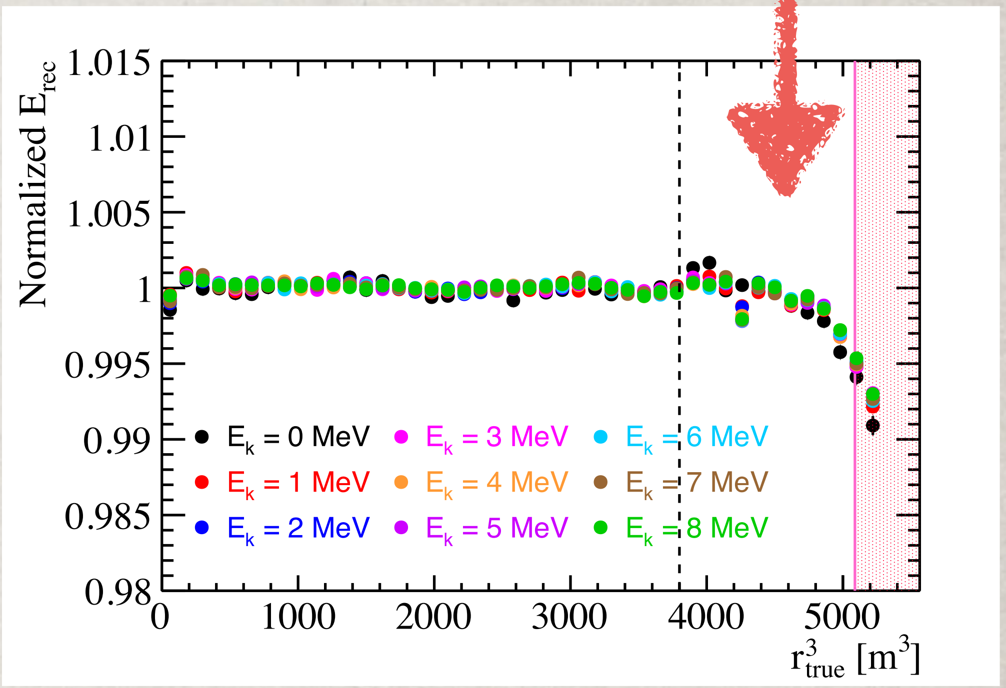
$$\hat{\mu}^{comb} = \frac{1}{E_{vis}} \cdot (E_{vis}^{Ge} \cdot \hat{\mu}^{Ge}(r,\theta,\theta_{PMT}) + E_k \cdot \hat{\mu}^{L}(r,\theta,\theta_{PMT}))$$

$$E_{vis} = E_{vis}^{Ge} + E_k$$

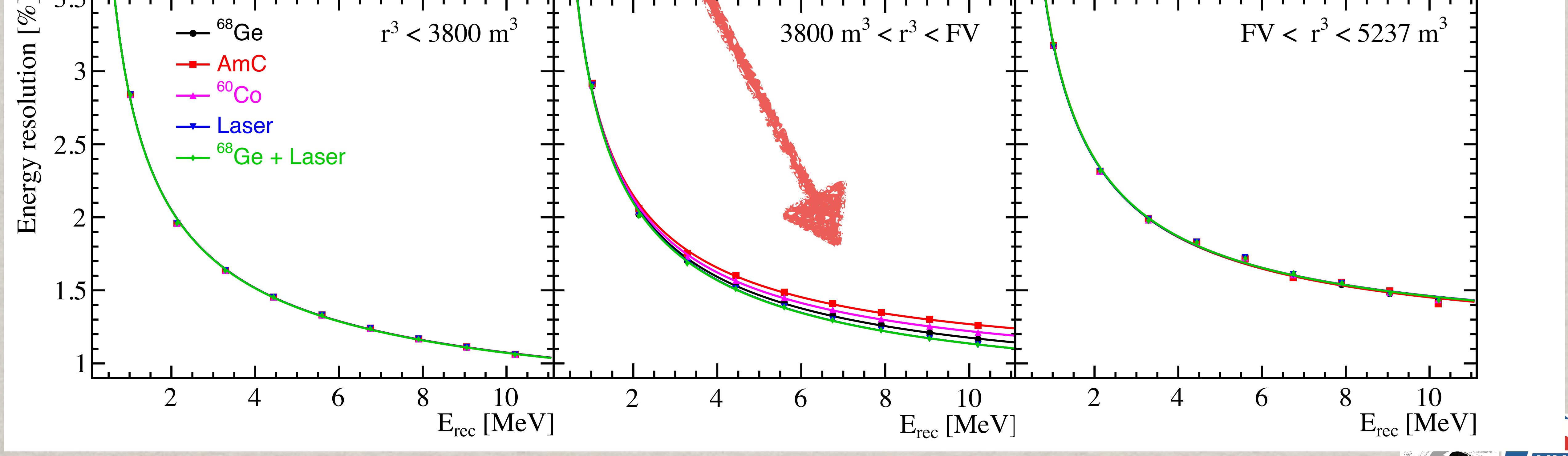
*E_k — kinetic energy of e^+

PERFORMANCE

- Combined source improves the energy-uniformity (consequently energy resolution) in the total reflection region



FV: Fiducial Volume



Machine Learning methods

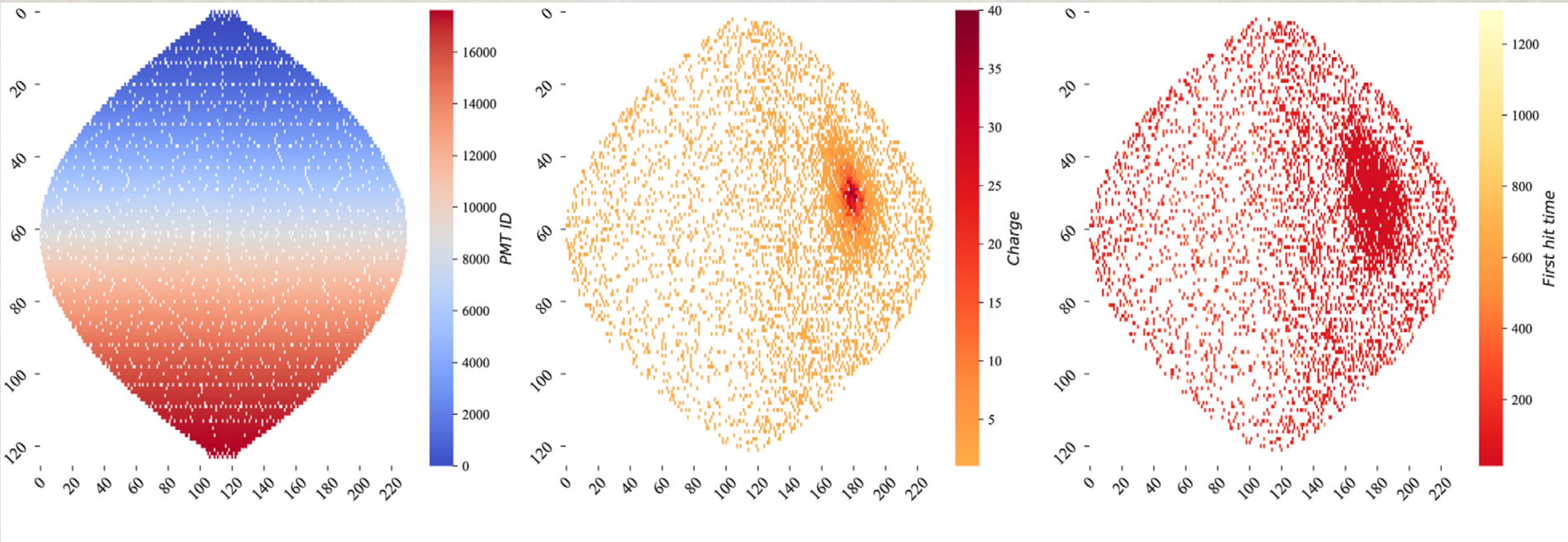
PRINCIPLE

NIMA 1010 (2021) 165527

- Applying Machine Learning to event reconstruction for Liquid Scintillator detectors
- Large number of PMTs $O(10^5)$
  - treating each PMT as a pixel
  - ensemble of PMTs charge/time form an image
- Image is highly vertex and energy dependent
- Image recognition <—> vertex/energy reconstruction

INPUTS

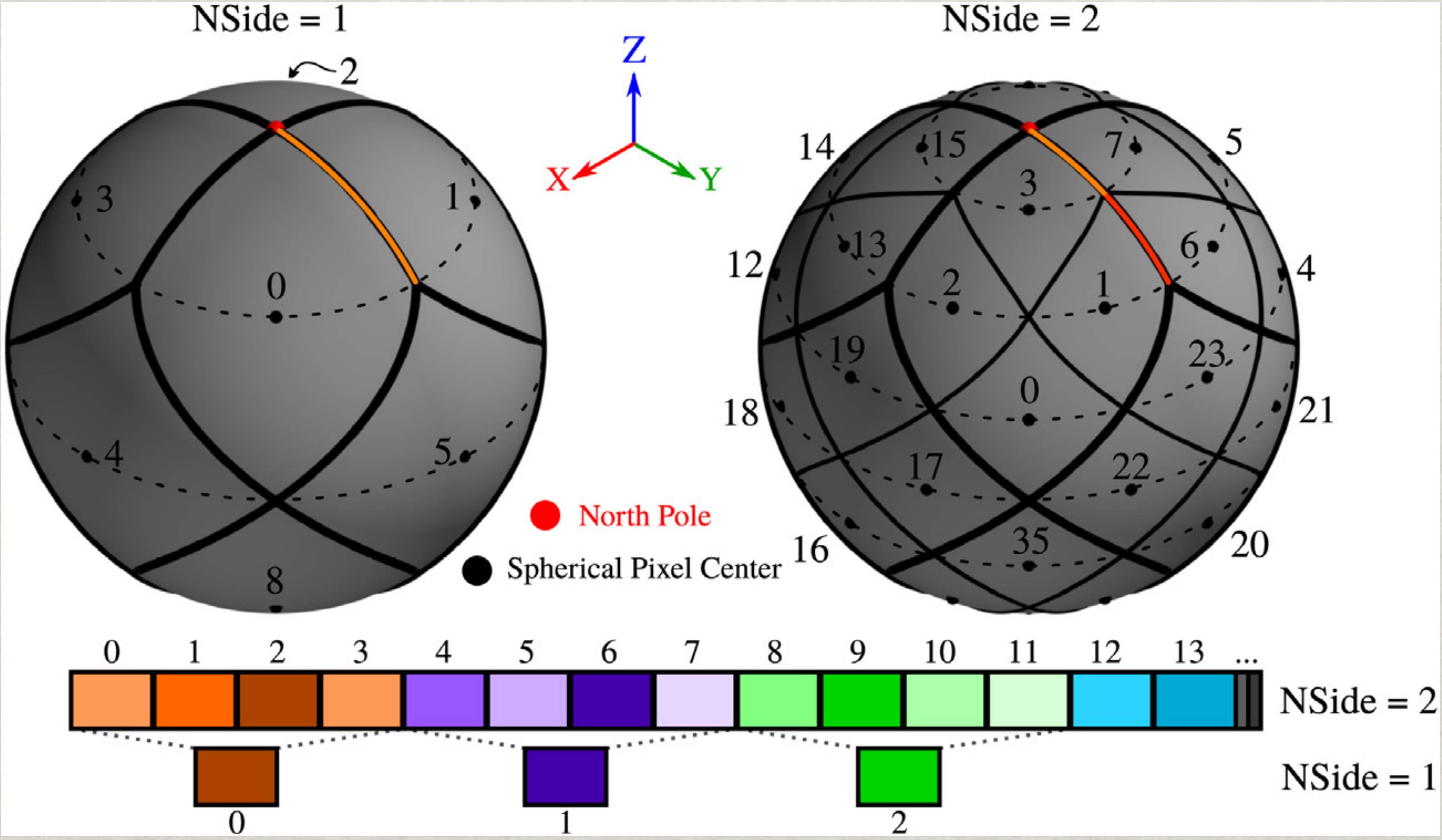
- PMTs installed on a sphere
- Method 1: projection to 2D plane —>Plane CNN



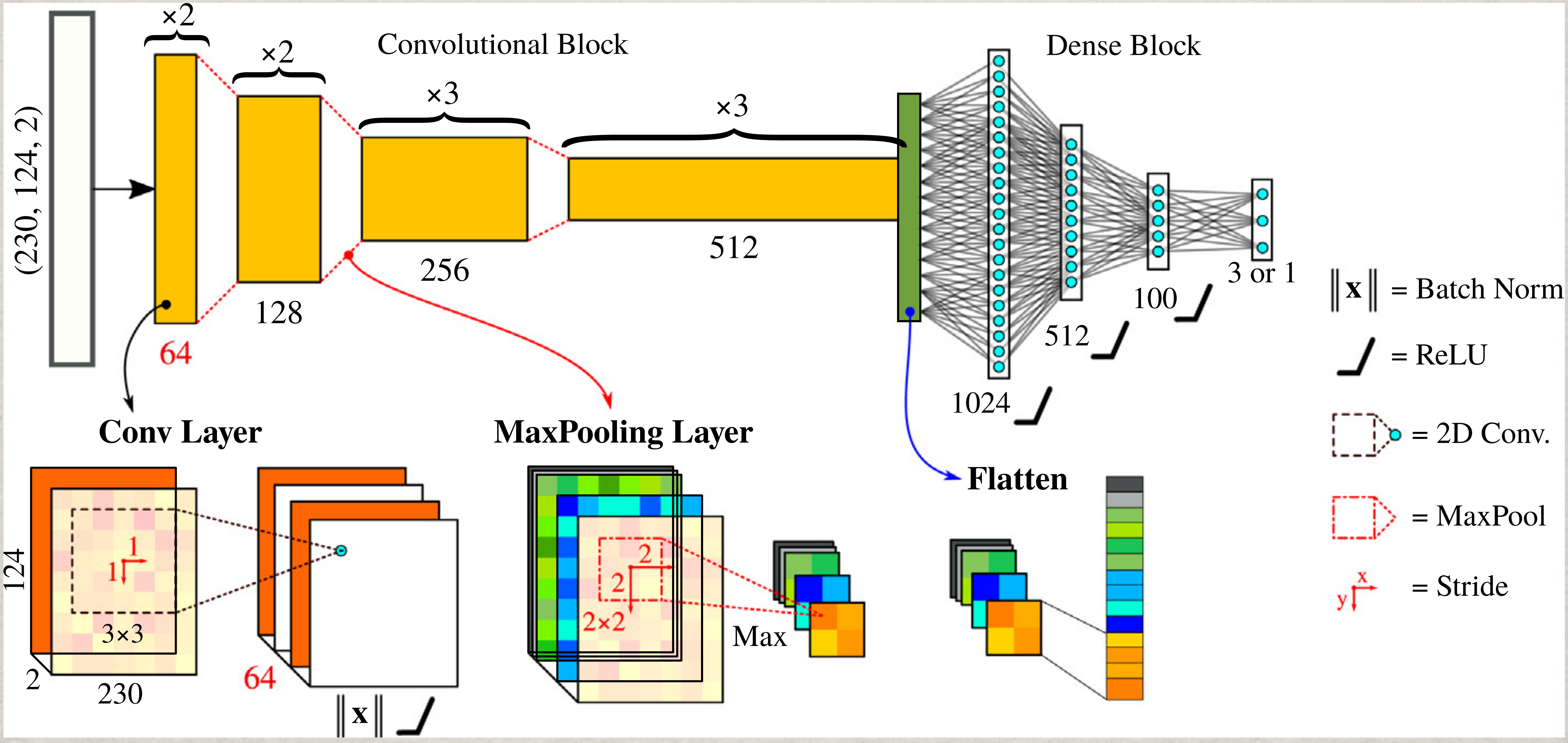
(a) Map of PMTs. **(b)** Charge channel. **(c)** First hit time channel.

INPUTS

- PMTs installed on a sphere
- Method 2: HEALPix —> plane/spherical CNN

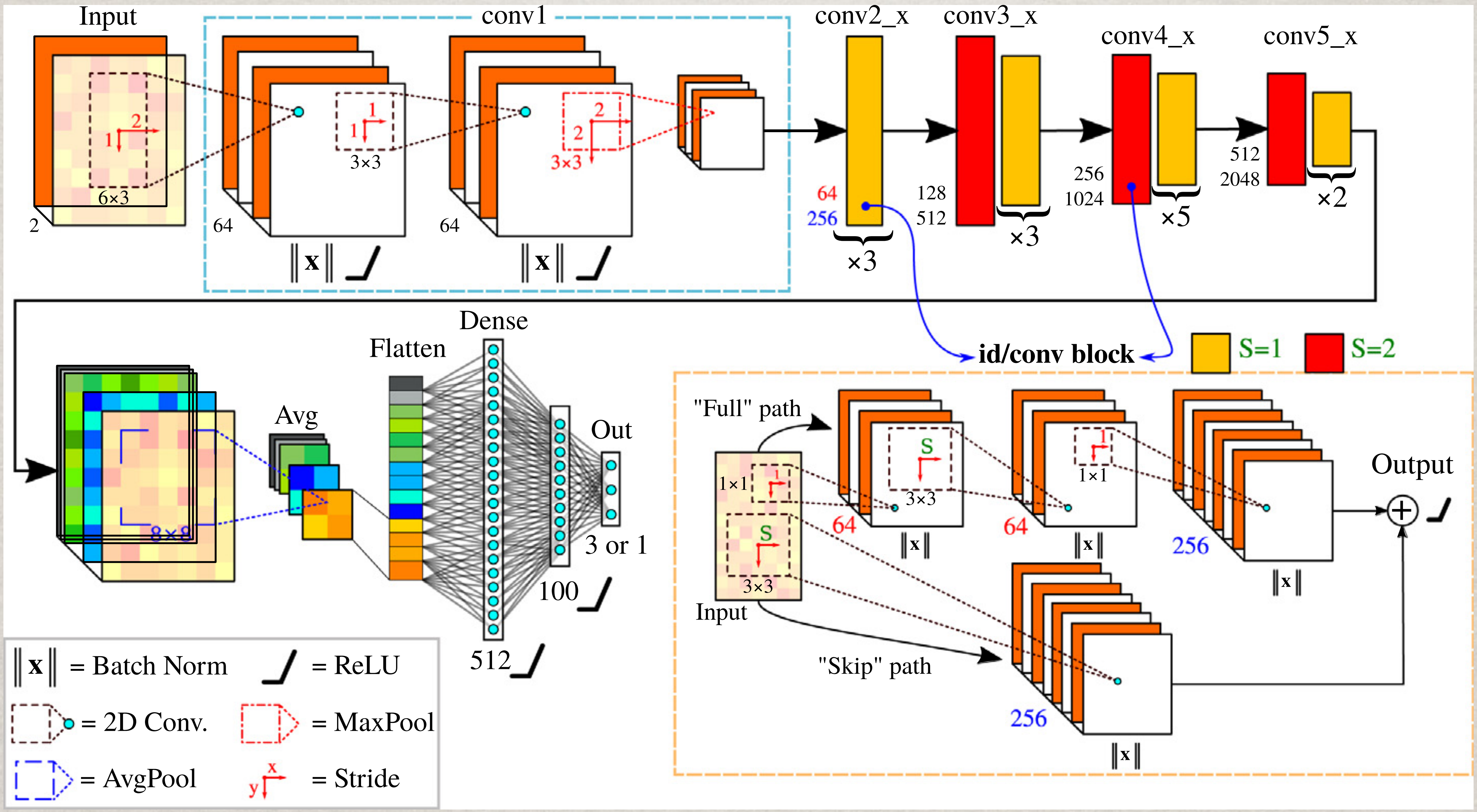


MODELS: VGG-J

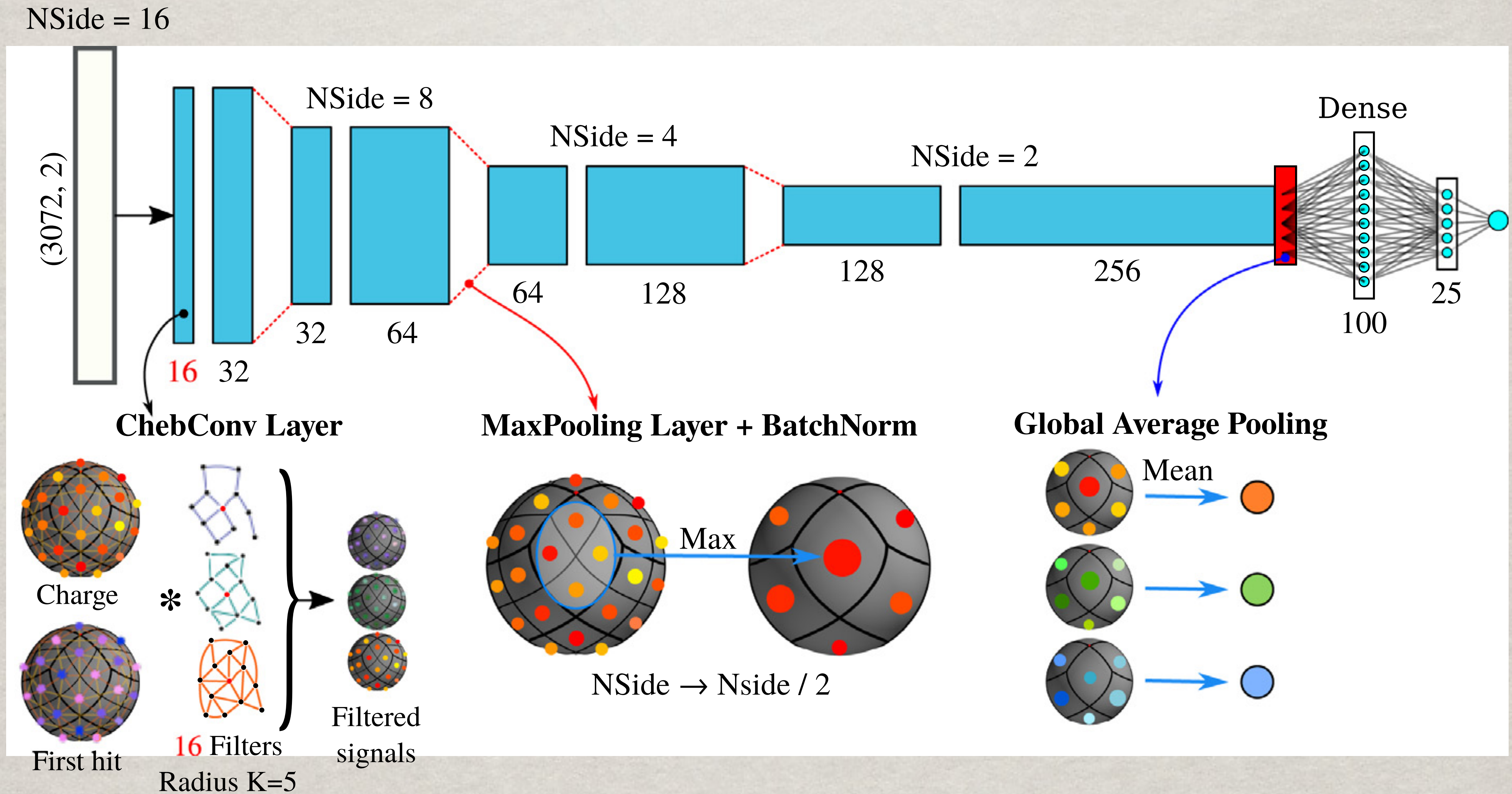


(230, 124, 2)
×2
×2
Convolutional Block
×3
×3
64
128
256
512
Dense Block
1024
512
100
3 or 1
= Batch Norm
= ReLU
= 2D Conv.
= MaxPool
= Stride
Conv Layer
MaxPooling Layer
Flatten
124
230
2
3×3
64
2×2
Max

MODELS: RESNET-J



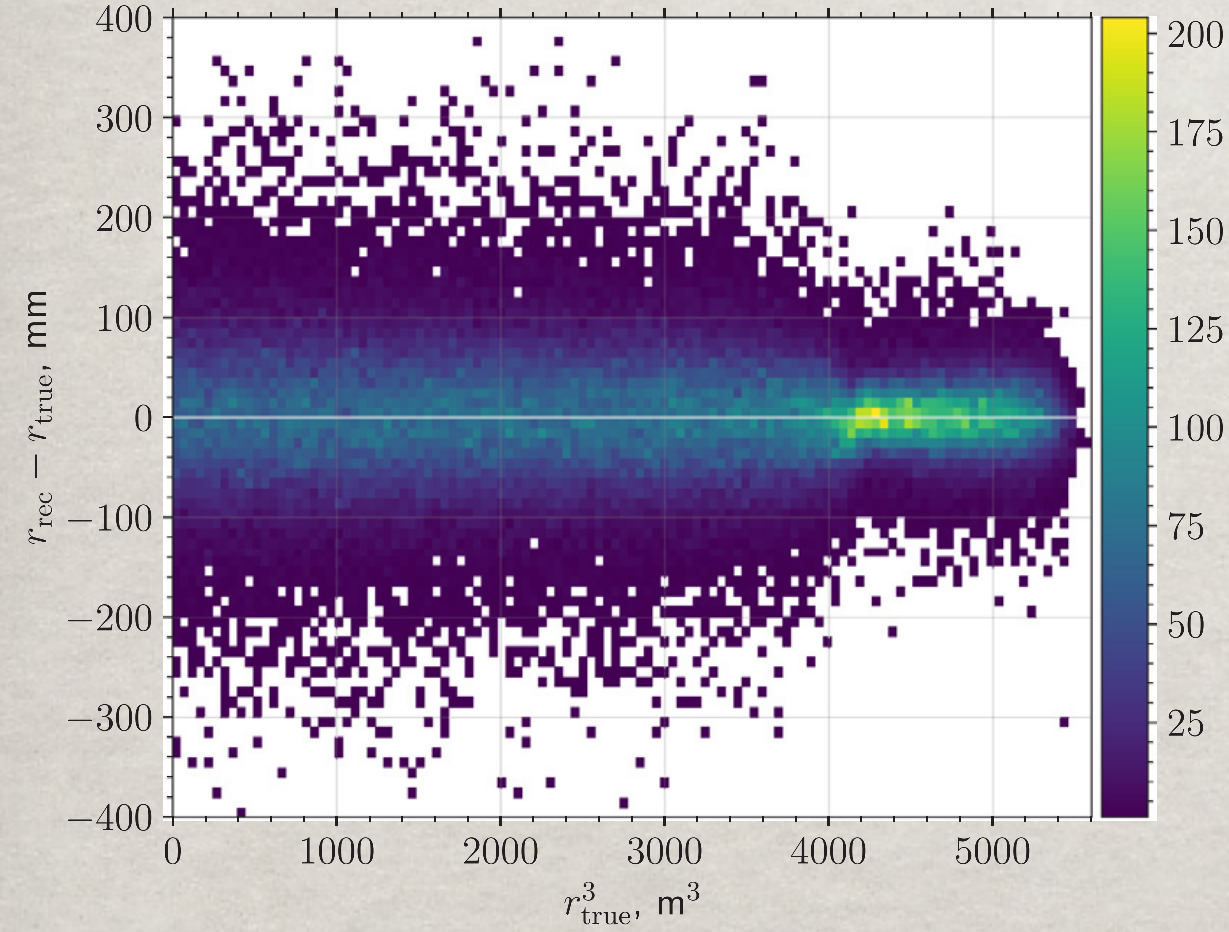
MODELS: GNN-J

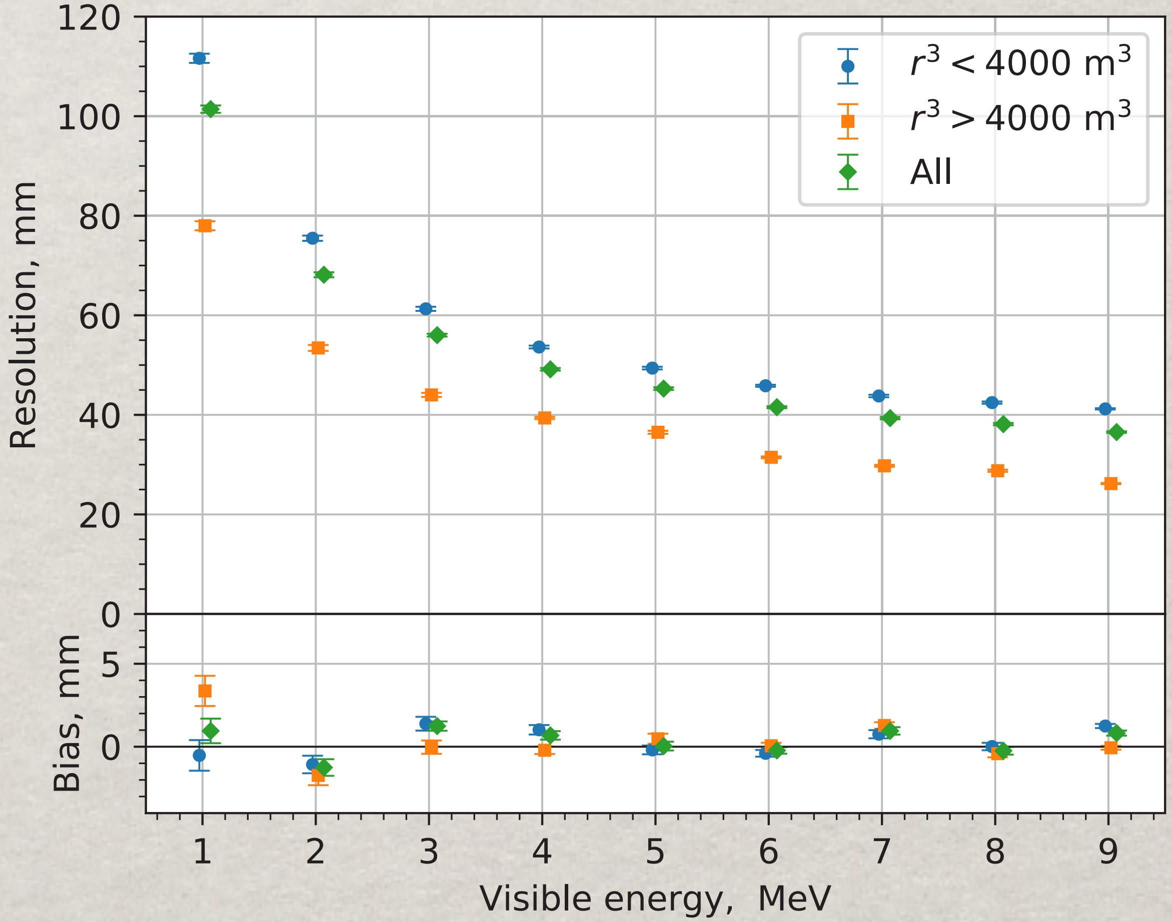


NSide = 16
(3072, 2)
NSide = 8
NSide = 4
NSide = 2
Dense
16
32
32
64
64
128
128
256
100
25
ChebConv Layer
MaxPooling Layer + BatchNorm
Global Average Pooling
Charge
First hit
*
16 Filters
Radius K=5
Filtered signals
Max
NSide → Nside / 2
Mean

PERFORMANCE

- Vertex reconstruction with ResNet-J as an example
  - small bias throughout the whole detector
  - comparable resolution w.r.t. traditional methods





SUMMARY

- Precise event reconstruction is crucial for JUNO
- Developed various traditional algorithms
- Applied ML to event reco. for LS detectors, promising first look
- Many further studies are still on-going, please stay tuned