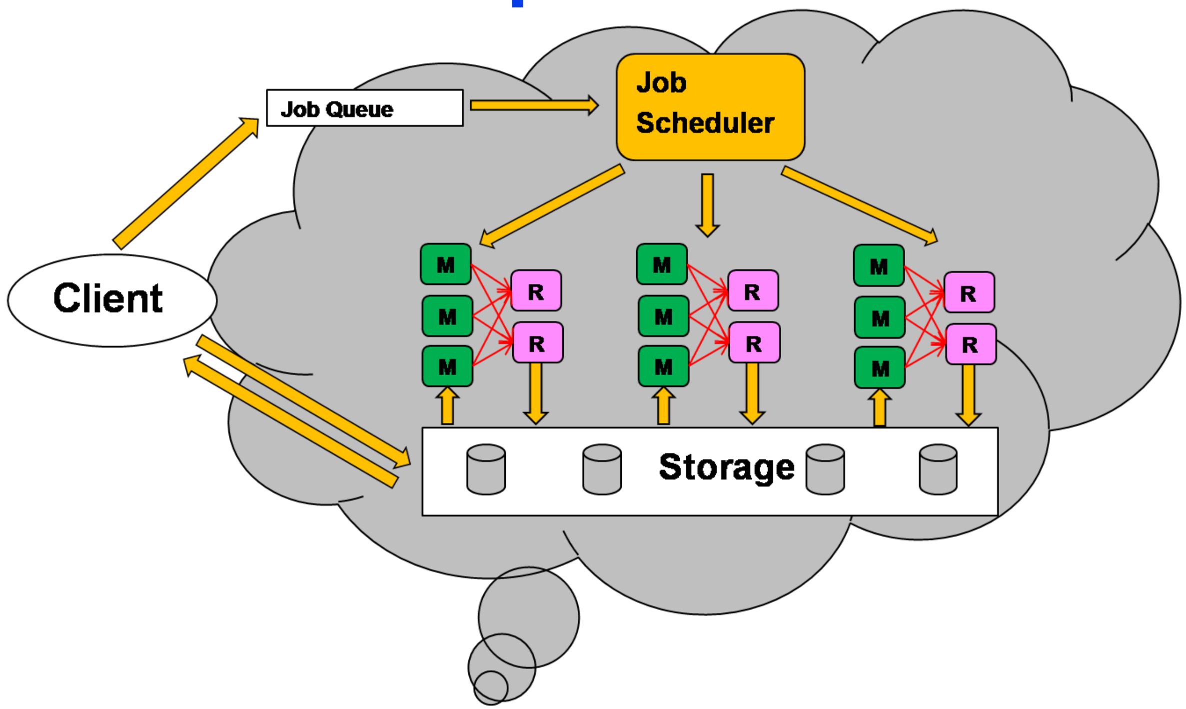
Relational Data Processing on MapReduce



http://www.csd.uoc.gr/~hy562

University of Crete

Peta-scale Data Analysis

12+ TBs **of tweet data every day**

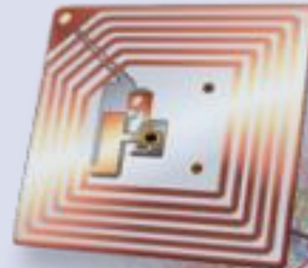
? TBs **of data every day**

25+ TBs **of log data every day generated by a new user being added every sec. for 3 years**

4 billion views/day

YouTube is the 2nd most used search engine next to Google

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**

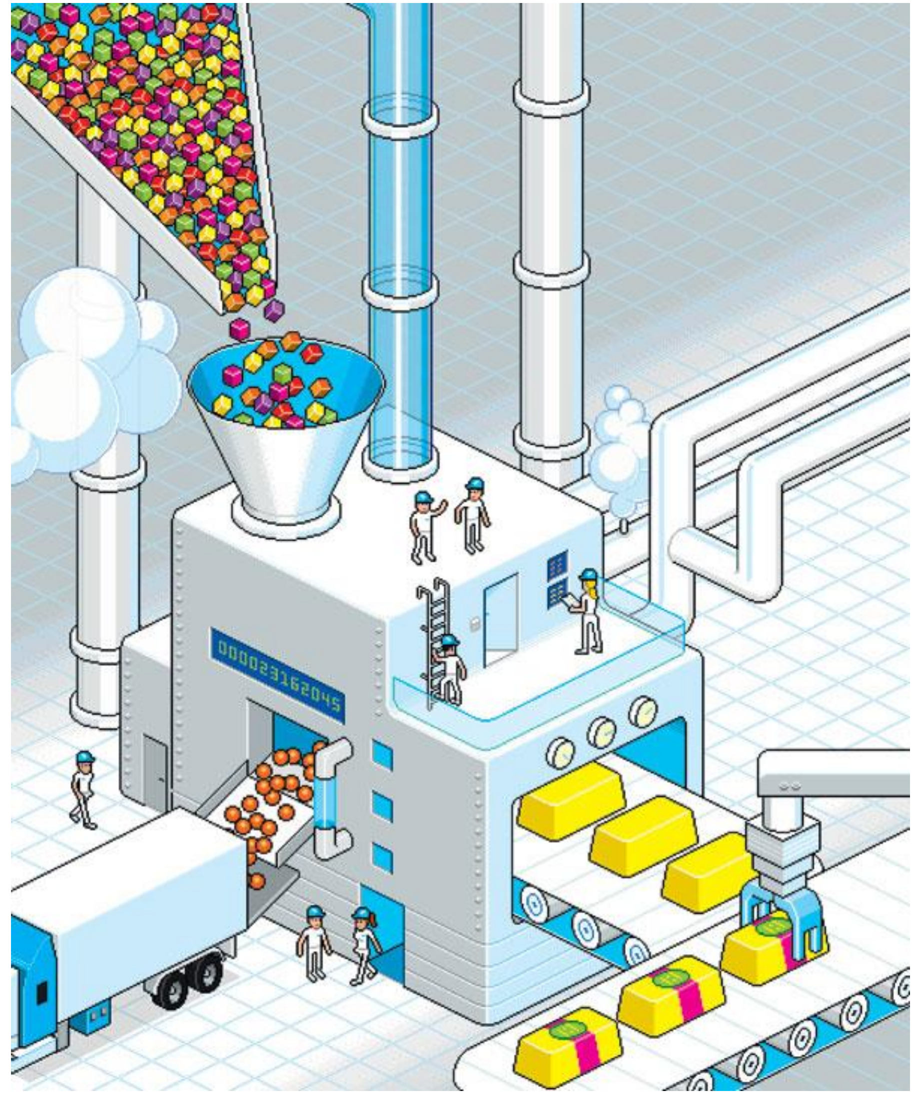
76 million **smart meters in 2009… 200M by 2014**

2+ billion **people on the Web by end 2011**

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:
  - Multi-purpose: 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

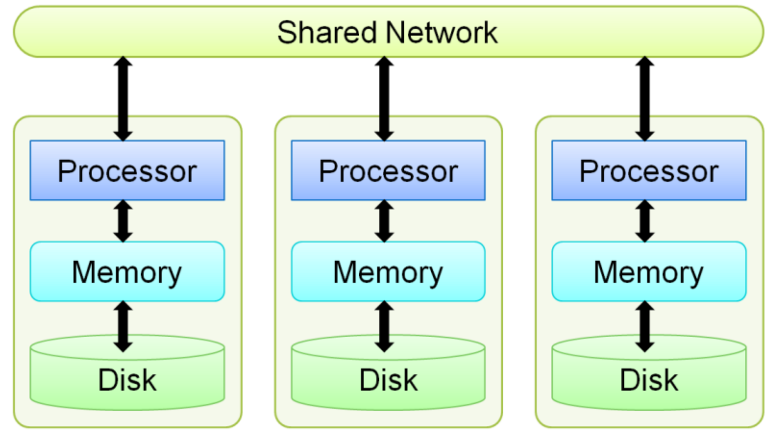
- MapReduce (Hadoop):
  - Designed for large clusters, fault tolerant
  - Data is accessed in “native format”
  - Supports many query languages
  - Programmers retain control over performance

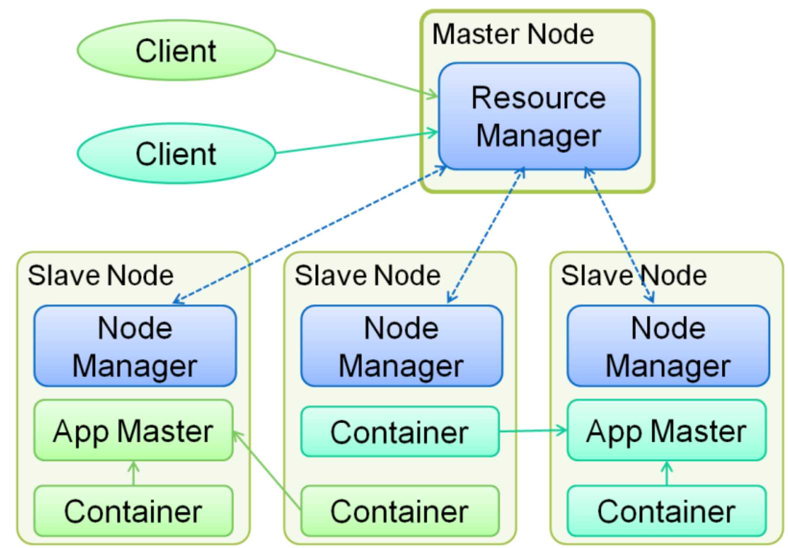
Parallel Relational Databases vs. MapReduce

- 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

Shared-nothing architecture for parallel processing





Hadoop v2.0 (YARN) architecture

MapReduce vs Parallel DBMS

	Parallel DBMS	MapReduce
Schema Support	✓	Not out of the box
Indexing	✓	Not out of the box
Programming Model	Declarative (SQL)	Imperative (C/C++, Java, …) Extensions through Pig and Hive
Optimizations (Compression, Query Optimization)	✓	Not out of the box
Flexibility	Not out of the box	✓
Fault Tolerance	Coarse grained techniques	✓

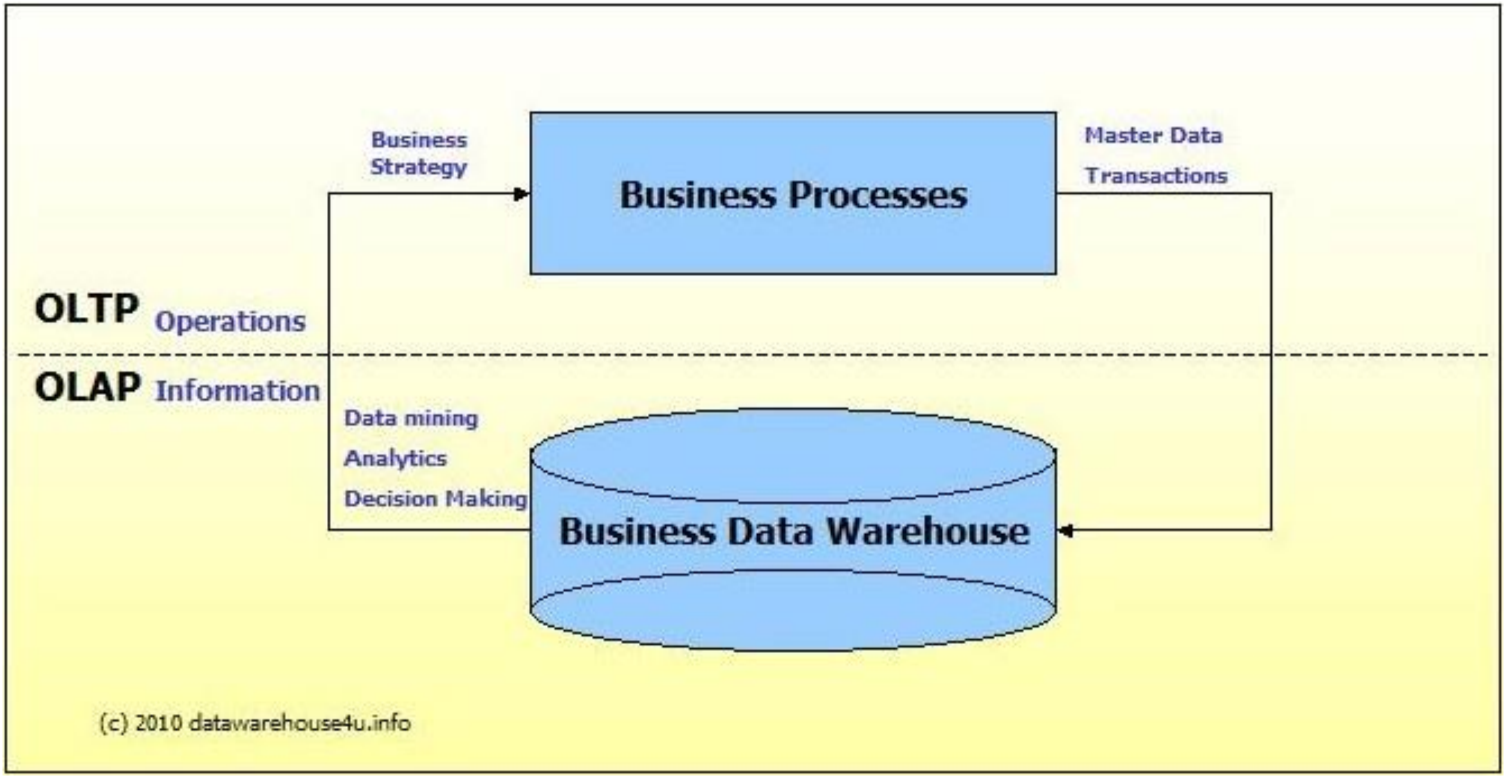
[Pavlo et al., SIGMOD 2009, Stonebraker et al., CACM 2010, …]

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

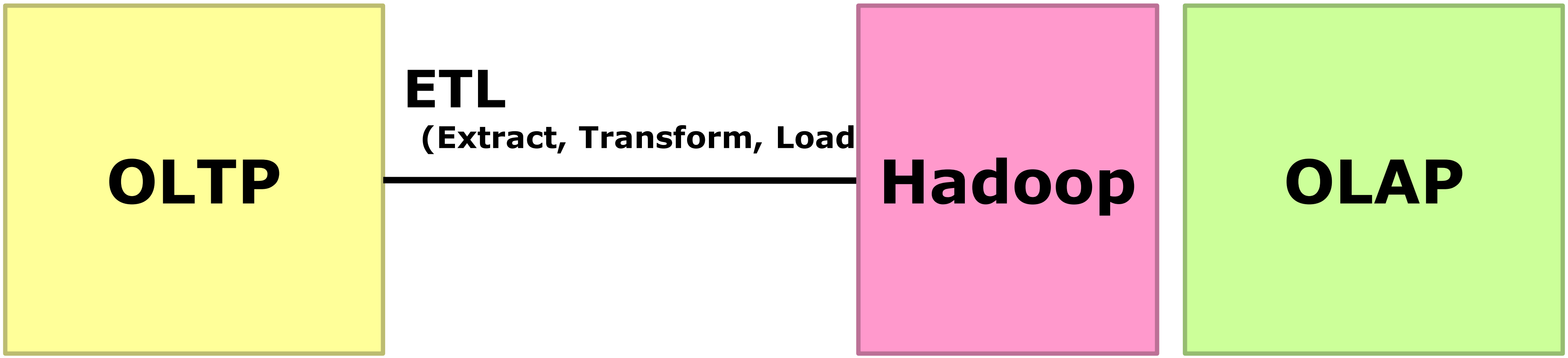
- OLTP database for user-facing transactions
  - Retain records of all activity
  - Periodic ETL (e.g., nightly)
- Extract-Transform-Load (ETL)
  - Extract records from source
  - Transform: clean data, check integrity, aggregate, etc.
  - Load into OLAP database
- OLAP database for data warehousing
  - Business intelligence: reporting, ad hoc queries, data mining, etc.
  - Feedback to improve OLTP services

OLTP/OLAP Architecture: Hadoop?

What about here?

Hadoop here?

OLTP/OLAP/Hadoop Architecture



- Why does this make sense?

ETL Bottleneck

- Reporting is often a nightly task:
  - ETL is often slow
    - processing 24 h of data may take longer than 24 h!
- Often, with noisy datasets, ETL is the analysis!
  - ETL necessarily involves brute-force data scans: L, then E and T?
- Using Hadoop:
  - 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!

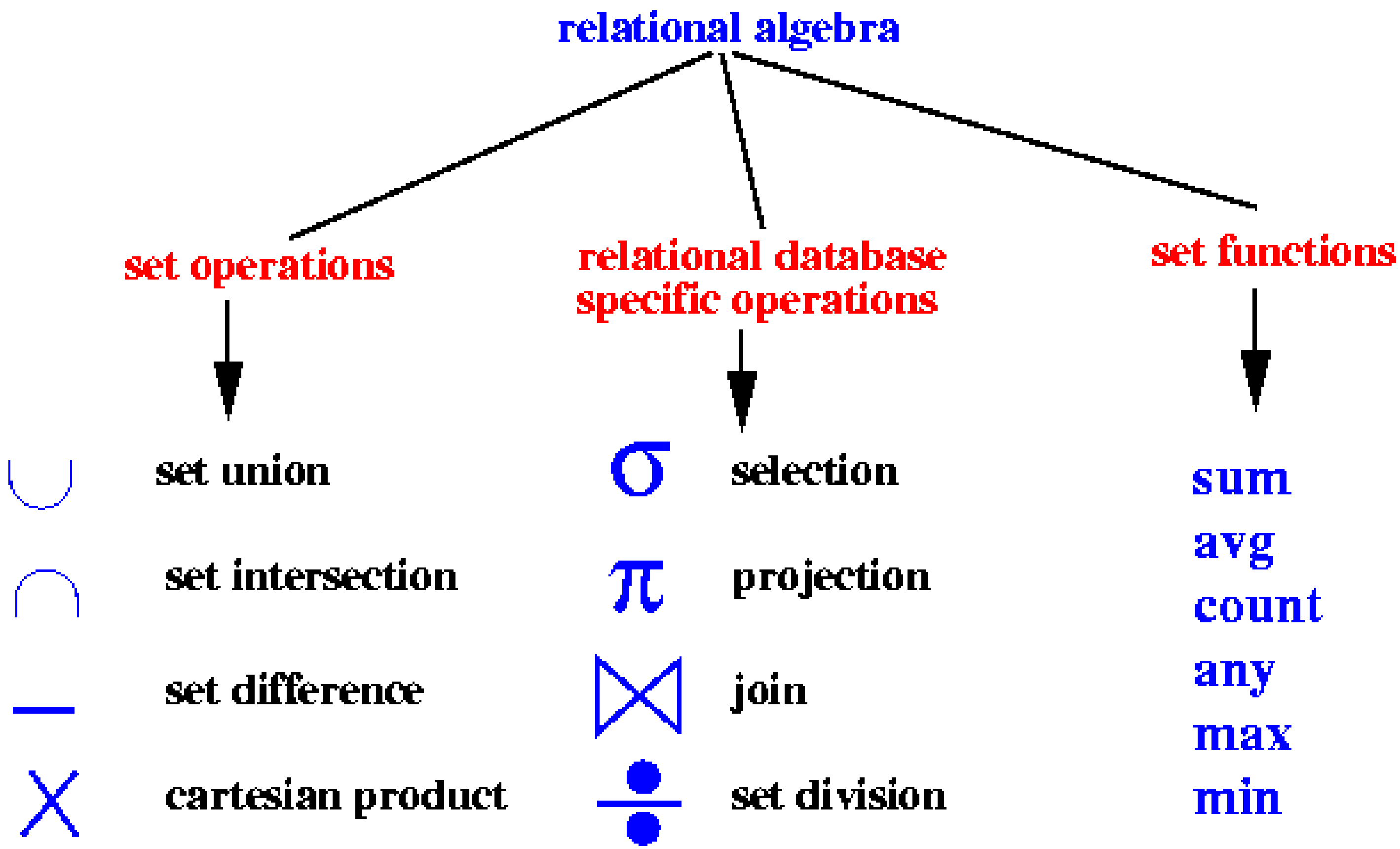
MapReduce Algorithms for Processing Relational Data

Working Scenario

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

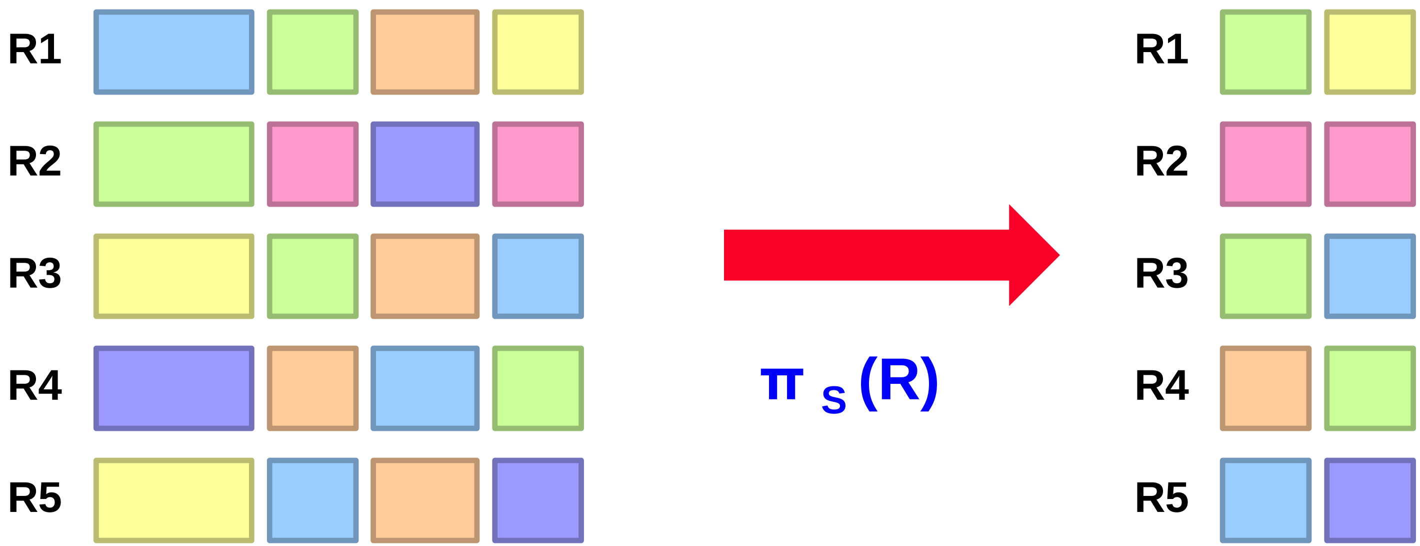
- Analyses we might want to perform:
  - Statistics on demographic characteristics
  - Statistics on page visits
  - Statistics on page visits by URL
  - Statistics on page visits by demographic characteristic
  - …

Relational Algebra



www.mathcs.emory.edu/~cheung/Courses/377/Syllabus/4-RelAlg/intro.html

Projection

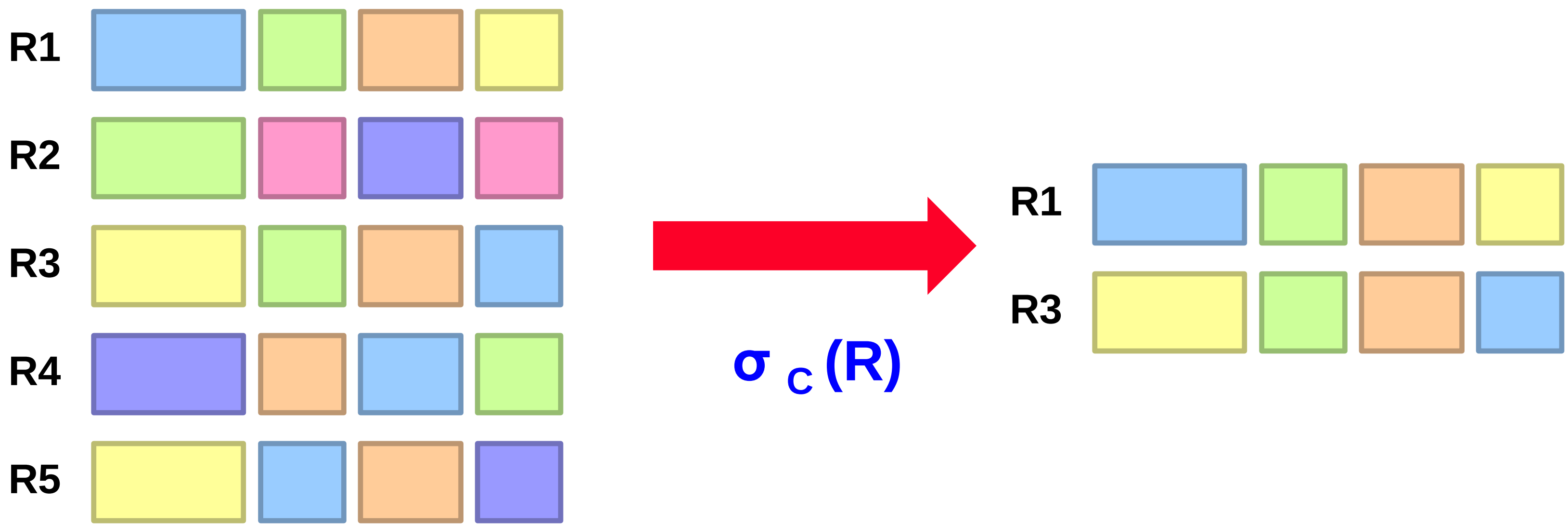


Projection in MapReduce

- 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



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)
      - *equivalent in Spark: filter()*
  - 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*
  - Semi-structured data? No problem!

Set Operations in Map Reduce

- R(X,Y) ∪ 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) ∩ 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)

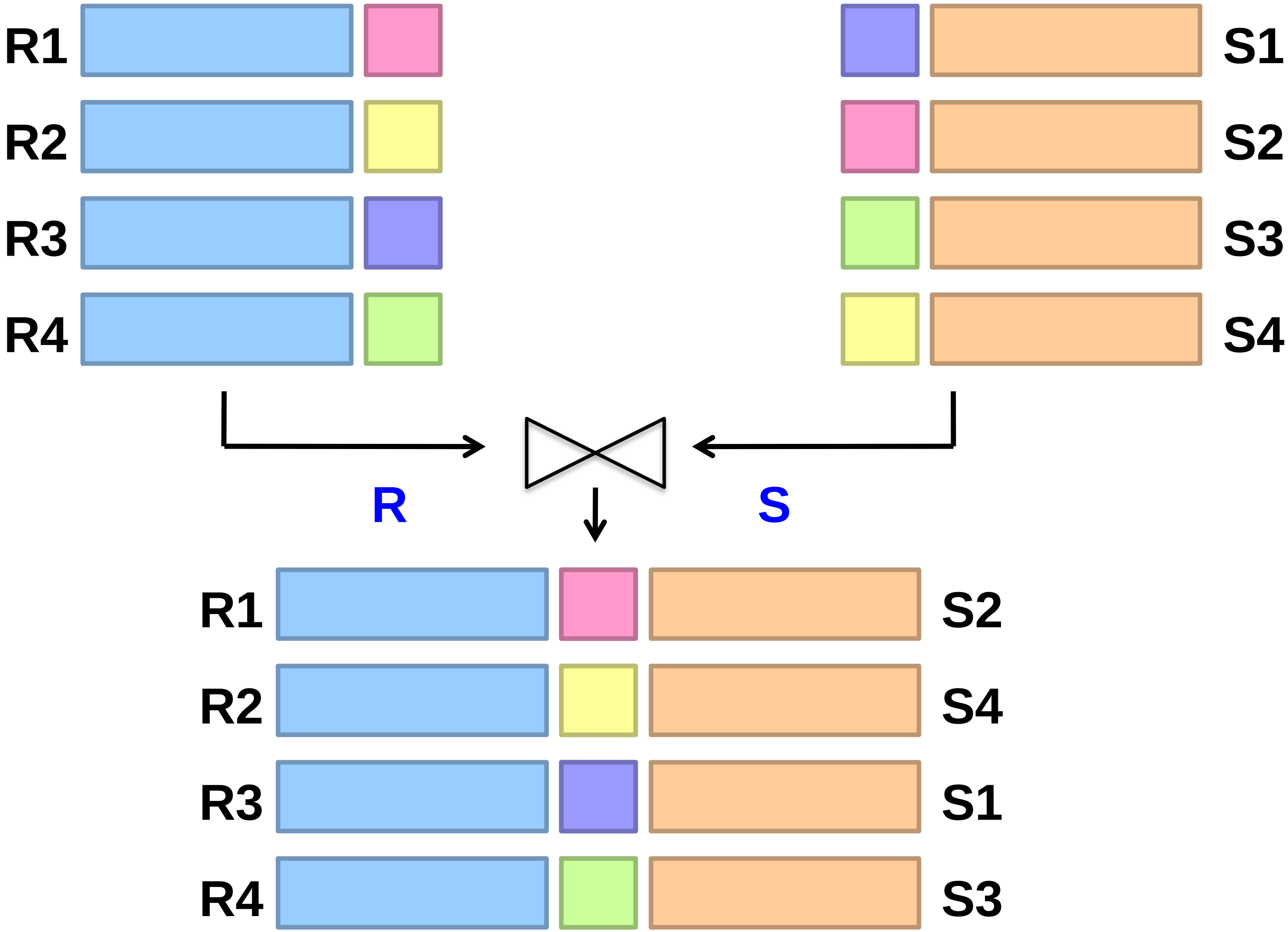
Group by… Aggregation

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

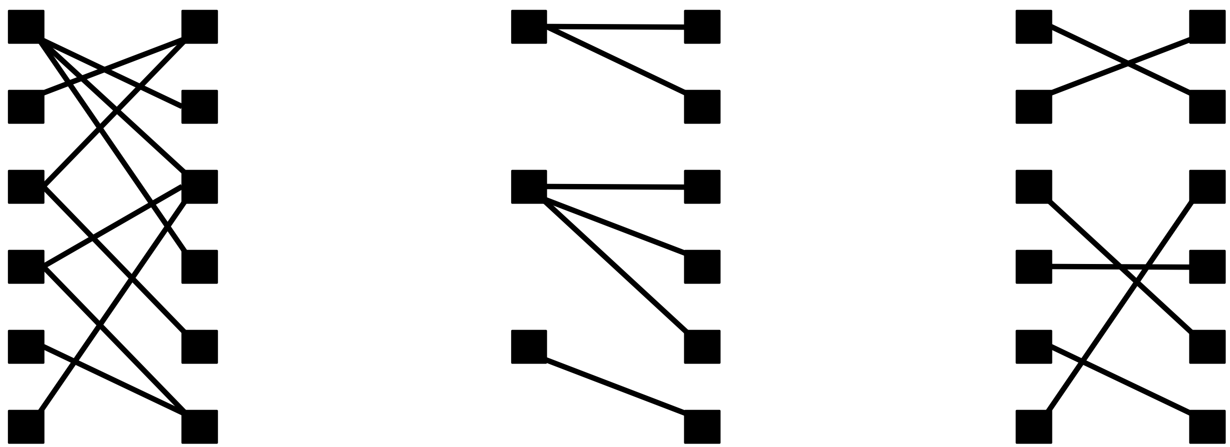
- In SQL:
  - `SELECT url, AVG(time) FROM visits GROUP BY url`

- In MapReduce: Let R(A, B, C) be a relation to which we apply $\gamma_{A,\theta(B)}(R)$
  - The map operation prepares the grouping e.g., emit (url, time) pairs
  - 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



Types of Relationships

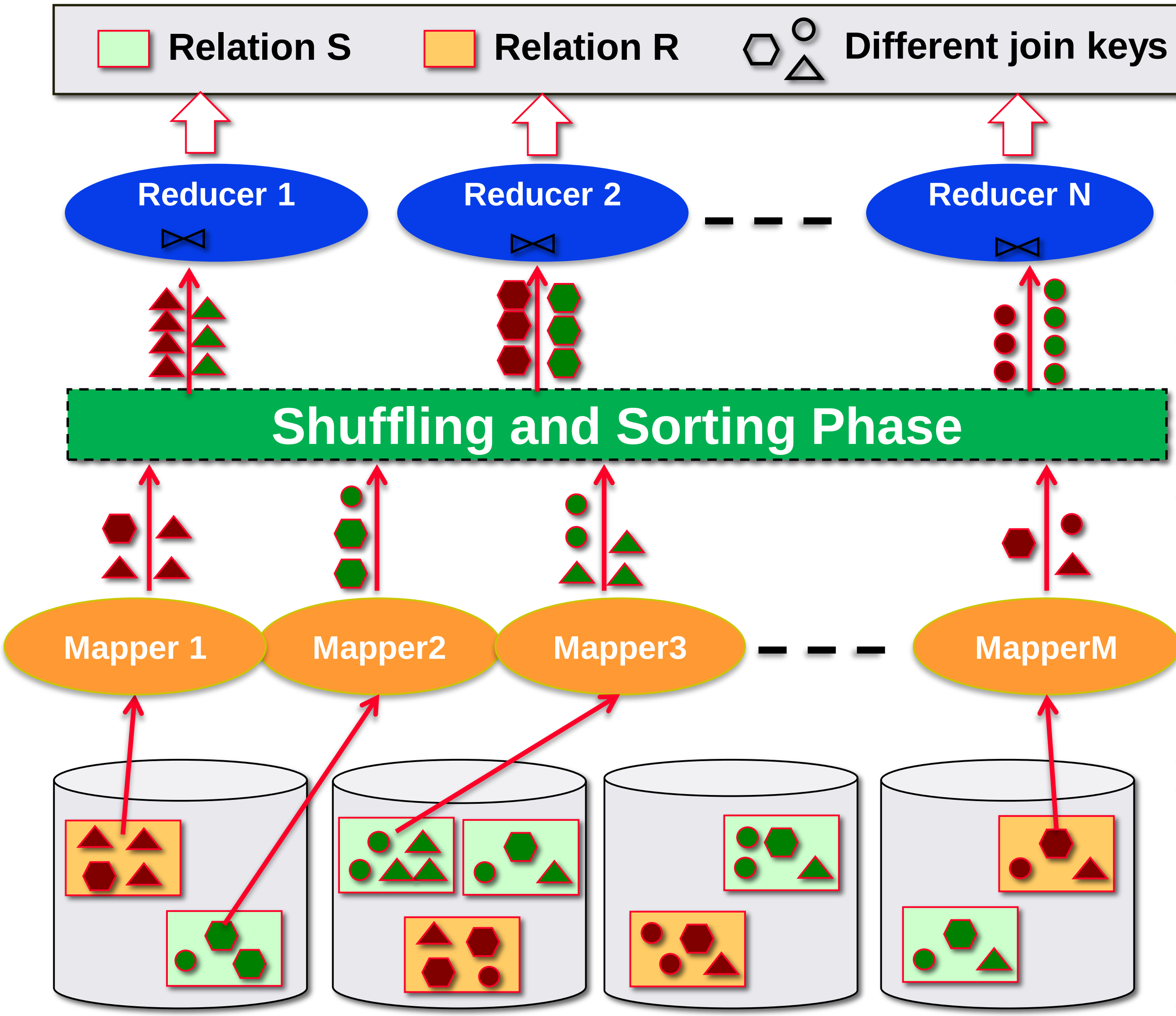


Many-to-Many **One-to-Many** **One-to-One**

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

Reduce-side Join



Reducers perform the actual join

Shuffling and sorting over the network

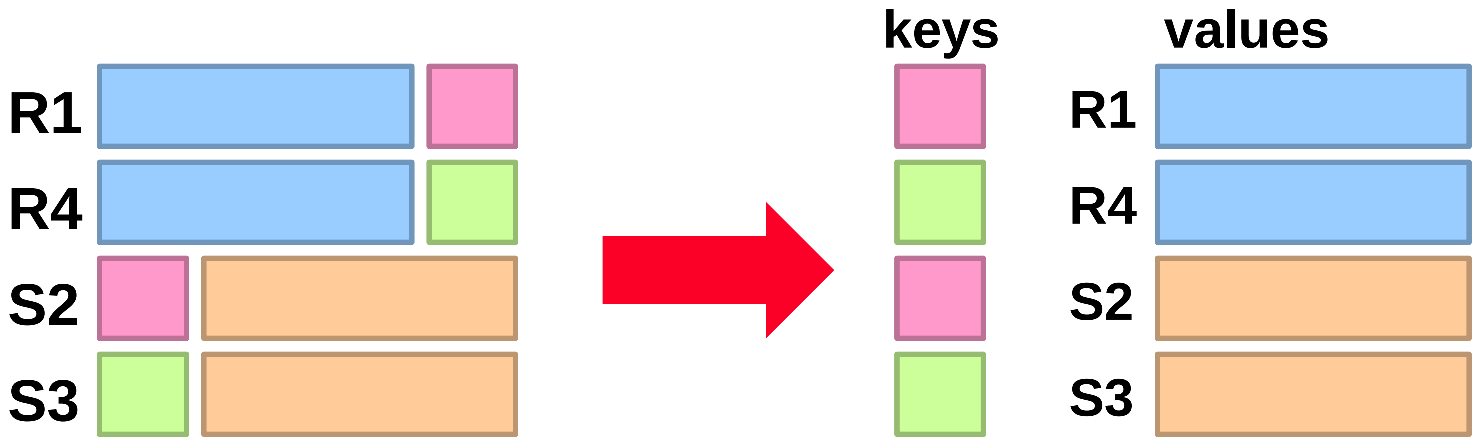
- Each mapper processes one block (split)

- Each mapper produces the join key and the record pairs

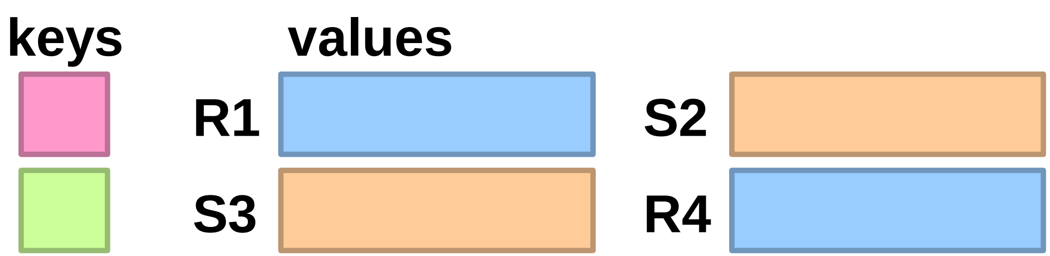
HDFS stores data blocks (Replicas are not shown)

Reduce-side Join: 1-to-1

Map

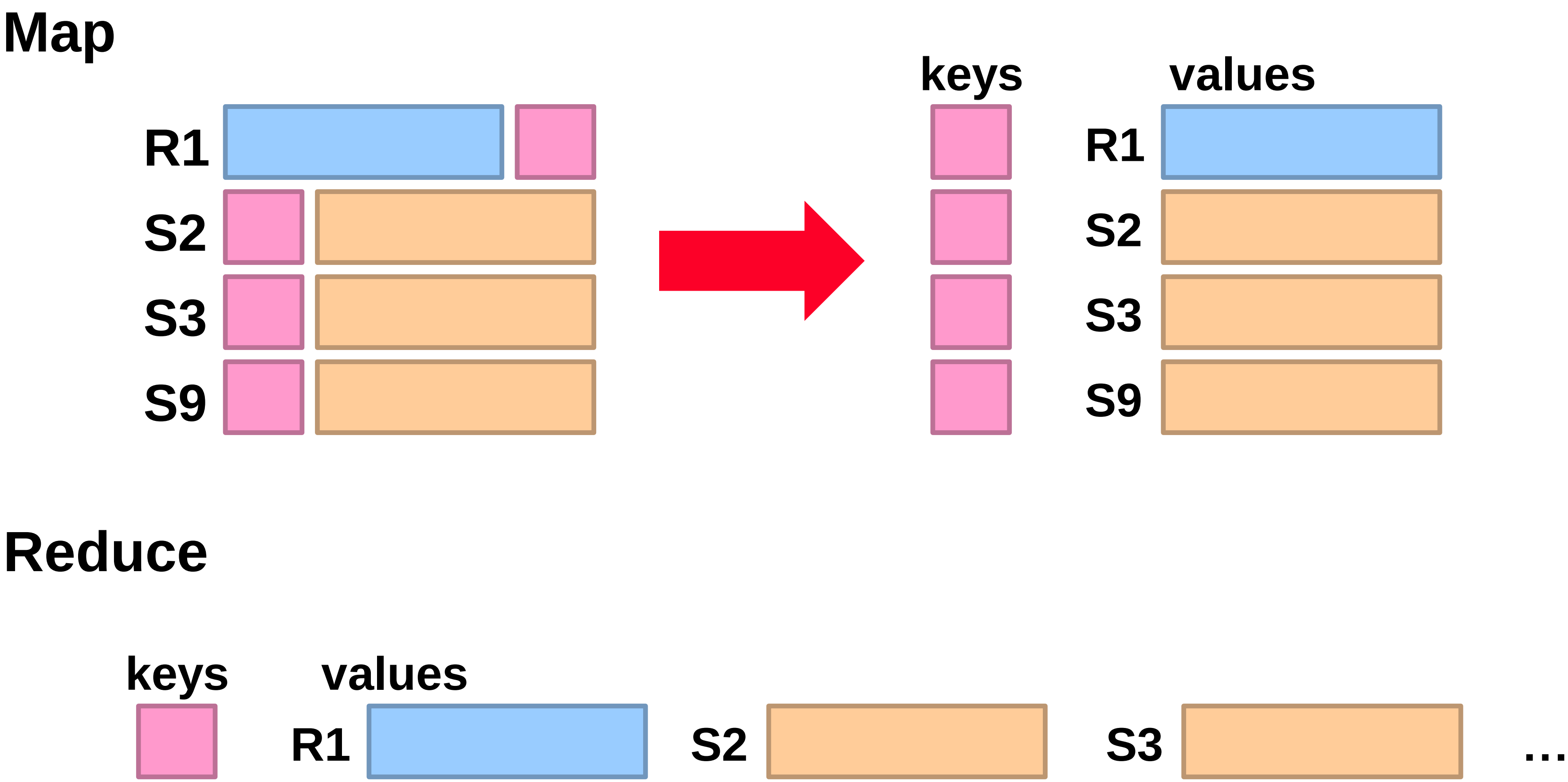


Reduce



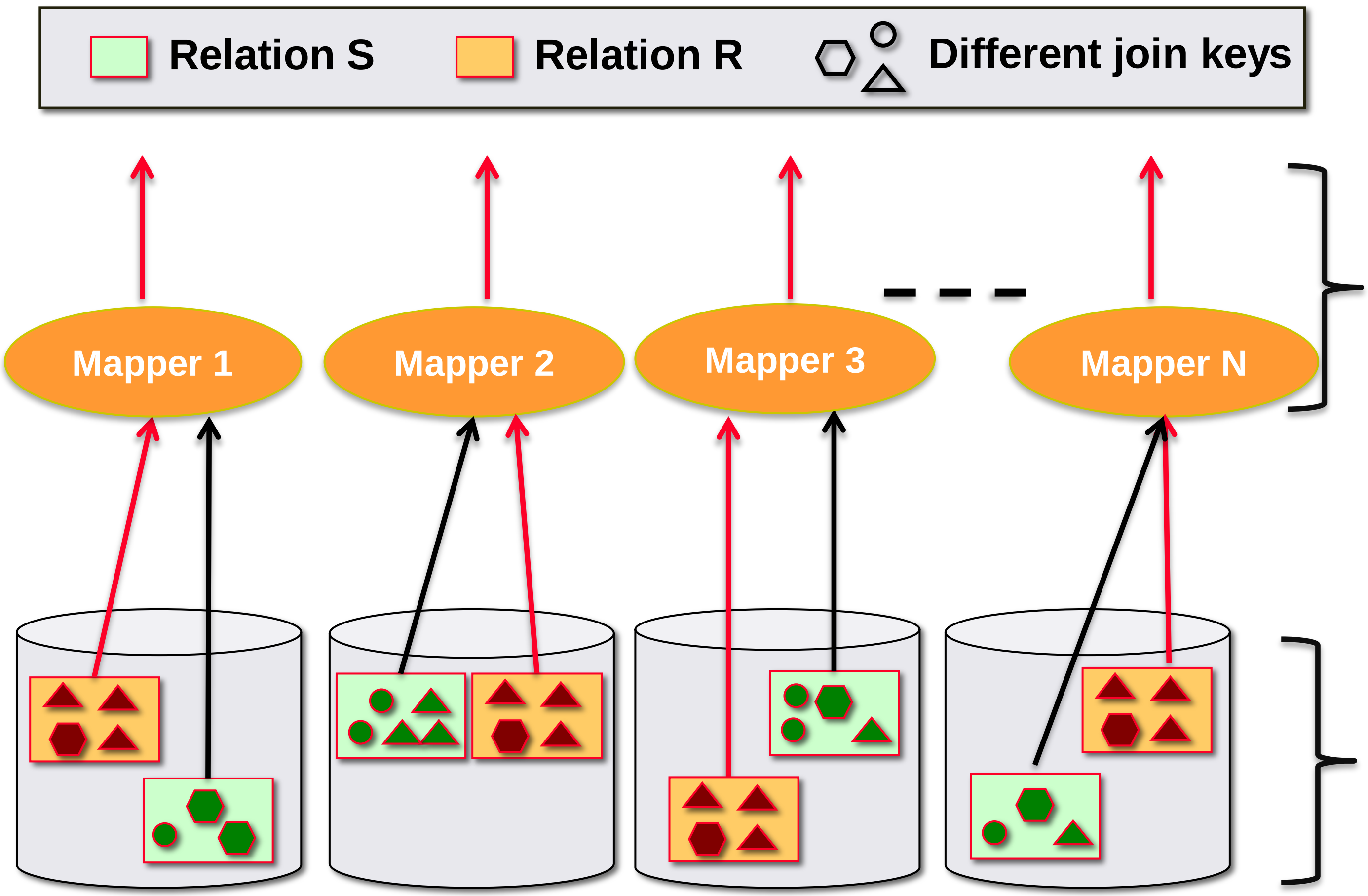
Note: no guarantee if R is going to come first or S!

Reduce-side Join: 1-to-Many



- What's the problem?
  - R is the one side, S is the many

Map-side (in-memory) Join



Load one dataset into memory, stream over other dataset

Distribute the smaller relation to all nodes

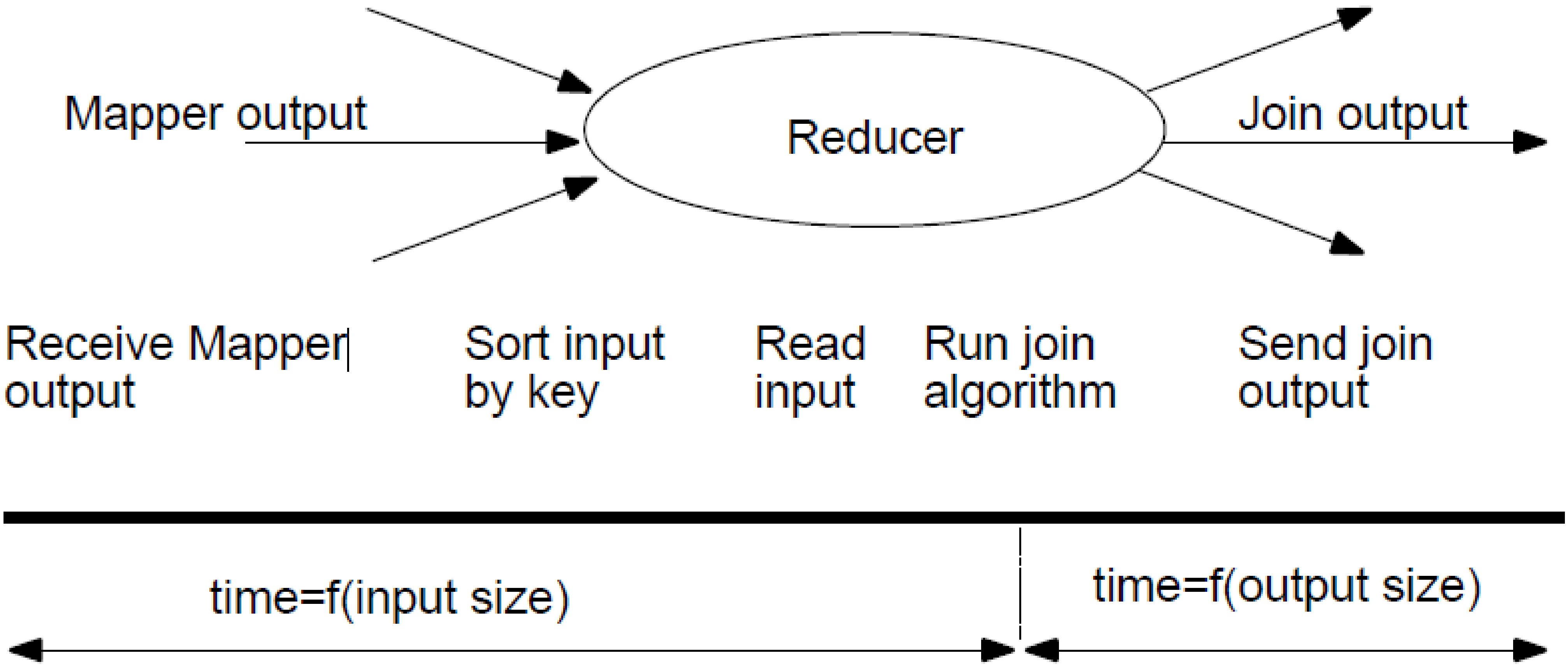
Map-side (in-memory) Join

- 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

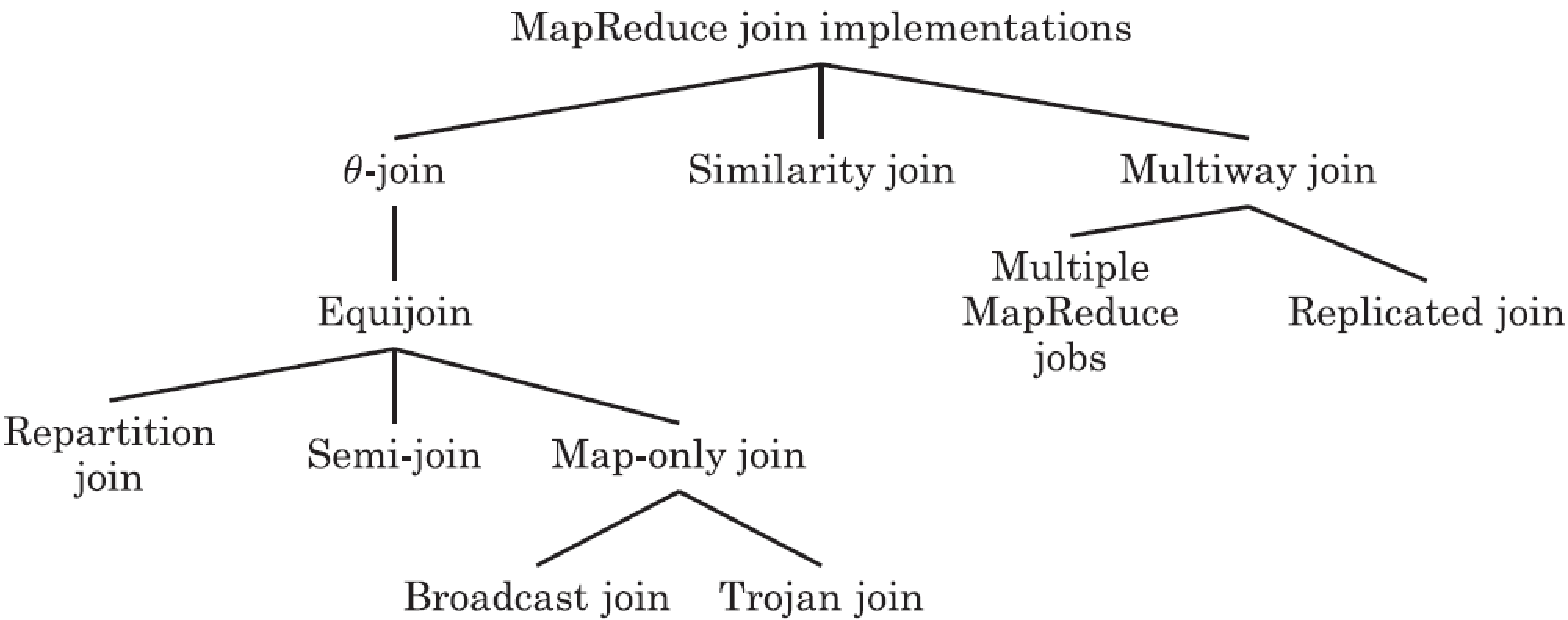
- Downside: need to copy R to all mappers
  - Not so bad, since R is small

Reducer-Centric Cost Model

- Difference between join implementations starts with Map output



Join Implementations on MapReduce



Feng Li, Beng Chin Ooi, M. Tamer Özsu, and Sai Wu. 2014. Distributed data management using MapReduce. ACM Comput. Surv. 46, 3, January 2014

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

Evolving Roles for Relational Database and MapReduce

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

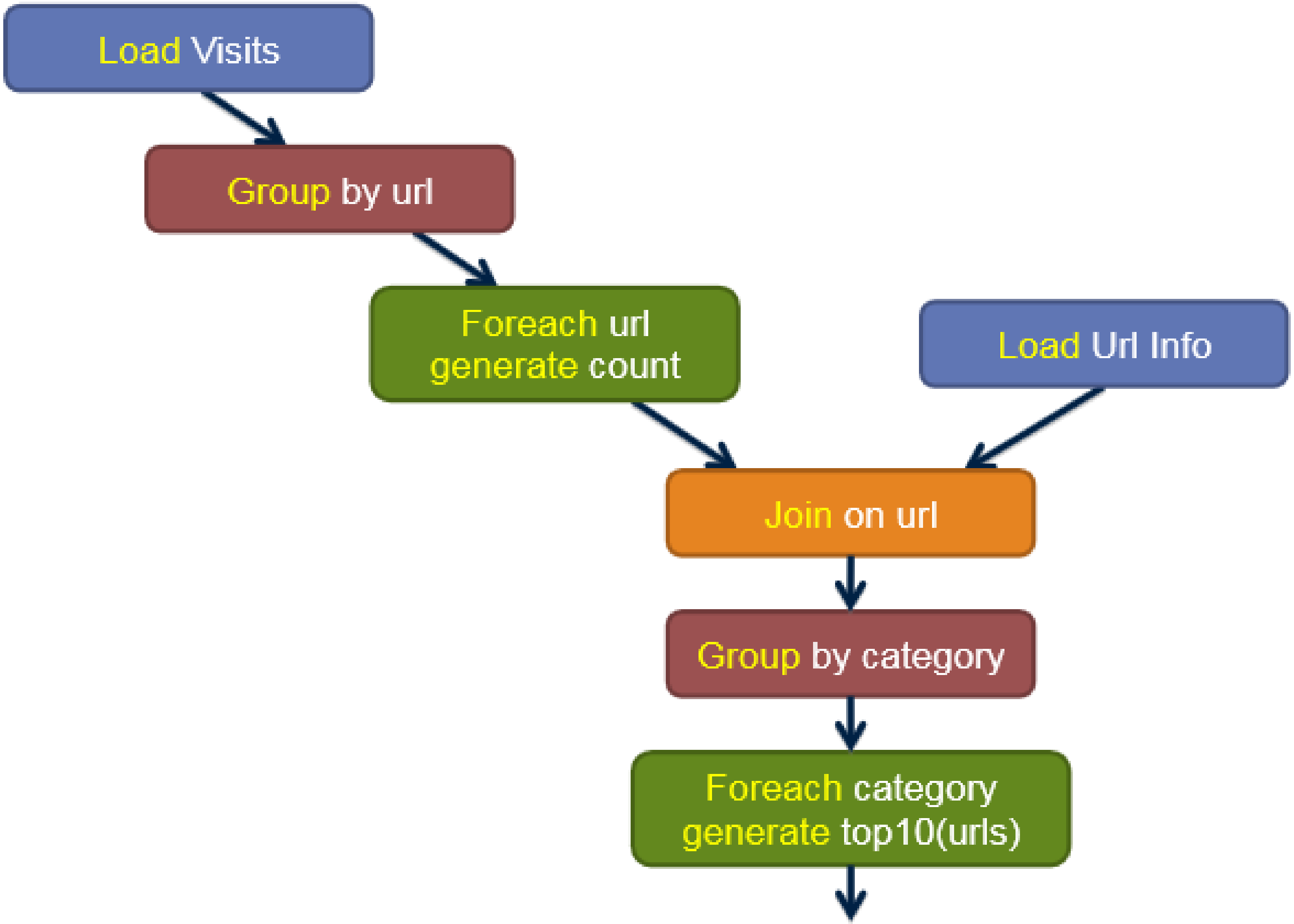
⋮

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 Query Plan

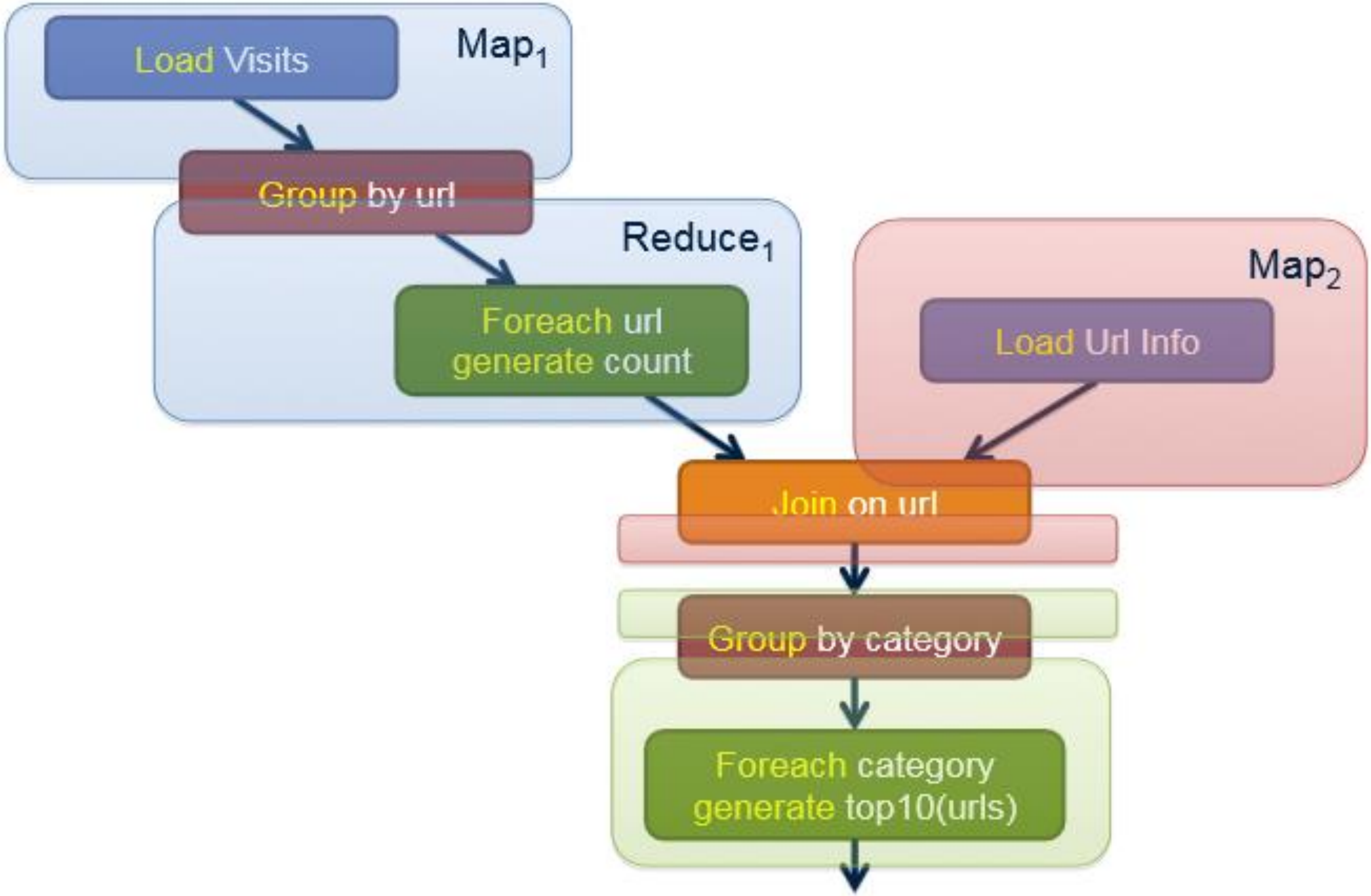


Pig Script

```
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 Query Plan



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