Cloud Programming:
Lecture7 – Query Processing on MapReduce

National Tsing-Hua University

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國立清華大學

Outline

- Role of relational databases in today's organizations
  - Where does MapReduce fit in?
- MapReduce algorithms for processing relational data
  - How do I perform a join, etc.?
- Evolving roles of relational databases and MapReduce
  - What's in store for the future?

*Slides provided from

Jimmy Lin @ University of Maryland

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 are (mostly) structured
  - 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

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)

  not only retrieval

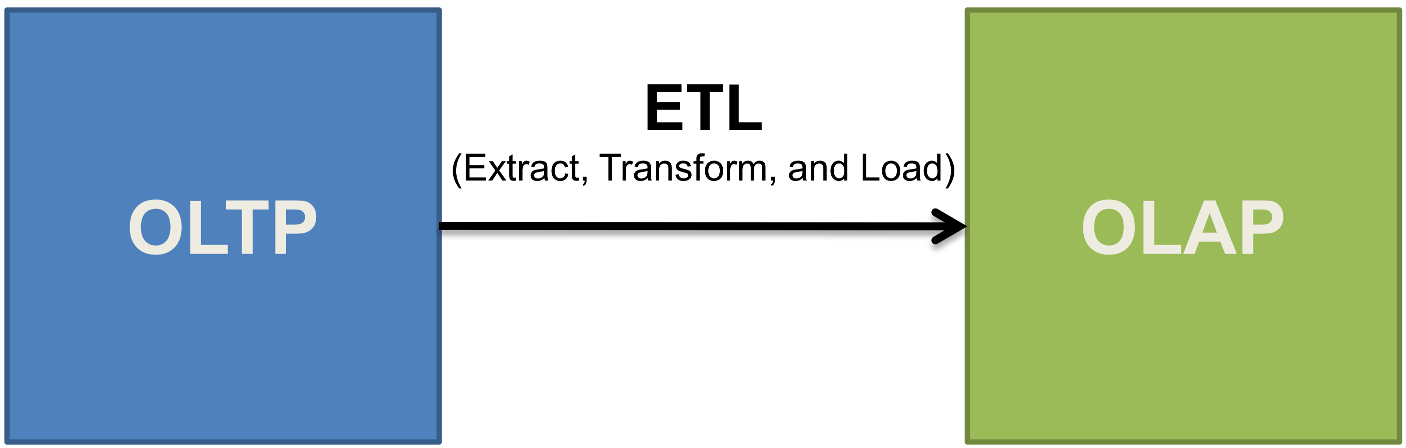
  - Typical applications: business intelligence, data mining
  - Back-end processing: batch workloads, less concurrency
  - Tasks: complex analytical queries, often ad hoc
  - Data access pattern: table scans, large amounts of data involved per query

    not random

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



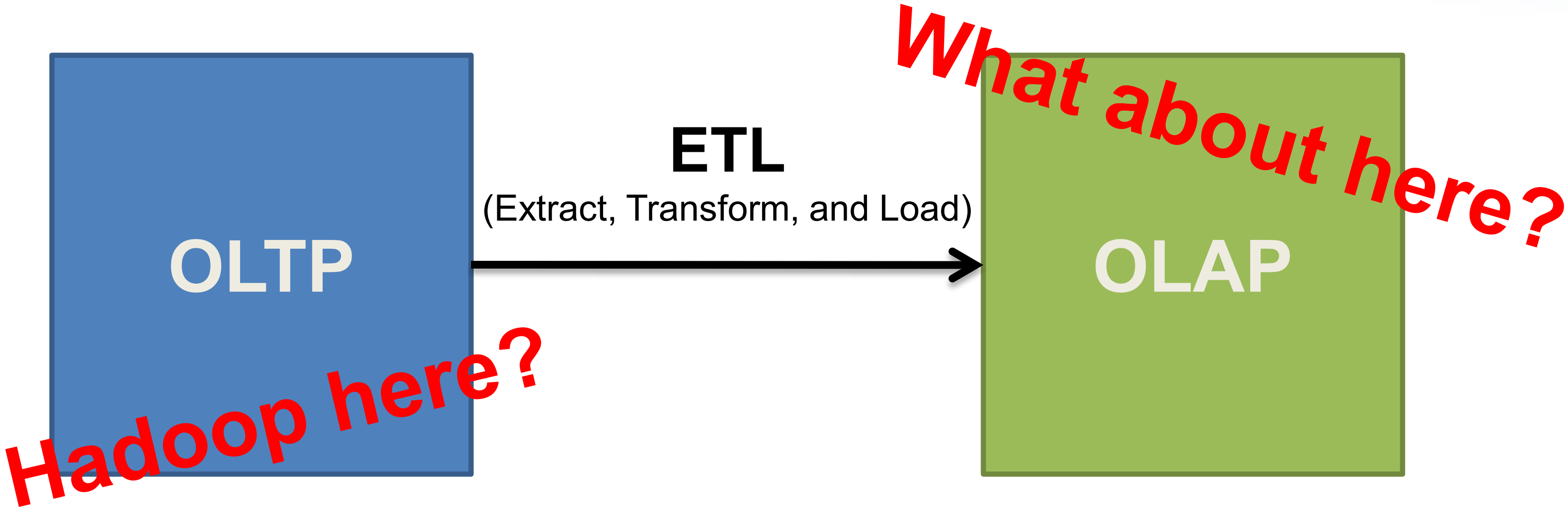
OLTP/OLAP Integration

- 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

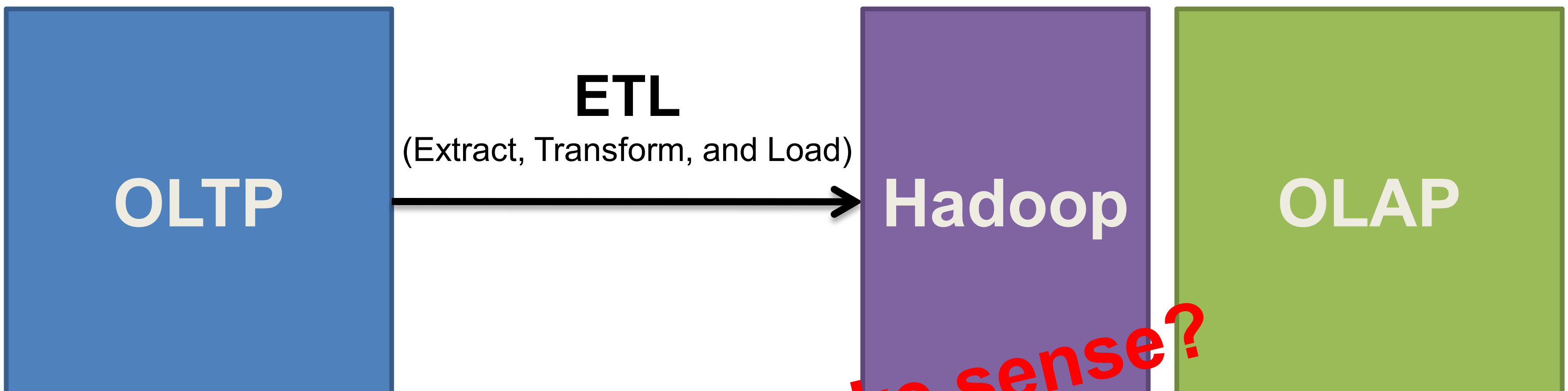
Business Intelligence

- 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!

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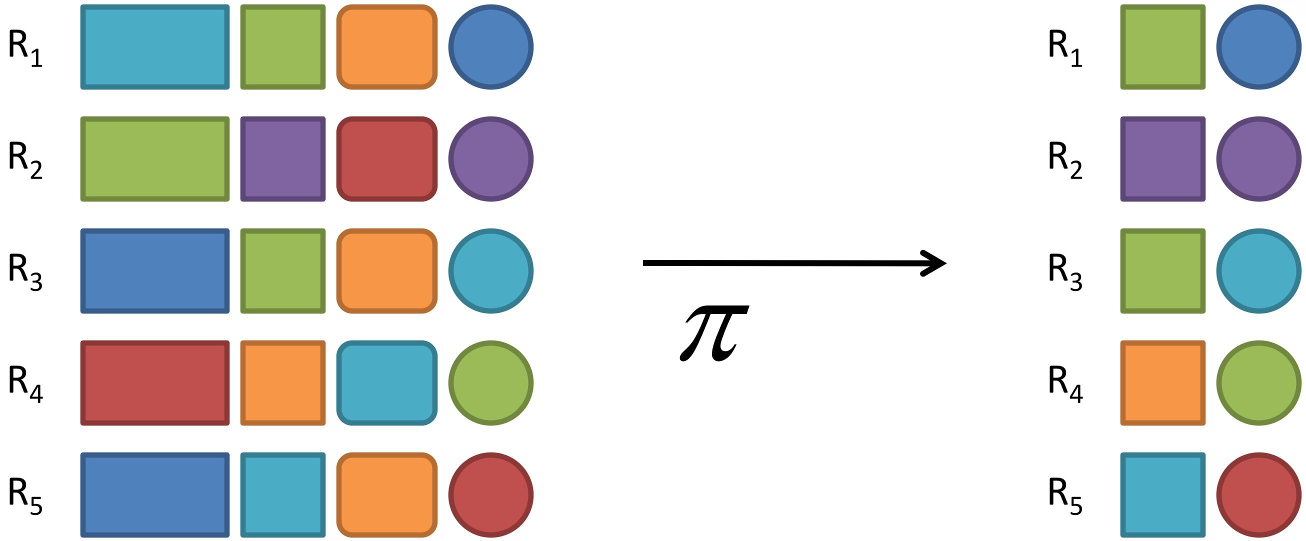
Working Scenario

- 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
  - …

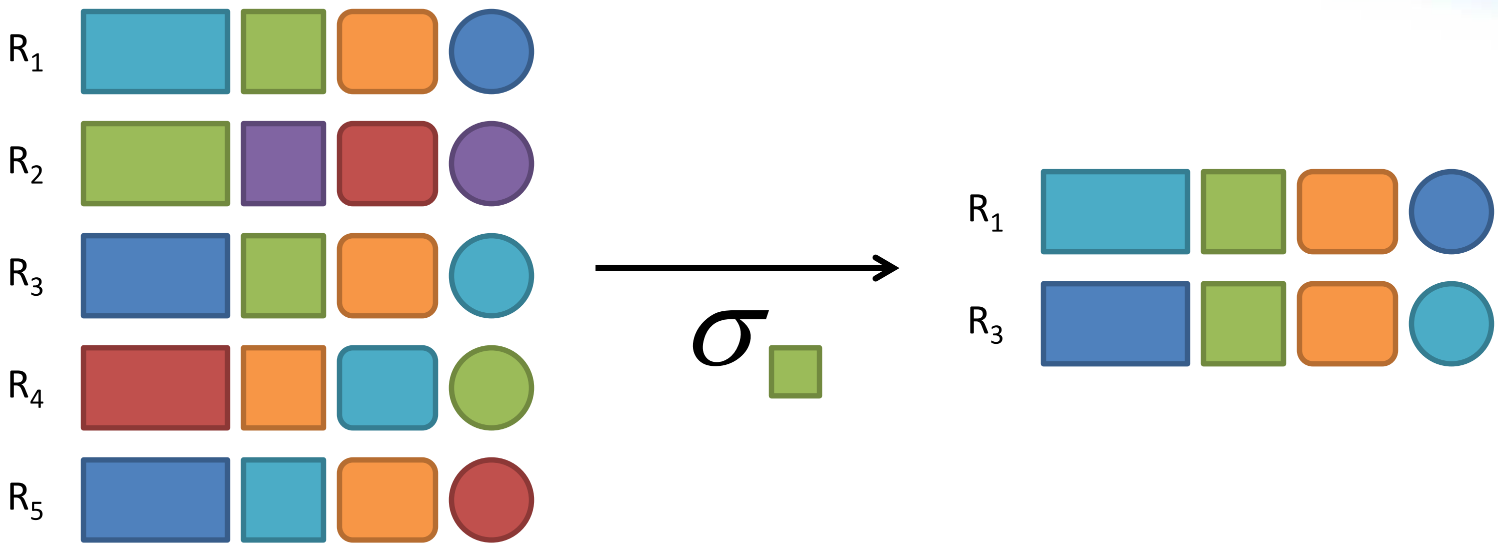
Projection



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!

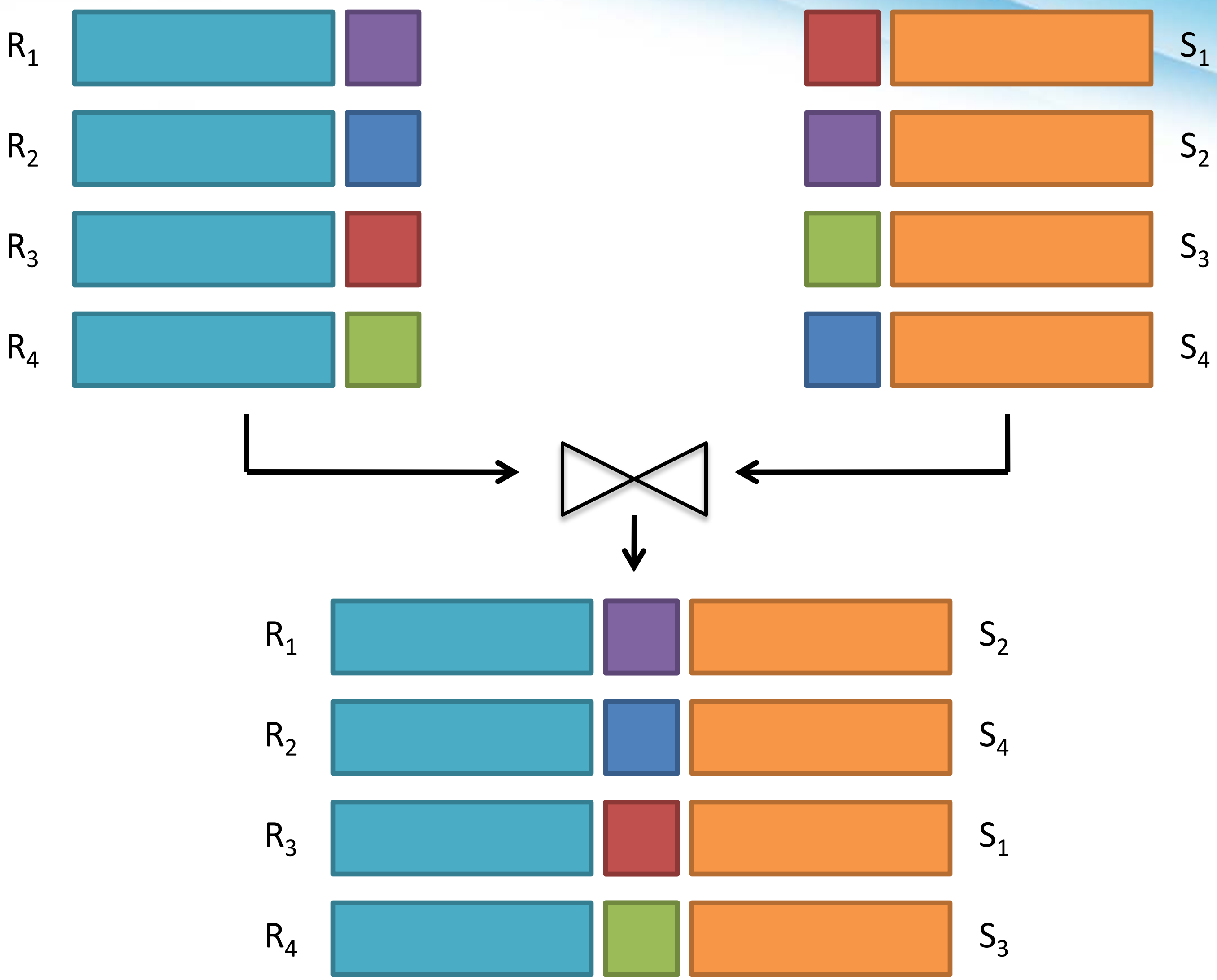
Group by… Aggregation

- 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

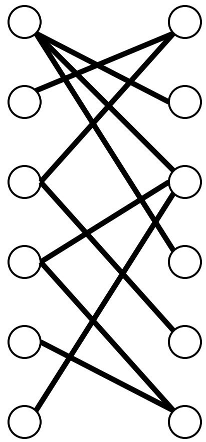
Relational Joins

Source: Microsoft Office Clip Art

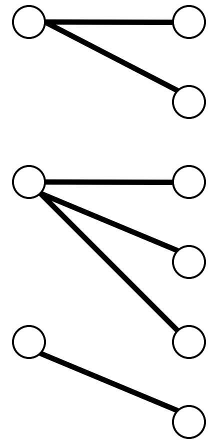
Relational Joins



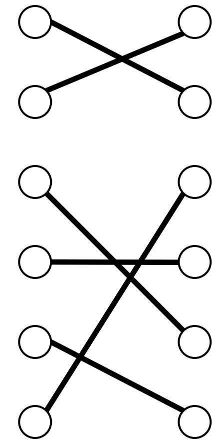
Types of Relationships



Many-to-Many



One-to-Many



One-to-One

Join Algorithms in MapReduce

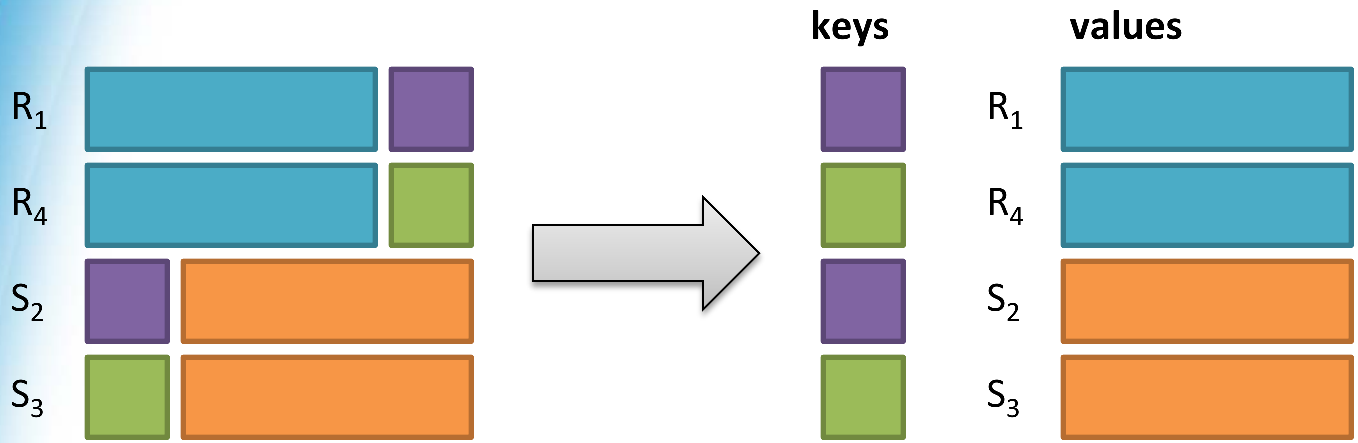
- Reduce-side join
- Map-side join
- In-memory join
  - Striped variant
  - Memcached variant

Reduce-side Join

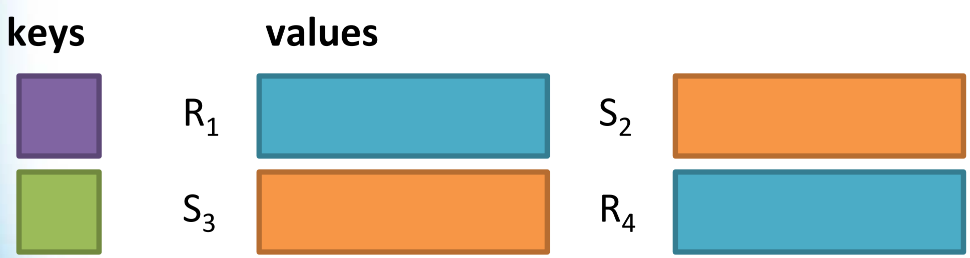
- Basic idea: group by join key
  - Map over both sets of tuples
  - Emit tuple as value with join key as the intermediate key
  - Execution framework brings together tuples sharing the same key
  - Perform actual join in reducer
  - Similar to a “sort-merge join” in database terminology
- Two variants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

Reduce-side Join: 1-to-1

Map



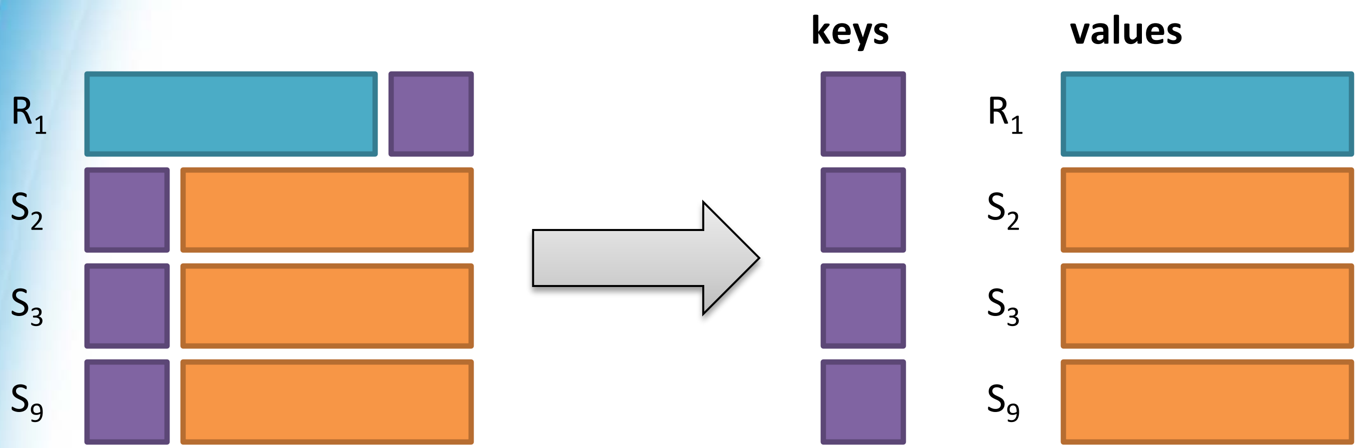
Reduce



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

Reduce-side Join: 1-to-many

Map

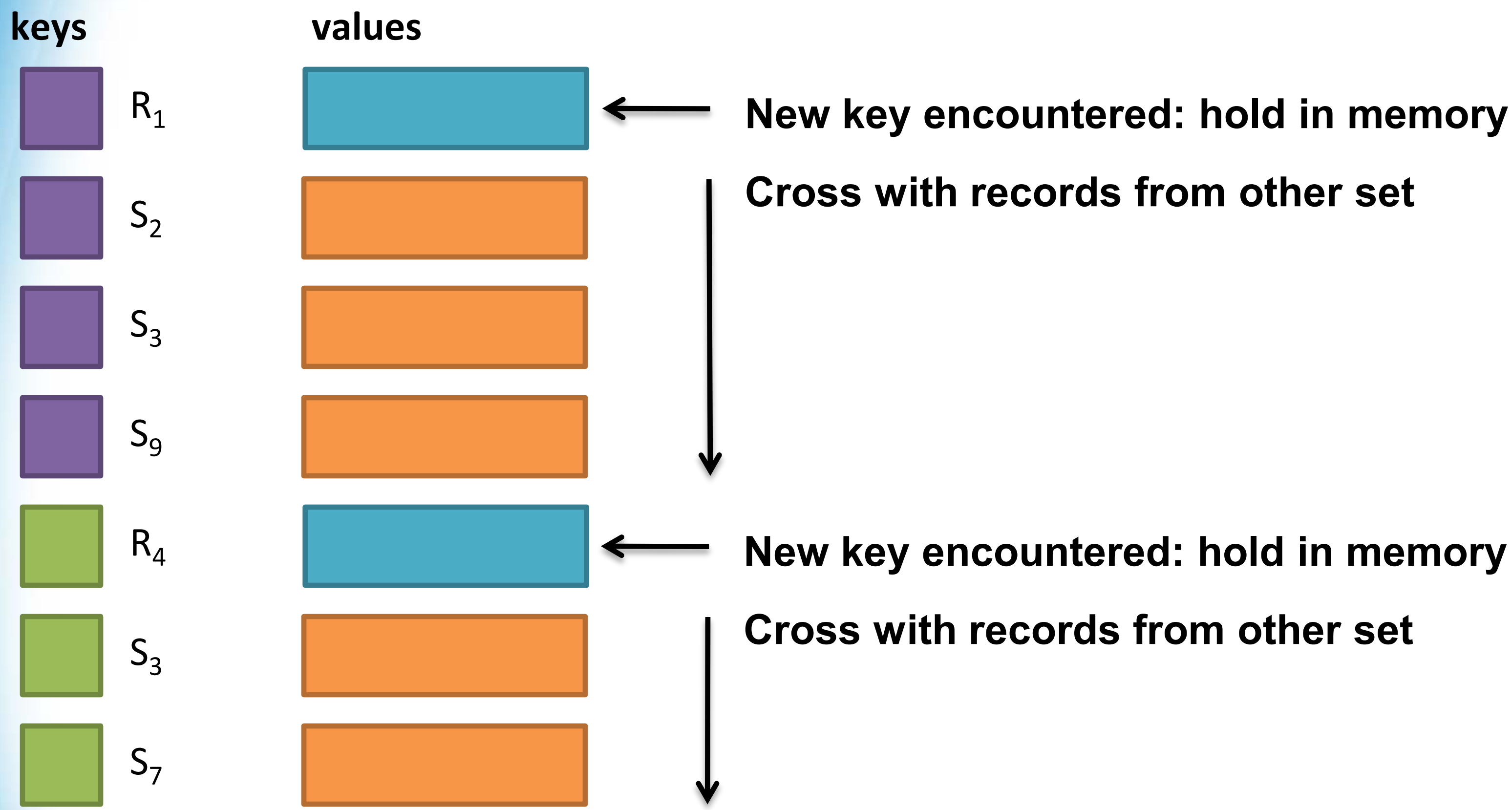


Reduce

What's the problem?

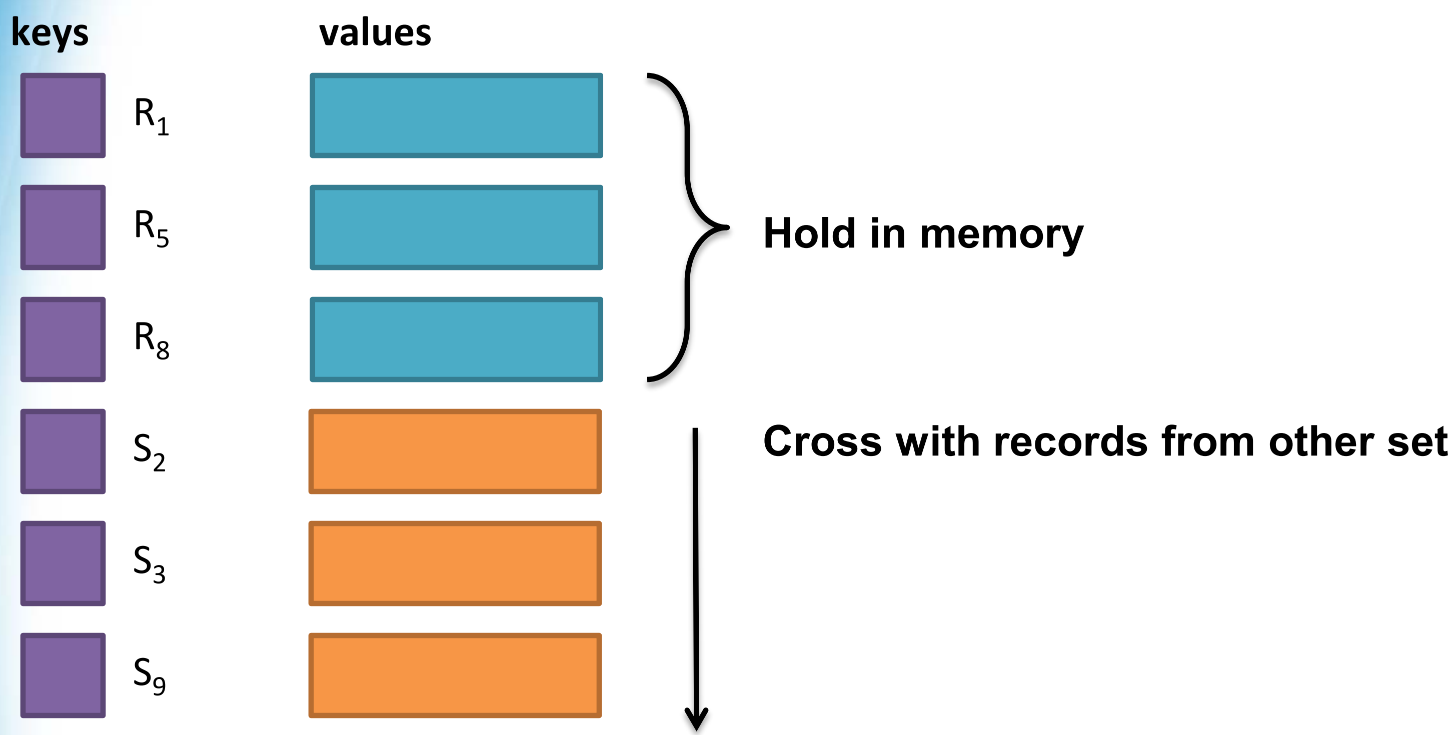
Reduce-side Join: V-to-K Conversion

In reducer…



Reduce-side Join: many-to-many

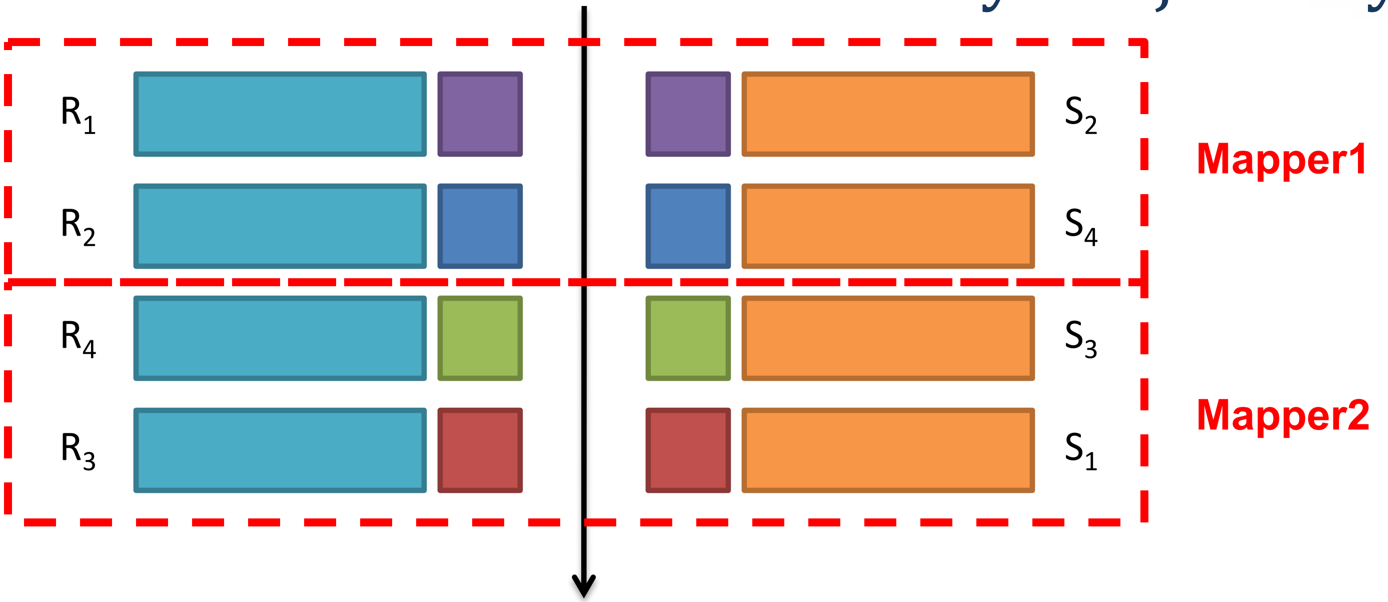
In reducer…



What's the problem?

Map-side Join: Basic Idea

Assume two datasets are sorted by the join key:



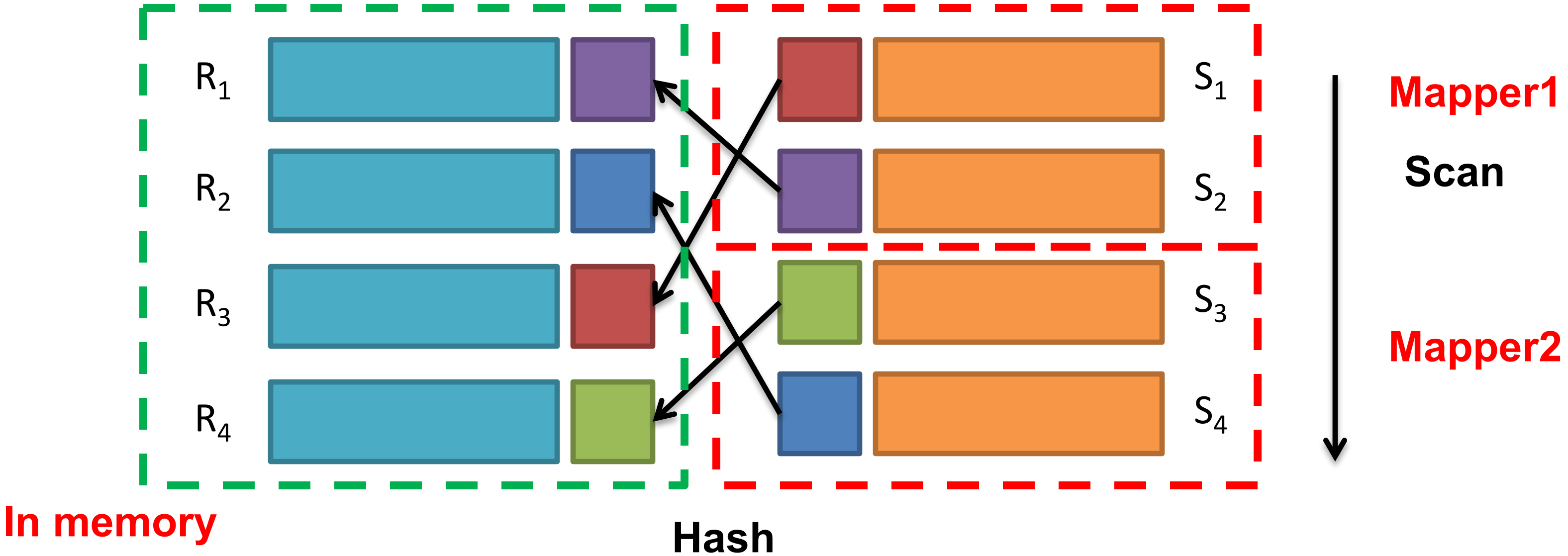
A sequential scan through both datasets to join
(called a "merge join" in database terminology)

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?

Map-side Join: In-Memory Join

Assume two datasets are sorted by the join key:



Store R in all mapper memory,
and sequential scan through S
(called a "hash join" in database terminology)

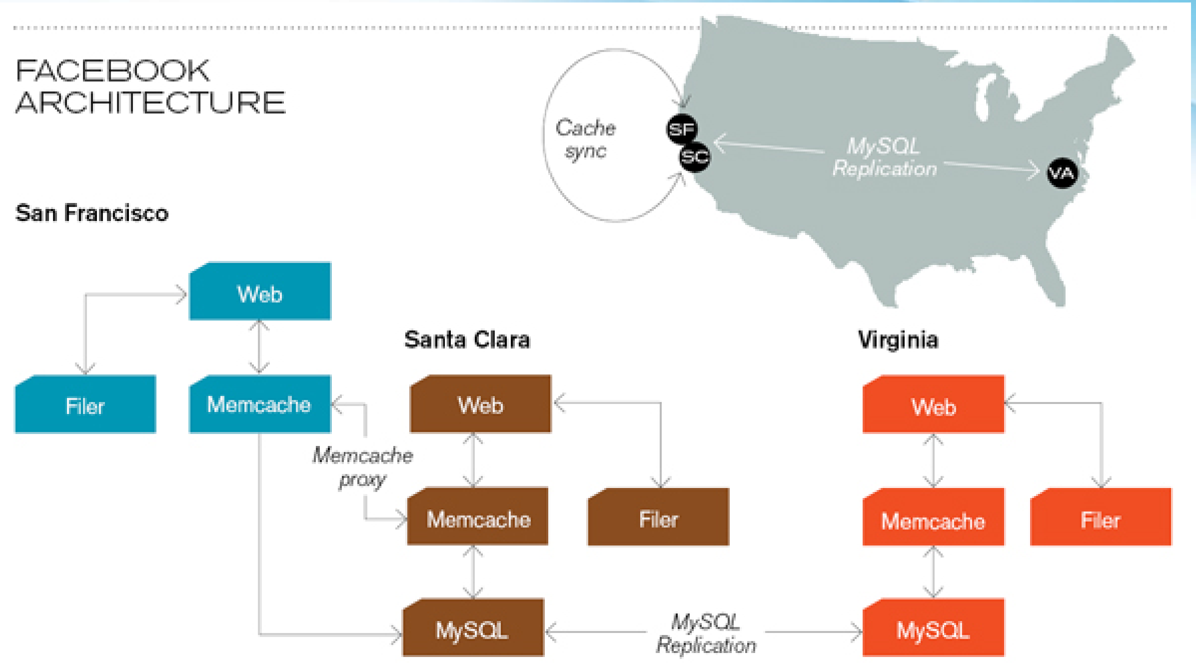
In-Memory Join

- 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 R_1, R_2, R_3, … s.t. each R_n fits into memory
  - Perform in-memory join: $\forall n$, $R_n \bowtie S$
  - 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?

speed comparison

- 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

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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

```
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

```
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
```

Pig: Example

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

Visits

User	Url	Time
Amy	cnn.com	8:00
Amy	bbc.com	10:00
Amy	flickr.com	10:05
Fred	cnn.com	12:00

⋮

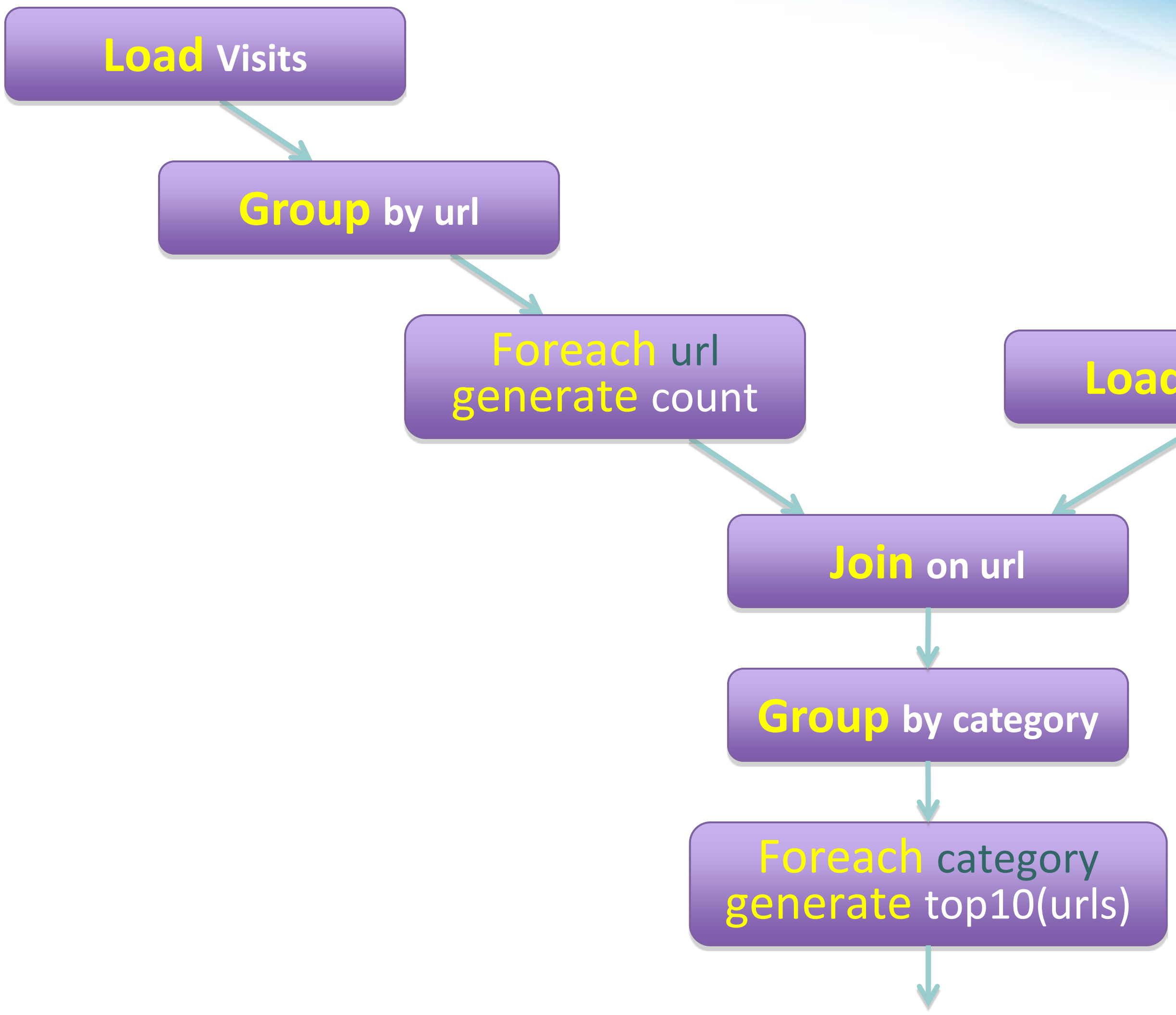
Url Info

Url	Category	PageRank
cnn.com	News	0.9
bbc.com	News	0.8
flickr.com	Photos	0.7
espn.com	Sports	0.9

⋮

Pig Slides adapted from Olston et al. (SIGMOD 2008)

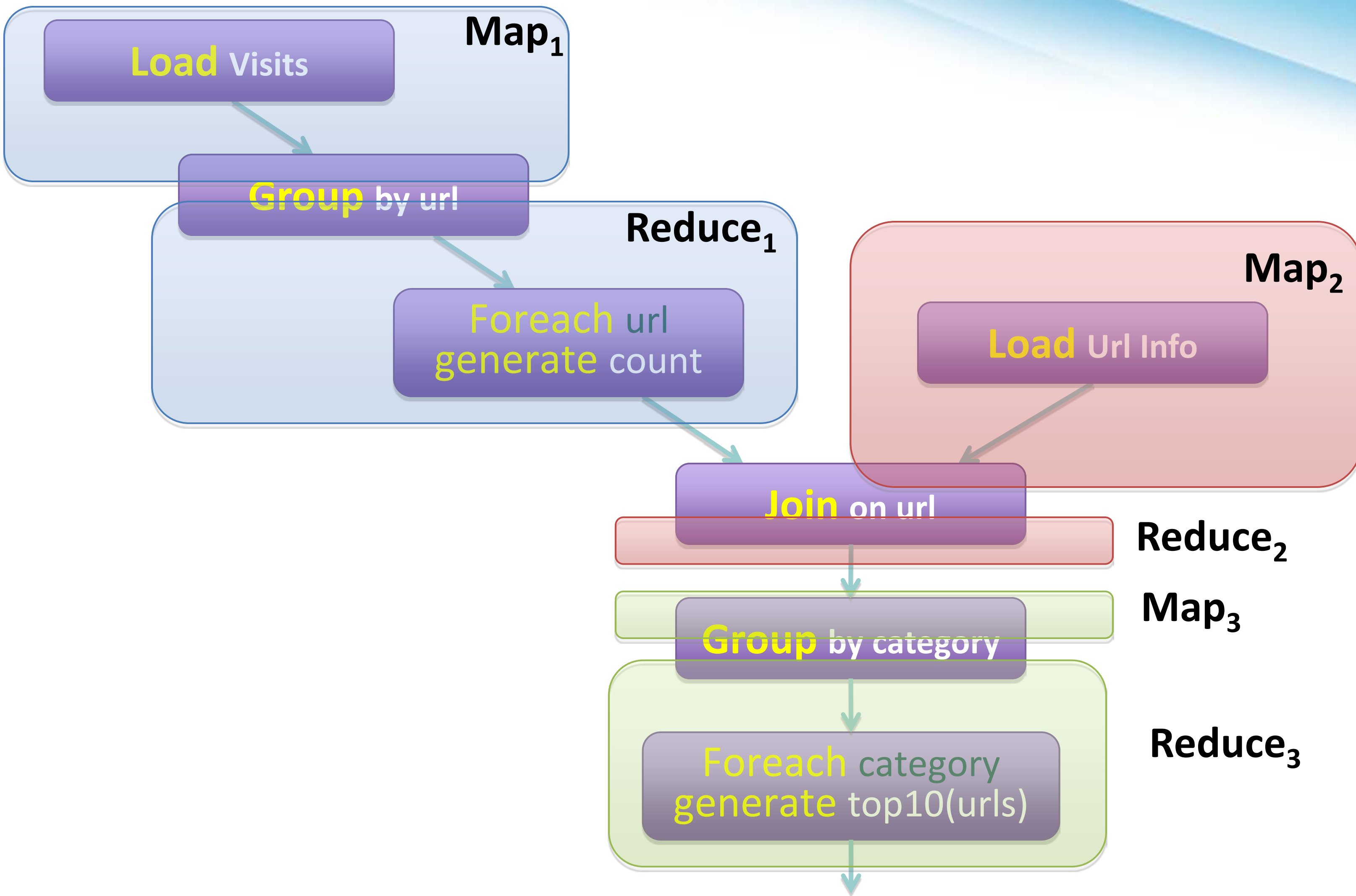
Pig Query Plan



Pig Script

```
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';
```

Pig Script in Hadoop



Pig Slides adapted from Olston et al. (SIGMOD 2008)

Parallel Databases ↔ MapReduce

- Lots of synergy between parallel databases and MapReduce
- Communities have much to learn from each other
- Bottom line: use the right tool for the job!