Data-intensive computing systems

MapReduce

Universtity of Verona
Computer Science Department

Damiano Carra

Acknowledgements

- Credits
  - *Part of the course material is based on slides provided by the following authors*
    - *Pietro Michiardi, Jimmy Lin*

Basic example: Word count

- Assume to have a large collection of texts
  - e.g., Web pages from the whole Internet

- We would like to count how many times each word is mentioned all over the collection
  - it represents the basis for more complex computations, such as frequencies, pairings, etc

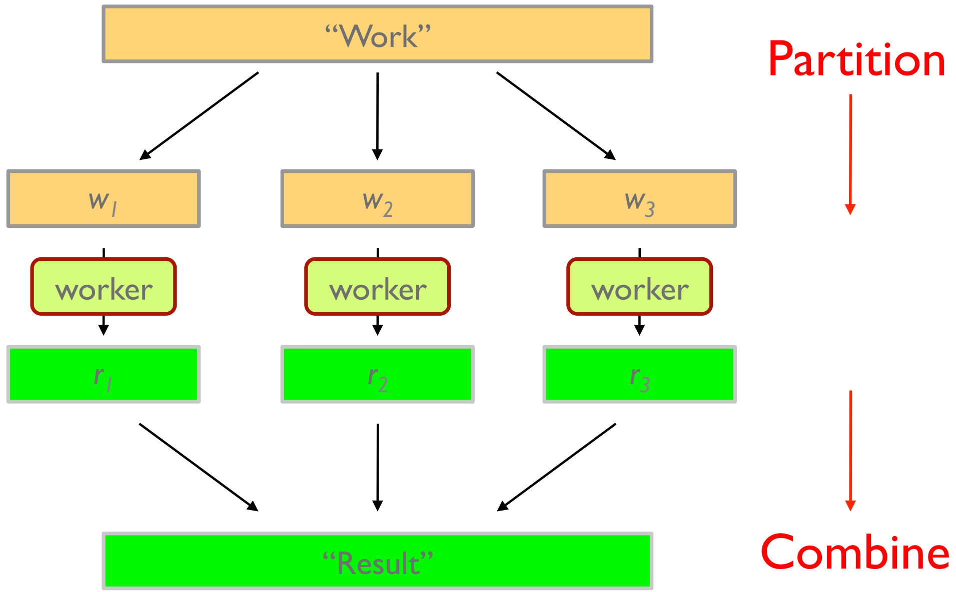
- Assuming that the collection is distributed among N machines, how would you proceed?

Basic example: Word count

- In a single machine, the solution is trivial
  - final output: [(fog, 3), (winter, 2), (and, 4), …]

- With multiple machines
  1. Use the solution for the single machine in each machine
     - intermediate output: [(fog, 3), (winter, 2), (and, 4), …]
  2. Join the results collected from the different machines and produce the final output
     - final output: [(tree, 8), (fog, 13), (cold, 3), (winter, 6), (and, 22), …]

Divide and Conquer



Word count: pseudo-code

```
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 sum)
```

- The two computational steps materializes into two methods, Map and Reduce
  - MapReduce is then a programming model
- These two methods are included in a framework that takes care of different aspects

Parallel computing: Concerns

- A parallel system needs to provide:
  - Data distribution
  - Computation distribution
  - Fault tolerance
  - Job scheduling

- The execution framework should hide these system-level details
  - Separate the *what* from the *how*
- MapReduce abstracts away the "distributed" part of the system
  - MapReduce is then an execution framework

What is MapReduce

- A programming model:
  - Inspired by functional programming
  - Allows expressing distributed computations on massive amounts of data

- An execution framework:
  - Designed for large-scale data processing
  - Designed to run on clusters of commodity hardware

The Programming Model

MapReduce: Programming model

- MapReduce is a new use of an old idea in Computer Science
- Map: Apply a function to every object in a list
  - Each object (e.g. document) is independent
    - Order is unimportant
    - Maps can be done in parallel
  - The function produces an intermediate result
- Reduce: Combine the intermediate results to produce a final result

What can we do with MapReduce?

- ❑ There are several important problems that can be adapted to MapReduce
  - Inverted indexing (web search), graph algorithms (PageRank), …
- ❑ The key point is how to design algorithms with the MapReduce programming model
  - We will show some "design patterns"
    - How to transform a problem and its input
    - How to save memory and bandwidth in the system

Data structures

- ❑ Key-value pairs are the basic data structure
  - Keys and values can be: integers, float, strings, raw bytes
    - E.g.: for a collection of Web pages, input keys may be URLs and values may be the HTML content
  - They can also be ***arbitrary data structures***
- ❑ The design of MapReduce algorithms involes:
  - Imposing the key-value structure on arbitrary datasets
    - E.g.: for a collection of Web pages, input keys may be URLs and values may be the HTML content
  - In some algorithms, input keys are not used, in others they uniquely identify a record
  - Keys can be combined in complex ways to design various algorithms

MapReduce jobs

- The programmer defines a mapper and a reducer as follows:
  - map: (k1, v1) → [(k2, v2)]
  - reduce: (k2, [v2]) → [(k3, v3)]

- A MapReduce job consists in:
  - A dataset, stored on the underlying **distributed** filesystem, which is split in a number of **blocks** across machines
  - The mapper, applied to every input key-value pair to generate intermediate key-value pairs
  - The reducer, applied to all values associated with the same intermediate key to generate output key-value pairs

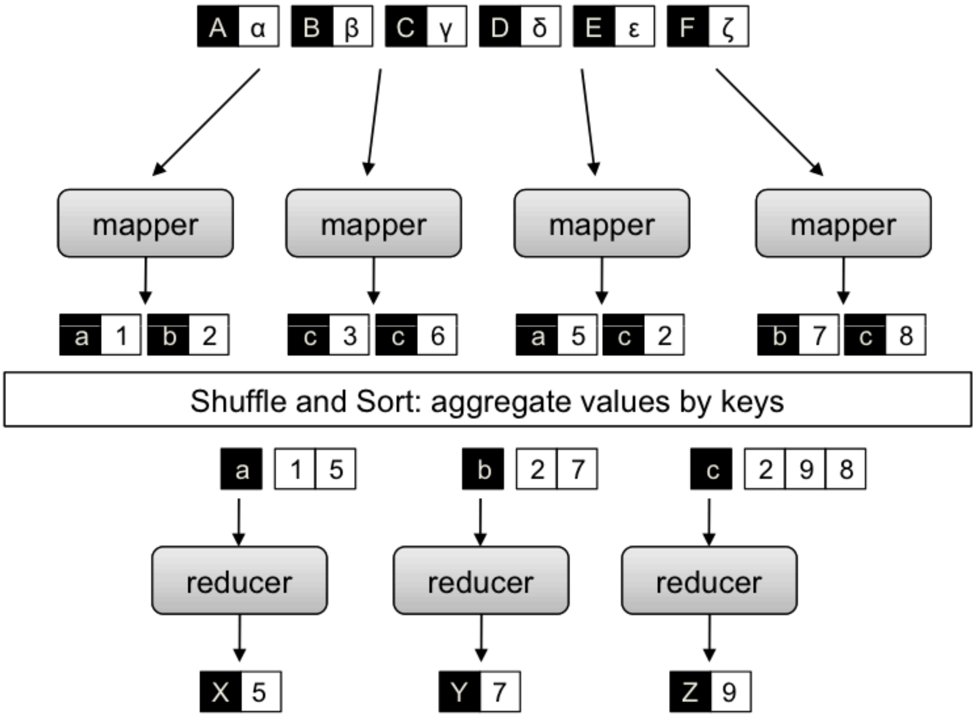
Where the magic happens

- Implicit between the map and reduce phases is a distributed “group by” operation on intermediate keys
  - Intermediate data arrive at each reducer in order, sorted by the key
  - No ordering is guaranteed across reducers

- Output keys from reducers are written back to the distributed filesystem
  - The output may consist of r distinct files, where r is the number of reducers
  - Such output may be the input to a subsequent MapReduce phase

- Intermediate keys are transient:
  - They are not stored on the distributed filesystem
  - They are “spilled” to the local disk of each machine in the cluster

A Simplified view of MapReduce



The Execution Framework

MapReduce: Execution framework

- MapReduce program, a.k.a. a job:
  - Code of mappers and reducers
  - Code for combiners and partitioners (optional)
  - Configuration parameters
  - All packaged together

- A MapReduce job is submitted to the cluster
  - The framework takes care of everything else
  - Next, we will delve into (some) details

Scheduling

- Each Job is broken into tasks
  - Map tasks work on fractions of the input dataset, as defined by the underlying distributed filesystem
  - Reduce tasks work on intermediate inputs and write back to the distributed filesystem

- The number of tasks may exceed the number of available machines in a cluster
  - The scheduler takes care of maintaining something similar to a queue of pending tasks to be assigned to machines with available resources

- Jobs to be executed in a cluster requires scheduling as well
  - Different users may submit jobs
  - Jobs may be of various complexity
  - Fairness is generally a requirement

Data/code co-location

- How to feed data to the code
  - In MapReduce, this issue is intertwined with scheduling and the underlying distributed filesystem
- How data locality is achieved
  - The scheduler starts the task on the node that holds a particular block of data required by the task
  - If this is not possible, tasks are started elsewhere, and data will cross the network
    - Note that usually input data is replicated
  - Distance rules help dealing with bandwidth consumption
    - Same rack scheduling

Synchronization

- In MapReduce, synchronization is achieved by the "shuffle and sort" barrier
  - Intermediate key-value pairs are grouped by key
  - This requires a distributed sort involving all mappers, and taking into account all reducers
  - If you have m mappers and r reducers this phase involves up to $m \times r$ copying operations
- IMPORTANT: the reduce operation cannot start until all mappers have finished
  - This is different from functional programming that allows "lazy" aggregation
  - In practice, a common optimization is for reducers to pull data from mappers as soon as they finish

Errors and faults

The MapReduce framework deals with:

- Hardware failures
  - Individual machines: disks, RAM
  - Networking equipment
  - Power / cooling
- Software failures
  - Exceptions, bugs
- Corrupt and/or invalid input data

Programming model: Optimizations

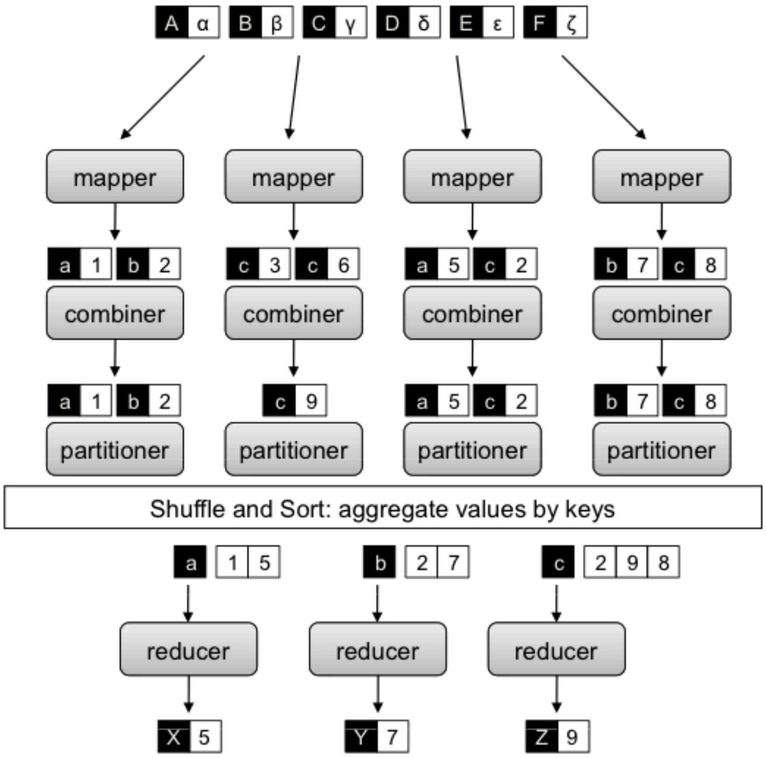
Local aggregation

- ❑ In the context of data-intensive distributed processing, the most important aspect of synchronization is the exchange of intermediate results
  - This involves copying intermediate results from the processes that produced them to those that consume them
  - In general, this involves **data transfers over the network**
  - In Hadoop, also disk I/O is involved, as intermediate results are written to disk
- ❑ Network and disk latencies are expensive
  - Reducing the amount of intermediate data translates into algorithmic efficiency
- ❑ Combiners and preserving state across inputs
  - Reduce the number and size of key-value pairs to be shuffled

Combiners

- ❑ Combiners are a general mechanism to reduce the amount of intermediate data
  - They could be thought of as “mini-reducers”
- ❑ Back to our running example: word count
  - Combiners aggregate term counts across documents processed by each map task
  - If combiners take advantage of all opportunities for local aggregation we have at most $m \times V$ intermediate key-value pairs
    - m: number of mappers
    - V : number of unique terms in the collection
  - Note: due to Zipfian nature of term distributions, not all mappers will see all terms

Combiners: an illustration



Combiners: considerations

- The input/output format of the combiners are determined by the Map and Reduce input/output
  - The input of the combiner has the same format of the input of the reducers
  - The output of the combiner has the same format of the output of the mappers
- In general, the code is very similar to the reducer's code
  - sometimes it is possible to use the reducers themselves
    - but this is not always true
- The execution of the combiners is not under control of the programmer
  - e.g., when the combiners are called

In-Mapper Combiners

- In-Mapper Combiners, a possible improvement

- Use an associative array to cumulate intermediate results
  - The array is used to sum up term counts within a single document
  - The `Emit` method is called only after all `InputRecords` have been processed

- Example (see next slide)
  - The code emits a key-value pair for each unique term in the document

In-Mapper Combiners: example

```
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})
```

In-Memory Combiners

- Taking the idea one step further
  - Exploit implementation details in Hadoop
  - A Java mapper object is created for each map task
  - JVM reuse must be enabled

- Preserve state within and across calls to the Map method
  - `Initialize` method, used to create a across-map persistent data structure
  - `Close` method, used to emit intermediate key-value pairs only when all map task scheduled on one machine are done

In-Memory Combiners: example

class $\textsc{Mapper}$
    method $\textsc{Initialize}$
        $H \leftarrow \text{new } \textsc{AssociativeArray}$
    method $\textsc{Map}(\text{docid } a, \text{doc } d)$
        for all term $t \in$ doc d **do**
            $H\{t\} \leftarrow H\{t\} + 1$ ▷ Tally counts *across* documents
    method $\textsc{Close}$
        for all term $t \in H$ **do**
            $\textsc{Emit}(\text{term } t, \text{count } H\{t\})$

In-Memory Combiners: Considerations

- Precautions
  - In-memory combining breaks the functional programming paradigm due to state preservation
  - Preserving state across multiple instances implies that algorithm behavior might depend on execution order
    - Ordering-dependent bugs are difficult to find
- Scalability bottleneck
  - The in-memory combining technique strictly depends on having sufficient memory to store intermediate results
    - And you don't want the OS to deal with swapping
  - Multiple threads compete for the same resources