CAP4770/5771
Introduction to Data Science
Fall 2015

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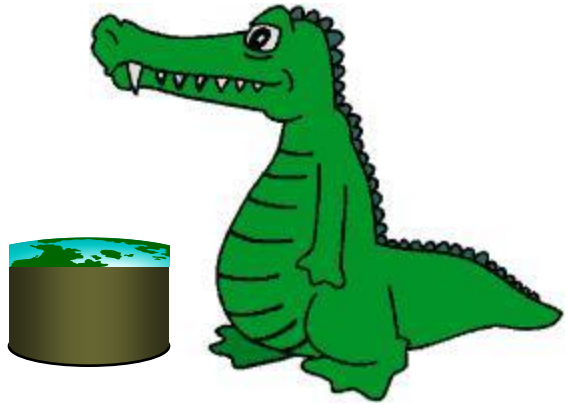


Based on notes from CS194 at UC Berkeley by Michael Franklin, John Canny, and Jeff Hammerbacher

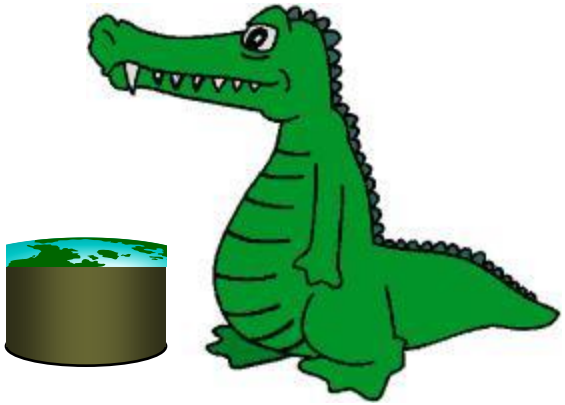
Map/Reduce: Simplified Data Processing on Large Clusters

Parallel/Distributed Computing

Distributed File System

M/R Programming Model

Parallel Analytics using M/R



Adapted Slides from Jeff Ullman, Anand Rajaraman and Jure Leskovec from Stanford

Logistics

- Finish all the AWS tutorials (AWS account, EC2, S3, EMR), setup and test run word-count M/R job by this Friday
- Lab 3:
  - Group of 2 due Friday
  - Out this weekend, due next Friday
  - Start early!!
- Midterm – the week after the next
- Pop quiz coming up

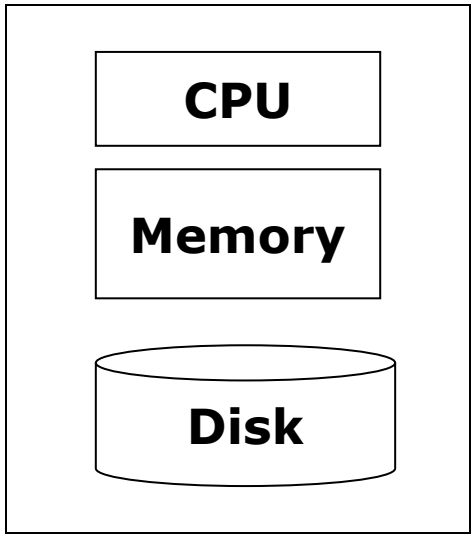
Parallel Computing

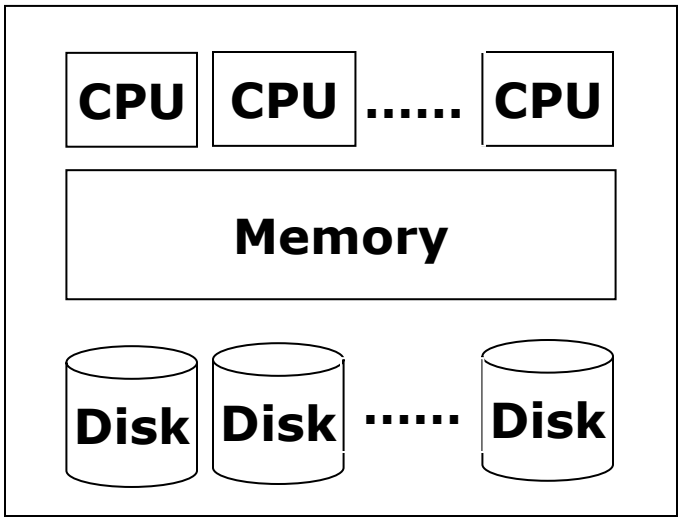
- MapReduce is designed for parallel computing
- Before MapReduce
  - Enterprise: a few super-computers, parallelism is achieved by parallel DBs (e.g., Teradata)
  - Science, HPC: MPI, openMP over commodity computer clusters or over super-computers for parallel computing, do not handle failures (i.e., Fault tolerance)
- Today:
  - Enterprise: map-reduce, parallel DBs
  - Science, HPC: openMP, MPI and map-reduce

MapReduce can apply over both multicore and **distributed environment**

Data Analysis on Single Server

- Many data sets can be very large
  - Tens to hundreds of terabytes
- Cannot always perform data analysis on large datasets on a single server (why?)
  - Run time (i.e., CPU), memory, disk space





Motivation: Google's Problem

- 20+ billion web pages * 20KB = 400+ TB
  - ~1000 hard drives to store the web
- 1 computer reads 30-35 MB/sec from disk
  - ~4 months to read the web

- Takes even more to do something useful with the data!
  - CPU
  - Memory

Distributed Computing

- Challenges:
  - Distributed/parallel programming is hard
    - How to distribute Data? Computation? Scheduling? Fault Tolerant? Debugging?
  - On the software side: what is the programming model?
  - On the hardware side: how to deal with hardware failures?
- MapReduce/Hadoop addresses all of the above
  - Google's computational/data manipulation model
  - Elegant way to work with big data

Commodity Clusters

- Recently standard commodity architecture for such problems:
  - Cluster of commodity Linux nodes
  - Gigabit ethernet interconnect
- Challenge: How to organize computations on this architecture?
  - handle issues such as hardware failure

Stable storage

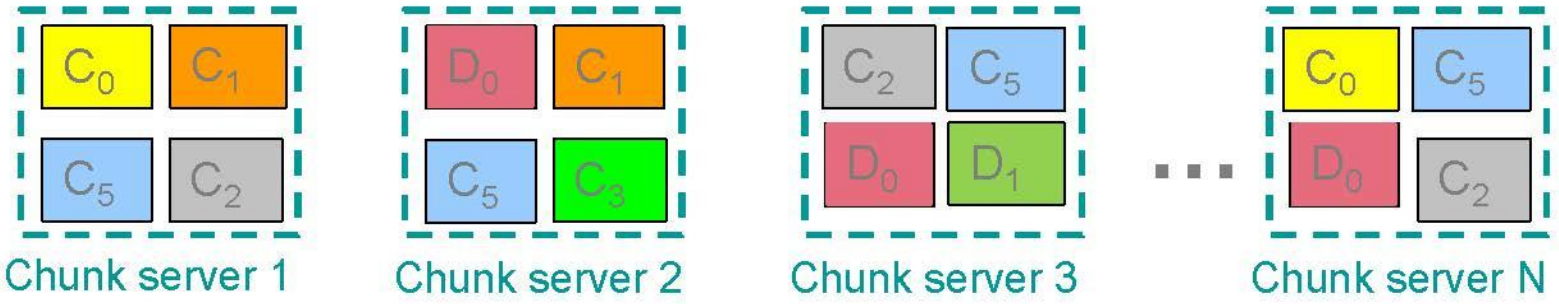
- First order problem: if nodes can fail, how can we store data persistently?
- Idea:
  - Store files multiple times for reliability
- Answer: Distributed File System
  - Provides global file namespace
  - Google GFS; Hadoop HDFS
- Typical usage pattern
  - Huge files (100s of GB to TB)
  - Data is rarely updated in place
  - Reads and appends are common

Distributed File System

- Chunk Servers
  - File is split into contiguous chunks
  - Typically each chunk is 16-64MB
  - Each chunk replicated (usually 2x or 3x)
  - Try to keep replicas in different racks
- Master node
  - a.k.a. Name Nodes in HDFS
  - Stores metadata
  - Likely to be replicated as well
- Client library for file access
  - Talks to master to find chunk servers
  - Connects directly to chunk servers to access data

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

MapReduce Motivation

- Large-Scale Data Processing
  - Want to use 1000s of CPUs, But don't want the hassle of scheduling, synchronization, etc.
- MapReduce provides
  - Automatic parallelization & distribution
  - Fault tolerance
  - I/O scheduling and synchronization
  - Monitoring & status updates

MapReduce Basics

- MapReduce
  - Programming model similar to Lisp
  - (and other functional languages)
- Many problems can be phrased using Map and Reduce functions
- Benefits for implementing an algorithm in MapReduce API
  - Automatic parallelization
  - Easy to distribute across nodes
  - Nice retry/failure semantics

Example Problem: Word Count

- We have a huge text file: doc.txt or a large corpus of documents: docs/*
- Count the number of times each distinct word appears in the file.. Apps?
- Sample application: analyze web server logs to find popular URLs

Word Count (2)

- Case 1: File too large for memory, but all <word, count> pairs fit in memory
- Case 2: File on disk, too many distinct words to fit in memory
  - Count occurrences of words

```
words(doc.txt) | sort | uniq -c
```

  - `words` takes a file and output the words in it, one word a line
  - Naturally capture the essence of MapReduce and naturally parallelizable

3 steps of MapReduce

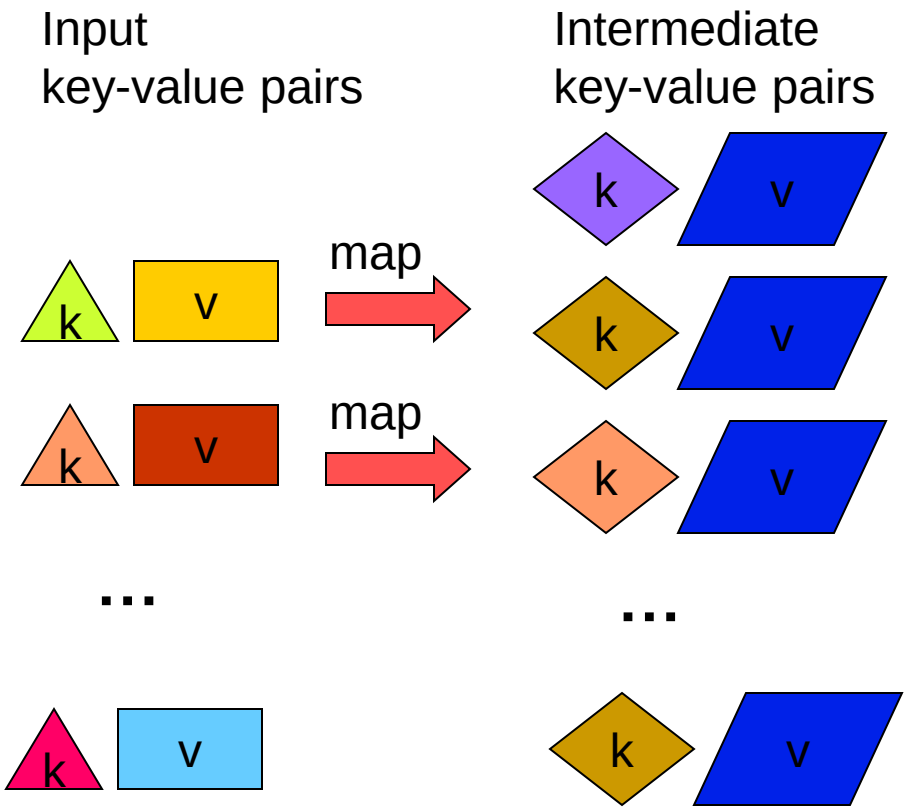
- Sequentially read a lot of data
- **Map:** Extract something you care about
- **Group by key:** Sort and shuffle
- **Reduce:** Aggregate, summarize, filter or transform
- Output the result

For different problems, steps stay the same,
Map and Reduce change to fit the problem

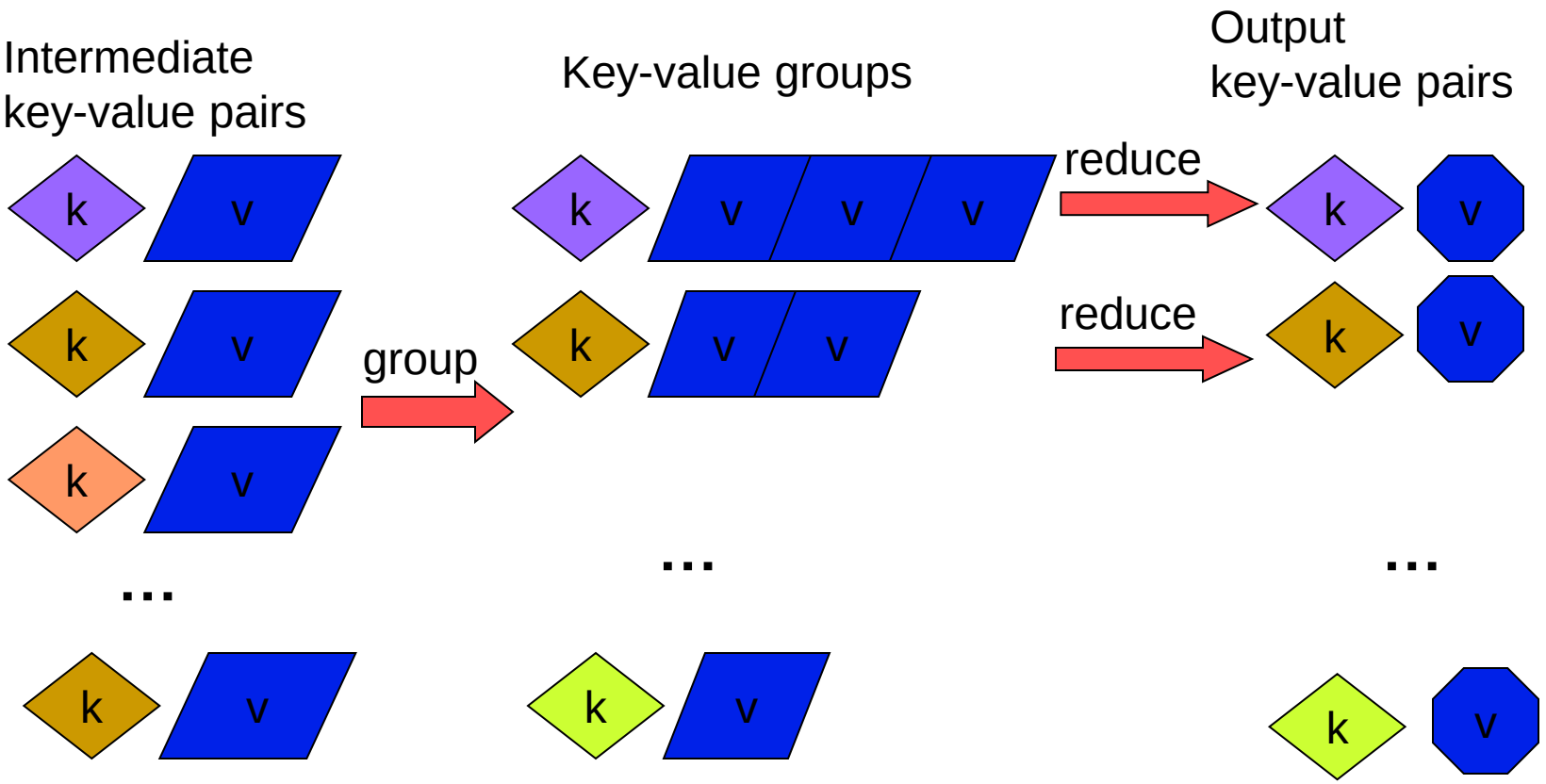
MapReduce: more detail

- Input: a set of key/value pairs
- Programmer specifies two methods
  - Map(k,v) → list(k1,v1)
    - Takes a key-value pair and outputs a set of key-value pairs (e.g., key is the file name, value is a single line in the file)
    - One map call for every (k,v) pair
  - Reduce(k1, list(v1)) → list (k1, v2)
    - All values v1 with the same key k1 are reduced together to produce a single value v2
    - There is one reduce call per unique key k1
- Group by key is executed by default in the same way: Sort(list(k1,v1)) → list (k1, list(v1))

MapReduce: The Map Step



MapReduce: The Group and Reduce Step

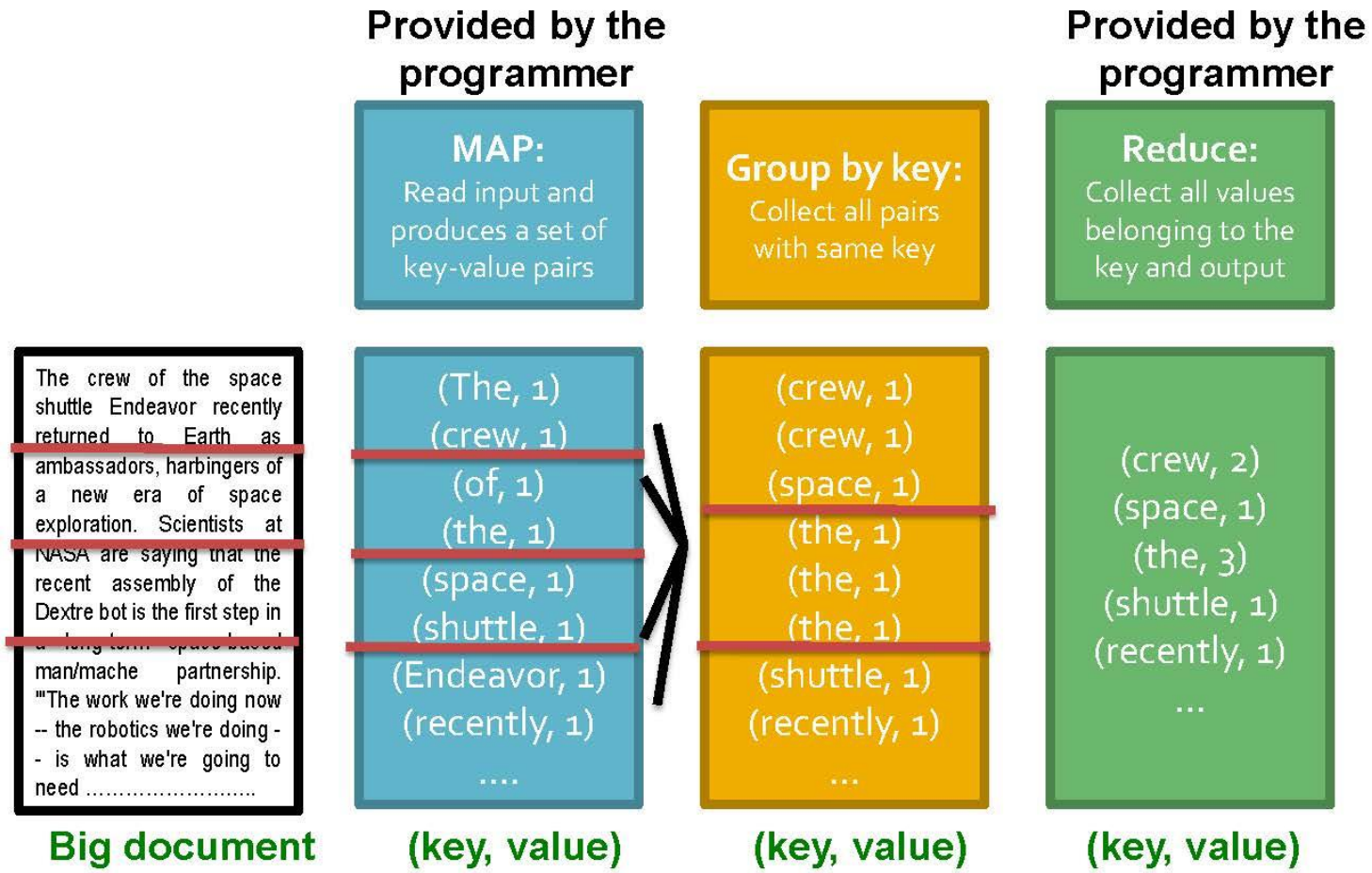


Word Count using MapReduce

```
map(key, value):
// key: document name; value: text of document
    for each word w in value:
        emit(w, 1)


reduce(key, values):
// key: a word; value: an iterator over counts
        result = 0
        for each count v in values:
            result += v
        emit(result)
```

MapReduce: Word Count

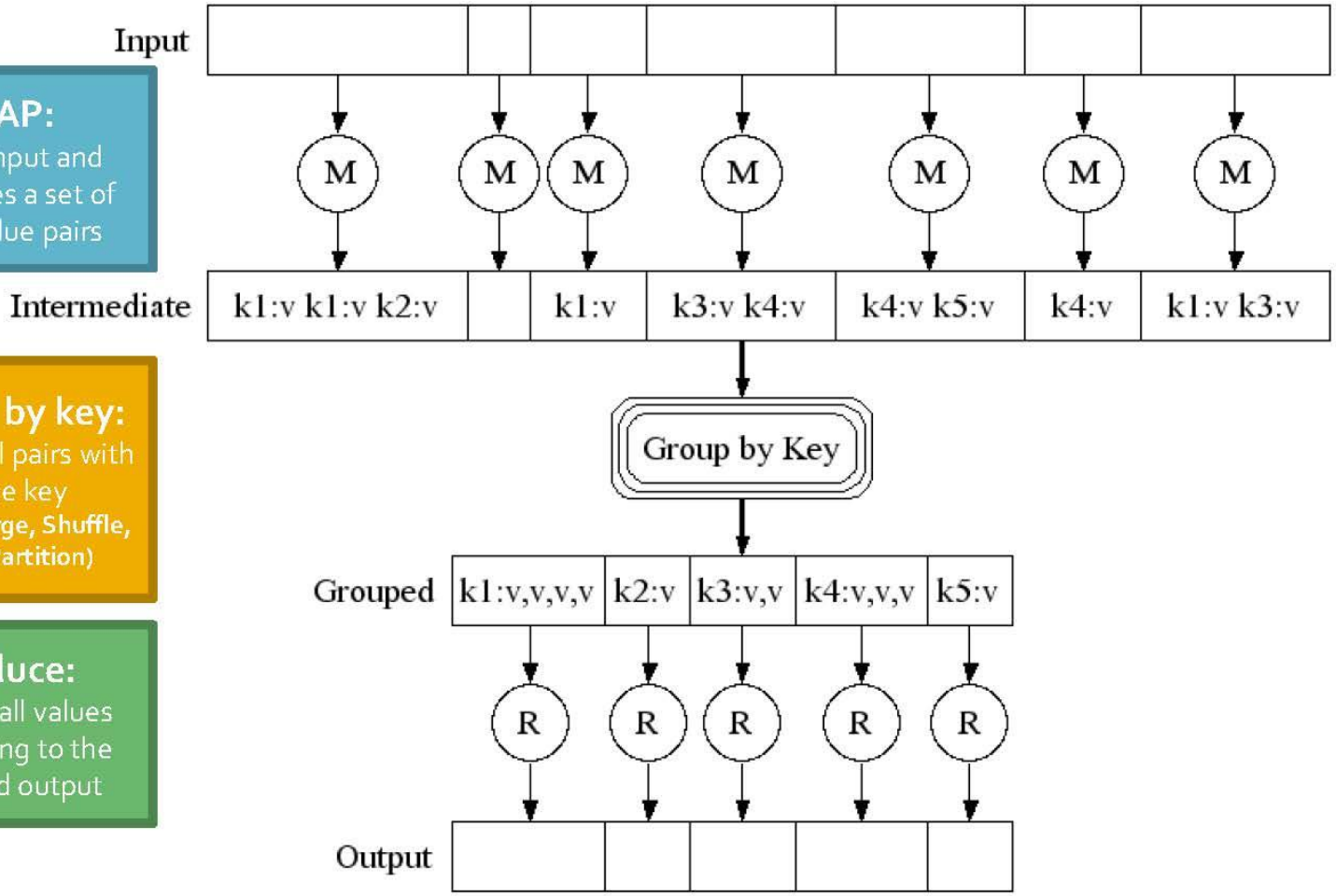


MapReduce Execution Details

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



Combiners

- Often a map task will produce many pairs of the form (k,v1), (k,v2), … for the same key k
  - E.g., popular words in Word Count
- Can save network time by pre-aggregating at mapper
  - combine(k1, list(v1)) → v2
  - Usually same as reduce function
- Works only if reduce function is commutative and associative

Implementations

- Google
  - Not available outside Google
- Hadoop
  - An open-source implementation in Java
  - Uses HDFS for stable storage
  - Download: http://lucene.apache.org/hadoop/

Many other Analytics and Algorithms can be Parallelized using MapReduce

Exercise 1: Host size

- Suppose we have a large web corpus
- Let's look at the metadata file
  - Lines of the form (URL, size, date, …)
- For each host, find the total number of bytes
  - i.e., the sum of the page sizes for all URLs from that host

Example 1: Host size (cont.)

- InputFormats: transform on-disk data representation on HDFS to in-memory key-value
  - Example: TextInputFormat, KeyValueTextInputFormat

- Mapper: (position, "URL, size, data,…") -> (hostname, size)
- Mapper: (URL, "size, data,…") -> (hostname, size)
- Reducer: (hostname, list (size)) -> (hostname, totalsize)