GPU APPLICATION IN JUNO

WUMING LUO

ON BEHALF OF

THE JUNO COLLABORATION

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ADELAIDE, AUSTRALIA

中国科学院高能物理研究所

Institute of High Energy Physics

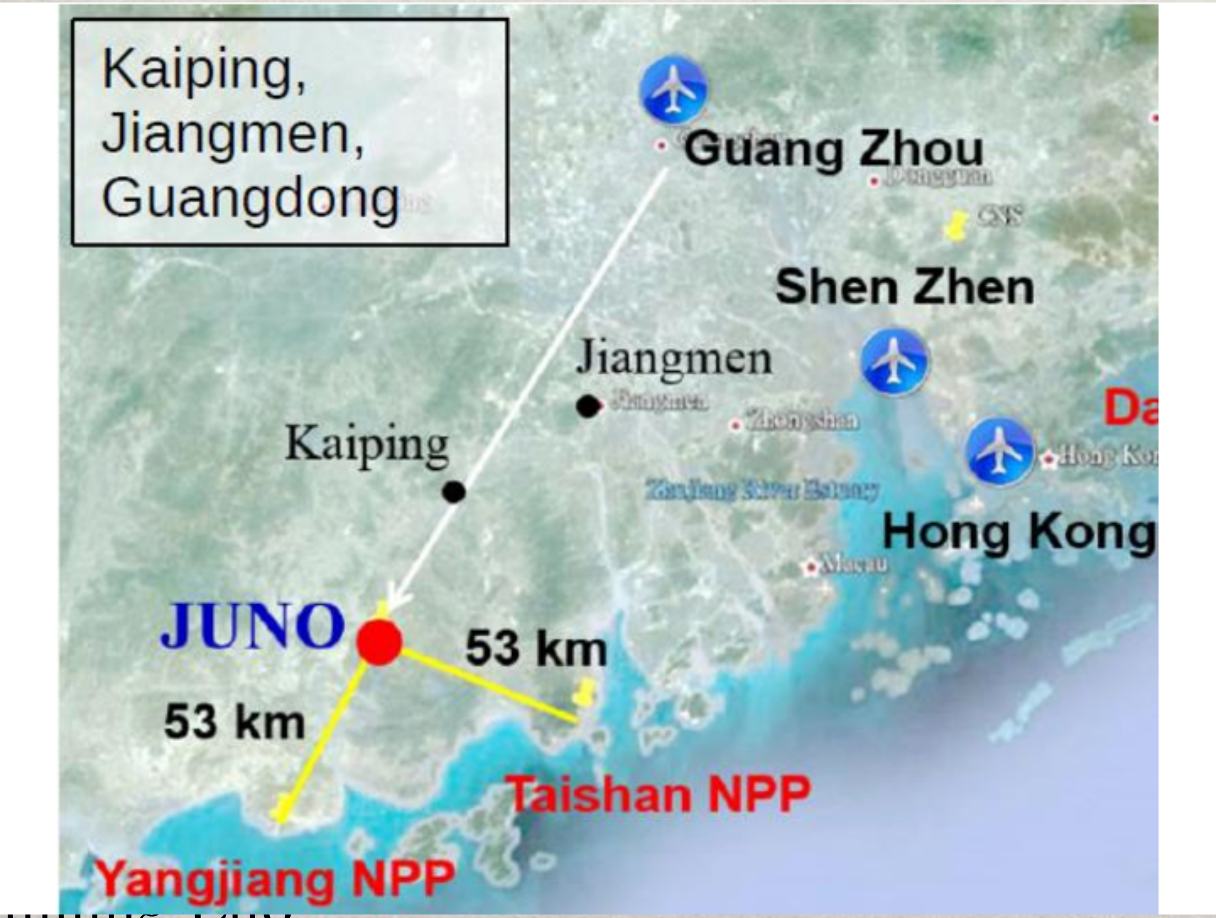
Chinese Academy of Sciences

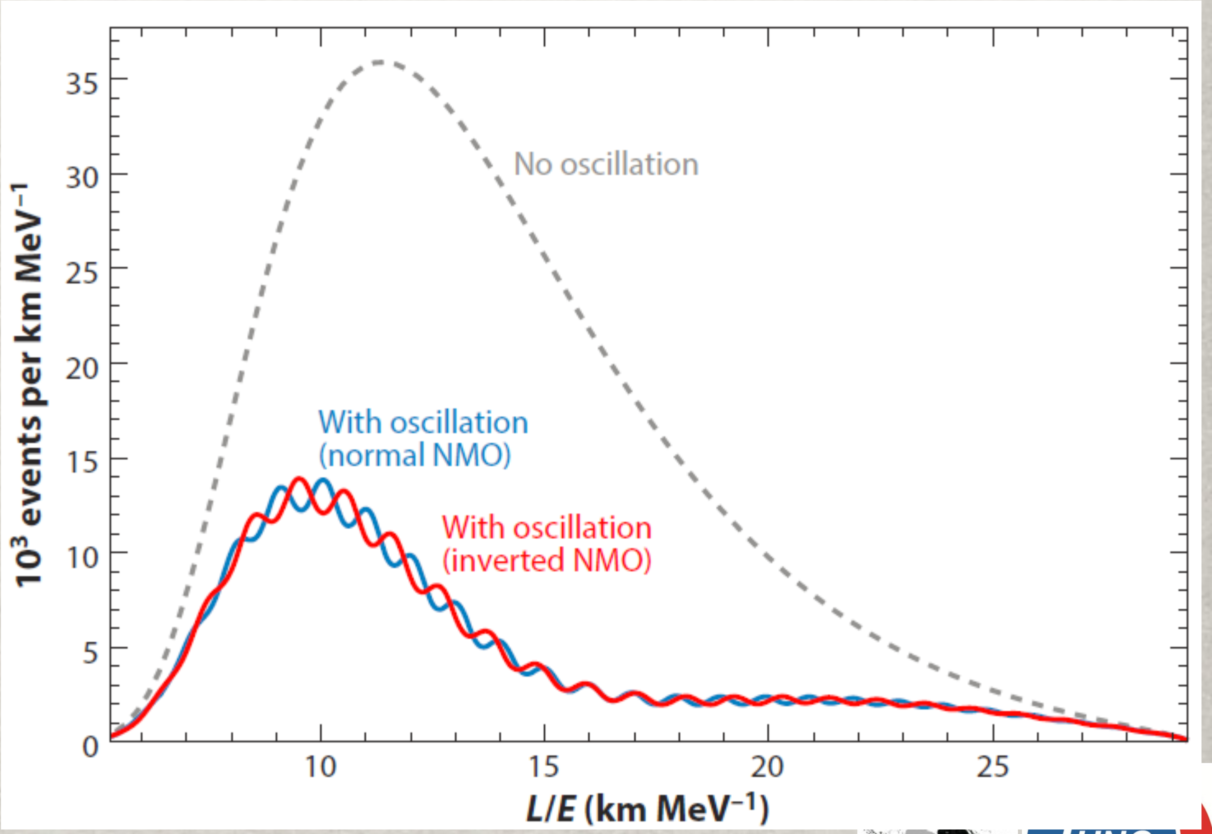
OUTLINE

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

JUNO

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





DETECTOR

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

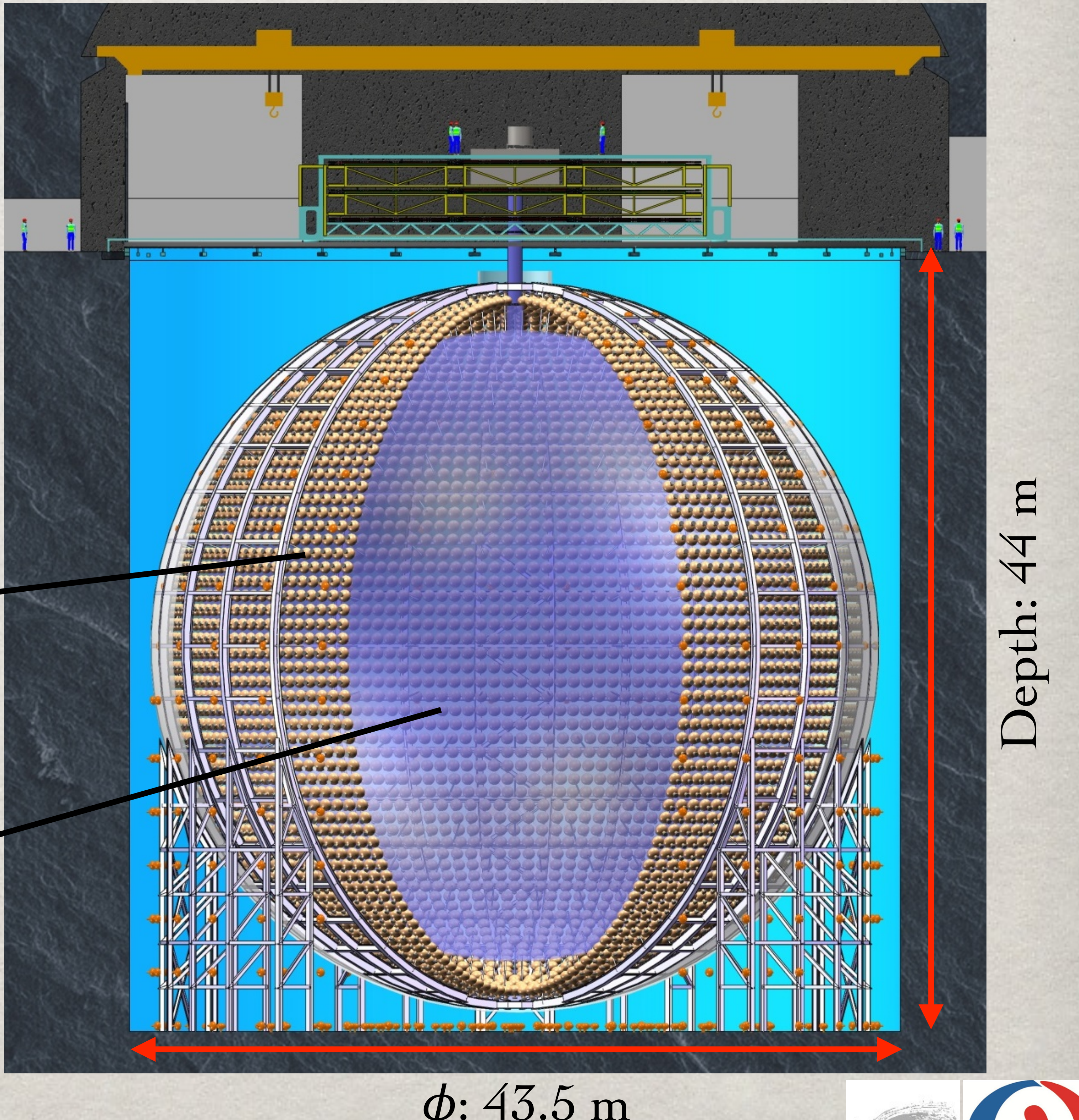
Central Detector PMT

~18,000 20" PMTs

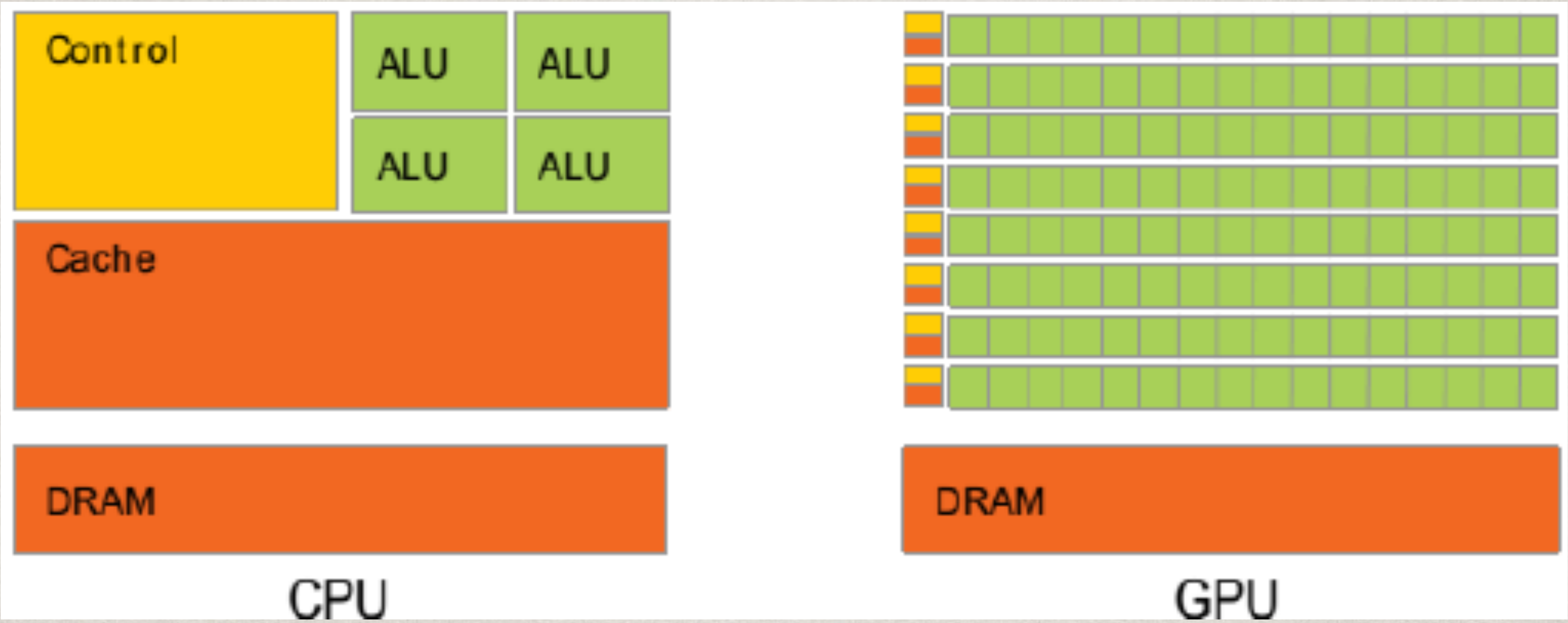
+ ~25,000 3" PMTs

Liquid Scintillator

20 kton



GPU VS CPU



Large Cache

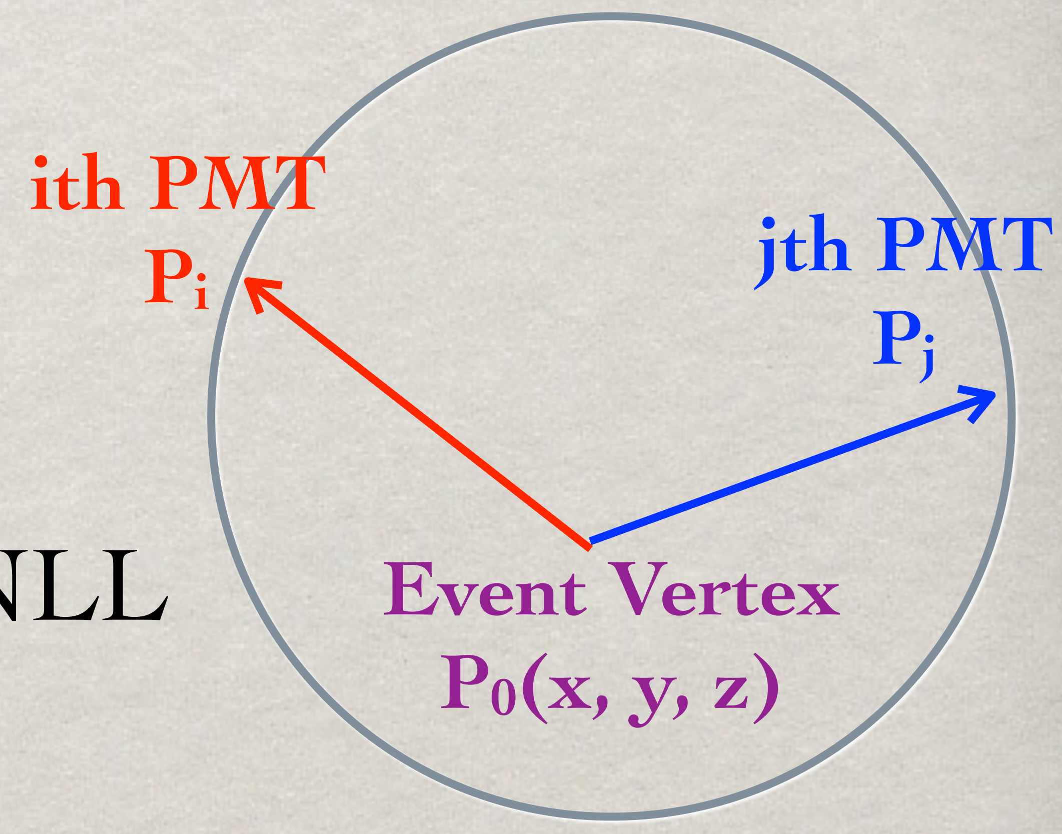
Optimized for serial operations

Many cores

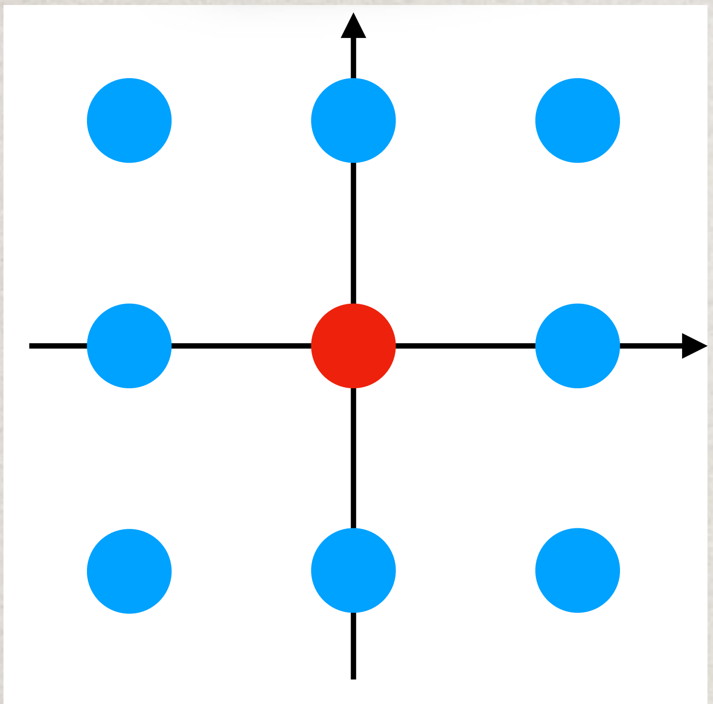
Built for parallel operations

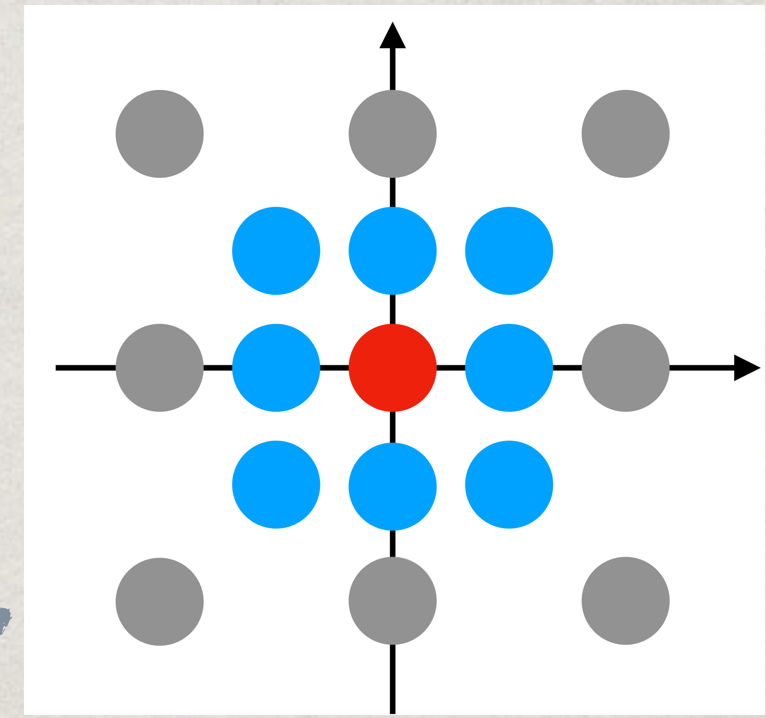
CASE 1: VERTEX RECONSTRUCTION

- Parameters to reconstruct: x, y, z, 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 PMT
  - t_{tof} : time of flight
  - t_0 : event start time
  - f_{res} : pdf of residual time
- Scan 4D grid to minimize the NLL

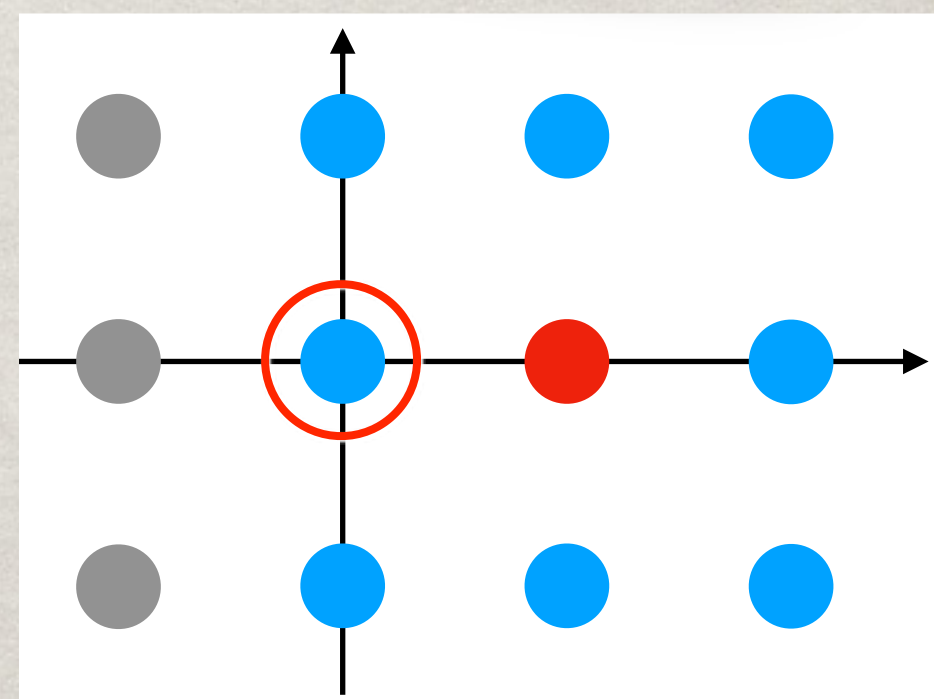


GRID SEARCH — 2D





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



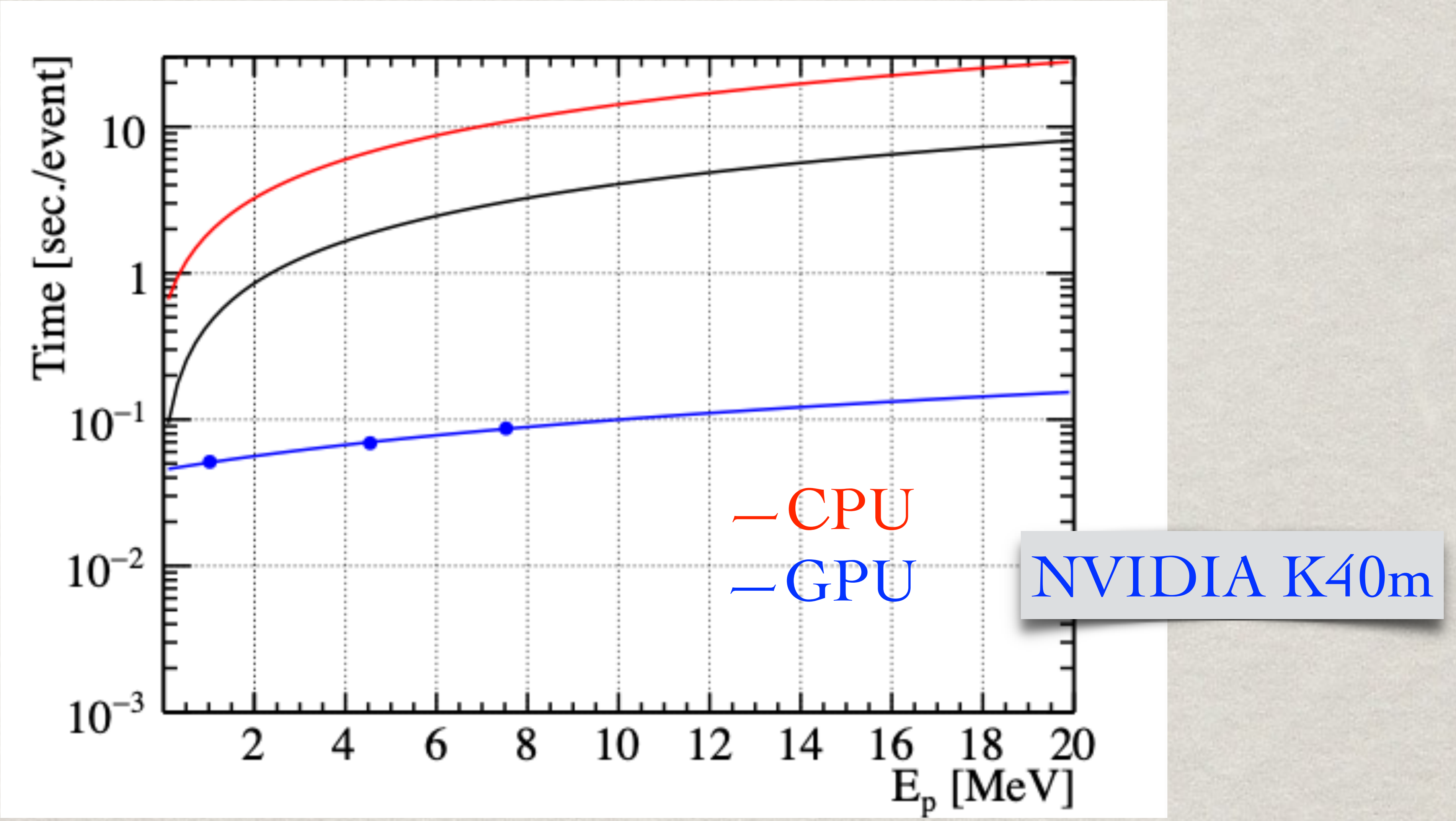
PARALLELIZATION ON GPU

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

ON CPU

- 4D Grid Search
- Number of loops: x-dim*y-dim*z-dim*t-dim*n_fired_PMTs = 3*3*3*9*1200/MeV = $3*10^5$/MeV
- Parallelize the calculations on GPU

PERFORMANCE

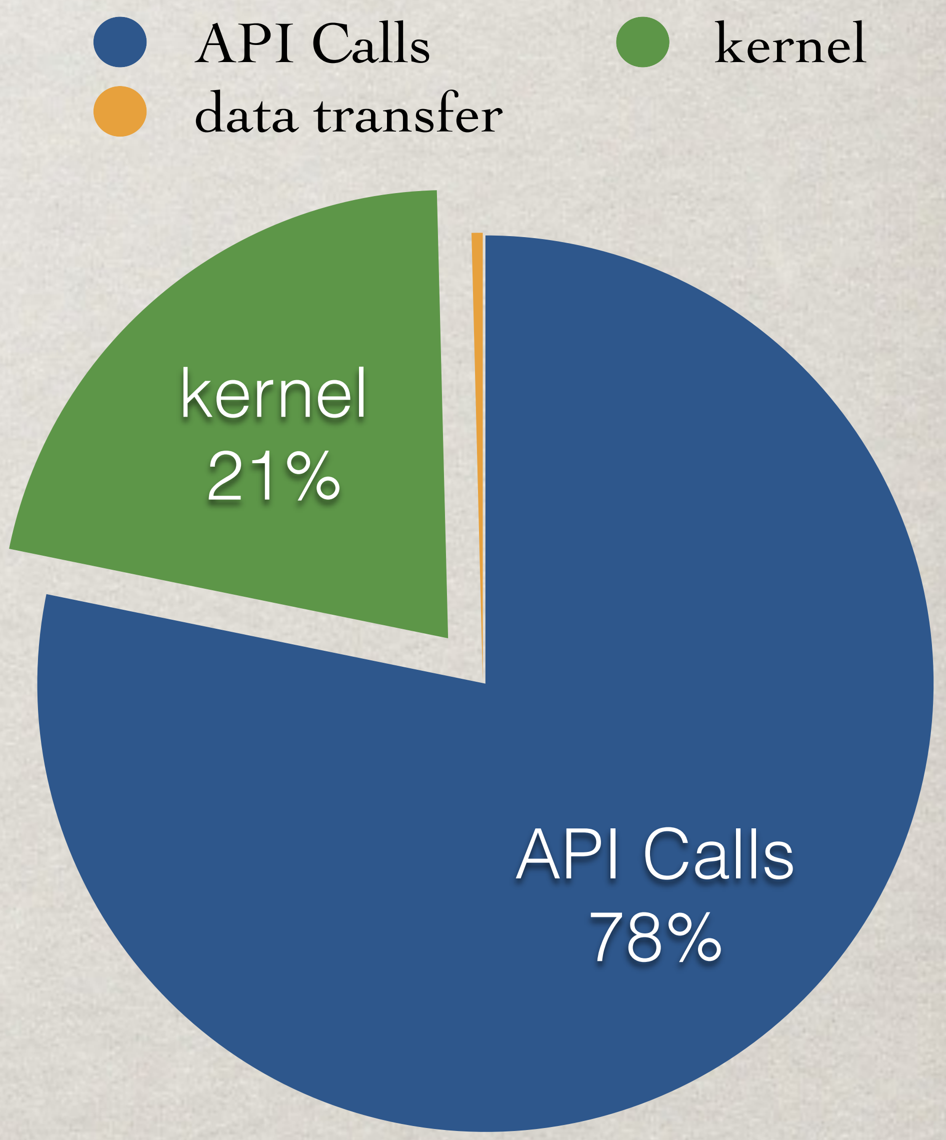


	CPU	GPU	Ration: CPU/GPU
Time@1MeV(s)	1.88	0.05	~40
Time@10MeV(s)	14.19	0.095	~150
Gradiant	1.37	0.005	—

DISCUSSION

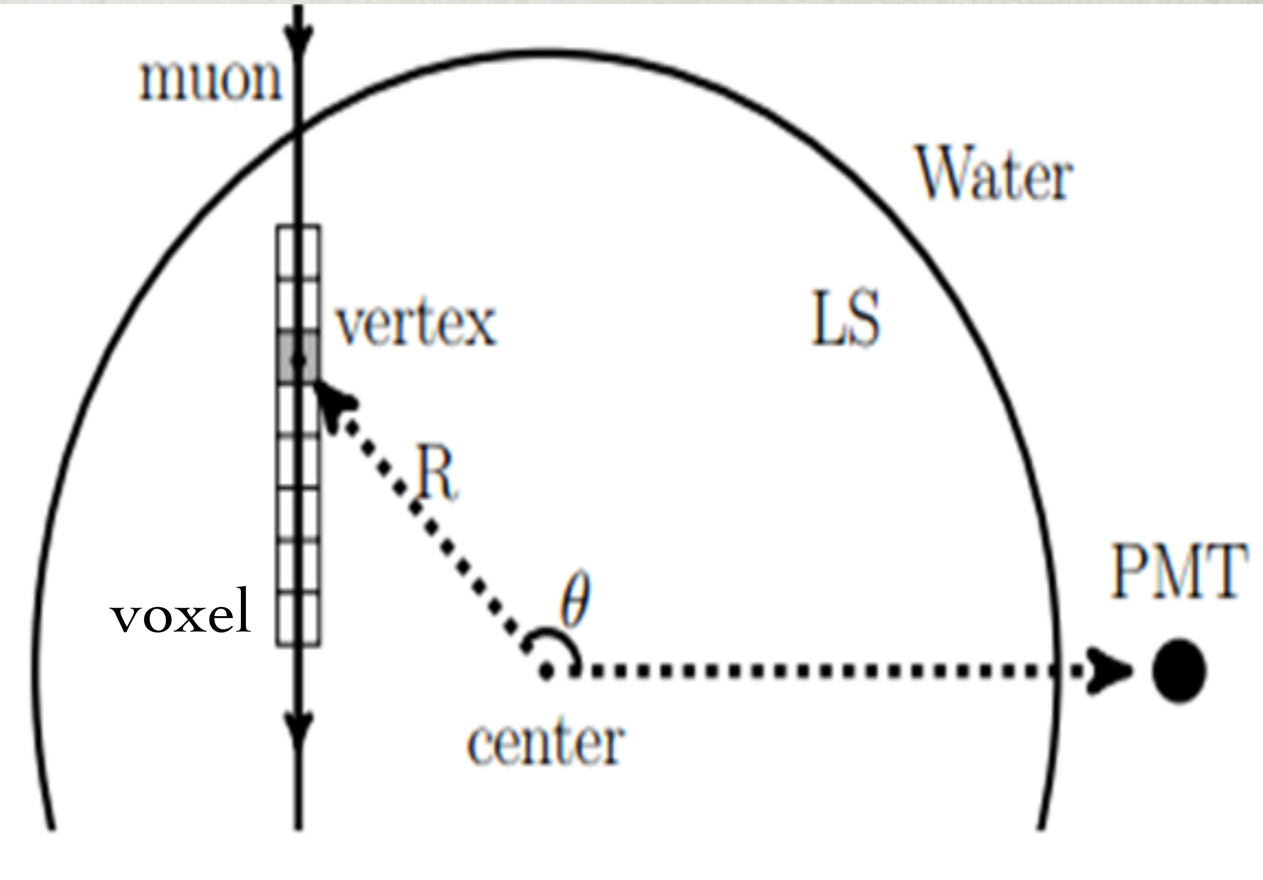
- Memory allocation and free, Synchronization etc… take up most of the time, room for future optimization
- Potential improvement with multiple GPUs
- Instead of Grid Search, divide the detector ROI to tiny units and parallelize with GPU(s)

NVIDIA K40m



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, θ), sampling nPE and $\{t_i\}$ from templates

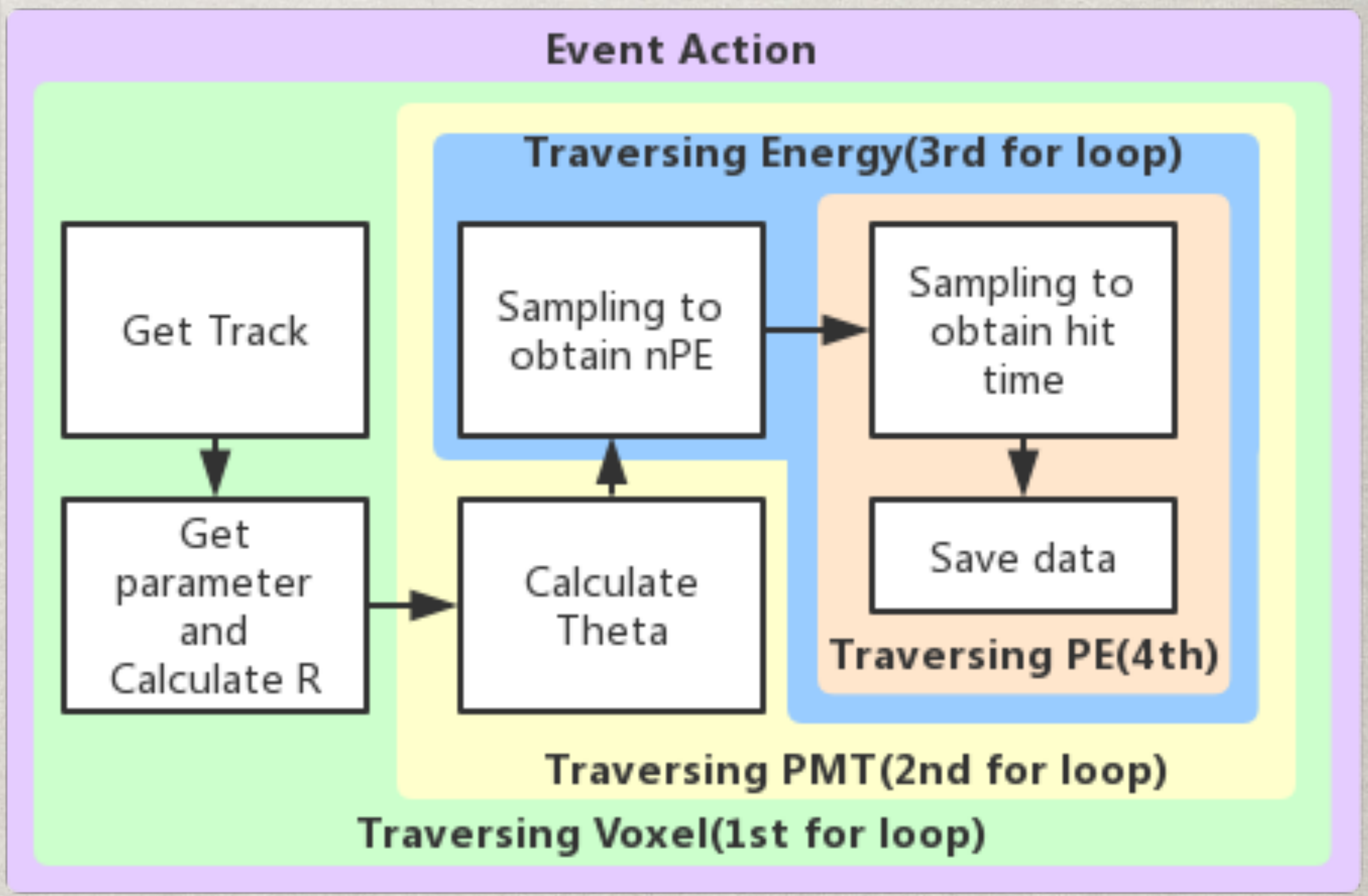


COMPUTATION FLOW

for(R){ // Voxel loop
    for(θ){ // PMT loop
        for(E){ // E loop
            for(nPE){
                sample t_i
            }
    …
}

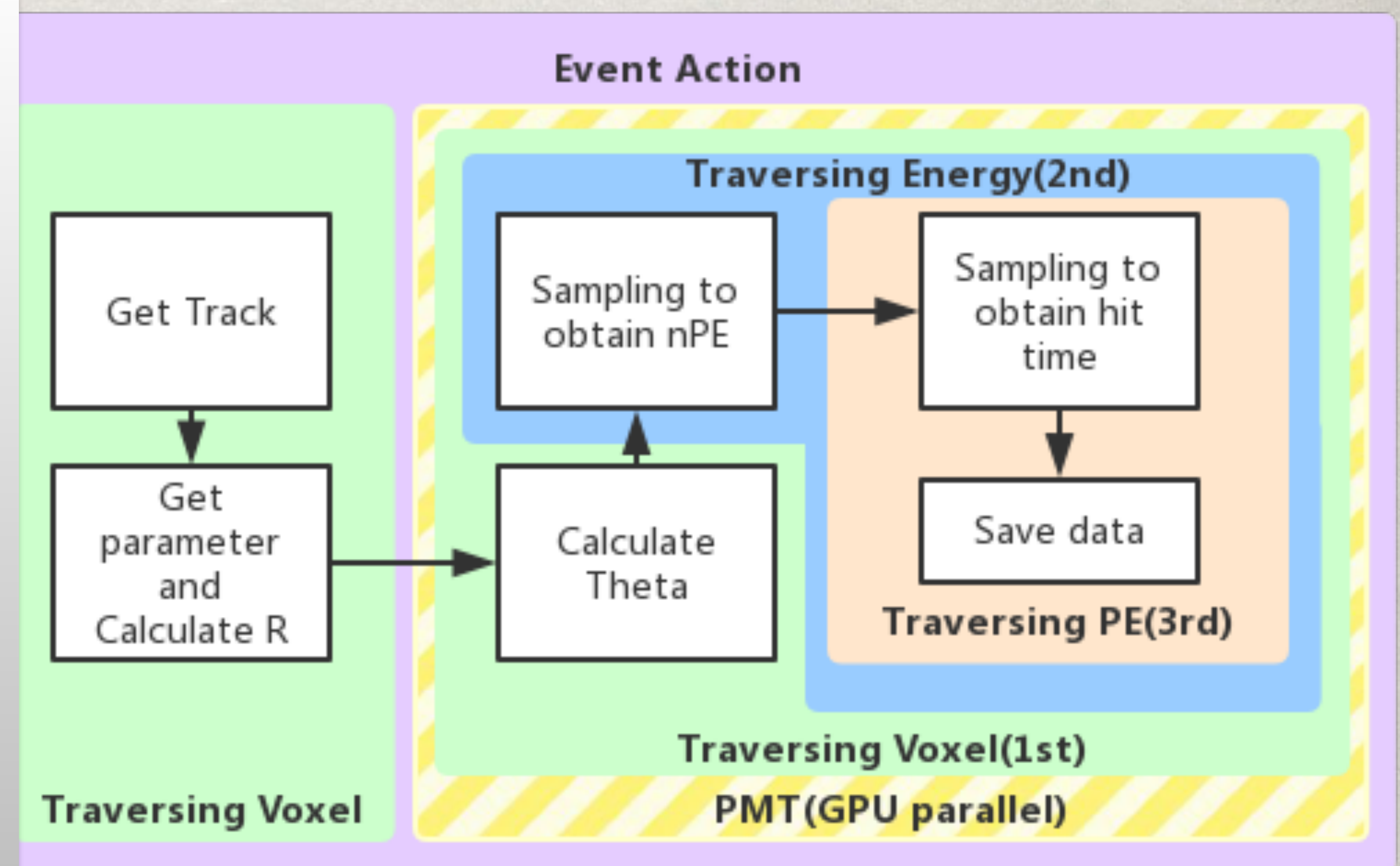
ON CPU

~18,000 PMTs



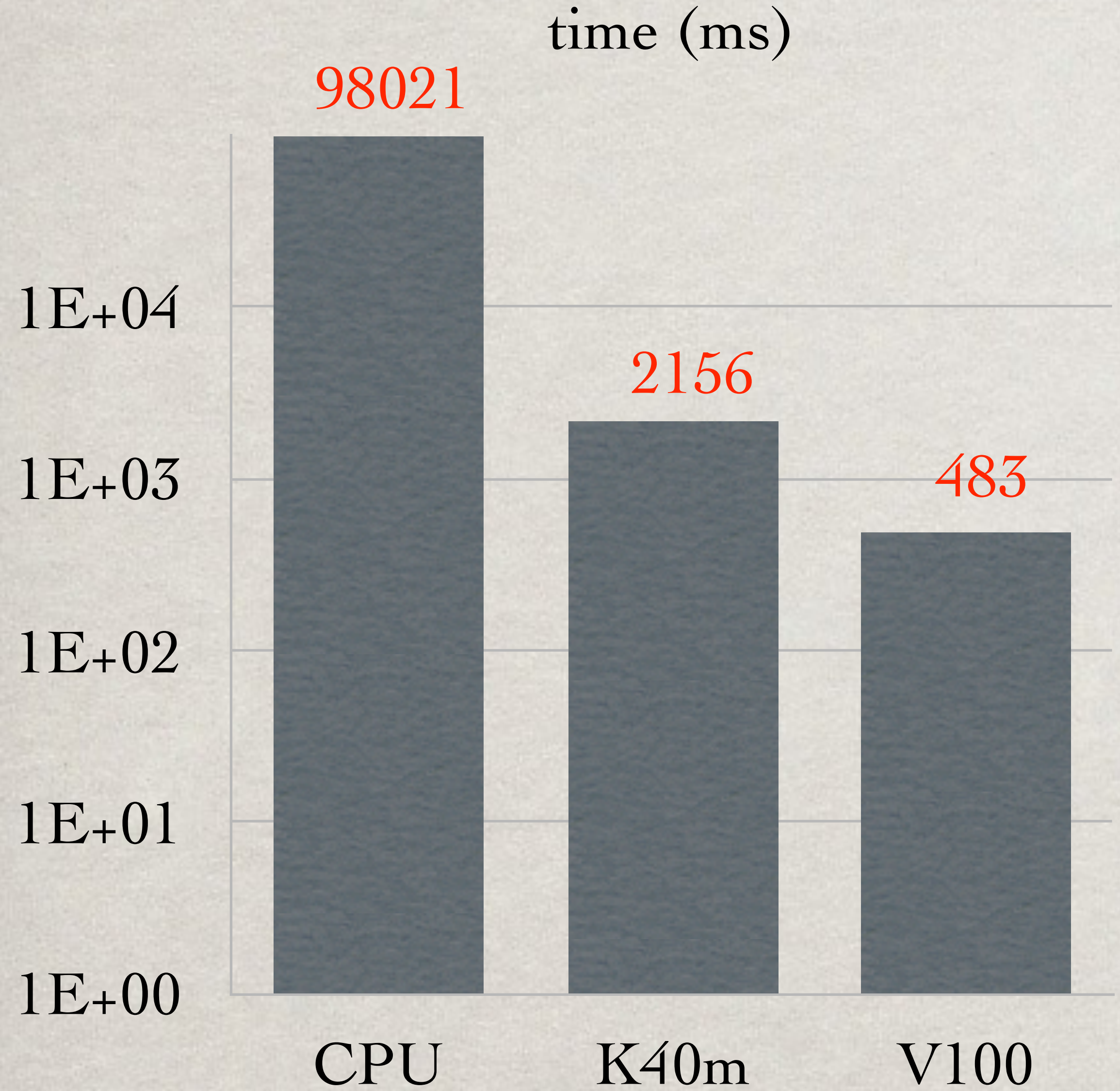
COMPUTATION FLOW

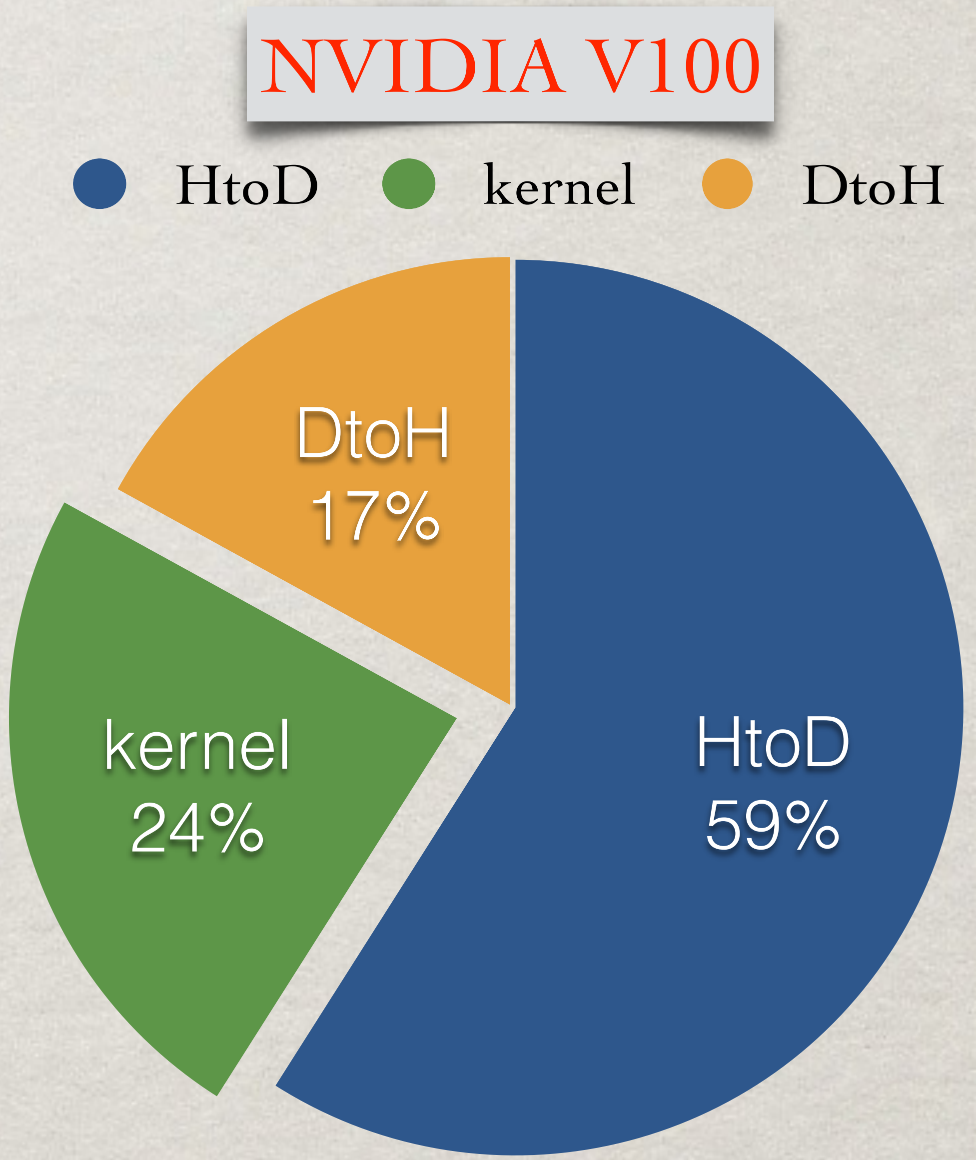
for(θ){ // PMT loop
    for(R){ // Voxel loop
        for(E){ // E loop
            for(nPE){
                sample t_i
            }
    …
}



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

PERFORMANCE





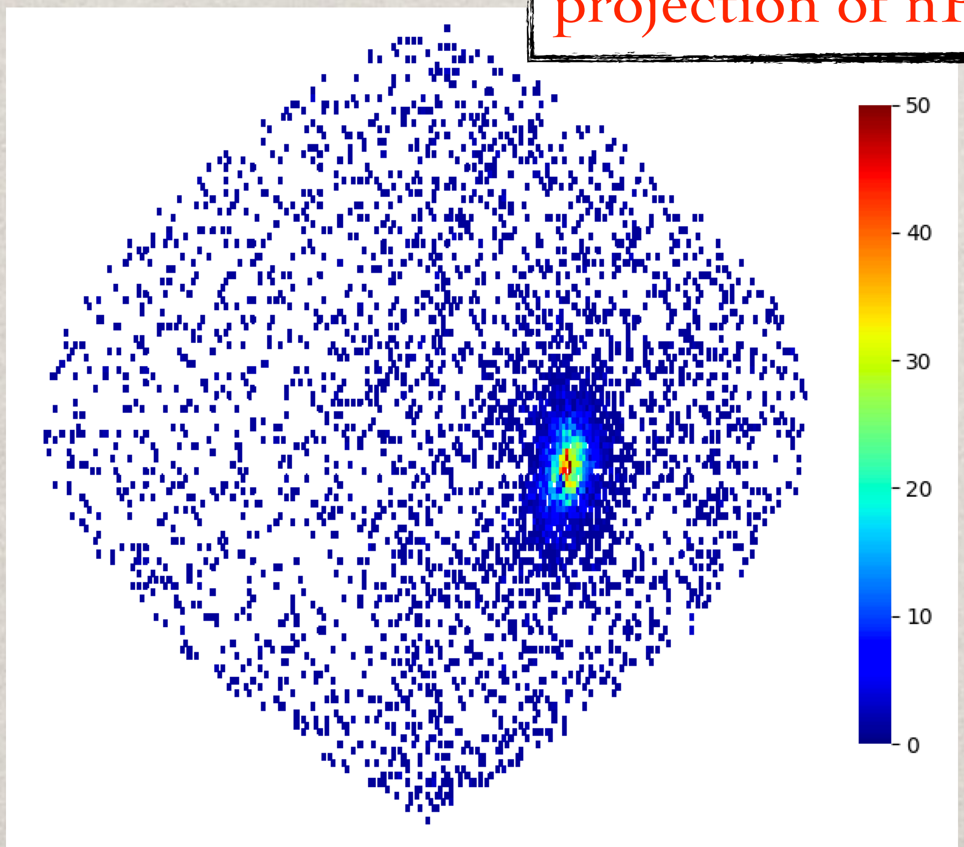
- O(10²) improvement with V100
- Future optimization: data transfer, more levels, multi-GPUs,

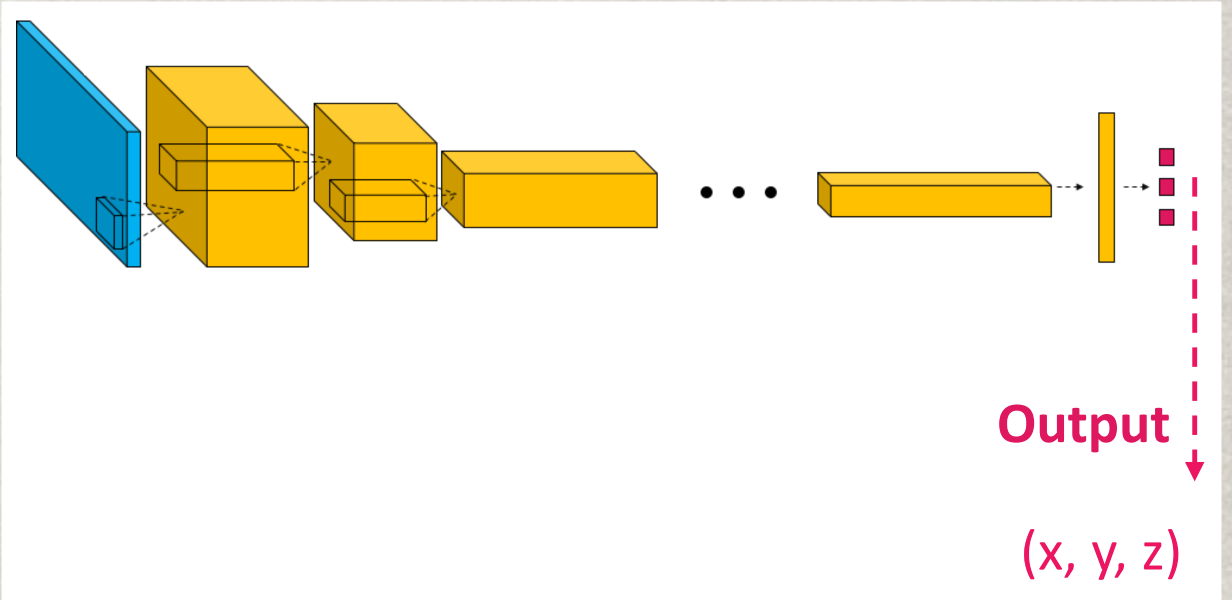
CASE 3: DEEP LEARNING

*see Yury Malyshkin's talk

- 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



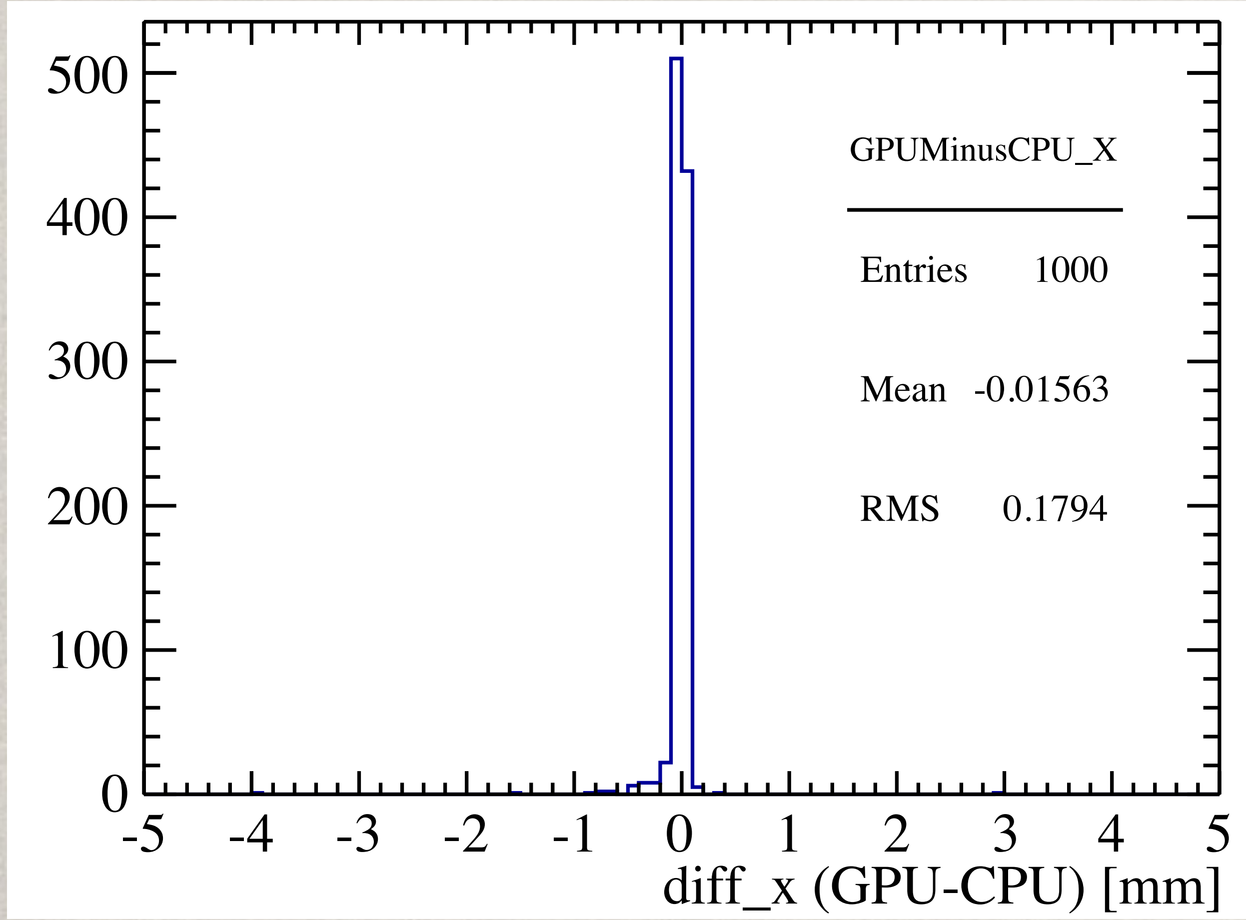


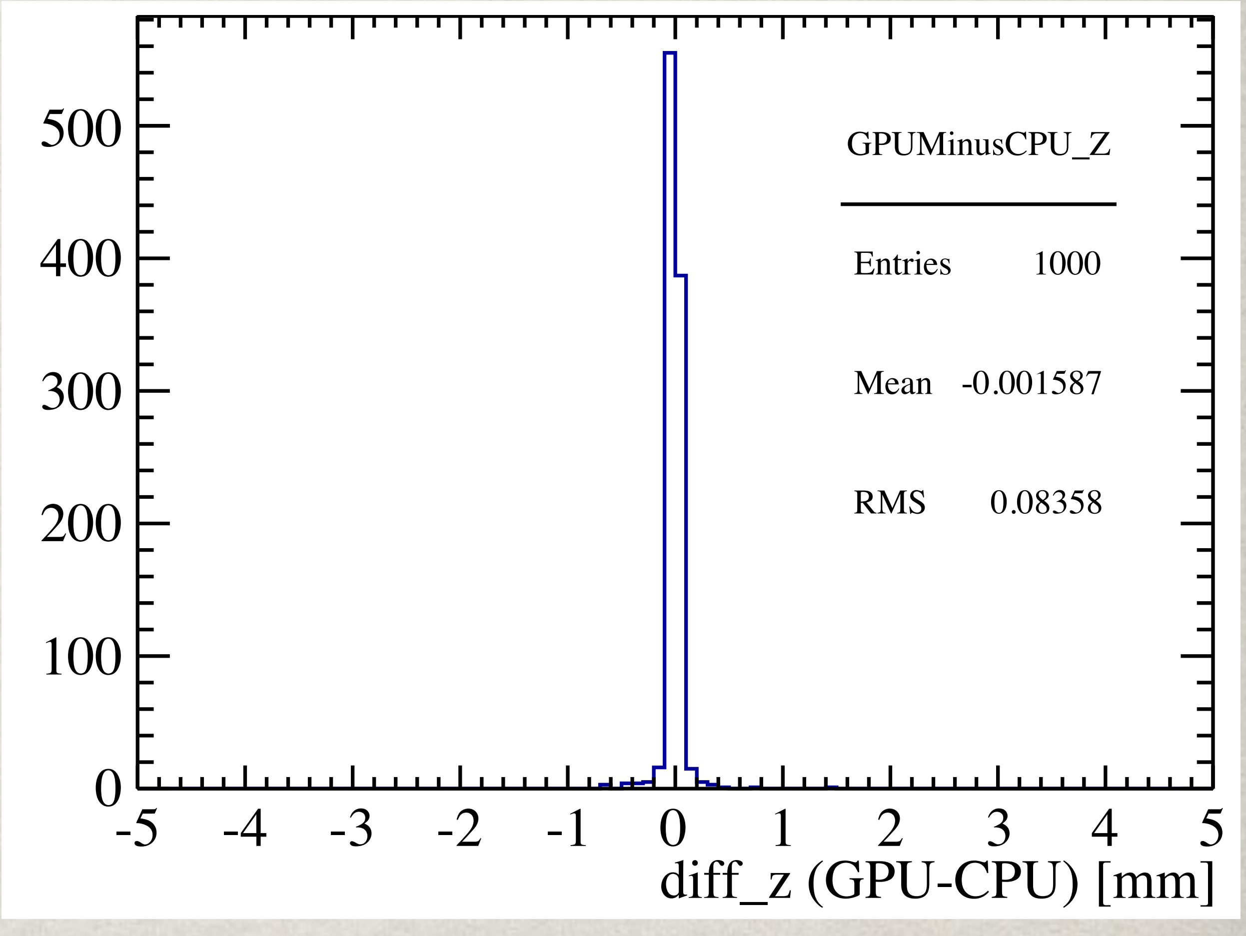
SUMMARY

- JUNO has ~O(10^5) PMTs, perfectly suitable for utilizing GPU
- Showed a few applications of GPU in JUNO
  - Vertex reconstruction/Muon simulation/Deep Learning*
  - Room for further improvements
- Could be used in other aspects of JUNO
- Huge potential for experiments with lots of PMTs

BACKUP

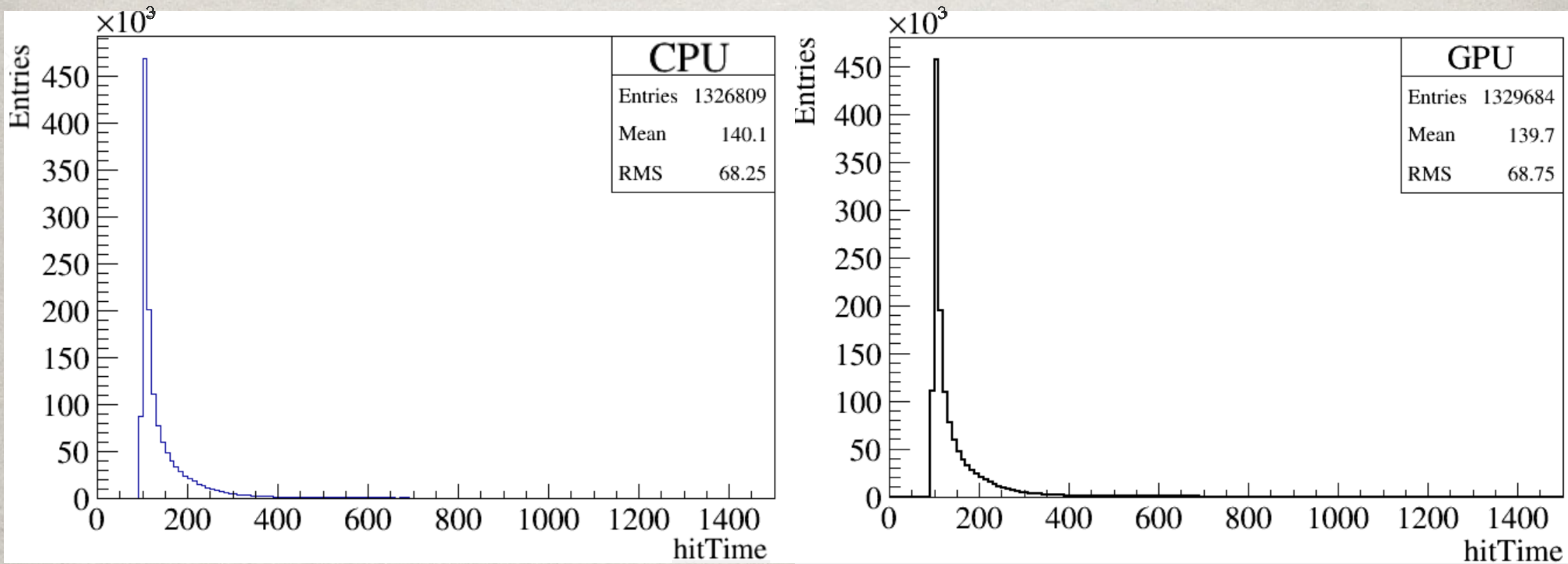
VALIDATION





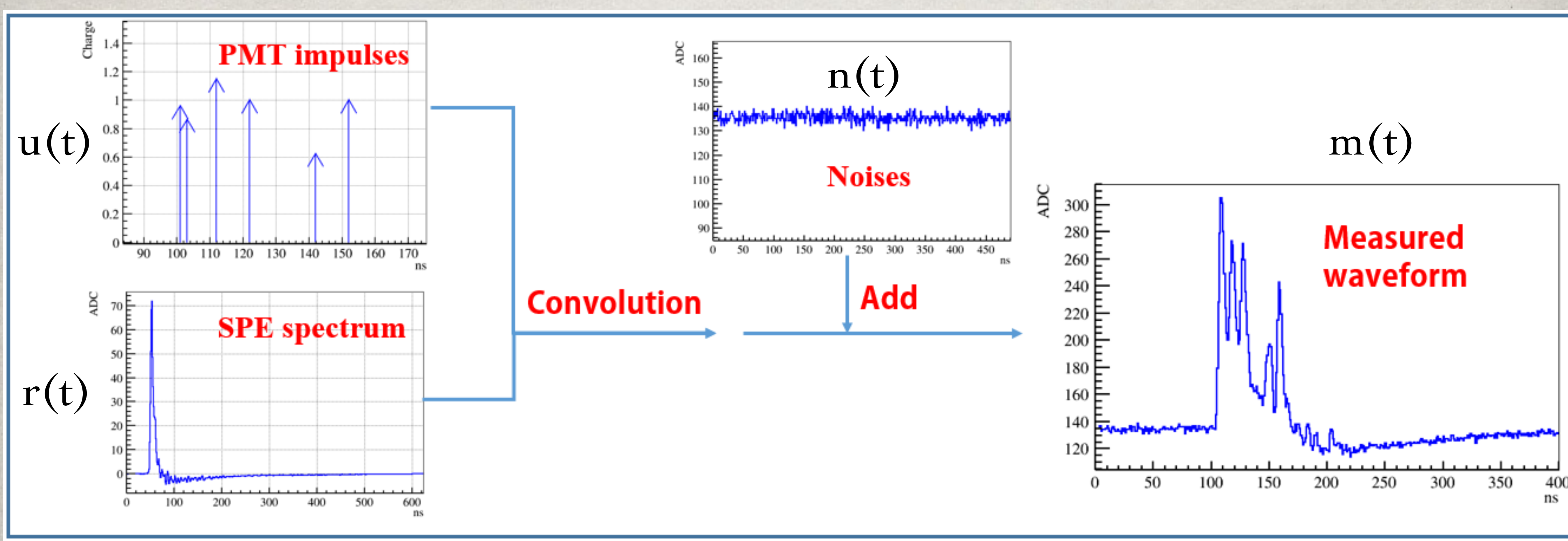
- GPU Rec was able to reproduce the CPU Rec results
- Tiny difference, negligible w.r.t. vertex resolution (60mm)

VALIDATION



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

PMT WAVEFORM REC



- $m(t) = s(t) + n(t) = r(t) * u(t) + n(t)$
- We need to reconstruct $\{t_j\}$ and $\{charge_j\}$ or ideally $\{nPE_j\}$

DL FOR WAVEFORM REC?

- FADC raw waveform —> Time series
- We know roughly what the feature looks like —> sPE response template
- We want to know $\{t_j, Q_j(nPE_j)\}$ for all pulses
- We have PMT testing data —> 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, ≥2]PE three categories

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?

TOOLS

- CUDA
- Thrust
- TensorFlow

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