A Comparison of Approaches to Large-Scale Data Analysis

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with

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In SIGMOD 2009

MapReduce (MR) vs. Databases

- Our goal: understand performance and architectural differences
- Both are suitable for large-scale data processing
  - I.e. analytical processing workloads
  - Bulk loads
  - Queries over large amounts of data
  - *Not transactional*

Why Compare Them?

- *Reason 1*: CACM '09: MapReduce is a new way of thinking about programming large distributed systems
  - To DBMS researchers, programming model doesn't feel new
  - Other communities don't know this; important to evangelize
- *Reason 2*: Facebook is using Hive (a SQL layer) on Hadoop (MapReduce) to manage 4 TB data warehouse*
- Database community risk losing hearts and minds
  - Important to show where database systems are the right choice
- Important to educate other communities
  - E.g., inform Hive developers about how to architect a parallel DBMS

*http://www.dbms2.com/2009/05/11/facebook-hadoop-and-hive/

This Talk

- Comparison of the Two Architectures
- Benchmark
  - Tasks that either system should execute well
- Results on two shared nothing DBMSs & Hadoop
- Navel Gazing

Architectural Differences

- MapReduce operates on *in-situ* data, without requiring transformation or loading
- Schemas:
  - MapReduce doesn't require them, DBMSs do
  - Easy to write simple MR problems
  - No logical data independence
- Indexes
  - MR provides no built in support

Architectural Differences: Programming Model

- Common to write multiple MapReduce jobs to perform a complex task
  - Google search index construction > 10 MR jobs
- Analogous to multiple joins/subqueries in DBMS
  - E.g., select from subquery
- No built in optimizer in MR to order/unnest these
  - Semantic analysis of arbitrary imperative programs is hard
- MR intermediate results go to disk, pulled by next task
  - Multiple rounds of redistribution likely slow

Architectural Differences: Expressiveness

- SQL+UDFs almost as expressive as MR
  - “Impedance mismatch” is no fun
    - Inelegant programming model
  - DBMS make this much harder than they should
  - UDFs complicate optimization

Architectural Differences: Fault Tolerance

- MR supports mid-query fault tolerance

- DBMSs typically don't
  - Only important as the number of nodes gets large
  - 1 failure/mo, 1 hour/query →

    Pr(mid query failure | 10 nodes)=1%

    Pr(mid query failure | 100 nodes)=13%

    Pr(mid query failure | 1000 nodes)=75%

- MR doesn't provide transactions, disaster recovery, etc…
  - Not fundamental

The Benchmark

- Goals
  - Understand differences in load and query time for some common data processing tasks
  - Choose representative set of tasks that:
    - Both should excel at
    - MapReduce should excel at
    - Databases should excel at
- Ran on 100 node Linux cluster at U. Wisconsin

Software

- Hadoop
  - 0.19.0
  - Java 1.6
- DBMS-X
  - Parallel shared nothing row-store from a major vendor
  - Hash partitioned, sorted and indexed beneficially
  - Compression enabled
  - Great deal of manual tuning required
- Vertica
  - Parallel shared nothing column-oriented database (version 2.6)
  - Compression enabled
  - Default parameters, except hints that only one query runs at a time
  - No secondary indices, tables sorted beneficially

Grep

- Used in original MapReduce paper

- Look for a 3 character pattern in 90 byte field of 100 byte records with schema:

```
key VARCHAR(10) PRIMARY KEY
field VARCHAR(90)
```

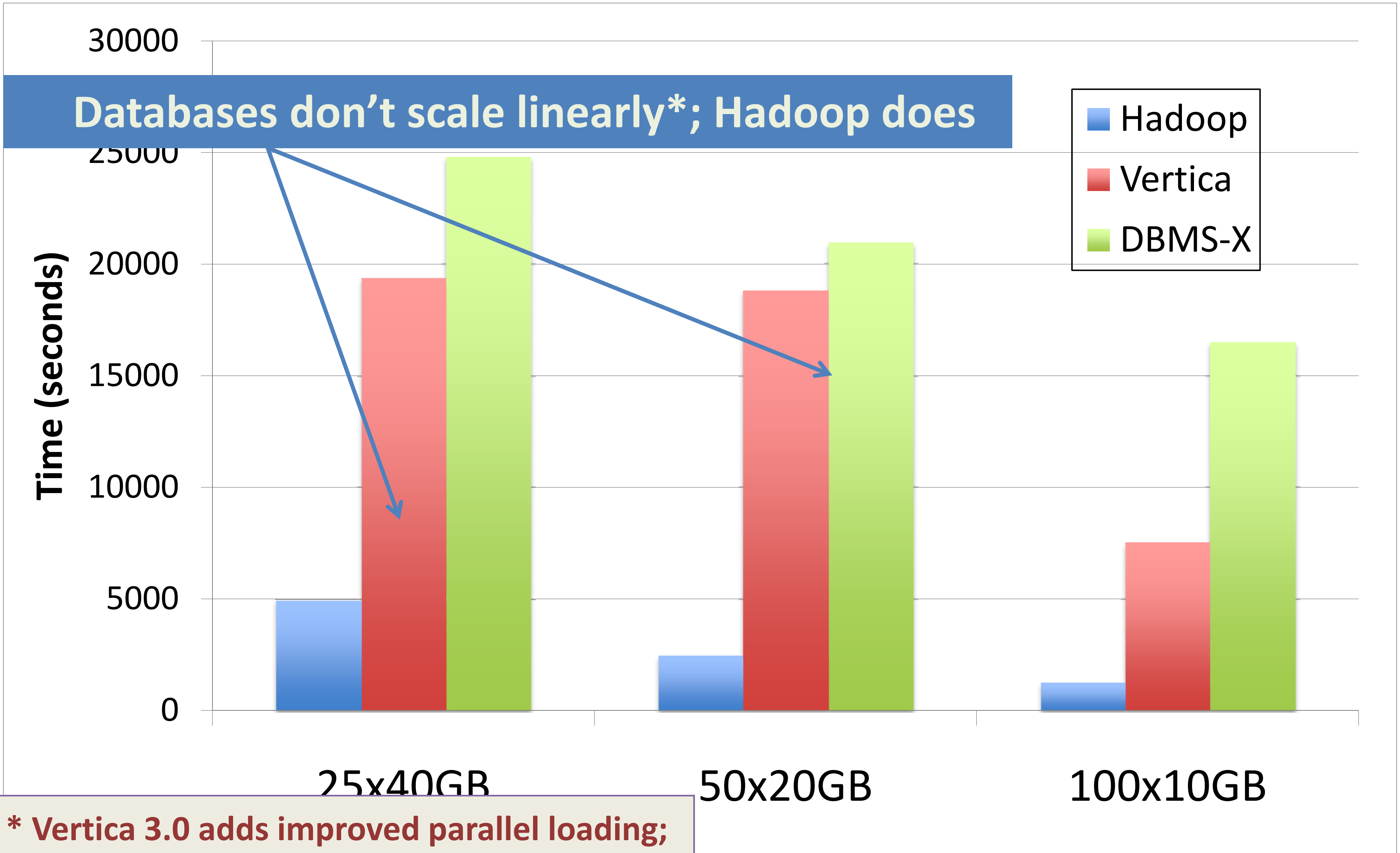
  - Pattern occurs in .01% of records

```
SELECT * FROM T WHERE field LIKE '%XYZ%'
```

- 1 TB of data spread across 25, 50, or 100 nodes
  - ~10 billion records, 10–40 GB / node

- Expected Hadoop to perform well

1 TB Grep – Load Times



* Vertica 3.0 adds improved parallel loading; early experiments show linear scalability

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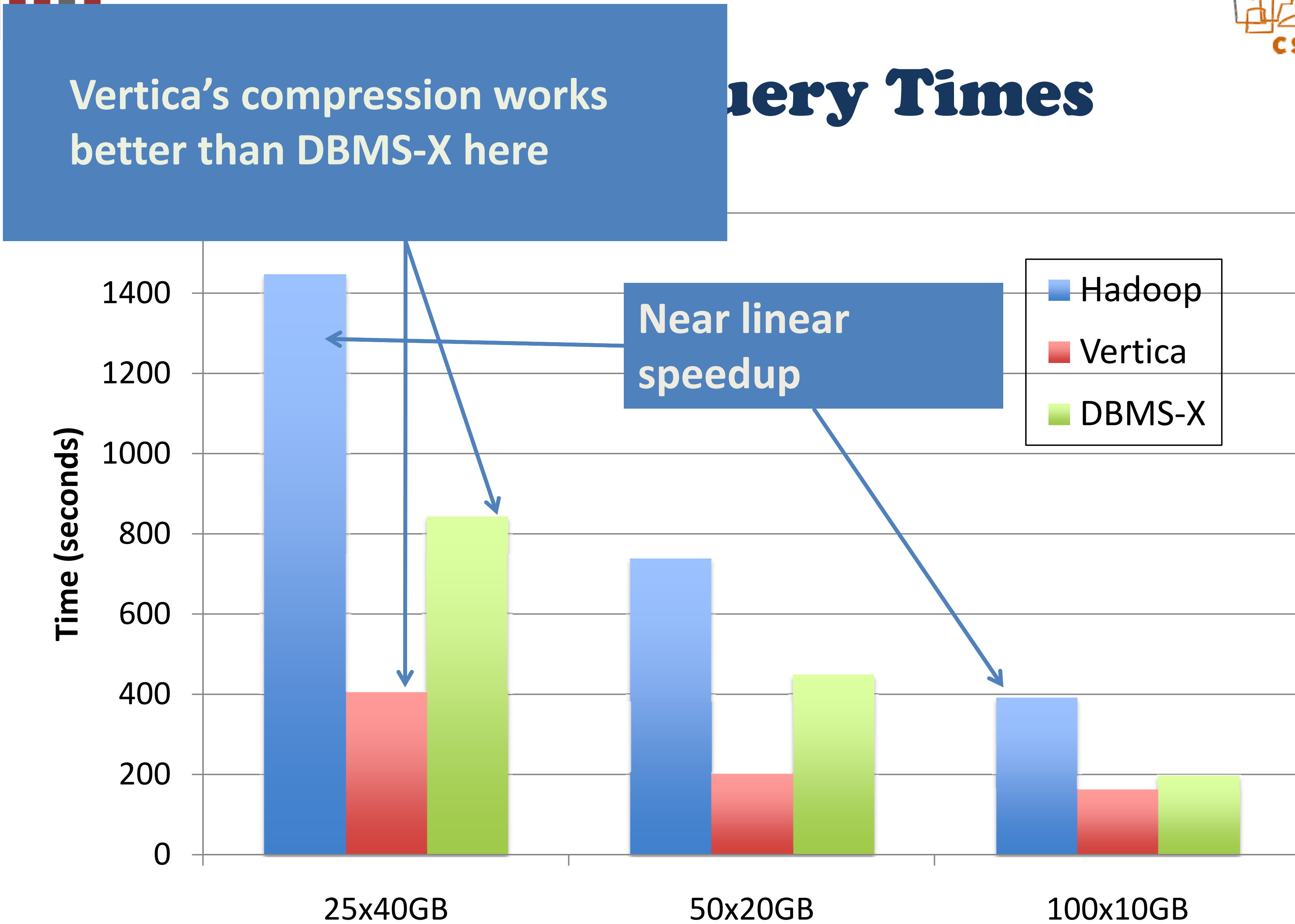


Vertica's compression works better than DBMS-X here
Near linear speedup
Time (seconds)
0
200
400
600
800
1000
1200
1400
25x40GB
50x20GB
100x10GB
Hadoop
Vertica
DBMS-X

Analytical Tasks

- Simple web processing schema
- 600,000 randomly generated documents /node
  - Contents embeds URLs
  - ~8 GB / node
- 155 million user visits / node
  - ~20 GB / node
- See paper for complete schema

```
CREATE TABLE Documents (
    url VARCHAR(100) PRIMARY KEY,
    contents TEXT
);

CREATE TABLE UserVisits (
   sourceIP VARCHAR(16),
   adRevenue FLOAT,
   … //fields omitted
);
```

Loading performance similar to grep

Aggregation Task

- Simple aggregation query to find adRevenue by IP prefix

```
SELECT SUBSTR(sourceIP, 1, 7), sum(adRevenue)
FROM userVisits GROUP BY SUBSTR(sourceIP, 1, 7)
```

- Parallel analytics query for DBMSs
  - Compute partial aggregate on each node, merge answers to produce result
  - Yields 2,000 records (24 KB)

Hadoop Code (Map)

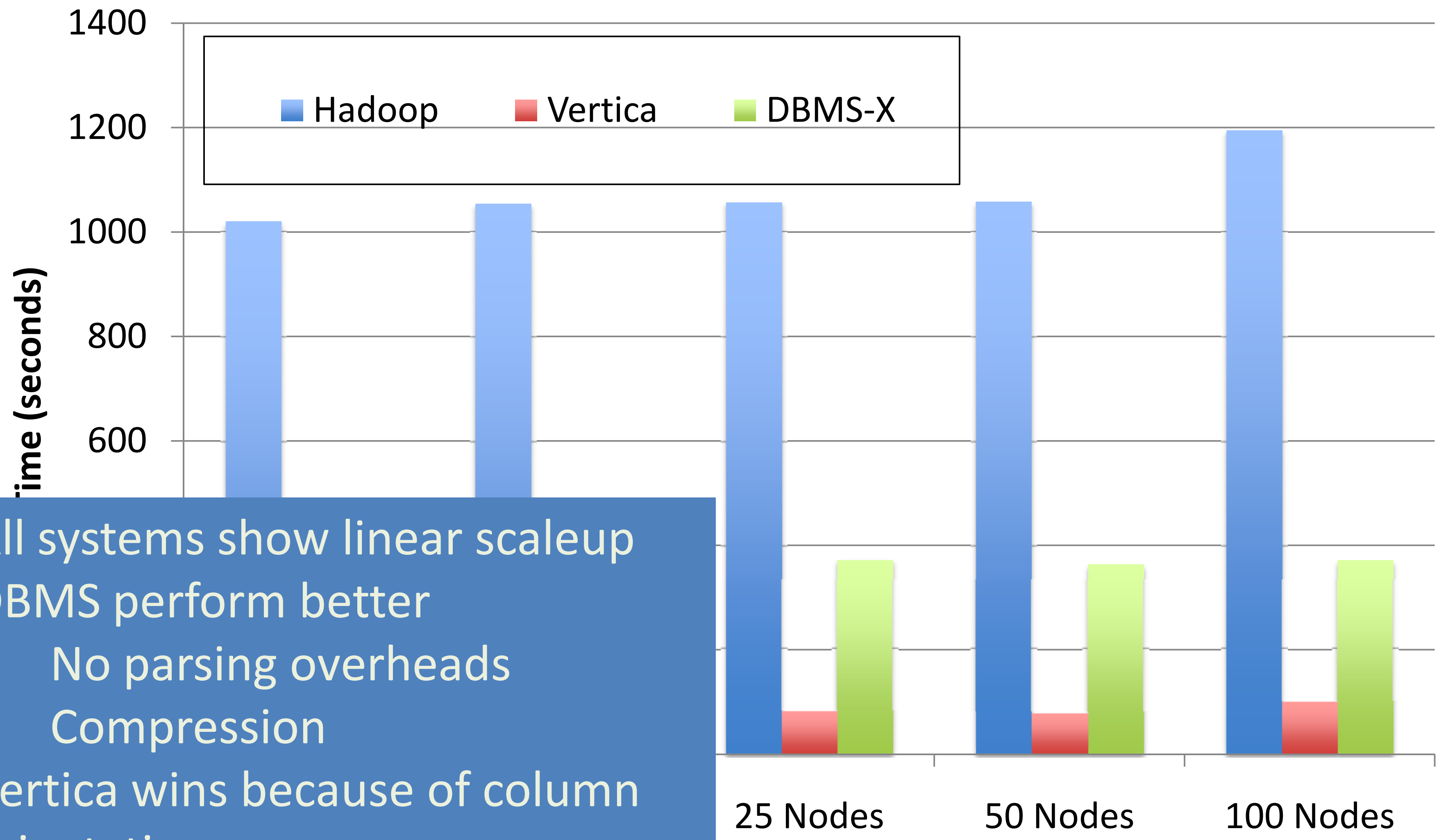
```
public void map(Text key, Text value, OutputCollector<Text,
    DoubleWritable> output,  Reporter reporter) throws IOException
    {
      //
      // Split the value using VALUE_DELIMITER into separate fields
      // The *third* field should be our revenue
      //
      String fields[] = value.toString().split("\\" +
          BenchmarkBase.VALUE_DELIMITER);
      if (fields.length > 0) {
        try {
          Double revenue = Double.parseDouble(fields[2]);
         key = new Text(key.toString().substring(0, 7));
          output.collect(key, new DoubleWritable(revenue));
        } catch (ArrayIndexOutOfBoundsException ex) {
          System.err.println("ERROR: Invalid record for key '" + key +
"'");
     } catch …
      } return;
    }
```

Implicit schema

Record parsing and validation (loading)

Reduce code simply sums revenue for assigned key

Performance Results



All systems show linear scaleup

DBMS perform better

- No parsing overheads
- Compression

Vertica wins because of column orientation

Additional DBMS-y Tasks

- Paper also reports selection and join tasks
- Hadoop also performs poorly on these
  - Hadoop code for join gets hairy
- Vertica does very well on some tasks due to column-orientation

Discussion

- Hadoop much easier to set up
- Hadoop load times are faster
  - (Loading is basically non-existent)
- Hadoop query times are a lot slower (1–2 orders of magnitude)
  - Parsing and indexing
  - Compression
  - Execution model

When to Choose MapReduce

- MapReduce is designed for one-off processing tasks
  - Where fast load times are important
  - No repeated access

- As such, lack of a schema, lack of indexing, etc is not so alarming

- However, no compelling reason to choose MR over a database for traditional database workloads
  - E.g., scalability appears to be comparable despite claims to the contrary

Conclusion

- MapReduce and Database Systems fill different niches
  - One-off processing vs repeated re-access
- MapReduce goodness
  - Ease of use, “out of box” experience
  - Single programming language
  - Attractive fault tolerance properties
  - Fast load times
- Database goodness
  - Fast query times
    - Due to indexing and compression
  - Supporting tools
- Many recently proposed hybrids
  - Hive, Pig, Scope, DryadLinq, HadoopDB, etc.
  - Interesting to see how their performance and usability compares
  - How much can be layered on top of MapReduce?

Call to arms

Because Hadoop is open source and massively parallel, people are using it

Open source shared nothing parallel DBMS is needed

Osprey – MapReduce Style Fault Tolerance for DBMSs

Christopher Yang, Christine Yen, Ceryen Tan

To Appear in ICDE 2010

Motivation

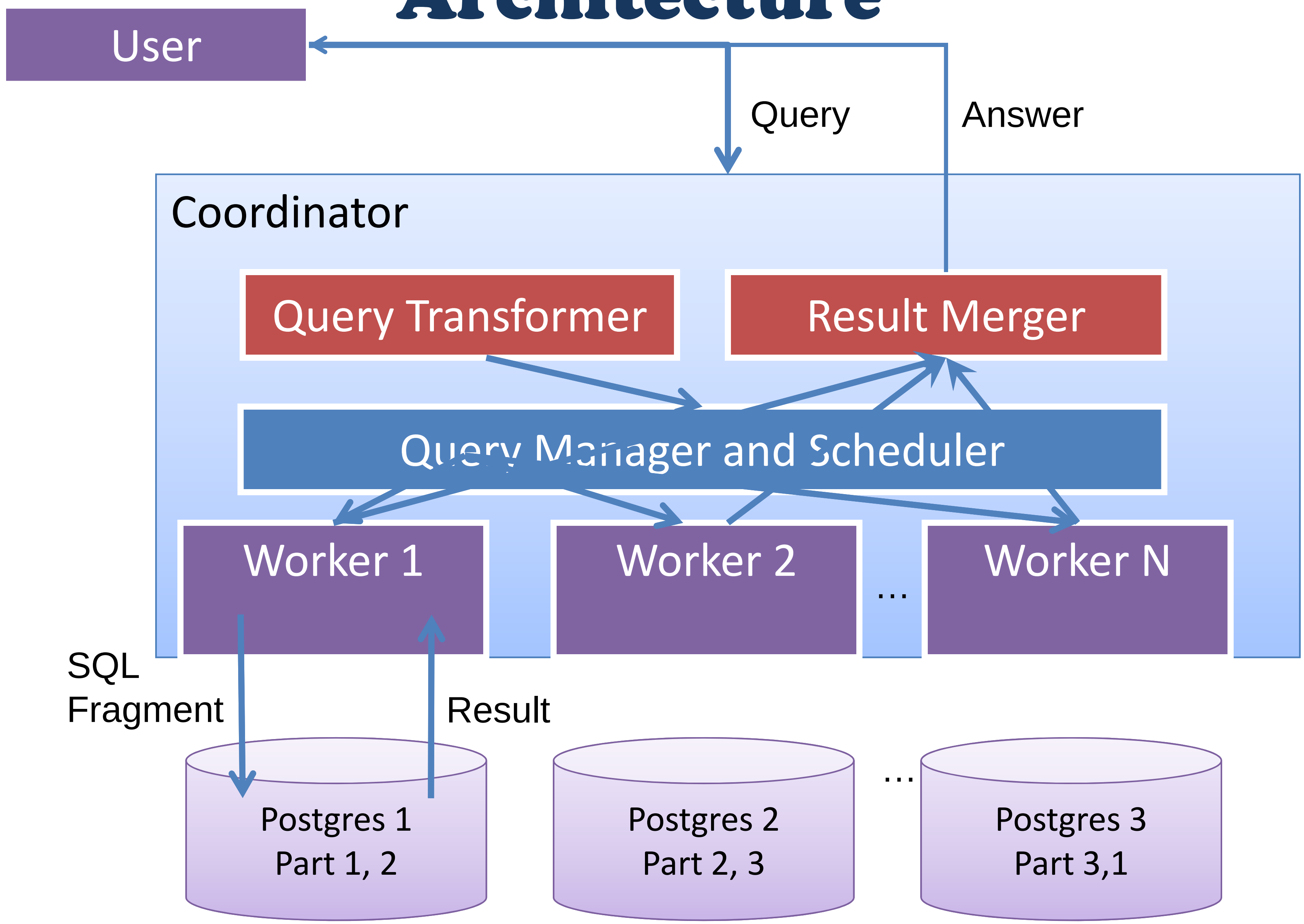
- Long running database queries on distributed databases may crash mid-flight
  - Especially as more nodes are added
- Workload skew, machine load, and other factors may lead to imbalanced distribution of work

Would be good to allow queries to tolerate faults and slow workers *a la* MapReduce

Approach

- OspreyDB is a middleware layer built of top of N Postgres installations
- Tables horizontally partitioned across machines
  - Partitions replicated *k* times using chained declustering
  - Each node is backup for previous *k* nodes
- Queries decomposed into *fragments*, each of which runs on one partition
  - *Coordinator* assembles answers to fragments to answer query
- *Job scheduler* tracks liveness of replicas, dispatches fragments
  - Fragments of slow and failed nodes reissued
  - Several different scheduling policies

Architecture



Experiments

Questions:

- How well does it scale?
- How high are the overheads?
- How well does it balance load?
- How well does it tolerate faults?

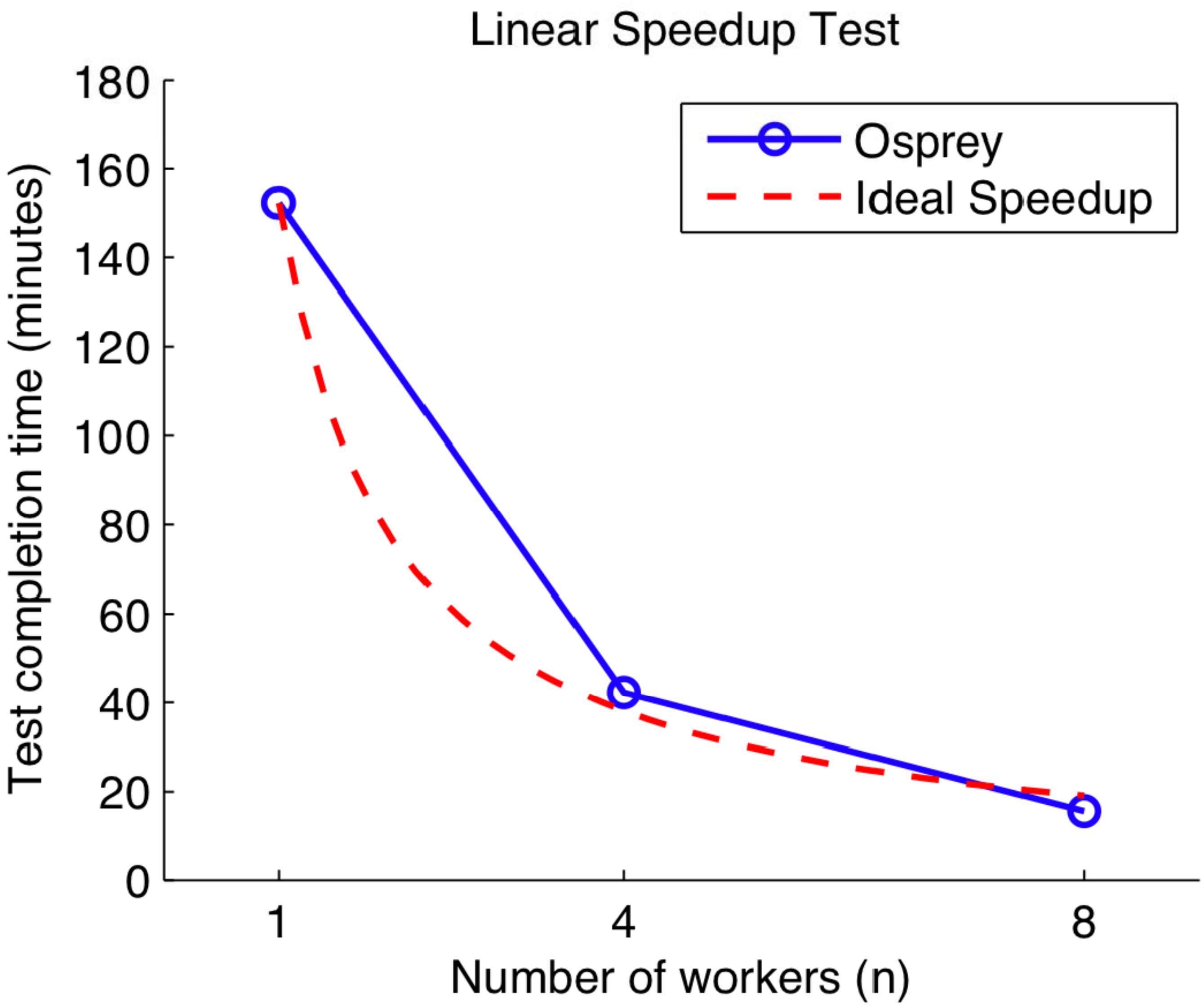
Setup:

8 Machines, Running Postgres 8.3; k=1

SSB scale 1 (5.5 GB) (1.1 GB/Node)

512 MB buffer pool per node

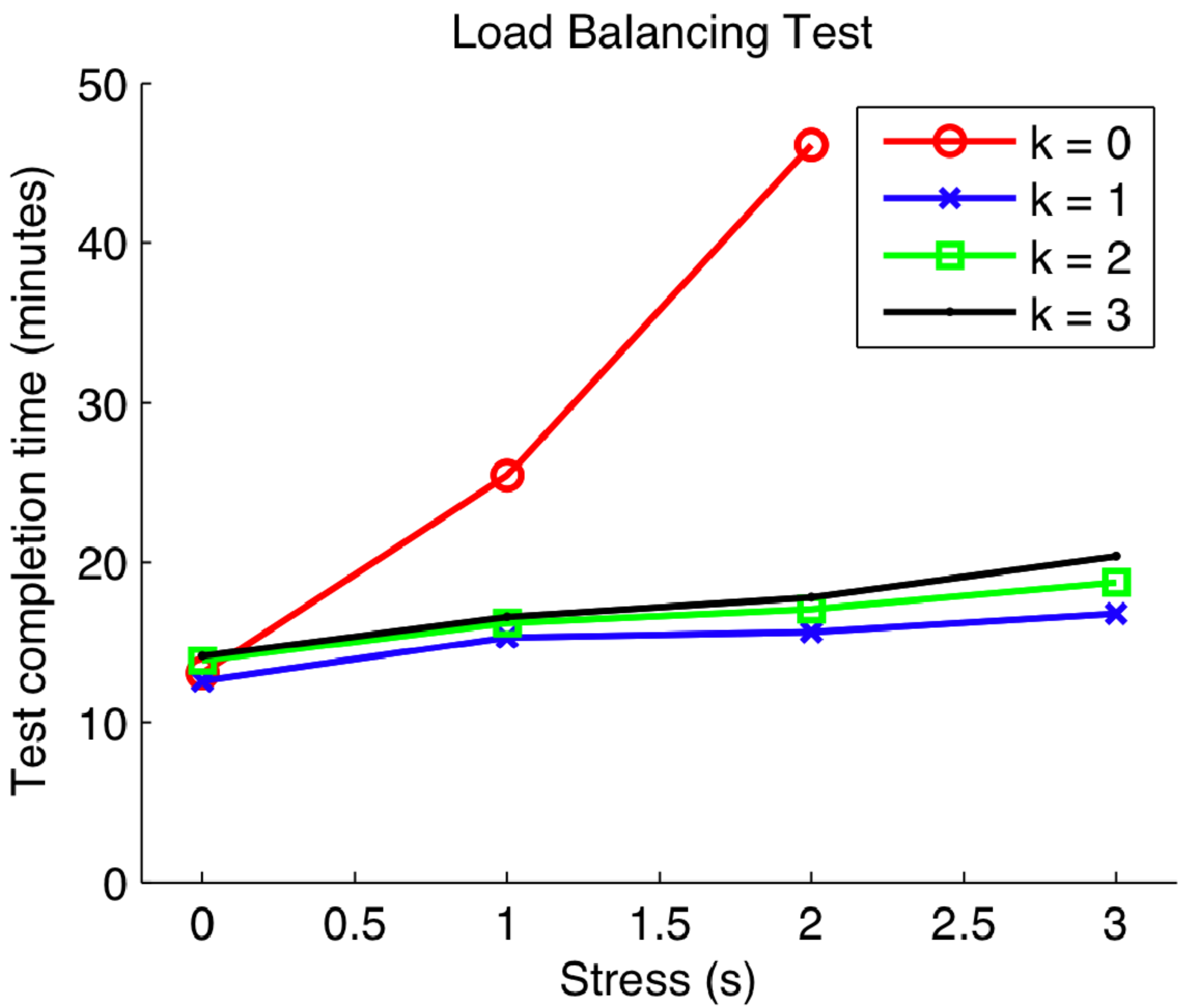
Scaleup



Linear Speedup Test
180
160
140
120
100
80
60
40
20
0
Test completion time (minutes)
1
4
8
Number of workers (n)
Osprey
Ideal Speedup

Stressing 1—3 Nodes (N=4)

Replication factor k



Failed Node

Load Balance Over Time
Worker 1
Worker 2
Worker 3
Relative Fraction of Total Computation Time
0.6
0.5
0.4
0.3
0.2
0.1
0
0
50
100
150
200
250
300
Time (s)

Conclusion

- Osprey: middleware-based solution for mid-query fault tolerance
- Decomposes queries into sub-jobs, schedules them with different policies
- Achieves linear speedup (for small numbers of nodes) and good fault tolerance properties
  – Results are not on MR cluster because we don't use Hadoop
- Next talk – similar idea, slightly different architecture, scales to many more nodes and with a much more robust query processor