Data-intensive HPC: opportunities and challenges

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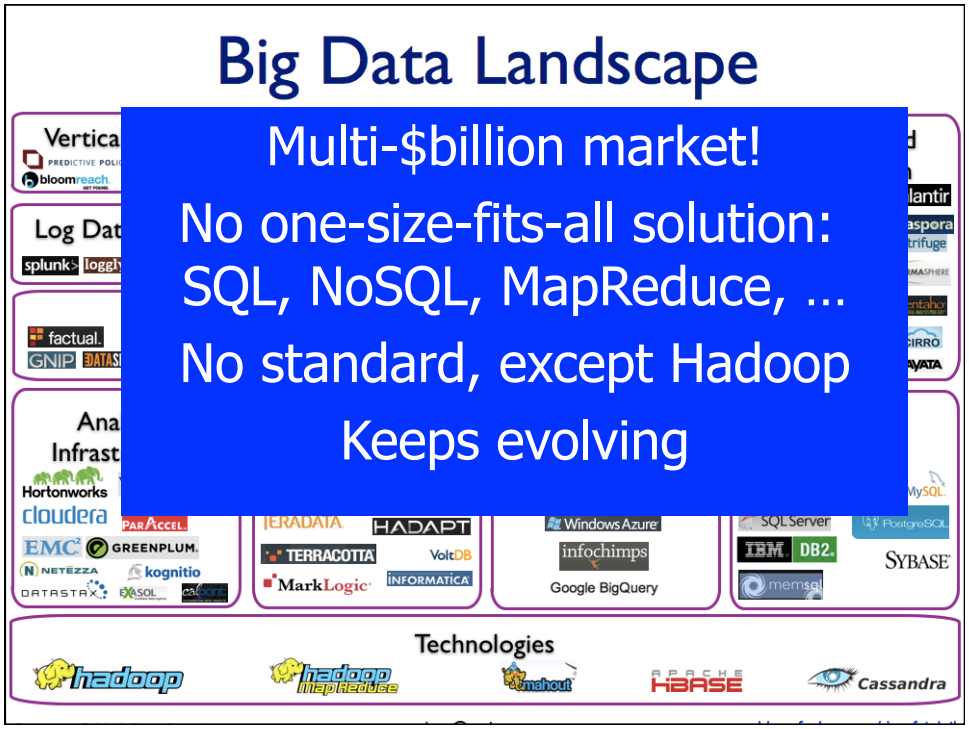
Zenith

Inria informatics mathematics

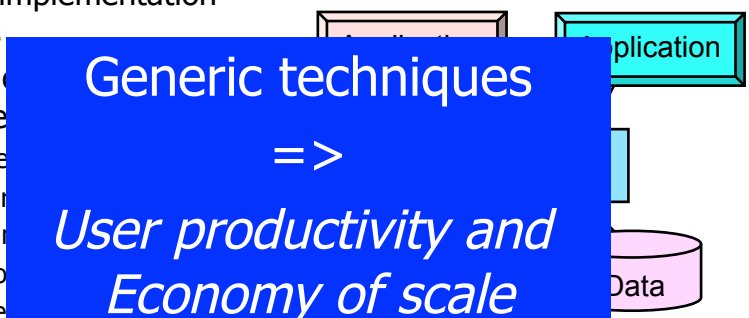


Big Data Killer App.: *Analytics*

- Objective: find useful information and discover knowledge in data
  - Typical uses: forecasting, decision making, research, science, …
  - Techniques: data analysis, data mining, machine learning, …
- Why is this hard?
  - External data from various sources
    - Hard to verify and assess, hard to integrate
  - Low information density (unlike in corporate data)
    - Like searching for needles in a haystack
  - Different structures
    - Unstructured text, semi-structured document, key/value, table, array, graph, stream, time series, etc.
    - Hard to integrate
  - Simple machine learning models don't work
    - Reality and context matter
      - See "When big data goes bad" stories

Data Management: basic principle

- *Data independence*
  - Hides implementation details
  - Provisi… service…
    - Sche…
    - Quer…
    - Opti…
    - Auto…
    - Inde…
    - Tran…
    - Consistency
    - Access control
    - …



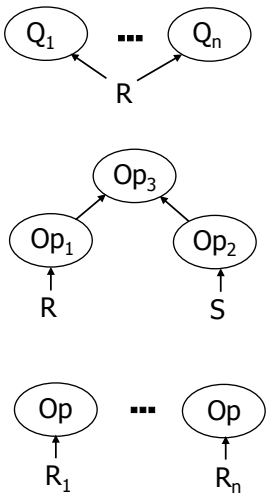
Generic techniques

=>

User productivity and Economy of scale

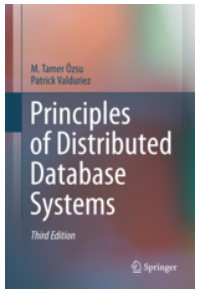
Parallel data processing

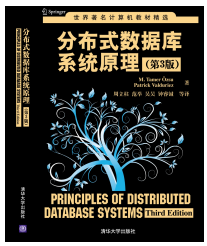
- Inter-query (task parallelism)
  - Different queries on the same data set (or data stream)
  - For lots of concurrent queries
  - e.g. Google search
- Inter-operation (task parallelism)
  - Different operations of the same query on different data sets
  - For complex queries
  - e.g. RDBMS
- Intra-operation (data parallelism)
  - The same operation on different data partitions of the same data set
  - For ops on big data sets
  - e.g. MapReduce



(Structured) Database Systems

- Volume
  - *Parallel database systems*
    - E.g. Oracle Exadata database machine
- Velocity
  - *Data stream management systems*
    - E.g. Streambase
- Variety
  - *Data integration systems*
    - E.g. DB2 Information Integrator





HPC: from simulation to big data analytics (BDA)

- Simulation: traditional HPC with big data
  - e.g. weather forecasting, climate modeling
- HPC applications need to deal with more and more data
  - More input data, e.g. from more powerful scientific instruments or sensor networks
  - More output data, e.g. with smarter mathematical models and algorithms
- Analytics: a newer, complementary market for HPC
  - Analytics methods applied to established HPC domains in industry, government, academia
  - High-end commercial analytics pushing up into HPC
  - Shorter journey from science to business, e.g. from cancer genomics to personalized medicine

Some BDA Killer Apps

- Real-time processing and analysis of raw data from high-throughput scientific instruments
- Uncertainty quantification in data, models, and experiments
  - E.g. to measure the reliability of simulations involving complex numerical models
- Fraud detection across massive databases
  - Applicable in many domains (e-commerce, banking, telephony, etc.)
- National security
  - Signal intelligence (SIGINT), anomaly detection, cyber analytics
  - Anti-terrorism (including evacuation planning), anti-crime
- Health care/medical science
  - Drug design, personalized medicine
  - Epidemiology
  - Systems biology
- Social network analysis
  - Modeling, simulation, visualization of large-scale networks

Cyber Analytics*

- Goal: identify malicious activity in high-throughput streaming data
  - More than 10 billion transactions/day
  - Tens of millions of unique IP addresses observed each month
  - Adjacency matrix may contain over a quadrillion elements but is sparse, with billions of values
  - Tens of TBs to PBs of raw data
  - Patterns can span seconds, months
- Current data analysis tools operate on thousands to hundreds of thousands of records

* J.R. Johnson. High Performance Computing for Data Intensive Science. 2014.

Pacific Northwest NATIONAL LABORATORY

Risers Fatigue Analysis (RFA)*

- Context: joint project between Zenith, UFRJ and LNCC, Rio de Janeiro (and Petrobras)
  - Pumping oil from ultra-deep water from thousand meters up to the surface through risers
- Problems
  - RFA requires a complex workflow of data-intensive activities which may take like 40 hours (SGI Altix ICE 8200 with 64 CPUs Quad Core cluster)
    - Input: 1,000 files (about 1 GB)
    - Riser information, such as finite element meshes, winds, waves and sea currents, and case studies
  - Output: 6,000 files (about 100 GB)
  - 10 activities (dynamic analysis of risers movements, tension analysis, curvature analysis, merging data from previous activities, etc.)
- An algebraic approach (inspired by relational algebra) and a parallel execution model
  - 4-fold improvement versus hard-coded parallel workflow

* E. Ogasarawa, J. Dias, D. Oliveira, F. Porto, P. Valduriez, M. Mattoso. An Algebraic Approach for Data-Centric Scientific Workflows. VLDB 2011.

BDA vs. HPC

	BDA	HPC
Computing model	**Data-centric**: move tasks to data and **Reduce**	**Compute-centric**: move data to tasks and **Accelerate**
Data storage	Uniform storage (sharding) on disks	Hierarchical storage (disks, tapes, etc.)
Parallel file management	Designed for few big files, e.g. HDFS	Designed for many small files, e.g. Lustre
Programming model	Algebraic operators, e.g. MapReduce, Spark	MPI versus OpenMP
Languages	Java, Python, C++	C, C++

- Opportunities
  - HPC: smarter file systems, with metadata and indexes; high-level programming frameworks, e.g. MapReduce-MPI
  - BDA: compute-centric nodes to run heavy tasks (machine learning)

Challenges for Data-intensive HPC

- Data-intensive HPC = HPC + BDA
- Collaboration from two big research communities
  - Data management and HPC
  - Is it a billion$ market?
- Some hard problems
  - Architecture: how does it fit with IT, data centers and cloud? No one-size-fits-all solution
  - Data storage: how to combine uniform and hierarchical storage models?
  - Data movement between applications and tasks
  - HPC data-oriented programming frameworks
  - Tools for data cleaning, data integration, data analysis

Thanks