Data Management in the Cloud

MAP/REDUCE II

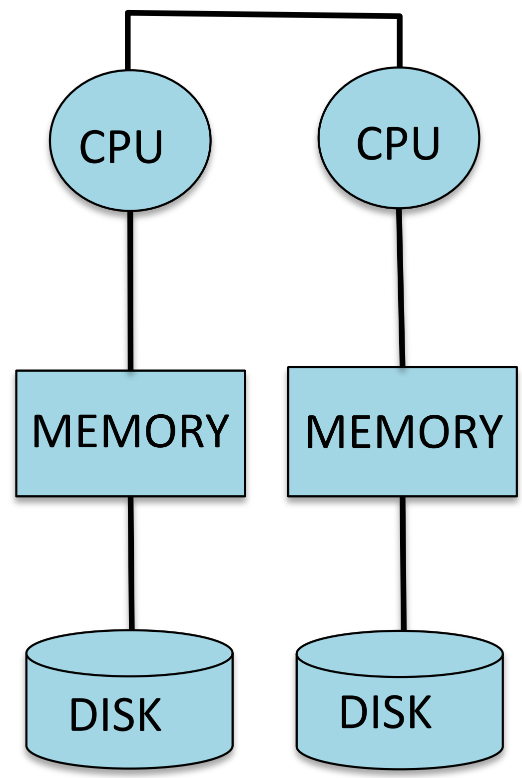
Map/Reduce Criticism

- Release of Map/Reduce caused a big reaction from the database community
  - The database community was initially very critical of Map Reduce
  - Now most DB people seem to believe that Map/Reduce style models and Parallel DBs will co-exist
- Initial arguments: “Why not use a parallel DBMS instead?”
  - map/reduce is a “giant step backwards”
  - no schema, no indexes, no high-level language
  - not novel at all (NCR Teradata)
  - does not provide features of traditional DBMS – indices, optimization, declarative query language
  - incompatible with DBMS tools

MapReduce - Comments

- Basic control flow for MapReduce has existed in parallel DBMS systems for years
- Almost any parallel processing task can be written as a set of database queries (UDFs/UDAs) or a set of MapReduce jobs
- Similarities
  - MR & P-DBMS both use "shared-nothing"
  - MR & P-DBMS both divide data into partitions / shards

Shared Nothing



Architectural Elements - Schema

DBMS	MapReduce
Schema Defined in Database	Schema defined in MR programs
Must define schema in advance (schemas are difficult!)	Easy to get started…
Schema is separate from application (re-use / sharing is easy)	Each MR program must parse the data and data structures in the MR files (sharing is difficult); programmers need to agree on structure
Keys enforce integrity constraints	Updates can corrupt data

Architectural Elements – Indexing

PDBMS	MapReduce
Indices: increase load time, but greatly improve performance	No built-in indices: easy to get started, but performance my suffer
Indices maintained by database, can be used by any user	Programmer implement indices? Reuse?

Architectural Elements – Programming Model & Flexibility

DBMS	MapReduce
Programming Model: High-level / SQL	Programming Model: Lower-level (procedural specification) Widespread sharing of code fragments High-level languages added – Pig/Hive
Flexibility: MR proponents: “SQL does not facilitate the desired generality that MR provides,” but DBMSs have UDFs/ UDAs	Flexibility: High flexibility - programming language…

Quote Credit: “A Comparison of Approaches to Large-Scale Data Analysis” by A. Pavlo et al., 2004

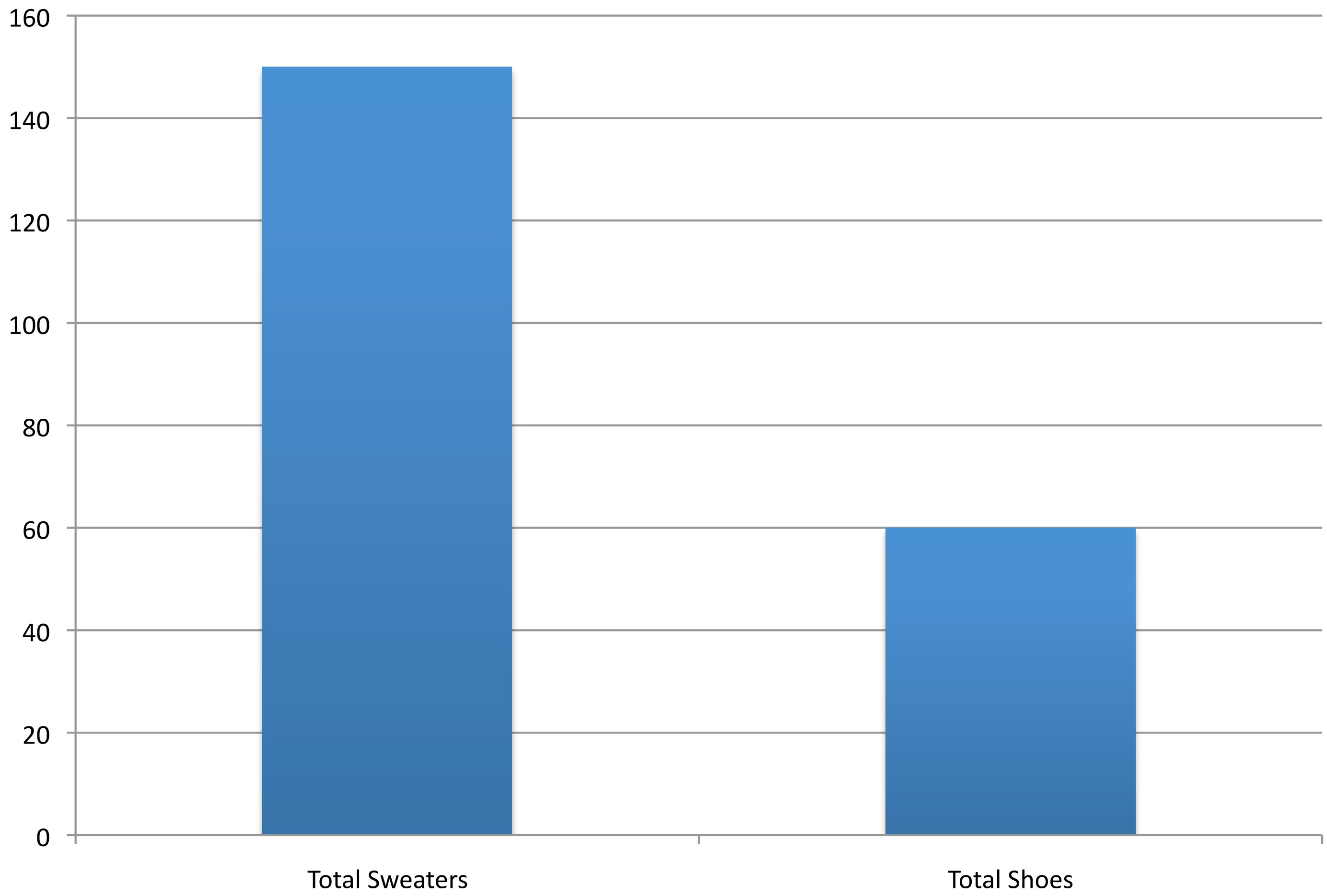
Architectural Elements – Execution Strategy & Fault Tolerance

DBMS	MapReduce
Disk Access: Database has coordinated, optimized disk access. Sends computation to disk.	Disk Access: 500,000 output files of Map, each Reducer pulls 1000 files –> poor disk performance. Sends computation to disk only for initial Map reads.
Optimization: Sophisticated query optimization	Optimization: No automatic optimization. No selection push down.
Fault Tolerance: Avoid saving/writing intermediate work, restart larger granules	MR – more sophisticated fault-tolerance; better at handling node failures in the middle of computation (local materialization vs. streaming/ push)

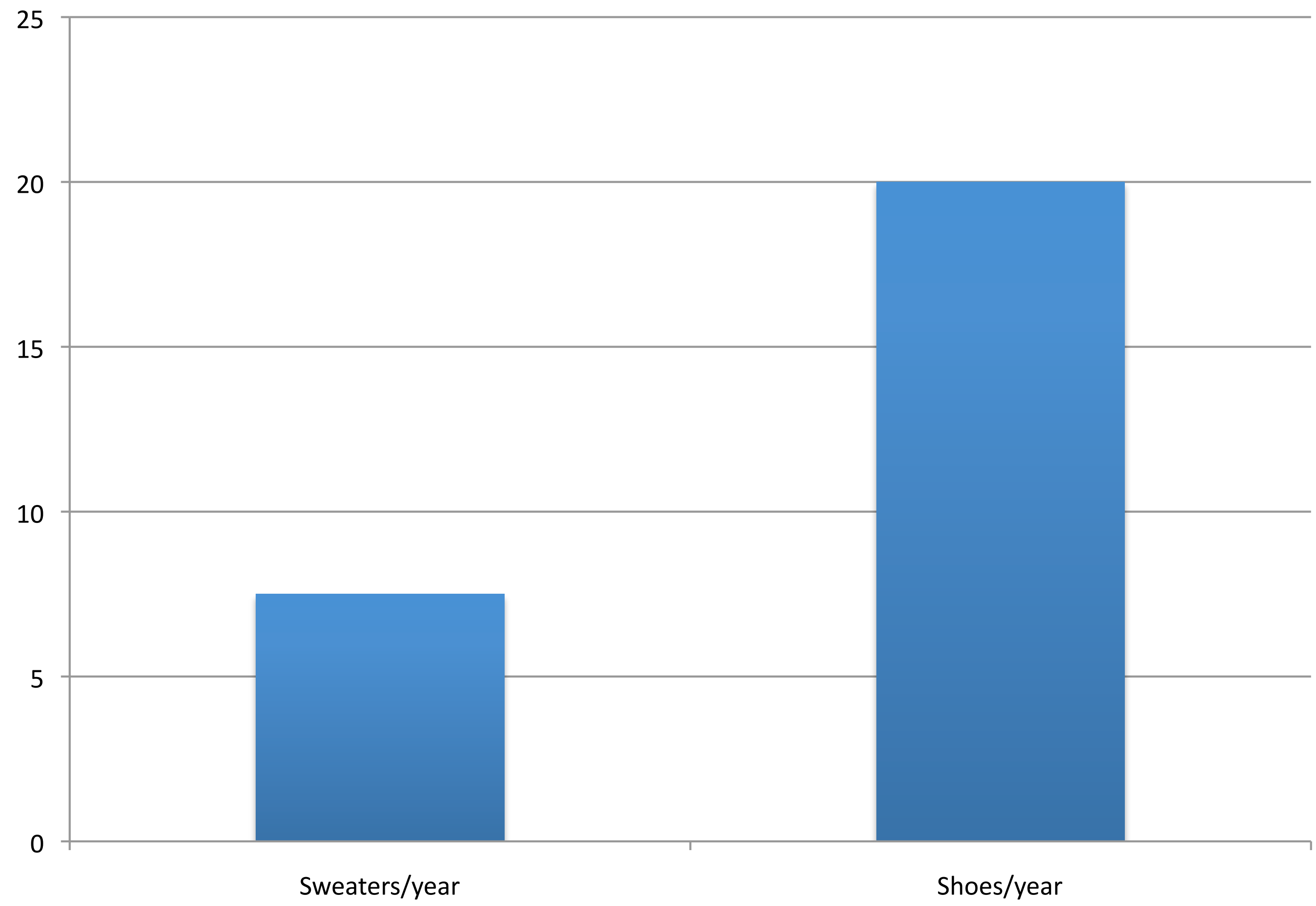
MapReduce – Performance Comments

- Performance experiments show tradeoffs
  - Parallel DBMSs require time to load & tune, but generally have shorter execution times
  - MapReduce generally has longer execution times

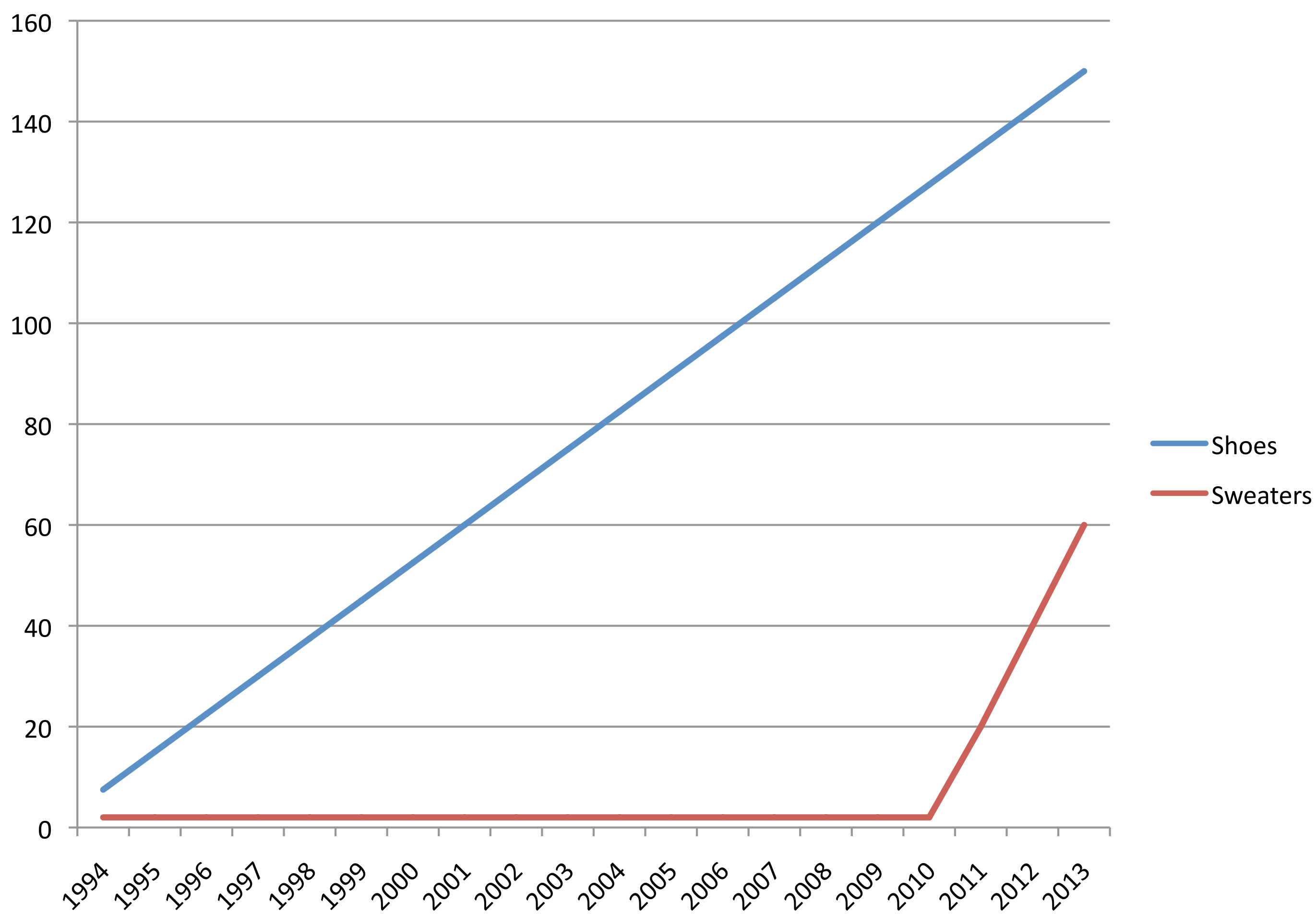
Total Purchases



Purchases per Year



Cumulative Purchases



MR vs. PDBMS Performance Analysis

- Systems
  - parallel DBMS (Vertica and DBMS-X) vs. map/reduce (Hadoop)
- Tasks
  - original map/reduce task: “grep” from Google paper
  - typical database tasks: selection, aggregation, join, UDF
- Cluster
  - 100-node cluster
- Comments:
  - MR can scale to 1000’s of nodes, but may not be necessary with efficient parallel DBMSs
  - Few data sets are really petabyte size – not many users really need 1000 nodes

Performance - Setup

- 5 tasks (Grep,
- 3 systems (Hadoop, DBMS-X, Vertica)
- 100-node cluster, 2.4 GHz Intel Core 2 Duo, Red Hat Linux, 4GB RAM, two 250 GB SATA-I hard disks
- Experiments run on 1, 10, 25, 50 and 100 nodes
- Two Data Sets:
  - 535 MB/node : fixes amount of data per node (amount of data increases as # nodes increase)
  - 1TB total : fixes total amount of data (data per node decreases as # nodes increase)
  - Note: original MR paper had 1TB on 1800 nodes, 535 MB/node

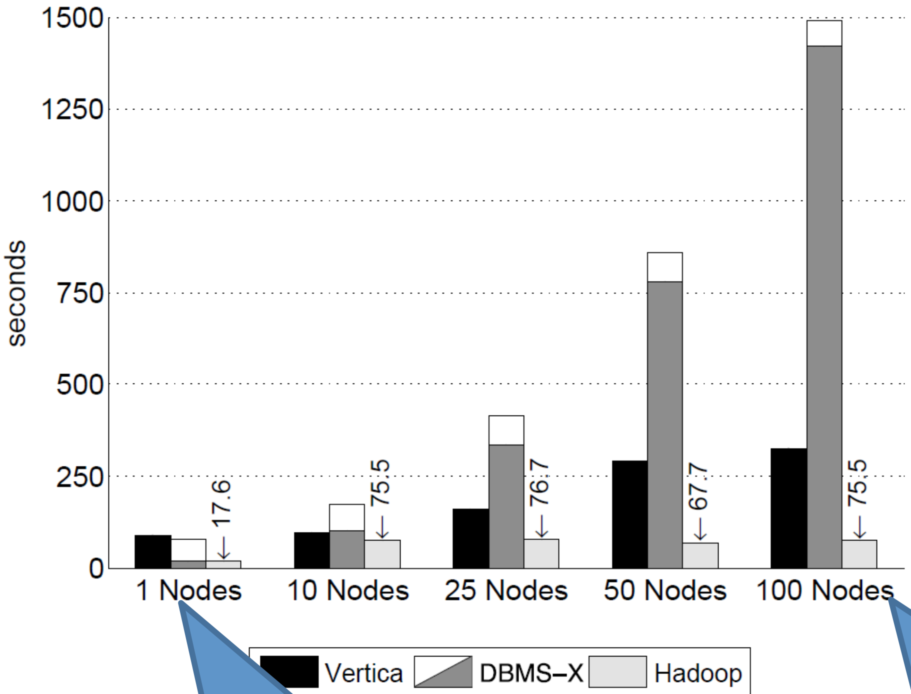
Grep Task: Load

- Hadoop
  - Data loaded as plain text using command-line utility
  - No need for custom data loader
- DBMS-X
  - Load command executed in parallel
  - Redistribute tuples to other node based on partitioning attribute
  - Reorganize on each node (compress, indices, housekeeping)
- Vertica
  - Similar to DBMS-X

- SQL: SELECT * FROM Data WHERE field like '%XYZ';

Grep Task: Load Times

535 MB/node



DBMS-X loaded data sequentially

Hadoop much faster – just copies data; also uses default of 3 replicas per block

1 TB/cluster

Administrative command to “reorganize” data on each node

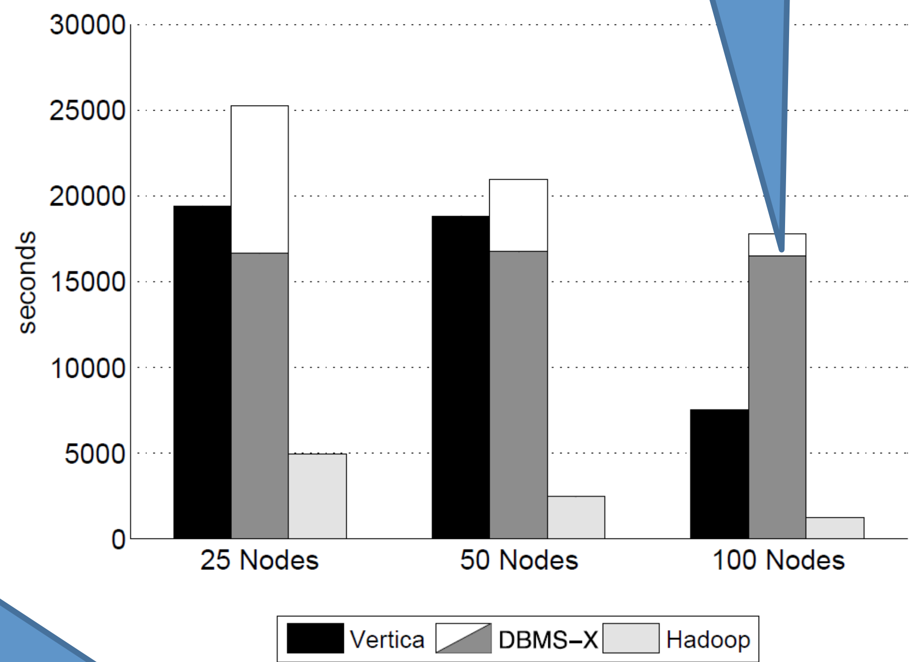
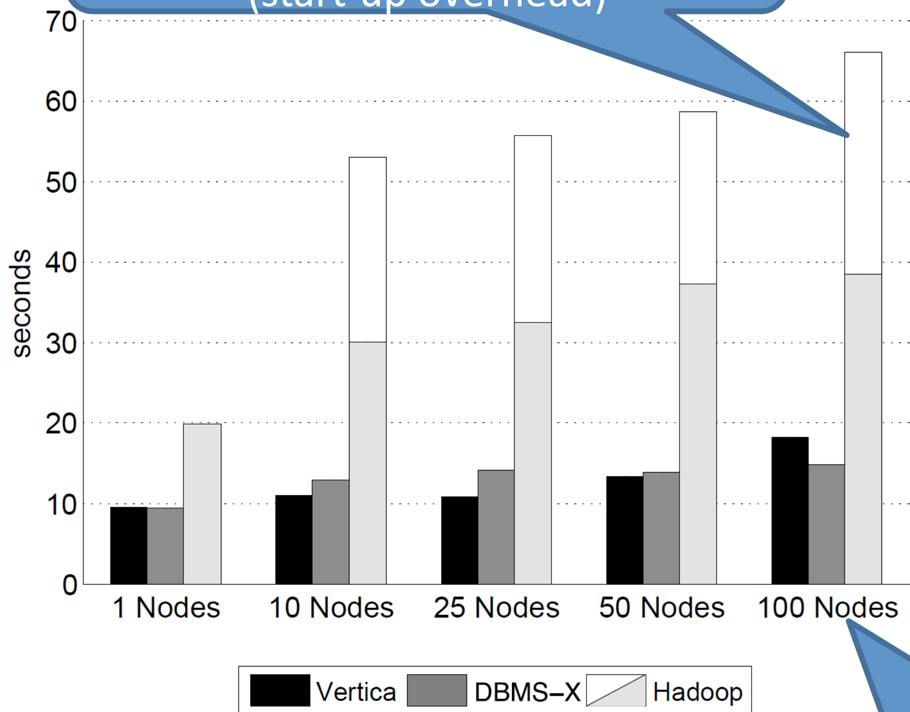


Figure Credit: “A Comparison of Approaches to Large-Scale Data Analysis” by A. Pavlo et al., 2004

Grep Task: Execution Times

535 MB/node

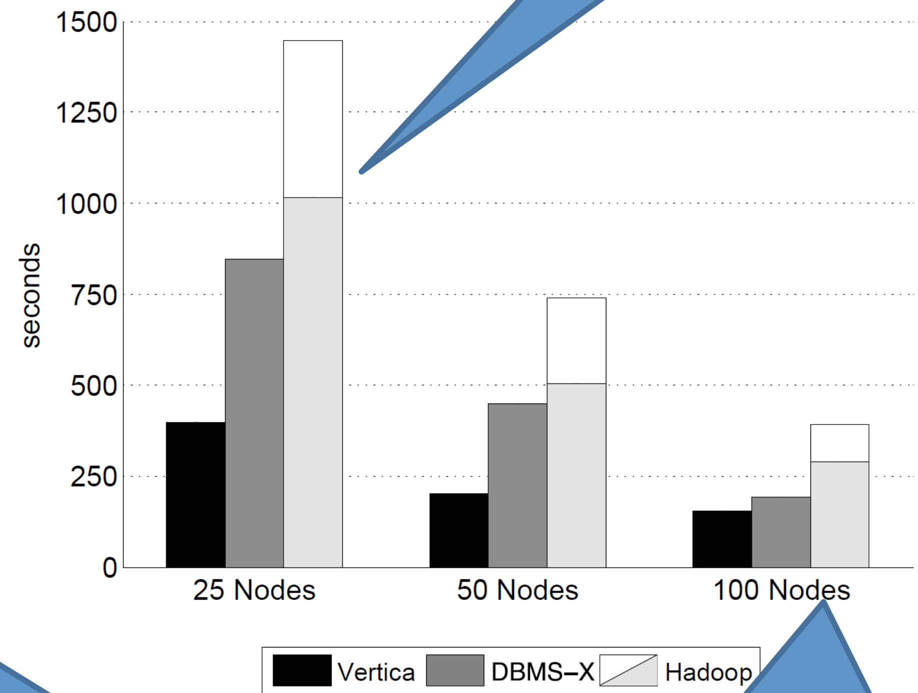
Time required to combine all reduce partitions into one result (start-up overhead)



Hadoop performance limited by start-up overhead (10-25 sec to get to full speed)

1 TB/cluster

All systems execute task on 2x number nodes in about ½ the time (as desired)



Vertica's good performance attributed to Vertica's aggressive use of compression

Figure Credit: "A Comparison of Approaches to Large-Scale Data Analysis" by A. Pavlo et al., 2004

Analytical Tasks

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

CREATE TABLE Rankings (
   pageURL VARCHAR(100)
           PRIMARY KEY,
   pageRank INT,
   avgDuration INT );
```

```
CREATE TABLE UserVisits (
   sourceIP VARCHAR(16),
   destURL VARCHAR(100),
   visitDate DATE,
   adRevenue FLOAT,
   userAgent VARCHAR(64),
   countryCode VARCHAR(3),
   languageCode VARCHAR(3),
   searchWord VARCHAR(32),
   duration INT );
```

- Data set (generated)
  - 600K unique HTML documents, with unique URL
  - Links to other pages randomly generated
  - 155M user visit records (20 GB/node)
  - 18M ranking records (1 GB/node)
- Loading
  - DBMS-X and Vertica use a UDF to process documents (temp table)= => no load results given
  - Map-Reduce – load time decreased by 3 due to custom data loader (but no custom input handler)

Selection

- SQL: SELECT pageURL, pageRank FROM Rankings WHERE pageRank > X

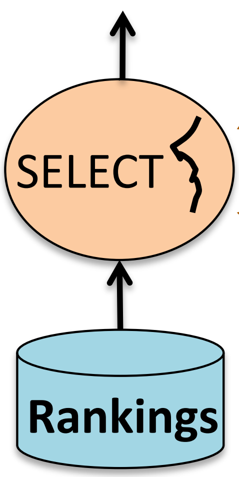
- Map Function: Splits input value based on delimiter, outputs pageURL and pageRank if pageRank > X

- Reduce Function: none/identity

Database Execution - Selection

SELECT pageURL, pageRank
FROM **Rankings**
WHERE pageRank > X

This is the SELECT operator, it reads the **Ranking** relation from disk and "selects" all tuples with PageRank > X

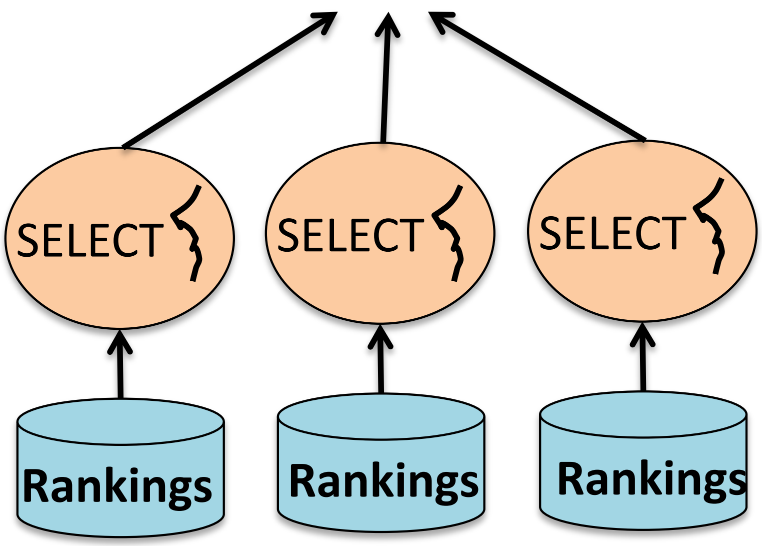


The SELECT operator corresponds to the WHERE clause in the SQL query.

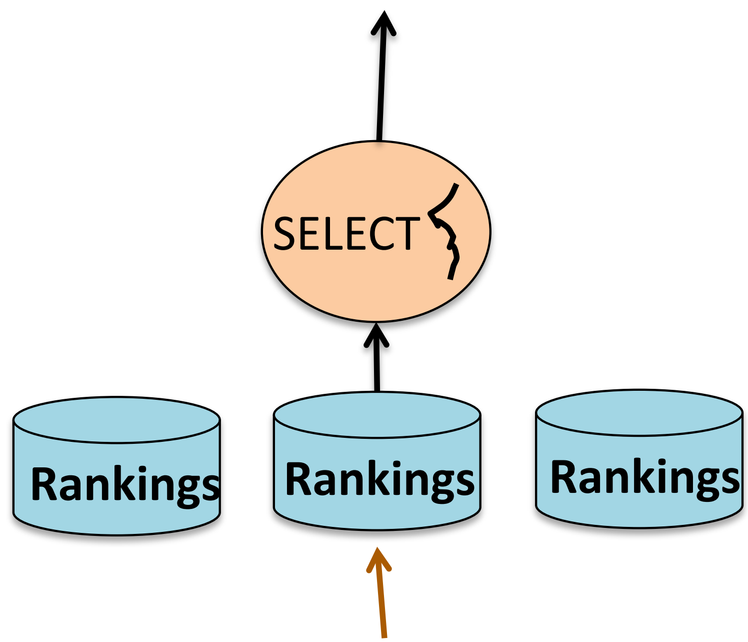
Parallel Database Execution - Selection

SELECT pageURL, pageRank
FROM **Rankings**
WHERE pageRank > X

Case 1: Tuples from **Rankings** are randomly or hash partitioned (sharded) across the three disks.

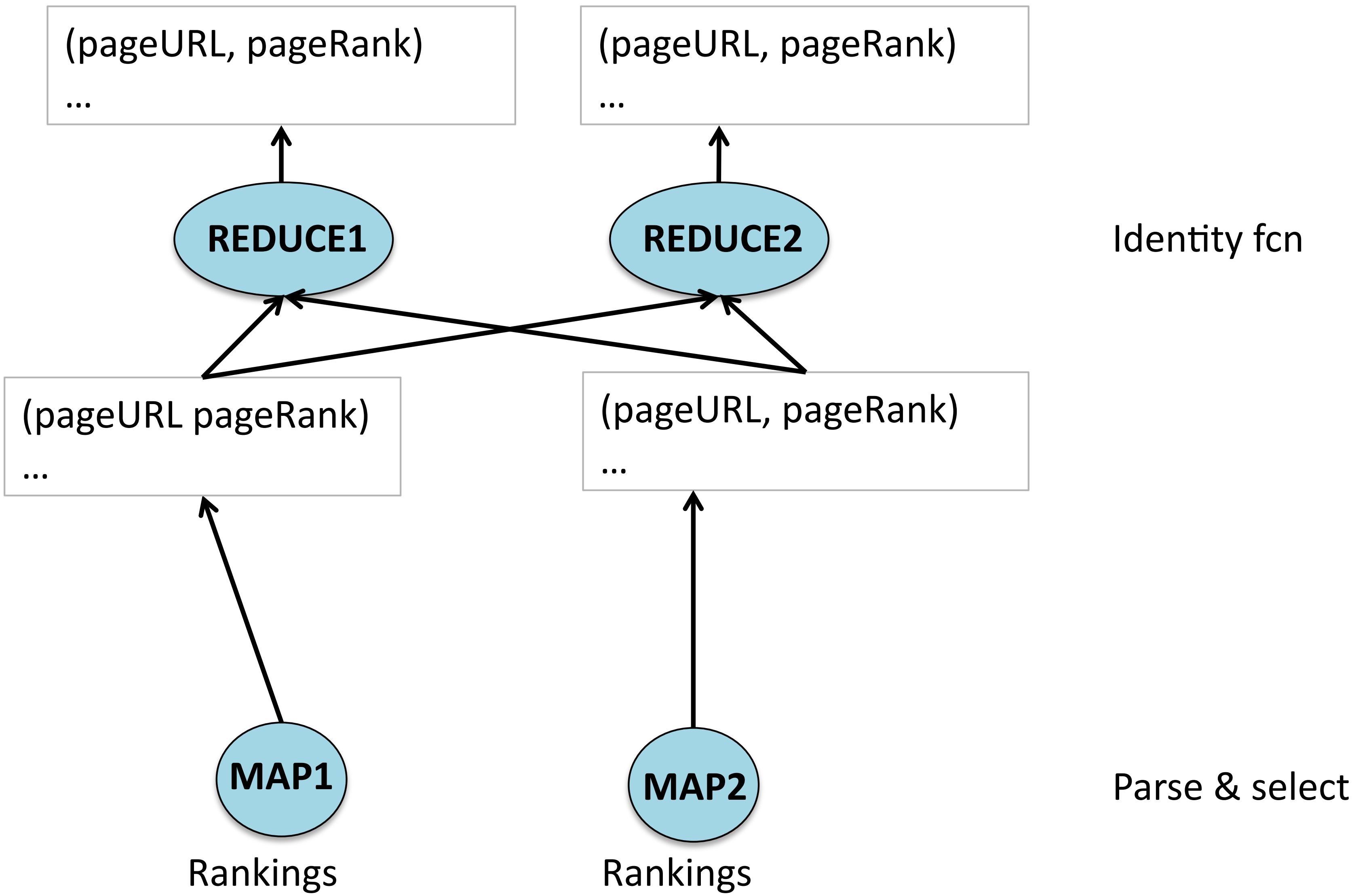


Case 2: Tuples from **Ranking** are partitioned (sharded) based on pageRank.



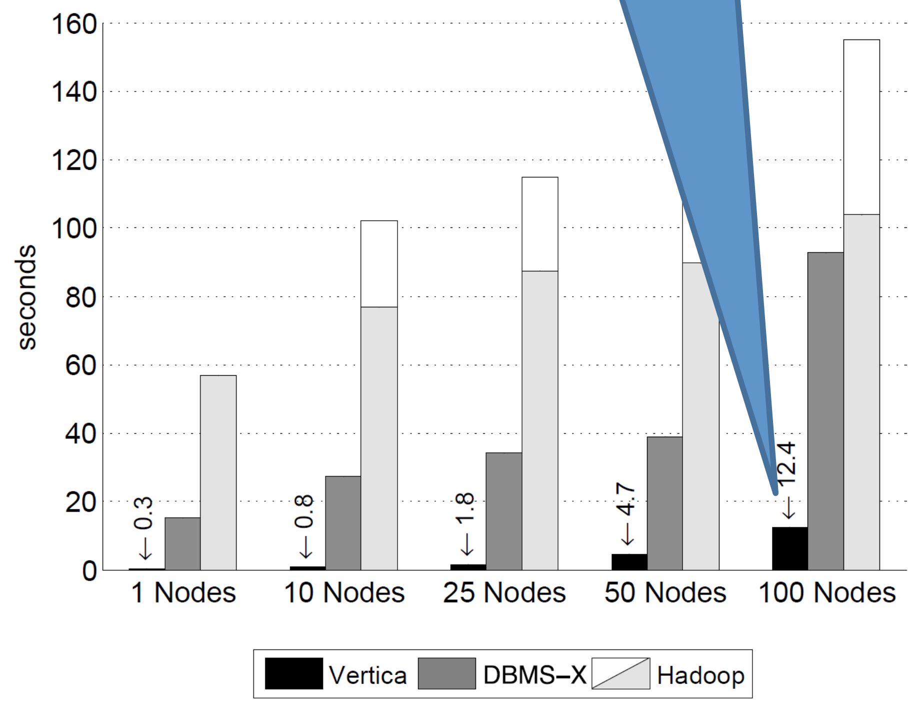
All pageRank > X tuples happen to be on this disk.

Selection – Map Reduce



Selection Task

Vertica: system becomes flooded with control messages



- SQL Query

```
SELECT pageURL, pageRank
FROM Rankings
WHERE pageRank > X
```

- Relational DBMS use index on pageRank column
- Relative performance degrades as number of nodes and amount of data increases
- Hadoop start-up cost increase with cluster size

Figure Credit: "A Comparison of Approaches to Large-Scale Data Analysis" by A. Pavlo et al., 2004

Join in MR

- Phase 1: filters records outside data range and joins with Rankings file
  - Input is all UserVisits and Rankings data files
  - Map: determine record type by counting number of fields
    - If UserVistis, apply date range predicate
    - Output – composite keys (destUrl, K1), (pageUrl, K2)
    - Hash function only on url portion of the key
  - Reduce
    - Input – single sorted run of records in URL order – divide into 2 sets and do cross product
- Phase 2: compute total adRevenue and average pageRank
  - Map: identity map fcn
  - Reduce gathers all records for a particular sourceIp on a single node
  - Reduce: computes adRevenue, pageRank – keep one with max total adRevenue

Join in MR

- Phase 3: find the record with the largest total adRevenue
  - Map: identity
  - Reduce: one reduce function to keep track of the record with the largest totalRevenue field

Aggregation Task

- Calculate the total ad revenue for each source IP using the user visits table
- Task: performance of parallel analytics on a single read-only table where nodes need to exchange data to compute result
- DBMS execution: local group by, groups merged at coordinator
- **Variant 1:** 2.5M groups

```
SELECT sourceIP, SUM(adRevenue)
FROM UserVisits
GROUP BY sourceIP
```

- **Variant 2:** 2,000 groups

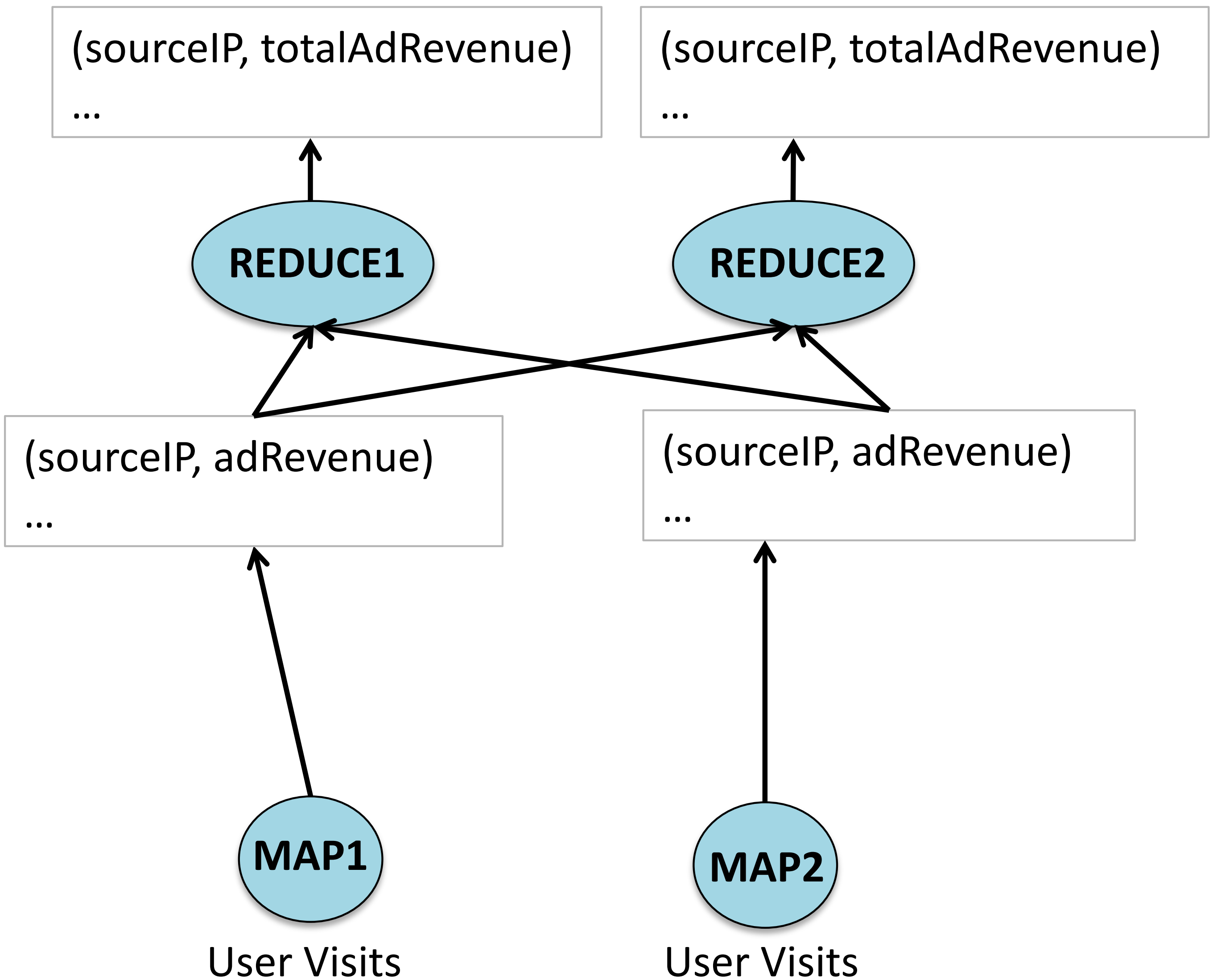
```
SELECT SUBSTR(sourceIP, 1, 7), SUM(adRevenue)
FROM UserVisits
GROUP BY SUBSTR(sourceIP, 1, 7)
```

Aggregation

- SQL: SELECT sourceIP, SUM(adRevenue) FROM UserVisits GROUP BY sourceIP;

- Map Function: split by delimiter, outputs (sourceIP, adRevenue)
- Reduce Function: adds revenue for each sourceIP (uses a combiner)

Aggregation – Map Reduce



Adds together revenue by source

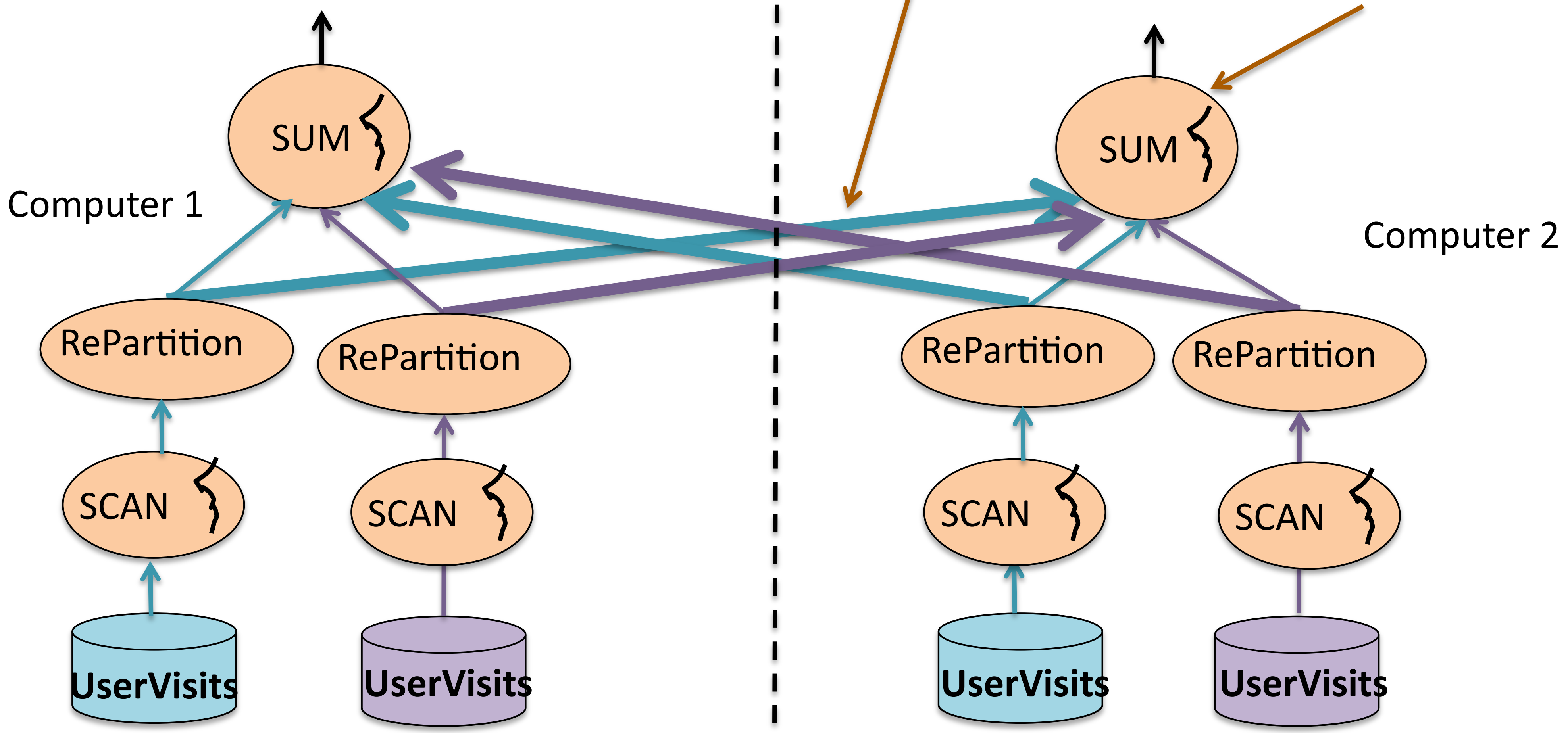
Parse & output ip and revenue

Parallel Database Execution - Sum

SELECT sourceIP, SUM(adRevenue)
FROM UserVisits
GROUP BY sourceIP

These are not disk writes…no IO in the middle in this query

SUM produces sums by sourceIp…



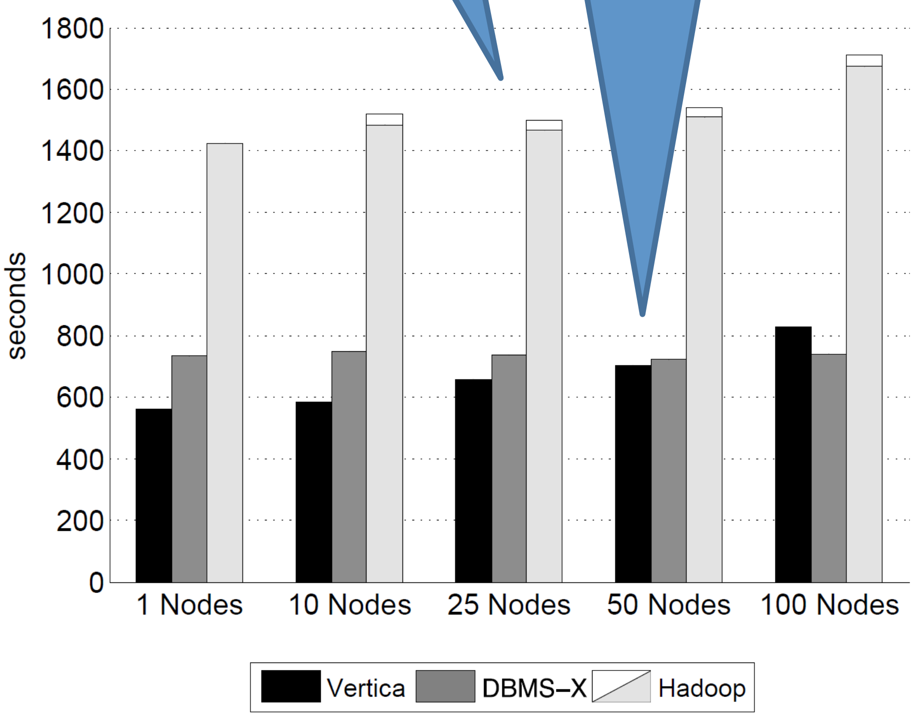
Aggregation Task

MR Execution time improved by use of “combine” to do local group by

DBMS runtimes dominated by communication costs to transmit groups to coordinator

Communication costs much lower in the variant plan

2.5M Groups



2,000 Groups

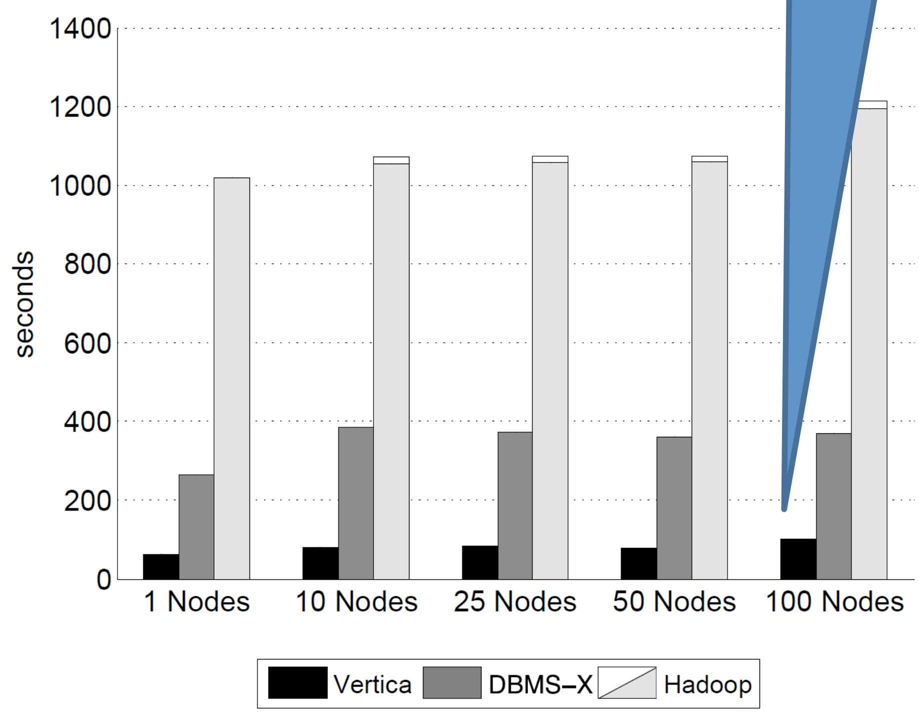


Figure Credit: “A Comparison of Approaches to Large-Scale Data Analysis” by A. Pavlo et al., 2004

Join Task

SQL Query

```
SELECT INTO Temp
   UV.sourceIP,
   AVG(R.pageRank) AS avgPageRank,
   SUM(UV.adRevenue) AS totalRevenue
FROM
   Rankings AS R, UserVisits AS UV
WHERE R.pageURL = UV.destURL
  AND UV.visitDate BETWEEN
         DATE('2000-01-15') AND
         DATE('2000-01-22')
GROUP BY UV.sourceIP

SELECT sourceIP,
       avgPageRank,
       totalRevenue
FROM Temp
ORDER BY totalRevenue DESC LIMIT 1
```

Map/reduce program

- Uses three phases
  - **Phase 1:** filters records outside date range and joins with rankings file
  - **Phase 2:** computes total ad revenue and average page rank based on source IP
  - **Phase 3:** produces the record with the largest total ad revenue
- Phases run in strict sequential order

In words: Find Url with highest total revenue and it's page rank

Join Task

Phase 1 - ~1400 seconds (600 sec I/O, 300 sec to parse & deserialize)

Hadoop performance limited by speed the UserVisits table can be read off of disk

Parallel databases take advantage of clustered indices on UserVisits.visit Date

And both tables are partitioned on the join key

Vertica optimizer bug

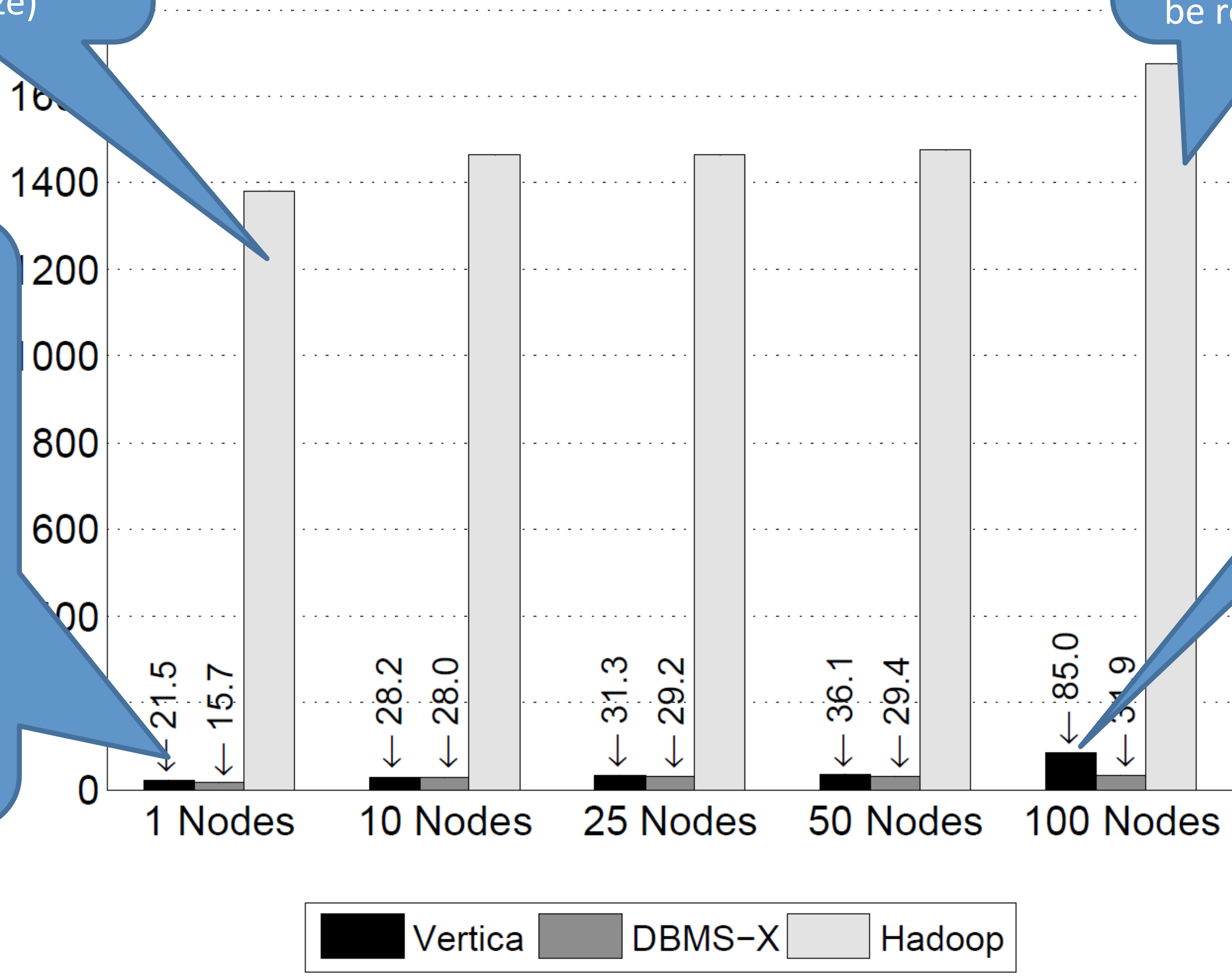


Figure Credit: “A Comparison of Approaches to Large-Scale Data Analysis” by A. Pavlo et al., 2004

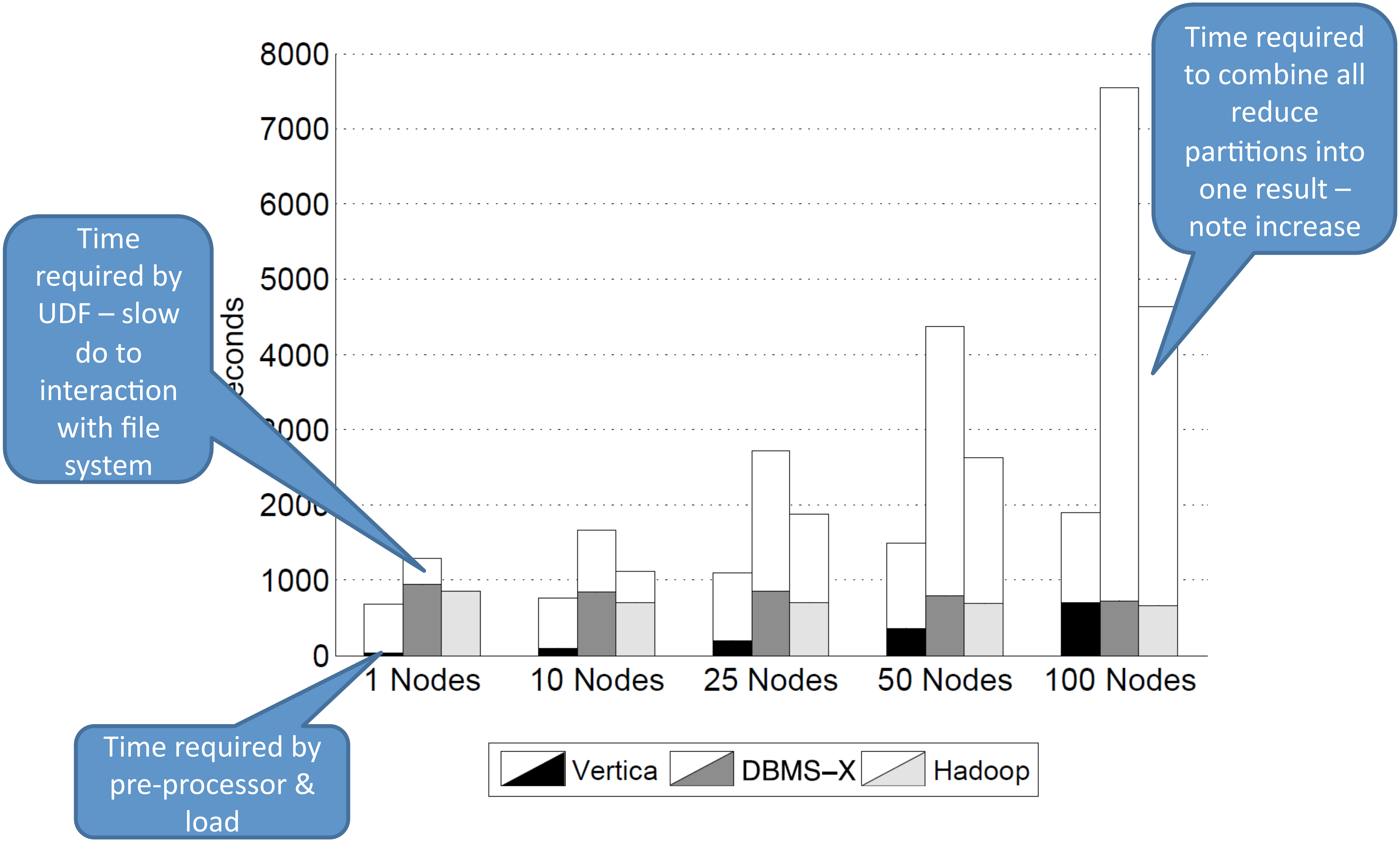
UDF Aggregation Task

- Compute in-link count for each document in the data set
- SQL Query

```
SELECT INTO Temp UDF(contents) FROM Documents
SELECT url, SUM(value) FROM Temp GROUP BY url
```

- Map/reduce program
  - documents are split into lines
  - input key/value pairs: <line number, line contents>
  - **map:** uses regex to find URLs and emits <URL, 1> for each URL
  - **reduce:** counts the number of values for a given key
- DBMS
  - Requires UDF to parse contents of records in Document table – nearly identical to Map function (difficult to implement in DBMS)
  - DBMS-X: not possible to run UDF over contents stored as BLOB in database; instead UDF has to access local file system
  - Vertica: does not currently support UDF, uses a special pre-processor – processed file, write to disk, then loads…

UDF Aggregation Task



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Map/Reduce vs. Parallel DBMS

- No schema, no index, no high-level language
  - faster loading vs. faster execution
  - easier prototyping vs. easier maintenance
- Fault tolerance
  - restart of single worker vs. restart of transaction
- Installation and tool support
  - easy to setup map/reduce vs. challenging to configure parallel DBMS
  - no tools for tuning vs. tools for automatic performance tuning
- Performance per node
  - results seem to indicate that parallel DBMS achieve the same performance as map/reduce in smaller clusters

Let's Review…

- Cluster
- Cloud Computing
- Cloud Data Management
- GFS
- Map Reduce

Let's Review…

- Cluster
  - "…large numbers of (low-end) processors working in parallel…"
- Cloud Computing
- Cloud Data Management
- GFS
- Map Reduce

Quote from: *"A Comparison of Approaches to Large-Scale Data Analysis" by A. Pavlo et al., 2004*

Discussion Question

How are clusters related to Map Reduce?

1.

2.

References

- A. Pavlo, E. Paulson, A. Rasin, D. J. Abadi, D. J. DeWitt, S. Madden, and M. Stonebraker: **A Comparison of Approaches to Large-Scale Data Analysis.** *Proc. Intl. Conf. on Management of Data (SIGMOD), pp. 165-178, 2009.*

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Join in MR

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  - Map: identity
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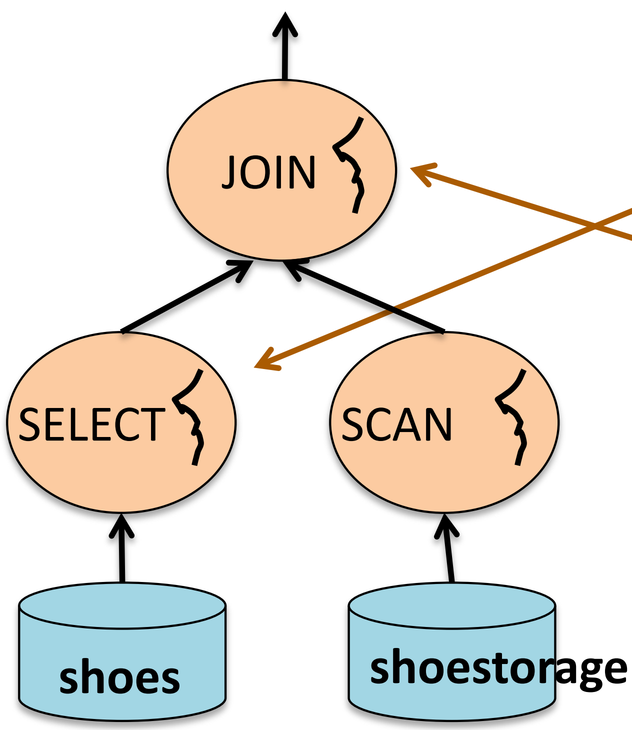
Database Execution - Join

Schema:
shoes (id integer, brand text, description text, size float, color text, lastworn date)
shoestorage (id integer, shelfnumber integer, shelfposition integer)

SELECT brand, description, size, shelfnumber, shelfposition
FROM **shoes, shoestorage**
WHERE shoes.id = shoestorage.id
AND color = ‘Green’
AND lastworn < ‘1-25-2014’



The SELECT operator “selects” all tuples containing green shoes that were last worn before 1-25-2014.

The JOIN operator combines the selected tupes from the **shoes** relation and the **shoestorage** to produce storage locations for the green shoes last worn before 1-25-2014.

Parallel Database Execution - Join

SELECT brand, description, size, shelfnumber, shelfposition
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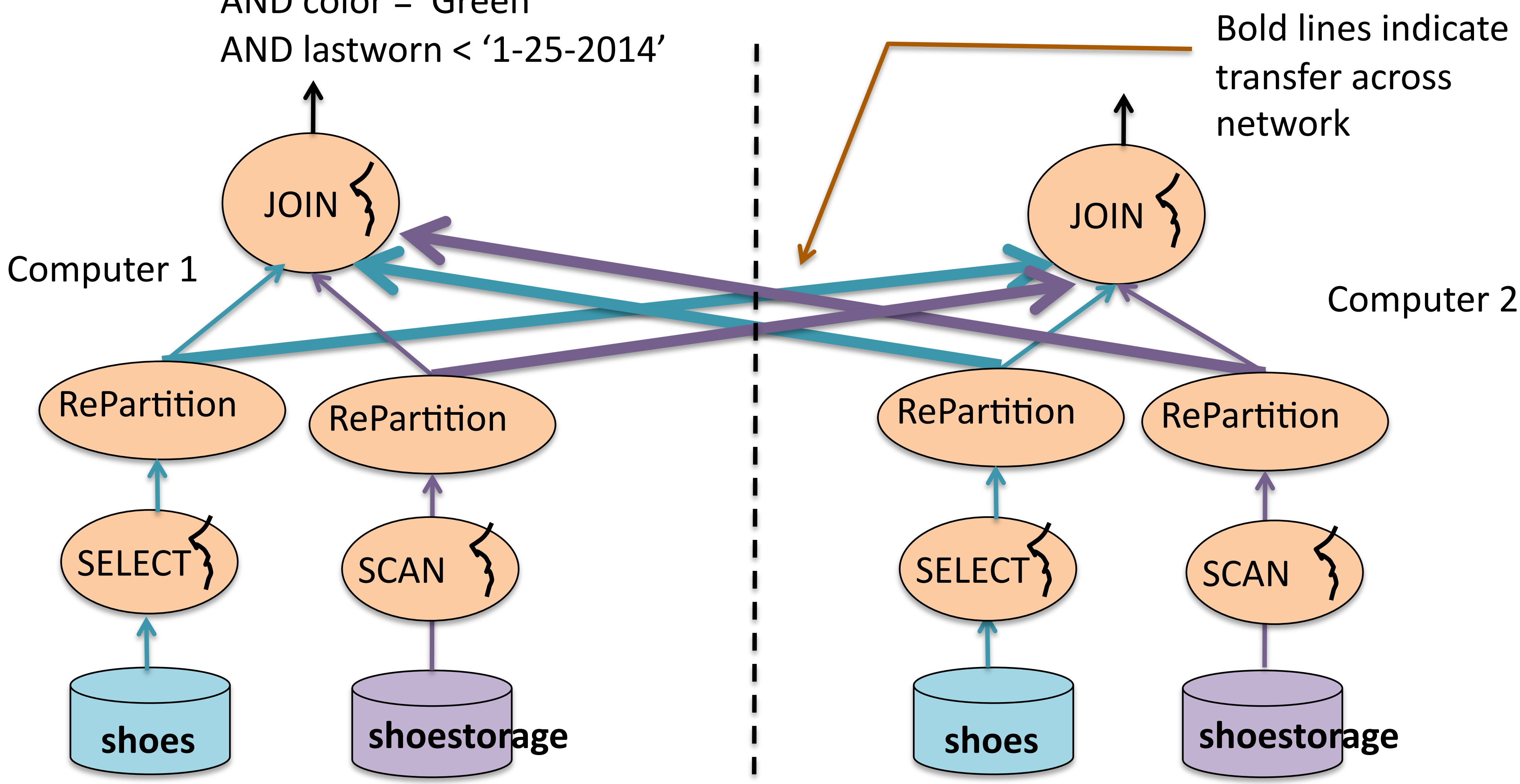
Case 1: Tuples from **shoes** and **shoestorage** are randomly partitioned (sharded) across the three disks.



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WHERE shoes.id = shoestorage.id
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Case 2: Tuples from **shoes** and **shoestorage** are partitioned (sharded) on id.

Joins are local, no transfer across network.