STRUCTURED STORAGE IN ATLAS DISTRIBUTED DATA MANAGEMENT

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Overview

- Structured storage
  - Concepts
  - Technologies
- ATLAS DDM use cases
  - Storage facility
  - Data-intensive analytics
- Operational experiences
  - Software
  - Hardware
- Conclusions

Structured Storage :: Concepts

- Is this about NoSQL? Yes, but…
  - NoSQL is a buzzword term to annoy RDBMS people
  - Correct CS term: *(distributed) structured storage*
  - Many products support SQL or SQL-derivatives anyway

- So what is NoSQL, pardon, structured storage about?
  - 1. ***Non-relational modelling and storage of data***
    - Use the native data layout of an application
  - 2. ***Linear scalability of data processing***
    - Scalability ≠ Performance

- **Performance:** Capability of a system to provide a certain response time
  - e.g., *generate a valid analysis of a sample within three seconds*

- **Scalability:** Dependency characteristics between resources and performance
  - e.g., *maintain the three seconds when the number of samples increase*

Structured Storage :: Concepts

- Relational database management systems
  - Vertical scalability ("scale up")
  - Few powerful nodes
  - Shared state
  - Explicit partitioning
  - Resistant hardware
  - ACID
  - Implicit queries *(WHAT)*

- Structured storage
  - Horizontal scalability ("scale out")
  - Lots of interconnected low cost nodes
  - Shared nothing architecture
  - Implicit partitioning
  - Reliability in software
  - BASE
  - Explicit data pipeline *(HOW)*

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  - Explicit data pipeline *(HOW)*

Main problems addressed:

1. There is an upper limit of processing power you can put in a single node
2. Explicit partitioning can be cumbersome
3. Relaxation of ACID properties can be necessary
4. Query plans need information about the data contents

Structured Storage :: Technologies

- Three technologies evaluated
  - **MongoDB** (*10gen, Inc.*)
  - **Cassandra** (*Apache Software Foundation*, formerly *Facebook*)
  - **Hadoop with HBase** (*Apache Software Foundation*, formerly *Yahoo*)
- Many more available, but these were chosen with the following things in mind
  - Large community available and widely installed
  - In production use at several larger companies with respectable data sizes
  - Potential commercial support
- 12 node cluster to evaluate technologies
  - Nodes located in CERN IT data centre
- Nodes managed by Puppet
  - Data centre automation framework
  - Implicit service and configuration definition
  - One-button push update on all nodes

	Cluster configuration
Nodes	12
Architecture	Linux x86_64
CPU Cores	96 (Intel Xeon 2.26 GHz, 8/node)
RAM	288 GB (24/node)
Storage	–
Storage Network	–
Disk	24 SATA (1TB each, 2/node)
Cache	–
Network	1 GigE

Structured Storage :: Technologies :: hadoop

- Hadoop is framework for distributed data processing
  - It is not a database like MongoDB or Cassandra

- Many components
  - **HDFS**: distributed filesystem
  - **MapReduce**: distributed processing of large data sets
  - **HBase**: distributed data base for structured storage
  - **Hive**: SQL frontend and warehouse
  - **Pig**: data-flow language for parallel execution
  - **ZooKeeper**: coordination service
  - … many more

Structured Storage :: Technologies :: Data Models

mongoDB

```
{
 _id: 'Main Account User',
 groups: ['group_a',
          'group_b',
          'group_c'],
 selections: {
              'select_a': 123,
              'select_b': abc
             }
}
```

- Explicit row-key
- Native datatypes
- Everything indexable

Cassandra

```
'Groups' : {
    'Main Account User' : {
        'groups' : ['group_a',
                    'group_b',
                    'group_c']
    }
}

'Selections' : {
    'Main Account User' : {
        'select_a' : 123,
        'select_b' : abc
    }
}
```

- Implicit row-keys
- Data is byte streams
- Column Families group row-keys

APACHE HBASE

```
'Main Account User' : {
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    },
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    }
}
```

- Implicit row-key
- Data is byte streams
- Row-keys group Column Families
- Row-keys are sorted

Structured Storage :: Technologies :: Data Bases

mongoDB

- Master/Slave
  - Smart client implements failover
- Write-ahead log
- Limited MapReduce
  - interleaved
  - bound to single thread
- Keyed binary storage
- Indexes
- Table locking
- Replica sets
- Explicit partitioning

Cassandra

- No single point of failure
  - ring of nodes
  - forwarding of requests
- Write-ahead log
- No MapReduce
  - can use Hadoop
- No file storage
- Bloom filter
- Row locking
- Snapshotting
- Implicit partitioning

APACHE HBASE

- No single point of failure
  - multiple masters
- Write-ahead log
- MapReduce
- File storage
  - Data on HDFS
  - Can be used as a source and sink within Hadoop
- Bloom filter
- Row locking
- HDFS-backed redundancy
- Implicit partitioning

Structured Storage :: Technology Selection

	MongoDB	Cassandra	Hadoop/HBase
Installation/ Configuration	Download, unpack, run	Download, unpack, configure, run	Distribution, Complex config
Buffered read 256	250'000/sec	180'000/sec	150'000/sec
Random read 256	20'000/sec	20'000/sec	20'000/sec
Relaxed write 256	10'000/sec	19'000/sec	9'000/sec
Durable Write 256	2'500/sec	9'000/sec	6'000/sec
Analytics	Limited MapReduce	Hadoop MapReduce	MapReduce, Pig, Hive
Durability support	Full	Full	Full
Native API	Binary JSON	Java	Java
Generic API	None	Thrift	Thrift, REST

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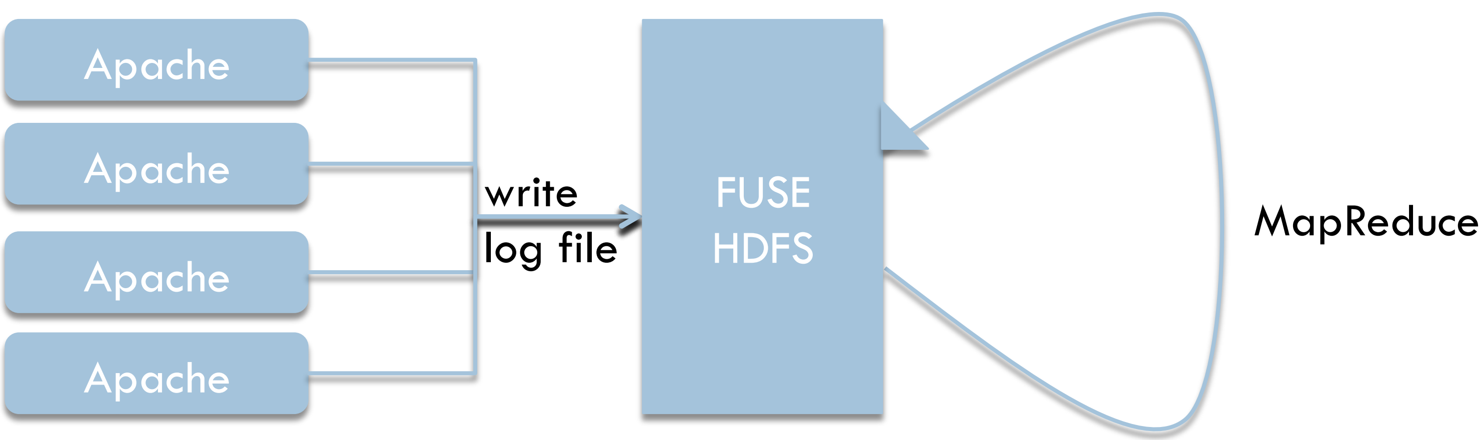
Use cases :: Log file aggregation

- HDFS is mounted as a POSIX filesystem via FUSE
  - Daily copies of all the ATLAS DDM log files are aggregated in a single place
  - 8 months of logs accumulated, already using 3 TB of space on HDFS
- Python MapReduce jobs analyse the log files
  - Streaming API: read from stdin, write to stdout
- Processing the data takes about 70 minutes
  - Average IO at 70MB/s
  - Potential for 15% performance increase if re-written in pure Java
    - Better read patterns and reducing temporary network usage



Use cases :: Trace mining

- Client interaction with ATLAS DDM generates traces
  - E.g., downloading a dataset/file from a remote site
  - Lots of information (25 attributes), time-based
  - One month of traces uncompressed 80GB, compressed 25GB
    - Can be mapreduced in under 2 minutes
- Implemented in HBase as distributed atomic counters
  - Previously developed in Cassandra
  - At various granularities (minutes, hours, days)
  - Size of HBase tables negligible
  - Average rate at 300 insertions/s
- Migrated from Cassandra within 2 days
  - Almost the same column-based data model
  - Get extra Hadoop benefits for free (mature ecosystem with many tools)
  - The single Cassandra benefit, HA, was implemented in Hadoop recently

Use cases :: DQ2Share

- HTTP cache for dataset/file downloads
  - Downloads via ATLAS DDM tools to HDFS, serves via Apache
  - Get all the features of HDFS for free, i.e., one large reliable disk pool

DQ2Share

ddo.000001.Atlas.Ideal.DBRelease.v0701010 Get dataset and files

Search results: **ddo.000001.Atlas.Ideal.DBRelease.v07010104** Displaying 20 on 84 files

Type	Name	Size of all files (Bytes)	Number of files	Date	In the Cache
Dataset	ddo.000001.Atlas.Ideal.DBRelease.v07010104	1 754 037 441	84	2009-07-02 02:18:11	.tar: ✗

☐ wget 19%...	Type	Name	Size (Bytes)	Checksum	In the Cache
☐	File	07010104._0121364.tar.gz	12 446 534	ad:b05542bb	✗
☐	File	07010104._0120760.tar.gz	12 183 186	ad:8bd6b6d3	✓
☐	File	07010104._0121457.tar.gz 100%	13 654 310	ad:2aee4fcc	✓
☐	File	07010104._0120884.tar.gz	11 927 416	ad:654e6578	✓
☐	File	07010104._0121416.tar.gz	18 179 853	ad:ed7f5d07	✗
☐	File	07010104._0121064.tar.gz	12 591 388	ad:a5464922	✓
☐	File	07010104._0120808.tar.gz	12 181 040	ad:203c2a15	✓
☑	File	07010104._0121198.tar.gz	13 648 670	ad:1afc7773	✓
☑	File	DBRelease-7.1.1.4.tar.gz	693 005 997	ad:3db1645e	✓
☑	File	07010104._0120713.tar.gz	11 958 239	ad:fa3b23a6	✗
☐	File	07010104._0120852.tar.gz	12 246 473	ad:a0d72443	✓
☐	File	07010104._0121412.tar.gz	12 455 380	ad:32a180f0	✗
☐	File	07010104._0121226.tar.gz	12 559 921	ad:d06936f5	✗
☐	File	07010104._0121414.tar.gz	12 461 831	ad:b8e44e10	✗

Use cases :: Wildcard search

- List contents of ATLAS DDM based on a pattern
  - e.g., all data11 datasets (query: *data11**)
  - RDBMS: *Index range scan (~2 seconds, in memory)*
- This becomes more expensive on sub-selections
  - e.g., all data11 datasets with a RAW datatype (query: *data11*RAW**)
  - RDBMS: *Index full scan (~10 seconds, in memory)*
- And worst if only later parts of the pattern are used
  - e.g., all datasets with a RAW datatype (query: *RAW*)
  - RDBMS: *Full table scan (~30 seconds in memory, ~60 seconds on disk)*

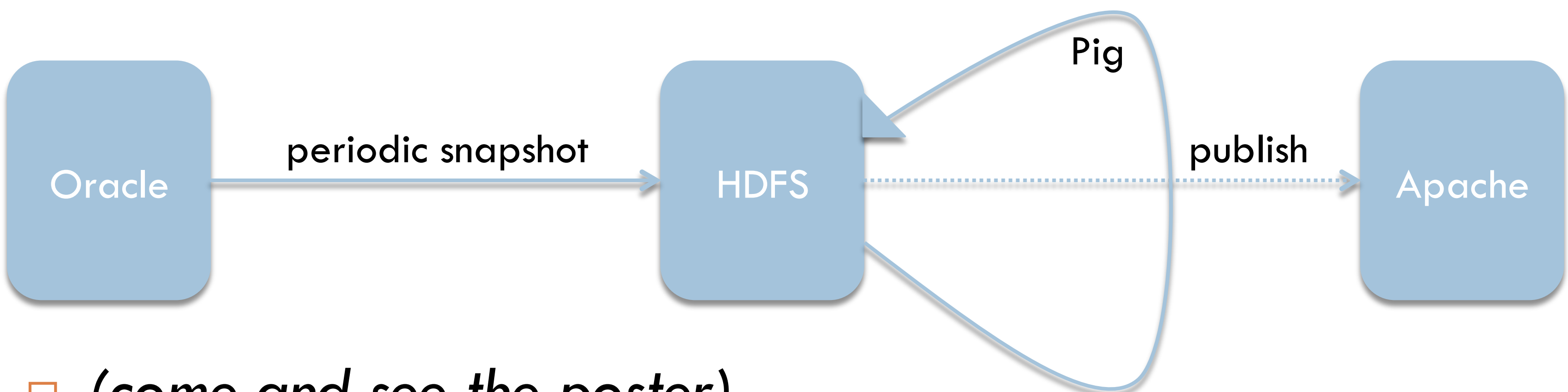
- Asynchronous wildcard search in Hadoop HDFS
  - Periodic dump of the necessary columns from RDBMS to a flat file
  - MapReduce with distributed grep (~*30 seconds*)
  - Prime example for RDBMS offloading

Use cases :: Accounting

- Break down usage of ATLAS data contents
  - Historical free-form meta data queries

```
{site, nbfiles, bytes} := {project=data10*, datatype=ESD, location=CERN*}
```

  - Non-relational periodic summaries
  - A full accounting run takes about 8 minutes
    - Pig data pipeline creates MapReduce jobs
    - 7 GB of input data, 100 MB of output data



- *(come and see the poster)*

Operational experiences :: Software

- MongoDB
  - Easiest to install (*download tarball, unpack, run*)
  - One line of configuration to change to create the cluster
- Cassandra
  - Packages from ASF
  - Straightforward installation and configuration via Puppet/tarball
  - However, nodes need special hardware configuration (two disks for commitlog and data)
- Hadoop
  - Cloudera distribution
    - Tests and packages the Hadoop ecosystem
  - Straightforward installation via Puppet/YUM
  - But the configuration was ... not so obvious
    - Many parameters, extensive documentation, but bad default performance
      - Cluster IO throughput maxing at 30MB/sec, network not saturated
    - But guidelines on how to set parameters properly only exist for large installations
    - Tweaked a lot, but most of the time it got worse and never better
    - Left it defaults *(next slide please...)*

Operational experiences :: Software

- SLC5 ?
  - But the throughput problem didn't come from Hadoop
  - Instead the 8-year-old kernel of SLC5 was the problem
    - No *epoll* (non-blocking-IO) support
- SLC6 !
  - Migrated the whole cluster in-flight to SLC6
    - Original reason for migration was because of a SLC5 kernel bug that broke Puppet
  - Procedure
    - 1. Drain one node (not exactly mandatory)
    - 2. Wipe and reinstall node with SLC6 + puppet template
    - 3. There is no step three (automatic resychronisation of node into cluster)
    - 4. Goto 1
  - Just a few minutes downtime while Hadoop headnode was migrated
    - Could have possibly averted downtime by manually assigning another headnode
    - (Latest Hadoop release can do it automatically now with high-availability headnode)
  - Performance increase of IO remarkable
    - Random read/write performance per node improved by factor 4
    - Cluster IO throughput now maxing at 80MB/sec, network saturated
- Backups
  - Hourly encrypted backups of the HDFS image
  - Cluster state can be restored within 3 minutes (including downloading and unpacking the backup)

Operational experiences :: Hardware

- Disk failure is common and cannot be ignored
- Data centre annual disk replacement rate up to 13% (Google & CMU, 2011)

- Within one year we had
  - 5 disk failures
    - 20% failure rate!
    - Out of which 3 happened at the same time
  - 1 Mainboard failure
    - Together with the disk failure, but another node

- Worst case scenario experienced up to now
  - 4 nodes out of 12 dead within a few minutes
  - Hadoop
    - Reported erroneous nodes
    - Blacklisted them
    - And resynced the remaining ones
  - No manual intervention necessary
  - Nothing was lost

Conclusions

- Structured storage systems are too useful to be ignored
- Hadoop proved to be the correct choice and an excellent platform for our analytical workloads
  - Stable – reliable – fast – easy to work with
  - Survived disastrous hardware failures
- DDM use cases well covered
  - Storage facility (*log aggregation*, *traces*, *web sharing*)
  - Data processing (*trace mining*, *accounting*, *searching*)
- Miscellaneous
  - All three evaluated products provide full durability, and transactions were not missed
  - We see Hadoop complementary to RDBMS, not as a replacement

- Future work
  - WAN replication as Hadoop is location aware
  - Generic RDBMS-to-HBase synchronisation framework
  - Improved data mining framework for generic analytics

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