CS246: Mining Massive Data Sets
Intro, MapReduce & Spark

CS246: Mining Massive Datasets
Jure Leskovec, Stanford University
http://cs246.stanford.edu

Data contains value and knowledge

Data Mining

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

Data Mining ≈ Big Data ≈
Predictive Analytics ≈
Data Science ≈ Machine Learning

What This Course Is About

- ***Data mining*** **= extraction of actionable information from (usually) very large datasets, is the subject of extreme hype, fear, and interest**

- It's not all about machine learning
- But some of it is

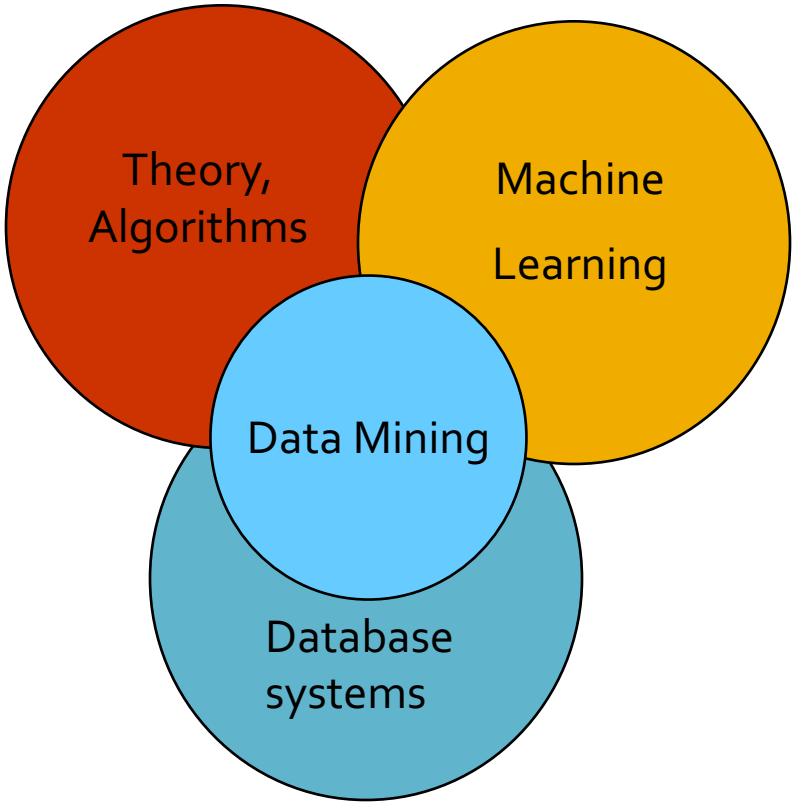
- Emphasis in CS246 on algorithms that **scale**
  - Parallelization often essential

Data Mining Methods

- **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

This Class: CS246

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



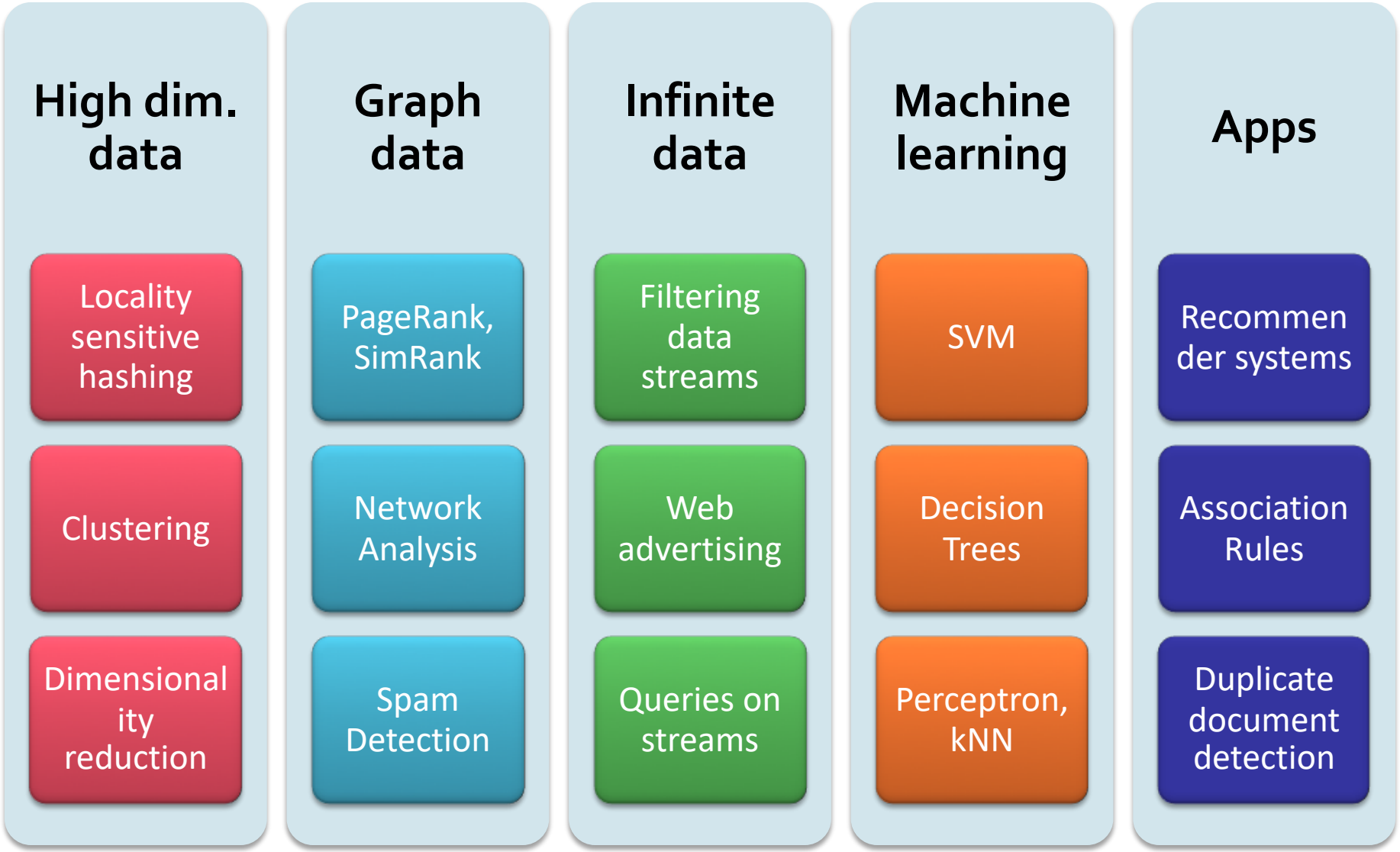
What will we learn?

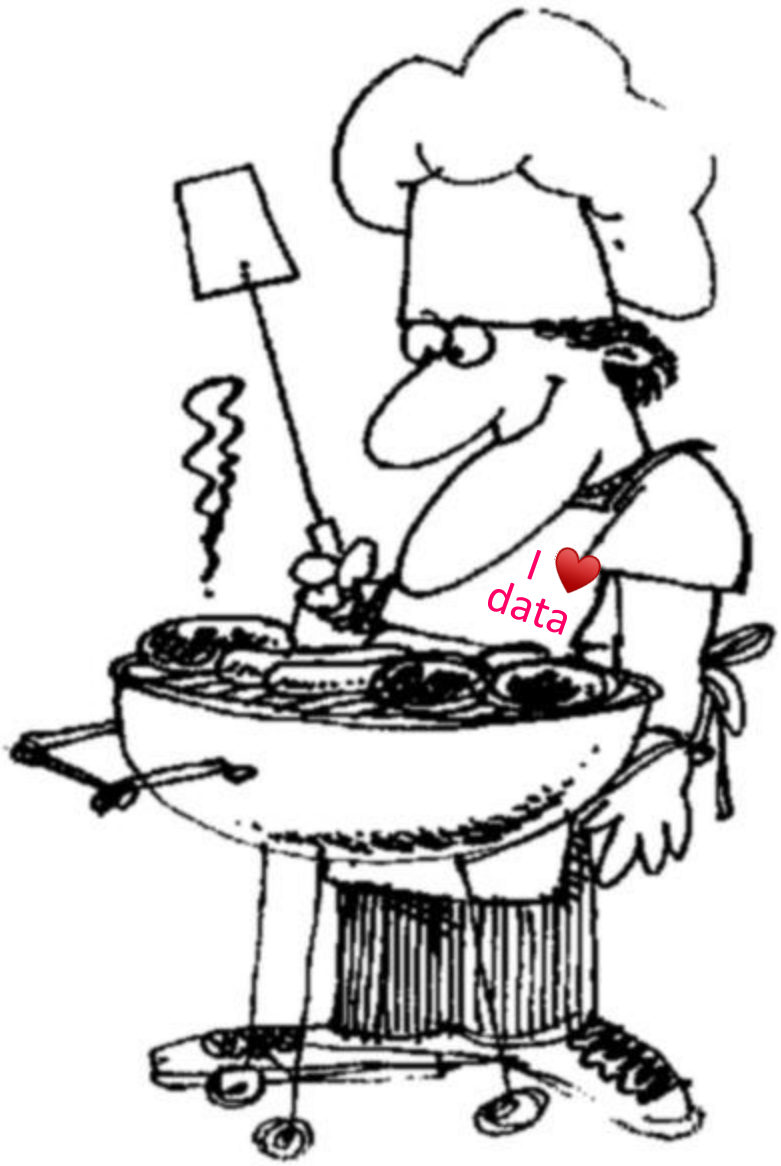
- **We will learn to mine different types of data:**
  - Data is high dimensional
  - Data is a graph
  - Data is infinite/never-ending
  - Data is labeled
- **We will learn to use different models of computation:**
  - MapReduce
  - Streams and online algorithms
  - Single machine in-memory

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?

Course Logistics

Course Staff


Stefanie Anna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Baige Liu


Lantao Mei


Eric Redondo


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Ansh Shukla


Hongtao Sun


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Wensi Yin

CS246 Course Staff

- **Office hours:**
  - See course website http://cs246.stanford.edu for TA office hours
    - **We start Office Hours next week**
  - **Jure:** Tuesdays 9-10am, Gates 418
  - **Michele:** Thursdays 5-7pm, Gates 452
  - For SCPD students we will use **Google Hangout**
    - **Link posted on Piazza**

Resources

- **Course website: http://cs246.stanford.edu**
  - Lecture slides (at least 30min before the lecture)
  - Homeworks, solutions, readings posted on Piazza
- **Class textbook: Mining of Massive Datasets** by A. Rajaraman, J. Ullman, and J. Leskovec
  - **Sold by Cambridge Uni. Press but available for free at http://mmds.org**
- **MOOC:** www.youtube.com /channel/UC_Oao2FYkLAUlUVkBfze4jg/videos

Special Tutorials

- **Spark tutorial and help session:**
  - Thursday, January 10, 4:30-5:50 PM, Location TBD
- **Review of basic probability and proof techniques**
  - Tuesday, January 15, 4:30-5:50 PM, Location TBD
- **Review of linear algebra:**
  - Thursday, January 17, 4:30-5:50 PM, Location TBD

Logistics: Communication

- **Piazza Q&A website:**
  - https://piazza.com/class/winter2019/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
- **For e-mailing course staff always use:**
  - cs246-win1819-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: Homeworks

- **4 longer homeworks: 40%**
  - Four major assignments, involving programming, proofs, algorithm development.
  - "Warmup" assignment, called "HW0," to introduce everyone to Spark has just been posted
  - Assignments take lots of time (+20h). **Start early!!**
- **How to submit?**
  - **Homework write-up:**
    - Submit via Gradescope
    - Course code: MNPBKE
  - **Everyone uploads code:**
    - Put all the code for 1 question into 1 file and submit at: http://snap.stanford.edu/submit/

Homework Calendar

- **Homework schedule:**

Date (23:59 PT)	Out	In
Today	HW0	
01/10, Thu	HW1	
01/24, Thu	HW2	HW0, HW1
02/07, Thu	HW3	HW2
02/21, Thu	HW4	HW3
03/07, Thu		HW4

  - **Two late periods for HWs for the quarter:**
    - **Late period expires on the following Monday 23:59 PT**
    - **Can use max 1 late period per HW**

Work for the Course: Gradiance

- **Short weekly Gradiance quizzes: 20%**
  - Quizzes are posted every **Tuesday**
  - Due 9 days later on **Thursday 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
    - Sign up at www.gradiance.com/services and use code **3DBCAD12**
  - As many submissions as you like, your score is based on the **most recent** submission
  - After the due date, you can see the solutions to all problems by looking at one of your submissions, so you must try at least once

Work for the Course: Gradiance

- You should work each of the implied problems before answering the multiple-choice questions.
- That way, if you have to repeat the work to get 100%, you will have available what you need for the questions you have solved correctly, and the process can go quickly.
- Note: There is a 10-minute delay between submissions, to protect against people who randomly fire off guesses.

Work for the Course: Final Exam

- **Final exam: 40%**
  - **Tuesday, March 19** 3:30pm-6:30pm
  - There is no alternative final, but if you truly have a conflict, we can arrange for you to take the exam immediately after the regular final

- **Extra credit:** Up to 1% of your grade
  - For participating in Piazza discussions
    - Especially valuable are answers to questions posed by other students
  - Reporting bugs in course materials

Prerequisites

- Programming: Python or Java
- Basic Algorithms: CS161 is surely sufficient
- Probability: e.g., CS109 or Stats116
  - There will be a review session and a review doc is linked from the class home page
- Linear algebra:
  - Another review doc + review session is available
- Multivariable calculus
- Database systems (SQL, relational algebra):
  - CS145 is sufficient but not necessary

What If I Don't Know All This Stuff?

- **Each of the topics listed is important for a small part of the course:**
  - If you are missing an item of background, you could consider just-in-time learning of the needed material
- **The exception is programming:**
  - To do well in this course, you really need to be comfortable with writing code in Python or Java

Honor Code

- **We'll follow the standard CS Dept. approach:** You can get help, but you *MUST* acknowledge the help on the work you hand in
- Failure to acknowledge your sources is a *violation of the Honor Code*
- We use MOSS to check the originality of your code

Honor Code – (2)

- **You can talk to others about the algorithm(s) to be used to solve a homework problem;**
  - As long as you then mention their name(s) on the work you submit
- **You should not use code of others or be looking at code of others when you write your own:**
  - You can talk to people but have to write your own solution/code
  - If you fail to mention your sources, MOSS will catch you, and you will be charged with an HC violation

CS246H: SparkLabs

- **CS246H** covers practical aspects of Spark 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)
  - CS246H lectures are recorded (available via SCPD)

What's after the class

- **CS341:** Project in Data Mining (Spring 2019)
  - 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 +20h
  - Gradiance quizzes take about 1-2h
- Form study groups

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

4 To-do items

- **4 to-do items for you:**
  - **Register to Piazza**
  - **Register to Gradescope**
  - **Register to Gradiance and complete the first quiz**
    - **Use your SUNet ID to register!** (so we can match grading records)
    - Complete the first quiz (we will announce when it is posted)
  - **Complete HW0**
    - HW0 should take you about 1-2 hours to complete
      (Note this is a "toy" homework to get you started. Real homeworks will be much more challenging and longer)

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

Distributed Computing for Data Mining

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 lose 1/day
    - With 1M machines 1,000 machines fail every day!

An Idea and a Solution

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

Storage Infrastructure

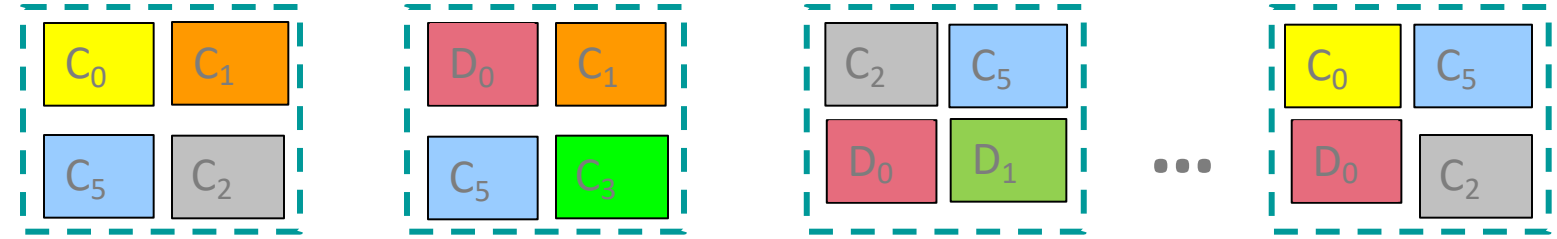
- **Problem:**
  - If nodes fail, how to store data persistently?
- **Answer:**
  - **Distributed File System**
    - Provides global file namespace
- **Typical usage pattern:**
  - Huge files (100s of GB to TB)
  - Data is rarely updated in place
  - Reads and appends are common

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 is a style of programming designed for:**
  1. Easy parallel programming
  2. Invisible management of hardware and software failures
  3. Easy management of very-large-scale data

- It has several implementations, including Hadoop, Spark (used in this class), Flink, and the original Google implementation just called "MapReduce"

MapReduce: Overview

3 steps of MapReduce

- **Map:**
  - Apply a user-written *Map function* to each input element
    - *Mapper* applies the Map function to a single element
      - Many mappers grouped in a *Map task* (the unit of parallelism)
  - The output of the Map function is a set of 0, 1, or more *key-value pairs*.
- **Group by key:** Sort and shuffle
  - System sorts all the key-value pairs by key, and outputs key-(list of values) pairs
- **Reduce:**
  - User-written *Reduce function* is applied to each key-(list of values)

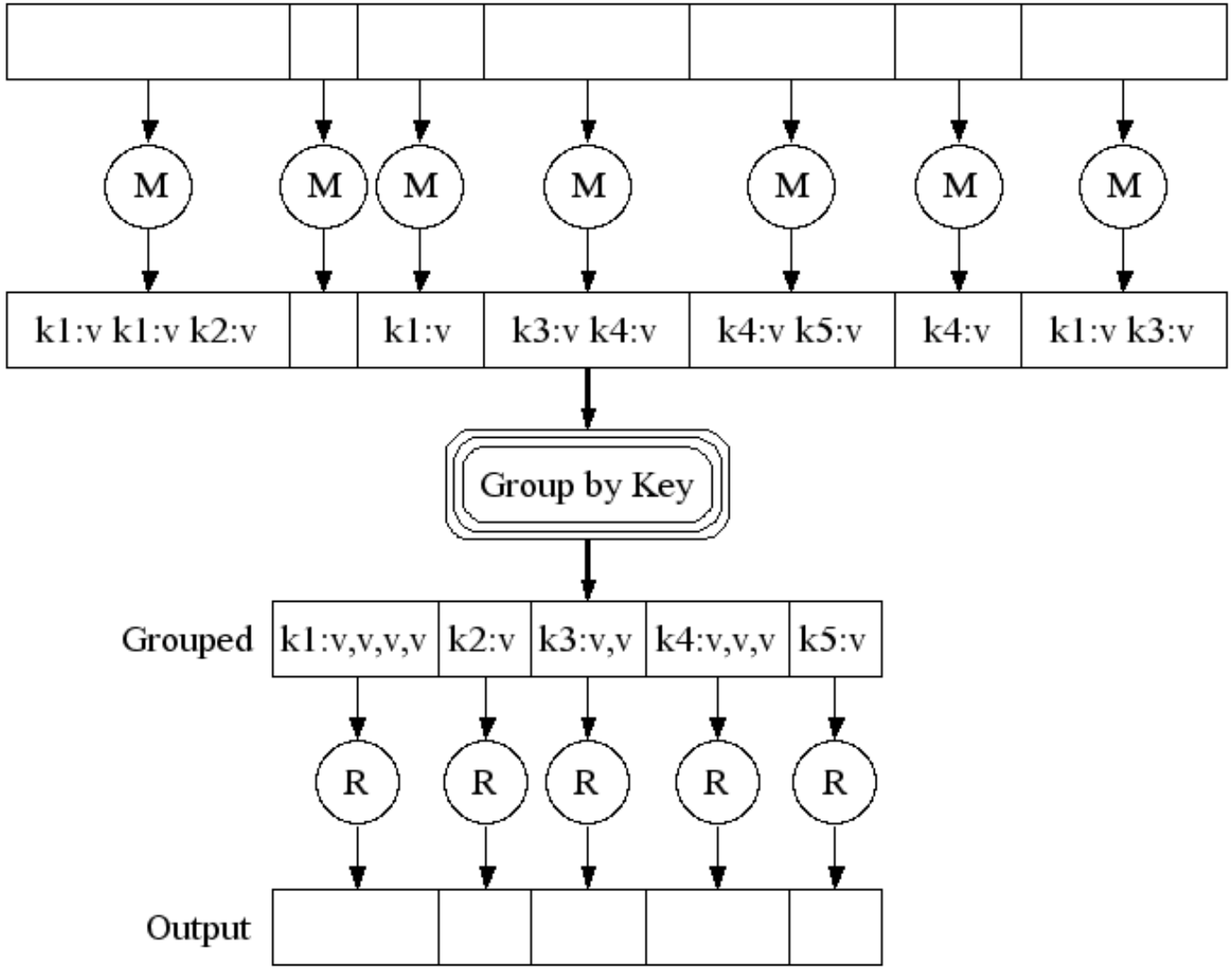
Outline stays the same, **Map** and **Reduce** change to fit the problem

Map-Reduce: A diagram

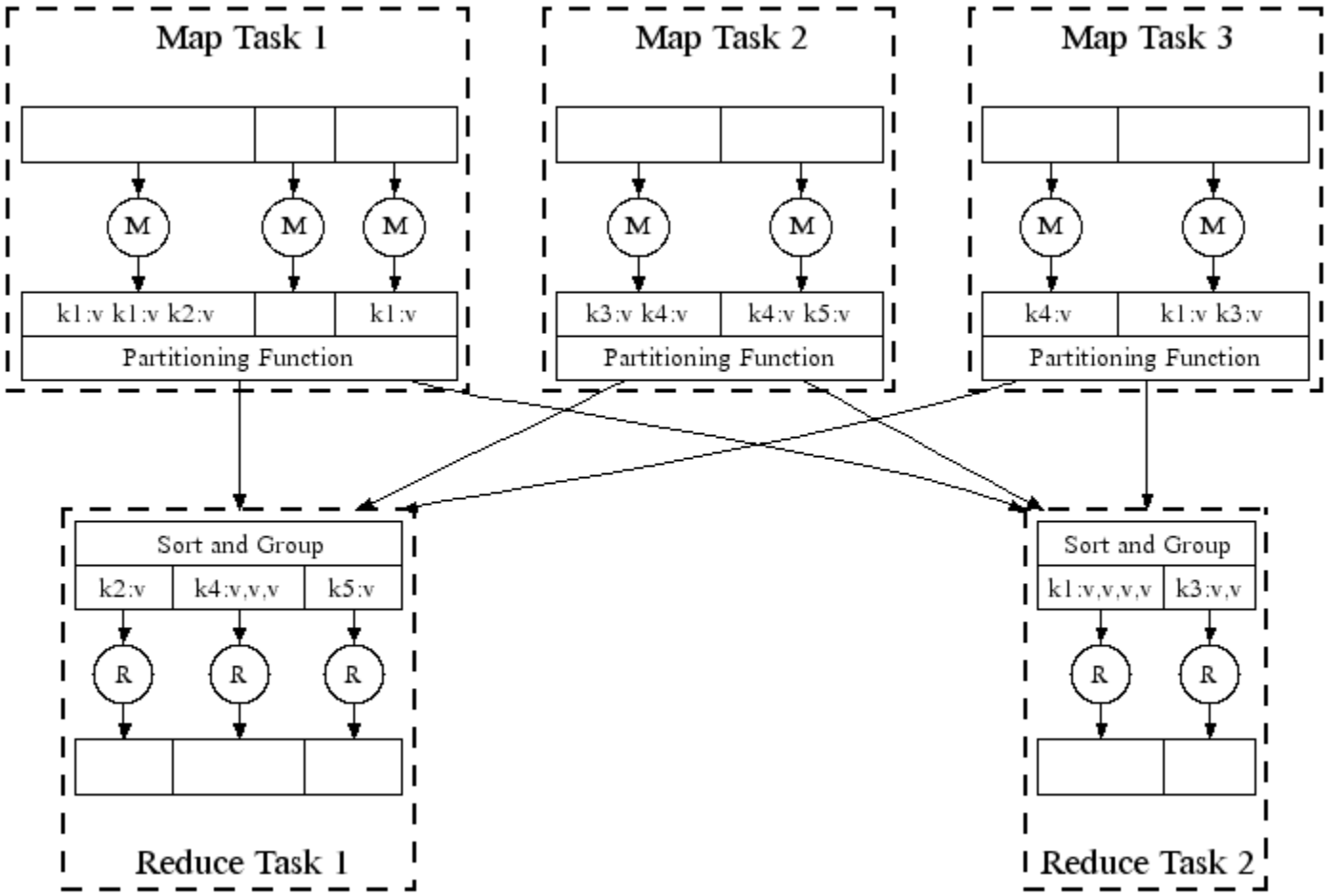
MAP:
Read input and produces a set of key-value pairs

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

Reduce:
Collect all values belonging to the key and output

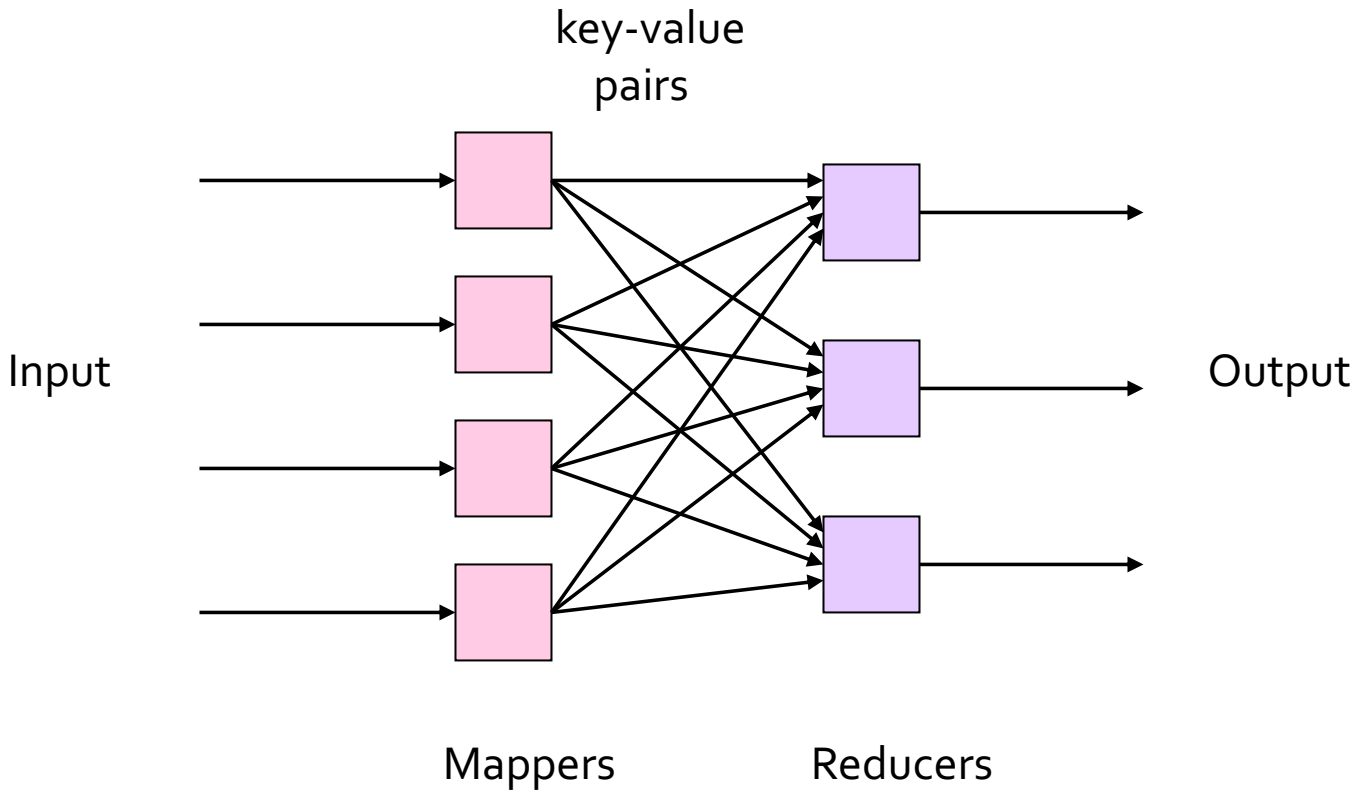


Map-Reduce: In Parallel



All phases are distributed with many tasks doing the work

MapReduce Pattern



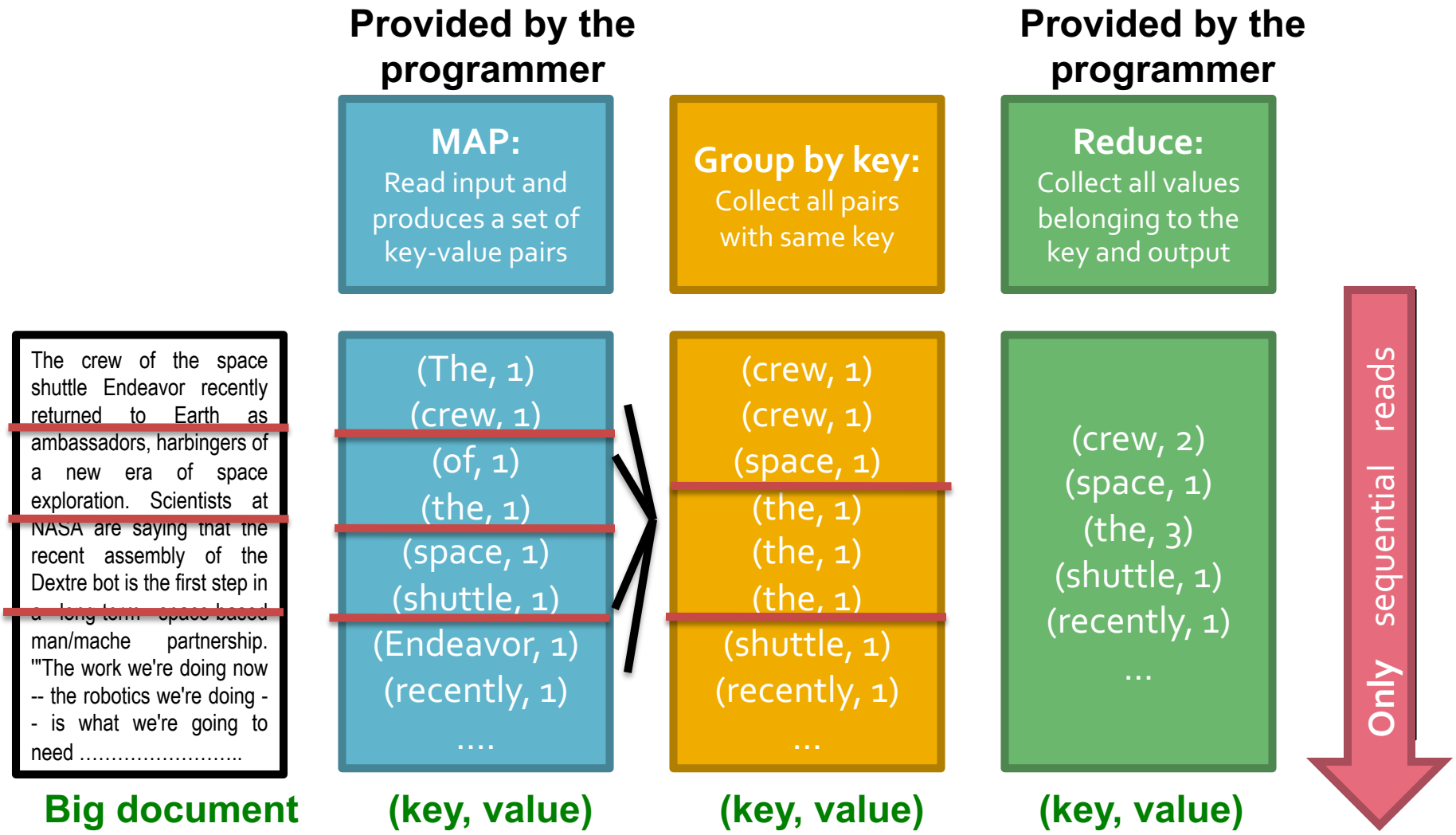
Example: Word Counting

Example MapReduce task:

- We have a huge text document
- Count the number of times each distinct word appears in the file

- **Many applications of this:**
  - Analyze web server logs to find popular URLs
  - Statistical machine translation:
    - Need to count number of times every 5-word sequence occurs in a large corpus of documents

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**

Dealing with Failures

- **Map worker failure**
  - Map tasks completed or in-progress at worker are reset to idle and rescheduled
  - Reduce workers are notified when map task is rescheduled on another worker
- **Reduce worker failure**
  - Only in-progress tasks are reset to idle and the reduce task is restarted

Spark

Problems with MapReduce

- **Two major limitations of MapReduce:**
  - Difficulty of programming directly in MR
    - Many problems aren't easily described as map-reduce
  - Performance bottlenecks, or batch not fitting the use cases
    - Persistence to disk typically slower than in-memory work
- **In short, MR doesn't compose well for large applications**
  - Many times one needs to chain multiple map-reduce steps

Data-Flow Systems

- **MapReduce uses two "ranks" of tasks:**
  One for Map the second for Reduce
  - Data flows from the first rank to the second

- **Data-Flow Systems generalize this in two ways:**
  1. Allow any number of tasks/ranks
  2. Allow functions other than Map and Reduce
  - As long as data flow is in one direction only, we can have the blocking property and allow recovery of tasks rather than whole jobs

Spark: Most Popular Data-Flow System

- **Expressive computing system, not limited to the map-reduce model**
- **Additions to MapReduce model:**
  - Fast data sharing
    - Avoids saving intermediate results to disk
    - Caches data for repetitive queries (e.g. for machine learning)
  - General execution graphs (DAGs)
  - Richer functions than just map and reduce
- Compatible with Hadoop

Spark: Overview

- Open source software (Apache Foundation)
- Supports **Java, Scala and Python**

- **Key construct/idea:** Resilient Distributed Dataset (RDD)

- **Higher-level APIs:** DataFrames & DataSets
  - Introduced in more recent versions of Spark
  - Different APIs for aggregate data, which allowed to introduce SQL support

Spark: RDD

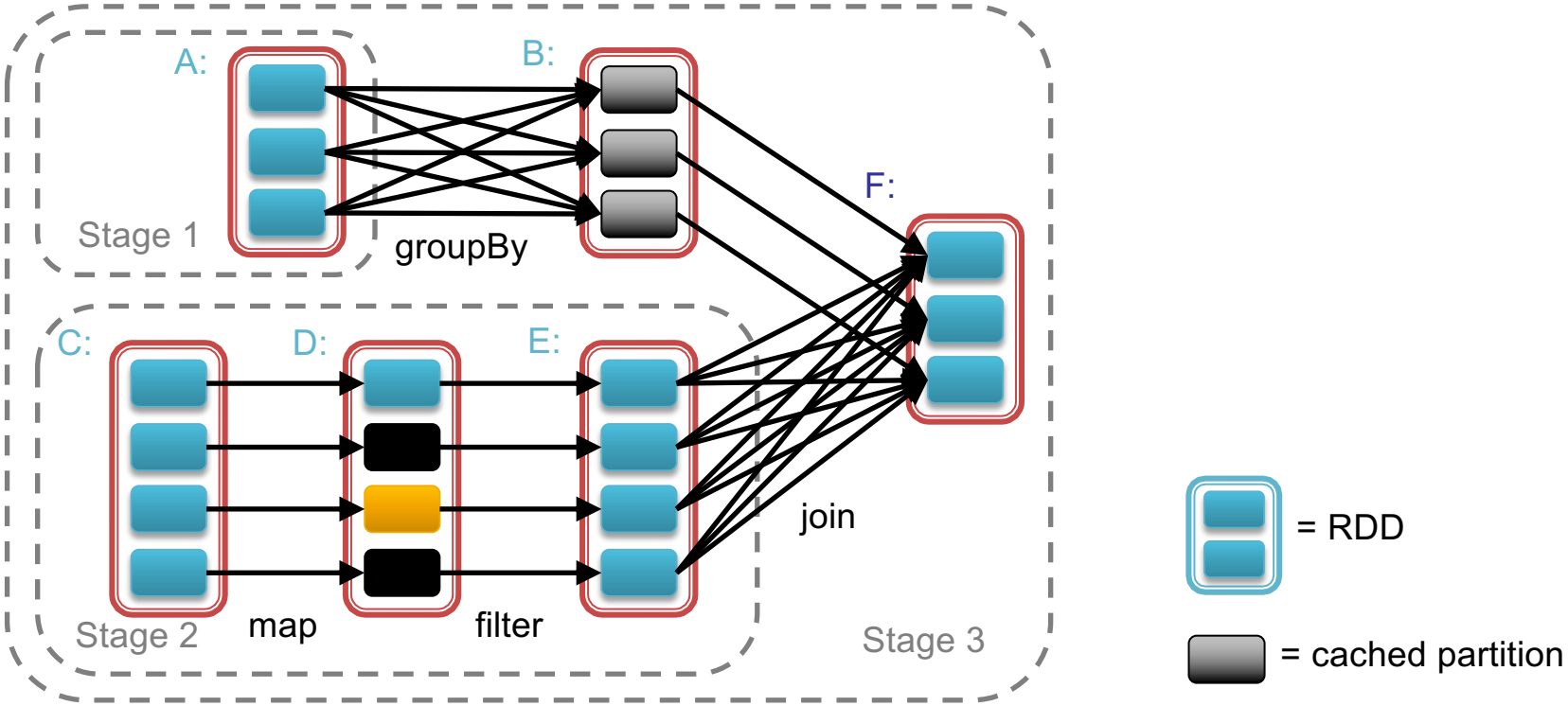
Key concept *Resilient Distributed Dataset* (RDD)

- Partitioned collection of records
  - Generalizes (key-value) pairs
- Spread across the cluster, Read-only
- Caching dataset in memory
  - Different storage levels available
  - Fallback to disk possible
- RDDs can be created from Hadoop, or by transforming other RDDs (you can stack RDDs)
- RDDs are best suited for applications that apply the same operation to all elements of a dataset

Spark RDD Operations

- **Transformations** build RDDs through deterministic operations on other RDDs:
  - Transformations include *map*, *filter*, *join, union, intersection, distinct*
  - **Lazy evaluation:** Nothing computed until an action requires it
- **Actions** to return value or export data
  - Actions include *count*, *collect*, *reduce, save*
  - Actions can be applied to RDDs; actions force calculations and return values

Task Scheduler: General DAGs



- Supports general task graphs
- Pipelines functions where possible
- Cache-aware data reuse & locality
- Partitioning-aware to avoid shuffles

DataFrame & Dataset

- DataFrame:
  - Unlike an RDD, data organized into named columns, e.g. a **table in a relational database**.
  - Imposes a structure onto a distributed collection of data, allowing higher-level abstraction
- Dataset:
  - Extension of DataFrame API which provides **type-safe, object-oriented programming interface** (compile-time error detection)

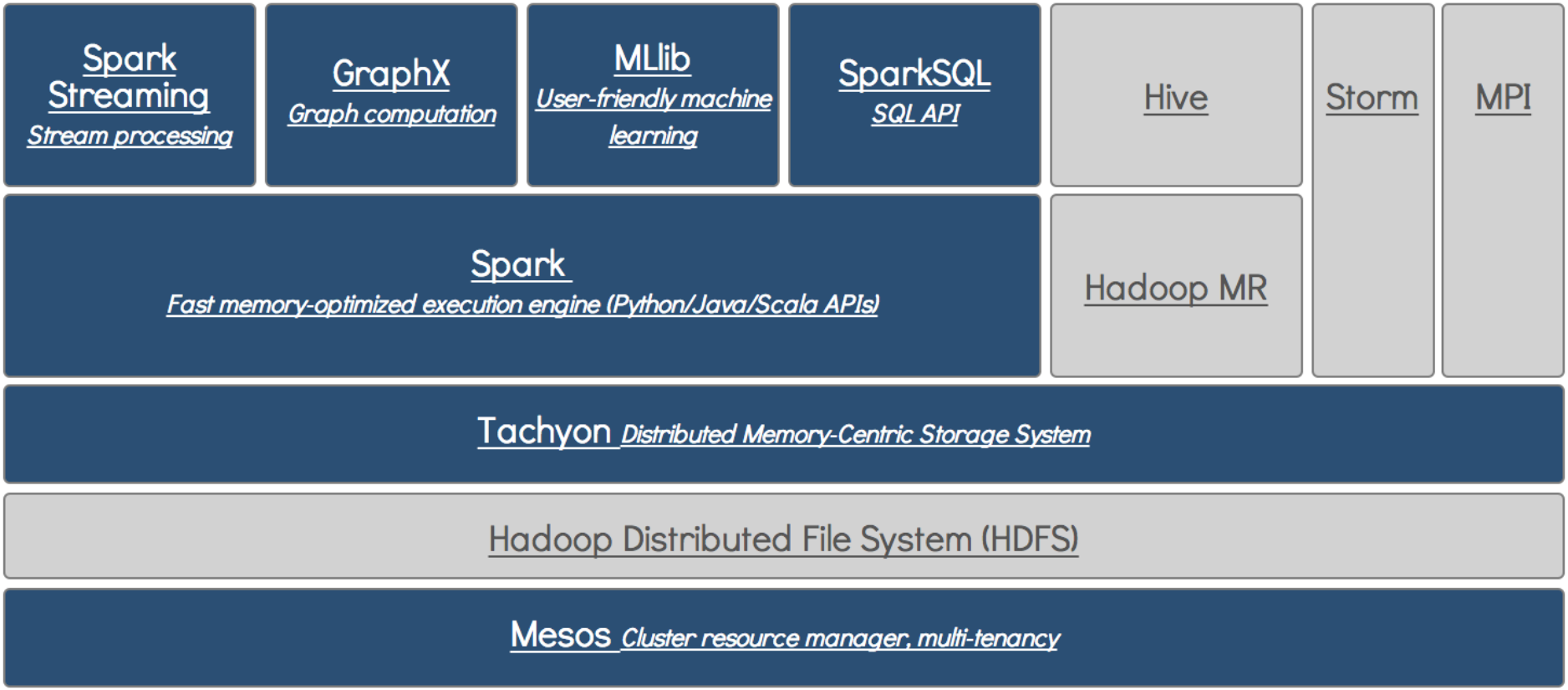
Both built on Spark SQL engine. both can be converted back to an RDD

Useful Libraries for Spark

- Spark SQL

- Spark Streaming – **stream processing of live datastreams**
- MLlib – **scalable machine learning**
- GraphX – **graph manipulation**
  - extends Spark RDD with Graph abstraction: a directed multigraph with properties attached to each vertex and edge

Data Analytics Software Stack



Spark vs. Hadoop MapReduce

- Performance: Spark normally faster but with caveats
  - Spark can process data in-memory; Hadoop MapReduce persists back to the disk after a map or reduce action
  - Spark generally outperforms MapReduce, but it **often needs lots of memory to perform well**; if there are other resource-demanding services or can't fit in memory, Spark degrades
  - MapReduce easily runs alongside other services with minor performance differences, & works well with the 1-pass jobs it was designed for
- Ease of use: **Spark is easier to program** (higher-level APIs)
- Data processing: **Spark more general**

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

CS246: Mining massive datasets

Grab a handout at the back of the room