MapReduce: Recap

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Some slides borrowed from Jimmy Lin, Jeff Ullman, Jerome Simeon, and Jure Leskovec

MapReduce: Recap

- Sequentially read a *lot* of data Why?
- Map: extract something we care about

  map (k, v) → <k', v'>*

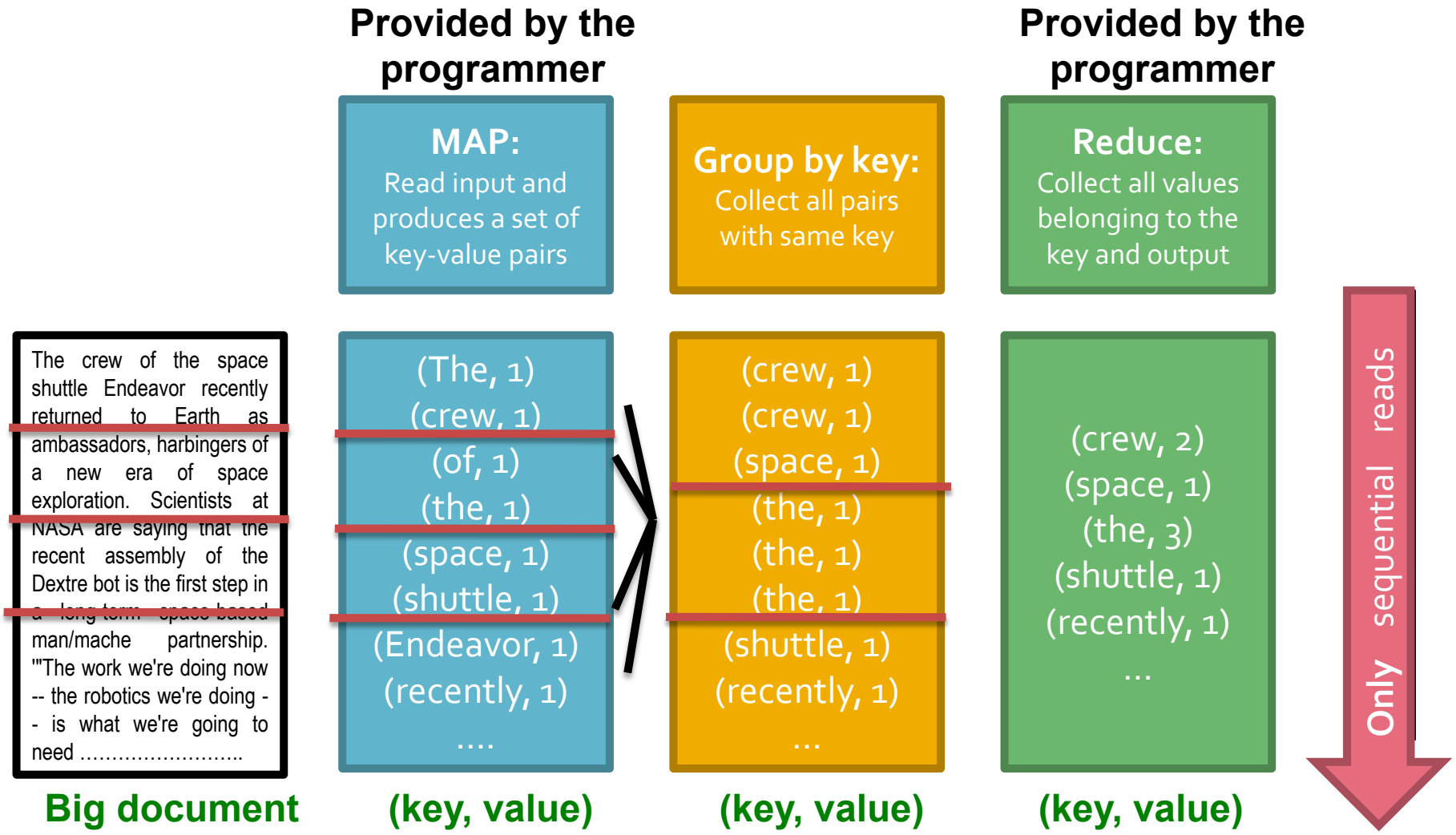
  There is one Map call for each (k,v) pair
- Group by key: Sort and Shuffle
- Reduce: aggregate, summarize, filter, or transform

  reduce (k', <v'>*) → <k', v''>*

  There is one Reduce per unique key k'
- Write the result

Structure remains the same, Map and Reduce change to fit the problem

Mapreduce: WordCount

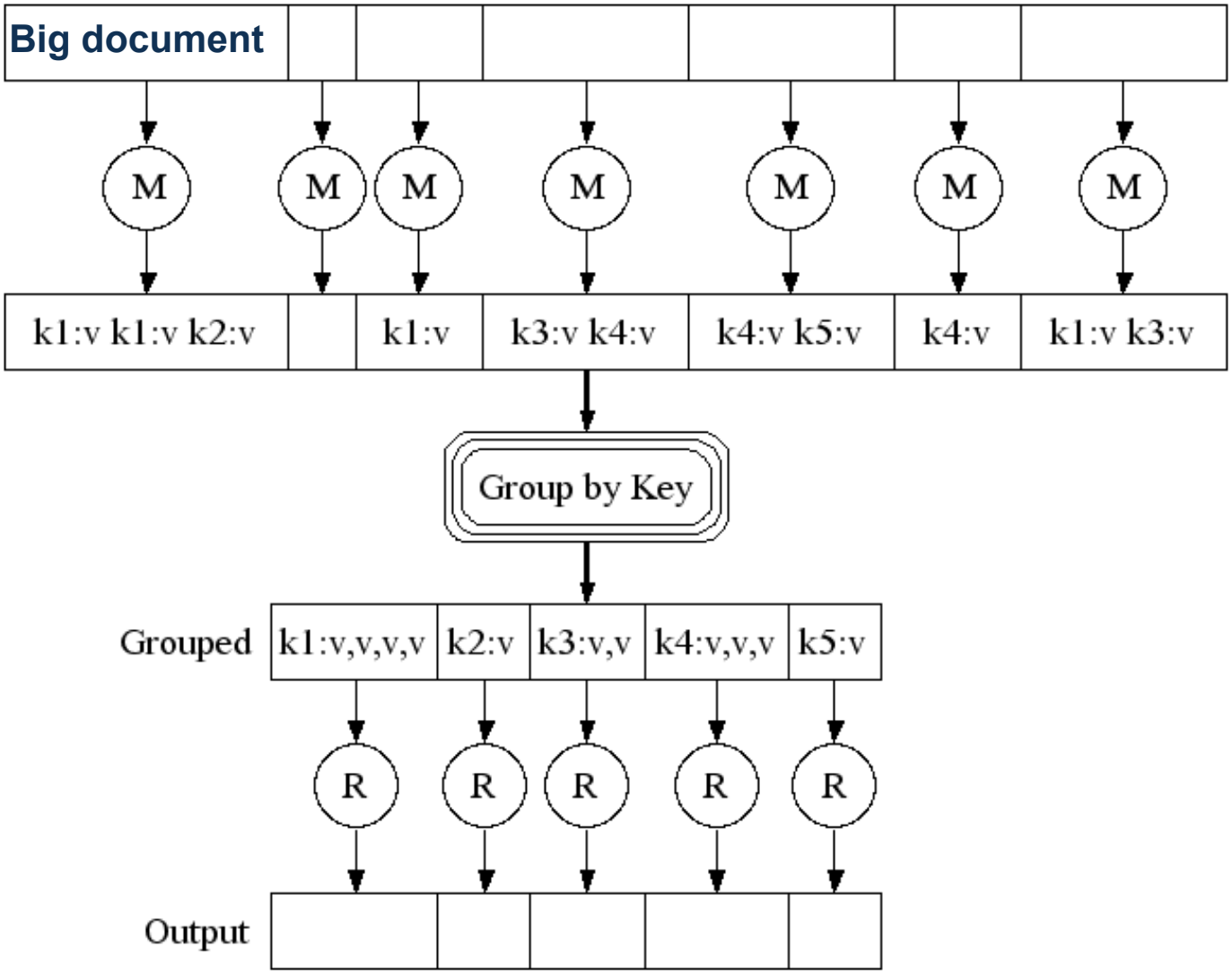


Map-Reduce: A Diagram

MAP:
Read input and produces a set of key-value pairs

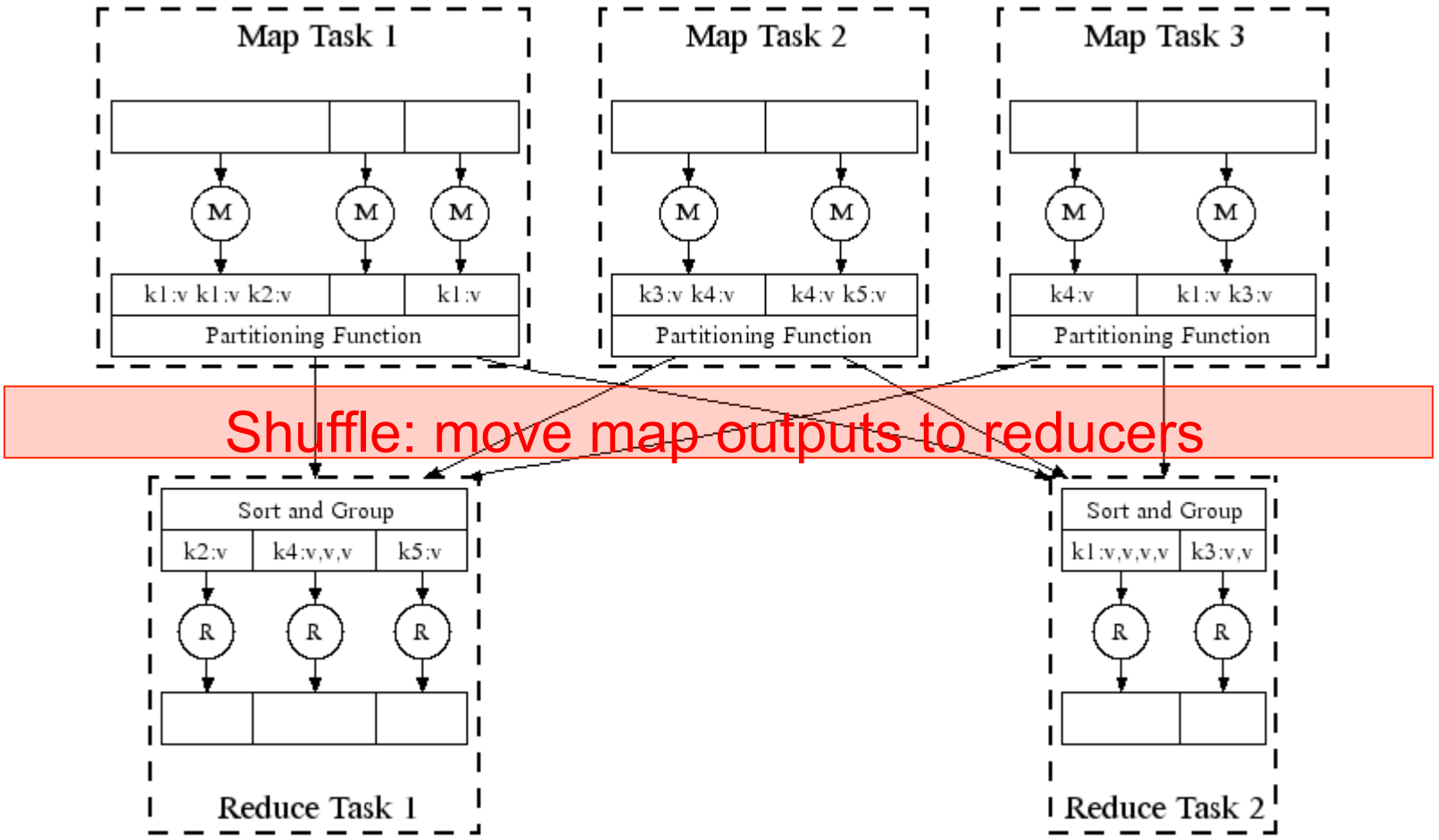
Group by key:
Collect all pairs with same key
(Hash merge, Shuffle, Sort, Partition)

Reduce:
Collect all values belonging to the key and output



J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

Map-Reduce: In Parallel

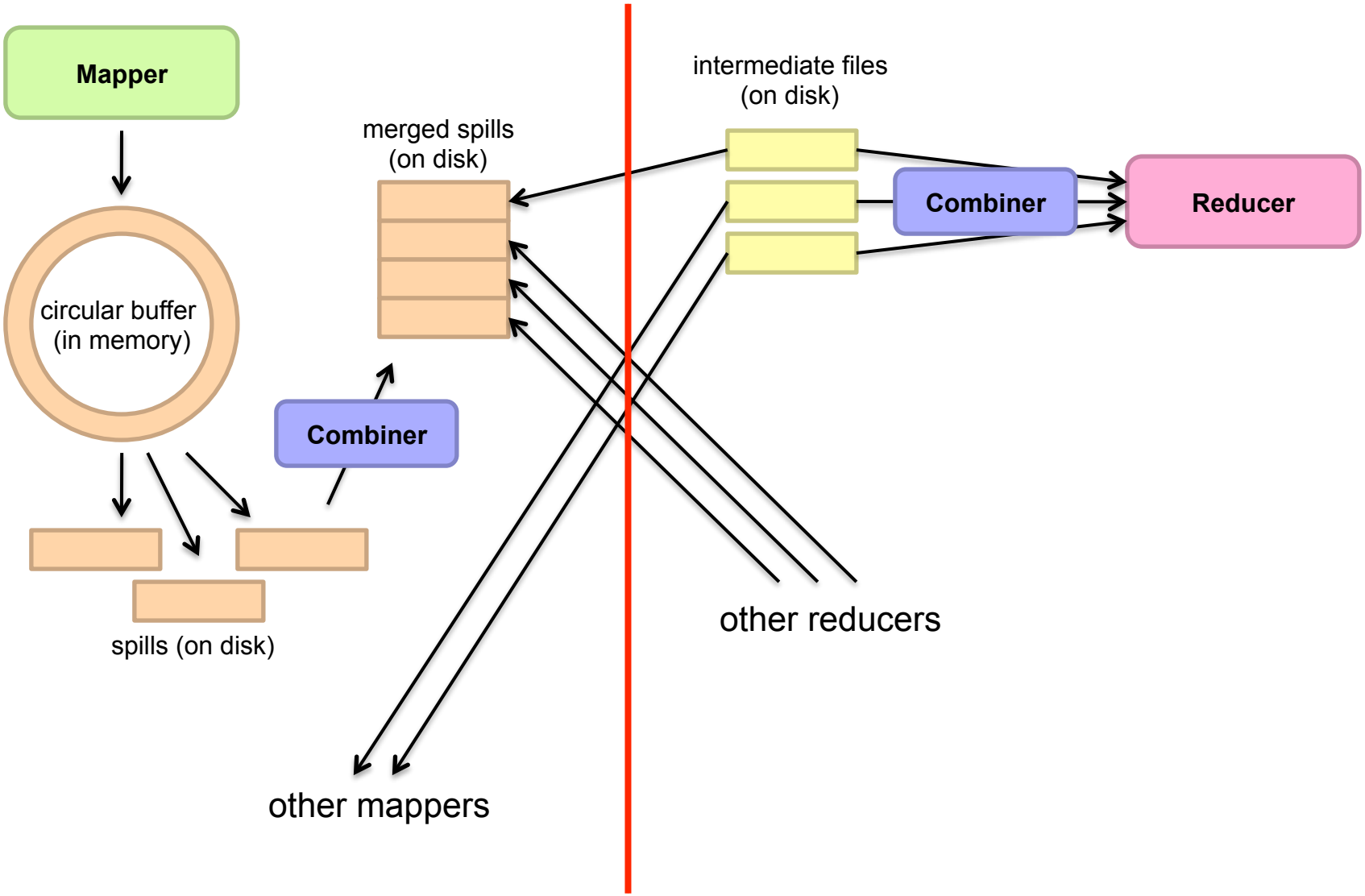


All phases are distributed with many tasks doing the work

Shuffle and Sort in Hadoop

- Probably the most complex aspect of MapReduce!
- Map side
  - Map outputs are buffered in memory in a circular buffer
  - When buffer reaches threshold, contents are “spilled” to disk
  - Spills merged in a single, partitioned file (sorted within each partition): combiner runs here
- Reduce side
  - First, *map outputs are copied over to reducer machine*
  - *“Sort” is a multi-pass merge of map outputs (happens in memory and on disk)*
  - Final merge pass goes directly into reducer

Shuffle and Sort



MapReduce: Data Flow

- *Input and final output* are stored on the *distributed file system* (DFS)
  - Scheduler tries to schedule map tasks "close" to physical storage location of input data

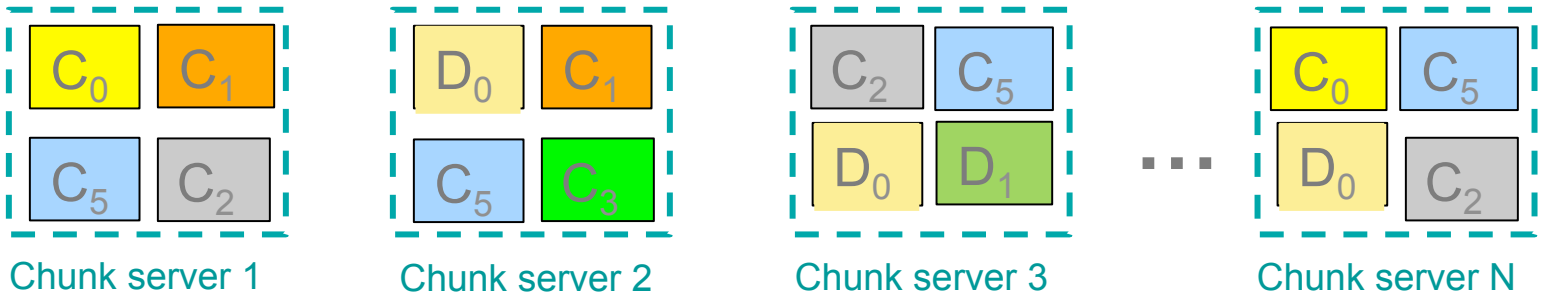
  You can specify a directory where your input files reside using *MultipleInputs.addInputPath*
- Typical usage pattern:
  - Huge files (100s of GB to TB)
  - Mostly reads and appends to data
- *Intermediate results* are stored on *local FS* of Map and Reduce workers
- Output is often input to another MapReduce task

Chaining Multiple MapReduce Jobs

- https://developer.yahoo.com/hadoop/tutorial/module4.html#chaining
- http://www.slideshare.net/martyhall/hadoop-tutorial-mapreduce-part-8-mapreduce-workflows
- MapReduce workflow systems:
  - Cascading (http://www.cascading.org)
  - Oozie (http://oozie.apache.org) - supports construction of complex DAG workflows

Distributed File System

- Reliable distributed file system
- Data kept in “chunks” spread across machines
- Each chunk replicated on different machines
  - Seamless recovery from disk or machine failure



Bring computation directly to the data!

Chunk servers also serve as compute servers

How many Map (M) and Reduce (R) tasks?

- **Rule of thumb:**
  - Make *M* much larger than the number of nodes in the cluster
  - Improves dynamic load balancing and speeds up recovery from worker failures
  - The number of maps is usually driven by the number of DFS blocks in the input files
    - One DFS chunk per map is common
    - You can adjust the DFS block size…

  Note: You can provide a hint about the number of Map tasks by modifying JobConf's *conf.setNumMapTasks(int num)*

  - Usually *R* is smaller than *M:* Output is spread across *R* files

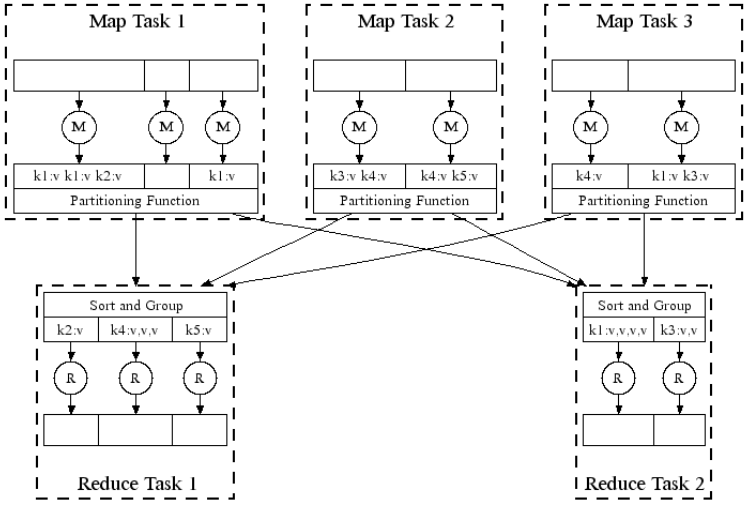
Refinements: Backup Tasks

- Problem: Slow workers significantly lengthen the job completion time:
  - Other jobs on the machine
  - Bad disks
- Solution: Near end of phase, spawn backup copies of tasks -- whichever one finishes first “wins”
- Effect: Dramatically shortens job completion time
- In Hadoop, *speculative tasks* are *on* by default

J. Leskovec, A. Rajaraman, J. Ullman: Mining of Massive Datasets, http://www.mmds.org

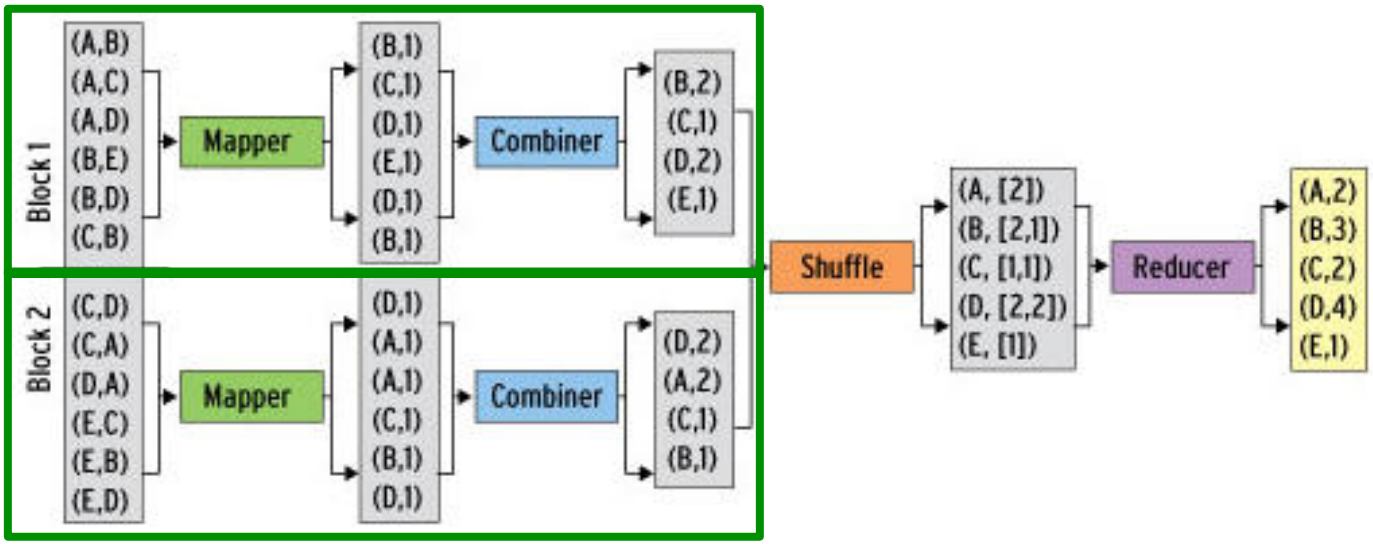
Refinement: Combiners

- Often a Map task will produce many pairs of the form $(k,v_1), (k,v_2), \ldots$ for the same key k
  - E.g., popular words in the word count example
- Can save network time by *pre-aggregating values in the mapper*:
  - combine(k, list(v_1)) → v_2
  - Combiner is usually same as the reduce function
- Works only if reduce function is commutative and associative



Refinement: Combiners

- Back to word counting example:
  - Combiner combines the values of all keys of a single mapper (single machine):



  - Much less data needs to be copied and shuffled!

Refinement: Partition Function

- Control how keys get partitioned
  - Inputs to map tasks are created by contiguous splits of input file
  - Reduce needs to *ensure that records with the same intermediate key end up at the same worker*
- System uses a default partition function:
  - hash(key) mod *R,* where R is the number of reducers
- Sometimes useful to override the hash function:
  - E.g., hash(hostname(URL)) mod *R* ensures URLs from a host end up in the same output file

Some Constraints and Unknowns

- 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