

Introduction to Apache Spark

Thomas Ropars

`thomas.ropars@univ-grenoble-alpes.fr`

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References

The content of this lectures is inspired by:

- The lecture notes of Yann Vernaz.
- The lecture notes of Vincent Leroy.
- The lecture notes of Renaud Lachaize.
- The lecture notes of Henggang Cui.

Goals of the lecture

- Present the main challenges associated with distributed computing
- Review the MapReduce programming model for distributed computing
 - Discuss the limitations of Hadoop MapReduce
- Learn about Apache Spark and its internals
- Start programming with PySpark

Agenda

Computing at large scale

Programming distributed systems

MapReduce

Introduction to Apache Spark

Spark internals

Programming with PySpark

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Distributed computing: Definition

A **distributed computing system** is a system including several computational entities where:

- Each entity has its own local memory
- All entities communicate by message passing over a network

Each entity of the system is called a **node**.

Distributed computing: Motivation

There are several reasons why one may want to distribute data and processing:

- Scalability
 - ▶ The data do not fit in the memory/storage of one node
 - ▶ The processing power of more processor can reduce the time to solution
- Fault tolerance / availability
 - ▶ Continuing delivering a service despite node crashes.
- Latency
 - ▶ Put computing resources close to the users to decrease latency

Increasing the processing power

Goals

- Increasing the amount of data that can be processed (weak scaling)
- Decreasing the time needed to process a given amount of data (strong scaling)

Two solutions

- Scaling up
- Scaling out

Vertical scaling (scaling up)

Idea

Increase the processing power by adding resources to existing nodes:

- Upgrade the processor (more cores, higher frequency)
- Increase memory volume
- Increase storage volume

Pros and Cons

Vertical scaling (scaling up)

Idea

Increase the processing power by adding resources to existing nodes:

- Upgrade the processor (more cores, higher frequency)
- Increase memory volume
- Increase storage volume

Pros and Cons

- 😊 Performance improvement without modifying the application
- 😞 Limited scalability (capabilities of the hardware)
- 😞 Expensive (non linear costs)

Horizontal scaling (scaling out)

Idea

Increase the processing power by adding more nodes to the system

- Cluster of commodity servers

Pros and Cons




Horizontal scaling (scaling out)

Idea

Increase the processing power by adding more nodes to the system

- Cluster of commodity servers

Pros and Cons

-  Often requires modifying applications
-  Less expensive (nodes can be turned off when not needed)
-  *Infinite* scalability

Horizontal scaling (scaling out)

Idea

Increase the processing power by adding more nodes to the system

- Cluster of commodity servers

Pros and Cons

- ☹ Often requires modifying applications
- 😊 Less expensive (nodes can be turned off when not needed)
- 😊 *Infinite* scalability

Main focus of this lecture

Large scale infrastructures

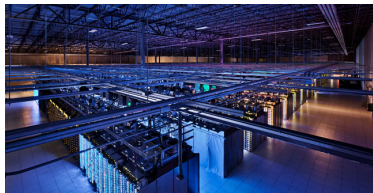


Figure: Google Data-center



Figure: Amazon Data-center



Figure: Barcelona Supercomputing Center

Programming for large-scale infrastructures

Challenges

- Performance
 - ▶ How to take full advantage of the available resources?
 - ▶ Moving data is costly
 - How to maximize the ratio between computation and communication?
- Scalability
 - ▶ How to take advantage of a large number of distributed resources?
- Fault tolerance
 - ▶ The more resources, the higher the probability of failure
 - ▶ MTBF (Mean Time Between Failures)
 - MTBF of one server = 3 years
 - MTBF of 1000 servers \simeq 19 hours (beware: over-simplified computation)

Programming in the Clouds

Cloud computing

- A service provider gives access to computing resources through an internet connection.

Pros and Cons

Programming in the Clouds

Cloud computing

- A service provider gives access to computing resources through an internet connection.

Pros and Cons

- 😊 Pay only for the resources you use
- 😊 Get access to large amount of resources
 - ▶ Amazon Web Services features millions of servers
- 😞 Volatility
 - ▶ Low control on the resources
 - ▶ Example: Access to resources based on bidding
 - ▶ See "The Netflix Simian Army"
- 😞 Performance variability
 - ▶ Physical resources shared with other users

A warning about distributed computing

You can have a second computer once you've shown you know how to use the first one. (P. Braham)

Horizontal scaling is very popular.

- But not always the most efficient solution (both in time and cost)

Examples

- Processing a few 10s of GB of data is often more efficient on a single machine than on a cluster of machines
- Sometimes a single threaded program outperforms a cluster of machines (F. McSherry et al. "Scalability? But at what COST!". 2015.)

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Summary of the challenges

Context of execution

- Large number of resources
- Resources can crash (or disappear)
 - Failure is the norm rather than the exception.
- Resources can be slow

Objectives

- Run until completion :-)
 - And obtain a correct result :-)
- Run fast

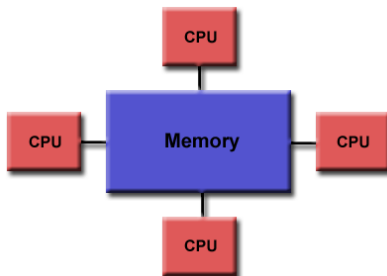
Shared memory and message passing

Two paradigms for communicating between computing entities:

- Shared memory
- Message passing

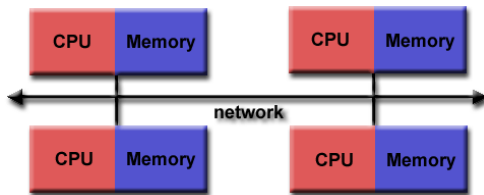
Shared memory

- Entities share a global memory
- Communication by reading and writing to the globally shared memory
- Examples: Pthreads, OpenMP, etc




Message passing

- Entities have their own private memory
- Communication by sending/receiving messages over a network
- Example: MPI



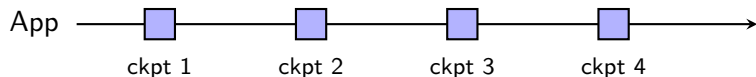
Dealing with failures: Checkpointing

Checkpointing

App 

Dealing with failures: Checkpointing

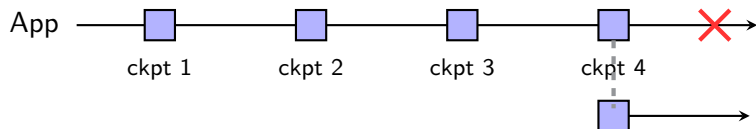
Checkpointing



- Saving the complete state of the application periodically

Dealing with failures: Checkpointing

Checkpointing



- Saving the complete state of the application periodically
- Restart from the most recent checkpoint in the event of a failure.

About checkpointing

Main solution when processes can apply fine-grained modifications to the data (Pthreads or MPI)

- A process can modify any single byte independently
- Impossible to log all modifications

Limits

- Performance cost
- Difficult to implement
- The alternatives (passive or active replication) are even more costly and difficult to implement in most cases

About slow resources (stragglers)

Performance variations

- Both for the nodes and the network
- Resources shared with other users

Impact on classical message-passing systems (MPI)

- Tightly-coupled processes
 - ▶ *Process A waits for a message from process B before continuing its computation*

```
Do some computation  
new_data = Recv(from B) /*blocking*/  
Resume computing with new_data
```

Figure: Code of process A. If B is slow, A becomes idle.

The Big Data approach

Provide a distributed computing execution framework

- Simplify parallelization
 - ▶ Define a programming model
 - ▶ Handle distribution of the data and the computation
- Fault tolerant
 - ▶ Detect failure
 - ▶ Automatically takes corrective actions
- **Code once (expert), benefit to all**

Limit the operations that a user can run on data

- Inspired from functional programming (eg, MapReduce)
- Examples of frameworks:
 - ▶ Hadoop MapReduce, Apache Spark, Apache Flink, etc

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MapReduce at Google

References

- *The Google file system*, S. Ghemawat et al. SOSP 2003.
- *MapReduce: simplified data processing on large clusters*, D. Jeffrey and S. Ghemawat. OSDI 2004.

Main ideas

- Data represented as key-value pairs
- Two main operations on data: Map and Reduce
- A distributed file system
 - Compute where the data are located

Use at Google

- Compute the index of the World Wide Web.
- Google has moved on to other technologies

Apache Hadoop



Apache Hadoop

In a few words

- Built on top of the ideas of Google
- A full data processing stack
- The core elements
 - ▶ A distributed file system: HDFS (Hadoop Distributed File System)
 - ▶ A programming model and execution framework: Hadoop MapReduce

MapReduce

- Allows simply expressing many parallel/distributed computational algorithms

MapReduce

The Map operation

- Transformation operation
- $\text{map}(f)[x_0, \dots, x_n] = [f(x_0), \dots, f(x_n)]$
- $\text{map}(*2)[2, 3, 6] = [4, 6, 12]$

The Reduce operation

- Aggregation operation (fold)
- $\text{reduce}(f)[x_0, \dots, x_n] = [f((x_0), f((x_1), \dots, f(x_{n-1}, x_n))))]$
- $\text{reduce}(+)[2, 3, 6] = (2 + (3 + 6)) = 11$

Hadoop MapReduce

Key/Value pairs

- MapReduce manipulate sets of Key/Value pairs
- Keys and values can be of any types

Functions to apply

- The user defines the functions to apply
- In Map, the function is applied independently to each pair
- In Reduce, the function is applied to all values with the same key

Hadoop MapReduce

About the Map operation

- A given input pair may map to zero or many output pairs
- Output pairs need not be of the same type as input pairs

About the Reduce operation

- Applies operation to all pairs with the same key
- 3 steps:
 - ▶ **Shuffle and Sort**: Groups and merges the output of mappers by key
 - ▶ **Reduce**: Apply the reduce operation to the new key/value pairs

Example: Word count

Description

- Input: A set of lines including words
 - ▶ Pairs \langle line number, line content \rangle
 - ▶ The initial keys are ignored in this example
- Output: A set of pairs \langle word, nb of occurrences \rangle

Input

- $\langle 1, \text{"aaa bb ccc"} \rangle$
- $\langle 2, \text{"aaa bb"} \rangle$

Output

- $\langle \text{"aaa"}, 2 \rangle$
- $\langle \text{"bb"}, 2 \rangle$
- $\langle \text{"ccc"}, 1 \rangle$

Example: Word count

```
map(key, value): /* ->(line num, content) */  
    foreach word in value.split():  
        emit(word, 1)
```

```
reduce(key, values): /* ->(word, occurrences) */  
    result = 0  
    for value in values:  
        result += value  
    emit(key, result)
```

Example: Web index

Description

Construct an index of the pages in which a word appears.

- Input: A set of web pages
 - ▶ Pairs $\langle \text{URL}, \text{content of the page} \rangle$
- Output: A set of pairs $\langle \text{word}, \text{set of URLs} \rangle$

Example: Web index

```
map(key, value): /* ->(URL, page_content) */  
    foreach word in value.parse():  
        emit(word, key)
```

```
reduce(key, values): /* ->(word, URLs) */  
    list=[]  
    for value in values:  
        list.add(value)  
    emit(key, list)
```


Running at scale

How to distribute data?

- Partitioning
- Replication

Partitioning

- Splitting the data into partitions
- Partitions are assigned to different nodes
- Main goal: Performance
 - ▶ Partitions can be processed in parallel

Replication

- Several nodes host a copy of the data
- Main goal: Fault tolerance
 - ▶ No data lost if one node crashes

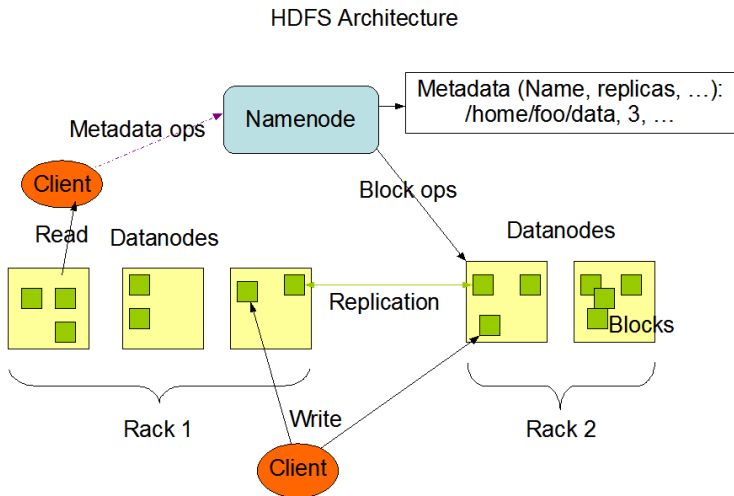
Hadoop Distributed File System (HDFS)

Main ideas

- Running on a cluster of commodity servers
 - ▶ Each node has a local disk
 - ▶ A node may fail at any time
- The content of files is stored on the disks of the nodes
 - ▶ Partitioning: Files are partitioned into blocks that can be stored in different *Datanodes*
 - ▶ Replication: Each block is replicated in multiple *Datanodes*
 - Default replication degree: 3
 - ▶ A *Namenode* regulates access to files by clients
 - Master-worker architecture

HDFS architecture

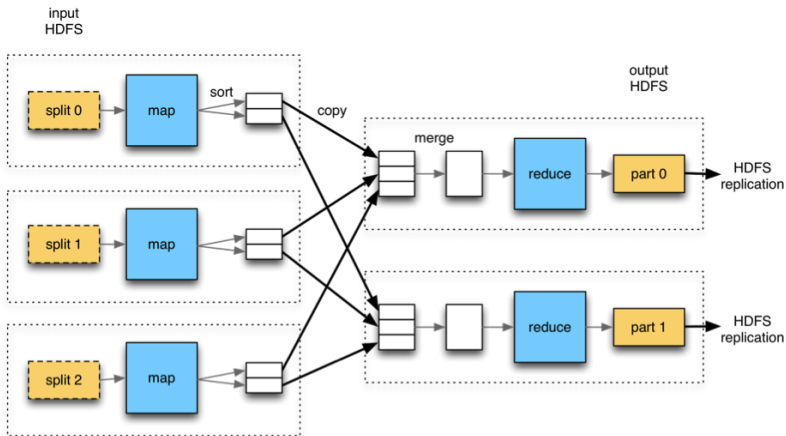
Figure from https://hadoop.apache.org/docs/r1.2.1/hdfs_design.html



Hadoop data workflow

Figure from

<https://www.supinfo.com/articles/single/2807-introduction-to-the-mapreduce-life-cycle>



Hadoop workflow: a few comments

Data movements

- Map tasks are executing on nodes where the data blocks are hosted
 - ▶ Or on close nodes
 - ▶ Less expensive to move computation than to move data
- Load balancing between the reducers
 - ▶ Output of mappers are partitioned according to the number of reducers (modulo on a hash of the key)

Synchronization

- Barrier at the end of the Map phase
 - ▶ The reduce phase starts only when all map operations are terminated.

Hadoop workflow: a few comments

I/O operations

- Map tasks read data from disks
- Output of the mappers are stored in memory if possible
 - ▶ Otherwise flushed to disk
- The result of reduce tasks is written into HDFS

Fault tolerance

- Execution of tasks is monitored by the master node
 - ▶ Tasks are launched again on other nodes if crashed or too slow

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Apache Spark



- Originally developed at Univ. of California
- *Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing*, M. Zaharia et al. NSDI, 2012.
- One of the most popular Big Data project today.

Spark vs Hadoop

Spark added value

- Performance
 - Especially for iterative algorithms
- Interactive queries
- Support more operations on data
- A full ecosystem (High level libraries)
- Running on your machine or at scale

Main novelties

- Computing in memory
- A new computing abstraction: [Resilient Distributed Datasets \(RDD\)](#)

Programming with Spark

Spark Core API

- Scala
- Python
- Java

Integration with Hadoop

Works with any storage source supported by Hadoop

- Local file systems
- HDFS
- Cassandra
- Amazon S3

Many resources to get started

- <https://spark.apache.org/>
- <https://sparkhub.databricks.com/>
- Many courses, tutorials, and examples available online

Starting with Spark

Running in local mode

- Spark runs in a JVM
 - Spark is coded in Scala
- Read data from your local file system

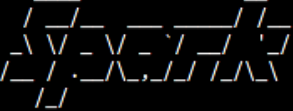
Use interactive shell

- Scala (*spark-shell*)
- Python (*pyspark*)
- Run locally or distributed at scale

A very first example with pyspark

Counting lines

```
File Edit View Search Terminal Help
```



```
version 2.2.0
```

```
Using Python version 3.6.3 (default, Nov 20 2017 20:41:42)
SparkSession available as 'spark'.
>>> lines = sc.textFile("./The_Iliad_by_Homer.txt")
>>> lines.count()
26175
>>>
```

The Spark Web UI



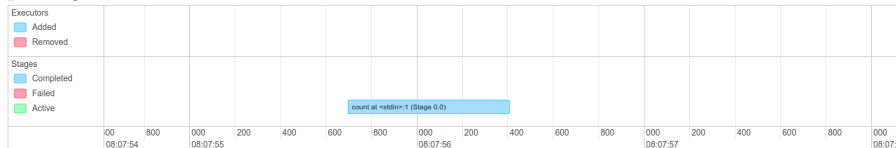
Details for Job 0

Status: SUCCEEDED

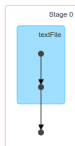
Completed Stages: 1

Event Timeline

☒ Enable zooming



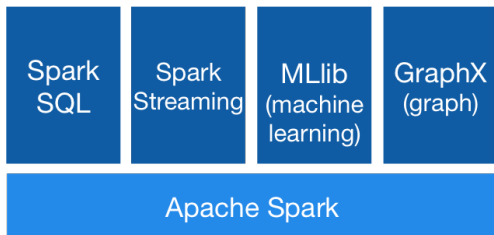
DAG Visualization



Completed Stages (1)

Stage Id ▾	Description	Submitted	Duration	Tasks: Succeeded/Total	Input	Output
0	count at <stdin>:1 <small>*details</small>	2017/12/03 08:07:55	0.7 s	2/2	1290.9 KB	

The Spark built-in libraries



- **Spark SQL**: For structured data (Dataframes)
- **Spark Streaming**: Stream processing (micro-batching)
- **MLlib**: Machine learning
- **GraphX**: Graph processing

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In-memory computing: Insights

See Latency Numbers Every Programmer Should Know

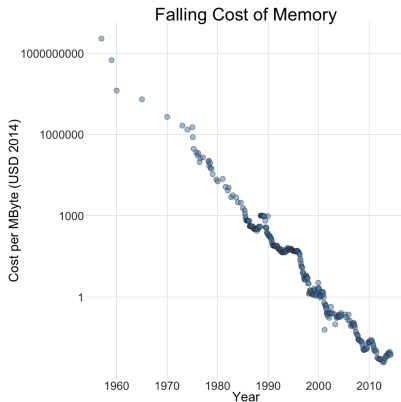
Memory is way faster than disks

Read latency

- HDD: a few milliseconds
- SSD: 10s of microseconds (100X faster than HDD)
- DRAM: 100 nanoseconds (100X faster than SSD)

In-memory computing: Insights

Graph by P. Johnson



Cost of memory decreases = More memory per server

Efficient iterative computation

Hadoop: At each step, data go through the disks



Spark: Data remain in memory (if possible)



Main challenge

Fault Tolerance

Failure is the norm rather than the exception

On a node failure, all data in memory is lost

Resilient Distributed Datasets

Restricted form of distributed shared memory

- Read-only partitioned collection of records
- Creation of a RDD through deterministic operations (transformations) on
 - Data stored on disk
 - an existing RDD

Transformations and actions

Programming with RDDs

- An RDD is represented as an object
- Programmer defines RDDs using **Transformations**
 - ▶ Applied to data on disk or to existing RDDs
 - ▶ Examples of transformations: map, filter, join
- Programmer uses RDDs in **Actions**
 - ▶ Operations that return a value or export data to the file system
 - ▶ Examples of actions: count, reduce

Fault tolerance with Lineage

Lineage = a description of an RDD

- The data source on disk
- The sequence of applied transformations
 - ▶ Same transformation applied to all elements
 - ▶ Low footprint for storing a lineage

Fault tolerance

- RDD partition lost
 - ▶ Replay all transformations on the subset of input data or the most recent RDD available
- Deal with stragglers
 - ▶ Generate a new copy of a partition on another node

Spark runtime

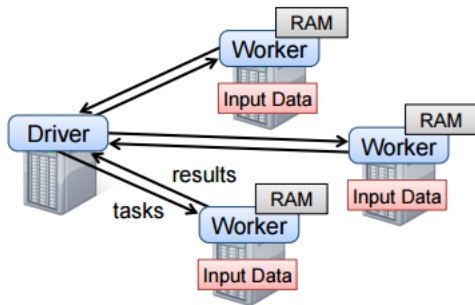
Figure by M. Zaharia et al

- Driver (= Master)

- ▶ Executes the user program
- ▶ Defines RDDs and invokes actions
- ▶ Tracks RDD's lineage

- Workers

- ▶ Store RDD partitions
- ▶ Performs transformations and actions
 - Run tasks



Persistence and partitioning

See [https:](https://spark.apache.org/docs/latest/rdd-programming-guide.html#rdd-persistence)

[//spark.apache.org/docs/latest/rdd-programming-guide.html#rdd-persistence](https://spark.apache.org/docs/latest/rdd-programming-guide.html#rdd-persistence)

Different options of persistence for RDDs

- Options:
 - ▶ Storage: memory/disk/both
 - ▶ Replication: yes/no
 - ▶ Serialization: yes/no

Partitions

- RDDs are automatically partitioned based on:
 - ▶ The configuration of the target platform (nodes, CPUs)
 - ▶ The size of the RDD
 - ▶ User can also specify its own partitioning
- Tasks are created for each partition

RDD dependencies

Transformations create dependencies between RDDs.

2 kinds of dependencies

- Narrow dependencies
 - Each partition in the parent is used by **at most one** partition in the child
- Wide (shuffle) dependencies
 - Each partition in the parent is used by **multiple** partitions in the child

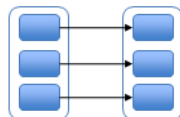
Impact of dependencies

- Scheduling: Which tasks can be run independently
- Fault tolerance: Which partitions are needed to recreate a lost partition

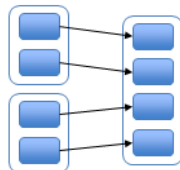
RDD dependencies

Figure by M. Zaharia et al

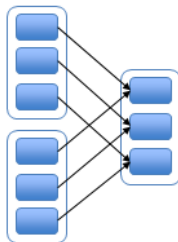
“Narrow” deps:



map, filter

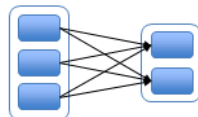


union

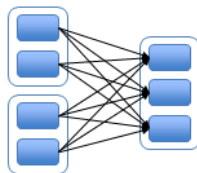


join with
inputs co-
partitioned

“Wide” (shuffle) deps:



groupByKey



join with inputs not
co-partitioned

Executing transformations and actions

Lazy evaluation

- Transformations are executed only when an action is called on the corresponding RDD
- Examples of optimizations allowed by lazy evaluation
 - ▶ Read file from disk + action `first()`: no need to read the whole file
 - ▶ Read file from disk + transformation `filter()`: No need to create an intermediate object that contains all lines

Persist an RDD

- By default, an RDD is recomputed for each action run on it.
- A RDD can be cached in memory calling `persist()` or `cache()`
 - ▶ Useful is multiple actions to be run on the same RDD (iterative algorithms)
 - ▶ Can lead to 10X speedup
 - ▶ Note that a call to `persist` does not trigger transformations evaluation

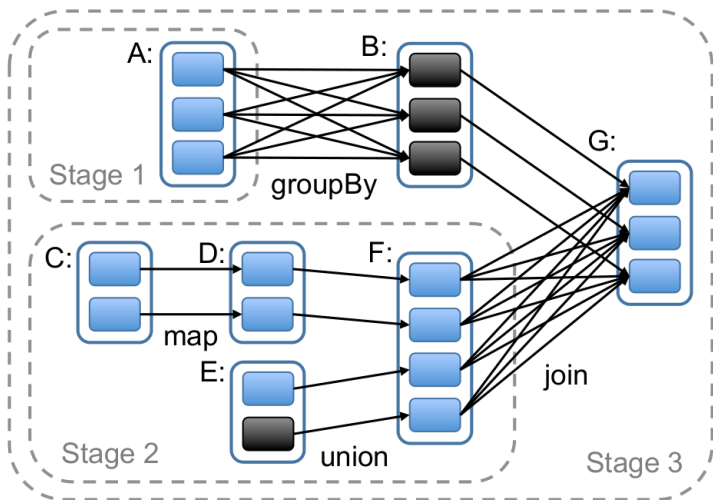
Job scheduling

Main ideas

- Tasks are run when the user calls an action
- A Directed Acyclic Graph (DAG) of transformations is built based on the RDD's lineage
- The DAG is divided into stages. Boundaries of a stage defined by:
 - ▶ Wide dependencies
 - ▶ Already computed RDDs
- Tasks are launch to compute missing partitions from each stage until target RDD is computed
 - ▶ Data locality is taken into account when assigning tasks to workers

Stages in a RDD's DAG

Figure by M. Zaharia et al



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The SparkContext

What is it?

- Object representing a connection to an execution cluster
- We need a SparkContext to build RDDs

Creation

- Automatically created when running in shell (variable `sc`)
- To be initialized when writing a standalone application

Initialization

- Run in local mode with nb threads = nb cores: `local[*]`
- Run in local mode with 2 threads: `local[2]`
- Run on a spark cluster: `spark://HOST:PORT`

The SparkContext

Python shell

```
$ pyspark --master local[*]
```

Python program

```
import pyspark

sc = pyspark.SparkContext("local[*]")
```

The first RDDs

Create RDD from existing iterator

- Use of `SparkContext.parallelize()`
- Optional second argument to define the number of partitions

```
data = [1, 2, 3, 4, 5]
distData = sc.parallelize(data)
```

Create RDD from a file

- Use of `SparkContext.textFile()`

```
data = sc.textFile("myfile.txt")
hdfsData = sc.textFile("hdfs://myhdfsfile.txt")
```

Some transformations

see [https:](https://spark.apache.org/docs/latest/rdd-programming-guide.html#transformations)

[//spark.apache.org/docs/latest/rdd-programming-guide.html#transformations](https://spark.apache.org/docs/latest/rdd-programming-guide.html#transformations)

- `map(f)`: Applies f to all elements of the RDD. f generates a single item
- `flatMap(f)`: Same as `map` but f can generate 0 or several items
- `filter(f)`: New RDD with the elements for which f return *true*
- `union(other)/intersection(other)`: New RDD being the union/intersection of the initial RDD and *other*.
- `cartesian(other)`: When called on datasets of types T and U , returns a dataset of (T, U) pairs (all pairs of elements)
- `distinct()`: New RDD with the distinct elements
- `repartition(n)`: Reshuffle the data in the RDD randomly to create either more or fewer partitions and balance it across them

Some transformations with $\langle K, V \rangle$ pairs

- `groupByKey()`: When called on a dataset of (K, V) pairs, returns a dataset of $(K, \text{Iterable}\langle V \rangle)$ pairs.
- `reduceByKey(f)`: When called on a dataset of (K, V) pairs, Merge the values for each key using an associative and commutative reduce function.
- `aggregateByKey()`: see documentation
- `join(other)`: Called on datasets of type (K, V) and (K, W) , returns a dataset of $(K, (V, W))$ pairs with all pairs of elements for each key.

Some actions

see

<https://spark.apache.org/docs/latest/rdd-programming-guide.html#actions>

- `reduce(f)`: Aggregate the elements of the dataset using f (takes two arguments and returns one).
- `collect()`: Return all the elements of the dataset as an array.
- `count()`: Return the number of elements in the dataset.
- `take(n)`: Return an array with the first n elements of the dataset.
- `takeSample()`: Return an array with a random sample of num elements of the dataset.
- `countByKey()`: Only available on RDDs of type (K, V) . Returns a hashmap of (K, Int) pairs with the count of each key.

An example

```
from pyspark.context import SparkContext
sc = SparkContext("local")

# define a first RDD
lines = sc.textFile("data.txt")
# define a second RDD
lineLengths = lines.map(lambda s: len(s))
# Make the RDD persist in memory
lineLengths.persist()
# At this point no transformation has been run
# Launch the evaluation of all transformations
totalLength = lineLengths.reduce(lambda a, b: a + b)
```

An example with key-value pairs

```
lines = sc.textFile("data.txt")
pairs = lines.map(lambda s: (s, 1))
counts = pairs.reduceByKey(lambda a, b: a + b)

# Warning: sortByKey implies shuffle
result = counts.sortByKey().collect()
```


Another example with key-value pairs

```
rdd = sc.parallelize([("a", 1), ("b", 1), ("a", 1)])  
# mapValues applies f to each value  
#       without changing the key  
sorted(rdd.groupByKey().mapValues(len).collect())  
# [('a', 2), ('b', 1)]  
sorted(rdd.groupByKey().mapValues(list).collect())  
# [('a', [1, 1]), ('b', [1])]
```

Shared Variables

see <https://spark.apache.org/docs/latest/rdd-programming-guide.html#shared-variables>

Broadcast variables

- Use-case: A read-only large variable should be made available to all tasks (e.g., used in a map function)
- Costly to be shipped with each task
- Declare a broadcast variable
 - ▶ Spark will make the variable available to all tasks in an efficient way

Example with a Broadcast variable

```
b = sc.broadcast([1, 2, 3, 4, 5])
print(b.value)
# [1, 2, 3, 4, 5]
print(sc.parallelize([0, 0]).
      flatMap(lambda x: b.value).collect())
# [1, 2, 3, 4, 5, 1, 2, 3, 4, 5]
b.unpersist()
```

Shared Variables

Accumulator

- Use-case: Accumulate values over all tasks
- Declare an Accumulator on the driver
 - ▶ Updates by the tasks are automatically propagated to the driver.
- Default accumulator: operator `'+='` on `int` and `float`.
 - ▶ User can define custom accumulator functions

Example with an Accumulator

```
file = sc.textFile(inputFile)
# Create Accumulator[Int] initialized to 0
blankLines = sc.accumulator(0)

def splitLine(line):
    # Make the global variable accessible
    global blankLines
    if not line:
        blankLines += 1
    return line.split("\n")

words = file.flatMap(splitLine)
print(blankLines.value)
```