

## **Big Data and Beyond**

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## Outline

- Who am I?
- CEDAR Project
  - Automated Reasoning
  - Big data
- Experiments with Big Data Technologies
- Beyond Today



## **WHO AM I?**

### • 30 years of RnD experience in Al

**Programming** (Knowledge Representation, Automated Reasoning, Al Implementation Technology)

- Directed cutting-edge research projects both in Industry (MCC, DEC, ILOG, IBM) and Academia (U. of Texas, SFU, UCBL)
- Contribution
  - innovative mathematics for AI, KR, CLP (OSF Constraint Logic)
  - efficient implementations (LogIn, LIFE, WAM)



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## CEDAR research areas – Automated Reasoning

- Semantic Web: proposing an alternative to mainstream (both formal logic and implementation)
- Experimenting with technology for scalable and distributed reasoning
- Data-as-Constraint paradigm



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# CEDAR's Approach to Big Data

- The CEDAR project deals with theoretical and experimental research related to Big Data
- The theoretical research focuses on:
  - parallel processing of distributed queries on large-scale datasets
  - intelligent data partitioning and distribution of data within and across clusters that consist of hundreds of nodes



## CEDAR research areas - Big Data

- optimization of complex queries (composed of several tens of joins)
- building efficient architecture for processing distributed queries on large datasets
- developing resource models for processing queries
- Experimenting with with Big Data technologies - mainly very large triplestores and parallel architectures (*Hadoop/Mapreduce* framework)



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- For our experiments, we have focused on Hadoop/MapReduce due to its enormous popularity with Big Data processing
- For example, we experimented with two high-performance applications for processing queries on large-scale RDF datasets:
  - SHARD (BBN technologies)
  - RDFPig (U. of Amsterdam and Yahoo!)
- We used the LUBM data generator for creating datasets.



## Outline

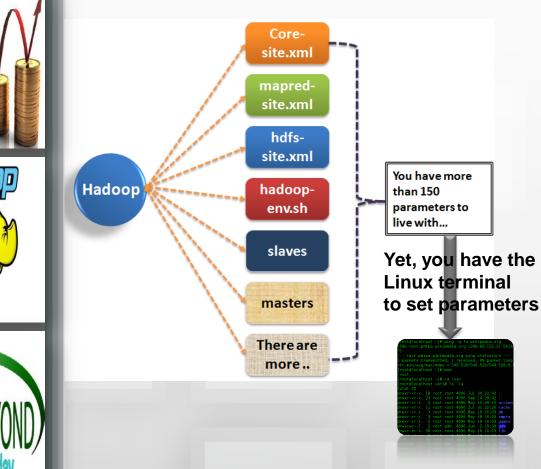
- Who am I?
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  What did we learn?

Beyond Today



- We discovered that Hadoop:
  - can provide a scalable infrastructure for processing Big Data
  - can be deployed on commodity hardware which is cost-effective
- But... Hadoop:
  - is not a "magic wand" to increase performance (tricky to get optimal # of nodes per cluster)
  - does not give the user much freedom to customize the data distribution process
  - is very slow in reading data from secondary storage

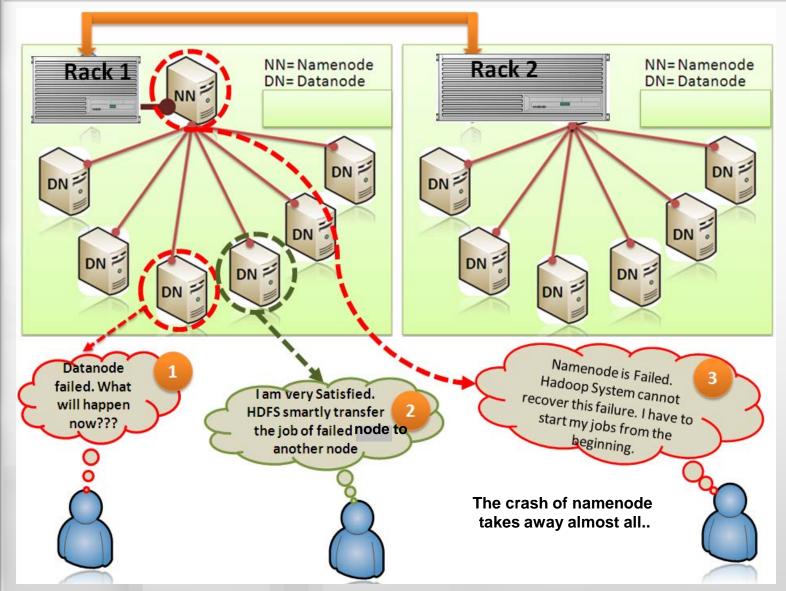




#### **Our Painful Experience**

- The 20-node Hadoop cluster configuration with basic parameters on LIRIS-Cloud took 24 hours of exhausting work
- For 100-node clusters, we spent more than four weeks!
- The configuration tasks was more painful than we expected when data nodes crashed
- Datanodes crash very often!
- This means that data reloading due to crashes of data nodes must be redone all the time!







### ERGO:

Big Data processing is in dire need of innovative, efficient, effective, and flexible architectures and techniques



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Design "HadoopGnX" to meet the demands of twenty-first century's users by building tomorrow's technologies that are innovative, intelligent, reliable, secure, efficient, scalable, and easy to use and maintain

Market



#### Query Processing and Optimization

- Aggregated search algorithm
- Adaptive search algorithm
- Hybrid approach (composition of static and dynamic) for optimization of complex queries on big datasets



#### Knowledge Discovery

- develop learning algorithms (*e.g.* Deep neural networks) for knowledge discovery in largescale structured and semi-structured datasets
- algorithm for high-quality information retrieval from unstructured data

#### System Architecture

- optimize computation power with minimum hardware
- optimize CPU and memory utilization for multithreaded job processing



#### File System

 develop faster data reading from secondary storage

#### Resource Scheduling

scheduling algorithms for efficient resource allocation

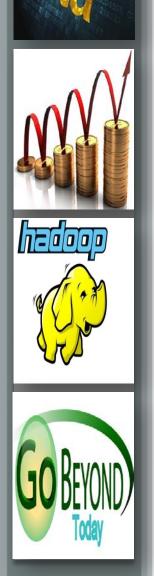
#### Resource Management

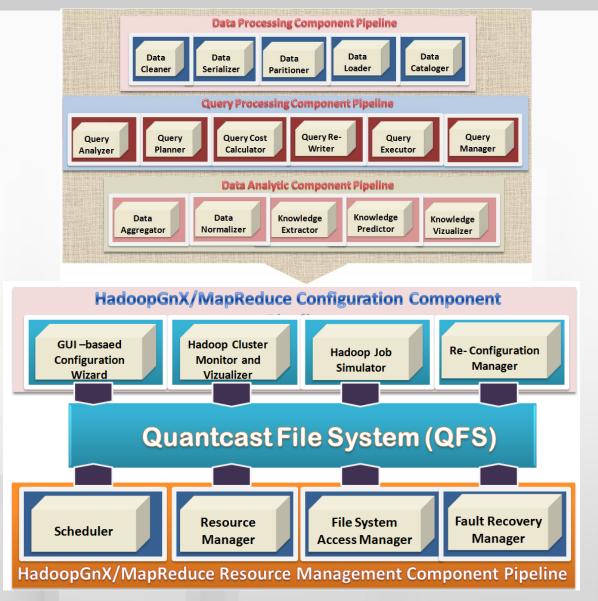
- dynamic data management within and across clusters of computation nodes
- dynamic memory management for processing jobs (*e.g.* queries)



#### Platform Configuration

- mathematical model for predicting required resources to build infrastructure (*e.g.* clusters) for deploying big data solutions
- simulation of complex job processing on large and distributed datasets
- user-friendly application environment for cluster configuration
- dynamic reconfiguration of clusters to adapt various system architectures







- Quintcast File System (QFS)
  - QFS is an open source distributed file system for large-scale batch processing improving on HDFS: data compression, faster disk reads, "Reed-Solomon error correction", ...
  - Adopt QFS in HadoopGnX instead of HDFS since it is faster



- Reengineering QFS:
  - storage of structured, semi-structured and unstructured data
  - customize job execution environment (*e.g.*, different sizes of data blocks distributed in nodes across clusters)
  - compress data to minimize the size of the dataset
  - handle real-time workloads
  - build multi-layer Hadoop clusters to increase parallel execution of *jobs* rather than *tasks within jobs* as in the classical Hadoop



- Scheduler
  - Follow a "scheduling on-demand" for HadoopGnX
  - Scheduler made of two modules:
    - Job Scheduler
    - Resource Scheduler



- Scheduler (ctd.)
  - Fair Scheduling: resource-scheduling method for assigning resources to application so that all applications receive an equal share of resources (in particular main memory)
  - Complex-Level Priority Scheduling : scheduling resources for jobs by their level of complexity in particular: jobs with higher complexity level receive more resources
  - Longest Processing Time Task First
  - Higher-ordered Tasks first Scheduling



#### Resource Manager

- Implement a resource manager that allocates resources specifically the data for Hadoop jobs
- Implement an *interactive*, *self-managed*, and *flexible* Hadoop (*e.g.*, dynamic resource allocation)

#### **Explore other processor layouts**

- Data Diffusion Machine (DDM): scalable virtual shared memory architecture (COMA, NUMA)
- Skewed-Associative Memory: efficient memory indexing using several hash functions (speeds up data finding and therefore job processing)



#### Fault-Handling Manager

- Self-healing architecture using a fault-handling manager capable of recovering the cluster in case of node failure
- Flexible multi-master/no-master policy to prevent the loss of failing master node failure
- Adopt the **Disruptor** job-scheduling pattern to build multi-master layouts
  - **Disruptor** enables assigning a new master node automatically upon failure of the running (current) one.



Data Processing Application:

- Data Cleaner: cleans data specifically if found redundant in the dataset
- Data Serializer: converts data from one format to another
- Data Partitioner: splitting data heuristics
  beyond predicate-splitting, and object-splitting
  (e.g., skew-joins)
- Data Loader: customize data-loading into distributed storage (thus taking the burden off Hadoop)
- Data Cataloger: create a data catalog after loading data into storage



• Query Processing Application:

- Query Analyzer: clean up redundant data
- Query Cost Calculator: estimate query evaluation costs
- Query Planner: efficient distributed querying
- Query Rewriter: query rewriting using the planned strategy
- Query Executor: evaluate a given query across the nodes of clusters
- Query Manager: manage queries during their lifetime



• Data Analytics Application:

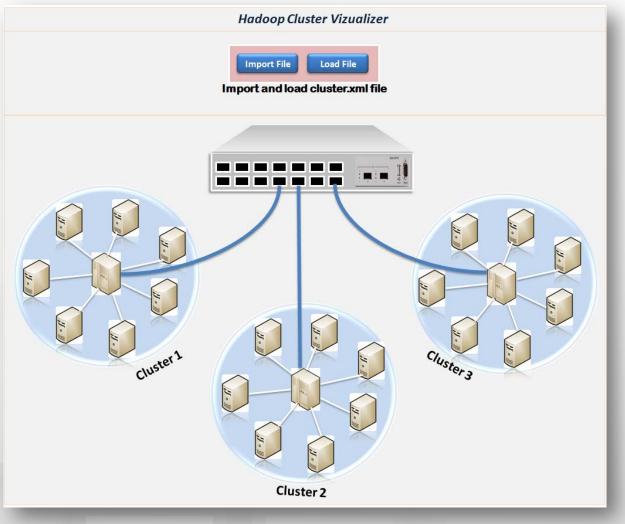
- Data Aggregator: collect data from multiple sources for analysis
- Knowledge Extractor: discover knowledge such as business knowledge from a large datasets
- Knowledge Predictor: summarize prediction of operational and business knowledge
- Knowledge Visualizer: display information on a dashboard that provides a comprehensive view of data





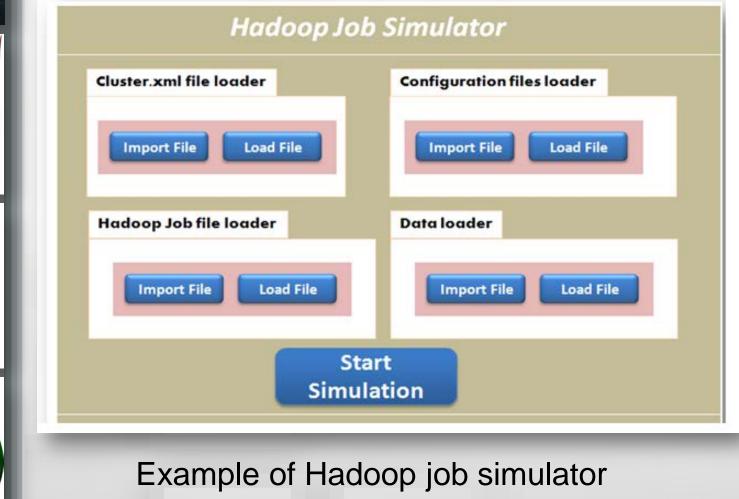
A sample of Hadoop configuration wizard





#### A sample of Hadoop cluster vizualizer







## Challenges

- Need resources: world-class theoretical computer scientists, applied computer scientists (mathematicians and implementers)
- Leverage human network of top quality scientists and engineers from all over the world.
- France's potential: excellence of research centers (LIX, ENS, INRIA, CNRS)



## Our Strengths

- Through CEDAR, we have built a solid foundation on Big Data state of the art
- This has enabled us to identify some critical issues and think up solutions that are not available in the market
- The experience of CEDAR has comforted us in defining a winning strategy for Big Data research and applications



## Conclusion

#### We are living exciting times!

- Big Data sure! Big Knowledge too...
- Analytics and Reasoning: the next step
- Don't follow the crowd: Innovation is the key
- We have many ideas ... but time is of the essence!



## Links

### • CEDAR:

- http://cedar.liris.cnrs.fr/
- PetaSky:
  - http://com.isima.fr/Petasky



Thank You Very Much!

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