

# Big Data Analytics: The Apache Spark Approach

Michael Franklin

ATPESC

August 2017

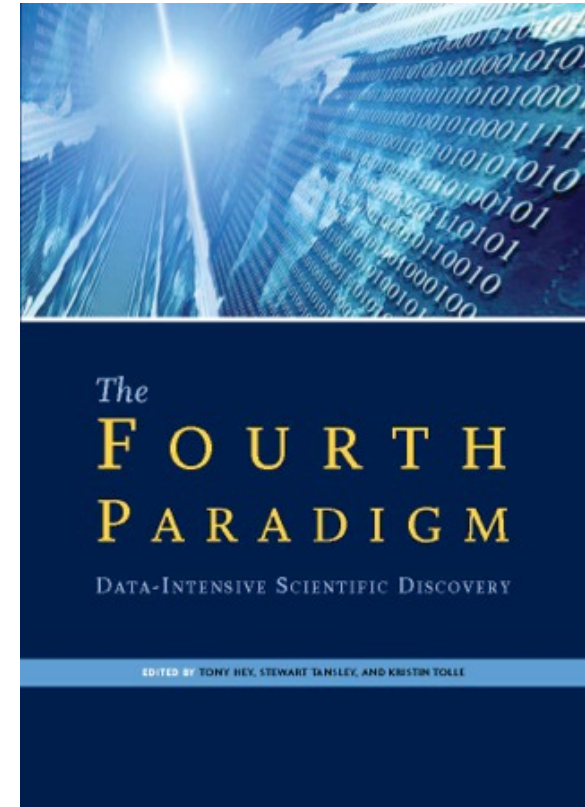
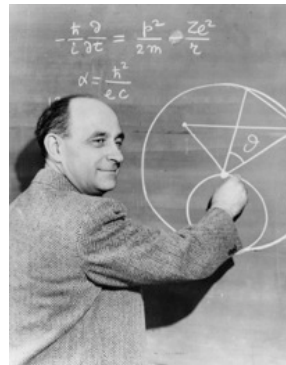


THE UNIVERSITY OF  
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# The Fourth Paradigm of Science

1. Empirical + experimental
2. Theoretical
3. Computational
4. Data-Intensive



# Open Source Ecosystem & Context



2006-2010

Autonomic Computing & Cloud

Usenix HotCloud Workshop 2010

## Spark: Cluster Computing with Working Sets

Matei Zaharia, Mosharaf Chowdhury, Michael J. Franklin, Scott Shenker, Ion Stoica  
University of California, Berkeley

### Abstract

MapReduce and its variants have been highly successful in implementing large-scale data-intensive applications on commodity clusters. However, most of these systems are built around an acyclic data flow model that is not suitable for other popular applications. This paper focuses on one such class of applications: those that reuse

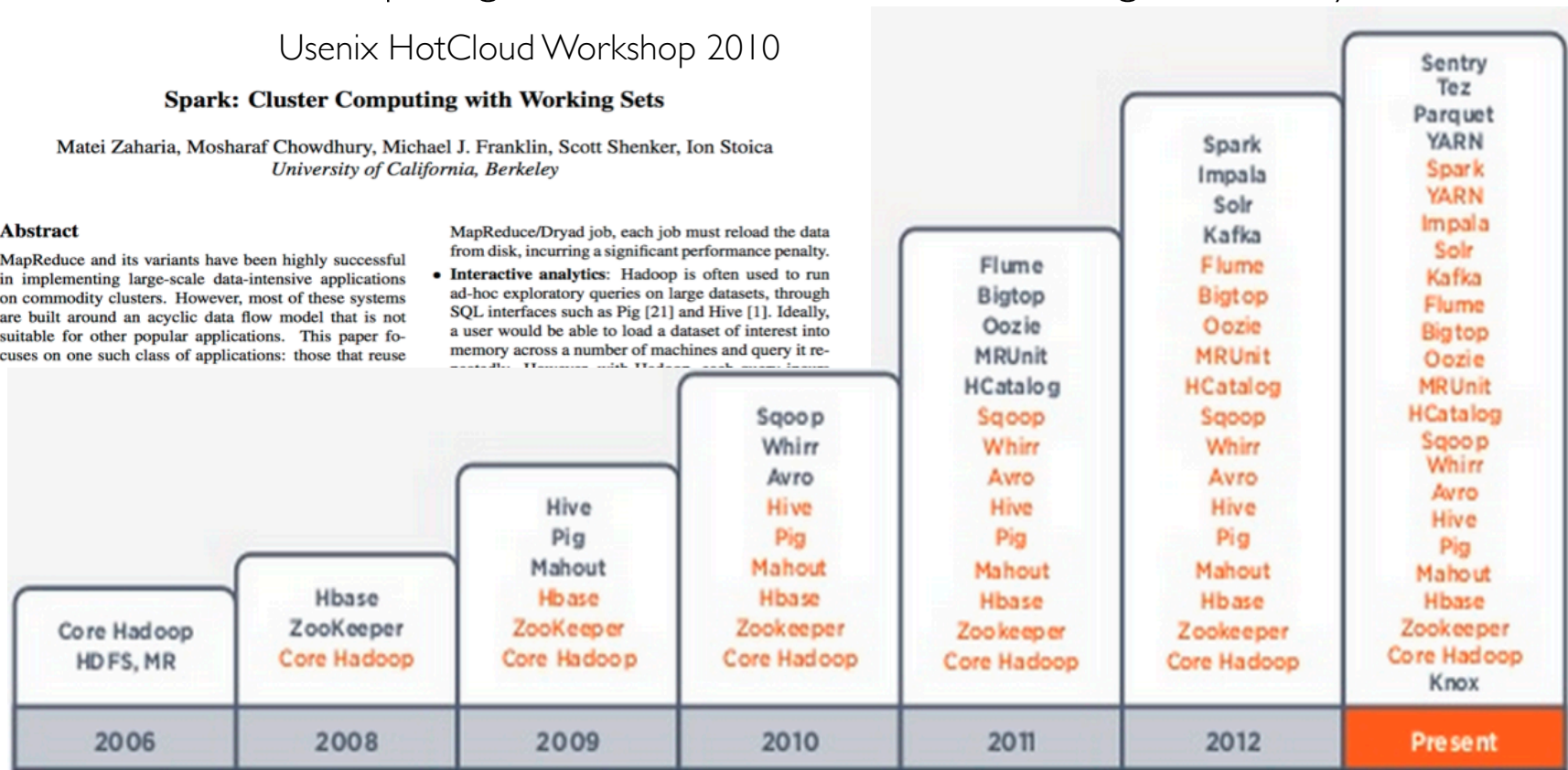
MapReduce/Dryad job, each job must reload the data from disk, incurring a significant performance penalty.

- **Interactive analytics:** Hadoop is often used to run ad-hoc exploratory queries on large datasets, through SQL interfaces such as Pig [21] and Hive [1]. Ideally, a user would be able to load a dataset of interest into memory across a number of machines and query it repeatedly. However, with Hadoop each query requires



2011-2016

Big Data Analytics



# Berkeley Data Analytics Stack

## In House Applications – Genomics, IoT, Energy, Cosmology



## Processing Engines



## Storage



## Resource Virtualization



# *Pathways to Convergence*

Mark Asch - [mark.asch@u-picardie.fr](mailto:mark.asch@u-picardie.fr)

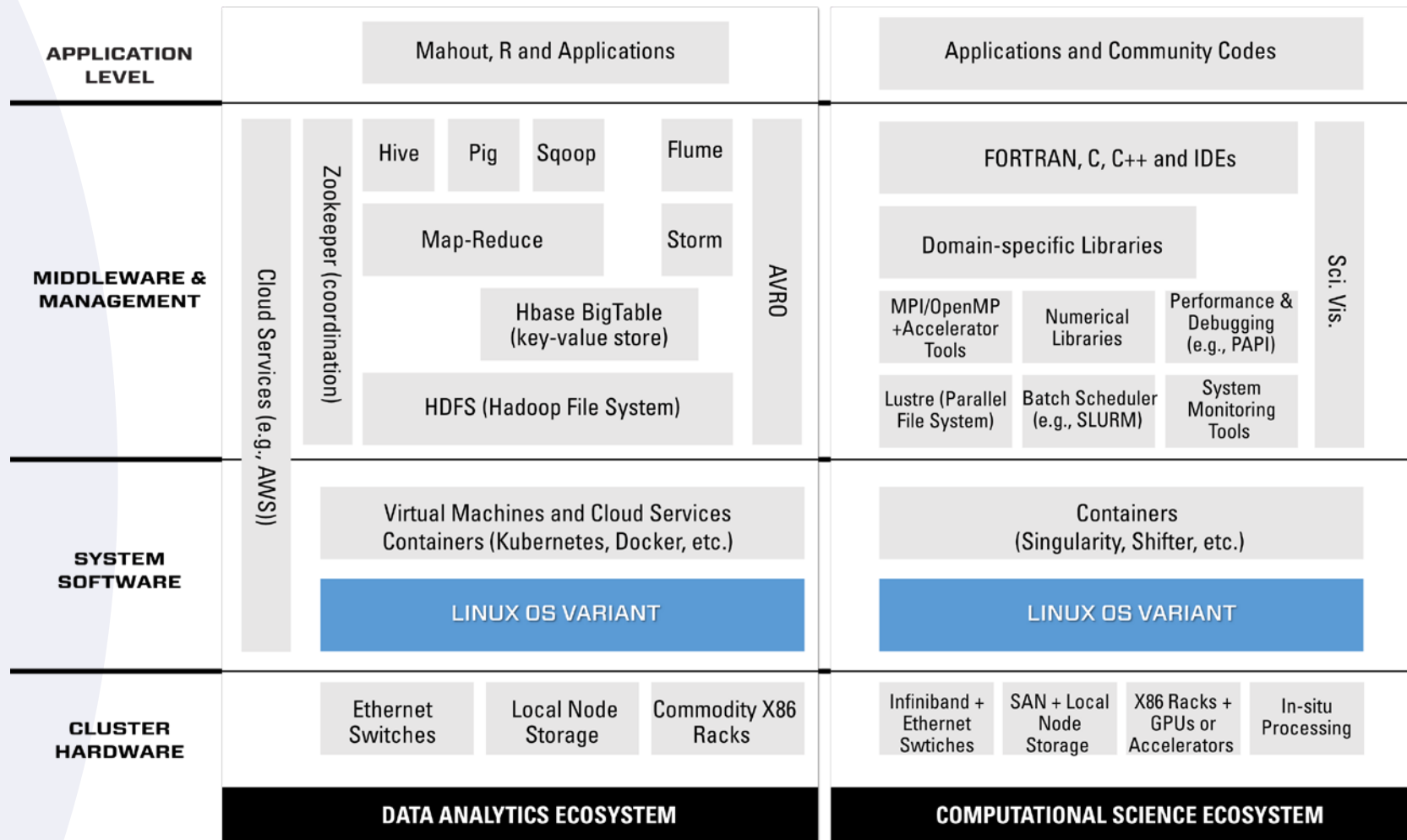
EXDCI – BDVA meeting

Bologna, July 4th 2017

July 3, 2017



# The 2 worlds: Big Data and HPC software stacks



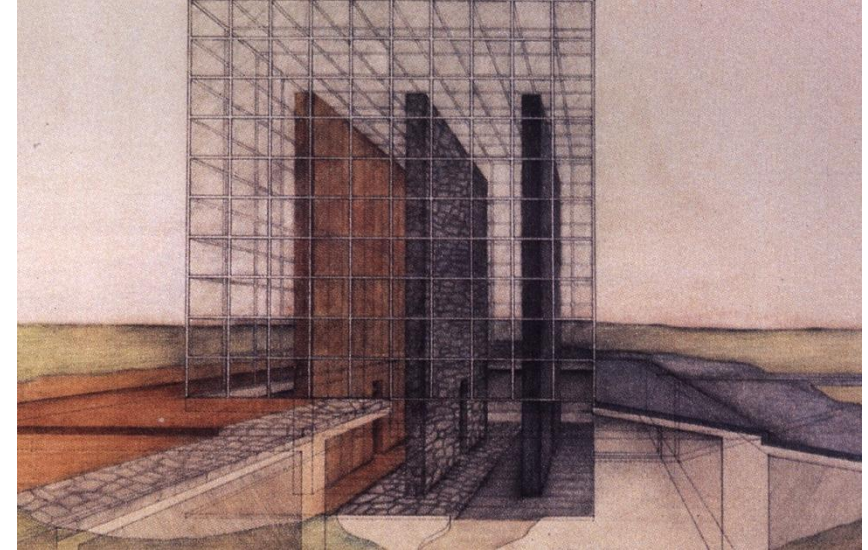


# Argonne Training Program on Extreme-Scale Computing (ATPESC)

Presented to  
**ATPESC 2017 Participants**

**Peter Kogge**  
**Data Intensive Computing, the 3<sup>rd</sup> Wall, and  
the Need for Innovation in Architecture**

Q Center, St. Charles, IL (USA)  
Date 08/04/2017



<http://deathofdrawing.com/wp-content/gallery/raimund-abraham/RA-House-With-Three-Walls.jpg>



EXASCALE COMPUTING PROJECT

# When Do We Need New Architectures

- Long-lasting architectural advances occur when a “wall” must be overcome
- 1<sup>st</sup> Wall – Mid 90s: the **Memory Wall**
- 2<sup>nd</sup> Wall – 2004: the **Power Wall**
- 3<sup>rd</sup> Wall – Now: the **Locality Wall**

**And this is largely due to emergence of apps with  
*Data Intensive* Characteristics**



# What Do I Mean by *Data Intensive*?

- Computation dominated by data access & movement – **not flops**
- Large sets of data often persistent
  - but little reuse during computation
- No predictable regularity
- Significantly different scaling
- Streaming becoming important

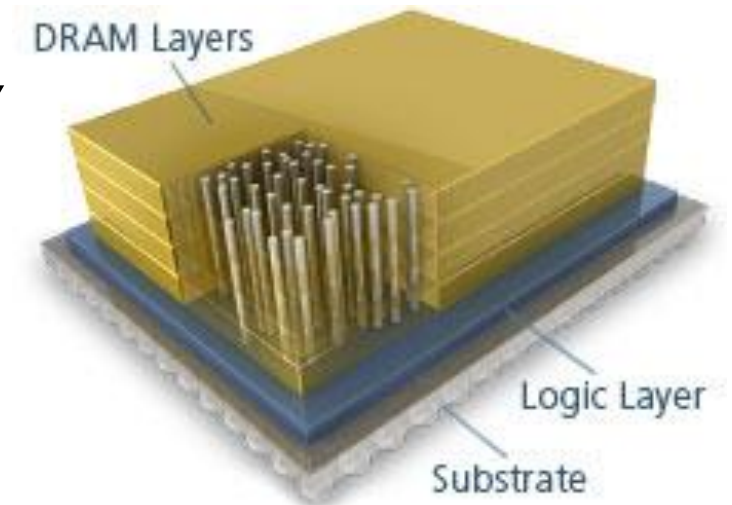
**The “Locality” we have come to expect from our apps is disappearing**

# This Talk

- Moore's Law and the Prior Walls
- Today's Architectures
- Evidence of a New "Locality" Wall
  - Benchmarks
  - A Big Data Application
- Migrational Computing: a Possible Architectural Fix

# Technology, Moore's Law, and Beyond

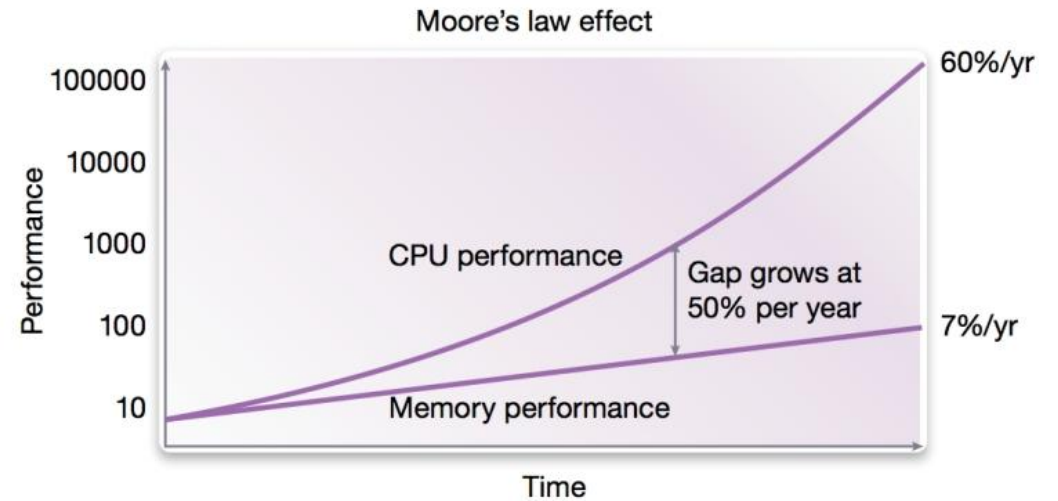
- Moore's Law: 2D transistors get smaller & faster
  - From 10um to 5nm feature size: **2,000X smaller & faster**
- Cores get smaller, faster, lower power
  - Power density approx. constant as long as  $V_{dd}$  declines
- Memory arrays get denser
  - To maximize density, access time drops at best slowly
  - Can increase bandwidth, but power skyrockets
- After Moore's Law: **we're going 3D!**
  - With a mix of die types



<http://www.micron.com/products/hybrid-memory-cube>

# The Memory Wall (mid 1990s)

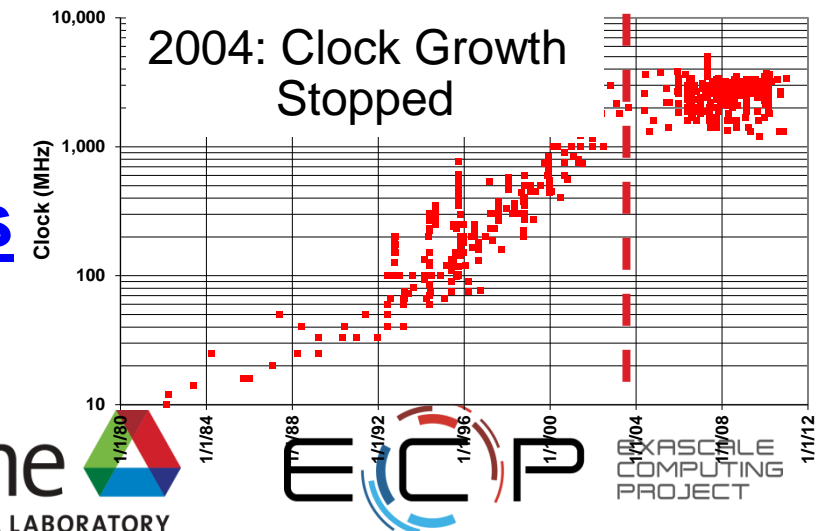
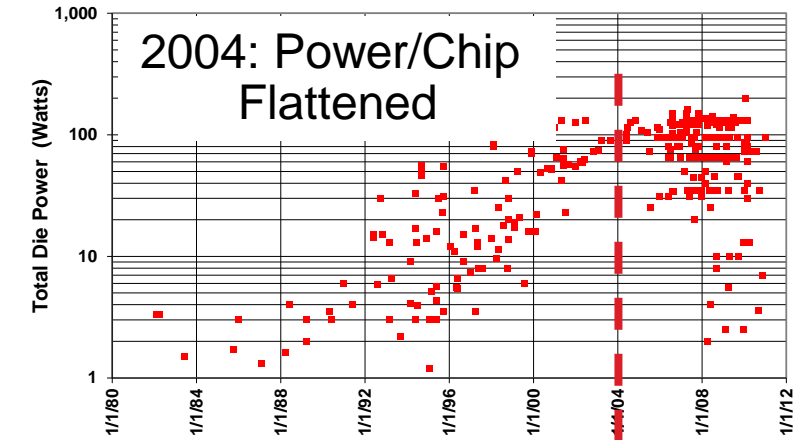
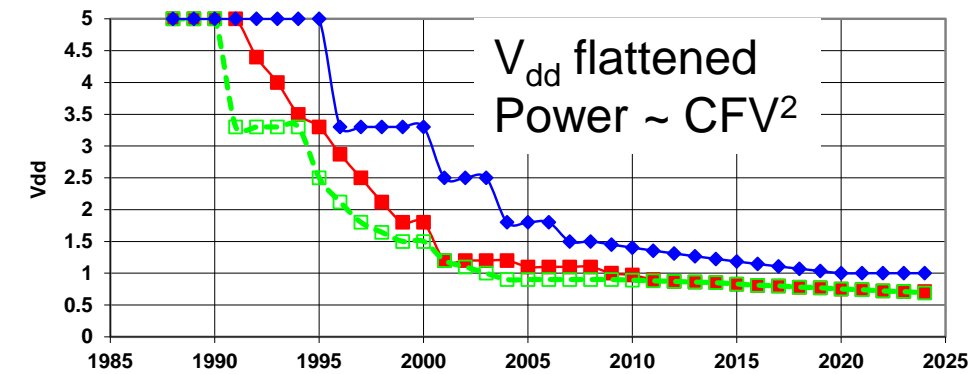
- Core clock speeds outran memory latency
- **Breaking the Wall:** Use extra transistors for
  - Bigger on-chip SRAM caches
  - More ILP to find more memory accesses
  - Add additional floating point capability
- Enablers: Applications had *plenty* of locality
- Example:  $Ax=b$ ,  $A$  is large, dense, matrix
  - Tremendous temporal locality
  - Assume caches can save  $n \times n$  patch of  $A$
  - $O(n^2)$  to read  $n \times n$  patch of  $A$  to cache
  - $O(n^3)$  operations on this patch
- With ***big enough cache***, don't care how slow memory is



<http://www.extremetech.com/wp-content/uploads/2014/07/140364245678419.jpg>

# The Power Wall (2004)

- Flattening  $V_{dd}$  increased power density
  - Bigger chips meant more logic to dissipate
- Result: at 120Watts, cooling uneconomical
- Breaking the wall:
  - **Lower the clock rate**
  - **Use *multiple* simpler cores**
  - **Increase *SIMD*-style parallelism**
- Side-effect: need more bandwidth
- Solution for dense apps: again **bigger caches**



# “A Vision for Exascale: Simulation, Data and Learning”

Rick Stevens

Argonne National Laboratory

The University of Chicago



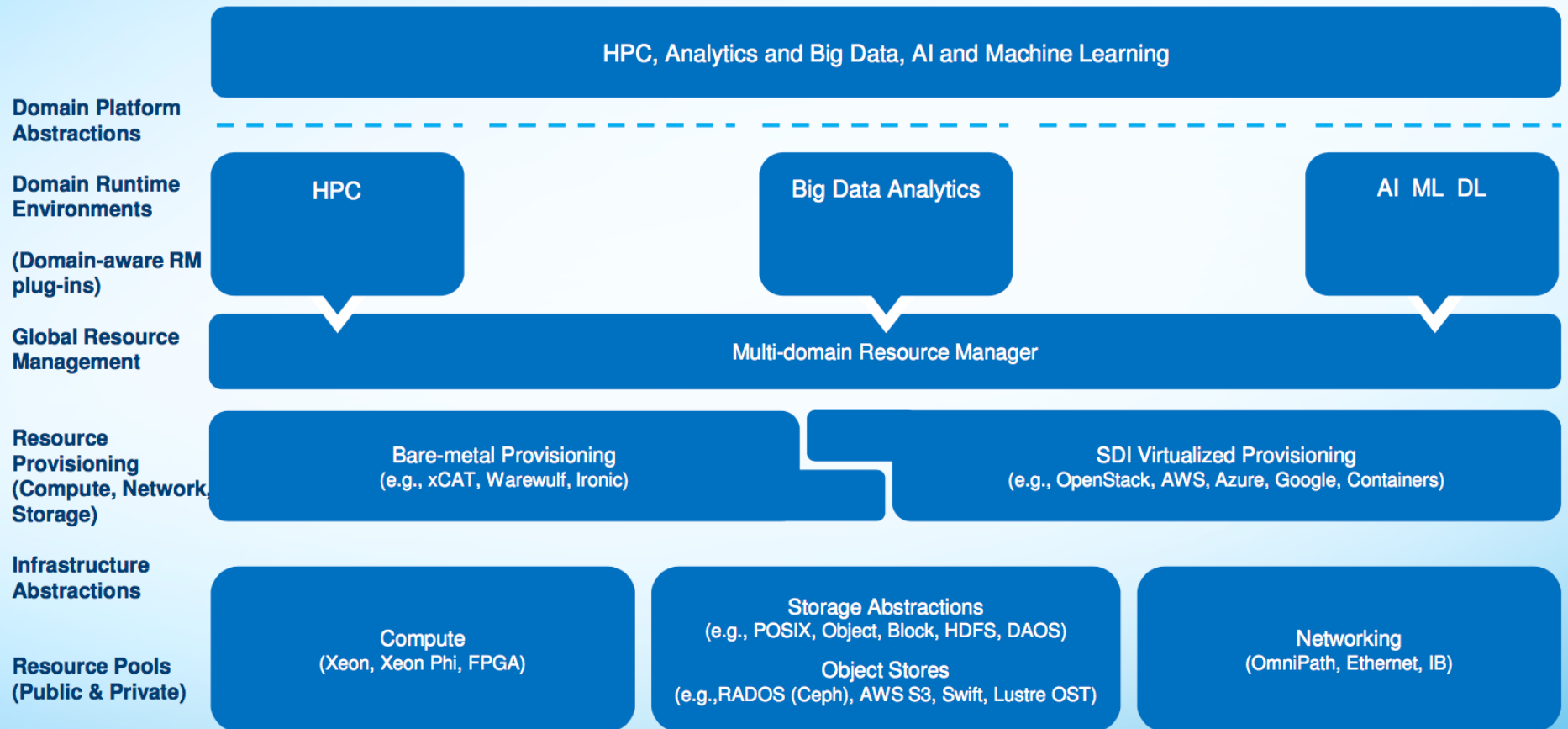
Crescat scientia; vita excolatur



# Aurora 21

- Argonne's Exascale System
- Balanced architecture to support three pillars
  - Large-scale Simulation (PDEs, traditional HPC)
  - Data Intensive Applications (science pipelines)
  - Deep Learning and Emerging Science AI
- Enable integration and embedding of pillars
- Integrated computing, acceleration, storage
- Towards a common software stack

# Towards an Integrated Stack



# The New HPC “Paradigm”

