Fundamental Techniques

Mirek Riedewald

Key Learning Goals

- Write the Map and Reduce functions for sorting in MapReduce. Does the choice of Partitioner matter?
- Does secondary sort require a special type of Partitioner, or could even the simple default hash Partitioner work?
- Why do we not just implement secondary sort as a total sort on a composite key?
- What is the difference between sort and secondary sort? Explain, using an example.

Key Learning Goals

- How do we implement a Combiner in Spark Scala?
- Which of the following performs per-partition aggregation during the grouping stage, before shuffling: groupByKey().reduce(), reduceByKey, foldByKey, aggregateByKey?
- Is DataSet’s groupBy(…).agg(…) performing per-partition aggregation before shuffling? Is it removing data columns that are neither in grouping list nor appear in the aggregation column list?

Introduction

- We discuss three fundamental techniques that appear in many big data analysis applications:
  - Aggregation (with or without grouping)
  - Sort
  - Secondary sort.
- Each of them highlights interesting aspects of the underlying system infrastructure.

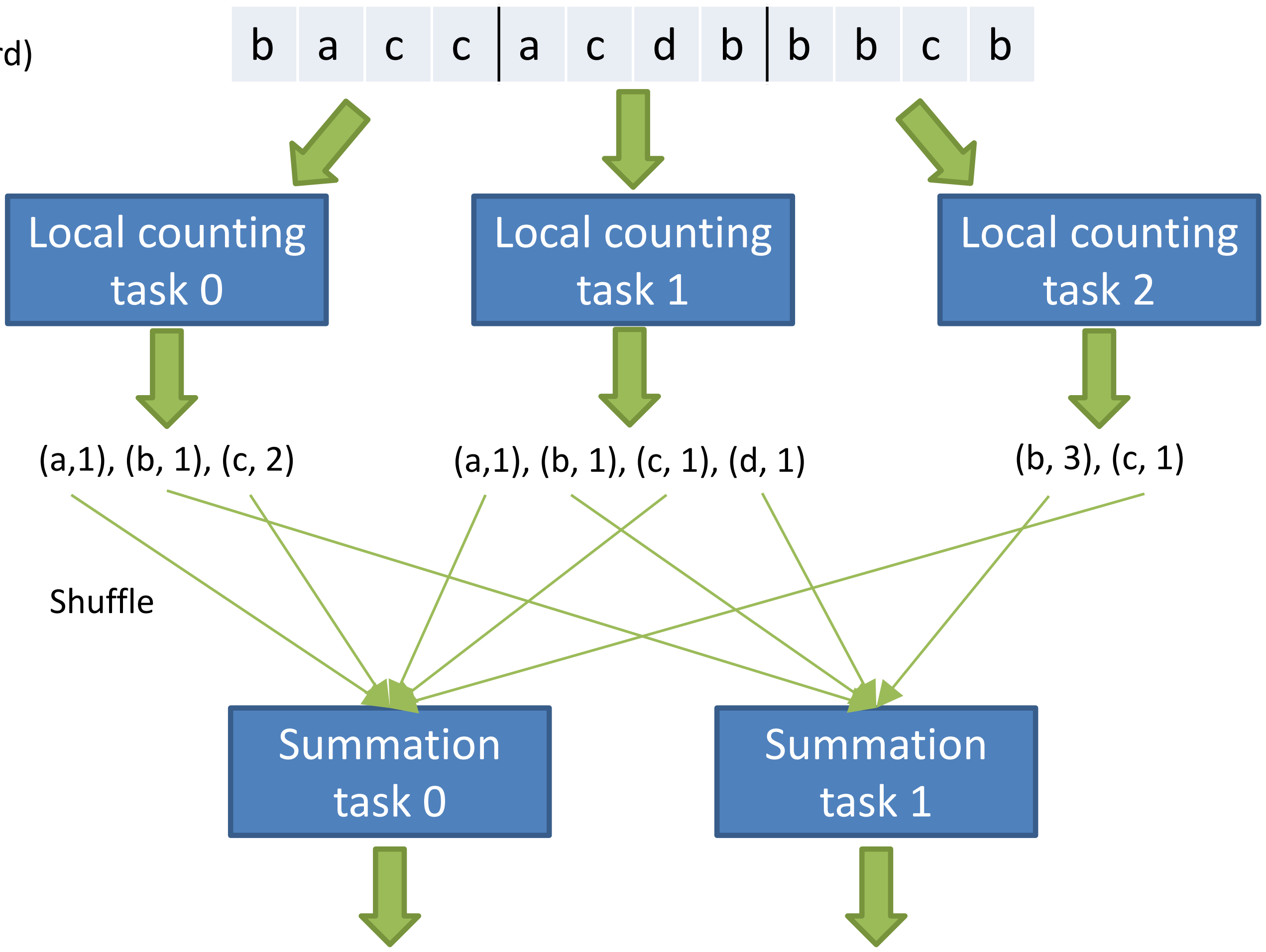
Aggregation

- For aggregation, we return to the Word Count program.
  - Recall that it determines the total number of occurrences of each word in a collection of documents.
- We will pay particular attention to the question of how to ensure that data will be aggregated as early as possible.
- First, recall the desired distributed execution.

Refresh: Word Count

Input (each letter represents a word)

h(a) mod 2 = 0
h(b) mod 2 = 1
h(c) mod 2 = 0
h(d) mod 2 = 1



Final output: (word, count) pairs

(a,2), (c, 4)

(b, 5), (d, 1)

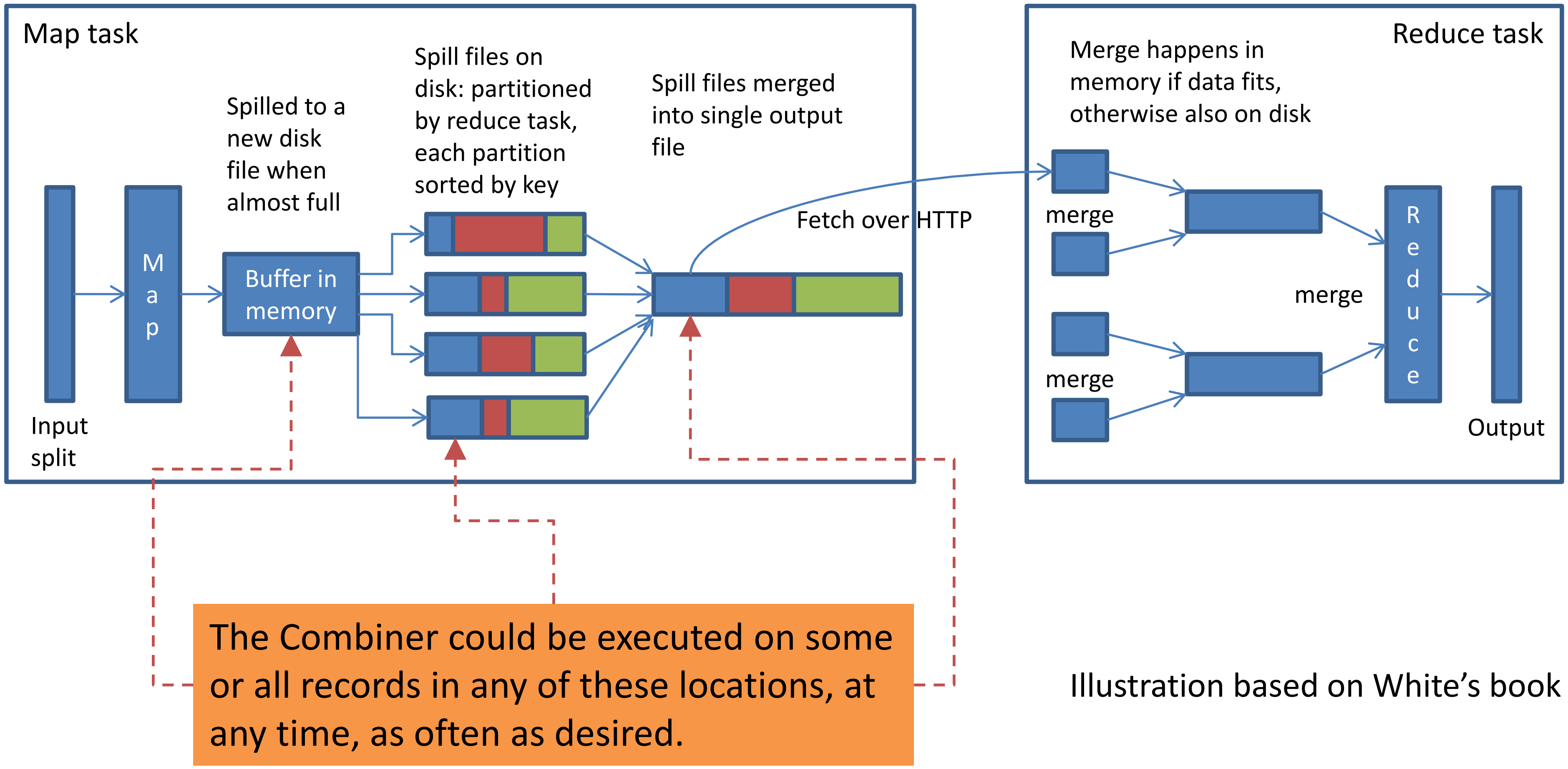
Early Aggregation Opportunities

- Consider local counting task 0. It should send (c, 2), not two copies of (c, 1) to the summation task.
  - In general, replacing k records (word, 1) by a single record (word, k) will reduce network traffic k-fold. It also reduces the cost for the summation task for receiving the data, merging the data (it is more likely to fit in memory or require fewer passes), and final aggregation.
  - On the downside, aggregation increases CPU cost for the local counting task.
- What if local counting tasks 0 and 2 are executed on the same machine—should we aggregate across tasks?
  - No. This complicates system design, because the tasks would have to agree on the final counts. What if one task fails half-way and the other succeeds? What if one gets re-scheduled on a different machine, but not the other?
- In summary, we want to aggregate *within* each local counting task, but aggregation *across* tasks is left to the summation tasks.

Early Aggregation in MapReduce

- In MapReduce, local aggregation happens in Map tasks, before transferring the data to the Reducers. Hence we want to aggregate counts for all words in the same input split.
- In Hadoop MapReduce, each map function call sees only a single line of text. Hence it cannot aggregate across different lines.
- We saw the Combiner feature, which elegantly supports the desired per-split aggregation.
  - Unfortunately the Combiner cannot be controlled by the user: the MapReduce system decides when and on which Map output records the Combiner is executed. It might not be executed at all. Or it might be executed only on some subset of the output records, e.g., only the records currently in memory. And it might be executed multiple times, possibly reading records output by an earlier Combiner execution together with “fresh,” recently emitted records.

Combiner Execution Options


Map task
Spilled to a new disk file when almost full
Spill files on disk: partitioned by reduce task, each partition sorted by key
Spill files merged into single output file
Input split
M a p
Buffer in memory
Fetch over HTTP
Reduce task
Merge happens in memory if data fits, otherwise also on disk
merge
merge
merge
R e d u c e
Output

The Combiner could be executed on some or all records in any of these locations, at any time, as often as desired.

Illustration based on White's book

How can the programmer take more control of combining?

Original MapReduce Program

- This version of the program does not aggregate any counts in the Mapper. It would need a Combiner.

```
map(offset B, line L )
 for each word x in L do
   emit(x, 1)
```

```
reduce(word x, [c1, c2,…])
 total = 0
 for each c in input list do
   total += c
 emit(x, total)
```

Tally Counts Per Line

```
map(offset B, line L )
 h = new hashMap              // stores count for each word in line L
 for each word x in L do
  h[x]++
 for each word x in h do
  emit(x, h[x])
```

- Our first attempt combines counts inside a single Map function call. To do so, we need a data structure in Map that tracks the word occurrences in the input line. The Reduce function does not change.
- While simple, this modification will typically not be very effective, because it combines the counts only within a single line of text.
- To increase combining opportunities, we would like to aggregate counts across the entire Map input split, not just a single line.

Tally Counts Per Map Task

- To aggregate counts across the entire Map task input, we have to work at the task level, i.e., above the level of individual Map calls. We need a data structure H that is a private member of the Mapper class and can be updated by each Map call in the same task.
  - Notice that H is local to a single task and only accessed by a single thread, i.e., it does not introduce any inter- or intra-task synchronization issues.
- Data structure H needs to be initialized before the first Map function call in the task. This is done inside the Map task's setup() function, which is guaranteed to be executed when the task starts, before any of the Map calls.
- Each Map function call then updates the counts for the words it finds in its input line. However, Map does not emit any output any more!
- To emit the final tally for the entire task, the counts in H have to be emitted after the *last* Map call in the task has completed. This is achieved by "emptying out" the contents of H in the cleanup() function of the Mapper class. Cleanup() is guaranteed to be executed after the last Map call.
- The Reducer remains unchanged.

```
Class Mapper {
 hashMap H

 setup() {
  H = new hashMap
 }

 map(offset B, line L ) {
  for each word x in L do
   H[x]++
 }

 cleanup() {
  for each word x in H do
   emit(x, H[x])
 }
}
```

Summary of the Design Pattern for Local Aggregation

- The tally-per-task version of Word Count is an example for the in-mapper combining design pattern in MapReduce. The main idea of this pattern is to preserve state at the task level, across different Map calls in the same task. The same pattern can also be applied to Reduce tasks.
- Advantages over using Combiners:
  - The Combiner does not guarantee if, when, or how often it will be executed.
  - A Combiner combines data *after* it was generated. In-mapper combining avoids generating large amounts of intermediate data by immediately aggregating it as it is produced by a Map call. This often results in significant reduction of local CPU and disk I/O cost on the Mappers.
- Drawbacks compared to Combiners:
  - In-mapper combining code needs to be integrated with the Mapper code, increasing code complexity and hence the probability for introducing errors.
  - It needs more memory for managing state, e.g., to hold the hashMap H in memory. If the data structure used for in-mapper combining exceeds the amount of available memory, the programmer has to write non-trivial memory-management code to page it to disk.

What is the equivalent of in-mapper combining in Spark?

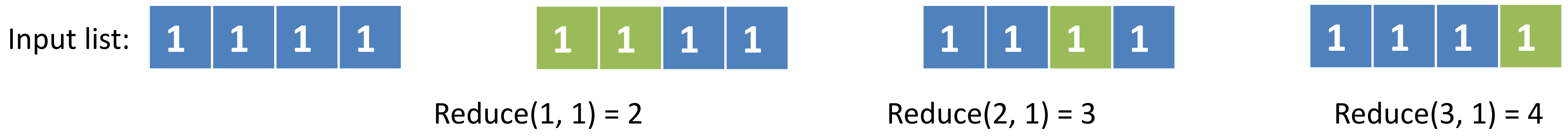
Refresh: Word Count in Spark

- In the Spark program, it is not obvious if the equivalent of a Combiner or in-mapper combining is used.
- This means that we have to (1) read the documentation of reduceByKey or (2) find out by asking Spark to explain the execution to us.

```
val textFile = sc.textFile("hdfs://...")
val counts = textFile.flatMap(line => line.split(" "))
             .map(word => (word, 1))
             .reduceByKey(_ + _)
counts.saveAsTextFile("hdfs://...")
```

Dissecting ReduceByKey

- ReduceByKey(_ + _) is shorthand for reduceByKey((x,y) => (x+y)). It iterates through a list of values, adding them one-by-one, as illustrated below.
- Spark understands the semantics of this aggregation and applies it, like in-mapper combining, to the RDD partition before shuffling.
  - The same holds for foldByKey and aggregateByKey.
- In contrast, groupByKey only performs grouping but no combining. Hence myRDD.groupByKey().reduce(…) or similar will perform aggregation only after shuffling, i.e., does not do the equivalent of in-mapper combining!



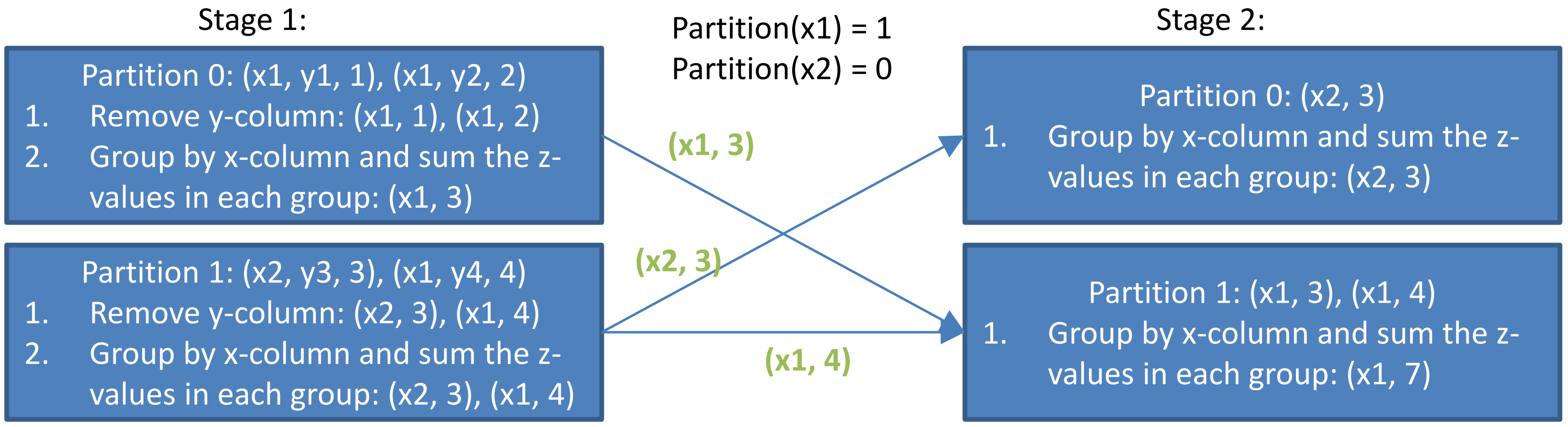
Aggregation with DataSets

- Unfortunately, the semantics of DataSet functions are a little more complex. To fully appreciate this, let us use a slightly more complicated example and compute annual sales using DataSet myDS with columns (year, month, day, sale).
  - Looking at the Spark Scala API, we find various versions of function `agg`. While powerful and flexible, it only supports aggregation across the *entire* dataset, not for separate groups.
  - Then we find groupBy, which, as we hoped, allows us to create groups based on any column(s).
  - Putting both together, we find the solution: myDS.groupBy("year").sum("sale")
- Challenge question: Will myDS.groupBy("year").sum("sale") perform combining or not? (Recall that pair RDD's groupByKey did not perform combining!) What happens to the other columns month and day? Are they in the output? Are they removed before shuffling?

DataSet Aggregation in Depth

- Try something like the code below in the Spark shell, and look closely at the explanation. Read it from bottom to top—it should say something like this:
  - …SerializeFromObject: this turns the sequence into the DataSet.
  - Project[_1 …, _3…]: this projects away all columns except for 1 (x) and 3 (z), which are needed for the aggregate.
  - HashAggregate(keys=…, functions=…): this shows that aggregation happens locally (like a Combiner), and what the grouping key and the aggregation function are.
  - Exchange hashpartitioning(…): now the shuffling happens, using hash partitioning.
  - HashAggregate(keys=…, functions=…): this is the global aggregation per group (like Reduce).

```
val myDS = sc.parallelize(Seq( (“x1”, “y1”, 1), (“x1”, “y2”, 2), (“x2”, “y3”, 3), (“x1”, “y4”, 4) )).toDF(“x”, “y”, “z”)
myDS.groupBy(“x”).agg(sum($”z”)).explain
```



Stage 1:

Partition 0: (x1, y1, 1), (x1, y2, 2)
1. Remove y-column: (x1, 1), (x1, 2)
2. Group by x-column and sum the z-values in each group: (x1, 3)

Partition 1: (x2, y3, 3), (x1, y4, 4)
1. Remove y-column: (x2, 3), (x1, 4)
2. Group by x-column and sum the z-values in each group: (x2, 3), (x1, 4)

Stage 2:

Partition 0: (x2, 3)
1. Group by x-column and sum the z-values in each group: (x2, 3)

Partition 1: (x1, 3), (x1, 4)
1. Group by x-column and sum the z-values in each group: (x1, 7)

More DataSet Subtleties

- You might think that applying a function to a DataSet will create another DataSet. This is what makes relational algebra in DBMS so elegant. And you will often be right…
- …but not always. For example, groupBy(…) returns a result of type RelationalGroupedDataset. This represents a DataSet that is grouped by some column(s).
  - Why do we need this? Note that we can write myDS.sum(…) or myDS.groupBy(…).sum(…). If myDS is a "simple" DataSet, then the former computes the sum over the entire DataSet, while the latter computes a sum for each group as specified in the groupBy function. However, if myDS2 is of type RelationalGroupedDataset, then even myDS2.sum(…) will compute separate sums—using the existing grouping.
- In short, you have to gain a deep understanding of Spark, in order to know what really happens internally. Become familiar with the explain function—it provides essential information about the execution of your program.

Let us move on to distributed sorting.

Distributed Sort

- Sorting is one of the most commonly used data processing operations. How can we sort big data in parallel? First attempt:
  - Since data is already managed as file splits, each task could sort a split locally.
  - Then these sorted splits (called “runs”) are merged, often in multiple passes.
- It is easy to see that the local sorting parallelizes nicely. How about the merge phase?
  - No matter how many rounds of merging we consider, at the end a *single task* will have to perform the final merge on the entire dataset.
  - This results in poor speedup and does not use multiple workers effectively.
- Can we avoid the merge phase altogether?
  - Yes, ask long as we partition the data in a clever way.

Distributed Sorting Through Range-Partitioning

- Consider a simple scenario with 2 tasks to sort the set {5, 2, 4, 6, 1, 3}. If all small numbers, i.e., set {2, 1, 3}, are assigned to task 0 and all large numbers, i.e., set {5, 4, 6} to task 1, then sorting is easy.
  - Task 0 sorts locally and writes [1, 2, 3] to output0.
  - Task 1 sorts locally and writes [4, 5, 6] to output1.
  - The totally sorted output [1, 2, 3, 4, 5, 6] is obtained by simply "concatenating" output0 with output1. (This is a constant-time operation and requires no merging.)
- The challenge for this approach is to separate the given set into "small" and "large" numbers. This is formally referred to as range partitioning. Range partitioning ensures that if records i and k, $i \leq k$, are assigned to a partition, then all records j between them, i.e., $i \leq j \leq k$, will be assigned to that same partition.
- In addition, we also would like the different partitions to be of about the same size, so that the local sort work is evenly distributed.

Challenge Question

- Where have you seen this sorting idea before?
    1. Bubble sort
    2. Merge sort
    3. Quicksort
    4. Heapsort

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- Where have you seen this sorting idea before?
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  4. Heapsort

In Quicksort, a pivot element is selected and then the data array is re-shuffled so that all elements less than or equal to the pivot come before all those greater than the pivot. Then each of these "halves" of the array is recursively sorted the same way. The ideal choice of pivot element is the data median, i.e., the element that has the property that as many other elements are smaller than it as there are elements larger than it.

Range-Partitioning in MapReduce: "Explicit" Approach

- Assume we want to sort a set of key-value pairs by input key, using two tasks. First we find the median of the keys. Exact median computation can be as expensive as sorting itself, but it can be estimated reliably and cheaply through sampling.
  - For correct uniform random sampling, all splits of the input data have to be accessed. We can reduce cost by sampling from only a few splits, but this might result in a sample that does not represent the entire distribution well.
  - After obtaining a sample that fits in memory, this sample can be sorted on a single worker. The median of the sample is used as an approximation for the true median.
- Once we know the (approximate) median, we can use the program below to sort the input. All small keys are processed by the Reduce call for intermediate key 0, all larger ones by the one for key 1. There is more to this program:
  - We also need a Partitioner that assigns the smaller input keys to lower task numbers to ensure ordering across tasks.
  - The approach generalizes to more partitions by using more quantiles, not just the median.
- The Reduce function below assumes that its input fits in memory. If not, then smaller partitions need to be created by using more quantiles; or a disk-based sort implementation is needed.

```
map( key k, value v )
 if (k < median)
  emit(0, (k, v))
 else
  emit(1, (k, v))
```

```
reduce(partitionNumber, [(r1.key, r1.value), (r2.key, r2.value),…])
 load the value list into memory and sort it on r.key
 for each record r in the sorted list
  emit(r)
```

Challenge Question

- What could go wrong if the median is determined from a few file splits only?
  - Consider a file that is already sorted and assume we only access the first out of a thousand splits. Instead of sampling uniformly from the entire data distribution, we would only sample from the smallest 1/1000-th of records. This sample would provide a poor representation of the entire data set, because it does not contain any of the larger keys.

Range-Partitioning in MapReduce: “Minimalist” Approach

- This approach is more elegant and exploits that the MapReduce system guarantees that for each Reduce task, the assigned set of intermediate keys is processed in key order. We leverage this guarantee for sorting, taking advantage of the fact that MapReduce is already optimized for dealing with big data.
- The program below shows how this is done. Map and Reduce both emit their input 1-to-1, i.e., they are identity functions. The “magic” of this program lies in the Partitioner’s getPartition function, which assigns the small keys to Reduce task 0 and the large ones to Reduce task 1. Since Reduce function calls in a task are processed in key order, all records are correctly sorted by input key.
  - For correct sorting we have to make sure that the appropriate key comparator is defined. Since Hadoop MapReduce keys have to implement WritableComparable, they have to have such a compareTo function anyway.
- This idea generalizes to arbitrary range partitions, e.g., quantiles. Instead of an explicit if-then-else or case statement in getPartition, Hadoop already offers the TotalOrderPartitioner class to assign key ranges to Reduce tasks.

```
map( key k, value v )
  emit(k, v)
```

```
reduce(key k, [v1, v2,…])
  for each value v in the input list
    emit( k, v )
```

```
getPartition( key k )
  if (k < median) return 0
  else return 1
```

Challenge Question

- Look at the sort program code in the Hadoop distribution and find the following:
  - How does it determine the approximate quantiles?
  - How are they passed to the TotalOrderPartitioner?
  - Where are Mapper and Reducer class defined?
- You can find a copy of the file from Hadoop 3.1.1 at http://www.ccs.neu.edu/home/mirek/code/Sort.java

Sort in a DBMS

- In SQL, sorting is done with the ORDER BY clause. Given a relation R with schema (key, value), the corresponding query is
  - SELECT * FROM R ORDER BY key.
- The exact implementation will be chosen automatically by the optimizer. If the data is already range-partitioned, the optimizer will most likely determine that no shuffling is needed.

Sort in Spark Scala

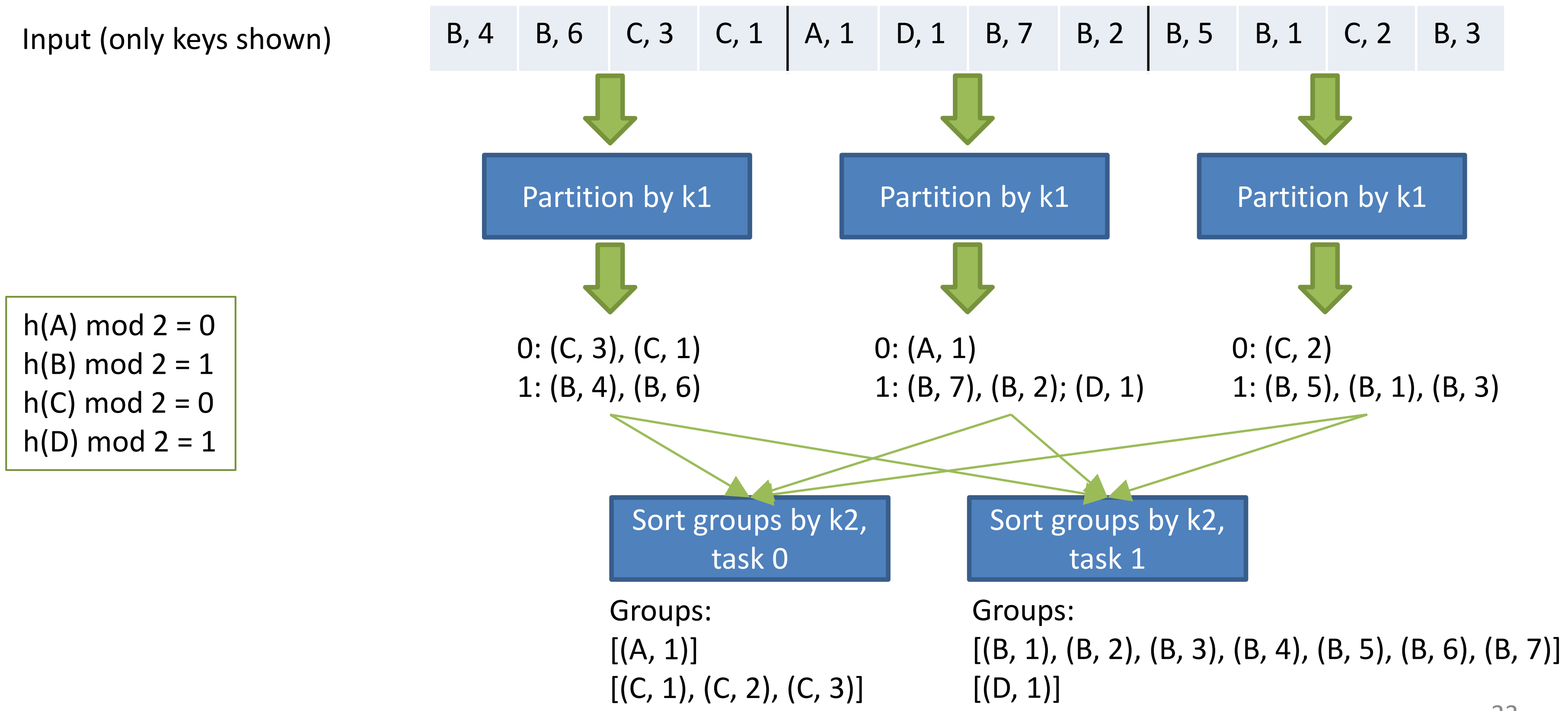
- On a pair RDD, transformation sortByKey() will efficiently sort the data by key.
- For DataSet, the corresponding transformation is sort("key"), assuming the DataSet has schema (key, value).
- Sorting is implemented using range partitioning, with range boundaries obtained from a sample, as discussed for MapReduce.

Secondary Sort

- Secondary sort requires two keys: one for grouping the data, and the other to locally sort each group. Hence the input conceptually is a set of (k1, k2, v) triples. How can secondary sort be implemented?
- We could perform a full sort on composite key (k1, k2).
  - The drawbacks of this approach are (1) that we potentially waste resources to sort on k1, even though we only need to group by it, and (2) that the range partitions might separate keys belonging to the same group. The latter is particularly undesirable, because secondary sort is generally applied with the goal of performing some operation on the (entire) sorted group.
- Both drawbacks can be addressed by partitioning the data on k1, and sorting each partition on k2.
  - A simple hash Partitioner suffices, avoiding the cost of finding approximate quantiles.
  - The sorting part is more subtle as we discuss next.

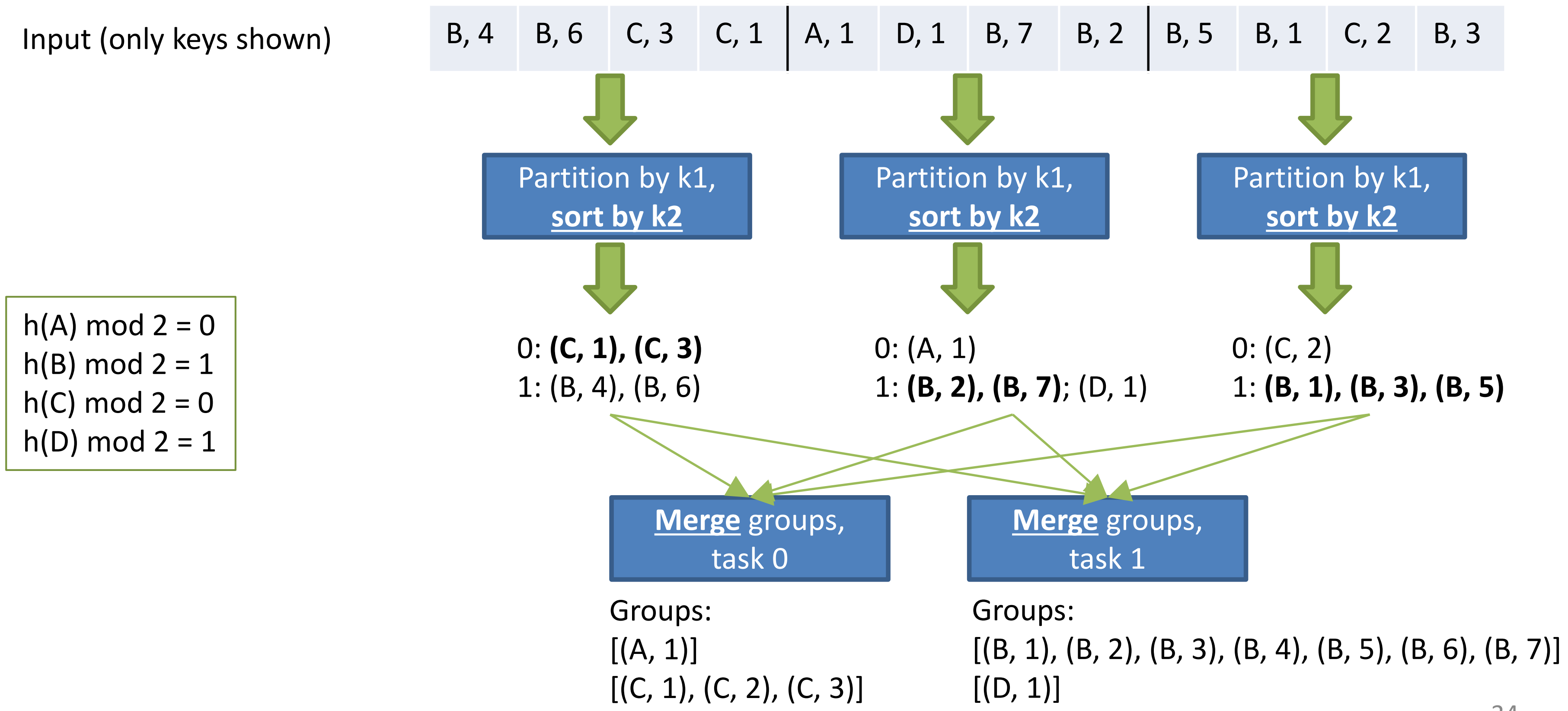
Where to Sort?

- This is the obvious approach: the first round of tasks only partitions the data, while all sorting happens in the next round. As the example illustrates, this can result in high sort cost for tasks receiving bigger groups. In general, this happens when the input is skewed on key k1.



Where to Sort?

- Now the cost for sorting input with k1=B is spread over multiple tasks in round 1. Task 1 in round 2 only needs to merge the pre-sorted B-records. In addition to better load distribution, this also simplifies the implementation in MapReduce.



Secondary Sort in MapReduce

- We illustrate the approach with an example of weather observations of type (station, date, temperature). (In reality there will be many more fields).
- Our goal is to compute the *temperature change* between all consecutive measurements by the same station. For simplicity, assume there is at most one temperature reported per station and date.
- How can we implement this in MapReduce? Recall that secondary sort uses two keys, but MapReduce allows only one key per record. We want to implement this in a single MapReduce job.
  - What should be the intermediate key of this job?

First Attempt: Station as Key

- Since we want to group the data by station, station would be a natural choice for the intermediate key. This way all weather reports from the same station end up in the same Reduce call. Unfortunately, they are not sorted by date.
  - Sorting then has to happen in user code, requiring non-trivial logic if the Reduce input list does not fit in memory.

```
map( station S, date D, temperature T )
  emit( S, (D, T) )
```

```
reduce( station S, [(D1, T1), (D2, T2),…] )
  L = load all (D, T) pairs into memory
  Sort L on the D field
  Iterate through L and emit all (S, T[i] –T[i-1])
```

Second Attempt: (Station, Date) as Key

- When using a composite key (station, date), Mappers automatically sort and partition on the two fields. The sorting on date is exactly what we wanted, when data for the same station is assigned to the same Reduce task.
  - Recall that Mappers sort all data going to the same Reduce task by key.
  - The Reducers then simply merge the pre-sorted runs, which is cheaper than sorting.
- Unfortunately there are two drawbacks:
  - Each Reduce call gets only reports from a single date, i.e., it cannot produce temperature differences. In-reducer combining could fix this.
  - The Partitioner might assign records of the same station to different Reduce tasks. Then even a task-level data structure cannot put reports rom the same station on different Reducers together.

```
map( station S, date D, temperature T )
 emit( (S, D), T )
```

```
reduce( (station S, date D), [T] )
  // We only have the temperature from a single date
  // How can we access the other dates for the same station?
```

Second Attempt—Problem Solved?

- We can use in-reducer combining, similar to in-mapper combining, to keep track of "state" across the different Reduce calls.
- For this to work, we need the right Partitioner that ensures that all temperatures for a given year are assigned to the same Reduce task. Any Partitioner that only considers the station field for partition assignment will have this property.
- Since all Reduce calls in the same task are executed in key order, we can easily collect the data in the right order from the Reduce calls.
- This looks a bit clumsy and incurs unnecessary overhead for executing too many Reduce calls, each doing trivial work.

```
map( station S, date D, temperature T )
 emit( (S, D), T )

getPartition( (station S, date D) )
 return myPartitionFct( S )

keyComparator( (station S, date D) )
 // Sorts on station first.
 // If the station is equal, sorts on date
```

```
Class Reducer {
 currentStation
 lastTemp

 setup() {
  currentStation = NULL
  lastTemp = NULL
 }

 reduce( (station S, date D), [T] ) {
  if (S <> currentStation)
   // New station found.
   currentStation = S
   lastTemp = T
  else { // Another call for current station
   emit( S, T – lastTemp)
   lastTemp = T
 }

 cleanup() {}
}
```

Third Attempt: Best of Both Worlds

- We use the same Mapper, Partitioner, and key comparator as for the second attempt, but will essentially use the Reducer from the first attempt (without the need for sorting in user code).
- To make this work, we need a special grouping comparator. It is used to determine which key-value pairs are passed to the same Reduce function call.

Pseudo-Code for Third Attempt

```
map( station S, date D, temperature T )
  emit( (S, D), T )

getPartition( (station S, date D) )
  return myPartitionFct( S )

keyComparator( (station S, date D) )
  // Sorts on station first.
  // If the station is equal, sorts on date

groupingComparator( (station S, date D) )
  // Considers station only.
  // Hence two keys with the same station
  // are considered identical, no matter the
  // date.

reduce( station S, [(D_1, T_1), (D_2, T_2),…] )
  for each (D_i, T_i) in input list
    emit( S, T_i – T_{i-1})
```

How Does this Actually Work?

Assume Reduce task 0 received the records below from the Mappers. Notice that these records are sorted based on the key comparator (sorted first by station, then by date.

Key: station	Key: date	Value: temperature
S1	2011	80
S1	2013	65
S1	2013	70
S2	2010	75
S2	2010	80
S2	2012	71

Example (Cont.)

Without the special grouping comparator, there is one Reduce call per distinct (station, date) pair.

Key: station	Key: date	Value: temperature
S1	2011	80
S1	2013	65
S1	2013	70
S2	2010	75
S2	2010	80
S2	2012	71

Reduce call for key (S1, 2011)

Reduce call for key (S1, 2013)

Reduce call for key (S2, 2010)

Reduce call for key (S2, 2012)

Example (Cont.)

With the special grouping comparator, keys such as (S1, 2011) and (S1, 2013) are considered identical. Hence they are processed in the same Reduce function call. In general, there is only a single Reduce function call per station.

Reduce call for key (S1, *)

Key: station	Key: date	Value: temperature
S1	2011	80
S1	2013	65
S1	2013	70
S2	2010	75
S2	2010	80
S2	2012	71

Reduce call for key (S2, *)

Real Code

- Take a look at the secondary sort program example from Tom White's book at http://www.ccs.neu.edu/home/mirek/code/MaxTemperatureUsingSecondarySort.java

Secondary Sort in MapReduce Summary

- The general design pattern for secondary sort is as follows:
  - To partition by key k1 and sort each k1-group by another key k2, make (k1, k2) the intermediate key.
  - Define a key comparator to order by composite key (k1, k2).
  - Define Partitioner and grouping comparator for key (k1, k2) to consider only k1 for partitioning and grouping. (The getPartition and compareTo functions should not use k2 at all.)
- Secondary sort is also useful for finding the greatest or smallest value of key k2 for each key k1. However, since MIN and MAX can be found trivially in linear time in the Reduce function input list, using only constant space to hold the current MIN/MAX, secondary sort is not necessarily faster.

Secondary Sort in a DBMS

- In SQL, GROUP BY cannot return individual records in a group, but only a single record representing an aggregate for the group. Given a relation R with schema (k1, k2, value), the closest to secondary sort would be SELECT * FROM R ORDER BY k1, k2. However, this would not compute the desired temperature differences.
- With the introduction of Window functions in SQL:2003, one can now write a query like SELECT k1, value - lag(value) OVER (PARTITION BY k1 ORDER BY k2) FROM D. The lag() function returns the value of the previous entry in the same partition.

Secondary Sort in Spark Scala

- For pair RDDs, secondary sort can be achieved using the repartitionAndSortWithinPartitions(partitionerObject) transformation. It partitions the RDD using the specified Partitioner, and sorts each partition by the key.
  - From the Spark 2.3.0 API (as of September 2018): "This is more efficient than calling repartition and then sorting within each partition because it can push the sorting down into the shuffle machinery."
- Interestingly, when using DataSet, one can write window functions like in SQL:2003, using org.apache.spark.sql.expressions.Window
  - Define the DataSet with schema (k1, k2, value)
  - val groupedSorted = Window.partitionBy(k1).orderBy(k2)
  - val diff = lag(value, 1).over(groupedSorted)

Module Summary: Local Aggregation

- Opportunities to perform local aggregation vary depending on problem type and data distribution.
- Combiners can significantly reduce cost by decreasing the amount of data sent from Mappers to Reducers. Unfortunately the programmer cannot control if and when a Combiner will be executed by Hadoop.
- In-mapper combining can be used instead of a Combiner. It gives the programmer explicit control, but requires changes to the Mappers.
- Both Combiners and in-mapper combining are only applicable for certain types of aggregate functions. They are only effective if many Map output records in the same Map task have the same key.
- In Spark, when using pair RDDs, use specialized aggregation operations such as reduceByKey, foldByKey, and aggregateByKey. They perform the equivalent of in-mapper combining—in contrast to using groupByKey followed by aggregation.
  - When using DataSets, DataSet.groupBy.agg is actually the right approach. Here the optimizer automatically determines that “in-mapper combining” can be applied.

Module Summary: Sorting

- In MapReduce, it is best to let the system take care of all sorting, using its highly optimized key-sorting algorithm during the shuffle phase. This eliminates the need for sorting in user code.
  - To do this, sort uses the identity function for both Map and Reduce, relying on range partitioning for correct sorting.
  - Secondary sort requires the secondary key to be part of the intermediate key. For correctness, Partitioner and grouping comparator need to ignore the secondary key.
- In Spark, one should choose the corresponding built-in functionality for sort and secondary sort.