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Universidad Politécnica de Madrid
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HPC and Big Data, A marriage of convenience?

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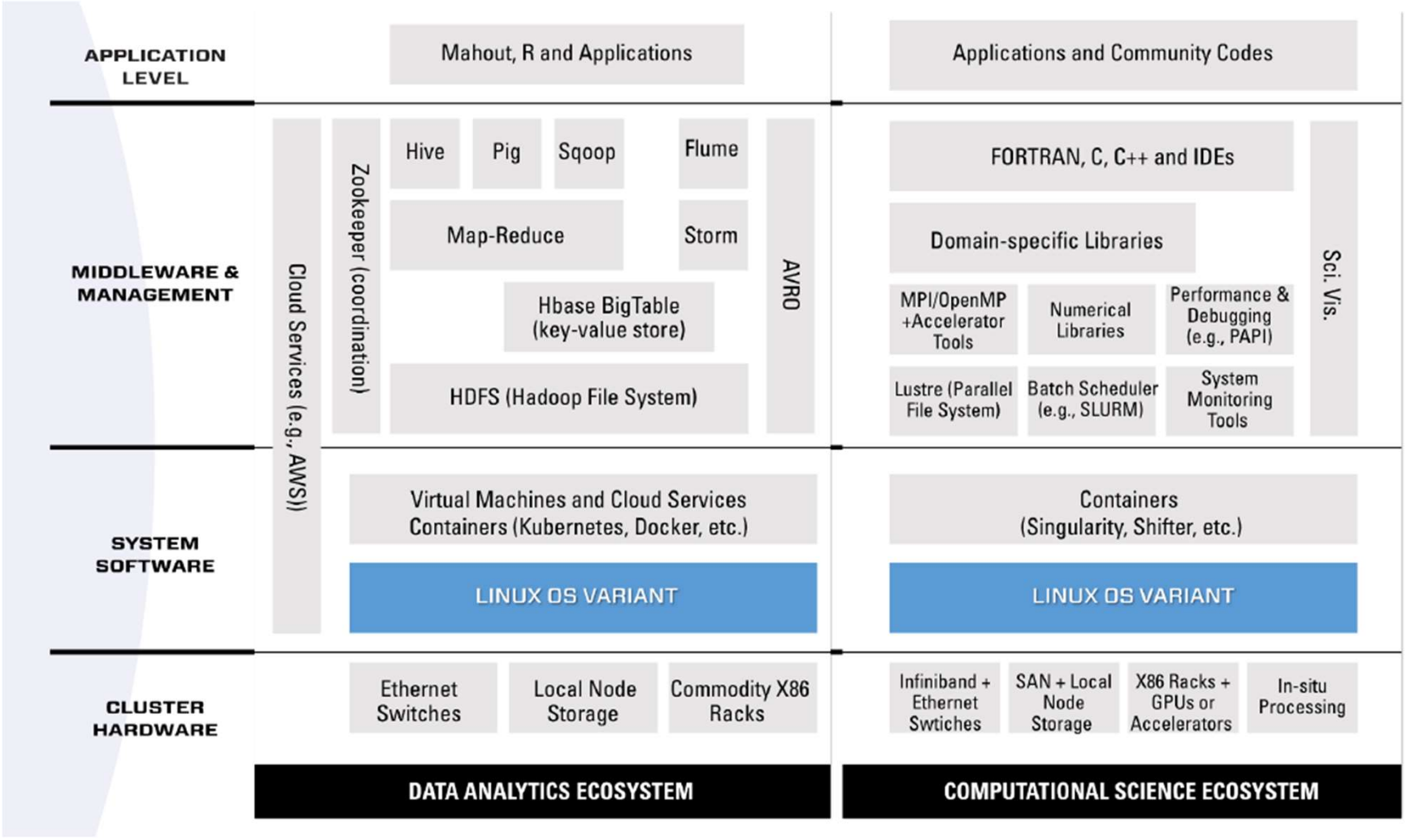
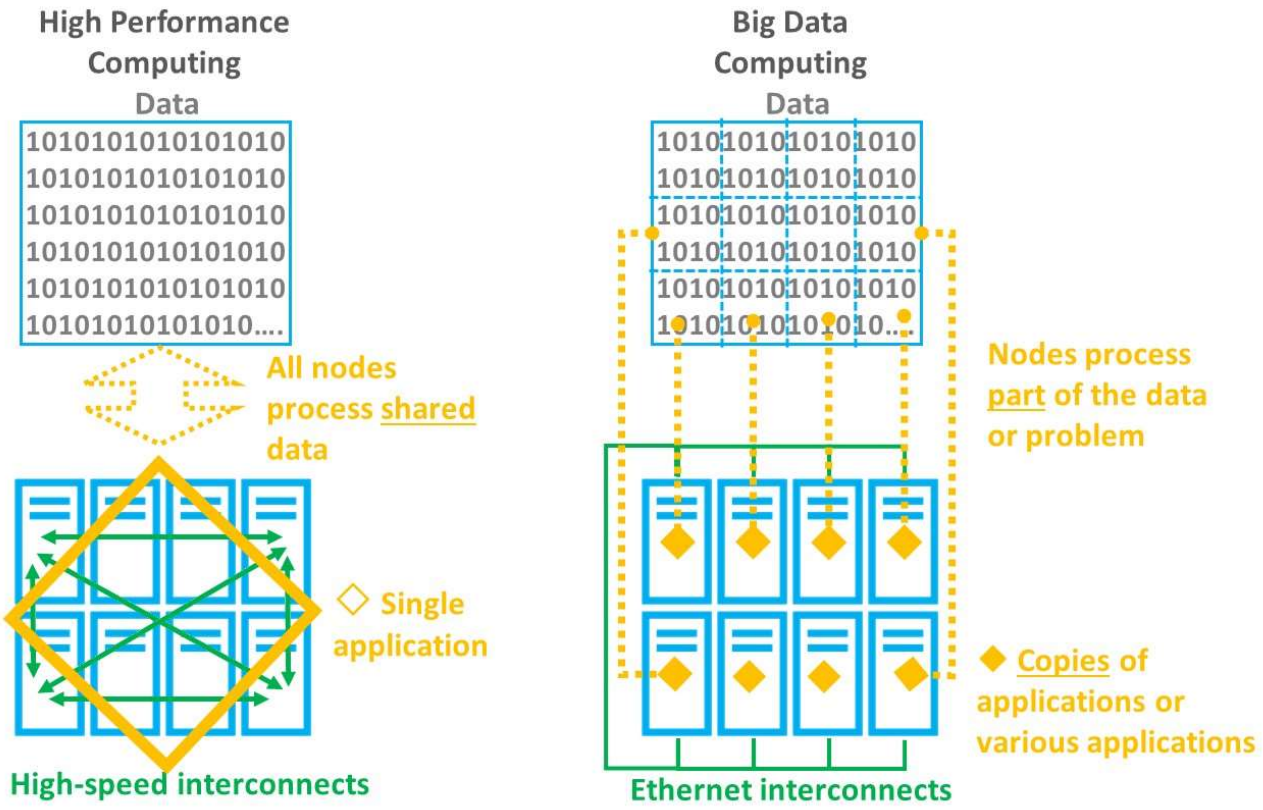
- **Introduction**
- Context
- General convergence HPC-Big Data problem
- Convergence HPC-Big Data at storage level
- Study and evaluation
- Conclusions

Divergence DA-CS



Source: Big Data and Extreme-Scale Computing, BDEC

Divergence at architecture level



Source: "Creating synergies across HPC & Big Data platforms", BDVA-ETP4HPC White Paper

Historical differences BD-HPC

	Typical workload	Design principles
Big Data	Data-intensive applications Most time is used for I/O and data management	Optimized for cost Less priority for performance
HPC	Compute-intensive applications Most time is used for computing	Optimized for performance Less priority for cost

Digital Single Market

POLICY

The European High-Performance Computing Joint Undertaking - EuroHPC

PAGE CONTENTS

Useful links

The European High-Perfomance Computing Joint Undertaking (EuroHPC JU) will pool European resources to develop top-of-the-range exascale supercomputers for processing big data, based on competitive European technology.

About HPC

Policies +

Blog posts

News

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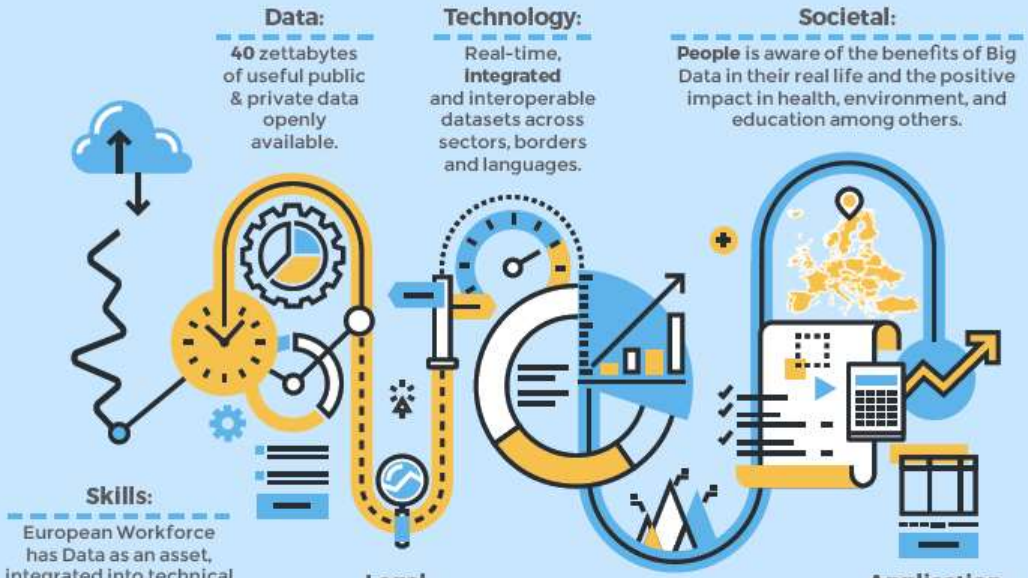
BDV BIG DATA VALUE ASSOCIATION

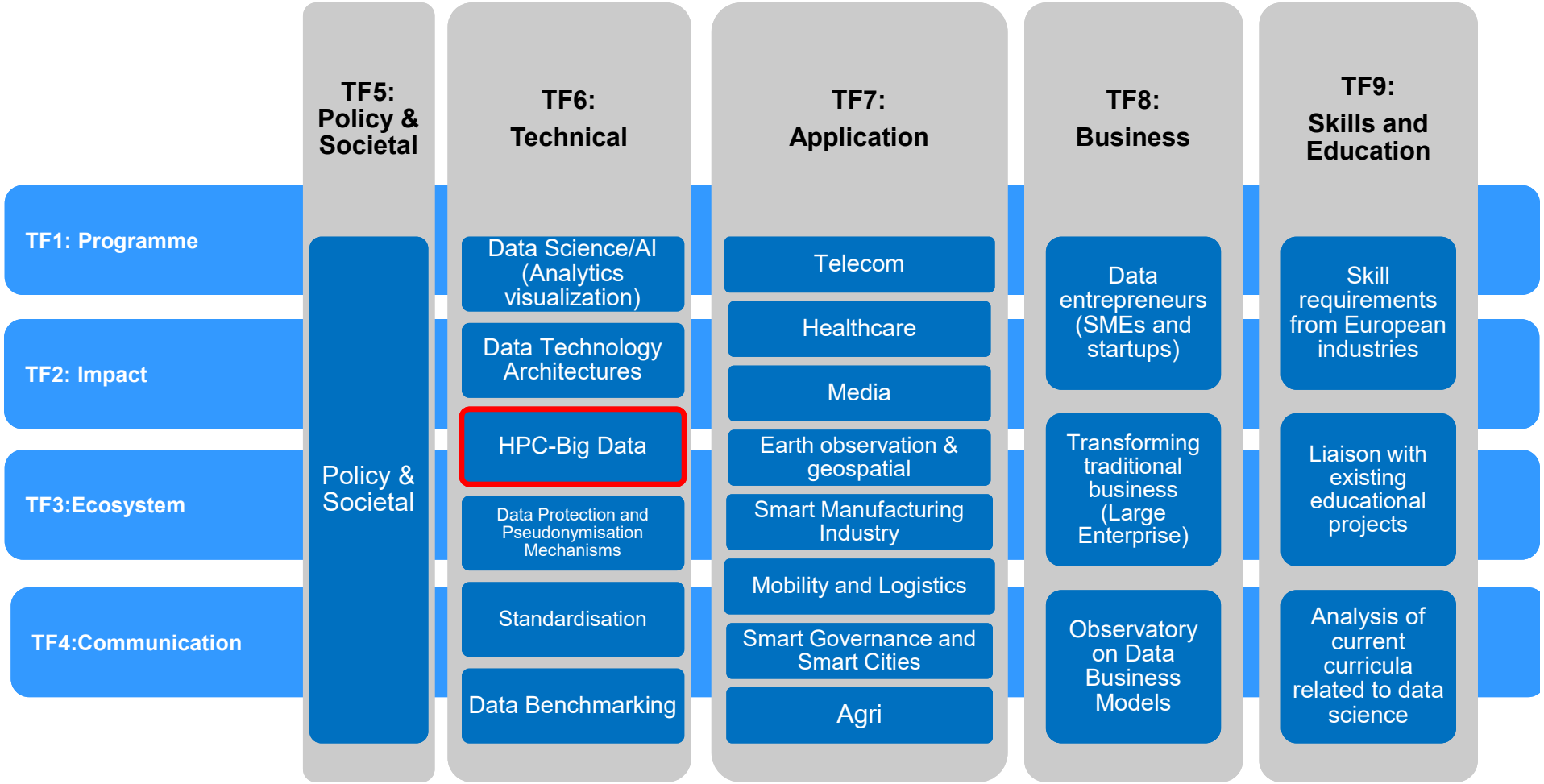
BDVA focuses its activities on updating the multi-annual roadmap and on providing regular advice to enable the European Commission to prepare, draft and adopt the periodic Work Programmes, as well as on delivering Data Innovation Recommendations, developing Big Data Value Ecosystem, guiding Standards, and, facilitating Know-how exchange.

BDVA (~200) members include large industries, SMEs, research organisations and data users and providers to support the development and deployment of the EU Big Data Value Public-Private Partnership with the European Commission

Big Data Value Vision for 2020



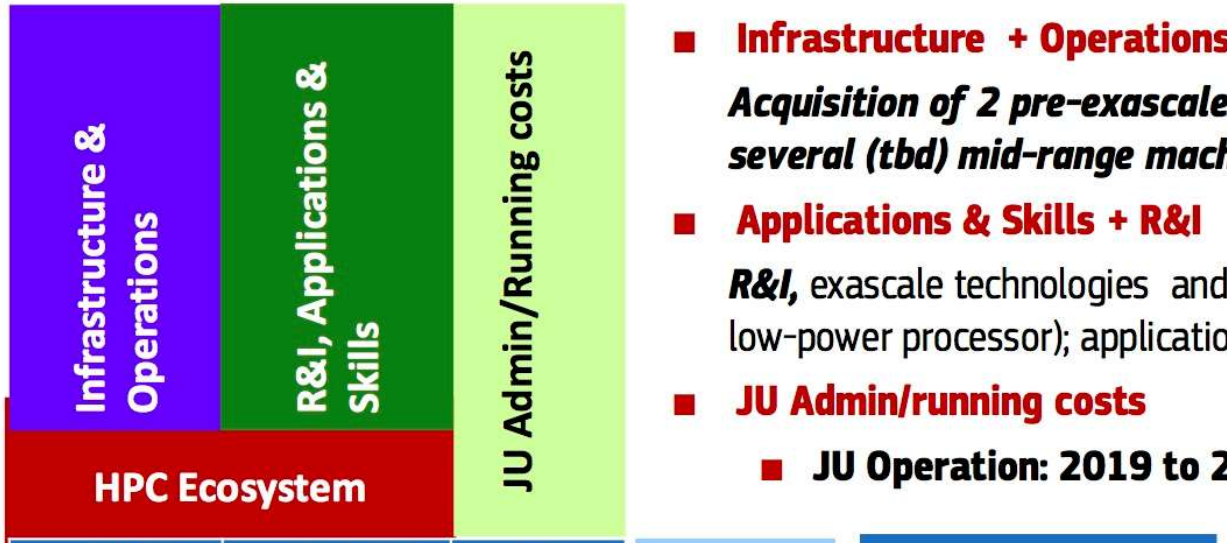
BDVA Task Forces



EuroHPC Joint Undertaking

https://eurohpc-ju.europa.eu

EuroHPC – Activities



- **Infrastructure + Operations**

  Acquisition of 2 pre-exascale machines and several (tbd) mid-range machines

- **Applications & Skills + R&I**

  R&I, exascale technologies and systems (incl. low-power processor); applications

- **JU Admin/running costs**
  - **JU Operation: 2019 to 2026**

~270	min 180	10	486 m€	EC
~290	~186	10	486 m€	Participating States
560	392	20	972 m€	Total
0	~420 (in kind)	2	422 m€	Private Members

https://eurohpc-ju.europa.eu/documents/EuroHPC-Work-Plan-2019.pdf

CABAHLA-CM: Convergence BD-HPC: From sensors to applications

- Project funded by the Community of Madrid, grants for R&D activities between research groups in technology and biomedicine (2019-2022)
- 4 groups:
  - ArTeCS, Universidad Complutense de Madrid
  - ARCOS, Universidad Carlos III de Madrid
  - SciTrack, Centro de Investigaciones Energéticas, Medioambientales y Tecnológicas
  - OEG, Universidad Politécnica de Madrid
- Goal: Improve the integration of HPC and Big Data paradigms
  - Computing and data intensive platform
  - Two use cases: capturing and modeling sensor data for the prediction of solar radiation with high spatio temporal resolution and processing massive data in brain's medical images

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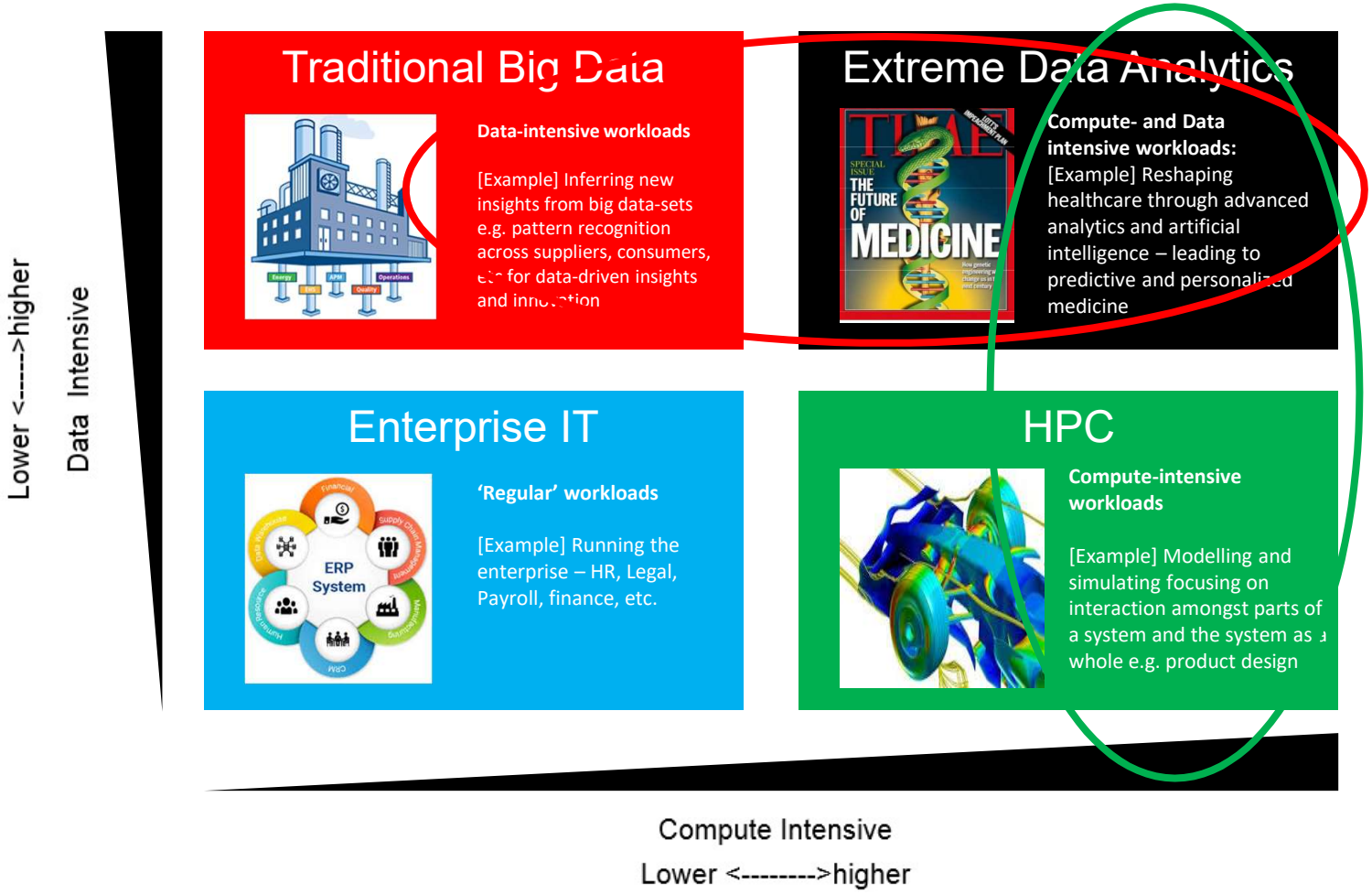
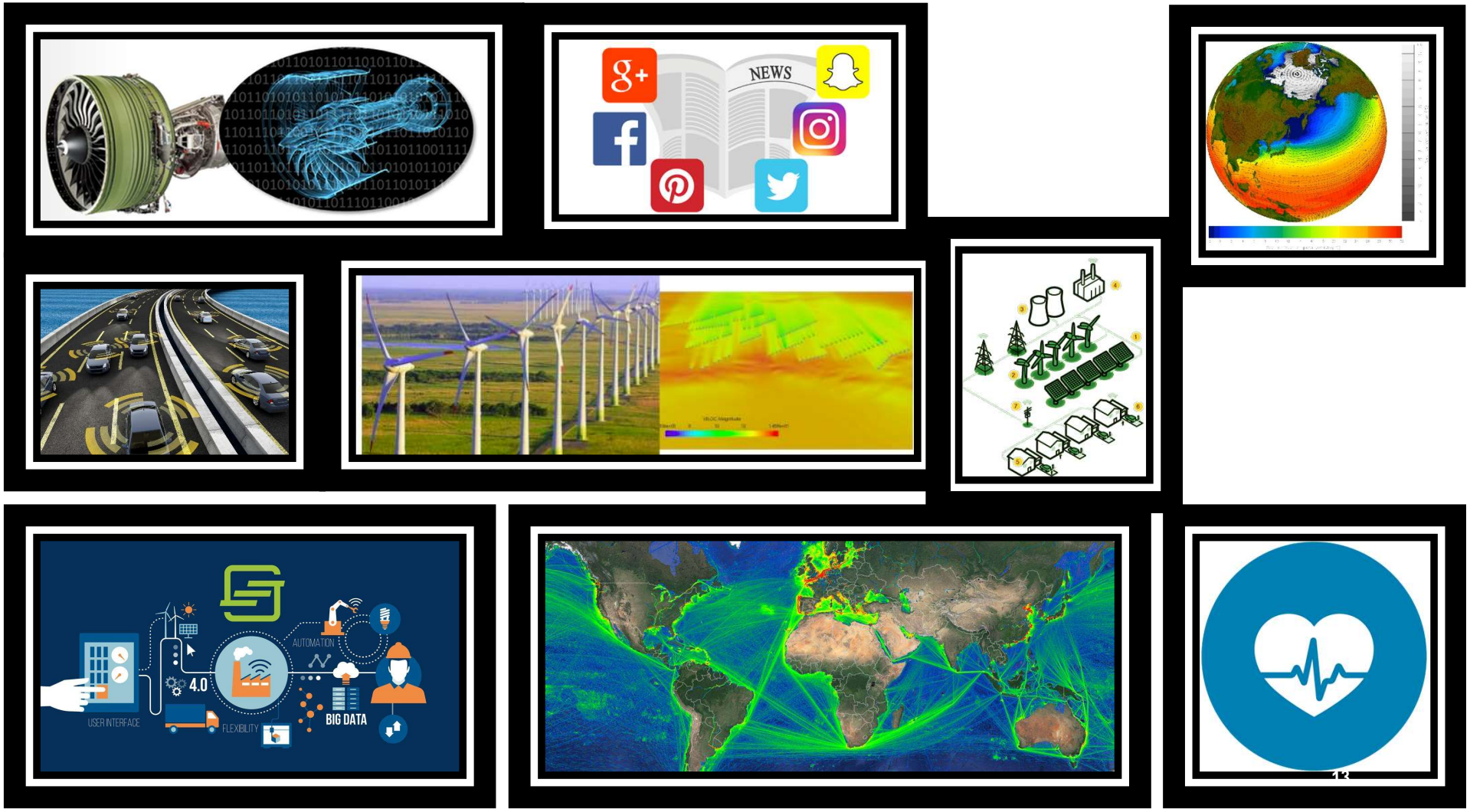


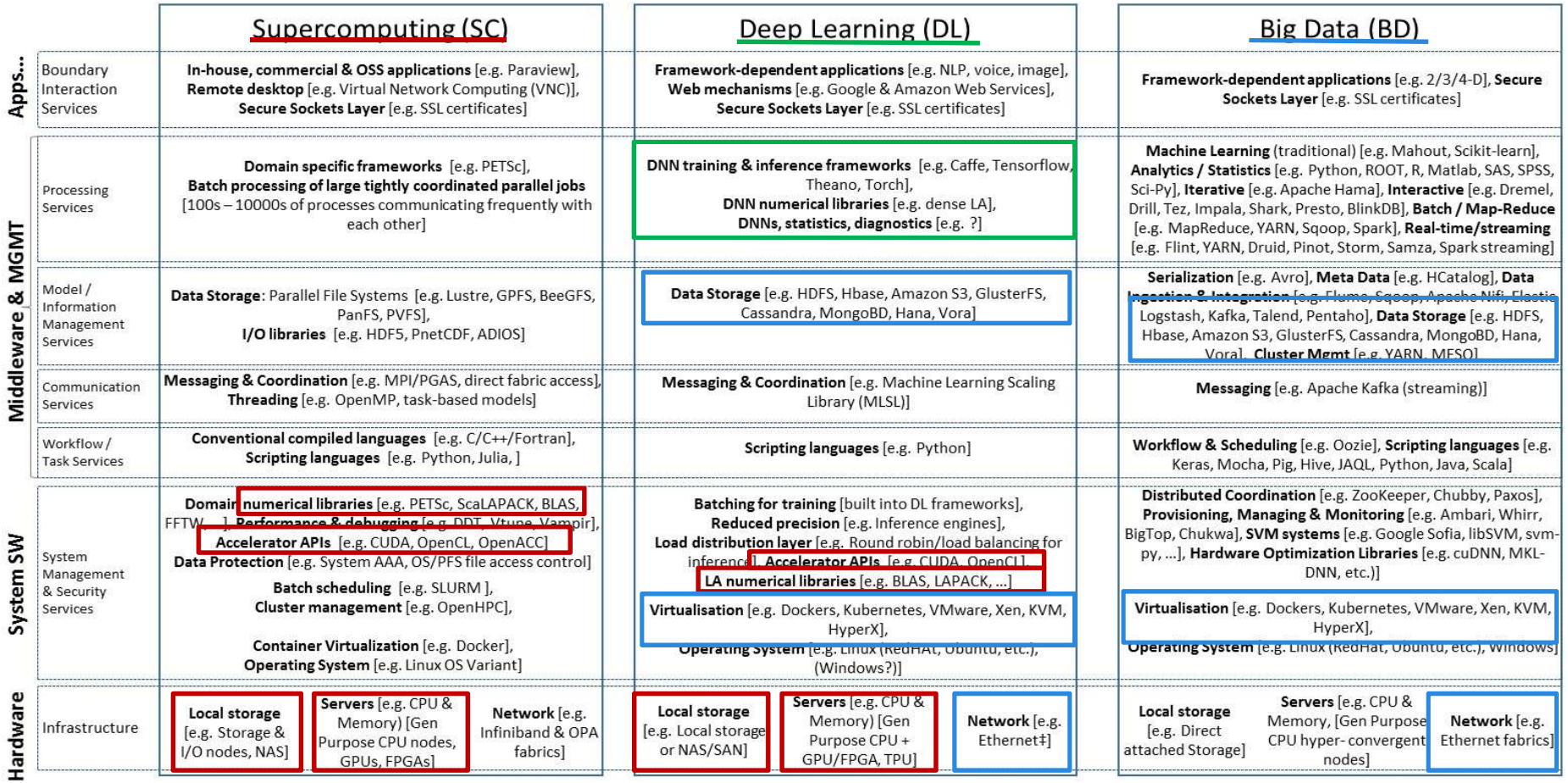
Source: Subgroup HPC-BD BDVA

Applications/Use cases



Source: Subgroup HPC-BD BDVA

HPC, Big Data and Deep Learning



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HPC at storage level

HPC application

POSIX file system

- Random reads and writes to file
- Folder/file hierarchies
- Permissions
- Atomic file rename
- Multi-user protection

POSIX

Random reads and writes to file
Folder/file hierarchies
Permissions
Atomic file rename
Multi-user protection

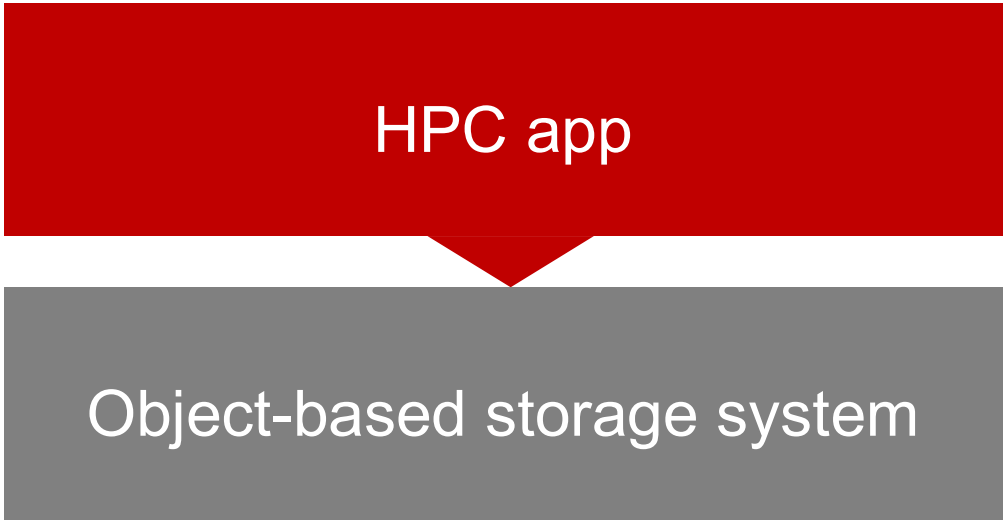
POSIX

Random reads and writes to file

POSIX

Random reads and writes to ~~file~~ Objects

HPC at storage level



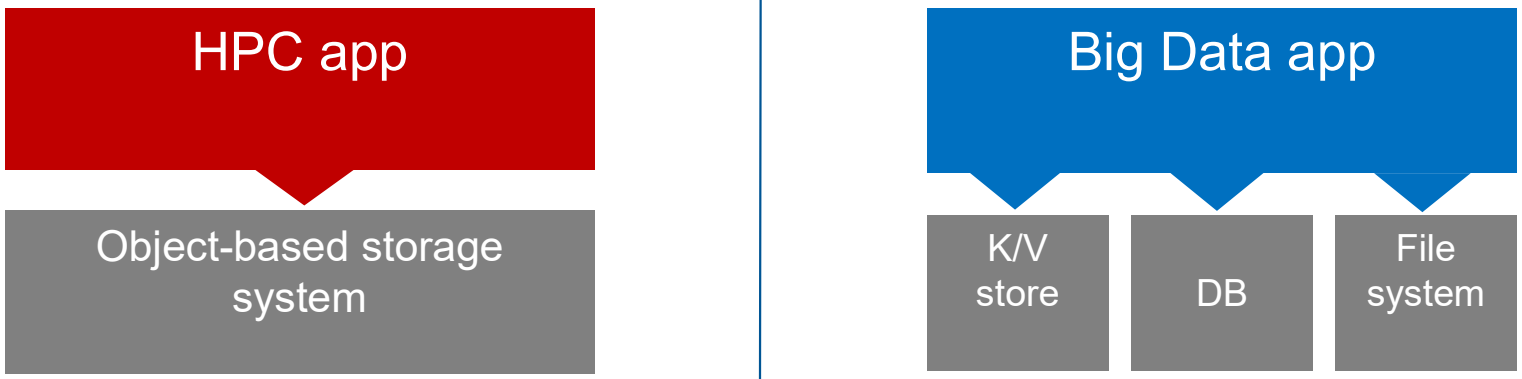
HPC and Big Data

HPC app

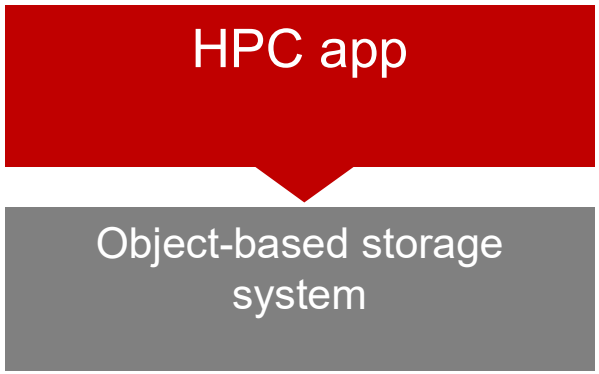
Object-based storage system

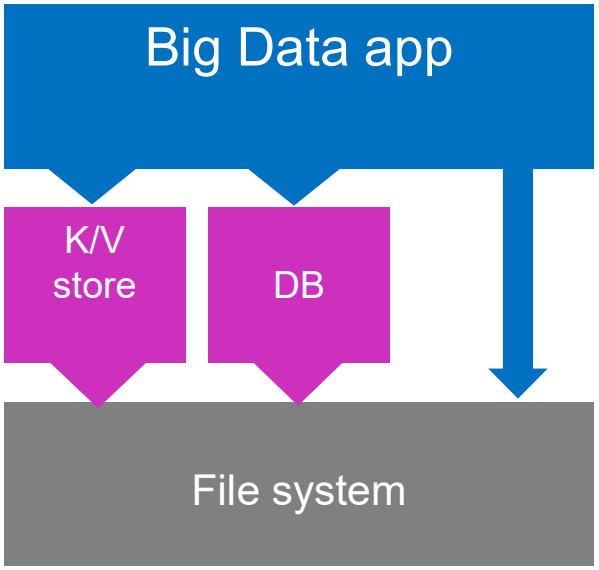
Big Data app

HPC and Big Data



HPC and Big Data





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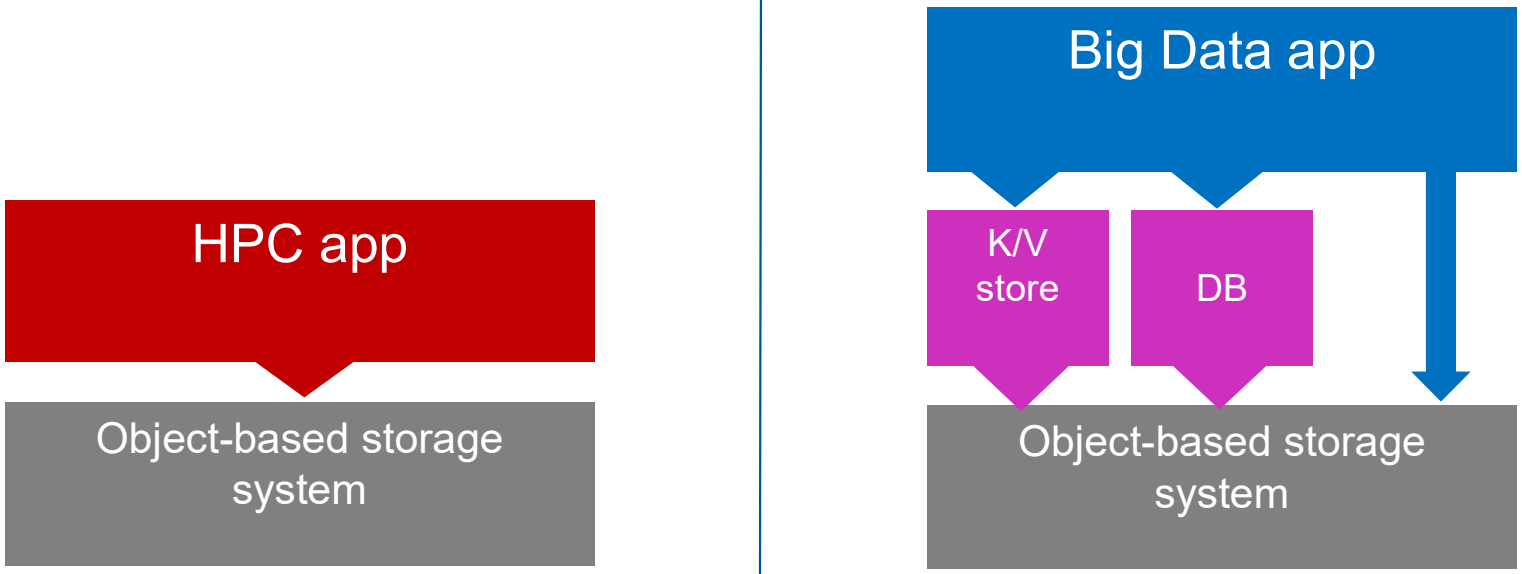
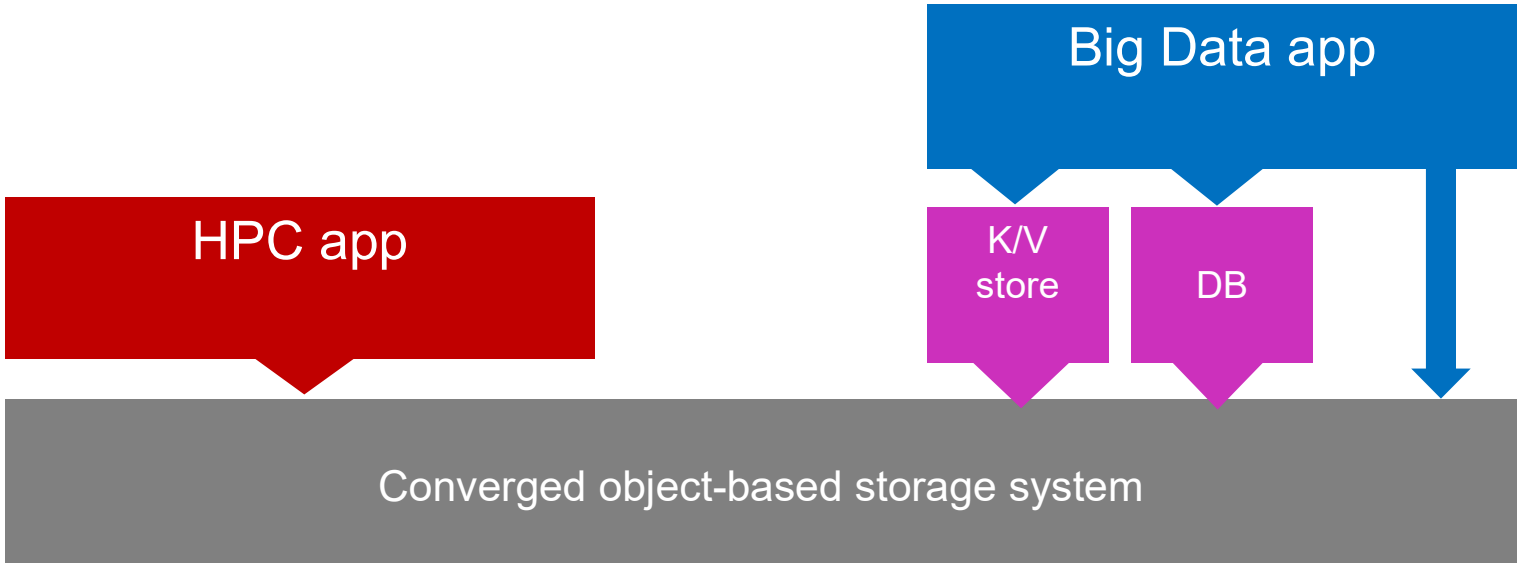
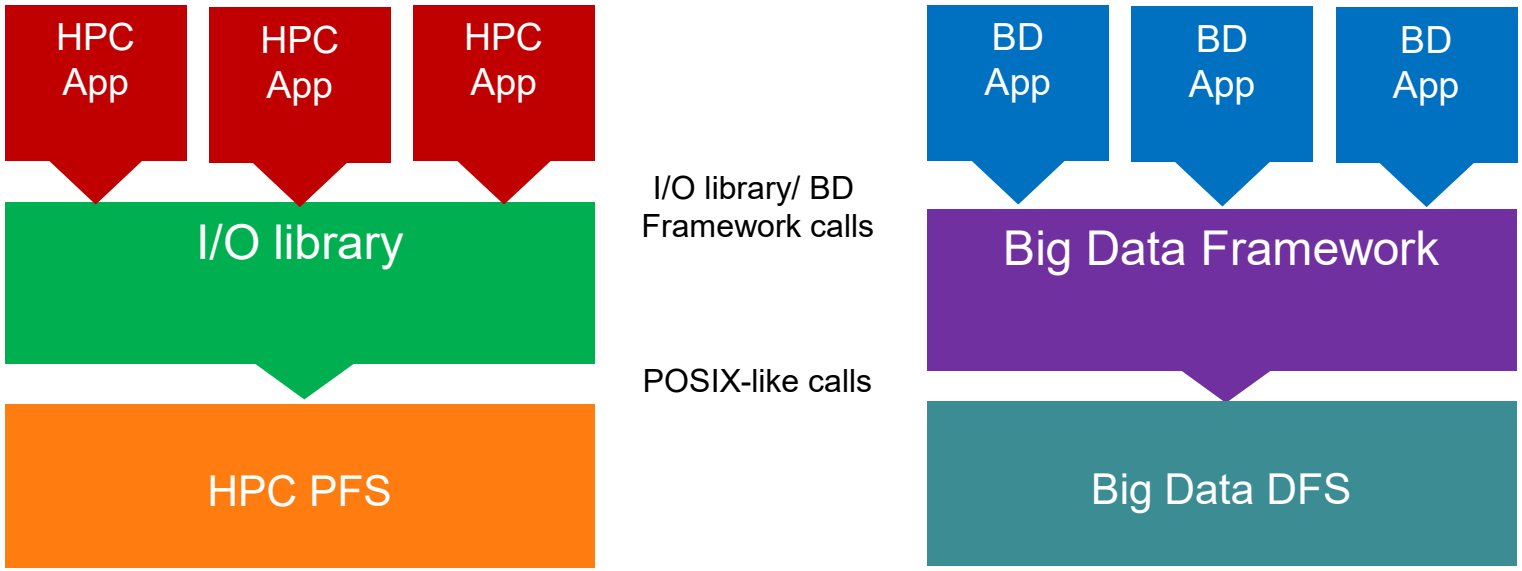


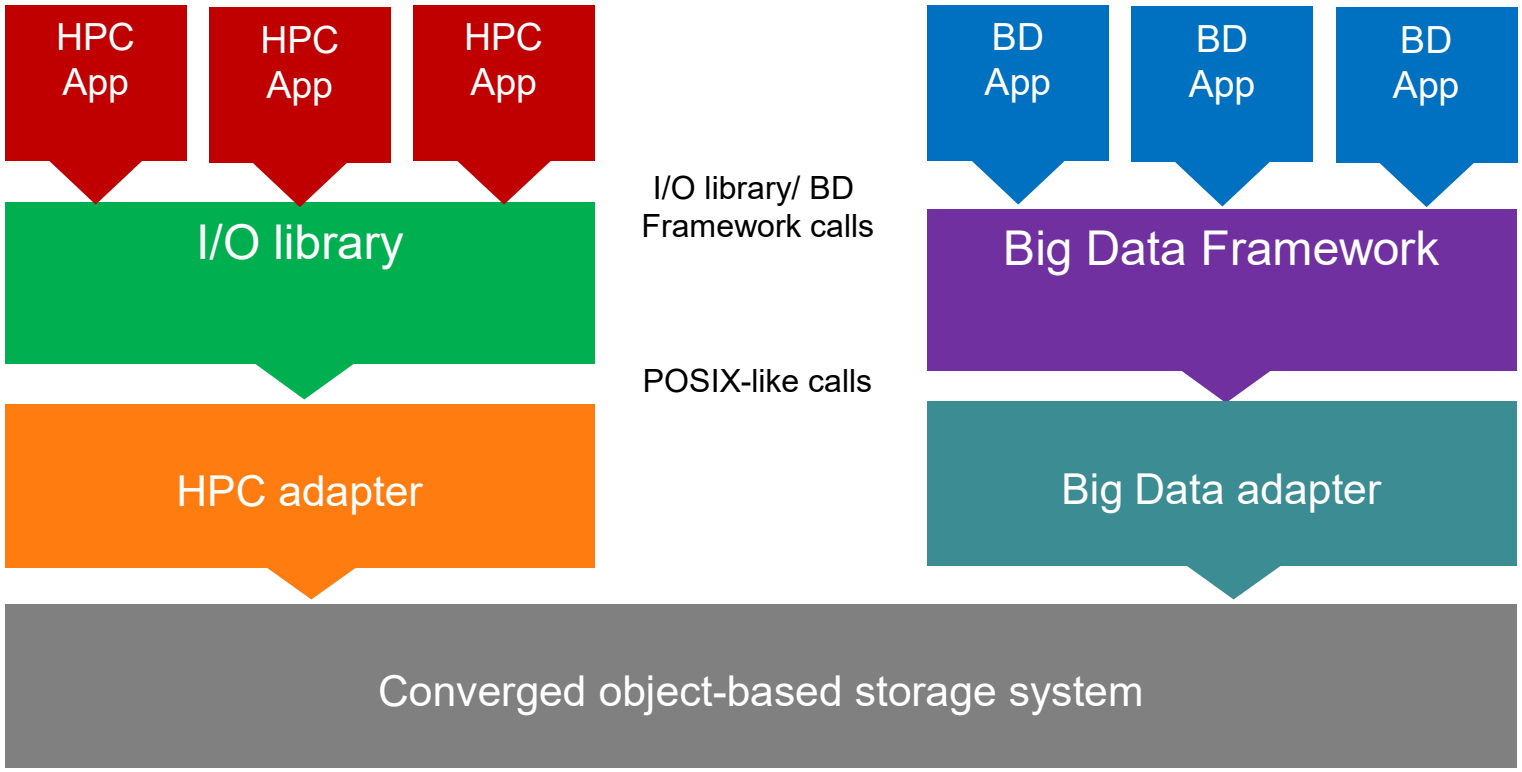
HPC and Big Data



Actual storage stack



Actual storage stack



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Object-oriented primitives

- Object access: random object read, object size
- Object manipulation: random object write, truncate
- Object administration: create object, delete object

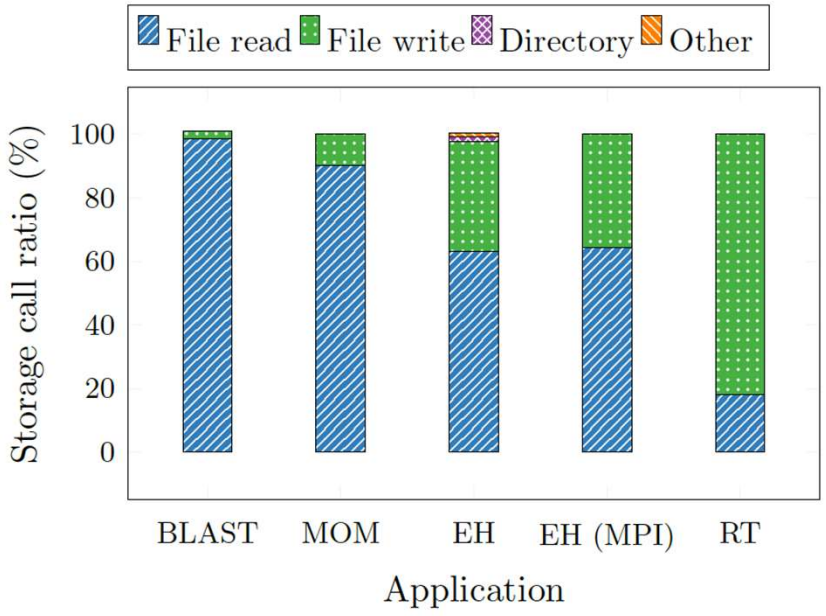
- These operations are similar to those permitted by the POSIX-IO API on a single file
- Directory-level operations do not have their object-based storage counterpart (flat nature of these kinds of systems):
  - Low number of them
  - Emulated using the scan operation (far from optimized, but compensated by the gains permitted by using a flat namespace and simpler semantics)

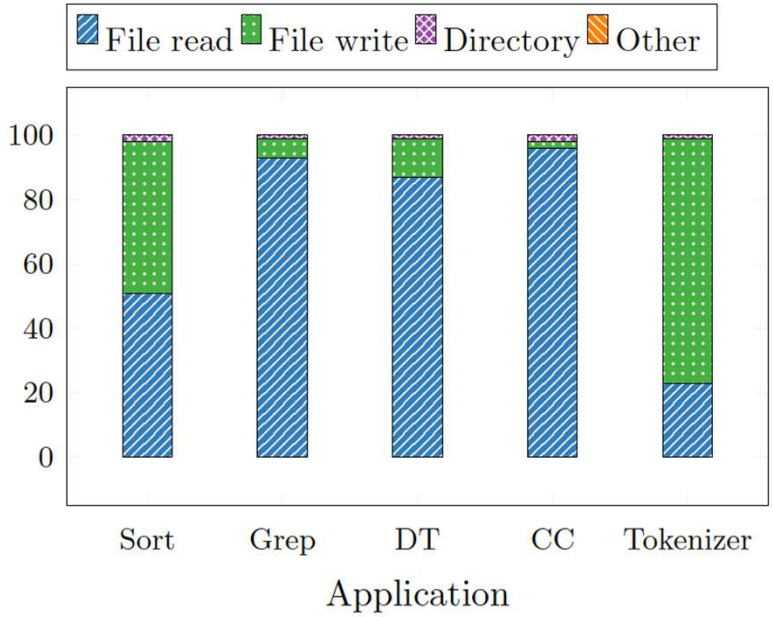
Representative set of HPC/BD Apps

Plataform	Application	Usage	Total reads	Total writes	R/W ratio	Profile
HPC/MPI	mpiBLAST	Protein docking	27.7 GB	12.8 MB	2.2*10^3	Read-intensive
	MOM	Oceanic model	19.5 GB	3.2 GB	6.09	Read-intensive
	ECOHAM	Sediment propagation	67.4 GB	71.2 GB	0.94	Balanced
	Ray Tracing	Video processing	0.4 GB	9.7 GB	4.1*10^-2	Write-intensive
Cloud/Spark	Sort	Text processing	5.8 GB	5.8 GB	1.00	Balanced
	Connected Component	Graph processing	13.1 GB	71.2 MB	1.8*10^2	Read-intensive
	Grep	Text processing	55.8 GB	863.8 MB	66.14	Read-intensive
	Decision Tree	Machine Learning	59.1 GB	4.7 GB	12.57	Read-intensive
	Tokenizer	Text processing	55.8 GB	235.7 GB	0.23	Write-intensive

Pierre Matri, Yevhen Alforov, Álvaro Brandón, María S. Pérez et al. Mission possible: Unify HPC and Big Data stacks towards application-defined blobs at the storage layer. Future Generation Computer Systems, In press.

Ops distribution



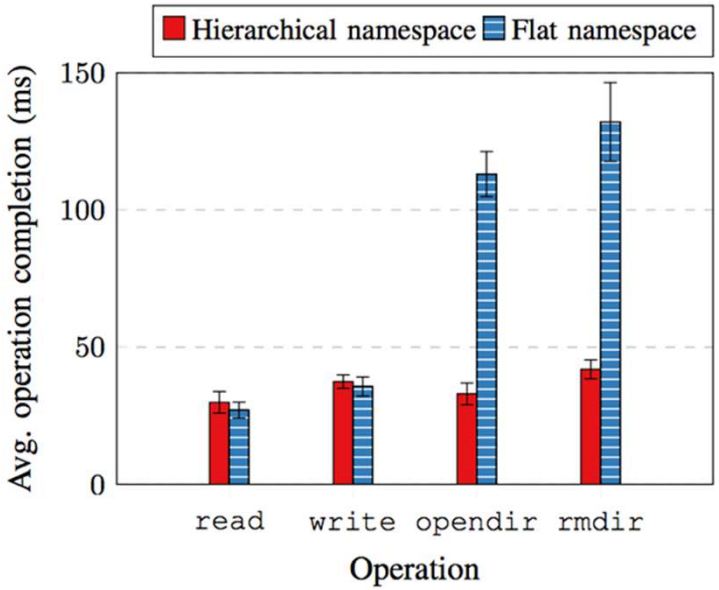


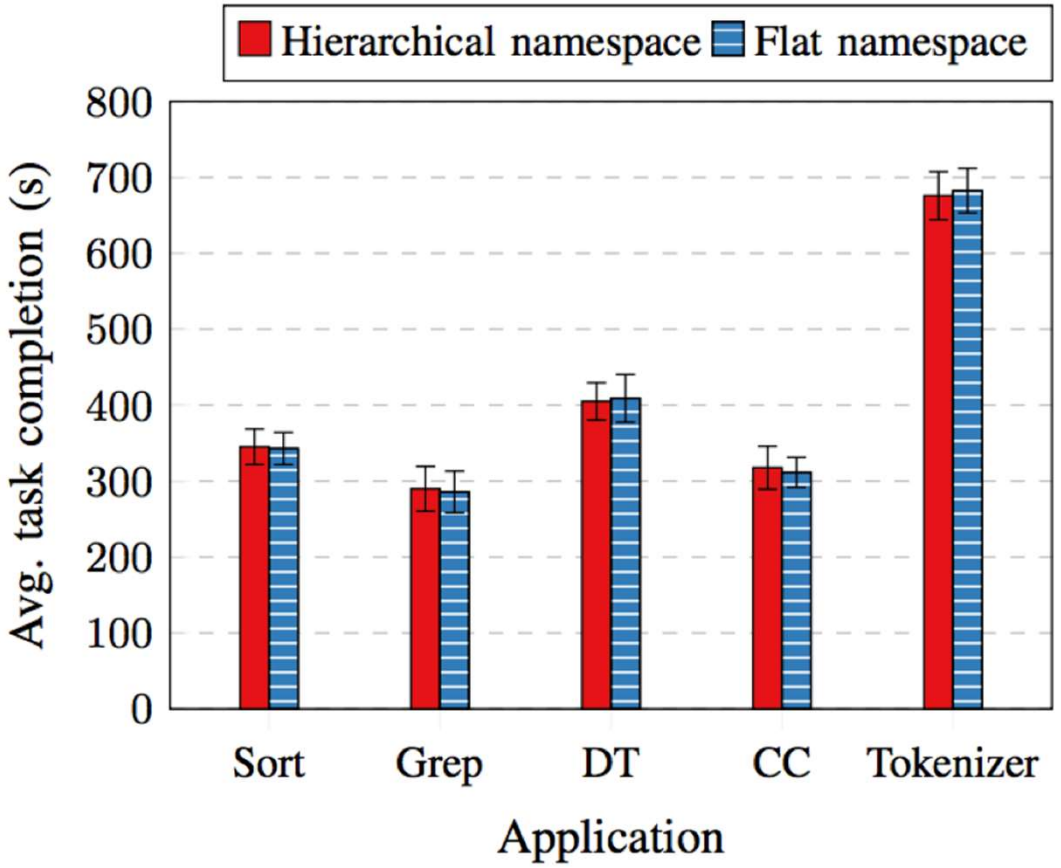
Directory operations (BD App)

Operation	Action	Oper. count
mkdir	Create directory	43
rmdir	Remove directory	43
opendir (Input data directory)	Open/List directory	5
opendir (other directories)	Open/List directory	0

Original operation	Rewritten operation
create(/foo/bar)	create(/foo__bar)
open(/foo/bar)	open(/foo__bar)
read(fd)	read(bd)
write(fd)	write(bd)
mkdir(/foo)	-----
opendir(/foo)	scan(/), return all files matching foo__*
rmdir(/foo)	scan(/), remove all files matching foo__*

Influence of directory operations

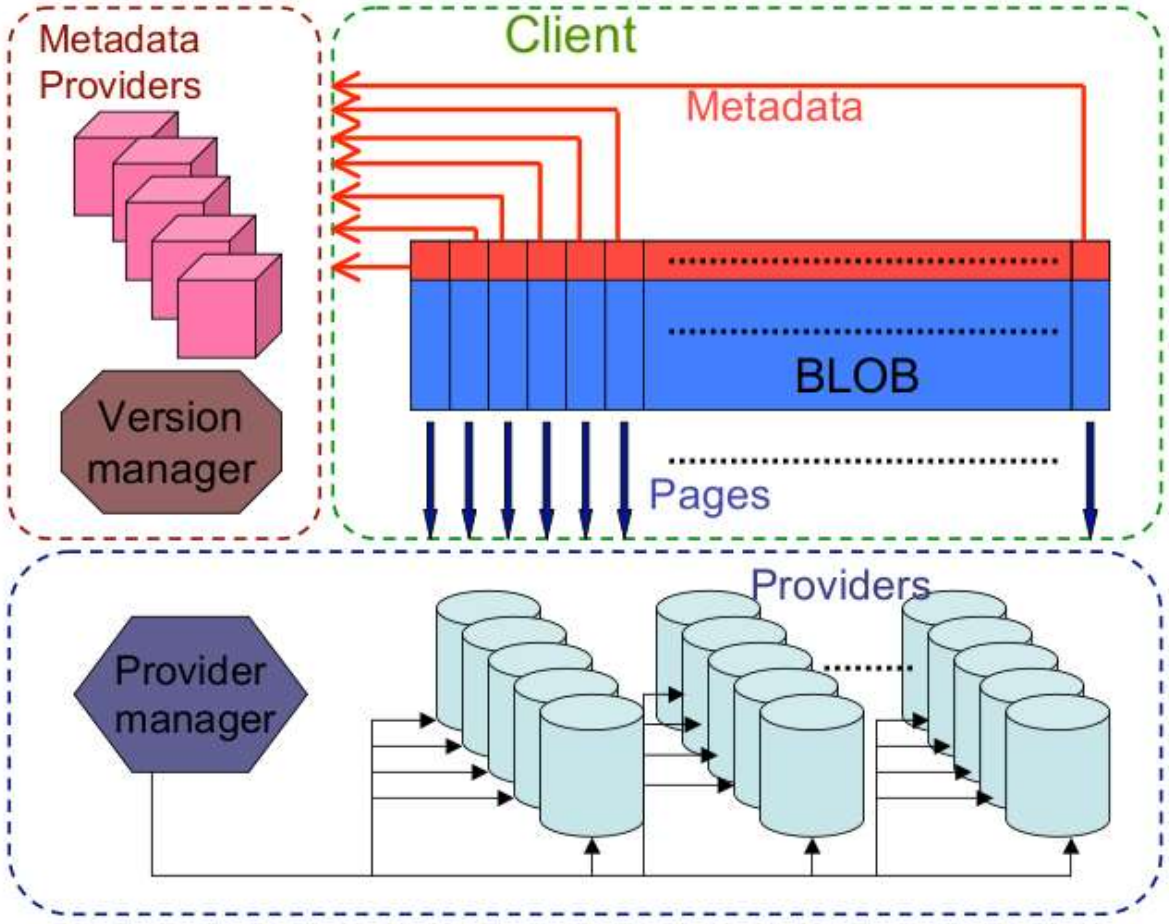




BlobSeer/RADOS vs Lustre (HPC) and HDFS/Ceph (BD)

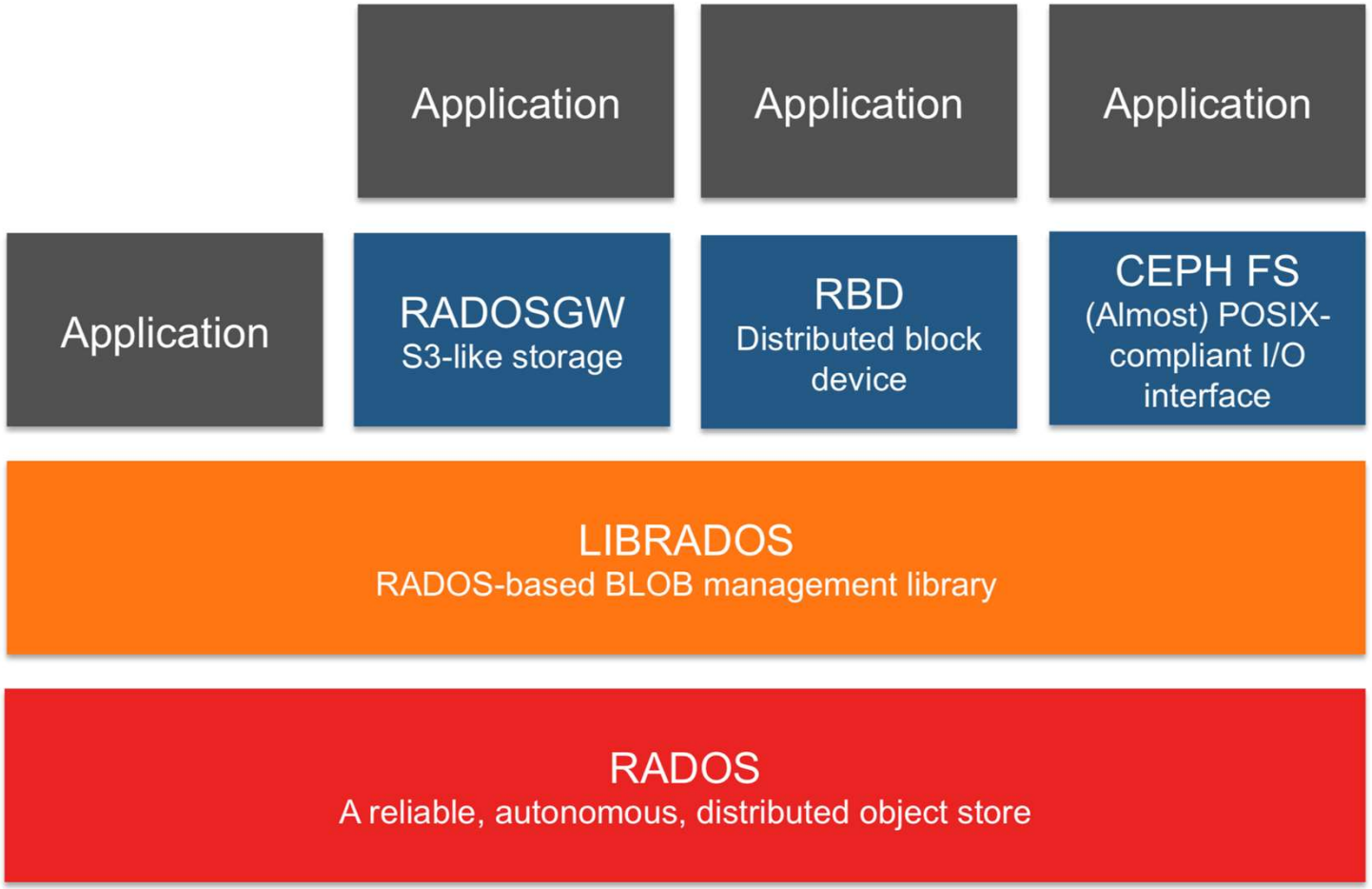
- Grid'5000 experimental testbed distributed over 11 sites in France and Luxembourg (parapluie cluster, Rennes)
- Each node: 2 x 12-core 1.7 Ghz 6164 HE, 48 GB of RAM and 250 GB HDD.
- HPC Apps: Lustre 2.9.0 and MPICH 3.2 [67], on a 32-node cluster (InfiniBand)
- BD Apps: Spark 2.1.0, Hadoop / HDFS 2.7.3 and Ceph Kraken, on a 32-node cluster (Gigabit Ethernet)

BlobSeer



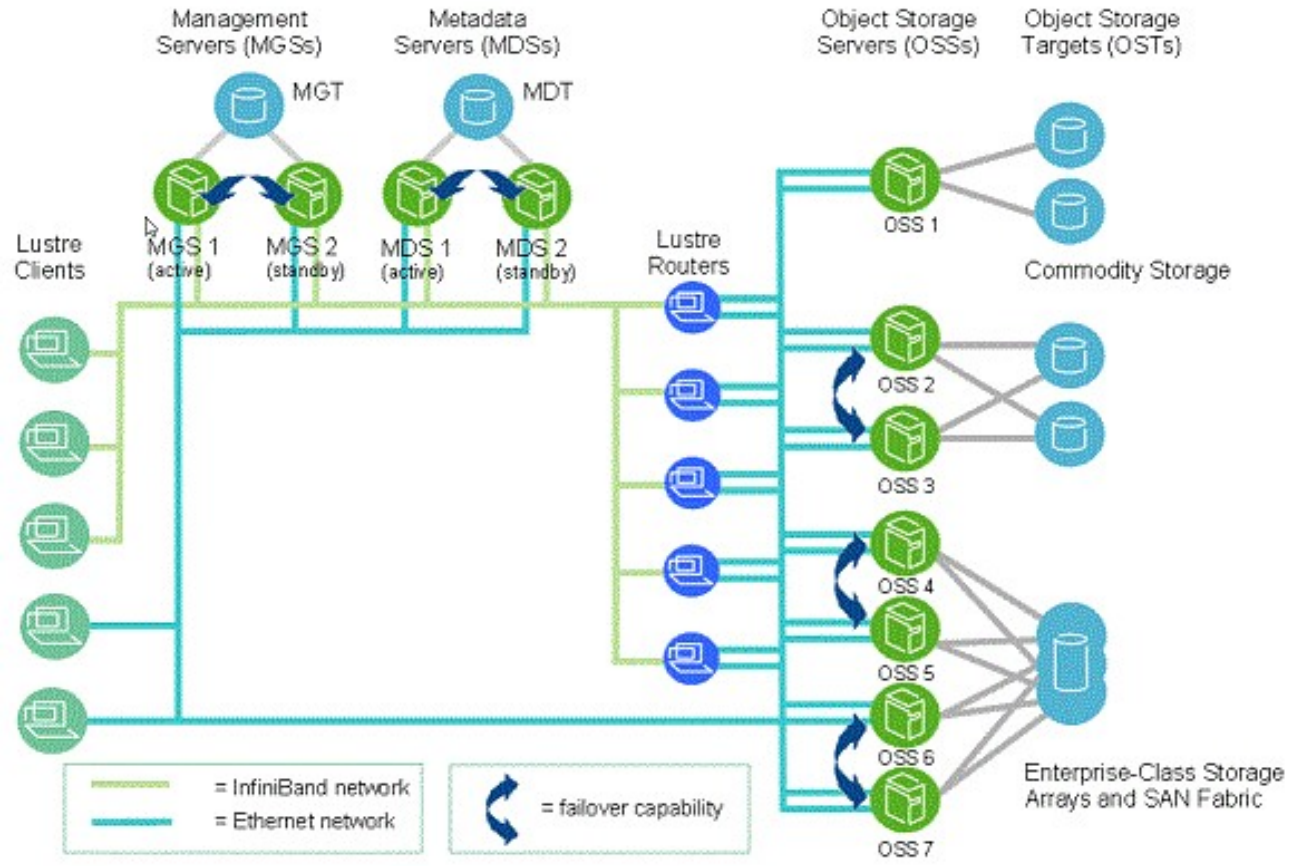
Bogdan Nicolae; Gabriel Antoniu; Luc Bougé; Diana Moise; Alexandra Carpen-Amarie. 2011. BlobSeer: Next-generation data management for large scale infrastructures. J. Parallel Distrib. Comput. 71, 2 (February 2011), 169-184.

RADOS/Ceph



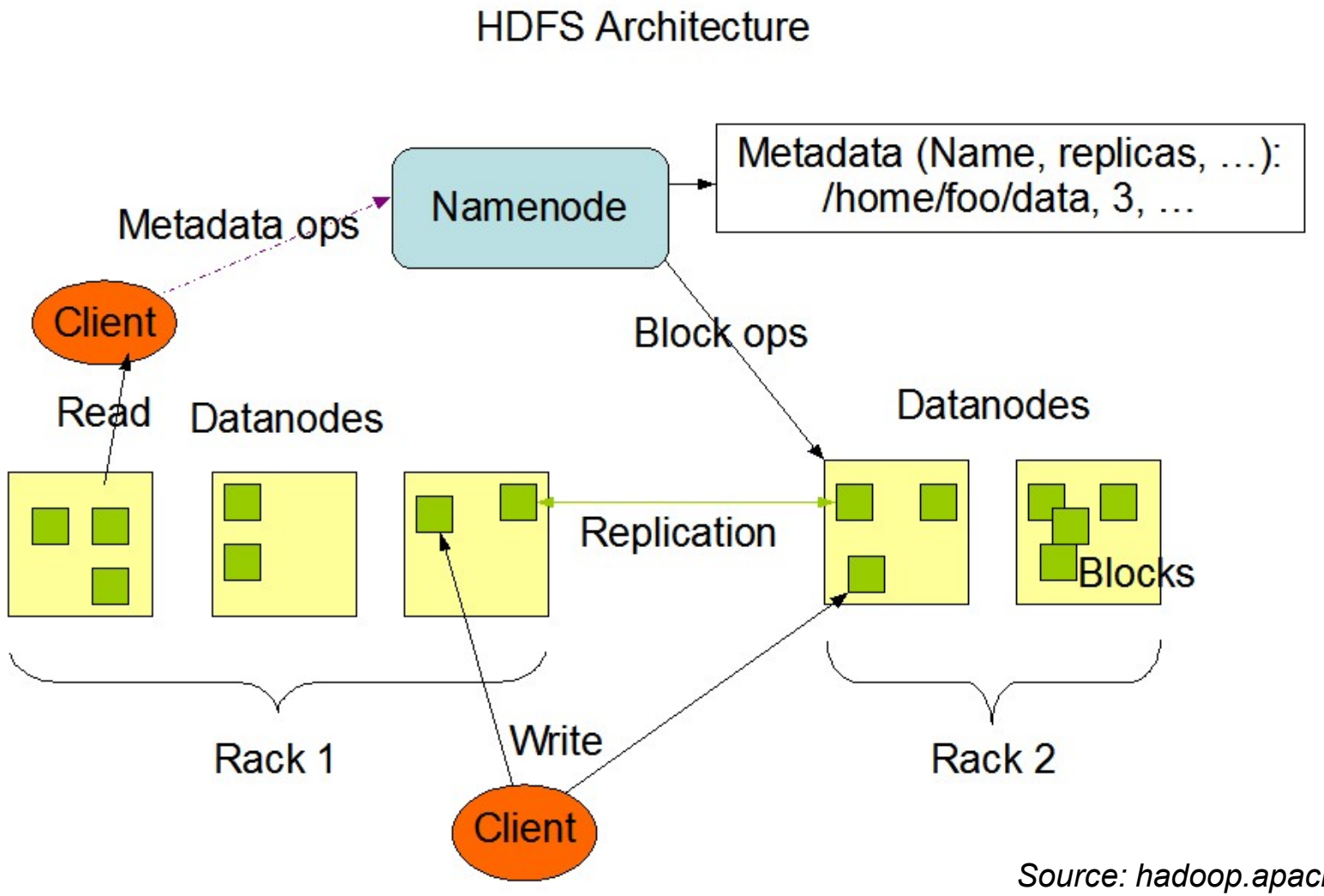
ceph.com

Lustre



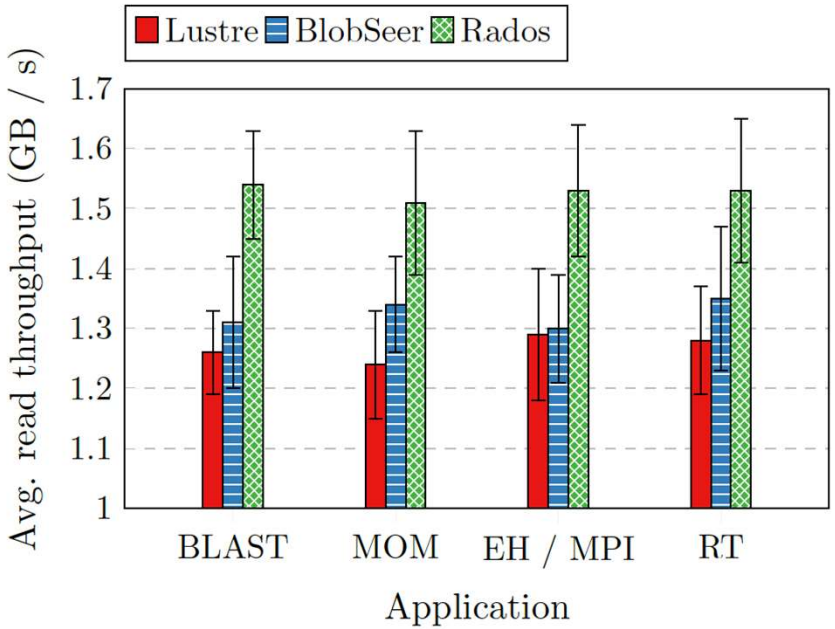
Source: lustre.org

HDFS



Source: hadoop.apache.org

HPC Apps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BlobSeer
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Avg. read throughput (GB / s)
1.7
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BLAST
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EH / MPI
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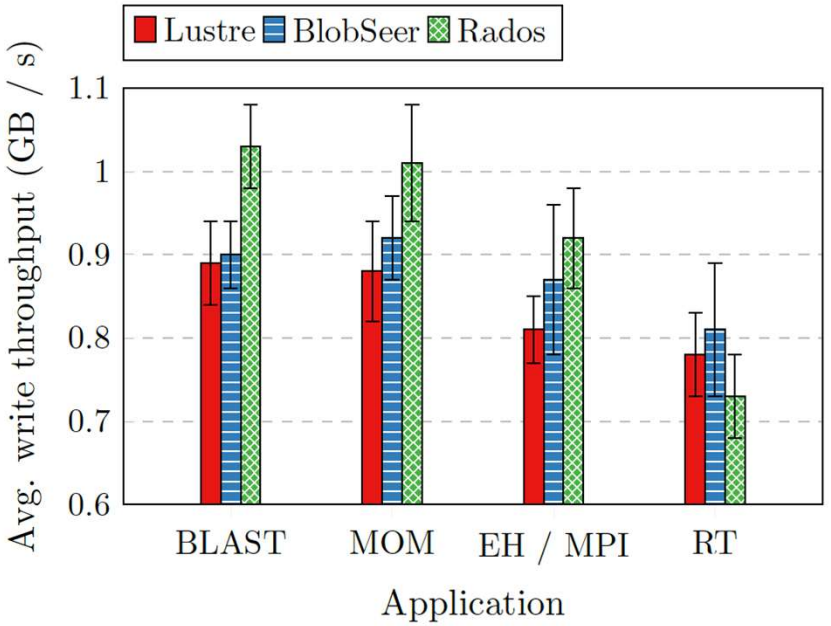
Application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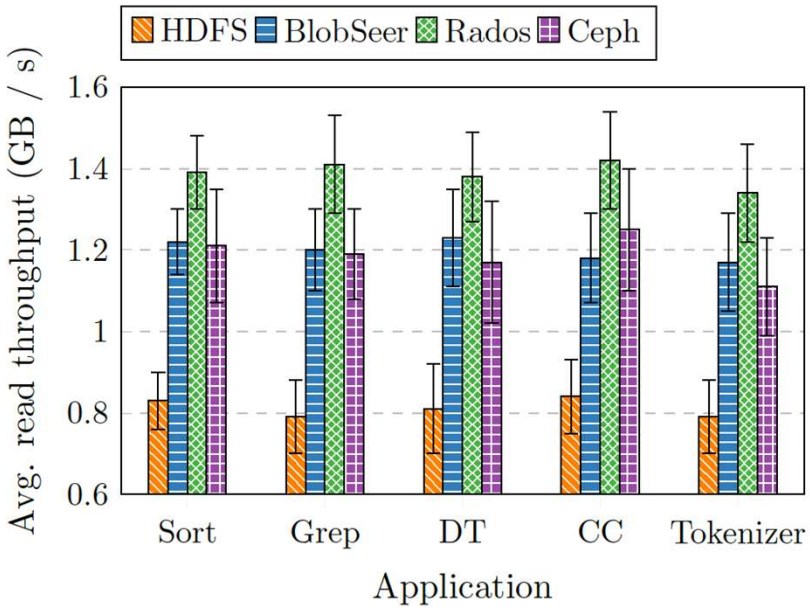
BD Apps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CC
Tokenizer
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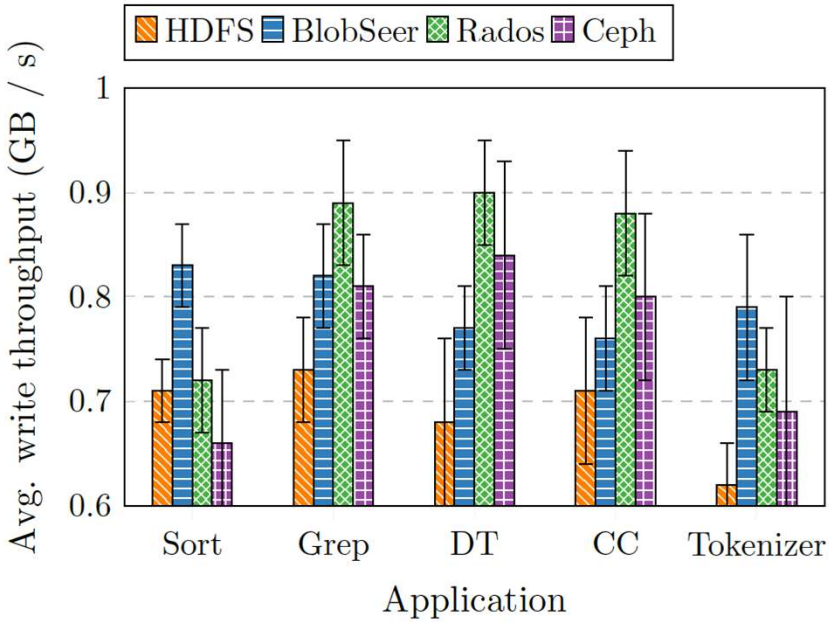
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Study insights

- The **convergence at storage level is possible by using object-based storage systems**, achieving an improvement in the performance for both platforms (HPC and Cloud)
- By using objects, it is possible to achieve a **maximum improvement of 32%**
  - Mainly because of the **flat namespace**
  - Rados: direct reads and simple and decentralized metadata management (high performance for read operations)
  - BlobSeer: multi-version concurrency control supports high-performance write operations with highly concurrent workloads (high performance for write operations)
- **Issues of both systems**:
  - Although the **Rados** performance is excellent when the write contention is low, its **lock-based concurrency control** limits the performance of highly concurrent use cases.
  - The multi-version concurrency control in BlobSeer provides good performance at write level, but the **distributed metadata in BlobSeer** provides a significant read latency

Týr

- Can we achieve both systems benefits?
- Apart from combining the best features of Rados and BlobSeer, there is a significant set of use cases with stricter consistency semantics
  - Indexing and data aggregation (E.g., ALICE CERN LHC experiment)
  - Distributed shared logs (E.g., Computational steering + in-situ visualization)

Týr

One problem…

A scientific monitoring service, monitoring t
ALICE CERN LHC experiment:

- Ingests events at a rate of up t
- Produces more than 10^9 d

Computes 35.000+

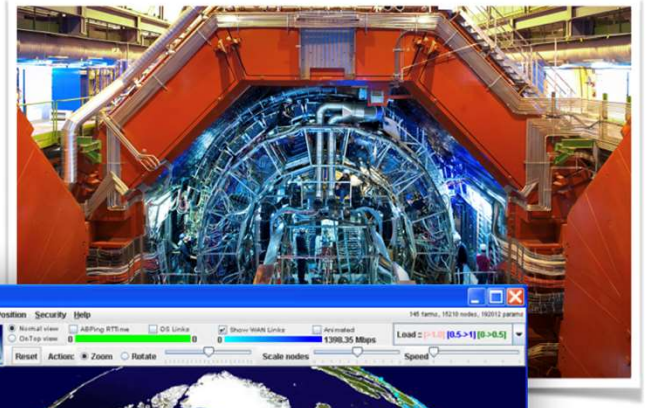
Current loc

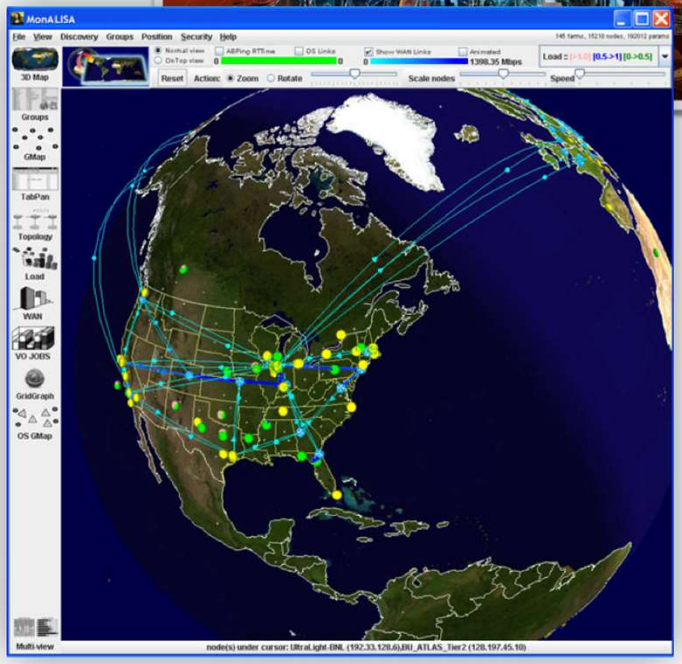
zation support

eads

bility

a (converged) blob store with built-in transactions





Pierre Matri; Alexandru Costan; Gabriel Antoniu; Jesús Montes; María S. Pérez. "Týr: Blob StorageSystems Meet Built-In Transactions". SC '16 Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis. Article n. 49, Best student paper award finalist

Týr

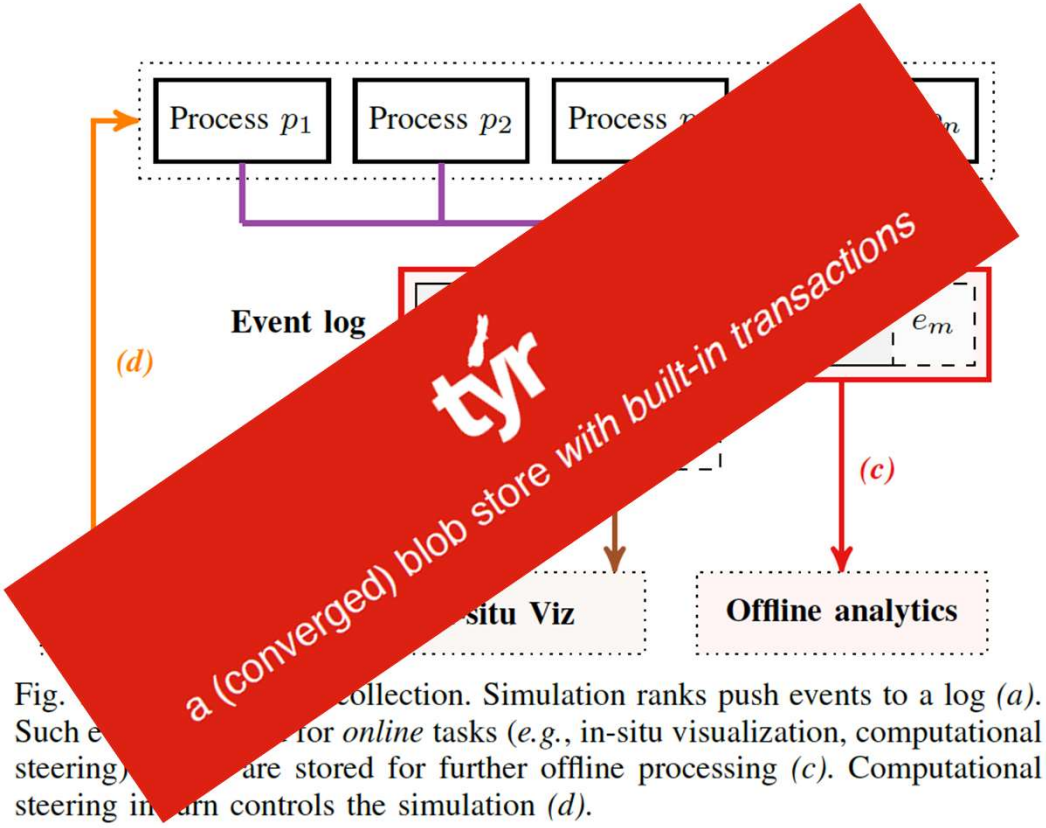


Fig. collection. Simulation ranks push events to a log *(a)*. Such e for *online* tasks (*e.g.*, in-situ visualization, computational steering) are stored for further offline processing *(c)*. Computational steering in rn controls the simulation *(d)*.

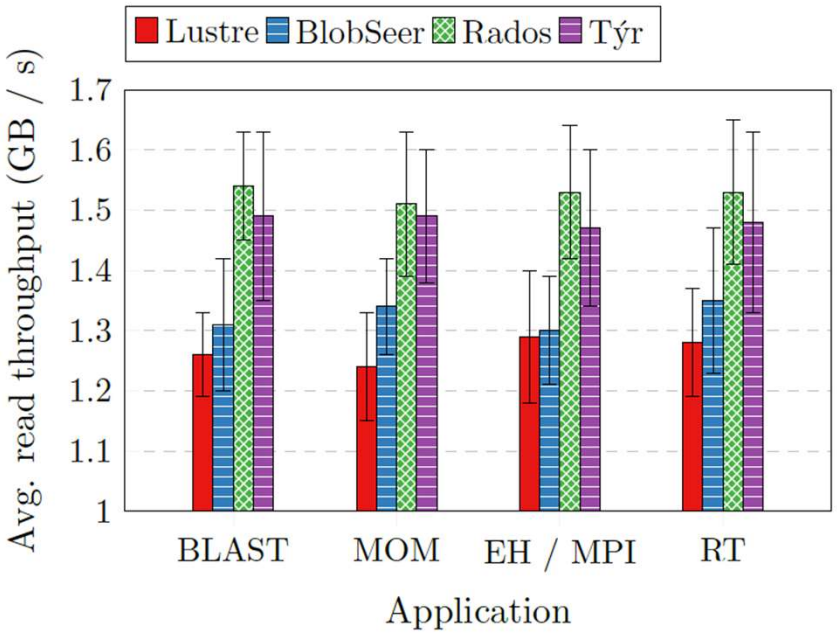
Pierre Matri; Philip Carns; Robert Ross; Alexandru Costan; María S. Pérez; Gabriel Antoniu;. ”SLoG: A large-scale Logging Middleware for HPC and Big Data convergence”. ICDCS’2018. pp. 1507-1512, 2018.

Týr design

- Predectible data distribution
  - Combining *data striping* and *consistent hashing* techniques
  - Avoiding the use of a centralized metadata server
- Transparent multi-version concurrency control
  - *Versioning* at *chunk* level
- Lightweigh ACID transactions
  - By using the transactional protocol Warp*
  - By using chains of the servers involved in transactions and dependency graphs
- Atomic transformation operations
  - Efficient *read-modify-write* ops
  - Particularly interesting for simple transformation operations (arithmetic, bit-wise)
  - The client does not send the new data to be written, but the modification, avoiding *two-round trips*
- Software prototype with around 25,000 Rust and GNU C code lines

* R. Escriva, B. Wong and E. Sirer. Warp: Lightweight multi-key transactions for key-value stores. arXiv preprint arXiv:1509.07815, 2015.

HPC Apps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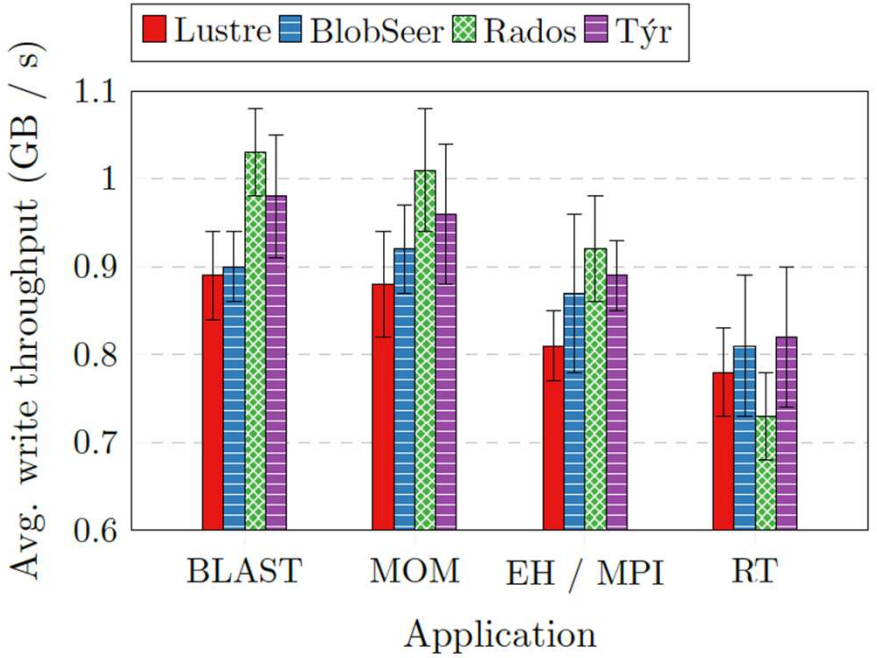
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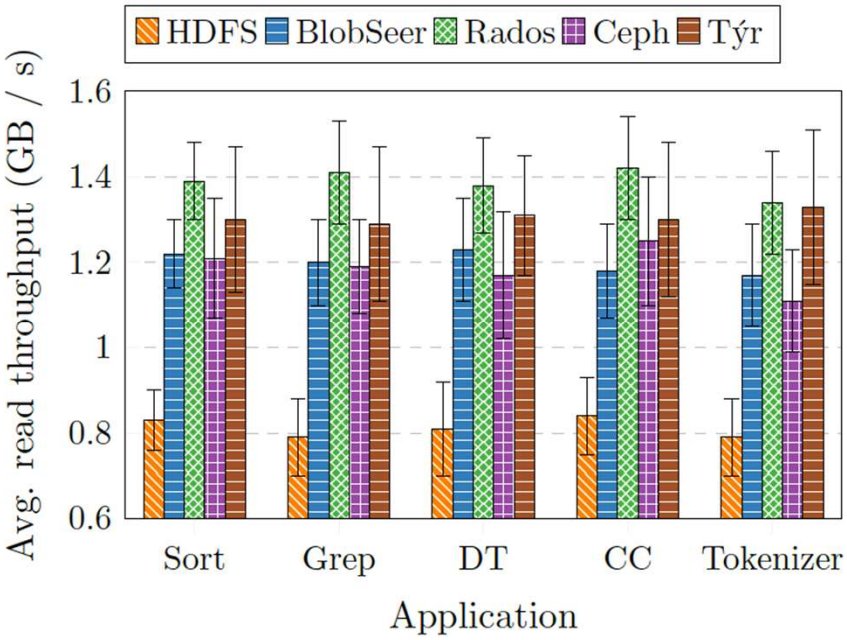
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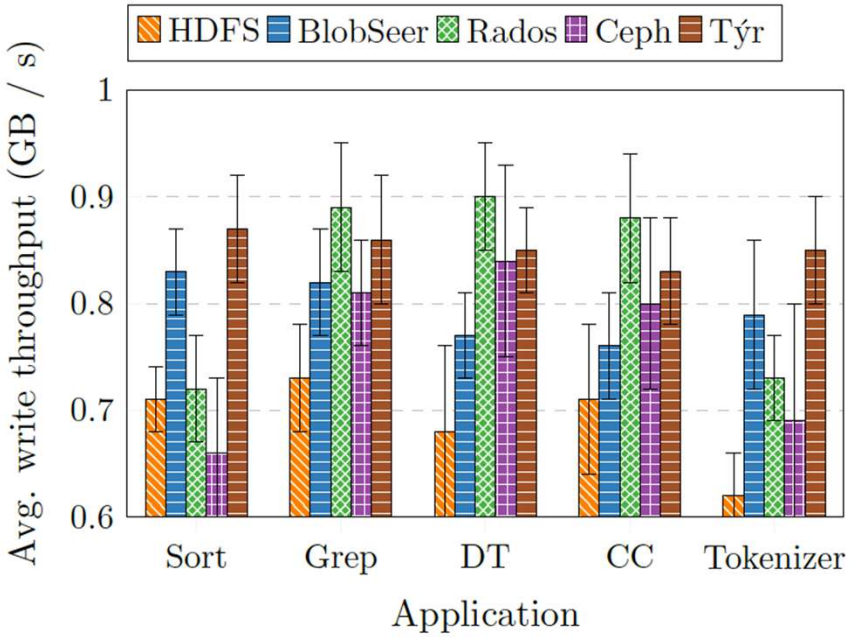
Tokenizer
Application


HDFS
BlobSeer
Rados
Ceph
Týr
Avg. write throughput (GB / s)
1
0.9
0.8
0.7
0.6
Sort
Grep
DT
CC
Tokenizer
Application

- Introduction
- Context
- General convergence HPC-Big Data problem
- Convergence HPC-Big Data at storage level
- Study and evaluation
- **Conclusions**

Conclusions

- **Týr outperforms BlobSeer and traditional file systems,** for both HPC and BDA applications
  - Non blocking writes, by means of multiversion concurrency control
  - Direct writes by using *consistent hashing*
- **Týr has some limitations in comparison with Rados**
  - **Except for write-intensive applications**, due to the efficiency of the multiversion concurrency control
  - **As a result of stronger consistency guarantees** (transactions)
- This is a **first step for the convergence between HPC and BDA** (at storage level)

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HPC and Big Data, A marriage of convenience?

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