2023 NCHC Hackathon - Final Report
TXM-AI-Group

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Team Mentor：

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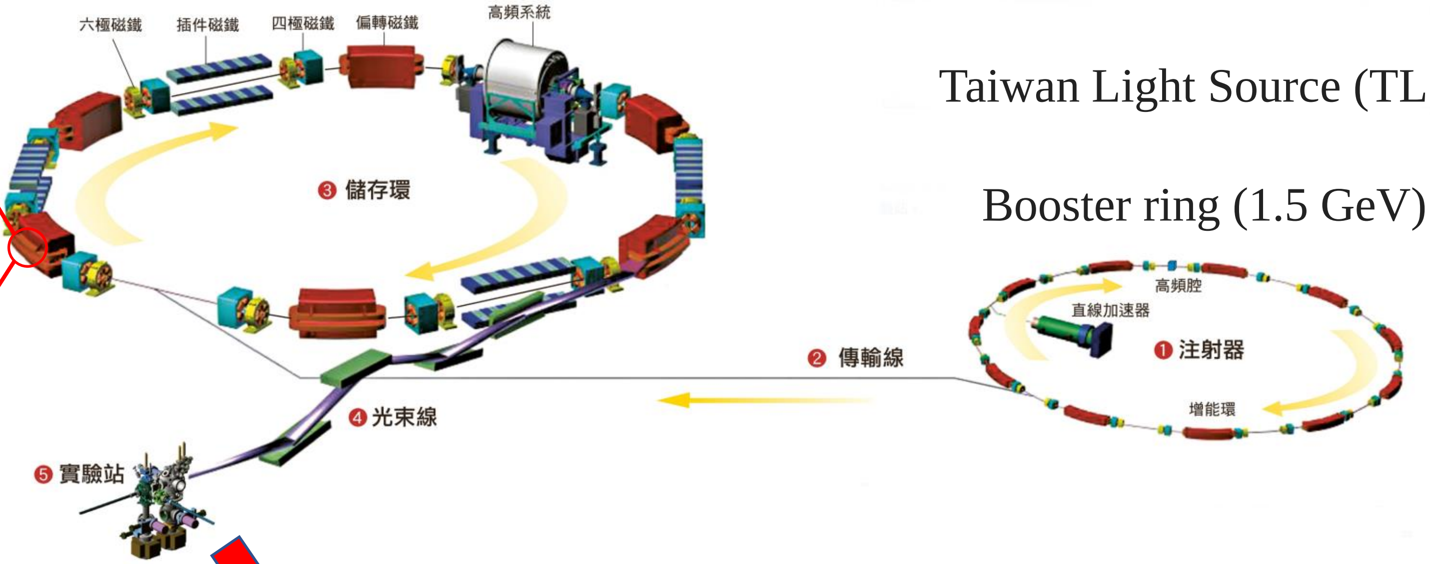
X-ray Background Correction Model

Medical CT	X-ray Micro-CT (PXM)	X-ray Nano-CT (TXM)
	 	
Low Resolution (100 μm) Large 3D volume (whole body)	Middle Resolution (1 μm) Middle 3D volume (centimeter^3)	High Resolution (60 nm) Small 3D volume (15x15x15 μm^3)

Low — Resolution — High

Large — Volume — Small

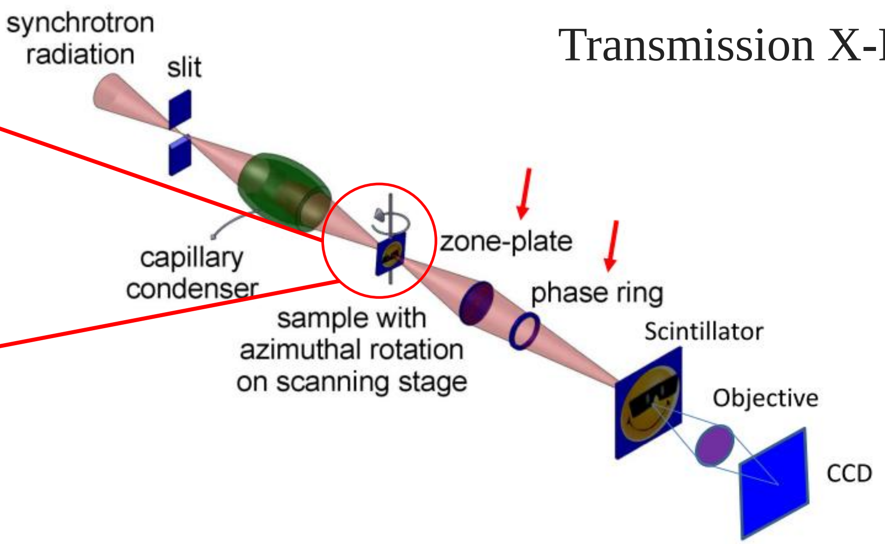
X-ray Background Correction Model



Taiwan Light Source (TLS)

Booster ring (1.5 GeV)

Transmission X-Ray Microscope (TXM)



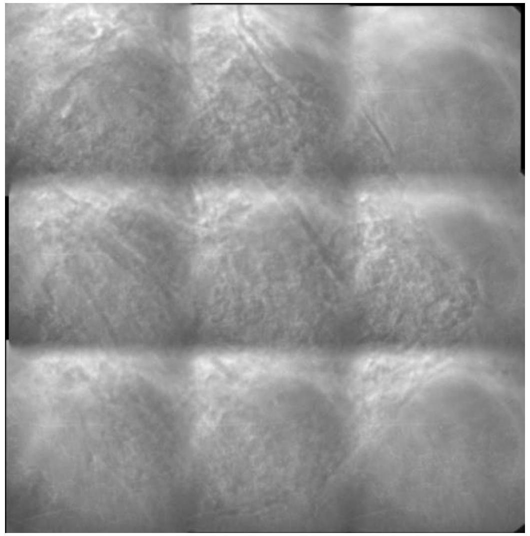
OPEN HACKATHONS

X-ray Background Correction Model

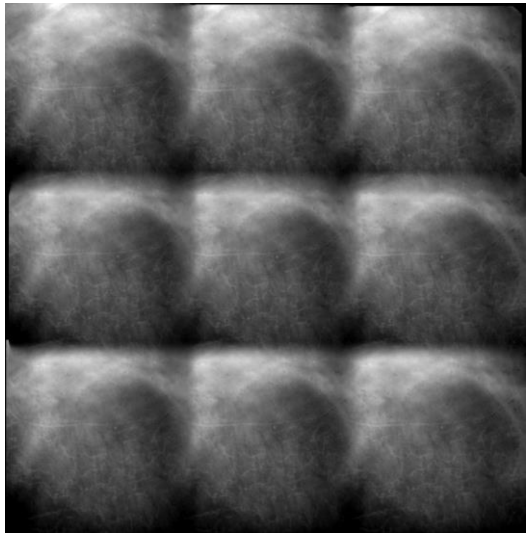
- Problem trying to solve

1. Uneven light sources cause blurriness in sample images, necessitating extra time for capturing background images for correction.
2. This method is time-consuming, especially when capturing large area images, making it challenging to obtain ideal background images.

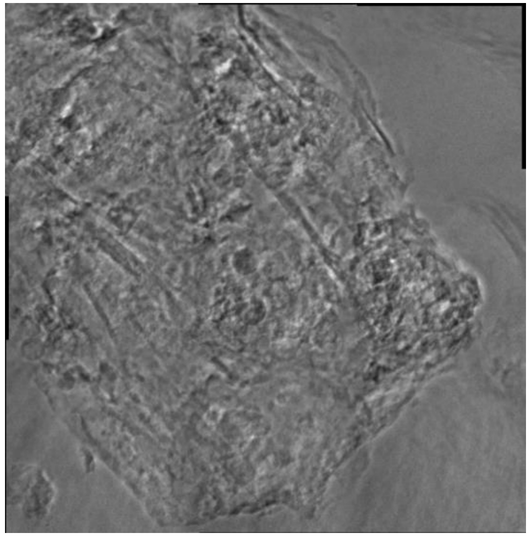
Raw image



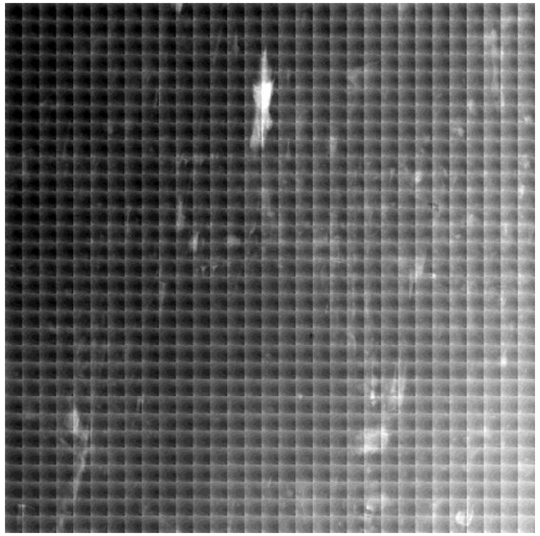
Background image



De-background image

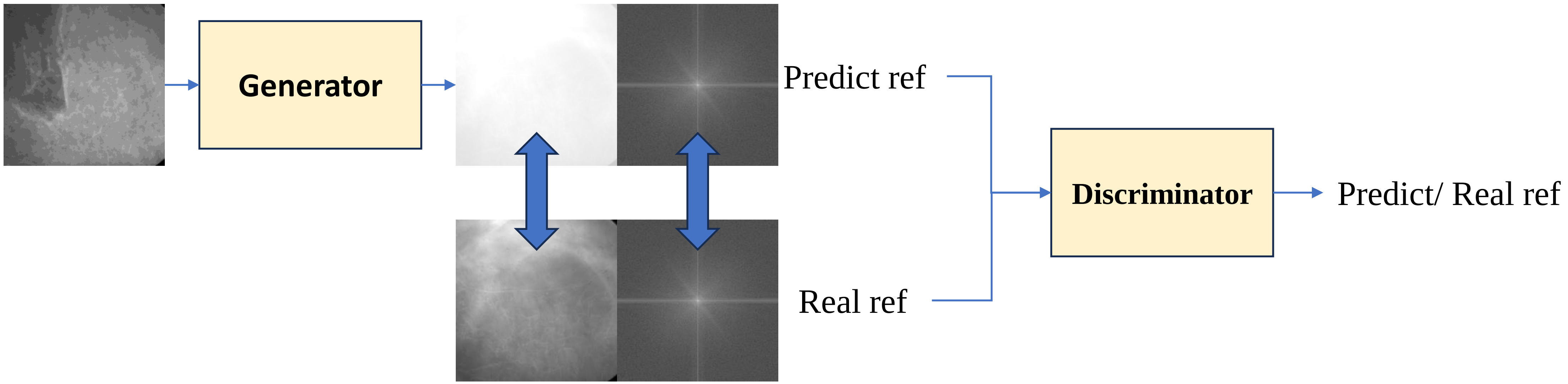


31x31 mosaic image



X-ray Background Correction Model

- Image to Image translation (pix2pix)



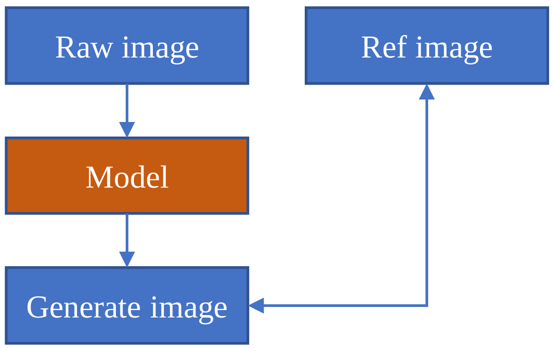
$$G^* = \arg\min_G \max_D \mathcal{L}_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G) + \text{lambda2*L3(G)}$$

Total loss = GAN loss + a*U-net loss + b*fft loss

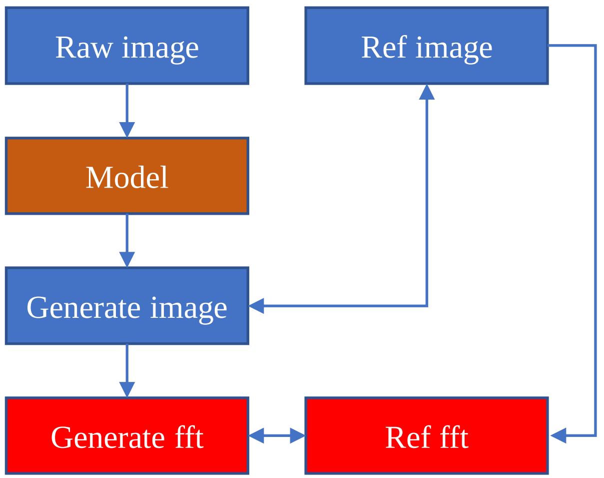
X-ray Background Correction Model

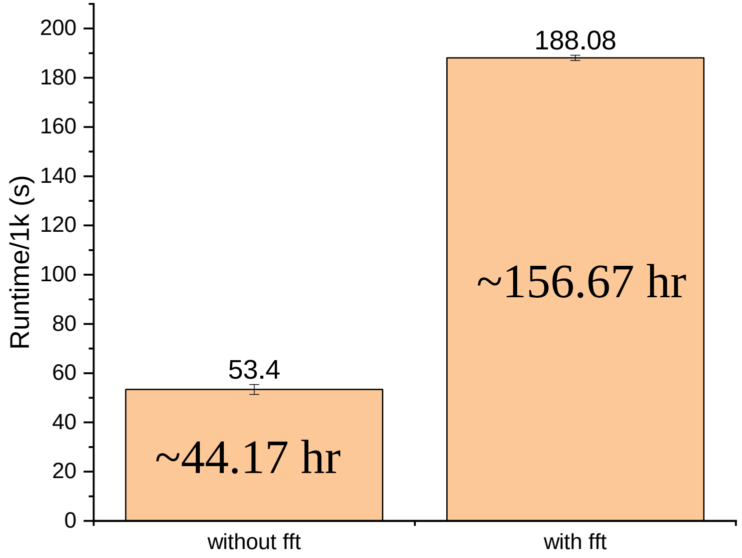
- Calculating loss for additional fft dimensions will increase computational costs.
- Software：TensorFlow 2.10.0
- Hardware：Intel(R) Xeon(R) Silver 4208 CPU @ 2.10GHz (16 core) with a A6000 gpu

Without fft loss



With fft loss





- Acceleration strategy
  - ➢ Software：Using MONAI with several common acceleration tools
  - ➢ Hardware：AMD EPYC 7742 64-Core Processor with a A100 gpu-40G

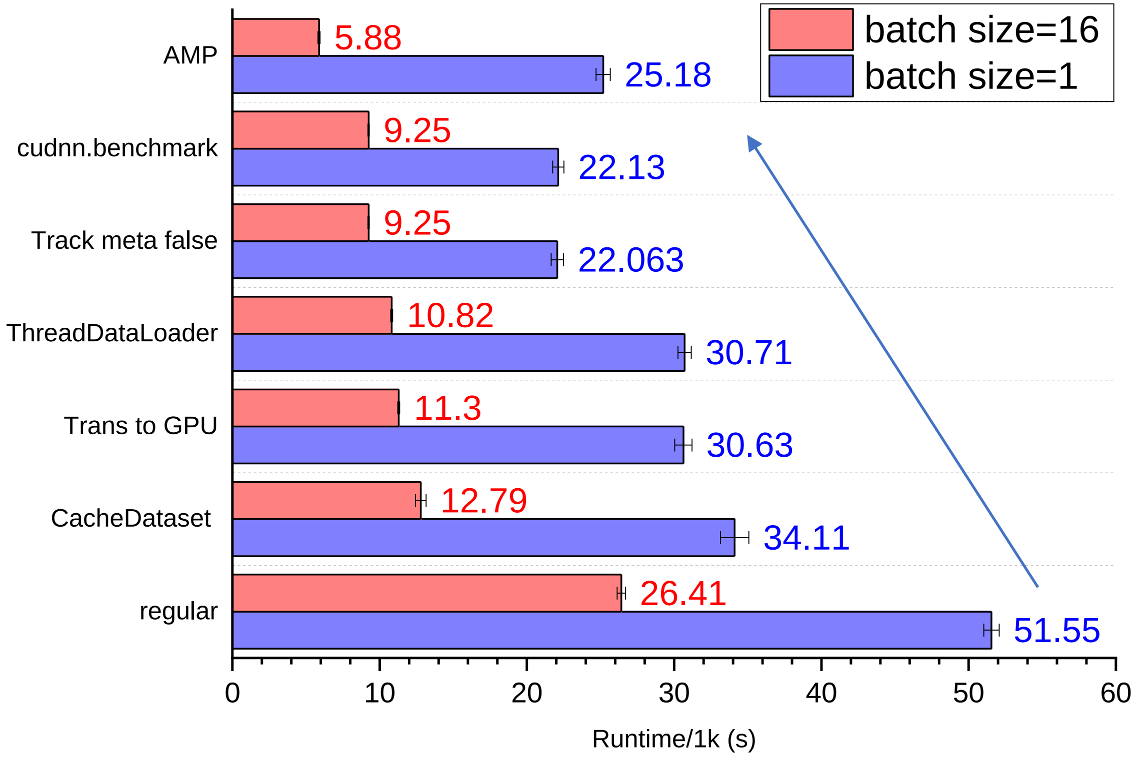
Accelerating Training for X-ray Background Correction Model

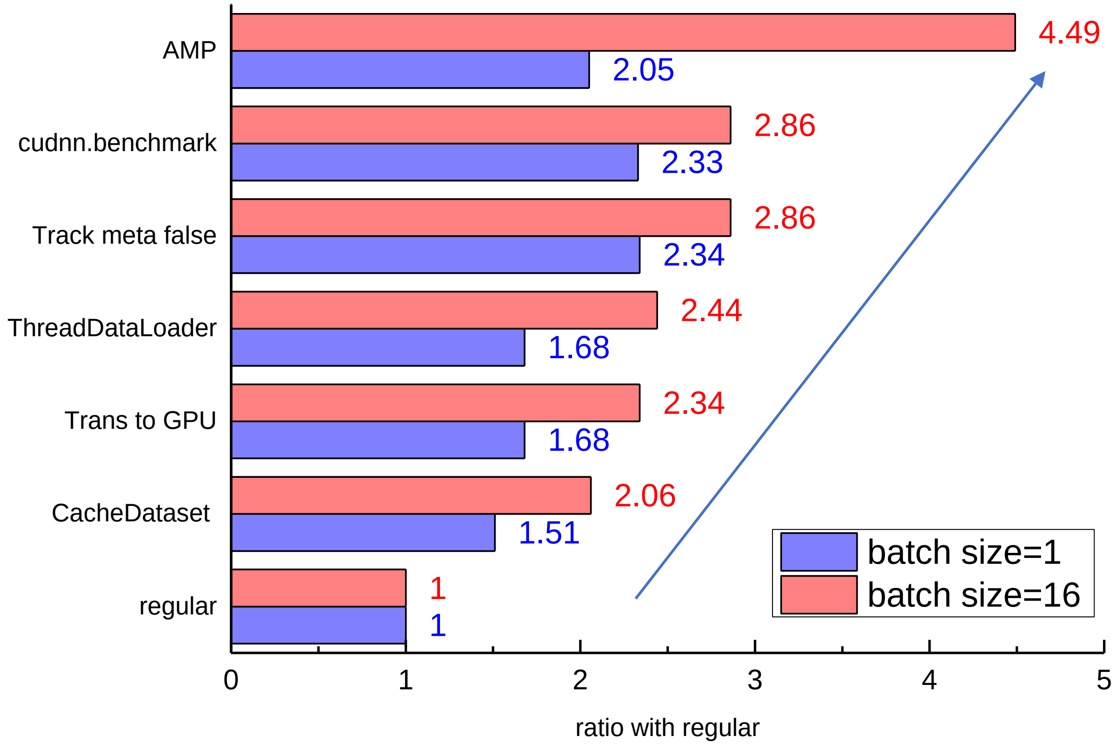
Acceleration tools benchmark test

1.Regular train	Data Path	Transforms	Dataset	DataLoader	Loss and Optimizer	Model	Training Loop
2.CacheDataset	Data Path	Transforms	CacheDataset	DataLoader	Loss and Optimizer	Model	Training Loop
3.Trans to GPU	Data Path	Transforms to GPU	CacheDataset	DataLoader	Loss and Optimizer	Model	Training Loop
4.ThreadDataLoader	Data Path	Transforms to GPU	CacheDataset	ThreadDataLoader	Loss and Optimizer	Model	Training Loop
5.Track meta false	Data Path	Transforms to GPU F_track meta	CacheDataset	ThreadDataLoader	Loss and Optimizer	Model	Training Loop
6.cudnn.benchmark	Data Path	Transforms to GPU F_track meta	CacheDataset	ThreadDataLoader	Loss and Optimizer	Model with cudnn.benchmark	Training Loop
7. Automatic Mixed Precision (AMP)	Data Path	Transforms to GPU F_track meta	CacheDataset	ThreadDataLoader	Loss and Optimizer	Model with cudnn.benchmark	Training Loop with AMP

Accelerating Training for X-ray Background Correction Model

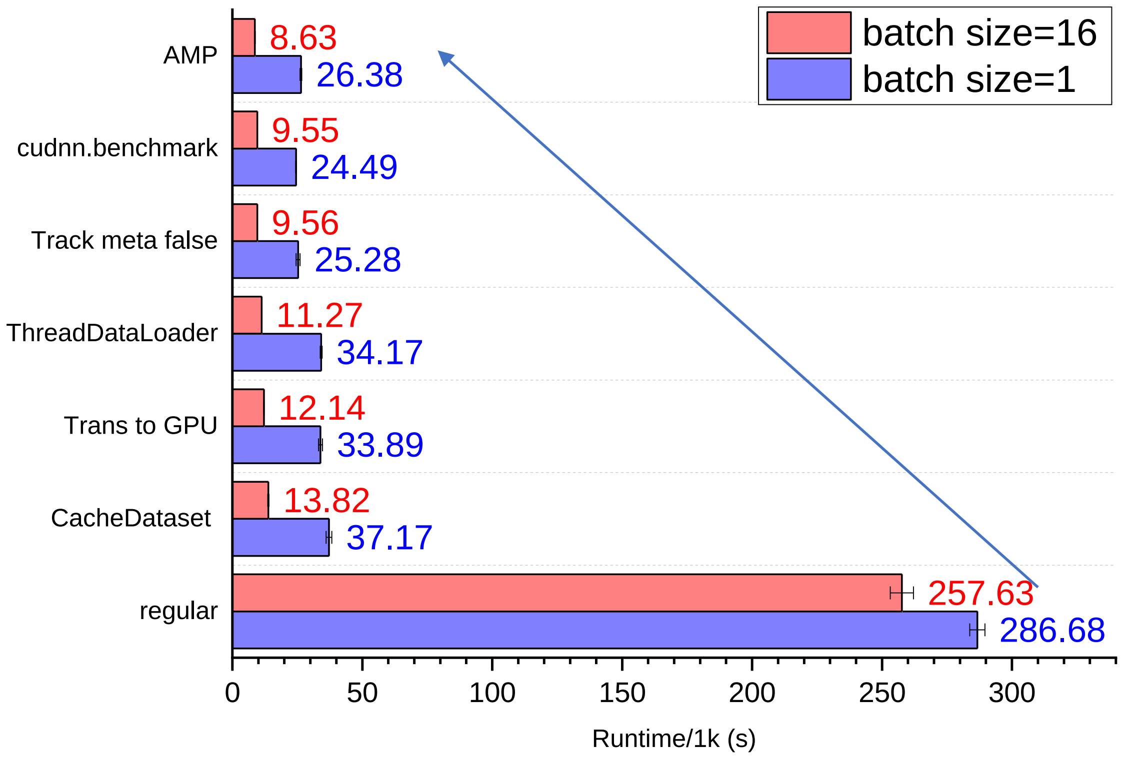
Train Background Correction Model without fft

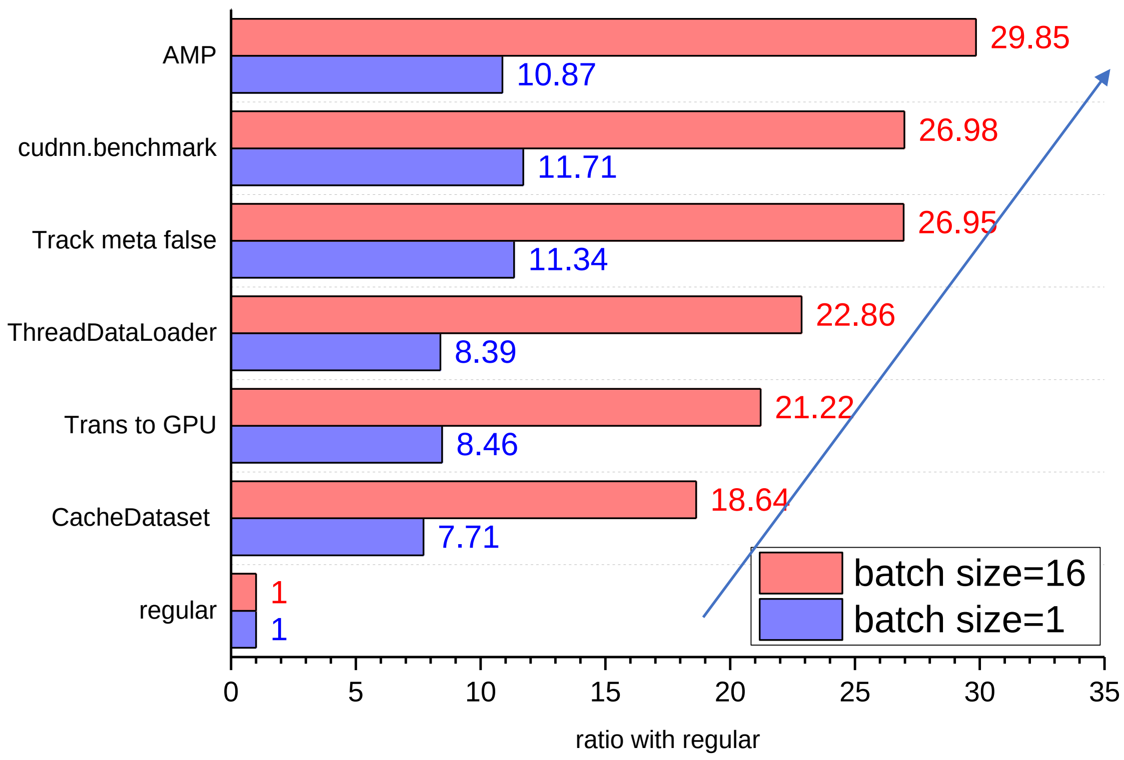




Accelerating Training for X-ray Background Correction Model

Train Background Correction Model with fft





Energy Efficiency

without fft

INPUTS	
# CPU Cores	64
# GPUs (A100)	1
Application Speedup	4.5x

Node Replacement 18.0x

GPU NODE POWER SAVINGS			
	AMD Dual Rome 7742	8x A100 80GB SXM4	Power Savings
Compute Power (W)	19,756	6,500	13,256
Networking Power (W)	834	93	741
Total Power (W)	**20,590**	**6,593**	13,997

Node Power efficiency **3.1x**

ANNUAL ENERGY SAVINGS PER GPU NODE			
	AMD Dual Rome 7742	8x A100 80GB SXM4	Power Savings
Compute Power (kWh/year)	173,063	56,940	116,123
Networking Power (kWh/year)	7,306	814	6,492
Total Power (kWh/year)	**180,368**	**57,754**	**122,615**

$/kWh	$ 0.34
Annual Cost Savings	$ 41,689.05
3-year Cost Savings	$ 125,067.16
Metric Tons of CO2	87
Gasoline Cars Driven for 1 year	19
Seedlings Trees grown for 10 years	1,437

(source: Link)

with fft

INPUTS	
# CPU Cores	64
# GPUs (A100)	1
Application Speedup	29.9x

Node Replacement 119.4x

GPU NODE POWER SAVINGS			
	AMD Dual Rome 7742	8x A100 80GB SXM4	Power Savings
Compute Power (W)	131,340	6,500	124,840
Networking Power (W)	5,545	93	5,452
Total Power (W)	**136,885**	**6,593**	130,292

Node Power efficiency **20.8x**

ANNUAL ENERGY SAVINGS PER GPU NODE			
	AMD Dual Rome 7742	8x A100 80GB SXM4	Power Savings
Compute Power (kWh/year)	1,150,538	56,940	1,093,598
Networking Power (kWh/year)	48,570	814	47,757
Total Power (kWh/year)	**1,199,109**	**57,754**	**1,141,355**

$/kWh	$ 0.34
Annual Cost Savings	$ 388,060.72
3-year Cost Savings	$ 1,164,182.15
Metric Tons of CO2	809
Gasoline Cars Driven for 1 year	175
Seedlings Trees grown for 10 years	13,377

(source: Link)

Results and Final Profile

Before After Speedup

- Dataset：10000
- Max epoch：300
- Before training time - without fft ：~44.17 hr
- Before training time - with ： ~156.67 hr
- After training time - without fft：~4.9 hr (x9, reduce 39.27 hr)
- After training time - with fft：~7.2 hr (x22, reduce 149.47 hr)

Future

- Further utilizing MONAI's functionalities with datasets like smartdataset and precisiondataset to expand training data and enhance training.
- Employing diverse data augmentation techniques to increase model accuracy.
- Exploring different models to study effective methods for improving background correction accuracy.
- Conducting a systematic study on the impact of FFT loss on the model.

Summary

- In this recent Hackathon, I've acquired extensive knowledge on techniques for accelerating model training using GPUs, including optimization tools in MONAI and PyTorch. Additionally, I've learned to leverage Nsight profiling tools to pinpoint computational bottlenecks in code.
- These techniques can expedite the development of X-ray background removal models, addressing issues stemming from the non-uniformity of light sources in synchrotron nano CT facilities.
- This will save considerable acquisition time and enhance the efficiency of nano CT scans, ultimately accelerating progress in paleontology, biomedical research, materials science, energy, and other related fields."

Thanks