# Big Data Infrastructure

CS 489/698 Big Data Infrastructure (Winter 2016)

## Week 7: Analyzing Relational Data (2/3)

February 23, 2016

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These slides are available at http://lintool.github.io/bigdata-2016w/

facebook®

Jeff Hammerbacher, Information Platforms and the Rise of the Data Scientist.
In, *Beautiful Data*, O'Reilly, 2009.

"On the first day of logging the Facebook clickstream, more than 400 gigabytes of data was collected. The load, index, and aggregation processes for this data set really taxed the Oracle data warehouse. Even after significant tuning, we were unable to aggregate a day of clickstream data in less than 24 hours."

SQL-on-Hadoop

**"OLTP"** —**ELT**→ **Hadoop**

What not just use a database to begin with?

Cost + Scalability

## Databases are great…

If your data has structure (and you know what the structure is)

If your data is reasonably clean

If you know what queries you're going to run ahead of time

## Databases are not so great…

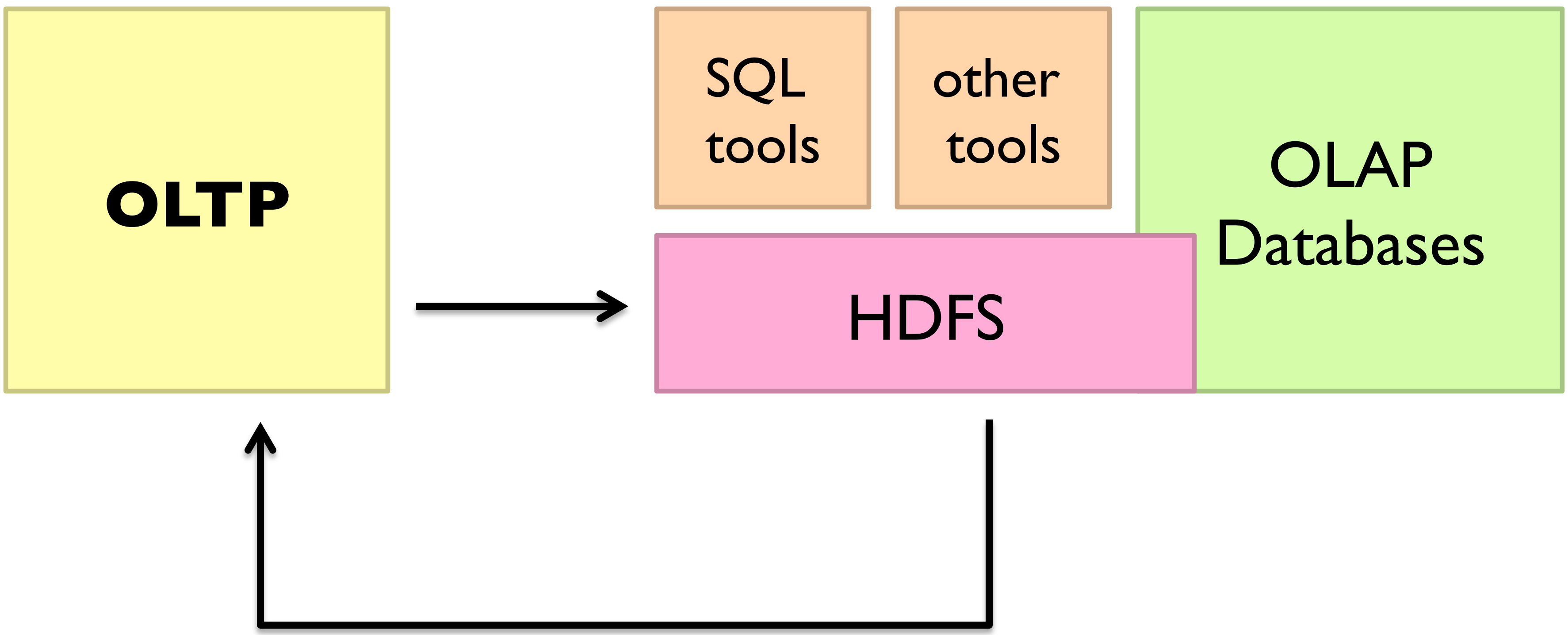
If your data has little structure (or you don't know the structure)

If your data is messy and noisy

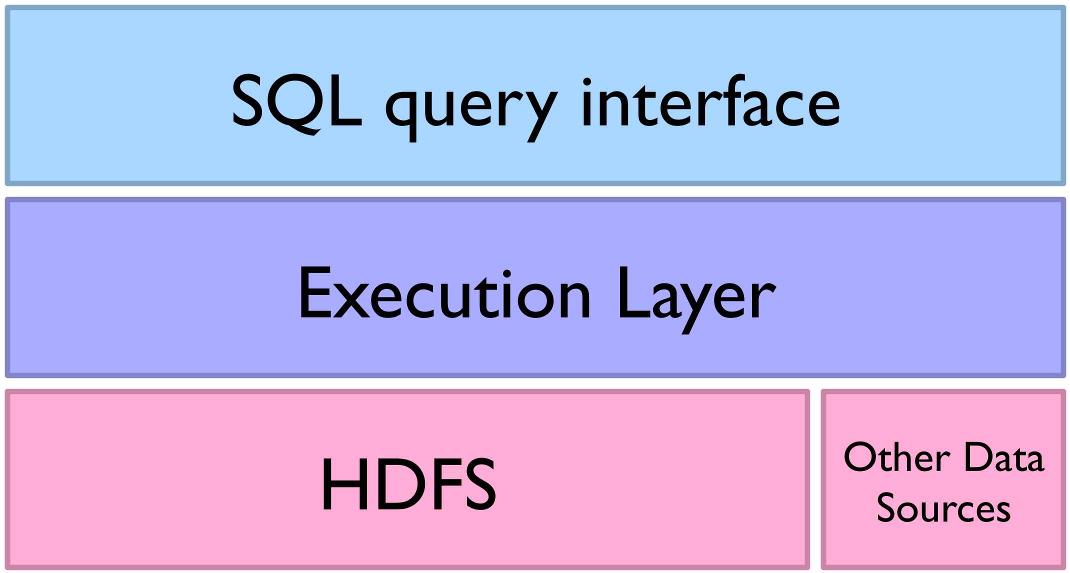
If you don't know what you're looking for

# What's the selling point of SQL-on-Hadoop?

## Trade (a little?) performance for flexibility



# SQL-on-Hadoop



# Hive: Example

- 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
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(Abstract Syntax Tree)

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(TOK_QUERY (TOK_FROM (TOK_JOIN (TOK_TABREF shakespeare s) (TOK_TABREF bible k) (= (. (TOK_TABLE_OR_COL s)
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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
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                  type: boolean
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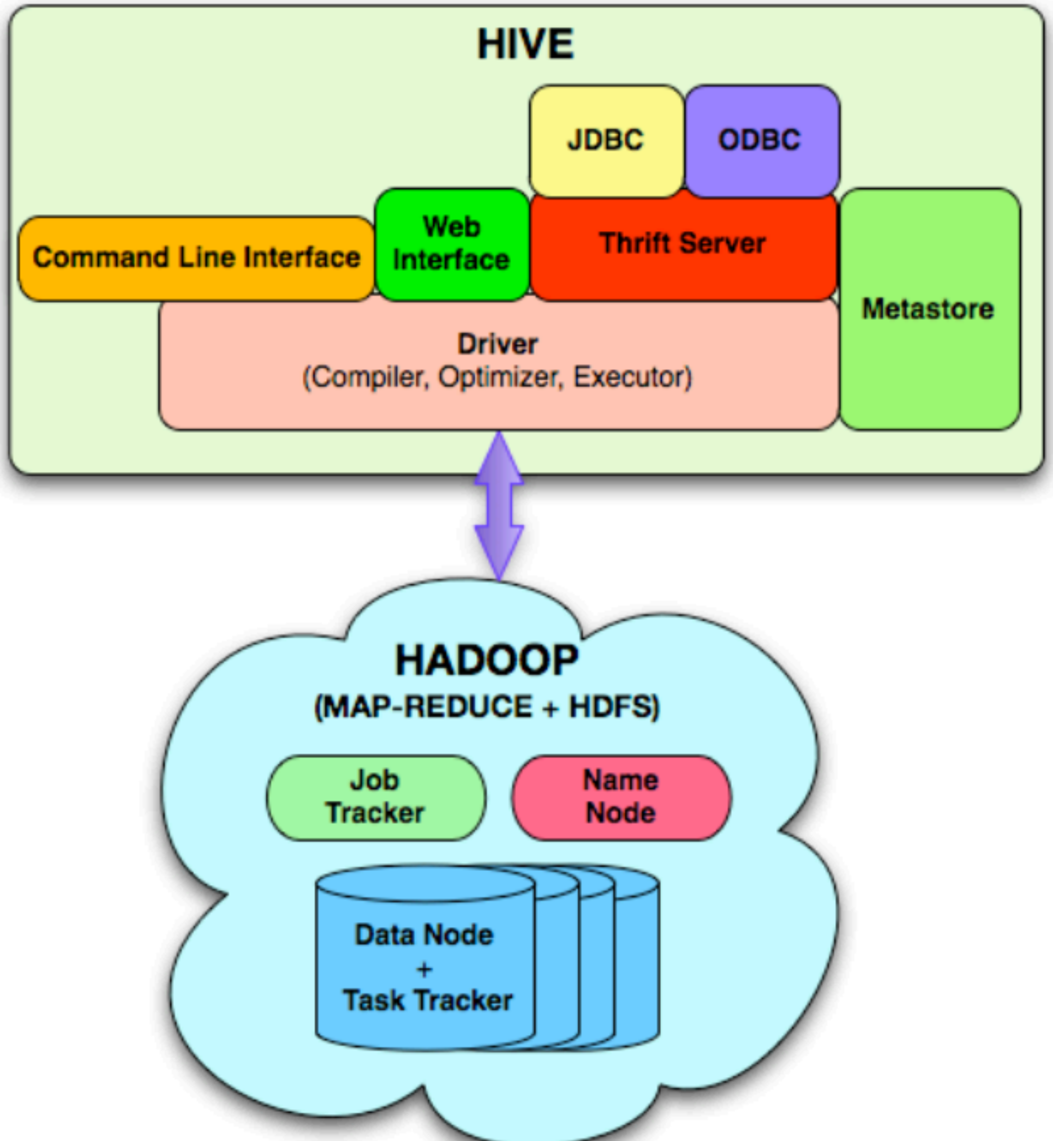
            1 {VALUE._col0}
          outputColumnNames: _col0, _col1, _col2
          Filter Operator
            predicate:
                expr: ((_col0 >= 1) and (_col2 >= 1))
                type: boolean
            Select Operator
              expressions:
                    expr: _col1
                    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
```

# Hive Architecture

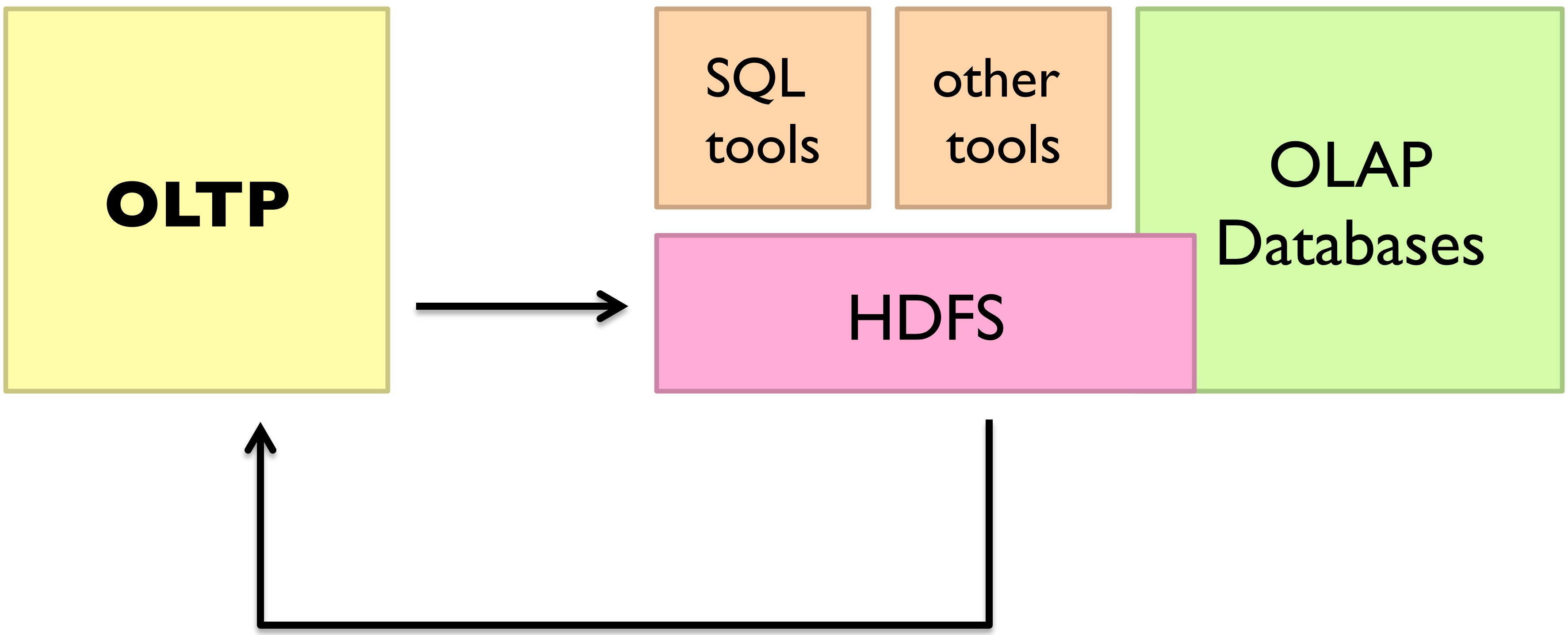


# Hive Implementation

- Metastore holds metadata
  - Databases, tables
  - Schemas (field names, field types, etc.)
  - Permission information (roles and users)
- Hive data stored in HDFS
  - Tables in directories
  - Partitions of tables in sub-directories
  - Actual data in files (plain text or binary encoded)

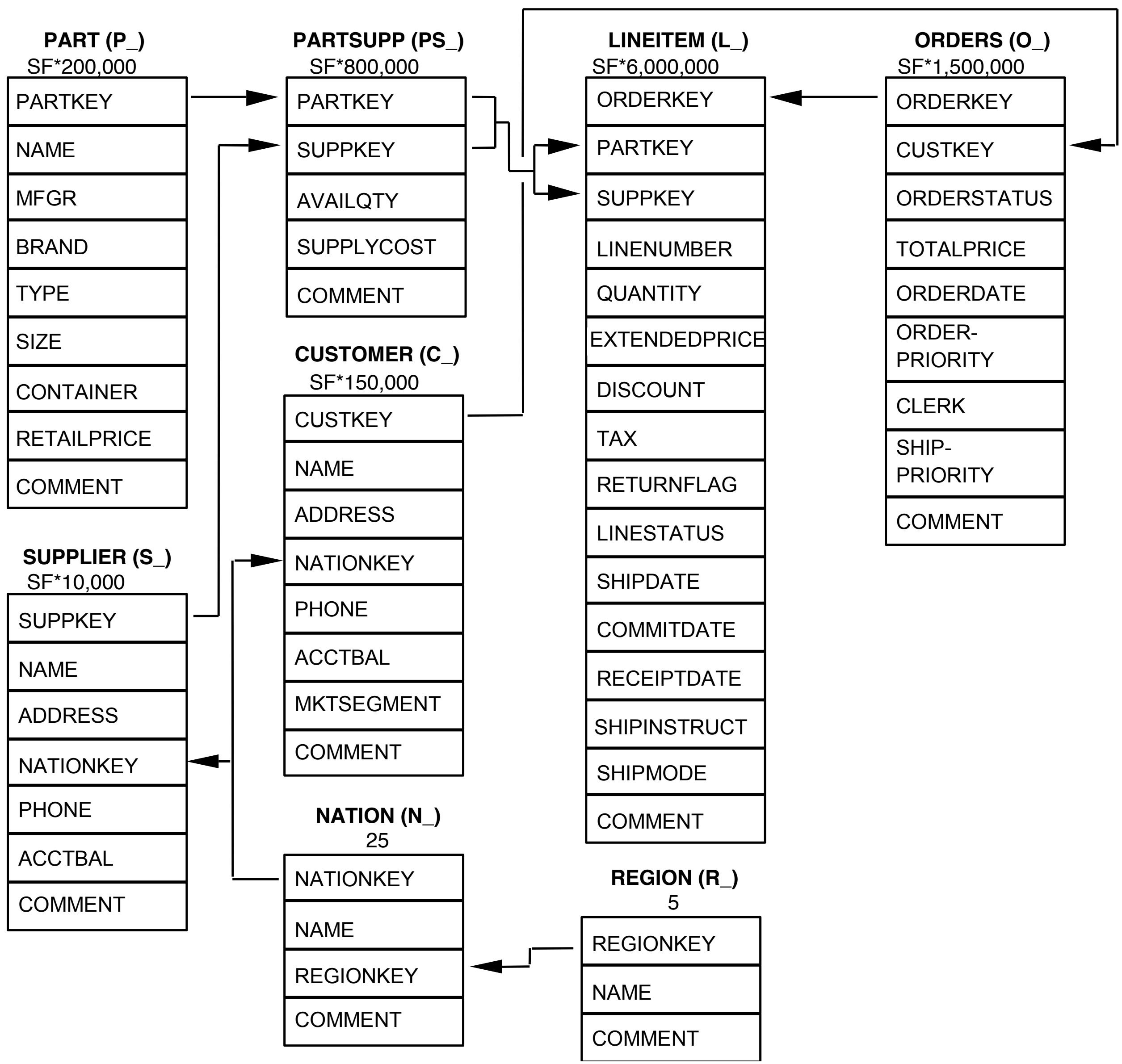
**Feature or bug?**

(this is the essence of SQL-on-Hadoop)



OLTP
SQL tools
other tools
OLAP Databases
HDFS

# TPC-H Data Warehouse



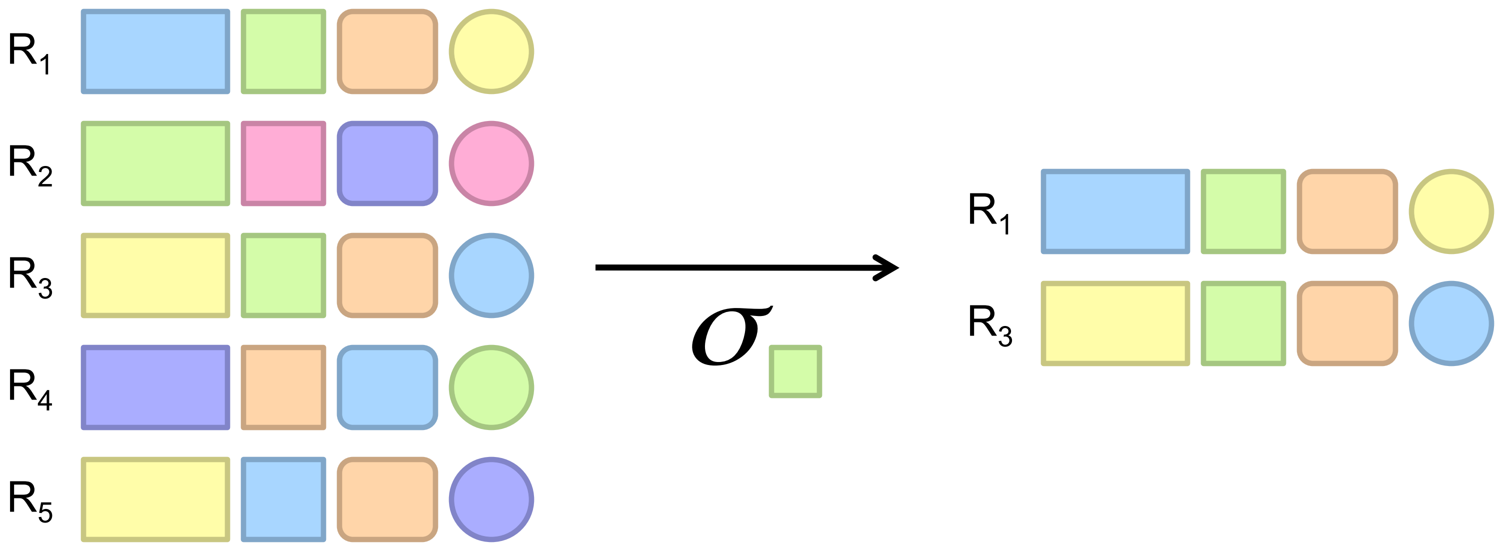
# MapReduce algorithms for processing relational data

Source: www.flickr.com/photos/stikatphotography/1590190676/

# Relational Algebra

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

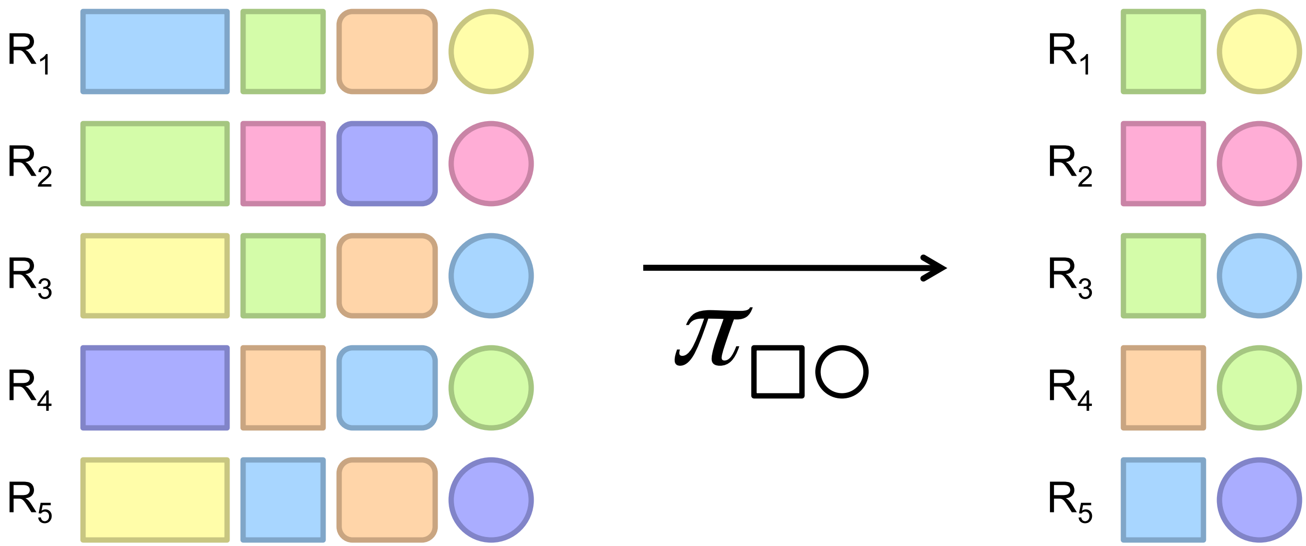
# Selection



# Selection in MapReduce

- Easy!
  - In mapper: process each tuple, only emit tuples that meet criteria
  - Can be pipelined with projection
  - No reducers necessary (unless to do something else)
- Performance mostly limited by HDFS throughput
  - Speed of encoding/decoding tuples becomes important
  - Take advantage of compression when available
  - Semistructured data? No problem!

# Projection



# Projection in MapReduce

- Easy!
  - In mapper: process each tuple, re-emit with only projected attributes
  - Can be pipelined with selection
  - No reducers necessary (unless to do something else)
- Implementation detail: bookkeeping required
  - Need to keep track of attribute mappings after projection
    e.g., name was r[4], becomes r[1] after projection
- Performance mostly limited by HDFS throughput
  - Speed of encoding/decoding tuples becomes important
  - Take advantage of compression when available
  - Semistructured data? No problem!

# Group by… Aggregation

- Aggregation functions:
  - AVG
  - MAX
  - MIN
  - SUM
  - COUNT
  - …
- MapReduce implementation:
  - Map over dataset, emit tuples, keyed by group by attribute
  - Framework automatically groups values by group by attribute
  - Compute aggregation function in reducer
  - Optimize with combiners, in-mapper combining

**You already know how to do this!**

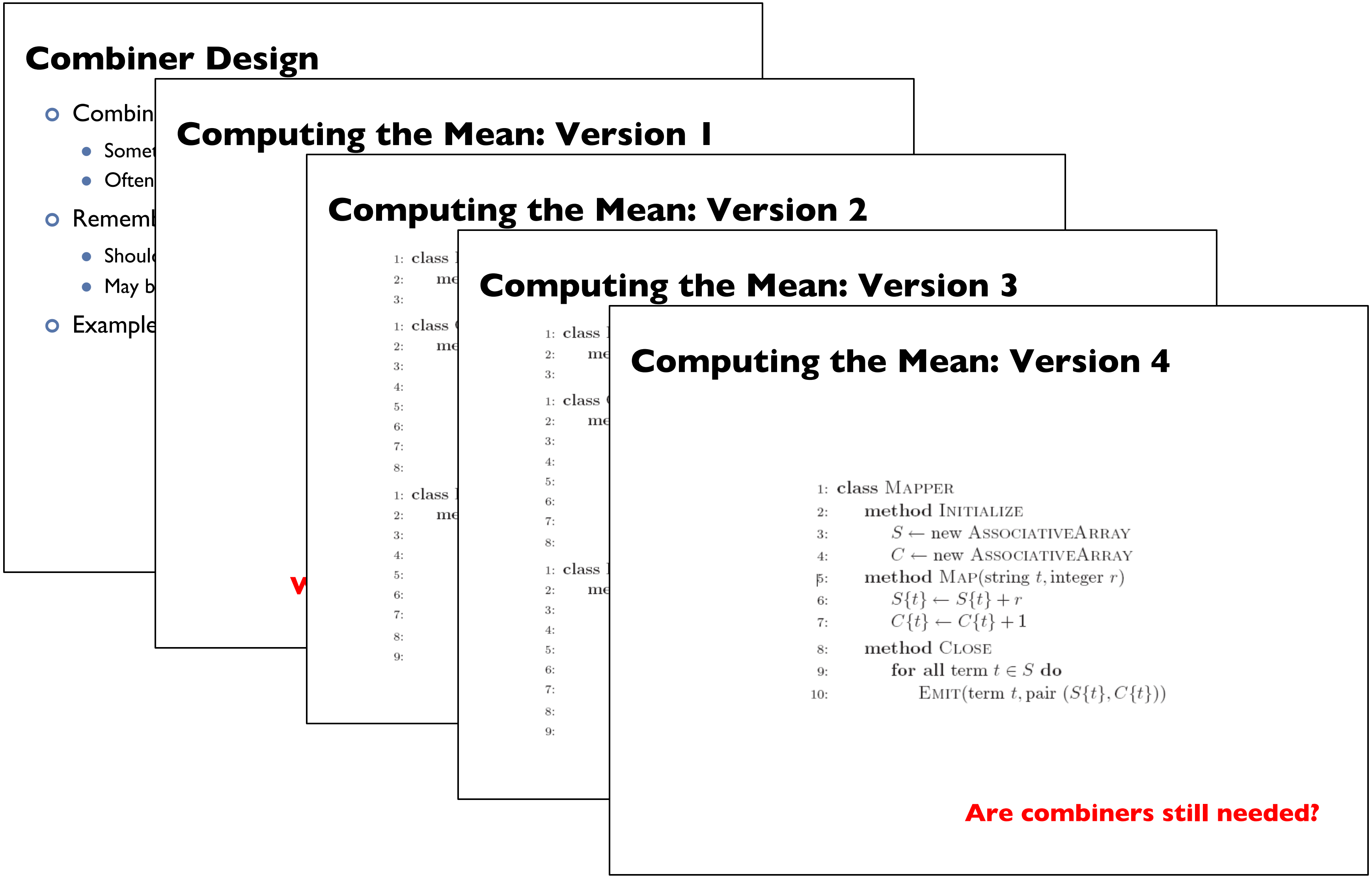
Remember this?
(week 2)

## Combiner Design

- Combiners and reducers share same method signature
  - Sometimes, reducers can serve as combiners
  - Often, not…
- Remember: combiner are optional optimizations
  - Should not affect algorithm correctness
  - May be run 0, 1, or multiple times
- Example: find average of integers associated with the same key

**Remember this?** (week 2)

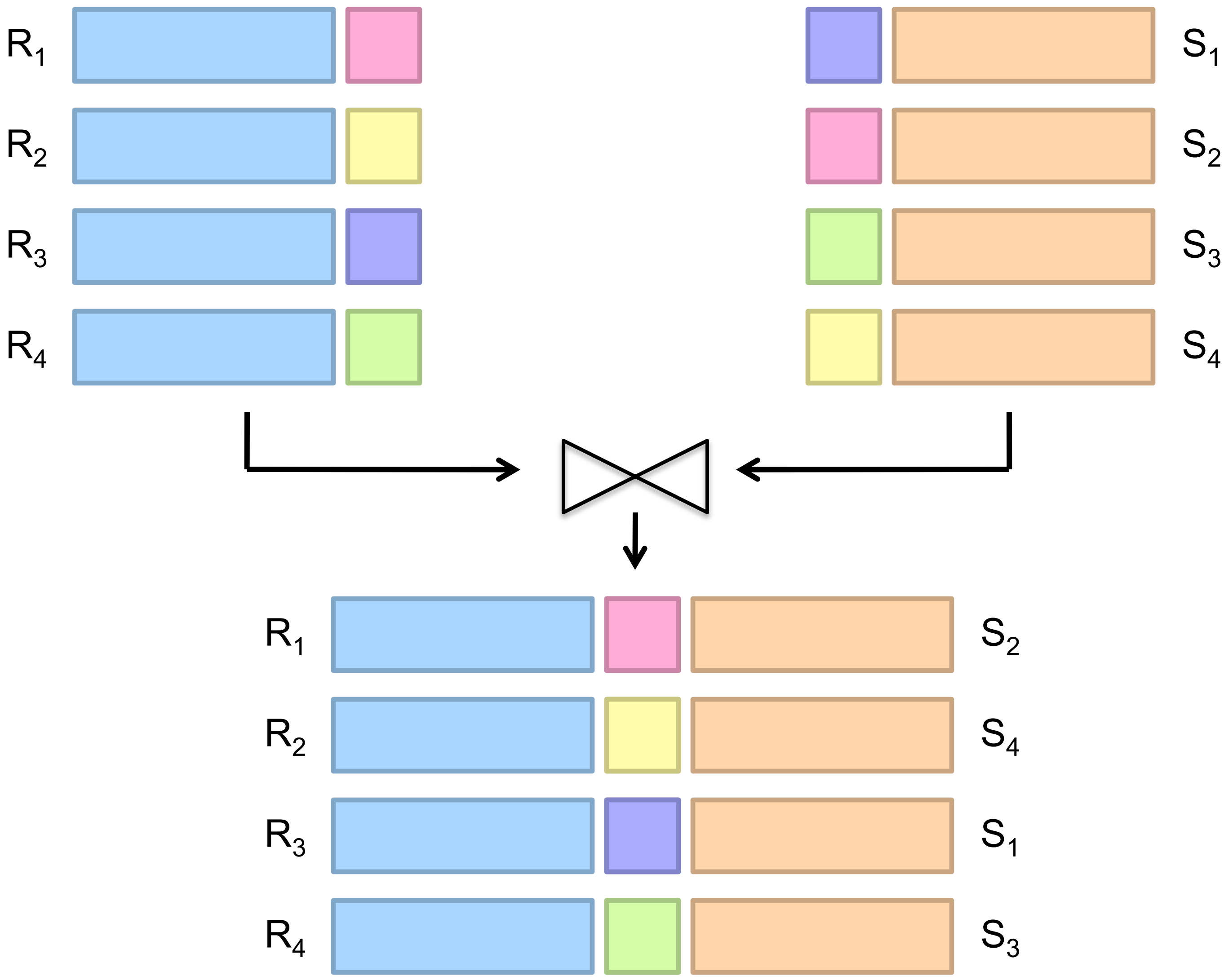
```
SELECT key, AVG(value) FROM r GROUP BY key;
```



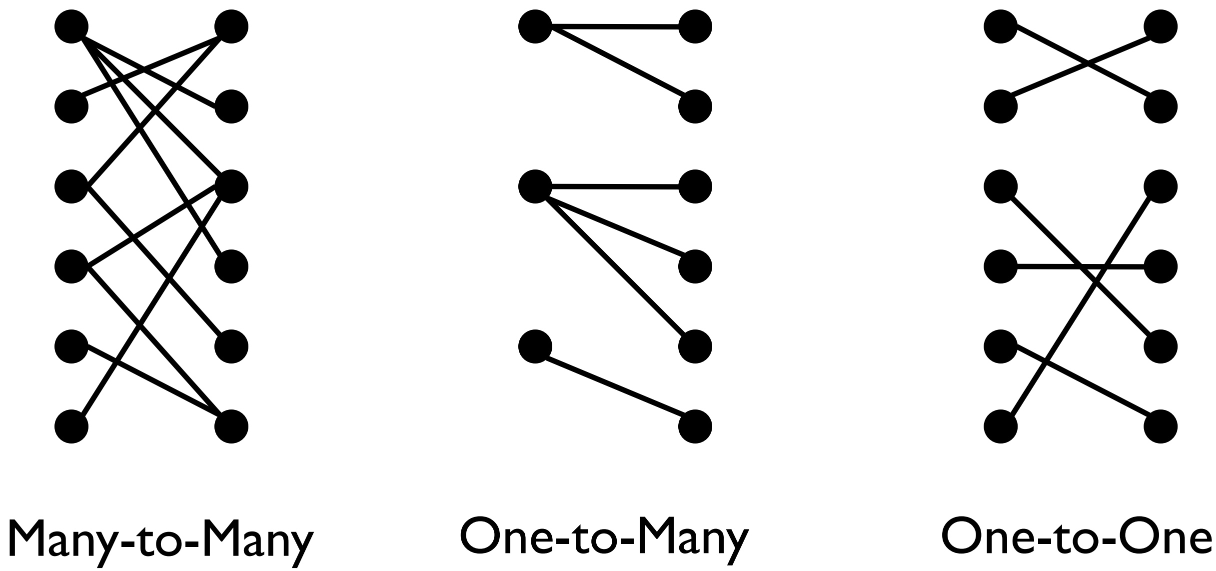
# Relational Joins

Source: Microsoft Office Clip Art

# Relational Joins



# Types of Relationships



# Join Algorithms in MapReduce

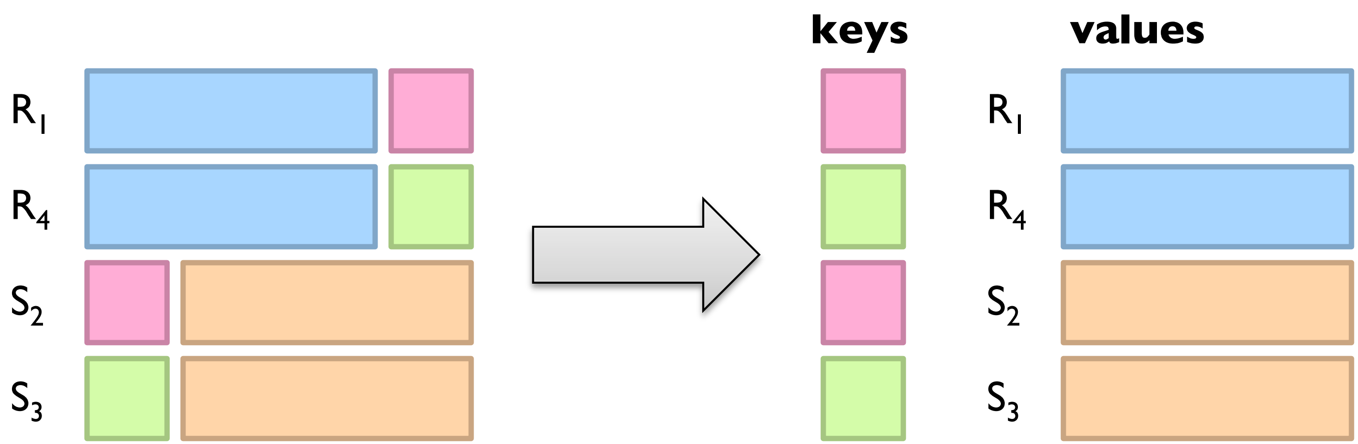
- Reduce-side join
  - aka repartition join
  - aka shuffle join
- Map-side join
  - aka sort-merge join
- Hash join
  - aka broadcast join
  - aka replicated join

# Reduce-side Join aka repartition join, shuffle join

- Basic idea: group by join key
  - Map over both datasets
  - Emit tuple as value with join key as the intermediate key
  - Execution framework brings together tuples sharing the same key
  - Perform join in reducer
- Two variants
  - 1-to-1 joins
  - 1-to-many and many-to-many joins

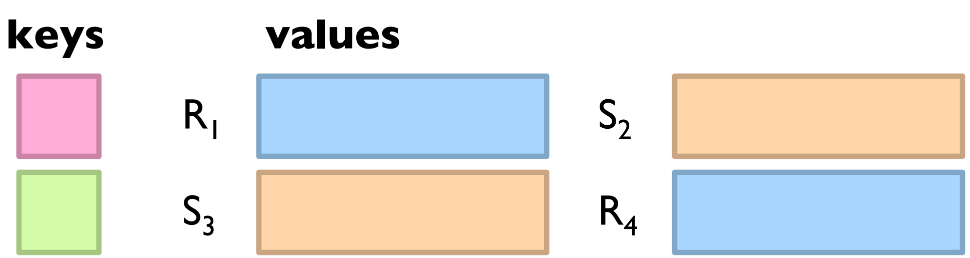
# Reduce-side Join: 1-to-1

## Map




Remember to "tag" the tuple as being from R or S…

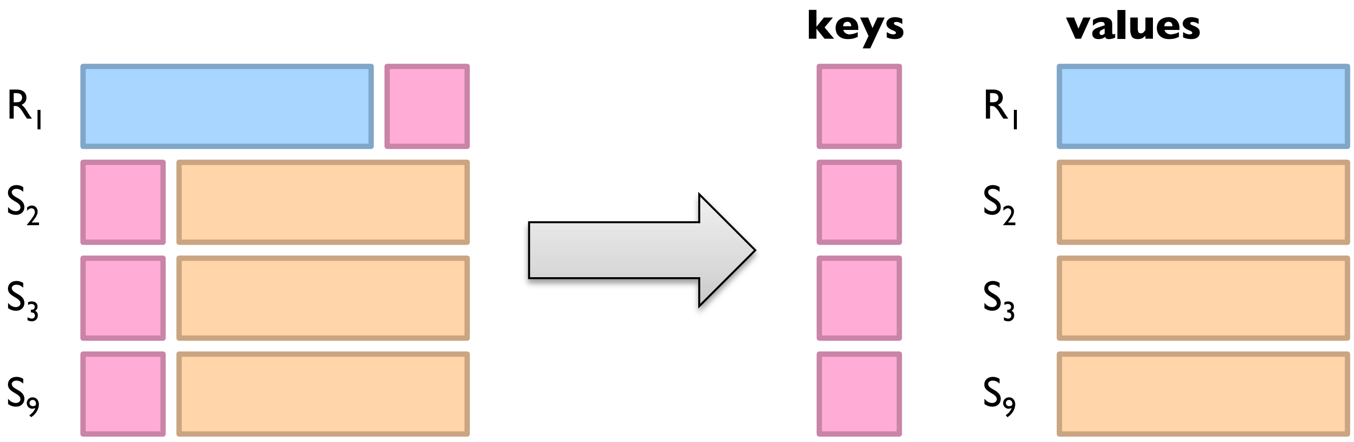
## Reduce




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

# Reduce-side Join: 1-to-many

## Map




## Reduce


**What's the problem?**

# Quick Aside: Secondary Sorting

- MapReduce sorts input to reducers by key
  - Values are arbitrarily ordered
- What if want to sort value also?
  - E.g., $k \rightarrow (v_1, r_1), (v_3, r_2), (v_4, r_3), (v_8, r_4)\ldots$

# 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, $v_1$)
  - 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**

$k \rightarrow (v_8, r_4), (v_1, r_1), (v_4, r_3), (v_3, r_2)\ldots$

Values arrive in arbitrary order…

**After**

$(k, v_1) \rightarrow r_1$

$(k, v_3) \rightarrow r_2$

$(k, v_4) \rightarrow r_3$

$(k, v_8) \rightarrow r_4$

…

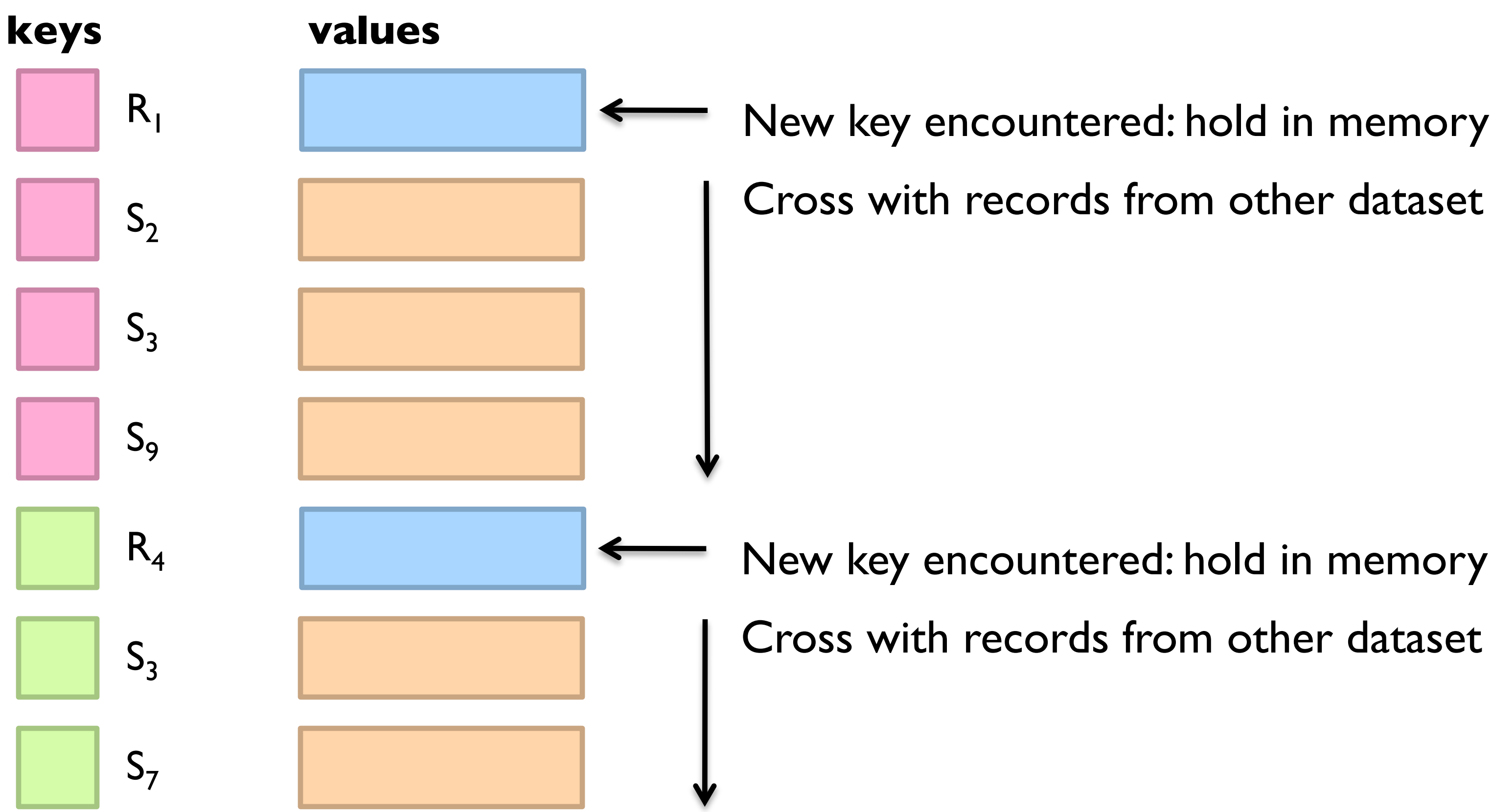
Values arrive in sorted order…

Process by preserving state across multiple keys

Remember to partition correctly!

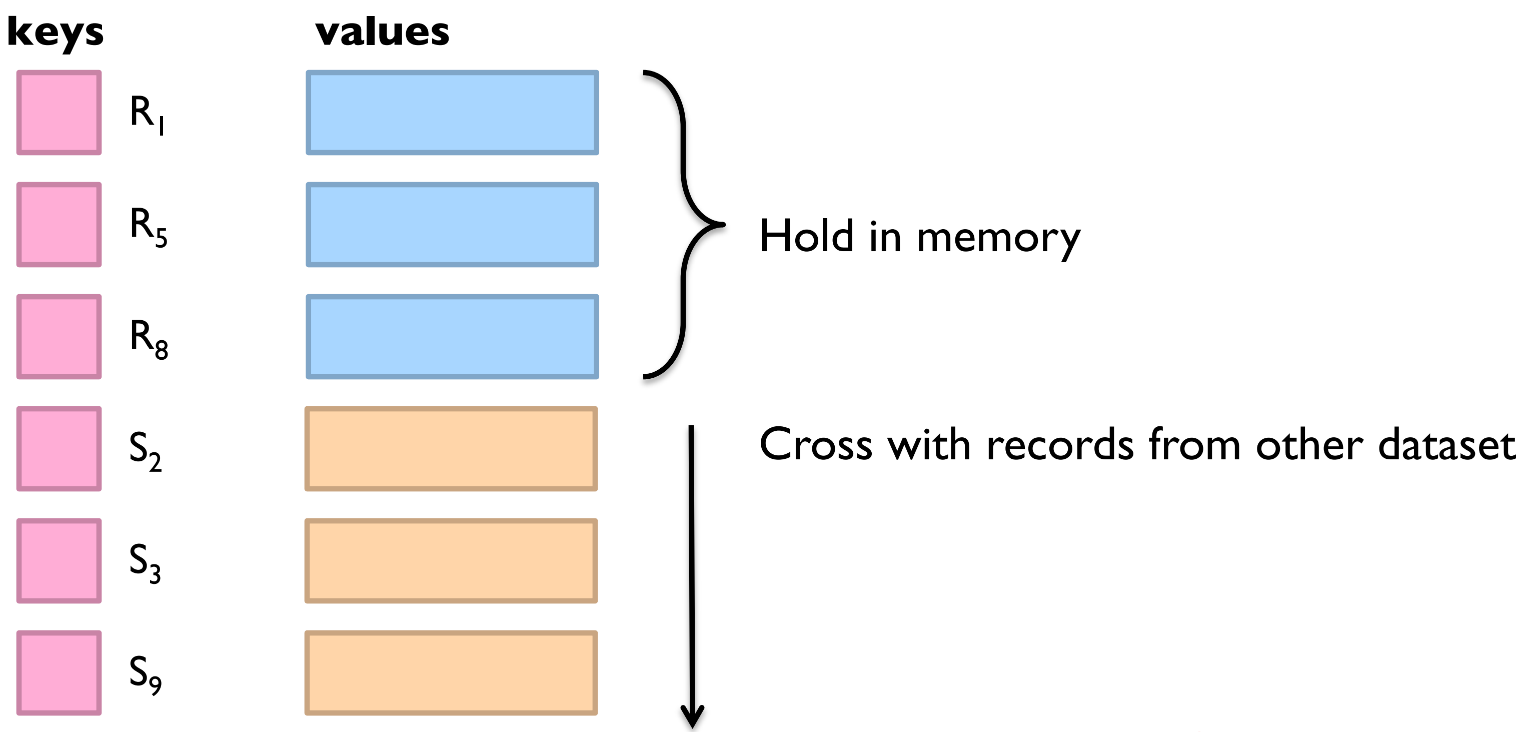
# Reduce-side Join: V-to-K Conversion

## In reducer…



# Reduce-side Join: many-to-many

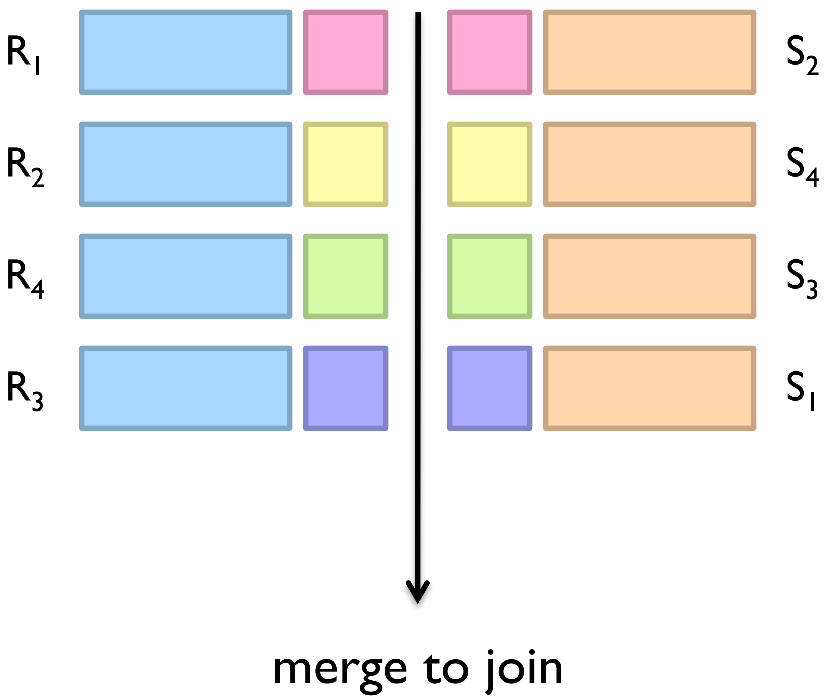
## In reducer…




What's the problem?

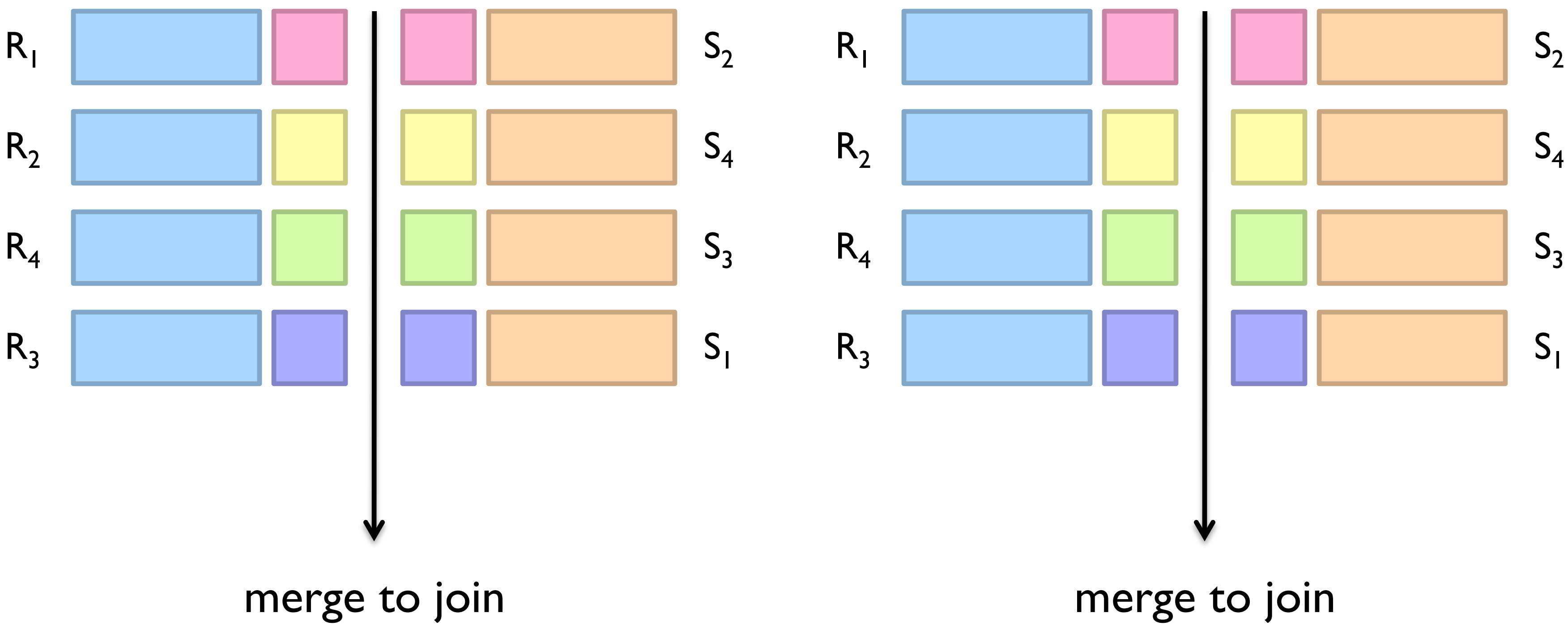
# Map-side Join aka sort-merge join

Assume two datasets are sorted by the join key:



# Map-side Join aka sort-merge join

Assume two datasets are sorted by the join key:




**How can we parallelize this? Co-partitioning**

# Map-side Join aka sort-merge join

- Works if…
  - Two datasets are co-partitioned
  - Sorted by join key
- MapReduce implementation:
  - Map over one dataset, read from other corresponding partition
  - No reducers necessary (unless to do something else)
- Co-partitioned, sorted datasets: realistic to expect?

# Hash Join aka broadcast join, replicated join

- Basic idea:
  - Load one dataset into memory in a hashmap, keyed by join key
  - Read other dataset, probe for join key
- Works if…
  - R << S and R fits into memory
- MapReduce implementation:
  - Distribute R to all nodes (e.g., DistributedCache)
  - Map over S, each mapper loads R in memory and builds the hashmap
  - For every tuple in S, probe join key in R
  - No reducers necessary (unless to do something else)

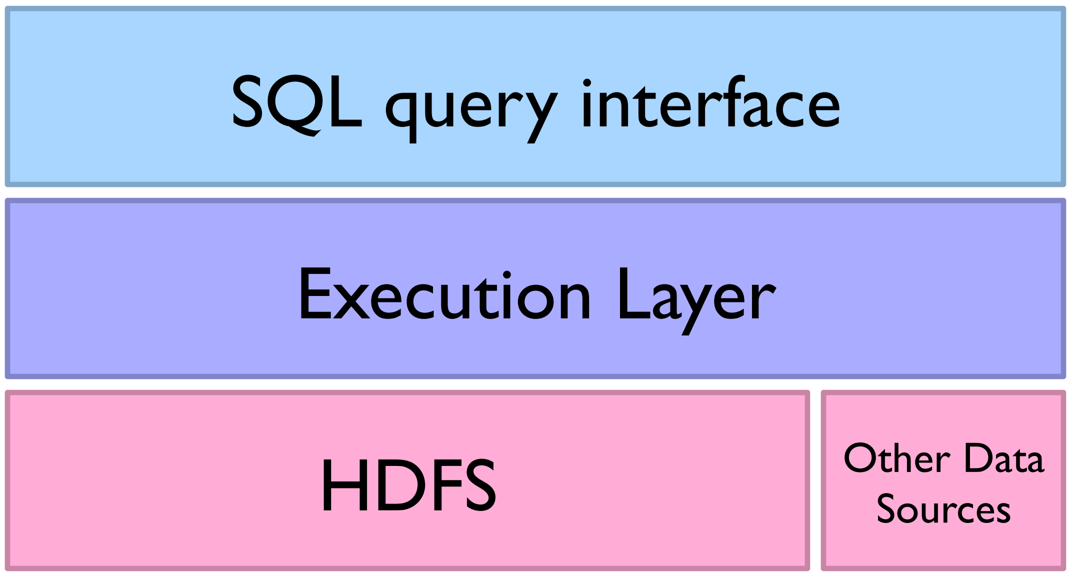
# Hash Join Variants

- Co-partitioned variant:
  - R and S co-partitioned (but not sorted)?
  - Only need to build hashmap on the corresponding partition
- 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 hash join: $\forall n$, $R_n \bowtie S$
  - Take the union of all join results
- Use a global key-value store:
  - Load R into memcached (or Redis)
  - Probe global key-value store for join key

# Which join to use?

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

# SQL-on-Hadoop




Spark SQL

# Putting Everything Together

```
SELECT big1.fx, big2,fy, small,fz
FROM big1
JOIN big2 ON big1.id1 = big2.id1
JOIN small ON big1.id2 = small.id2
WHERE big1.fx = 2015 AND
      big2.f1 < 40 AND
      big2.f2 > 2;
```

Build logical plan

Optimize logical plan

Select physical plan

Note: generic SQL-on-Hadoop implementation; not exactly what Hive does, but pretty close.

# Putting Everything Together

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SELECT big1.fx, big2,fy, small,fz
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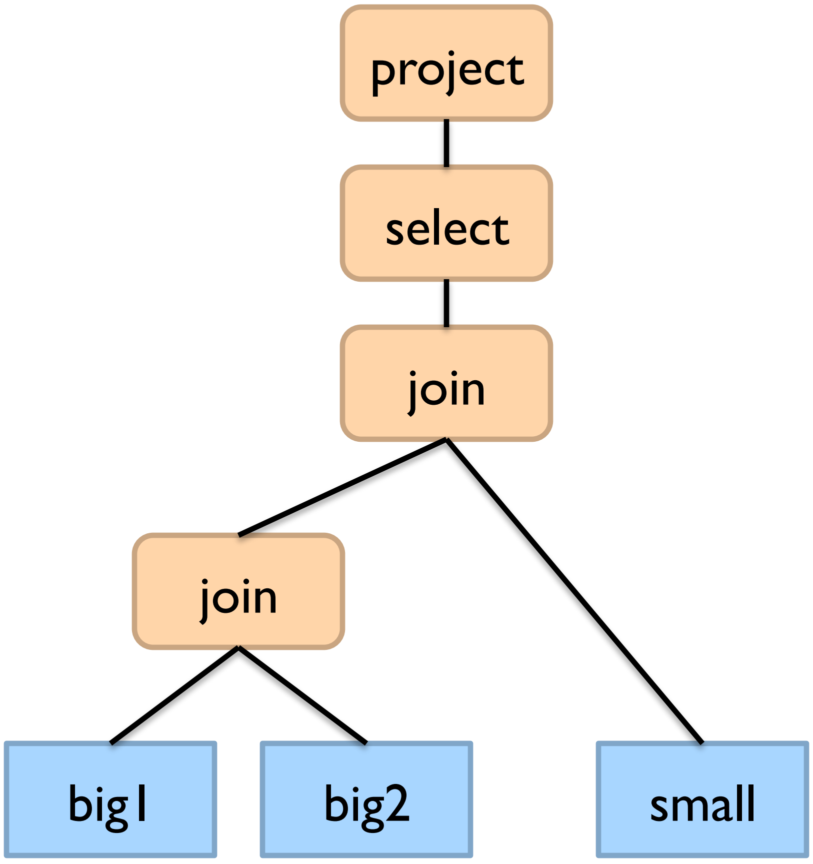


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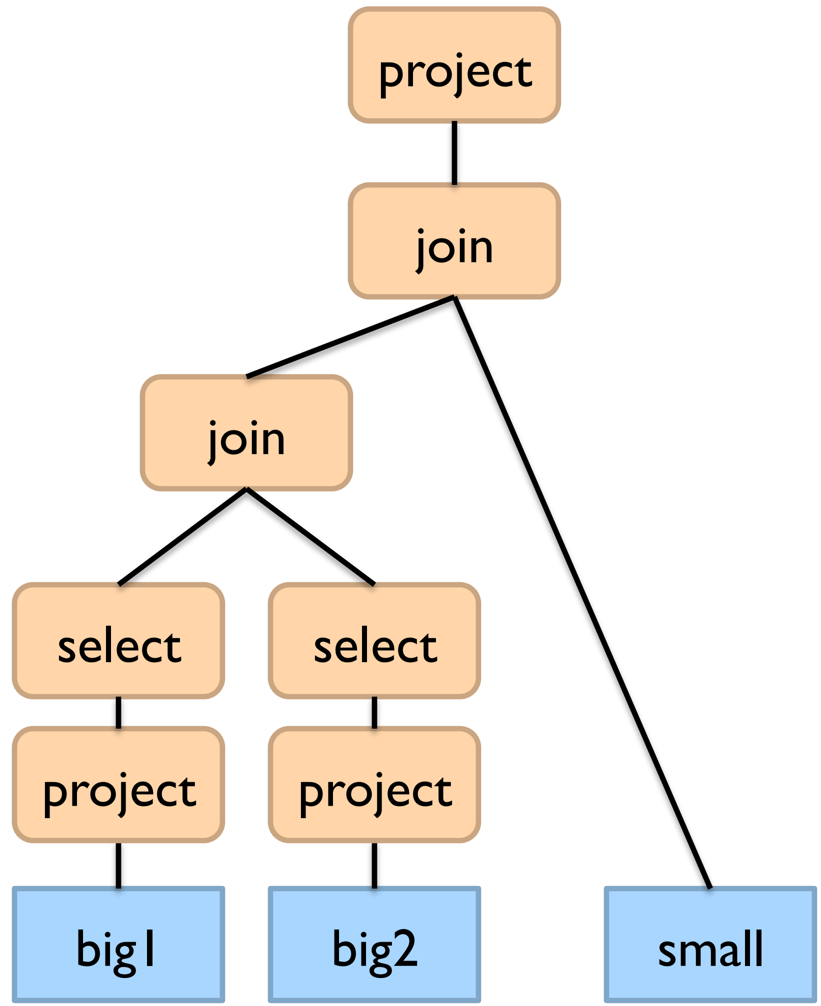


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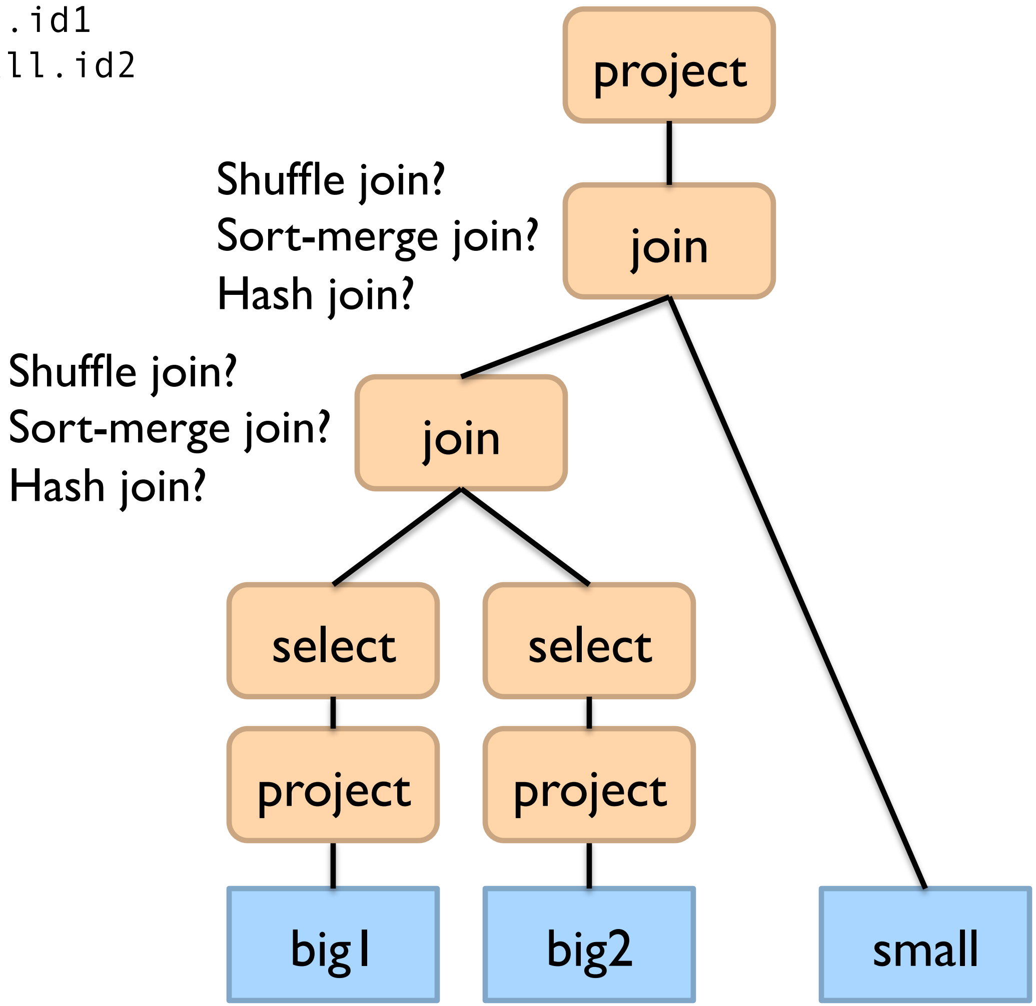


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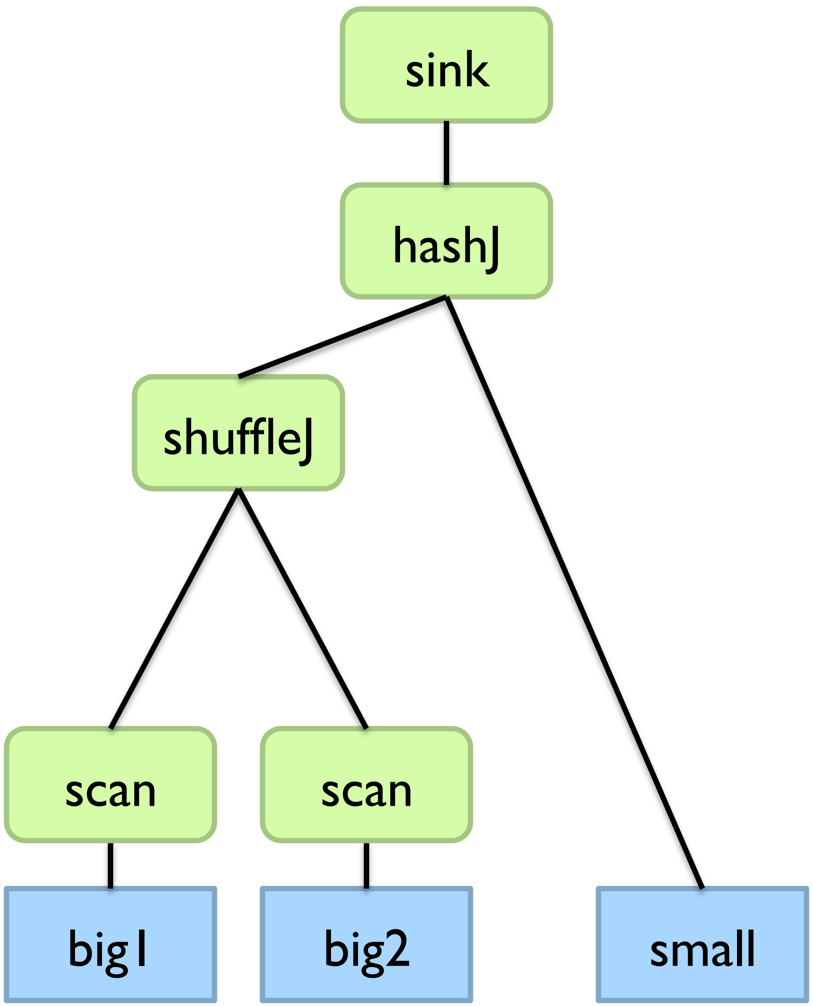


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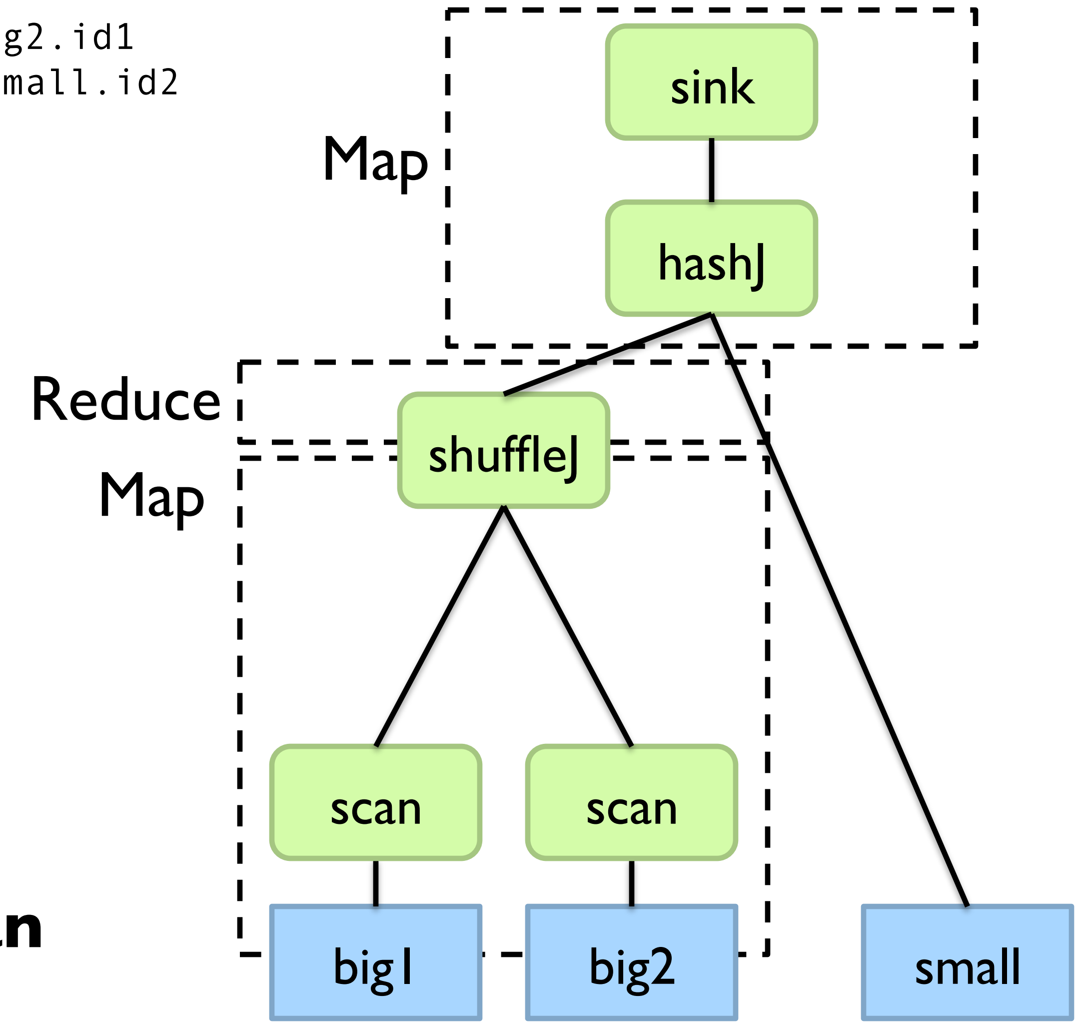


Build logical plan

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# Hive: Behind the Scenes

**Now you understand what's going on here!**

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(one or more of MapReduce jobs)

# Hive: Behind the Scenes

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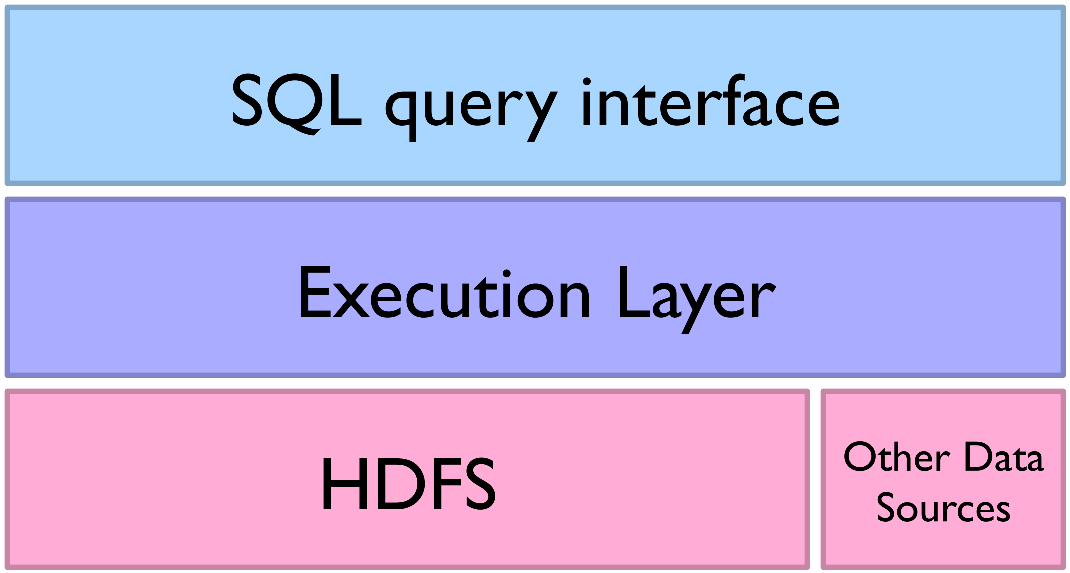
                    type: int
              sort order: -
              tag: -1
              value expressions:
                    expr: _col0
                    type: string
                    expr: _col1
                    type: int
                    expr: _col2
                    type: int
      Reduce Operator 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
```

# SQL-on-Hadoop



# What about Spark SQL?

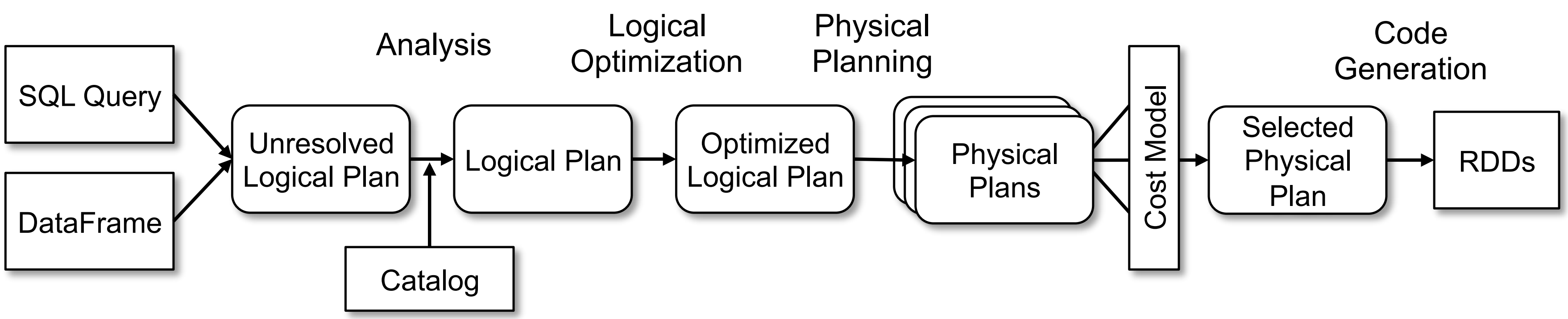
- Based on the DataFrame API:
  - A distributed collection of data organized into named columns
- Two ways of specifying SQL queries:
  - Directly:

```
val sqlContext = ... // An existing SQLContext
val df = sqlContext.sql("SELECT * FROM table")
// df is a dataframe, can be further manipulated...
```

  - Via DataFrame API:

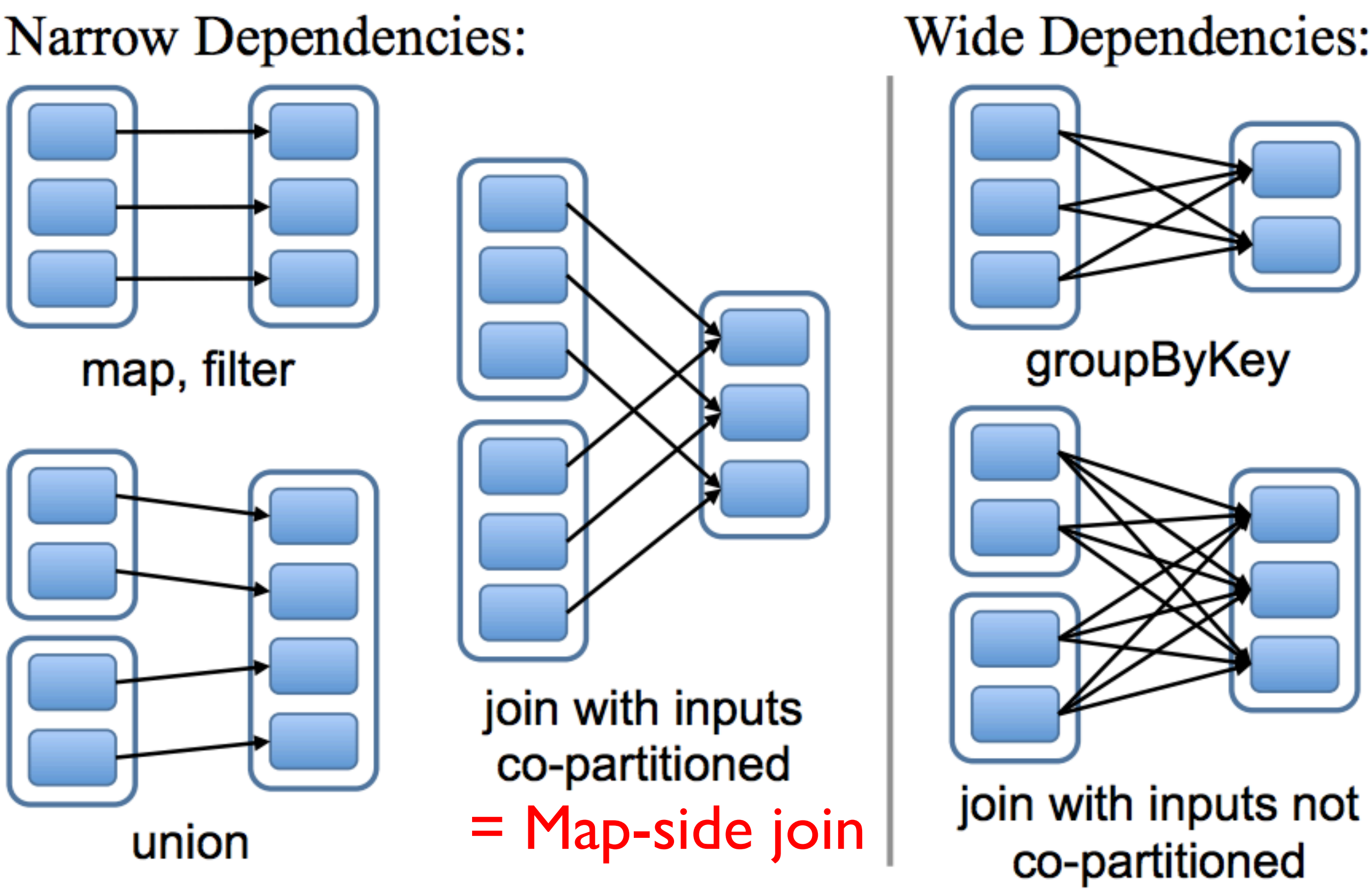
```
// employees is a dataframe:
employees
  .join(dept, employees ("deptId") === dept ("id"))
  .where(employees("gender") === "female")
  .groupBy(dept("id"), dept ("name"))
  .agg(count("name"))
```

# Spark SQL: Query Planning




At the end of the day… it's transformations on RDDs

# Spark SQL: Physical Execution




= Map-side join

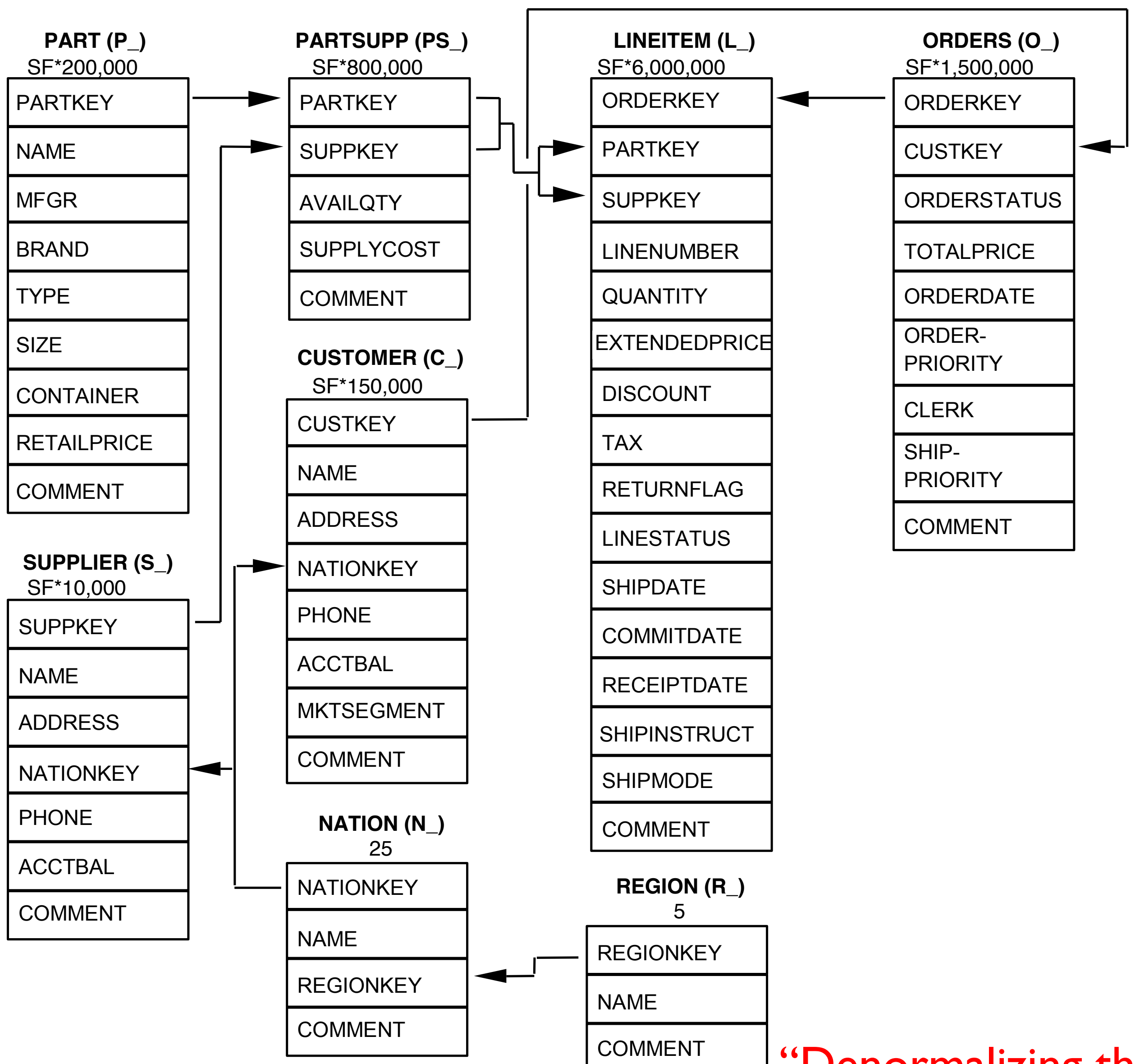
= Reduce-side join

Hash join with broadcast variables

# Hadoop Data Warehouse Design

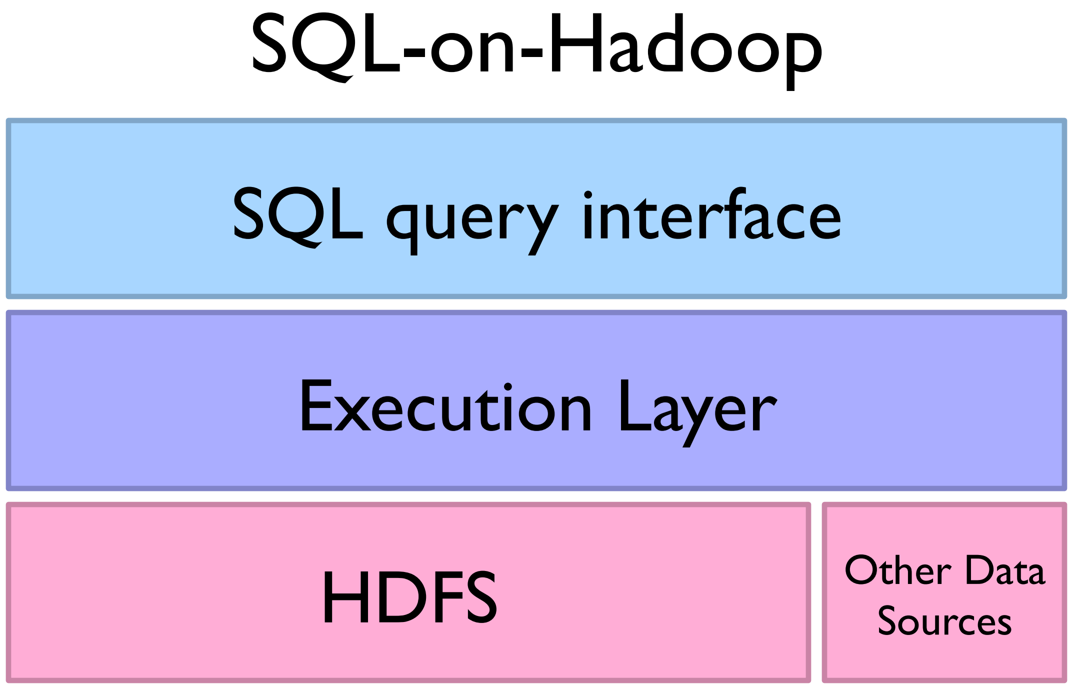
- Observation:
  - Joins are relatively expensive
  - OLAP queries frequently involve joins
- Solution: denormalize
  - What's normalization again?
  - Why normalize to begin with?
  - Fundamentally a time-space tradeoff
  - How much to denormalize?
  - What about consistency?

# Denormalization Opportunities?



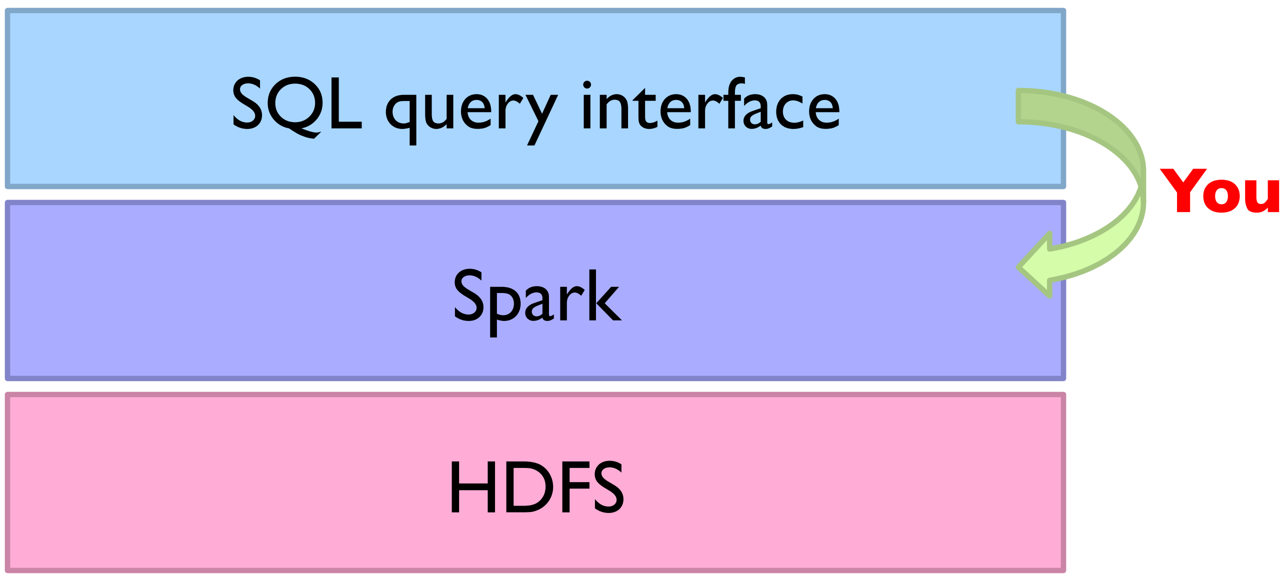

"Denormalizing the snowflake"

# What's the assignment?

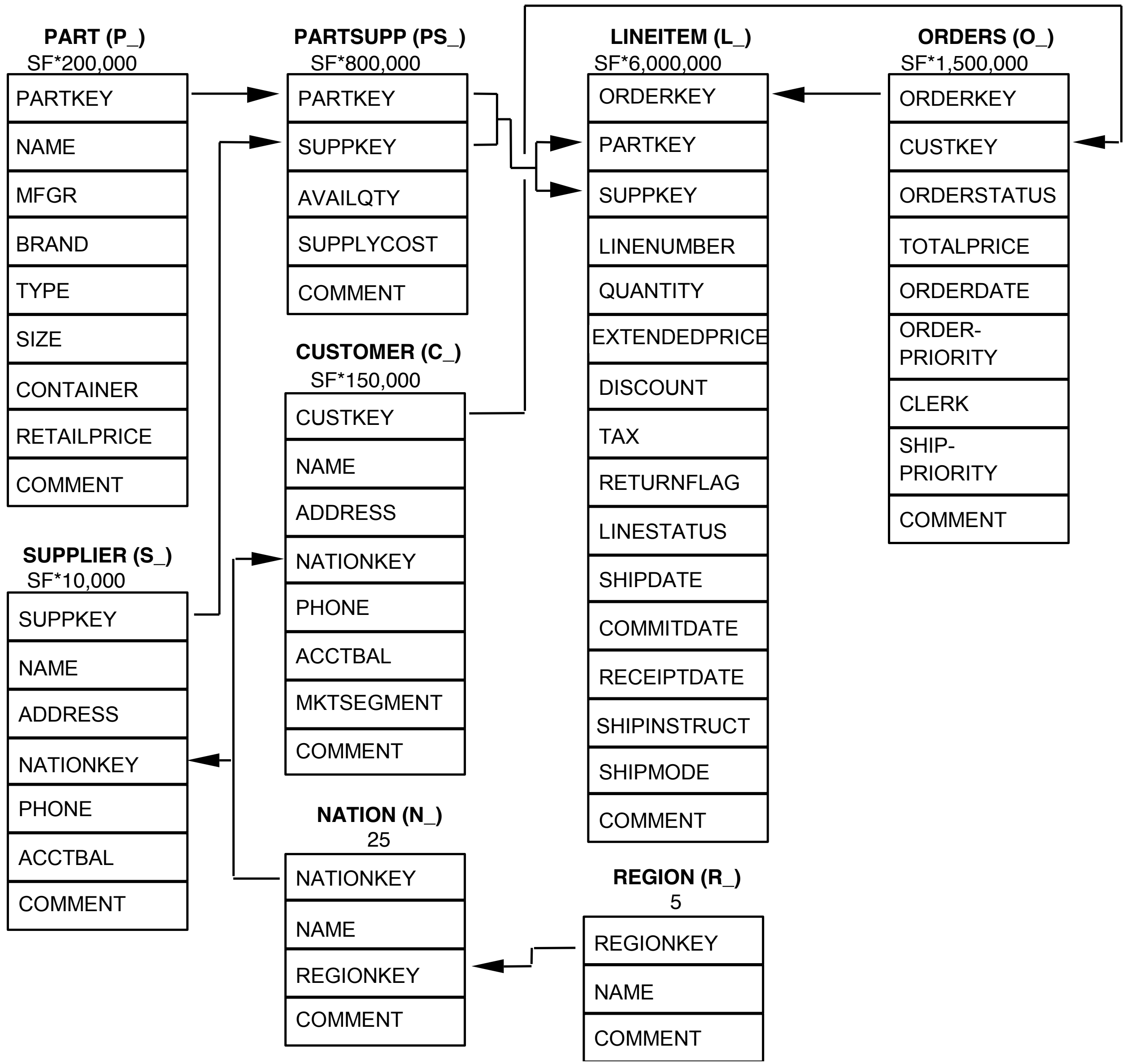


# What's the assignment?

SQL-on-Hadoop



# What's the assignment?



# What's the assignment?

```
select
  l_returnflag,
  l_linestatus,
  sum(l_quantity) as sum_qty,
  sum(l_extendedprice) as sum_base_price,
  sum(l_extendedprice*(1-l_discount)) as sum_disc_price,
  sum(l_extendedprice*(1-l_discount)*(1+l_tax)) as sum_charge,
  avg(l_quantity) as avg_qty,
  avg(l_extendedprice) as avg_price,
  avg(l_discount) as avg_disc,
  count(*) as count_order
from lineitem
where
  l_shipdate = 'YYYY-MM-DD'
group by l_returnflag, l_linestatus;
```

input parameter

SQL query → Raw Spark program

Your task…


Questions?
Source: Wikipedia (Japanese rock garden)