MapReduce and Parallel DBMSs: Friends or Foes?

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DB Lunch, May 3rd, 2010

Papers to Be Covered in This Talk

- CACM'10
 - MapReduce and Parallel DBMSs: Friends or Foes?
- VLDB'09
 - HadoopDB: An Architectural Hybrid of MapReduce and DBMS Technologies for Analytical Workloads
- SIGMOD'08 (Pig), VLDB'08(SCOPE), VLDB'09(Hive)

Outline

- Architectural differences between MR and PDBMS (CACM'10)
 - Workload differences
 - System requirements
 - Performance benchmark results
- Integrate MR and PDBMS (VLDB'09)
 - Pig, SCOPE, Hive
 - HadoopDB
- Conclusions

Workload Differences

- Parallel DBMSs were introduced when
 - Structured data dominates
 - Regular aggregations, joins
 - Terabyte (today petabyte, 1000 nodes)
- MapReduce was introduced when
 - Unstructured data is common
 - Complex text mining, clustering, etc
 - Exabyte (100,000 nodes)

System Requirements: From order of 1000 to 100,000

- Finer granularity runtime fault tolerance
 - Mean Time To Failure (MMTF)
 - Checkpointing

- Heterogeneity support over the cloud
 - Load Balancing

Parallel DBMSs	MapReduce
Transactional-level fault tolerance	Checkpointing intermediate results

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SQL language	Dataflow programming models

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Execution time determined by slowest node	Cannot globally optimize execution plans
Awkward for semi- structured data	Cannot do indexing, compression, etc
Not suitable for unstructured data analysis	Too low-level, not reusable, not good for joins

Least But Not Last ..

- Parallel DBMS
 - Expensive, no open-source option

- MapReduce
 - Hadoop
 - Attractive for modest budgets and requirements

Benchmark Study

- Tested Systems:
 - Hadoop (MapReduce)
 - Vertica (Column-store DBMS)
 - DBMS-X (Row-store DBMS)
- 100-node cluster at Wisconsin
- Tasks
 - Original MR Grep Task in OSDI'04 paper
 - Web Log Aggregation
 - Table Join with Aggregation

	Hadoop	DBMS-X	Vertica
Grep Task	284 sec	194 sec	108 sec
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- MR: parsing in runtime, no compression and pipelining, etc
- PDBMS: parsing while loading, compression, query plan optimization

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We Want Features from Both Sides:

- Data Storage
 - From MR: semi-structured data loading/parsing
 - From DBMS: compression, indexing, etc
- Query Execution
 - From MR: load balancing, fault-tolerance
 - From DBMS: query plan optimization
- Query Interface
 - From MR: procedural
 - From DBMS: declarative

Pig

- Data Storage: MR
 - Run Pig Latin queries over any external files given user defined parsing functions
- Query Execution: MR
 - Compile to MapReduce plan and get executed on Hadoop
- Query Interface: MR+DBMS
 - Declarative spirit of SQL + procedural operators

SCOPE

- Data Storage: DBMS+MR
 - Load to Cosmos Storage System, which is append-only, distributed and replicated
- Query Execution: MR
 - Compile to Dryad data flow plan (DAG), and executed by the runtime job manager
- Query Interface: DBMS+MR
 - Resembles SQL with embedded C# expressions

Hive

- Data Storage: DBMS+MR
 - Use one HDFS dir to store one "table", associated with builtin serialization format
 - Hive-Metastore
- Query Execution: MR
 - Compile to a DAG of map-reduce jobs, executed over Hadoop
- Query Interface: DBMS
 - SQL-like declarative HiveQL

So Far..

	Pig	SCOPE	Hive
	SIGMOD'08	VLDB'08	VLDB'09
Query Interface	Procedural Higher than MR	SQL-like + C#	HiveQL
Data	External	Cosmos	HDFS w/
Storage	Files	Storage	Metastore
Query Execution	Hadoop	Dryad	Hadoop

HadoopDB

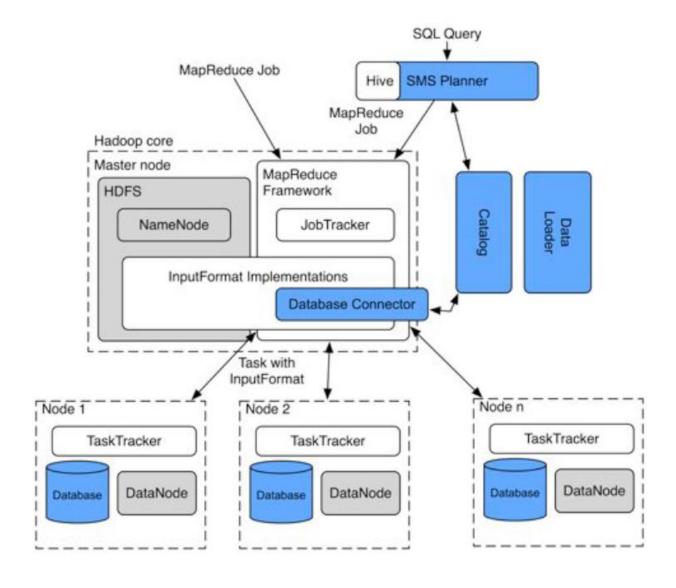
	Pig	SCOPE	Hive	HadoopDB
	SIGMOD'08	VLDB'08	VLDB'09	VLDB'09
Query Interface	Procedural Higher than MR	SQL-like + C#	HiveQL	SQL
Data	External	Cosmos	HDFS w/	HDFS +
Storage	Files	Storage	Metastore	DBMS
Query Execution	Hadoop	Dryad	Hadoop	As much DBMS as possible

Basic Idea

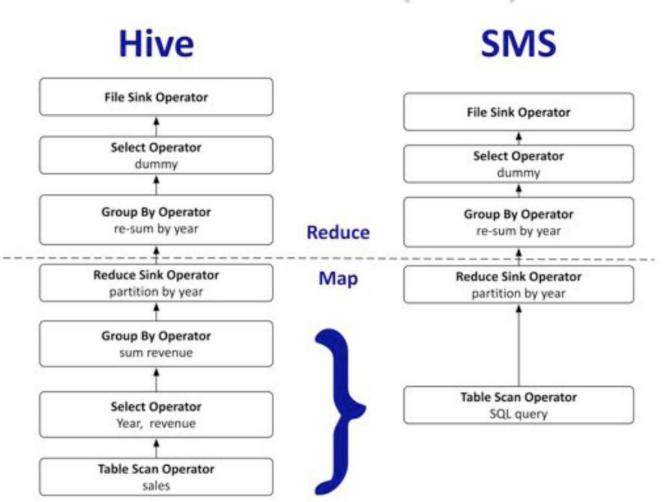
 Multiple, independent single node databases coordinated by Hadoop

 SQL queries first compiled to MapReduce, then a sub-sequence of map-reduce converts back to SQL

Architecture

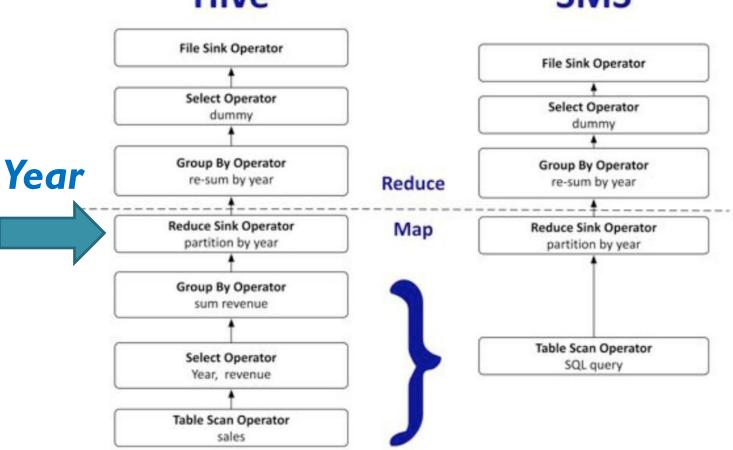


SQL - MR - SQL (SMS)



SELECT YEAR(saleDate), SUM(revenue) FROM sales GROUP BY YEAR(saleDate);

SQL – MR – SQL (SMS) Hive SMS



SELECT YEAR(saleDate), SUM(revenue) FROM sales GROUP BY YEAR(saleDate);

SQL - MR - SQL (SMS)Hive **SMS File Sink Operator** File Sink Operator Select Operator Select Operator dummy Not dummy **Group By Operator Group By Operator** Year Year re-sum by year Reduce re-sum by year Reduce Sink Operator Map Reduce Sink Operator partition by year partition by year **Group By Operator** sum revenue **Table Scan Operator** Select Operator SQL query Year, revenue **Table Scan Operator** sales

SELECT YEAR(saleDate), SUM(revenue) FROM sales GROUP BY YEAR(saleDate);

Evaluation Setup

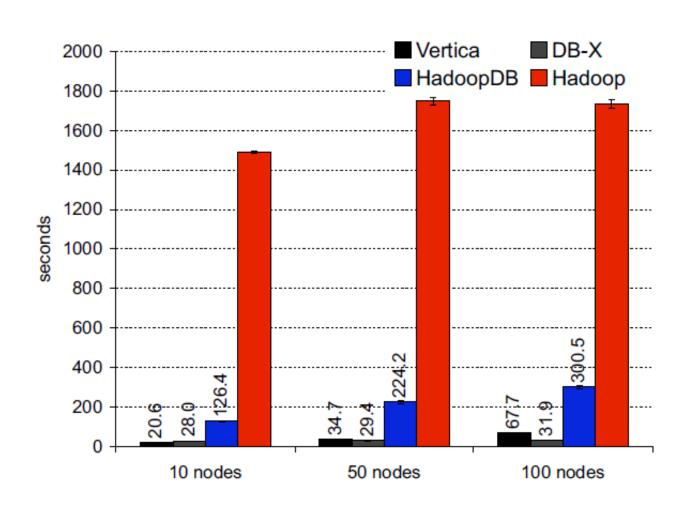
Tasks: Same as the CACM'10 paper

Amazon EC2 "large" instances

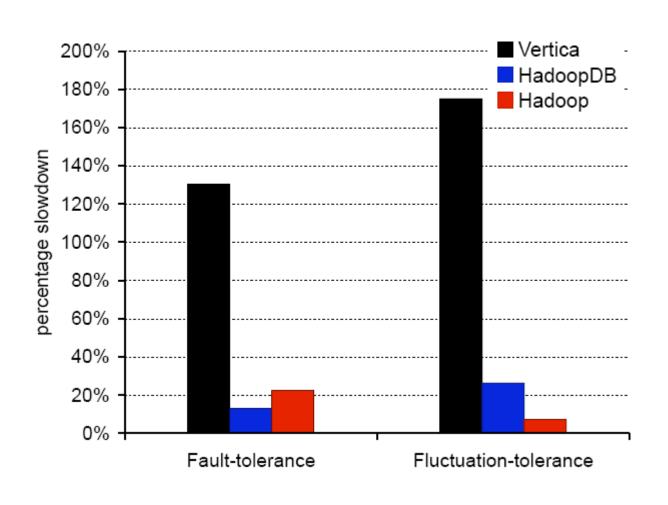
 For fault-tolerance: terminate a node at 50% completion

 For fluctuation-tolerance: slow down a node by running an I/O-intensive job

Performance: join task



Scalability: aggregation task



Conclusions

 Sacrificing performance is necessary for fault tolerance/heterogeneity in the case of order 100,000 nodes

 MapReduce and Parallel DBMSs completes each other for large scale analytical workloads.

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Questions?

Other MR+DBMS Work

(part of the slide from Andrew Pavlo)

- Commercial MR Integrations
 - Vertica
 - Greenplum
 - AsterData
 - Sybase IQ

- Research
 - MRi (Wisconsin)
 - Osprey (MIT)

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- MR: Record parsing in run time
- PDBMS: Record parsed/compressed when loaded

	Hadoop	DBMS-X	Vertica
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- MR:Write intermediate results to disks
- PDBMS: Pipelining

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- MR: Cannot handle joins very efficiently
- PDBMS: Optimization for joins

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Summary:

- Trade performance to have runtime scheduling and checkpointing
- Trade execution time to reduce load time at storage layer

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