Données massives et apprentissage profond
Lecture 1 – Apache Spark

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CentraleSupélec

Organization of the course

- MapReduce and Spark.
- Spark programming.
- SQL and NoSQL.
- MongoDB practice.
- Hadoop technologies.
- Scaling.

Class material

Available online

https://tinyurl.com/p7jb5wra

Click here

- Slides of the lectures.
- Tutorials and lab assignments.
- References (books and articles).

Evaluation

- **Lab assignments**. Lab assignments 1 and 2 will be graded.
  - Lab assignment 1. Spark programming
  - Lab assignment 2. MongoDB
  - **Submission**: Code source + written report.

- **Written exam.** 1 hour.
  - Spark programming.
  - Data modeling in MongoDB.
  - Querying in MongoDB.

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What you will learn

In this lecture you will learn:

- What **Spark** is and its main features.
- The components of the **Spark stack**.
- The high-level **Spark architecture**.
- The notion of **Resilient Distributed Dataset** (RDD).
- The main **transformations** and **actions** on RDDs.

Apache Spark

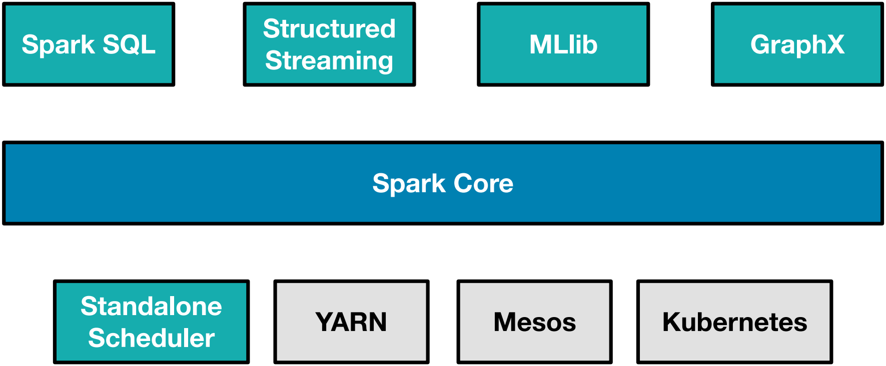
Definition (Apache Spark)

Apache Spark is a *distributed computing framework* designed to be *fast* and *general-purpose*. ▸ Source

Main features

- **Speed**. Run computations in **memory** (Hadoop relies on disks).
- **General-purpose**. Different workloads in the same system.
  - Batch applications, iterative algorithms.
  - Interactive queries, streaming applications.
- **Accessibility.** Python, Scala, Java, SQL and R; rich built-in libraries.
- **Integration.** With other Big Data tools, such as **Hadoop**.

Spark components



▸ Image source

Spark components

Spark core

- **Scheduling**, **distributing**, and **monitoring** applications.
- Data structures for manipulating data (RDDs, DataFrames).

Spark SQL

- Spark's package for working with **(semi-)structured data**.
- Data querying with **SQL** and **HQL** (Hive Query Language).
- Many sources of data: JSON, XML, Parquet...

Spark components

Structured streaming

- Processing of live **streams** of data (e.g., real-time event logs)
- Similar API to batch processing.

MLlib

- **Machine learning** algorithms (e.g., classification, regression, clustering)
- All methods designed to scale out across a cluster.

Spark components

GraphX

- Manipulation of **graph data**.
- Library with common graph algorithms (e.g., PageRank)

Cluster managers

- Control how tasks are distributed across a cluster.
- Spark provides its own **standalone** cluster manager.
- Spark can also use other cluster managers.

Spark unified stack: benefits

- **Shallow learning curve.** Same **programming model** across all components.
- **Optimization propagation.** Higher-level components automatically benefit from improvements on lower-layer components.
- **Cost minimization.** No need for further software components.
- **Heterogeneous processing models** in the same application.
  - Read a stream of data.
  - Apply machine learning algorithms.
  - Uses SQL to analyze the results.

Using Spark

Interactive mode

Using a command-line interface (CLI) or **shell**.

- Python and Scala shell.
- SparkSQL shell.
- SparkR shell.

Data processing applications

Building an **application** by using the **Spark APIs**.

- Scala (Spark's native language).
- Python.
- Java.

Who uses Spark

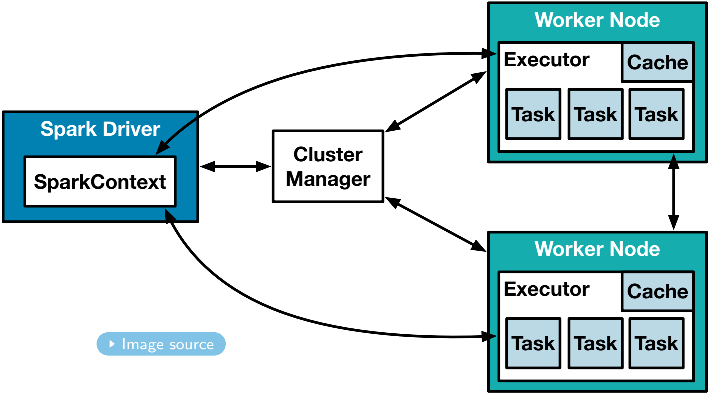
Several important actors use Spark:

- **Amazon**.
- **eBay**. Log transaction aggregation and analytics.
- **Groupon**.
- **Stanford DAWN**. Research project aiming at democratizing AI.
- **TripAdvisor**.
- **Yahoo!**

☞ Full list available at http://spark.apache.org/powered-by.html

Spark application

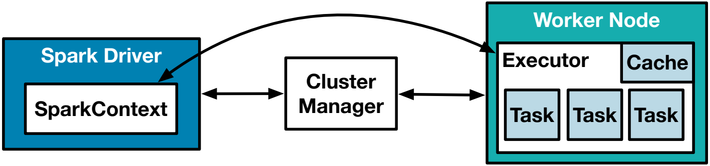
- Spark application: set of independent processes called **executors**.
- Executor run computations and store the data for the application.
- Executors are coordinated by the **driver**.



▸ Image source

Spark application execution

- The **driver** is launched and creates the **SparkContext** object.
- The **SparkContext** obtains **executors** from the **cluster manager**.
- The driver sends the **user's code** to the executors.
- The driver assigns each executor a set of **tasks**.
- A **task** is a computation on a **chunk of data**.



Spark application execution

- Applications are **isolated** from one another.
  - Each application has its own SparkContext.
  - An executor only runs tasks of one application.
  - A driver only schedules tasks for one application.
  - Data cannot be shared across different applications.
- Spark is **agnostic** to the underlying cluster manager.
- The driver listens to incoming connections from the executors on a network port.
- The driver should be in the same local network as the executors.

☞ Two different Spark applications can still share data through an external storage system (e.g., a database or HDFS files).

Spark programming

Two options exist to write a Spark application:

- **Low-level** programming, using operations on a low-level data structure called **Resilient Distributed Dataset (RDD)**.
- **High-level** programming, using high-level libraries, such as SparkSQL and Structured Streaming.

☞ In this lecture, we'll focus on low-level programming to better understand the inner workings of Spark.

Low-level Spark programming

- A Spark program uses an object called **SparkContext**.
- **SparkContext** represents a connection to a cluster.

Initializing the SparkContext

```
from pyspark import SparkConf, SparkContext

conf = SparkConf().setMaster(<cluster URL>).setAppName(<app_name>)
sc = SparkContext(conf = conf)
```

- A Spark program is a sequence of operations invoked on the **SparkContext (sc)**.
- These operations manipulate a special type of data structure, called **Resilient Distributed Dataset (RDD)**.

Resilient Distributed Dataset (RDD)

Definition (Resilient Distributed Dataset)

A **Resilient Distributed Dataset**, or simply **RDD**, is an **immutable**, **distributed** collection of objects. ▸ Source

- The data in each RDD is split across multiple **partitions**.
- Each partition resides on one node of the cluster.
- Two partitions can reside on the same node.

Resilient Distributed Dataset (RDD)

Input file

Call me Ishmael. Some years ago--never mind how long precisely--having little or no money in my purse, and nothing particular to interest me on shore, I thought I would sail about a little and see the watery part of the world. It is a way I have of driving off the spleen and regulating the circulation. Whenever I find myself growing grim about the mouth; whenever it is a damp, drizzly November in my soul; whenever I find myself involuntarily pausing before coffin warehouses, and bringing up the rear of every funeral I meet; and especially whenever my hypos get such an upper hand of me, that it requires a strong moral principle to prevent me from deliberately stepping into the street, and methodically knocking people's hats off--then, I account it high time to get to sea as soon as I can. This is my substitute for pistol and ball. With a philosophical flourish Cato throws himself upon his sword; I quietly take to the ship. There is nothing surprising in this. If they but knew it, almost all men in their degree, some time or other, cherish very nearly the same feelings towards the ocean with me.

File in HDFS
By default
1 block = 1 partition

It is possible to specify a different number of partitions

RDD

Partition 0

Call me Ishmael. Some years ago--never mind how long precisely--having little or no money in my purse, and nothing particular to interest me on shore, I thought I would sail about a little and see the watery part of the world. It is a way I have of driving off the spleen and

Partition 1

regulating the circulation. Whenever I find myself growing grim about the mouth; whenever it is a damp, drizzly November in my soul; whenever I find myself involuntarily pausing before coffin warehouses, and bringing up the rear of every funeral I meet; and especially

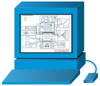
Partition 2

whenever my hypos get such an upper hand of me, that it requires a strong moral principle to prevent me from deliberately stepping into the street, and methodically knocking people's hats off--then, I account it high time to get to sea as soon as I can. This is my substitute for pistol

Partition 3

and ball. With a philosophical flourish Cato throws himself upon his sword; I quietly take to the ship. There is nothing surprising in this. If they but knew it, almost all men in their degree, some time or other, cherish very nearly the same feelings towards the ocean with me.

Resilient Distributed Dataset (RDD)



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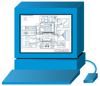

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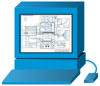


and ball. With a philosophical flourish Cato throws himself upon his sword; I quietly take to the ship. There is nothing surprising in this. If they but knew it, almost all men in their degree, some time or other, cherish very nearly the same feelings towards the ocean with me.

Creating an RDD

1. From an **in-memory collection** (e.g., a list or a set).

```
sc.parallelize([1, 5, 3, 2, 6, 7])
```

> ☞ This method is used for **debugging** and **prototyping** on **small datasets**.

2. From an **data source on disk** (e.g., a file or a database).

```
sc.textFile("hdfs://sar01:9000/data/sample_text.txt")
```

> ☞ This method is used **in production** to process **large datasets**.

About the number of partitions

RDDs created with `parallelize`

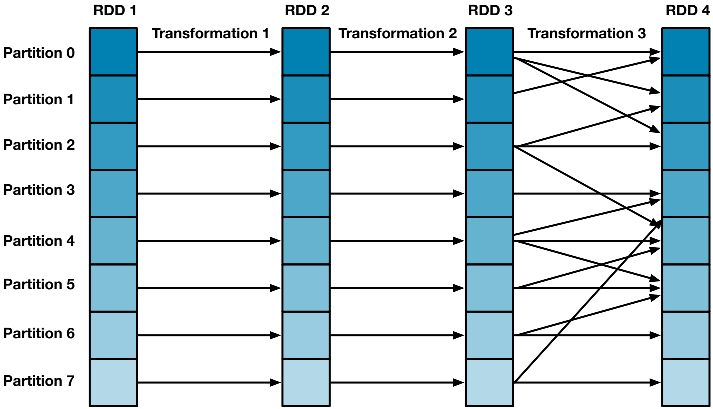
- **Local mode**: number of cores on the local machines.
- **Cluster mode**: total **number of cores** on all executor nodes, or 2, whichever is larger.

RDDs created from files stored in HDFS

- Number of HDFS blocks in the input file, or 2, whichever is larger.

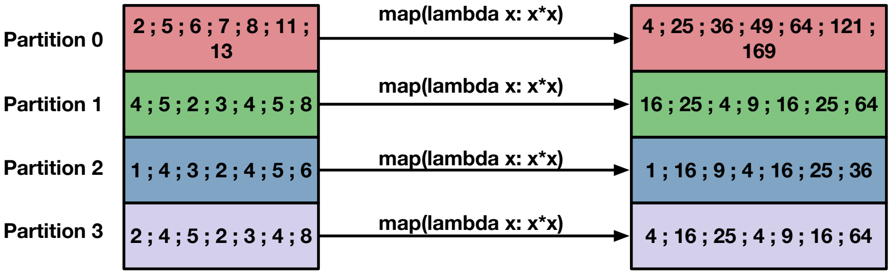
RDD transformations

A **transformation** is an operation that takes in one or more RDDs and returns a **new RDD**. A transformation is applied **in parallel** on each partition.



RDD transformations: `map`

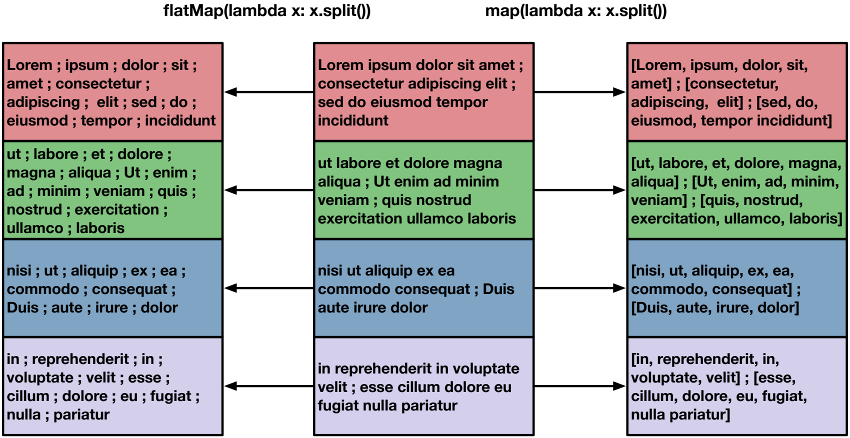
`map()` takes in a **function** f and a RDD $< x_i \mid 0 \leq i \leq n >$; returns a **new RDD** $< f(x_i) \mid 0 \leq i \leq n >$.



☞ Partition i of the input RDD is on the same node as partition i of the output RDD.

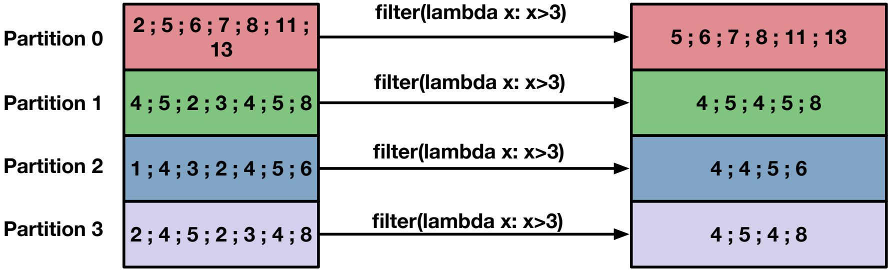
RDD transformations: `flatMap`

`flatMap` is used instead of `map` when the function f returns a list and we need the results to be flattened.



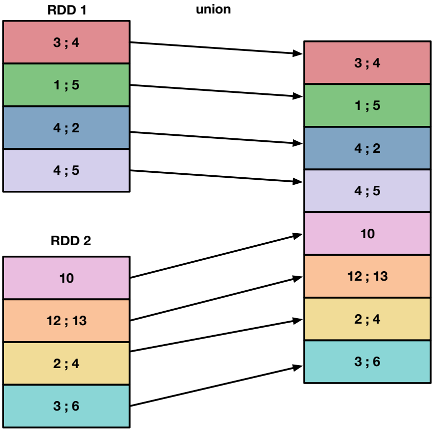
RDD transformations: `filter`

`filter()` takes in a **predicate** p and a RDD $< x_i \mid 0 \leq i \leq n >$; returns a **new RDD** $< x_i \mid 0 \leq i \leq n,\ p(x_i)\ \mathit{is\ true} >$



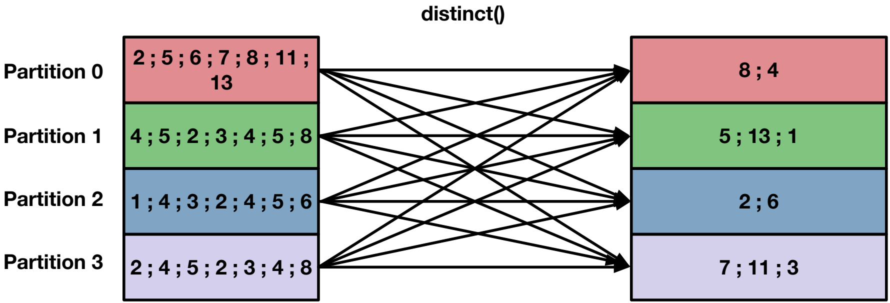
RDD transformations: `union`

`union()` takes in two RDDs and returns a **new RDD** containing the items of the first and second RDD **with repetitions**.



RDD transformations: `distinct`

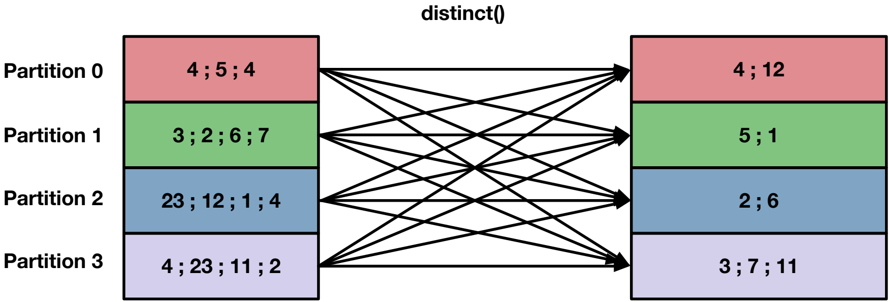
`distinct()` takes in one RDD and returns a **new RDD** containing the items of the input RDD **without repetitions**.



☞ Unlike the previous transformations, `distinct` leads to data being **shuffled**.

About data shuffling ★

Which partition does the element 23 belong to in the RDD obtained after applying the transformation `distinct`?



About data shuffling ★

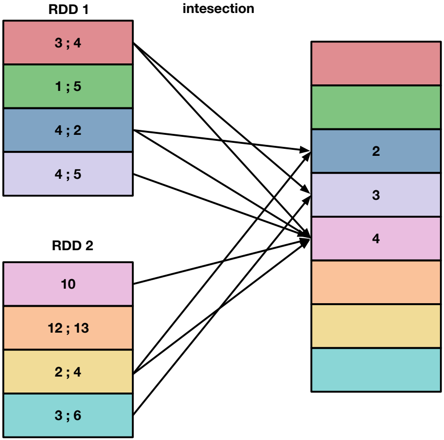
The element 23 belongs to the **partition 3**.

While shuffling, the **destination partition** p of an element K in a RDD with n partitions is computed as follows:

$$p = hashCode(K) \; mod \; n$$

RDD transformations: `intersection`

`intersection()` takes in one or two RDDs and returns a **new RDD** containing the items that occur in both RDDs.



Narrow transformations ★

Definition (Narrow transformation)

A **narrow transformation** is one where each partition of the output RDD depends on at most one partition of the input RDD.

Which of the above transformations are narrow?

- Narrow transformations are **inexpensive**.
- No need for **communication** between executors.

Narrow transformations ★

Definition (Narrow transformation)

A **narrow transformation** is one where each partition of the output RDD depends on at most one partition of the input RDD.

`filter`, `map`, `flatMap` and `union` are narrow transformations.

- Narrow transformations are **inexpensive**.
- No need for **communication** between executors.

Wide transformations ★

Definition (Wide transformation)

A **wide transformation** is one where each partition of the output RDD may depend on several partitions of the input RDD.

Which of the above transformations are wide?

- Wide transformations are more **costly**.
- Executors need to communicate.
- Data is **shuffled** across the cluster network.

Wide transformations ★

Definition (Wide transformation)

A **wide transformation** is one where each partition of the output RDD may depend on several partitions of the input RDD.

`distinct` and `intersection` are wide transformations.

- Wide transformations are more **costly**.
- Executors need to communicate.
- Data is **shuffled** across the cluster network.

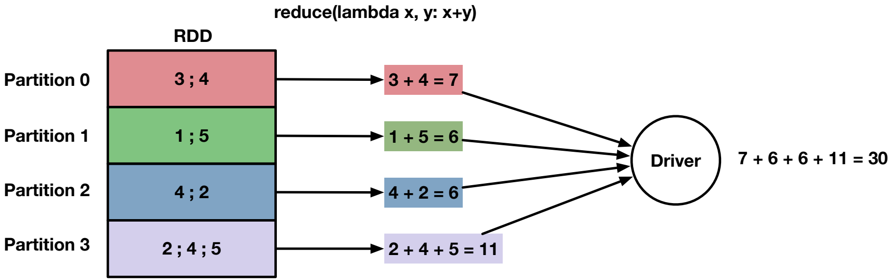
RDD actions

An **action** is an operation that takes in a RDD and returns a value to the **driver** after running a computation of the dataset.

- The result of an action is sent to the driver.
- If the result is a list of values, **all values** are sent to the driver.
- The result of an action can also be **written to disk**.
- Disk writes can be to the **local file system** or **HDFS**.

RDD actions: `reduce`

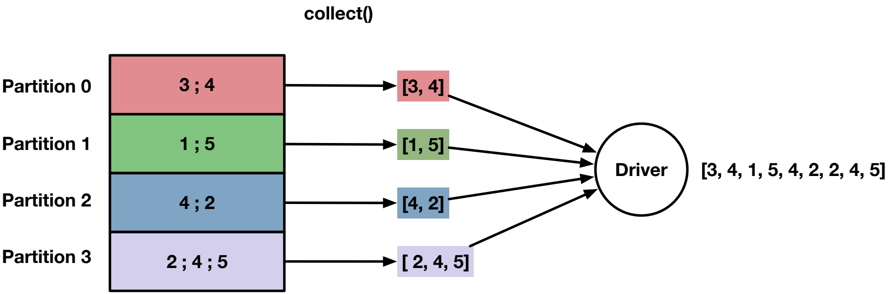
`reduce()` takes in an RDD and a function f and applies the function pair-wise to all elements of the input RDD.



- The function f **must** take in **2 arguments**.
- The type of the value returned by the function f **must be the same** as the type of the elements of the input RDD.

RDD actions: `collect`

`collect()` takes in an RDD and returns the **list** of the elements in the RDD.



Is `collect()` a safe action? ★

What are the risks, if any, while invoking `collect()` on a large RDD?

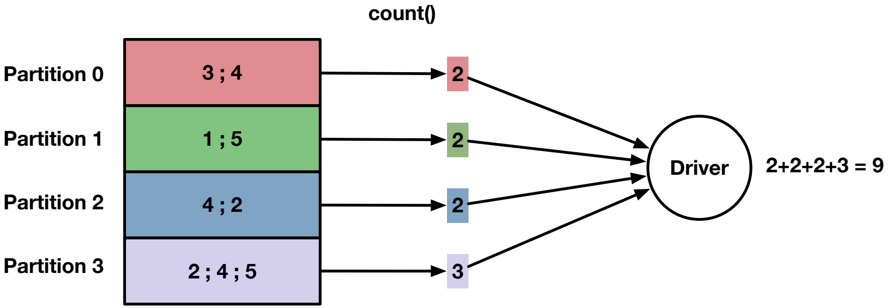
Is `collect()` a safe action? ★

What are the risks, if any, while invoking `collect()` on a large RDD?

- High network traffic.
- The driver's memory may not enough to store all the RDD elements.

RDD actions: `count`

`count()` takes in an RDD and returns the number of items in the RDD.



Understanding the code ★

What does the following code?

```
r1 = sc.parallelize(["computer science", "geology", \
    "chemistry", "biology", "astronomy"])
r2 = r1.map(lambda x: x.capitalize())
```

Understanding the code ★

What does the following code?

```
r1 = sc.parallelize(["computer science", "geology", \
    "chemistry", "biology", "astronomy"])
r2 = r1.map(lambda x: x.capitalize())
```

- r2 is an RDD (result of a transformation).
- r2 has as many elements as r1.
- Each item of r2 is a string from r1 with the first letter capitalized.

What does the following code? ★

What does the following code?

```
r1 = sc.parallelize(["computer science", "geology", \
    "chemistry", "biology", "astronomy"])
r2 = r1.filter(lambda x: len(x) > 10)
```

What does the following code? ★

What does the following code?

```
r1 = sc.parallelize(["computer science", "geology", \
    "chemistry", "biology", "astronomy"])
r2 = r1.filter(lambda x: len(x) > 10)
```

- `r2` is an RDD (result of a transformation).
- `r2` has less elements than `r1`.
- `r2` only contains the items from `r1` that have more than 10 characters.

What does the following code? ★

What does the following code?

```
r1 = sc.parallelize(["computer science", "geology", \
    "chemistry", "biology", "astronomy"])
r2 = r1.reduce(lambda x, y: "{} - {}".format(x, y))
```

What does the following code? ★

What does the following code?

```
r1 = sc.parallelize(["computer science", "geology", \
    "chemistry", "biology", "astronomy"])
r2 = r1.reduce(lambda x, y: "{} - {}".format(x, y))
```

- r2 is a string, **not a RDD** (result of an action).
- r2 is the string "computer science - geology - chemistry - biology - astronomy".

What does the following code? ★

What does the following code?

```
r1 = sc.parallelize(["computer science", "geology", \
    "chemistry", "biology", "astronomy"])
r2 = r1.reduce(lambda x, y: [x + y])
```

What does the following code? ★

What does the following code?

```
r1 = sc.parallelize(["computer science", "geology", \
    "chemistry", "biology", "astronomy"])
r2 = r1.reduce(lambda x, y: [x + y])
```

The code is incorrect, because the return type (`list`) of the `reduce` function is different from the type of the input RDD elements (`string`).

What does the following code? ★

What does the following code?

```
r1 = sc.parallelize(["author", "title", "edition"])
r2 = r1.flatMap(lambda x: [c for c in x])
```

What does the following code? ★

What does the following code?

```
r1 = sc.parallelize(["author", "title", "edition"])
r2 = r1.flatMap(lambda x: [c for c in x])
```

- `r2` is an RDD (result of a transformation).
- Each element of `r2` is a letter from a string in `r1`. How would that be different if we had used `map` instead of `flatMap`?

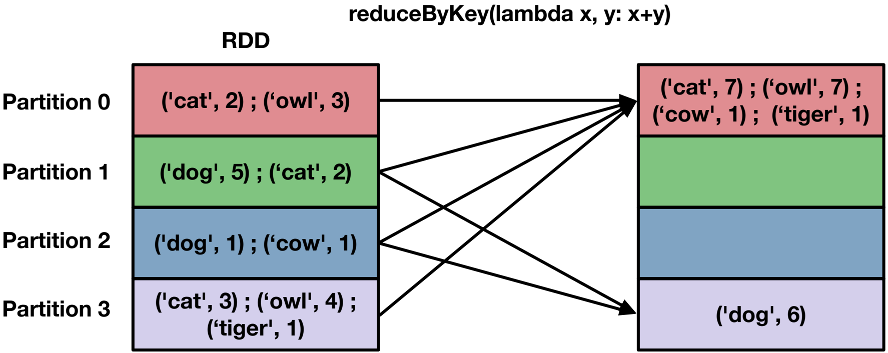
Key-value RDDs

Key-value RDDs (a.k.a., **Pair RDDs**) are RDDs where each item is a pair (k, v), k being the key and v being the value.

- Key-value RDDs are important building blocks in many applications.
- Key-value RDDs support all the transformations and actions that can be applied on regular RDDs.
- Key-value RDDs support special transformations and actions.

Key-value RDDs transformations: `reduceByKey`

`reduceByKey` takes in a RDD with (K, V) pairs and a function f and returns a **new RDD** of (K, V) pairs where the values for each key are aggregated using f, which must be of type $(V, V) \rightarrow V$.



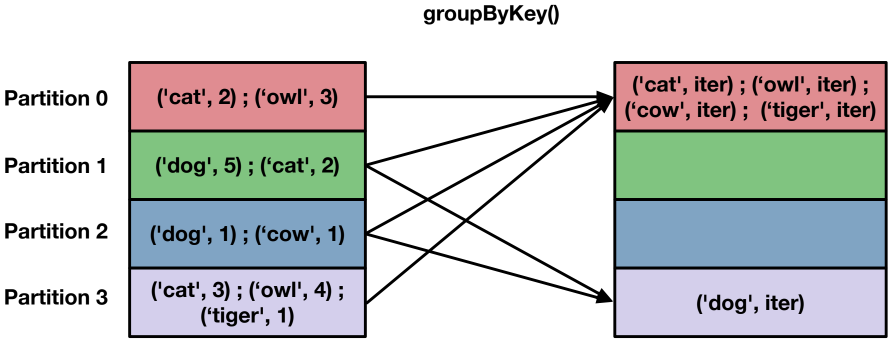
Key-value RDDs transformations: `reduceByKey`

- The input RDD has a certain number of partitions n.
- No assumption can be made on which elements belong to which partition.
- The RDD returned by `reduceByKey` is **hash partitioned**. Each item belongs to a precise partition.
- The partition number p of a pair (K, V) is derived as follows:

$$p = hashCode(K)\ mod\ num\_partitions$$

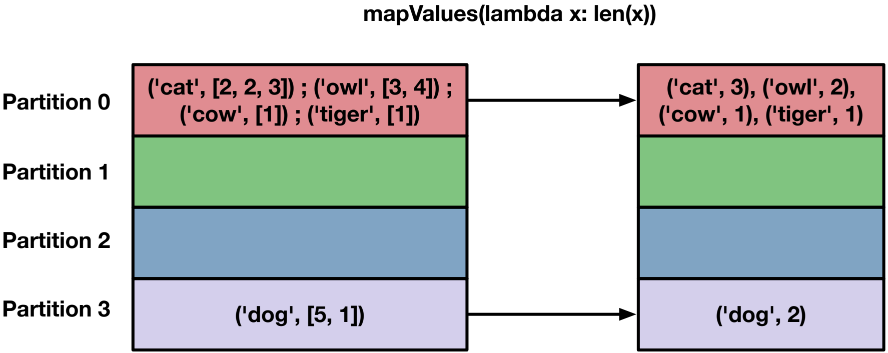
Key-value RDDs transformations: `groupByKey`

`groupByKey` takes in a RDD with (K, V) pairs and returns a **new RDD** of $(K, Iterable < V >)$ pairs.



Key-value RDDs transformations: `mapValues`

`mapValues` takes in a RDD with (K, V) pairs and a function f and returns a **new RDD** where the function f is applied to each value V (keys are not modified).



Example: Word count

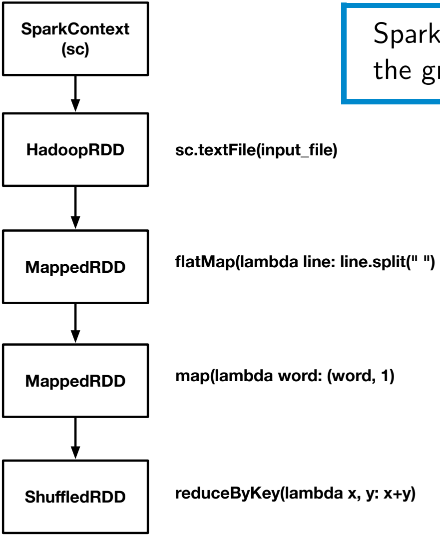
```
def word_count(input_file):
    text = sc.textFile(input_file)
    return text.flatMap(lambda line: line.split(" "))\
              .map(lambda word: (word, 1))\
              .reduceByKey(lambda x, y: x+y)
```

- The function `textFile` reads a text file into a RDD.
- Two narrow transformations (`flatMap` and `map`) and one wide transformation (`reduceByKey`).

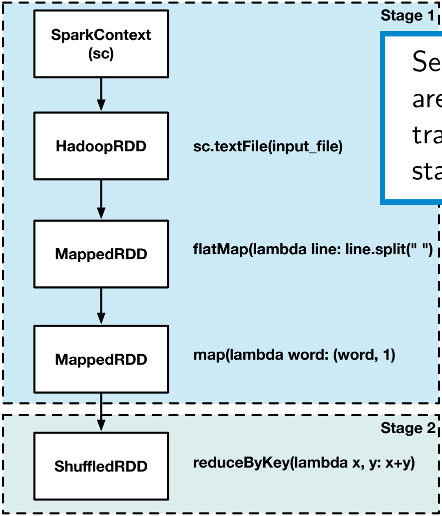
☞ Spark maintains a **logical execution plan** (called **RDD lineage**) described as a **Directed Acyclic Graph (DAG)**.

RDD lineage

Spark has a **DAG scheduler** that splits the graph into multiple **stages**.

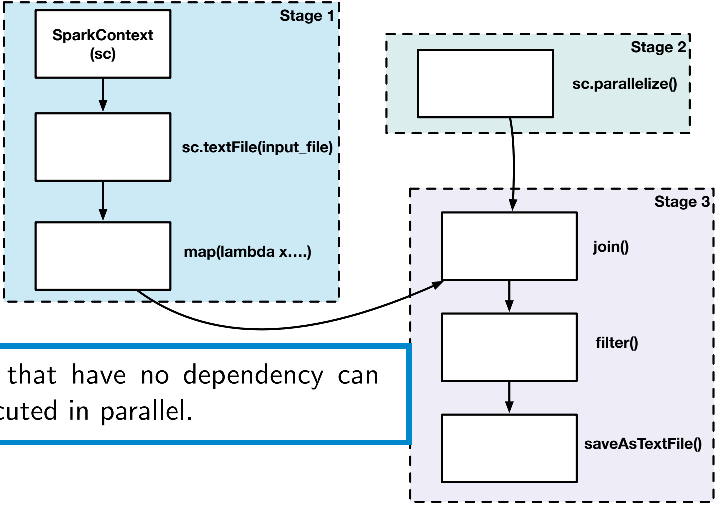


RDD lineage: stages



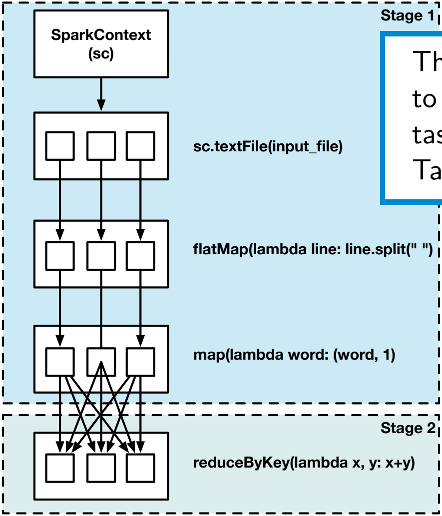
Sequences of **narrow transformations** are pipelined into a **single stage**. Wide transformations always trigger a new stage.

RDD lineage: stages



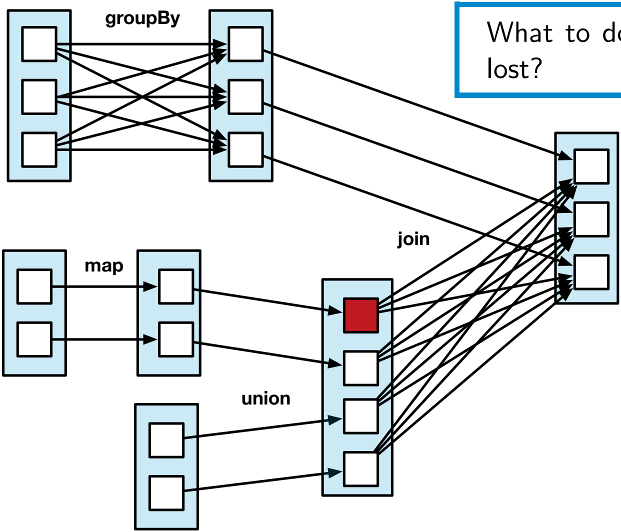
Stages that have no dependency can be executed in parallel.

RDD lineage: tasks



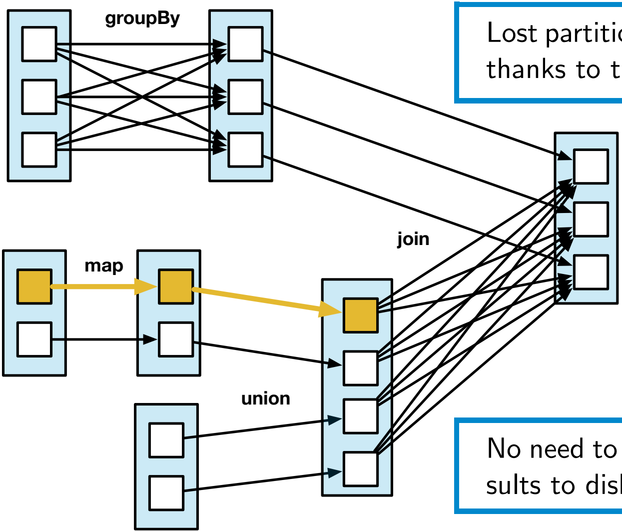
The DAG scheduler submits the stages to the **task scheduler**. Creates as many tasks as there are partitions in the RDD. Tasks are executed in parallel.

RDD lineage: fault tolerance



What to do when a partition is lost?

RDD lineage: fault tolerance



Lost partitions can be recomputed thanks to the lineage graph.

No need to save intermediate results to disk.

Lazy evaluation

- In Spark, transformations are **lazily evaluated**.

Definition (Lazy evaluation)

When a transformation is invoked, Spark **does not execute it** immediately. Transformations are only executed when **the first action** is called.

- An RDD can be thought of a set of *instructions* on how to compute the data that we build up through transformations.

- Lazy evaluation helps **reducing the number of passes** needed to load and transform the data.

Lazy evaluation: motivating example ★

```
lines = sc.textFile("./data/logfile.txt")
exceptions = lines.filter(lambda line : "exception" in line)
nb_lines = exceptions.count()
print("Number of exception lines ", nb_lines)
```

What happens if Spark executes **immediately** each transformation?

Lazy evaluation: motivating example ★

- Invoking `sc.textFile()` does not load immediately the data.
- The transformation `filter()` is not applied when it is invoked.
- Transformations are applied only when the action `count()` is invoked.
- **Only the data** that meet the constraint of the `filter` is loaded from the file.

```
lines = sc.textFile("./data/logfile.txt")
exceptions = lines.filter(lambda line : "exception" in line)
nb_lines = exceptions.count()
print("Number of exception lines ", nb_lines)
```

☞ **Without lazy evaluation** we would have loaded into main memory **the whole content** of the input file.

Lazy evaluation: consequences ★

- The following code invokes **two actions**: which ones?
- What happens when we invoke the **second action**?

Example

```
lines = sc.textFile("./data/logfile.txt")
exceptions = lines.filter(lambda line : "exception" in line)
nb_lines = exceptions.count()
exceptions.collect()
```

Lazy evaluation: consequences ★

- With lazy evaluation, transformations are computed **each time** an action is invoked on a given RDD.
- In the following example, all transformations are computed when we invoke the function `count()` **and** the function `collect()`.

Example

```
lines = sc.textFile("./data/logfile.txt")
exceptions = lines.filter(lambda line : "exception" in line)
nb_lines = exceptions.count()
exceptions.collect()
```

To avoid computing transformations multiple times, we can **persist** the data.

Persisting the data

- Persisting the data means **caching** the result of the transformations.
  - Either in main memory (default), or disk or both.
- If a node in the cluster fails, Spark **recomputes** the persisted partitions.
  - We can **replicate** persisted partitions on other nodes to recover from failures without recomputing.

```
lines = sc.textFile("./data/logfile.txt")
exceptions = lines.filter(lambda line : "exception" in line)
exceptions.persist(StorageLevel.MEMORY_AND_DISK)
nb_lines = exceptions.count()
exceptions.collect()
```

- `persist()` is called right before the first action.
- `persist()` does not force the evaluation of transformations.
- `unpersist()` can be called to evict persisted partitions.

References

- Karau, Holden, et al. *Learning spark: lightning-fast big data analysis*. O'Reilly Media, Inc., 2015. Click here

Playing with transformations and actions

Notebook available on Google Colab ▸ Click here

☞ Select File → Save a copy in Drive to create a copy of the notebook in your Drive and play with it.