CS246 2022: Mining Massive Data Sets Intro, MapReduce & Spark

CS246: Mining Massive Data Sets
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http://cs246.stanford.edu

Data contains value and knowledge

Data Mining, Data Science, …

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

Data Mining ≈ Predictive Analytics ≈ Data Science ≈ Machine Learning ≈ Data-Centric AI

What This Course Is About

- **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 most of it is!**

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

Data Mining/ML Pipeline

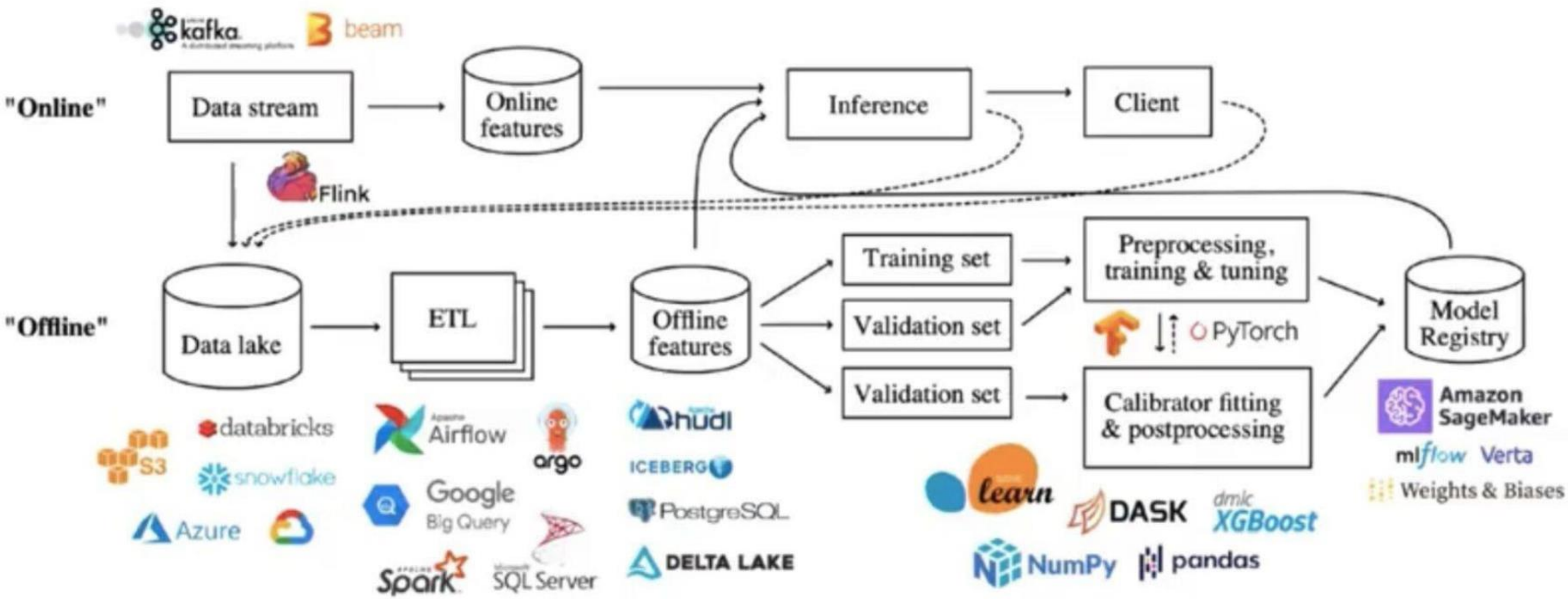


Figure 1: High-level architecture of a generic end-to-end machine learning pipeline. Logos represent a sample of tools used to construct components of the pipeline, illustrating heterogeneity in the tool stack. *Shankar et al. 2021*

"This class is a must if you want to become a Data Scientist or an ML Engineer."

(anonymous CS246 student)

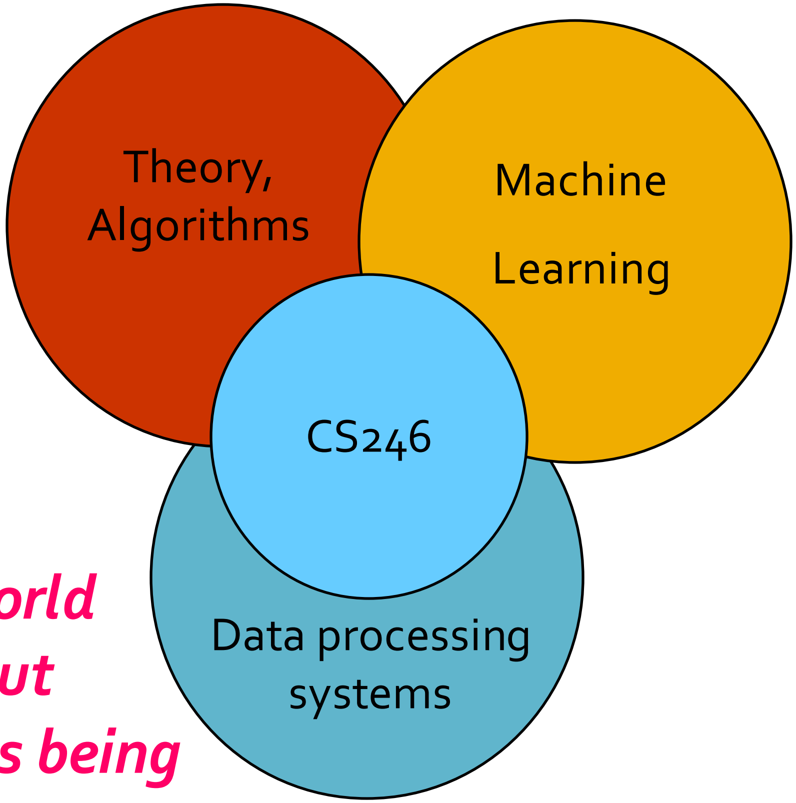
Data Mining Methods

- **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

"Definitely take the course if you will be working with massive datasets in the future, either in the industry or in academia."
(anonymous CS246 student)

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**



"The class has a great focus on real-world study cases, so you will learn a lot about realistic ML problems and the solutions being used in practice at places like Netflix, Amazon, Facebook, Pinterest, etc." (anonymous CS246 student)

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

High dim. data	Graph data	Infinite data	Machine learning	Apps
Locality sensitive hashing	PageRank, SimRank	Filtering data streams	Learning Embeddings	Recommen der systems
Clustering	Graph Neural Networks	Web advertising	Decision Trees	Association Rules
Dimensional ity reduction	Spam Detection	Queries on streams	Experiment ation	Duplicate document detection

Course Logistics

Course Staff

Instructor

Jure Leskovec

Co-Instructor

Mina Ghashami

Course Coordinator

Lata Nair

Course Assistants

Aman Bansal (Head TA)

Zhuoyi Huang

Paridhi Maheshwari

Luca Pistor

Nirali Parekh

Course Format: Zoom&Canvas

Lectures: Tue/Thu 3:00-4:20pm PST

Live in-person (in NVIDIA classroom), recording available on Canvas

- **~70 min lecture:**
  - If you have a clarification question, post it in Ed, TAs will answer
- **~10 min Q&A:**
  - Ask questions, Jure will answer and discuss

Logistics: Communication

- **Ed:**
  - **Use Ed for all questions and public communication**
    - Search the feed before asking a duplicate question
    - Please tag your posts and please no one-liners
- **For e-mailing course staff always use:**
  - cs246-spr2223-staff@lists.stanford.edu
- **We will post course announcements to Ed (hence check it regularly!)**

Auditors are welcome!

(please send request to <cs246-spr2223-staff@lists.stanford.edu> to add you to Canvas)

Logistics: Communication

- **High-frequency feedback:**
  - **Weekly survey about class morale**
  - **Randomly select students to give us feedback**
    - **Content**
    - **Course setup**
    - **Anything the teaching team should know/improve**
    - **Anything that is confusing to you**
    - **…**

Resources

- **Course website: http://cs246.stanford.edu**
  - Lecture slides (at least 30min before the lecture)
  - Homework, solutions, readings posted on Ed/Canvas
- **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

CS246 Office Hours

- **Office hours:**
  - TA office hours will be updated on the website http://cs246.stanford.edu by Friday
    - **We start Office Hours next week!**
  - **Office hours will be held on Zoom and use QueueStatus**
    - Links will be posted on Canvas and the course calendar
    - We will be holding **(1)** in-person office hours, **(2)** virtual group office hours, and **(3)** virtual one-on-one office hours

Recitation Sessions

- Videos and materials on Canvas
- **Spark tutorial:**
  - Video
  - Follows Colab 0
- **Review of basic probability and proof techniques:**
  - Video and handout
- **Review of linear algebra:**
  - Video and handout

Work for the Course: Homework

- **4 longer homeworks: 40%**
  - Four major assignments, involving programming, proofs, algorithm development.
  - Assignments take lots of time (+20h). **Start early!!**
- **How to submit?**
  - **Homework write-up:**
    - Submit via Gradescope
    - Enroll to CS246 on Canvas, and you will be automatically added to the course Gradescope
  - **Homework code:**
    - If the homework requires a code submission, you will find a separate assignment for it on Gradescope, e.g., **HW1 (Code)**
    - Forgetting to submit code will result in point deduction.

Homework Calendar

- **Homework schedule:**

Date (23:59 PT)	Out	In
04/06, Thu	HW1	
04/20, Thu	HW2	HW1
05/04, Thu	HW3	HW2
05/18, Thu	HW4	HW3
06/01, Thu		HW4

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

Work for the Course: Colabs

- **Short weekly Colab notebooks: 30%**
  - Colab notebooks are posted every **Thursday**
    - 10 in total, from 0 to 9, each worth 3%
  - Due one week later on **Thursday 23:59 PST. No late days!**
    - First 2 Colabs will be posted on Thu, including detailed submission instructions to Gradescope
    - Colab 0 (Spark Tutorial) is solved step-by-step in the Spark Recitation video.
  - Colabs require around **1hr of work.**
    - **And a few lines of code.**
  - "Colab" is a **free cloud service from Google**, hosting Jupyter notebooks with free access to GPU and TPU

Work for the Course: Final Exam

- **Final exam: 30%**
  - Exact format will be announced later this week.
  - Most likely we will do a take-home 3h exam which you will be able to take at any time during a 24h time window.
- **Extra credit:** Proportional to your contribution (up to 2%)
  - Course attendance, asking questions, discussion
  - For participating in Ed 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 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:**
  - (don't search/post code on Github, and similar)
  - You can talk to people but have to write your own solution/code
  - If you fail to mention your sources, MOSS will catch it, which will result in an HC violation.

Final Thoughts

- **CS246 is fast paced!**
  - Requires programming maturity
  - Strong math skills
    - SCPD students tend to be rusty on math/theory
- **Course time commitment:** *"The colabs are easy and can be done within an hour but the homework assignments take a lot more time so start early!" (CS246 student)*
  - Homeworks take ~20h
  - Colab notebooks take about 1h
- Form study groups!

Final Thoughts

CS246 is one of the most useful classes at you'll take at Stanford if you want to become a Data Scientist or an ML Engineer.

CS246 going to be <u>fun</u> and <u>hard</u> work. ☺

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

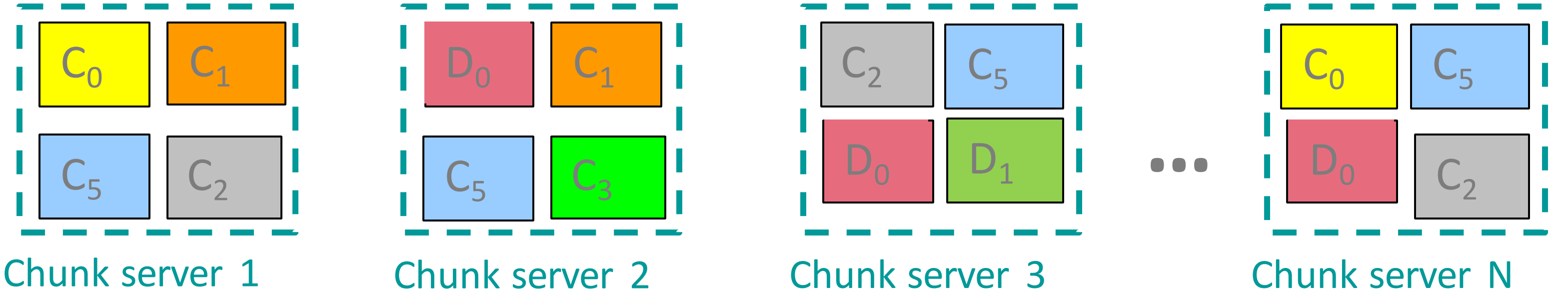
- **Problem:**
  - If nodes fail, how to store data persistently?
- **Answer:**
  - **Distributed File System**
    - Provides global file namespace
- **Typical usage pattern:**
  - Huge files (100s of GB to TB)
  - Data is rarely updated in place
  - Reads and appends are common

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
  - Master nodes are typically more robust to hardware failure and run critical cluster services.
- **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



Notation: C_2… chunk no. 2 of file C

Bring computation directly to the data!

Chunk servers also serve as compute servers

MapReduce: Early Distributed Computing Programming Model

Programming Model: MapReduce

- **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"

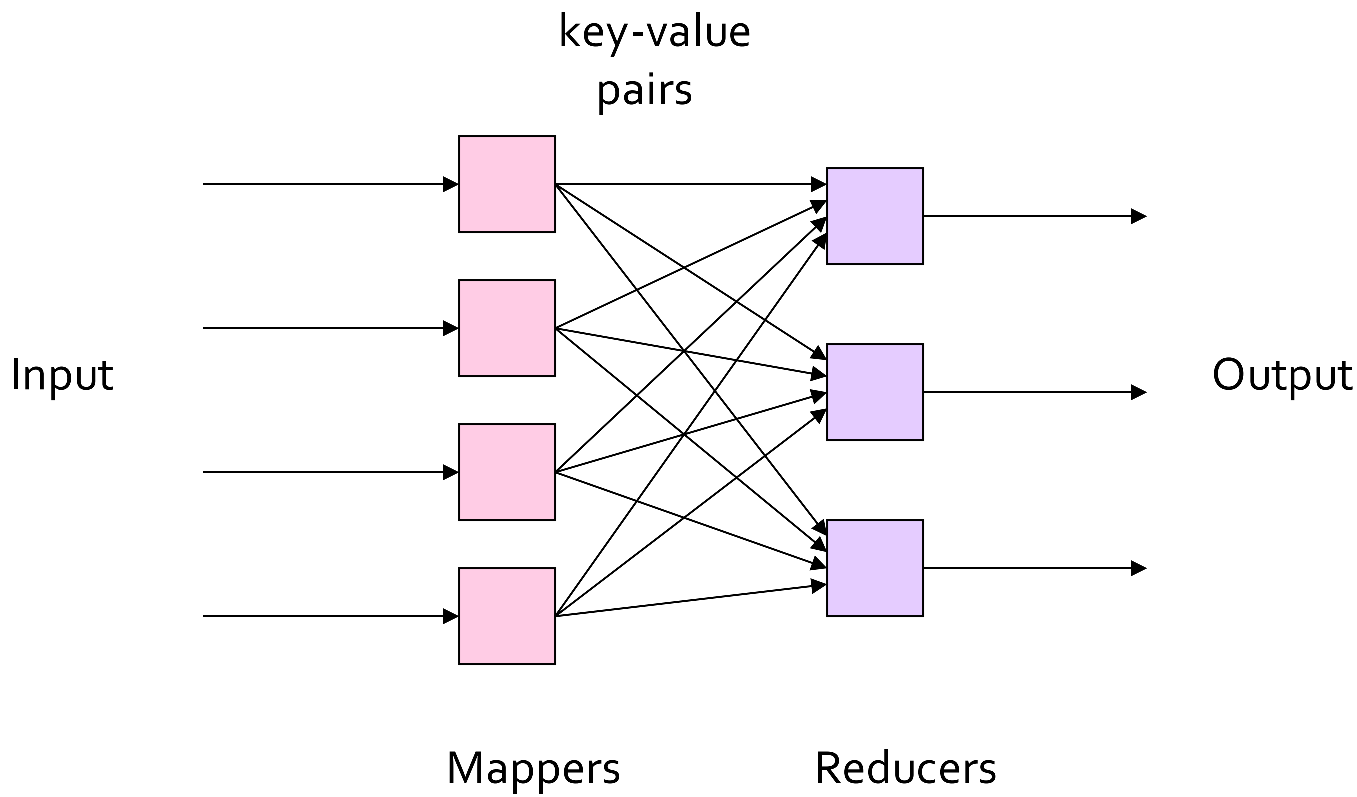
MapReduce: Overview

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

MapReduce Pattern



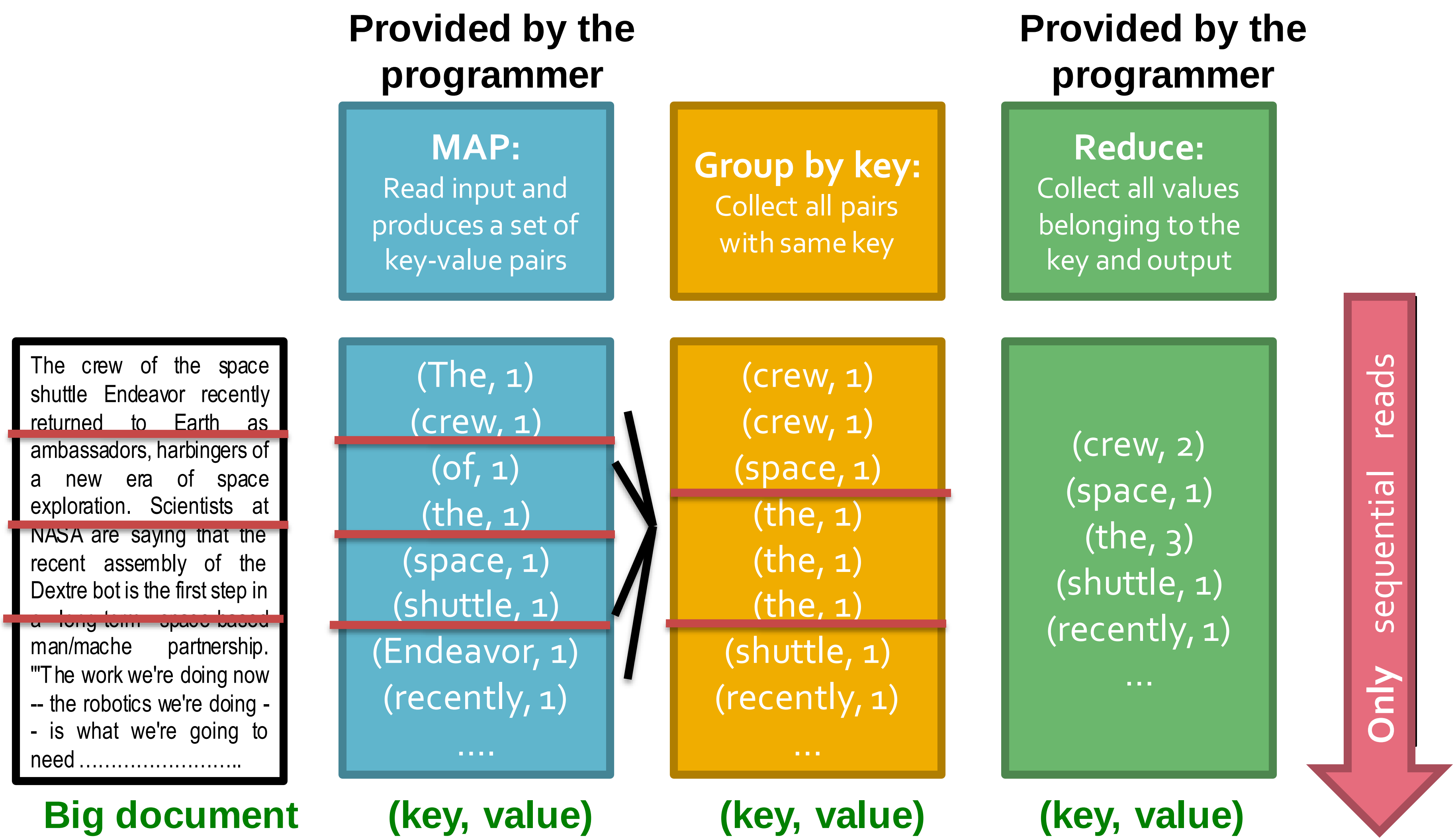
Example: Word Counting

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

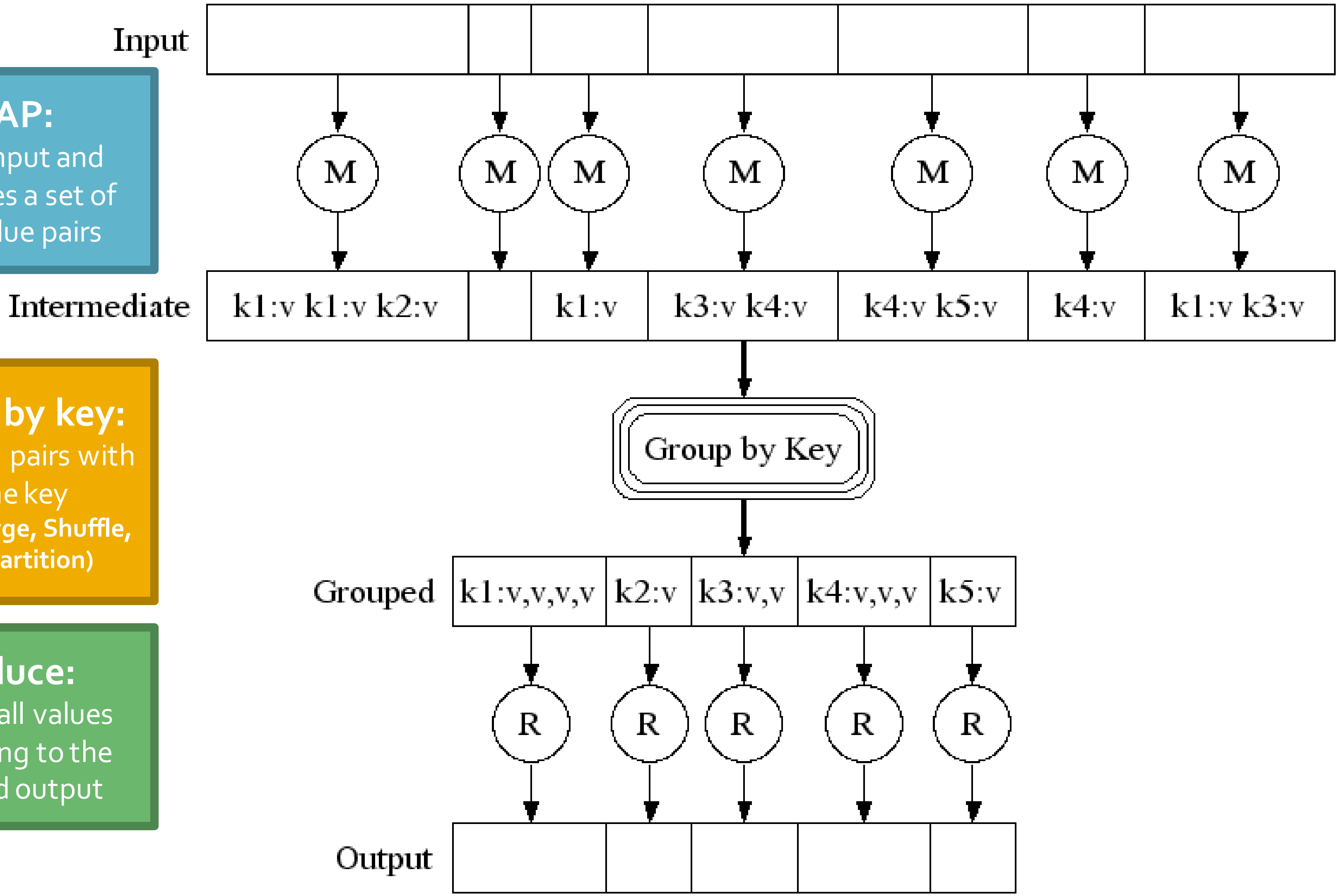
```
map(key, value):
# key: document name; value: text of the document
  for each word w in value:
      emit(w, 1)


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

Map-Reduce: A diagram

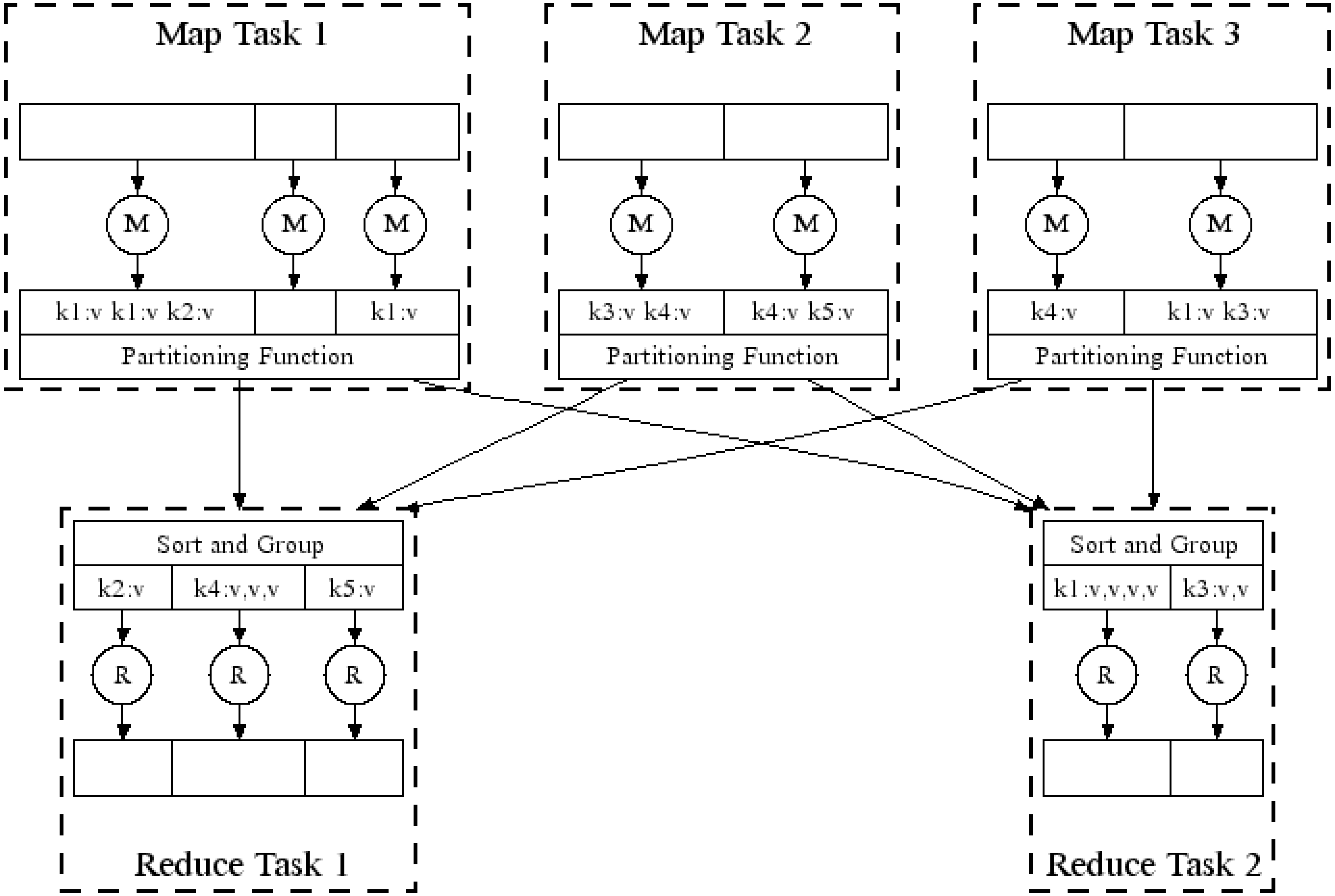
MAP:
Read input and produces a set of key-value pairs

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: Environment

MapReduce environment takes care of:

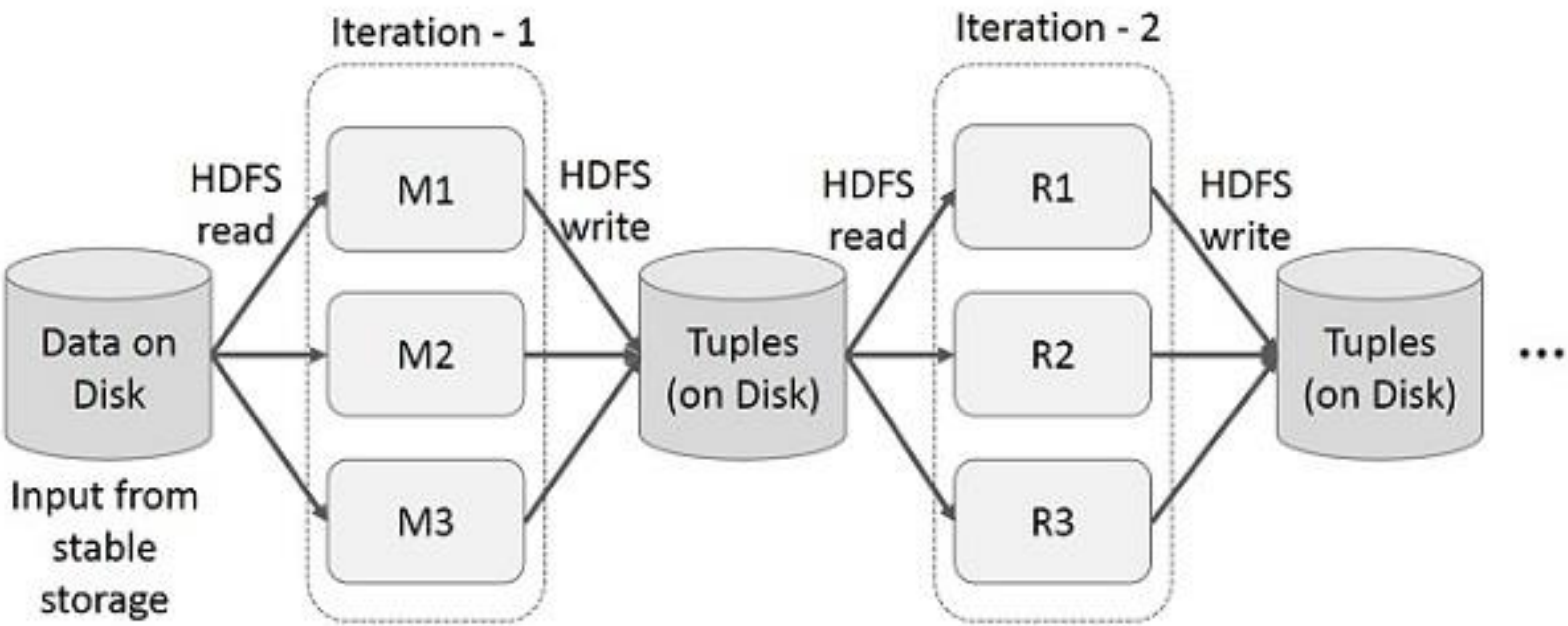
- **Partitioning** the input data
- **Scheduling** the program's execution across a set of machines
- Performing the **group by key** step
  - In practice this is is the bottleneck
- Handling machine **failures**
- Managing required inter-machine **communication**

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: Extends MapReduce

Problems with MapReduce



- **MapReduce:**
  - Incurs substantial overheads due to data replication, disk I/O, and serialization

Problems with MapReduce

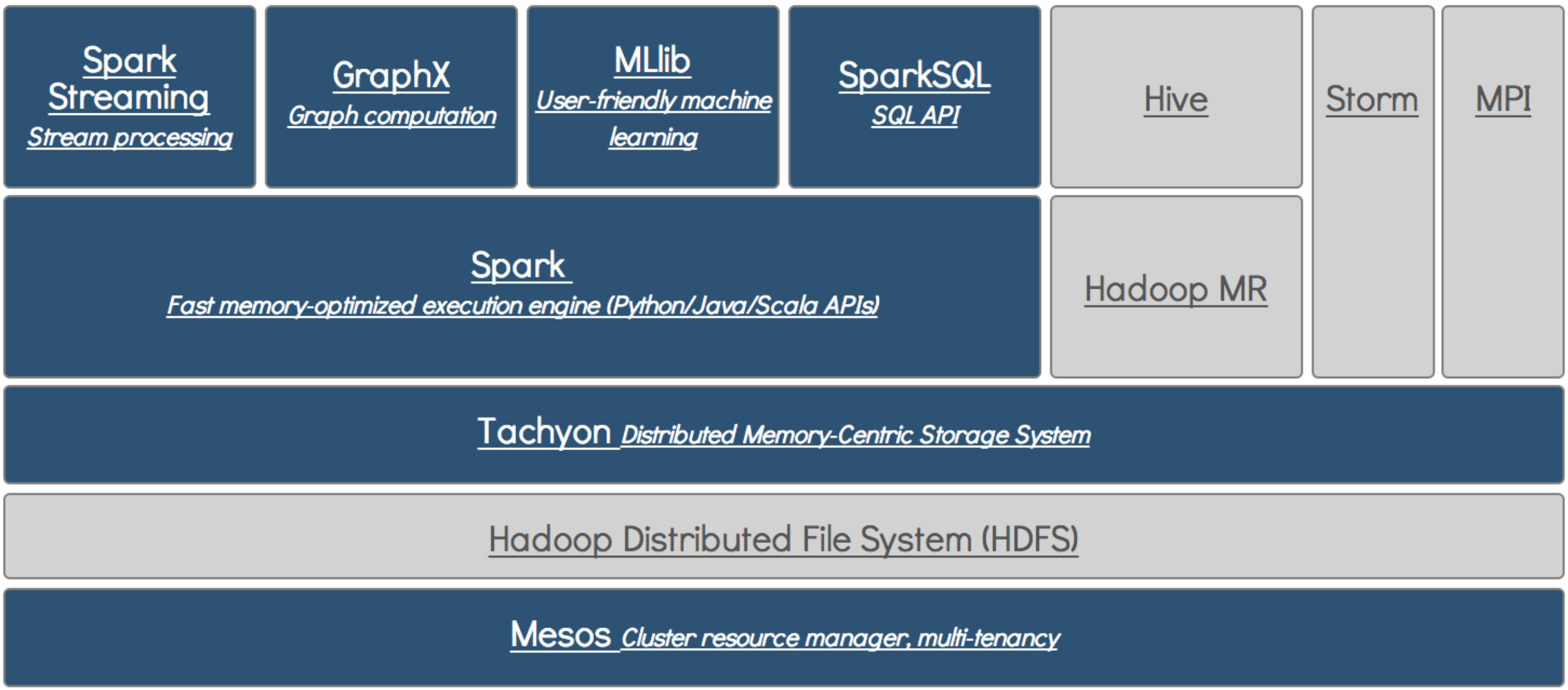
- **Two major limitations of MapReduce:**
  - Difficulty of programming directly in MapReduce
    - Many problems aren't easily described as map-reduce
  - Performance bottlenecks, or batch not fitting the use cases
    - Persistence to disk typically slower than in-memory work
- **In short, MapReduce 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

- **<u>Data-Flow Systems</u> 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

Data Analytics Software Stack



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

- **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

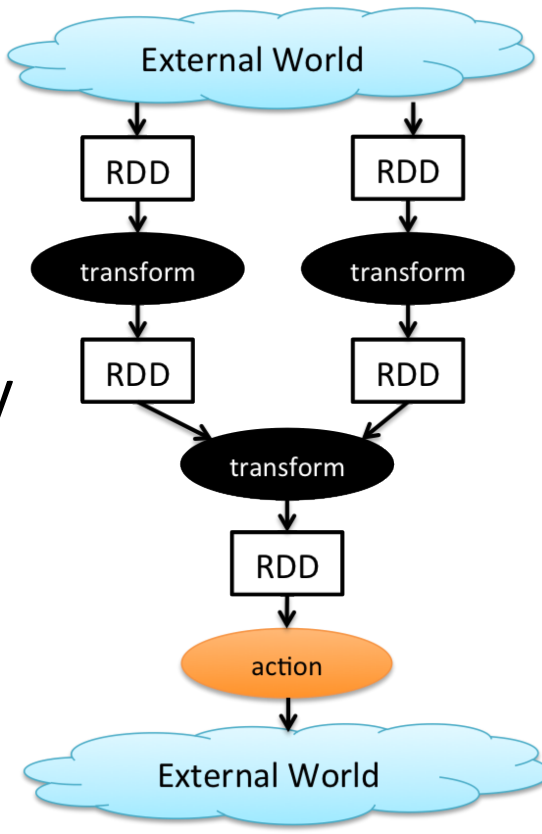
Spark: RDD

Key concept: ***Resilient Distributed Dataset*** **(RDD)**

  - Partitioned collection of records
    - Generalizes (key-value) pairs
- Spread across the cluster, Read-only
- Caching dataset in memory
  - Fallback to disk possible

- **RDDs** can be created from Hadoop, or by transforming other RDDs (you can stack RDDs)

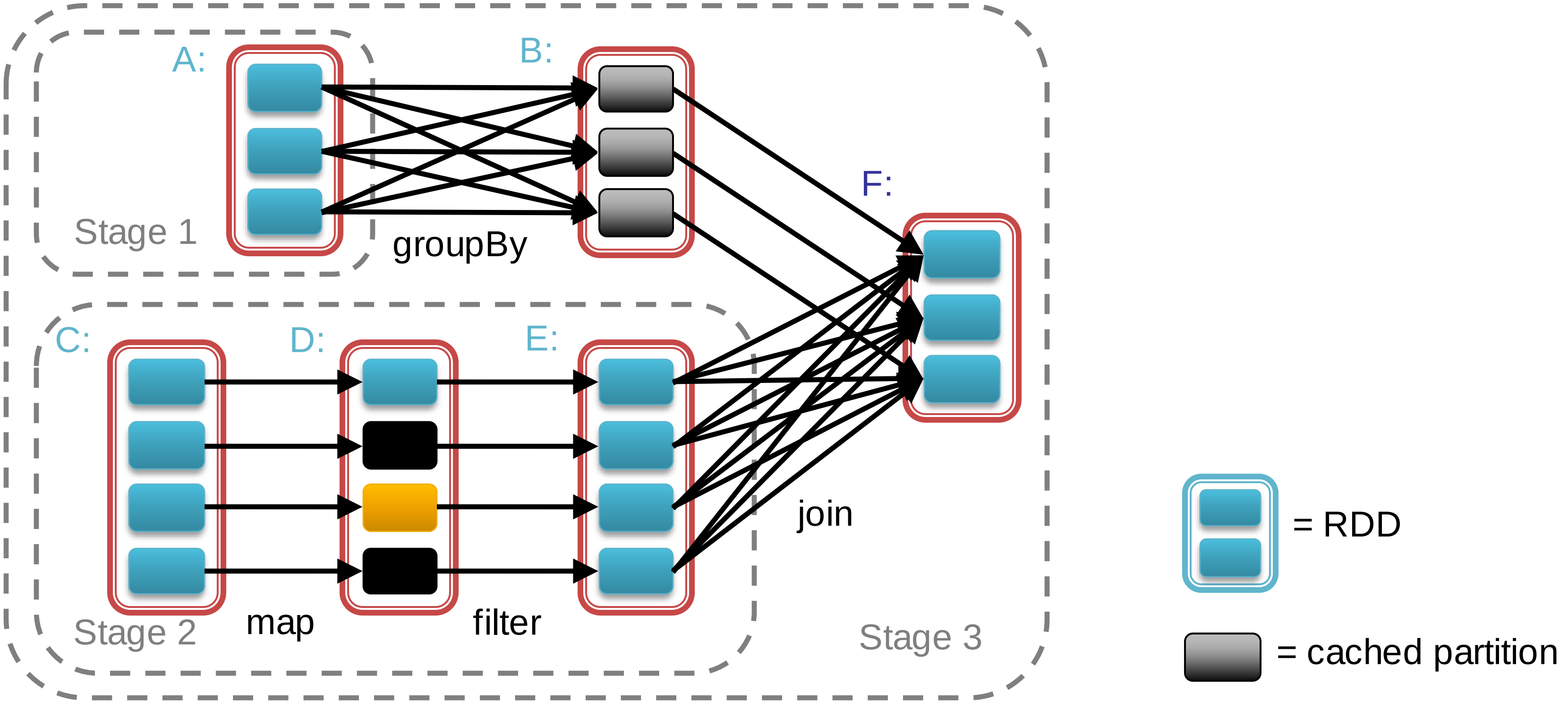
- **RDDs** are best suited for applications that apply the same operation to all elements of a dataset



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

Higher-Level API: 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

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 communication cost