Big Data

Hands on PySpark

How do we process Big Data?

Main issues

- Where do we store the data?
- How do we process it?

Big Data greatly exceeds the size of the typical drives

- Even if a big drive existed, it would be too slow (at least for now)

Year: 1990
Size: 1.3 GB
Speed: 4,4 MB/s

5 minutes

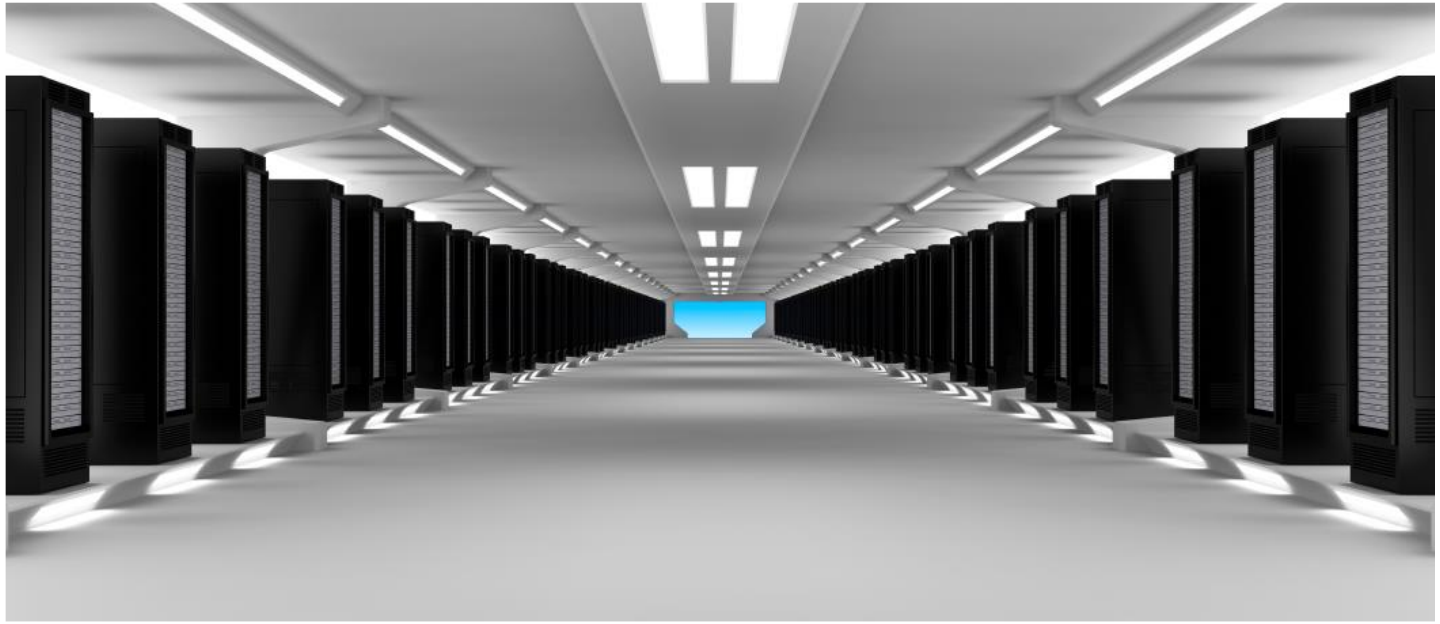
Year: 2014
Size: 1 TB
Speed: 100 MB/s

3 hours

Year: 2015
Size: 1 TB
Speed: 600 MB/s

30 minutes

The answer: cluster computing



100 hard disks? 18 seconds to read 1TB

Commodity hardware

You are not tied to expensive, proprietary offerings from a single vendor

You can choose standardized, commonly available hardware from a large range of vendors to build your cluster

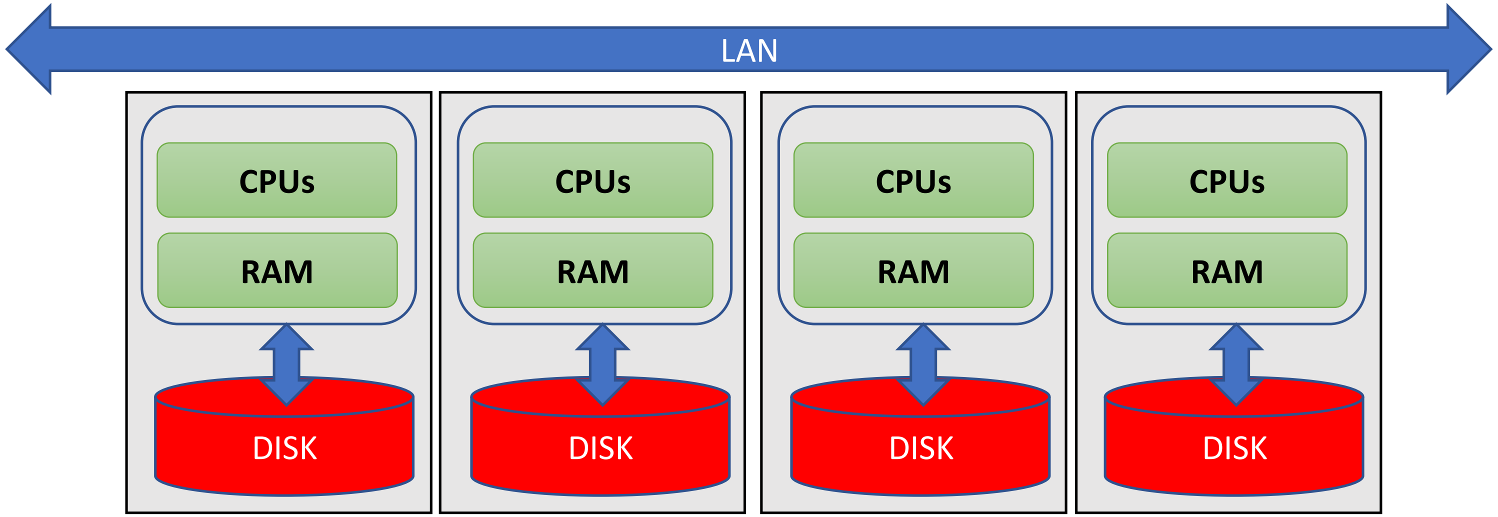
Commodity ≠ Low-end!

- Cheap components with high failure rate can be a false economy

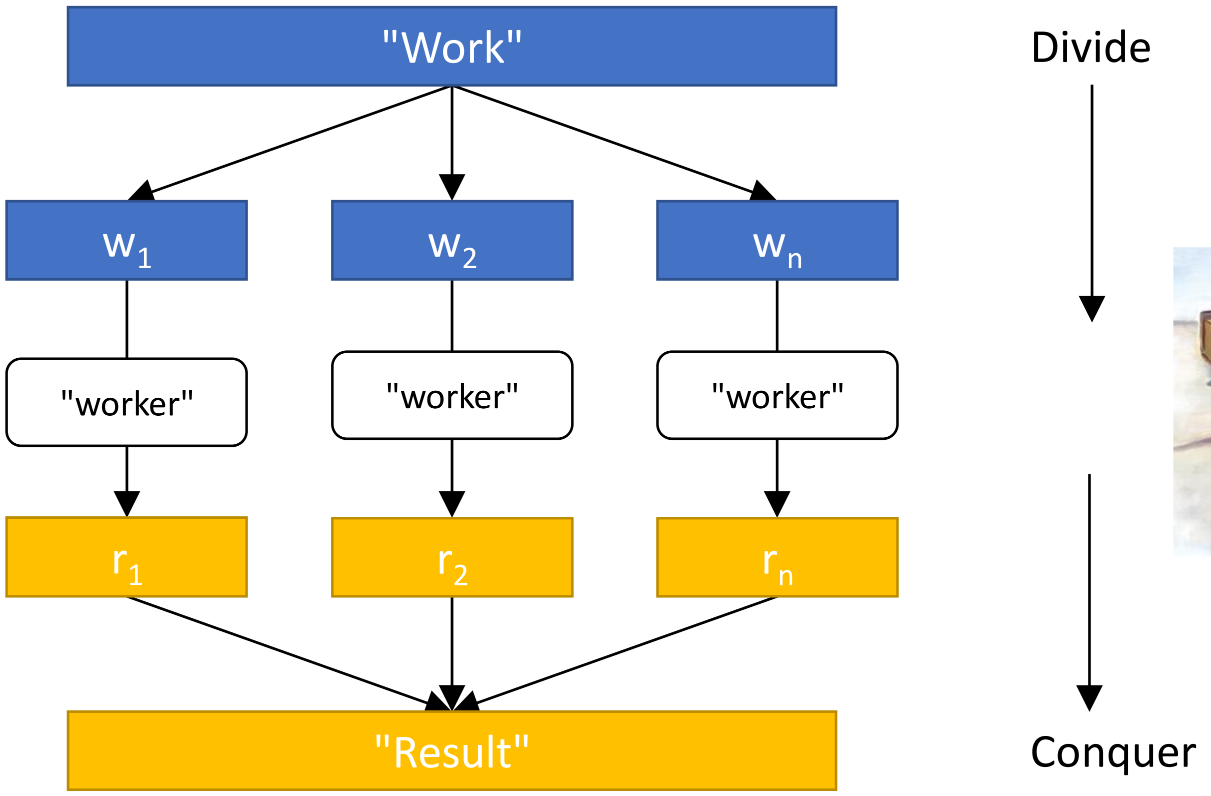
Cluster Computing Architecture

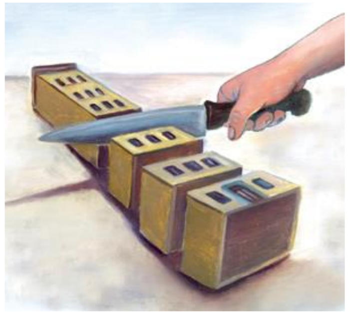
A computer cluster is a group of linked computers (nodes), working together closely so that in many respects they form a single computer

- Typically connected to each other through fast LAN
- Every node is a system on its own, capable of independent operations
  - Unlimited scalability, no vendor lock-in
- Number of nodes in the cluster >> Number of CPUs in a node



Distributed computing: an old idea





MapReduce

"MapReduce is a programming model and an associated implementation for processing and generating large data sets.

Users specify a map function that processes a key/value pair to generate a set of intermediate key/value pairs, and a reduce function that merges all intermediate values associated with the same intermediate key."

-- Dean J., Ghemawat S. (Google)

Hadoop MapReduce is an open-source implementation of the MapReduce programming model

How it works

Take a typical large-data analytical problem

- Iterate over a large number of records
- Extract something of interest from each
- Shuffle and sort intermediate results
- Aggregate intermediate results
- Generate final output

Map

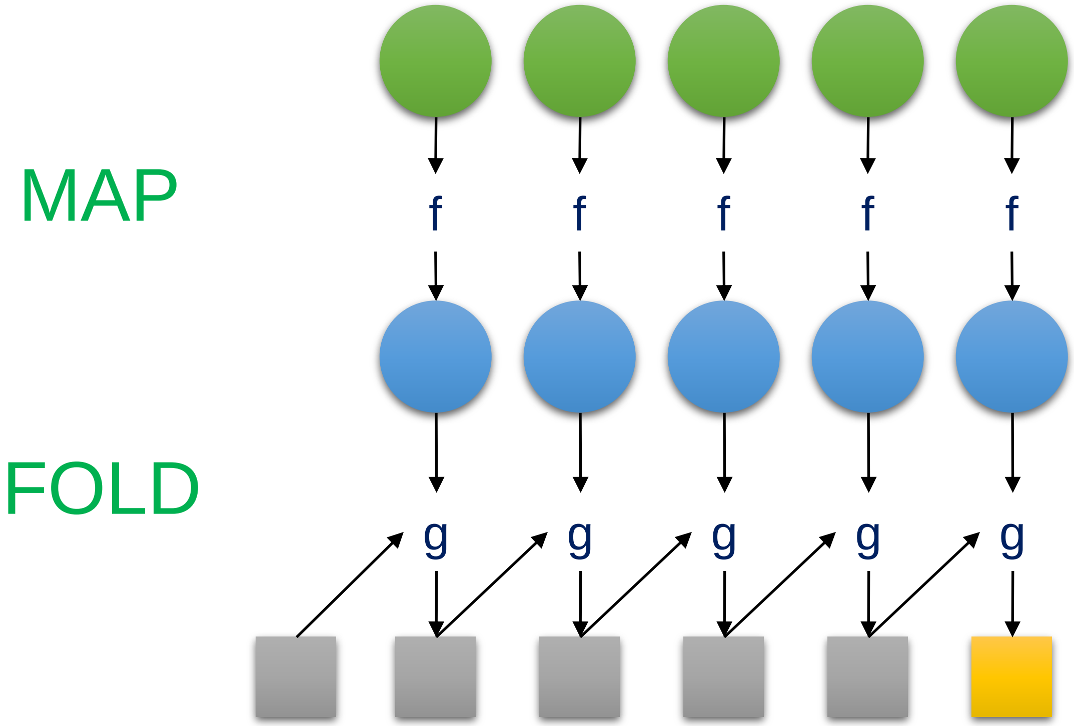
Reduce

The idea is to provide a functional abstraction for these two operations

Roots in Functional Programming

MAP takes a function f and applies it to every element in a list,

FOLD iteratively applies a function g to aggregate results



Example of Functional Programming

Imperative programming

```
a = 0
b = a + 1
```

```
### Map example
names = ['Mary', 'Isla', 'Sam']
name_lengths = []
for i in range(len(names)):
  name_lengths[i] = len(names[i])
```

```
### Reduce example
sentences = [
   'Mary read a story to Sam and Isla.',
   'Isla cuddled Sam.', 'Sam chortled.' ]
sam_count = 0
for sentence in sentences:
    sam_count += sentence.count('Sam')
```

Functional programming

```
a = 0
b = increment(a)
def increment(a):
  return a + 1;
```

```
### Map example
names = ['Mary', 'Isla', 'Sam']
name_lengths = map(len, names)
```

```
### Reduce example
sentences = [
   'Mary read a story to Sam and Isla.',
   'Isla cuddled Sam.', 'Sam chortled.' ]
sam_count = reduce(
  lambda a, x: a + x.count('Sam'),
  sentences, 0
)
```

Parallelization of Map and Reduce

The map operation (i.e., the application of *f* to each item in a list) can be parallelized in a straightforward manner, since each functional application happens in isolation

- In a cluster, these operations can be distributed across many different machines

The reduce operation has more restrictions on data locality

- Elements in the list must be "brought together" before the function *g* can be applied

However, many real-world applications do not require *g* to be applied to all elements of the list

- If elements in the list can be divided into groups, the fold aggregations can proceed in parallel

MapReduce program

Basic data structure: key-value pairs

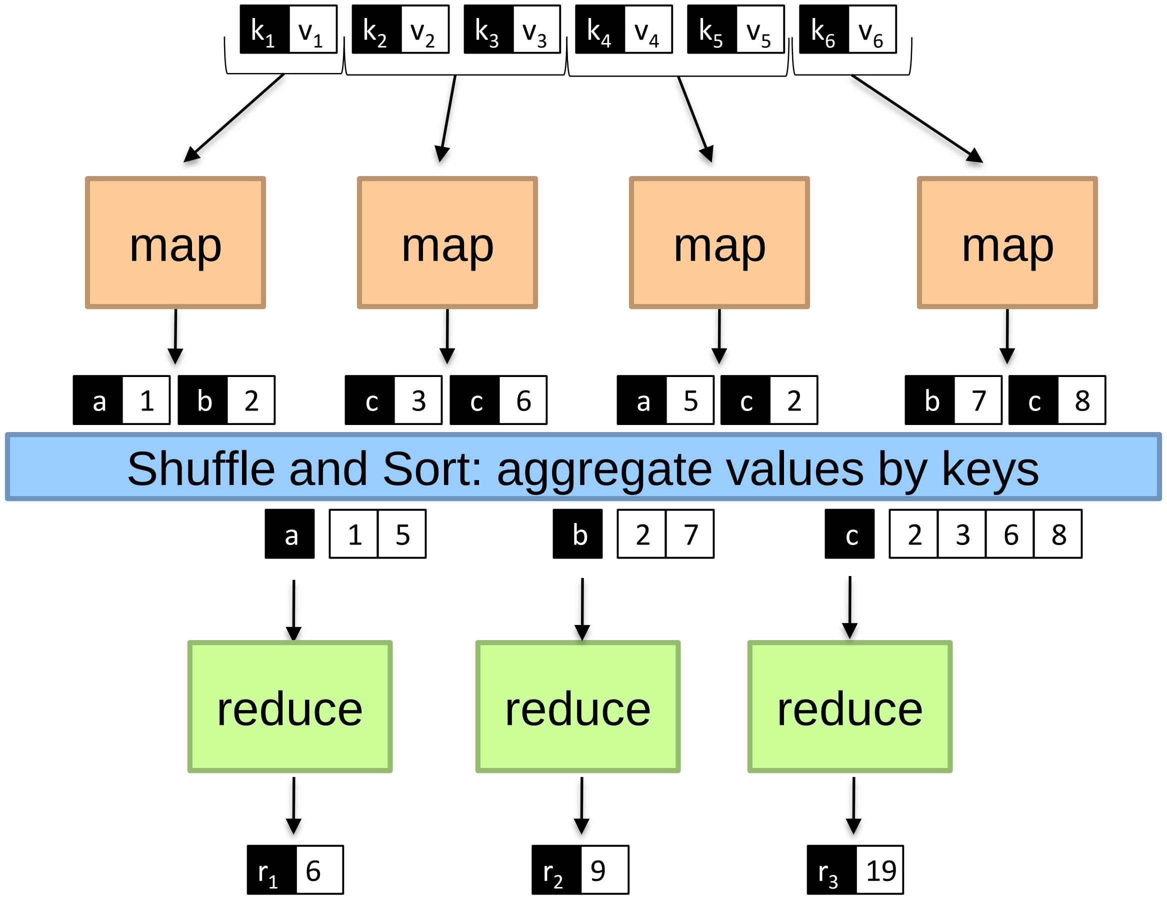
- The type of key-value pair can be chosen by the programmer

Programmers specify two functions:

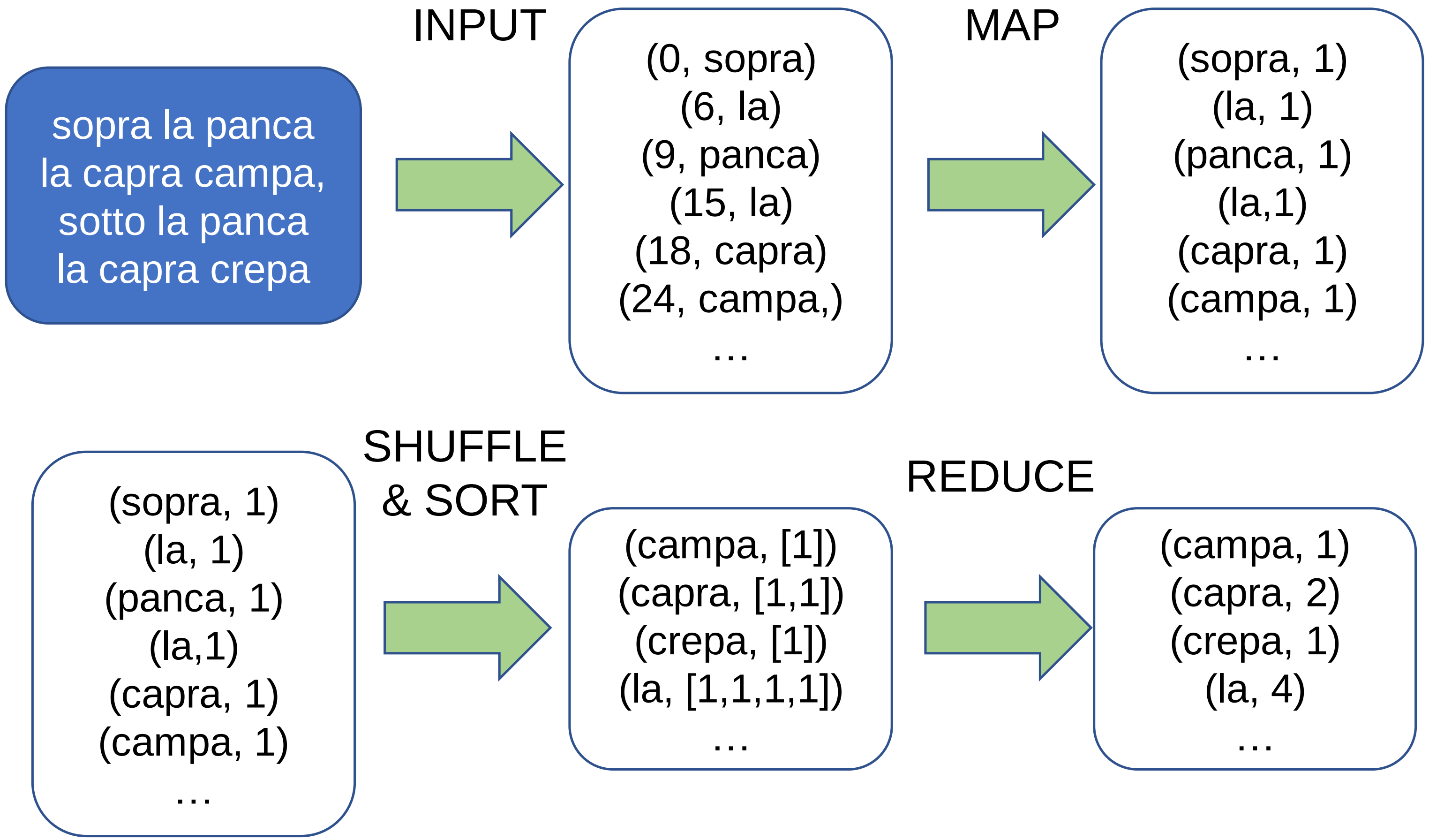
- **map** (k1, v1) → list(k2, v2)
- **reduce** (k2, list(v2)) → list(k3, v3)
  - (k, v) denotes a (key, value) pair
  - Keys do not have to be unique: different pairs can have the same key
  - In text files, each line is treated as a new record;
    the key is the offset of the line within the file (usually irrelevant), the value is the line itself

The execution framework handles everything else!

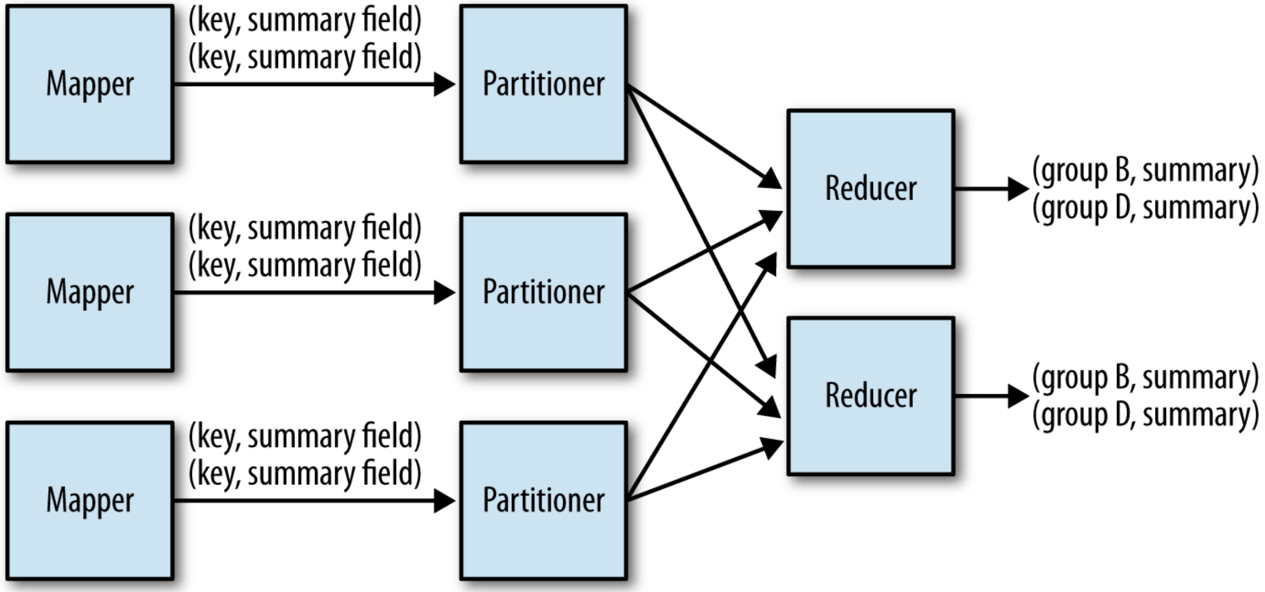
MapReduce process: an example



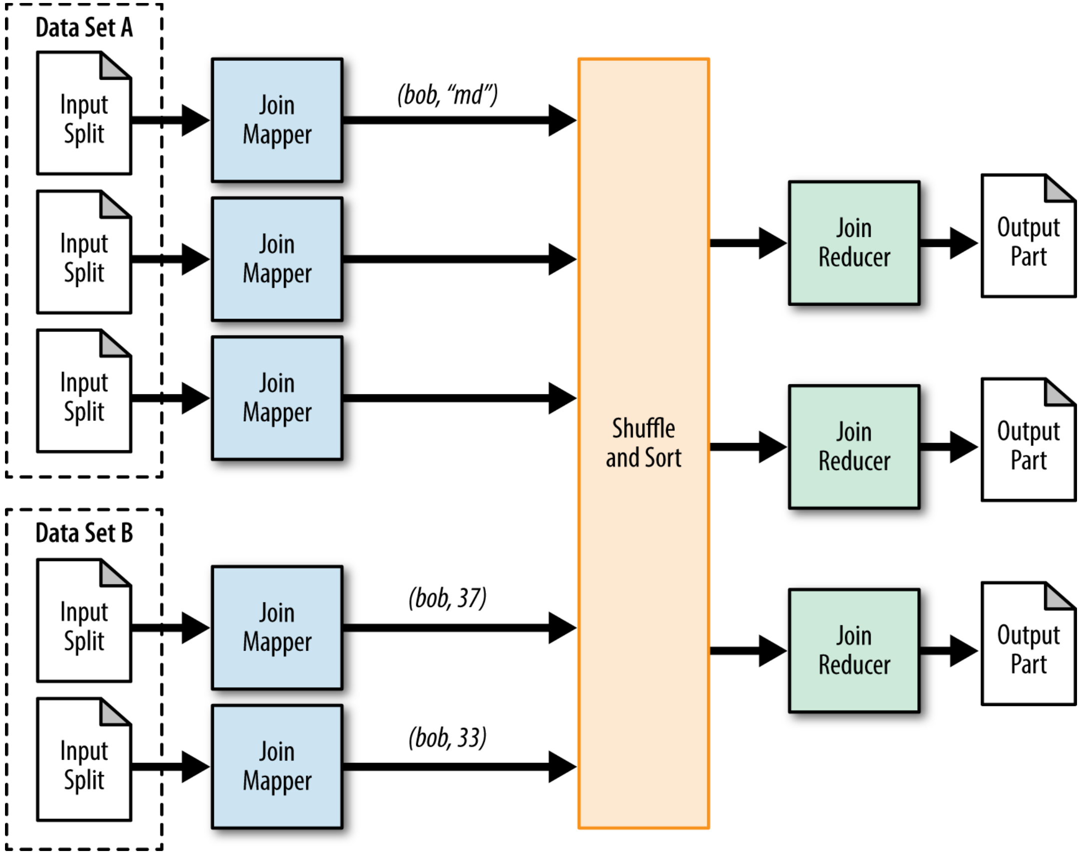
Word count


INPUT
MAP
sopra la panca
la capra campa,
sotto la panca
la capra crepa
(0, sopra)
(6, la)
(9, panca)
(15, la)
(18, capra)
(24, campa,)
…
(sopra, 1)
(la, 1)
(panca, 1)
(la,1)
(capra, 1)
(campa, 1)
…
SHUFFLE
& SORT
REDUCE
(sopra, 1)
(la, 1)
(panca, 1)
(la,1)
(capra, 1)
(campa, 1)
…
(campa, [1])
(capra, [1,1])
(crepa, [1])
(la, [1,1,1,1])
…
(campa, 1)
(capra, 2)
(crepa, 1)
(la, 4)
…

Summarization pattern



Join pattern



Two stage MapReduce

As map-reduce calculations get more complex, it's useful to break them down into stages

- The output of the first stage serves as input to the next one
- The same output may be useful for different subsequent stages
- The output can be stored in the DFS, forming a materialized view

Early stages of map-reduce operations often represent the heaviest amount of data access, so building and saving them once as a basis for many downstream uses saves a lot of work!

Limitations of Map Reduce

Designed for batch processing

- Not suitable for iterative algorithms or interactive data mining

Strict paradigm

- Everything has to fit into Map and Reduce
- Complex algorithms will take multiple jobs and passes on hard disk

New hardware capabilities are not exploited

- Too much pressure on disk; RAM and multicore not adequately exploited

Too much complex

Spark

It is a fast and general-purpose execution engine

- In-memory data storage for very fast iterative queries
- Easy interactive data analysis
- Combines different processing models (machine learning, SQL, streaming, graph computation)
- Provides (not only) a MapReduce-like engine...
- ... but it's up to 100x faster than Hadoop MapReduce

Compatible with Hadoop's storage APIs

- Can run on top of a Hadoop cluster
- Can read/write to any database and any Hadoop-supported system, including HDFS, HBase, Parquet, etc.

RDD

RDDs are immutable distributed collection of objects

- **Resilient**: automatically rebuild on failure
- **Distributed**: the objects belonging to a given collection are split into *partitions* and spread across the nodes
  - RDDs can contain any type of Python, Java, or Scala objects
  - Distribution allows for scalability and locality-aware scheduling
  - Partitioning allows to control parallel processing

Fundamental characteristics (mostly from *pure functional programming*)

- **Immutable**: once created, it can’t be modified
- **Lazily evaluated**: optimization before execution
- **Cacheable**: can persist in memory, spill to disk if necessary
- **Type inference**: data types are not declared but inferred (≠ dynamic typing)

RDD operations

RDDs are **lazily evaluated**, i.e., they are computed when they are used in an action

- Until no action is fired, the data to be processed is not even accessed

Example (in Python)

```
sc = new SparkContext
rddLines = sc.textFile("myFile.txt")
rddLines2 = rddLines.filter (lambda line: "some text" in line)
rddLines2.first()
```

Transformations

Action

There is no need to compute and store everything

- In the example, Spark simply scans the file until it finds the first matching line

RDD operations

RDDs offer two types of operations: *transformations* and *actions*

Transformations construct a new RDD from a previous one

- E.g.: map, flatMap, reduceByKey, filtering, etc.
- https://spark.apache.org/docs/latest/programming-guide.html#transformations

Actions compute a result that is either returned to the driver program or saved to an external storage system (e.g., HDFS)

- E.g.: saveAsTextFile, count, collect, etc.
- https://spark.apache.org/docs/latest/programming-guide.html#actions

DataFrame and DataSet

RDDs are immutable distributed collection of objects

DataFrames and DataSets are immutable distributed collection of records organized into named columns (i.e., a table)

- **Simply put, RDDs with a schema attached**
- Support both relational and procedural processing (e.g., SQL, Scala)
- Support complex data types (struct, array, etc.) and user defined types
- Cached using columnar storage

Can be built from many different sources

- DBMSs, files, other tools (e.g., Hive), RDDs

Type conformity is checked

- At *compile time* for DataSets; at *runtime* for DataFrames

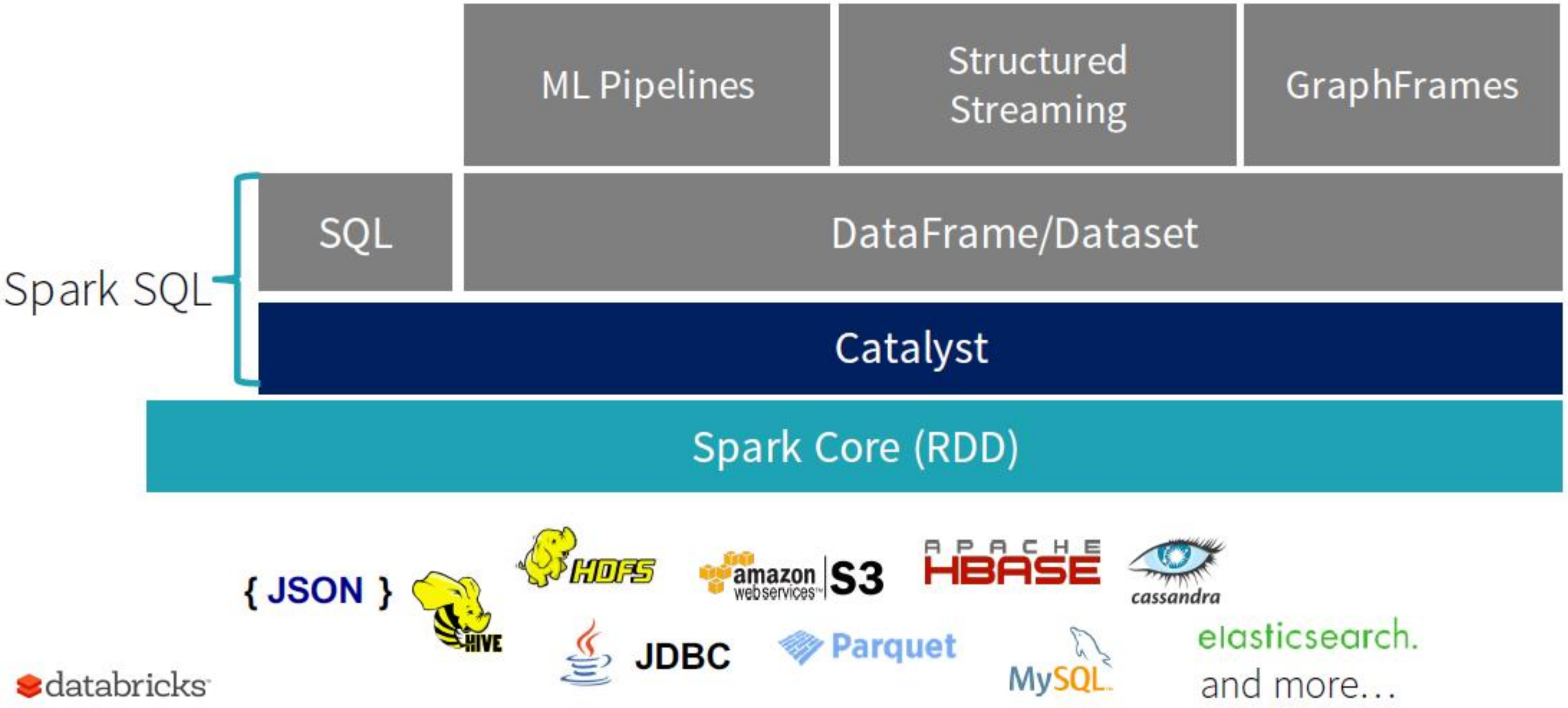
DataFrame and DataSet

Still lazily evaluated…

…but supports under-the-hood optimizations and code generation

- **Catalyst optimizer creates optimized execution plans**
  - IO optimizations such as skipping blocks in parquet files
  - Logic push-down of selection predicates
- JVM code generation for all supported languages
  - Even non-native JVM languages; e.g., Python

Spark structured



Why structure?

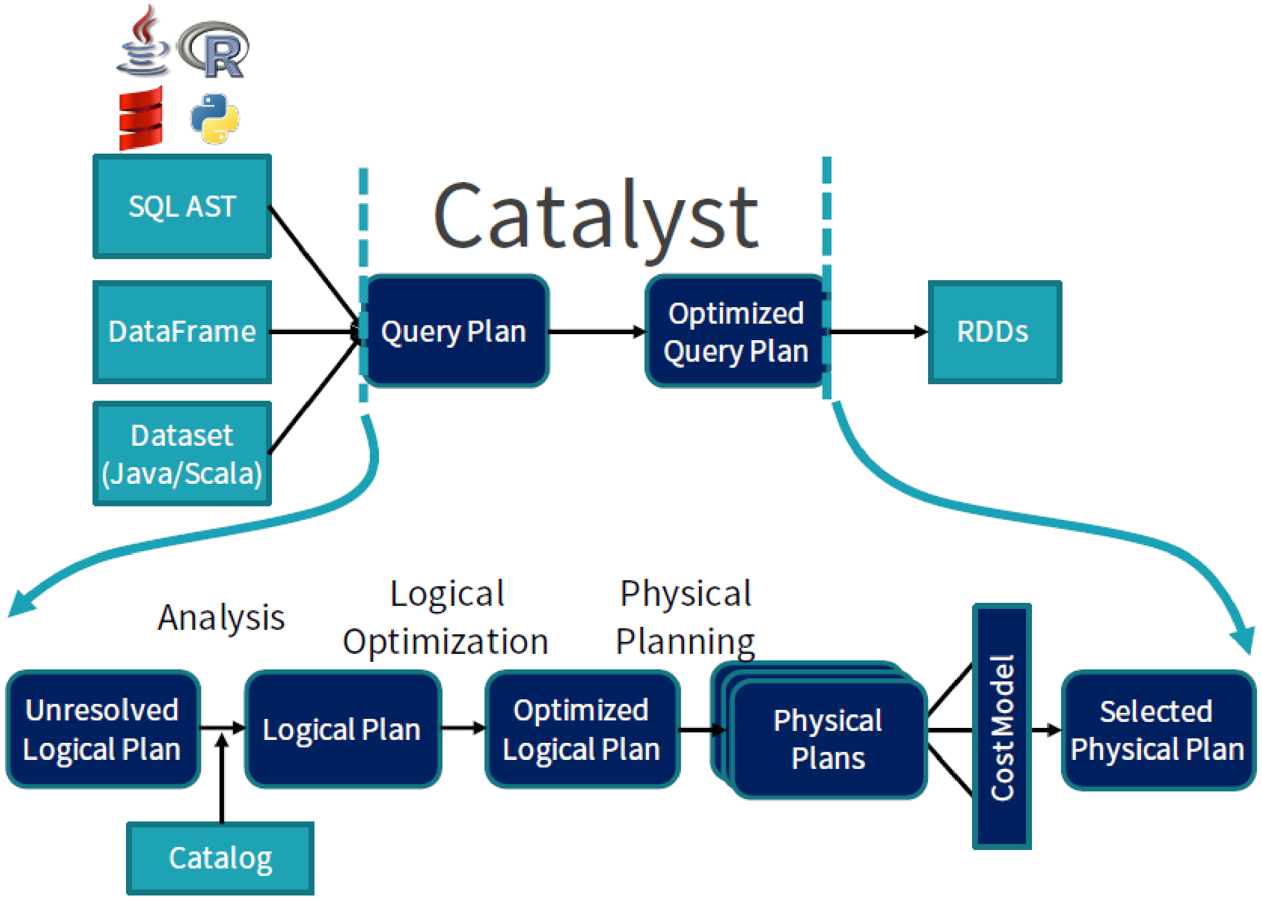
Cons

- **Structure imposes some limits**
  - RDDs enable any computation through user defined functions

Pros

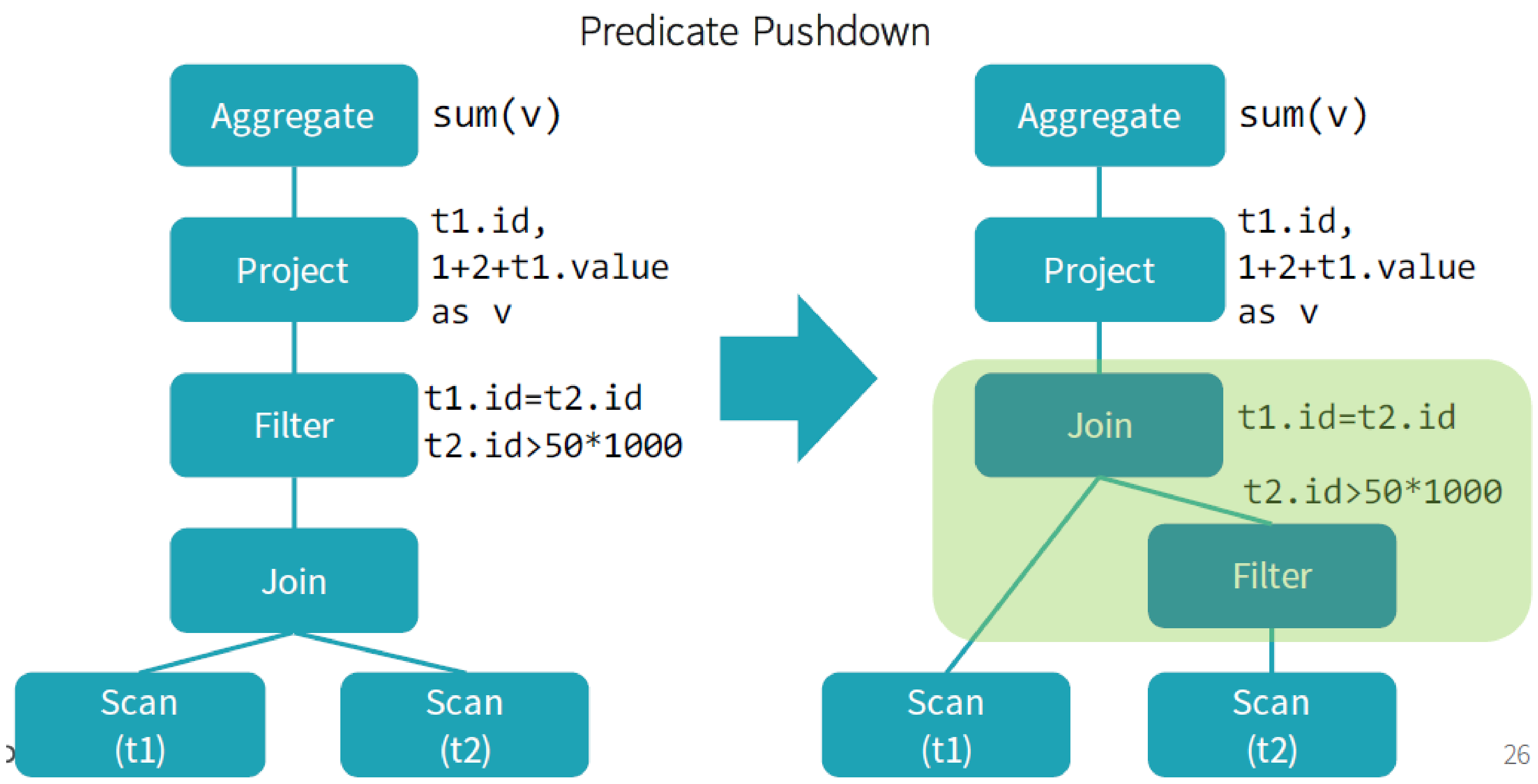
- The most common computations are supported
- Language simplicity
- **Opens the room to optimizations**
  - Hard to optimize a user defined function

Catalyst



SQL AST
DataFrame
Dataset (Java/Scala)
Catalyst
Query Plan
Optimized Query Plan
RDDs
Analysis
Logical Optimization
Physical Planning
Unresolved Logical Plan
Logical Plan
Optimized Logical Plan
Physical Plans
Cost Model
Selected Physical Plan
Catalog

Logical optimization



Adaptive Query Execution (AQE)

Introduced with version 3.0

Main idea

- The execution plan is not final
- Reviews are made at each stage boundary
- Additional optimizations are possibly applied, given the information available on the intermediate data

AQE can be defined as a layer on top of the Spark Catalyst which will modify the Spark plan on the fly

Drawbacks

- The execution stops at each stage boundary for Spark to review its plan
  - But the gain in performance is usually worth
- The Spark UI is more difficult to read
  - Each stage becomes a different job

Spark

Suggested reading and resources