MapReduce Algorithm Design

Based on Jimmy Lin's slides

Midterm – Take Home Exam

- Take Home Exam, Open Books and Notes
- No collaboration is allowed!
- 1 day (24 hours) to complete and submit using Gradescope
- Based on material before the break
  - Lecture Notes and Slides from Jan 22 to March 4
  - Papers and Book Chapters
  - Topics:
    - B-tree and Linear Hashing
    - Spatial databases and Indexing
    - Temporal databases and Indexing
    - Spatio-temporal Databases
    - Time Series

Midterm

- When?
  - One option April 8, Wednesday
  - Second option, April 13, Monday
  - Other days?

  - We decided to do a poll for potential days on Piazza…

MapReduce: Recap

- Programmers must specify:

  map (k, v) → <k’, v’>*

  reduce (k’, v’) → <k’, v’>*

  – All values with the same key are reduced together
- Optionally, also:

  partition (k’, number of partitions) → partition for k’

  – Often a simple hash of the key, e.g., hash(k’) mod n

  – Divides up key space for parallel reduce operations

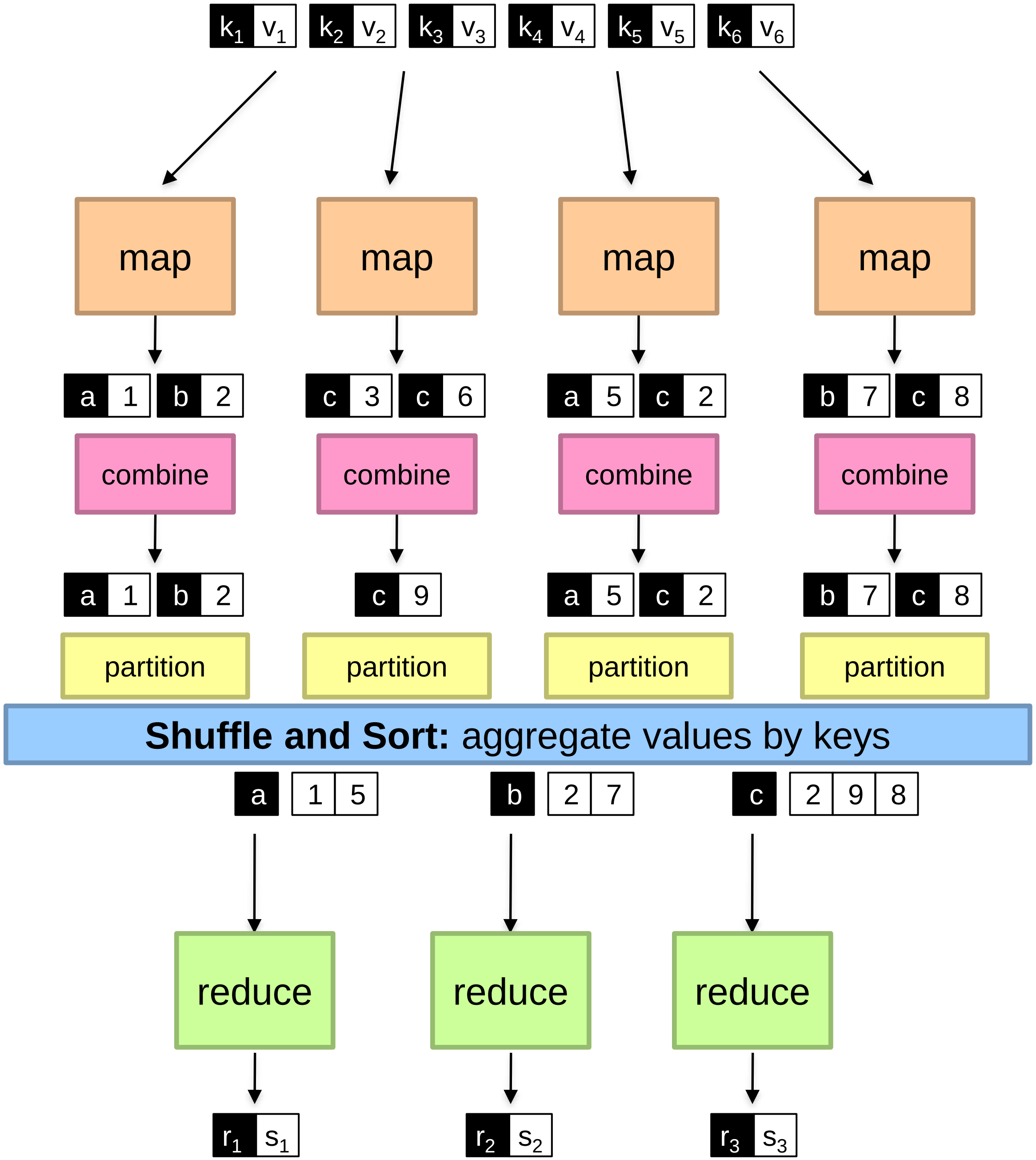
  combine (k’, v’) → <k’, v’>*

  – Mini-reducers that run in memory after the map phase

  – Used as an optimization to reduce network traffic
- The execution framework handles everything else…

"Everything Else"

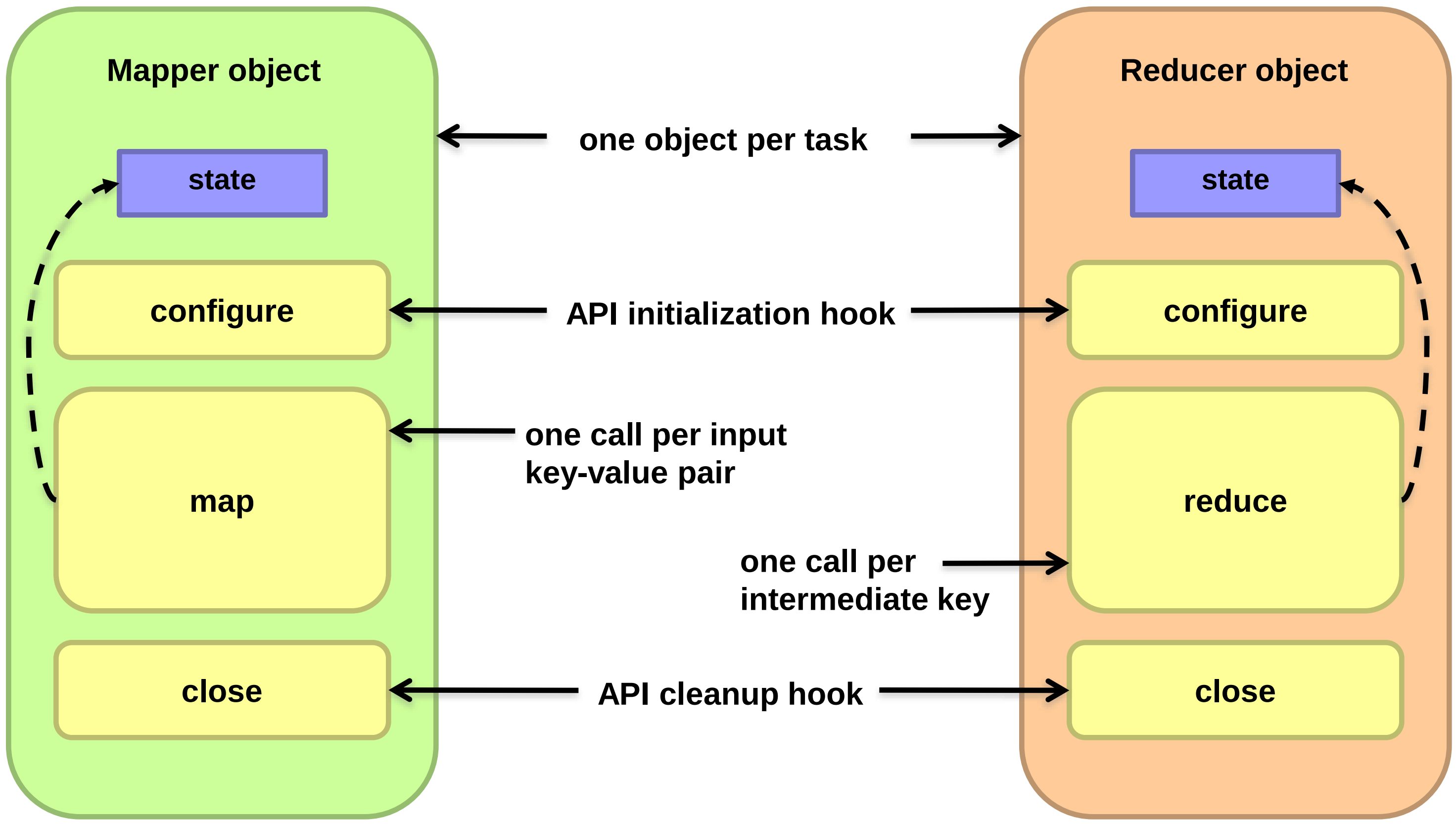
- The execution framework handles everything else…
  - Scheduling: assigns workers to map and reduce tasks
  - "Data distribution": moves processes to data
  - Synchronization: gathers, sorts, and shuffles intermediate data
  - Errors and faults: detects worker failures and restarts
- Limited control over data and execution flow
  - All algorithms must expressed in m, r, c, p
- You don't know:
  - Where mappers and reducers run
  - When a mapper or reducer begins or finishes
  - Which input a particular mapper is processing
  - Which intermediate key a particular reducer is processing


k_1 v_1 k_2 v_2 k_3 v_3 k_4 v_4 k_5 v_5 k_6 v_6
map
map
map
map
a 1 b 2
c 3 c 6
a 5 c 2
b 7 c 8
combine
combine
combine
combine
a 1 b 2
c 9
a 5 c 2
b 7 c 8
partition
partition
partition
partition
Shuffle and Sort: aggregate values by keys
a 1 5
b 2 7
c 2 9 8
reduce
reduce
reduce
r_1 s_1
r_2 s_2
r_3 s_3

Tools for Synchronization

- Cleverly-constructed data structures
  - Bring partial results together
- Sort order of intermediate keys
  - Control order in which reducers process keys
- Partitioner
  - Control which reducer processes which keys
- Preserving state in mappers and reducers
  - Capture dependencies across multiple keys and values

Preserving State



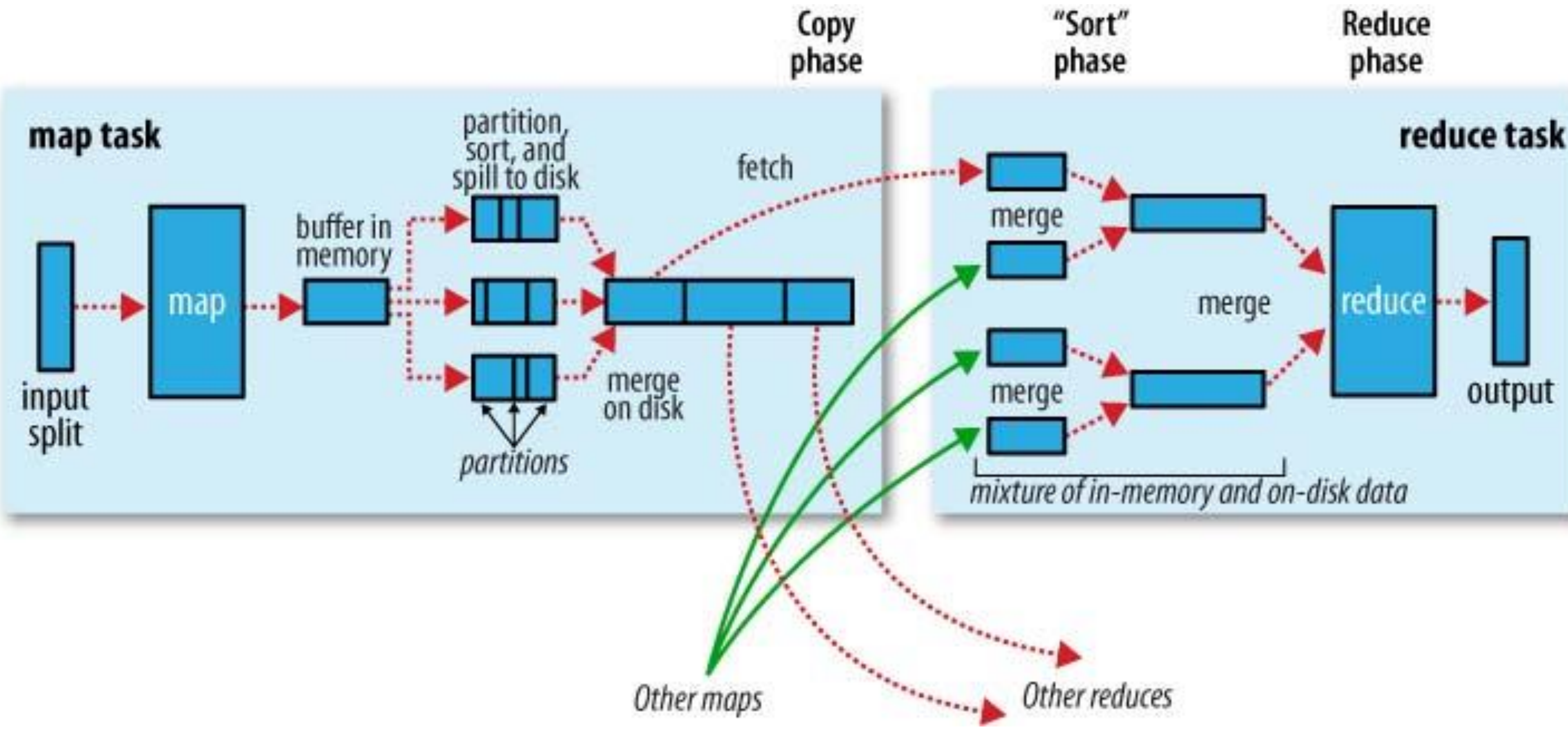
Scalable Hadoop Algorithms: Themes

- Avoid object creation
  - Inherently costly operation
  - Garbage collection
- Avoid buffering
  - Limited heap size
  - Works for small datasets, but won’t scale!

Importance of Local Aggregation

- Ideal scaling characteristics:
  - Twice the data, twice the running time
  - Twice the resources, half the running time
- Why can’t we achieve this?
  - Synchronization requires communication
  - Communication kills performance
- Thus… avoid communication!
  - Reduce intermediate data via local aggregation
  - Combiners can help

Shuffle and Sort



Word Count: Baseline

```
class Mapper
    method Map(docid a, doc d)
        for all term t ∈ doc d do
            Emit(term t, count 1)

class Reducer
    method Reduce(term t, counts [c1, c2, ...])
        sum ← 0
        for all count c ∈ counts [c1, c2, ...] do
            sum ← sum + c
        Emit(term t, count s)
```

What's the impact of combiners?

Word Count: Version 1

```
class Mapper
    method Map(docid a, doc d)
        H ← new AssociativeArray
        for all term t ∈ doc d do
            H{t} ← H{t} + 1                ▷ Tally counts for entire document
        for all term t ∈ H do
            Emit(term t, count H{t})
```

Are combiners still needed?

Word Count: Version 2

```
class Mapper
    method Initialize
        H ← new AssociativeArray
    method Map(docid a, doc d)
        for all term t ∈ doc d do
            H{t} ← H{t} + 1                    ▷ Tally counts across documents
    method Close
        for all term t ∈ H do
            Emit(term t, count H{t})
```

Key: preserve state across input key-value pairs!

Are combiners still needed?

Design Pattern for Local Aggregation

- "In-mapper combining"
  - Fold the functionality of the combiner into the mapper by preserving state across multiple map calls
- Advantages
  - Speed
  - Why is this faster than actual combiners?
- Disadvantages
  - Explicit memory management required
  - Potential for order-dependent bugs

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 all integers associated with the same key

Computing the Mean: Version 1

class Mapper
    method Map(string t, integer r)
        Emit(string t, integer r)

class Reducer
    method Reduce(string t, integers $[r_1, r_2, \ldots]$)
        $sum \leftarrow 0$
        $cnt \leftarrow 0$
        for all integer $r \in$ integers $[r_1, r_2, \ldots]$ **do**
            $sum \leftarrow sum + r$
            $cnt \leftarrow cnt + 1$
        $r_{avg} \leftarrow sum/cnt$
        Emit(string t, integer r_{avg})

Why can’t we use reducer as combiner?

Computing the Mean: Version 2

class MAPPER
    method MAP(string t, integer r)
        EMIT(string t, integer r)

class COMBINER
    method COMBINE(string t, integers $[r_1, r_2, \ldots]$)
        $sum \leftarrow 0$
        $cnt \leftarrow 0$
        for all integer $r \in$ integers $[r_1, r_2, \ldots]$ **do**
            $sum \leftarrow sum + r$
            $cnt \leftarrow cnt + 1$
        EMIT(string t, pair (sum, cnt)) ▷ Separate sum and count

class REDUCER
    method REDUCE(string t, pairs $[(s_1, c_1), (s_2, c_2) \ldots]$)
        $sum \leftarrow 0$
        $cnt \leftarrow 0$
        for all pair $(s, c) \in$ pairs $[(s_1, c_1), (s_2, c_2) \ldots]$ **do**
            $sum \leftarrow sum + s$
            $cnt \leftarrow cnt + c$
        $r_{avg} \leftarrow sum / cnt$
        EMIT(string t, integer r_{avg})

Why doesn't this work?

Computing the Mean: Version 3

class Mapper
  method Map(string t, integer r)
    Emit(string t, pair $(r, 1)$)

class Combiner
  method Combine(string t, pairs $[(s_1, c_1), (s_2, c_2) \ldots]$)
    $sum \leftarrow 0$
    $cnt \leftarrow 0$
    for all pair $(s, c) \in$ pairs $[(s_1, c_1), (s_2, c_2) \ldots]$ **do**
      $sum \leftarrow sum + s$
      $cnt \leftarrow cnt + c$
    Emit(string t, pair (sum, cnt))

class Reducer
  method Reduce(string t, pairs $[(s_1, c_1), (s_2, c_2) \ldots]$)
    $sum \leftarrow 0$
    $cnt \leftarrow 0$
    for all pair $(s, c) \in$ pairs $[(s_1, c_1), (s_2, c_2) \ldots]$ **do**
      $sum \leftarrow sum + s$
      $cnt \leftarrow cnt + c$
    $r_{avg} \leftarrow sum/cnt$
    Emit(string t, pair (r_{avg}, cnt))

Fixed?

Computing the Mean: Version 4

```
class Mapper
    method Initialize
        S ← new AssociativeArray
        C ← new AssociativeArray
    method Map(string t, integer r)
        S{t} ← S{t} + r
        C{t} ← C{t} + 1
    method Close
        for all term t ∈ S do
            Emit(term t, pair (S{t}, C{t}))
```

Are combiners still needed?

Algorithm Design: Running Example

- Term co-occurrence matrix for a text collection
  - M = N x N matrix (N = vocabulary size)
  - M_{ij}: number of times *i* and *j* co-occur in some context (for concreteness, let's say context = sentence)
- Why?
  - Distributional profiles as a way of measuring semantic distance
  - Semantic distance useful for many language processing tasks

MapReduce: Large Counting Problems

- Term co-occurrence matrix for a text collection = specific instance of a large counting problem
  - A large event space (number of terms)
  - A large number of observations (the collection itself)
  - Goal: keep track of interesting statistics about the events
- Basic approach
  - Mappers generate partial counts
  - Reducers aggregate partial counts

How do we aggregate partial counts efficiently?

First Try: “Pairs”

- Each mapper takes a sentence:
  - Generate all co-occurring term pairs
  - For all pairs, emit (a, b) → count
- Reducers sum up counts associated with these pairs
- Use combiners!

Pairs: Pseudo-Code

```
class Mapper
    method Map(docid a, doc d)
        for all term w ∈ doc d do
            for all term u ∈ Neighbors(w) do
                Emit(pair (w, u), count 1)        ▷ Emit count for each co-occurrence

class Reducer
    method Reduce(pair p, counts [c1, c2, ...])
        s ← 0
        for all count c ∈ counts [c1, c2, ...] do
            s ← s + c                             ▷ Sum co-occurrence counts
        Emit(pair p, count s)
```

“Pairs” Analysis

- Advantages
  - Easy to implement, easy to understand
- Disadvantages
  - Lots of pairs to sort and shuffle around (upper bound?)
  - Not many opportunities for combiners to work

Another Try: "Stripes"

- Idea: group together pairs into an associative array

$$
\begin{aligned}
(a, b) &\rightarrow 1 \\
(a, c) &\rightarrow 2 \\
(a, d) &\rightarrow 5 \\
(a, e) &\rightarrow 3 \\
(a, f) &\rightarrow 2
\end{aligned}
\qquad\qquad a \rightarrow \{\ b: 1,\ c: 2,\ d: 5,\ e: 3,\ f: 2\ \}
$$

- Each mapper takes a sentence:
  - Generate all co-occurring term pairs
  - For each term, emit a $\rightarrow$ { b: count_b, c: count_c, d: count_d … }
- Reducers perform element-wise sum of associative arrays

$$
\begin{array}{lll}
 & a \rightarrow \{\ b: 1, & \quad\quad d: 5,\ e: 3\ \} \\
+ & a \rightarrow \{\ b: 1,\ c: 2,\ d: 2, & \quad\quad\quad f: 2\ \} \\
\hline
 & a \rightarrow \{\ b: 2,\ c: 2,\ d: 7,\ e: 3,\ f: 2\ \} &
\end{array}
$$

Key: cleverly-constructed data structure brings together partial results

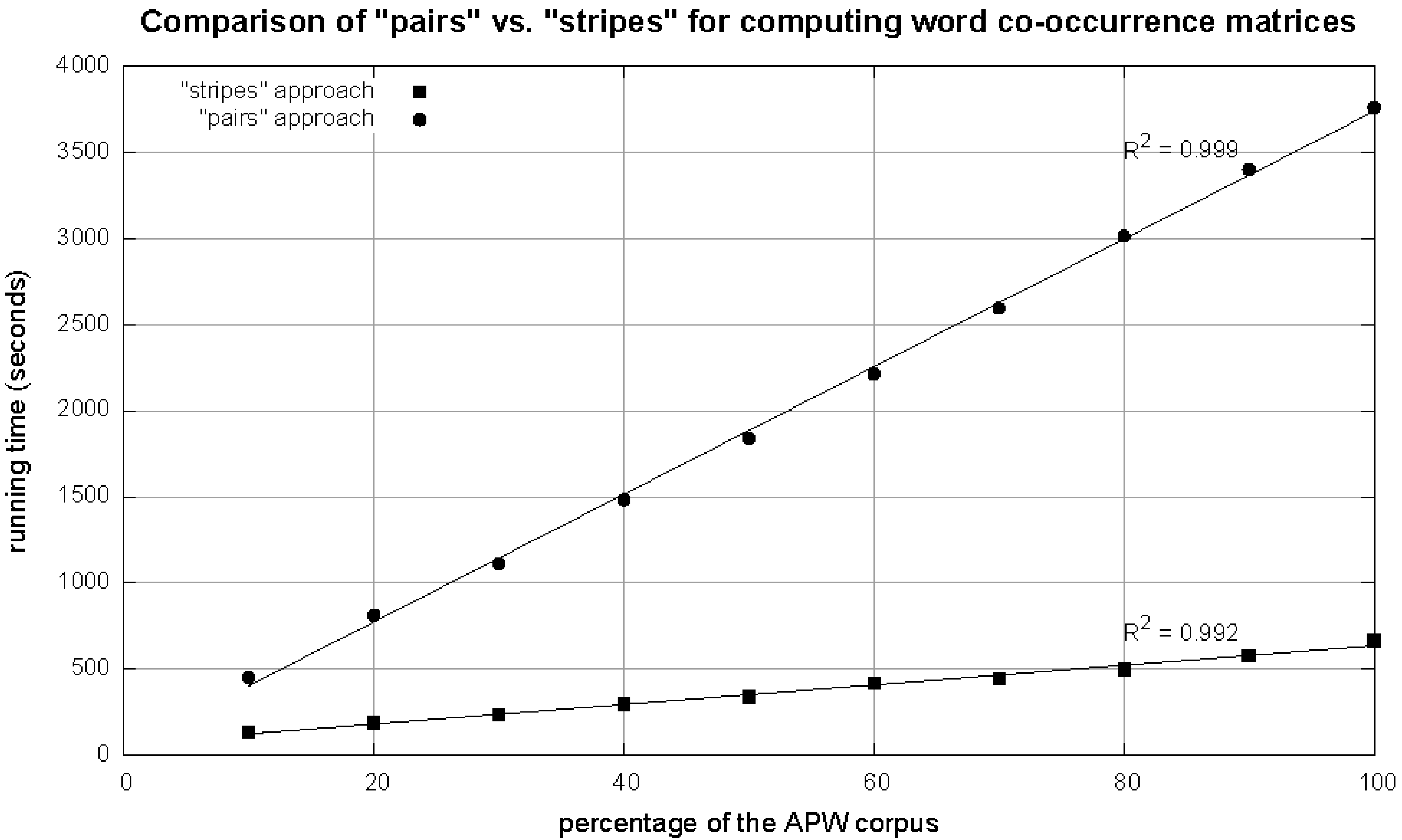
Stripes: Pseudo-Code

```
class Mapper
    method Map(docid a, doc d)
        for all term w ∈ doc d do
            H ← new AssociativeArray
            for all term u ∈ Neighbors(w) do
                H{u} ← H{u} + 1                    ▷ Tally words co-occurring with w
            Emit(Term w, Stripe H)

class Reducer
    method Reduce(term w, stripes [H_1, H_2, H_3, ...])
        H_f ← new AssociativeArray
        for all stripe H ∈ stripes [H_1, H_2, H_3, ...] do
            Sum(H_f, H)                            ▷ Element-wise sum
        Emit(term w, stripe H_f)
```

"Stripes" Analysis

- Advantages
  - Far less sorting and shuffling of key-value pairs
  - Can make better use of combiners
- Disadvantages
  - More difficult to implement
  - Underlying object more heavyweight
  - Fundamental limitation in terms of size of event space



Cluster size: 38 cores
Data Source: Associated Press Worldstream (APW) of the English Gigaword Corpus (v3), which contains 2.27 million documents (1.8 GB compressed, 5.7 GB uncompressed)

Relative Frequencies

- How do we estimate relative frequencies from counts?

$$f(B \mid A) = \frac{\text{count}(A, B)}{\text{count}(A)} = \frac{\text{count}(A, B)}{\sum_{B'} \text{count}(A, B')}$$

- Why do we want to do this?
- How do we do this with MapReduce?

f(B|A): "Stripes"

- Easy!
  - One pass to compute (a, *)
  - Another pass to directly compute f(B|A)

f(B|A): "Pairs"

$(a, *) \rightarrow 32$ **Reducer holds this value in memory**

$(a, b_1) \rightarrow 3$	$(a, b_1) \rightarrow 3 / 32$
$(a, b_2) \rightarrow 12$	$(a, b_2) \rightarrow 12 / 32$
$(a, b_3) \rightarrow 7$	$(a, b_3) \rightarrow 7 / 32$
$(a, b_4) \rightarrow 1$	$(a, b_4) \rightarrow 1 / 32$
…	…

- For this to work:
  - Must emit extra (a, *) for every b_n in mapper
  - Must make sure all a's get sent to same reducer (use partitioner)
  - Must make sure (a, *) comes first (define sort order)
  - Must hold state in reducer across different key-value pairs

“Order Inversion”

- Common design pattern
  - Computing relative frequencies requires marginal counts
  - But marginal cannot be computed until you see all counts
  - Buffering is a bad idea!
  - Trick: getting the marginal counts to arrive at the reducer before the joint counts
- Optimizations
  - Apply in-memory combining pattern to accumulate marginal counts

Synchronization: Pairs vs. Stripes

- Approach 1: turn synchronization into an ordering problem
  - Sort keys into correct order of computation
  - Partition key space so that each reducer gets the appropriate set of partial results
  - Hold state in reducer across multiple key-value pairs to perform computation
  - Illustrated by the “pairs” approach
- Approach 2: construct data structures that bring partial results together
  - Each reducer receives all the data it needs to complete the computation
  - Illustrated by the “stripes” approach

Secondary Sorting

- MapReduce sorts input to reducers by key
  - Values may be 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

Recap: Tools for Synchronization

- Cleverly-constructed data structures
  - Bring data together
- Sort order of intermediate keys
  - Control order in which reducers process keys
- Partitioner
  - Control which reducer processes which keys
- Preserving state in mappers and reducers
  - Capture dependencies across multiple keys and values

Issues and Tradeoffs

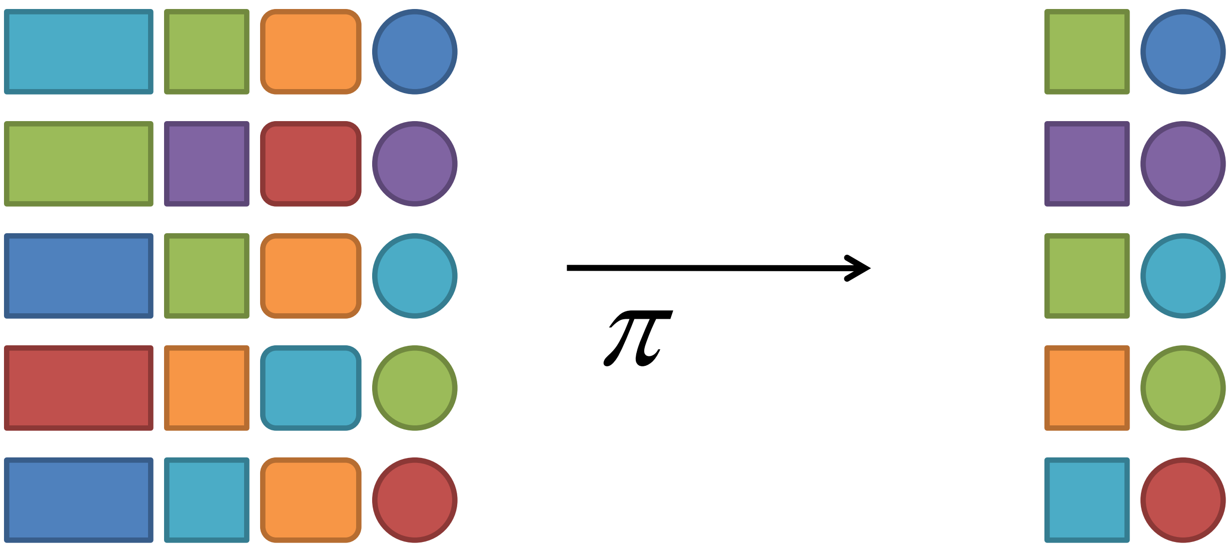
- Number of key-value pairs
  - Object creation overhead
  - Time for sorting and shuffling pairs across the network
- Size of each key-value pair
  - De/serialization overhead
- Local aggregation
  - Opportunities to perform local aggregation varies
  - Combiners make a big difference
  - Combiners vs. in-mapper combining
  - RAM vs. disk vs. network

Mapreduce and Databases

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

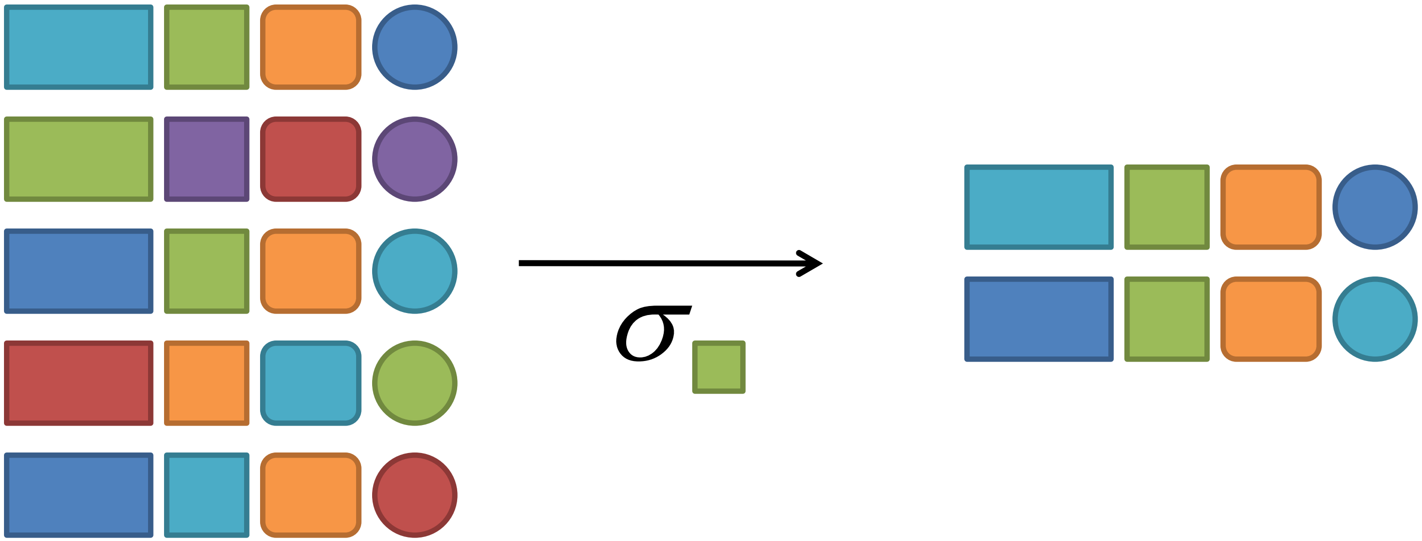


Projection in MapReduce

- Easy!
  - Map over tuples, emit new tuples with appropriate attributes
  - Reduce: take tuples that appear many times and emit only one version (duplicate elimination)
    - Tuple t in R: Map(t, t) -> (t',t')
    - Reduce (t', [t', …,t']) -> [t',t']

- Basically limited by HDFS streaming speeds
  - Speed of encoding/decoding tuples becomes important
  - Relational databases take advantage of compression

Selection



Selection in MapReduce

- Easy!
  - Map over tuples, emit only tuples that meet criteria
  - No reducers, unless for regrouping or resorting tuples (reducers are the identity function)
  - Alternatively: perform in reducer, after some other processing
- But very expensive!!! Has to scan the database
  - Better approaches?

Union, Set Intersection and Set Difference

- Similar ideas: each map outputs the tuple pair (t,t). For union, we output it once, for intersection only when in the reduce we have (t, [t,t])
- For Set difference?

Set Difference

- Map Function: For a tuple t in R, produce key-value pair (t, R), and for a tuple t in S, produce key-value pair (t, S).
- Reduce Function: For each key t, do the following.

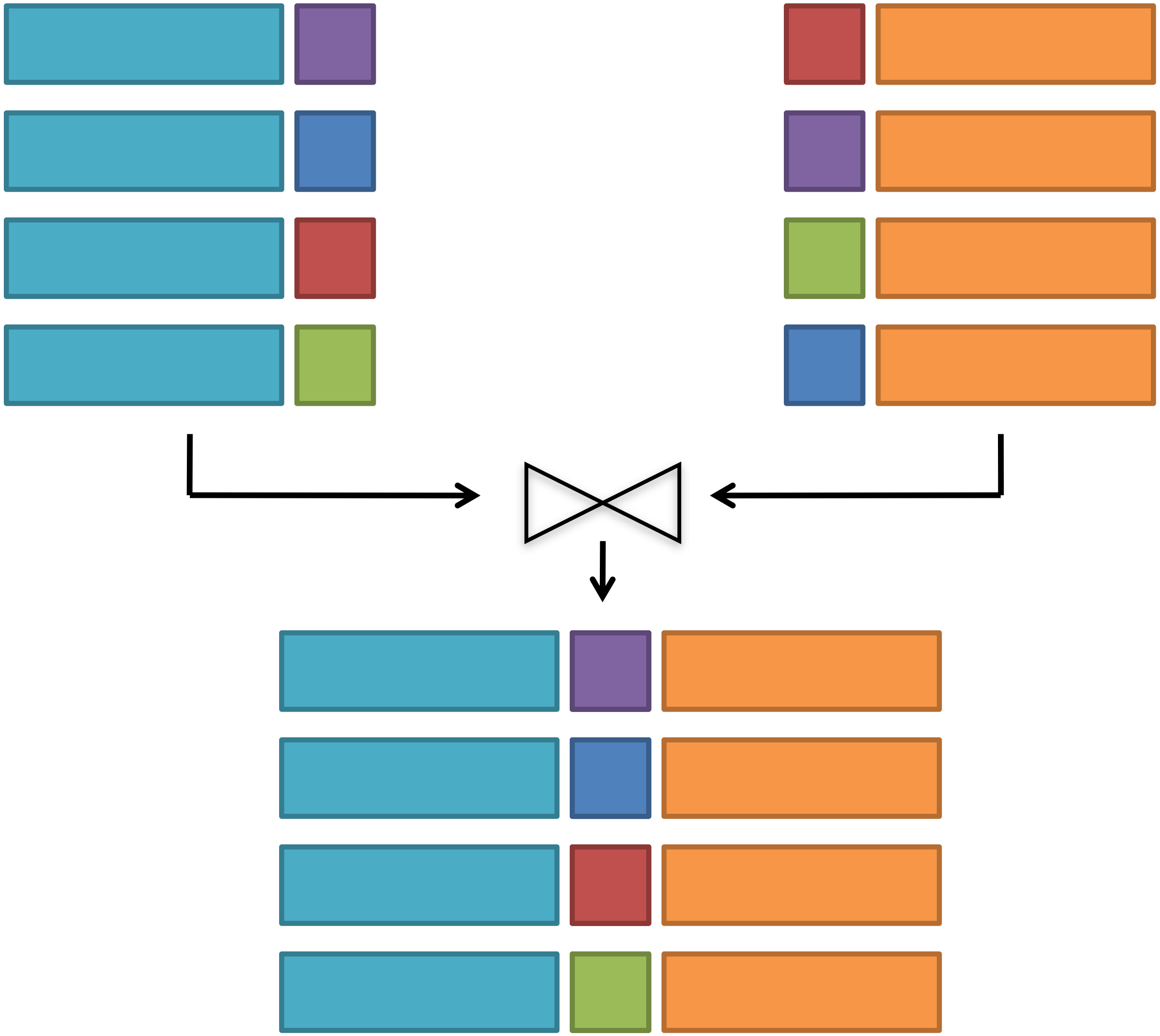
  1. If the associated value list is [R], then produce (t, t).

  2. If the associated value list is anything else, which could only be [R, S], [S, R], or [S], produce (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:
  - Map over tuples, emit time, keyed by url
  - Framework automatically groups values by keys
  - Compute average in reducer
  - Optimize with combiners

Relational Joins



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

Example: Join By Map-Reduce

- **Compute the natural join *R(A,B)* ⋈ *S(B,C)***
- *R* and *S* are each stored in files
- Tuples are pairs *(a,b)* or *(b,c)*

A	B
a_1	b_1
a_2	b_1
a_3	b_2
a_4	b_3

R

⋈

B	C
b_2	c_1
b_2	c_2
b_3	c_3

S

=

A	C
a_3	c_1
a_3	c_2
a_4	c_3

Map-Reduce Join

- **Use a hash function *h* from B-values to *1...k***
- **A Map process turns:**
  - Each input tuple *R(a,b)* into key-value pair *(b,(a,R))*
  - Each input tuple *S(b,c)* into *(b,(c,S))*

- **Map processes** send each key-value pair with key *b* to Reduce process *h(b)*
  - Hadoop does this automatically; just tell it what *k* is.
- Each **Reduce process** matches all the pairs *(b,(a,R))* with all *(b,(c,S))* and outputs *(a,b,c)*.

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?

In-Memory Join

- Basic idea: load one dataset into memory, stream over other dataset
  - Works if R << S and R fits into memory
  - Similar to “hash Join” algorithm
- 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 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