## AI FACTORIES: CONVERGENCE OR COMPLEMENT?

NCP and duality of use

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## **EOS NVIDIA Flagship System**



576 DXH: 4608 H100 GPU NDR400 IB Compute and Storage Storage: 48 AI400NVX2 EXAScaler 6 12 PB flash 4.3 TB/s Read 3.1 TB/s Write

DDN Hot node for Accelerated AI

Training

EOS IS THE <u>THIRD-GENERATION</u> FLASGHIP DGX SUPERPOD NVIDIA HAS CHOSEN TO DEPLOY WITH DDN



## EOS is part of a long list of DDN and NVIDIA SuperPODs





## EOS looks very much like a fat-node fat-tree HPC system

Hierarchical Design: 32N Scalable units, 128N PODs

- DGX H100: 8xNDR400 ports for compute and 2x NDR400 port storage
- Separated, non-blocking fabrics for both compute and storage
- Three-level fat tree topologies



- 48 DDN AI400X2 storage appliances connected with HDR IB
- Appliance IB connections are interleaved across 4 PODs
- Target a minimum performance of 2 TB/s (read) to support DL training at scale





## **DGX Architecture Overview**

- DGX H100: Dual Networks 8 NDR400 Compute / 2 NDR400 Storage
- Internal Storage for no-interference small latency data access
- 2 NDR400 for high bandwidth / high capacity storage





## **Storage micro-benchmarking**



Comparative bandwidth measurements on a DGX platform. Using FIO with threads number ranging from 1 to 256 and large payload. The Lustre delivers x5 the read performance and x2 the write performance of the local storage.

Comparative latency measurements on a DGX platform. Using FIO with a threads number ranging from 1 to 256 with a small payload. Local storage delivers x5 the IOPS (IO operations per second) than Lustre and x100 the IOPS of Lustre for write operations. Lustre version 2.12 used in this experiment does not support the most recent IOPS write optimizations



## Next-Gen Al Data Caching with DDN Hot Nodes

Leverage local flash to maximize benefits of unified, global shared namespace



- Achieve full AI application performance with data cached on local nvme devices in client, without any manual and risky data management overhead.
- Automated data movement from shared space to local node with intelligent policy-based cache management makes the process entirely transparent for users.
- Delivers significant efficiencies and AI workload improvements with large number of nodes engaged simultaneously for training, especially for at-scale NLP.



## Cacheing Data in DGX Local NVMe for Multi-Epoch Training

- ResNet50 benchmark on DGX-A100 + AI400 without caching
- Each phase reads same data from network (purple)
- Compute runs in parallel with IO (CPU orange, GPU green)
- ResNet50 with caching on internal NVMe devices
- First phase also reads from network (purple)
   Total data read volume is similar, second read from RAM
- · Computation also reads from network/RAM while files copied
- Write to cache storage on NVMe (red)
- Second phase reads from NVMe at double bandwidth (cyan)
- GPU usage (green) the same, CPU usage (orange) lower
   No network/server load on second and later runs





## Waiting on Data can be a Critical Bottleneck

As models scale the Data Movement component for Multi-Epoch Training can become the dominant factor in Training Time ResNet-50 Training (Average Epoch Time at Different Scales)





## **AI Training is Storage Intensive**







## **Checkpoints are a Critical Step in Deep Learning Training**

- **Prediction Accuracy** improve accuracy by lowering learning rate from a checkpoint
- **Multi-System Training** continue training model across different nodes or clusters/cloud
- **Transfer Learning** if goals change, start afresh from a checkpoint
- **Better Fine Tuning** pick out less trained states to restart new experiments
- **Early Stopping** for large models, without sufficient regularization, the error on the evaluation dataset can start to increase



Number of Epochs





## **Checkpoints are a Critical Step in Deep Learning Training**



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## **Master AI Infrastructure: Learnings from the past 5 years**

### Reference Architectur@i400∩vx2



#### Workload Guidelines Storage BW per GPU

- Small data set. LLM. Text processing: 1.4 GB/s Read 1 GB/s Write
- Medium dataset. Compressed video processing. Checkpointing Distributed training LLM: 2.8 GB/s Read 2 GB/s Write
- Large dataset. Uncompressed video processing. Checkpointing Distributed training LLM 5.6 GB/s Read 4 GB/s Write

#### **Operation Guidance: EXAScaler Management Facility**

- Automated deployment and upgrade
- HA configuration
- Health Monitoring
- Prometheus Exporter

## Oddn

## **Machine Learning Needs Fast Reads and Writes**

Average Number of Calls per Job

Analysis of over 23,000 Machine Learning Jobs at OakRidge

- "Most ML jobs are perceived to be readintensive with a lot of small reads while a few ML jobs also perform small writes."
- "Our study showed that ML workloads generate a large number of small file reads and writes..."

#### ~50% W/R ALSO VALIDATED DURING EOS PRESENTATION (SC23)



PAUL, Arnab K., KARIMI, Ahmad Maroof, et WANG, Feiyi.

Characterizing machine learning i/o workloads on leadership scale hpc systems.

In : 2021 29th International Symposium on Modeling, Analysis, and Simulation of Computer and Telecommunication Systems (MASCOTS).

IEEE, 2021. p. 1-8. https://arnabkrpaul.github.io/publications/mascots21.pdf

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## New DGX SuperPOD RAs: AI400X2-QLC and AI400X2-Turbo

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	AI400X2-QLC	AI400X2	AI400X2 TURBO	
	More Useable Capacity	Optimal Performance/Capacity	Extra Performance Boost	
	90 GB/s (r), 70 GB/s (w), 3.5M IOPs	90 GB/s (r), 65 GB/s (w), 3M IOPs	115 GB/s (r), 75 GB/s (w)*	
ULLY GRATED!	1 or 2 PB useable (QLC)	120, 250, 500 TB useable (TLC)	120, 250, 500 TB useable (TLC)	
KTERNAL TCHES!	6 RU • 4.4 KW • 15K BTU/hr	2 RU • 2.2 KW • 7.5K BTU/hr	2 RU • 2.2 KW • 7.5K BTU/hr	
H	IDR200/100GbE/200GbE QSFP 56 (8) or NDR200/200GbE QSFP 112 (8)	HDR200/100GbE/200GbE QSFP 56 (8) or NDR200/200GbE QSFP 112 (8)	NDR200/200GbE QSFP 112 (16)	



## **EXAScaler Roadmap 2024**

Updated 2024-02-15



#### Appliances

**QLC** Appliance

#### **Data Management**

Client-Side Compression

#### EMF

- HA Reliability Improvements Data Services
- Data Services as software
- Per User BucketFS path

#### Appliances

• AI400X2T "Turbo" appliance

#### **Core File System**

- Reliability on unstable networks
- . EMF

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- Simplified Online Upgrades
- **Enhanced SOS reports** ٠
- Data Services
- **Prometheus Exporter** ٠

#### CSI

OpenShift support ٠

#### Data Management

Client-Side Compression v2

#### EMF

- Prometheus Exporters GA ٠
- FXA Health GA •

#### **Data Services**

• S3 AD authentication support

#### **Core File System**

- Large Idiskfs OSTs
- IPv6

#### EMF

- Push-button Online Upgrades •
- **Configuration Management**

#### Data Services

**EMF** Deployment

#### Subject to Change

## From AI Training to AI Data Center



## **AI Data Centers Operates Different Rings of Data**





## **Data Journey from Acquisition to Training**





## **Addressing Each Challenge with the Most Relevant Solution**





## **AI Data Center: Inferences and Training**

Data management for inference with versatile numerous inputs differs from high performance training on curated data





## **Storage Designed for Next Generation Al**

Software Driven. Powerful Analytics. Strong Security. Highly Efficient for All Workloads

#### Scale Out S3 Object Storage

Start with 500TB and scale out just by adding servers

#### **Zero Service Disruption**

Expand, remove, upgrade, introduce new generations of hardware without service disruption

#### **Cloud-Like Multi Tenancy**

Manage SLAs for Tenants and Subtenants dynamically and easily

#### **100% QLC Flash Simplicity and Stability**

HDD-free Architecture, hyper simple management





## DDN Infinia is 100% Fit Into Modern AI Development

- Fully Containerized Architecture → Elastic Scalability. Always On
- Multi-Tenancy that is 100% Dynamic → Easily change Tenant Allocation
- Massive Unstructured Data → Tag & Search without limits, collapse complexity





### Infinia Implementation of the Bε-Tree Core Data Structure

- **Efficient Space Utilization**: good use of space within nodes
- **Reduced Disk I/O**: By optimizing the node fill factor, they can reduce disk operations, which is crucial for performance in large DB systems or metadata operations.
- **Scalability**: well-suited for large datasets and can scale.
- **Range Queries Efficiency:** efficient in performing range queries, making them useful in applications where such queries are common.
- **Flexibility in Node Size**: flexibility in setting node size, which can be tuned for specific application/workload needs.
- **Dynamic Nature**: dynamically adjust to insertions and deletions, maintaining balanced tree structure.

## **Keeping Every Application Optimized Regardless of Type**

Hybrid IO Engines Handle Diverse Workload Needs with High Efficiency

- Autonomous optimization for low latency and IOPs and throughput and metadata intensive workloads
- No read/modify/write overhead due to log structured operations
- Byte addressable with wide striping for large I/O blocks
- No Complexity for Administration Elastic space for metadata and data





## Infinia is Fast - Accelerates S3 workloads by 10-100X

- DDN Infinia exceeds the claimed performance of all other object stores in Objects/sec and Throughput
- Accelerate Enterprise Analytics workloads like Apache Spark, Starburst Presto/Trino, Clickhouse,

Object Size	GET	PUT
4K	147 K	67 K
4M	49 GB/s	26.8 GB/s

#### DDN Infinia S3 Throughput (MB/s)



GET PUT



## **Infinia is Responsive - 100x Lower Latencies**

- Infinia is the first Object Storage to deliver **sub-millisecond latencies** for PUTs and GETs
- 100x lower than AWS S3
- Improve website load times, database response times, accelerates Spark queries etc improving end user satisfaction



Infinia Latency - 6 Nodes



## Infinia – Data Plane and Control Plane Architecture

- Infinia is a 100% software, dataplane designed to deliver storage services on a variety of protocols
- SW upgrades will introduce additional services including an Optimized Parallel Client, NFS and SQL.





## **DDN Infinia Protects Service Levels Automatically**

- DDN Infinia will automatically defend your Tenants and Subtenant Performance
- Full protection from Noisy Neighbours
- Complete Fair Share implementation in Software





## **Blurring Borders Between Metadata and Data**

- AI Data tend to be metadata heavy
  - Every frame of an autonomous car is annotated by 100s of metadata
- Metadata allow to structure the Data-lake
   Prevent Data-lake to turn in Data-Swamp
- Query-able Metadata: Data-LakeHouse
  - Data Lake + Data Warehouse





## **DDN Infinia SQL**

- Create Tables, Insert Rows, Select a Subset
- Scale Out Performance
- Manage S3 Tags and File Extended Attributes like a Database

Create a 3 Column Table: Integer: Integer: Variable Character

[redsql> CREATE TABLE redtest (col1 BIGINT, col2 BIGINT, col3 VARCHAR(48))
redsql> time milliseconds: 2.533413

#### Insert Values 1, 20 and "test"

[redsql> INSERT INTO redtest VALUES (1, 20, 'test')
redsql> time milliseconds: 5.021347

redsql> SELECT \* FROM redtest WHERE col1 > 70 AND col1 < 85 {"col1":83, "col2":20, "col3":"test83"} {"col1":73, "col2":20, "col3":"test73"} {"col1":80, "col2":20, "col3":"test80"} {"col1":84, "col2":20, "col3":"test84"} {"col1":78, "col2":20, "col3": "test78"} {"col1":79, "col2":20, "col3":"test79"} {"col1":71, "col2":20, "col3":"test71"} {"col1":74, "col2":20, "col3":"test74"} {"col1":75, "col2":20, "col3": "test75"} {"col1":76, "col2":20, "col3":"test76"} {"col1":82, "col2":20, "col3":"test82"} {"col1":77, "col2":20, "col3":"test77"} {"col1":72, "col2":20, "col3":"test72"} {"col1":81,"col2":20,"col3":"test81"} redsql> time milliseconds: 6.005832 redsql>



## **Infinia Primary Dashboard**





## Scale Out S3 in the Data Center and in the Cloud Up to 100's of PBs



- S3 Object Storage
- **Multi-Tenancy Namespace**
- **No Restrictions on Object Size**
- - **No Restrictions on Metadata**
- **Full Multi-Part Upload Support**
- Sub Millisecond Latency for PUTs and Gets



## **DDN Infinia will Enable the Next Generation of AI**

The 4 big data challenges of the new Era of AI: Efficiency | Metadata | Sharing | Moving



Data services



Containerized MicroServices



Scalable Data & Unlimited Metadata Native Tenancy Architecture



Move Data; Edge, Cloud, Datacenter

## And the Best Storage is?









# ddn