CS246:Mining Massive Datasets Intro & MapReduce

CS246: Mining Massive Datasets
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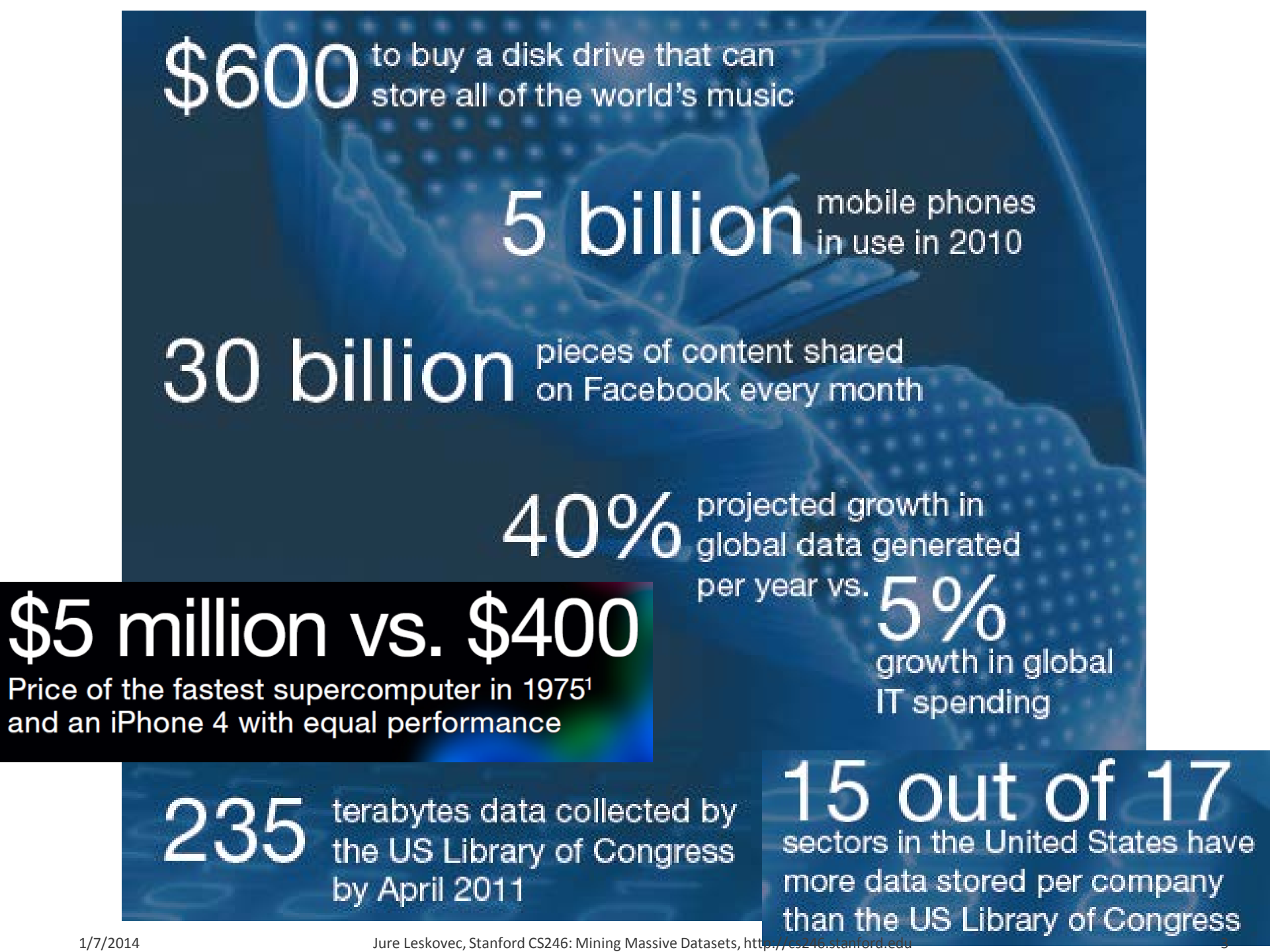
http://cs246.stanford.edu

What is Data Mining?
Knowledge discovery from data


$600 to buy a disk drive that can store all of the world's music
5 billion mobile phones in use in 2010
30 billion pieces of content shared on Facebook every month
40% projected growth in global data generated per year vs. 5% growth in global IT spending
$5 million vs. $400
Price of the fastest supercomputer in 1975[1] and an iPhone 4 with equal performance
235 terabytes data collected by the US Library of Congress by April 2011
15 out of 17 sectors in the United States have more data stored per company than the US Library of Congress

Data contains value and knowledge

Data Mining

- **But to extract the knowledge data needs to be**
  - **Stored**
  - **Managed**
  - **And ANALYZED ← this class**

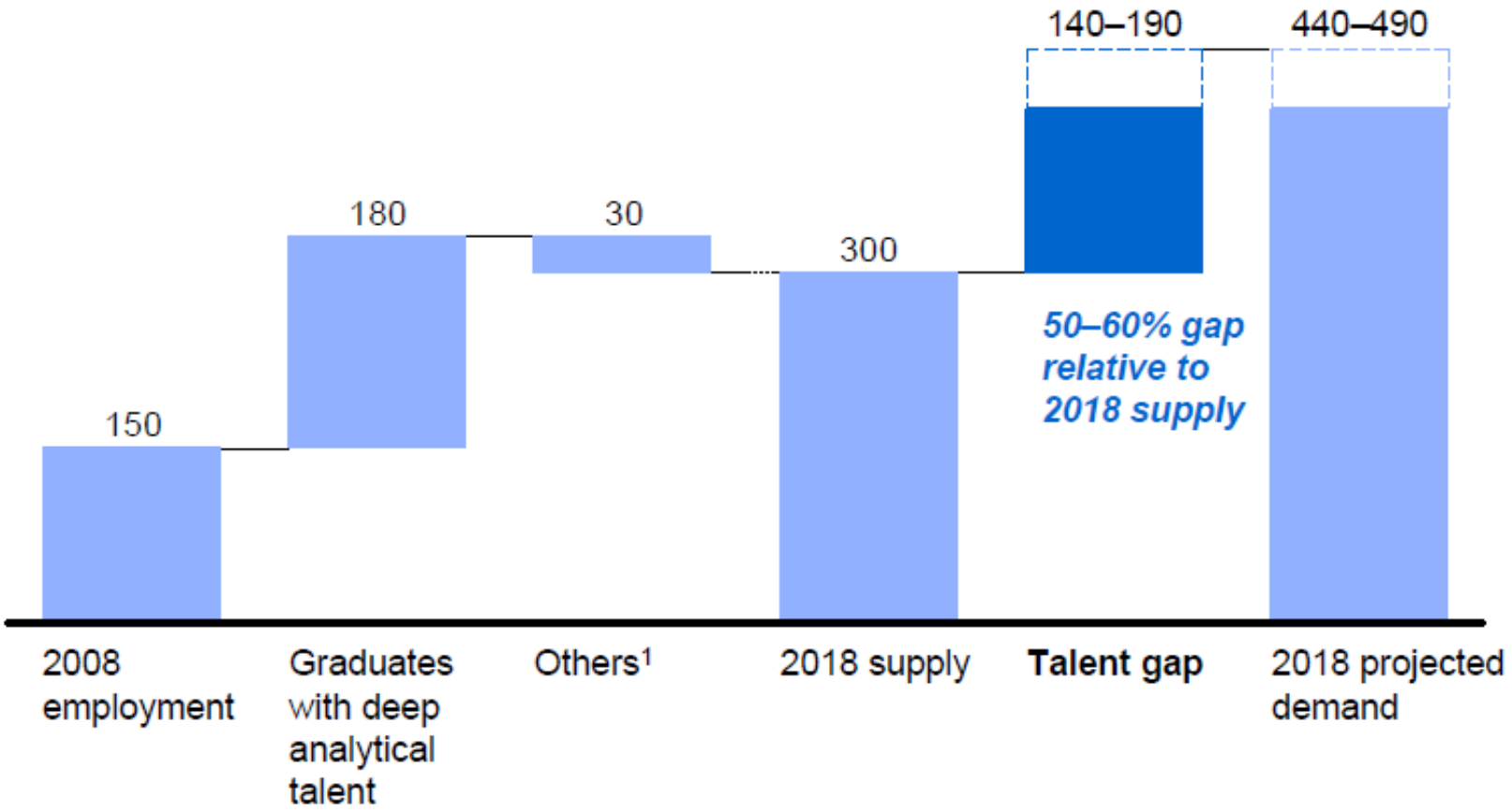
Data Mining ≈ Big Data ≈ Predictive Analytics ≈ Data Science

Good news: Demand for Data Mining

Demand for deep analytical talent in the United States could be 50 to 60 percent greater than its projected supply by 2018

Supply and demand of deep analytical talent by 2018

Thousand people



1 Other supply drivers include attrition (-), immigration (+), and reemploying previously unemployed deep analytical talent (+).

SOURCE: US Bureau of Labor Statistics; US Census; Dun & Bradstreet; company interviews; McKinsey Global Institute analysis

What is Data Mining?

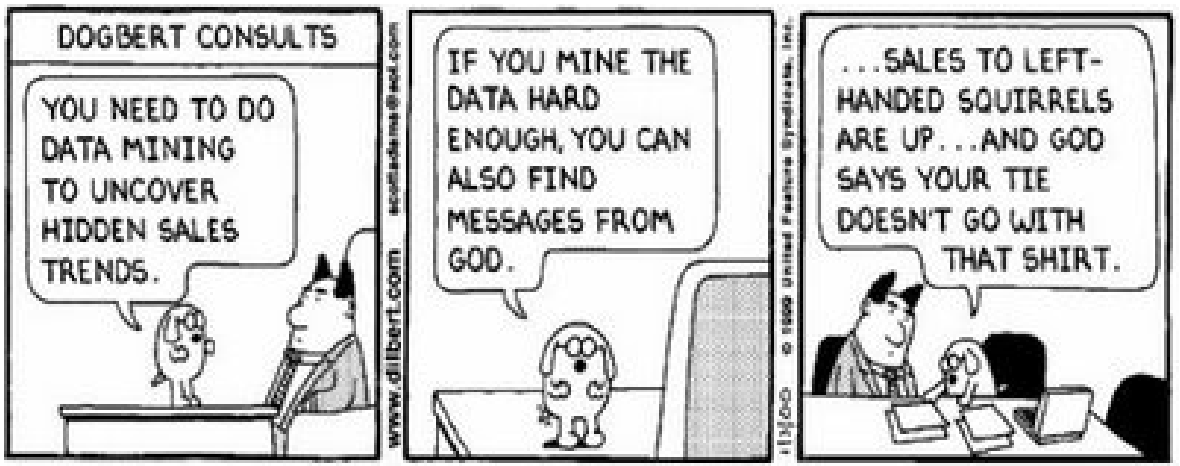
- **Given lots of data**
- **Discover patterns and models that are:**
  - **Valid:** hold on new data with some certainty
  - **Useful:** should be possible to act on the item
  - **Unexpected:** non-obvious to the system
  - **Understandable:** humans should be able to interpret the pattern

Data Mining Tasks

- **Descriptive methods**
  - Find human-interpretable patterns that describe the data
    - **Example:** Clustering
- **Predictive methods**
  - Use some variables to predict unknown or future values of other variables
    - **Example:** Recommender systems

Meaningfulness of Analytic Answers

- A risk with "Data mining" is that an analyst can "discover" patterns that are meaningless
- Statisticians call it **Bonferroni's principle**:
  - Roughly, if you look in more places for interesting patterns than your amount of data will support, you are bound to find crap

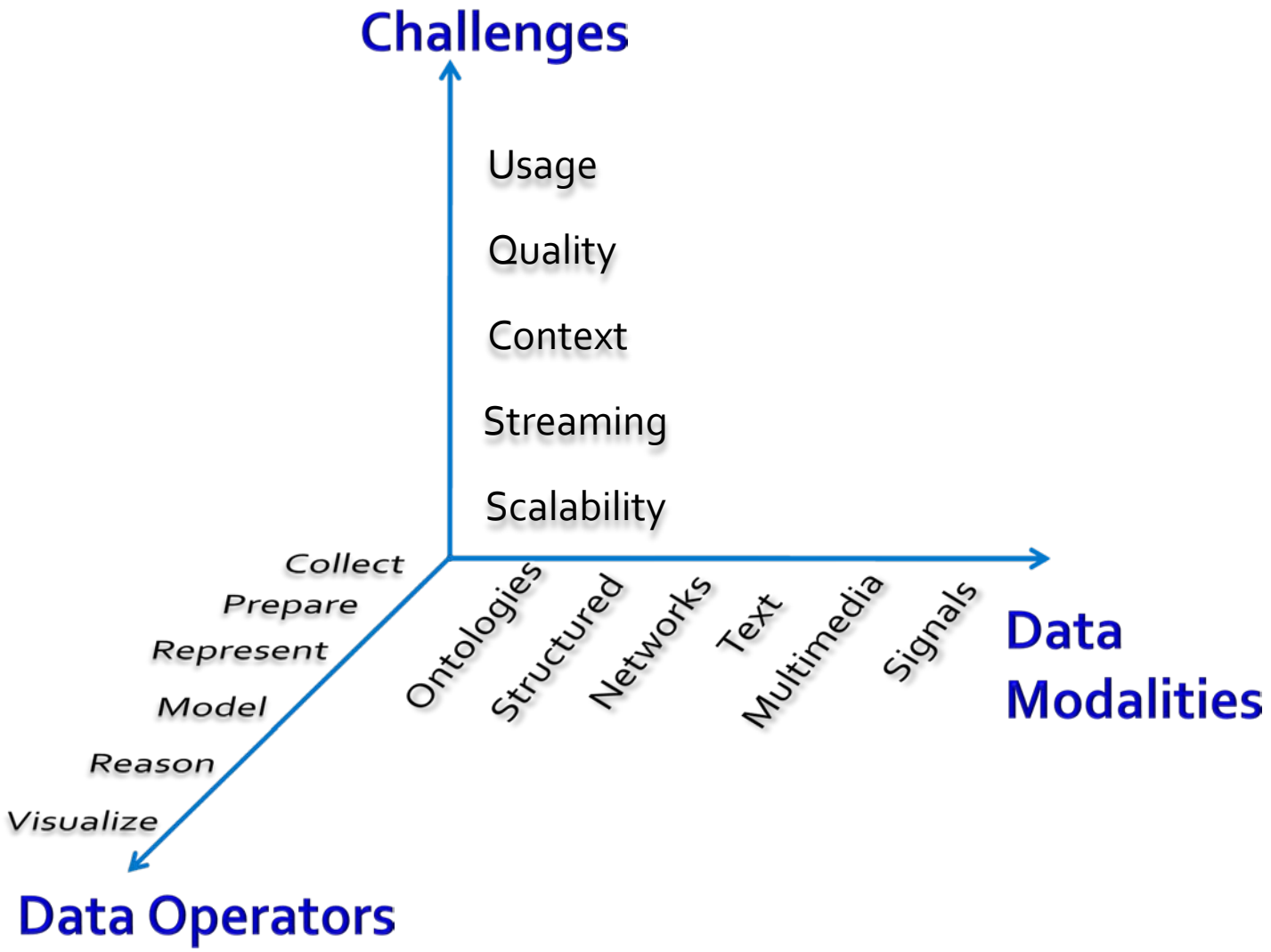


Meaningfulness of Analytic Answers

Example:

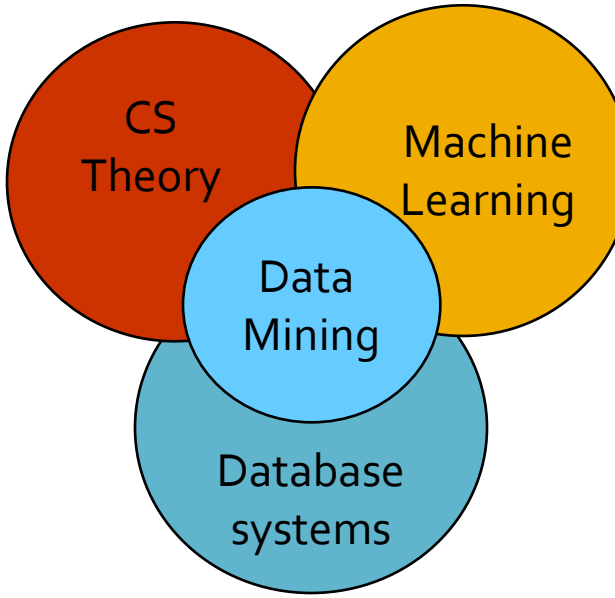
- We want to find (unrelated) people who **at least twice have stayed at the same hotel on the same day**
  - 10^9 people being tracked
  - 1,000 days
  - Each person stays in a hotel 1% of time (1 day out of 100)
  - Hotels hold 100 people (so 10^5 hotels)
  - **If everyone behaves randomly (i.e., no terrorists) will the data mining detect anything suspicious?**
- **Expected number of "suspicious" pairs of people:**
  - 250,000
  - … too many combinations to check – we need to have some additional evidence to find "suspicious" pairs of people in some more efficient way

What matters when dealing with data?



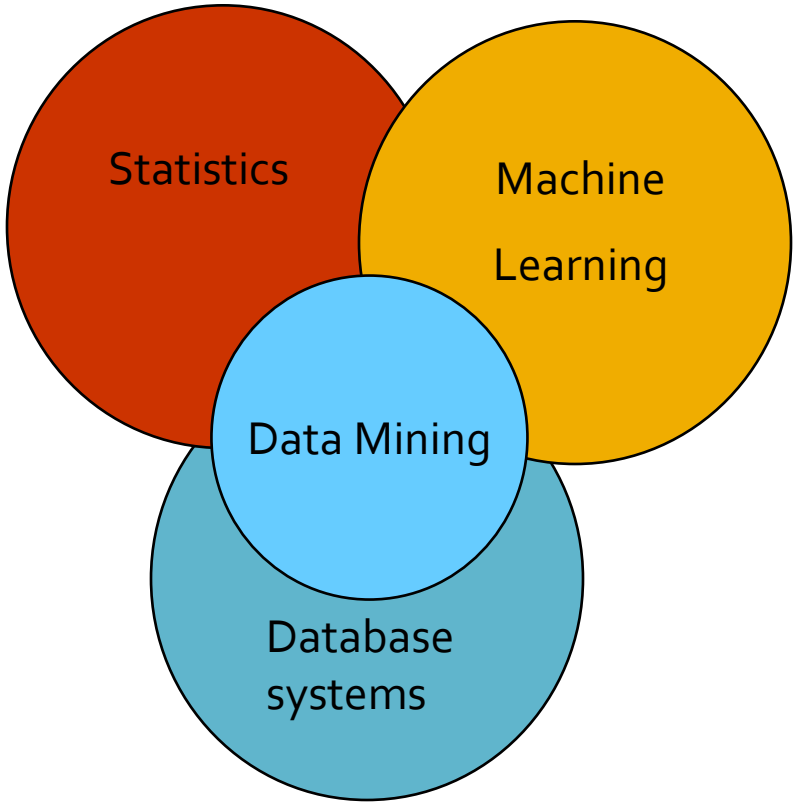
Data Mining: Cultures

- **Data mining overlaps with:**
  - **Databases:** Large-scale data, simple queries
  - **Machine learning:** Small data, Complex models
  - **CS Theory:** (Randomized) Algorithms
- **Different cultures:**
  - To a DB person, data mining is an extreme form of **analytic processing** – queries that examine large amounts of data
    - Result is the query answer
  - To a ML person, data-mining is the **inference of models**
    - Result is the parameters of the model
- **In this class we will do both!**



This Class: CS246

- **This class overlaps with machine learning, statistics, artificial intelligence, databases but more stress on**
  - **Scalability** (big data)
  - **Algorithms**
  - **Computing architectures**
  - Automation for handling **large data**



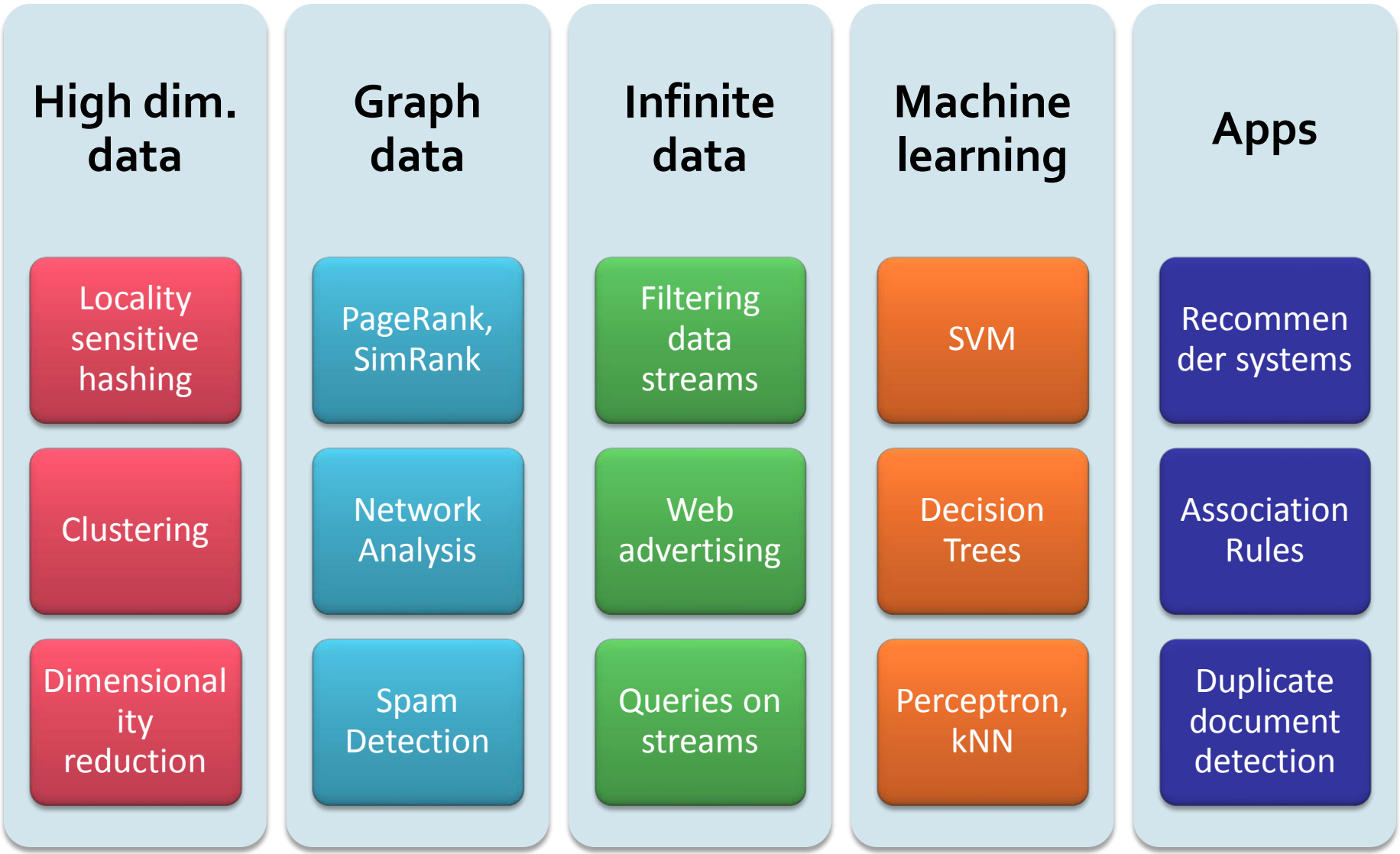
What will we learn?

- **We will learn to mine different types of data:**
  - Data is high dimensional
  - Data is a graph
  - Data is infinite/never-ending
  - Data is labeled
- **We will learn to use different models of computation:**
  - MapReduce
  - Streams and online algorithms
  - Single machine in-memory

What will we learn?

- **We will learn to solve real-world problems:**
  - Recommender systems
  - Market Basket Analysis
  - Spam detection
  - Duplicate document detection
- **We will learn various "tools":**
  - Linear algebra (SVD, Rec. Sys., Communities)
  - Optimization (stochastic gradient descent)
  - Dynamic programming (frequent itemsets)
  - Hashing (LSH, Bloom filters)

How the Class Fits Together



How do you want that data?

About the Course

CS246 Course Staff

- **TAs:**
  - **We have 9 great TAs!**
    - **Bob** West (Head TA), **Ashwin** Apte, **Mike** Chrzanowski, **Sammy** El Ghazzal, **Alex** Fandrianto, **Ashley** Jin, **Jason** Jong, **Hristo** Paskov, **Neeraj** Pradhan
- **Office hours:**
  - **Jure:** Wednesdays 9-10am, Gates 418
  - See course website for TA office hours
    - We start Office Hours next week
  - For SCPD students we will use **Google Hangout**
    - We will post Hangout link on Piazza 1min before the OH

Website and Readings

- **Course website: http://cs246.stanford.edu**
  - Lecture slides (at least 30min before the lecture)
  - Homeworks, solutions
  - Readings
- **Readings: Mining of Massive Datasets** by A. Rajaraman, J. Ullman, and J. Leskovec
  Free online: http://i.stanford.edu/~ullman/mmds.html
  - Note there are **2** editions:
    - Use the **2nd** edition for class readings
    - Gradiance quizzes often refer to chapters of the **1st** edition

Logistics: Communication

- **Piazza Q&A website:**
  - https://piazza.com/class#winter2014/cs246
    - Use Piazza for all questions and public communication
      - Search the forum before asking a question
      - Please tag your posts and please no one-liners
    - Jure will give **extra credit** for Piazza participation
- **For e-mailing course staff always use:**
  - cs246-win1314-staff@lists.stanford.edu
- **We will post course announcements to Piazza (make sure you check it regularly)**

Auditors are welcome to sit-in & audit the class

Work for the Course

- **(1+)4 longer homeworks: 40%**
  - Theoretical and programming questions
  - HW0 (Hadoop tutorial) has just been posted
  - Assignments take lots of time (+20h). **Start early!!**
- **How to submit?**
  - **Homework write-up:**
    - **Stanford students:** In class or in Gates submission box
    - **SCPD students:** Submit write-ups via SCPD
    - **Always attach the cover sheet** (+SCPD routing form, if SCPD)
  - **Everyone uploads code:**
    - Put all the code for 1 question into 1 file and submit at: http://snap.stanford.edu/submit/

Work for the Course

- **Short weekly Gradiance quizzes: 20%**
  - Quizzes are posted on **Fridays**
    - Due **exactly** 7 days later (Friday 23:59 PT) **No late days!**
    - First quiz has already been posted
  - To register on Gradiance please use **SUNetID** or **<legal first name>_<legal last name>** for username
    - We have to be able to match your Gradiance ID and SUNetId
- **Final exam: 40%**
  - **Monday, March 17** 12:15pm-3:15pm
  - Alternate final: Friday, March 14 7-10pm

Course Calendar

- **Homework schedule:**

Date	Out	In
01/01, Tue	HW0	
01/09, Thu	HW1	
01/14, Tue		HW0
01/23, Thu	HW2	HW1
02/06, Thu	HW3	HW2
02/20, Thu	HW4	HW3
03/06, Thu		HW4

  - **2 late "days" (late periods) for HWs for the quarter:**
    - 1 late period expires at the start of next class
    - **You can use max 1 late period per assignment**

Prerequisites

- **Algorithms** (CS161)
  - Dynamic programming, basic data structures
- **Probability** (CS109 or Stat116)
  - Moments, typical distributions, MLE, …
- **Programming** (CS107 or CS145)
  - Your choice, but Java will be very useful

- **We provide some background at recitation sessions, but the class will be fast paced**

Recitation Sessions

- **Recitation sessions:**
  - **Review of probability & stats:** 1/10, at 4:15pm
  - **Review of linear algebra:** 1/13, at 4:15pm

  - All sessions will be held in **Gates B03**
  - Sessions will be video recorded

New this year: CS246H: Hadoop Labs

- **CS246H** covers practical aspects of Hadoop and other distributed computing architectures
  - HDFS, Combiners, Partitioners, Hive, Pig, Hbase, …
  - 1 unit course, optional homeworks
- **CS246H runs (somewhat) parallel to CS246**
  - CS246 discusses theory and algorithms
  - CS246H tells you how to implement them
- **Instructor:** Daniel Templeton (Cloudera)
- First session of CS246H will give a Hadoop tutorial and cover HW0
  - Think of it as CS246 Hadoop recitation
- CS246H lectures are recorded (available via SCPD)

What's after the class

- **InfoSeminar (CS545):**
  - http://i.stanford.edu/infoseminar
  - Great industrial & academic speakers
  - Topics include data mining and large scale data processing
- **CS341:** Project in Data Mining (Spring 2014)
  - Research project on big data
  - Groups of 3 students
  - We provide interesting data, computing resources (Amazon EC2) and mentoring
- **My group has RA positions open:**
  - **See** http://snap.stanford.edu/apply/

Final Thoughts

- **CS246 is fast paced!**
  - Requires programming maturity
  - Strong math skills
    - SCPD students tend to be rusty on math/theory
- Course time commitment:
  - Homeworks take about 20h
  - Gradiance quizes take about 1-2h
- Form study groups

- **It's going to be fun and hard work. ☺**

3 To-do items

- **3 to-do items for you:**
  - **Register to Piazza**
  - **Complete HW0: Hadoop tutorial**
    - HW0 should take your about 2 hours to complete
      (Note this is a "toy" homework to get you started. Real homeworks will be much more challenging and longer)
  - **Register to Gradiance and complete the first quiz**
    - **Use your SUNet ID to register!** (so we can match grading records)
    - Complete the first quiz (it is already posted)

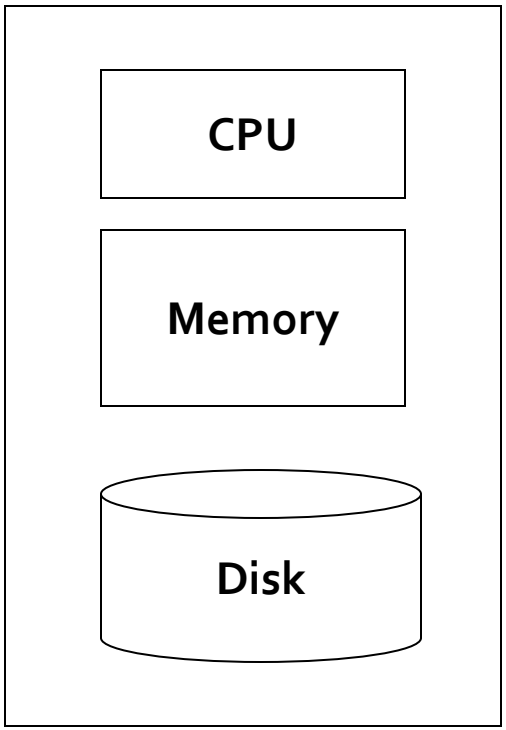
- **Additional details/instructions at http://cs246.stanford.edu**

Computational Model: MapReduce

MapReduce

- Much of the course will be devoted to **large scale computing** for **data mining**
- **Challenges:**
  - How to distribute computation?
  - Distributed/parallel programming is hard
- **MapReduce** addresses all of the above
  - Google's computational/data manipulation model
  - Elegant way to work with big data

Single Node Architecture



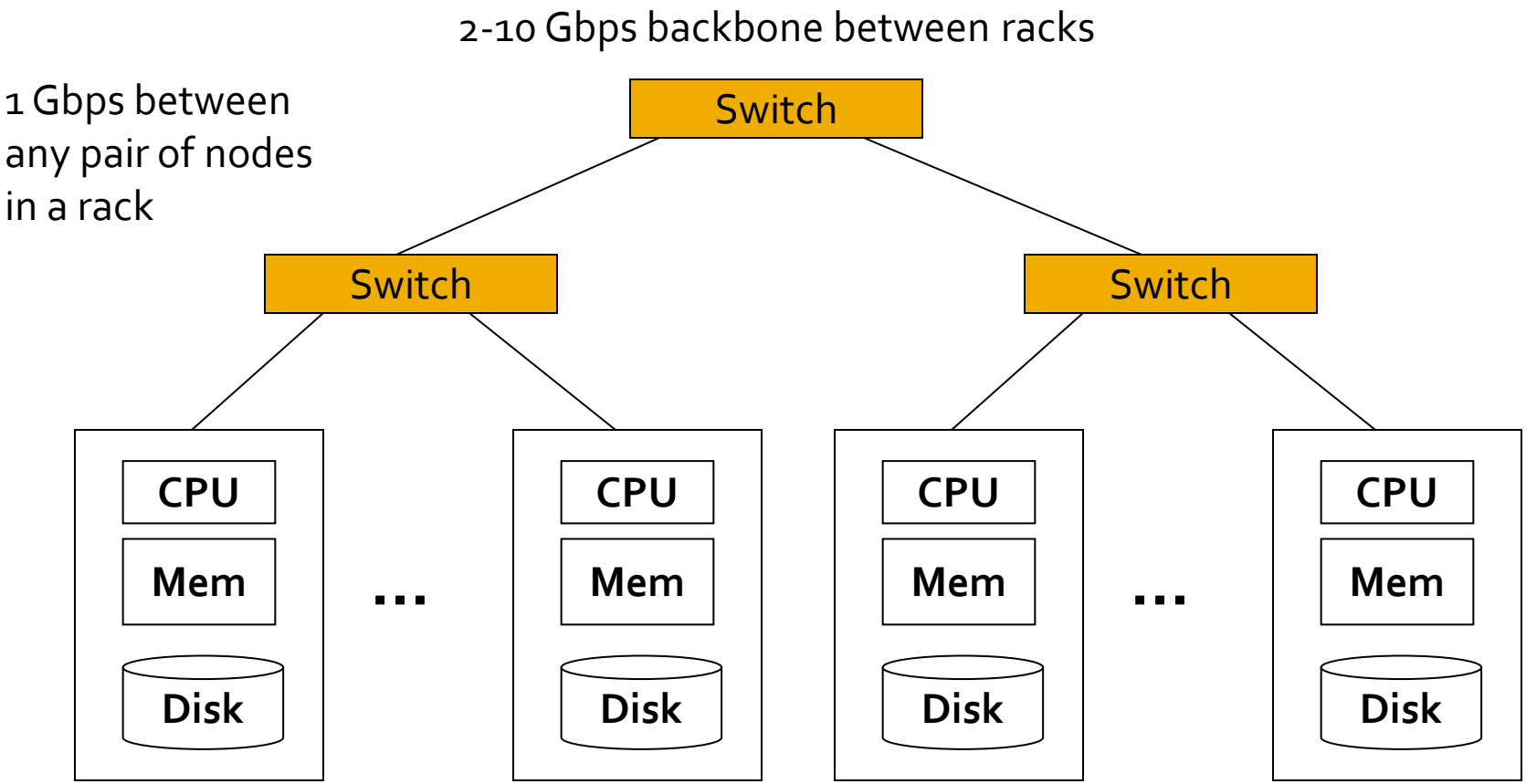
Machine Learning, Statistics

"Classical" Data Mining

Motivation: Google Example

- 20+ billion web pages x 20KB = 400+ TB
- 1 computer reads 30-35 MB/sec from disk
  - ~4 months to read the web
- ~1,000 hard drives to store the web
- Takes even more to **do** something useful with the data!
- **Recently standard architecture for such problems emerged:**
  - Cluster of commodity Linux nodes
  - Commodity network (ethernet) to connect them

Cluster Architecture



In 2011 it was guestimated that Google had 1M machines, http://bit.ly/Shh0RO

Large-scale Computing

- **Large-scale computing** for **data mining** problems on **commodity hardware**
- **Challenges:**
  - **How do you distribute computation?**
  - **How can we make it easy to write distributed programs?**
  - **Machines fail:**
    - One server may stay up 3 years (1,000 days)
    - If you have 1,000 servers, expect to loose 1/day
    - With 1M machines 1,000 machines fail every day!

Idea and Solution

- **Issue: Copying data over a network takes time**
- **Idea:**
  - Bring computation to data
  - Store files multiple times for reliability
- **MapReduce** addresses these problems
  - **Storage Infrastructure – File system**
    - Google: GFS. Hadoop: HDFS
  - **Programming model**
    - MapReduce

Storage Infrastructure

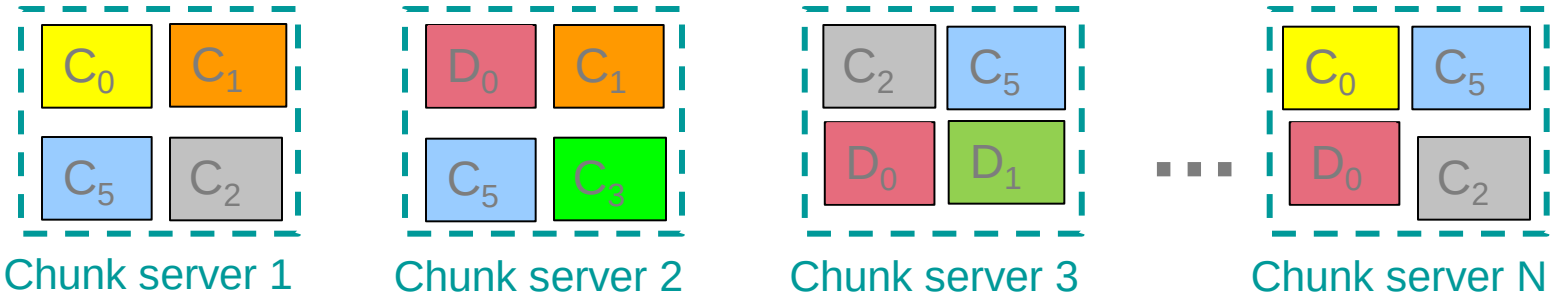
- **Problem:**
  - If nodes fail, how to store data persistently?
- **Answer:**
  - **Distributed File System:**
    - Provides global file namespace
- **Typical usage pattern**
  - Huge files (100s of GB to TB)
  - Data is rarely updated in place
  - Reads and appends are common

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 Node in Hadoop's HDFS
  - Stores metadata about where files are stored
  - Might be replicated
- **Client library for file access**
  - Talks to master to find chunk servers
  - Connects directly to chunk servers to access data

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

Programming Model: MapReduce

Warm-up task:

- We have a huge text document
- Count the number of times each distinct word appears in the file
- **Sample application:**
  - Analyze web server logs to find popular URLs

Task: Word Count

Case 1:

- File too large for memory, but all <word, count> pairs fit in memory

Case 2:

- Count occurrences of words:
  - **`words(doc.txt) | sort | uniq -c`**
    - where **`words`** takes a file and outputs the words in it, one word per a line
- **Case 2** captures the essence of **MapReduce**
  - Great thing is that it is naturally parallelizable

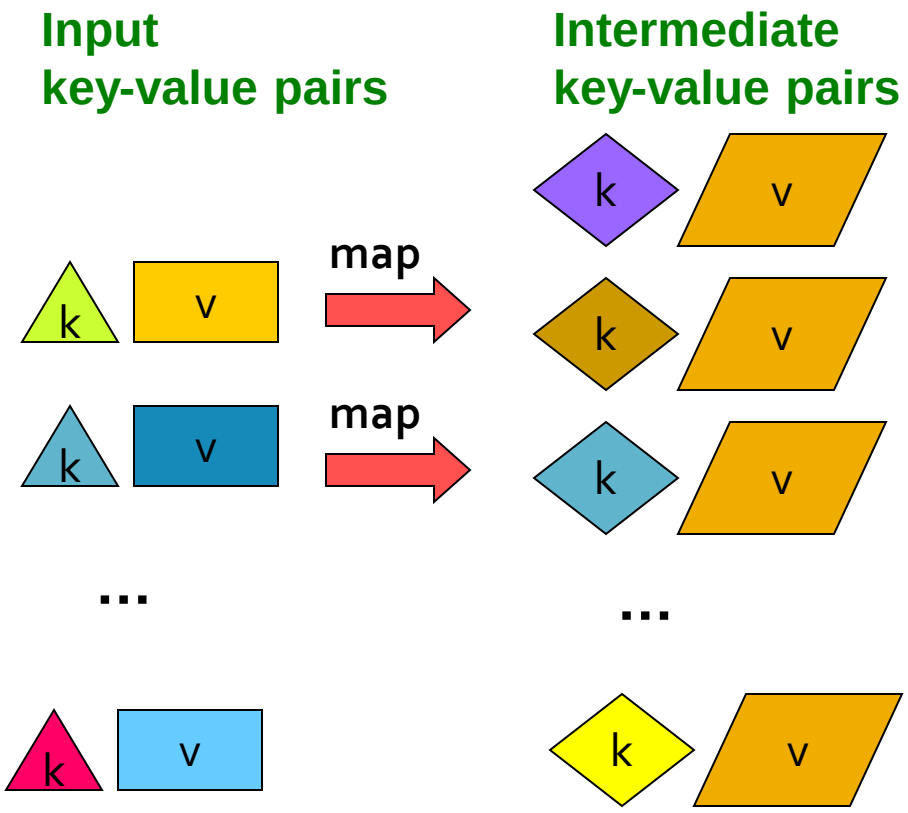
MapReduce: Overview

3 steps of MapReduce

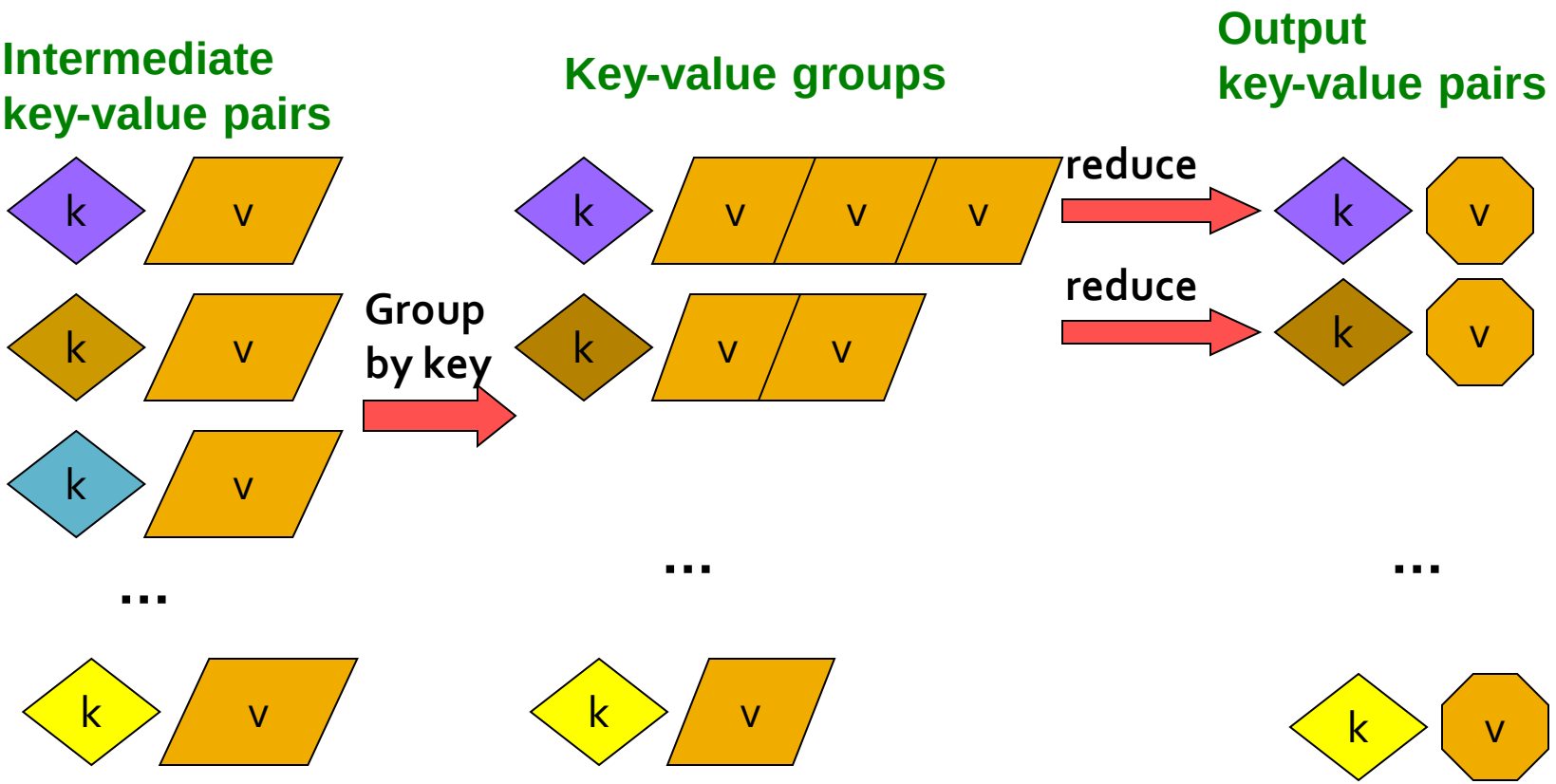
- Sequentially read a lot of data
- **Map:**
  - Extract something you care about
- **Group by key:** Sort and shuffle
- **Reduce:**
  - Aggregate, summarize, filter or transform
- Output the result

Outline stays the same, **Map** and **Reduce** change to fit the problem

MapReduce: The Map Step



MapReduce: The Reduce Step



More Specifically

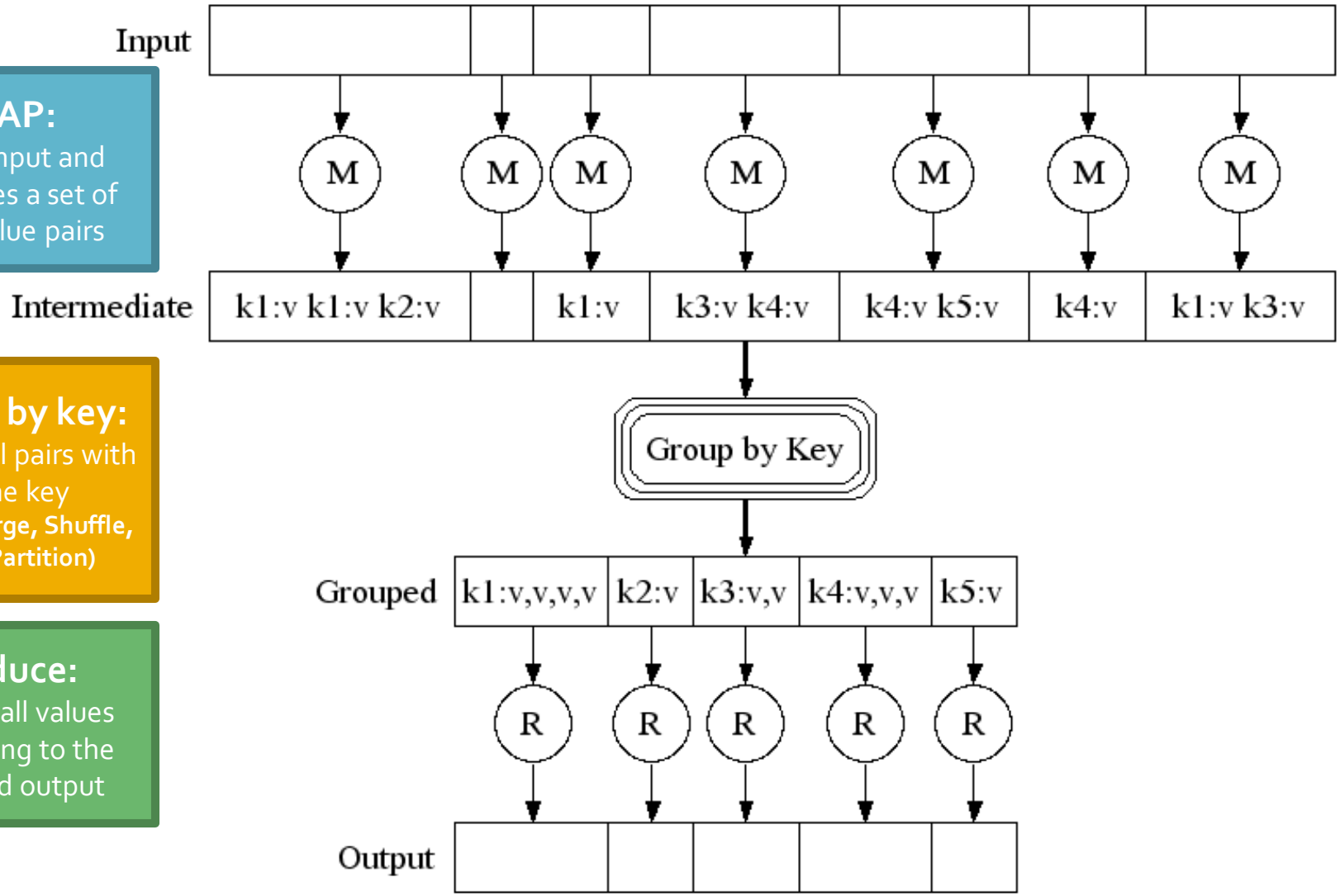
- **Input:** a set of key-value pairs
- **Programmer specifies two methods:**
  - **Map(k, v)** $\rightarrow$ <k', v'>*
    - Takes a key-value pair and outputs a set of key-value pairs
      - E.g., key is the filename, value is a single line in the file
    - There is one Map call for every *(k,v)* pair
  - **Reduce(k', <v'>*)** $\rightarrow$ <k', v''>*
    - **All values *v'* with same key *k'* are reduced together and processed in *v'* order**
    - There is one Reduce function call per unique key *k'*

Map-Reduce: A diagram

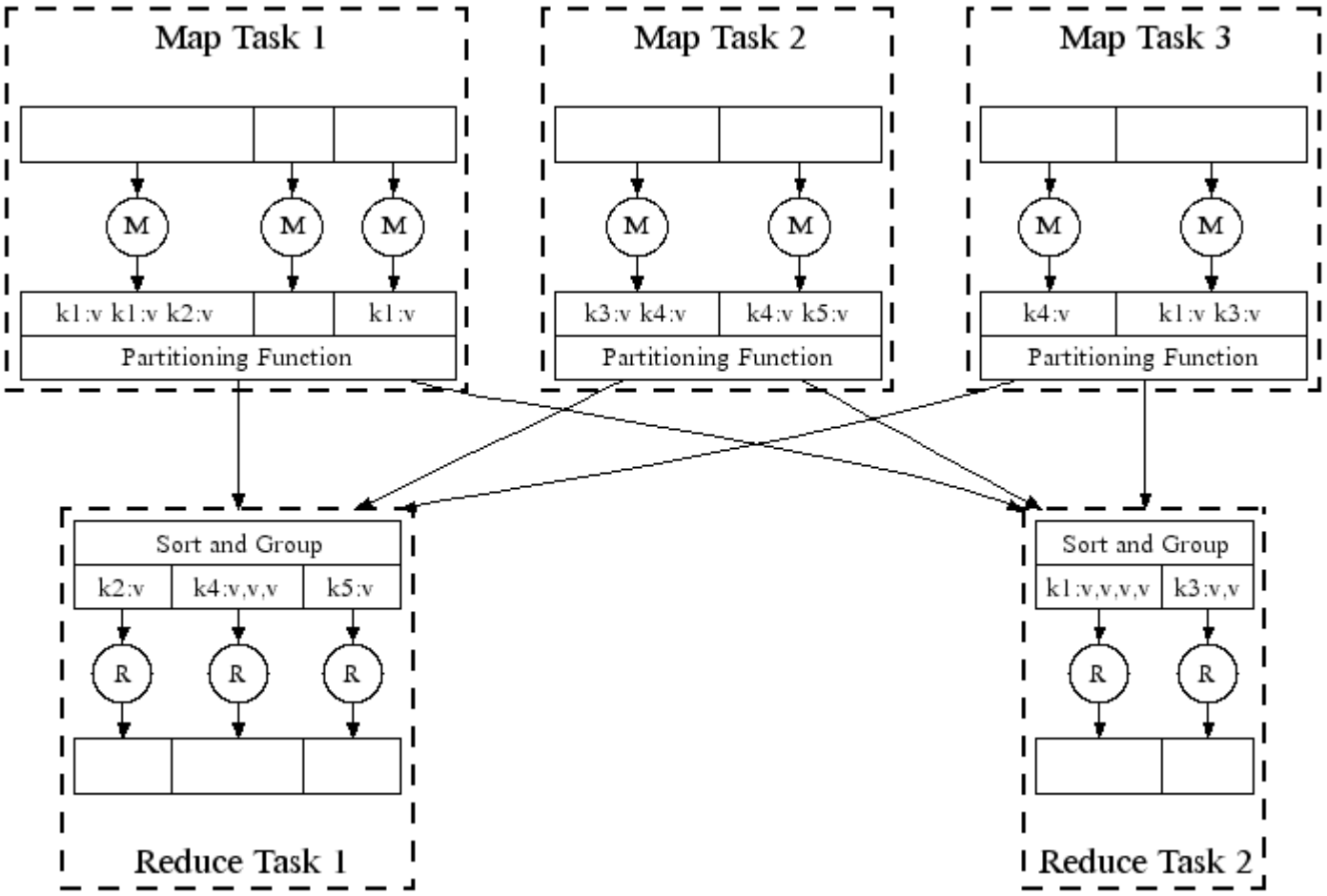
MAP:
Read input and produces a set of key-value pairs

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

Reduce:
Collect all values belonging to the key and output

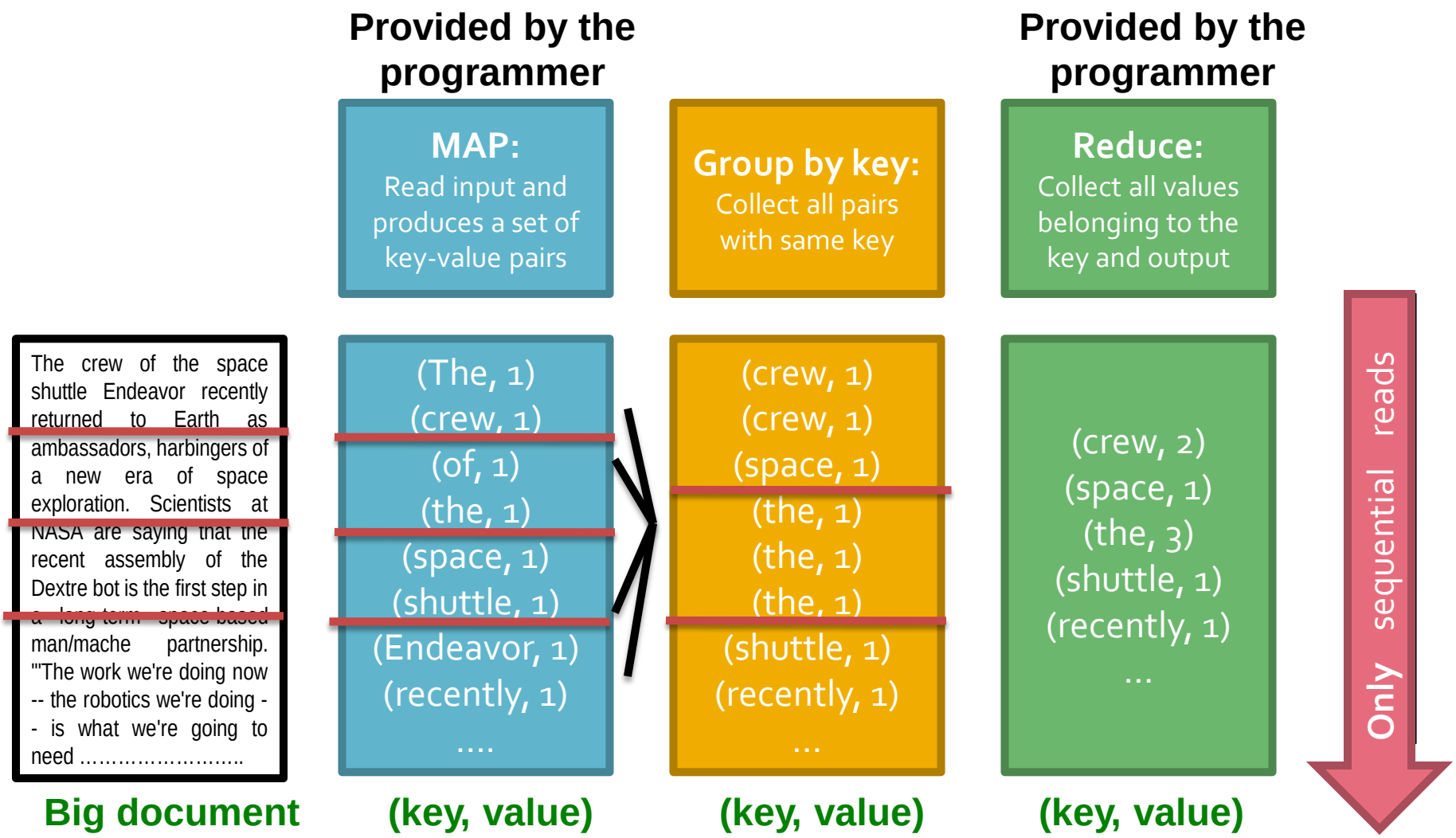


Map-Reduce: In Parallel



All phases are distributed with many tasks doing the work

MapReduce: Word Counting



Word Count Using MapReduce

```
map(key, value):
// key: document name; value: text of the 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(key, result)
```

MapReduce: Environment

MapReduce environment takes care of:

- **Partitioning** the input data
- **Scheduling** the program's execution across a set of machines
- Performing the **group by key** step
  - In practice this is is the bottleneck
- Handling machine **failures**
- Managing required inter-machine **communication**

Data Flow

- Input and final output are stored on a distributed file system (HDFS):
  - 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 MapReduce task

Coordination: Master

- **Master node takes care of coordination:**
  - **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 intermediate files, one for each reducer
  - Master pushes this info to reducers
- Master pings workers periodically to detect failures

Dealing with Failures

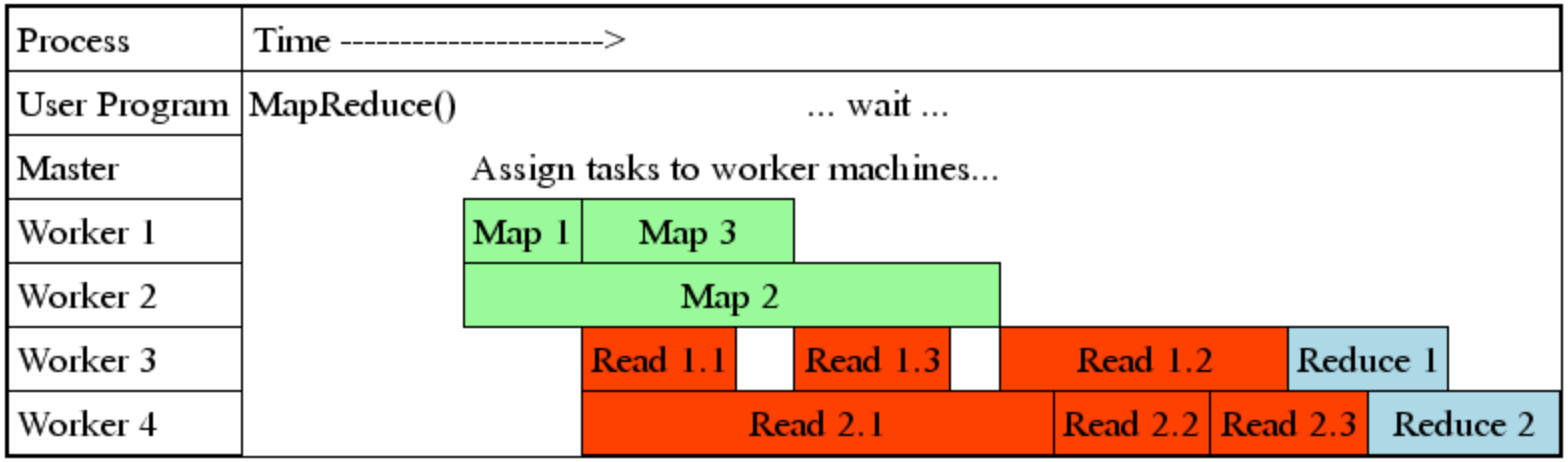
- **Map worker failure**
  - Map tasks completed or in-progress at worker are reset to idle
  - Reduce workers are notified when task is rescheduled on another worker
- **Reduce worker failure**
  - Only in-progress tasks are reset to idle
  - Reduce task is restarted
- **Master failure**
  - MapReduce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

How many Map and Reduce jobs?

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

Task Granularity & Pipelining

- **Fine granularity tasks:** map tasks >> machines
  - Minimizes time for fault recovery
  - Can do pipeline shuffling with map execution
  - Better dynamic load balancing

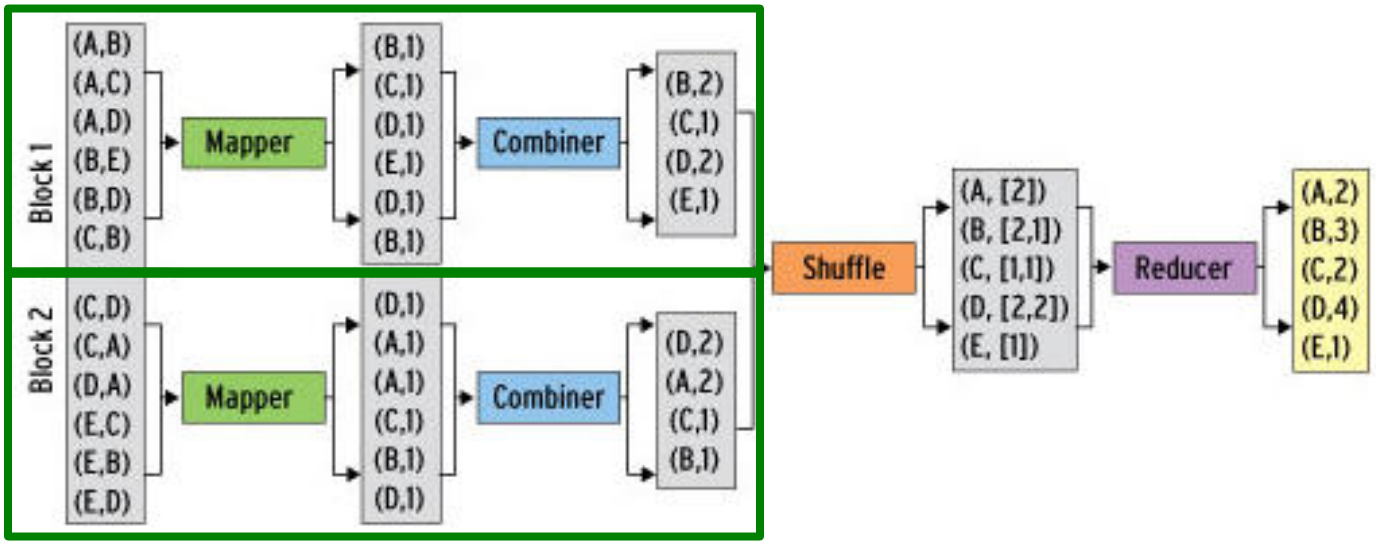


Refinements: Backup Tasks

- **Problem**
  - Slow workers significantly lengthen the job completion time:
    - Other jobs on the machine
    - Bad disks
    - Weird things
- **Solution**
  - Near end of phase, spawn backup copies of tasks
    - Whichever one finishes first "wins"
- **Effect**
  - Dramatically shortens job completion time

Refinement: Combiners

- **Back to our 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!
  - Works if reduce function is commutative and associative

Refinement: Partition Function

- **Want to 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***
- **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

Problems Suited for MapReduce

Example: Host size

- **Suppose we have a large web corpus**
- Look at the metadata file
  - Lines of the form: (URL, size, date, …)
- **For each host, find the total number of bytes**
  - That is, the sum of the page sizes for all URLs from that particular host
- **Other examples:**
  - Link analysis and graph processing
  - Machine Learning algorithms

Example: Language Model

- **Statistical machine translation:**
  - Need to count number of times every 5-word sequence occurs in a large corpus of documents
- **Very easy with MapReduce:**
  - **Map:**
    - Extract (5-word sequence, count) from document
  - **Reduce:**
    - Combine the counts

Example: Join By Map-Reduce

- **Compute the natural join *R(A,B)* ⋈ *S(B,C)***
- *R* and *S* are each stored in files
- Tuples are pairs *(a,b)* or *(b,c)*

A	B
a_1	b_1
a_2	b_1
a_3	b_2
a_4	b_3

R

⋈

B	C
b_2	c_1
b_2	c_2
b_3	c_3

S

=

A	C
a_3	c_1
a_3	c_2
a_4	c_3

Map-Reduce Join

- **Use a hash function *h* from B-values to *1...k***
- **A Map process turns:**
  - Each input tuple *R(a,b)* into key-value pair *(b,(a,R))*
  - Each input tuple *S(b,c)* into *(b,(c,S))*
- **Map processes** send each key-value pair with key *b* to Reduce process *h(b)*
  - Hadoop does this automatically; just tell it what *k* is.
- Each **Reduce process** matches all the pairs *(b,(a,R))* with all *(b,(c,S))* and outputs *(a,b,c)*.

Problems NOT suitable for MapReduce

- **MapReduce is great for:**
  - Problems that require sequential data access
  - Large batch jobs (**not** interactive, real-time)
- **MapReduce is inefficient for problems where random (or irregular) access to data required:**
  - **Graphs**
  - Interdependent data
    - Machine learning
    - Comparisons of many pairs of items

Cost Measures for Algorithms

- **In MapReduce we quantify the cost of an algorithm using**

1. *Communication cost* = total I/O of all processes
2. *Elapsed communication cost* = max of I/O along any path
3. (*Elapsed*) *computation cost* analogous, but count only running time of processes

Note that here the big-O notation is not the most useful (adding more machines is always an option)

Example: Cost Measures

- **For a map-reduce algorithm:**
  - **Communication cost =** input file size + 2 × (sum of the sizes of all files passed from Map processes to Reduce processes) + the sum of the output sizes of the Reduce processes.
  - **Elapsed communication cost** is the sum of the largest input + output for any map process, plus the same for any reduce process

What Cost Measures Mean

- Either the I/O (communication) or processing (computation) cost dominates
  - Ignore one or the other
- Total cost tells what you pay in rent from your friendly neighborhood cloud
- Elapsed cost is wall-clock time using parallelism

Cost of Map-Reduce Join

- **Total communication cost**
  = $O(|R|+|S|+|R \bowtie S|)$
- **Elapsed communication cost** = $O(s)$
  - We're going to pick ***k*** and the number of Map processes so that the I/O limit ***s*** is respected
  - We put a limit ***s*** on the amount of input or output that any one process can have. ***s* could be:**
    - What fits in main memory
    - What fits on local disk
- With proper indexes, computation cost is linear in the input + output size
  - So computation cost is like comm. cost

Pointers and Further Reading

Implementations

- **Google's MapReduce**
  - 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

Cloud Computing

- Ability to rent computing by the hour
  - Additional services e.g., persistent storage
- Amazon's "Elastic Compute Cloud" (EC2)
- Aster Data and Hadoop can both be run on EC2
- **For CS341 (offered next quarter) Amazon will provide free access for the class**

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

Resources

- Hadoop Wiki
  - Introduction
    - http://wiki.apache.org/lucene-hadoop/
  - Getting Started
    - http://wiki.apache.org/lucene-hadoop/GettingStartedWithHadoop
  - Map/Reduce Overview
    - http://wiki.apache.org/lucene-hadoop/HadoopMapReduce
    - http://wiki.apache.org/lucene-hadoop/HadoopMapRedClasses
  - Eclipse Environment
    - http://wiki.apache.org/lucene-hadoop/EclipseEnvironment
- Javadoc
  - http://lucene.apache.org/hadoop/docs/api/

Resources

- Releases from Apache download mirrors
  - http://www.apache.org/dyn/closer.cgi/lucene/hadoop/
- Nightly builds of source
  - http://people.apache.org/dist/lucene/hadoop/nightly/
- Source code from subversion
  - http://lucene.apache.org/hadoop/version_control.html

Further Reading

- Programming model inspired by functional language primitives
- Partitioning/shuffling similar to many large-scale sorting systems
  - NOW-Sort ['97]
- Re-execution for fault tolerance
  - BAD-FS ['04] and TACC ['97]
- Locality optimization has parallels with Active Disks/Diamond work
  - Active Disks ['01], Diamond ['04]
- Backup tasks similar to Eager Scheduling in Charlotte system
  - Charlotte ['96]
- Dynamic load balancing solves similar problem as River's distributed queues
  - River ['99]