Relational Processing

on MapReduce

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- IBM Watson Research

- Content obtained from many sources,
- notably: Jimmy Lin course on MapReduce.

•Our Plan Today

1. Recap:
   - Key relational DBMS notes
   - Key Hadoop notes
2. Relational Algorithms on MapReduce
   - How to do a select, groupby, join etc
3. Queries on MapReduce: Hive and Pig

Big Data Analysis

- Peta-scale datasets are everywhere:
  - Facebook has 2.5 PB of user data + 15 TB/day (4/2009)
  - eBay has 6.5 PB of user data + 50 TB/day (5/2009)
  - …
- 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
  - Open source

Source: O'Reilly Blog post by Joseph Hellerstein (11/19/2008)

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 Architecture

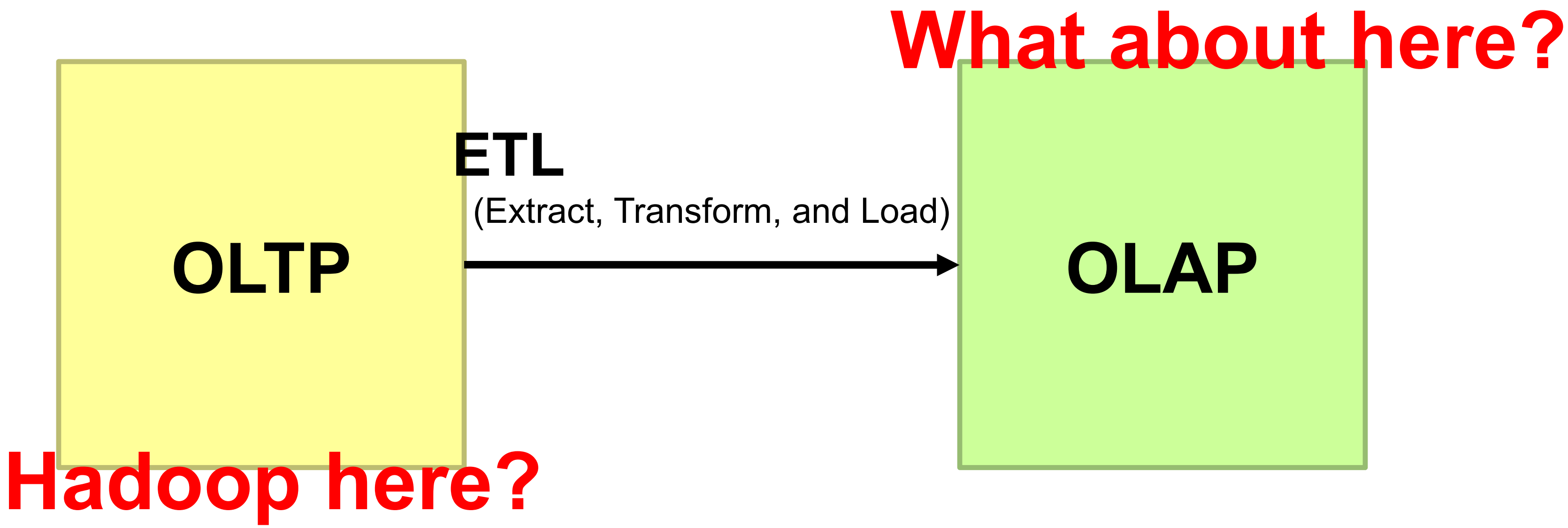
OLTP/OLAP Integration

- 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

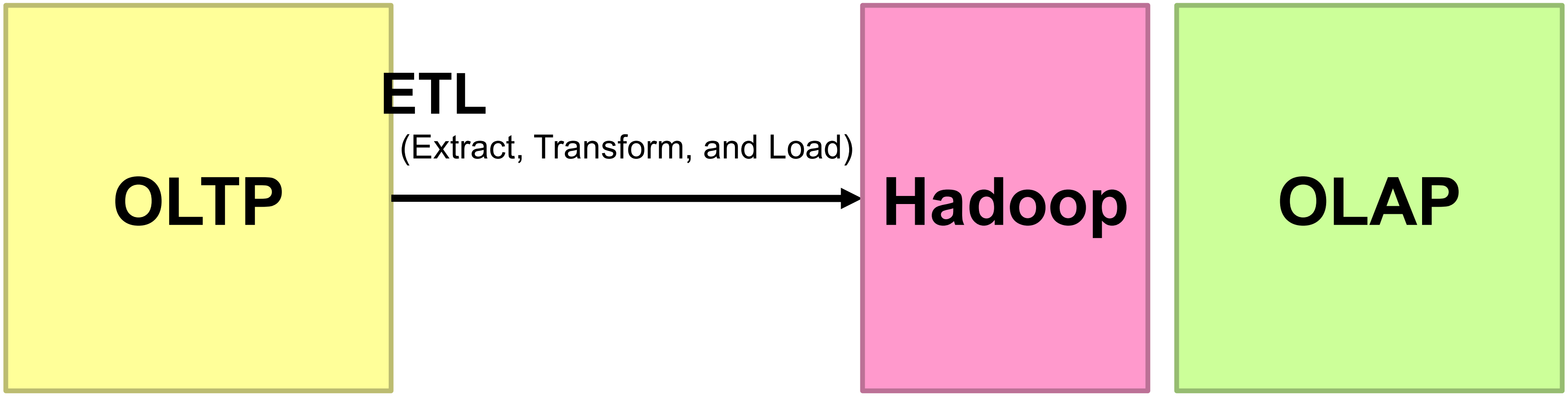
Business Intelligence

- Premise: more data leads to better business decisions
  - Periodic reporting as well as ad hoc queries
  - Analysts, not programmers (importance of tools and dashboards)
- Examples:
  - Slicing-and-dicing activity by different dimensions to better understand the marketplace
  - Analyzing log data to improve OLTP experience
  - Analyzing log data to better optimize ad placement
  - Analyzing purchasing trends for better supply-chain management
  - Mining for correlations between otherwise unrelated activities

OLTP/OLAP Architecture: Hadoop?



OLTP/OLAP/Hadoop Architecture



Why does this make sense?

ETL Bottleneck

- Reporting is often a nightly task:
  - ETL is often slow: why?
  - What happens if processing 24 hours of data takes longer than 24 hours?
- 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
  - Ability to use any processing tool
  - Much cheaper than parallel databases
  - ETL is a batch process anyway!

MapReduce: Recap

- Programmers must specify:

map (k, v) → <k’, v’>*
reduce (k’, v’) → <k’, v’>*

  - All values with the same key are reduced together

- Optionally, also:

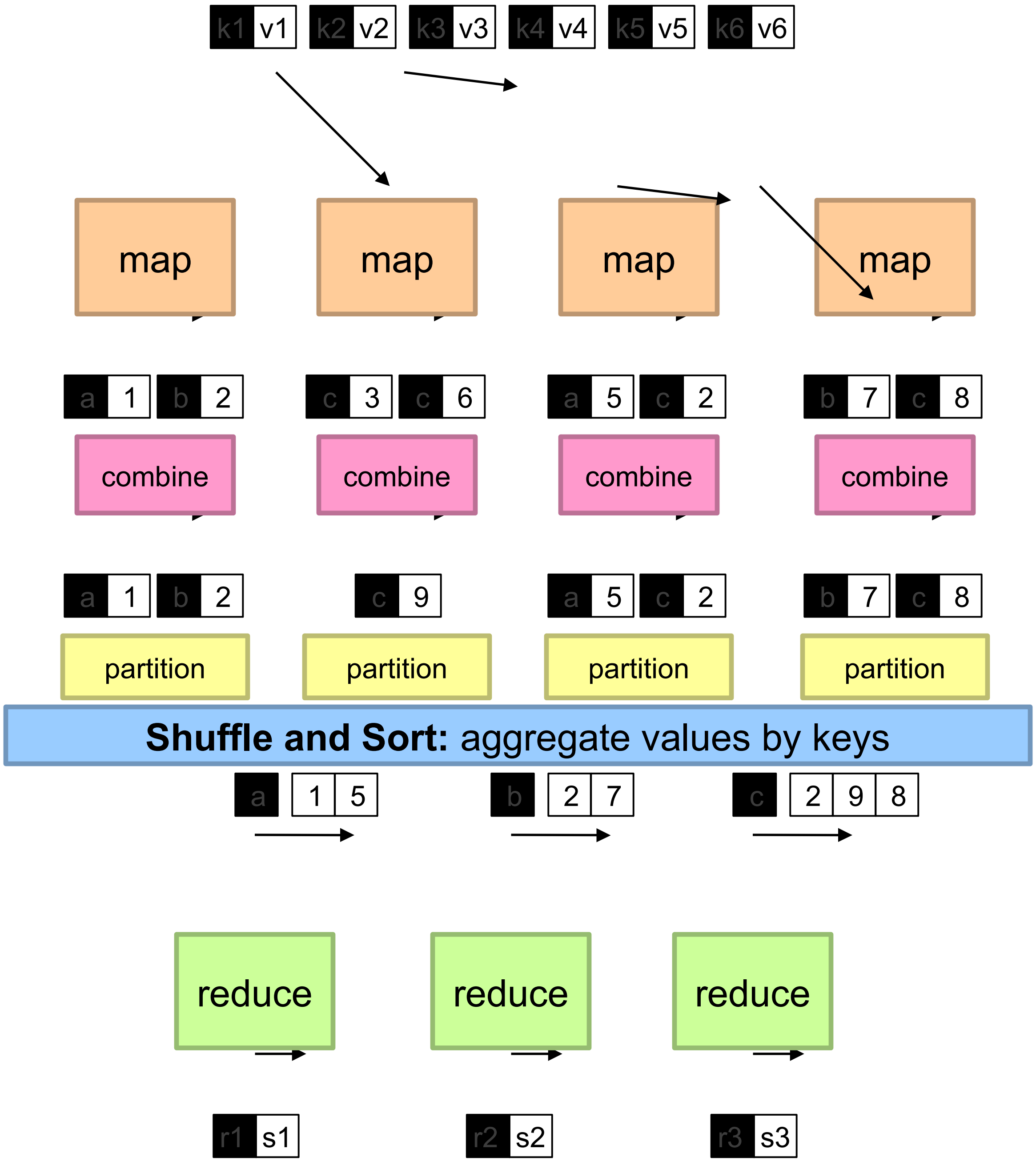
partition (k’, number of partitions) → partition for k’

  - Often a simple hash of the key, e.g., hash(k’) mod n
  - Divides up key space for parallel reduce operations

combine (k’, v’) → <k’, v’>*

  - Mini-reducers that run in memory after the map phase
  - Used as an optimization to reduce network traffic

- The execution framework handles everything else…


k1 v1 k2 v2 k3 v3 k4 v4 k5 v5 k6 v6
map
map
map
map
a 1 b 2
c 3 c 6
a 5 c 2
b 7 c 8
combine
combine
combine
combine
a 1 b 2
c 9
a 5 c 2
b 7 c 8
partition
partition
partition
partition
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 9 8
reduce
reduce
reduce
r1 s1
r2 s2
r3 s3

"Everything Else"

- The execution framework handles everything else…
  - Scheduling: assigns workers to map and reduce tasks
  - "Data distribution": moves processes to data
  - Synchronization: gathers, sorts, and shuffles intermediate data
  - Errors and faults: detects worker failures and restarts
- Limited control over data and execution flow
  - All algorithms must expressed in m, r, c, p
- You don't know:
  - Where mappers and reducers run
  - When a mapper or reducer begins or finishes
  - Which input a particular mapper is processing
  - Which intermediate key a particular reducer is processing

MapReduce algorithms
for processing relational data

Design Pattern: Secondary Sorting

- MapReduce sorts input to reducers by key
  - Values are arbitrarily ordered
- What if want to sort value also?
  - E.g., k → (v1, r), (v3, r), (v4, r), (v8, r)…

Secondary Sorting: Solutions

- Solution 1:
  - Buffer values in memory, then sort
  - Why is this a bad idea?
- Solution 2:
  - “Value-to-key conversion” design pattern: form composite intermediate key, (k, v1)
  - 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 → (v1, r), (v4, r), (v8, r), (v3, r)…

Values arrive in arbitrary order…

After

(k, v1) → (v1, r)
(k, v3) → (v3, r)
(k, v4) → (v4, r)
(k, v8) → (v8, r)
…

Values arrive in sorted order…

Process by preserving state across multiple keys

Remember to partition correctly!

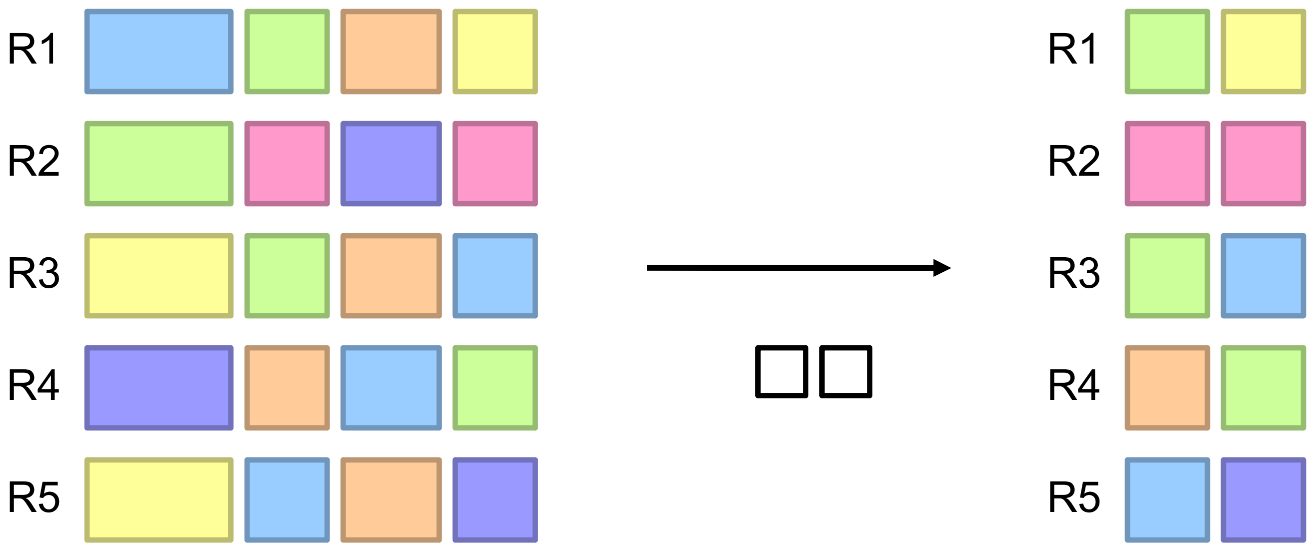
Working Scenario

- 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

- Primitives
  - Projection (π)
  - Selection (σ)
  - Cartesian product ($\times$)
  - Set union ($\cup$)
  - Set difference ($-$)
  - Rename (ρ)
- Other operations
  - Join ($\bowtie$)
  - Group by… aggregation
  - …

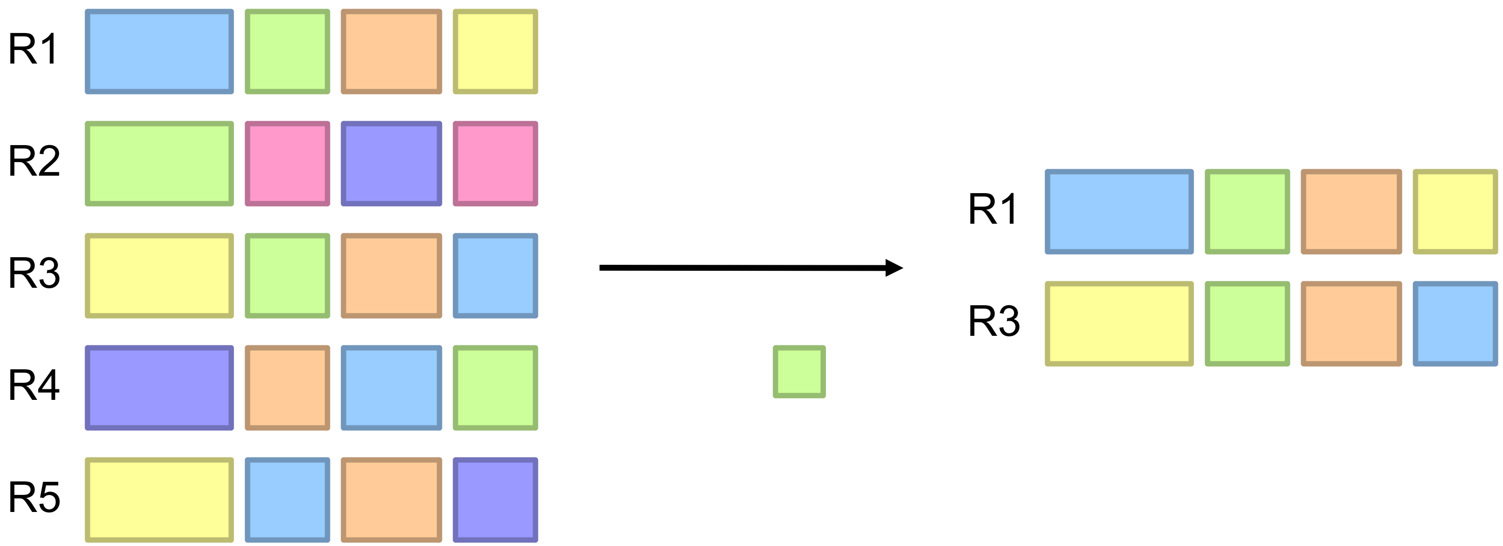
Projection



Projection in MapReduce

- Easy!
  - Map over tuples, emit new tuples with appropriate attributes
  - No reducers, 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!

Selection



Selection in MapReduce

- Easy!
  - Map over tuples, emit only tuples that meet criteria
  - No reducers, 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!

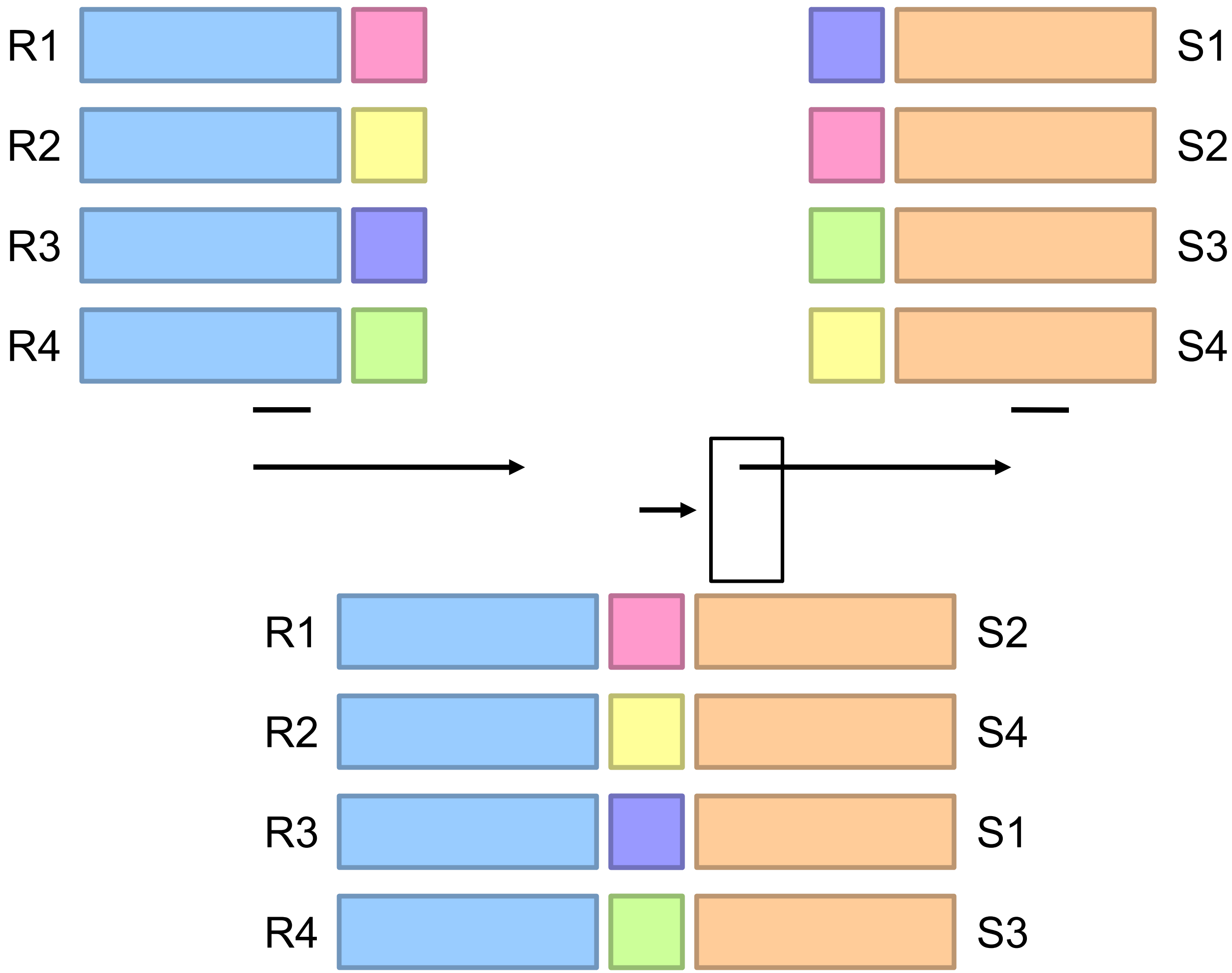
Group by… Aggregation

- Example: What is the average time spent per URL?
- In SQL:
  - SELECT url, AVG(time) FROM visits GROUP BY url
- In MapReduce:
  - Map over tuples, emit time, keyed by url
  - Framework automatically groups values by keys
  - Compute average in reducer
  - Optimize with combiners

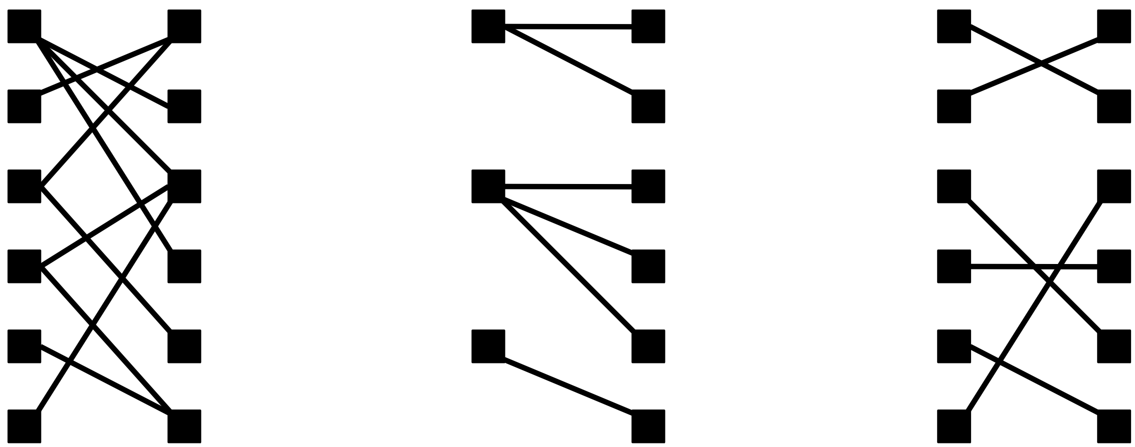
Relational Joins

Source: Microsoft Office Clip Art

Relational Joins



Types of Relationships



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

Join Algorithms in MapReduce

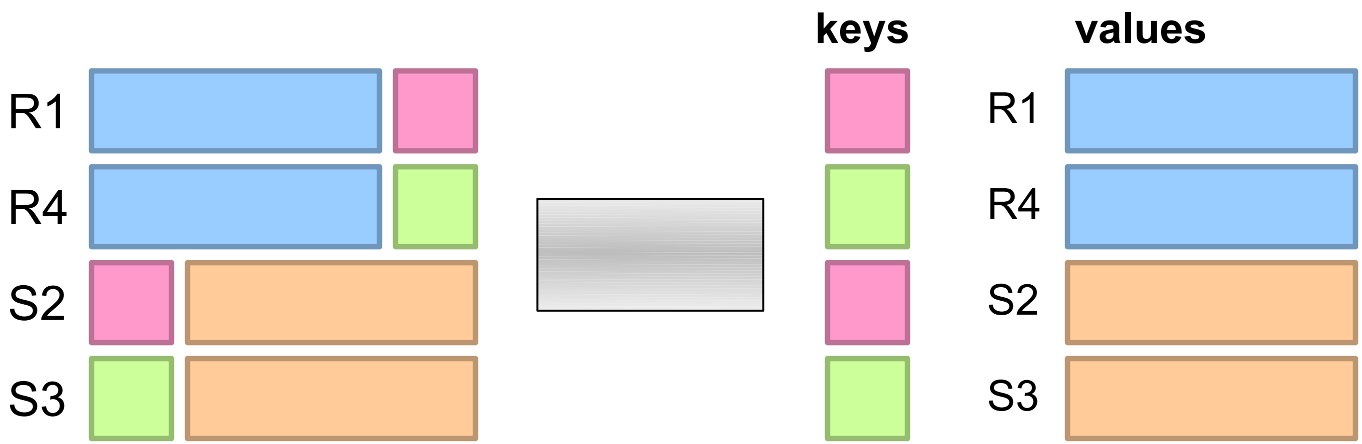
- Reduce-side join
- Map-side join
- In-memory join
  - Striped variant
  - Memcached variant

Reduce-side Join

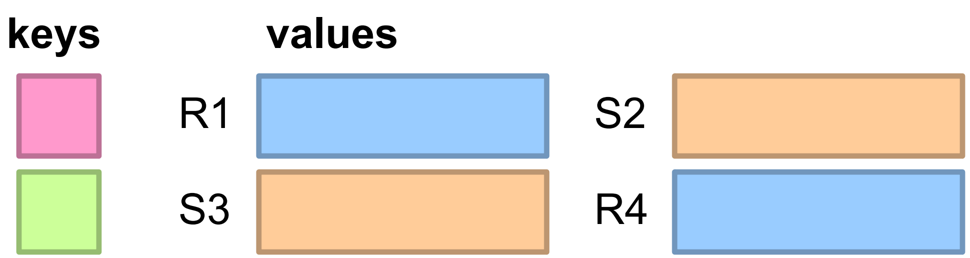
- Basic idea: group by join key
  - Map over both sets of tuples
  - Emit tuple as value with join key as the intermediate key
  - Execution framework brings together tuples sharing the same key
  - Perform actual join in reducer
  - Similar to a “sort-merge join” in database terminology
- Two variants
  - 1-to-1 joins
  - 1-to-many and many-to-many joins

Reduce-side Join: 1-to-1

Map



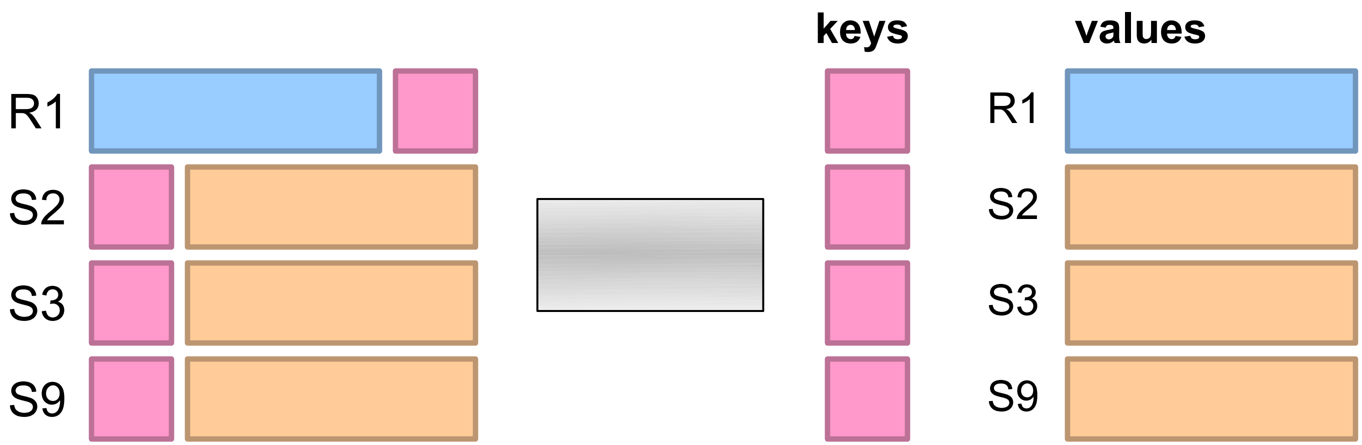
Reduce



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

Reduce-side Join: 1-to-many

Map

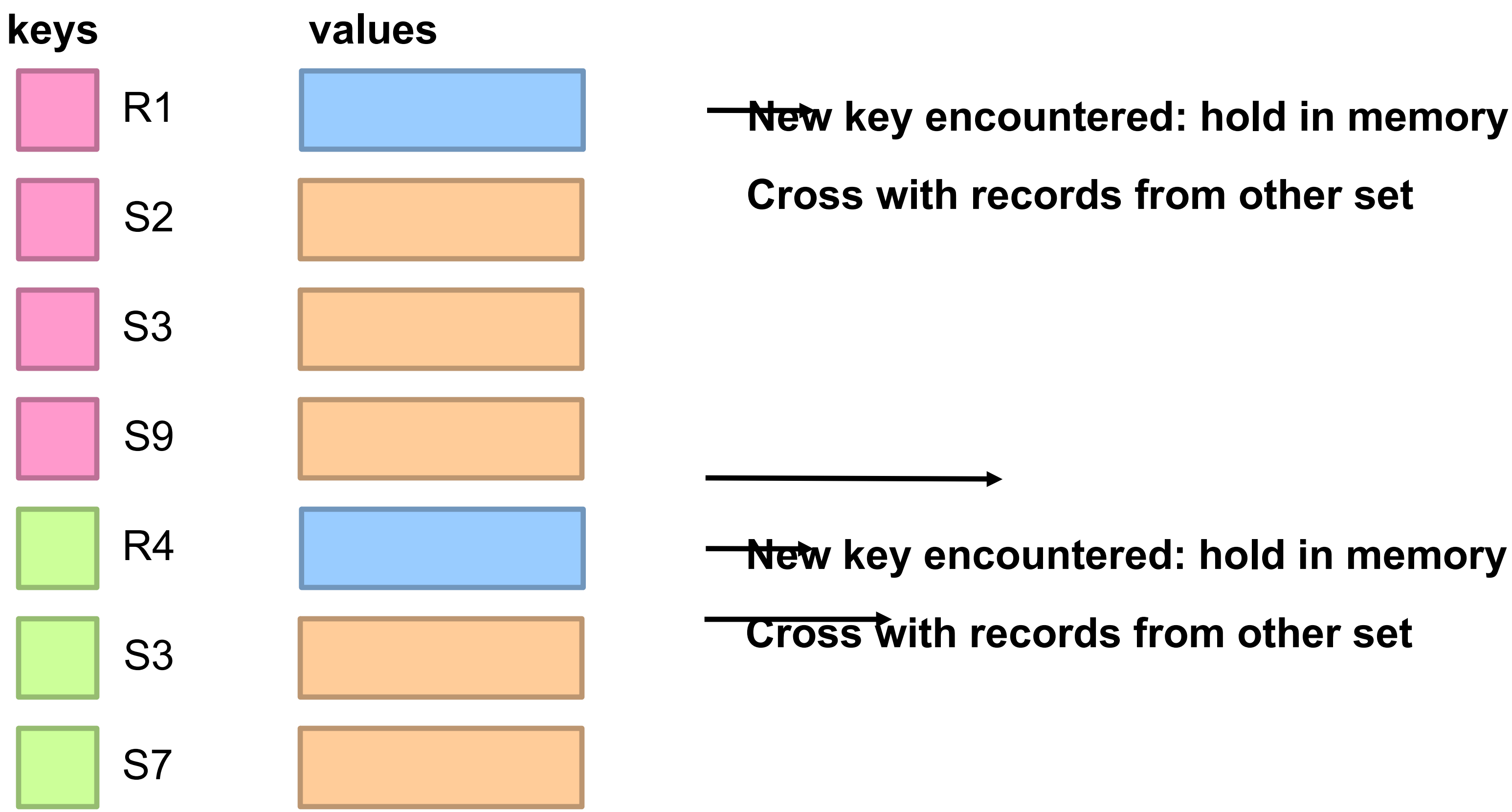


Reduce

What's the problem?

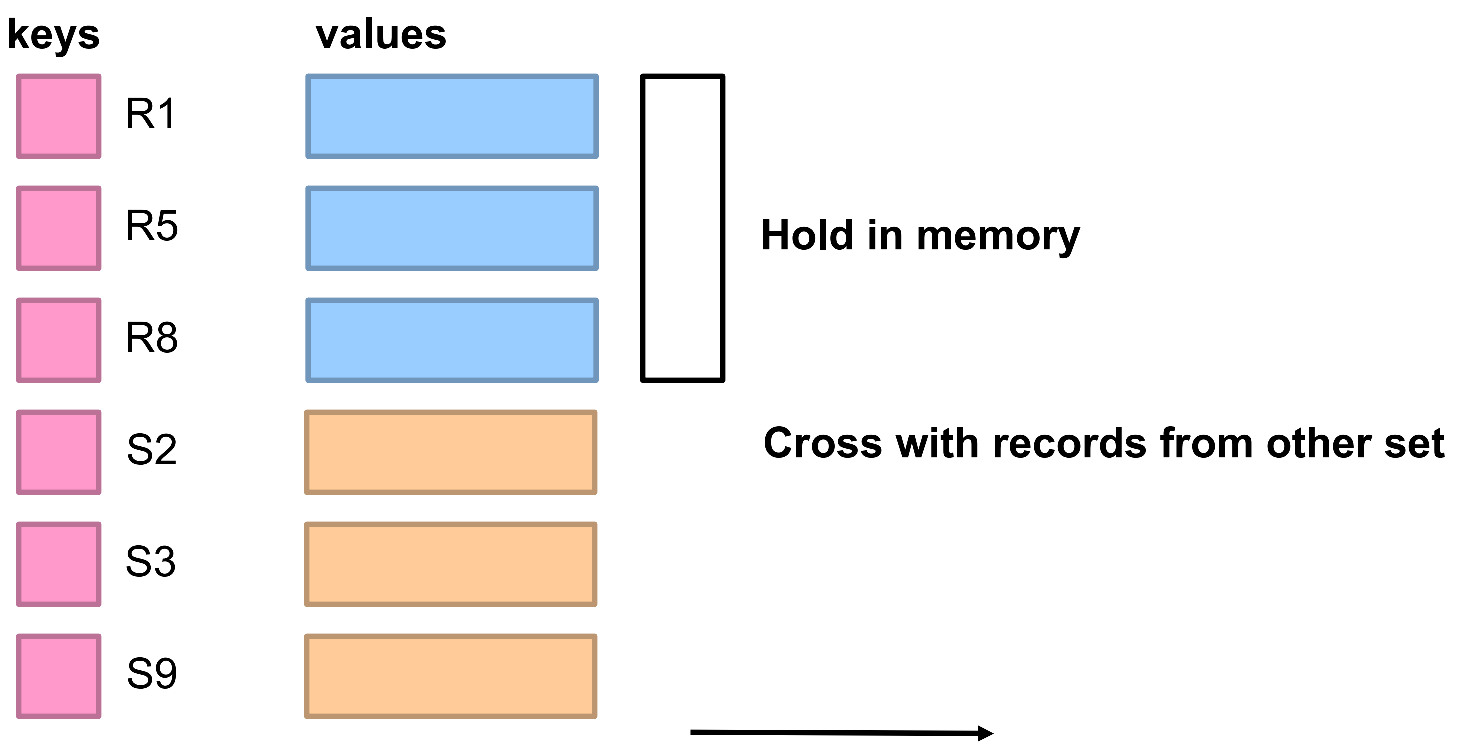
Reduce-side Join: V-to-K Conversion

In reducer…



Reduce-side Join: many-to-many

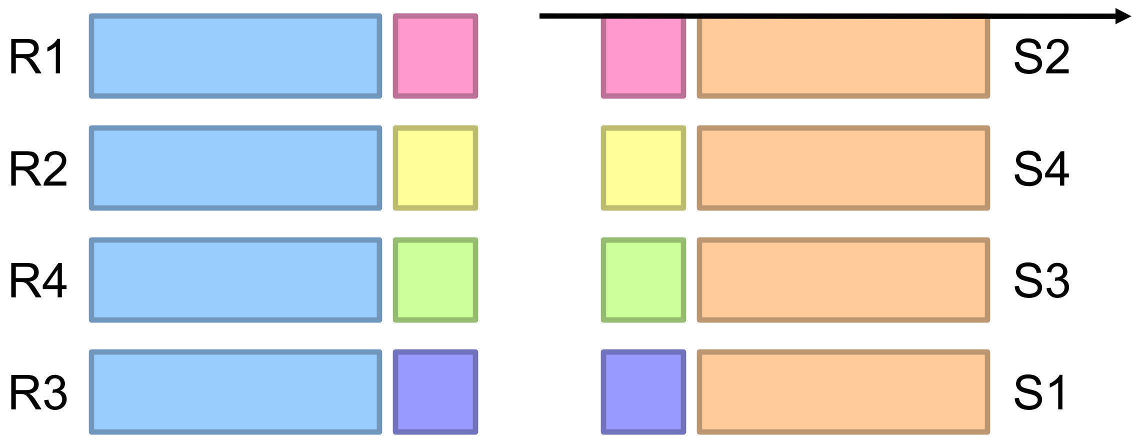
In reducer…



What's the problem?

Map-side Join: Basic Idea

Assume two datasets are sorted by the join key:



A sequential scan through both datasets to join
(called a "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?

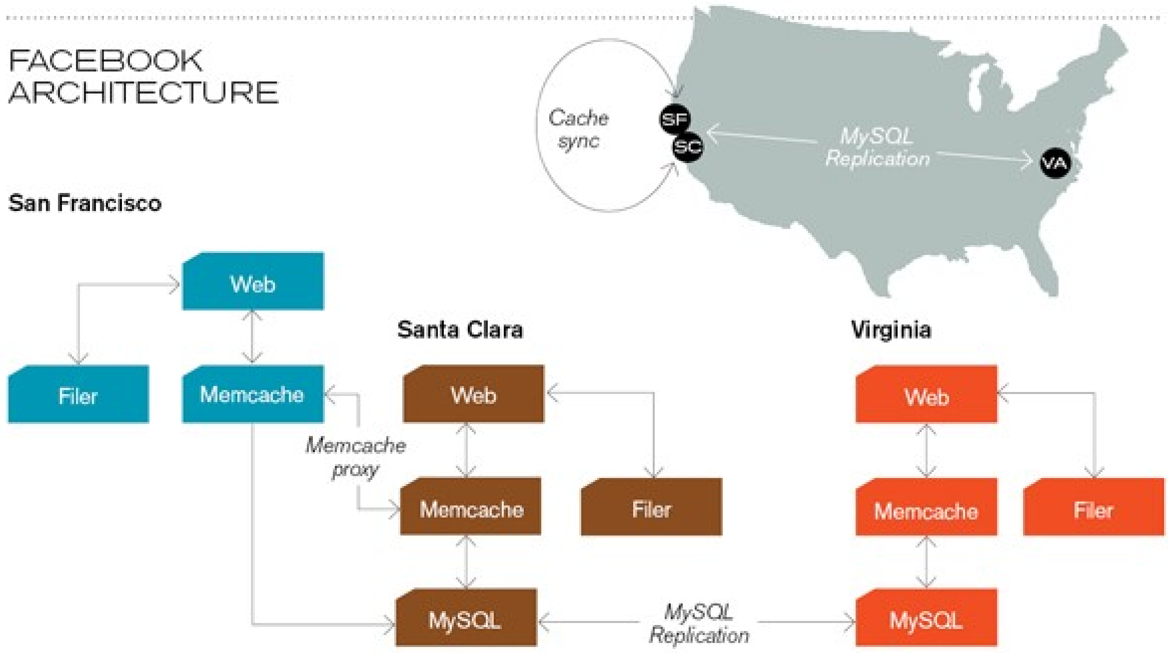
In-Memory Join

- 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

In-Memory Join: Variants

- Striped variant:
  - R too big to fit into memory?
  - Divide R into R1, R2, R3, … s.t. each R*n* fits into memory
  - Perform in-memory join: $\forall n$, $Rn \bowtie S$
  - Take the union of all join results
- Memcached join:
  - Load R into memcached
  - Replace in-memory hash lookup with memcached lookup

Memcached



Caching servers: 15 million requests per second, 95% handled by memcache (15 TB of RAM)

Database layer: 800 eight-core Linux servers running MySQL (40 TB user data)

Source: Technology Review (July/August, 2008)

Memcached Join

- Memcached join:
  - Load R into memcached
  - Replace in-memory hash lookup with memcached lookup
- Capacity and scalability?
  - Memcached capacity >> RAM of individual node
  - Memcached scales out with cluster
- Latency?
  - Memcached is fast (basically, speed of network)
  - Batch requests to amortize latency costs

Source: See tech report by Lin et al. (2009)

Which join to use?

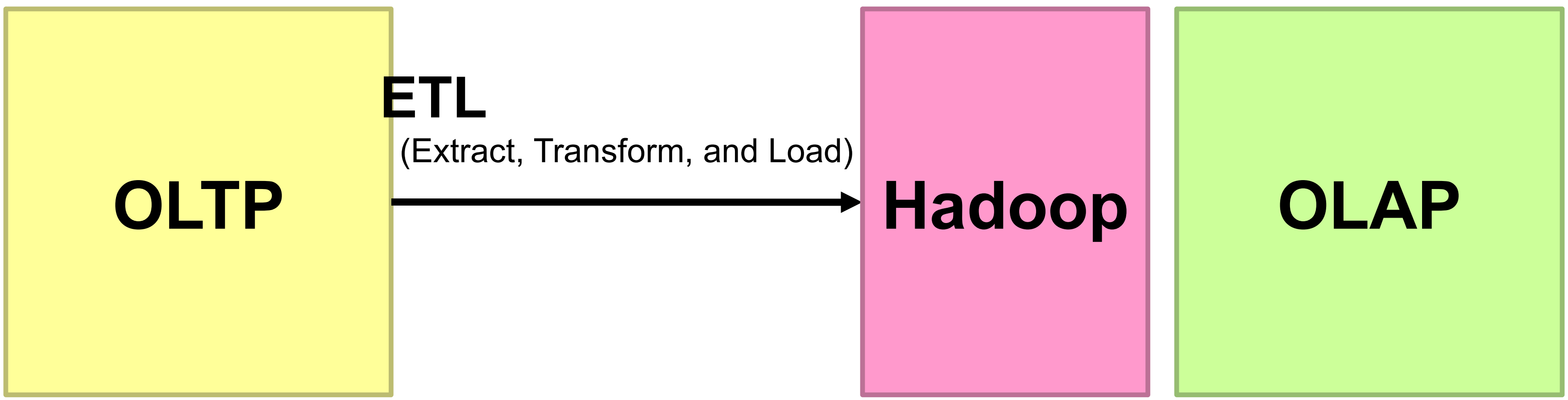
- In-memory join > map-side join > reduce-side join
  - Why?
- Limitations of each?
  - In-memory join: memory
  - Map-side join: sort order and partitioning
  - Reduce-side join: general purpose

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

Evolving roles for relational database and MapReduce

OLTP/OLAP/Hadoop Architecture



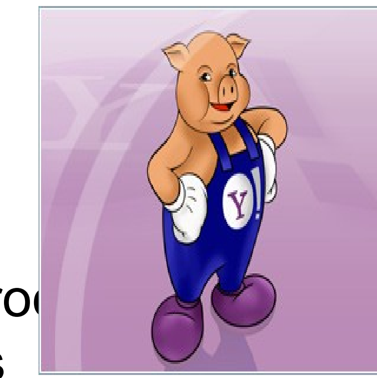
Why does this make sense?

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 proc
  - 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

```
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	88826884	

Source: Material drawn from Cloudera training VM

Hive: Behind the Scenes

```
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)

```
(TOK_QUERY (TOK_FROM (TOK_JOIN (TOK_TABREF shakespeare s) (TOK_TABREF bible k) (= (. (TOK_TABLE_OR_COL s)
word) (. (TOK_TABLE_OR_COL k) word)))) (TOK_INSERT (TOK_DESTINATION (TOK_DIR TOK_TMP_FILE)) (TOK_SELECT
(TOK_SELEXPR (. (TOK_TABLE_OR_COL s) word)) (TOK_SELEXPR (. (TOK_TABLE_OR_COL s) freq)) (TOK_SELEXPR (.
(TOK_TABLE_OR_COL k) freq))) (TOK_WHERE (AND (>= (. (TOK_TABLE_OR_COL s) freq) 1) (>= (. (TOK_TABLE_OR_COL k)
freq) 1))) (TOK_ORDERBY (TOK_TABSORTCOLNAMEDESC (. (TOK_TABLE_OR_COL s) freq))) (TOK_LIMIT 10)))
```

(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:
        s
          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
                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
                value expressions:
                      expr: freq
                      type: int
      Reduce Operator Tree:
        Join Operator
          condition map:
               Inner Join 0 to 1
          condition expressions:
            0 {VALUE._col0} {VALUE._col1}
            1 {VALUE._col0}
          outputColumnNames: _col0, _col1, _col2
          Filter Operator
            predicate:
                expr: ((_col0 >= 1) and (_col2 >= 1))
                type: boolean
            Select Operator
              expressions:
                    expr: _col1
                    type: string
                    expr: _col0
                    type: int
                    expr: _col2
                    type: int
              outputColumnNames: _col0, _col1, _col2
              File Output Operator
                compressed: false
                GlobalTableId: 0
                table:
                    input format: org.apache.hadoop.mapred.SequenceFileInputFormat
                    output format: org.apache.hadoop.hive.ql.io.HiveSequenceFileOutputFormat

  Stage: Stage-2
    Map Reduce
      Alias -> Map Operator Tree:
        hdfs://localhost:8022/tmp/hive-training/364214370/10002
            Reduce Output Operator
              key expressions:
                    expr: _col1
                    type: int
              sort order: -
              tag: -1
              value expressions:
                    expr: _col0
                    type: string
                    expr: _col1
                    type: int
                    expr: _col2
                    type: int
      Reduce Operator Tree:
        Extract
          Limit
            File Output Operator
              compressed: false
              GlobalTableId: 0
              table:
                  input format: org.apache.hadoop.mapred.TextInputFormat
                  output format: org.apache.hadoop.hive.ql.io.HiveIgnoreKeyTextOutputFormat

  Stage: Stage-0
    Fetch Operator
      limit: 10
```