# EVENT RECONSTRUCTION IN JUNO

Wuming Luo
on behalf of JUNO

"Reconstruction and Machine Learning in Neutrino Experiments" workshop
16—18, Sep. 2019, DESY Hamburg

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

# DISCLAIMER

- All studies are based on Monte Carlo Simulation
- Many aspects of JUNO rec. are under-development
- Performance results are preliminary
- We will focus on the reconstruction methods
- We are here to share and LEARN!

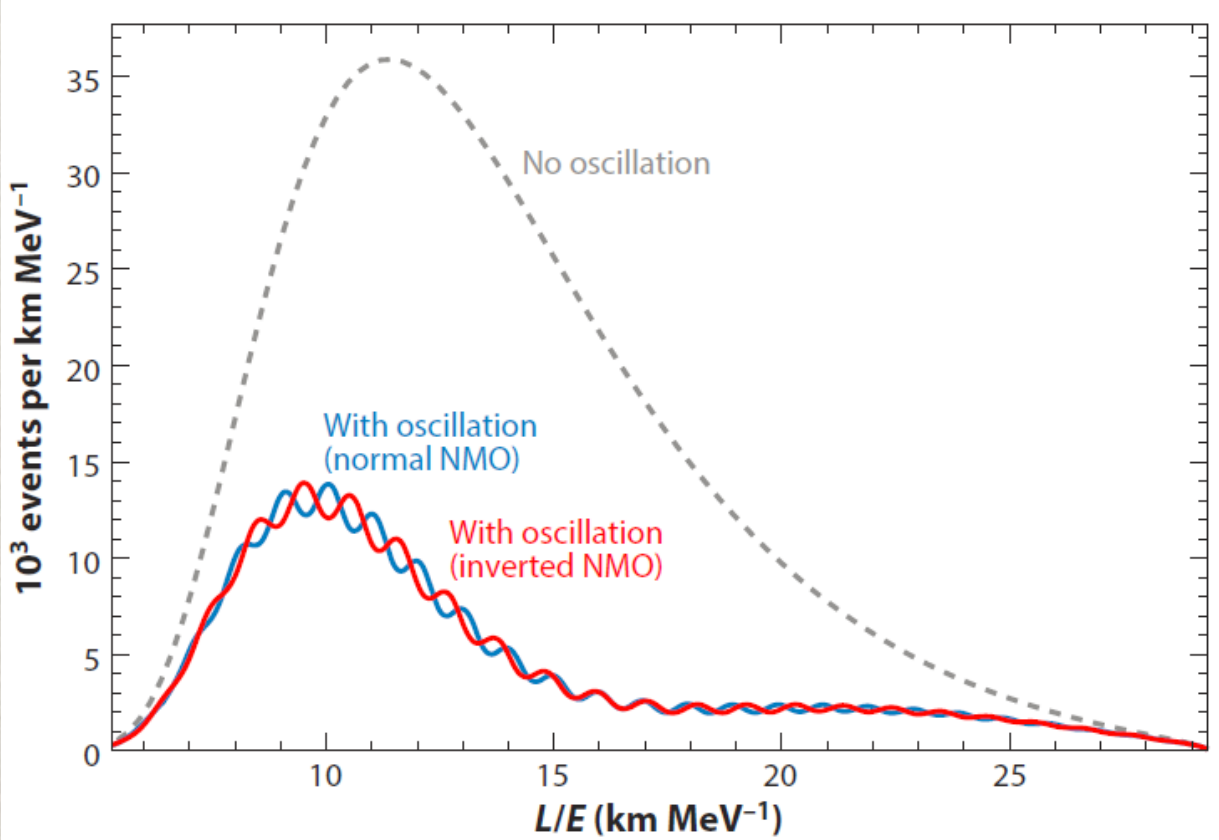
# OUTLINE

- Intro to JUNO
- Waveform Reconstruction
- Vertex Reconstruction
- Energy Reconstruction
- Summary

# JUNO

- Jiangmen Underground Neutrino Observatory(JUNO):
  - Determine the neutrino mass hierarchy
  - Measure neutrino oscillation parameters precisely etc
  - SuperNova, Solar, Atm. Geo. etc

| | DETECTOR TARGET MASS | ENERGY RESOLUTION |
|---|---|---|
| KamLAND | 1000 t | $6\%/\sqrt{E}$ |
| D. Chooz | 8+22 t | $8\%/\sqrt{E}$ |
| RENO | 16 t | $8\%/\sqrt{E}$ |
| Daya Bay | 20 t | $8\%/\sqrt{E}$ |
| Borexino | 300 t | $5\%/\sqrt{E}$ |
| JUNO | **20000 t** | **$3\%/\sqrt{E}$** |

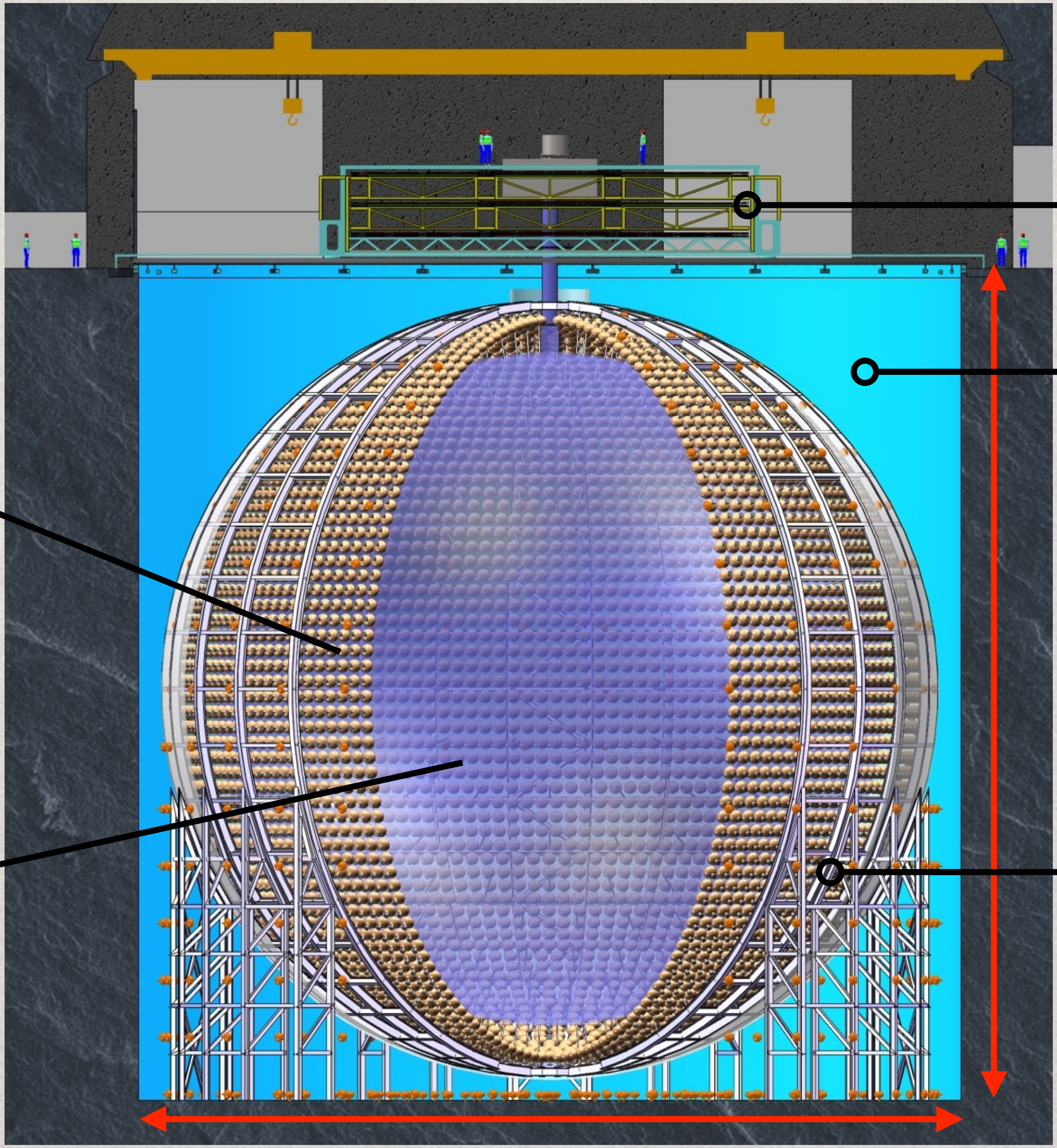
# DETECTOR

Central Detector*

**~18,000 20" PMTs**

\+ ~25,000 3" PMTs

\+ ~75% coverage



**Top Tracker**

**Water Pool**

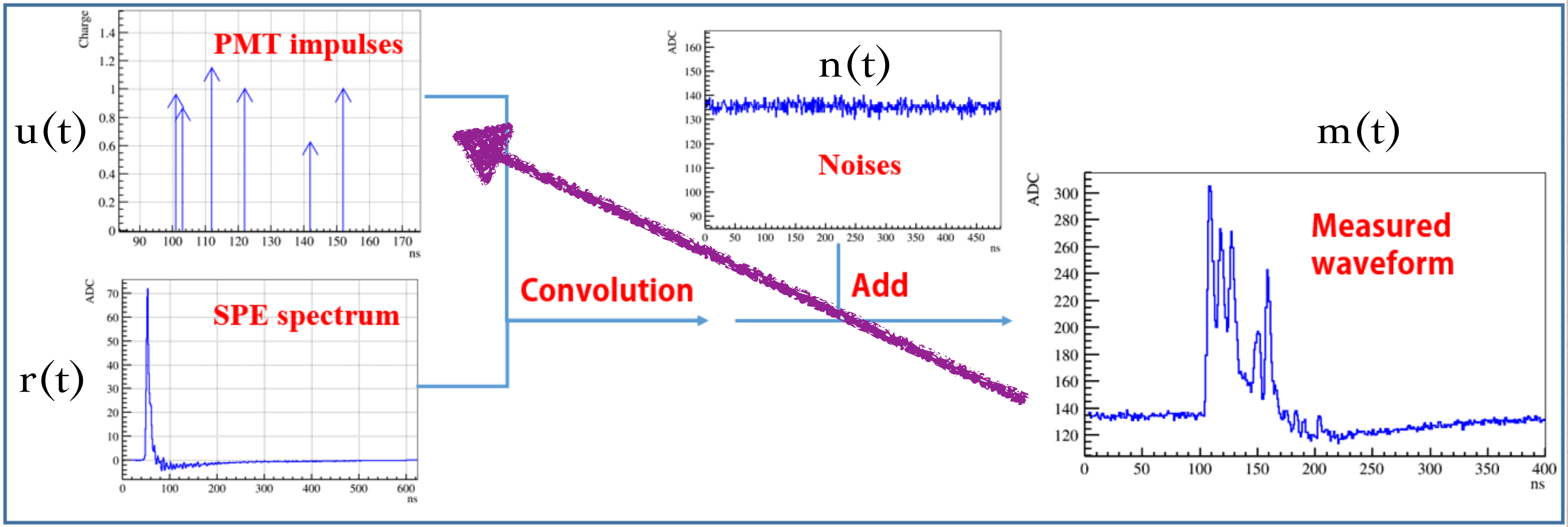
Depth: 44m

**Liquid Scintillator**
20kton

**Central Detector***
Acrylic sphere
Stainless steel truss

$\phi$: 43.5m

# PMT WAVEFORM REC

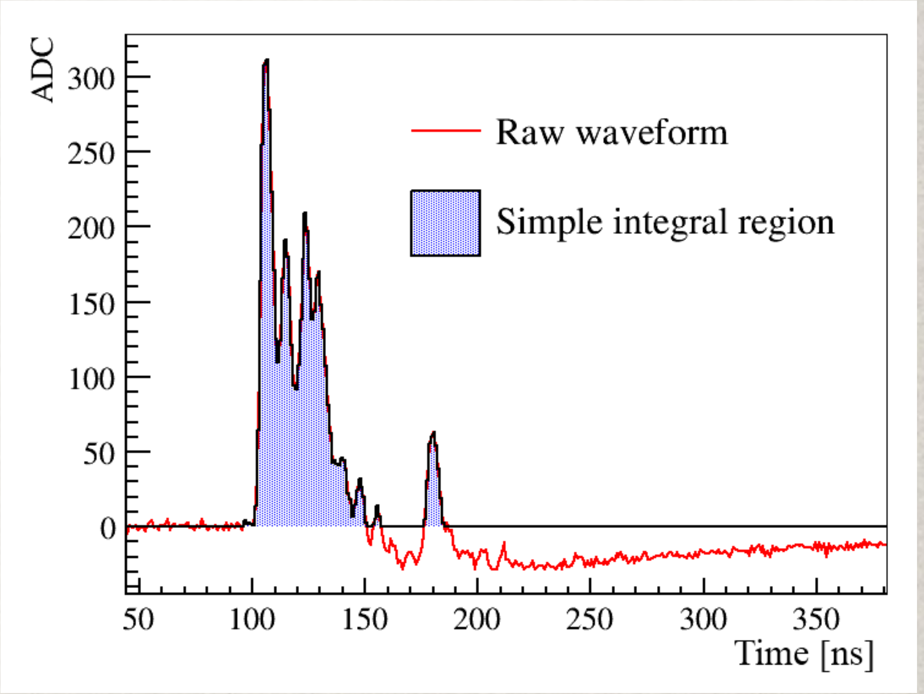



- $m(t) = s(t) + n(t) = r(t) * u(t) + n(t)$
- Goal: for any WaveForm, reconstruct $\{t_j, Q_j\}$ or ideally $\{nPE_j\}$

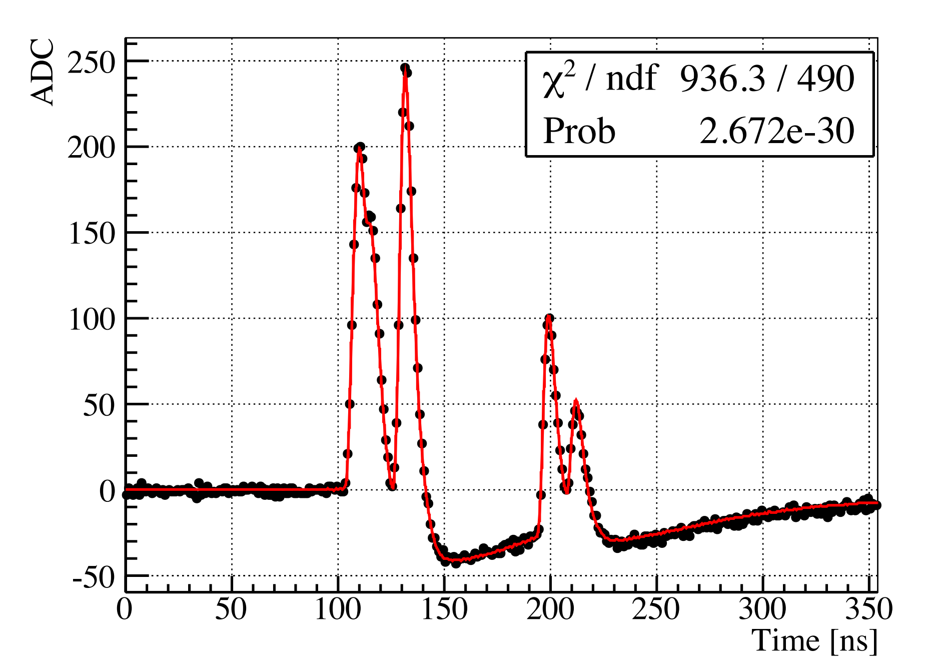
# WF REC ALGORITHMS

arXiv:1707.03699

- Single Charge Integral



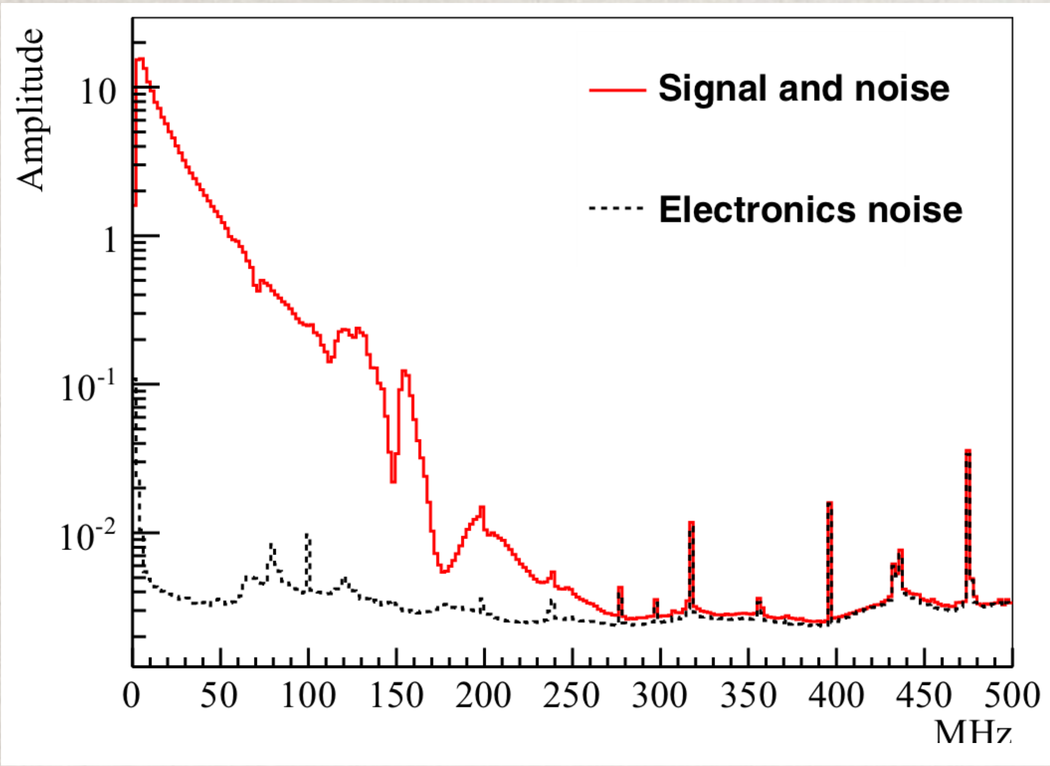

- Waveform Fitting

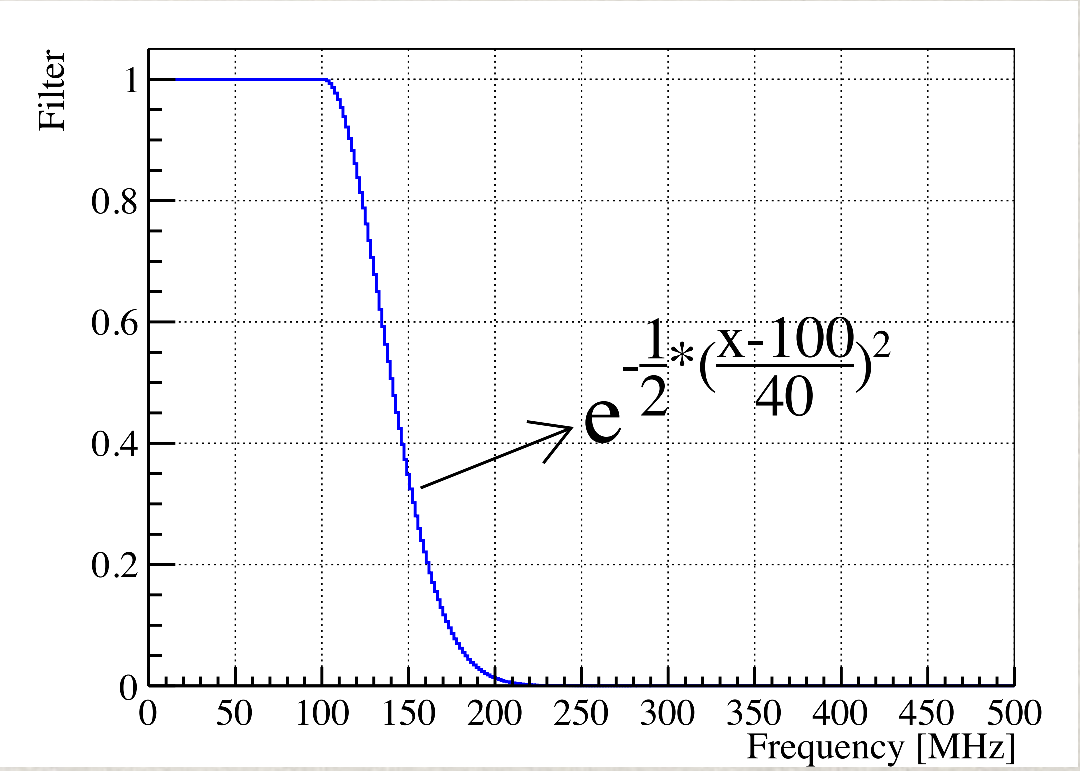



- Deconvolution

# STEP1: NOISE FILTER

arXiv:1707.03699



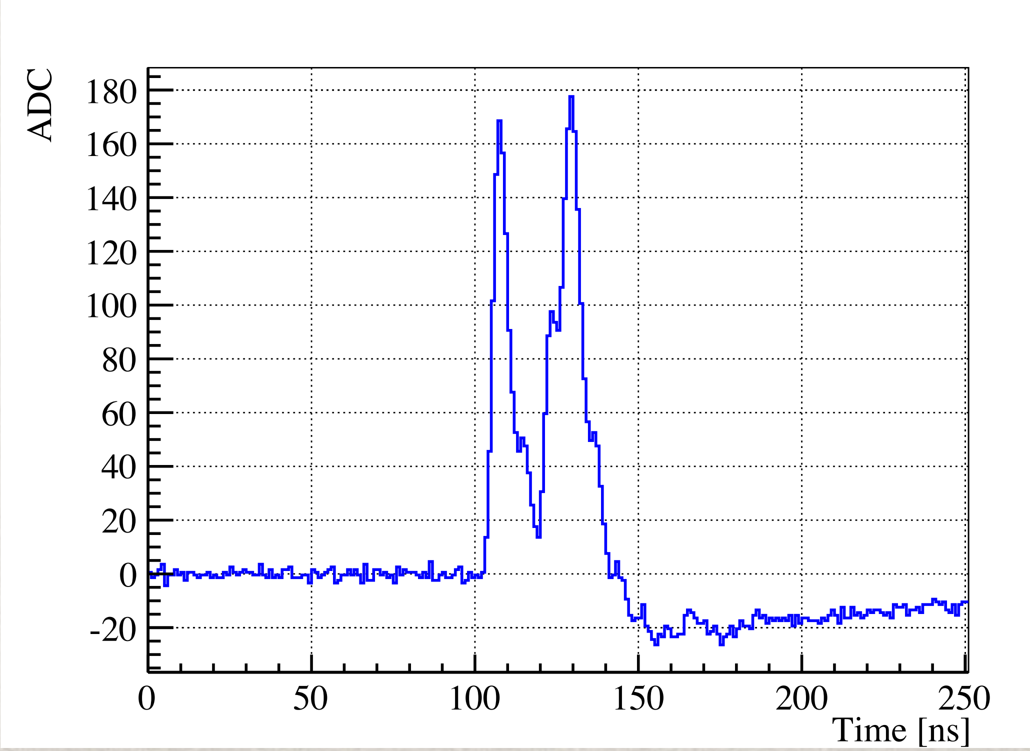

- Fourier Transform: Time → Frequency domain
- White noise, signal mostly concentrates in low Frequency region, filter high Freq. noise
- Residual noise?

# STEP2: DECONVOLUTION

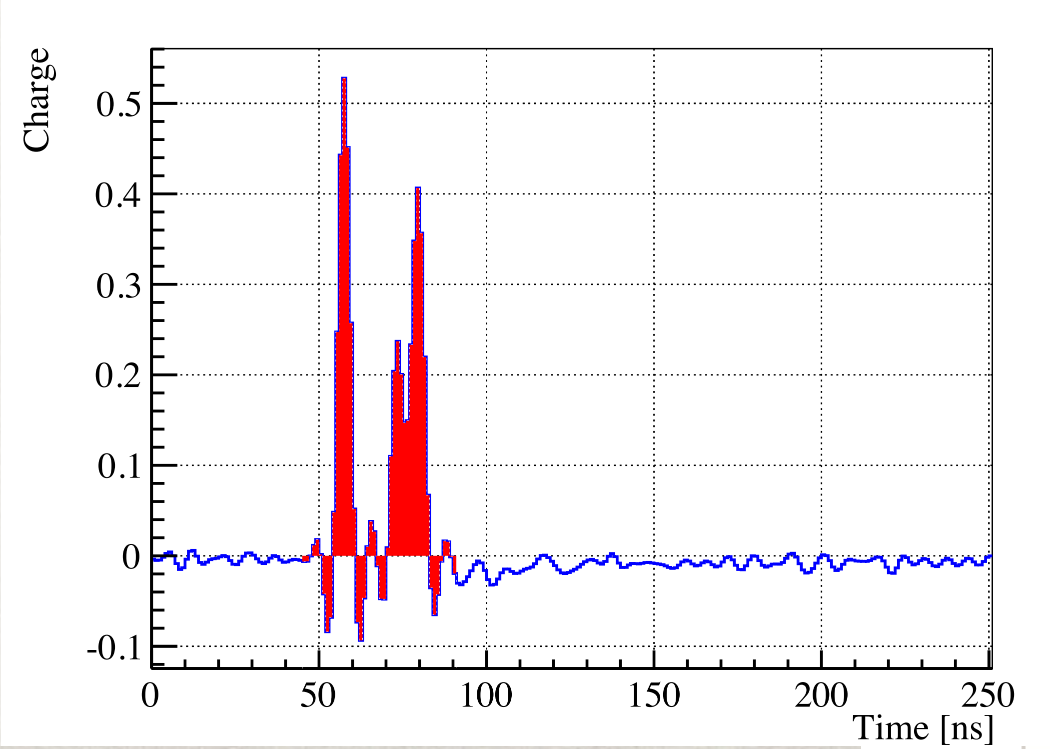
arXiv:1707.03699

- Deconvolute the waveform by the sPE spectrum in Freq. domain
- Convert back to Time domain
- No more overshoot, better separation

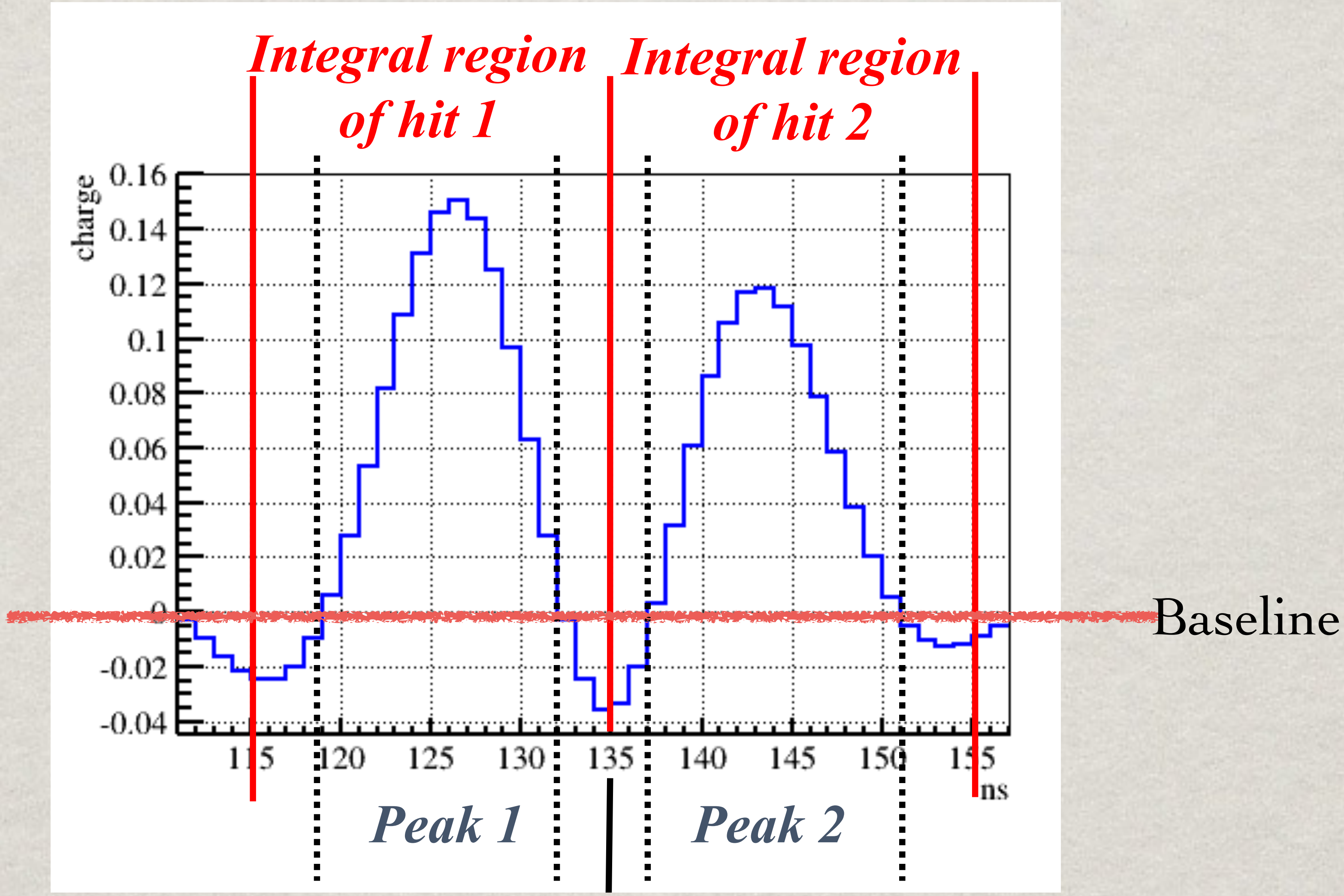
**raw waveform**




**waveform after deconvolution**



# STEP3: CHARGE AND TIME




- Baseline → Peak Finding → Integration
- t: baseline-crossing, rising edge fitting etc
- Q: region integral

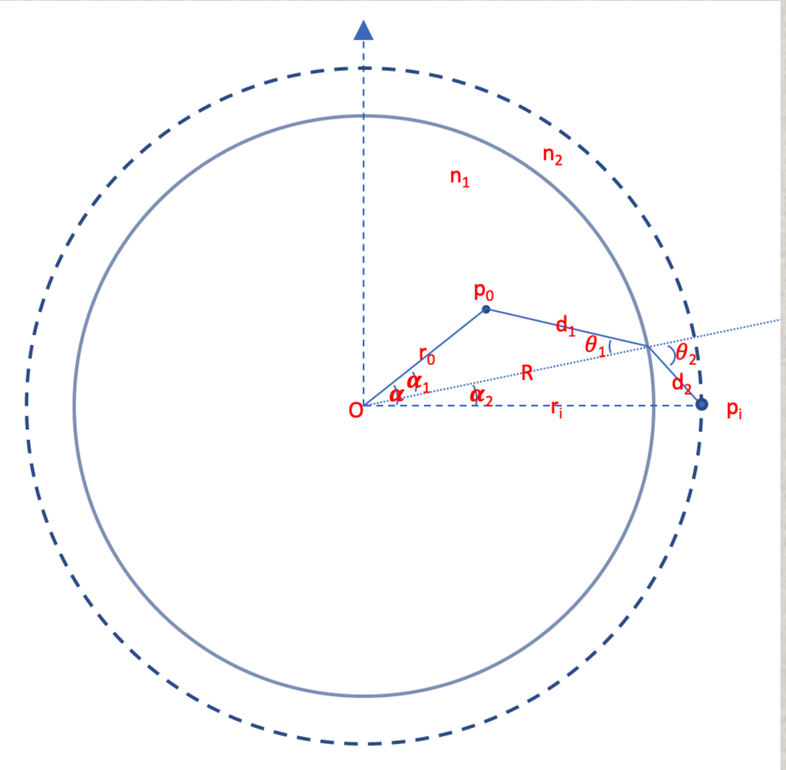
# VERTEX: LIKELIHOOD METHOD

arXiv:1803.09394

- Build an optical model for photon propagation
- Define Residual time:

$$t_{i,res}(\vec{R}_0, t_0) = t_i - \sum_{\alpha} \frac{D_\alpha(\vec{R}_0, \vec{R}_i)}{c_\alpha} - t_0$$

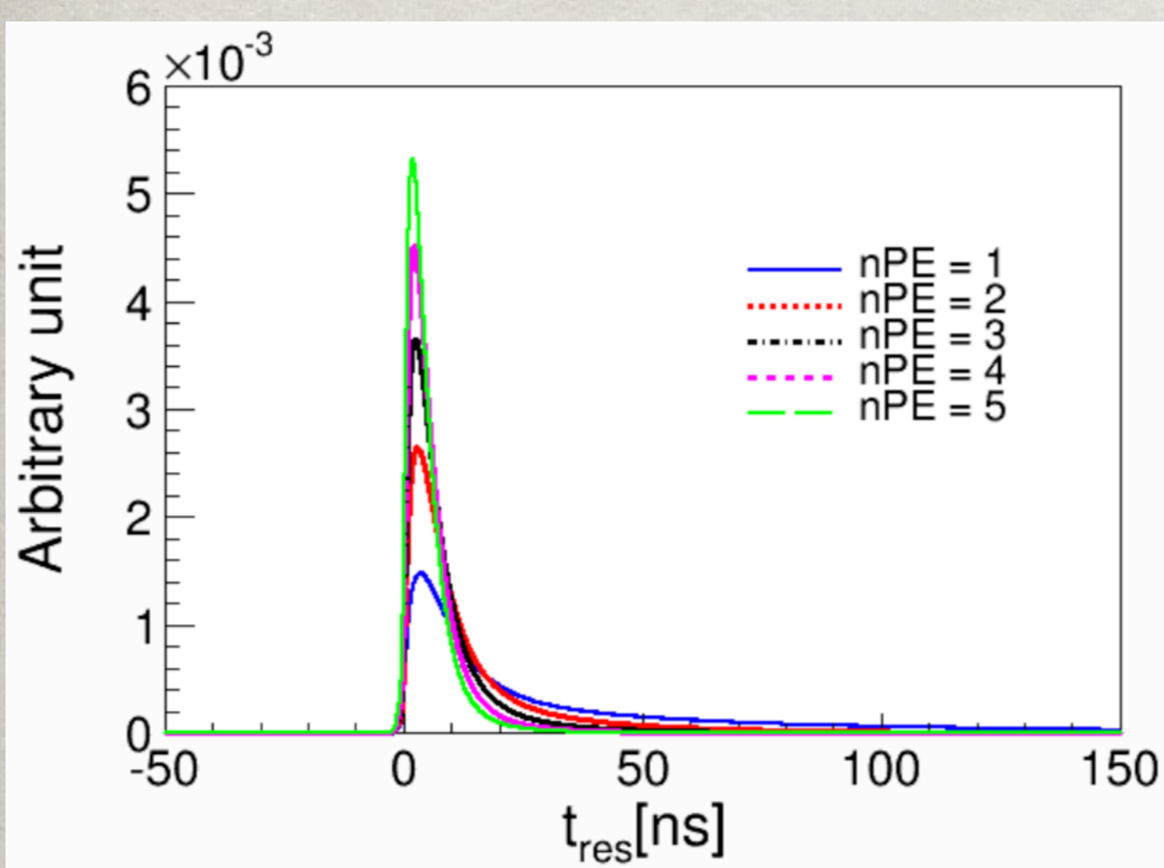
- Algorithm: $-\ln\mathscr{L} = -\sum \ln f_{res}(t_{i,res}) = -\sum \ln f_{res}(t_i - t_{i,tof} - t_0)$
  - $t_i$ : first hit time of ith fired PMT
  - $t_{tof}$: time of flight
  - $t_0$: event start time
  - $f_{res}$ : pdf of residual time
- Charge Center as initial vertex
- Minimize the NLL



# RESIDUAL TIME PDF

arXiv:1803.09394

- Residual time depends on the characteristics of the PMT and the Liquid Scintillator
  - PMT term: dominated by Transit Time Spread
  - LS term: luminescence time, fast and slow components



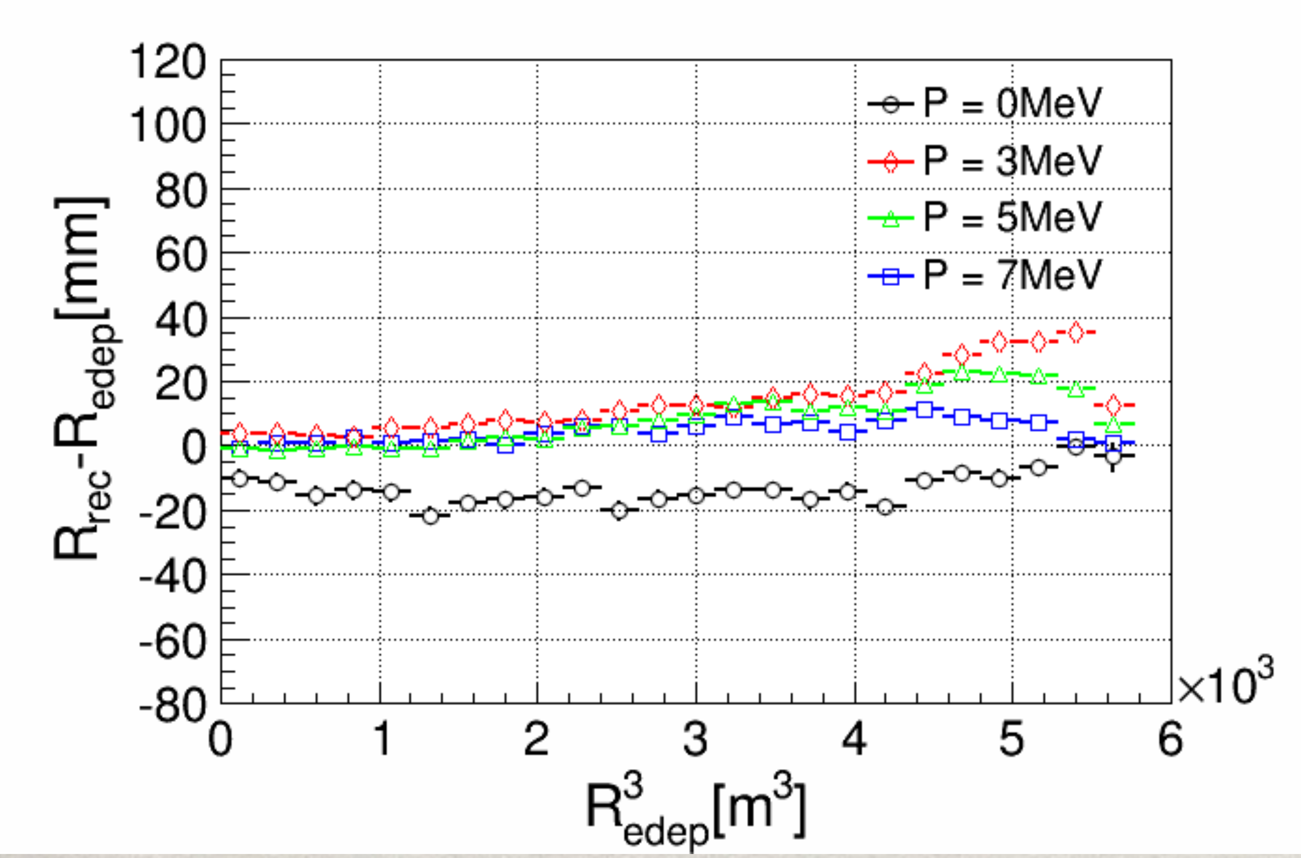

$$f(t_{i,res}) = \frac{1}{\sqrt{2\pi\sigma}} \overbrace{\boxed{\exp\left\{-\frac{(t-t_0)^2}{2\sigma^2}\right\}}}^{\textbf{PMT}} \otimes \overbrace{\boxed{\left[\frac{\omega}{\tau_1} e^{\frac{t}{\tau_1}} + \frac{1-\omega}{\tau_2} e^{\frac{t}{\tau_2}}\right]}}^{\textbf{LS}}$$

$$f(t, N) = Nf(t)\left(\int_t^{\infty} f(x)dx\right)^{N-1}$$

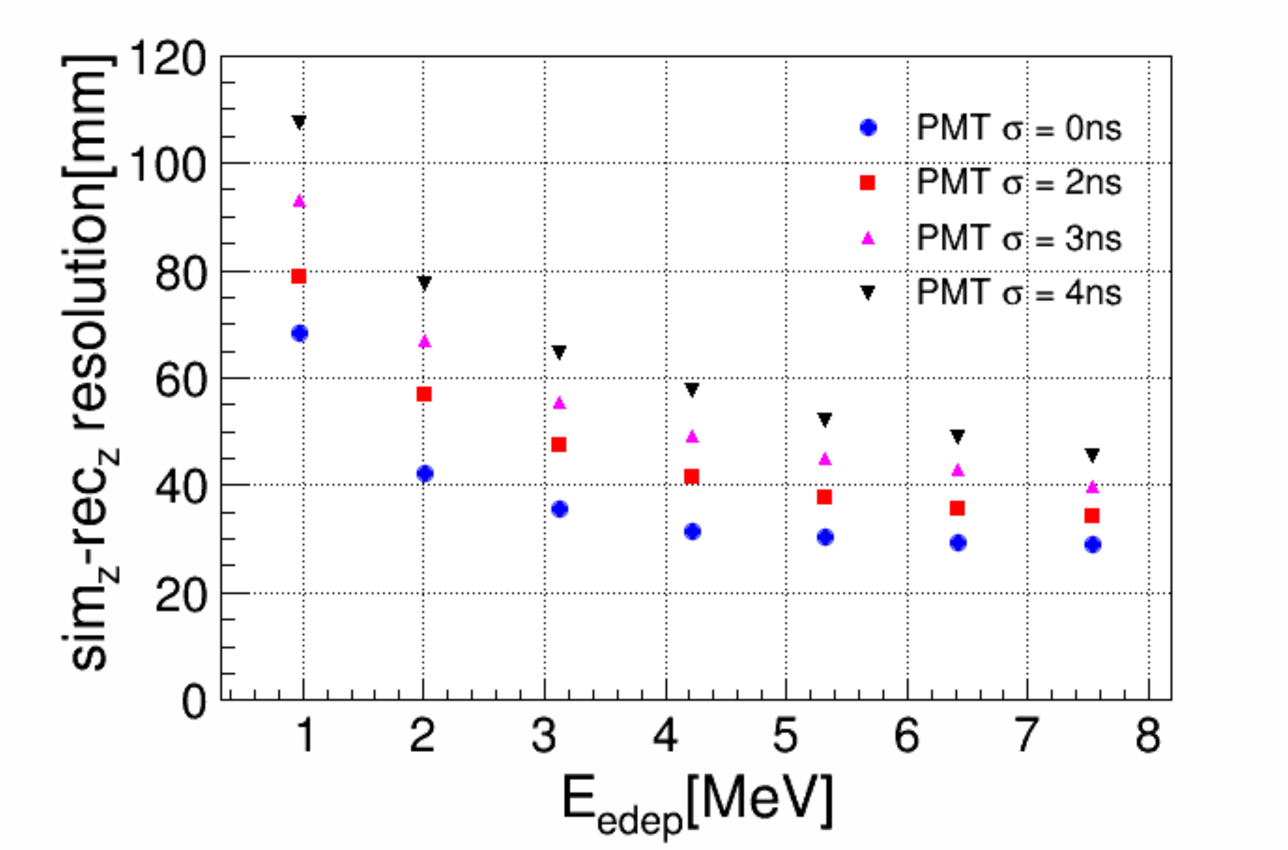
# VERTEX REC PERFORMANCE

arXiv:1803.09394

Bias vs R³

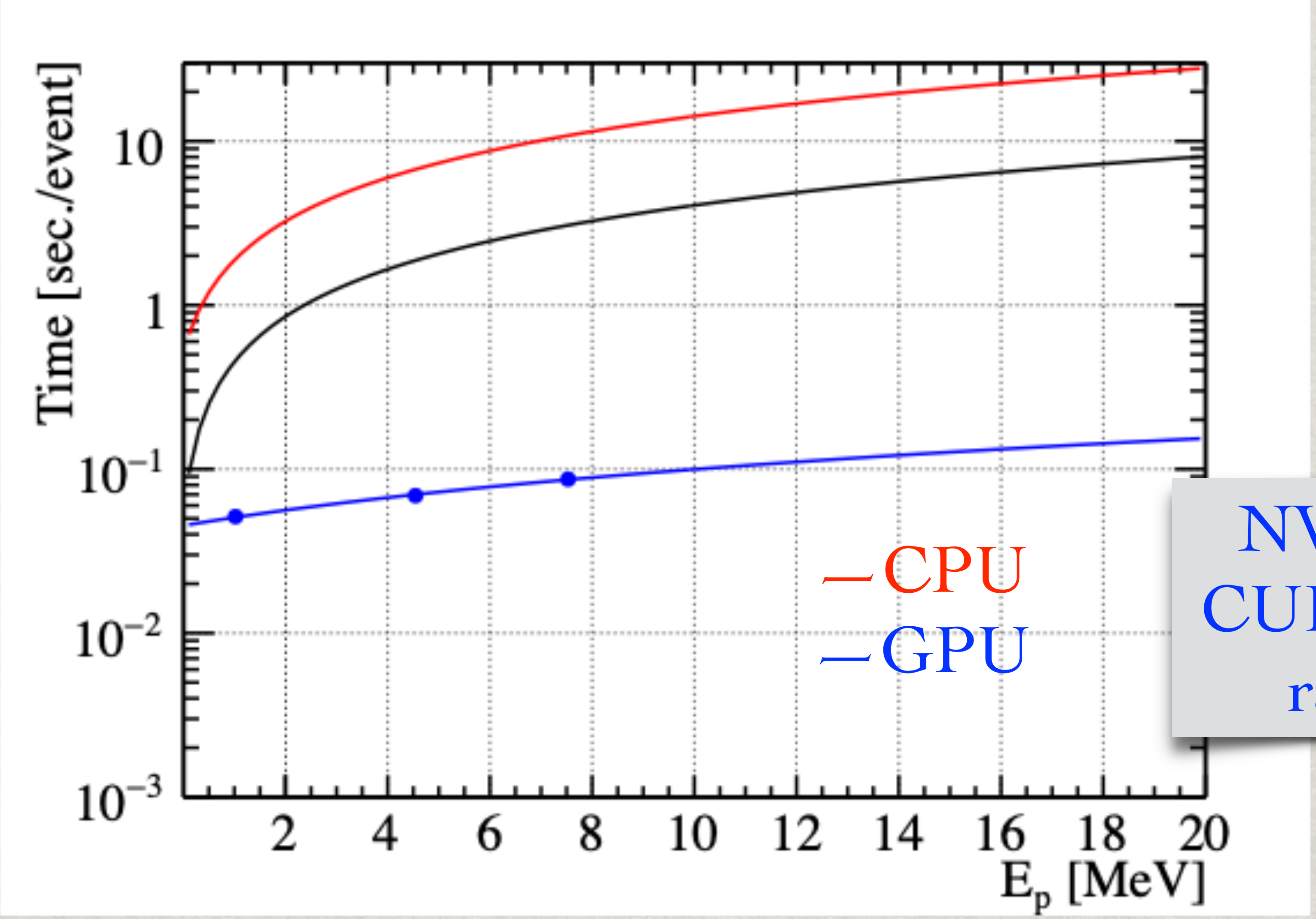



Res. vs E




- Dark Noise etc not taken into account yet, studies underway

# TIME PERFORMANCE




NVIDIA K40m
CUDA cores:2880
ram(GB):12

| | CPU | GPU | Ration: CPU/GPU |
|---|---|---|---|
| Time@1MeV(s) | 1.88 | 0.05 | ~40 |
| Time@10MeV(s) | 14.19 | 0.095 | ~150 |
| Gradiant | 1.37 | 0.005 | — |

# ENERGY REC.

arXiv:1812.01799

- Optical Model Independent Likelihood Rec.
- Ideal case： PMT nPE collection — $\{k_i\}$

$$\mathcal{L}(k_1, k_1, \dots, k_m | R_s, \theta_s, E) = \prod_{i=1}^{m} P(k_i | R_s, \theta_s, E) = \prod_{i=1}^{m} \frac{e^{-\mu_i} \cdot {\mu_i}^{k_i}}{k_i!};$$

  - $k_i$ — recorded nPE of i-th PMT
  - $\mu_i = E * \mu_{i,0}$ — expected nPE of i-th PMT
  - $\mu_{i,0}$ — <nPE> per unit energy
- $\{\mu_{i,0}\}$ can be obtained using calibration data
  - Source position
  - Distance between source and PMT

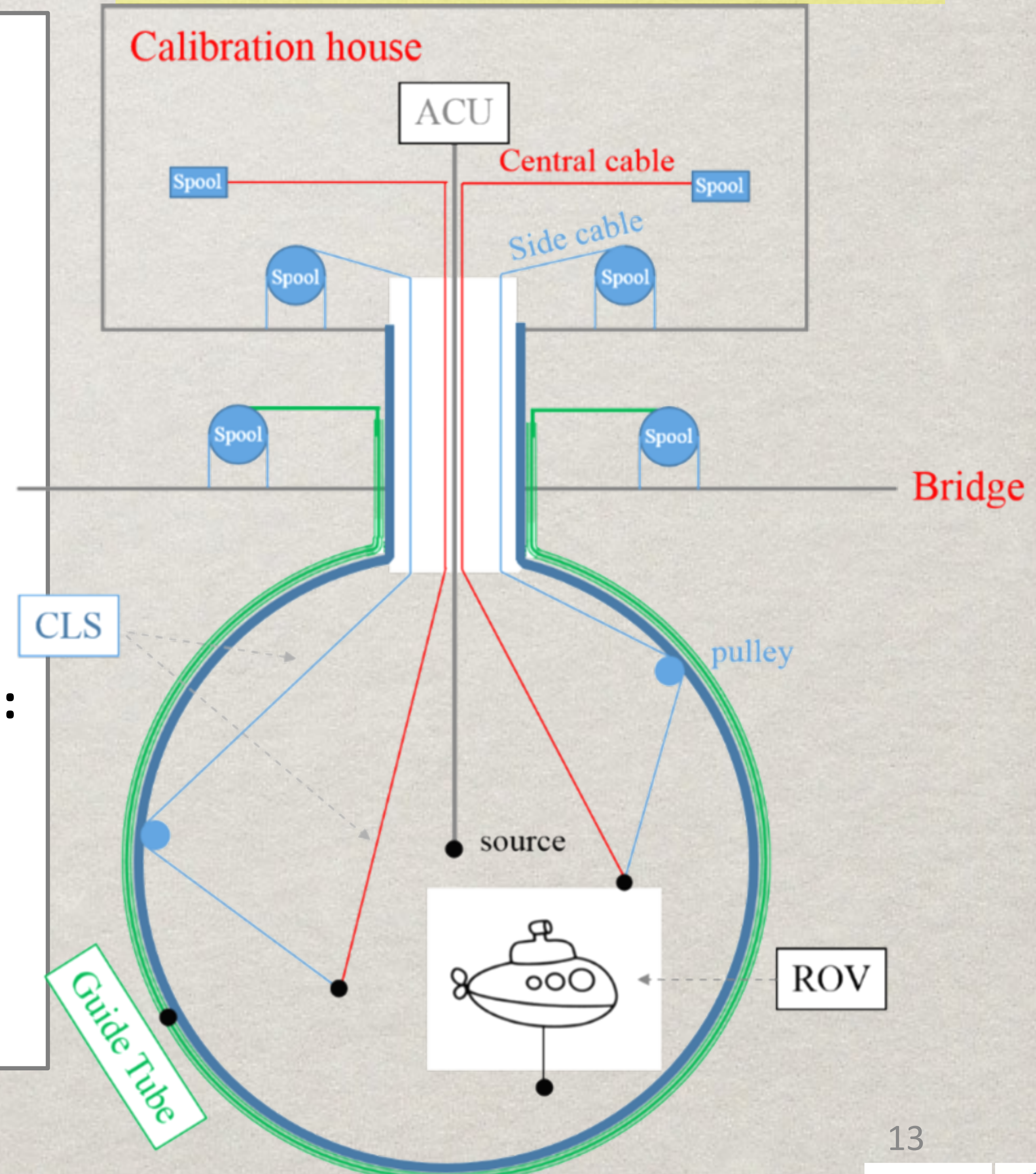
# Calibration Coverage

**JUNO: 4 complementary systems**

- **Internal source deployment:**
  - **ACU (Automatic Calibration Unit):**
    **1D-scan the central axis**
  - **CLS (Cable Loop System):**
    **2D-scan one vertical plane**

  * The two systems are above water, more convenient to change sources

  - **ROV (Remotely Operated Vehicle):**
    **3D-scan "everywhere"**
- **External source deployment:**
  - **GT (Guide Tube):**
    **Boundary scan CD outer surface**

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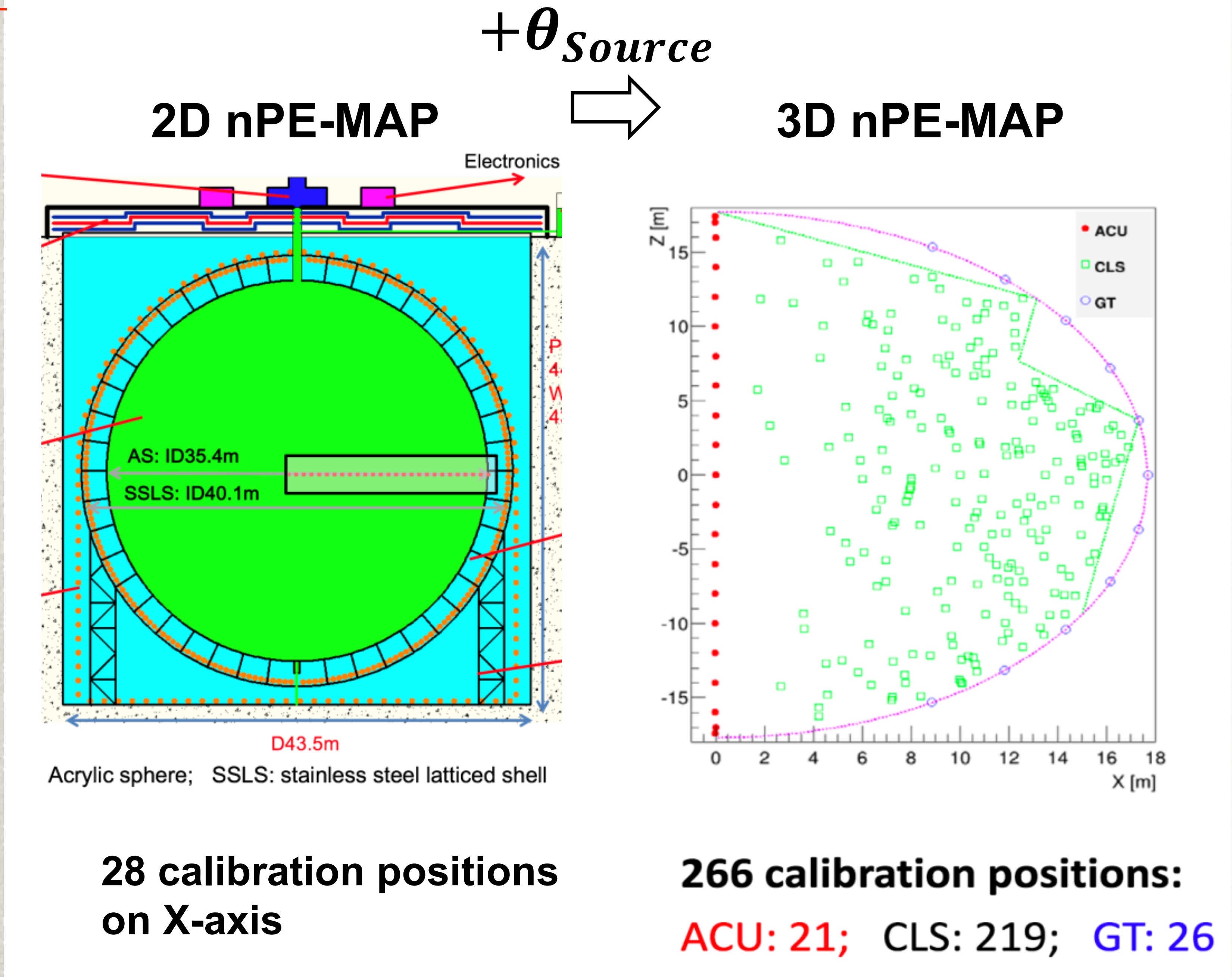
# nPE MAP $\{\mu_{i,0}\}$

arXiv:1812.01799

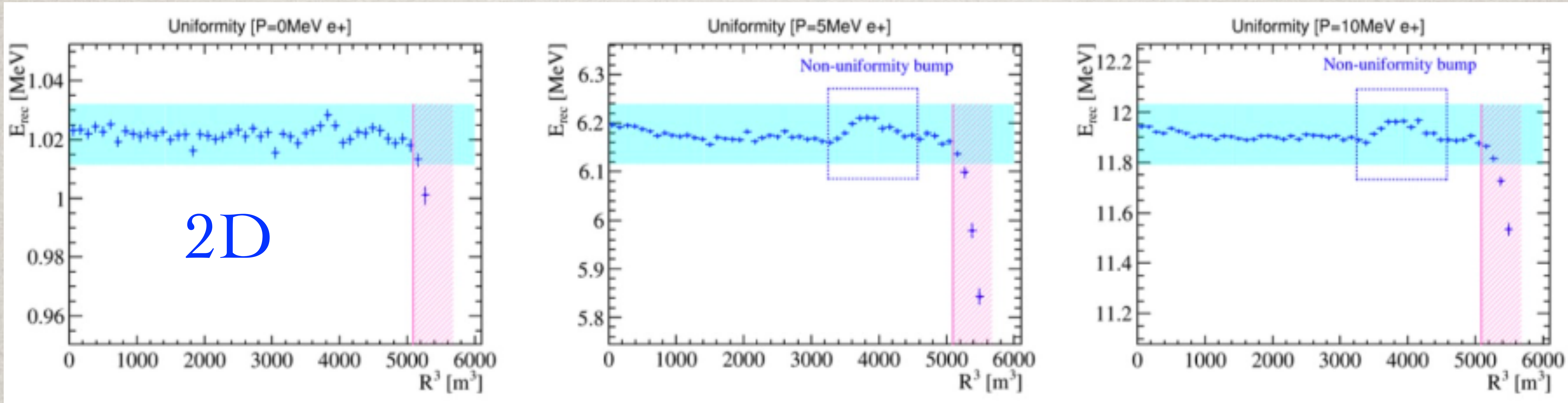
$(r, \Delta r)$

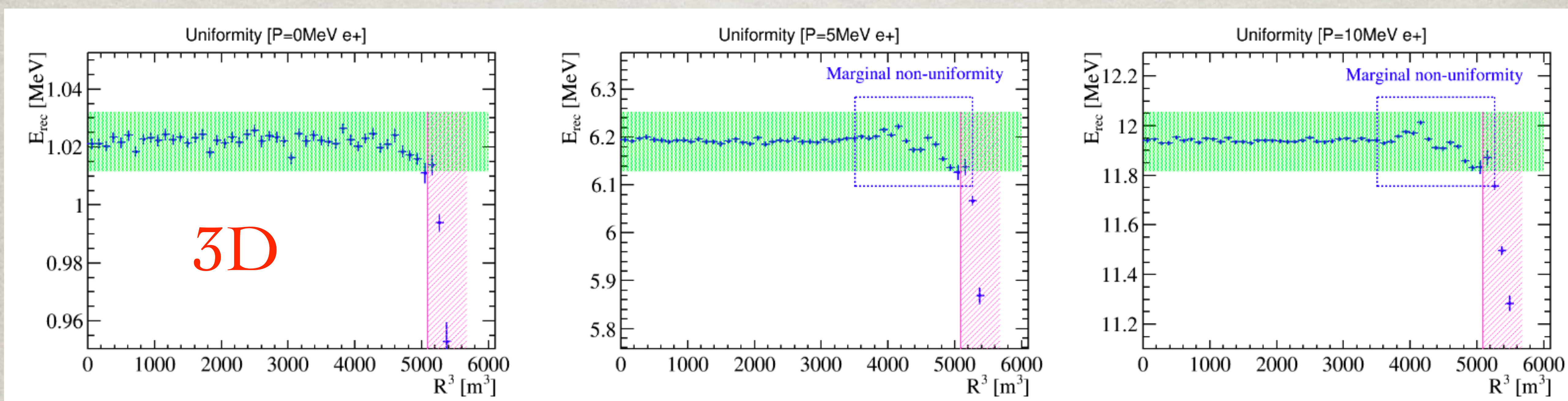



$(r, \theta, \Delta r)$

- 3D nPE-MAP mitigates the impact due to detector asymmetry

# UNIFORMITY



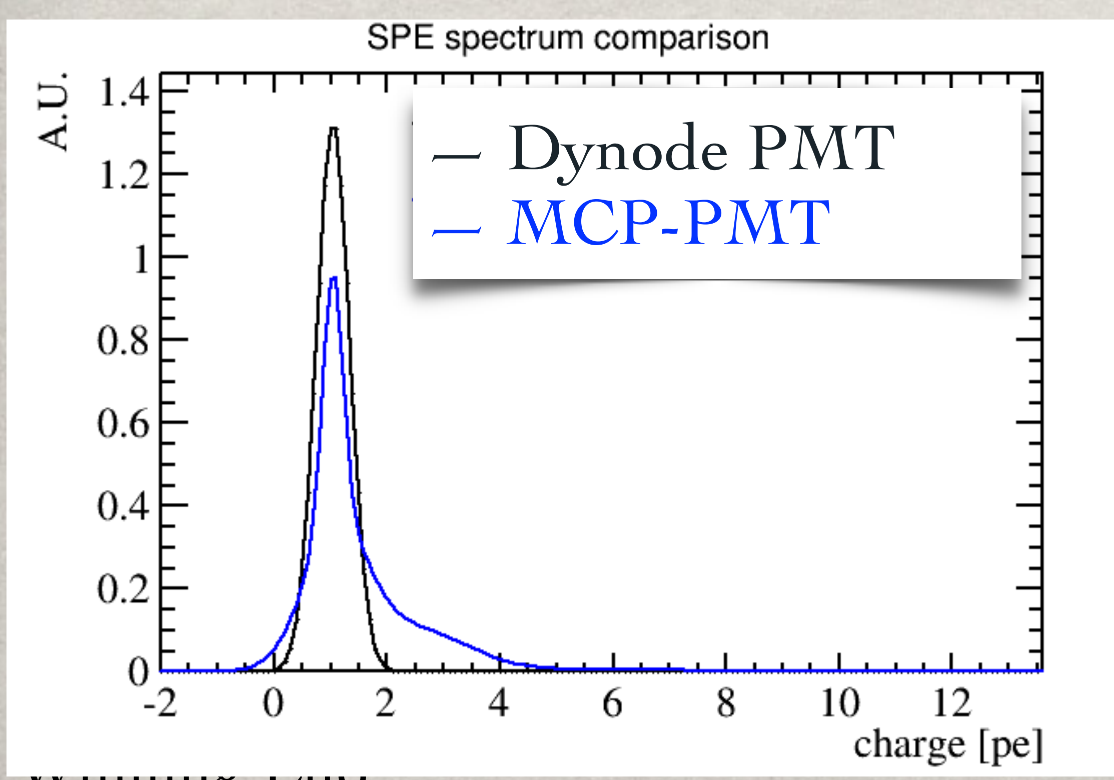

- Further improvement with more calibration points

# ENERGY REC.

- Real case： PMT charge collection — $\{q_i\}$

$$\mathcal{L}(q_1,q_2,\dots,q_n|R_s,\theta_s,E)=\prod_{unhit}P(q_j|R_s,\theta_s,E)\prod_{hit}P(q_i|R_s,\theta_s,E)=\prod_{unhit}e^{-\mu_j}\prod_{hit}\left(\sum_{k=1}^{+\infty}\frac{e^{-\mu_i}\cdot{\mu_i}^k}{k!}P(q_i|k)\right)$$

- PMT nPE charge response → $P(q_i|k)$
- Dynode/MCP-PMT have different sPE response
- Energy res. will decrease w.r.t. ideal case




Dynode PMT

$$SPEs(x)=Gauss(x_{SPE},\sigma_{SPE});$$

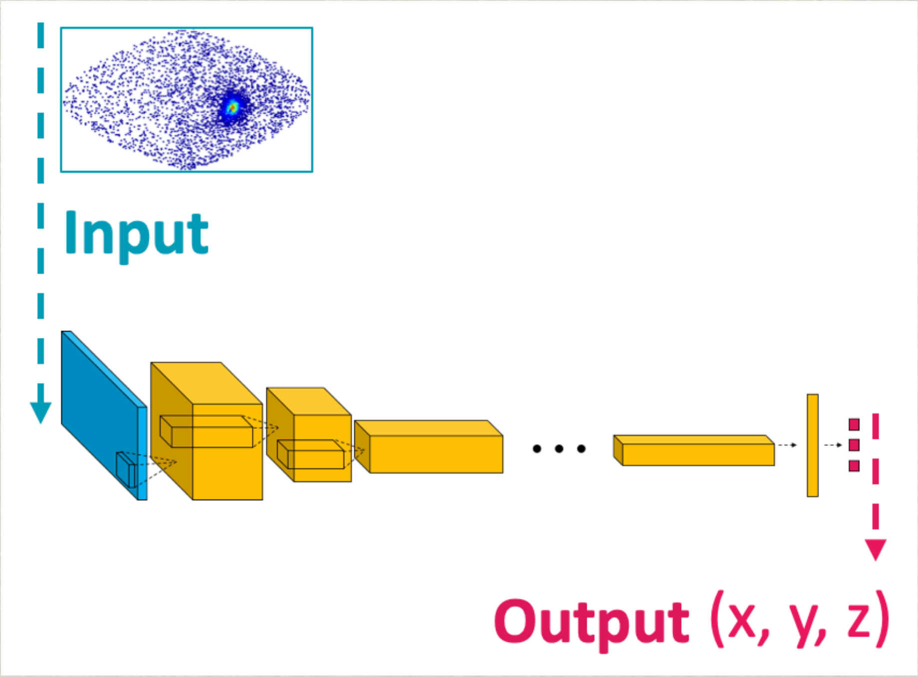
V.S.

MCP-PMT

$$SPEs(x)=a_1Gauss(x_1,\sigma_1)+a_2Gauss(x_2,\sigma_2)+a_3Gauss(x_3,\sigma_3);$$

# MISCELLANEOUS

- Alternative Rec approach: Machine Learning*
  - see Maxim's talk
- Combined Vertex and Energy Rec.
- Muon Rec: Top Tracker, Water Pool, Center Detector
- Particle Identification
  - Pulse Shape Discrimination
  - Machine Learning



# SUMMARY

- Brief description of reconstruction strategies for JUNO Center Detector
  - Waveform Rec. — Deconvolution
  - Vertex Rec. — Time Likelihood
  - GPU — parallel computing
  - Energy Rec. — Optical Model Independent Likelihood
- Lots of interesting and challenging problems
- JUNO wants you!

# BACKUP

# WAVEFORM REC ALGS

Table 2: The summary table for different charge reconstruction algorithms.

| Algorithms | Speed per channel | Robustness | Residual non-linearity | Pile-up hits separation |
|---|---|---|---|---|
| Simple integral | less than 0.1 ms | No failure | 3% to 10% | Larger than 20 ns |
| $CR\text{-}(RC)^4$ | 0.2 ms | No failure | 10% | Larger than 40 ns |
| Waveform fitting | 0.5 s | Sometimes fails and difficult to define failure | 2% | Larger than 10 ns |
| Deconvolution | 0.5 ms | No failure | 1% | Larger than 10 ns |

# DISCUSSION

- Memory allocation and free, Synchronization etc… take up most of the time, room for future optimization
- Potential improvement with multiple GPUs
- Instead of Grid Search, divide the detector ROI to tiny units and parallelize with GPU(s)