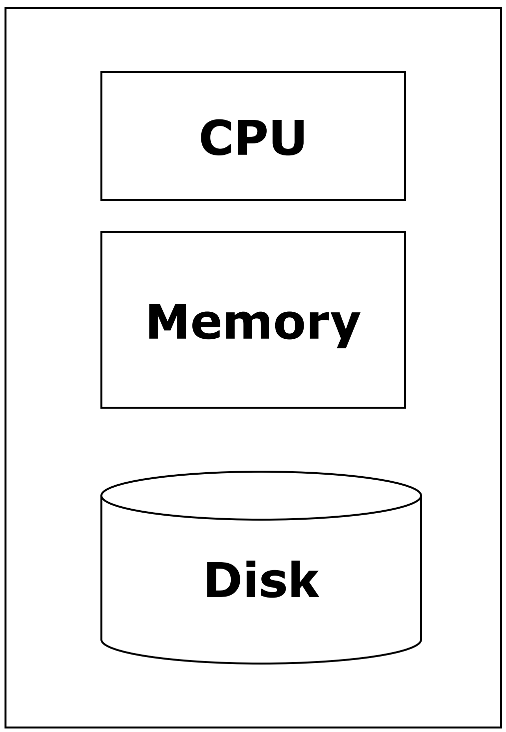
CS 345A
Data Mining

MapReduce

Single-node architecture



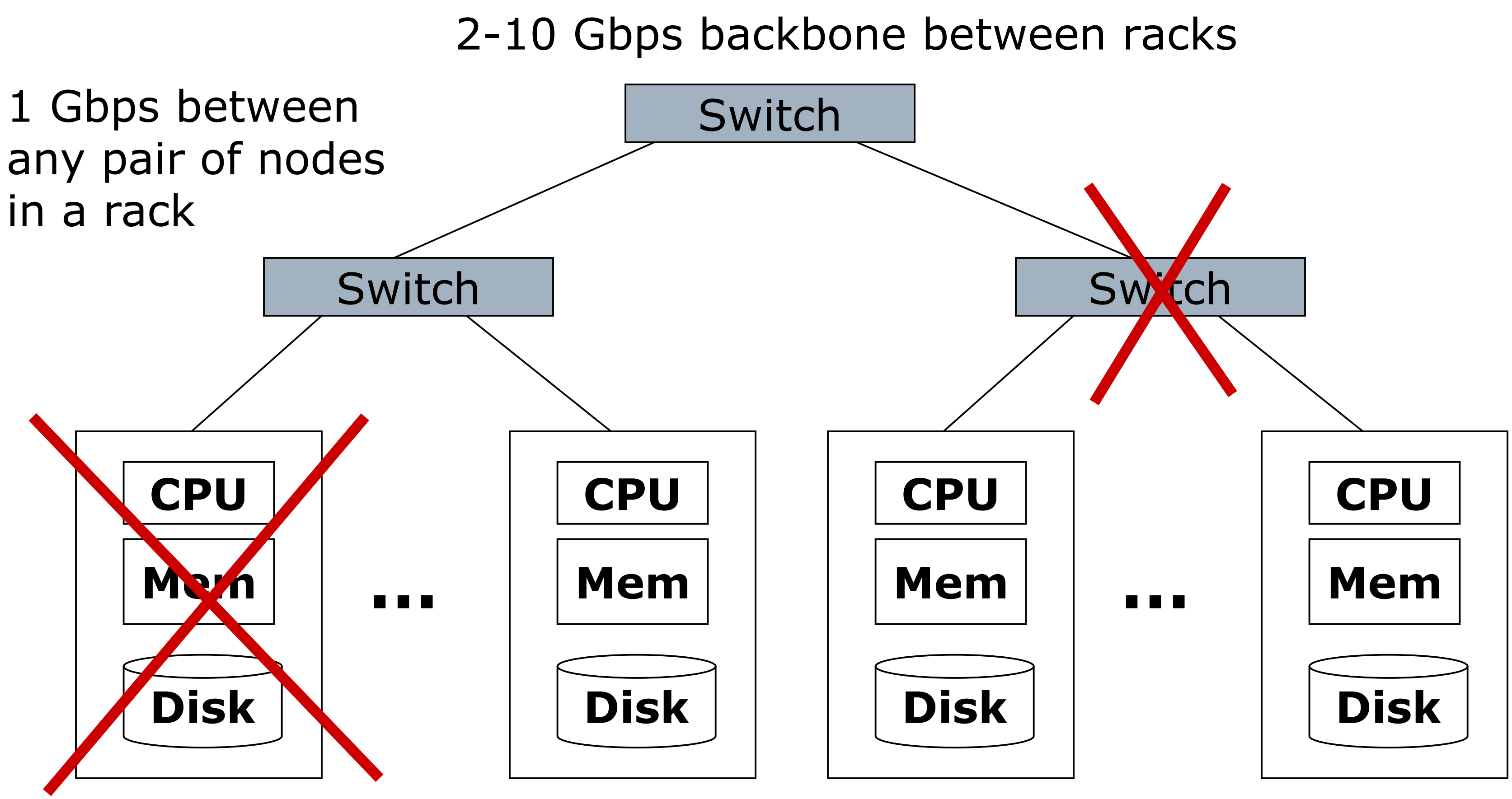
Machine Learning, Statistics

"Classical" Data Mining

Commodity Clusters

- Web data sets can be very large
  - Tens to hundreds of terabytes
- Cannot mine on a single server (why?)
- Standard architecture emerging:
  - Cluster of commodity Linux nodes
  - Gigabit ethernet interconnect
- How to organize computations on this architecture?
  - Mask issues such as hardware failure

Cluster Architecture



Each rack contains 16-64 nodes

Stable storage

- First order problem: if nodes can fail, how can we store data persistently?
- Answer: Distributed File System
  - Provides global file namespace
  - Google GFS; Hadoop HDFS; Kosmix KFS
- 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
  - Might be replicated
- Client library for file access
  - Talks to master to find chunk servers
  - Connects directly to chunkservers to access data

Warm up: Word Count

- We have a large file of words, one word to a line
- Count the number of times each distinct word appears in the file
- Sample application: analyze web server logs to find popular URLs

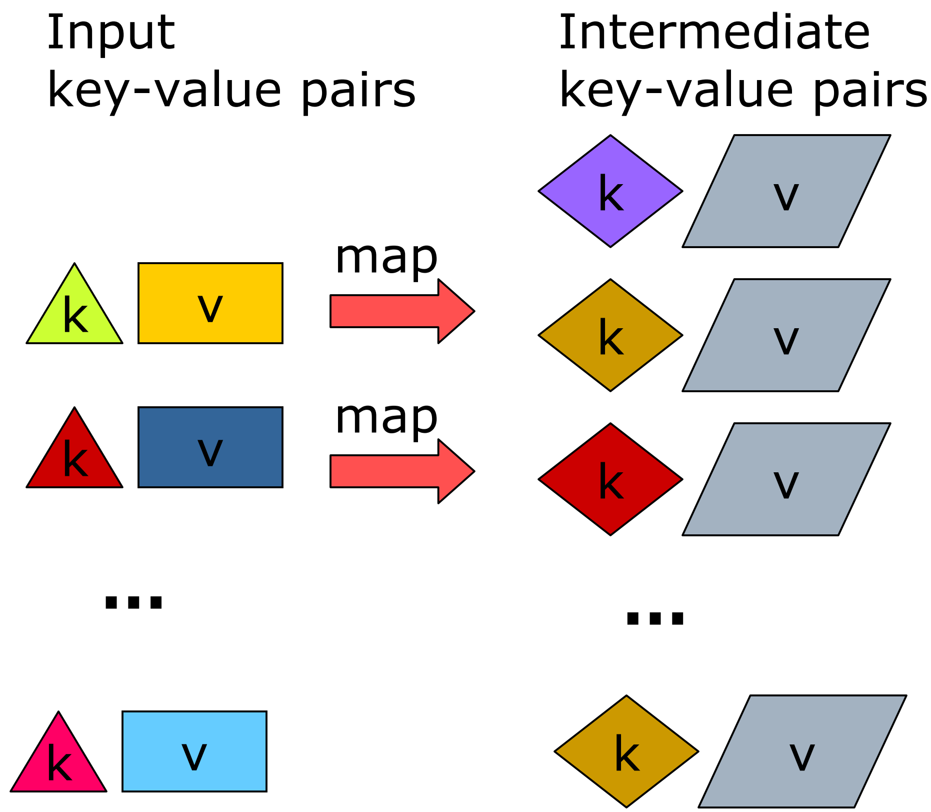
Word Count (2)

- Case 1: Entire file fits in memory
- Case 2: File too large for mem, but all <word, count> pairs fit in mem
- Case 3: File on disk, too many distinct words to fit in memory
  - **`sort datafile | uniq -c`**

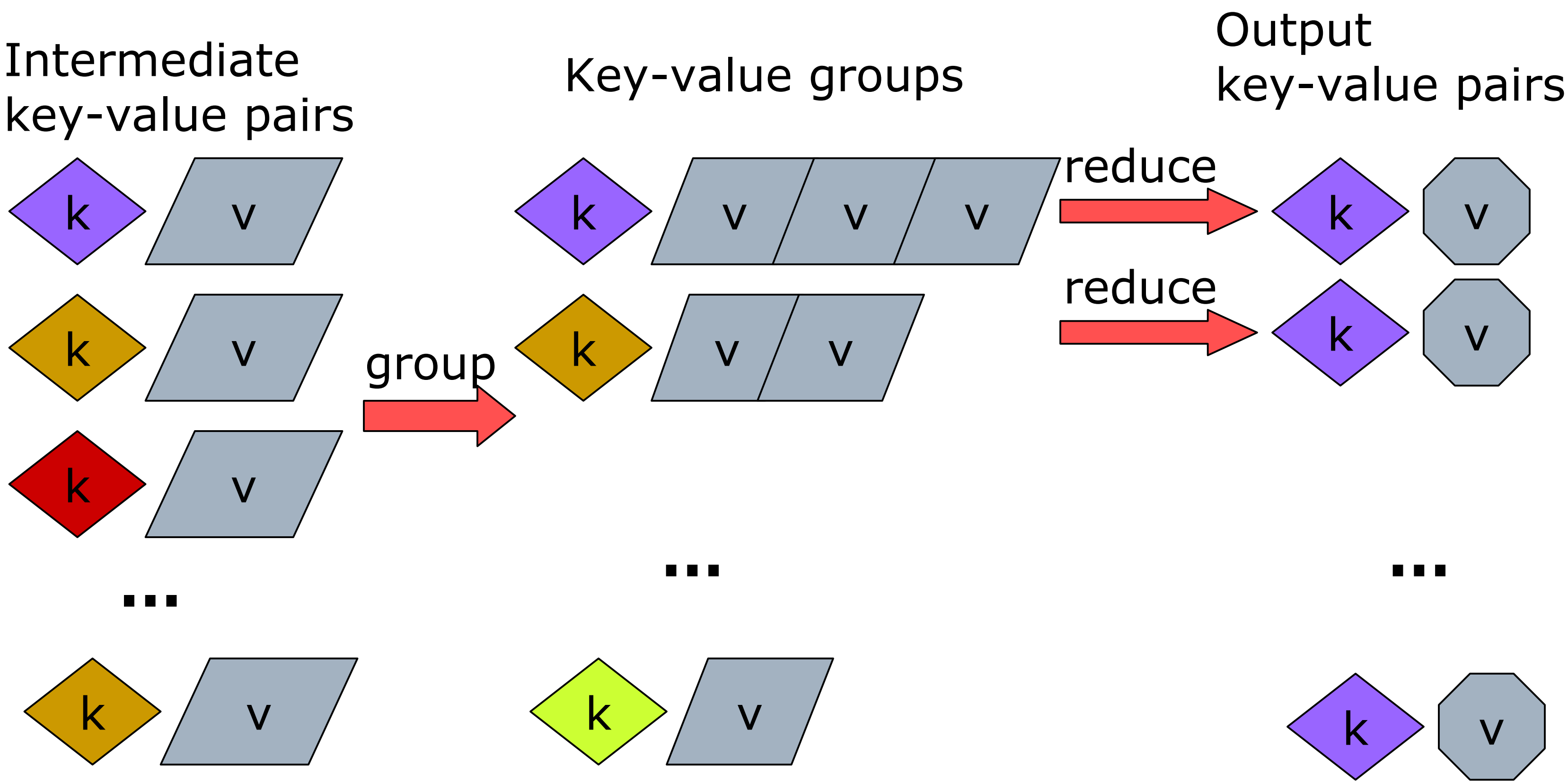
Word Count (3)

- To make it slightly harder, suppose we have a large corpus of documents
- Count the number of times each distinct word occurs in the corpus
  - **`words(docs/*) | sort | uniq -c`**
  - where **`words`** takes a file and outputs the words in it, one to a line
- The above captures the essence of MapReduce
  - Great thing is it is naturally parallelizable

MapReduce: The Map Step



MapReduce: The Reduce Step



MapReduce

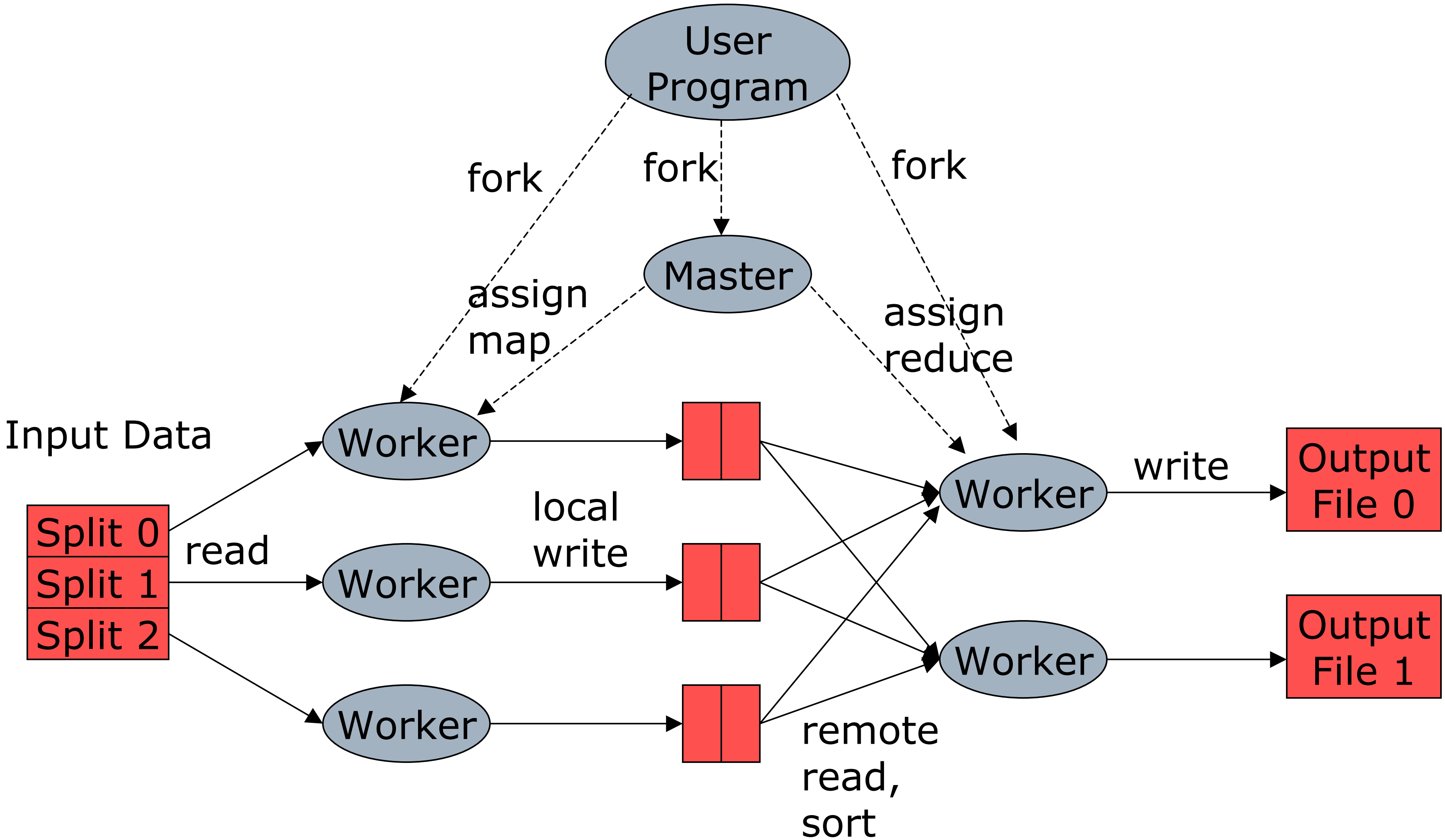
- Input: a set of key/value pairs
- User supplies two functions:
  - map(k,v) → list(k1,v1)
  - reduce(k1, list(v1)) → v2
- (k1,v1) is an intermediate key/value pair
- Output is the set of (k1,v2) pairs

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)
```

Distributed Execution Overview



Data flow

- Input, final output are stored on a distributed file system
  - Scheduler tries to schedule map tasks “close” to physical storage location of input data
- Intermediate results are stored on local FS of map and reduce workers
- Output is often input to another map reduce task

Coordination

- Master data structures
  - Task status: (idle, in-progress, completed)
  - Idle tasks get scheduled as workers become available
  - When a map task completes, it sends the master the location and sizes of its R intermediate files, one for each reducer
  - Master pushes this info to reducers
- Master pings workers periodically to detect failures

Failures

- Map worker failure
  - Map tasks completed or in-progress at worker are reset to idle
  - Reduce workers are notified when task is rescheduled on another worker
- Reduce worker failure
  - Only in-progress tasks are reset to idle
- Master failure
  - MapReduce task is aborted and client is notified

How many Map and Reduce jobs?

- M map tasks, R reduce tasks
- Rule of thumb:
  - Make M and R much larger than the number of nodes in cluster
  - One DFS chunk per map is common
  - Improves dynamic load balancing and speeds recovery from worker failure
- Usually R is smaller than M, because output is spread across R files

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

Partition Function

- Inputs to map tasks are created by contiguous splits of input file
- For reduce, we need to ensure that records with the same intermediate key end up at the same worker
- System uses a default partition function e.g., hash(key) mod R
- Sometimes useful to override
  - E.g., hash(hostname(URL)) mod R ensures URLs from a host end up in the same output file

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

Exercise 2: Distributed Grep

- Find all occurrences of the given pattern in a very large set of files

Exercise 3: Graph reversal

- Given a directed graph as an adjacency list:

src1: dest11, dest12, …

src2: dest21, dest22, …

- Construct the graph in which all the links are reversed

Exercise 4: Frequent Pairs

- Given a large set of market baskets, find all frequent pairs
  - Remember definitions from Association Rules lectures

Implementations

- Google
  - Not available outside Google
- Hadoop
  - An open-source implementation in Java
  - Uses HDFS for stable storage
  - Download: http://lucene.apache.org/hadoop/
- Aster Data
  - Cluster-optimized SQL Database that also implements MapReduce
  - Made available free of charge for this class

Cloud Computing

- Ability to rent computing by the hour
  - Additional services e.g., persistent storage
- We will be using Amazon's "Elastic Compute Cloud" (EC2)
- Aster Data and Hadoop can both be run on EC2
- In discussions with Amazon to provide access free of charge for class

Special Section on MapReduce

- Tutorial on how to access Aster Data, EC2, etc
- Intro to the available datasets
- Friday, January 16, at 5:15pm
  - Right after InfoSeminar
  - Tentatively, in the same classroom (Gates B12)

Reading

- Jeffrey Dean and Sanjay Ghemawat,

  MapReduce: Simplified Data Processing on Large Clusters

http://labs.google.com/papers/mapreduce.html

- Sanjay Ghemawat, Howard Gobioff, and Shun-Tak Leung, **The Google File System**

http://labs.google.com/papers/gfs.html