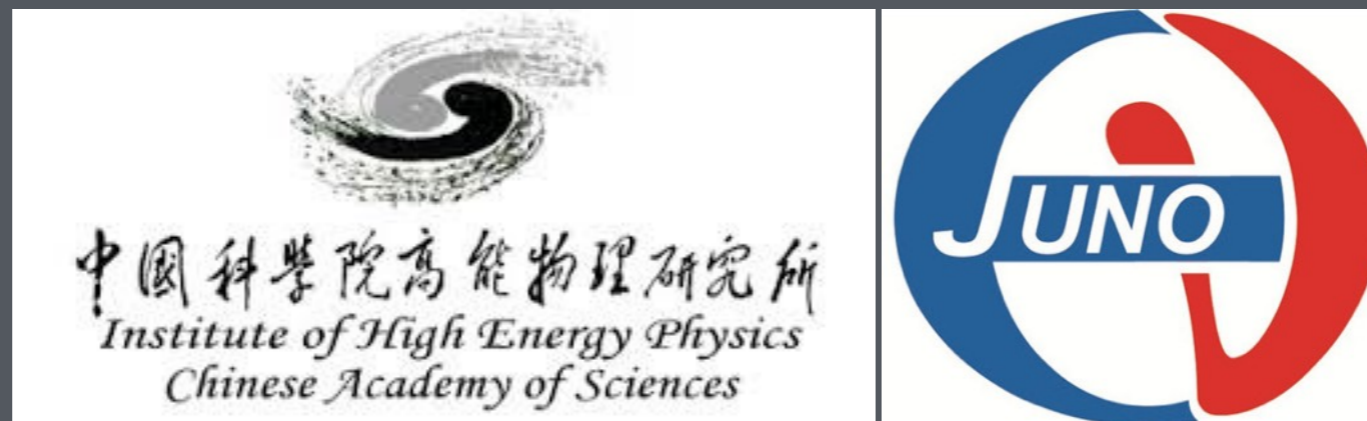


# GPU APPLICATION IN JUNO

W U M I N G L U O  
M A Y 3 0 T H 2 0 1 9

高能物理计算和软件会议  
南京大学



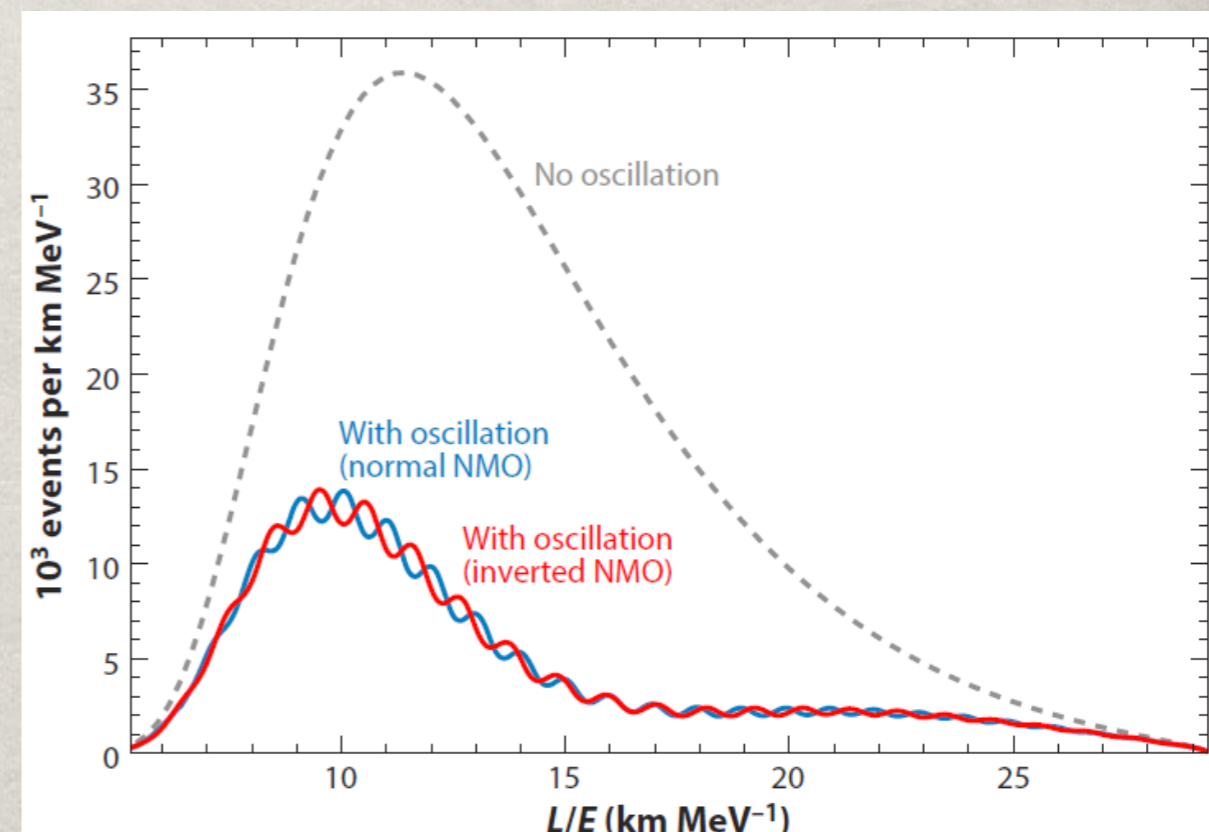
# OUTLINE

- ✿ Introduction to JUNO
- ✿ GPU vs CPU
- ✿ Applications
  - ✿ Vertex Reconstruction
  - ✿ Muon Simulation
  - ✿ Deep Learning
- ✿ Discussion
- ✿ Summary

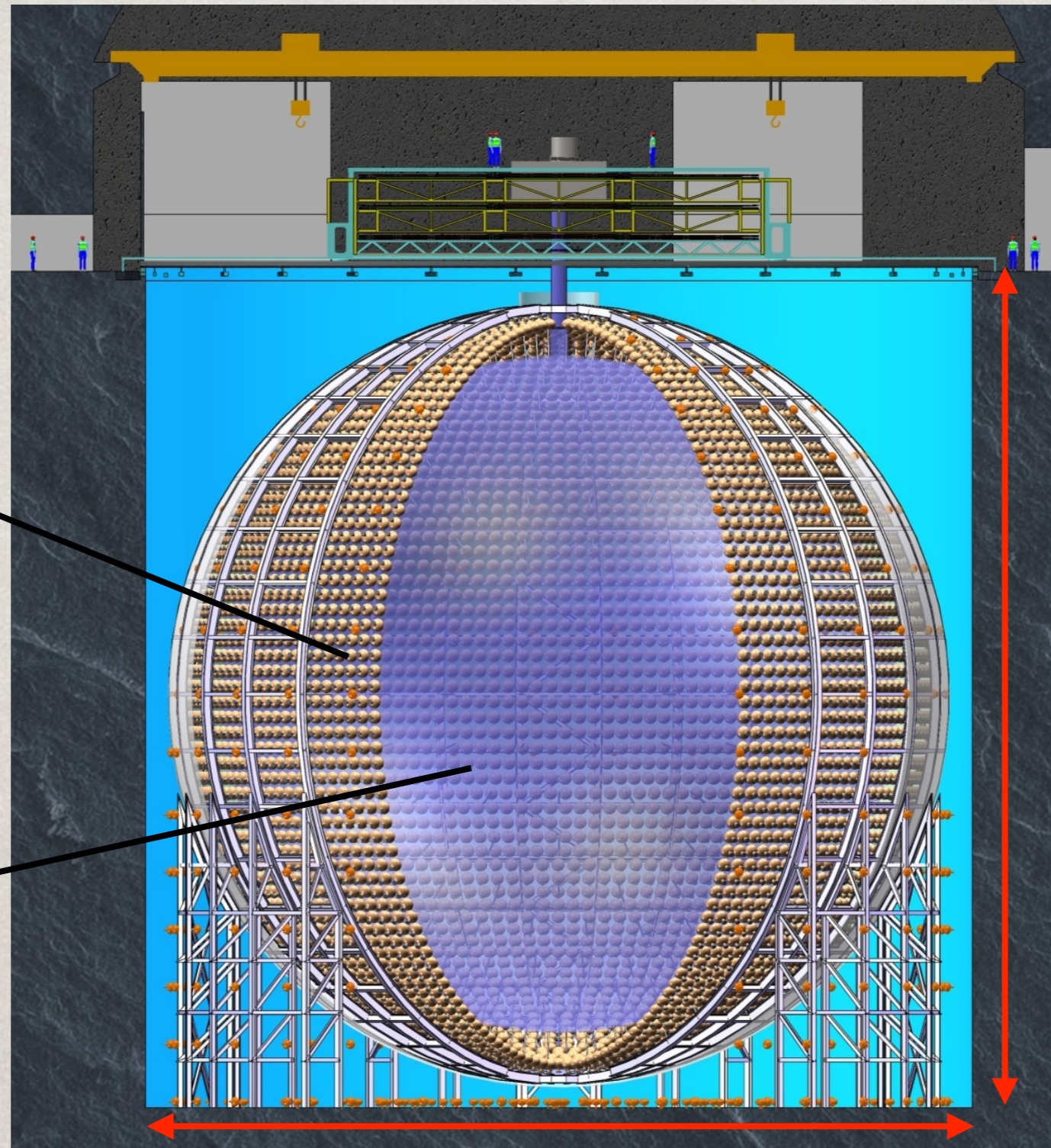


# JUNO

- ☀ Jiangmen Underground Neutrino Observatory(JUNO):
  - ☀ **Largest** liquid scintillator detector (20 kton)
- ☀ Primary physics goals:
  - ☀ Determine the neutrino mass hierarchy
  - ☀ Measure neutrino oscillation parameters precisely



# DETECTOR



Central Detector PMT  
~18,000 20" PMTs  
+ ~25,000 3" PMTs

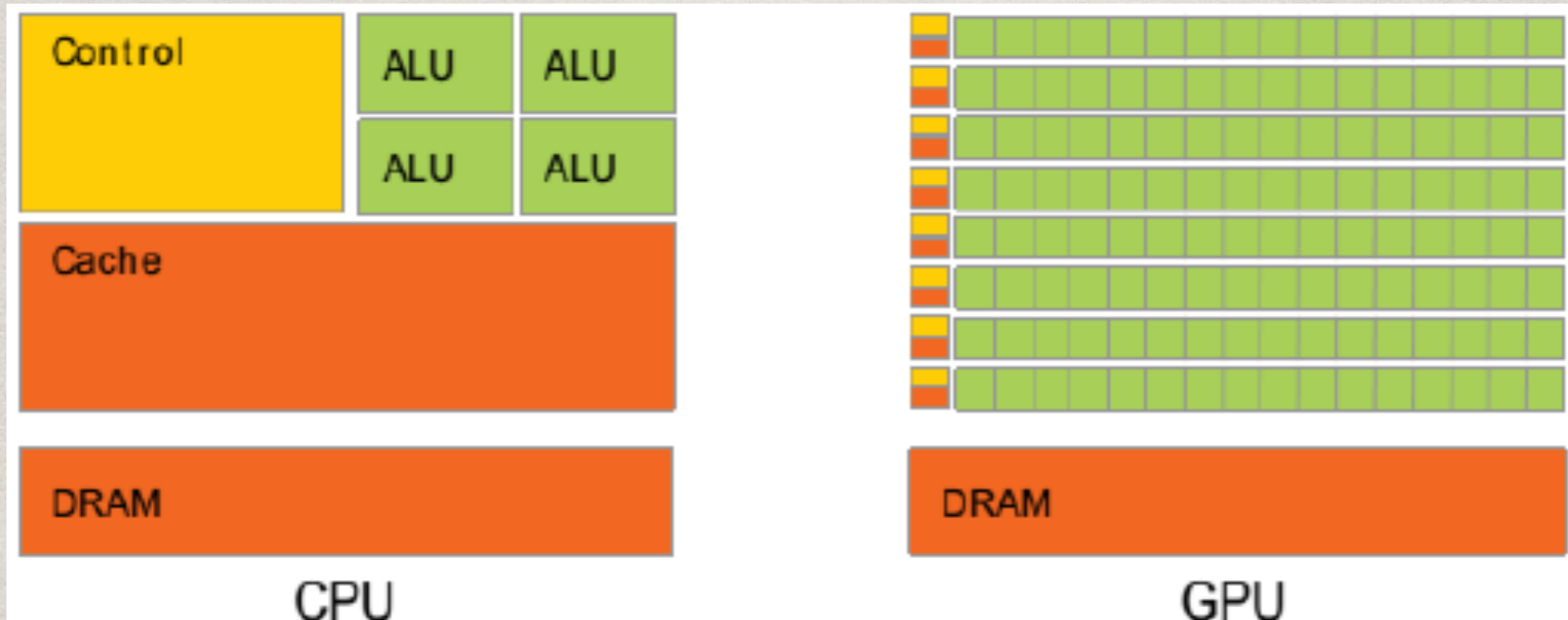
Depth: 44m

Liquid Scintillator  
20kton

$\phi$ : 43.5m

4

# GPU VS CPU



Large Cache

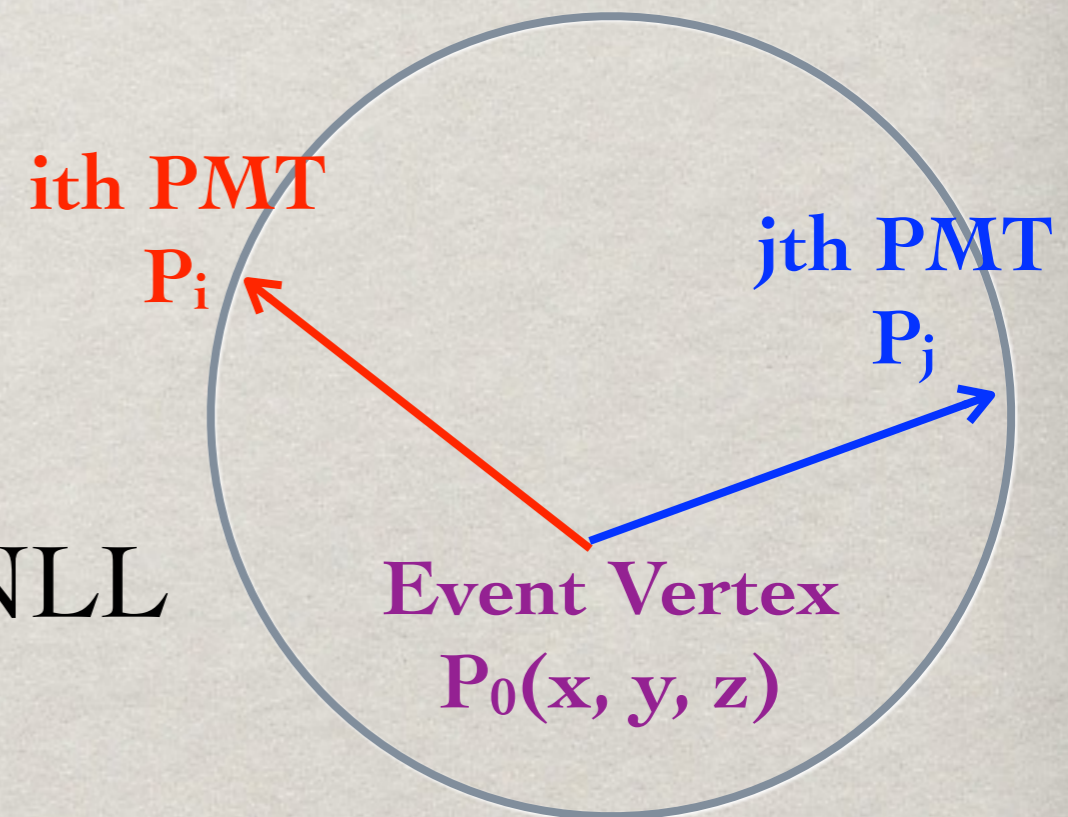
Many cores

Optimized for serial operations

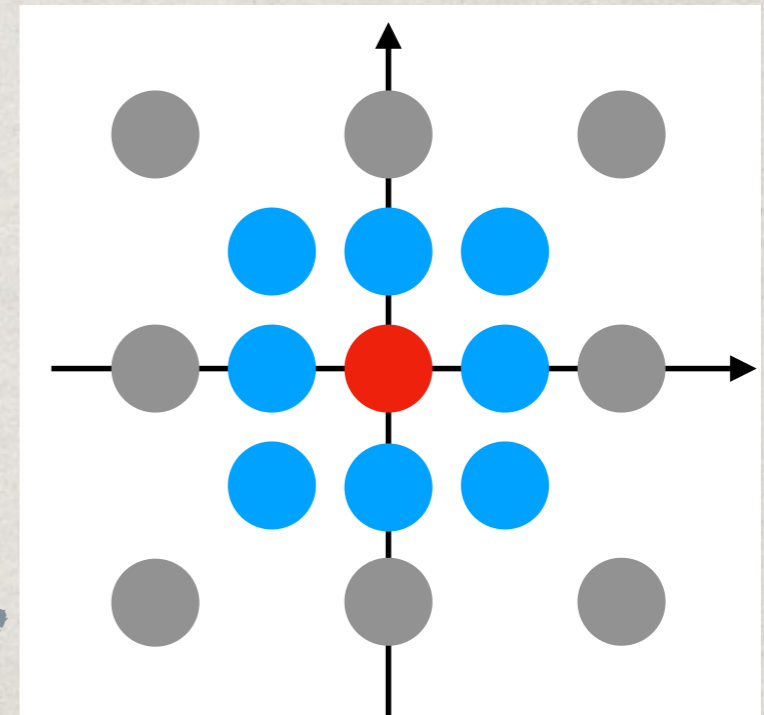
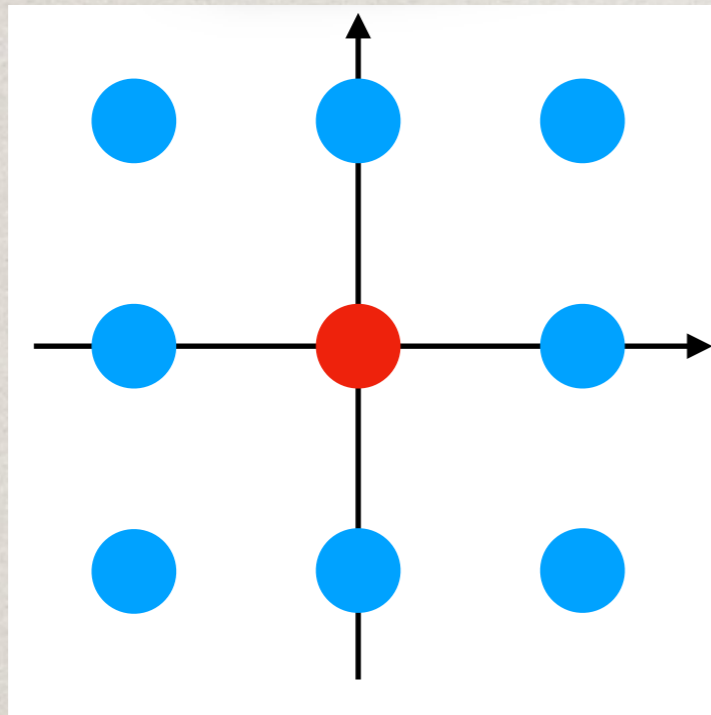
Built for parallel operations

# CASE 1: VERTEX RECONSTRUCTION

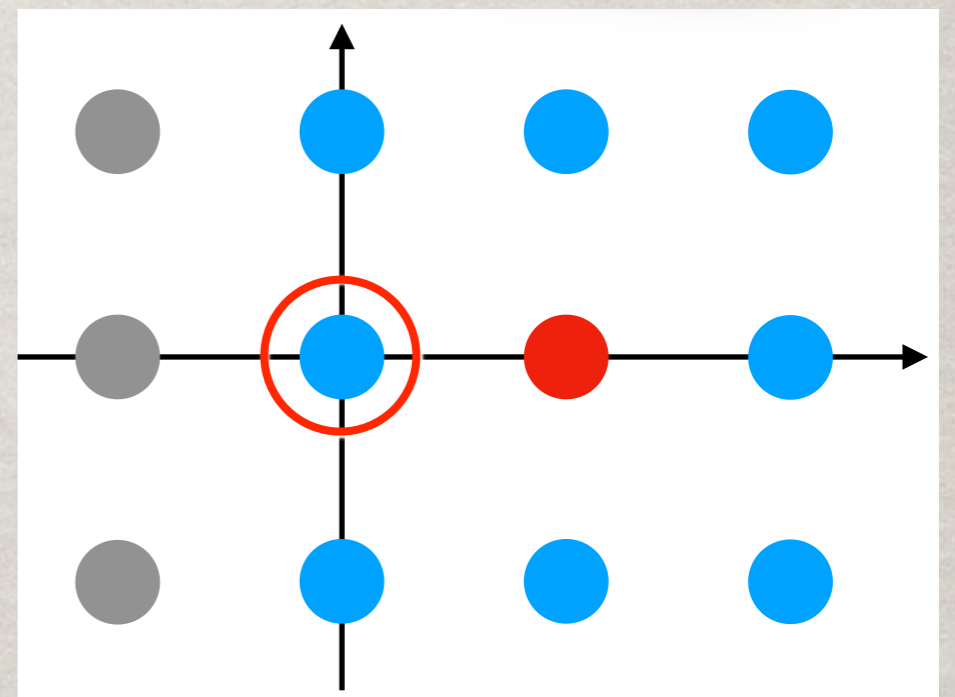
- Parameters to reconstruct:  $x, y, z, t_0$
- Algorithm:  $-\ln \mathcal{L} = -\sum \ln f_{res}(t_{i,res}) = -\sum \ln f_{res}(t_i - t_{i,tof} - t_0)$ 
  - $t_i$ : first hit time of  $i$ th fired PMT
  - $t_{tof}$ : time of flight
  - $t_0$ : event start time
  - $f_{res}$ : pdf of residual time
- Scan 4D grid to minimize the NLL



# GRID SEARCH — 2D



```
if(Center is minimum){  
  step /= 1/2  
}  
else{  
  move to NEW center  
}
```



# PARALLELIZATION ON GPU

```
for(t) {  
  for(x) {  
    for(y) {  
      for(z) {  
        for(ith PMT) {  
          calc.  $NLL_i$   
        }  
      }  
    }  
  }  
  ...  
}
```

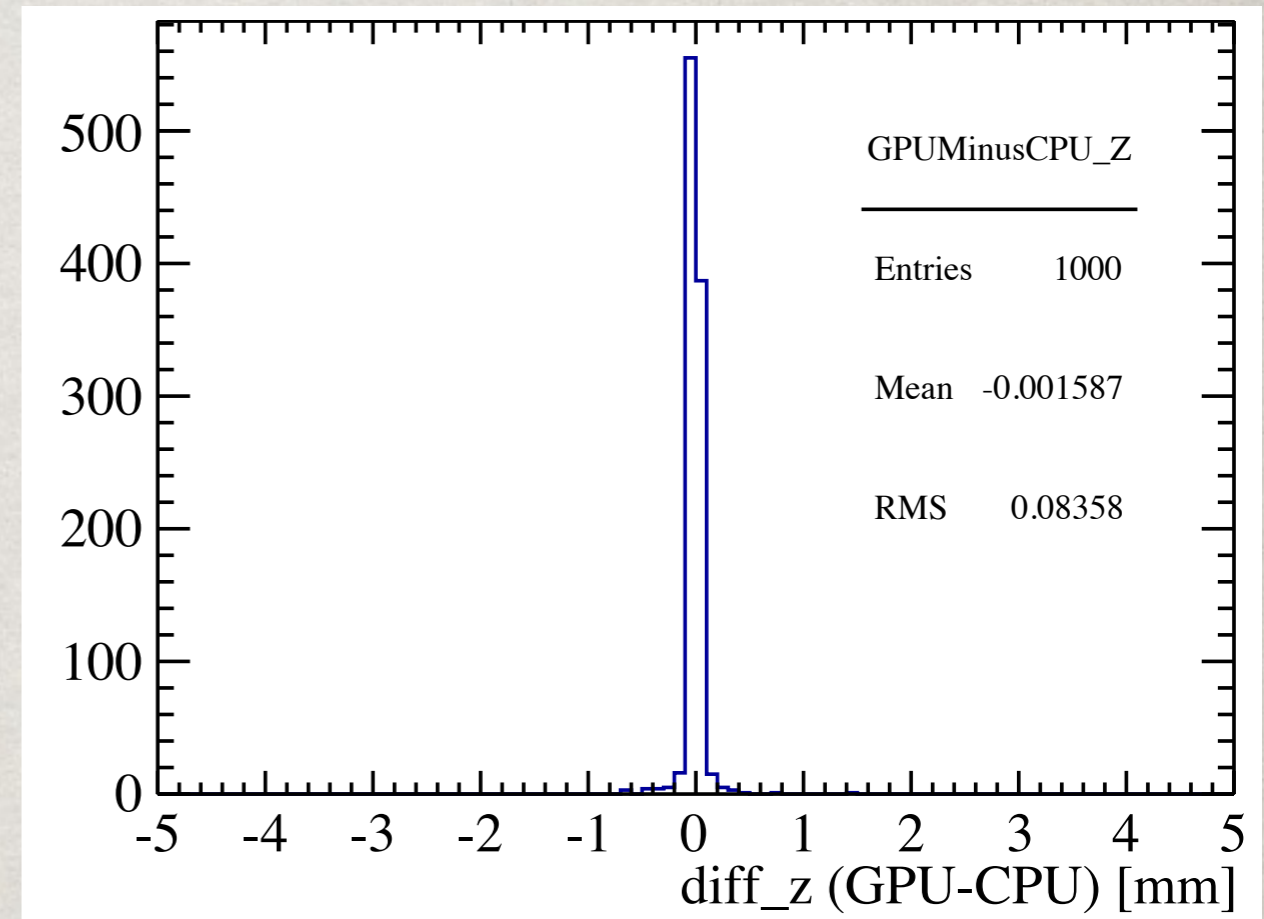
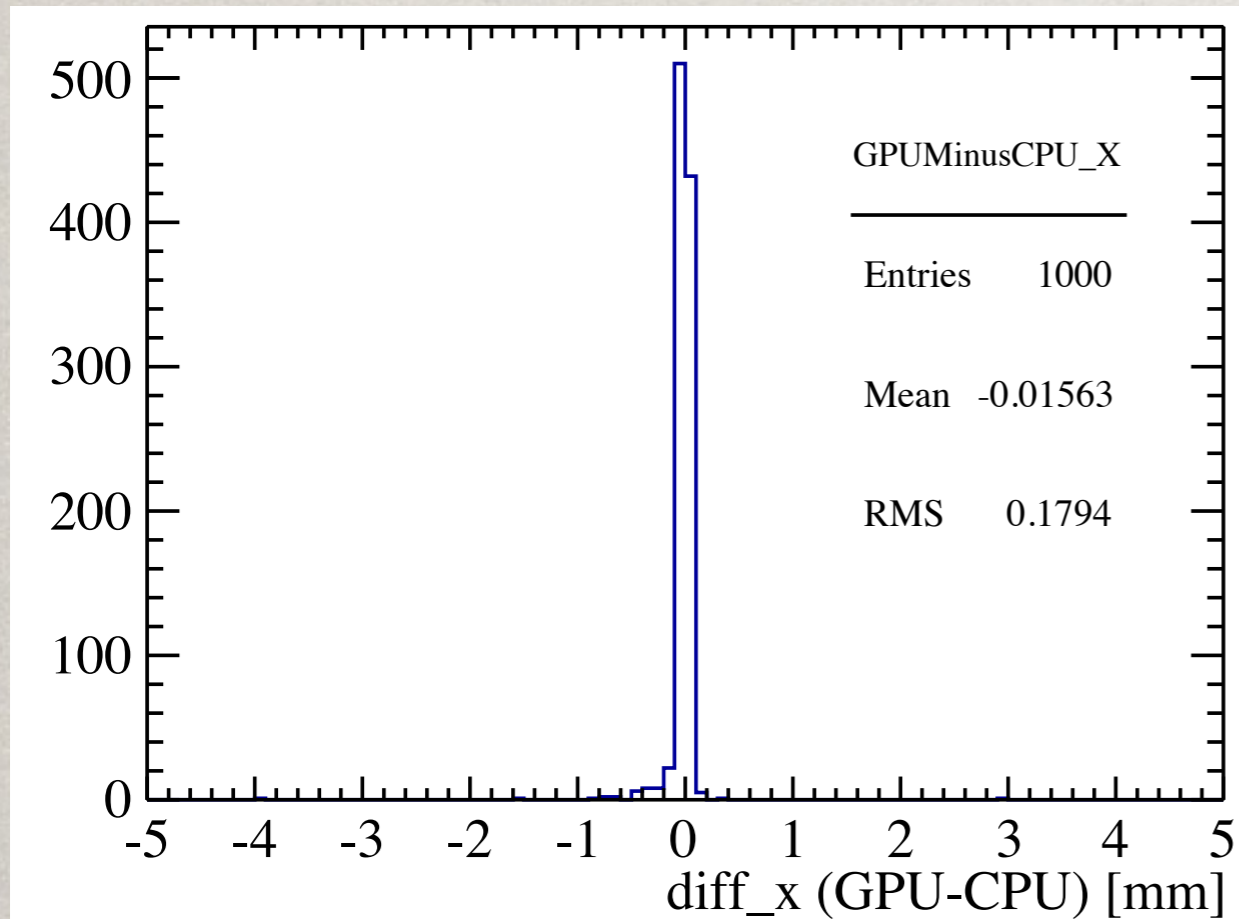
**ON CPU**

- ✱ 4D Grid Search
- ✱ Number of loops:  $x\text{-dim} * y\text{-dim} * z\text{-dim} * t\text{-dim} * n_{\text{fired\_PMTs}} = 3 * 3 * 3 * 9 * 1200 / \text{MeV} = 3 * 10^5 / \text{MeV}$
- ✱ Parallelize the calculations on GPU



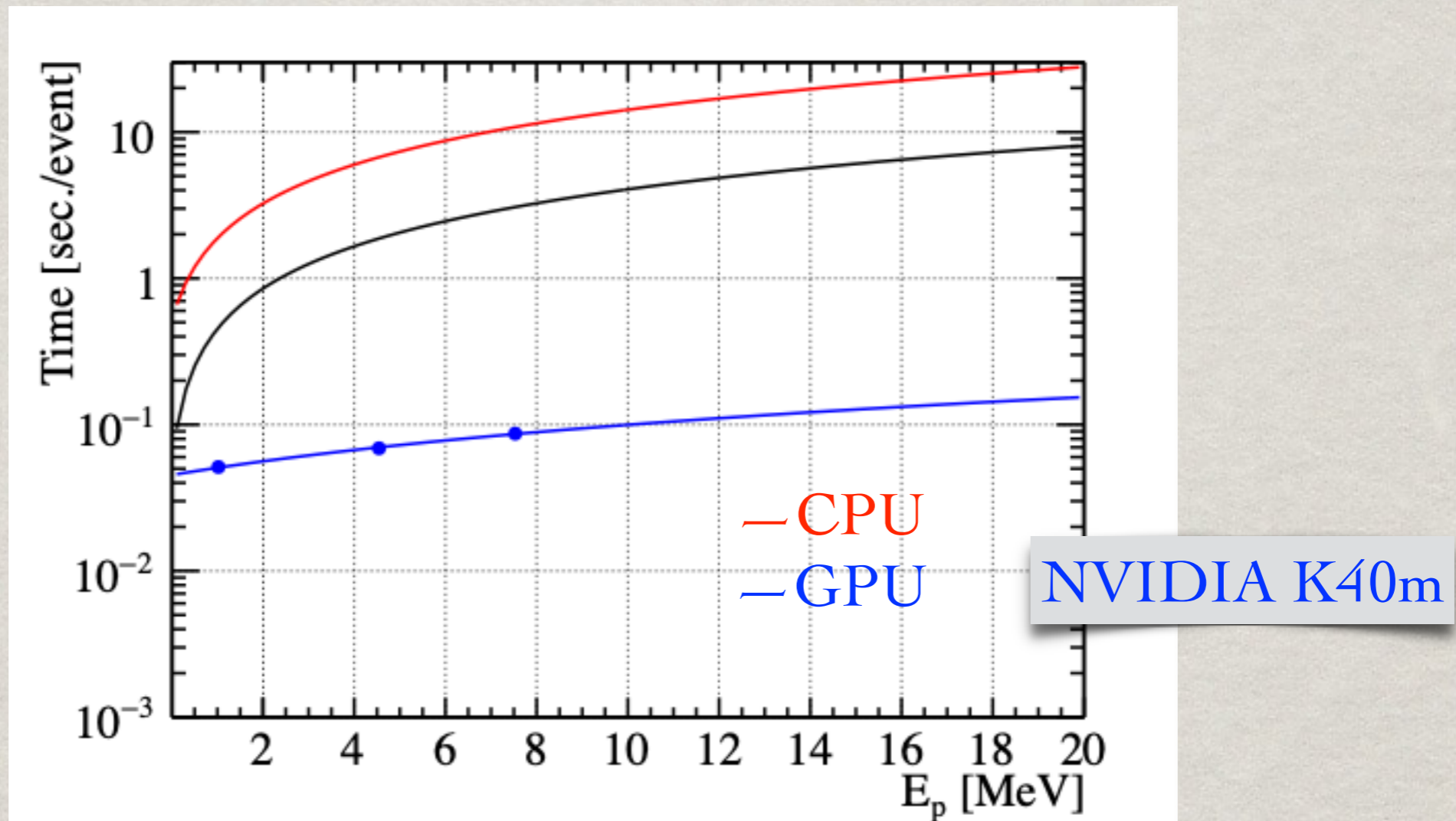


# VALIDATION



- ✿ GPU Rec was able to reproduce the CPU Rec results
- ✿ Tiny difference ( $<0.5\text{mm}$ ), negligible w.r.t. vertex resolution (60mm)

# PERFORMANCE



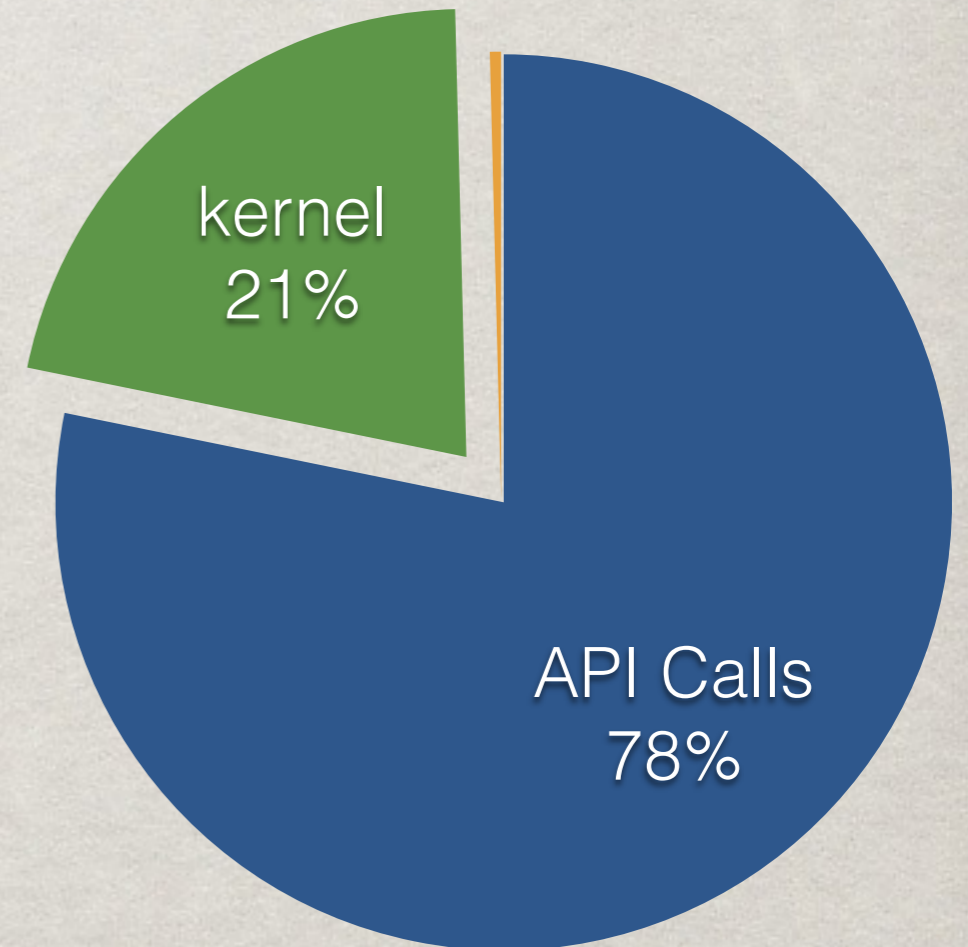
|               | CPU   | GPU   | Ration: CPU/GPU |
|---------------|-------|-------|-----------------|
| Time@1MeV(s)  | 1.88  | 0.05  | ~40             |
| Time@10MeV(s) | 14.19 | 0.095 | ~150            |
| Gradient      | 1.37  | 0.005 | —               |

# 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)

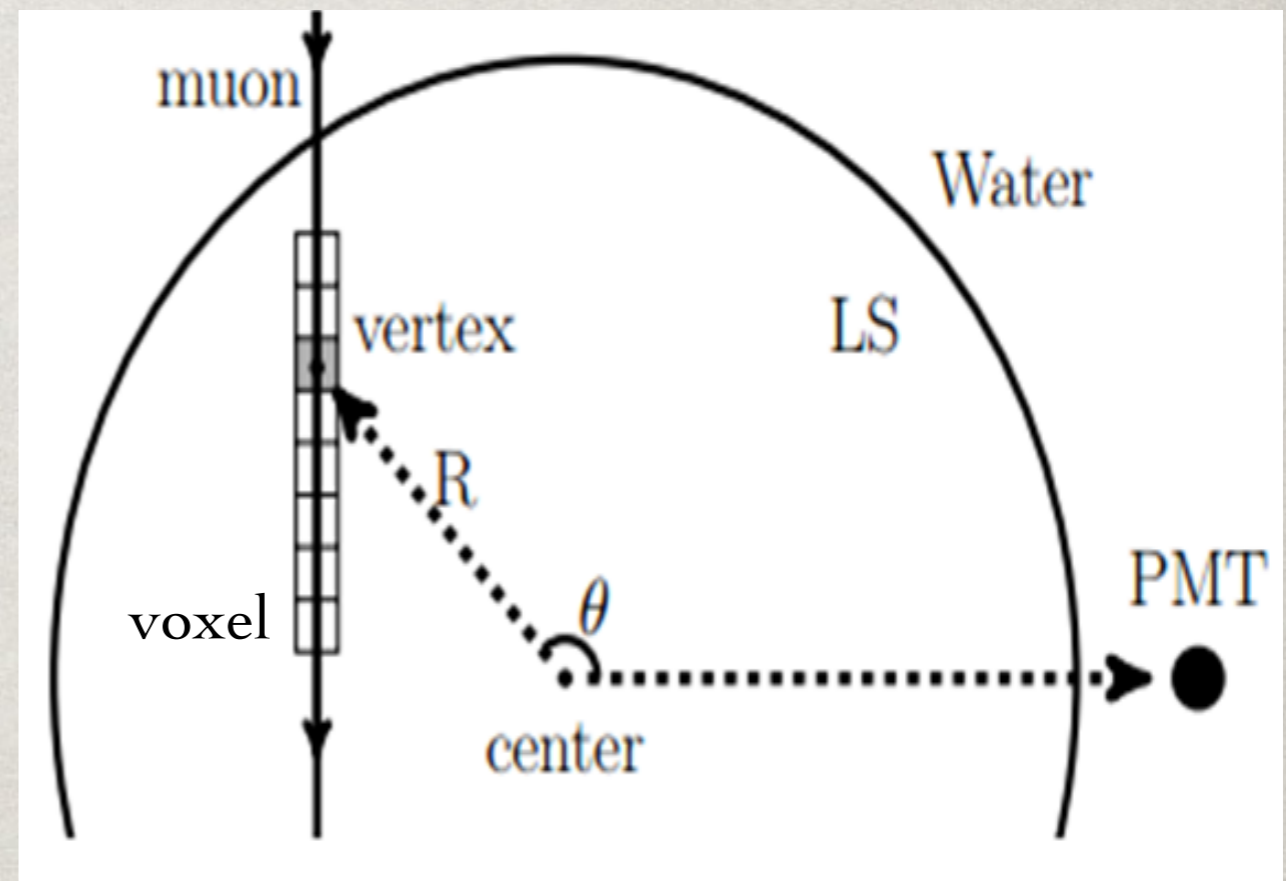
NVIDIA K40m

● API Calls      ● kernel  
● data transfer



# CASE 2: MUON SIMULATION

- ✿ Simulate the number of photons (nPE) and the corresponding hit time ( $\{t_i\}$ ) collected by each PMT for a traversing Muon
- ✿ Voxel: segments along the muon track
- ✿ For fixed  $(R, \theta)$ , sampling nPE and  $\{t_i\}$  from templates

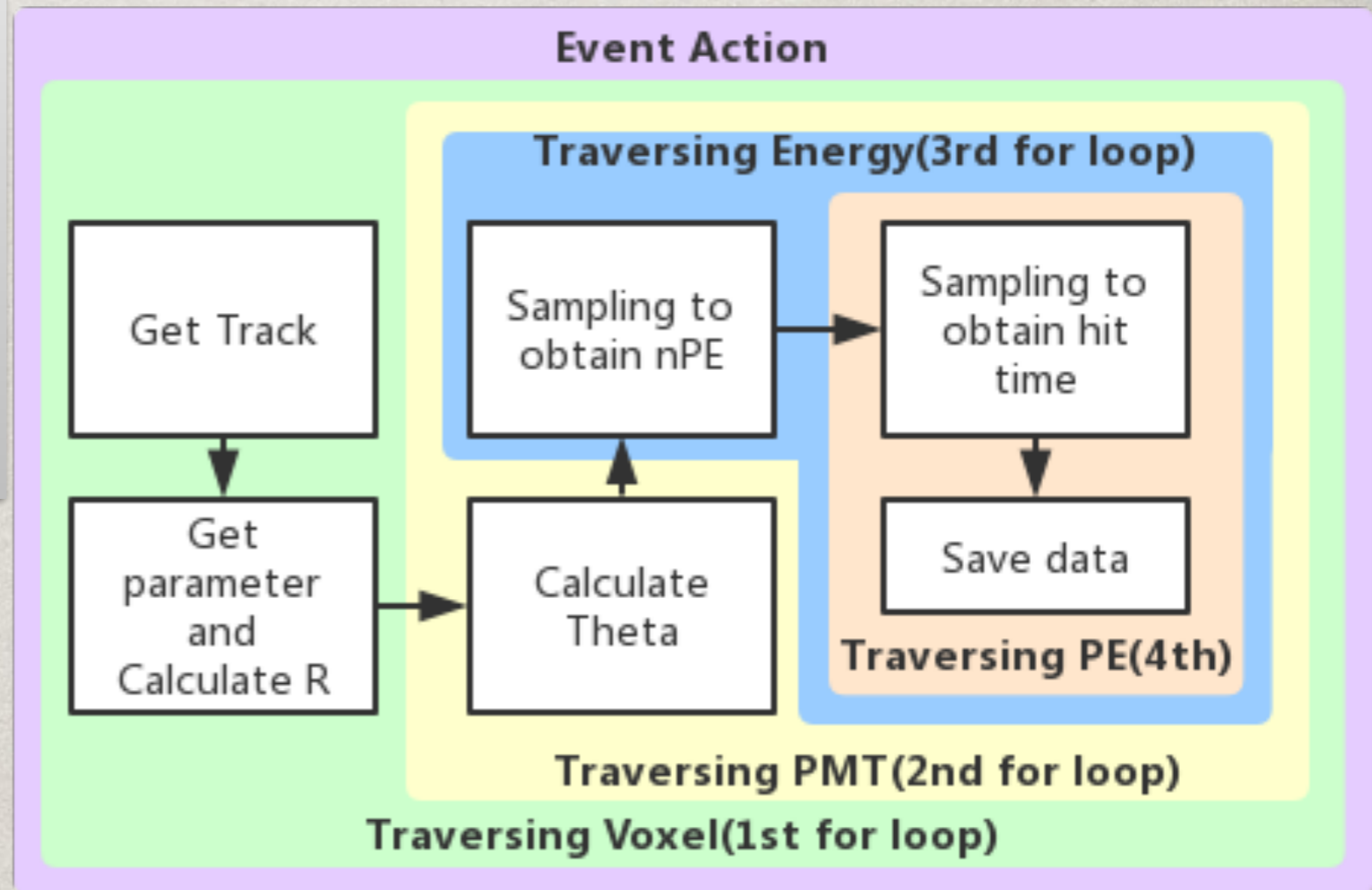


# COMPUTATION FLOW

```
for(R) { // Voxel loop
  for( $\theta$ ) { // PMT loop
    for(E) { // E loop
      for(nPE) {
        sample  $t_i$ 
      }
    }
  }
  ...
}
```

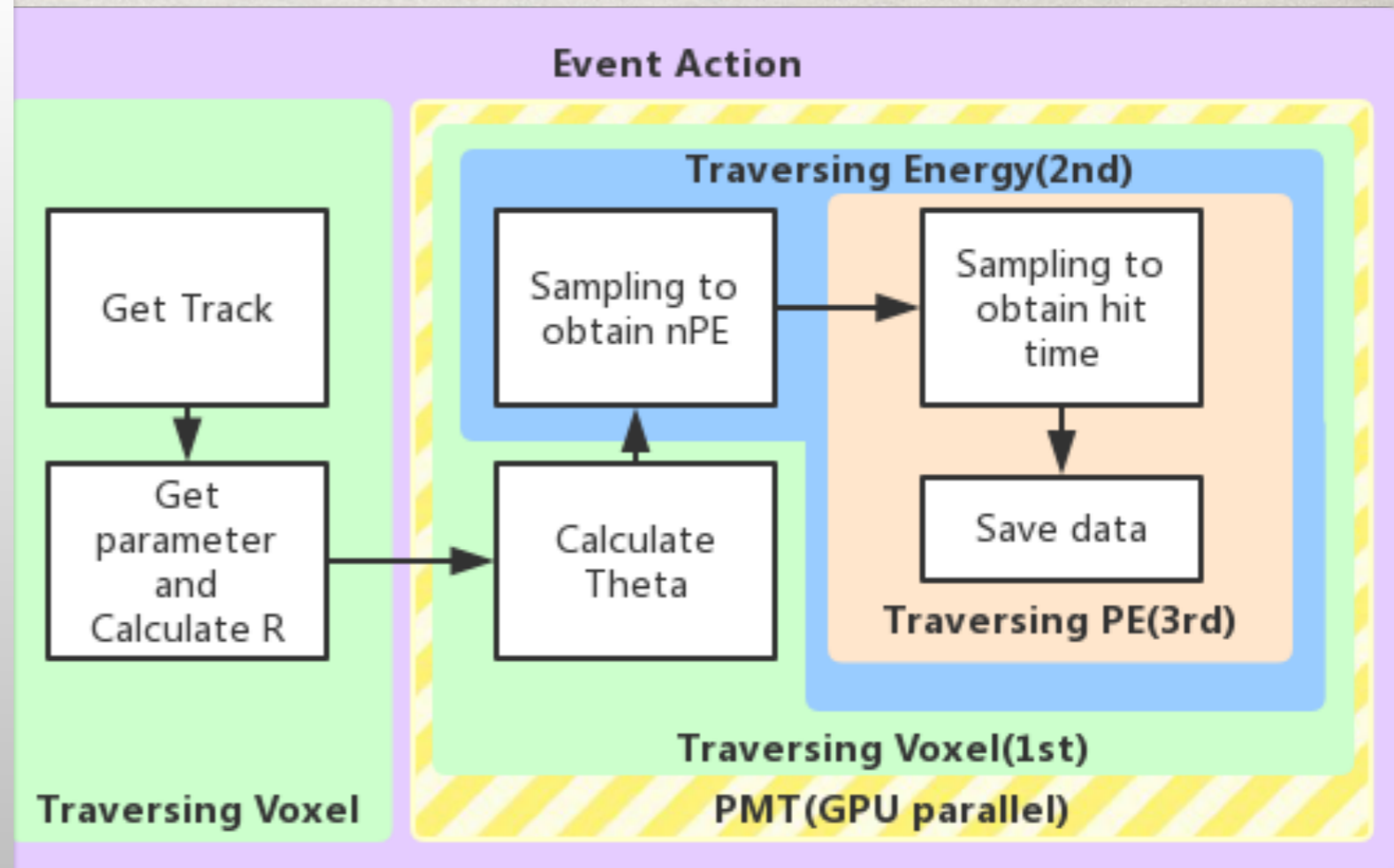
**ON CPU**

**~18,000 PMTs**



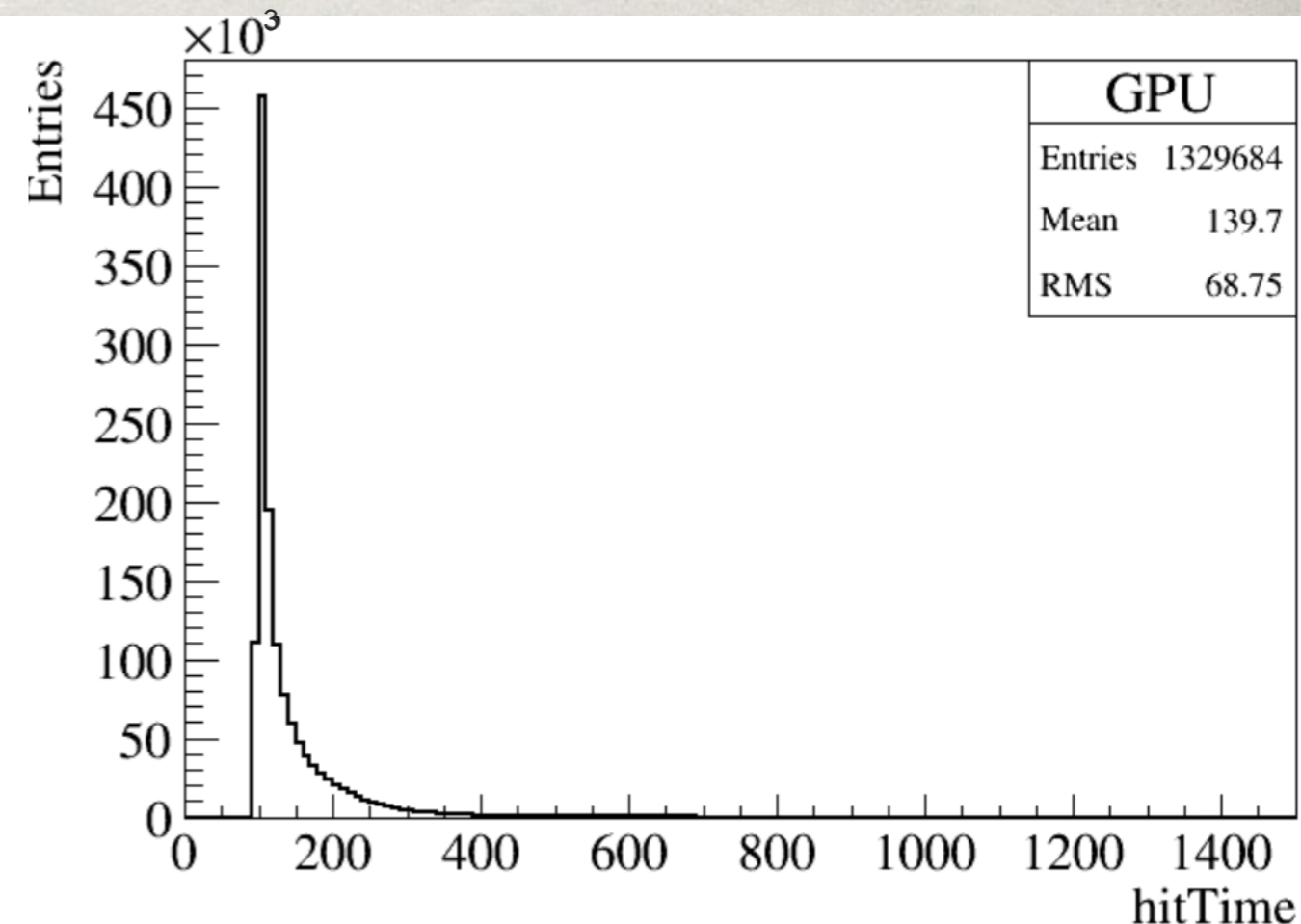
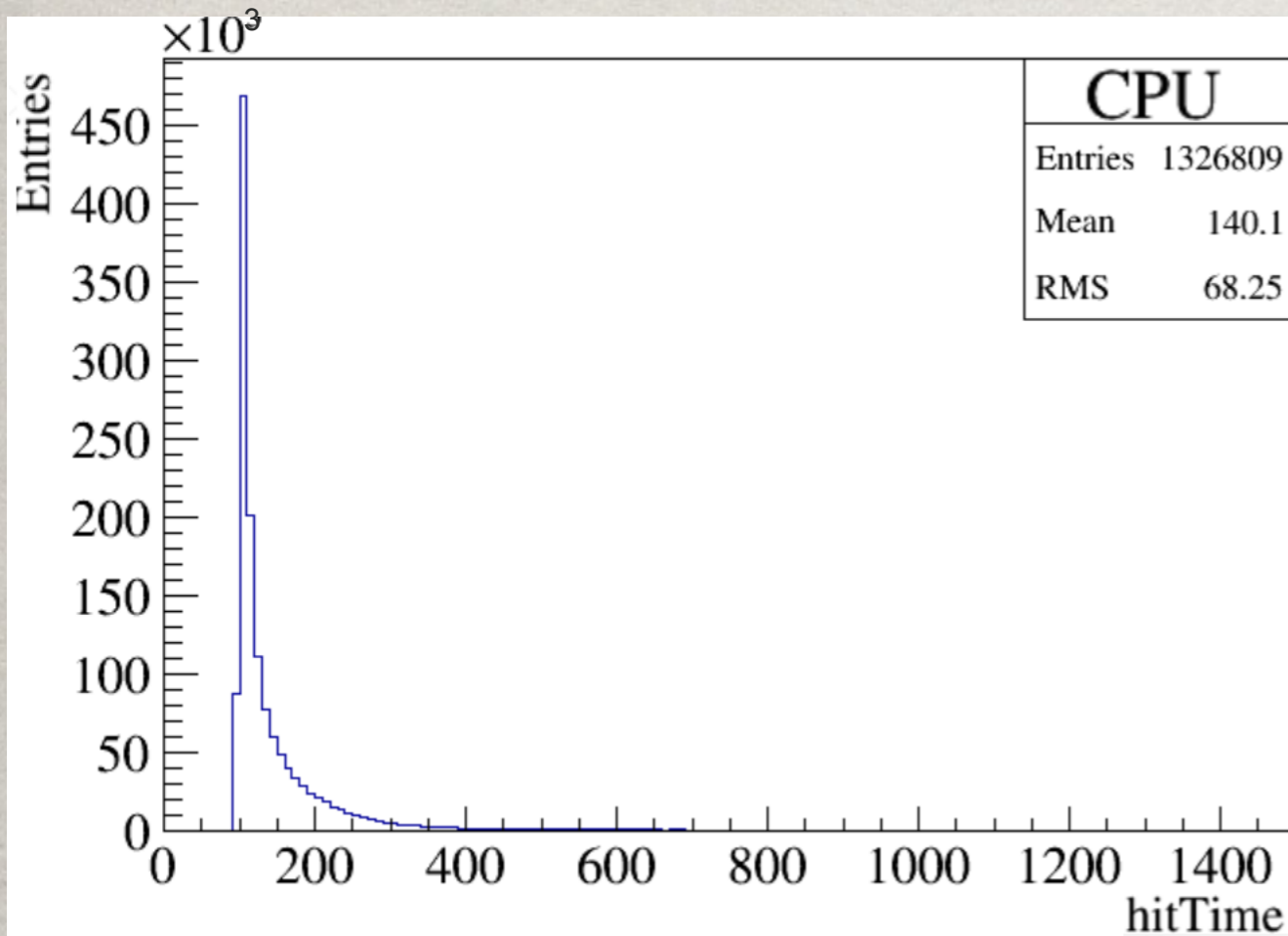
# COMPUTATION FLOW

```
for( $\theta$ ) { // PMT loop
  for(R) { // Voxel loop
    for(E) { // E loop
      for(nPE) {
        sample  $t_i$ 
      }
    }
  }
  ...
}
```



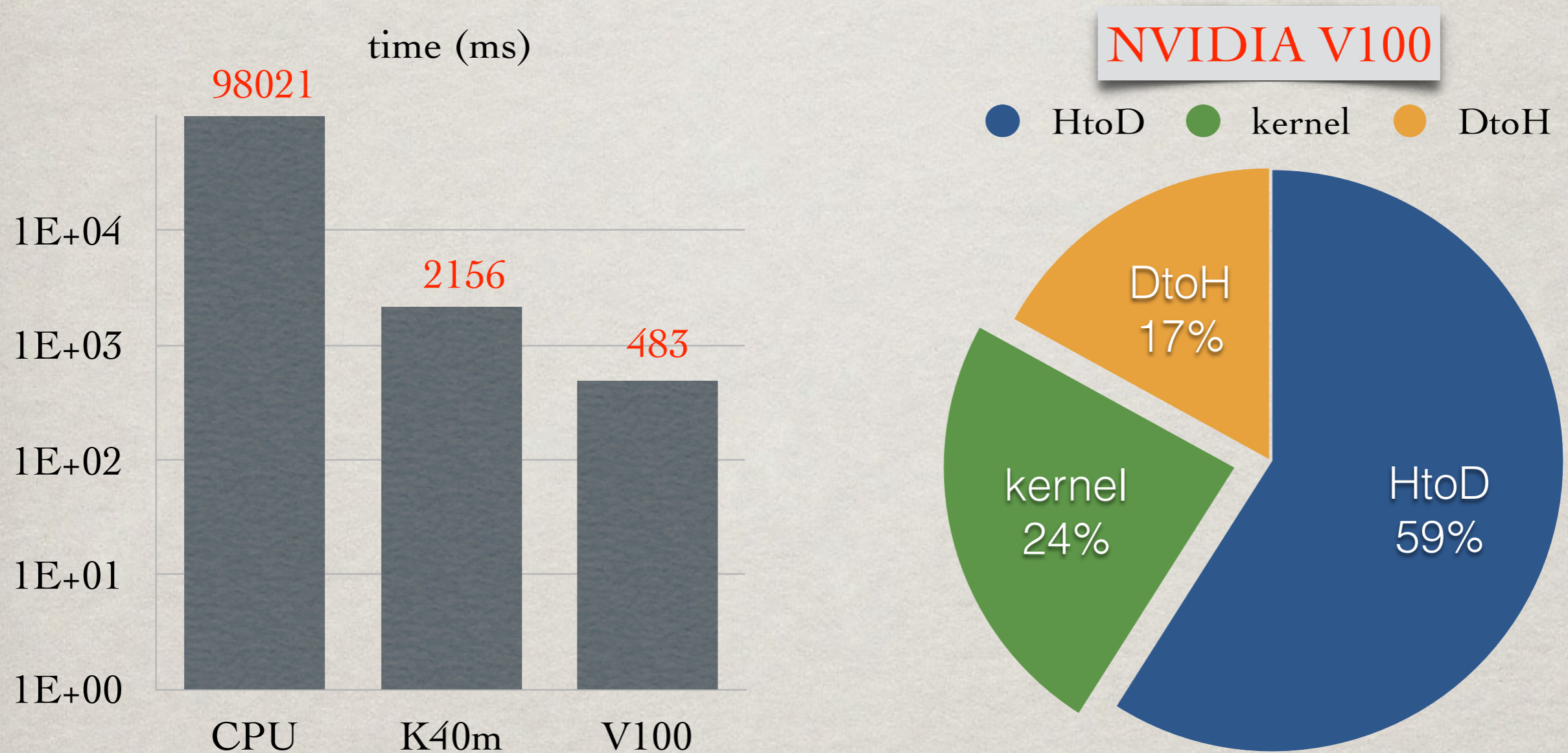
- ✿ Switch the Voxel loop and PMT loop levels
- ✿ Parallelize the PMT loop with GPU

# VALIDATION



- ☼ GPU Sim was able to reproduce the CPU Sim results
- ☼ Negligible difference

# PERFORMANCE



✿  $O(10^2)$  improvement with V100

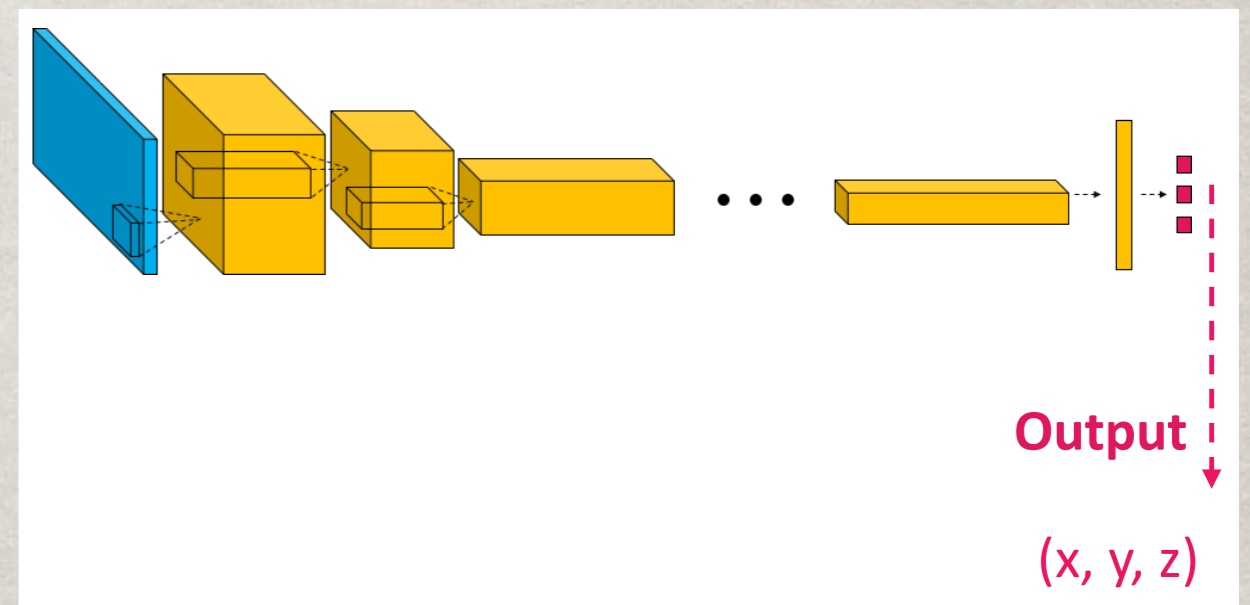
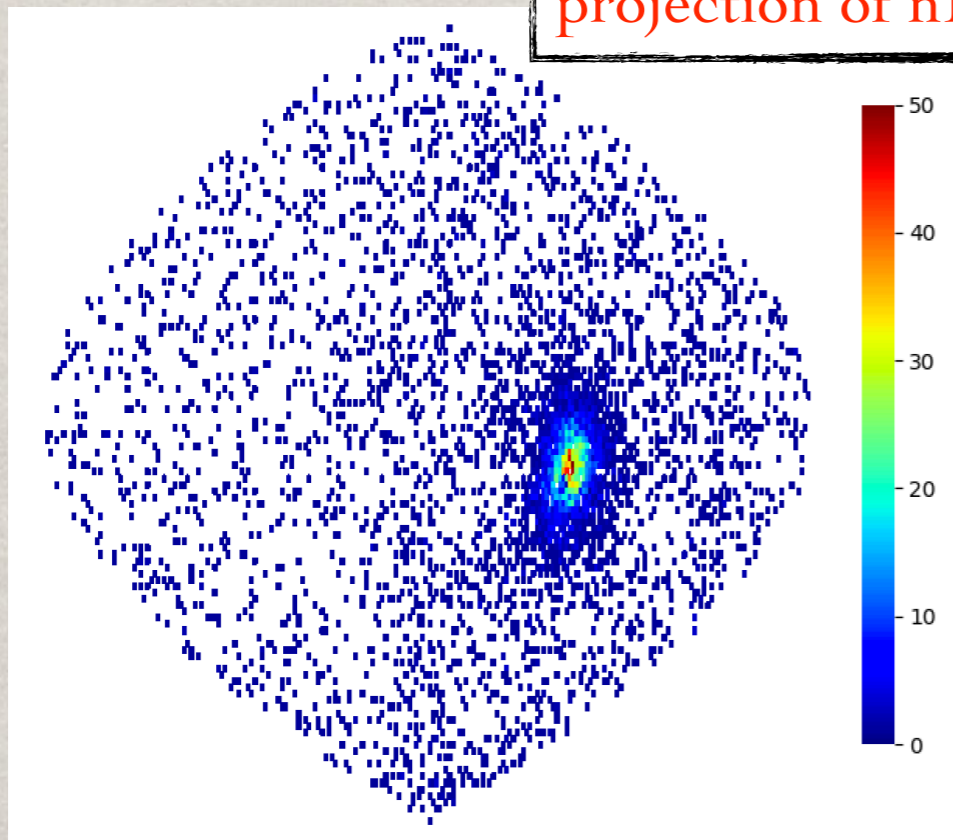
✿ Future optimization: data transfer, more levels, multi-GPUs,



# CASE 3: DEEP LEARNING

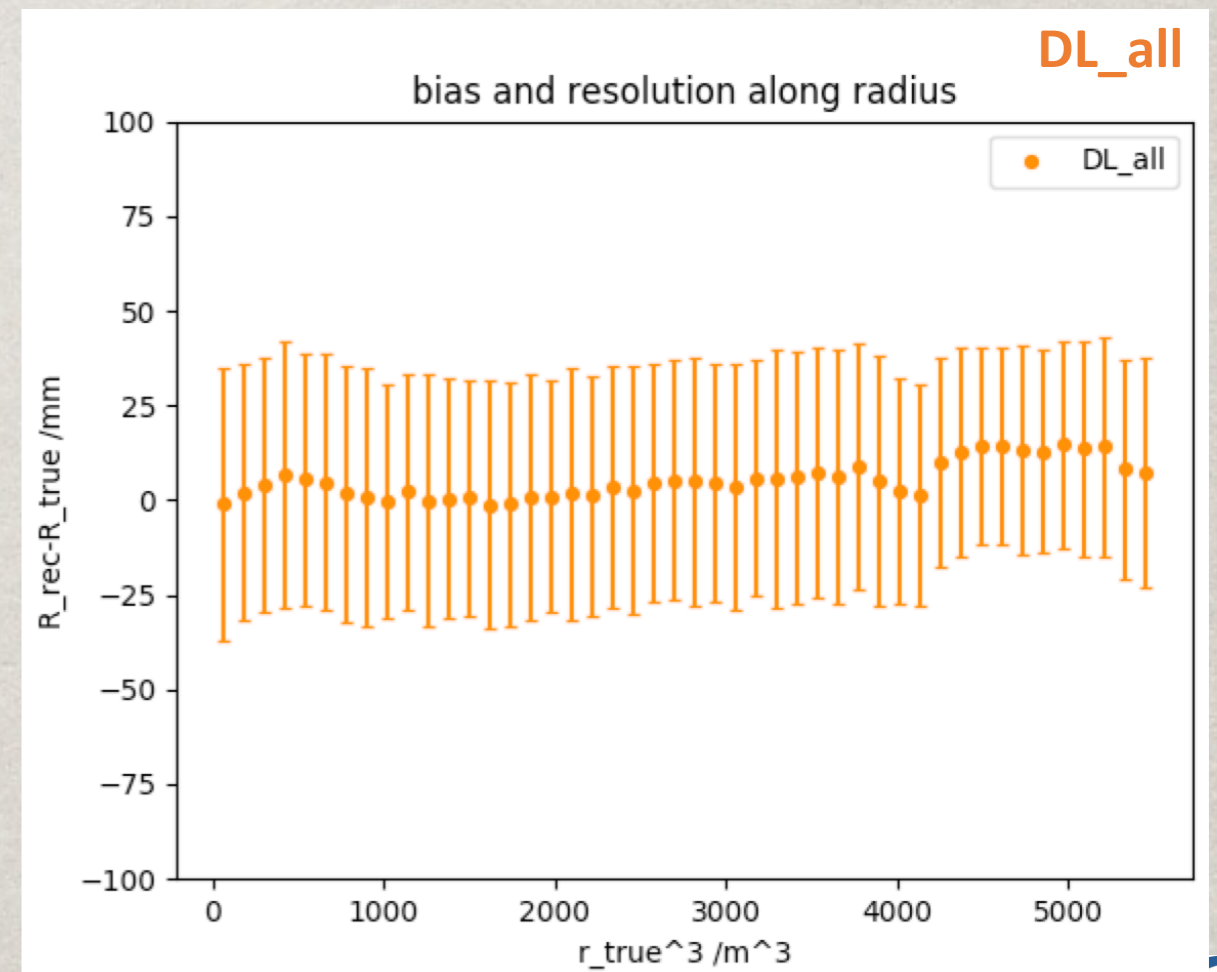
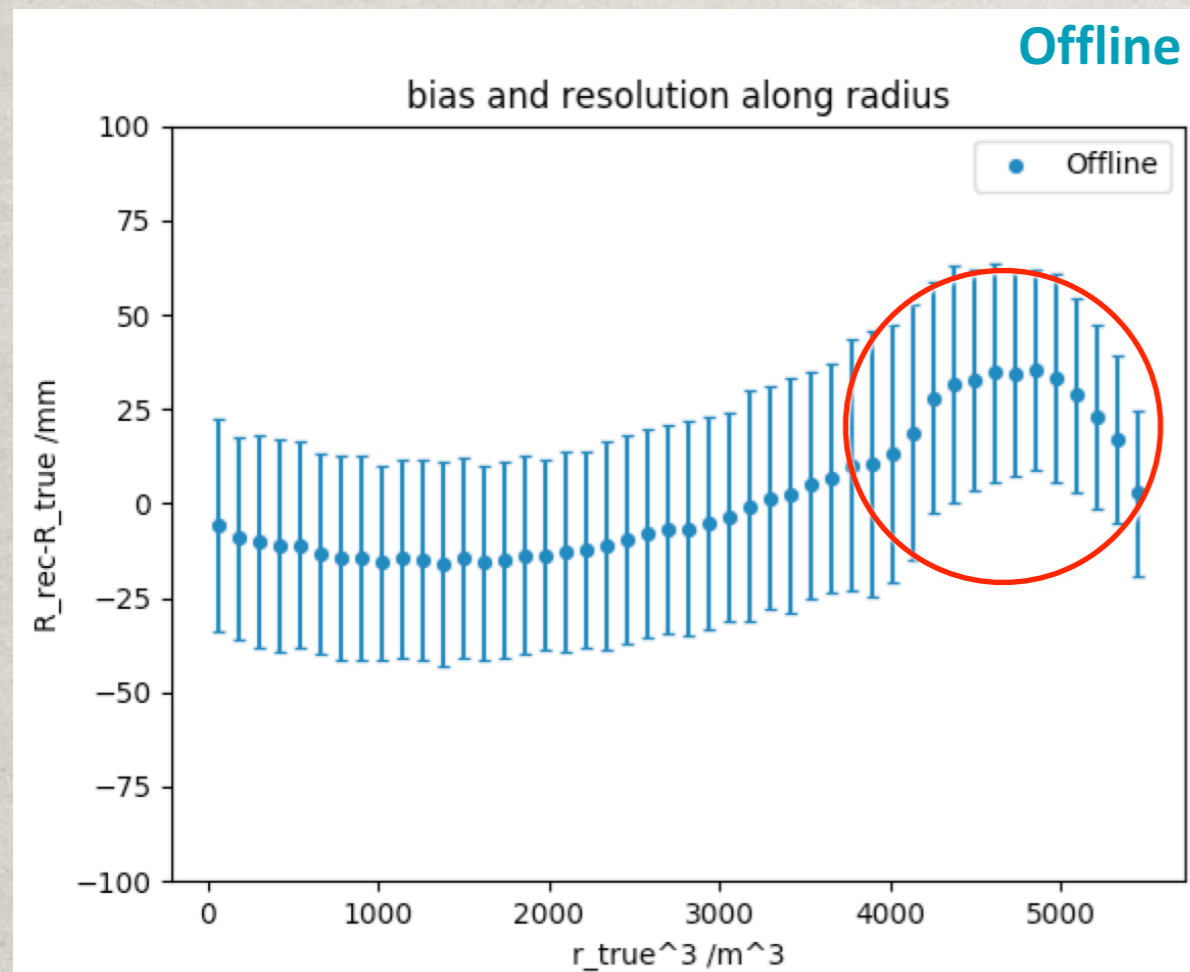
- ☀ GPU is widely used for DL
- ☀ Try Vertex Reconstruction with CNN in JUNO
- ☀ Input: hit time  $\{t_i\}$ , number of photoelectrons  $\{nPE_i\}$
- ☀ Output: event vertex  $(x, y, z)$

projection of nPE



# PERFORMANCE

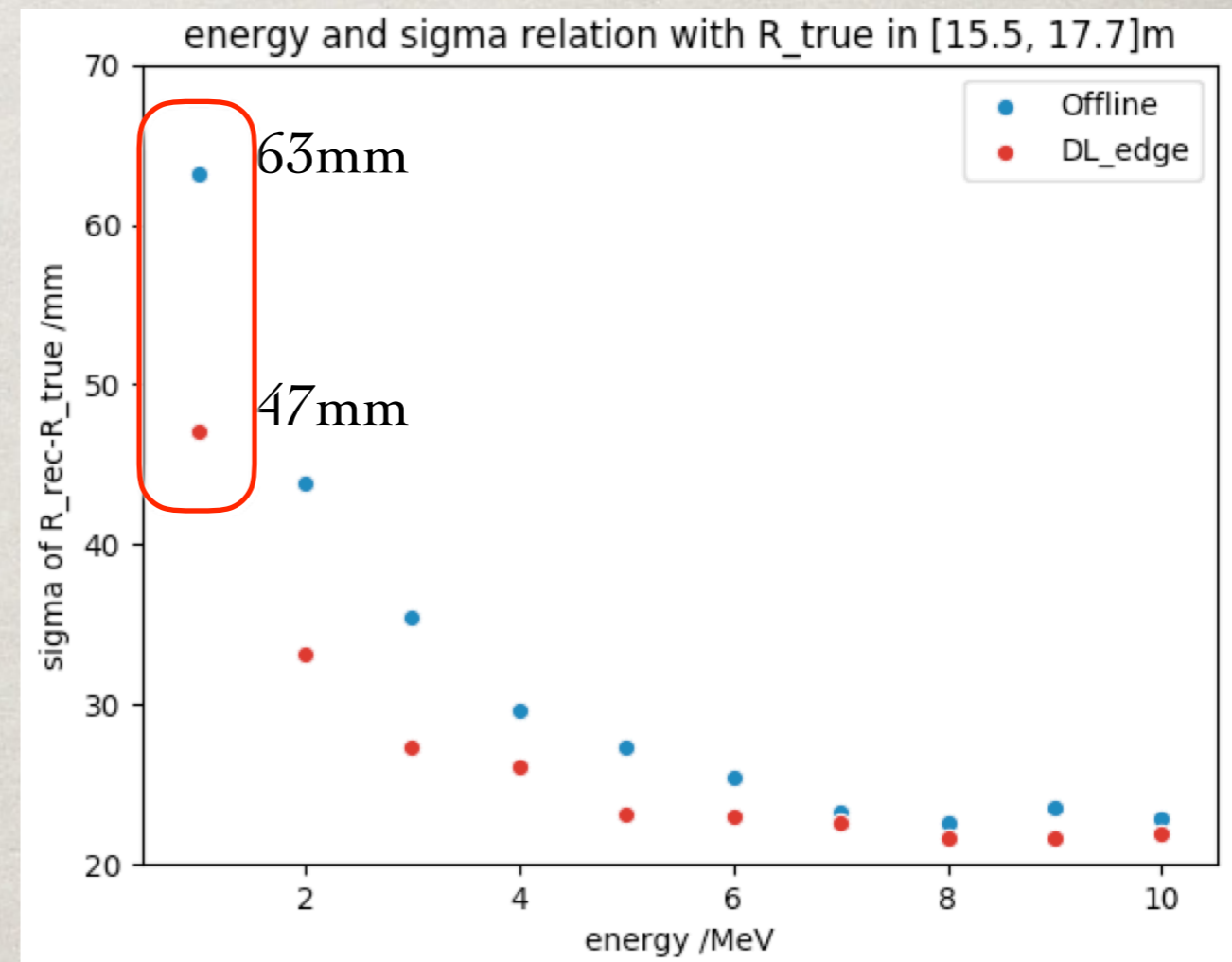
- ✿ Smaller Bias for DL w.r.t. traditional method
- ✿ Better uniformity for DL w.r.t. traditional method



# PERFORMANCE

## Resolution vs E

- ✱ For events near the detector edge, **total refraction** complicates the optical model
- ✱ Better resolution for DL w.r.t. traditional method using a specialized model



# DISCUSSION FOR DL

## ☼ Pros:

- ☼ fast speed, energy independent
- ☼ avoid the complex optical model

## ☼ Cons:

- ☼ rely heavily on **GOOD** Monte Carlo simulation

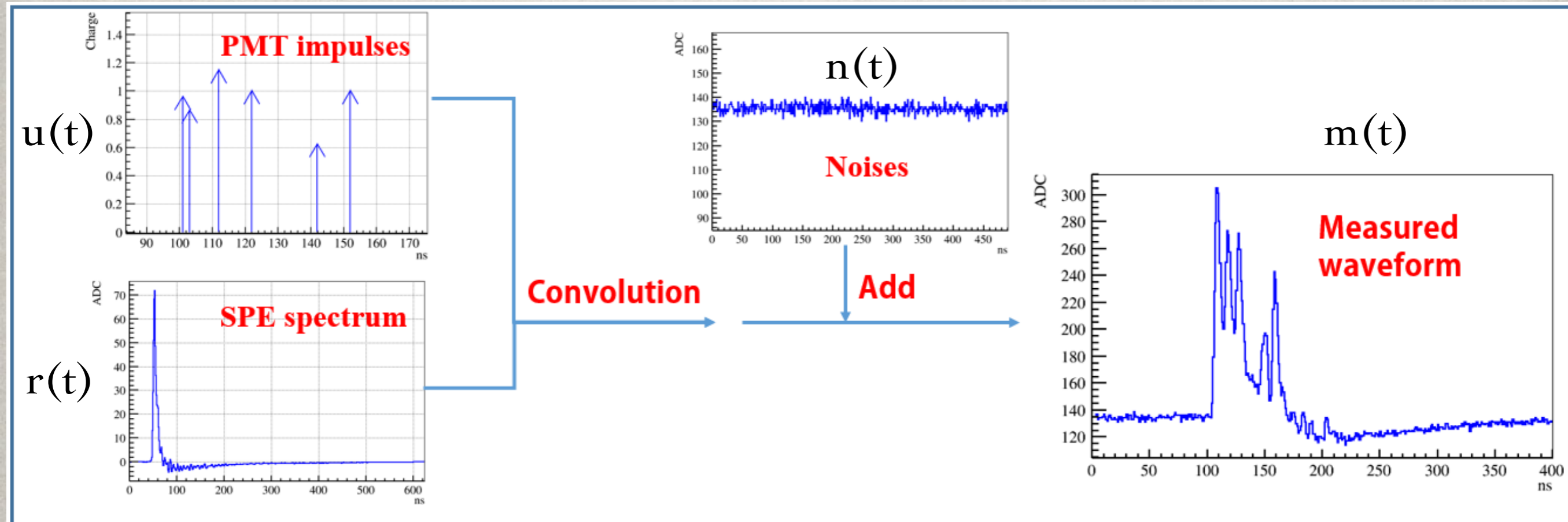
## ☼ Training samples

- ☼ MC: large statistics, might be different w.r.t. real data
- ☼ Calibration data: close to real data, limited stats.

## ☼ Possible solutions?



# PMT WAVEFORM REC



$$\ast m(t) = s(t) + n(t) = r(t) \ast u(t) + n(t)$$

- $\ast$  We need to reconstruct  $\{t_j\}$  and  $\{\text{charge}_j\}$  or ideally  $\{nPE_j\}$

# DL FOR WAVEFORM REC?

- ✱ FADC raw waveform  $\rightarrow$  Time series
- ✱ We know roughly what the feature looks like  $\rightarrow$  sPE response template
- ✱ We want to know  $\{t_j, Q_j(nPE_j)\}$  for all pulses
- ✱ We have PMT testing data  $\rightarrow$  real waveform
  - ✱ Issue: unsupervised, real labels unknown
- ✱ Analogies? Voice recognition? Suggestions?
- ✱ Try to answer simpler questions:
  - ✱ Q1: what is the first hit time?
  - ✱ Q 2: classify waveform to  $[0, 1, \geq 2]$ PE three categories



# SUMMARY

- ✱ JUNO has  $\sim O(10^5)$  PMTs, perfectly suitable for utilizing GPU
- ✱ Showed a few simple applications of GPU in JUNO
  - ✱ Vertex reconstruction, Muon simulation, Deep Learning
  - ✱ Large room for further improvements
- ✱ Could be used in other aspects of JUNO
- ✱ Huge potential for experiments with lots of PMTs



**BACKUP**



# TOOLS

- ☼ CUDA
- ☼ Thrust
- ☼ TensorFlow

|      | multi-processors | CUDA<br>cores | ram(GB) |
|------|------------------|---------------|---------|
| K40m | 15               | 2880          | 12      |
| V100 | 80               | 5120          | 32      |

