MapReduce & Spark

CS524: Big Data Visualization & Analytics

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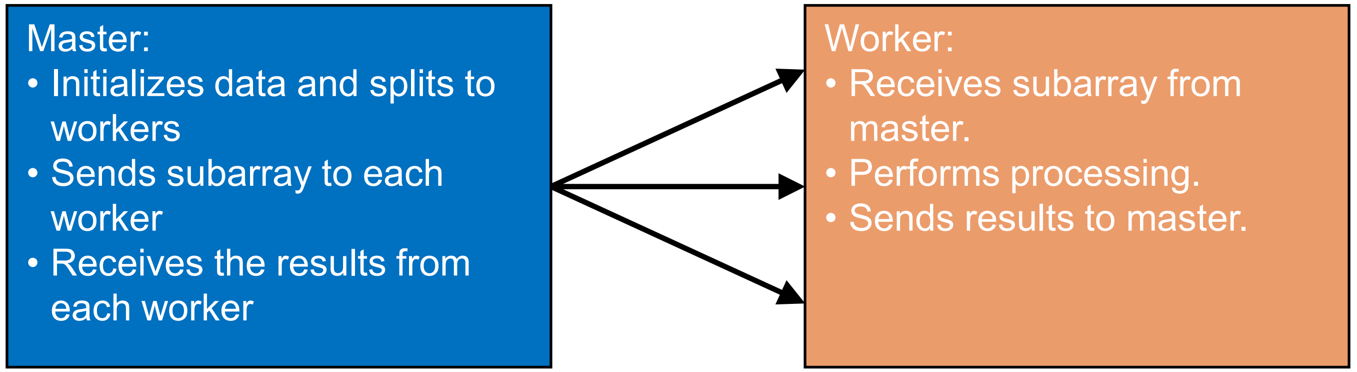
Background

- Traditional programming is serial.
- Parallel programming: breaks processing into parts that can be executed concurrently on multiple processors.
- Challenge: identify tasks or groups of data that can be processed concurrently.

Background

- Simple environment for parallel processing?
  - No data dependency.
  - Data can be split into smaller chunks.
  - Each process can work on a different chunk.
- Master / worker approach:


Master:
• Initializes data and splits to workers
• Sends subarray to each worker
• Receives the results from each worker
Worker:
• Receives subarray from master.
• Performs processing.
• Sends results to master.

Motivation: large-scale data processing

- Several tasks process lots of data to produce other data.
  - Easily parallelized to hundreds or thousands of CPUs.
  - Needs to be easy!
- MapReduce: programming model for processing big data.
- Main ideas:
  1. Abstraction
  2. Scale out vs. scale up
  3. Fault tolerance
  4. Move processing to data
  5. Avoid random access

Idea 1: abstraction

- Finding the right level of abstraction:
  - Hide system-level details from the developers.
  - No more race conditions, lock contention, etc.
- MapReduce separates the *what* from *how*:
  - Developer specifies the computation that needs to be performed.
  - Execution framework handles actual execution.
  - Inspired by LISP – functional programming.

Idea 2: scale out vs. scale up

- Scale up: small number of high-end servers.
  - Large shared memory.
  - Not cost effective: cost of machine does not scale linearly; no single machine is big enough.
- Scale out: large number of commodity low-end servers.
  - 8 128-core machines vs. 128 8-core machines.

"Low-end server platform is about 4 times more cost efficient than a high-end shared memory platform from the same vendor"

Barroso and Hölzle, 2009

Idea 3: fault tolerance

- Suppose a cluster is built using machines with a mean-time between failures (MTBF) of 1,000 days.
- For a 10,000-server cluster, there are on average 10 failures per day.
- MapReduce copes with failures:
  - Automatic task restarts.
  - Store files multiple times for reliability.

Idea 4: move processing to data

- HPC: often have processing nodes and storage nodes.
  - Computationally expensive tasks.
  - High-capacity connection to move data around.
- Many data-intensive applications are not processor demanding.
  - Data movement leads to a bottleneck in the network.
  - Idea: move processing to where the data reside.
- MapReduce: processors and storage are co-located, leveraging locality.

Idea 5: avoid random access

- Disk seek times are determined by mechanical factors.
- Example:
  - 1 TB database containing 10^10 100 byte records.
  - Random access: each update takes ~30 ms (seek, read, write).
  - Updating 1% of the records takes ~35 days.
  - Sequential access: 100 MB/s throughput
  - Reading the whole database and rewriting all records takes 5.6 hours.
- MapReduce was designed for batch processing: organize computations into long streaming operations.

Large-scale problem

- Data: large number of records.
- Naïve solution:
  - Iterate over a large number of records.
  - Extract something of interest from each.
  - Sort and shuffle intermediate results.
  - Aggregate intermediate results.
  - Generate final output.

MapReduce key idea: provide a functional abstraction for these operations

Large-scale problem in MapReduce

- Data: large number of records.
- MapReduce solution:
  - Iterate over a large number of records.
  - Map: Extract something of interest from each.

$$map(k, v) \rightarrow < k', v' >^*$$

  - Group by key: sort and shuffle intermediate results.
  - Reduce: Aggregate intermediate results.

$$reduce(k', < v' >^*) \rightarrow < k', v'' >^*$$

  - Generate final output.

Structure remains the same, map and reduce functions change to fit the problem.

MapReduce

- Map:
    - Grab the relevant data from the source.
    - User function gets called for each chunk of input.
    - Spits out (key, value) pairs.
- Reduce:
    - Aggregate the results.
    - User function gets called for each unique key with all values corresponding to that key.

Simple example: map

```
var a = [1, 2, 3];

for(var i=0; i<a.length; i++){
    a[i] = a[i] * 2;
}

for(var i=0; i<a.length; i++){
    console.log(a[i]);
}
```

```
var a = [1, 2, 3];

function map(f, a){
    for(var i=0; i<a.length; i++){
        a[i] = f(a[i]);
    }
}

map(function(x){return x * 2;}, a);
map(alert, a);
```

Simple example: reduce

```javascript
var nums = [1, 2, 3, 4];

function sum(a){
    var sum = 0;
    for(var i=0; i<a.length; i++)
        sum += a[i];
    return sum;
}

function mult(a){
    var mult=1;
    for(var i=0; i<a.length; i++)
        mult *= a[i];
    return mult;
}

console.log(sum(nums));
console.log(mult(nums));
```

```javascript
var nums = [1, 2, 3, 4];

function reduce(f, a, init){
    var s = init;
    for(var i=0; i<a.length; i++)
        s = f(s, a[i]);
    return s;
}

function add(a, b){
    return a+b;
}
function mult(a, b){
    return a*b;
}

console.log(reduce(add, nums, 0));
console.log(reduce(mult, nums, 1));
```

Moving towards MapReduce

- Adapt to a restricted model of computation.
- Goals:
  - Scalability: more machines, algorithm run faster.
  - Efficiency: resources will not be wasted.
- Translating some algorithms into MapReduce isn't obvious.
  - Think in terms of map & reduce.
  - Decompose complex algorithms into a sequence of jobs.

Moving towards MapReduce

- Ideal scenario:
  - Twice the data, twice the running time.
  - Twice the resources, half the running time.
- Why can't we achieve this?
  - Synchronization requires communication.
- Big idea: avoid communication.
  - Reduce intermediate data via local aggregation.

MapReduce: complete picture

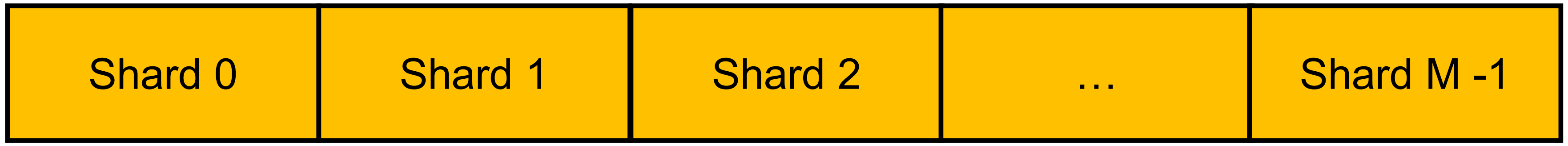
- Map - $map(k, v) \rightarrow < k', v' >^*$
    - (input shard) → intermediate(key / value pairs)
    - Automatically partition input data into M shards.
    - Generate (key, value) sets.
    - Groups together intermediate values with the same intermediate key & pass them to the reduce function.
- Reduce - $reduce(k', < v' >^*) \rightarrow < k', v'' >^*$
    - Intermediate(key / value pairs) → result files
    - Input: key * set of values.
    - Merge these values together to form a smaller set of values.

MapReduce: step by step

- Step 1: split input into chunks (shards)
- Step 2: fork processes
- Step 3: run map tasks
- Step 4: intermediate files
- Step 5: sorting
- Step 6: reduce
- Step 7: result

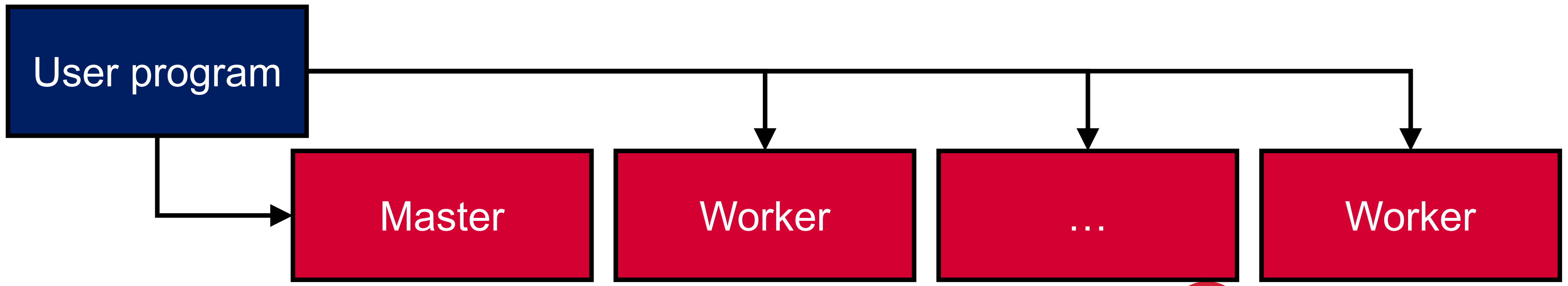
Step 1: split input into chunks (shards)

- Break data into M smaller pieces.



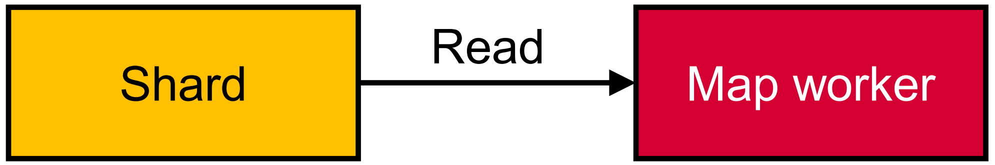
Step 2: fork processes

- Start up many copies of the program on a cluster of machines.
  - One master to schedule & coordinate.
  - Lots of workers.
- Idle workers are assigned to:
  - Map tasks, each working on a shard: M map tasks
  - Reduce tasks, each working on intermediate files: R reduce tasks



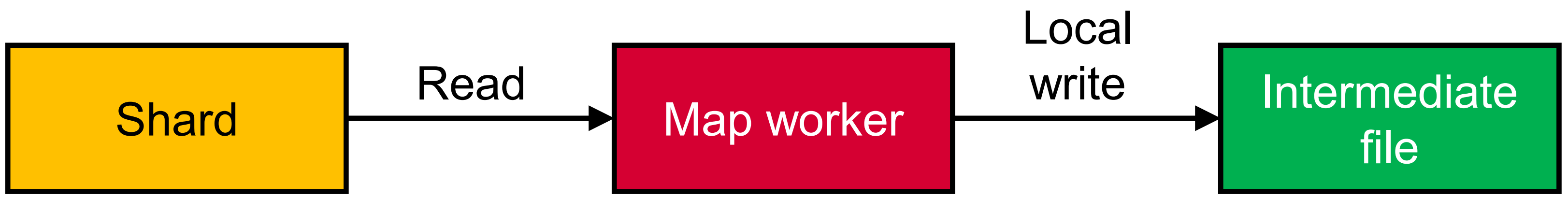
Step 3: run map tasks

- Reads input shard assigned to it.
- Parses key / value pairs of the input data.
- Passes *each* pair to a user-defined map function.
  - Produces intermediate key / value pairs.
  - Buffered in memory.



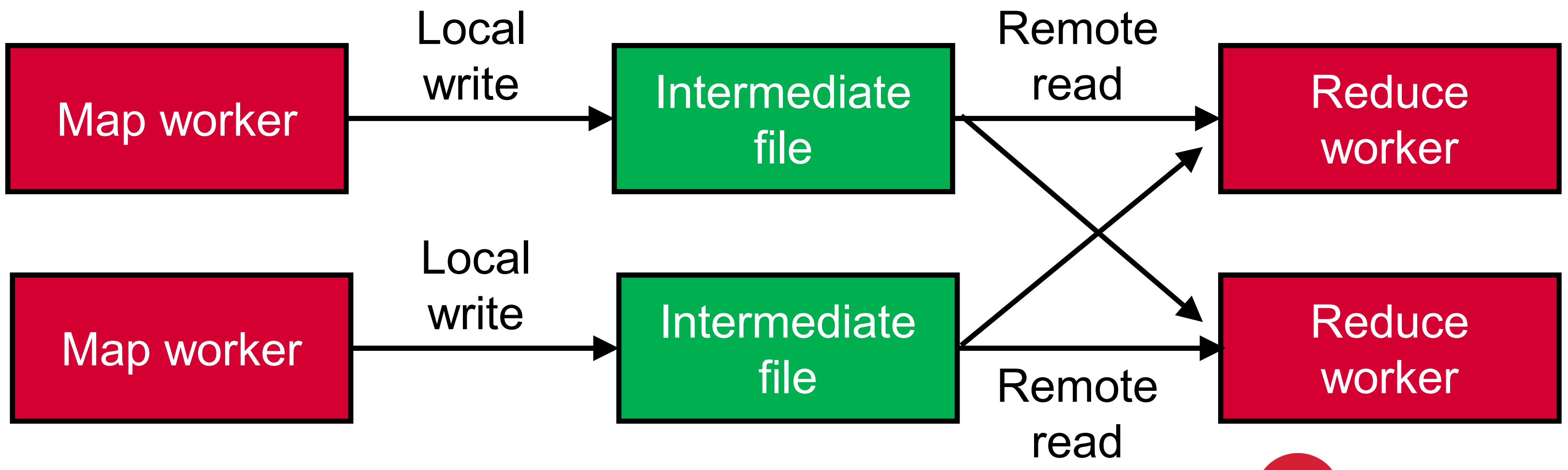
Step 4: intermediate files

- Intermediate key / value pairs produced by user's map function are buffered in memory and written to local disk.



Step 5: sorting

- Reduce workers access intermediate files.
- Sort: reduce workers read intermediate data.
  - Sorts data by intermediate keys.
  - All occurrence of the same key are grouped together

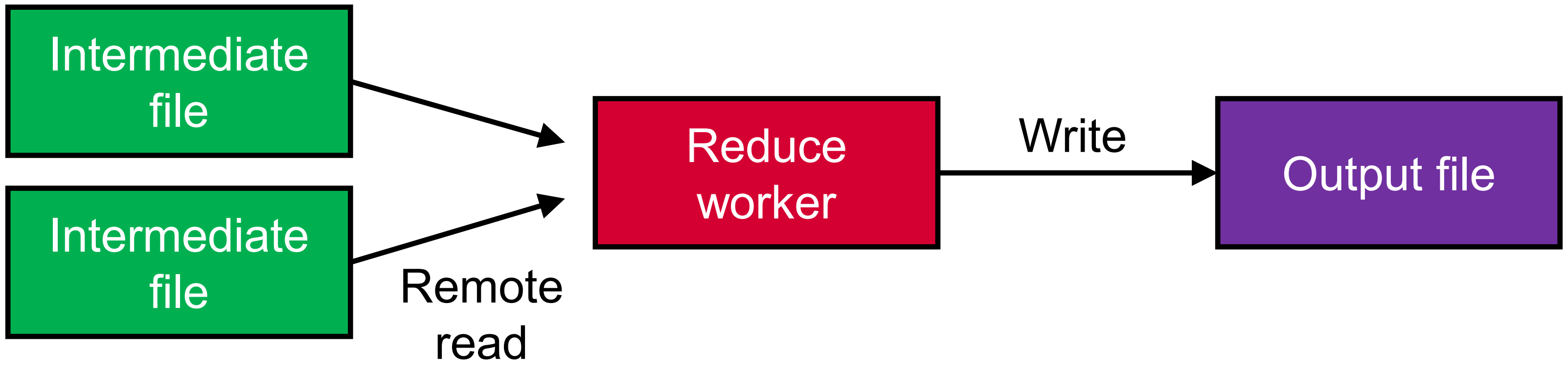


Step 6: reduce

- Step 5 (sort) groups data with a unique intermediate key.
- User's reduce function is given the key and the set of intermediate values for that key.

$$reduce(k', < v' >^*) \rightarrow < k', v'' >^*$$

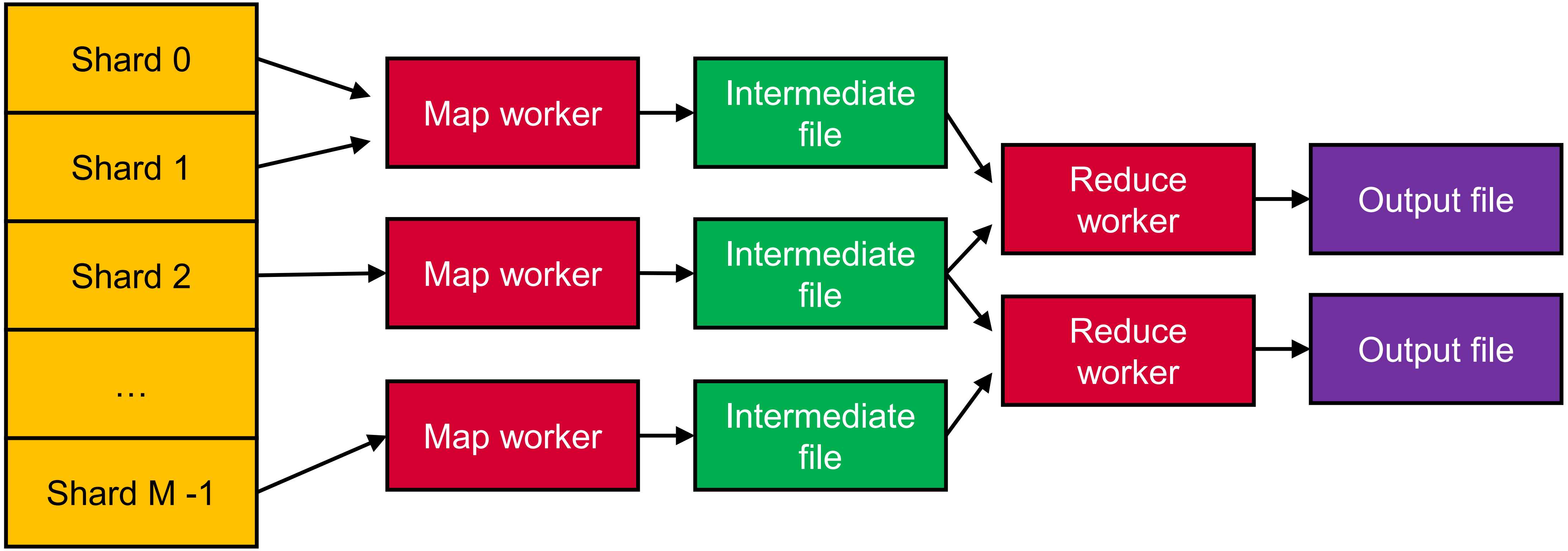
- Output of the reduce function is appended to an output file.



Step 7: result

- When all map and reduce tasks have completed, master starts user program.
- Output of MapReduce is available in output files.

MapReduce: complete picture

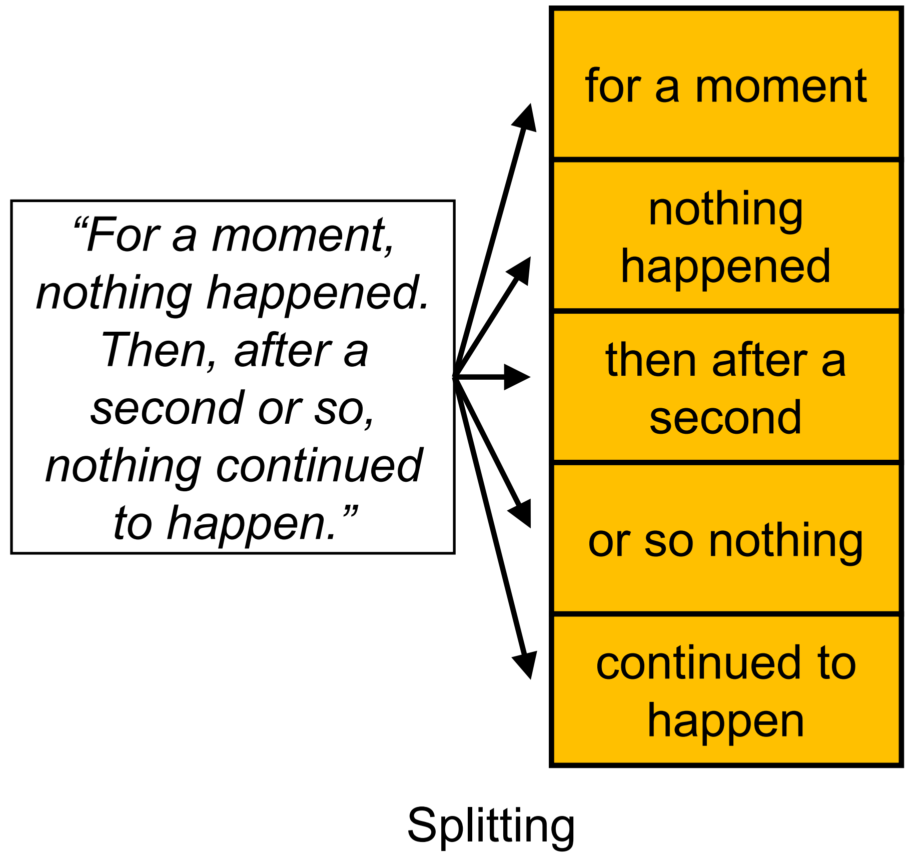


MapReduce word count example

- Simple example: word count.
- Two programs:
  - mapper.py
  - reducer.py

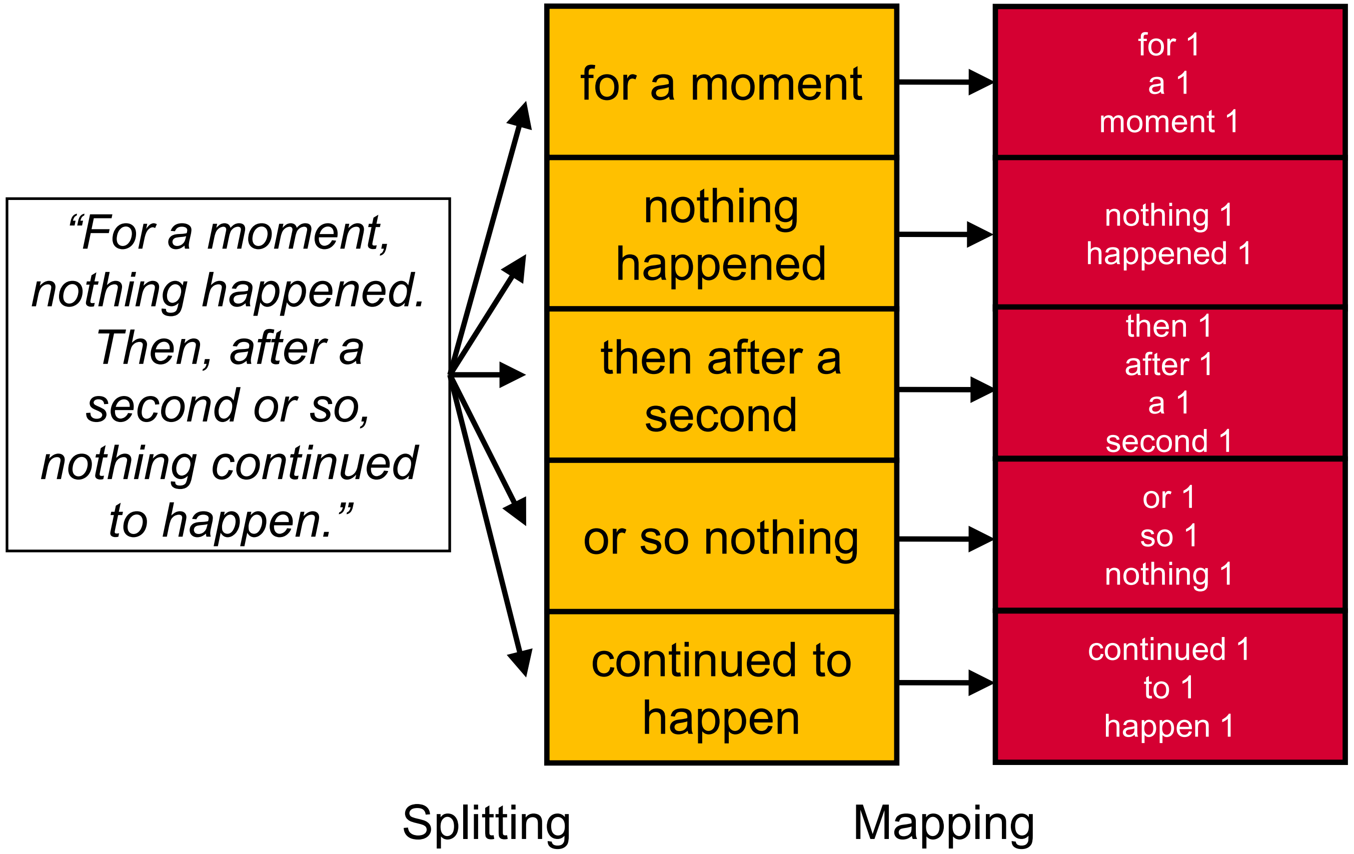
“For a moment, nothing happened. Then, after a second or so, nothing continued to happen.”

MapReduce word count example

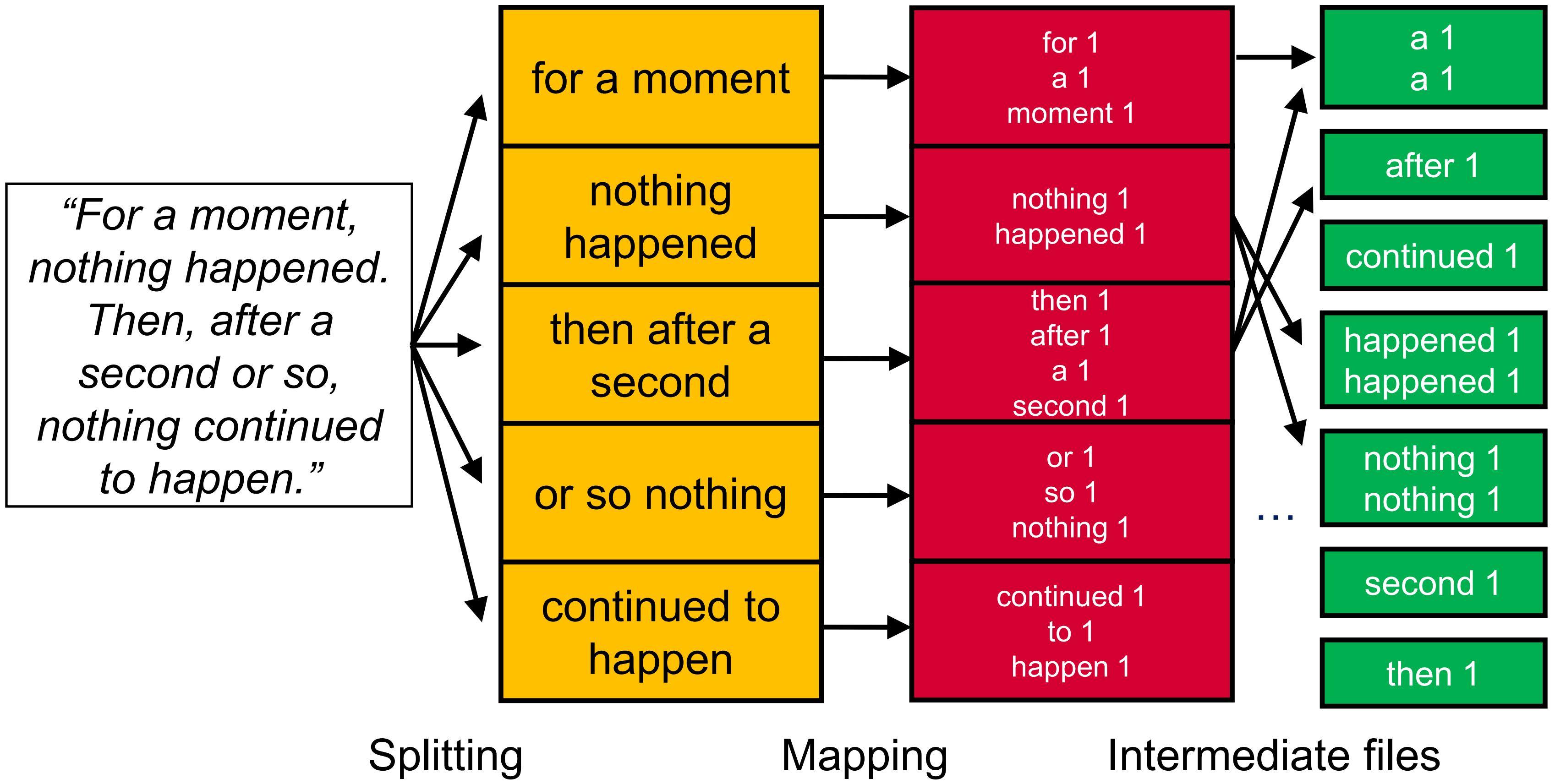


"For a moment, nothing happened. Then, after a second or so, nothing continued to happen."
for a moment
nothing happened
then after a second
or so nothing
continued to happen
Splitting

MapReduce word count example



MapReduce word count example



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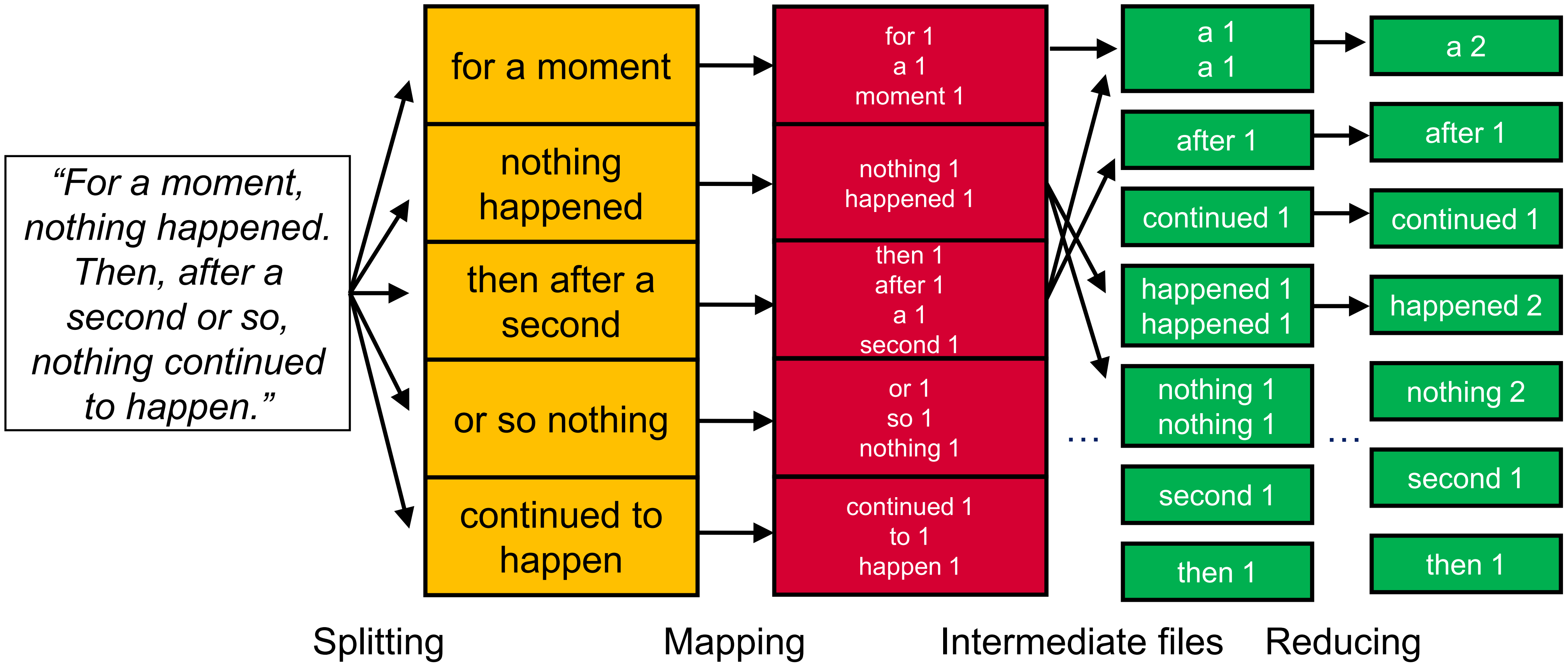
MapReduce word count example



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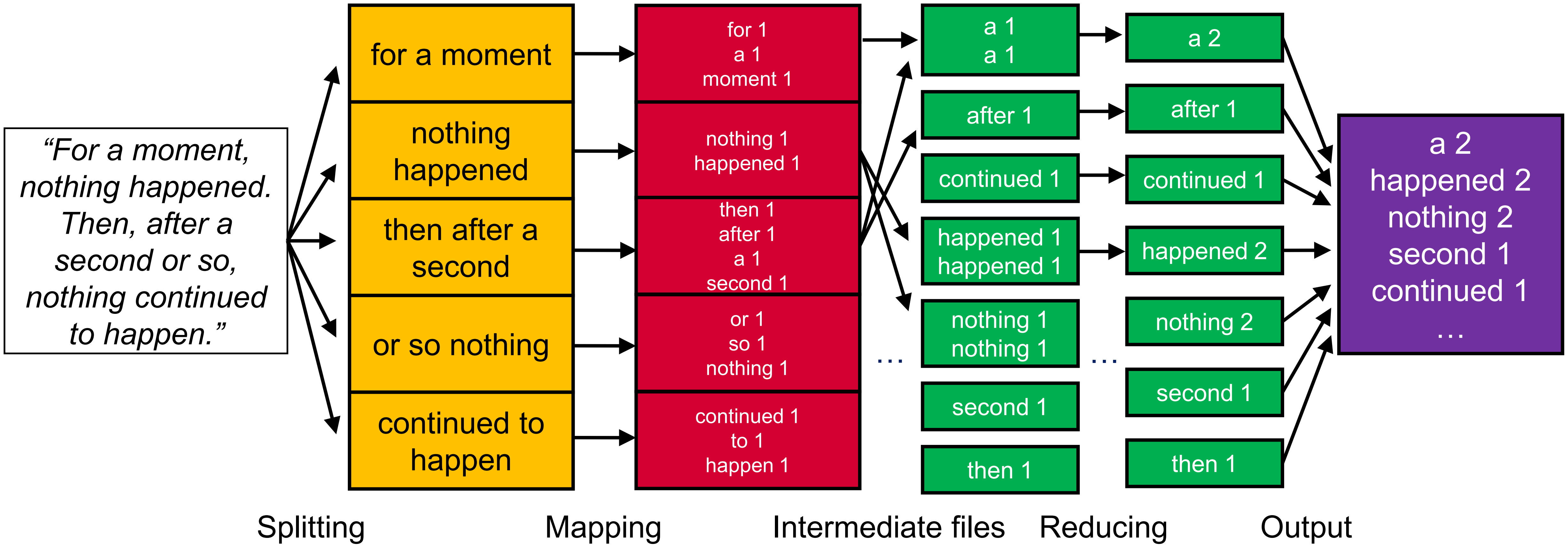

MapReduce word count example

mapper.py

```
import sys
for line in sys.stdin:
  words = line.strip().split()
  for word in words:
    print('%s\t%s'%(word, 1))
```

reducer.py

```
import sys
cur_word = None
cur_count = 0
word = None
for line in sys.stdin:
  word, count = line.strip().split('\t’,1)
  count = int(count)
  if cur_word == word:
    cur_count += count
  else:
    if cur_word:
      print('%s\t%s'% (cur_word, cur_count))
    cur_count = count
    cur_word = word
if cur_word == word:
  print('%s\t%s'%(cur_word, cur_count))
```

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MapReduce word count example

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    if cur_word:
      print('%s\t%s'% (cur_word, cur_count))
    cur_count = count
    cur_word = word
if cur_word == word:
  print('%s\t%s'%(cur_word, cur_count))
```

```
$ cat example.txt | python.exe map.py
for       1
a         1
moment    1
nothing   1
happened  1
then      1
after     1
a         1
second    1
or        1
so        1
nothing   1
continued 1
to        1
happen    1
```

MapReduce word count example

mapper.py

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after     1
a         1
second    1
or        1
so        1
nothing   1
continued 1
to        1
happen    1
```

```
$ cat example.txt | python.exe map.py |
sort -k1,1 | python.exe reduce.py
a         2
after     1
continued 1
for       1
happen    1
happened  1
moment    1
nothing   2
or        1
second    1
so        1
then      1
to        1
```

Using Hadoop

- Hadoop is an Apache project that solves the problem of long data processing time.
- MapReduce is one part of Hadoop.

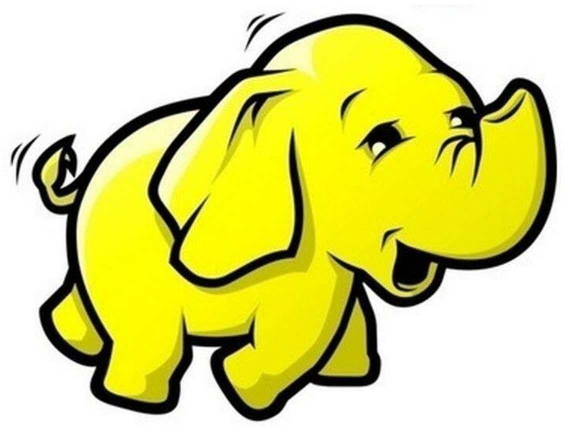
```
user@DESKTOP MINGW64 ~/example
$ hadoop jar contrib/hadoop-streaming-2.7.7.jar \
  -mapper mapper.py \
  -reducer reducer.py \
  -input ./*.txt \
  -output ./output/
```

MapReduce summary

- MapReduce to handle large-scale problems.
- Map: parse & extract items of interest.
- Sort & partition.
- Reduce: aggregate results.
- Write to output files.

MapReduce implementations

- Google: proprietary implementation in C++ (bindings in Java and Python).
- Hadoop: open-source implementation in Java.
  - Development led by Yahoo, now an Apache project.

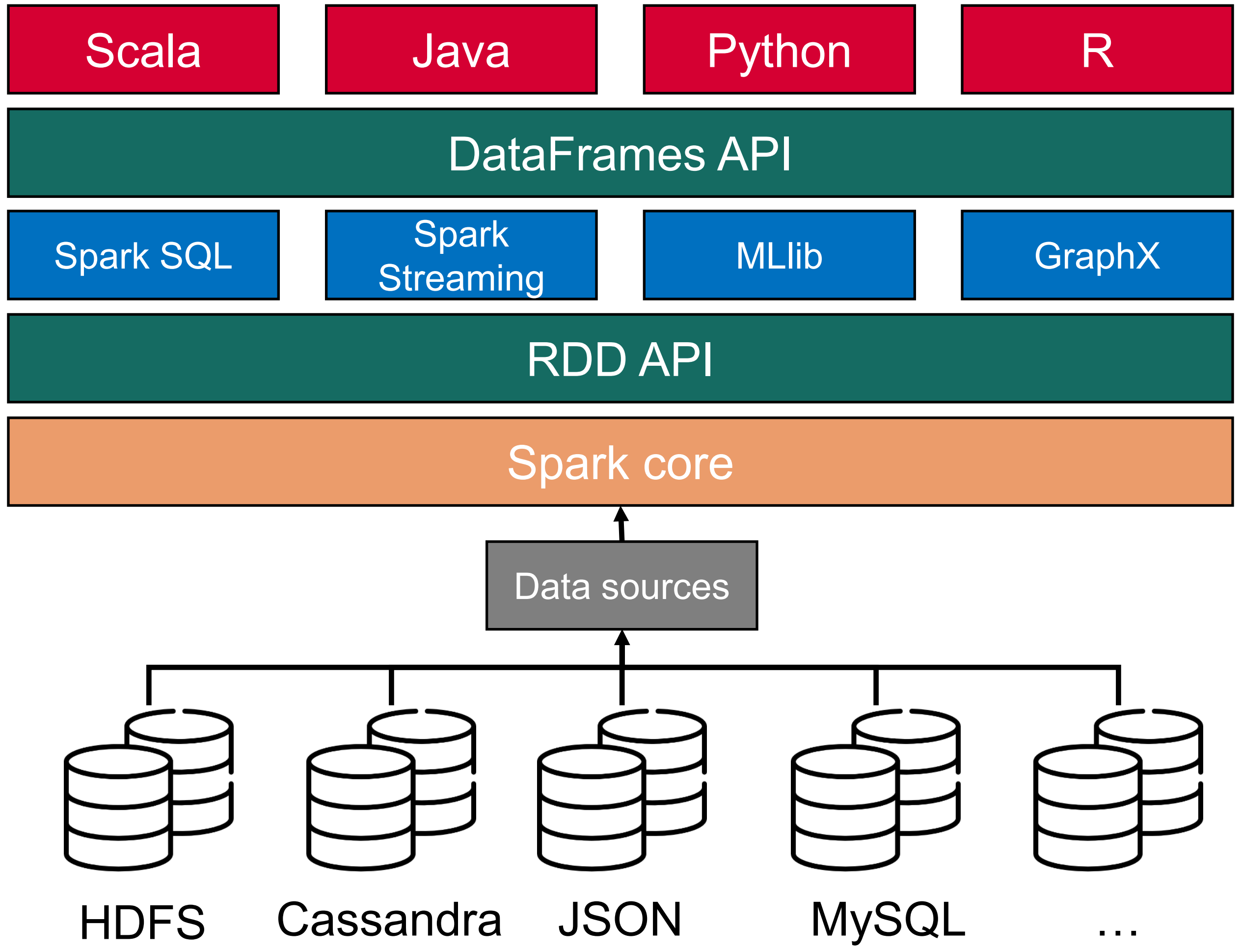


Spark

- Hadoop relies on data distributed across nodes using on HDFS.
  - Master / worker architecture.
  - Out of memory approach.
- Spark to the rescue:
  - Processes data in RAM using RDD (Resilient Distributed Dataset).
  - Requires a lot of RAM to run in-memory (increased cluster cost in general).
- Hadoop: processes data in batches, reading and writing intermediate data to disk. Spark: in-memory analytics.

Spark

- Spark unifies:
  - Batch processing
  - Real-time processing
  - Analytics
  - Machine learning
  - SQL

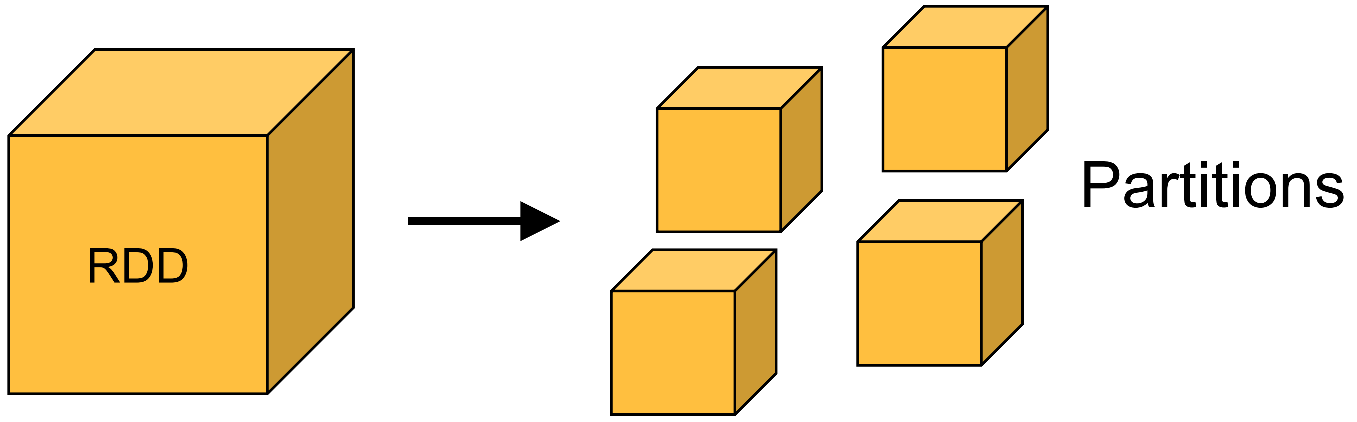


Spark

- Framework designed for in-memory computation and fast performance.
- Performs different types of big data workloads:
  - Stream processing
  - Machine learning
  - Graph processing
- Easy to use high-level API:
  - Easily integrate with many libraries, including PyTorch and TensorFlow.

Resilient distributed datasets

- Represents data or transformations on data.
- Distributed collection of items.
- Read only: immutable.
- Enables operations to be performed in parallel.

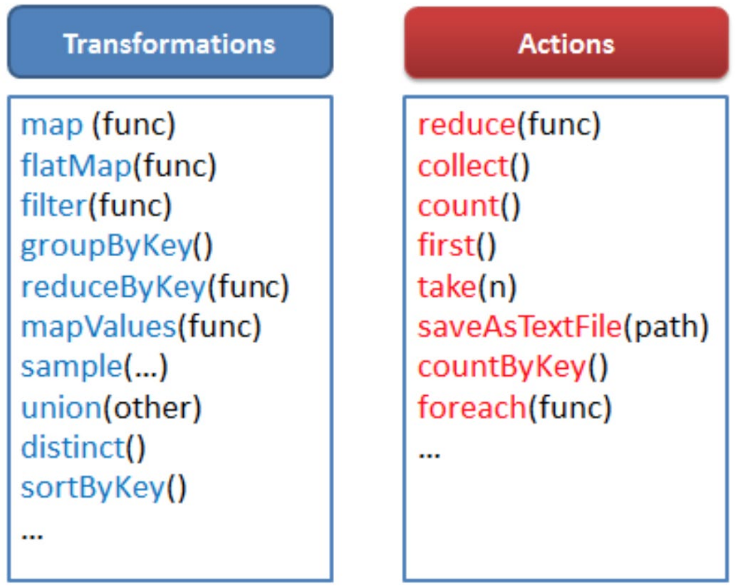


Programming with RDDs

- Work is expressed either by:
  - Creating new RDDs.
  - Transforming existing RDDs.
  - Calling operations on RDDs to compute a result.
- Spark: distributes the data contained in RDDs across the nodes (executors) in the cluster, parallelizing the operations.
- Each RDD is split into multiple partitions, computed on different nodes of the cluster.

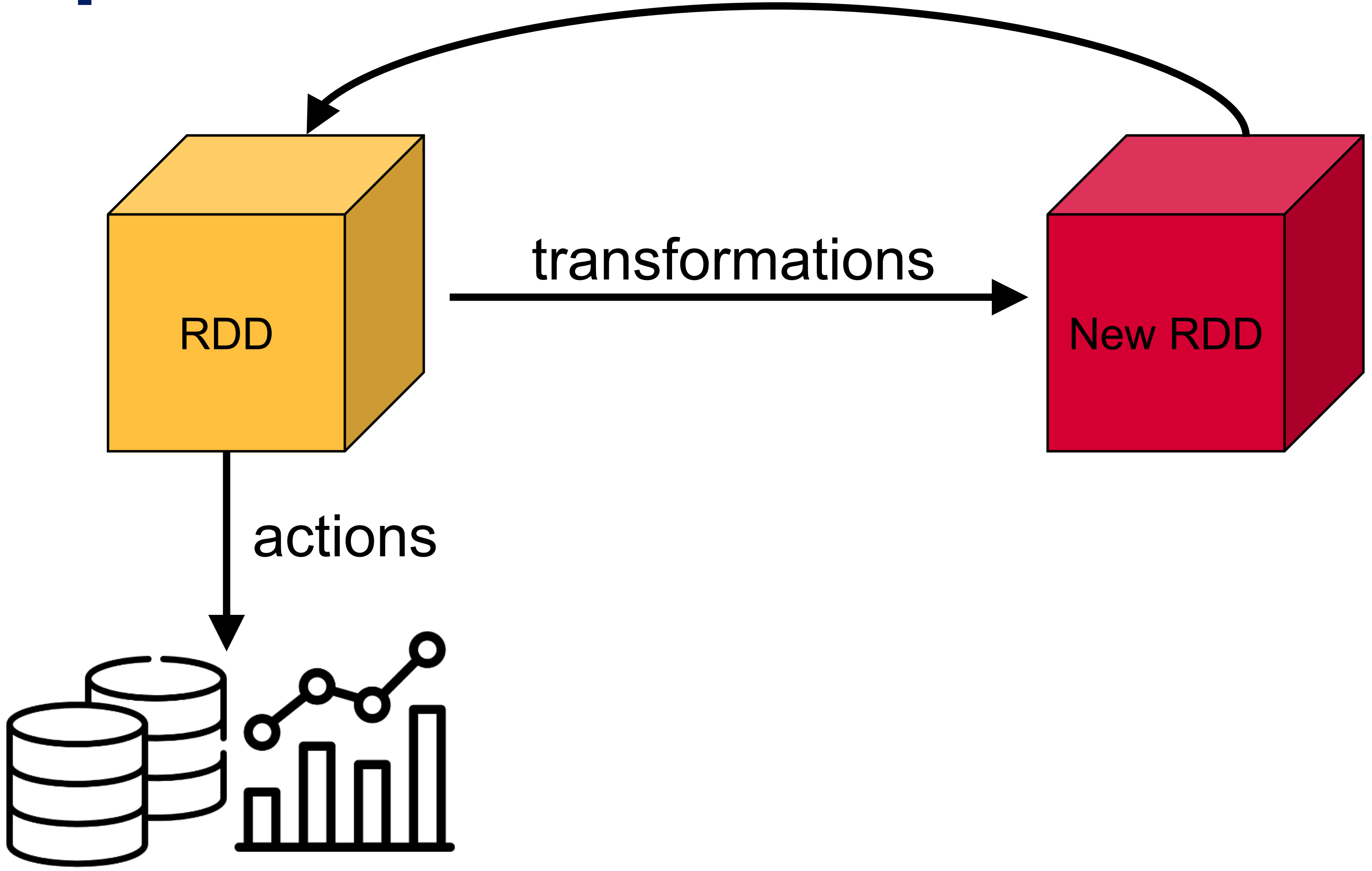
RDD operations

- RDDs offer two types of operations:
  - **Transformations**
    - Map, filter, join, …
    - Lazy operation to build RDDs from other RDDs
  - **Actions**
    - Count, collect, save, …
    - Return a result or write it to storage



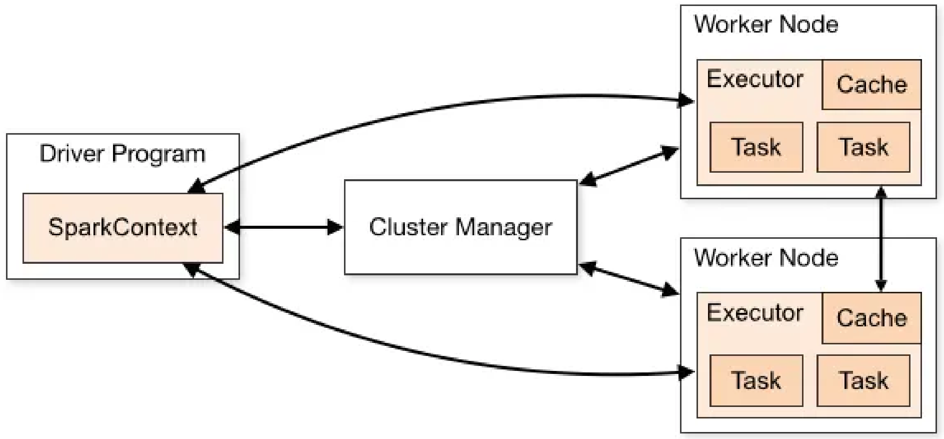
Transformations	Actions
map (func)	reduce(func)
flatMap(func)	collect()
filter(func)	count()
groupByKey()	first()
reduceByKey(func)	take(n)
mapValues(func)	saveAsTextFile(path)
sample(…)	countByKey()
union(other)	foreach(func)
distinct()	…
sortByKey()	
…	

RDD operations



Overview of a Spark program

1. Create input RDDs from external data or parallelize a collection.
2. Lazily transform them to define new RDDs using transformations.
3. Request Spark to cache any intermediate RDDs that will need to be reused.
4. Launch actions to start parallel computation, then executed by Spark.



Spark initialization

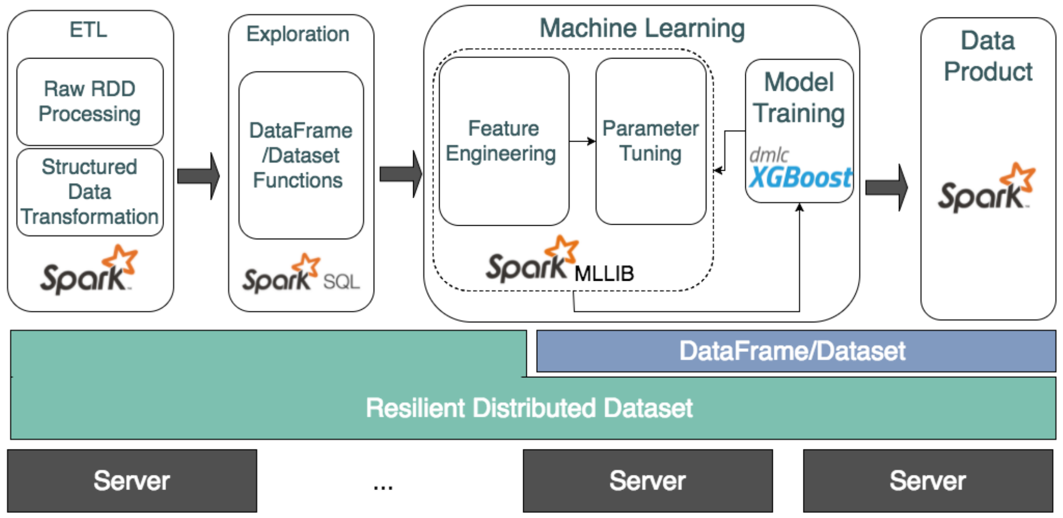
```
from pyspark import SparkContext, SparkConf

conf = SparkConf().setAppName(appName).setMaster(master)
sc = SparkContext(conf=conf)

data = [1, 2, 3, 4, 5]
distData = sc.parallelize(data)
rdd.saveAsSequenceFile("path/to/file")
print(sorted(sc.sequenceFile("path/to/file").collect()))

distFile = sc.textFile("data.txt")
```

Creates RDDs (lazily)

Action

Spark and machine learning

- Spark's APIs interoperates with NumPy, and Hadoop data sources.
- Several algorithms and utilities:
  - Classification: logistic regression, …
  - Linear regression
  - Random forest
  - K-means
- Machine learning workflows:
  - Feature transformation
  - Hashing



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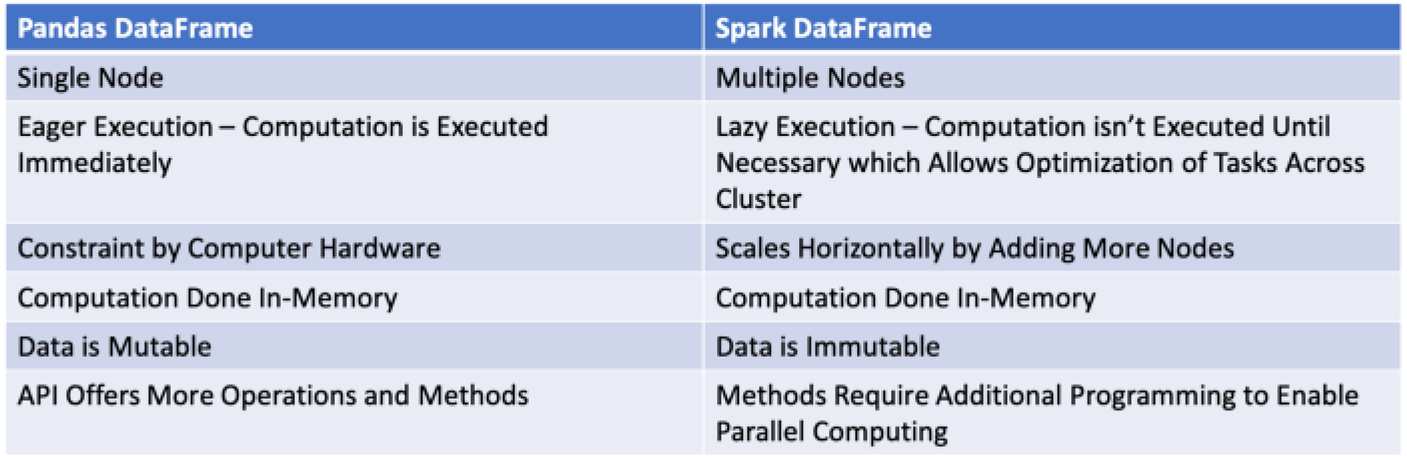
Spark and Pandas

- Spark can easily access Panda's DataFrames.
- Pandas: data exploration with limited sample.
- Spark: large-scale analytics.



Pandas DataFrame	Spark DataFrame
Single Node	Multiple Nodes
Eager Execution – Computation is Executed Immediately	Lazy Execution – Computation isn't Executed Until Necessary which Allows Optimization of Tasks Across Cluster
Constraint by Computer Hardware	Scales Horizontally by Adding More Nodes
Computation Done In-Memory	Computation Done In-Memory
Data is Mutable	Data is Immutable
API Offers More Operations and Methods	Methods Require Additional Programming to Enable Parallel Computing

Spark and DataFrames

Computing summaries with Spark and DataFrames:

```python
from pyspark.sql.functions import sum, avg, count, first

ls = [['x', 'y',3], ['x', 'y', 4], ['x', 'z', 3], ['y', 'y', 5]]
df = spark.createDataFrame(ls, schema=['A', 'B', 'C'])

group_df = df.groupby(['A', 'B'])
df_grouped = group_df.agg(sum("C").alias("sumC"),
                          avg("C").alias("avgC"),
                          count("C").alias("countC"),
                          first("C").alias("firstC"))
df_grouped.show()
```

Spark and UDFs

Spark can evaluate user-defined functions (UDFs).

```python
@udf
def to_upper(s):
    if s is not None:
        return s.upper()

@udf(returnType=IntegerType())
def mult(x):
    if x is not None:
        return x * 2

df = spark.createDataFrame([(1, "John Doe", 21)], ("id", "name", "age"))
df.select("age", mult("age")).show()
df.select("name", to_upper("name")).show()
```

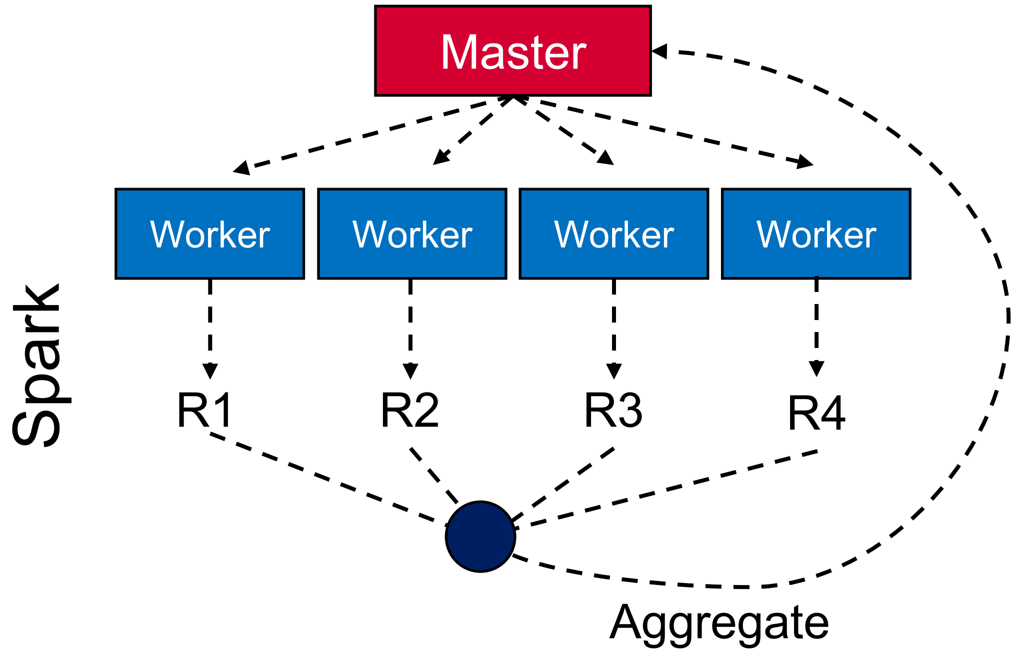
Taxi data using Spark

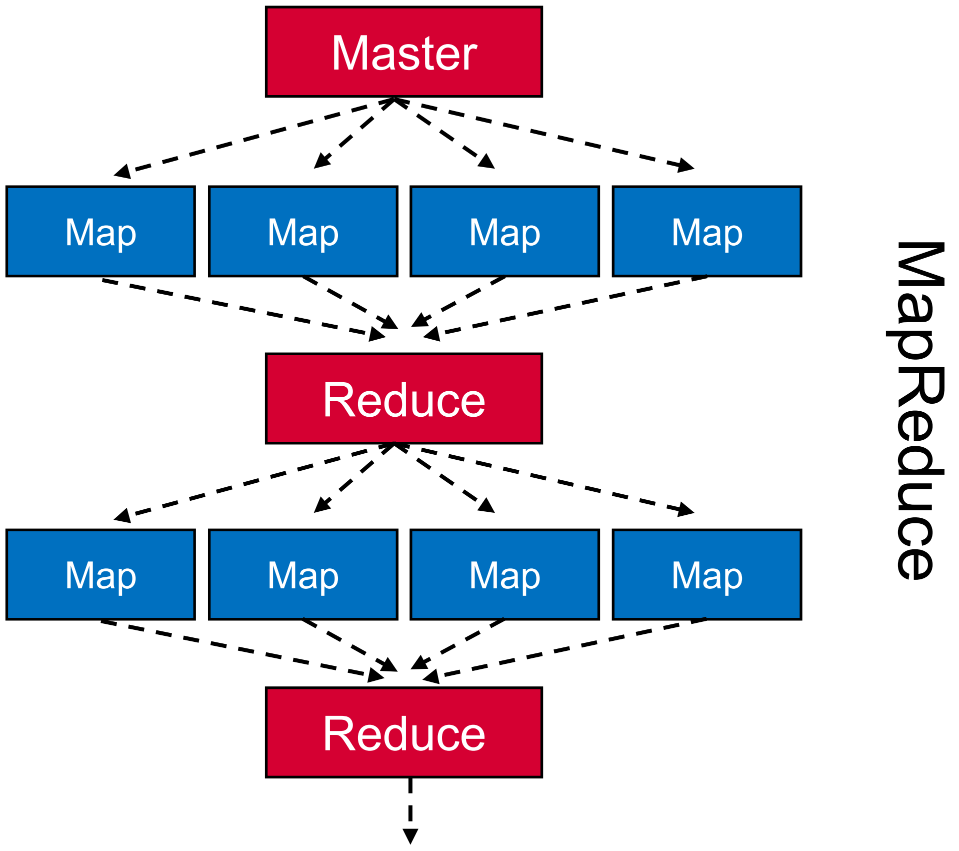
Loading the data and storing as parquet files:

```
from pyspark.sql import SparkSession

conf = SparkConf().setAppName(appName).setMaster(master)
sc = SparkContext(conf=conf)

df = spark.read.csv("yellow*.csv", header="true", inferSchema="true")
df.write.parquet("2009-yellow.parquet")
spark.stop()
```

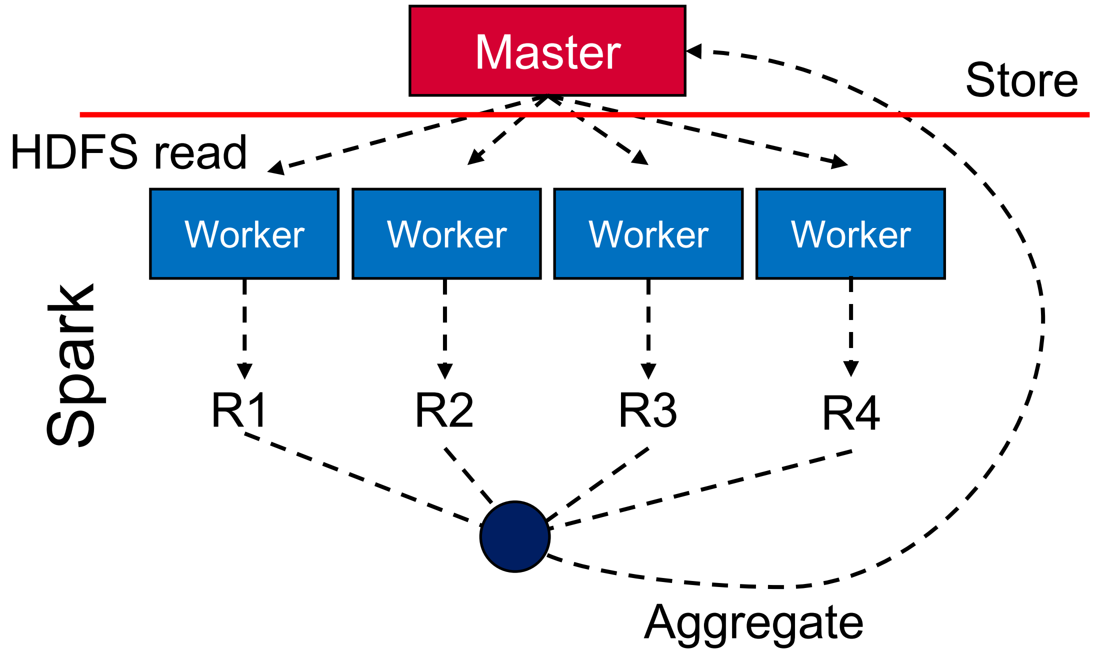
```
columns = ['passenger_count']
df = spark.read.parquet('2009-yellow.parquet').select(*columns)
df.agg({'passenger_count': 'sum'}).collect()
df.agg({'passenger_count': 'avg'}).collect()
df.groupby('passenger_count').agg({'*': 'count'}).collect()
```

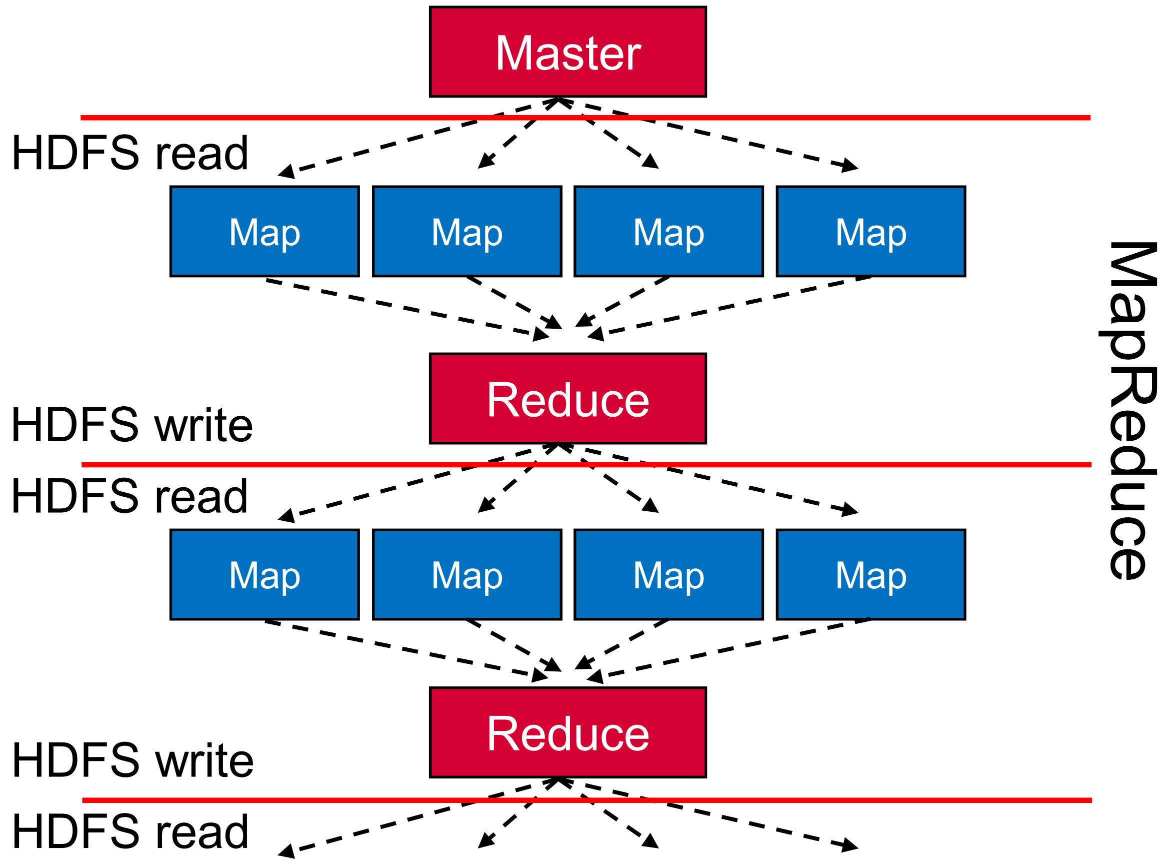
Spark vs. MapReduce



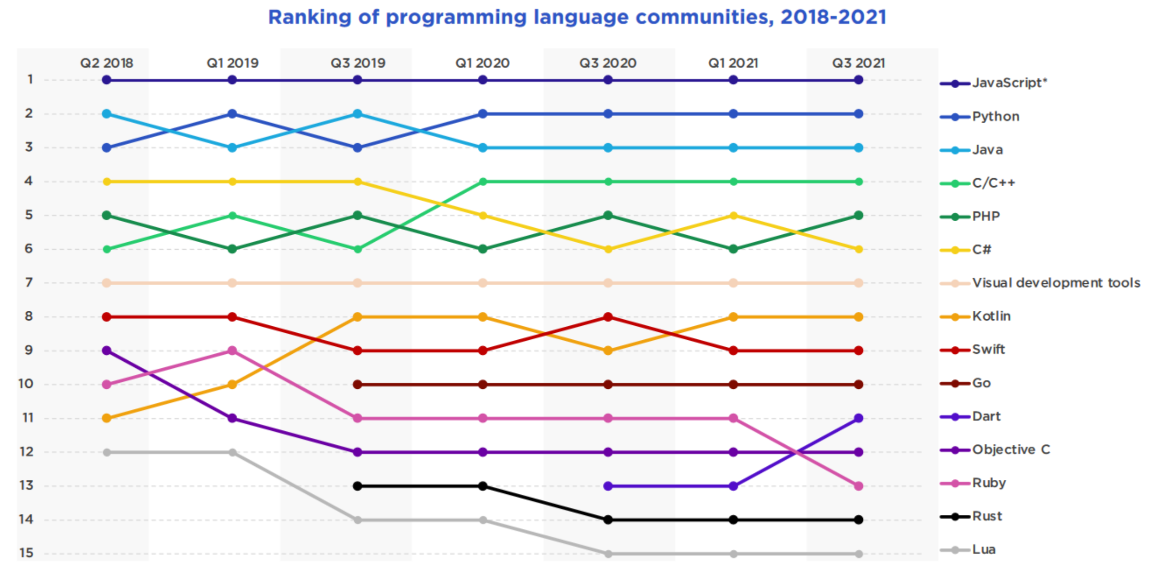


Spark vs. MapReduce





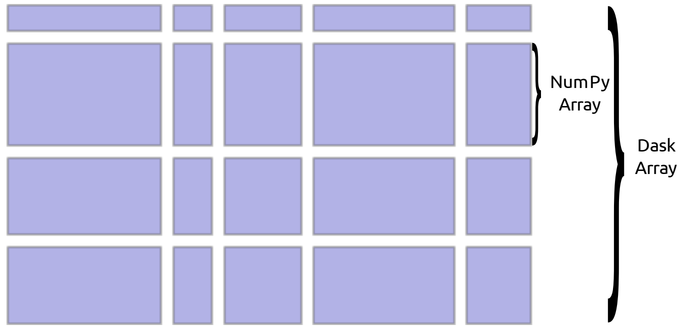
Dask: parallel Pandas dataframe

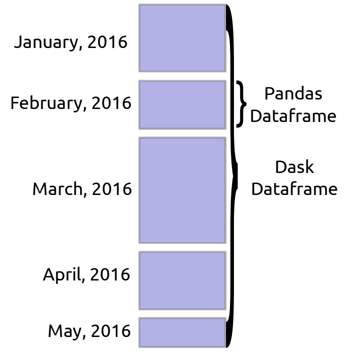


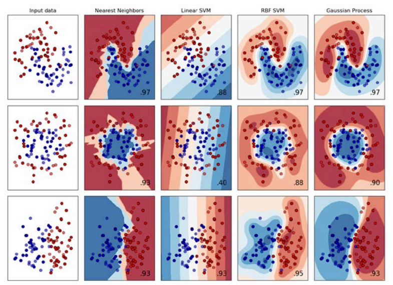
- Python: leading platform for analytics and data science.
- Major libraries fail for big data or scalable computing.
- Python library for parallel computing:
  - Scales Numpy, Pandas, and Scikit-Learn
- Dask accelerates existing Python ecosystems.

Dask

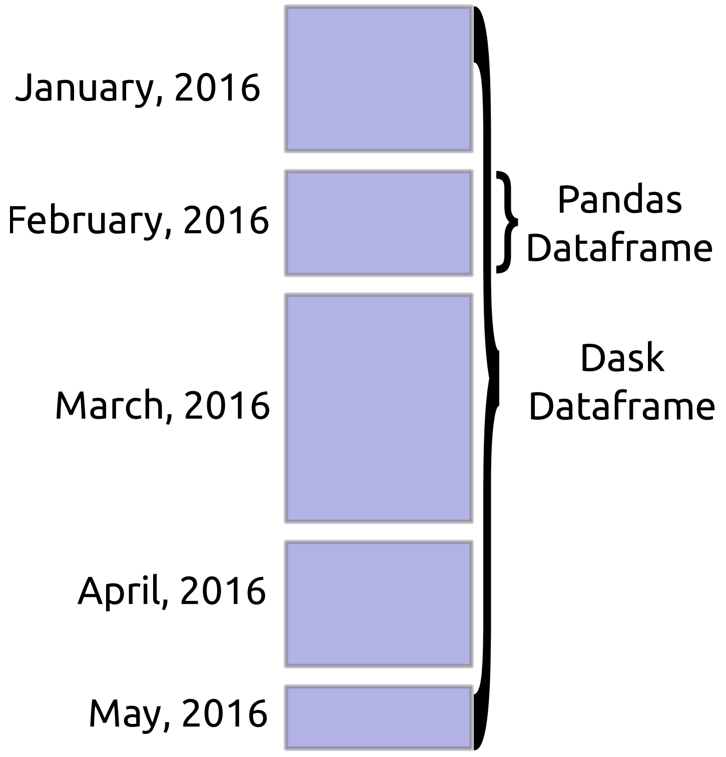
- “Hadoop / Spark for Python”.
- Platform to build distributed applications.
- Dask can scale scikit-learn, Pandas and NumPy workflows:
  - Extends existing Python libraries
  - Enables easy transition for users
  - Leverages existing work, rather than reinvests the wheels.







Dask



```
import pandas as pd

df = pd.read_csv("file.csv")
df.groupby("x").y.mean()
```

```
import dask.dataframe as dd

df = dd.read_csv("*.csv")
df.groupby("x").y.mean()
```