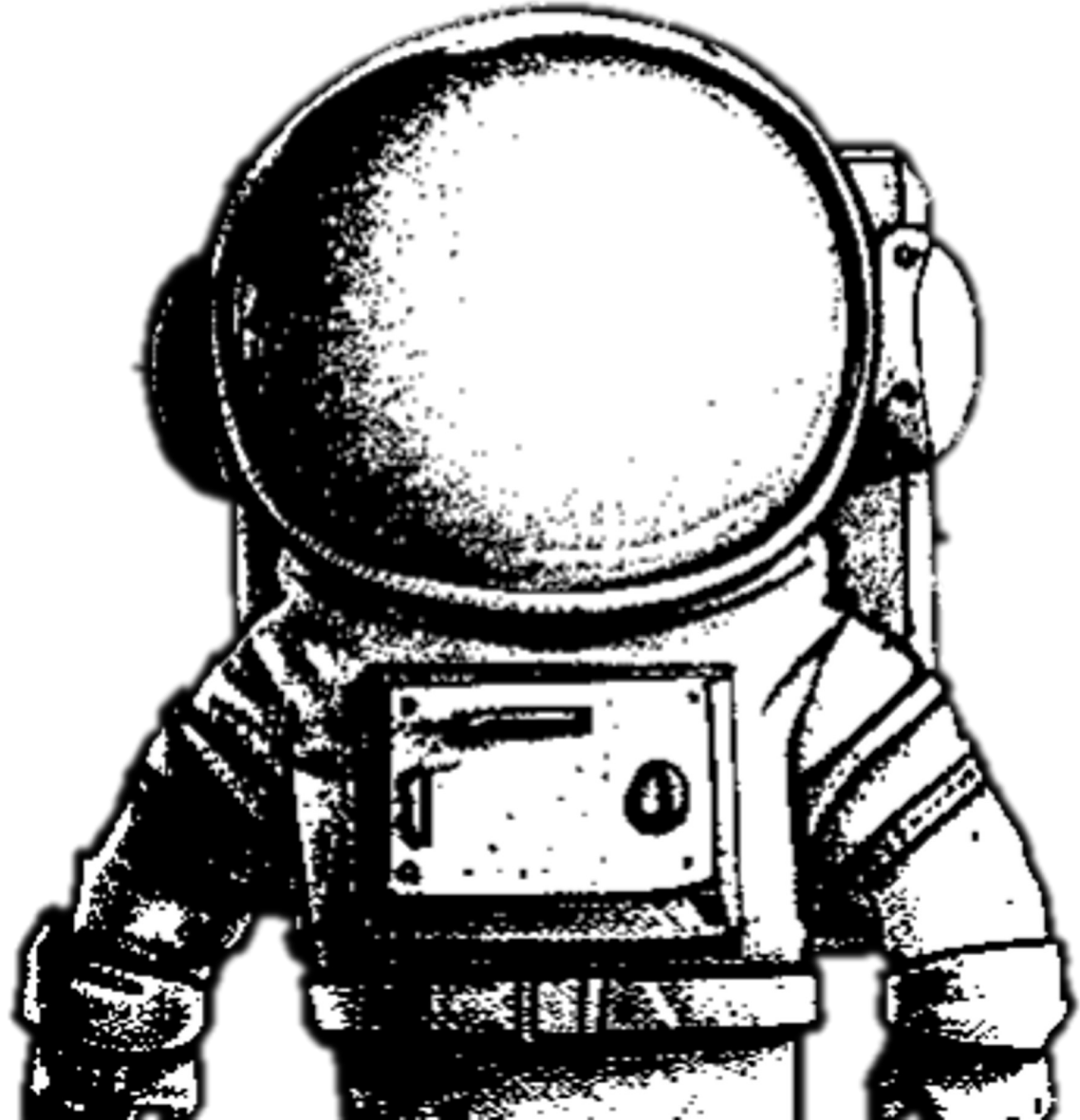


Experiences Building AI Data Infrastructure at Exascale

Jeff

Co-Founder: VAST Data



Selene
(source: NVIDIA)

4,500
GPUS

2022



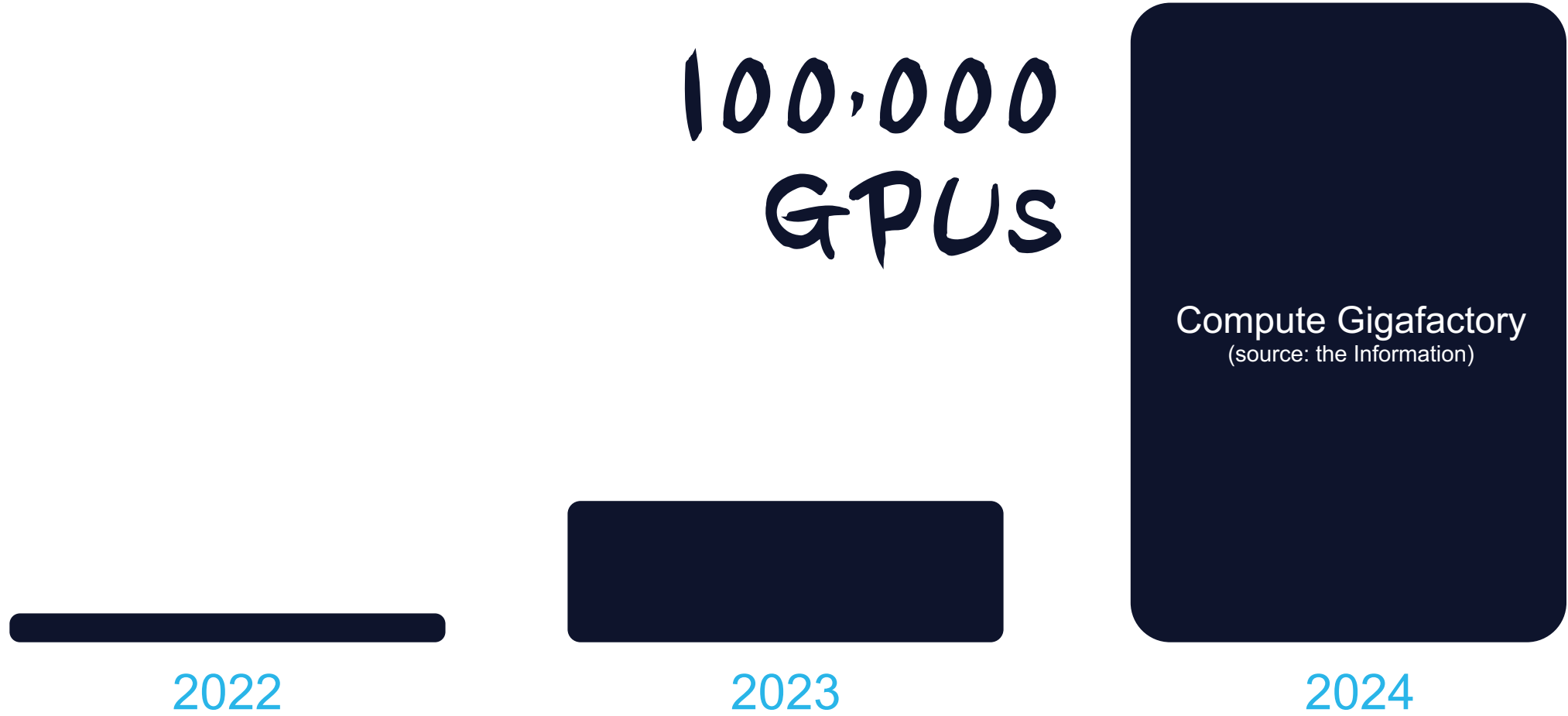
2021



Inflection
(source: Inflection.AI)

2023

22,000
GPUS



\$10Bs of AI Infrastructure • 100ks of GPUs



 CoreWeave

core42

 **Lambda**

 Genesis Cloud

 Crusoe

 DigitalOcean

 **TAIGA**
CLOUD
BY NORTHERN DATA GROUP

ampz

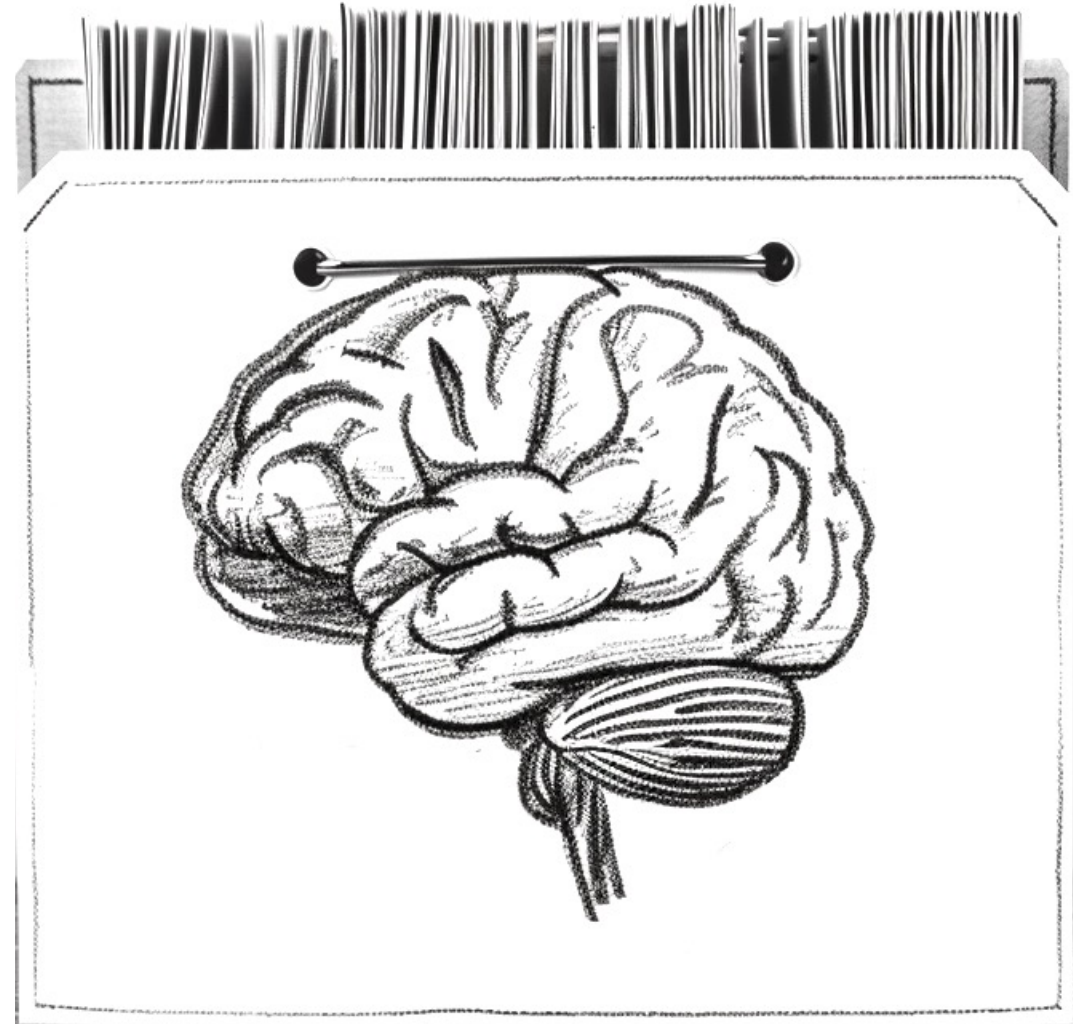
 **HYPERSCALE**
NEXUS

 **NEBUL**

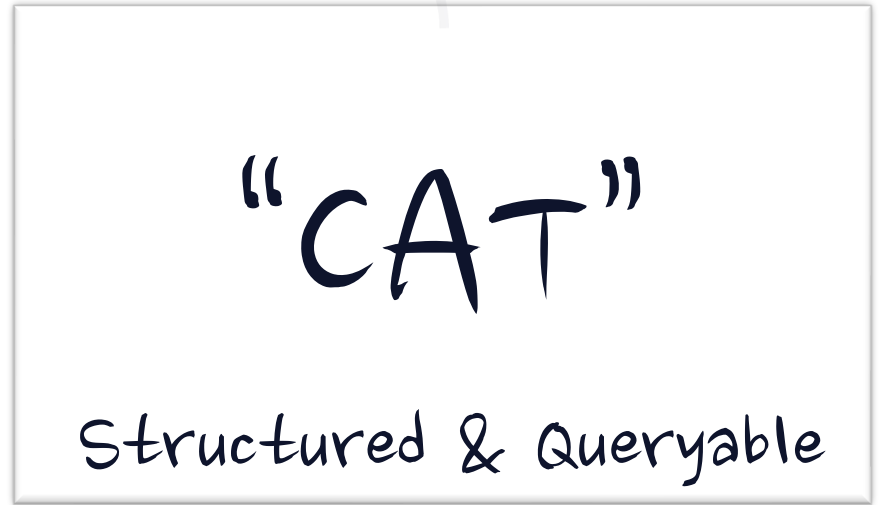
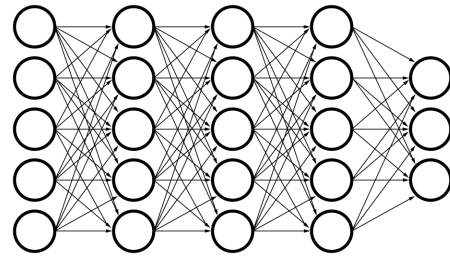
GREENNODE

ETC.

Today's AI prescription lacks depth.



LABELS

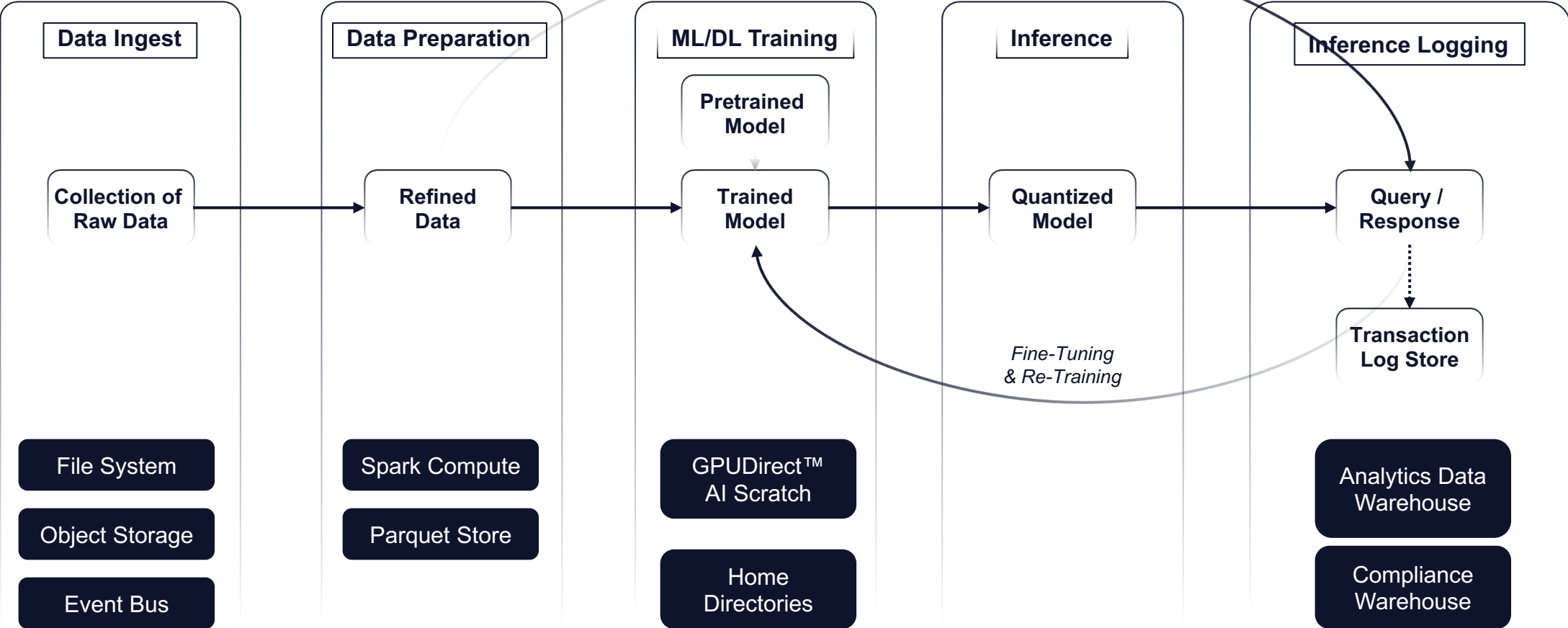


INFERENCE

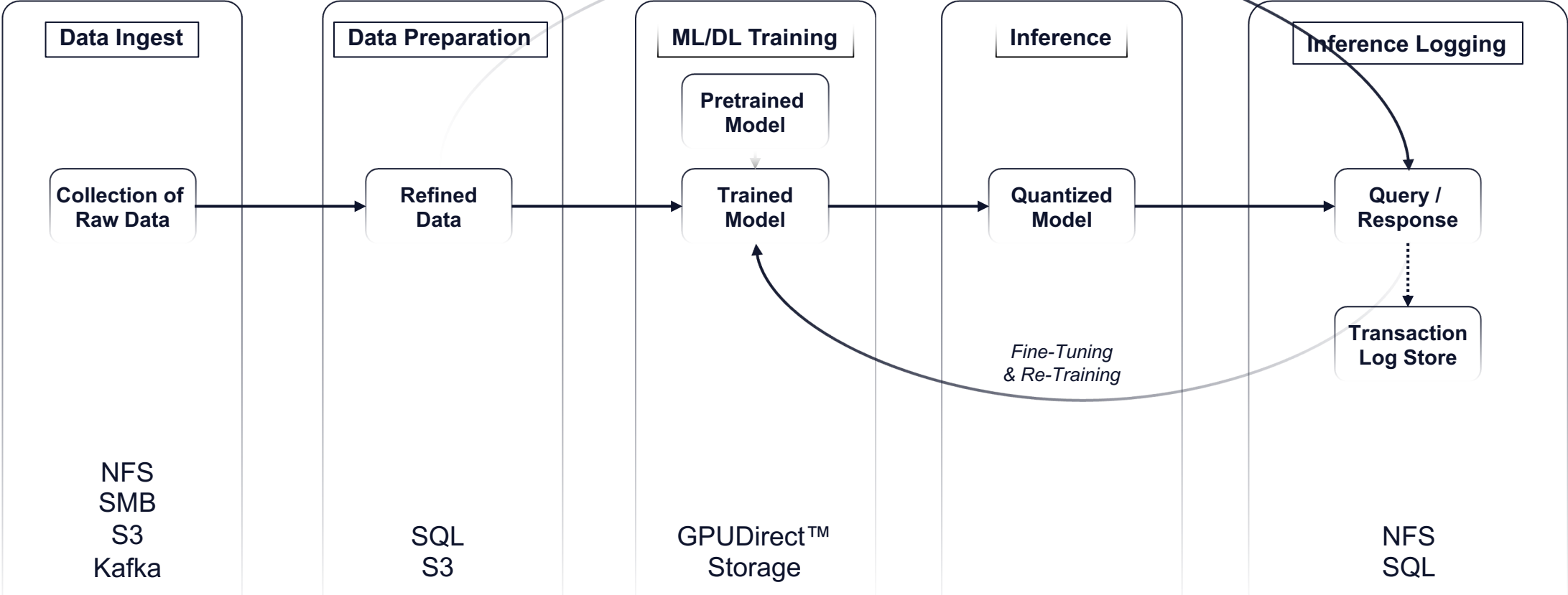
- Massive datasets
 - Text in SoTA LLMs uses just O(1-10s) TB; Images O(100s) TB
 - LHC or SKA alone each produce O(100s) PB per year!
 - **Challenge:** Scaling LLMs on systems (I/O) for such datasets would be daunting
- Semi-structured (and tabular) data
 - Bio/life science datasets are in specific complicated
 - **Challenge: Data manager** → loading, organizing, cleaning, labeling etc
 - **Challenge:** Designing models (LLMs) to ingest such semi-structured data
- High dimensional data: encoders enough to solve this problem?
 - LLMs designed, and proven effective w/ low dimensional data
 - Text, images, audio, video
 - Scientific datasets can have higher dimensional data
 - **Challenge:** pushing the boundary for using LLMs with high dim data



RAG



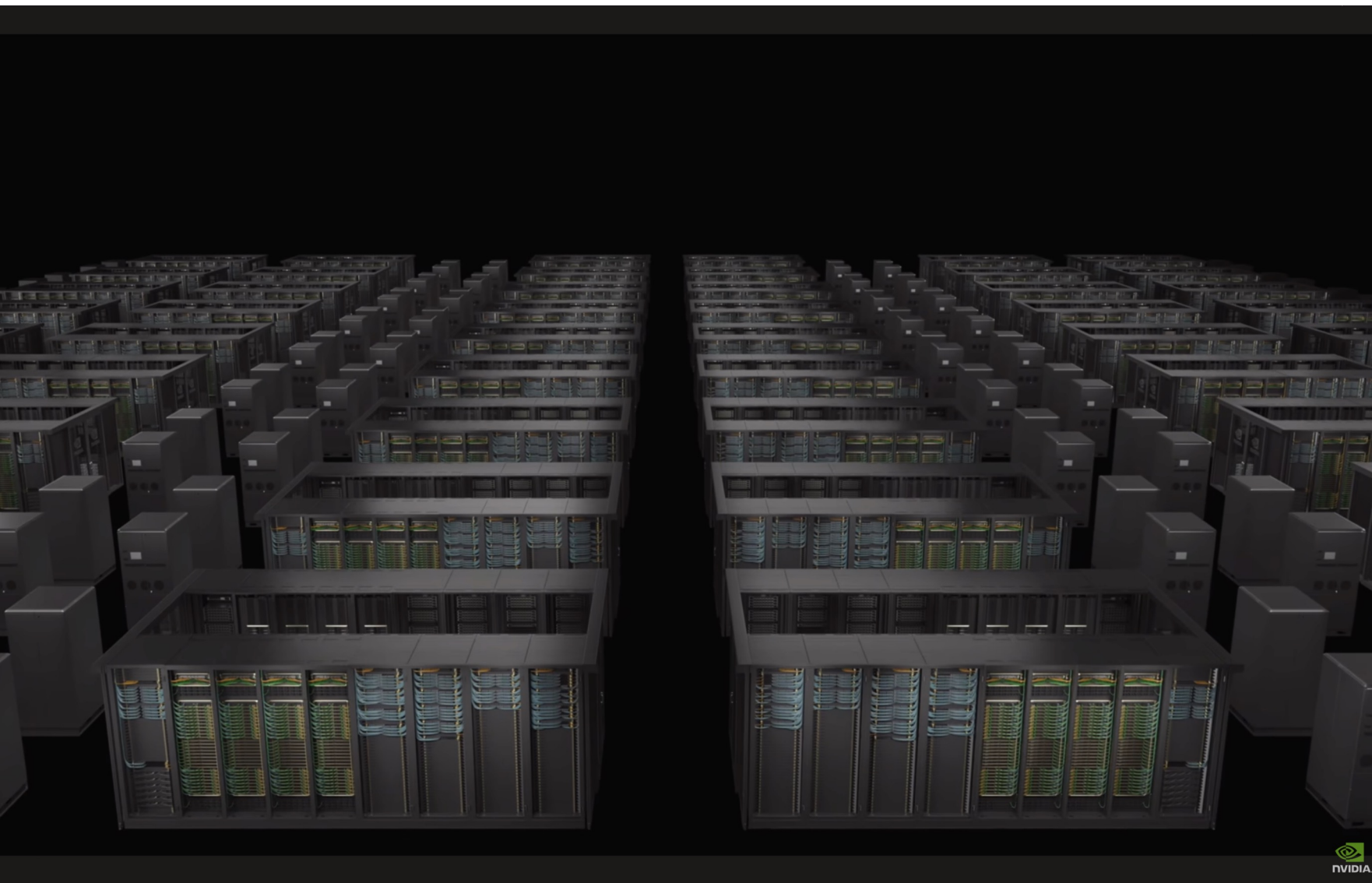
RAG



VAST DATA PLATFORM: ACCELERATE ACCESS ACROSS PROTOCOLS + LANGUAGES

Power will change infra consumption.





← 100MW



The Rise of Cloud AI

Confidential computing infrastructure.

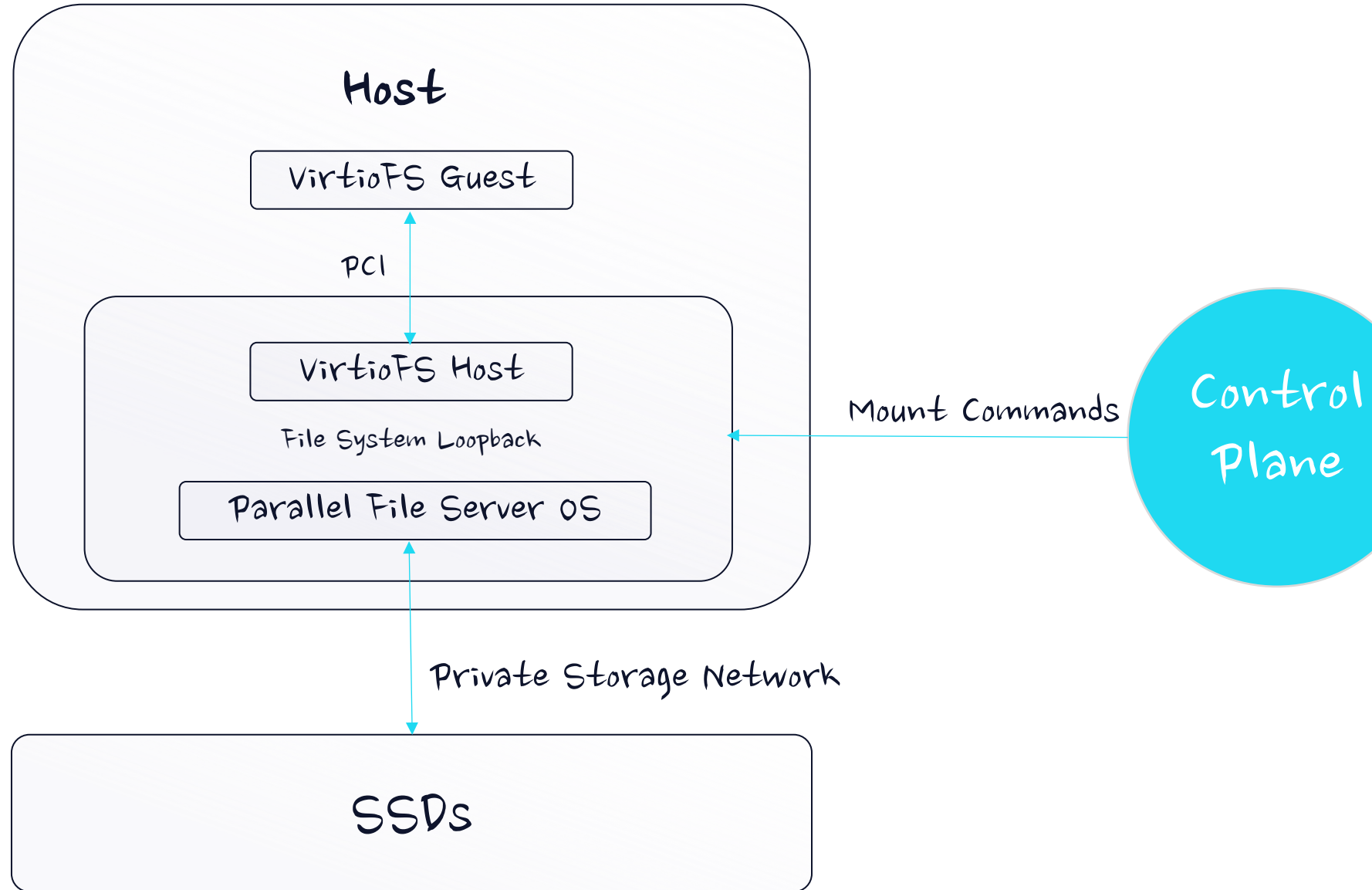
Multi-tenant, host-based isolation, EKM

Data Mobility

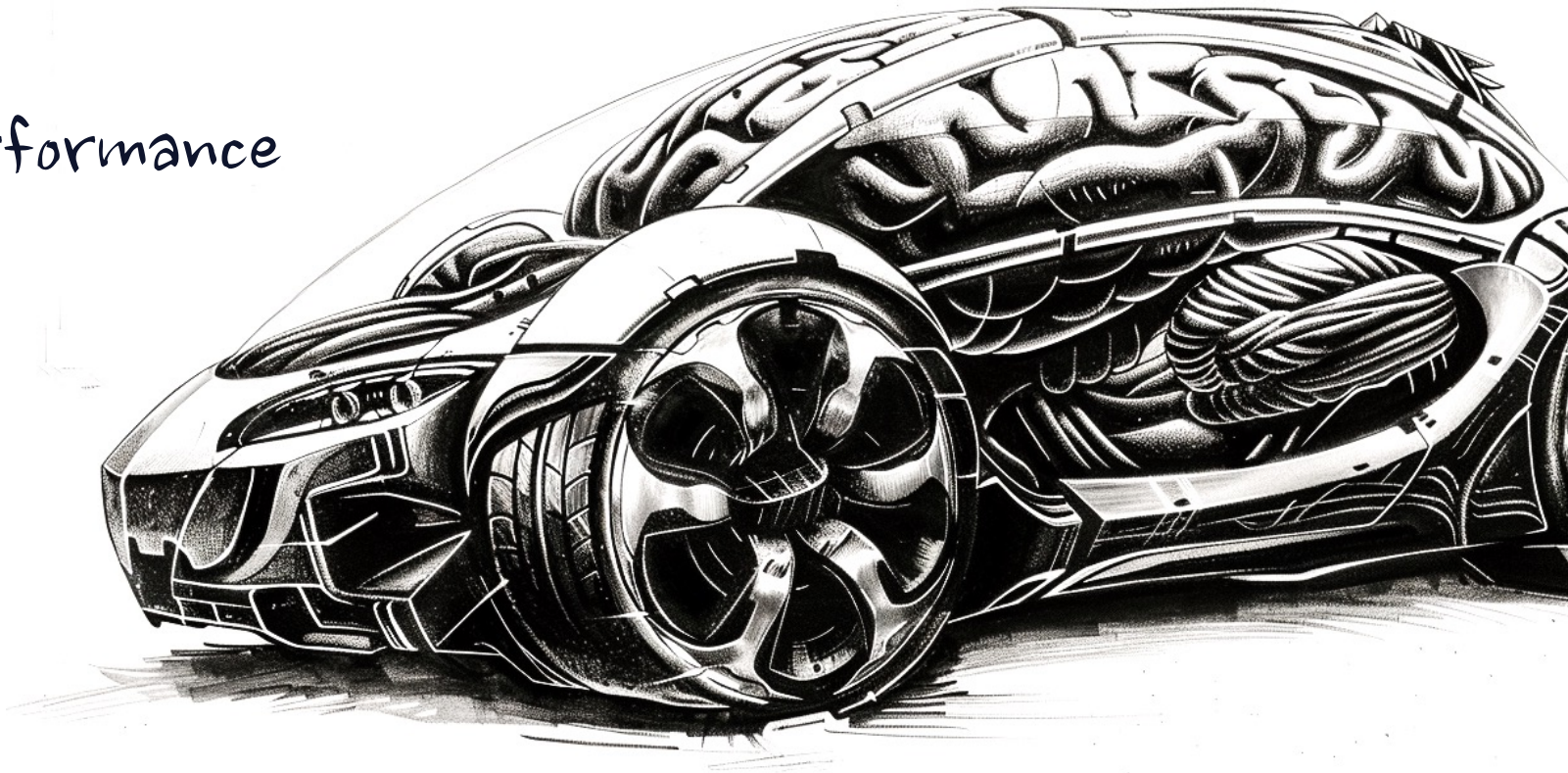
Solve for processor and power gravity

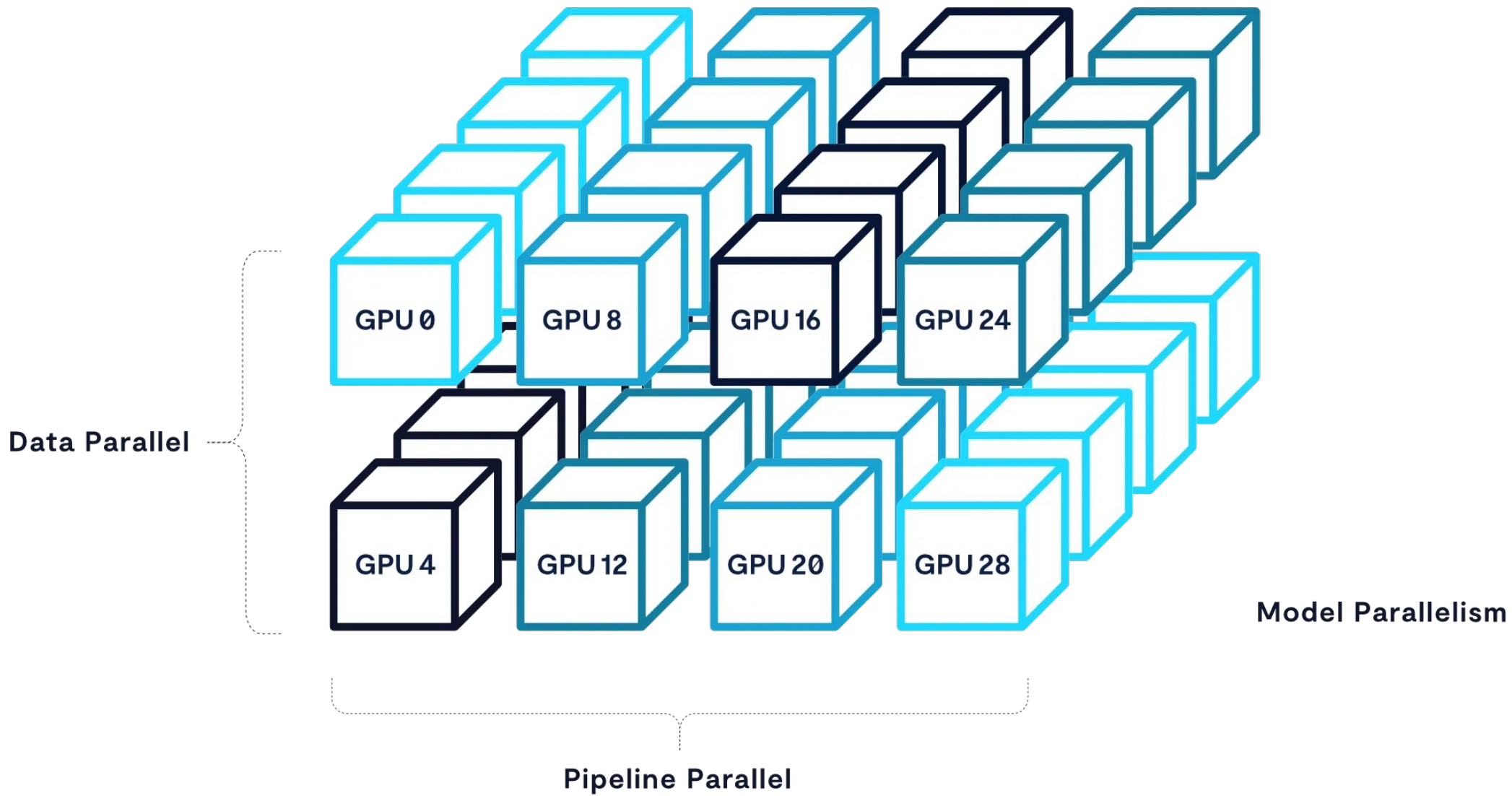
AI Factory Architecture

Cloud Enables
New Infrastructure Modalities



AI performance \neq HPC performance

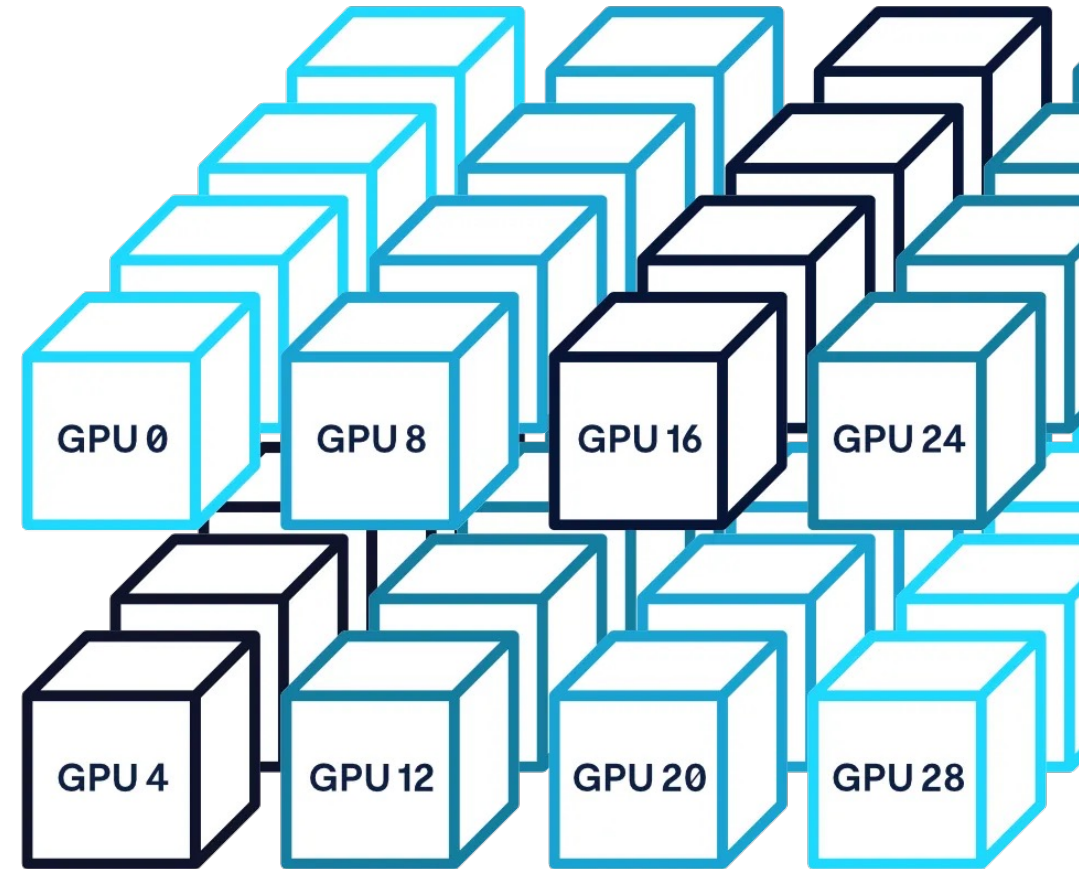




Pipeline Parallel octets are self-contained and includes the entire model and pipeline for an LLM, and hence **only one octet needs to be checkpointed per system**, regardless of the overall size of the cluster because it is a complete representation of the system.

One thread per GPU.
Eight threads per 8-way GPU system.

Restores are **data parallel**.



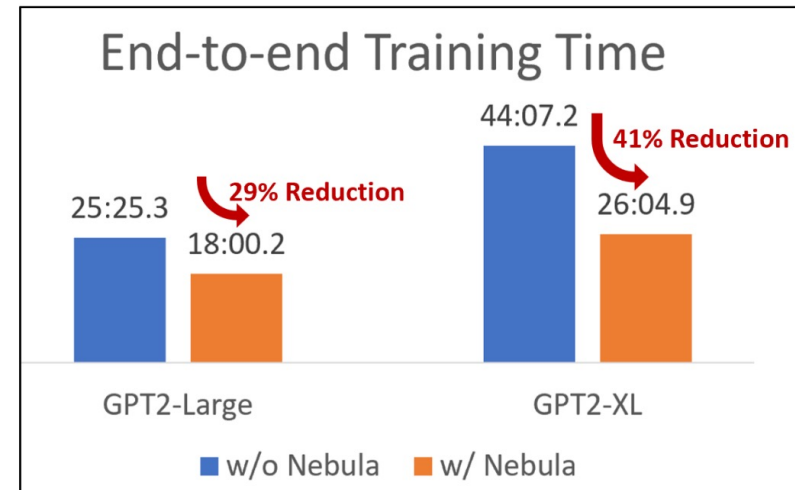
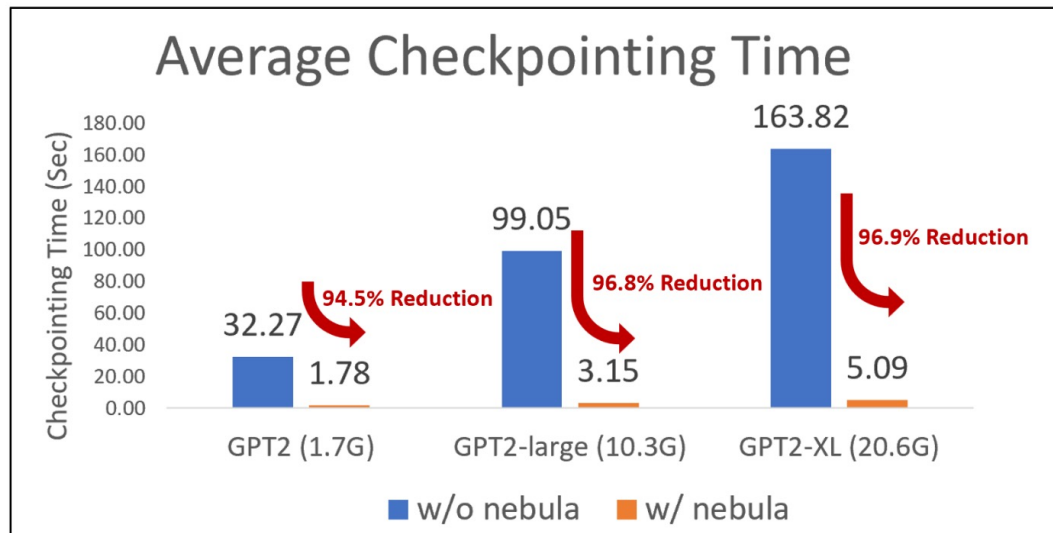
5.10 Checkpoint Loading and Saving

An important practical consideration for the training of large models is loading and saving model checkpoints, which are especially large for the models considered in this paper. For example, the trillion-parameter model has a checkpoint of size 13.8 terabytes. The initial load of checkpoints for the trillion-parameter model by all 384 nodes (3072 GPUs) reaches a peak read bandwidth of 1TB/s, the maximum read throughput possible from the parallel filesystem. Checkpoint saves reach 40% of peak write bandwidth (273 GB/s).

Source: NVIDIA + MICROSOFT + STANFORD Megatron-LM paper

Checkpoints are going asynchronous.

Nebula Saving with DeepSpeed and ORT



PS: Saving 4 checkpoints in an end-to-end training, with saving every checkpoint by 500 steps.

w/o Nebula: DeepSpeed and ORT enabled
w/ Nebula: DeepSpeed, ORT, and Nebula enabled

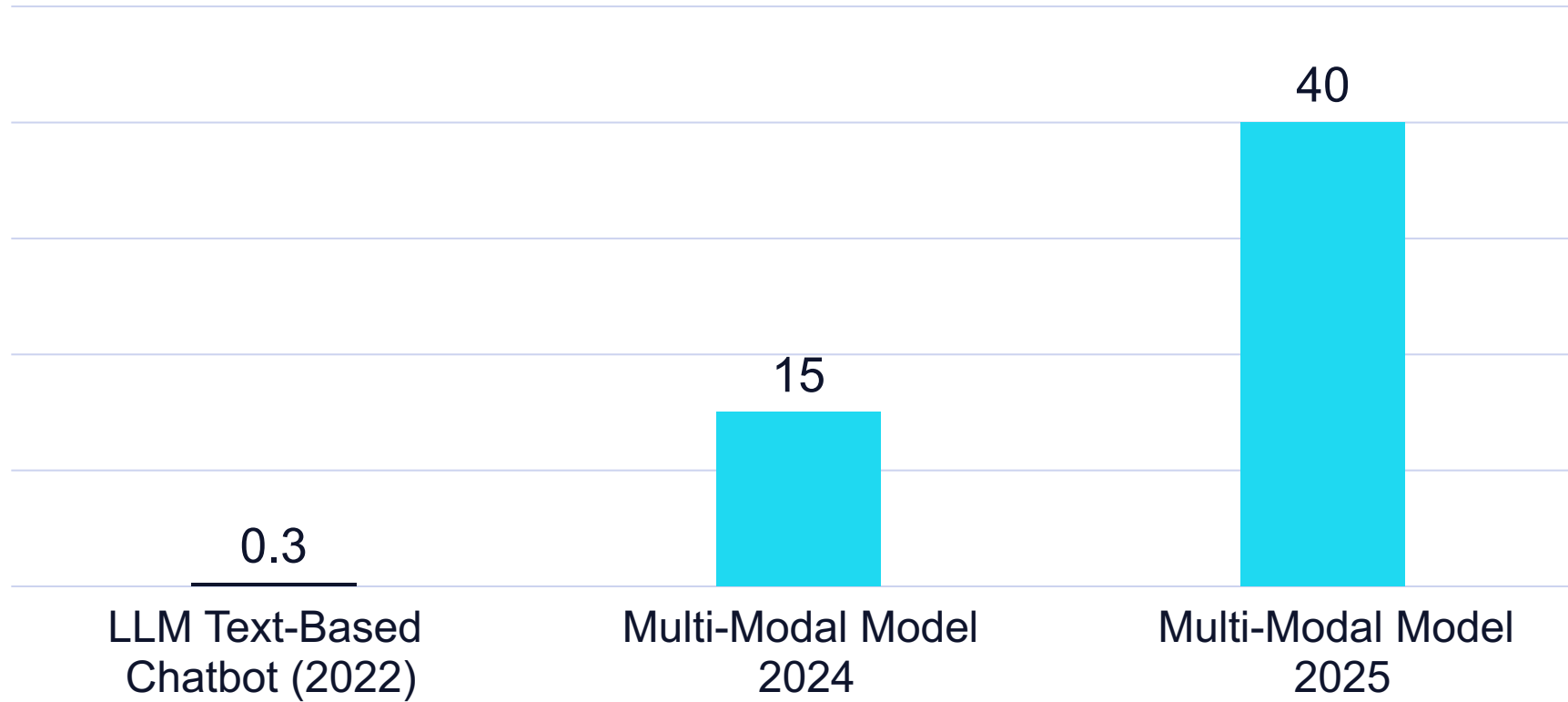
Environment: V100, 1 node, 8 GPUs
Image: ptebic.azurecr.io/public/azureml/aifx/stable-ubuntu2004-cu117-py38-torch1131:latest
DeepSpeed 0.8.0, ORT: 1.13.1, Nebula: 0.15.9

Source: Microsoft

New Trend: Multi-Modal

Video & Imagery are driving up LLM capacities quickly.

PBs per 1K GPUs



Conclusion #1:

Growth of system size & power increases will drive up MTBF

Conclusion #2:

Async makes write bandwidth, checkpoint-speed a non-issue

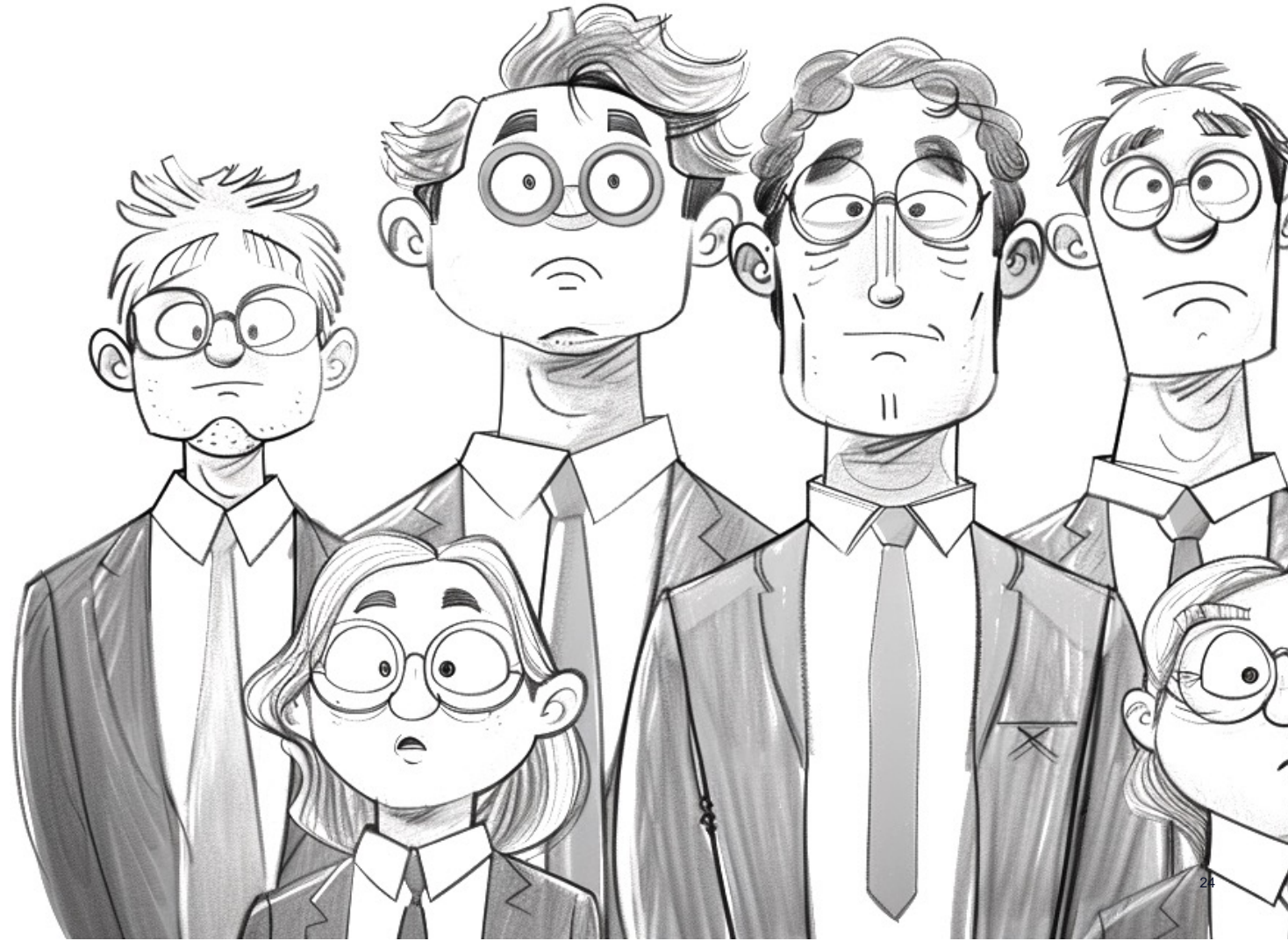
Conclusion #3:

Recovery Speeds will scale much larger as systems grow in size

Conclusion #4:

Multi-Modal: Capacity = Performance with All-NVME

AI's Sarbanes-Oxley Moment





“ We think that regulatory intervention by governments will be critical to mitigate the risks of increasingly powerful models

Sam Altman –2023

EU AI Act: Risk-based approach



Article 72

Post-Market Monitoring by Providers and Post-Market Monitoring Plan for High-Risk AI Systems

2. The post-market monitoring system shall actively and systematically collect, document and analyse relevant data which may be provided by *deployers or which may be* collected through other sources on the performance of high-risk AI systems throughout their lifetime, and which allow the provider to evaluate the continuous compliance of AI systems with the requirements set out in Chapter III, Section 2

The “it” in AI models is the dataset.

Posted on June 10, 2023 by jbetker

Trained on the same dataset for long enough, pretty much every model with enough weights and training time converges to the same point... Model behavior is not determined by architecture, hyperparameters, or optimizer choices. **It's determined by your dataset, nothing else.**

When you refer to “Lambda”, “ChatGPT”, “Bard”, or “Claude” then, it's not the model weights that you are referring to. **It's the dataset.**

Cyber Resilience



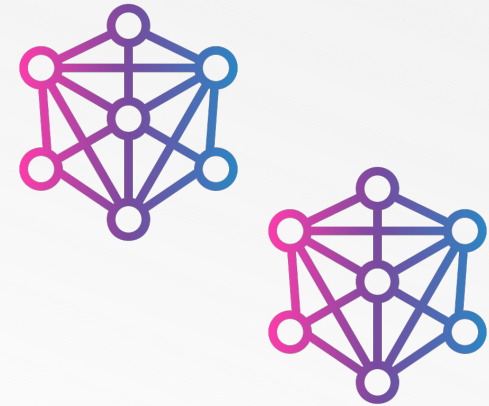
Ransomware Protection

Data Provenance



Data Tampering Protection

Model Reproducibility



Pipeline Versioning

Cyber Resilience



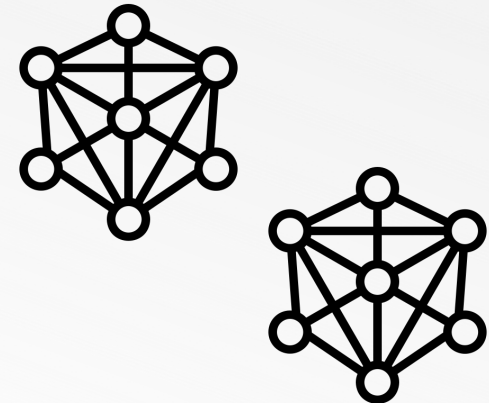
Ransomware Protection
Indestructible Snapshots
Ransomware Detection

Data Provenance



Data Tampering Protection
WORM Data Retention
SQL-Accessible Audit Logs

Model Reproducibility



Pipeline Versioning
An enterprise-grade python
dataset with immutability

Point #1:

Consider the whole pipeline

Conclusion #2:

Cloud is coming, whether we like it or not

Conclusion #3:

HPC Performance \neq AI Performance, Multi-Modal Solves All

Conclusion #4:

Enterprise Data Management is Having Its Moment

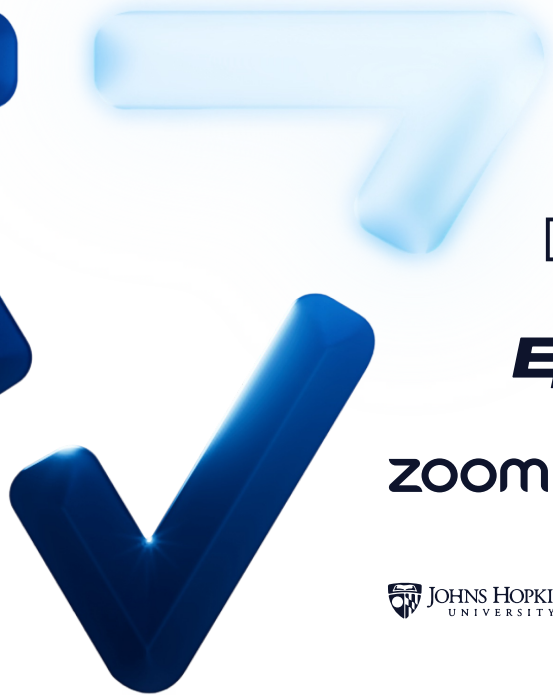
Fastest-Growing in Infrastructure History

Enterprise-Grade

Massively-Scalable

Radically-Affordable

Cloud-Native



Thank you!
www.vastdata.com

