Data-Intensive Distributed Computing

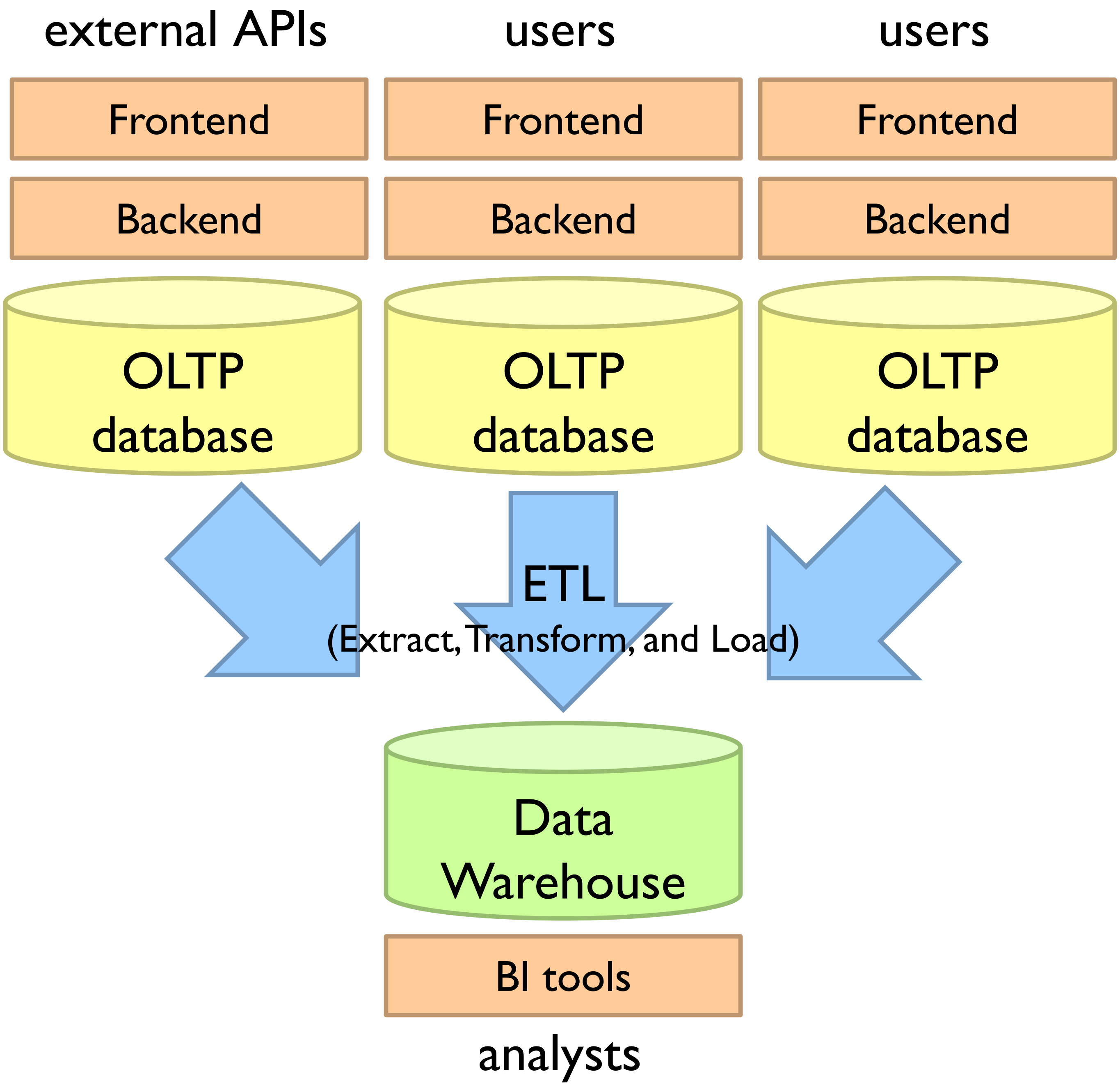
CS 451/651 (Fall 2018)

Part 5: Analyzing Relational Data (2/3)

October 18, 2018

Jimmy Lin
David R. Cheriton School of Computer Science
University of Waterloo

These slides are available at http://lintool.github.io/bigdata-2018f/

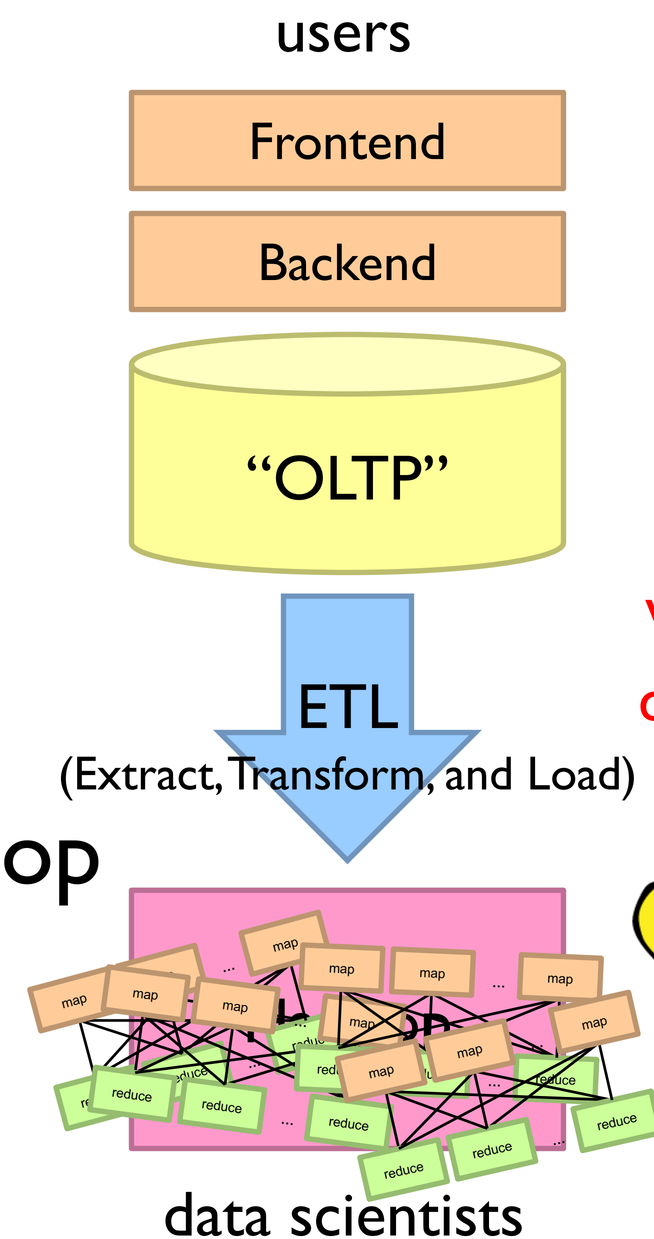

external APIs
users
users
Frontend
Frontend
Frontend
Backend
Backend
Backend
OLTP database
OLTP database
OLTP database
ETL
(Extract, Transform, and Load)
Data Warehouse
BI tools
analysts

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



Wait, so why not use a database to begin with?

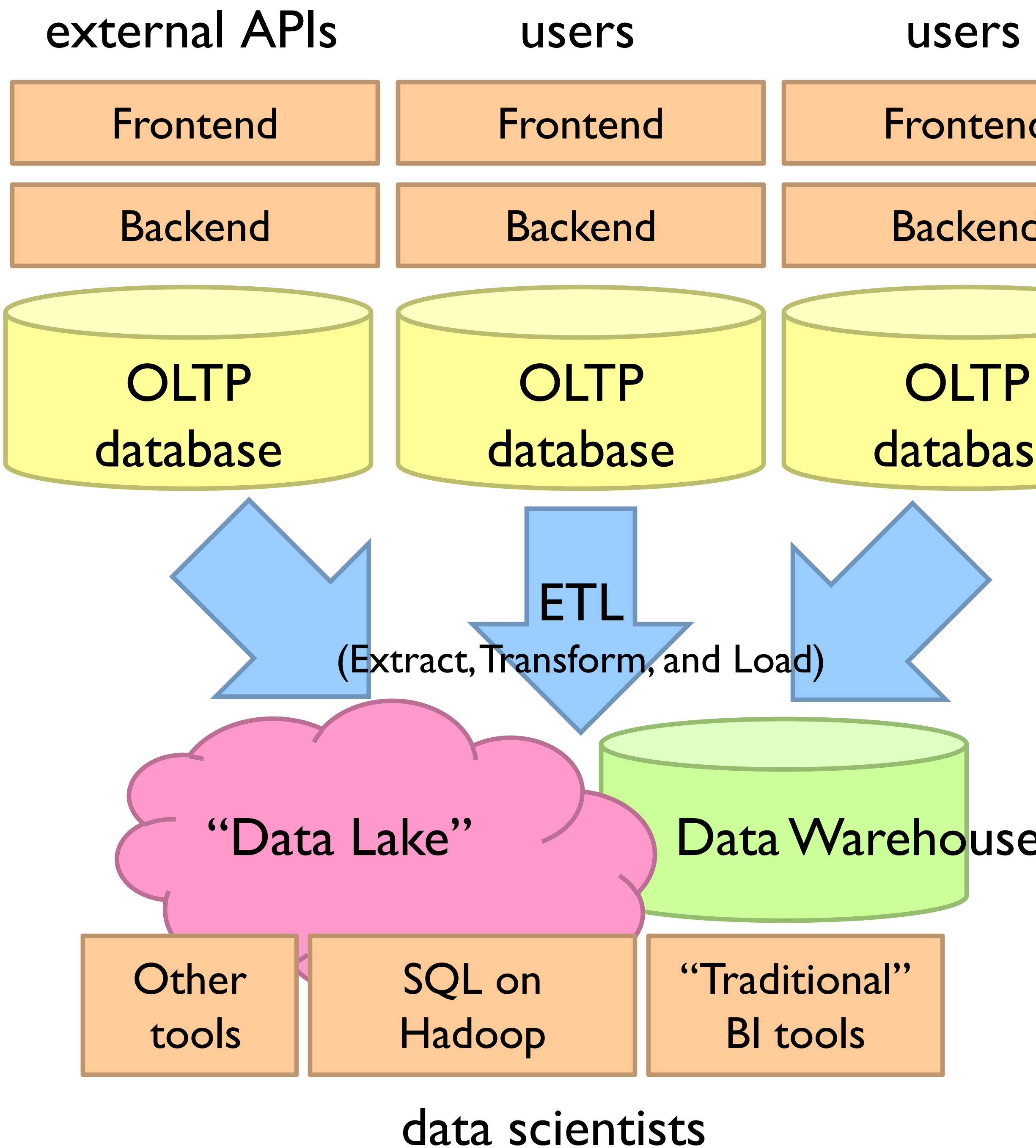
Cost + Scalability

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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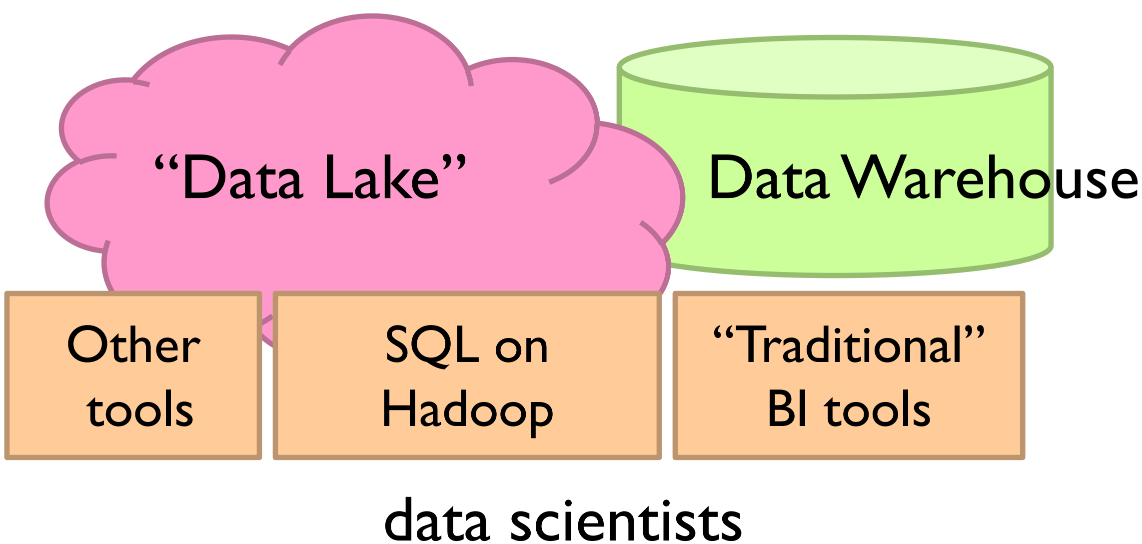
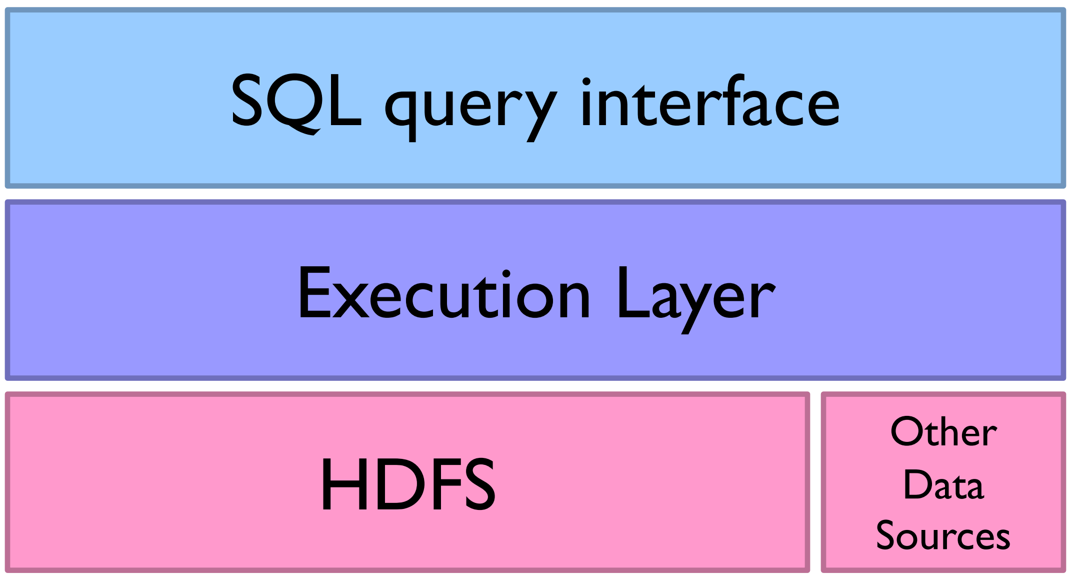
(Extract, Transform, and Load)
"Data Lake"
Data Warehouse
Other tools
SQL on Hadoop
"Traditional" BI tools
data scientists

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

Trade (a little?) performance for flexibility



SQL-on-Hadoop



Today: How all of this works…

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
  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

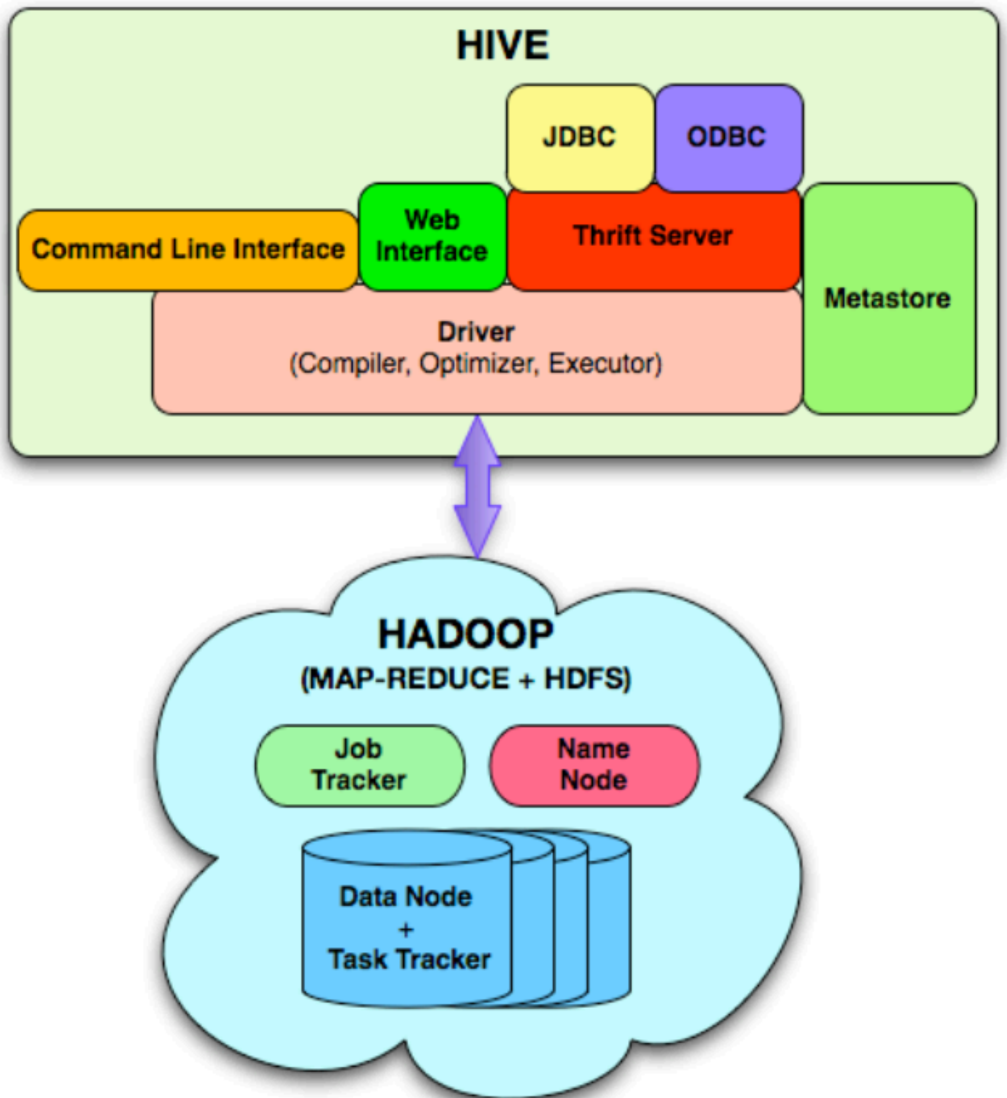
```
STAGE DEPENDENCIES:
  Stage-1 is a root stage
  Stage-2 depends on stages: Stage-1
  Stage-0 is a root stage

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
```

Hive Architecture



Hive Implementation

Metastore holds metadata

Tables schemas (field names, field types, etc.) and encoding

Permission information (roles and users)

Hive data stored in HDFS

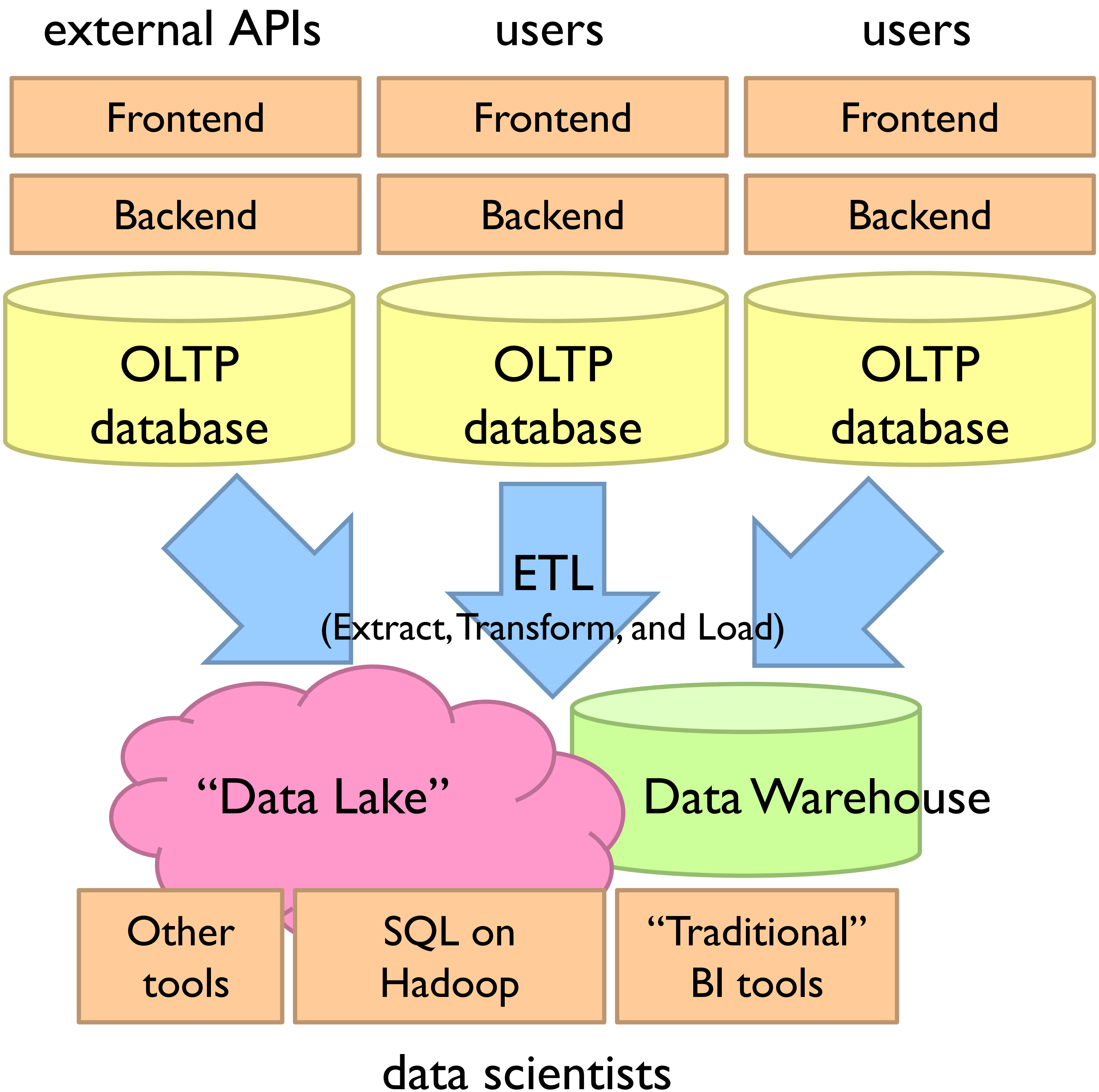
Tables in directories

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)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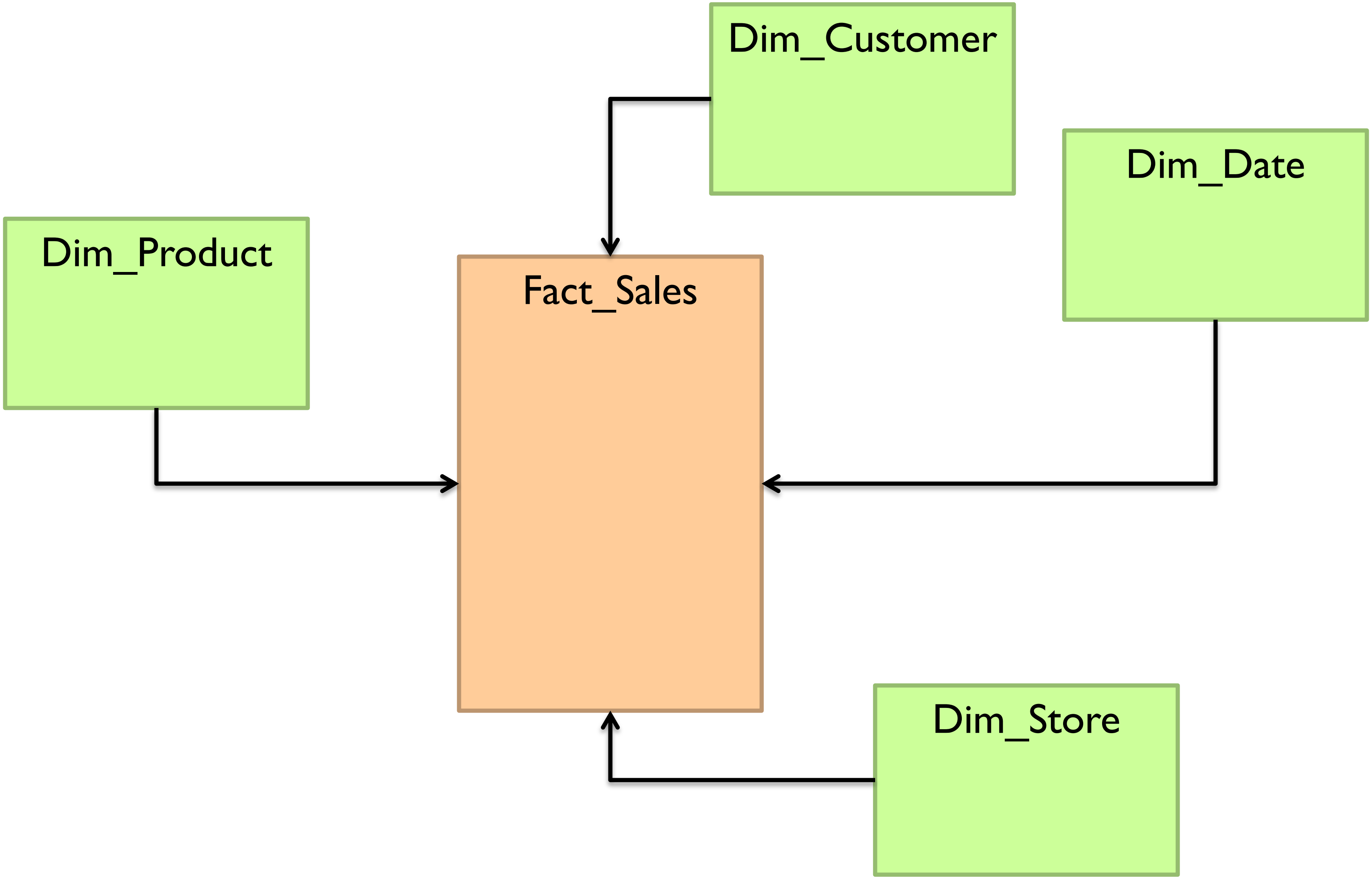
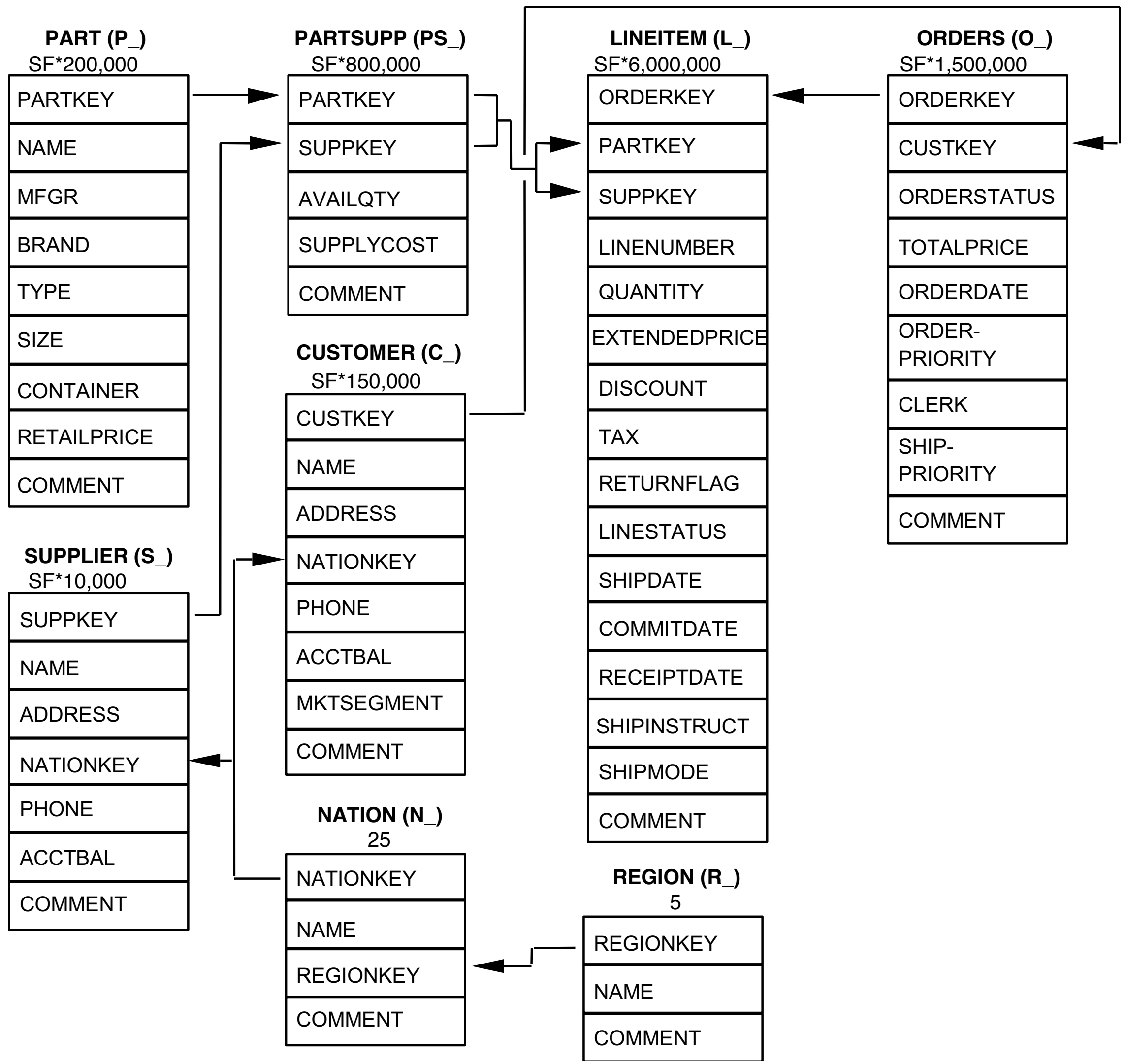
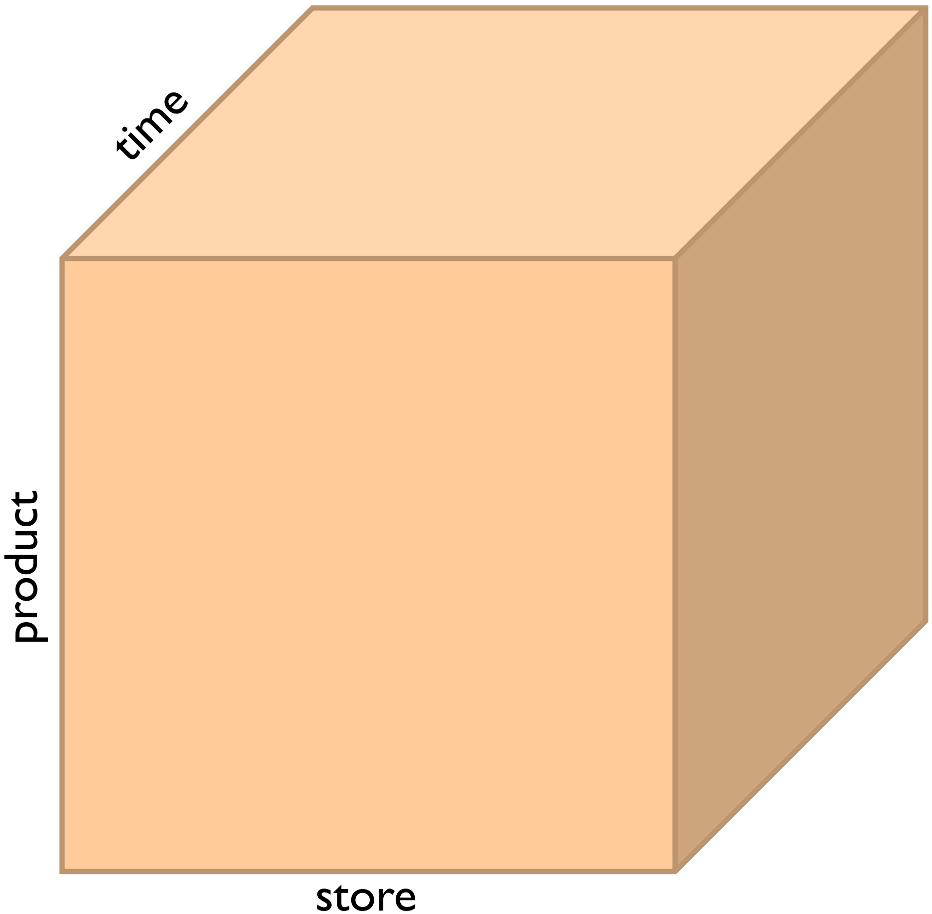
A Simple OLAP Schema



TPC-H Data Warehouse



OLAP Cubes



Common operations

- slice and dice
- roll up/drill down
- pivot

MapReduce algorithms for processing relational data

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

Relational Algebra

Primitives

Projection (π)

Selection (σ)

Cartesian product ($\times$)

Set union ($\cup$)

Set difference ($-$)

Rename (ρ)

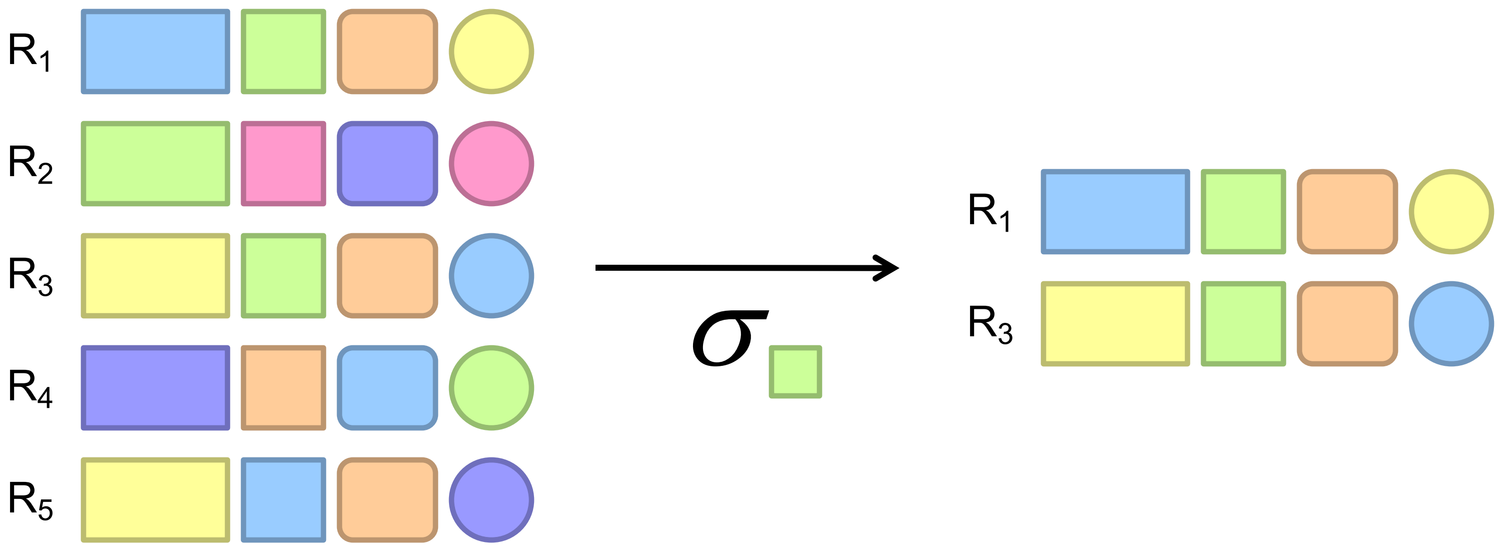
Other Operations

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)

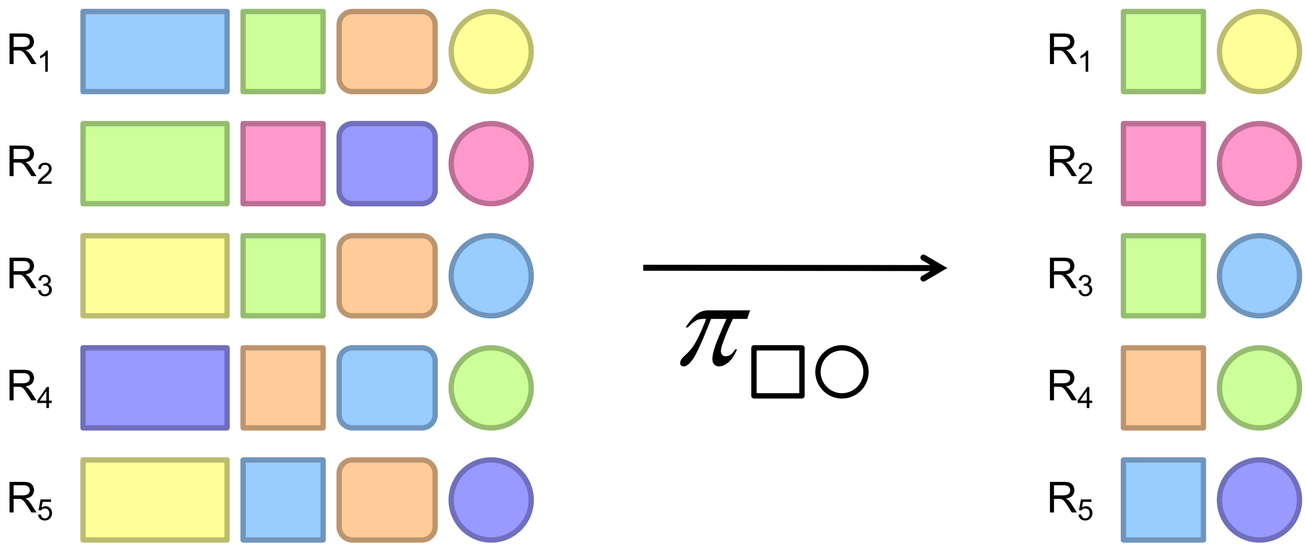
Performance mostly limited by HDFS throughput

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

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

Computing the Mean: Version 1

```
class Mapper {
  def map(key: Text, value: Int, context: Context) = {
    context.write(key, value)
  }
}

class Reducer {
  def reduce(key: Text, values: Iterable[Int], context: Context) {
    for (value <- values) {
      sum += value
      cnt += 1
    }
    context.write(key, sum/cnt)
  }
}
```

Computing the Mean: Version 2

```
class Mapper {
  def map(key: Text, value: Int, context: Context) =
    context.write(key, value)
}
class Combiner {
  def reduce(key: Text, values: Iterable[Int], context: Context) = {
    for (value <- values) {
      sum += value
      cnt += 1
    }
    context.write(key, (sum, cnt))
  }
}
class Reducer {
  def reduce(key: Text, values: Iterable[Pair], context: Context) = {
    for (value <- values) {
      sum += value.left
      cnt += value.right
    }
    context.write(key, sum/cnt)
  }
}
```

Computing the Mean: Version 3

```
class Mapper {
  def map(key: Text, value: Int, context: Context) =
    context.write(key, (value, 1))
}
class Combiner {
  def reduce(key: Text, values: Iterable[Pair], context: Context) = {
    for (value <- values) {
      sum += value.left
      cnt += value.right
    }
    context.write(key, (sum, cnt))
  }
}
class Reducer {
  def reduce(key: Text, values: Iterable[Pair], context: Context) = {
    for (value <- values) {
      sum += value.left
      cnt += value.right
    }
    context.write(key, sum/cnt)
  }
}
```

Computing the Mean: Version 4

```
class Mapper  {
  val sums = new HashMap()
  val counts = new HashMap()

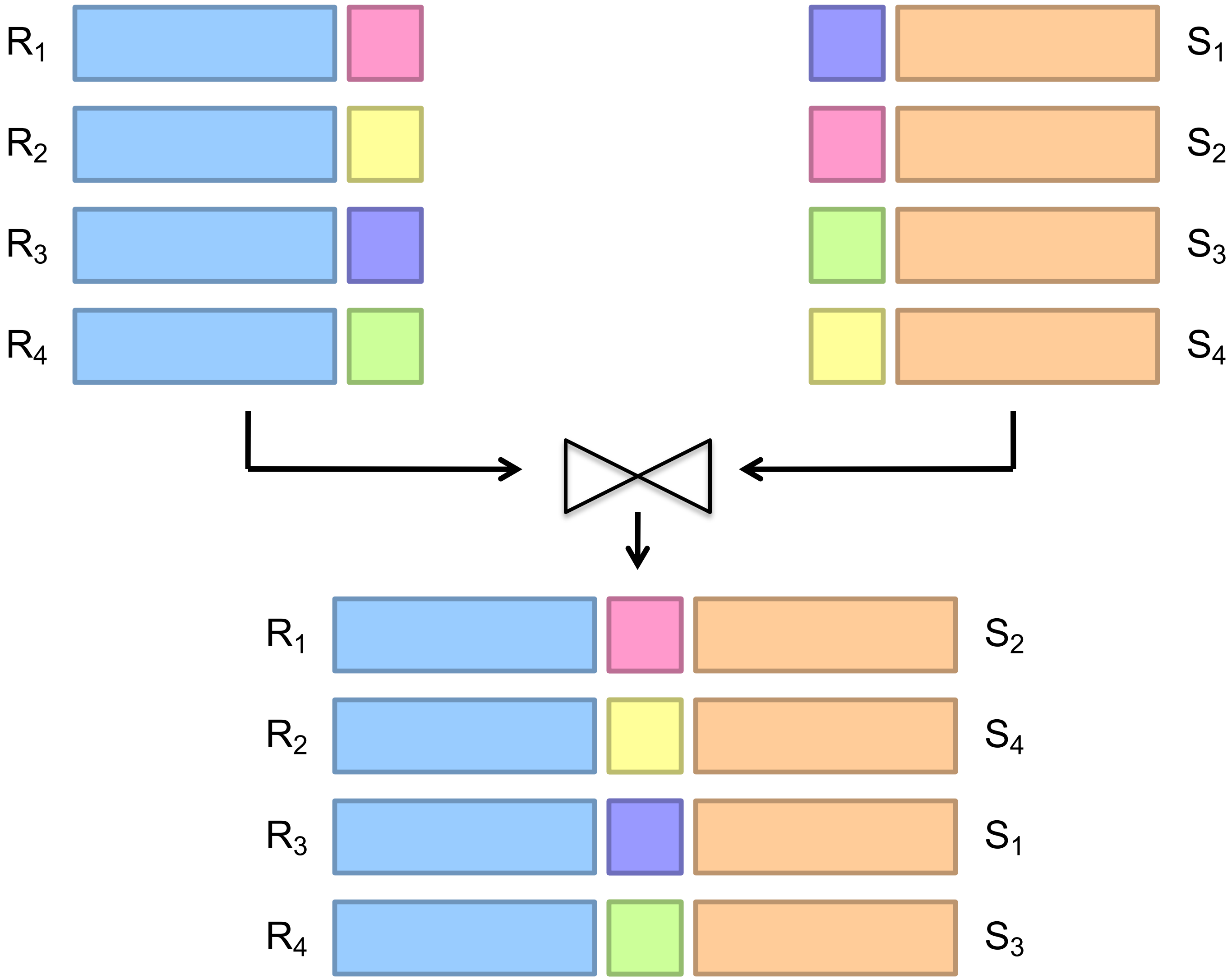
  def map(key: Text, value: Int, context: Context) = {
    sums(key) += value
    counts(key) += 1
  }

  def cleanup(context: Context) = {
    for (key <- counts) {
      context.write(key, (sums(key), counts(key)))
    }
  }
}
```

Relational Joins

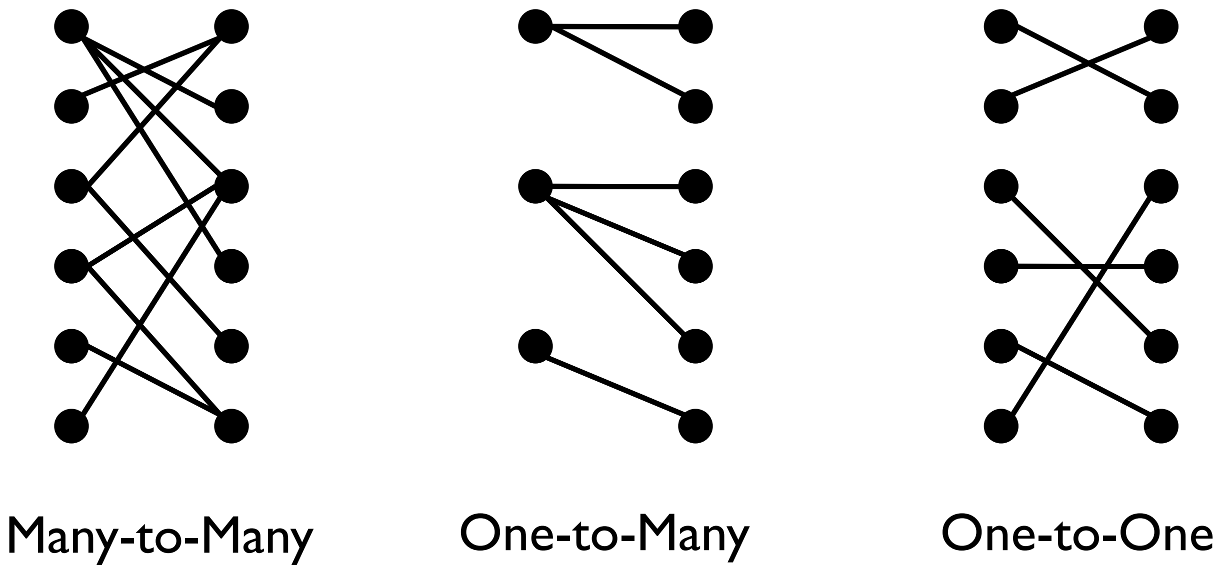
Source: Microsoft Office Clip Art

Relational Joins



(More precisely, an inner join)

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 <Huh?

Emit tuple as value with join key as the intermediate key

Execution framework brings together tuples sharing the same key

Perform join in reducer

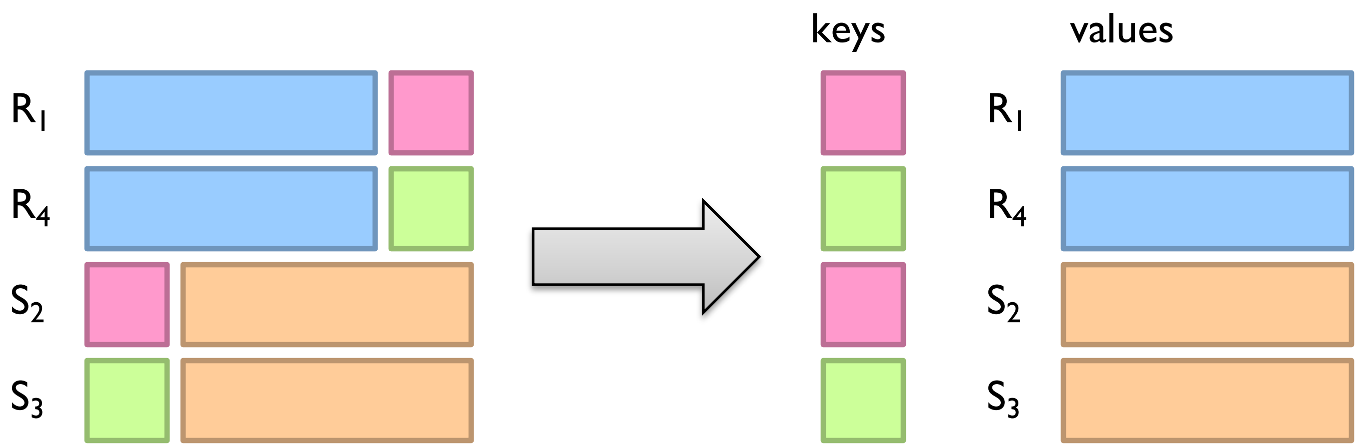
Two variants

1-to-1 joins

1-to-many and many-to-many joins

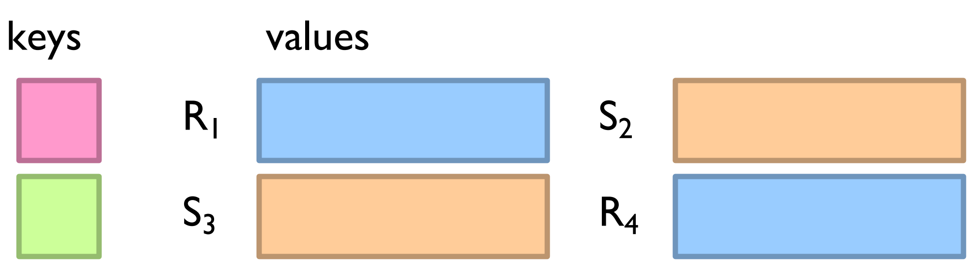
Reduce-side Join: 1-to-1

Map



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

Reduce

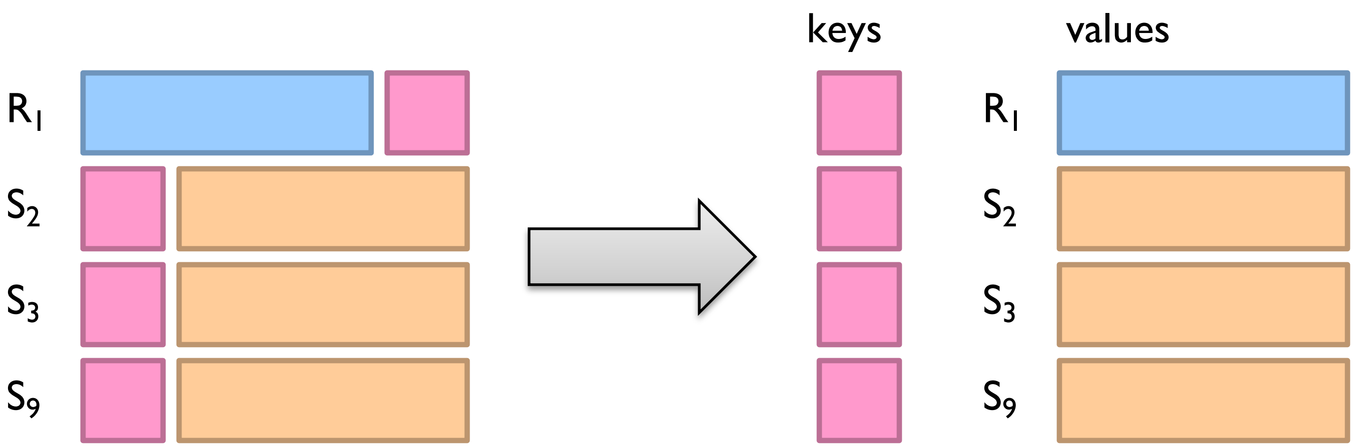


Note: no guarantee if R is going to come first or S

More precisely, an inner join: What about outer joins?

Reduce-side Join: 1-to-many

Map



Reduce

What's the problem?

Secondary Sorting

MapReduce sorts input to reducers by key

Values may be arbitrarily ordered

What if we want to sort value also?

E.g., $k \rightarrow (v_1, r), (v_3, r), (v_4, r), (v_8, r) \ldots$

Secondary Sorting: Solutions

Solution 1

Buffer values in memory, then sort
Why is this a bad idea?

Solution 2

"Value-to-key conversion" : form composite intermediate key, (k, v_1)
Let the 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

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

Values arrive in arbitrary order…

After

$(k, v_1) \longrightarrow r_1$

$(k, v_3) \longrightarrow r_2$

$(k, v_4) \longrightarrow r_3$

$(k, v_8) \longrightarrow r_4$

…

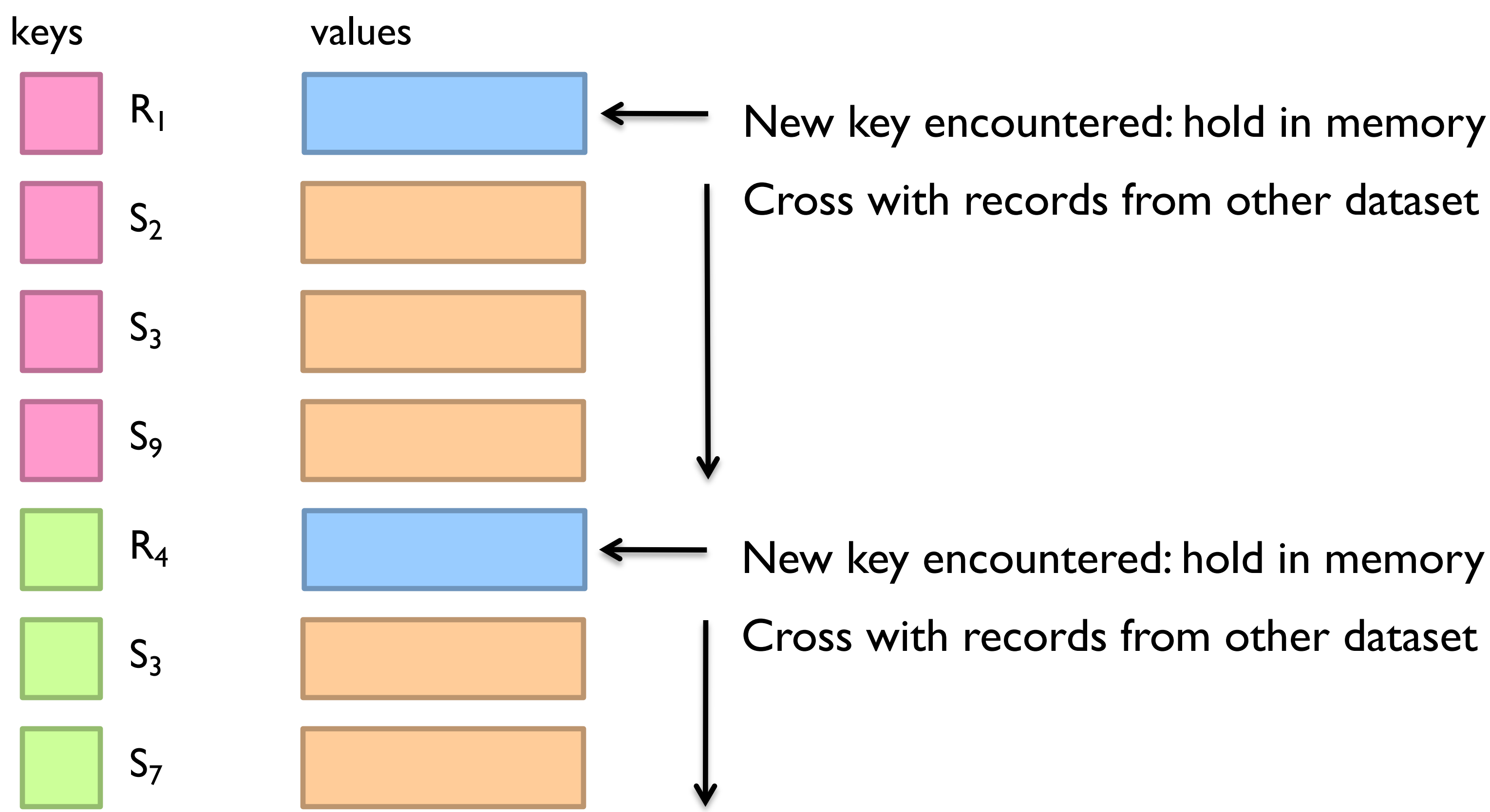
Values arrive in sorted order…

Process by preserving state across multiple keys

Remember to partition correctly!

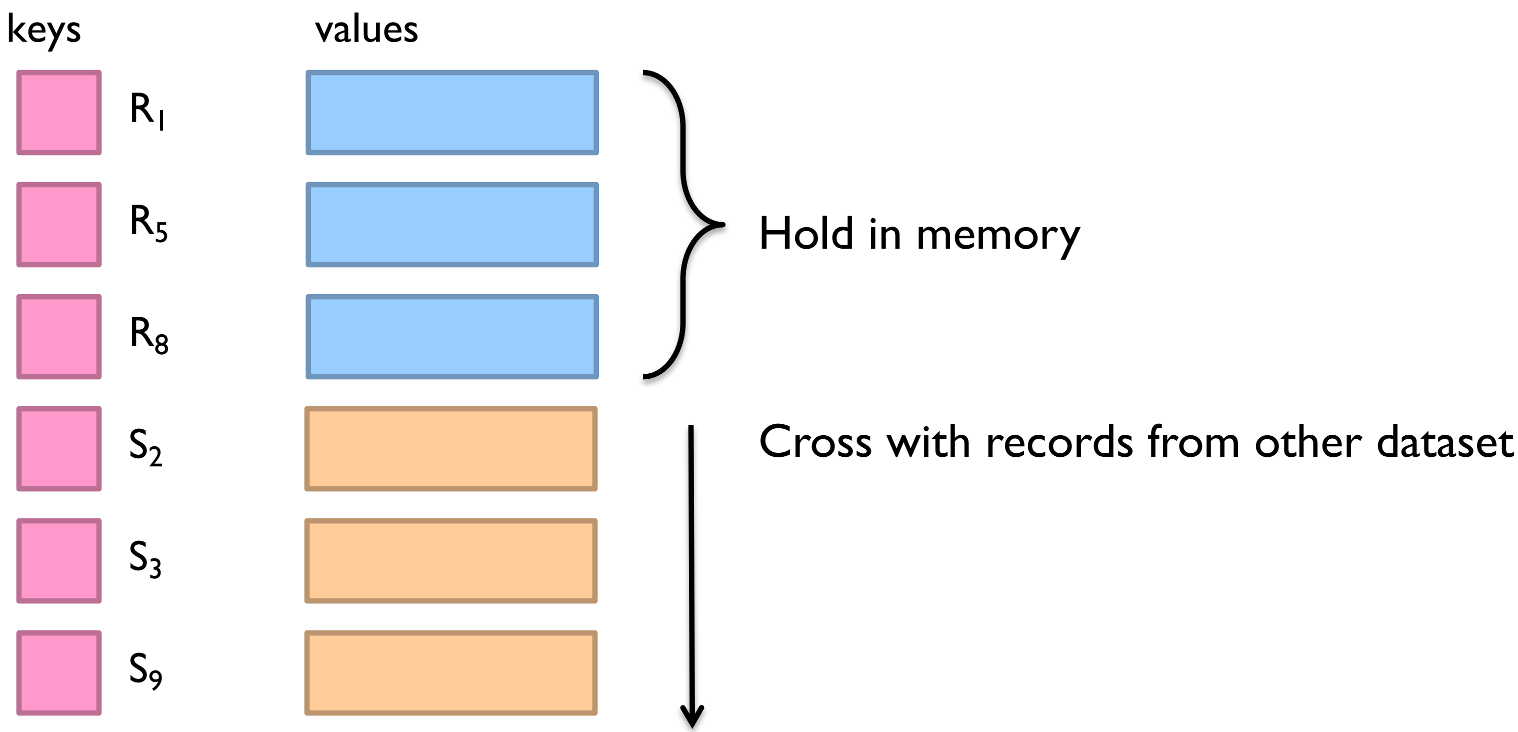
Reduce-side Join: V-to-K Conversion

In reducer…



Reduce-side Join: many-to-many

In reducer…

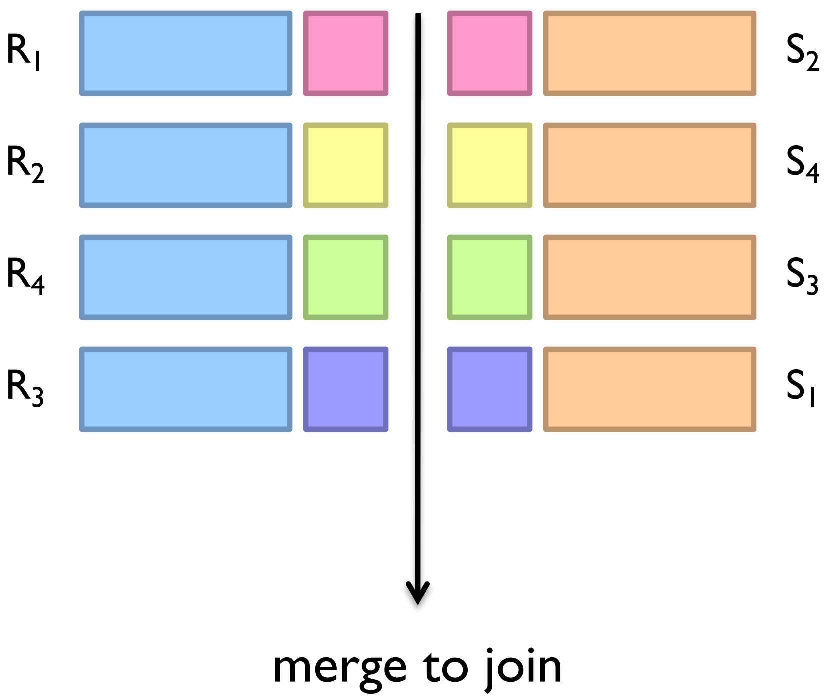


What's the problem?

Map-side Join

aka sort-merge join

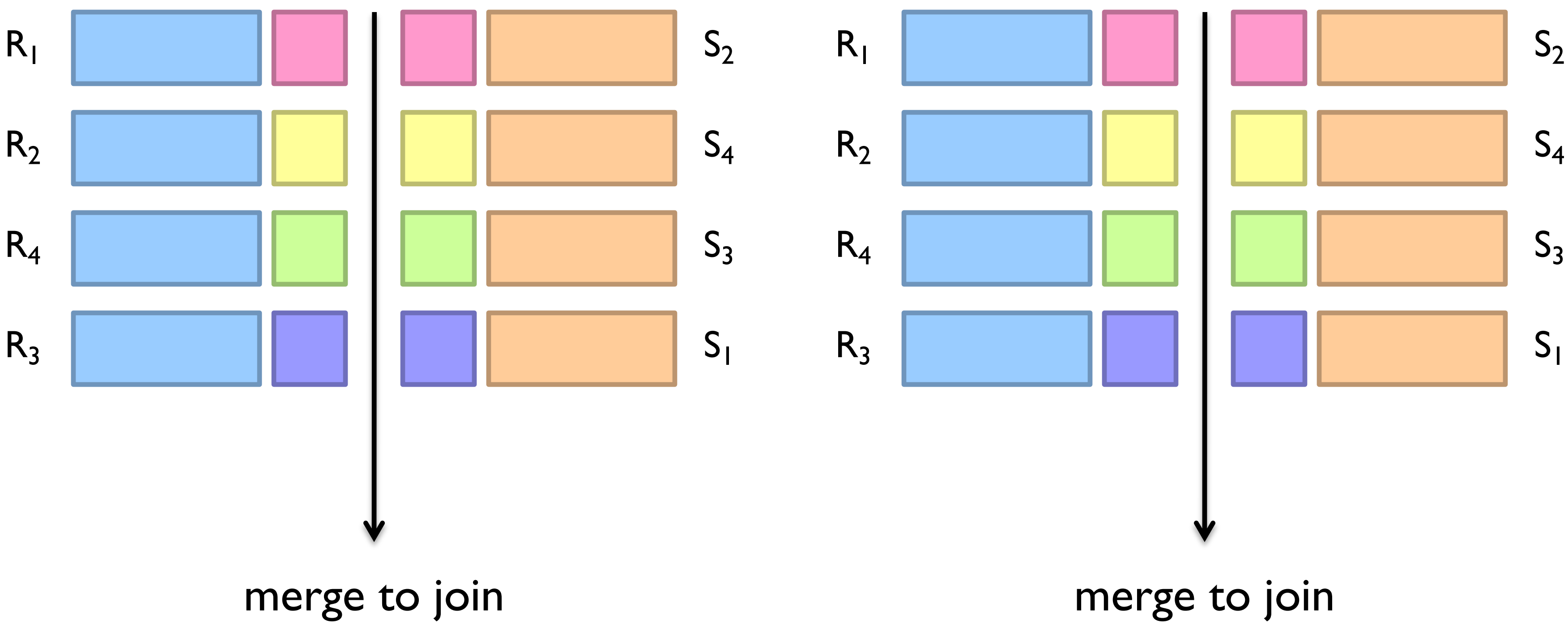
Assume two datasets are sorted by the join key:



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 <When?

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?

Hash join > map-side join > reduce-side join

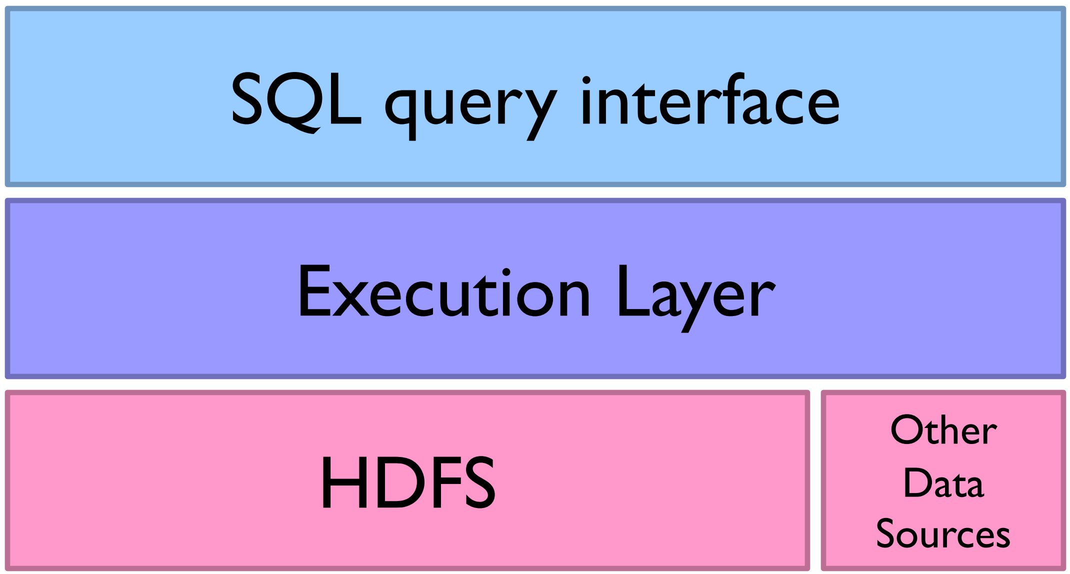
Limitations of each?

In-memory join: memory

Map-side join: sort order and partitioning

Reduce-side join: general purpose

SQL-on-Hadoop



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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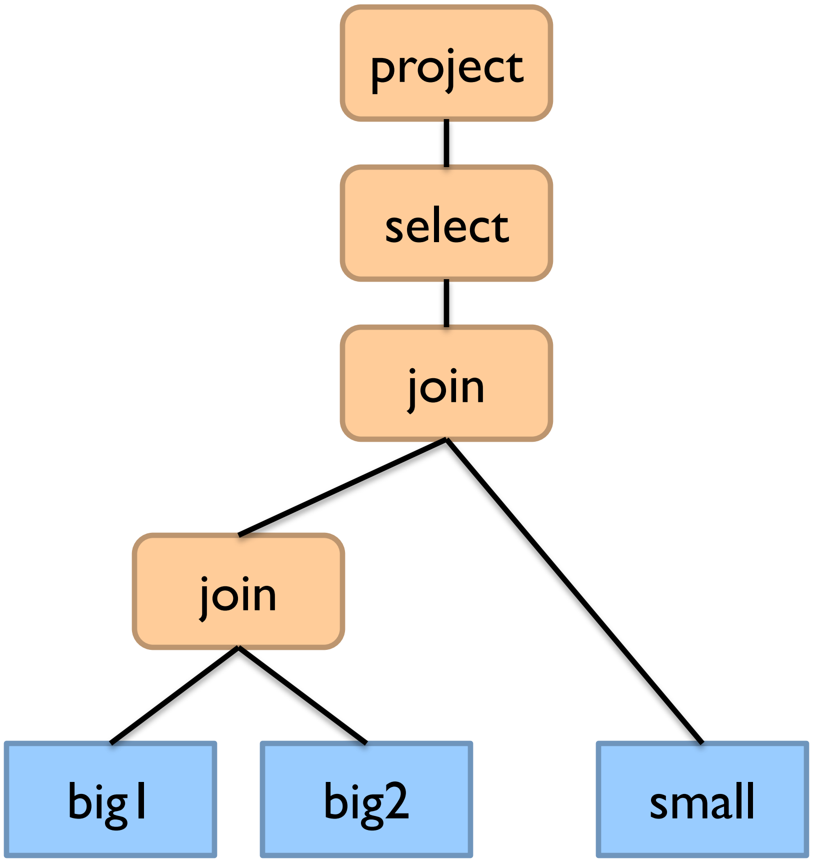

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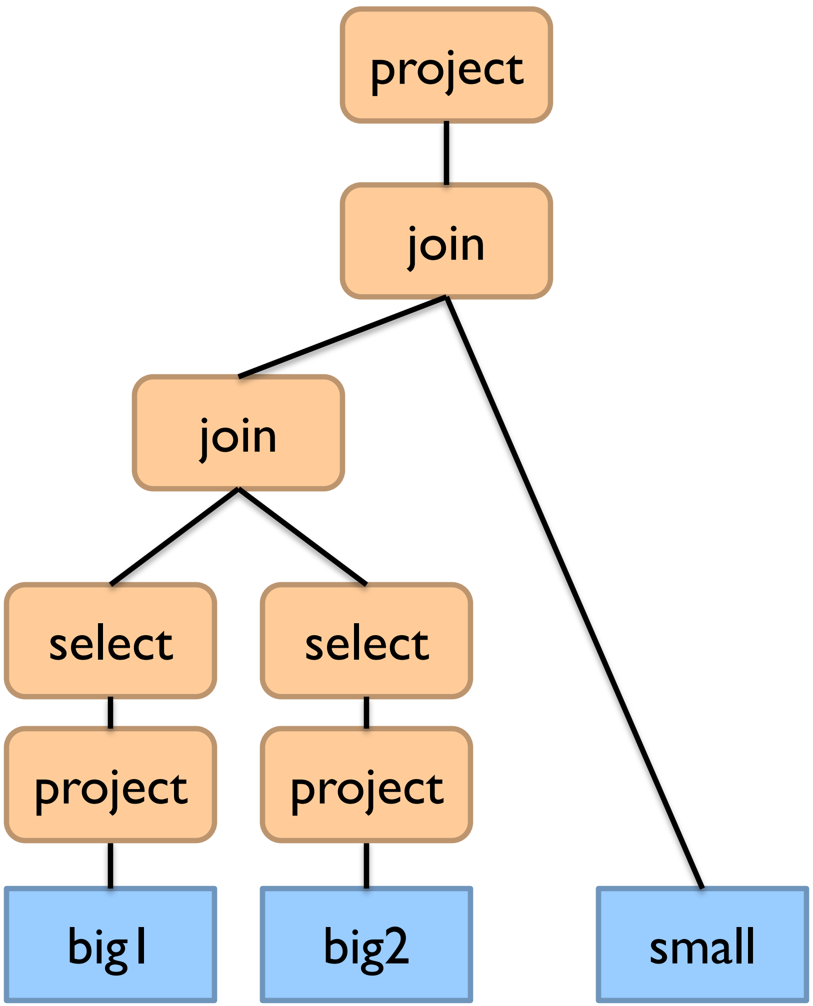

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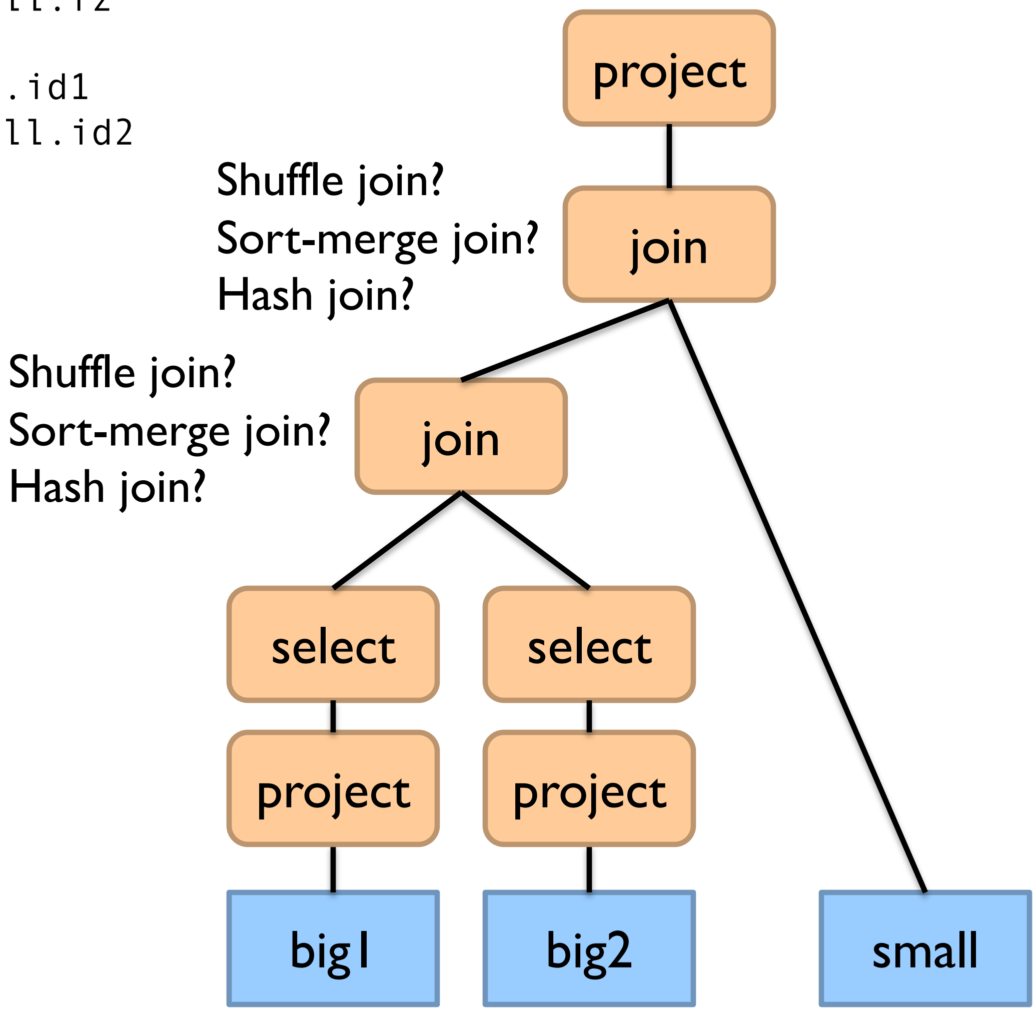

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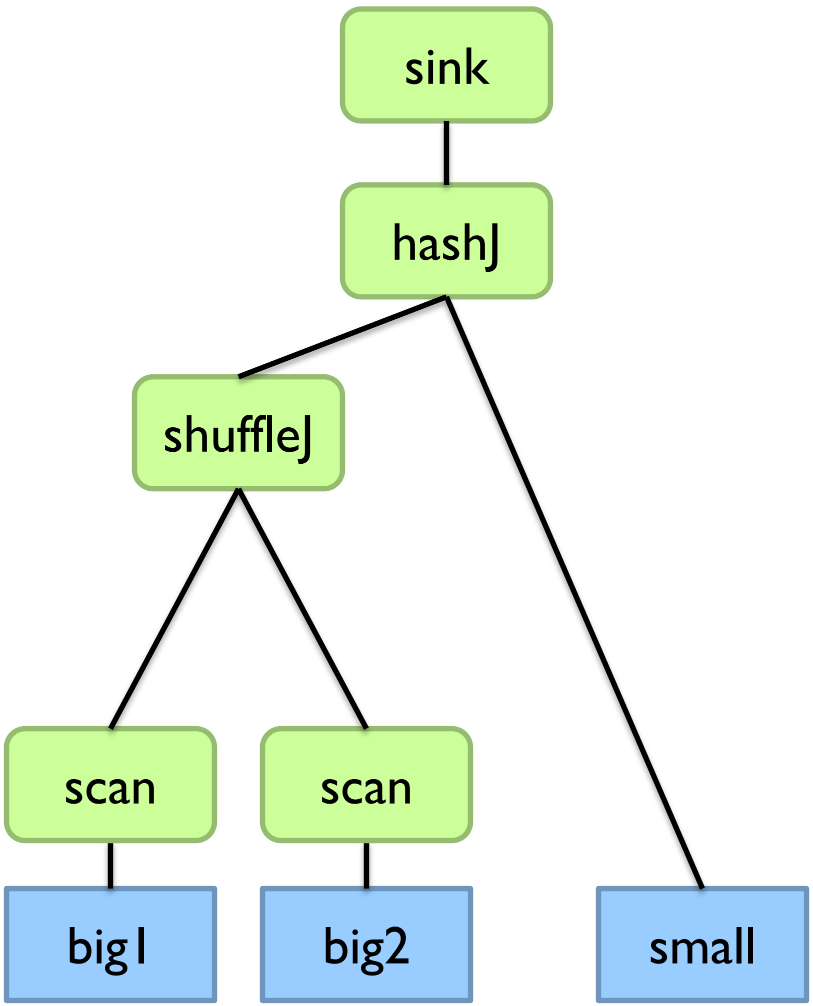

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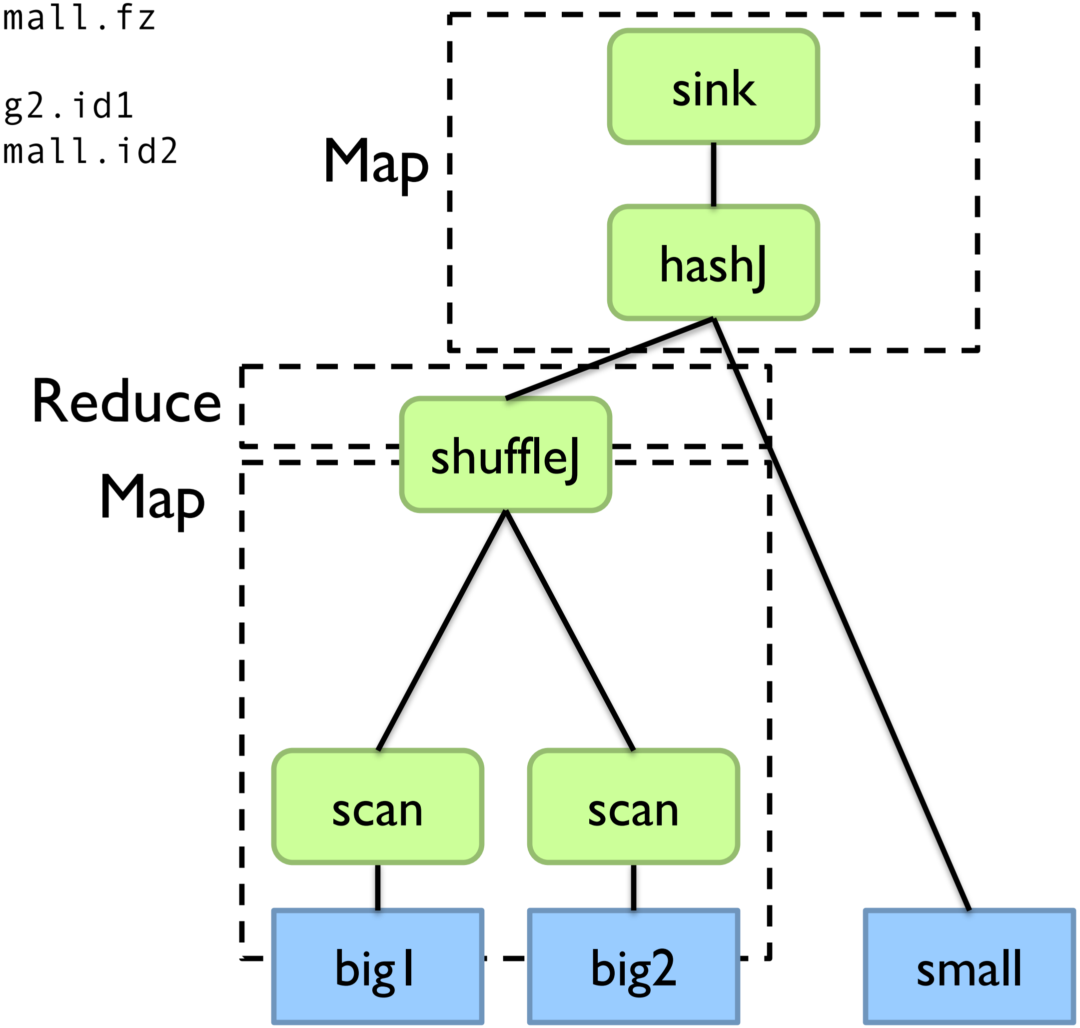

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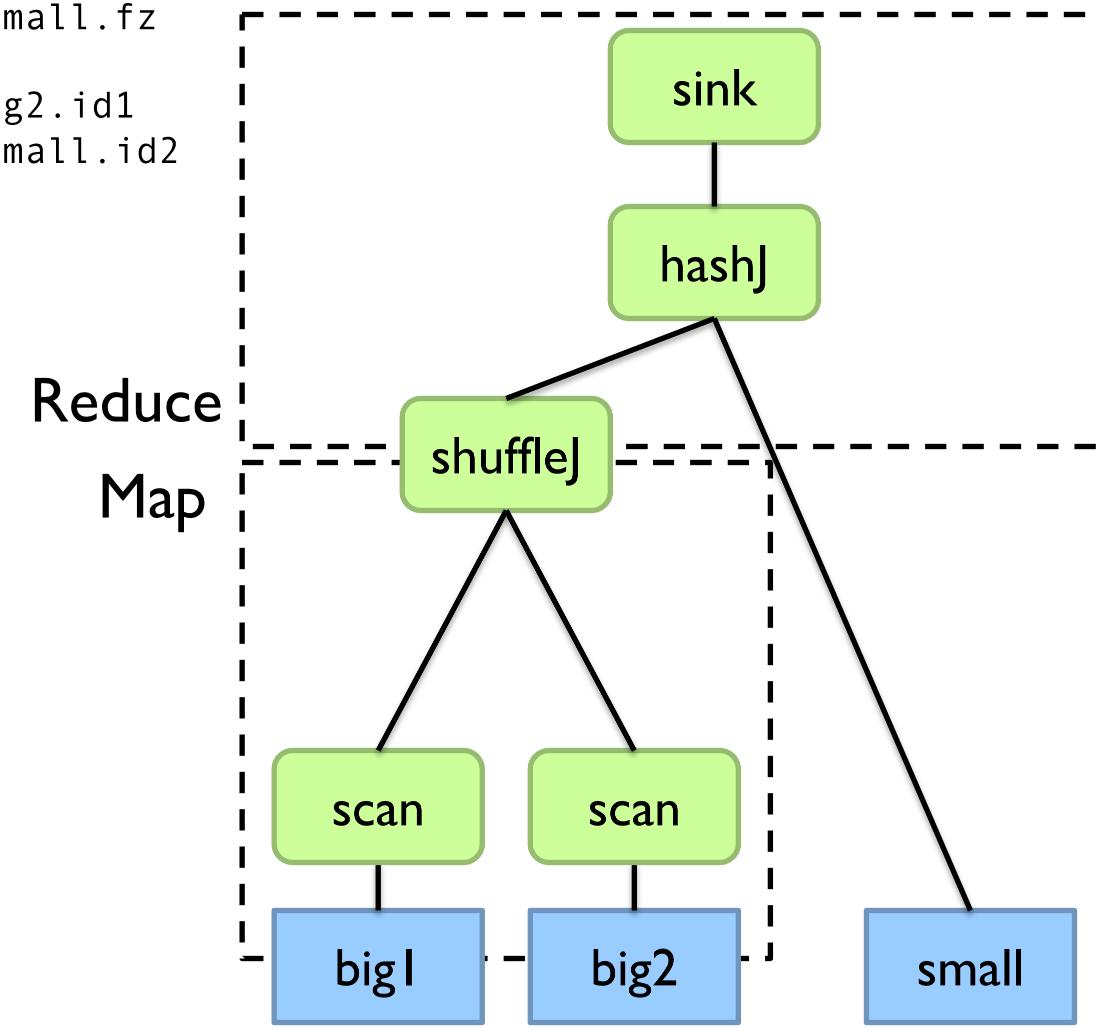
      big2.f2 > 2;
```



Build logical plan

Optimize logical plan

Select physical plan

Hive: Behind the Scenes

Now you understand what's going on here!

```
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

Now you understand what's going on here!

```
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
```

SQL-on-Hadoop

SQL query interface

Execution Layer

HDFS

Other Data Sources

What about Spark SQL?

Based on the DataFrame API:

A distributed collection of data organized into named columns

Two ways of specifying SQL queries:

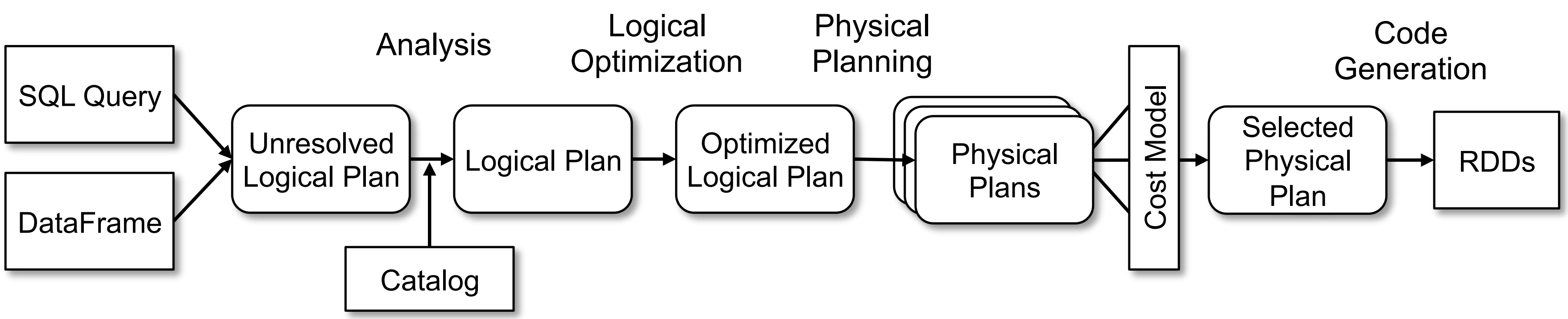
Directly:

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

Via DataFrame API:

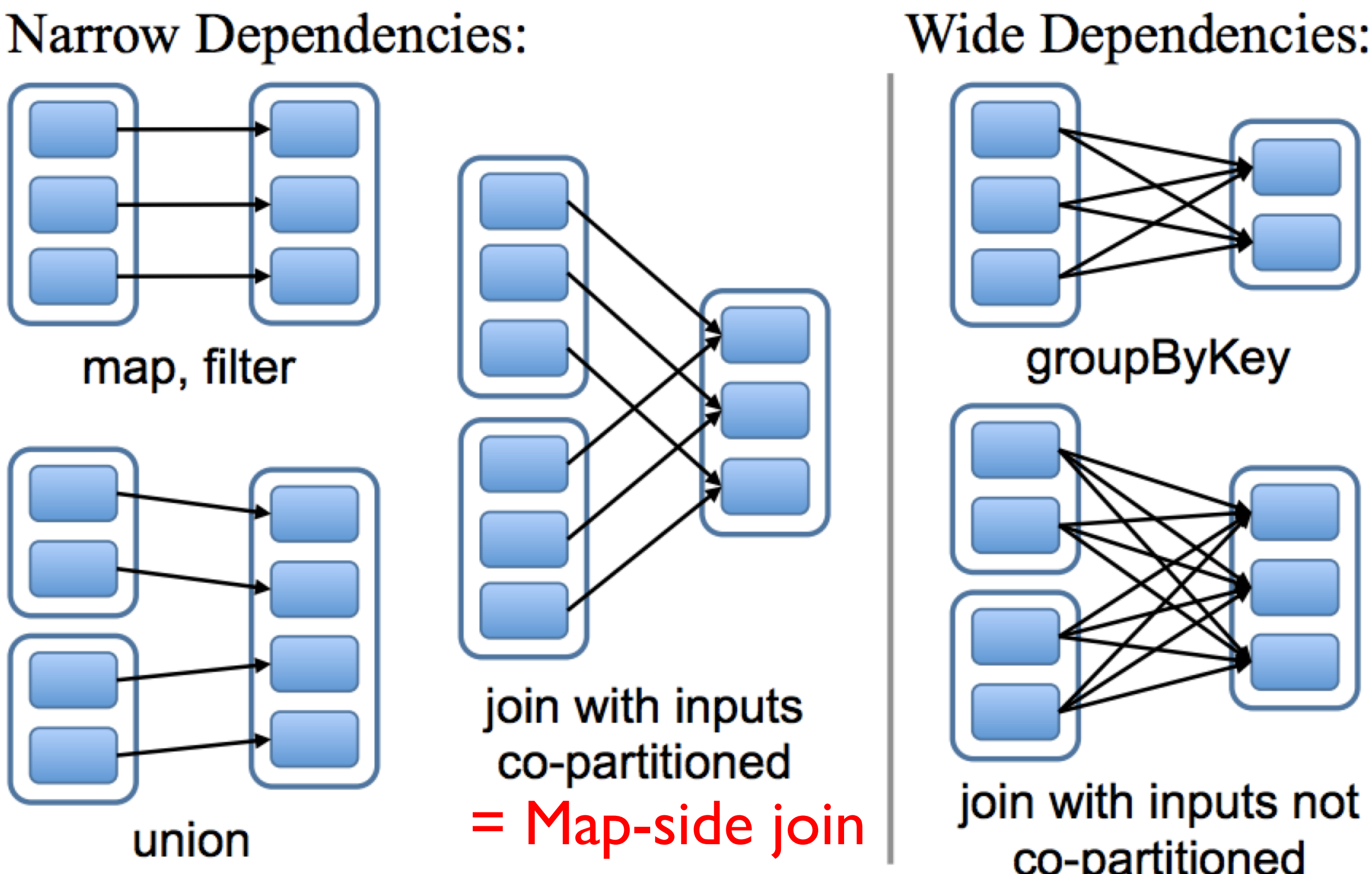
```
// employees is a dataframe:
employees
  .join(dept, employees ("deptId") === dept ("id"))
  .where(employees("gender") === "female")
  .groupBy(dept("id"), dept ("name"))
  .agg(count("name"))
```

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?

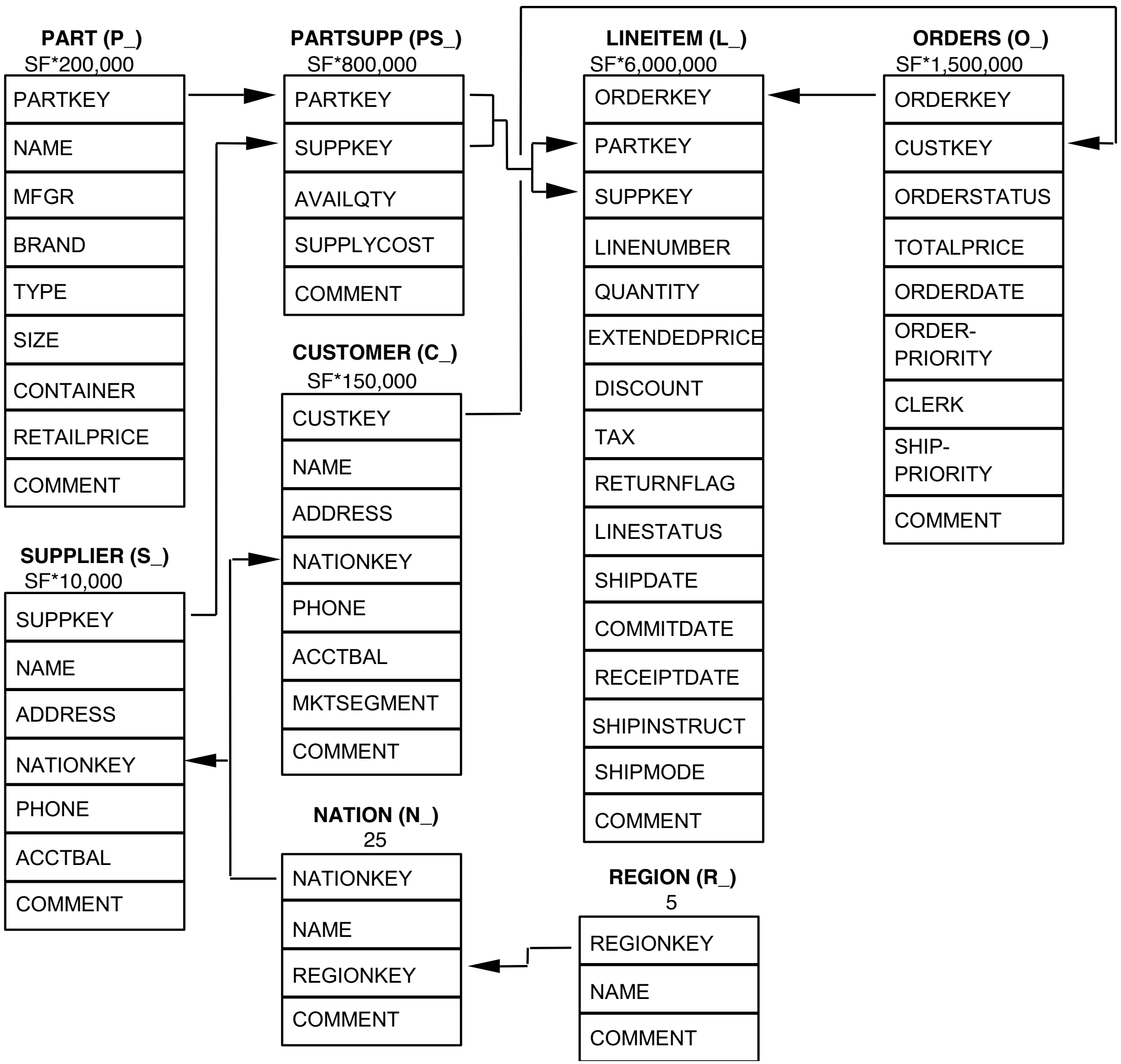
Why normalize to begin with?

Fundamentally a time-space tradeoff

How much to denormalize?

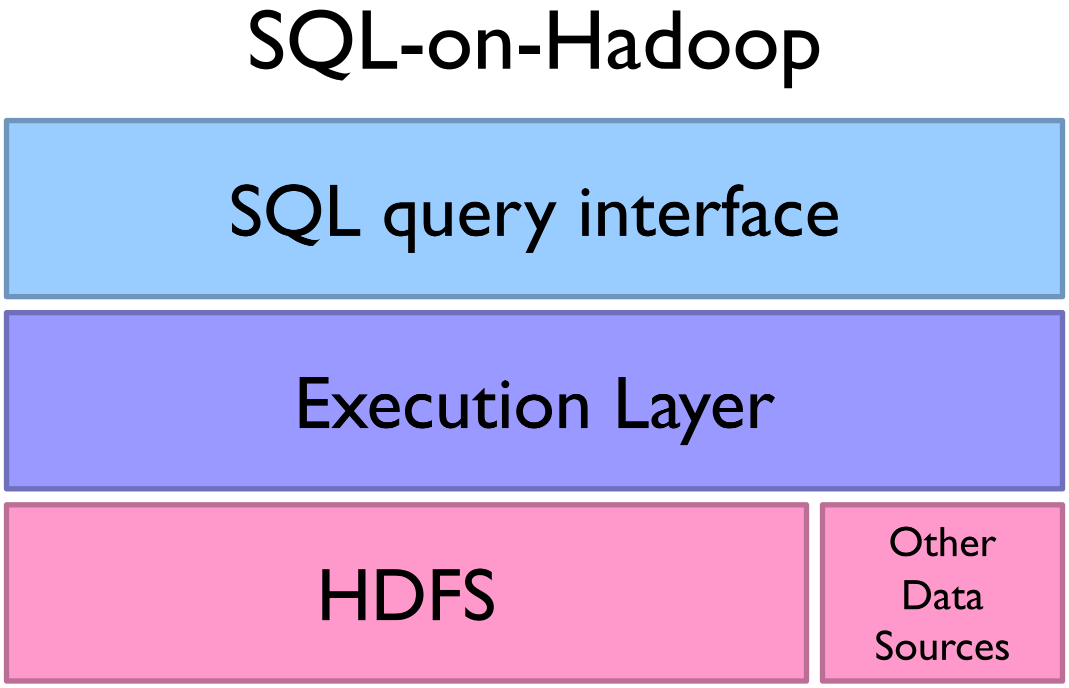
What about consistency?

Denormalization Opportunities?

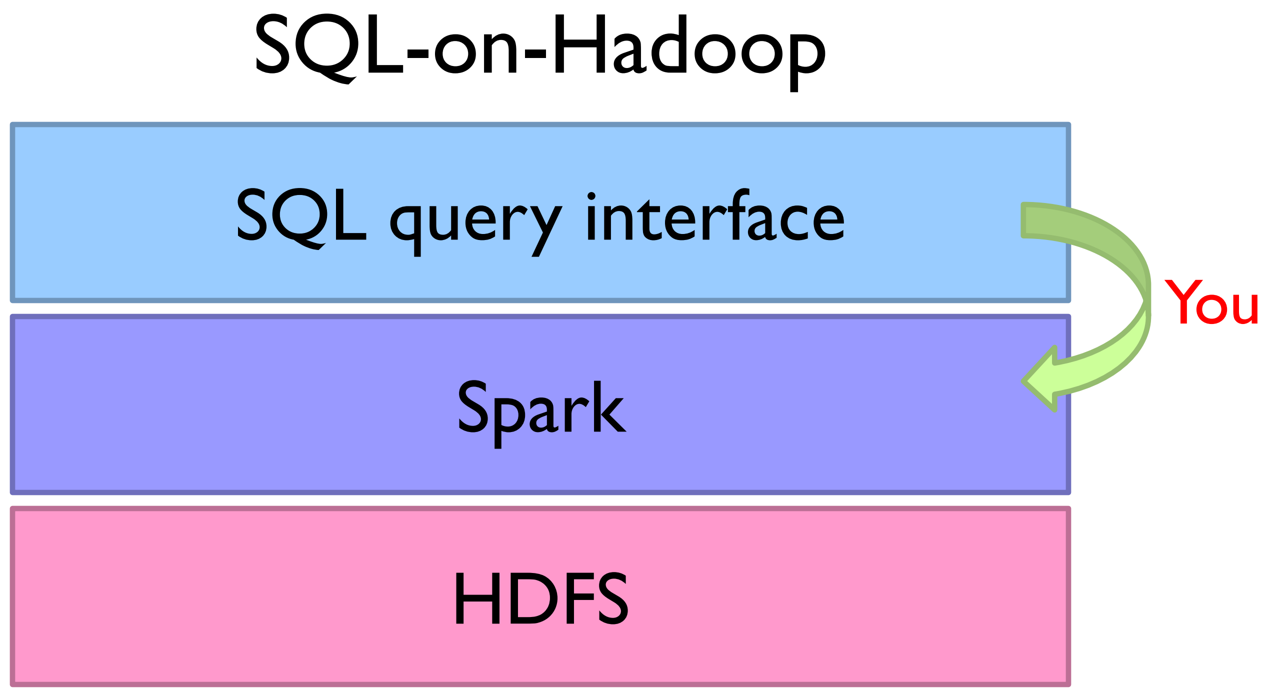


"Denormalizing the snowflake"

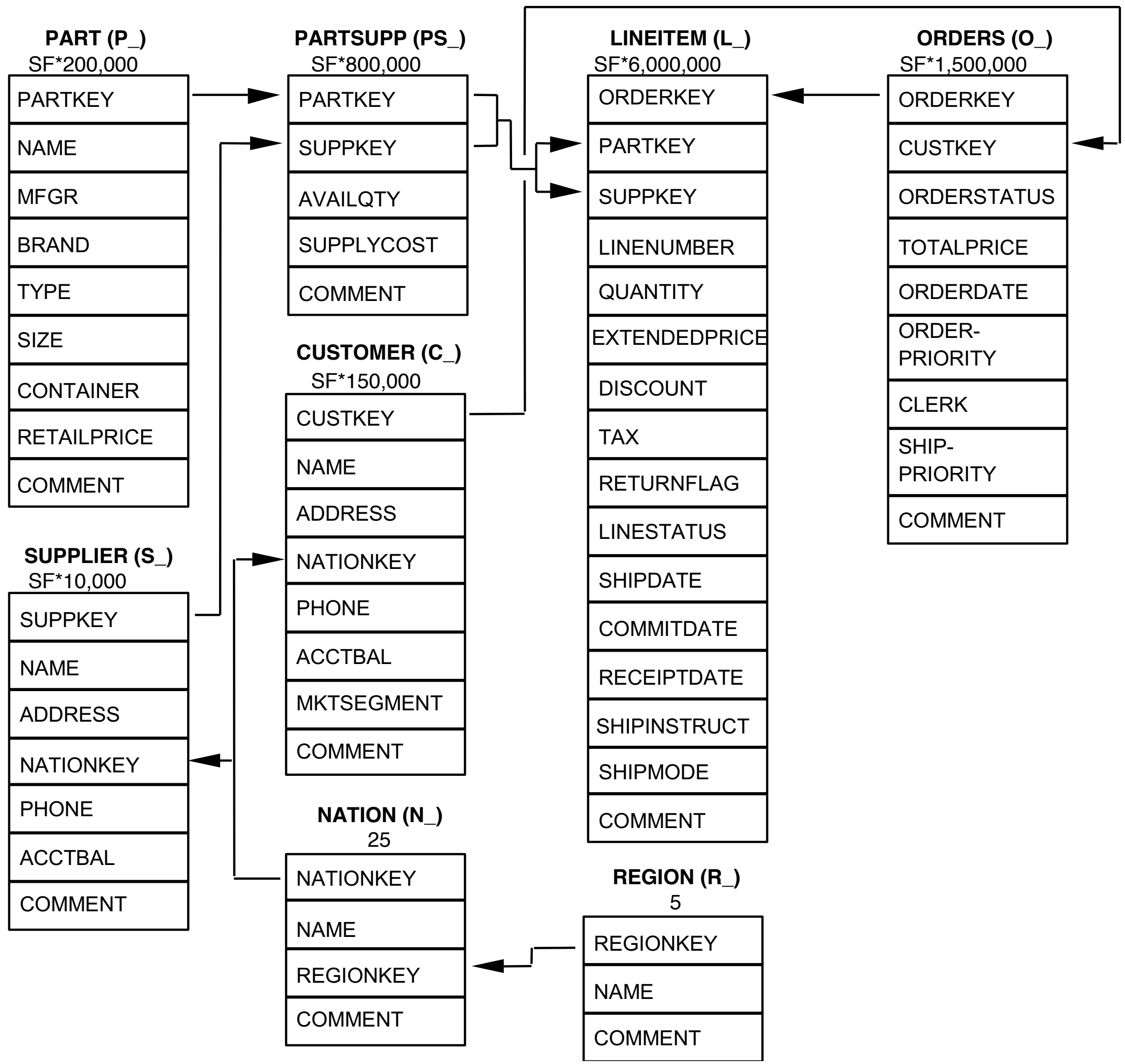
What's the assignment?



What's the assignment?



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…

Source: Wikipedia (Japanese rock garden)