MapReduce and Parallel DBMSs:
A Comparison of Approaches to Large-Scale Data Analysis

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BROWN

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Today's Talk

- SIGMOD '09
  - *A Comparison of Approaches to Large-Scale Data Analysis*
- CACM '09 (*submitted*)
  - *MapReduce and Parallel DBMSs: Friends or Foes?*
  - *Compare/Contrast with Jeff Dean (Google)*

A Comparison of Approaches to Large-Scale Data Analysis

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ABSTRACT

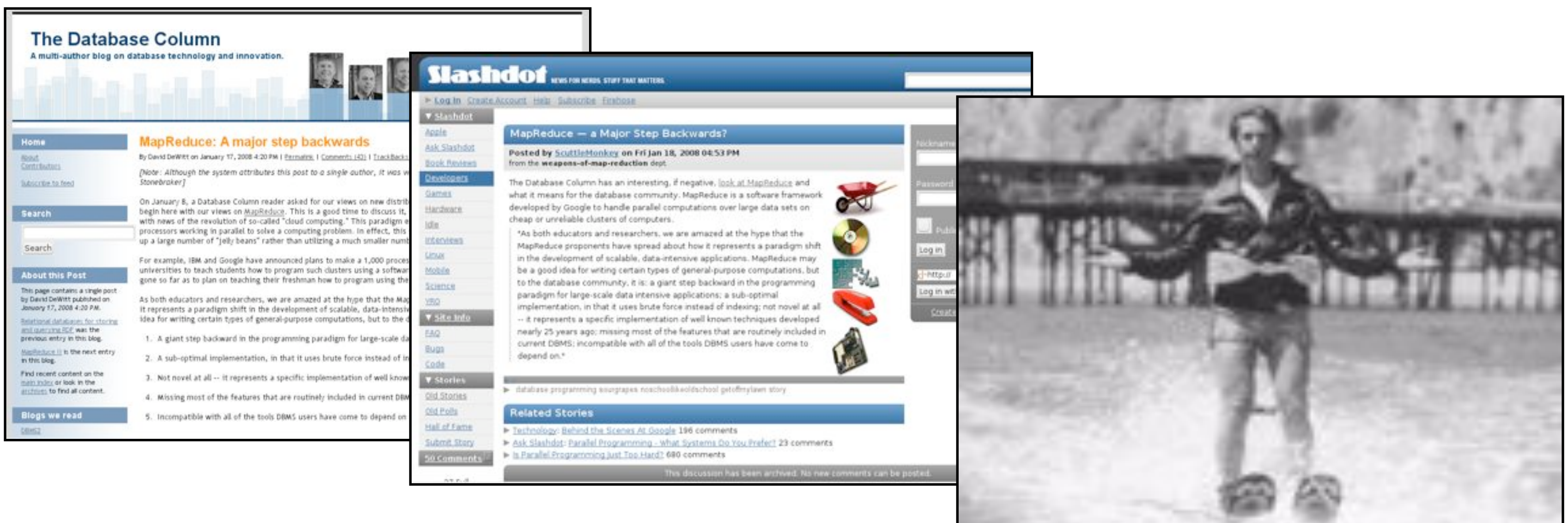
Categories and Subject Descriptors

General Terms

1. INTRODUCTION

In the beginning…

- **DeWitt + Stonebraker Article**
  - ***MapReduce: A Major Step Backwards [1]***



[1] MapReduce: A Major Step Backwards – January 8th, 2008
http://databasecolumn.vertica.com/2008/01/mapreduce-a-major-step-back.html

MapReduce and Databases

- **Understand loading and execution behaviors for common processing tasks.**
- **Large-scale data access (>1TB):**
  - ***Analytical query workloads***
  - ***Bulk loads***
  - ***Non-transactional***

Outline

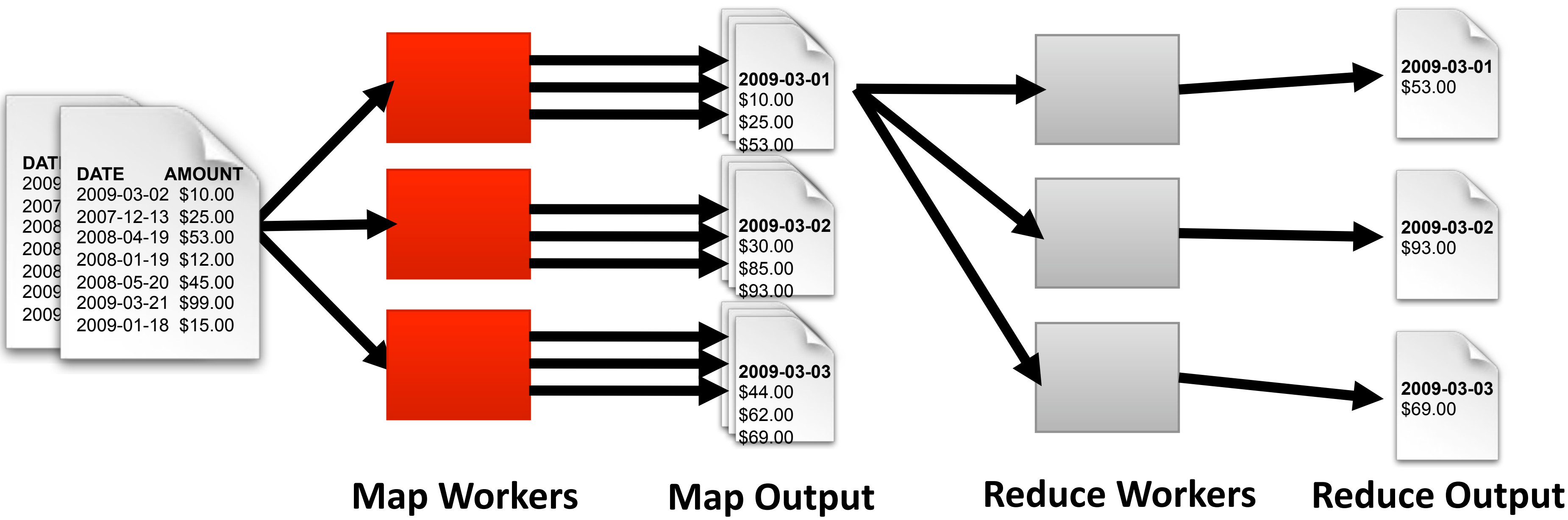
- MapReduce/DBMS Overview
- Benchmark Study
- Results Analysis & Discussion
- Google's Response
- Sweet Spots
- Concluding Remarks

MapReduce Overview

- **Massively parallel data processing**
  - ***Programming Model vs. Execution Platform***
- **Programs consist of only two functions:**
  - ***Map(k1, v1) → (k2, list(v2))***
  - ***Reduce(k2, list(v2)) → (key3, list(v3))***

MapReduce Example

- Calculate total order amount per day.



Shared-Nothing Parallel Databases

- Common characteristics:
  - *Data partitioning.*
  - *Inter- and intra-query parallelism.*
- Modern systems are based on pioneering work from 1980s:
  - *TeraData ('86)*
  - *Gamma (DeWitt '86)*
  - *Grace (Fushimi '86)*

Benchmark Environment

- **Tested Systems:**
  - ***Hadoop (MapReduce)***
  - ***Vertica (Column-store DBMS)***
  - ***DBMS-X (Row-store DBMS)***
- **100-node cluster at Wisconsin**
- **Additional configuration information is available on our website.**

XXX

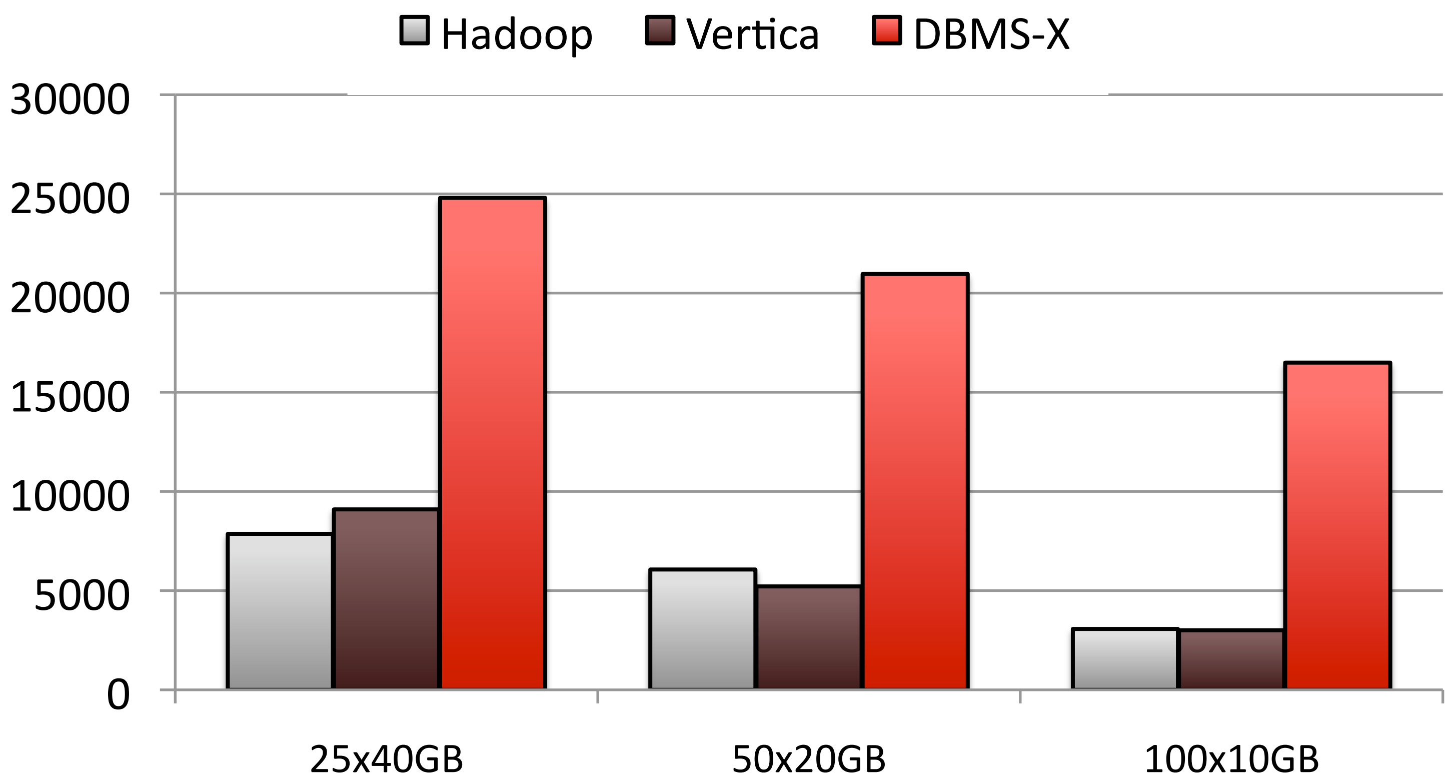
Methodology

- Report load & execution times.
  - *All results are an average of three trials.*
  - *Flush caches to ensure cold start.*
- Hadoop results include separate combine task to consolidate results on a single-node.
  - *Numbers are reported separately.*

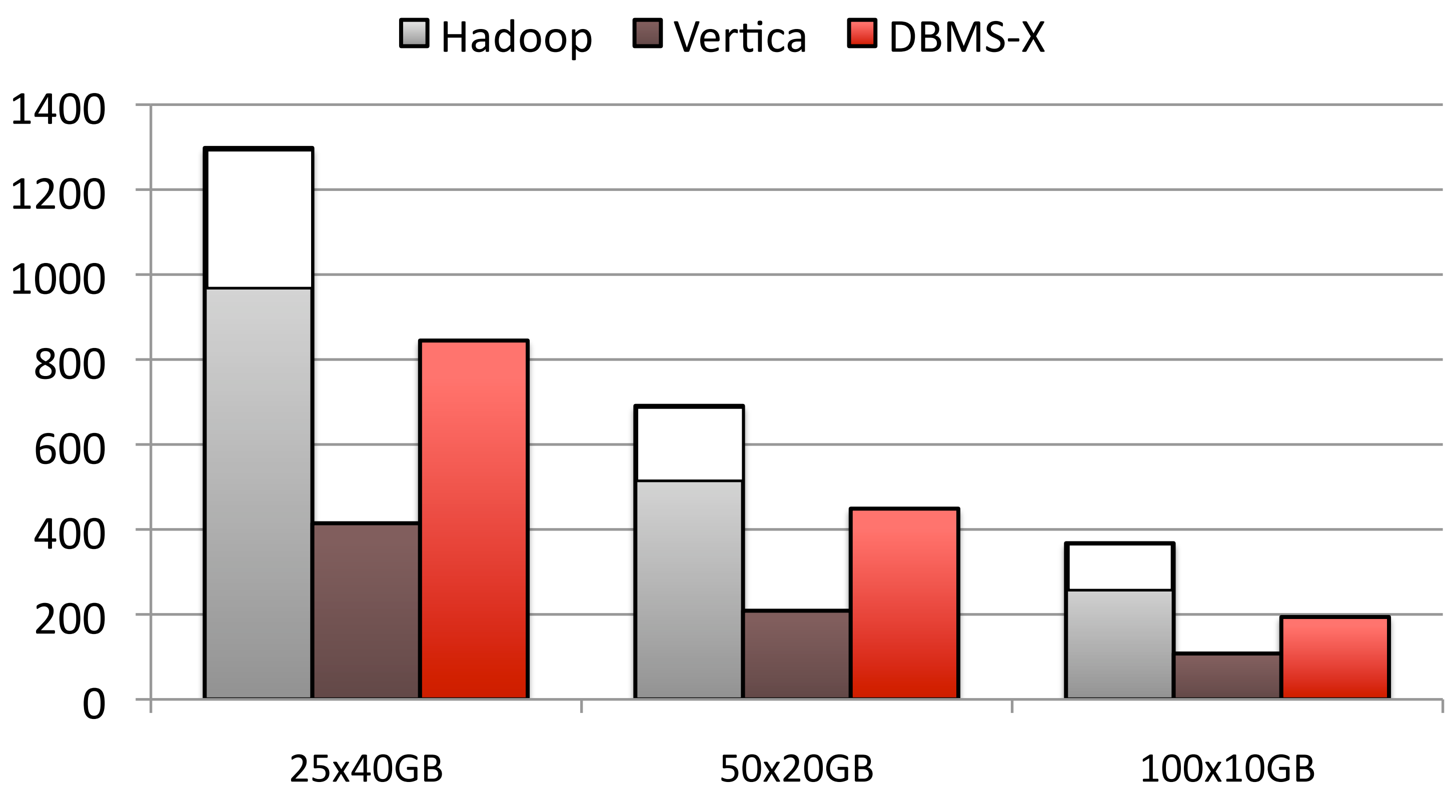
Grep Task

- **Find 3-byte pattern in 100-byte record**
  - *1 match per 10,000 records*
- **Data set:**
  - *10-byte unique key, 90-byte value*
  - *1TB spread across 25, 50, or 100 nodes*
  - *10 billion records*
- **Original MR Paper (Dean et al. 2004)**

Grep Task Loading Results



Grep Task Execution Results



Analytical Tasks

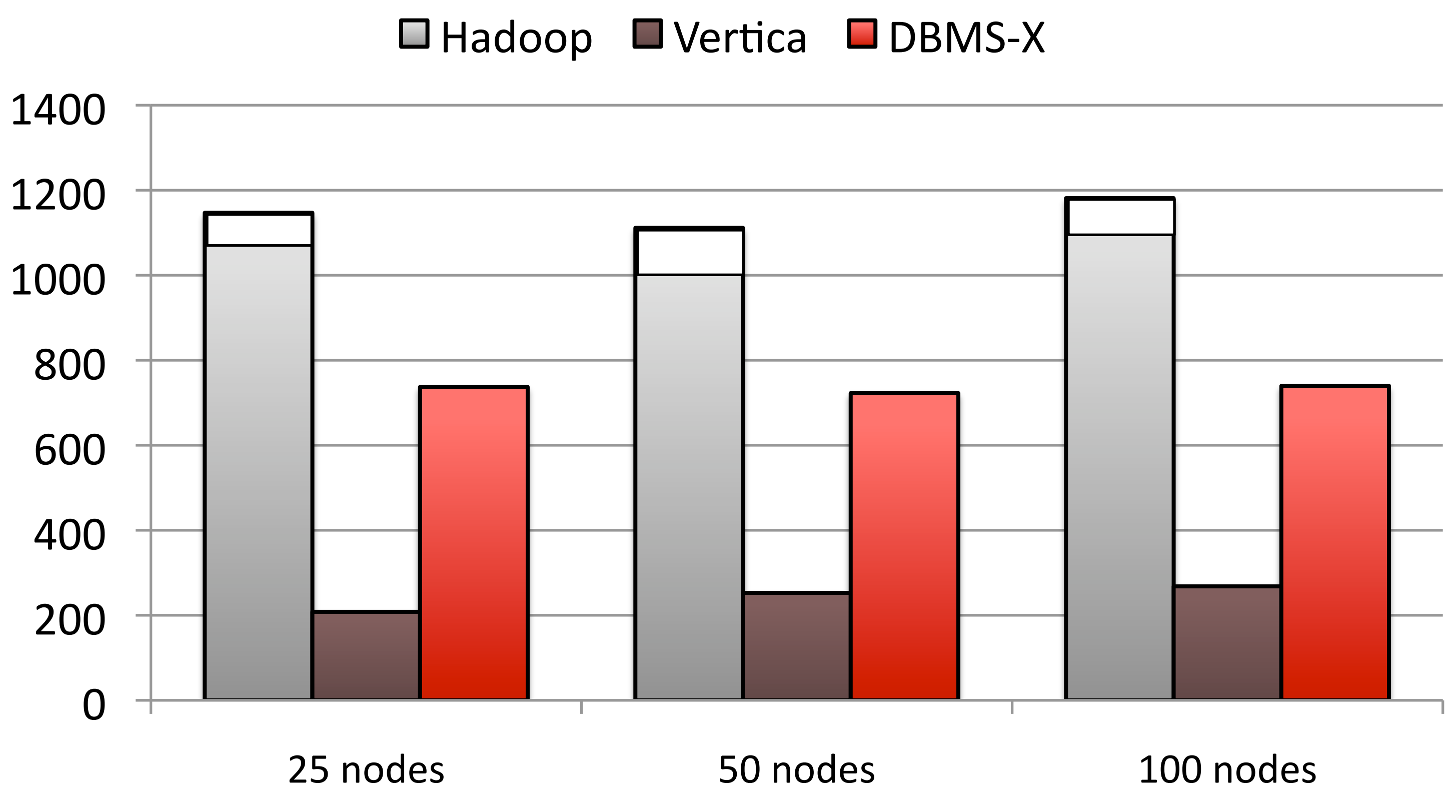
- **Simple web processing schema**
- **Data set:**
  - ***600k HTML Documents (6GB/node)***
  - ***155 million UserVisit records (20GB/node)***
  - ***18 million Rankings records (1GB/node)***

Aggregate Task

- **Simple query to find adRevenue by IP prefix**

```
SELECT SUBSTR(sourceIP, 1, 7),
       SUM(adRevenue)
  FROM userVistits
 GROUP BY SUBSTR(sourceIP, 1, 7)
```

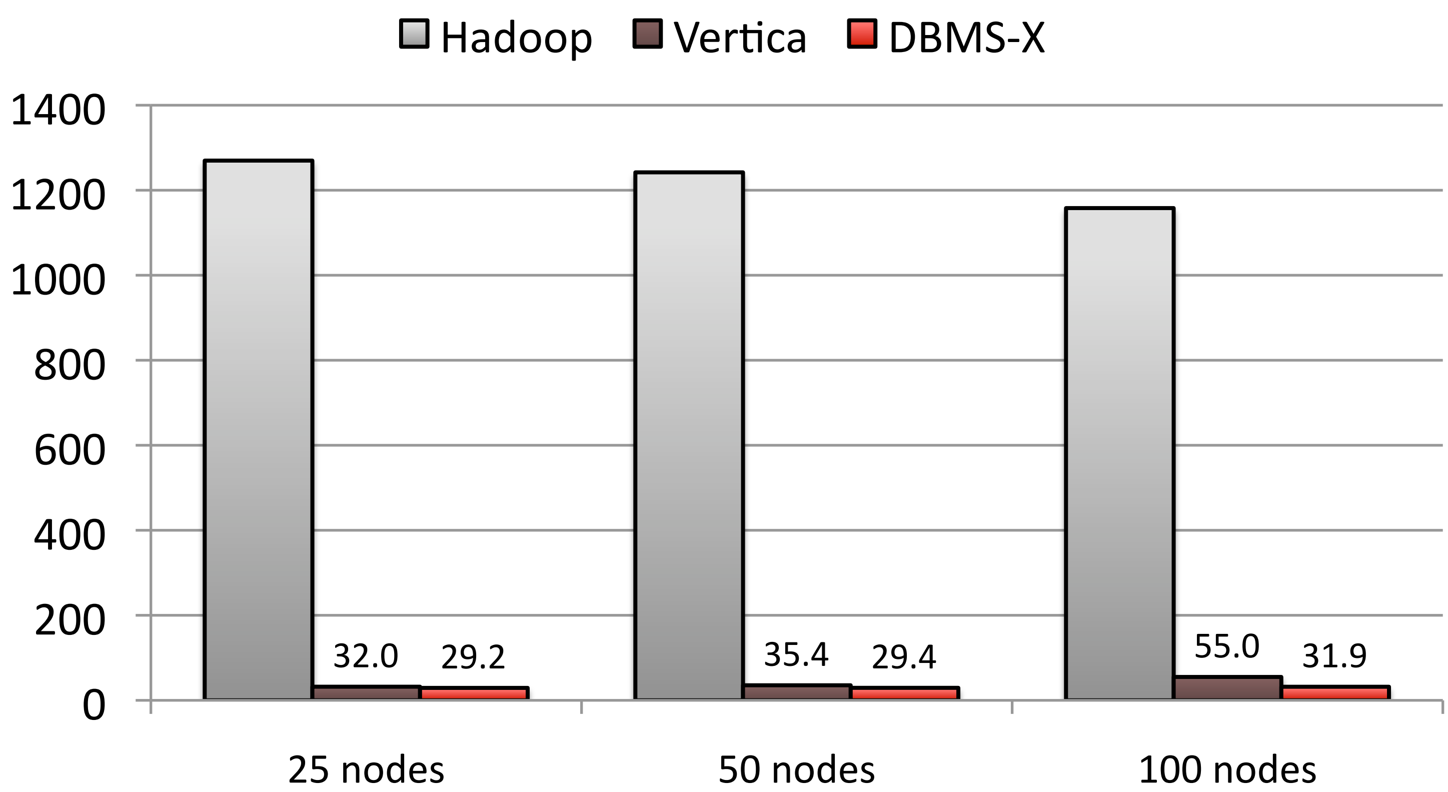
Aggregate Task Results



Join Task

- **Find the sourceIP that generated the most adRevenue along with its average pageRank.**
- **Implementations:**
  - ***DBMSs – Complex SQL using temporary table.***
  - ***MapReduce – Three separate MR programs.***

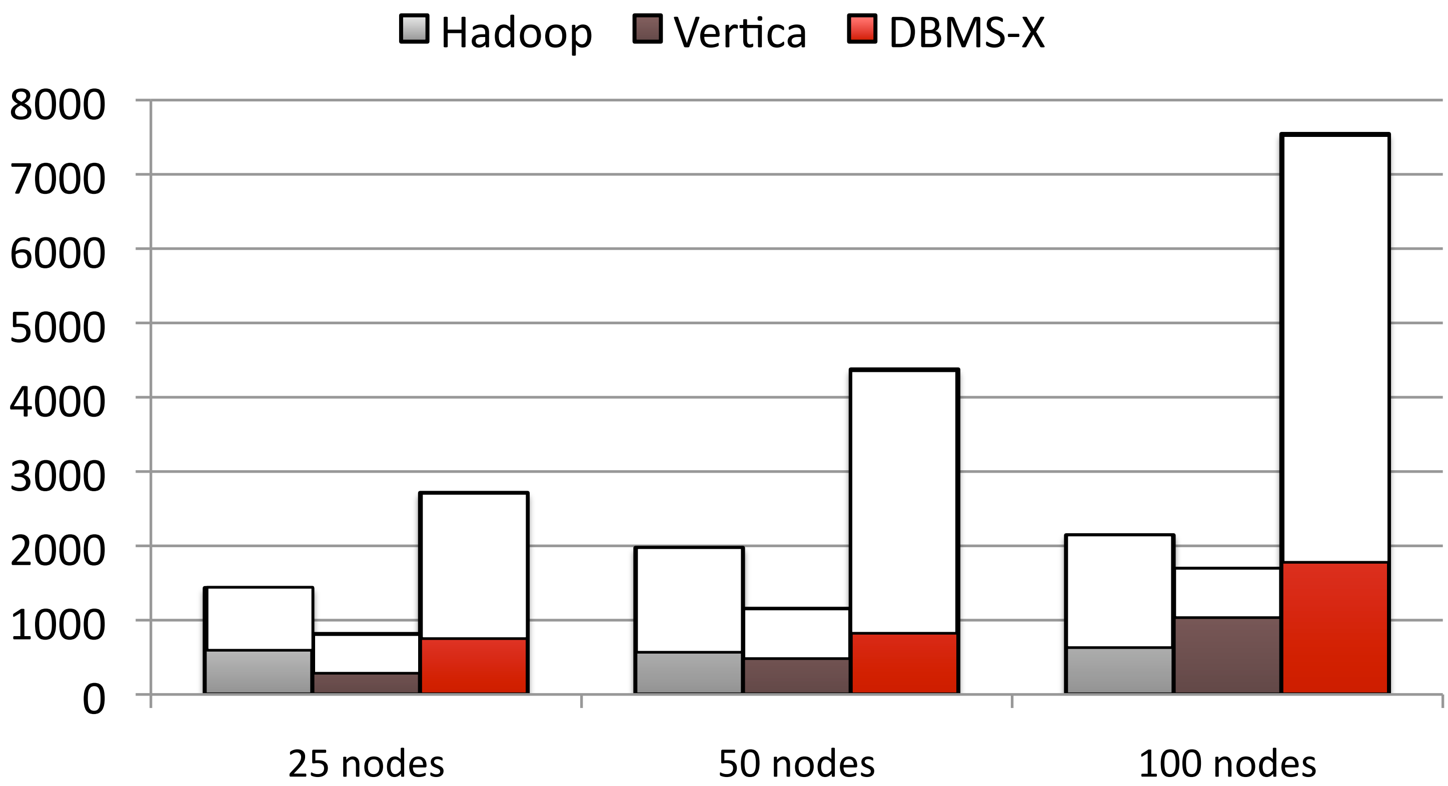
Join Task Results



UDF Task

- First phase of PageRank Algorithm
  - *Count number of links for each URL.*
- DBMS Troubles:
  - *Vertica did not support UDFs.*
  - *DBMS-X had buggy BLOBs.*
- Hadoop implementation is straightforward.

UDF Task Results



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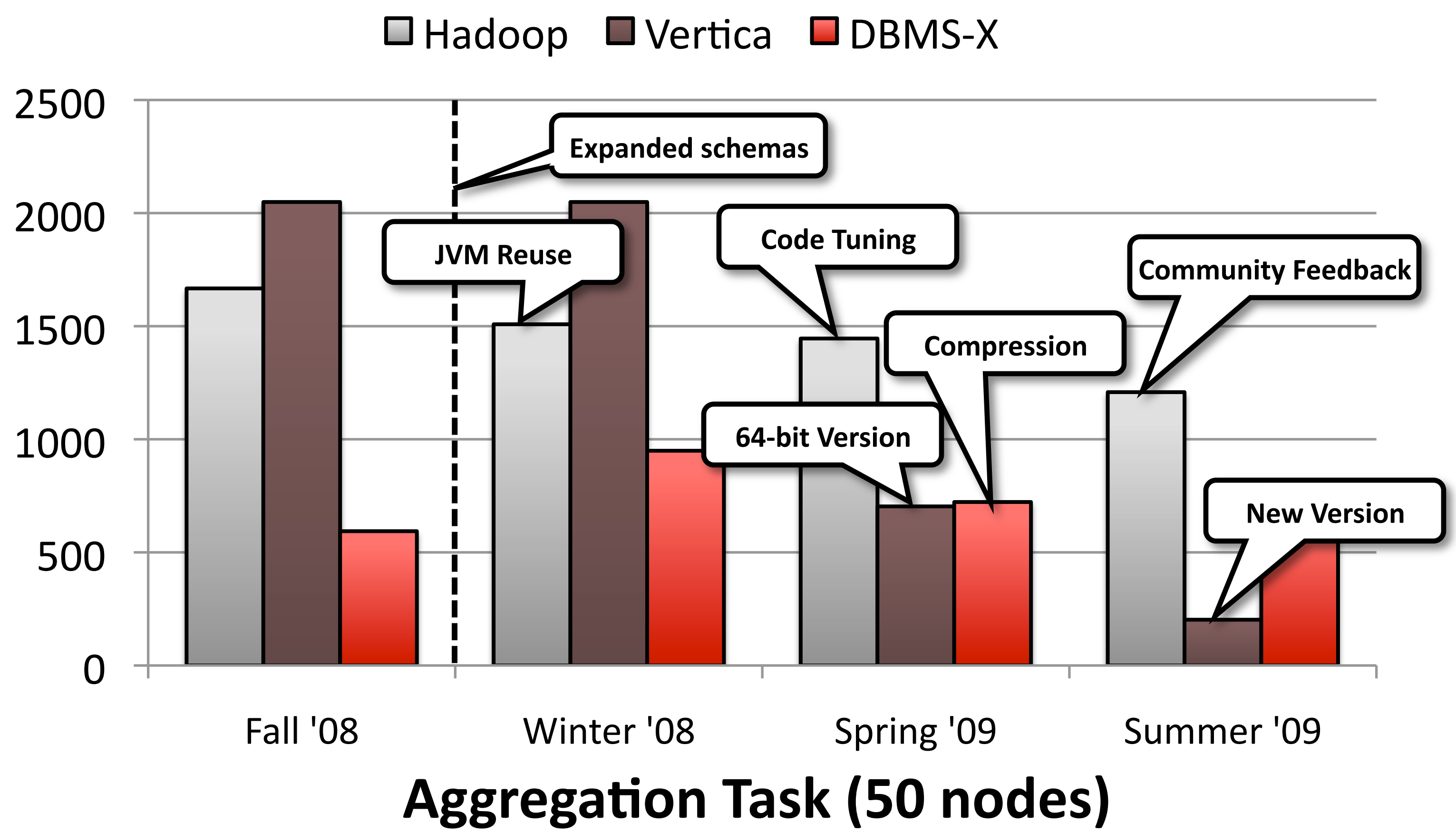
Implementation Refinement



Task Start-up

- **Hadoop is slow to start executing programs:**
  - ***10 seconds until first Map starts.***
  - ***25 seconds until all 100 nodes are executing.***
  - ***7 buffer copies per record before reaching Map function [1].***

- **Parallel DBMSs are always "warm"**

[1] The Anatomy of Hadoop I/O Pipeline - August 27th, 2009
http://developer.yahoo.net/blogs/hadoop/2009/08/the_anatomy_of_hadoop_io_pipel.html

Repetitive Data Parsing

- Hadoop has to parse/cast values every time:
  - *SequenceFiles provide serialized key/value.*
  - *Multi-attribute values must still handled by user code.*
- DBMSs parse records at load time:
  - *Allows for efficient storage and retrieval.*

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Google's Response

- **Jeffrey Dean and Sanjay Ghemawat**
  - ***MapReduce: A Flexible Data Processing Tool CACM'09***
- **Key points:**
  - ***Flaws in benchmark.***
  - ***Fault-tolerance in large clusters.***
  - ***MapReduce ≠ DBMS***

Google's Response: Flaws

- **MR can load and execute queries in the same time that it takes DBMS-X just to load.**
- **Alternatives to reading all of the input data:**
  - ***Select files based on naming convention.***
  - ***Use alternative storage (BigTable).***
- **Combining final reduce output.**

Google's Response: Cluster Size

- **Largest known database installations:**
  - ***Greenplum – 96 nodes – 4.5 PB (eBay) [1]***
  - ***Teradata – 72 nodes – 2+ PB (eBay) [1]***
- **Largest known MR installations:**
  - ***Hadoop – 3658 nodes – 1 PB (Yahoo) [2]***
  - ***Hive – 600+ nodes – 2.5 PB (Facebook) [3]***

[1] eBay's two enormous data warehouses – April 30th, 2009
http://www.dbms2.com/2009/04/30/ebays-two-enormous-data-warehouses/

[2] Hadoop Sorts a Petabyte in 16.25 Hours and a Terabyte in 62 Seconds – May 11th, 2009
http://developer.yahoo.net/blogs/hadoop/2009/05/hadoop_sorts_a_petabyte_in_162.html

[3] Hive - A Petabyte Scale Data Warehouse using Hadoop – June 10th, 2009
http://www.facebook.com/note.php?note_id=89508453919

Google's Response: Functionality

- **MapReduce enables parallel computations not easily performed in a DBMS:**
  - ***Stitching satellite images for Google Earth.***
  - ***Generating inverted index for Google Search.***
  - ***Processing road segments for Google Maps.***
- **Programming Model vs. Execution Platform**

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Extract-Transform-Load

- "Read Once" data sets:
  - *Read data from several different sources.*
  - *Parse and clean.*
  - *Perform complex transformations.*
  - *Decide what attribute data to store.*
  - *Load the information into a DBMS.*
- Allows for quick-and-dirty data analysis.

Semi-Structured Data

- **MapReduce systems can easily stored semi-structured data since no schema is needed:**
  - *Typically key/value records with a varying number of attributes.*
- **Awkward to stored in relational DBMS:**
  - *Wide-tables with many nullable attributes.*
  - *Column store fairs better.*

Limited Budget Operations

- **MapReduce frameworks:**
  - ***Community supported and driven.***
  - ***Attractive for projects with modest budgets and requirements.***
- **Parallel DBMSs are expensive:**
  - ***No open-source option.***

Concluding Remarks

- What can *MapReduce* learn from *Databases*?
  - *Declarative languages are a good thing.*
  - *Schemas are important.*
- What can *Databases* learn from *MapReduce*?
  - *Query fault-tolerance.*
  - *Support for in situ data.*
  - *Embrace open-source.*

Other Benchmarked Systems

- HadoopDB (Abadi ’09 - Yale)
  - *Replaced Hadoop filesystem with Postgres.*
  - *Makes JDBC calls inside of MR functions.*
- Hive (Thusoo ’09 - Facebook)
  - *Data warehouse interface on top of Hadoop.*
  - *Converts SQL-like language to MR programs.*

Conclusion

- **MapReduce goodness:**
  - ***Ease of use, "out of box" experience..***
  - ***Attractive fault tolerance properties.***
  - ***Fast load times.***
- **Database goodness:**
  - ***Fast query times.***
  - ***Schemas.***
  - ***Supporting tools.***

More Information

- **Complete benchmark information and source code is available at our website:**
  - ***http://database.cs.brown.edu/sigmod09/***

- **Questions/Comments?**