Large-Scale Data Analysis: Bridging the Gap

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Outline

- Motivation: Parallel DBMS vs Map/Reduce
- Schema & Benchmarks Overview
- Original(Pavlo) Map/Reduce Plans
- Improved(SAVY) Design & Implementation
- Improving Hadoop
 - Indexing
 - Co-Partitioning
- Experiments
- Conclusion

Motivation

- Ever growing data
 About 20TB per Google crawl!
- Computing Solutions
 - O High-end server: 1625.60€/core, 97.66€/GB
 - Share-nothing nodes: 299.50€/core, 166.33
 €/GB
- Two Paradigms • Parallel DBMS
 - Map/Reduce

Parallel DBMS



[DeWitt, D. and Gray, J. 1992.]

Parallel DBMS: Advantages

- Can be column based
 - Example: Vertica
- Local joins possible
 Partition based on join key
- Can work on compressed data
 reduced data transfer
- Flexible query plans
- Supports Declarative languages like SQL

Parallel DBMS - Shortcomings

- Not free of cost
- Not open source
- Cannot scale to thousands of nodes: why?
 - Less fault tolerant
 - Assumes homogeneous nodes
- Not so easy to achieve high performance
 Needs highly skilled DBA
 Needs high maintenance

Map/Reduce(Hadoop):

Advantages

- Free of cost
- Open source
- Fault tolerant
- Scales well to thousands of nodes
- Less maintenance
- Flexible query framework

Map/Reduce(Hadoop): Shortcomings

- Lack of inbuilt Indexin
 Current Focus
- Cannot guarantee local join Current Focus
- Performance degradation for SQL like queries
 - Multiple MR phases



- $\circ\,\text{Each}\,\,\text{MR}$ phase adds extra cost
- No Flexible query plans
- Data transfer not optimized

Benchmarks and Schema

Schema

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

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

Schema

CREATE TABLE UserVisits (sourcelP VARCHAR(16), destURL VARCHAR(100), visitDate DATE, adRevenue FLOAT, userAgent VARCHAR(64), countryCode VARCHAR(3), languageCode VARCHAR(6), searchWord VARCHAR(32), duration INT

Benchmarks 1&2

- Selection task (Benchmark 1)
 - SELECT pageURL, pageRank FROM Rankings
 WHERE pageRank > X;
- Aggregation task (Benchmark 2)
 - SELECT sourceIP, SUM(adRevenue) FROM
 - UserVisits GROUP BY sourceIP;
 - SELECT SUBSTR(sourceIP, 1, 7), SUM(adRevenue)
 FROM UserVisits GROUP BY SUBSTR(sourceIP, 1, 7);

Benchmark 3: Join Task Projection & SELECT INTO Temp sourceIP, AVG (pageRank) as avgPageRank, SUM (adRevenue) as totalRevenue FROM Rankings AS R, UserVisits AS UV Join HERE **R.pageURL = UV.destURL** AND UV. visitDate BETWEEN Date('2000-01-15') AN selectio ('2000-01-22') GROUP BY UV.sourceIP; • SELECT sourceIP, totalRevenue, avgPageRank FROM Temp ORDER BY totalRevenue DESC

Original (Pavlo) MR Plans



SELECT pageURL, pageRank FROM Rankings WHERE pageRank > 10;

Benchmark 2: Phase 1





Benchmark 3 – Phase 1



Benchmark 3 – Phase 2



Benchmark 3 – Phase 3



Improved (Savy) MR Plans

Binary Data

- Eliminates delimiters
- Avoids splitting
- Makes tuples of fixed length
- Helps in indexing





Benchmark 3(Design I) – Phase



Benchmark 3(Design I) – Phase





Benchmark 3(Design I) – Phase



Improving Hadoop

Improving Hadoop

- Improve Selection (Indexing)
- Improve Join (Co-partitioning)

Indexing

Data Loading

 $\circ\,\text{index}$ and load data into DFS

Query Execution
 o index look-up and selection

• Implementation on Hadoop

Data Loading

- Partitioning
- Sorting
- Bulk Loading
- HID Splits



Partitioning

Split input data at tuple boundaries

Partitioning

Split input data at tuple boundaries

Tuple	aldni																								
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Partitioning

Split input data at tuple boundaries


Split input data at tuple boundaries



Sorting

Sort each split on the index key

50 23 78 19 3 42 60 13 88 17 5 47 70 25 57	0 23 78	78 19 3 42	60 13 88	17 5 47	70 25 57	14 34 45
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Sorting

Sort each split on the index key



Bulk Loading

Bulk load CSS tree index



Construct Header-Index-Data Split

Data

Construct Header-Index-Data Split

Index	Data
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Construct Header-Index-Data Split



Header: Index end offset Data end offset Start index key End index key

Construct Header-Index-Data Split



Header: Index end offset Data end offset Start index key End index key

Query Execution

- Partitioning
- Split selection
- Index lookup
- Extractor

Query Execution









Split Selection

Discard splits containing out of range index keys





















Extractor

Perform selection on data



Extractor

Pass sub-split to Record Reader for processing



Implementation on Hadoop

Loading

- CSS Tree Index
- Indirect index
- Four key types supported Int, Float, Date, String
- Index stored as byte array
- Reducer to reduce number of files
- Integral number of HID splits per reducer output

Querying

- Discover HID split boundaries from respective headers
- Read only the selected data from HDFS

Co-Partitioning

- Data loading
- Query execution



Relation 1

Relation 2







Query Execution




Query Execution



Query Execution



Query Execution



Indexing on top of Co-partitioning



Indexing on top of Co-partitioning











Experiments

Experimental Setup

- Hadoop 0.19.1
- 5 nodes
- Speed?
- RAM?
- Gigabit Ethernet
- Data size
 - User Visits: 20GB
 - Rankings: 32MB



Data Size







Benchmark3



Benchmark1

Roadblocks Faced

• Data generation:

20GB UserVisits, 338MB Rankings in HDFS
Took 16 hours for generation
Too many OS/library dependencies
Poor documentation

• Number of nodes:

- Allocated 6 nodes
- Effective (up-and-running) 4 nodes
- Map/Reduce parallelism not exploited
- Per-split indexing ideally suited for highly parallel execution

Roadblocks Faced

- Data normalization
 - Schema uses VARCHAR data types
 - \circ Input data normalized to fixed tuple-sized binaries
 - Byte oriented processing speedup negated by increased input size
 - \circ However, facilitates indexing and co-partitioning
- Low selectivity
 - Selection task has selectivity close to 1
 Indexing benefits are sabotaged
- Incorrect base result

 Reported join task result was not correct

Roadblocks Faced

Implementation deviation from the paper
 Composite key is not really used in join task

Discussion: Loopholes

- Benchmarks are well suited (biased) for databases
- Huge difference in data loading time
- Queries make heavy use of indexing, sorting data
- Query optimization not done for Map/Reduce
- Fault tolerance not compared

Discussion: We can do better!

- Map/Reduce plans can be optimized
- Normalized binary input data can help
- Indexing feasible and performs good
- Co-partitioning feasible and looks promising

Conclusions

References

- Pavlo, A., Paulson, E., Rasin, A., Abadi, D. J., DeWitt, D. J., Madden, S., and Stonebraker, M. 2009. A comparison of approaches to large-scale data analysis. SIGMOD '09.
- DeWitt, D. and Gray, J. 1992. Parallel database systems: the future of high performance database systems. *Commun. ACM*35, 6 (Jun. 1992)