

SurrogateTrain: Drastically Improving Performance of Data Loading for Training Scientific Surrogate Models

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Background & Motivation

Ptychography Imaging

APS-U
High-Energy X-Ray Beams Experiments

Data Scale
Hundreds of **Peta Bytes** brain initiatives

Surrogate Models

PtychoNN
Predicts the 2D amplitude and phase images.

AutoPhaseNN
Predicts the 3D amplitude and phase patterns.

BraggNN
Predicts the positions of diffraction peaks.

- Ptychography imaging techniques aim to **increase the resolution** of images beyond x-ray optics.
- Traditional iterative algorithms are **computationally expensive**.
- Advanced Photon Source Upgrade (APS-U) will provide **immense data**.
- **Surrogate models** are designed to achieve the task more efficiently.

From Single Device to Distributed Training

The Architecture of DGX-A100 Nodes

PtychoNN

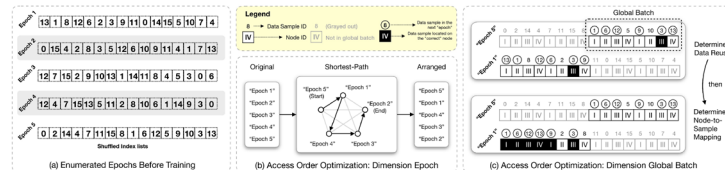
Data-Parallel

Training Time Breakdown

- To train surrogates on large datasets:
 - Utilize **supercomputers** like ThetaGPU.
 - Utilize **data parallelism** in distributed training.
- Data loading takes **>80%** of training time!

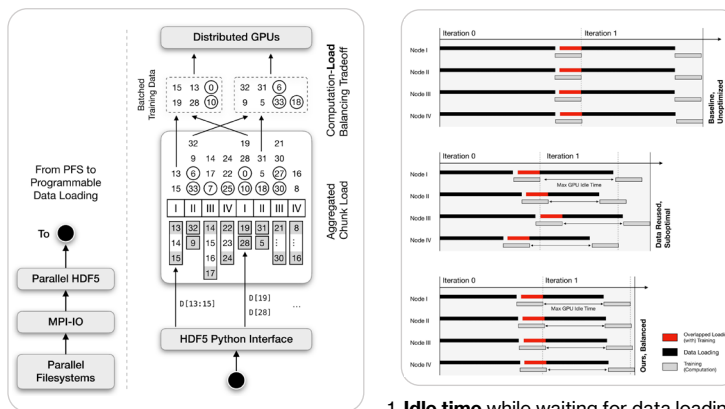
Proposed Design

Part I: Offline Scheduling



- (a & b) Epoch order optimization.
- (c) Data locality optimization + Load balancing scheduling

Part II: Runtime Buffering



1. Idle time while waiting for data loading.
2. Load imbalance incurred.
3. Overall time reduced from balancing the load.

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Evaluation

Setup

- **Environment:** ThetaGPU supercomputer
- **Baseline:** PtychoNN using Pytorch DataLoader.
- **Dataset:** In-house dataset from ANL APS. 262,896 images

Number of Data Loaded From PFS

		rank															avg.	stdev	median	max	
V1		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15				
Iteration	1	67	107	69	54	57	58	41	69	75	48	68	74	54	79	58	55	64.6	15.4	62.5	107
	2	56	75	82	69	96	63	75	62	69	88	74	57	60	87	59	81	72.1	12.3	71.5	96
	3	67	56	71	71	85	105	65	72	79	71	60	81	84	53	80	87	74.2	13.1	71.5	105
	4	110	70	91	92	68	77	61	59	64	79	79	62	79	85	89	68	77.1	13.9	78.0	110
	5	84	89	94	80	73	83	75	70	86	100	110	81	74	73	79	77	83.0	10.8	80.5	110
																	total:	74.2	14.2	74.0	110

		rank															avg.	stdev	median	max	
V2		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15				
Iteration	1	72	51	55	67	59	62	52	70	77	53	59	75	54	66	62	66	64.6	8.3	62.0	77
	2	59	81	83	73	65	63	61	64	66	77	55	64	73	55	74	58	72.1	8.9	64.5	83
	3	66	61	71	80	66	68	63	68	68	73	79	63	83	62	73	72	74.2	6.6	68.0	83
	4	72	71	73	64	75	75	65	72	62	81	69	64	81	80	74	76	77.1	6.1	72.5	81
	5	67	64	75	93	72	83	69	71	63	82	78	81	76	64	78	71	83.0	8.2	73.5	93
																	total:	69.1	8.6	69.0	93

- The baseline method loads 512 images on each rank in each step.
- Compared to Pytorch data loading, we reduced data loading by **6.7x**.

Full Randomization
Epoch Order Optimization
Node-Sample Mapping (Locality)
Load Balancing
Aggregated Chunk Load

• technique in use
○ data loading achieved via inter-node communication

1 PyTorch DataLoader [6]

2 Locality Aware [7]

3 DeepIO [8]

4 NoPFS [9]

5 SurrogateTrain (Ours)

Performance on Each Optimization Step

Performance Breakdown and Comparison

(V1) Data access order optimization,
(V2) V1 + load balancing optimization,
(V3) V2 + chunked loading optimization.

Optimization	Speedup
V1	2.45x
V2	4.60x
V3	4.70x

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