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 $\rightarrow$ (v_1, r), (v_3, r), (v_4, r), (v_8, 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, 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

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

Values arrive in arbitrary order…

After

$(k, v_1) \rightarrow (v_1, r)$

$(k, v_3) \rightarrow (v_3, r)$

$(k, v_4) \rightarrow (v_4, r)$

$(k, v_8) \rightarrow (v_8, r)$

…

Values arrive in sorted order…

Process by preserving state across multiple keys

Remember to partition correctly!

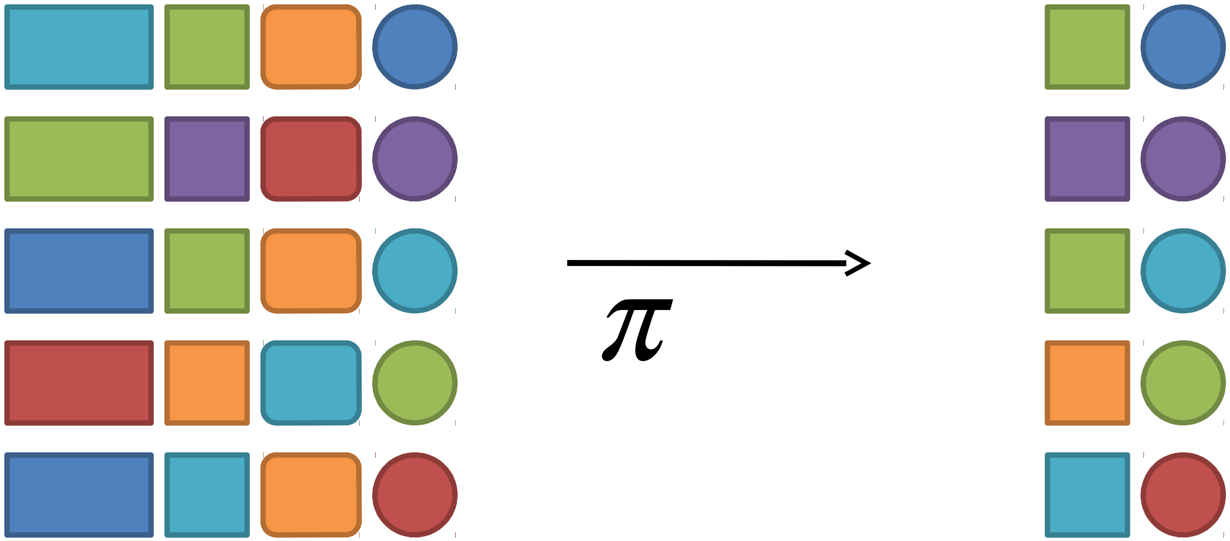
Working Scenario

- 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
  - …

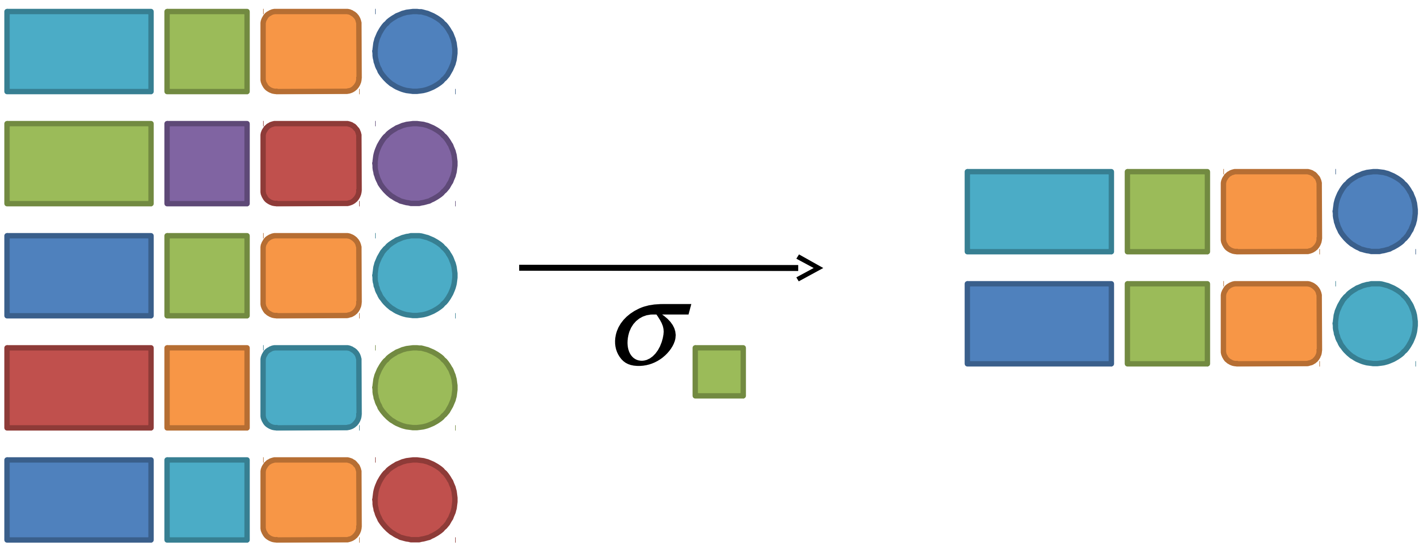
Projection



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!

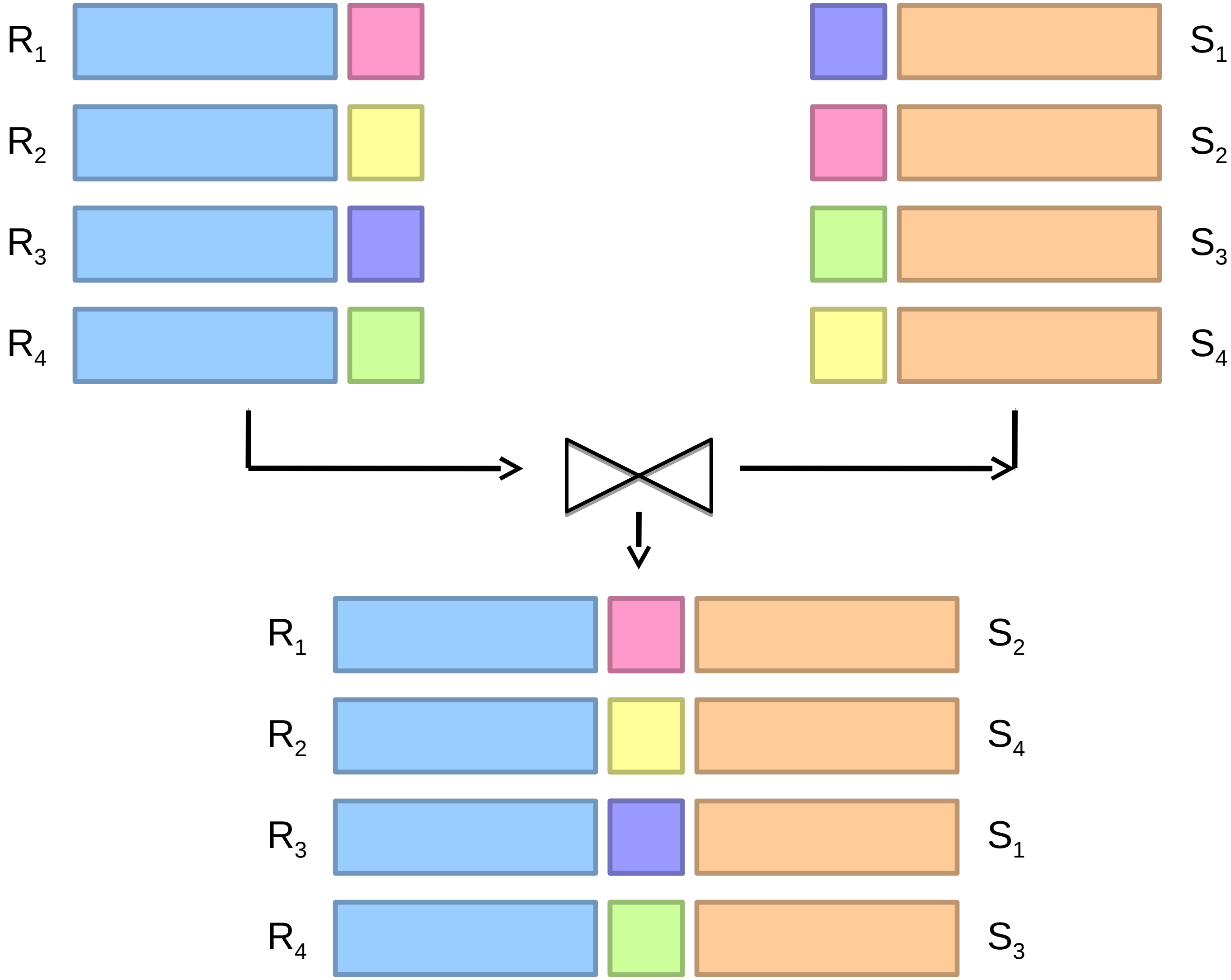
Group by… Aggregation

- 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



Natural Join Operation – Example

- Relations r, s:

A	B	C	D
α	1	α	a
β	2	γ	a
γ	4	β	b
α	1	γ	a
δ	2	β	b

r

B	D	E
1	a	α
3	a	β
1	a	γ
2	b	δ
3	b	$\in$

s

$r \bowtie s$

A	B	C	D	E
α	1	α	a	α
α	1	α	a	γ
α	1	γ	a	α
α	1	γ	a	γ
δ	2	β	b	δ

Natural Join Example

sid	bid	day
22	101	10/10/96
58	103	11/12/96

R1

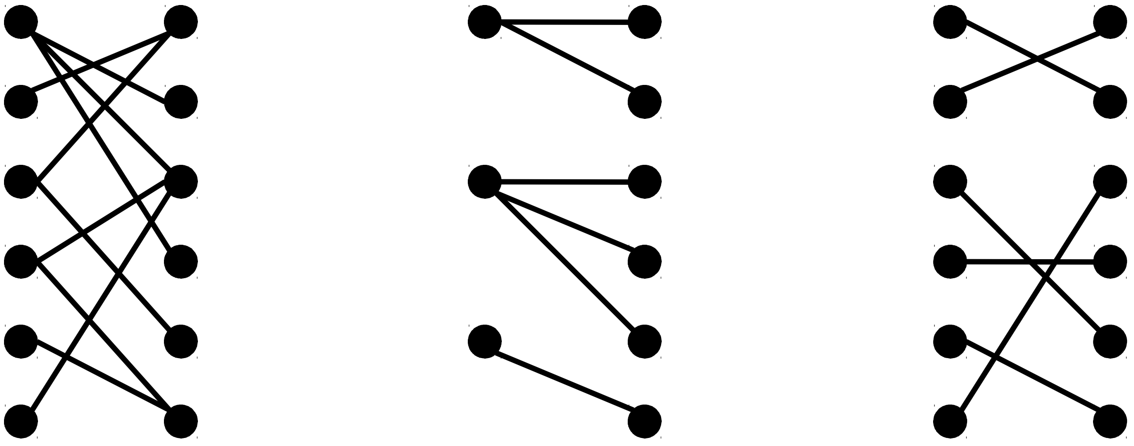
sid	sname	rating	age
22	dustin	7	45.0
31	lubber	8	55.5
58	rusty	10	35.0

S1

R1 $\bowtie$ **S1 =**

sid	sname	rating	age	bid	day
22	dustin	7	45.0	101	10/10/96
58	rusty	10	35.0	103	11/12/96

Types of Relationships



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

Join Algorithms in MapReduce

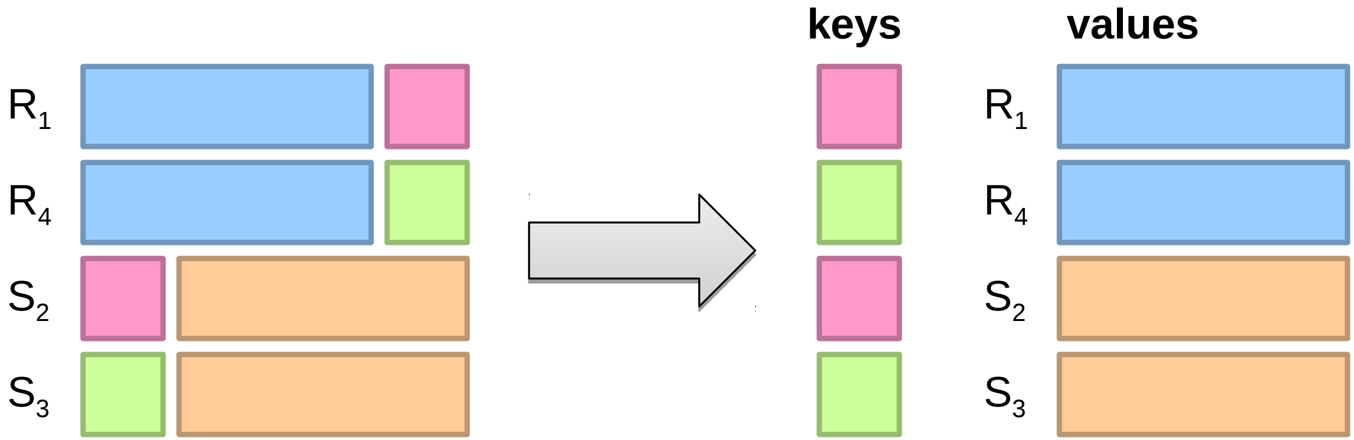
- Reduce-side join
- Map-side join
- In-memory join
  - Striped variant
  - Memcached variant

Reduce-side Join

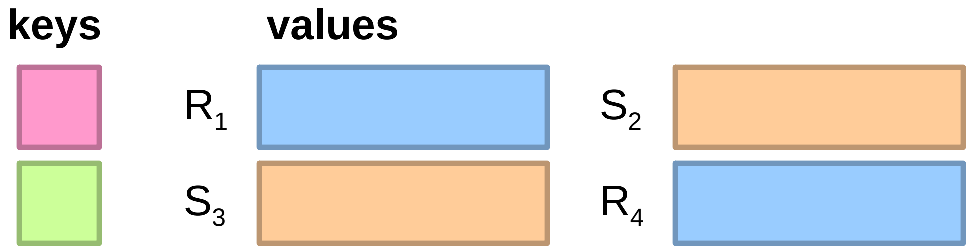
- Basic idea: group by join key
  - Map over both sets of tuples
  - Emit tuple as value with join key as the intermediate key
  - Execution framework brings together tuples sharing the same key
  - Perform actual join in reducer
  - Similar to a “sort-merge join” in database terminology
- Two variants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

Reduce-side Join: 1-to-1

Map



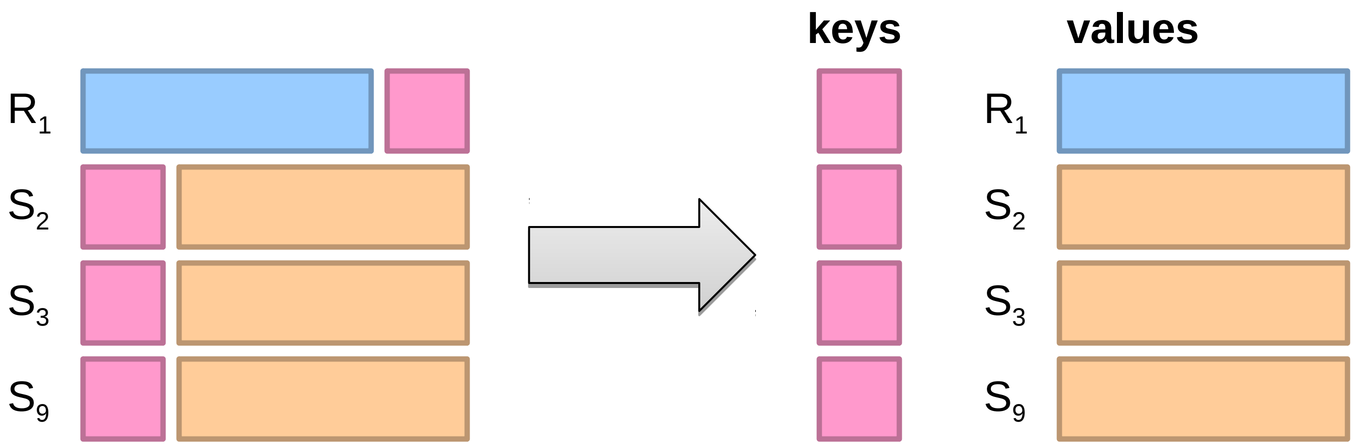
Reduce



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

Reduce-side Join: 1-to-many

Map

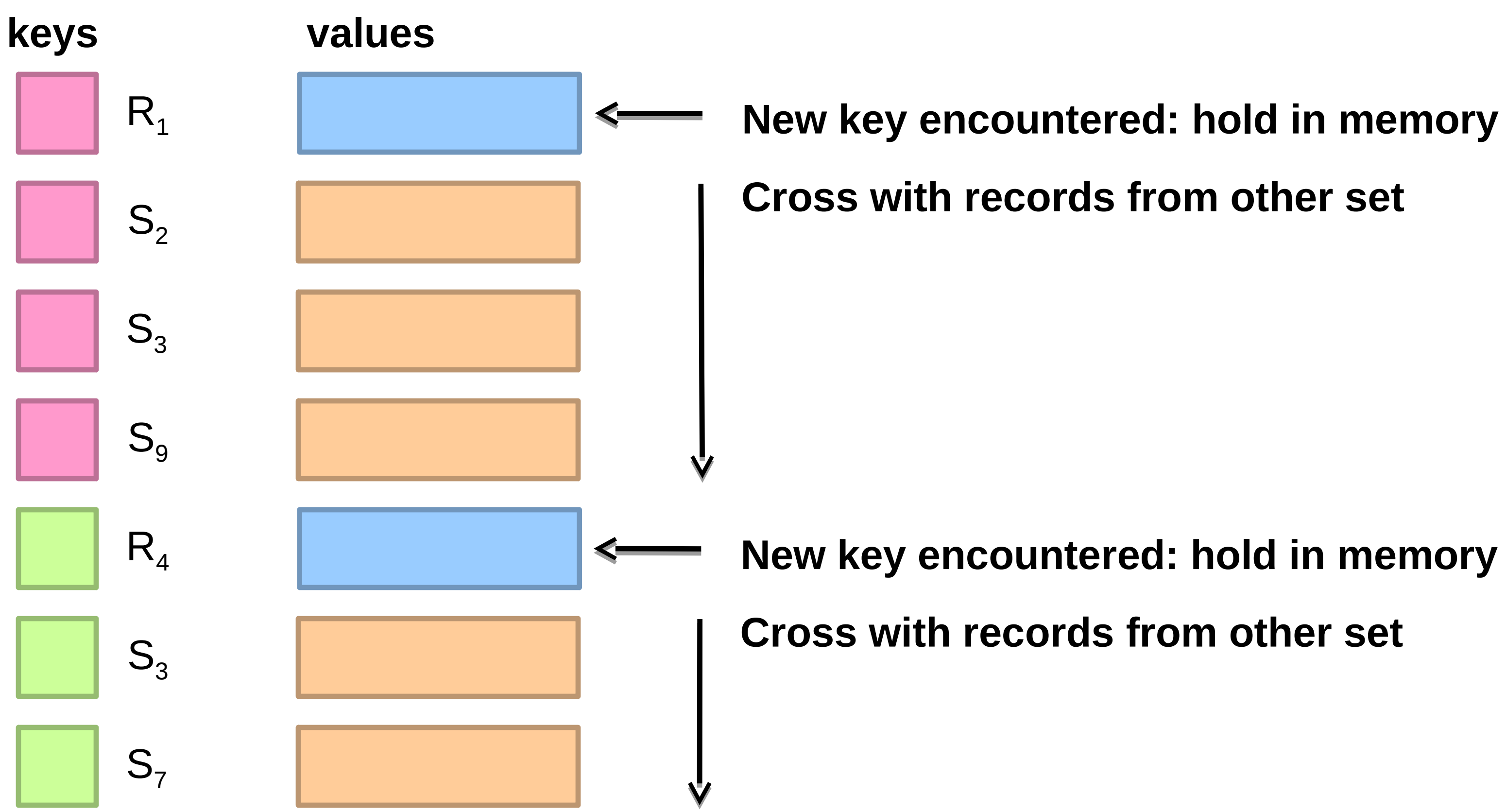


Reduce

What’s the problem?

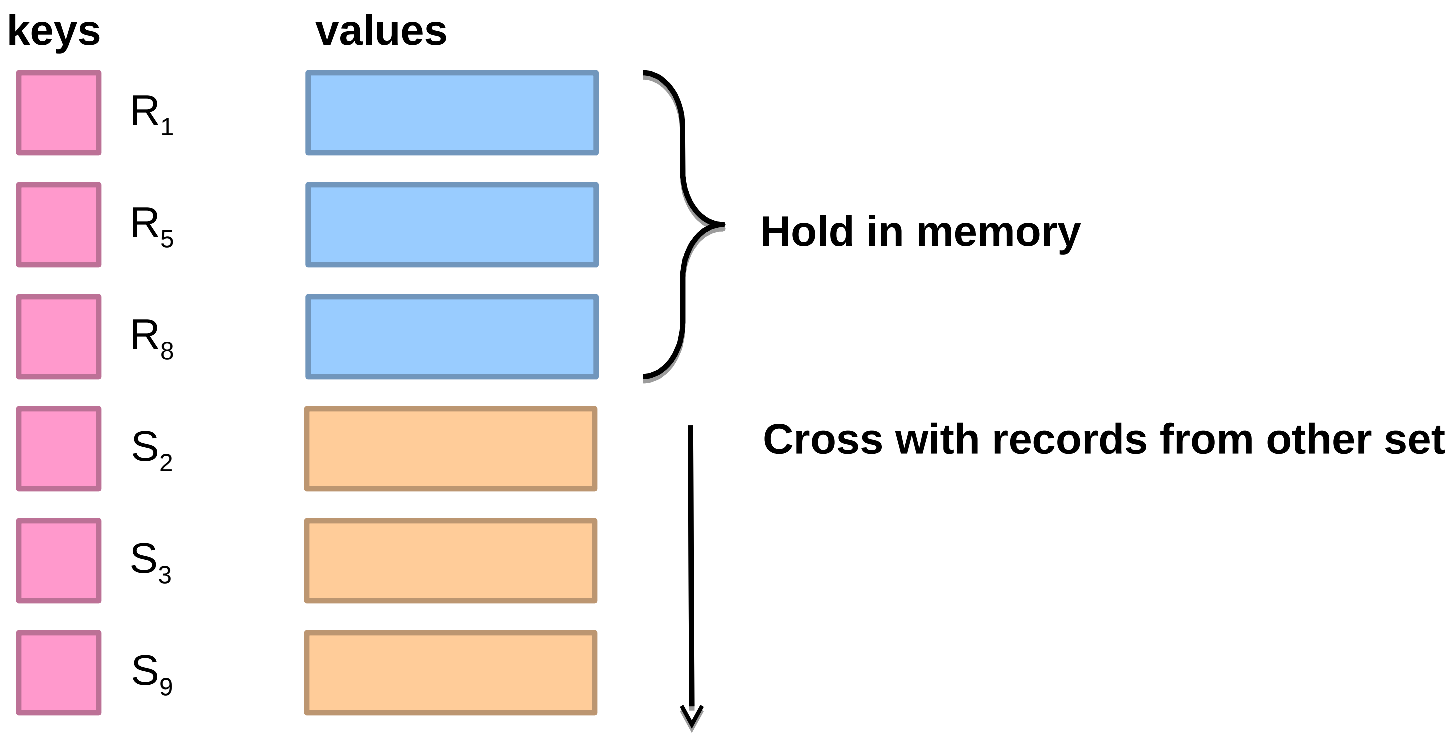
Reduce-side Join: V-to-K Conversion

In reducer…



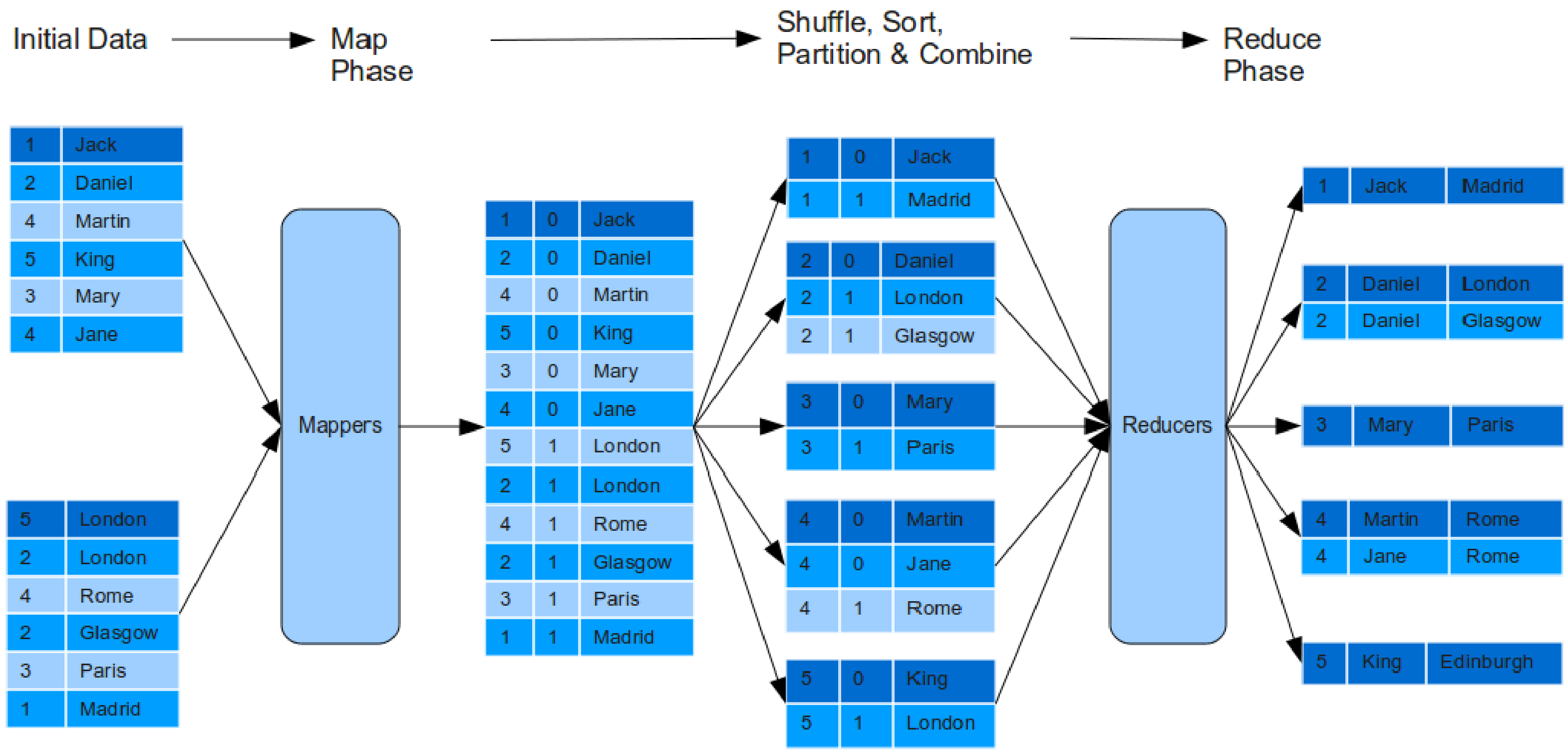
Reduce-side Join: many-to-many

In reducer…



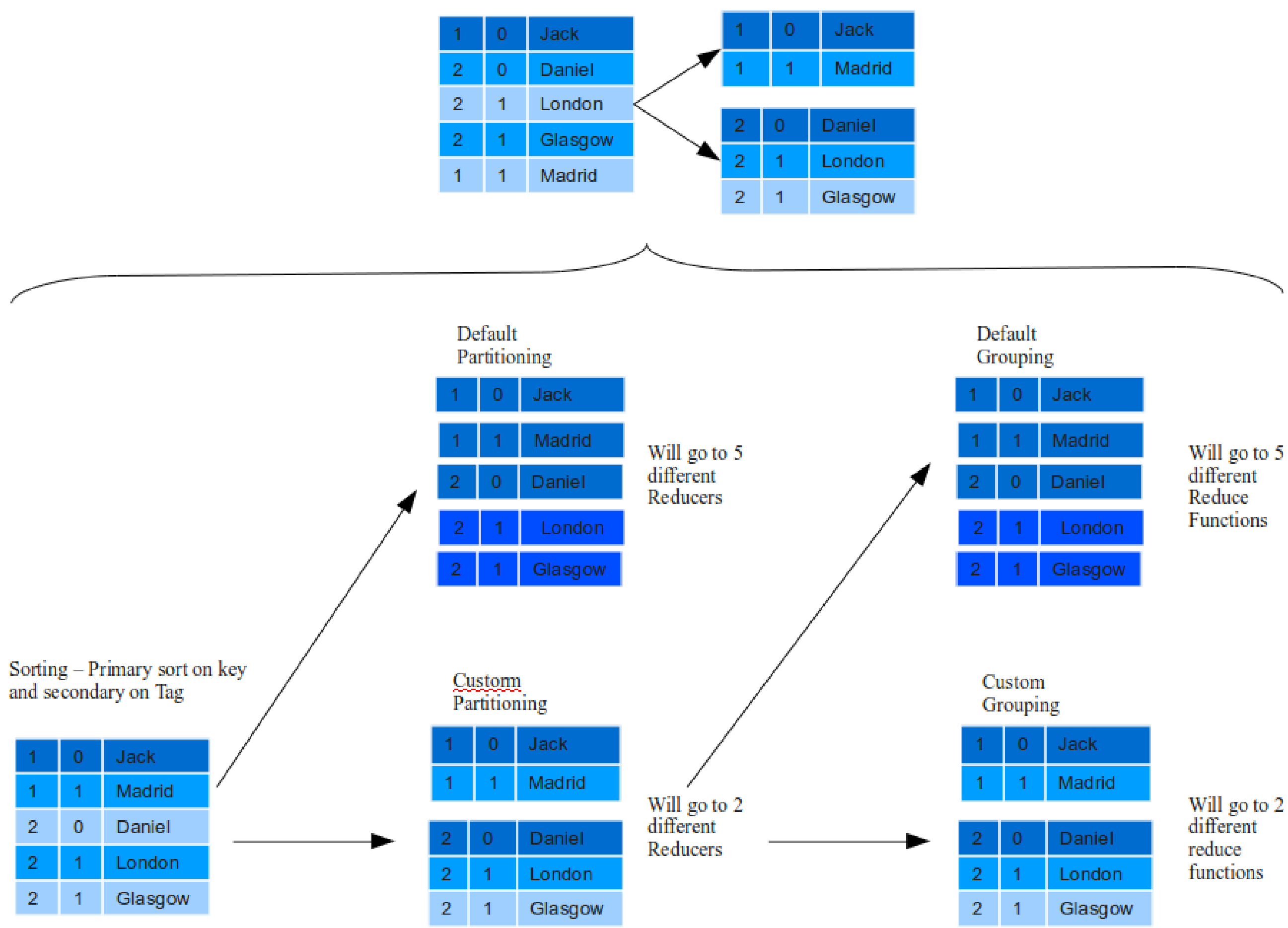
What's the problem?

Reduce-side Join: many-to-many



Produce mapper output with composite key that includes foreign key and table name

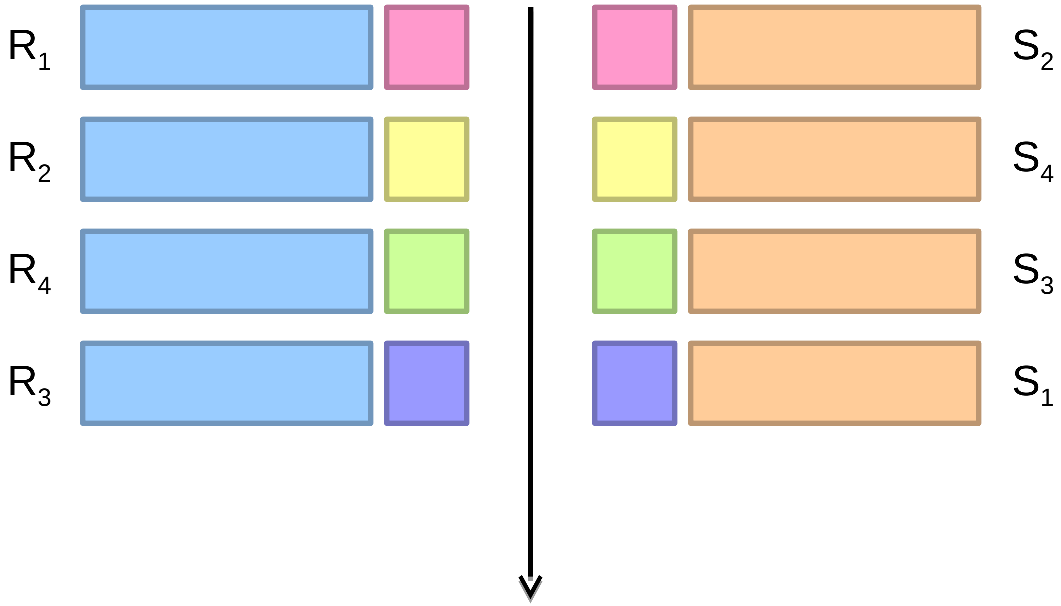
Reduce-side Join: many-to-many



Use custom partitioning and grouping to send data with same key to a single reducer

Map-side Join: Basic Idea

Assume two datasets are sorted by the join key:

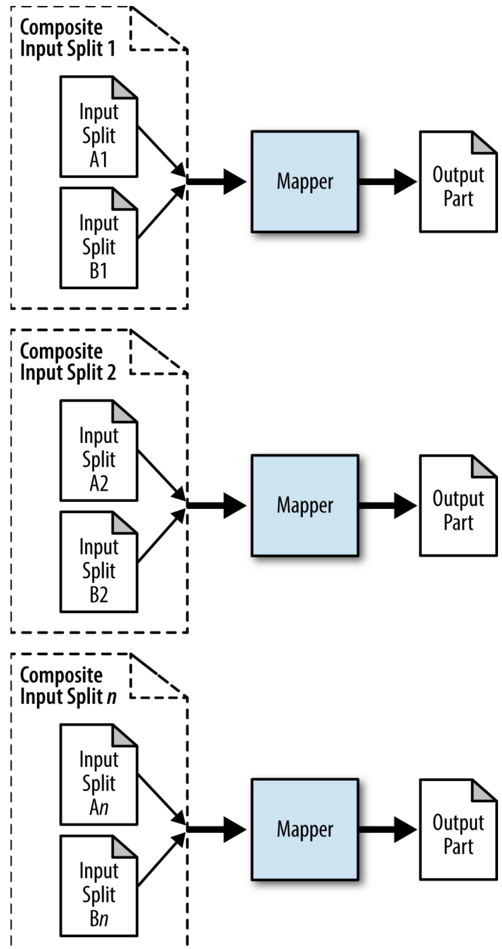


A sequential scan through both datasets to join
(called a “merge join” in database terminology)

Map-side Join: Parallel Scans

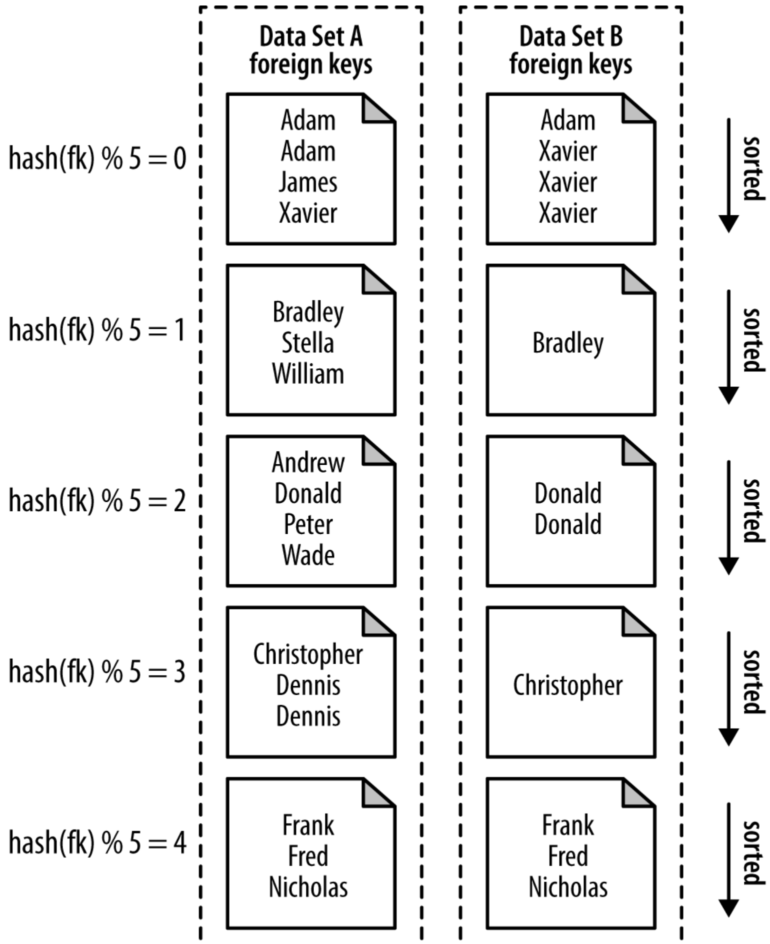
- If datasets are sorted by join key, join can be accomplished by a scan over both datasets
- How can we accomplish this in parallel?
  - Partition and sort both datasets in the same manner
- In MapReduce:
  - Map over one dataset, read from other corresponding partition
  - No reducers necessary (unless to repartition or resort)
- Consistently partitioned datasets: realistic to expect?

Map-side Join: Parallel Scans



and split both A and B before sending to mapper. Mapper will produce output,
educer needed.

Map-side Join: Parallel Scans



Parallel Scan & Join

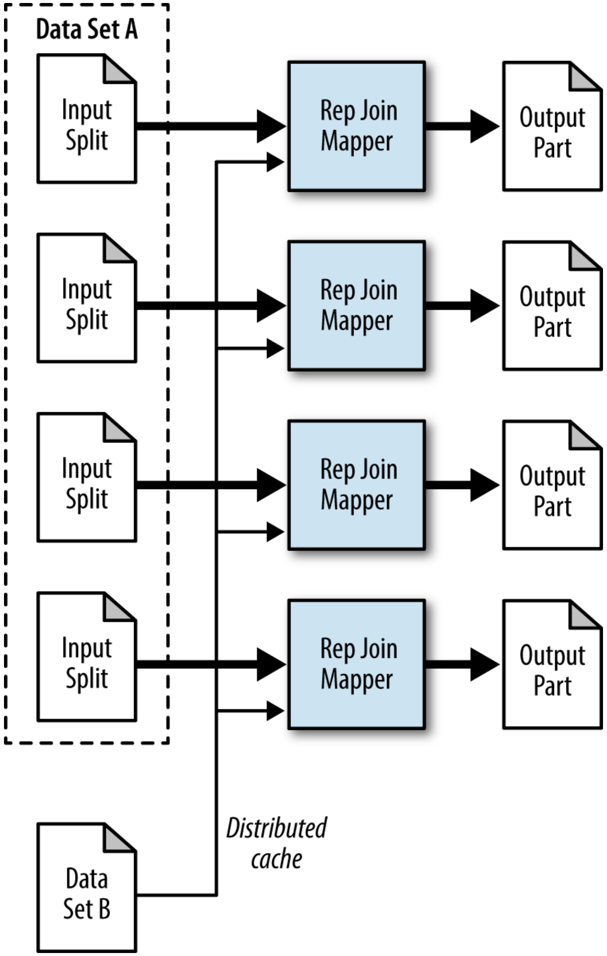
```
p ∈ P; q ∈ Q; gq ∈ Q
while more tuples in inputs do

  while p.a < gq.b do
    advance p
  end while
  while p.a > gq.b do
    advance gq {a group might begin here}
  end while
  while p.a == gq.b do
    q = gq {mark group beginning}
    while p.a == q.b do
      Add ⟨p,q⟩ to the result
      Advance q
    end while
    Advance p {move forward}
  end while
  gq = q {candidate to begin next group}
end while
```

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

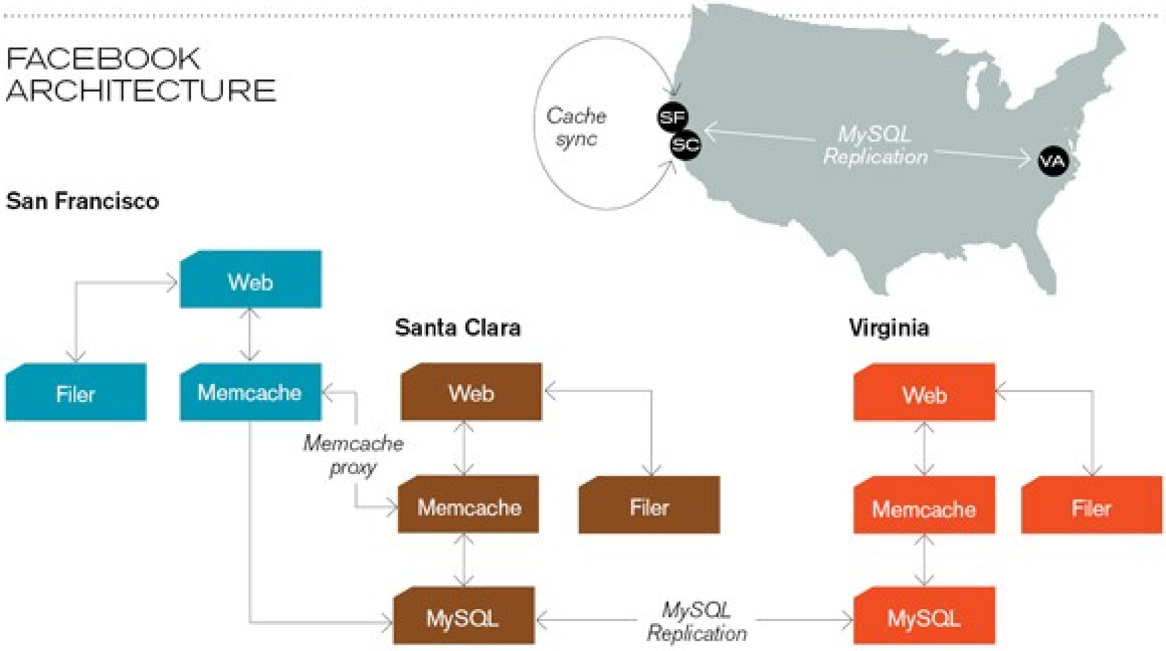


and distribute dataset B to all the mappers. For each key in B, iterate over all th
r joining

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



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