## **Hewlett Packard** Enterprise

# What comes after Exascale?

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## **SYSTEMS OF SYSTEMS**



#### ~10x Exascale

Productivity and agility for HPC and AI applications



#### Today

#### **Exascale Supercomputer**





#### **Federated workflows**

For modeling, simulation, data analytics, and artificial intelligence

#### Systems-of-systems

Integrate, automate and optimize workflows that combine theory, simulation, experiments and observations from scientific instruments

#### World's fastest Workflows

#### World's fastest **Supercomputers**

# LABORATORY CAMPUS

supercomputer

Radioactive Ion Beam

High-temperature materials



Metal Processing

**Chemical and** Materials

**Irradiated Fuels** 

**Graphite Reactor** 

and the second second

**Biological Sciences** 



**Environmental Science** 



## THE DATA AND AI CHALLENGE



## A MOTIVATING EXAMPLE: EDGE-TO-HPC SCIENCE WORKFLOW





# (1) PERFORMANCE PRODUCTIVITY & PROGRAMMING ENVIRONMENT

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https://github.com/CrayLabs/SmartSim

# (2) EDGE-TO-EXASCALE ORCHESTRATION

## • Edge-to-Exascale SDK

- Helps to manage the lifecycle of edge AI + HPC workflows
- Coordinates data movement, data transfer nodes, models and job scheduling

## Edge-friendly job scheduling

• Intelligent techniques and tools for orchestrating workflows and refactoring experiments

## Instrument stack

 Software stack based on open platforms





**Data Center Compute** 

# (3) SELF LEARNING, TRUSTWORTHY, AI DATA FOUNDATION

#### Separate layer

- Common Metadata Framework (API, client, and server)
- Agnostic of storage and ML platforms
- Links data, pipelines, models and outcomes
- Tracks and learns from workflow history

#### • Open, community-based

- Built on open-source foundation (Git, DVC, MLMD...)
- Designed for scale, and exponential growth in scientific data and artifacts
- Makes data, metadata, models and experiments shareable across teams and communities
- Speed up data-driven scientific discovery

https://github.com/HewlettPackard/cmf

#### Machine Learning Platform

#### **AI Pipelines**

Data Ingestion, Cleanup, Model Engineering, Validation, Serving

#### **Frameworks and MLOps Platforms**

Spark, Sklearn, TensorFLow / Pytorch, Mlflow, Kubeflow, etc.

#### **Self-Learning Data Foundation**

Northbound Connectors and Intelligence Data Selection, AI Pipeline Quality, etc.

### **Git for Al Data**

Data and Metadata Management, Versioning, Workflow Lineage

#### **Southbound Connectors and Intelligence** Data Gradation for Tiering & Movement, Data Shaping, etc.

**Data Storage Systems** PFS, object stores (HPC, Cloud, Edge)

# **EXAMPLE: NORTHBOUND INTELLIGENCE**

- Extract insights from data in complex workflows
- Utilities and infrastructure for lineage and provenance interception of AI/ML workflows
- Meta-learning capabilities: historical correlations help building robust and explainable models
- Identify data of highest importance for quality
- Spans the training and inference flows, closing the loop between monitoring and model update



#### Accuracy vs. Number of Iterations

Number of Iterations



# (5) HETEROGENEOUS COMPUTING



# **EXAMPLE: ANALOG IN-MEMORY COMPUTING FOR DECISION TREES**

X-TIME: eXplainable Tree In-Memory Engine

Dataset [ID]

GPU (V100) at higher throughput

Up to **9,740x lower latency** compared with

#### **Novel Microarchitecture Analog Computing Element** Scalable performance <del>ار</del> ال CHIP External I/O OUTPUT Latency | -01 CAN CP INPUT С C C С $10^{-8}$ 5 4 Dataset [ID] ughput [Sa/s] 0 01 0 01 0 01 С С DÁC DAC С С С С Shift Shift Buffer G. Pedretti et al. С С Nature Comm. 12, 5806 (2021) 5

68M ACAM elements (4k cores of 256x65) connected with an H-tree NoC

**On-the-fly parallel reduction** avoids overheads for large scale models

20W power budget

**Depth and width independent** throughput scaling, **massively parallel** node traversal in ACAM

Enables **large scale model inference** without performance loss

# Up to **8x higher throughput** compared to digital ASIC at lower latency

GPU

Digital ASIC

X-TIME

## (5) DATA-ACCELERATED STORAGE



# (6) NETWORK INFRASTRUCTURE

- Extending HPC networks to the edge: compute, storage, devices
- Accelerators driving injection (100 Gbps → 200 Gbps)
- Photonics remains challenging (copper @ 200 Gbps within rack works!)
- Blending of supercomputer + cloud: HPC-aaS, single job with 1,000 instances, QoS, privacy and security
- Growing interest in HPC functionality at Ethernet link / transport (RDMA, offloading, isolation, progression, collectives, flow-based congestion, ...)



Converged Ethernet for interoperability

erformance at scale

#### Congestion control + multi-tenancy

# (7) PERVASIVE SECURITY

#### Platform trust + Real time detection



- Advanced Persistent Threats (APT)
  - Breech-to-discovery time: ~100 days [FireEye 2018]
- Supply Chain: top security concern of most governments
  - How to secure what is manufactured, delivered, where
- Extend silicon root of trust in real time
  - Detect zero-day threats without signatures
  - Continuous kernel integrity check (in seconds)
  - Verification of pluggable hw components and firmware
- IDevID and Platform Certificates (launched June '21)
  - Factory-issued X.509 server and TCG certificates
  - Manifest of pluggable hardware components
- Deep Supply Chain Attestation
  - Manifest of <u>all</u> parts, signed, maintained via blockchain

https://www.hpe.com/us/en/security/project-aurora.html

## **WRAPPING UP**

- AI and data are disrupting science "AI will **not** replace scientists, but scientists that use AI will replace those who don't"
- Complex science workflows will span from the experimental edge to extreme-scale computing
- Today's Exascale generation may be the last of "monolithic" supercomputers
- The next breakthrough will require a "Systems-of-Systems" view



## SYSTEMS OF SYSTEMS