# INTRODUCTION TO HADOOP AND MAPREDUCE

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Big Data analysis with Hadoop and RHadoop, March 3-4, 2022

# Outline

- Introduction
- What is Big Data?
- The Hadoop distributed computing architecture
- HDFS hands-on exercises
- The YARN resource manager
- MapReduce
- MapReduce hands-on
- MRjob
- Concluding remarks

# Timetable

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| | |
|---|---|
| *March 3rd* | |
| 13:00–13:15 | **Introduction to the course** |
| 13:15–14:00 | **Hadoop for distributed computing**<br>Big Data and the Hadoop architecture |
| 14:00–14:15 | *break* |
| 14:15–15:00 | **Hadoop Distributed File System (HDFS)**<br>Basic concepts and hands-on: manage data on HDFS |
| 15:00–15:15 | *break* |
| 15:15–16:00 | **MapReduce (MR)**<br>MR computing model: split/map/sort/shuffle/reduce |
| 16:00–16:15 | *break* |
| 16:15–17:00 | **Hands-on exercises with MapReduce** |

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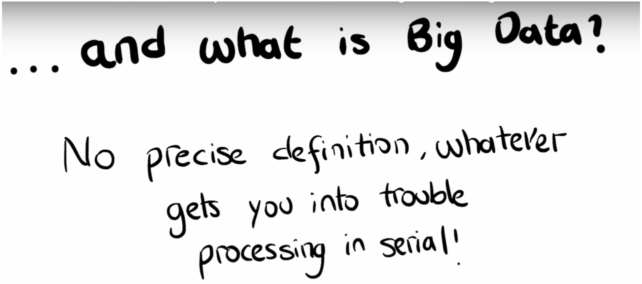
# What is Big Data?

# What is Big Data?


"**Big Data**" is the catch-all term for massive amounts of data as well as for frameworks and R&D initiatives aimed at working with them efficiently.

Image source: erpinnews.com

# A short definition of Big Data




A nice definition from last year's PRACE Summer of HPC presentation "Convergence of HPC and Big Data".

# The three V's of Big Data

Big Data is often characterized by three V's:

- **V**olume (the sheer volume of data)
- **V**elocity (rate of flow of the data and processing speed needs)
- **V**ariety (different sources and formats)

# The three V's of Big Data

Data arise from disparate sources and come in many sizes and formats. Velocity refers to the speed of data generation as well as to processing speed requirements.

| Volume | Velocity | Variety |
|---|---|---|
| MB | batch | table |
| GB | periodic | database |
| TB | near-real time | multimedia |
| PB | real time | unstructured |
| ... | ... | ... |

# Reference: metric prefixes

| | | | | |
|---|---|---|---|---|
| 1000000000000000000000000 | $10^{24}$ | yotta | Y | septillion |
| 1000000000000000000000 | $10^{21}$ | zetta | Z | sextillion |
| 1000000000000000000 | $10^{18}$ | exa | E | quintillion |
| 1000000000000000 | $10^{15}$ | peta | P | quadrillion |
| 1000000000000 | $10^{12}$ | tera | T | trillion |
| 1000000000 | $10^{9}$ | giga | G | billion |
| 1000000 | $10^{6}$ | mega | M | million |
| 1000 | $10^{3}$ | kilo | k | thousand |

**Note:** 1 Gigabyte (GB) is $10^9$ bytes. Sometimes GB is also used to denote $1024^3$ or $2^{30}$ bytes, which is actually one *gibibyte* (GiB).

# Different processing paradigms

- *Batch processing* is when data are collected and submitted to the system in batches without human interaction. Processing is carried out at a later time depending on the availability of resources. Examples of batch processing are: monthly reporting, scientific simulations, model building.
- *Real-time processing* is when a response is guaranteed within a given time frame (seconds, milliseconds, ...). Real-time processing is required by interactive applications such as ATM transactions or computer vision.

Hadoop's MapReduce is a typical batch processing tool.

# Structured vs. unstructured data

- by *structured* data one refers to highly organized data that are usually stored in relational databases or data warehouses. Structured data are easy to search but unflexible in terms of the three "V"s.
- *Unstructured* data come in mixed formats, usually require pre-processing, and are difficult to search. Structured data are usually stored in noSQL databases or in *data lakes* (these are scalable storage spaces for raw data of mixed formats).
- With *semi-structured* data one usually refers to structured data containing unstructured elements (such as free text).

# Examples of structured/unstructured data

| Industry | Structured data | Unstructured data |
|---|---|---|
| e-commerce | • products & prices<br>• customer data<br>• transactions | • product reviews<br>• phone transcripts<br>• social media mentions |
| banking | • financial transactions<br>• customer data | • customer communication<br>• regulations & compliance<br>• financial news |

# Examples of structured/unstructured data

| Industry | Structured data | Unstructured data |
| --- | --- | --- |
| healthcare | • patient records<br>• medical billing data<br>• genomic data | • clinical reports<br>• radiology imagery<br>• clinical speech |
| seismology | • satellite images<br>• seismic wave sensor data | • historic records |

# Forecast: Big Data in 2025

| Data Phase | Astronomy | Twitter | YouTube | Genomics |
|---|---|---|---|---|
| **Acquisition** | 25 zetta-bytes/year | 0.5–15 billion tweets/year | 500–900 million hours/year | 1 zetta-bases/year |
| **Storage** | 1 EB/year | 1–17 PB/year | 1–2 EB/year | 2–40 EB/year |
| **Analysis** | In situ data reduction | Topic and sentiment mining | Limited requirements | Heterogeneous data and analysis |
| | Real-time processing | Metadata analysis | | Variant calling, ~2 trillion central processing unit (CPU) hours |
| | Massive volumes | | | All-pairs genome alignments, ~10,000 trillion CPU hours |
| **Distribution** | Dedicated lines from antennae to server (600 TB/s) | Small units of distribution | Major component of modern user's bandwidth (10 MB/s) | Many small (10 MB/s) and fewer massive (10 TB/s) data movement |

doi:10.1371/journal.pbio.1002195.t001

This table[1] shows the projected annual storage and computing needs in four domains (astronomy, social media, genomics).

[1] Stephens ZD et al. "Big Data: Astronomical or Genomical?" In: *PLoS Biol* (2015).

# The V's of Big Data: additional dimensions

Three more "V"s to be considered:

- **V**eracity (quality or trustworthiness of data)
- **V**alue (economic value of the data)
- **V**ariability (change over time of any of the aforementioned characteristics)

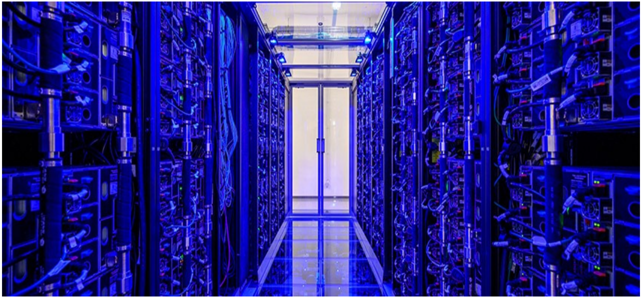
# The challenges of Big Data

When working with large amounts of data you will sooner or later face one or more of these challenges:

- disk and memory space
- processing speed
- hardware faults
- network capacity and speed
- need to optimize resources use

Big Data software tools address these challenges.

# Distributed computing for Big Data

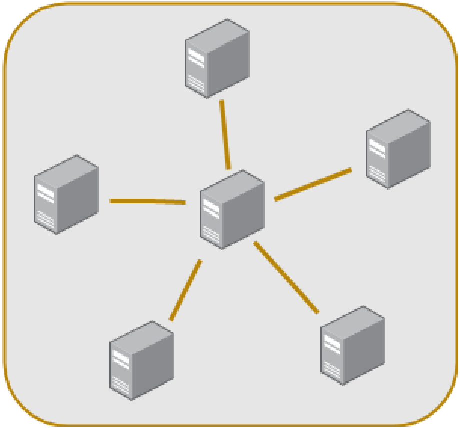


Source: VSC-4 ©Matthias Heisler

Traditional data processing tools are inadequate for large amounts of data.

Distributed computation makes it possible to work with Big Data optimizing time and available resources.

# What is distributed computing?



A distributed computer system consists of several interconnected *nodes*. Nodes can be physical as well as virtual machines or containers.

When a group of nodes provides services and applications to the client as if it were a single machine, then it is also called a *cluster*.

# Benefits of distributed computing

- **Performance**: supports intensive workloads by spreading tasks across nodes
- **Scalability**: new nodes can be added to increase capacity
- **Fault tolerance**: resilience in case of hardware failures

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# The Hadoop distributed computing architecture

# Hadoop for distributed data processing

Hadoop is a framework for running jobs on clusters of computers that provides a good abstraction of the underlying hardware and software.

"*Stripped to its core, the tools that Hadoop provides for building distributed systems—for data storage, data analysis, and coordination—are simple. If there's a common theme, it is about raising the level of abstraction—to create building blocks for programmers who just happen to have lots of data to store, or lots of data to analyze, or lots of machines to coordinate, and who don't have the time, the skill, or the inclination to become distributed systems experts to build the infrastructure to handle it.*[2]"

[2] White T. *Hadoop: The Definitive Guide*. O'Reilly, 2015.

# Hadoop: some facts

Hadoop[3] is an open-source project of the Apache Software Foundation. The project was created to facilitate computations involving massive amounts of data.

- its core components are implemented in Java
- initially released in 2006. Last stable version is 3.3.1 from June 2021
- originally inspired by Google's MapReduce[4] and the proprietary GFS (Google File System)

[3] Apache Software Foundation. *Hadoop*. url: https://hadoop.apache.org.

[4] J. Dean and S. Ghemawat. "MapReduce: Simplified data processing on large clusters." In: *Proceedings of Operating Systems Design and Implementation (OSDI)*. 2004. url: https://www.usenix.org/legacy/publications/library/proceedings/osdi04/tech/full_papers/dean/dean.pdf.

# Hadoop's features

Hadoop's features addressing the challenges of Big Data:

- scalability
- fault tolerance
- high availability
- distributed cache/data locality
- cost-effectiveness as it does not need high-end hardware
- provides a good abstraction of the underlying hardware
- easy to learn
- data can be queried trough SQL-like endpoints (Hive, Cassandra)

# Mini-glossary of Hadoop's distinguishing features

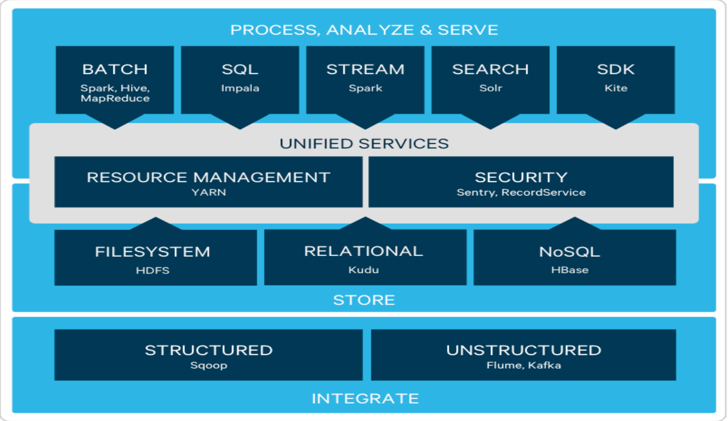
- ***fault tolerance***: the ability to withstand hardware or network failures (also: *resilience*)
- ***high availability***: this refers to the system minimizing downtimes by eliminating single points of failure
- ***data locality***: task are run on the node where data are located, in order to reduce time-consuming transfer of data

# The Hadoop core

The core of Hadoop consists of:

- Hadoop common, the core libraries
- HDFS, the Hadoop Distributed File System
- MapReduce
- the YARN (Yet Another Resource Negotiator) resource manager

# The Hadoop ecosystem




Source: Cloudera

There's a whole constellation of open source components for collecting, storing, and processing big data that integrate with Hadoop.

# Some useful tools that integrate with Hadoop

Just to mention a few:

- **Spark** in-memory computation engine superseding MapReduce
- **Kafka** a distributed streaming system that allows to integrate multiple streams of data for real-time processing
- **Zookeeper** synchronization tool for distributed systems
- **Hbase** a noSQL database (key-value store) that runs on the Hadoop distributed filesystem
- **Hive** a distributed datawarehouse system
- **Presto** a distributed SQL query engine
- **Oozie** a workflow scheduler

All these tools are open source.

# The Hadoop Distributed File System (HDFS)

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HDFS stands for Hadoop Distributed File System and it takes care of partitioning data across a cluster.

In order to prevent data loss and/or task termination due to hardware failures HDFS uses either

- replication (creating multiple copies —usually 3— of the data)
- erasure coding

Data redundancy (obtained through replication or erasure coding) is the basis of Hadoop's fault tolerance.

# Replication vs. Erasure Coding

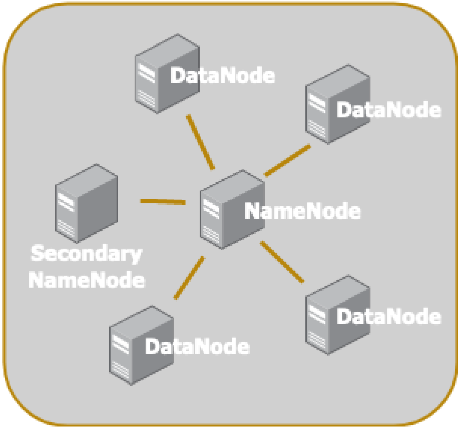
In order to provide protection against failures one introduces:

- data redundancy
- a method to recover the lost data using the redundant data

*Replication is the simplest method for coding data by making $n$ copies of the data. $n$-fold replication guarantees the availability of data for at most $n-1$ failures and it has a storage overhead of 200% (this is equivalent to a storage efficiency of 33%).*

*Erasure coding provides a better storage efficiency (up to to 71%) but it can be more costly than replication in terms of performance.*

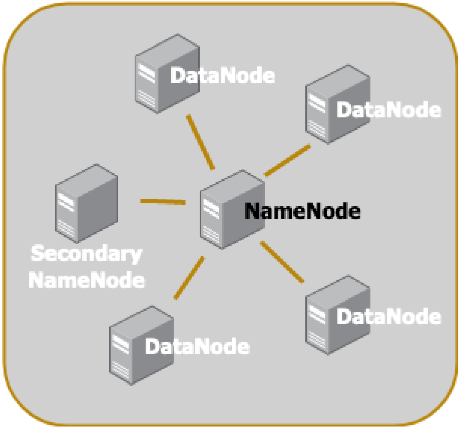
# HDFS architecture




A typical Hadoop cluster installation consists of:

- a NameNode
- a secondary NameNode
- multiple DataNodes

# HDFS architecture: NameNode

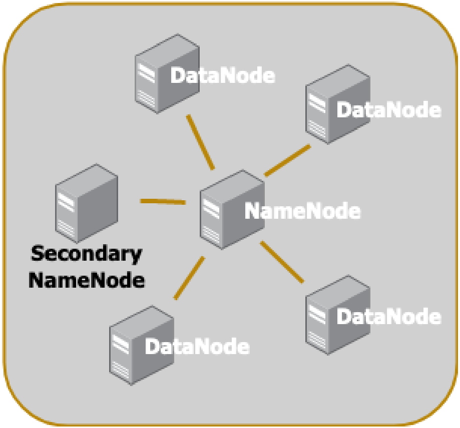



## NameNode

The NameNode is the main point of access of a Hadoop cluster. It is

responsible for the bookkeeping of the data partitioned across the DataNodes, manages the whole filesystem metadata, and performs load balancing

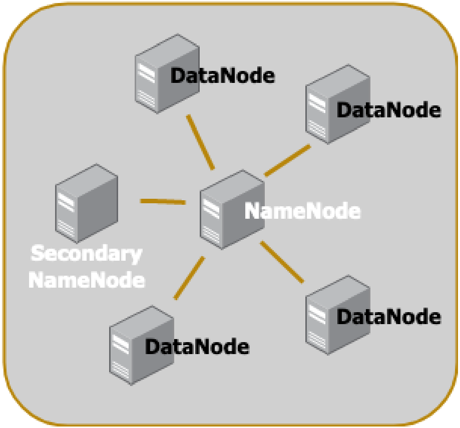
# HDFS architecture: Secondary NameNode




## Secondary NameNode

Keeps track of changes in the NameNode performing regular snapshots, thus allowing quick startup.
An additional *standby node* is needed to guarantee high availability (since the NameNode is a single point of failure).

# HDFS architecture: DataNode




## DataNode

Here is where the data is saved and the computations take place (data nodes should actually be called "data and compute nodes").

# HDFS architecture: internal data representation

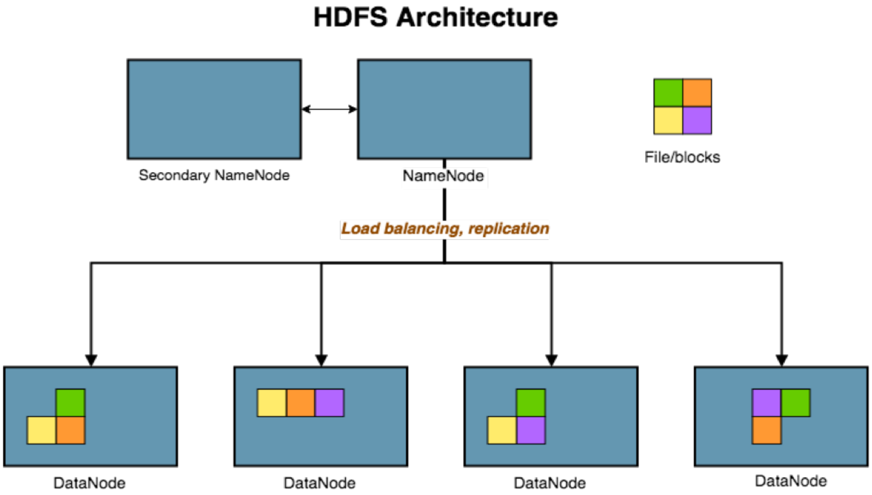
HDFS supports working with very large files.

Internally, data are split into *blocks*. One of the reason for splitting data into blocks is that in this way block objects all have the same size.

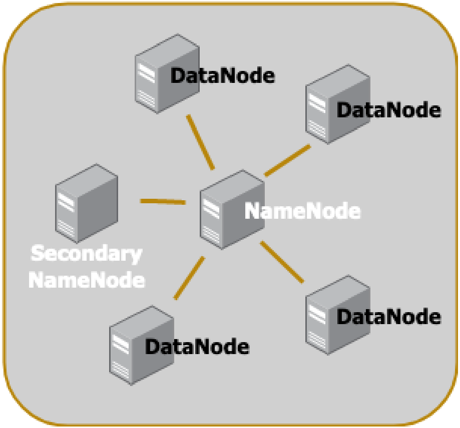
The block size in HDFS can be configured at installation time and it is by default **128MiB** (approximately **134MB**).

**Note:** Hadoop sees data as a bunch of records and it processes multiple files the same way it does with a single file. So, if the input is a directory instead of a single file, it will process all files in that directory.

# HDFS architecture



# Management of DataNode failures




Each DataNode sends a *heartbeat* message to the NameNode periodically.

Whenever a DataNode becomes unavailable (due to network or hardware failure), the NameNode stops sending requests to that node and creates new replicas of the blocks stored on that node.

# Blocks versus partitions

In the next part of the course you will hear about *data partitioning*.

File partitions are logical divisions of the data and should not be confused with blocks, that are physical chunks of data (i.e. each block has a physical location on the hardware).

# The WORM principle of HDFS

The Hadoop Distributed File System relies on a simple design principle for data known as Write Once Read Many (WORM).

"*A file once created, written, and closed need not be changed except for appends and truncates. Appending the content to the end of the files is supported but cannot be updated at arbitrary point. This assumption simplifies data coherency issues and enables high throughput data access.*[5]"

The data immutability paradigm is also discussed in Chapter 2 of "Big Data".[6]

[5] Apache Software Foundation. *Hadoop*. url: https://hadoop.apache.org/docs/stable/hadoop-project-dist/hadoop-hdfs/HdfsDesign.html.

[6] Warren J. and Marz N. *Big Data*. Manning publications, 2015.

# Etymology and grammar of the word "data"

The word "data" comes from the Latin "*datum*", which means "given"—something that can't be derived from anything else. This meaning is reflected in Hadoop data immutability design.

In case you're wondering whether "data" should be considered a plural count noun (singular "datum") or a singular count noun, the answer is: both are allowed.

The correct English form is the plural one ("these data") but the singular form ("Big Data is") is also commonly used (see[7]).

[7] J. Aronson. *A Word About Evidence: 7. Data—etymology and grammar.* https://blogs.bmj.com/bmjebmspotlight/2018/07/01/a-word-about-evidence-7-data-etymology-and-grammar/.

# Data biases

Whenever one works with data, one should keep in mind that data is inherently biased.

For instance, in data harvested from the web some categories of people or themes could be underrepresented due to social, cultural, economic conditions.

And if that's not enough, alone choosing what kind of data to focus on introduces bias.

A good starting point for thinking about biases is.[8]

[8] Ricardo Baeza-Yates. "Bias on the web." In: *Communications of the ACM* 61.6 (2018), pp. 54–61.

# Prerequisites for Hands-on

## NoMachine - Cluster Connection

After NoMachine Client installation and configuration connect to:

```
Name:  HPCSLO (or a name of your liking)
Host:  viz.hpc.fs.uni-lj.si
Port:  4000
Protocol:  NX
```

After entering your credentials and connecting, click on **Create new desktop -> Create new virtual desktop**

Change Keyboard Layout if needed: **Trinity Control Center -> Keyboard** Layout

# Prerequisites for Hands-on

## Course Resources

Pull all resources (slides, code files, ..) from the BitBucket repository **BDR_resources** to your account.

On the command-line:

```
git clone https://git@bitbucket.org/bdtrain/resources.git
```

Folder **day_1** contains all resources for today´s training and folder **day_2** for tomorrow's.

# Prerequisites for Hands-on

**Jupyter Installation**

Create Jupyter environment for Hands-on exercises:

```
python3 -m venv local
local/bin/pip install jupyter
local/bin/pip install mrjob
local/bin/jupyter-notebook
```

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# HDFS hands-on exercises

# Get familiar with the module library

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Module is a Python library used to manage software environments.

```
# show available Hadoop installations
module avail Hadoop
# load the default Hadoop installation
module load Hadoop
# show loaded modules
module list
# unload all modules
module purge
# show currently loaded Hadoop version
module show Hadoop
```

These commands can be found in
`resources/day_1/HDFS/useful_commands.txt`

# Where to find commands listing

For this part of the training you will need to activate the Hadoop module using the command:

```
module load Hadoop
```

All commands in this section can be found in the file:

`HDFS_commands.txt`

in the directory `resources/day_1/HDFS`

# Show cluster configuration

```
# show namenode(s)
hdfs getconf -namenodes
# show datanodes
yarn node -list -all
# show more details for each datanode
yarn node -list
# show blocksize
hdfs getconf -confKey dfs.blocksize|numfmt --to=iec
# show replication factor
hdfs getconf -confKey dfs.replication
```

These commands can be found in
`resources/day_1/HDFS/useful_commands.txt`

# Basic HDFS filesystem commands

One can regard HDFS as a regular file system, in fact many HDFS shell commands are inherited from the corresponding bash commands.

To run a command on an Hadoop filesystem use the prefix `hdfs dfs`, for instance use:

```
hdfs dfs -mkdir myDir
```

to create a new directory `myDir` on HDFS.

**Note:** One can use interchangeably `hadoop` or `hdfs dfs` when working on a HDFS file system. The command `hadoop` is more generic because it can be used not only on HDFS but also on other file systems that Hadoop supports (such as Local FS, WebHDFS, S3 FS, and others).

# Basic HDFS filesystem commands

Basic HDFS filesystem commands that also exist in bash

| | |
|---|---|
| `hdfs dfs -mkdir` | create a directory |
| `hdfs dfs -ls` | list files |
| `hdfs dfs -cp` | copy files |
| `hdfs dfs -cat` | print files |
| `hdfs dfs -tail` | output last part of a file |
| `hdfs dfs -rm` | remove files |

# Basic HDFS filesystem commands

Here's three basic commands that are specific to HDFS.

| | |
|---|---|
| `hdfs dfs -put` | Copy single src, or multiple srcs from local file system to the destination file system |
| `hdfs dfs -get` | Copy files to the local file system |
| `hdfs dfs -usage` | get help on hadoop fs |

# Basic HDFS filesystem commands

To get more help on a specific `hdfs` command use: `hdfs -help <command>`

```
$ hdfs dfs -help tail
# -tail [-f] <file> :
#   Show the last 1KB of the file.

#   -f  Shows appended data as the file grows.
```

# Some things to try

```
# create a new directory called "input" on HDFS
hdfs dfs -mkdir input
# copy local file wiki_1k_lines to input on HDFS
hdfs dfs -put wiki_1k_lines input/
# list contents of directory ("-h" = human)
hdfs dfs -ls -h input
# disk usage
hdfs dfs -du -h input
# get help on "du" command
hdfs dfs -help du
# remove directory
hdfs dfs -rm -r input
```

# Some things to try

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What is the size of the file `wiki_1k_lines`? What is its disk usage?

```
# show the size of wiki_1k_lines on the regular filesystem
ls -lh wiki_1k_lines
# show the size of wiki_1k_lines on HDFS
hdfs dfs -put wiki_1k_lines
hdfs dfs -ls -h wiki_1k_lines

# disk usage of wiki_1k_lines on the regular filesystem
du -h wiki_1k_lines
# disk usage of wiki_1k_lines on HDFS
hdfs dfs -du -h wiki_1k_lines
```

# Disk usage on HDFS

The command `hdfs dfs -help du` will tell you that the output is of the form:

`size disk space consumed filename.`

You'll notice that the space on disk is larger than the file size (38.6MB versus 19.3MB):

```
hdfs dfs -du -h wiki_1k_lines
# 19.3 M  38.6 M  wiki_1k_lines
```

This is due to replication. You can check the replication factor using:

```
hdfs dfs -stat 'Block size: %o Blocks: %b Replication: %r'
   input/wiki_1k_lines
# Block size: 134217728 Blocks: 20250760 Replication: 2
```

# Disk usage on HDFS

From the previous output:

```
Block size: 134217728 Blocks: 20250760 Replication: 2
```

we can see that the HDFS filesystem currently supports a replication factor of 2.

Note that the Hadoop block size is defined in terms of *mebibytes*, in fact 134217728 bytes corresponds to 128MiB and 134MB. One MiB is larger than a MB since one MiB is $1024^2 = 2^{20}$ bytes, while one MB is $10^6$ bytes.

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# The YARN resource manager

# YARN: Yet Another Resource Negotiator

Hadoop jobs are usually managed by YARN (acronym for Yet Another Resource Negotiator), that is responsible for allocating resources and managing job scheduling. Basic resource types are:

- memory (memory-mb)
- virtual cores (vcores)

YARN supports an extensible resource model that allows to define any countable resource. A countable resource is a resource that is consumed while a container is running, but is released afterwards. Such a resource can be for instance:

- GPU (gpu)

# YARN architecture

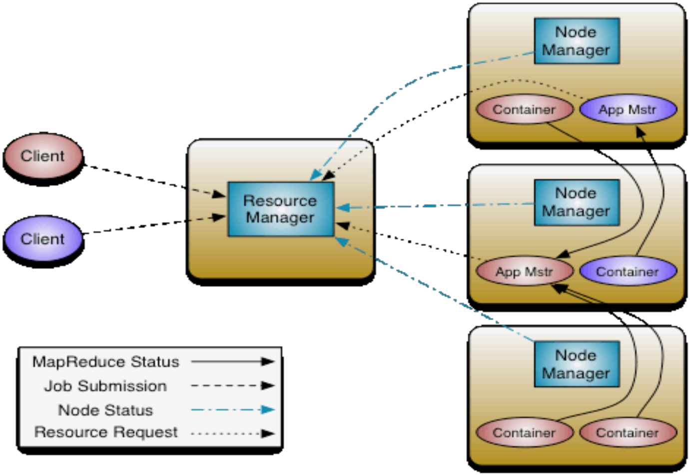


Image source: Apache Software Foundation

# YARN architecture

Each job submitted to the Yarn is assigned:

- a ***container***: this is an abstract entity which incorporates resources such as memory, cpu, disk, network etc. Container resources are allocated by YARN's *Scheduler*.
- an ***ApplicationMaster*** service assigned by the Application Manager for monitoring the progress of the job, restarting tasks if needed

# YARN architecture

The main idea of Yarn is to have two distinct daemons for job monitoring and scheduling, one *global* and one *local* for each application:

- the **Resource Manager** is the global job manager, consisting of:
  - **Scheduler**: allocates resources across all applications
  - **Applications Manager**: accepts job submissions, restart Application Masters on failure
- an **Application Master** is the local application manager, responsible for negotiating resources, monitoring status of the job, restarting failed tasks

# Dynamic resource pools

Sharing computing resources fairly can be a big issue in multi-user environments.

YARN supports *dynamic resource pools* for scheduling applications.

A resource pool is a given configuration of resources to which a group of users is granted access. Whenever a group is not active, the resources are *preempted* and granted to other groups.

Groups are assigned a priority and resources are shared among groups according to these priority values.

Additionally, resource configurations can be scheduled for specific intervals of time.

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# MapReduce

# MapReduce: Idea

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The MapReduce paradigm is inspired by the computing model commonly used in functional programming.

Applying the same function independently to items in a dataset either to transform (*map*) or collate (*reduce*) them into new values, works well in a distributed environment.

# MapReduce: Idea

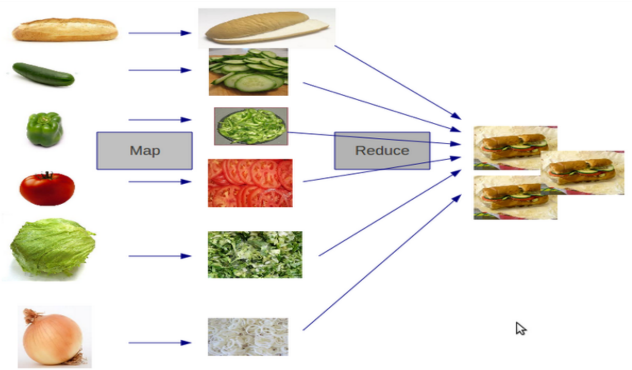



Image source: Stack Overflow

# The origins of MapReduce

The 2004 paper "*MapReduce: Simplified Data Processing on Large Clusters*" by two members of Google's R&D team, Jeffrey Dean and Sanjay Ghemawat, is the seminal article on MapReduce.

The article describes the methods used to split, process, and aggregate the large amount of data for the Google search engine.

The open-source version of MapReduce was later released within the Apache Hadoop project.

# The phases of MapReduce

The phases of a MapReduce job:

- **split**: data is partitioned across several computer nodes
- **map**: apply a map function to each chunk of data
- **sort & shuffle**: the output of the mappers is sorted and distributed to the reducers
- **reduce**: finally, a reduce function is applied to the data and an output is produced

# The phases of MapReduce

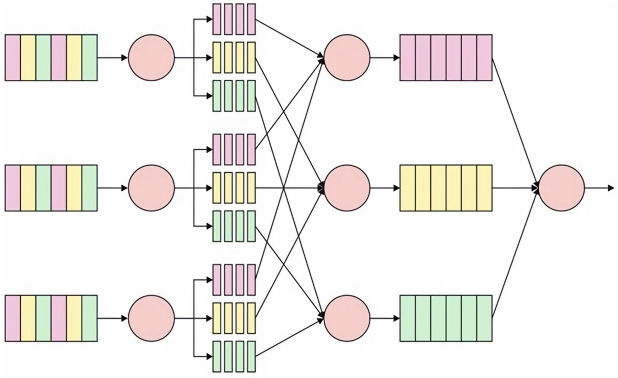


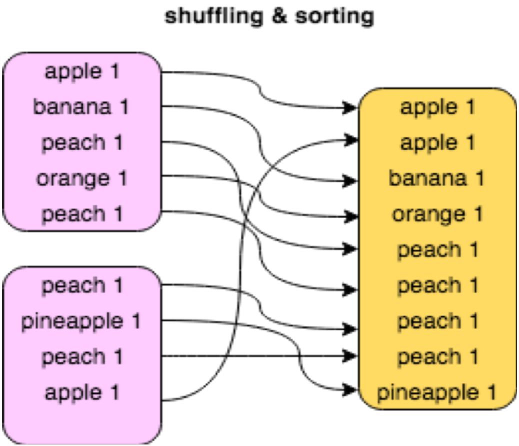
Image source: Nature

# MapReduce: shuffling and sorting

The shuffling and sorting phase is often the the most costly in a MapReduce job as the mapping outputs has to be merged and sorted in order to transfer them to the reducer(s). The purpose of sorting is to

provide data that is already grouped by key to the reducer. This way reducers can iterate over all values from each group.

# MapReduce: shuffling and sorting



# MapReduce: shuffling and sorting

It is also possible for the user to interact with the splitting, sorting and shuffling phases and change their default behavior, for instance by managing the amount of splitting or defining the sorting comparator. This will be illustrated in the hands-on exercises.

While splitting, sorting and shuffling are done by the framework, the map and reduce functions are defined by the user.

# MapReduce: Additional Notes

- Usually a single mapper and reducer do not suffice for a task -> Chaining MapReduce Jobs
- Output key-value pair can contain custom input format or custom data types in case e.g more or special objects have to be passed.

# MapReduce: Key Takeaways

- the same map (and reduce) function is applied to all the chunks in the data
- the mapping and reduce functions have to be defined, custom splitting or sorting are optional as they are given by most MapReduce libraries.
- the map computations can be carried out in parallel because they're completely independent from one another.

# Outline/next

- Introduction
- What is Big Data?
- The Hadoop distributed computing architecture
- HDFS hands-on exercises
- The YARN resource manager
- MapReduce
- MapReduce hands-on
- MRjob
- Concluding remarks

# MapReduce hands-on

## Where to find commands listing

Activate the Hadoop module if you haven´t:

```
module load Hadoop
```

All commands in this section can be found in the file:

```
MapReduce_commands.txt
```

# MapReduce streaming

EURO

The mapreduce streaming library allows to use any executable as mappers and reducers.

- read the input from stdin (line by line)
- emit the output to stdout

```
# check if streaming library is present
echo $STREAMING
# opt/apps/software/Hadoop/2.6.0-cdh5.8.0-native/share/
   hadoop/tools/lib/hadoop-streaming-2.6.0-cdh5.8.0.jar
```

# Check input and output

We're going to use the file `wiki_1k_lines` (later you can experiment with a larger, for instance `wiki_1k_lines`.

```
# check that the output directory does not exist
hdfs dfs -rm -r output

# check if file is in /public
hdfs dfs -cat /public/wiki_1k_lines | head
```

**Note:** If you use a directory or file name that doesn't start with a slash ('/') then the directory or file is meant to be in your home directory (both in bash and on HDFS). A path that starts with a slash is called an *absolute path name*.

# Run a simple MapReduce job

Using the streaming library, we can run the simplest MapReduce job.

```
# launch MapReduce job
hadoop jar $STREAMING \
        -input  /public/wiki_1k_lines  \
        -output  output   \
        -mapper /bin/cat   \
        -reducer  '/bin/wc -l'
```

This job uses as a mapper the `cat` command, that does nothing else than echoing the input. The reducer `wc -l` counts the lines in the given input. Note how we didn't need to write any code for the mapper and reducer

because the executables (`cat` and `wc`) are already there as par of any standard Linux distribution.

# Run a simple MapReduce job

EURO

```
# launch MapReduce job
hadoop jar $STREAMING \
       -input  /public/wiki_1k_lines  \
       -output  output   \
       -mapper /bin/cat   \
       -reducer  '/bin/wc -l'
```

If the job was successful, the output directory on HDFS (we called it output) should contain an empty file called _SUCCESS.

The file part-* contains the output of our job.

```
# check if job was successful (output should contain a file
   named _SUCCESS)
hdfs dfs -ls output
# check result
hdfs dfs -cat output/part-00000
```

# Run a simple MapReduce job

EURO

Launch a MapReduce job with 4 mappers

```
hdfs dfs -rm -r output

# launch MapReduce job
hadoop jar $STREAMING \
        -D mapreduce.job.maps=4 \
        -input  /public/wiki_1k_lines  \
        -output  output   \
        -mapper /bin/cat   \
        -reducer  '/bin/wc -l'

# check if job was successful (output should contain a file
    named _SUCCESS)
hdfs dfs -ls output
# check result
hdfs dfs -cat output/part-00000
```

# Run a simple MapReduce job

Note how it is necessary to delete the `output` directory on HDFS (`hdfs dfs -rm -r output`) because according to the WORM principle, Hadoop will not delete or overwrite existing data!

The option `-D mapreduce.job.maps=4` right after the `jar` directive (in this example `-D mapreduce.job.maps=4`) allows to change MapReduce properties at runtime.

The list of all MapReduce options can be found in: mapred-default.xml

**Note:** this is the link to the last stable version, there might be some slight changes with respect to the version that is currently installed on the cluster.

# Wordcount

We are now going to run a wordcount job using Python executables as mapper and reducer.

The mapper will be called `mapper.py` and the reducer `reducer.py`. Since these executables are not known to Hadoop, it is necessary to add them with the options

```
-files mapper.py -files reducer.py
```

**Note:** it is possible to have several mappers and reducers in one Mapreduce job, the output of each function is sent as input to the next one.

# Define the mapper

```
#!/bin/python3
import sys
for line in sys.stdin:
    words = line.strip().split()
    for word in words:
        print("{}\t{}".format(word,1))
```

Listing 1: mapper.py

# Define the reducer

```
#!/bin/python3
import sys
current_word, current_count = None, 0
for line in sys.stdin:
    word, count = line.strip().split('\t', 1)
    try:
        count = int(count)
    except ValueError:
        continue
    if current_word == word:
        current_count += count
    else:
        if current_word:
            print("{}\t{}".format(current_word,
  current_count))
        current_count = count
        current_word = word
if current_word == word:
    print("{}\t{}".format(current_word, current_count))
```

# Run the job

```
# remove output directory
hdfs dfs -rm -r output

hadoop jar $STREAMING \
      -files mapper.py \
      -files reducer.py \
      -mapper mapper.py \
      -reducer reducer.py \
      -input /public/wiki_1k_lines \
      -output output
```

Check results.

```
# check if job was successful (output should contain a file
   named _SUCCESS)
hdfs dfs -ls output
# check result
hdfs dfs -cat output/part-00000|head
```

# Sorting the output after the job

The reducer just writes the list of words and their frequency in the order given by the mapper.

The output of the reducer is sorted by key (the word) because that's the ordering that the reducer becomes from the mapper. If we're interested in sorting the data by frequency, we can use the Unix `sort` command with the options `k2`, `n`, `r` meaning respectively "by field 2", "numeric", "reverse".

```
hdfs dfs -cat output/part-00000|sort -k2nr|head
```

The output should be something like:

```
the 193778
of  117170
and 89966
in  69186
. . .
```

# Sorting with MapReduce

To sort by frequency using the mapreduce framework, we can employ a simple trick: create a mapper that interchanges words with their frequency values. Since by construction mappers sort their output by key, we get the desired sorting as a side-effect.

Create a script swap_keyval.py

```
#!/bin/python3
import sys
for line in sys.stdin:
    word, count = line.strip().split('\t')
    if int(count)>100:
        print("{}\t{}".format(count, word))
```

Listing 3: swap_keyval.py

# Sorting with MapReduce

EURO

Run the new MapReduce job using output as input and writing results to a new directory output2.

```
# write the output to the directory output2
hdfs dfs -rm -r output2

hadoop jar $STREAMING \
      -files swap_keyval.py \
      -input output \
      -output output2 \
      -mapper swap_keyval.py
```

Looking at the output, one can see that it is sorted by frequency but alphabetically.

```
hdfs dfs -cat output2/part-00000|head
# 10021 his
# 1005  per
# 101 merely
#
```

# Using comparator classes for sorting

In general, we can determine how mappers are going to sort their output by configuring the comparator directive to use the special class `KeyFieldBasedComparator`:

```
-D mapreduce.job.output.key.comparator.class=\
    org.apache.hadoop.mapred.lib.KeyFieldBasedComparator
```

This class has some options similar to the Unix sort (`-n` to sort numerically, `-r` for reverse sorting, `-k pos1[,pos2]` for specifying fields to sort by). See documentation: KeyFieldBasedComparator.html

# Using comparator classes for sorting

```
hdfs dfs -rm -r output2

comparator_class=org.apache.hadoop.mapred.lib.
    KeyFieldBasedComparator

hadoop jar $STREAMING \
     -D mapreduce.job.output.key.comparator.class=
    $comparator_class \
     -D mapreduce.partition.keycomparator.options=-nr \
     -files swap_keyval.py \
     -input output \
     -output output2 \
     -mapper swap_keyval.py
```

# Using comparator classes for sorting

Now MapReduce has performed the desired sorting on the data.

```
hdfs dfs -cat output2/part-00000|head
193778  the
117170  of
89966 and
69186 in
. . .
```

# Modify the Wordcount example

Try to modify the wordcount example:

- using executables in other programming languages
- adding a mapper that filters certain words
- using larger files

# Run the MapReduce examples

The MapReduce distribution comes with some standard examples including source code.

To get a list of all available examples use:

```
hadoop jar \
  $HADOOP_HOME/hadoop-mapreduce-examples-2.6.0-cdh5.8.0.jar
```

Run the Wordcount example:

```
hadoop jar \
  $HADOOP_HOME/hadoop-mapreduce-examples-2.6.0-cdh5.8.0.jar
    wordcount /public/wiki_1k_lines output3
```

# MapReduce example: Electricity Consumption

**Goal:** Get the average daily electricity consumption of a consumer per year. **Data:** 2.9 million rows of data

| NA | date_time | region | date_measurement | time_txt | validity | consumption | year | month | day | day_name | week | v3 | v4 | id_new |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2016-10-08 23:15:00 | 02 | 2016-10-08 | 231500 | PD0 | 6.96 | 2016 | 10 | 8 | Saturday | 40 | 92 | 0.2 | 512132 |
| 2 | 2016-10-08 23:30:00 | 02 | 2016-10-08 | 233000 | PD0 | 6.4 | 2016 | 10 | 8 | Saturday | 40 | 92 | 0.2 | 512132 |
| 3 | 2016-10-08 23:45:00 | 02 | 2016-10-08 | 234500 | PD0 | 6.48 | 2016 | 10 | 8 | Saturday | 40 | 92 | 0.1 | 512132 |
| 4 | 2016-10-09 00:00:00 | 02 | 2016-10-09 | 000000 | PD0 | 7.76 | 2016 | 10 | 9 | Sunday | 40 | 92 | 0.1 | 512132 |
| 5 | 2016-10-09 00:15:00 | 02 | 2016-10-09 | 001500 | PD0 | 6.8 | 2016 | 10 | 9 | Sunday | 40 | 93 | 0.1 | 512132 |
| 6 | 2016-10-09 00:30:00 | 02 | 2016-10-09 | 003000 | PD0 | 6.96 | 2016 | 10 | 9 | Sunday | 40 | 93 | 0.1 | 512132 |
| 7 | 2016-10-09 00:45:00 | 02 | 2016-10-09 | 004500 | PD0 | 6.52 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0 | 512132 |
| 8 | 2016-10-09 01:00:00 | 02 | 2016-10-09 | 010000 | PD0 | 6.8 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0 | 512132 |
| 9 | 2016-10-09 01:15:00 | 02 | 2016-10-09 | 011500 | PD0 | 7.52 | 2016 | 10 | 9 | Sunday | 40 | 93 | 0.1 | 512132 |
| 10 | 2016-10-09 01:30:00 | 02 | 2016-10-09 | 013000 | PD0 | 6.56 | 2016 | 10 | 9 | Sunday | 40 | 93 | 0.1 | 512132 |
| 11 | 2016-10-09 01:45:00 | 02 | 2016-10-09 | 014500 | PD0 | 8.4 | 2016 | 10 | 9 | Sunday | 40 | 93 | 0 | 512132 |
| 12 | 2016-10-09 02:00:00 | 02 | 2016-10-09 | 020000 | PD0 | 6.76 | 2016 | 10 | 9 | Sunday | 40 | 93 | 0 | 512132 |
| 13 | 2016-10-09 02:15:00 | 02 | 2016-10-09 | 021500 | PD0 | 7.2 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0.2 | 512132 |
| 14 | 2016-10-09 02:30:00 | 02 | 2016-10-09 | 023000 | PD0 | 7.88 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0.2 | 512132 |
| 15 | 2016-10-09 02:45:00 | 02 | 2016-10-09 | 024500 | PD0 | 7.16 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0.4 | 512132 |
| 16 | 2016-10-09 03:00:00 | 02 | 2016-10-09 | 030000 | PD0 | 6.36 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0.4 | 512132 |
| 17 | 2016-10-09 03:15:00 | 02 | 2016-10-09 | 031500 | PD0 | 6.56 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0.1 | 512132 |
| 18 | 2016-10-09 03:30:00 | 02 | 2016-10-09 | 033000 | PD0 | 6.76 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0.1 | 512132 |
| 19 | 2016-10-09 03:45:00 | 02 | 2016-10-09 | 034500 | PD0 | 7.4 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0 | 512132 |
| 20 | 2016-10-09 04:00:00 | 02 | 2016-10-09 | 040000 | PD0 | 6.64 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0 | 512132 |
| 21 | 2016-10-09 04:15:00 | 02 | 2016-10-09 | 041500 | PD0 | 7.12 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0 | 512132 |
| 22 | 2016-10-09 04:30:00 | 02 | 2016-10-09 | 043000 | PD0 | 6.72 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0 | 512132 |
| 23 | 2016-10-09 04:45:00 | 02 | 2016-10-09 | 044500 | PD0 | 8.28 | 2016 | 10 | 9 | Sunday | 40 | 94 | 0 | 512132 |
| 24 | 2016-10-09 05:00:00 | 02 | 2016-10-09 | 050000 | PD0 | [illegible] | 2016 | 10 | 9 | Sunday | 40 | 94 | 0 | [illegible] |

# Electricity Consumption: First Mapper

```
#!/bin/python3
import sys

# input comes from STDIN (standard input)
for line in sys.stdin:
    # remove leading and trailing whitespace
    line = line.strip()
    # split the line into words
    words = line.split(",")

    customerID_date= words[-1] + "_" + words[3]
    consumptionPerDay = words[6]

    print("{}\t{}".format(customerID_date, consumptionPerDay
    ))
```

Listing 4: mapper.py

# Electricity Consumption: First Reducer

EURO

```
#!/bin/python3
import sys
from operator import itemgetter

currentCustomer = None
currentConsumption = 0

for line in sys.stdin:
    line = line.strip()

    customerID_date, consumptionPerDay = line.split("\t", 1)
    consumptionPerDay = int(consumptionPerDay)

    if currentCustomer == customerID_date:
        currentConsumption += consumptionPerDay
    else:
        if currentConsumption:
            print("{}\t{}".format(currentCustomer, currentConsumption))
        currentConsumption = consumptionPerDay
        currentCustomer = customerID_date

if currentCustomer == customerID_date:
    print("{}\t{}".format(currentCustomer, currentConsumption))
```

Listing 5: reducer.py

# Electricity Consumption: Second Mapper

```
#!/bin/python3
import sys

for line in sys.stdin:
    line = line.strip()

    customerID_date, consumptionPerDay = line.split("\t", 1)
    customerID_date = customerID_date.split("-",1)[0]

    print("{}\t{}".format(customerID_date, consumptionPerDay
   ))
```

Listing 6: second_mapper.py

# Electricity Consumption: Second Reducer

```
#!/bin/python3
import sys
from operator import itemgetter

allConsumptions = {}

for line in sys.stdin:
    line = line.strip()

    customerID_date, consumptionPerDay = line.split("\t", 1)
    consumptionPerDay = int(consumptionPerDay)


    if customerID_date in allConsumptions:
        allConsumptions[customerID_date].append(consumptionPerDay)
    else:
        allConsumptions[customerID_date] = []
        allConsumptions[customerID_date].append(consumptionPerDay)


for year in sorted(allConsumptions):
    print("{}\t{}".format(year, sum(allConsumptions[year]) / len(allConsumptions[
     year])))
```

Listing 7: second_reducer.py

# Run jobs

```
hadoop jar $STREAMING \
      -mapper mapper.py \
      -reducer reducer.py \
      -input /public/electricity_data_recorded.csv \
      -output output
```

And second job:

```
hadoop jar $STREAMING \
      -mapper second_mapper.py \
      -reducer second_reducer.py \
      -input output \
      -output result
```

# MapReduce example: Electricity Consumption

EURO

## Results

```
# check if job was successful (output should contain a file
    named _SUCCESS)
hdfs dfs -ls result
# check result
hdfs dfs -cat result/part-00000|head
```

```
1018508_2016    12
1018508_2017    21
1054499_2016    17
1054499_2017    11
1104818_2017    572
1104818_2018    697
1117919_2017    417
1117919_2018    586
1119320_2016    37
1119320_2017    22
```

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# MRjob

# MRjob

What is MRjob? It's a wrapper for MapReduce that allows to write MapReduce jobs in pure Python.

The library can be used for testing MapReduce as well as Spark jobs without the need of a Hadoop cluster.

Here's a quick-start tutorial:
https://mrjob.readthedocs.io/en/latest/index.html

# A MRjob wordcount

```
from mrjob.job import MRJob

class MRWordFrequencyCount(MRJob):
    """
    A class to represent a Word Frequency Count mapreduce
    job
    """
    def mapper(self, _, line):
        yield "chars", len(line)
        yield "words", len(line.split())
        yield "lines", 1

    def reducer(self, key, values):
        yield key, sum(values)

if __name__ == '__main__':
    MRWordFrequencyCount.run()
```

Listing 8: word_count.py

# A MRjob wordcount

Run the job:

```
mypython/bin/python3 word_count.py data/wiki_1k_lines
```

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# Concluding remarks

# Big Data on VSC course

As part of the Vienna Scientific cluster training program, we offered a course "Big Data on VSC" in 2021.

Our Hadoop expertise comes from managing a Big Data cluster named LBD (Little Big Data*) at the Vienna University of Technology (TU Wien). The cluster—available since December 2017—is used for teaching and research.

(*) https://lbd.zserv.tuwien.ac.at/

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