Relational Data Processing on MapReduce

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Peta-scale Data Analysis

- 12+ TBs of tweet data every day
- 25+ TBs of log data every day generated by a new user being added every sec. for 3 years
- 30 billion RFID tags today (1.3B in 2005)
- 4.6 billion camera phones world wide
- 100s of millions of GPS enabled devices sold annually
- 76 million smart meters in 2009...
- 200M by 2014
- 2+ billion people on the Web by end 2011

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Big Data Analysis

- A lot of these datasets have some structure
  - Query logs
  - Point-of-sale records
  - User data (e.g., demographics)
  - …

- How do we perform data analysis at scale?
  - Relational databases and SQL
  - MapReduce (Hadoop)

Relational Databases vs. MapReduce

- Relational databases:
  - Multipurpose: analysis and transactions; batch and interactive
  - Data integrity via ACID transactions
  - Lots of tools in software ecosystem (for ingesting, reporting, etc.)
  - Supports SQL (and SQL integration, e.g., JDBC)
  - Automatic SQL query optimization

- MapReduce (Hadoop):
  - Designed for large clusters, fault tolerant
  - Data is accessed in “native format”
  - Supports many query languages
  - Programmers retain control over performance
Parallel Computation & Data Size Matters!

Parallel Relational Databases vs. MapReduce

- **Parallel relational databases**
  - Schema on “write”
  - Failures are relatively infrequent
  - “Possessive” of data
  - Mostly proprietary

- **MapReduce**
  - Schema on “read”
  - Failures are relatively common
  - In situ data processing
  - Open source
MapReduce: A Major Step Backwards?

- MapReduce is a step backward in database access
  - Separation of the schema from the application is good
    - Sharing across multiple MR programs is difficult
  - Declarative access languages are good
    - Does not require highly-skilled programmers
- MapReduce is poor implementation
  - Brute force and only brute force
    - No indexes: Wasteful access to unnecessary data
  - Don’t need 1000 nodes to process petabytes
    - Parallel DBs do it in fewer than 100 nodes
- MapReduce is missing features
  - Bulk loader, indexing, updates, transactions...
  - No support for JOINs:
    - Requires multiple MR phases for the analysis

Agrawal et al., VLDB 2010 Tutorial

Database Workloads

- OLTP (online transaction processing)
  - Typical applications: e-commerce, banking, airline reservations
  - User facing: real-time, low latency, highly-concurrent
  - Tasks: relatively small set of “standard” transactional queries
  - Data access pattern: random reads, updates, writes (involving relatively small amounts of data)
- OLAP (online analytical processing)
  - Typical applications: business intelligence, data mining
  - Back-end processing: batch workloads, less concurrency
  - Tasks: complex analytical queries, often ad hoc
  - Data access pattern: table scans, large amounts of data involved per query
One Database or Two?

- **Downsides of co-existing OLTP and OLAP workloads**
  - Poor memory management
  - Conflicting data access patterns
  - Variable latency

- **Solution**: separate databases
  - User-facing OLTP database for high-volume transactions
  - Data warehouse for OLAP workloads
  - How do we connect the two?

OLTP/OLAP Integration

- **OLTP database for user-facing transactions**
  - Retain records of all activity
  - Periodic ETL (e.g., nightly)

- **Extract-Transform-Load (ETL)**
  - Extract records from source
  - Transform: clean data, check integrity, aggregate, etc.
  - Load into OLAP database

- **OLAP database for data warehousing**
  - Business intelligence: reporting, ad hoc queries, data mining, etc.
  - Feedback to improve OLTP services
OLTP/OLAP Architecture: Hadoop?

What about here?

OLTP

Hadoop here?

OLAP

ETL
(Extract, Transform, Load)

OLTP/OLAP/Hadoop Architecture

Why does this make sense?
ETL Bottleneck

- Reporting is often a nightly task:
  - ETL is often slow (see next picture)!
    - What happens if processing 24 h of data takes longer than 24 h?
- Often, with noisy datasets, ETL is the analysis!
  - ETL necessarily involves brute force data scans: L, then E and T?
- Hadoop is perfect:
  - Most likely, you already have some data warehousing solution
  - Ingest is limited by speed of HDFS
  - Scales out with more nodes
  - Massively parallel and much cheaper than parallel databases
  - Ability to use any processing tool
  - ETL is a batch process anyway!

A Closer Look at ETL
MapReduce Algorithms for Processing Relational Data

Secondary Sorting

- MapReduce sorts input to reducers by key
  - Values are arbitrarily ordered
- What if want to sort value also?
  - E.g., \( k \rightarrow (v1, R), (v3, R), (v4, R), (v8, R) \)...
- Solution 1:
  - Buffer values in memory, then sort
  - Why is this a bad idea?
- Solution 2:
  - “Value-to-key conversion”: extends the key with part of the value
  - Let execution framework do the sorting
  - Preserve state across multiple key-value pairs to handle processing
  - Anything else we need to do?
Value-to-Key Conversion

Before
\[ k \rightarrow (v_1, R), (v_4, R), (v_8, R), (v_3, R) \ldots \]

Values arrive in arbitrary order...

After
\[ (k, v_1) \rightarrow (v_1, R) \]
\[ (k, v_3) \rightarrow (v_3, R) \]
\[ (k, v_4) \rightarrow (v_4, R) \]
\[ (k, v_8) \rightarrow (v_8, R) \]

- Default comparator, group comparator, and Partitioner has to be tuned to use the appropriate part of the key

Working Scenario

- Two tables:
  - User demographics (gender, age, income, etc.)
  - User page visits (URL, time spent, etc.)

- Analyses we might want to perform:
  - Statistics on demographic characteristics
  - Statistics on page visits
  - Statistics on page visits by URL
  - Statistics on page visits by demographic characteristic
  - ...
Relational Algebra

Set operations
- set union
- set intersection
- set difference
- cartesian product

Relational algebra
- selection
- projection
- join
- set division

Set functions
- sum
- avg
- count
- any
- max
- min

Projection

\[ \pi_S(R) \]
**Projection in MapReduce**

- Easy!
  - Map over tuples, emit new tuples with the projected attributes
    - For each tuple \( t \) in \( R \), construct a tuple \( t' \) by eliminating those components whose attributes are not in \( S \), emit a key/value pair \( (t', t') \)
  - No reducers (reducers are the *identity* function), unless for regrouping or resorting tuples
    - the Reduce operation performs *duplicate elimination*
  - Alternatively: perform in reducer, after some other processing

- Basically limited by HDFS streaming speeds
  - Speed of *encoding/decoding* tuples becomes important
  - Relational databases take advantage of *compression*
  - Semi-structured data? No problem!

---

**Selection**

\[ \sigma_c(R) \]

- \( R_1 \)
- \( R_2 \)
- \( R_3 \)
- \( R_4 \)
- \( R_5 \)
Selection in MapReduce

- Easy!
  - Map over tuples, emit only tuples that meet selection criteria
    - For each tuple t in R, check if t satisfies C and if so, emit a key/value pair (t, t)
  - No reducers (reducers are the identity function), unless for regrouping or resorting tuples
  - Alternatively: perform in reducer, after some other processing

- Basically limited by HDFS streaming speeds:
  - Speed of encoding/decoding tuples becomes important
  - Relational databases take advantage of compression
  - Semistructured data? No problem!

Set Operations in Map Reduce

- $R(X, Y) \cup S(Y, Z)$
  - Map: for each tuple t either in R or in S, emit (t,t)
  - Reduce: either receive (t,[t,t]) or (t,[t])
    - Always emit (t,t)
    - We perform duplicate elimination

- $R(X, Y) \cap S(Y, Z)$
  - Map: for each tuple t either in R or in S, emit (t,t)
  - Reduce: either receive (t,[t,t]) or (t,[t])
    - Emit (t,t) in the former case and nothing (t, NULL) in the latter

- $R(X, Y) - S(Y, Z)$
  - Map: for each tuple t either in R or in S, emit (t, R or S)
  - Reduce: receive (t,[R]) or (t,[S]) or (t,[R,S])
    - Emit (t,t) only when received (t,[R]) otherwise nothing (t, NULL)
Group by... Aggregation

- Example: What is the average time spent per URL?

- In SQL:
  - `SELECT url, AVG(time) FROM visits GROUP BY url`

- In MapReduce: Let $R(A, B, C)$ be a relation to which we apply $\gamma_{A,B}(R)$
  - The map operation prepares the grouping (e.g., emit time, keyed by `url`)
  - The grouping is done by the framework
  - The reducer computes the aggregation (e.g. average)
  - Eventually, optimize with combiners
  - Simplifying assumptions: one grouping attribute and one aggregation function

Relational Joins

```
R1  R2  R3  R4
S1  S2  S3  S4
```

```
R   S
R1  S2
R2  S4
R3  S1
R4  S3
```
Types of Relationships

Many-to-Many  One-to-Many  One-to-One

Join Algorithms in MapReduce

- “Join” usually just means equi-join, but we also want to support other join predicates
- Hadoop has some built-in join support, but our goal is to understand important algorithm design principles
- Algorithms
  - Reduce-side join
  - Map-side join
  - In-memory join
    - Striped variant
    - Memcached variant
Re-Partition Join

- Reducers perform the actual join
- Shuffling and sorting over the network
  - Each mapper processes one block (split)
  - Each mapper produces the join key and the record pairs
- HDFS stores data blocks (Replicas are not shown)

Reduction and Sorting Phase

Mapper 1 - Mapper M

Reduce-side Join

- Basic idea: group by join key
  - Execution framework brings together tuples sharing the same key
  - Similar to a "sort-merge join" in the database terminology
- A map function
  - Receives a record in R and S
  - Emits its join attribute value as a key and the record as a value
- A reduce function
  - Receives each join attribute value with its records from R and S
  - Perform actual join between the records in R and S
- Two variants
  - 1-to-1 joins
  - 1-to-many and many-to-many joins
Reduce-side Join: 1-to-1

Map

<table>
<thead>
<tr>
<th>R1</th>
<th>R4</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
</table>

Reduce

<table>
<thead>
<tr>
<th>keys</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td></td>
</tr>
<tr>
<td>S3</td>
<td></td>
</tr>
<tr>
<td>R4</td>
<td></td>
</tr>
</tbody>
</table>

Note: no guarantee if R is going to come first or S!

Reduce-side Join: 1-to-Many

Map

<table>
<thead>
<tr>
<th>R1</th>
<th>S2</th>
<th>S3</th>
<th>S9</th>
</tr>
</thead>
</table>

Reduce

<table>
<thead>
<tr>
<th>keys</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>S2</td>
</tr>
<tr>
<td>S3</td>
<td></td>
</tr>
<tr>
<td>S9</td>
<td>...</td>
</tr>
</tbody>
</table>

- What’s the problem?
  - R is the one side, S is the many
### Reduce-side Join: Value-to-Key Conversion

**In reducer...** Buffer all values in memory, pick out the tuple from R, and then cross it with every tuple from S to perform the join.

<table>
<thead>
<tr>
<th>keys</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td></td>
</tr>
<tr>
<td>S2</td>
<td></td>
</tr>
<tr>
<td>S3</td>
<td></td>
</tr>
<tr>
<td>S9</td>
<td></td>
</tr>
<tr>
<td>R4</td>
<td></td>
</tr>
<tr>
<td>S3</td>
<td></td>
</tr>
<tr>
<td>S7</td>
<td></td>
</tr>
</tbody>
</table>

- New key encountered: hold in memory
- Cross with records from other set

### Reduce-side Join: Many-to-Many

**In reducer...**

<table>
<thead>
<tr>
<th>keys</th>
<th>values</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td></td>
</tr>
<tr>
<td>R5</td>
<td></td>
</tr>
<tr>
<td>R8</td>
<td></td>
</tr>
<tr>
<td>S2</td>
<td></td>
</tr>
<tr>
<td>S3</td>
<td></td>
</tr>
<tr>
<td>S9</td>
<td></td>
</tr>
</tbody>
</table>

- Hold in memory
- Cross with records from other set

#### What's the problem?
- *R is the smaller dataset*
Map-side Join: Basic Idea

- What are the limitations of reduce-side joins?
  - Both datasets are transferred over the network

- Assume two datasets are sorted by the join key:

```
R1  S2
R2  S4
R4  S3
R3  S1
```

A sequential scan through both datasets to join: called a “sort-merge join” in database terminology

Map-side Join: Parallel Scans

- If datasets are sorted by join key, join can be accomplished by a scan over both datasets

- How can we accomplish this in parallel?
  - Partition and sort both datasets in the same manner

- In MapReduce:
  - Map over one dataset, read from other corresponding partition
  - No reducers necessary (unless to repartition or resort)

- Consistently partitioned datasets: realistic to expect?
  - Depends on the workflow
  - For ad hoc data analysis, reduce-side are more general, although less efficient
Broadcast/Replication Join

- Relation S
- Relation R
- Different join keys

Mapper 1  Mapper 2  Mapper 3  Mapper N

Load one dataset into memory, stream over other dataset
Distribute the smaller relation to all nodes

In-Memory Join: Variants

- Basic idea: load one dataset into memory, stream over other dataset
  - Works if R << S and R fits into memory
  - Called a “hash join” in database terminology

- MapReduce implementation
  - Distribute R to all nodes
  - Map over S, each mapper loads R in memory, hashed by join key
  - For every tuple in S, look up join key in R
  - No reducers, unless for regrouping or resorting tuples

- Downside: need to copy R to all mappers
  - Not so bad, since R is small
In-Memory Join: Variants

- **Distributed Cache**: Efficient way to copy files to all nodes processing a certain task
  - Use it to send small R to all mappers
  - Part of the *job configuration*

- Striped variant:
  - R too big to fit into memory?
  - Divide R into R1, R2, R3, ... s.t. each Rn fits into memory
  - Perform in-memory join: \( \forall n, R_n \bowtie S \)
  - Take the union of all join results

- Hadoop *still needs to move the data to the workers*, so use this with care
  - But it avoids copying the file for every task on the same node

Which Join to Use?

- In-memory join > map-side join > reduce-side join
  - Why?

- Limitations of each?
  - In-memory join: memory
  - Map-side join: sort order and partitioning
  - Reduce-side join: general purpose algorithm but sensible to *data skewness*?

- What about non-equi joins?
  - Inequality (S.A < R.A): map just forwards R-tuples, but replicates S-tuples for all larger R.A values as keys
Problems With Standard Equi-Joins

- Degree of parallelism limited by number of distinct join values
- Data skew
  - If one join value dominates, reducer processing that key will become bottleneck
- Does not generalize to other joins

Standard Repartition Equi-Join Algorithm

- Consider only the pairs with the same join attribute values
Standard Repartition Equi-Join Algorithm

Reducer-Centric Cost Model

- Difference between join implementations starts with Map output
Optimization Goal: Minimal Job Completion time

- Job completion time depends on the slowest map and reduce functions
- Balancing the workloads of map functions is easy and thus we ignore them
- Balance the workloads of reduce functions as evenly as possible
  - Assume all reducers are similarly capable
- Processing time at reducer is approx. monotonic in input and output size
- Hence need to minimize max-reducer-input or max-reducer-output
- Join problem classification
  - Input-size dominated: minimize max-reducer-input
  - Output-size dominated: minimize max-reducer-output
  - Input-output balanced: minimize combination of both

Join Model

- Join-matrix $M(i, j)$: $M(i, j) = true$, if and only if $(s_i, t_j)$ in join result
- Cover each true-valued cell by exactly one reducer

\[ \begin{array}{cccccc}
\text{T} & 5 & 7 & 7 & 8 & 9 \\
\text{S} & & & & & \\
5 & & & & & \\
7 & & & & & \\
7 & & & & & \\
8 & & & & & \\
9 & & & & & \\
\end{array} \]

\[ \begin{array}{cccccc}
\text{T} & 5 & 7 & 7 & 8 & 9 \\
\text{S} & & & & & \\
5 & & & & & \\
7 & & & & & \\
7 & & & & & \\
8 & & & & & \\
9 & & & & & \\
\end{array} \]

\[ \begin{array}{cccccc}
\text{T} & 5 & 7 & 7 & 8 & 9 \\
\text{S} & & & & & \\
5 & & & & & \\
7 & & & & & \\
7 & & & & & \\
8 & & & & & \\
9 & & & & & \\
\end{array} \]

\[ \begin{array}{cccccc}
\text{T} & 5 & 7 & 7 & 8 & 9 \\
\text{S} & & & & & \\
5 & & & & & \\
7 & & & & & \\
7 & & & & & \\
8 & & & & & \\
9 & & & & & \\
\end{array} \]
Reduce Allocations for Repartition Equi-joins

Simple/Standard

Random

Balanced

Comparison of Reduce Allocation Methods

- Simple allocation
  - Minimize the maximum input size of reduce functions
  - Output size may be skewed

- Random allocation
  - Minimize the maximum output size of reduce functions
  - Input size may be increased due to duplication

- Balanced allocation
  - Minimize both maximum input and output sizes
How to Balance Reduce Allocation

- Assume $r$ is desired number of reduce functions
- Partition join-matrix $M$ into $r$ regions
- A map function sends each record in $R$ and $S$ to mapped regions
- A reduce function outputs all possible $(r,s)$ pairs satisfying the join predicates in its value-list
- Propose M-Bucket-I algorithm [Okcan Riedewald: SIGMOD 2011]

Processing Relational Data: Summary

- MapReduce algorithms for processing relational data:
  - Group by, sorting, partitioning are handled automatically by shuffle/sort in MapReduce
  - Selection, projection, and other computations (e.g., aggregation), are performed either in mapper or reducer

- Complex operations require multiple MapReduce jobs
  - Example: top ten URLs in terms of average time spent
  - Opportunities for automatic optimization

- Multiple strategies for relational joins
Join Implementations on MapReduce

MapReduce join implementations

\( \theta \)-join

Equijoin

Replication join

Semi-join

Broadcast join

Multiway join

Similarity join

Map-only join

Trojan join

Multiple MapReduce jobs

Replicated join

Evolving Roles for Relational Database and MapReduce
The Traditional Way: Bringing Data to Compute

- **Complex Architecture**
  - Many special-purpose systems
  - Moving data around
  - No complete views

- **Cost of Analytics**
  - Existing systems strained
  - No agility
  - "BI backlog"

- **Time to Data**
  - Up-front modeling
  - Transforms slow
  - Transforms lose data

- **Missing Data**
  - Leaving data behind
  - Risk and compliance
  - High cost of storage

---

The New Way: Bringing Compute to Data

- **Diverse Analytic Platform**
  - Bring applications to data
  - Combine different workloads on common data (i.e. SQL + Search)
  - True analytic agility

- **Self-Service Exploratory BI**
  - Simple search + BI tools
  - "Schema on read" agility
  - Reduce BI user backlog requests

- **Persistent Staging**
  - One source of data for all analytics
  - Persist state of transformed data
  - Significantly faster & cheaper

- **Active Compliance Archive**
  - Full fidelity original data
  - Indefinite time, any source
  - Lowest cost storage

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Evolution from Apache Hadoop to the Enterprise Data Hub A. Awadallah Co-Founder & CTO of Cloudera SMDB 2014
Need for High-Level Languages

- Hadoop is great for large-data processing!
  - But writing Java programs for everything is verbose and slow
  - Analysts don’t want to (or can’t) write Java

- Solution: develop higher-level data processing languages
  - Hive: HQL is like SQL
  - Pig: Pig Latin is a bit like Perl

Hive and Pig

- Hive: data warehousing application in Hadoop
  - Query language is HQL, variant of SQL
  - Tables stored on HDFS as flat files
  - Developed by Facebook, now open source

- Pig: large-scale data processing system
  - Scripts are written in Pig Latin, a dataflow language
  - Developed by Yahoo!, now open source
  - Roughly 1/3 of all Yahoo! internal jobs

- Common idea:
  - Provide higher-level language to facilitate large-data processing
  - Higher-level language “compiles down” to Hadoop jobs
Hive: Example

- Hive looks similar to an SQL database
- Relational join on two tables:
  - Table of word counts from Shakespeare collection
  - Table of word counts from the bible

```sql
SELECT s.word, s.freq, k.freq FROM shakespeare s
JOIN bible k ON (s.word = k.word) WHERE s.freq >= 1 AND k.freq >= 1
ORDER BY s.freq DESC LIMIT 10;
```

```
the  25848  62394
I    23031  8854
and  19671  38985
to   18038  13526
of   16700  34654
a    14170  8057
you  12702  2720
my   11297  4135
in   10797  12445
is   8882   6884
```

Source: Material drawn from Cloudera training VM

Hive: Behind the Scenes

```sql
SELECT s.word, s.freq, k.freq FROM shakespeare s
JOIN bible k ON (s.word = k.word) WHERE s.freq >= 1 AND k.freq >= 1
ORDER BY s.freq DESC LIMIT 10;
```

(Abstract Syntax Tree)

(one or more of MapReduce jobs)
Hive: Behind the Scenes

STAGE DEPENDENCIES:
Stage -1 is a root stage
Stage -2 depends on stages: Stage -1
Stage -0 is a root stage

STAGE PLANS:
Stage: Stage -1
Map Reduce
Alias
> Map Operator Tree:
TableScan
alias: s
Filter Operator
predicate:
expr: (freq >= 1)
type: boolean
Reduce Output Operator
key expressions:
expr: word
type: string
sort order: +
Map - reduce partition columns:
expr: word
type: string
tag:
0
tag:
value expressions:
expr: freq
type: int
expr: word
type: string
k

TableScan
alias: k
Filter Operator
predicate:
expr: (freq >= 1)
type: boolean
Reduce Output Operator
key expressions:
expr: word
type: string
sort order: +
Map - reduce partition columns:
expr: word
type: string
tag:
1
tag:
value expressions:
expr: freq
type: int
expr: word
type: string

Fall 2016

Hive: Behind the Scenes

Pig: Example

Task: Find the top 10 most visited pages in each category

Visits

<table>
<thead>
<tr>
<th>User</th>
<th>Url</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amy</td>
<td>cnn.com</td>
<td>8:00</td>
</tr>
<tr>
<td>Amy</td>
<td>bbc.com</td>
<td>10:00</td>
</tr>
<tr>
<td>Amy</td>
<td>flickr.com</td>
<td>10:05</td>
</tr>
<tr>
<td>Fred</td>
<td>cnn.com</td>
<td>12:00</td>
</tr>
</tbody>
</table>

Url Info

<table>
<thead>
<tr>
<th>Url</th>
<th>Category</th>
<th>PageRank</th>
</tr>
</thead>
<tbody>
<tr>
<td>cnn.com</td>
<td>News</td>
<td>0.9</td>
</tr>
<tr>
<td>bbc.com</td>
<td>News</td>
<td>0.8</td>
</tr>
<tr>
<td>flickr.com</td>
<td>Photos</td>
<td>0.7</td>
</tr>
<tr>
<td>espn.com</td>
<td>Sports</td>
<td>0.9</td>
</tr>
</tbody>
</table>
visits = load 'data/visits' as (user, url, time);
gVisits = group visits by url;
visitCounts = foreach gVisits generate url, count(visits);
urlInfo = load 'data/urlInfo' as (url, category, pRank);
visitCounts = join visitCounts by url, urlInfo by url;
gCategories = group visitCounts by category;
topUrls = foreach gCategories generate top(visitCounts,10);

store topUrls into 'data/topUrls';
References

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- MapReduce Algorithms for Big Data Analysis Kyuseok Shim VLDB 2012 TUTORIAL
Taxonomy of Parallel Architectures

Scales to 1000s of computers

a) shared nothing
b) shared disc
c) shared memory

Easiest to program, but $$$

Unicore vs Multi-core Architectures

Unicore

Multicore
Positioning Big Data

- Operational systems
- Data Warehousing
- Operational Analytics
- Ad-hoc Deep Analytics
- The New Data

Density of Data Value

Data Volume - Terabytes

Variety

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