1. INTRODUCTION TO APACHE SPARK

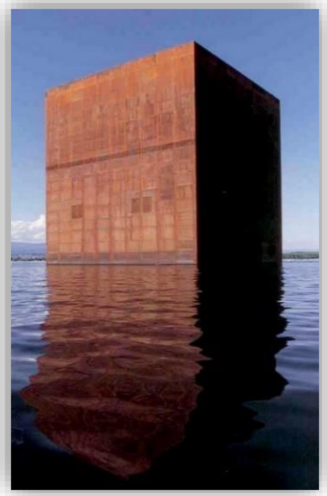
Apache Spark - 2022

EDEM
Escuela de Empresarios

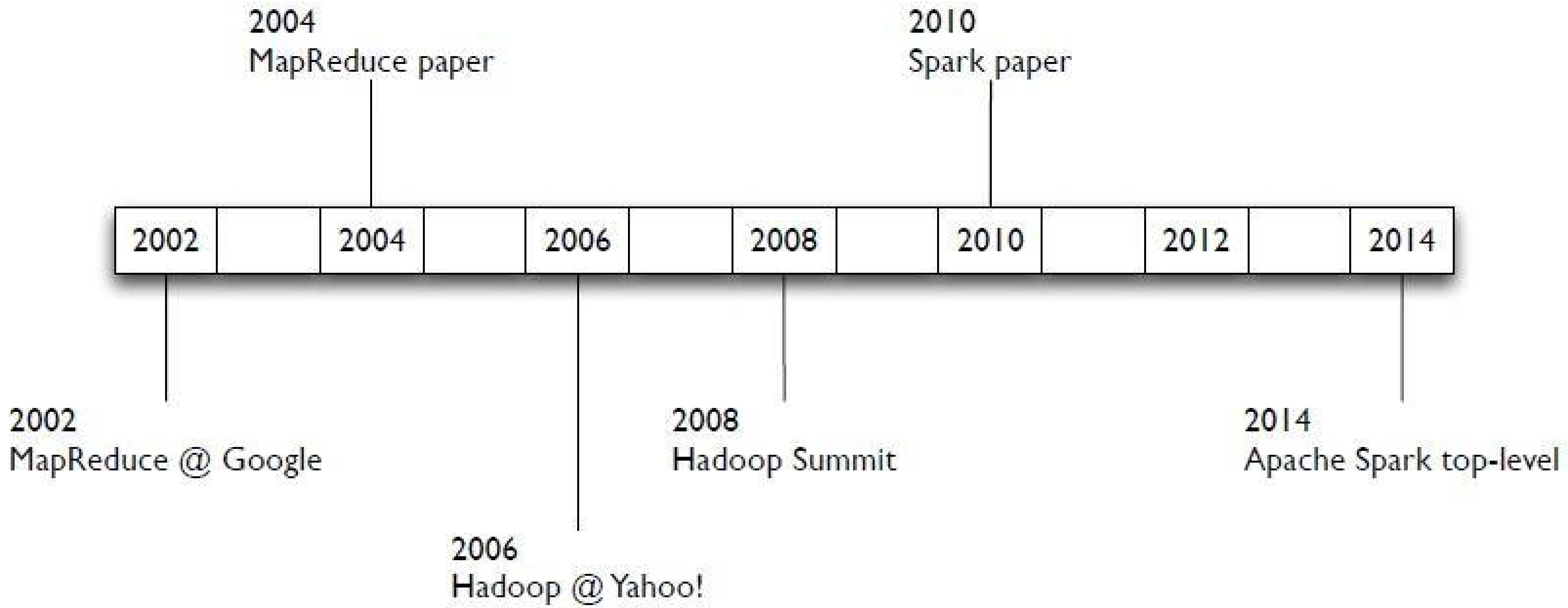
1. Before Apache Spark
2. Introducing Apache Spark
3. Apache Spark. Architecture
4. RDD
5. Key/Value Pairs RDD
6. Executing Spark
7. Architectures

Hadoop

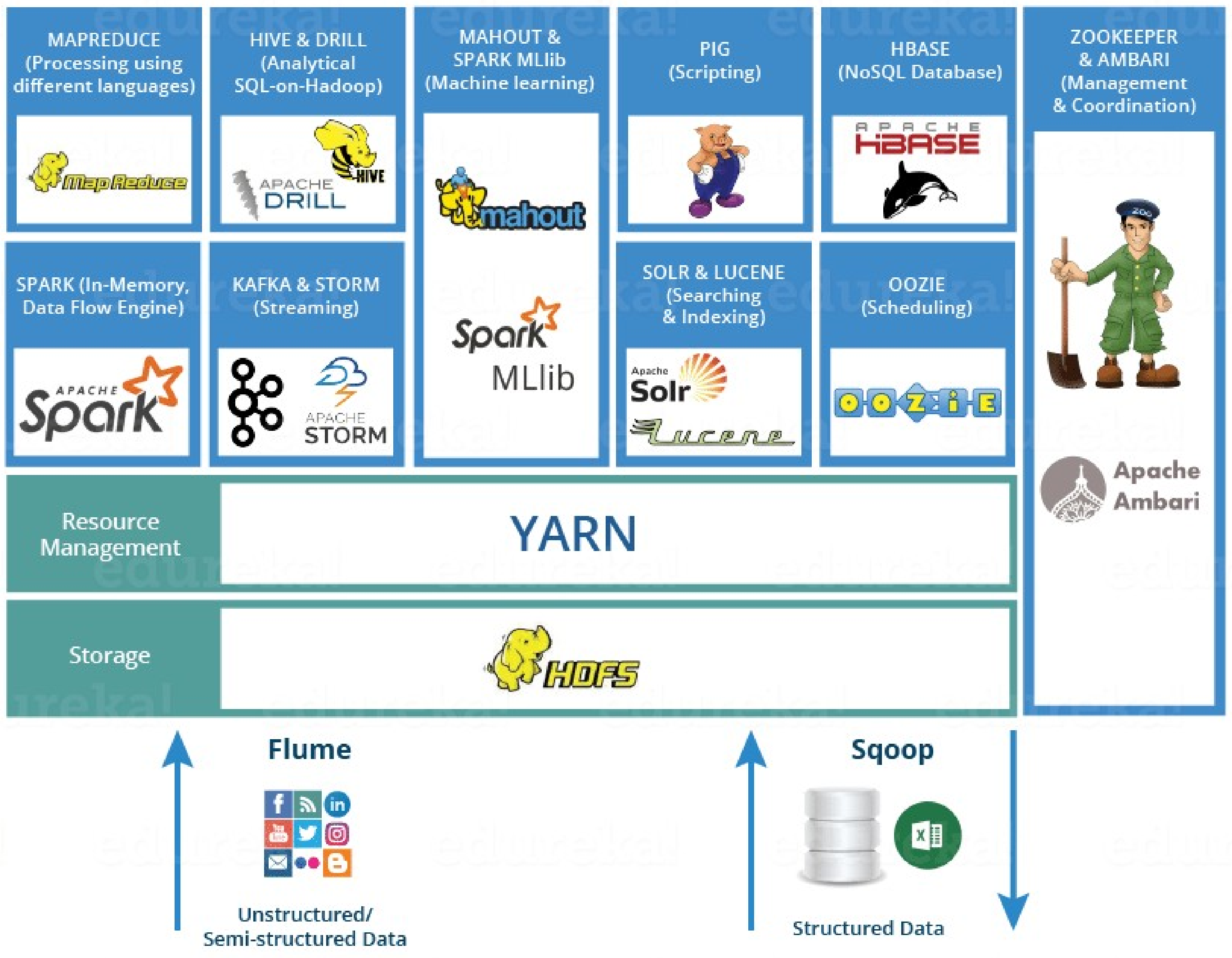
- **Monolithic Computing**
  - For decades, the goal was a bigger, more powerful machine
  - This approach has limitations
    - High Cost
    - Limited scalability



History


2004
MapReduce paper
2010
Spark paper
2002
2004
2006
2008
2010
2012
2014
2002
MapReduce @ Google
2006
Hadoop @ Yahoo!
2008
Hadoop Summit
2014
Apache Spark top-level

Hadoop



CLOUDERA

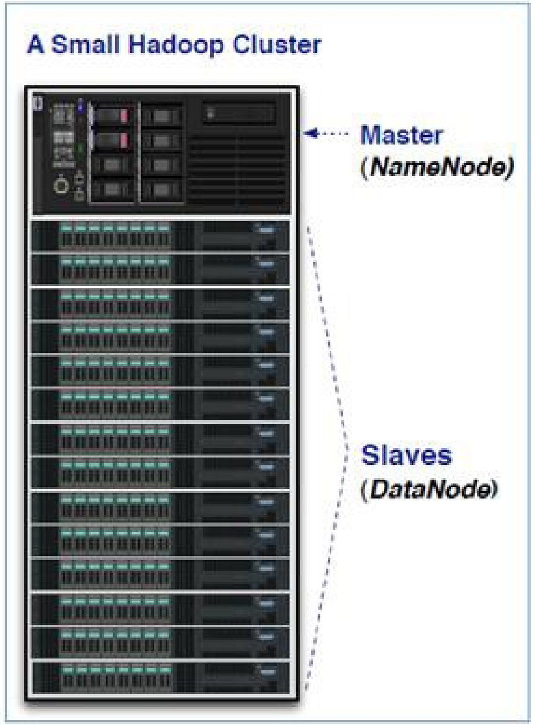
MAPR

HDFS

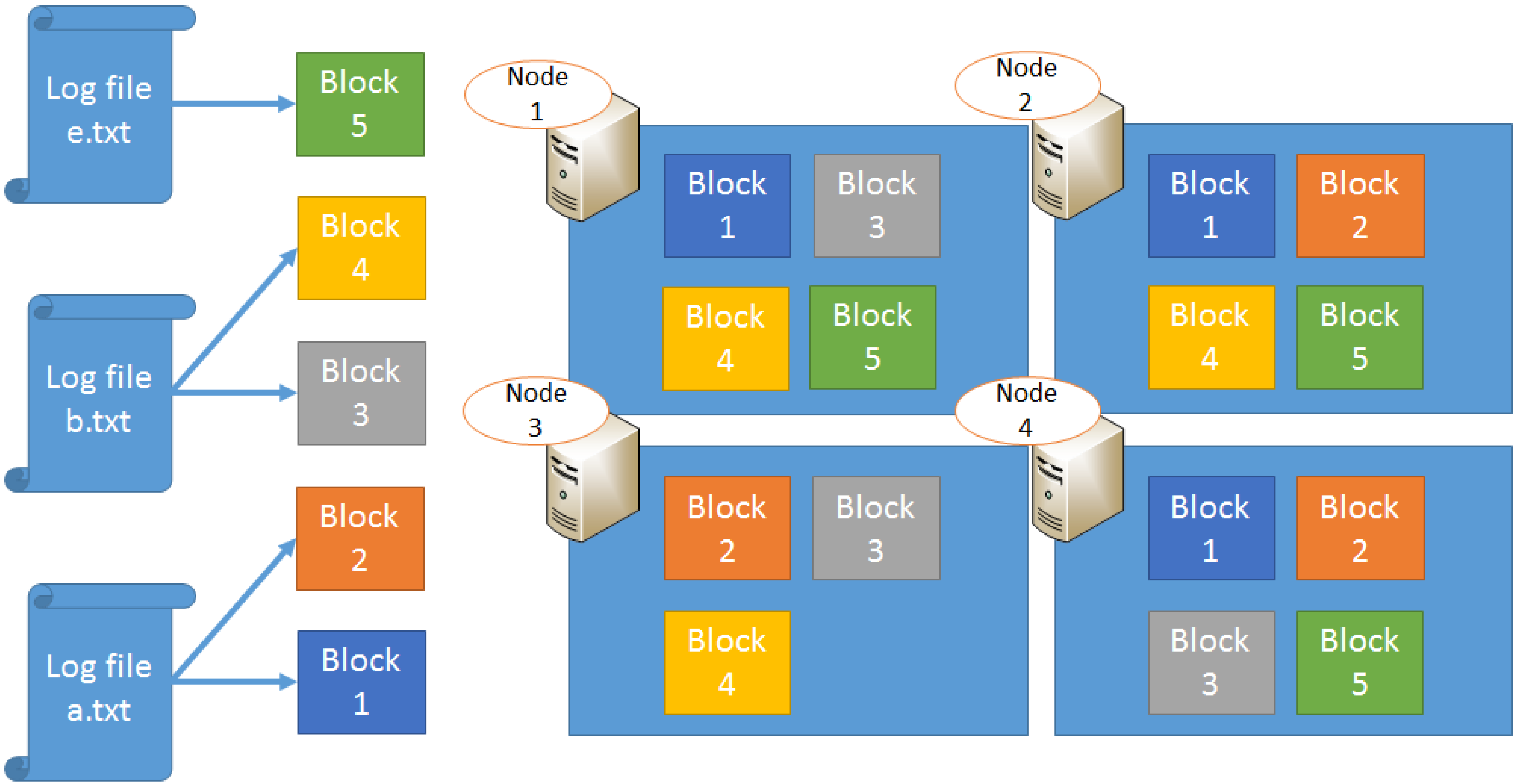
- **HDFS**, the Hadoop Distributed File System, is responsible for storing data on the cluster
- Data is split into blocks and distributed across multiple nodes in the cluster
- **Each block is replicated multiple times:**
  - Replicas are stored on different nodes

HDFS

- Blocks are replicated across multiple machines, known as **DataNodes**
- A master node called **NameNode** keeps track of which blocks make up a file, and where those blocks are located



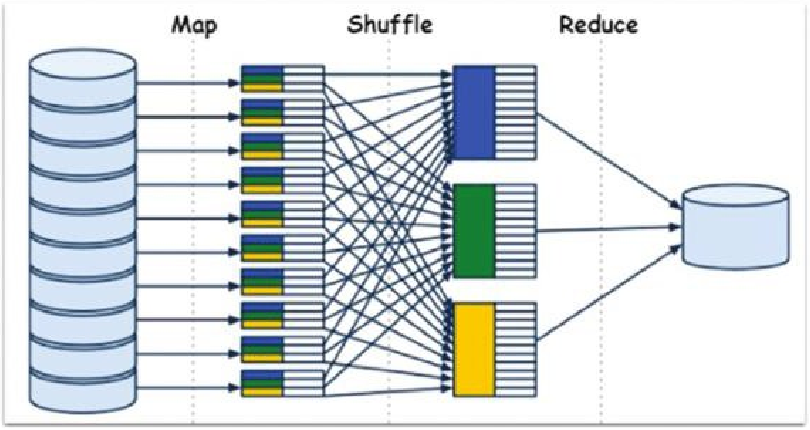
HDFS



Log file e.txt
Block 5
Log file b.txt
Block 4
Block 3
Log file a.txt
Block 2
Block 1
Node 1
Block 1
Block 3
Block 4
Block 5
Node 2
Block 1
Block 2
Block 4
Block 5
Node 3
Block 2
Block 3
Block 4
Node 4
Block 1
Block 2
Block 3
Block 5

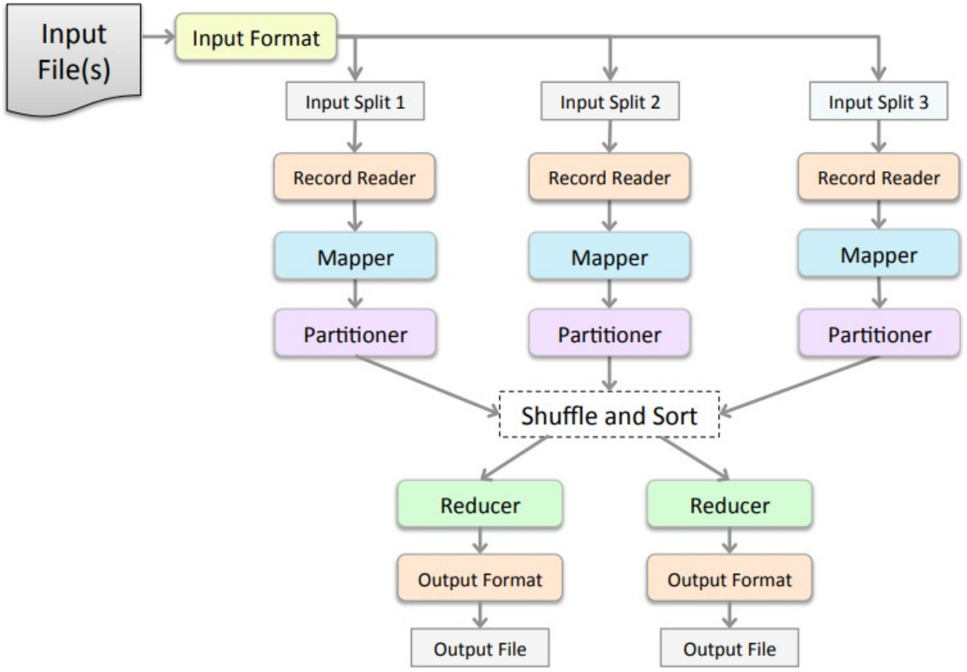
MapReduce

- **MapReduce**
  - Is batch oriented
    - So Hive, Pig and all MR-based systems too
  - Great throughput but high latency
    - Not for BI tools
    - Not for real time (Stream) processing
    - Just ingesting streaming data with Flume
  - Forces to concatenate multiple jobs
    - External orchestration
  - Each job flushes to disk
  - Data sharing requires external storage



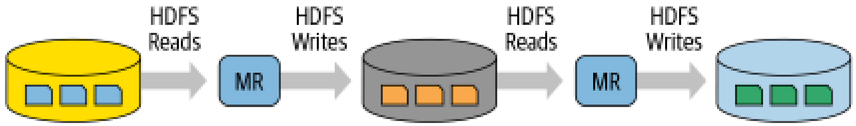
MapReduce

- **Key concepts to keep in mind with MapReduce**
  - The **Mapper** works on an individual record at a time
  - The **Reducer** aggregates results from the Mappers
  - The **intermediate keys** produced by the Mapper are the keys on which the aggregation will be based



MapReduce

- **Problems with MR:**
  - It was hard to manage and administer, with cumbersome operational complexity
  - Its general batch-processing MapReduce API was verbose
  - With large batches of data jobs with many pairs of MR tasks, each pair's intermediate computed result is written to the local disk for the subsequent stage of its operation
  - This repeated performance of disk I/O took its toll: large MR jobs could run for hours on end, or even days.



What Is Apache Spark?

- Apache Spark is a unified engine designed for large-scale distributed data processing on premises in data centers or in the cloud

- It incorporates libraries with composable APIs for:
  - Machine learning (MLlib)
  - SQL for interactive queries (Spark SQL)
  - Stream processing (Structured Streaming)
  - Graph processing (GraphX)

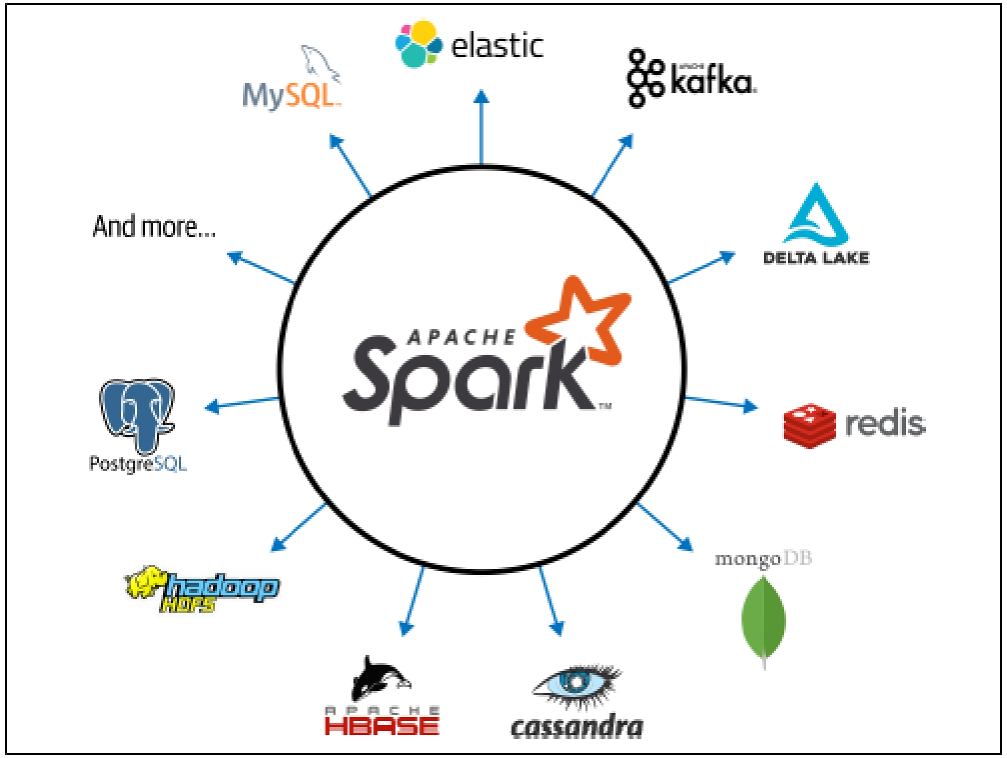
- We will cover Spark SQL in these course

What Is Apache Spark?

- Spark provides the following major benefits
  - **Lightning speed of computation**
    - Data are loaded in distributed memory (RAM) over a cluster of machines
    - Query computations as a directed acyclic graph (DAG) that can usually be decomposed into tasks that are executed in parallel
    - Intermediate results retained in memory and its limited disk I/O, this gives it a huge performance boost
  - **Highly accessible**
    - Through standard APIs built in Java, Scala, Python R or SQL
  - **Compatibility**
    - With the existing Hadoop ecosystems
  - **Convenient**
    - Interactive shells in Scala and Python (REPL)
  - **Enhanced productivity**
    - Due to high level constructs that keep the focus on content of computation

What Is Apache Spark?

- **Extensibility**
  - Spark ecosystem of connectors



What Is Apache Spark?

- Apache Spark is an open-source cluster computing framework
- Requires
  - **Cluster manager**
    - Standalone – a simple cluster manager included with Spark
    - Apache Mesos – a general cluster manager
    - Hadoop YARN – the resource manager in Hadoop 2
  - **Distributed storage system**
    - Hadoop Distributed File System (HDFS)
    - Cassandra
    - Amazon S3
- Also supports pseudo-distributed mode for development and testing
  - Local file system and one worker per CPU core

What Is Apache Spark?

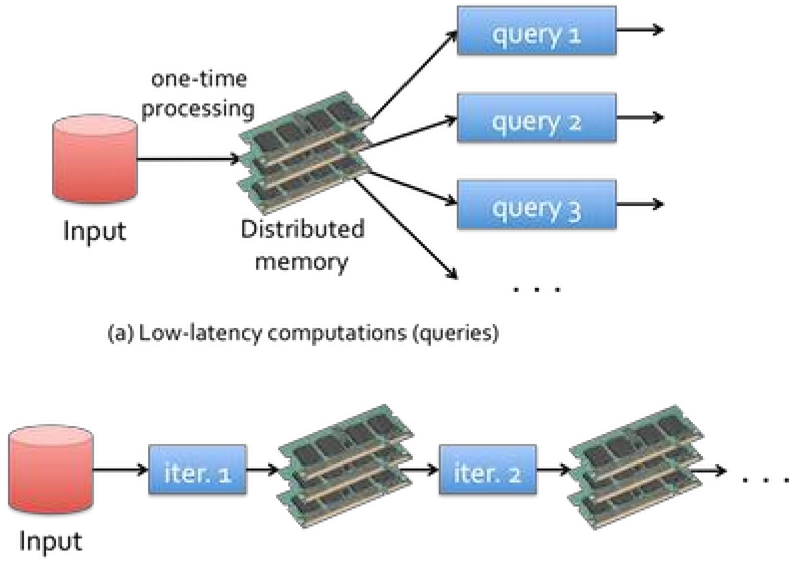
- Spark deployment modes

Mode	Spark driver	Spark executor	Cluster manager
Local	Runs on a single JVM, like a laptop or single node	Runs on the same JVM as the driver	Runs on the same host
Standalone	Can run on any node in the cluster	Each node in the cluster will launch its own executor JVM	Can be allocated arbitrarily to any host in the cluster
YARN (client)	Runs on a client, not part of the cluster	YARN's NodeManager's container	YARN's Resource Manager works with YARN's Application Master to allocate the containers on NodeManagers for executors
YARN (cluster)	Runs with the YARN Application Master	Same as YARN client mode	Same as YARN client mode
Kubernetes	Runs in a Kubernetes pod	Each worker runs within its own pod	Kubernetes Master

What Is Apache Spark?

- Apache Spark is a cluster computing platform designed to be **fast**, **highly-accessible** and **general-purpose**

- Speed
  - Spark extends the MapReduce model to:
    - Efficiently support more types of computations
      - *e.g:* interactive queries, stream processing
    - Ability to run computations in memory
      - Also faster than MR for complex applications running on disk



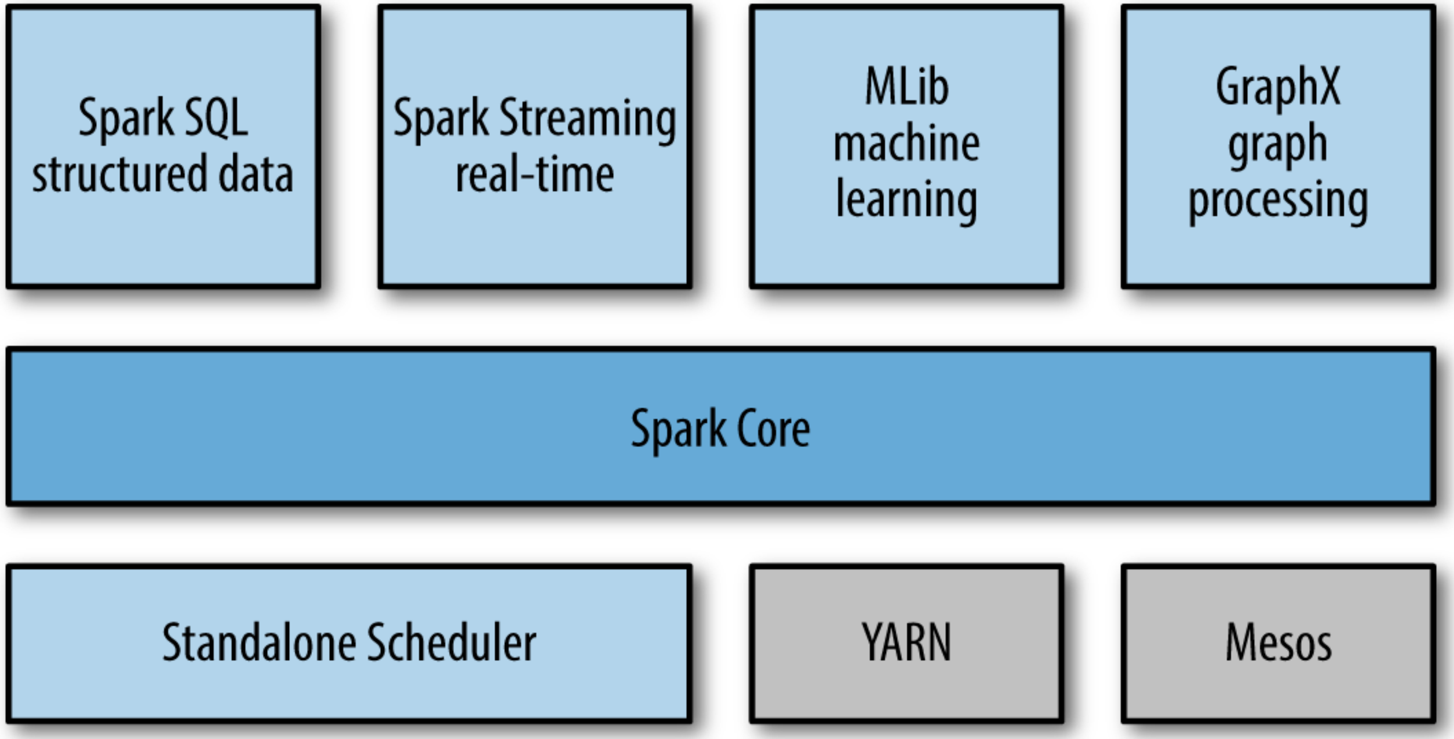
(a) Low-latency computations (queries)

(b) Iterative computations

What Is Apache Spark?

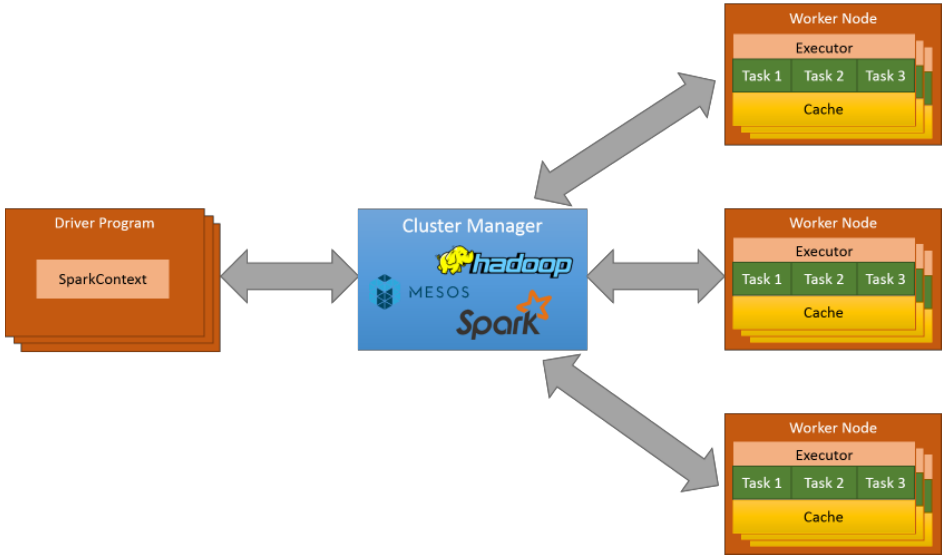
- Popular Spark use cases:
  - Processing in parallel large data sets distributed across a cluster
  - Performing ad hoc or interactive queries to explore and visualize data sets
  - Building, training, and evaluating machine learning models using MLlib
  - Implementing end-to-end data pipelines from myriad streams of data
  - Analyzing graph data sets and social networks

Architecture

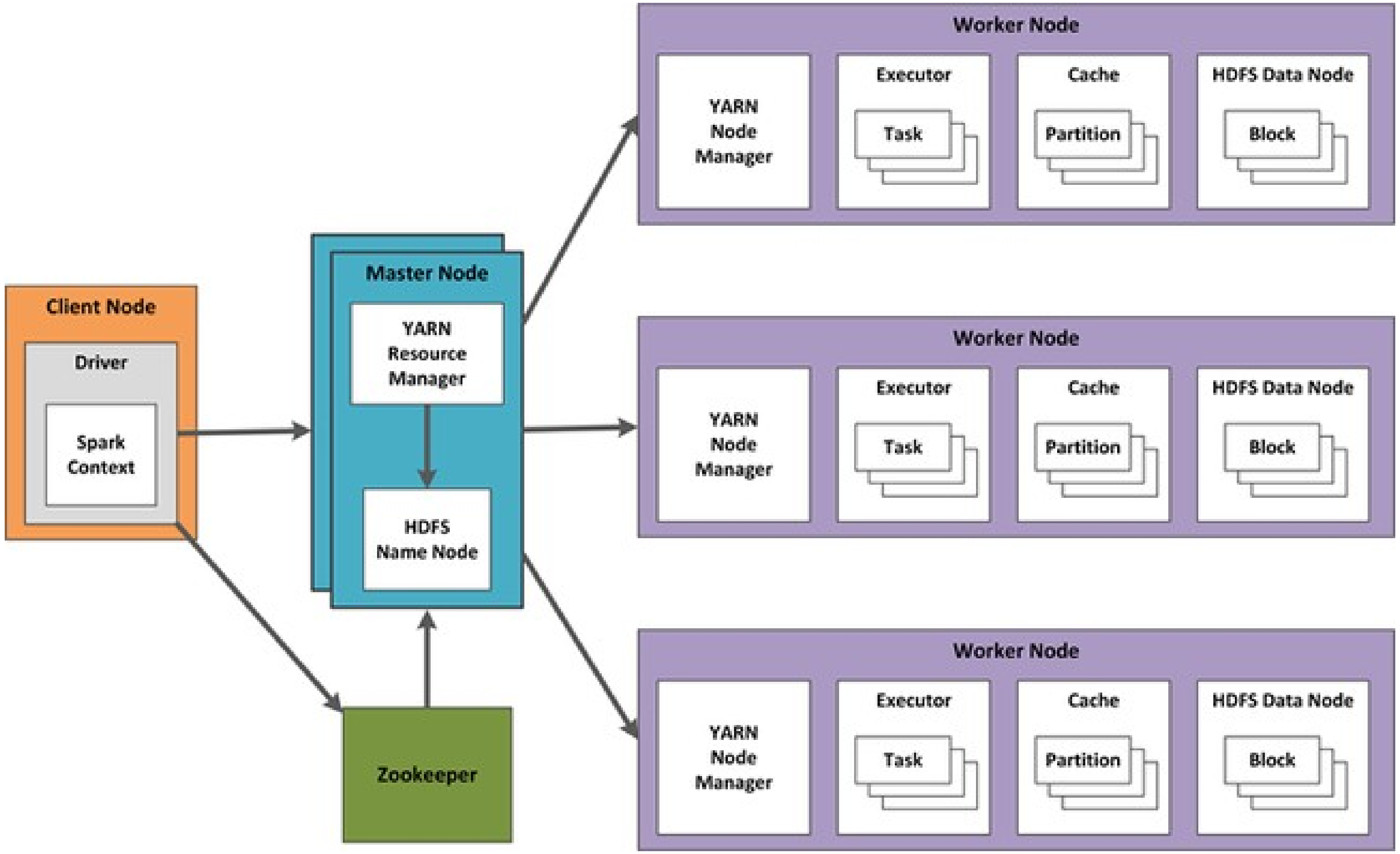


Spark Runtime Architecture

- Master/slave architecture
- Central coodinator **driver** (own java process)
- Daemons on workers called **executor** (own java process)
- **Driver + executors = Spark application**
- Application is launched using a **cluster manager**



Spark Runtime Architecture



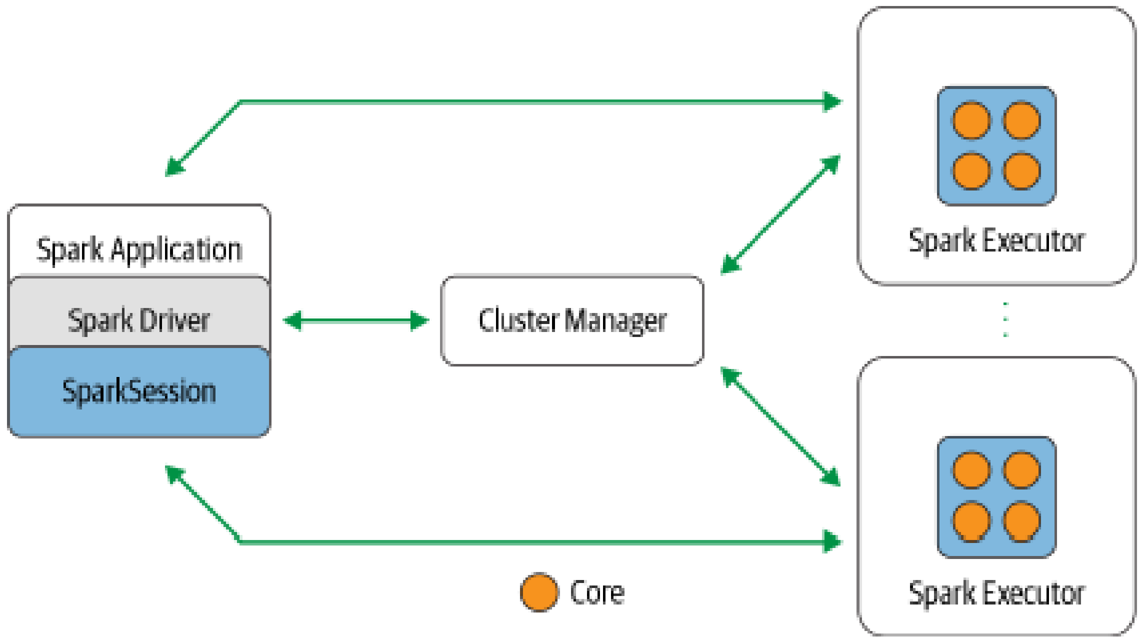
Core Spark Concepts

- Every Spark application consists of a **Driver program** that defines distributed datasets on a cluster and then launches various parallel operations to them

- Driver can be your own program or the **Spark shell** to type operations you want to run

- Driver access Spark through a **SparkSession object** which represents a connection to a cluster

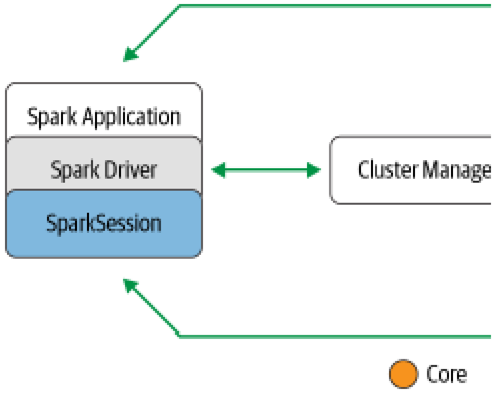
Apache Spark – Dataflow



Apache Spark – Dataflow

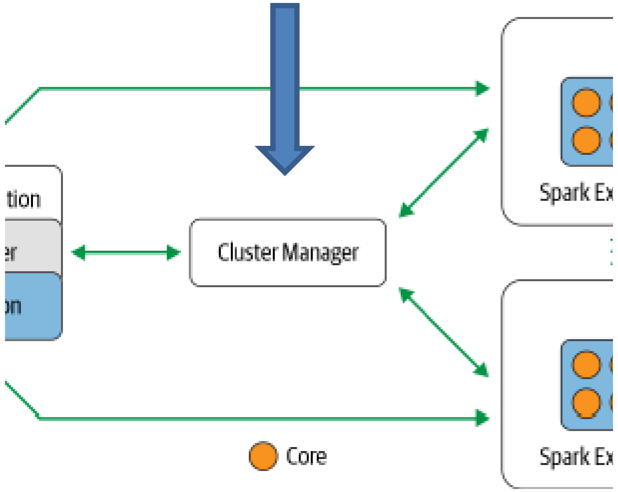
- Spark code is developed in the **Driver program**, connecting cluster through *SparkSession*
- We will define all resources and configuration in *SparkSession*, where RDDs and other structures will be created as well

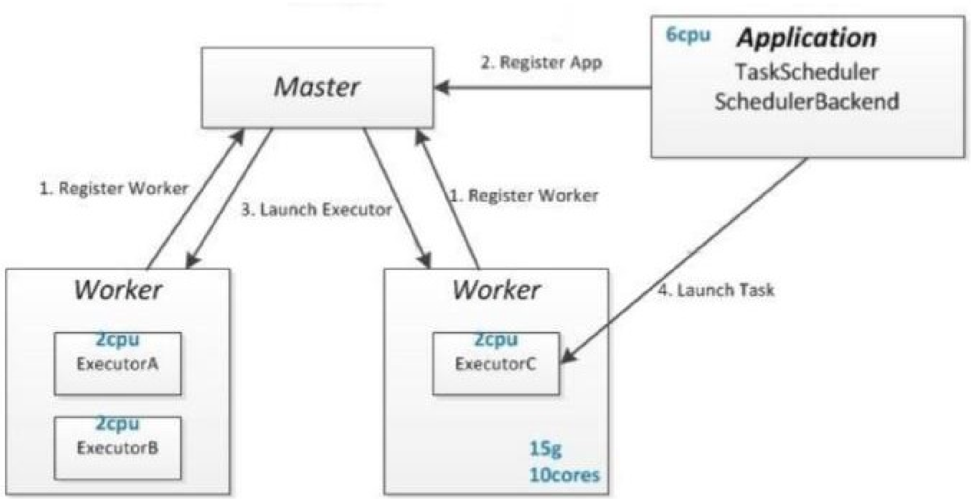
```
import findspark
findspark.init('/opt/mapr/spark/spark-2.0.1/')
import pyspark
from pyspark.sql import SparkSession

spark=SparkSession.builder.appName("variable_selection")\
                          .config("spark.master","yarn")\
                          .config("spark.eventLog.enabled","true")\
                          .config("spark.executor.instances","5")\
                          .config("spark.executor.cores","3")\
                          .config("spark.executor.memory","5g")\
                          .getOrCreate()



df=spark.read.csv('hdfs:/data/databases/cars.csv')

df.show()
```



Apache Spark – Dataflow

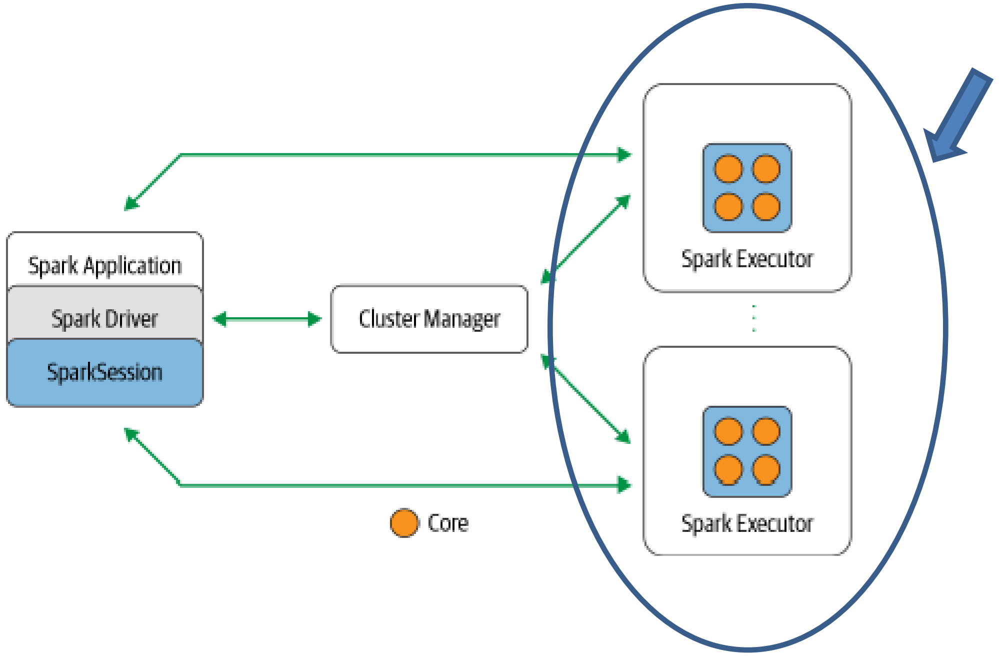
- Spark works with the following services as **cluster manager**:
  - YARN
  - Mesos
  - Kubernetes
  - Standalone. A simple cluster manager included with Spark





Apache Spark – Dataflow

- There is a background process called **Executor** for each Worker Node
- Executor launches different task for each transformation
- Distribute data into chunks or partitions allows Spark executors to process only data that is close to them, minimizing network bandwidth



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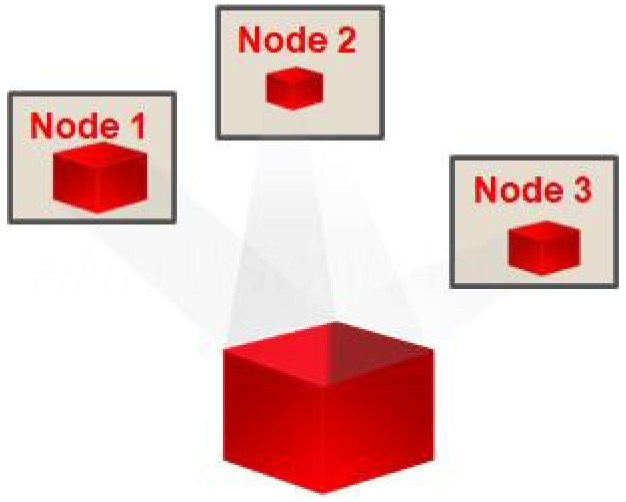
Resilient Distributed Dataset (RDD)

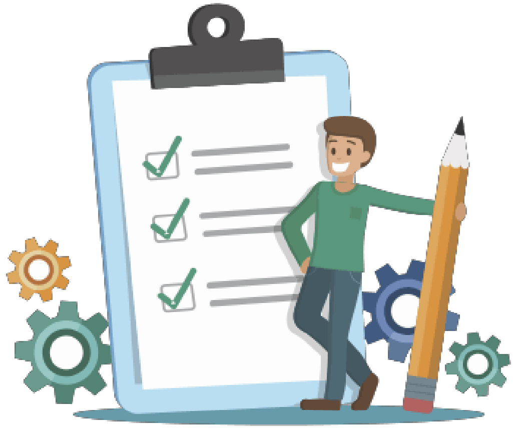
- It is an **immutable distributed** collection of data, which is **partitioned** across machines in a cluster
- It facilitates two types of operations:
  - **Transformation**
    - An operation such as filter(), map(), or union() on an RDD that yields another RDD
    - **Lazily evaluated**, in that they don't run until an action warrants it
  - **Action**
    - An action is an operation such as count(), first(), take(n), or collect() that triggers a computation, returns a value back to the Master, or writes to a stable storage system
- The Driver remembers the transformations applied to an RDD (lineage), so if a partition is lost, that partition can easily be reconstructed on other machine in the cluster
  - That is why is it called "**Resilient**"

RDD

- RDD stands for **Resilient Distributed Datasets**
- ***Resilient*** because RDDs are immutable
  - *They can't be modified once created*
- ***Distributed*** because it is distributed across cluster
- ***Dataset*** because it holds data

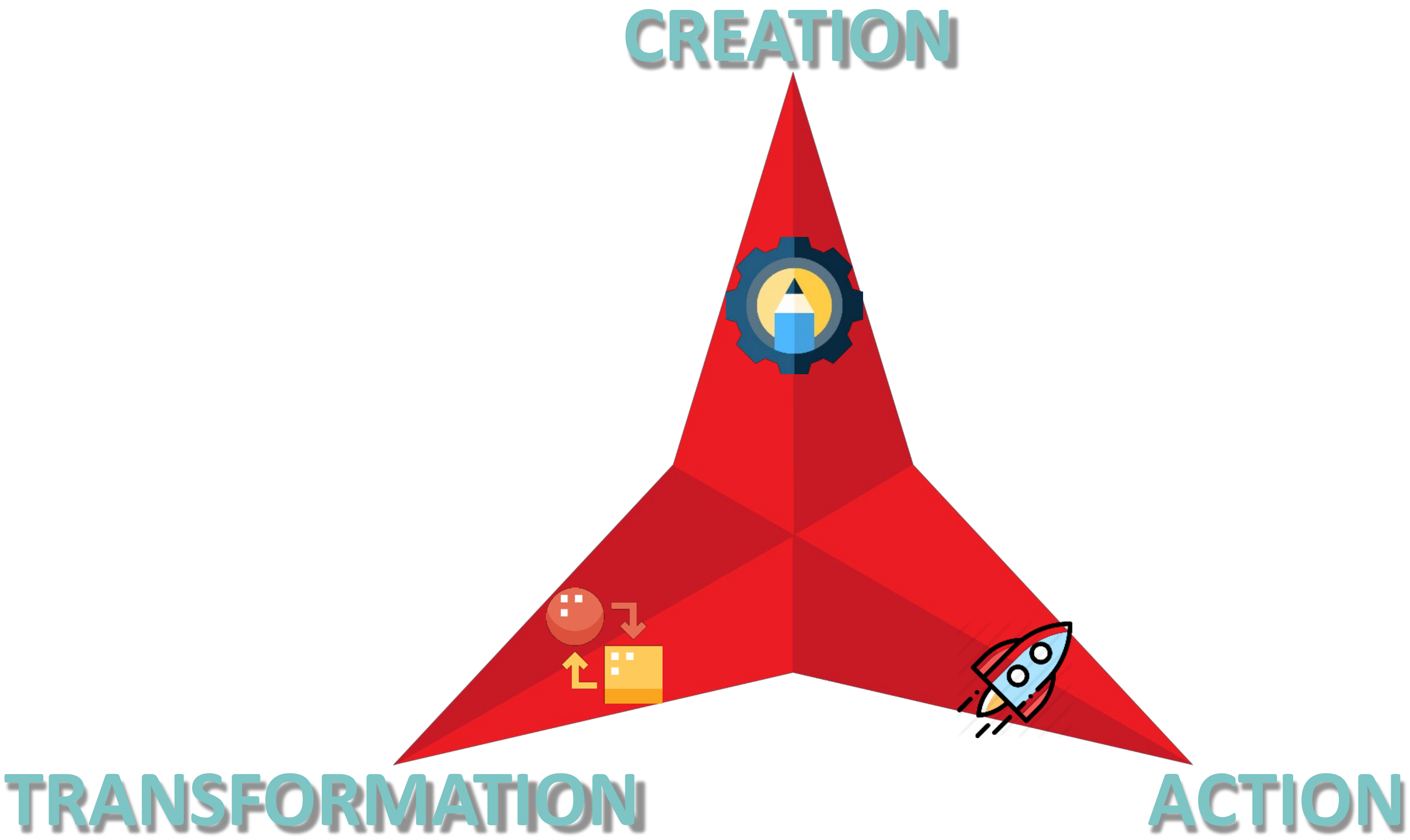


Hands-on

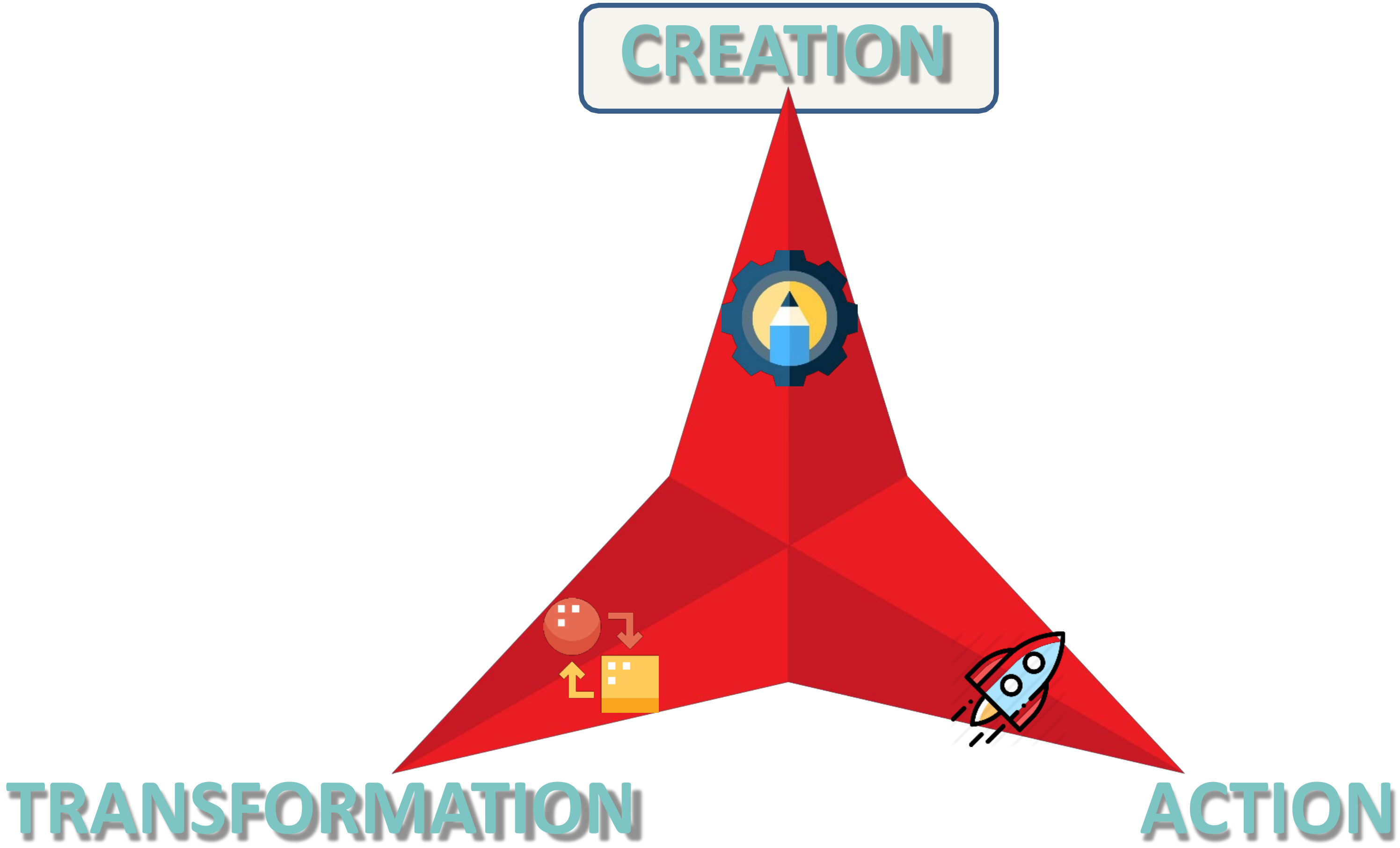


- Open “Exercises_00_Introduction.ipynb” in Google Colab:
    - Execute examples 1 and 2
    - Try exercise 1 and 2

RDD – OPERATIONS



RDD – OPERATIONS



RDD – Creation

- Three ways to create a RDD:
  - From external source
    - File
    - Kafka, Mysql, ….

    ```
    spark.sparkContext().textFile("file.csv")
    ```

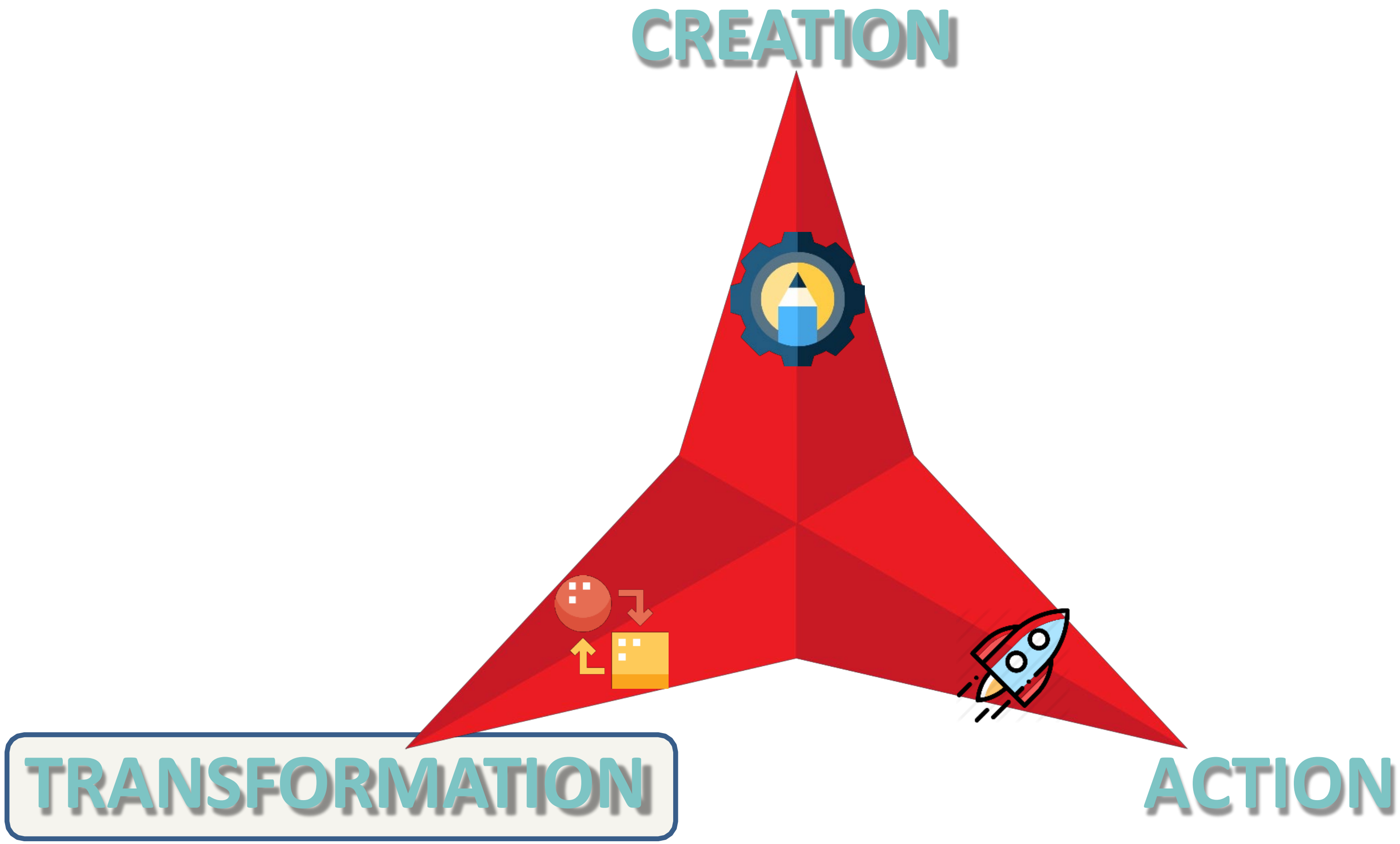
  - From an internal structure

    ```
    spark.sparkContext().parallelize(List(1, 2, 3, 4))
    ```

  - From other RDD

    ```
    otherRDD.map(word => (word, word.length)
    ```

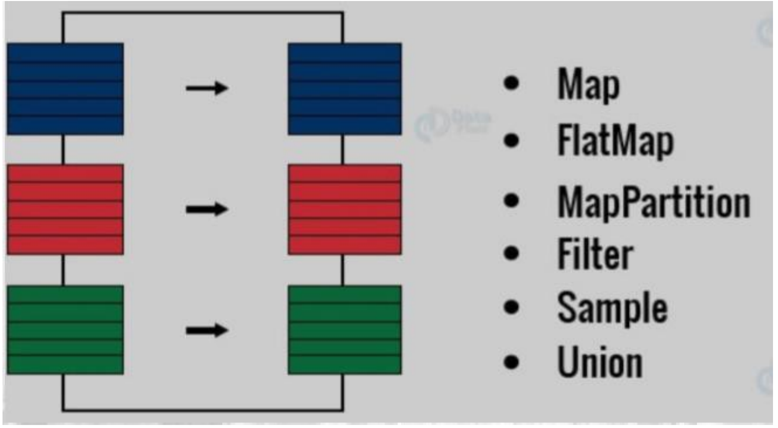
RDD – OPERATIONS



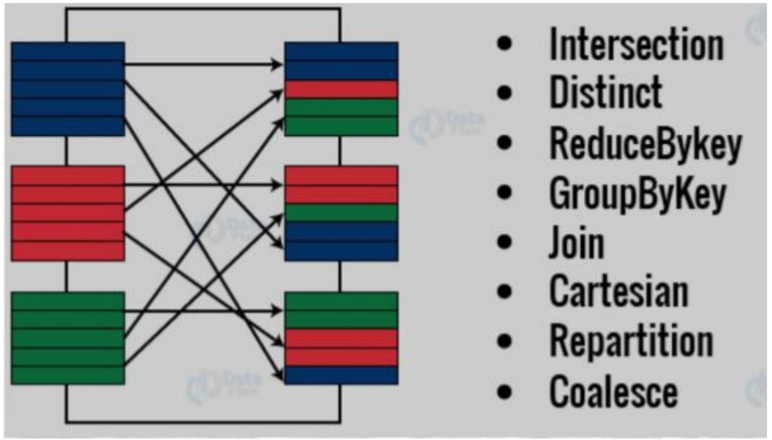
RDD – Transformation

- Operations over RDDs which return a new RDD
- Transformations are **lazy** (most of them)
  - Only computed when an action requires a result to be returned to the driver program

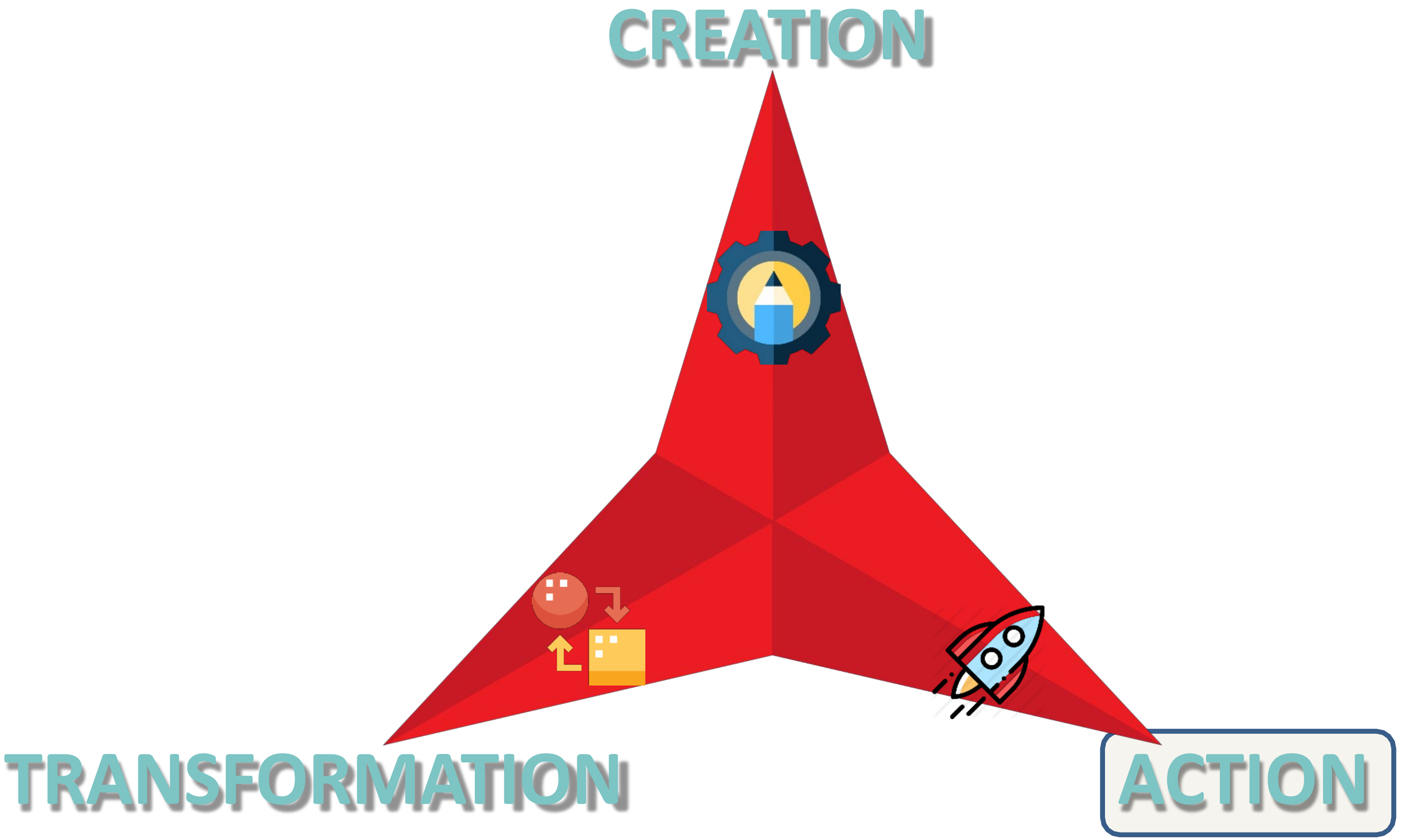
Narrow Transformations: no suffling



Wide Transformations: needs suffling

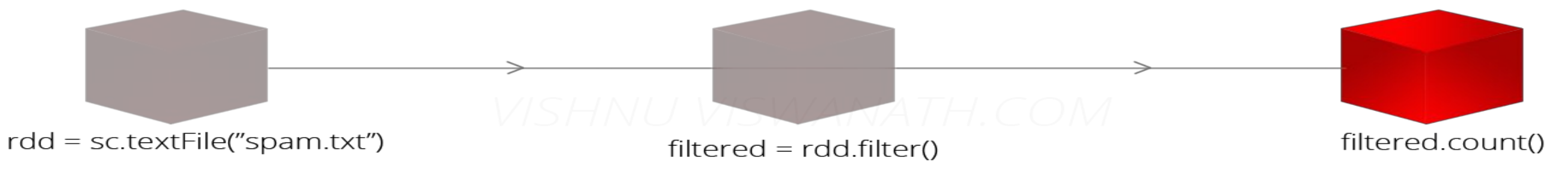


RDD – OPERATIONS

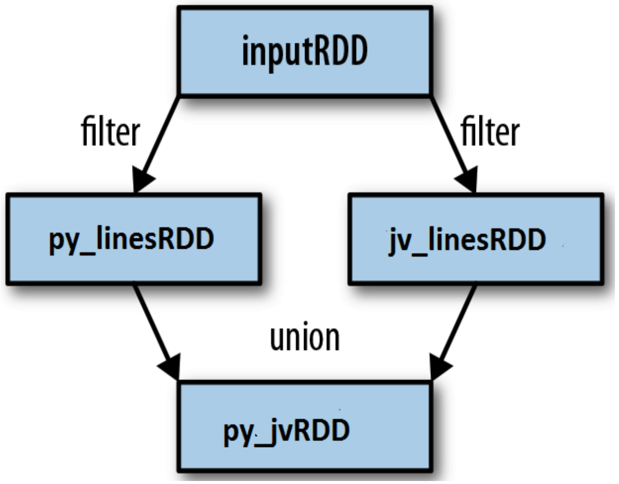


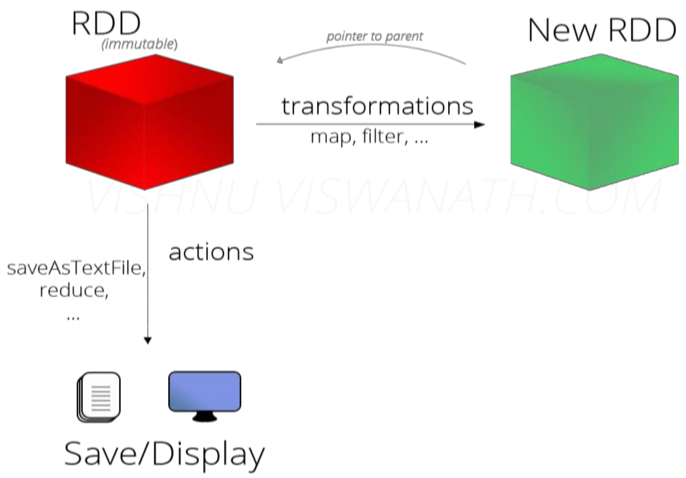
RDD – Actions

- Actions, which **return a value to the driver program** after running a computation on the dataset
  - Eg. Reduce, count, ….
- Action is used to either **save a result to some location or to display it**



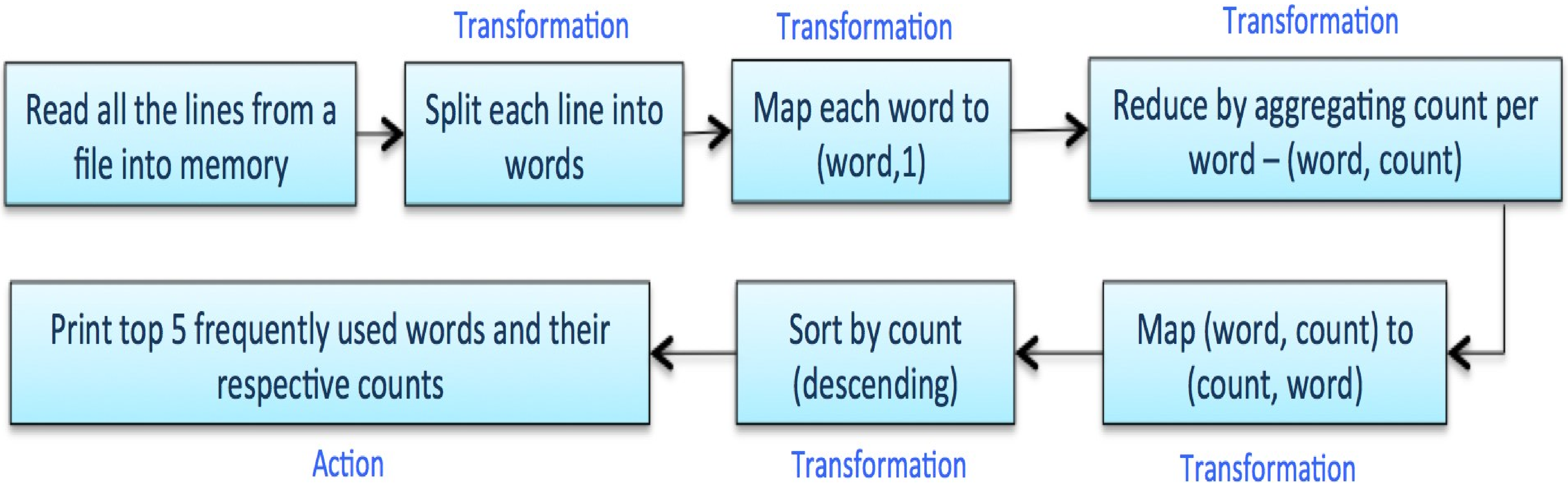
Resilient Distributed Dataset (RDD)





inputRDD = sc.textFile("README.md") **-> Transformation**
py_linesRDD = inputRDD.filter(**lambda** line: "Python" **in** line) **-> Transformation**
jv_linesRDD = inputRDD.filter(**lambda** line: "Java" **in** line) **-> Transformation**
py_jvRDD **=** py_linesRDD.union(jv_linesRDD) **-> Transformation**
print py_jvRDD.count() -> Action

Resilient Distributed Dataset (RDD)



Resilient Distributed Dataset (RDD)

Transformation	Meaning
➢ **map**(func)	Return a new RDD formed by passing each element of the source through a function *func*
➢ **filter**(func)	Return a new RDD formed by selecting those elements of the source on which *func* returns true
flatMap(func)	Similar to map, but each input item can be mapped to 0 or more output items
➢ **mapPartitions**(func)	Similar to map, but runs separately on each partition (block) of the RDD, so *func* must be of type *Iterator<T> => Iterator<U>* when running on an RDD of type *T*
➢ **mapPartitionsWithIndex** (func)	Similar to mapPartitions, but also provides *func* with an integer value representing the index of the partition, so *func* must be of type *(Int, Iterator<T>) => Iterator<U>* when running on an RDD of type *T*
➢ **sample**(withReplacement, fraction, seed)	Sample a fraction of the data, with or without replacement, using a given random number generator seed
➢ **union**(otherRDD)	Return a new RDD that contains the union of the elements in the calling RDD and the argument
➢ **intersection**(otherRDD)	Return a new RDD that contains the intersection of the elements in the calling RDD and the argument

Resilient Distributed Dataset (RDD)

Transformation	Meaning
➢ **distinct**()	Return a new RDD that contains the distinct elements of the source dataset
➢ **groupByKey**()	When called on a dataset of *(K, V)* pairs, returns a dataset of *(K, Iterable<V>)* pairs
➢ **reduceByKey**(func)	When called on a dataset of *(K, V)* pairs, returns a dataset of *(K, V)* pairs where the values for each key are aggregated using the given reduce function *func*, which must be of type *(V,V) => V*
➢ **aggregateByKey**(zeroValue)(seqOp, combOp)	When called on an RDD of *(K, V)* pairs, returns an RDD of *(K, U)* pairs where the values for each key are aggregated using the given combine functions and a neutral "zero" value; **allows an aggregated value type that is different than the input value type**, while avoiding unnecessary allocations
➢ **sortByKey**([ascending])	When called on an RDD of *(K, V)* pairs where *K* implements Ordered, returns an RDD of *(K, V)* pairs **sorted by keys** in ascending or descending order
➢ **join**(otherRDD)	When called on RDDs of type *(K, V)* and *(K, W)*, returns an RDD of *(K, (V, W))* pairs with all pairs of elements for each key
➢ **cogroup**(otherRDD)	When called on RDDs of type *(K, V)* and *(K, W)*, returns an RDD of *(K, Iterable<V>, Iterable<W>)* tuples; this operation is also called *groupWith*

Resilient Distributed Dataset (RDD)

Transformation	Meaning
➢ **cartesian**(otherRDD)	When called on RDDs of types *T* and *U*, returns an RDD of all *(T, U)* pairs
➢ **pipe**(command, [envVars])	Pipe each partition of the RDD through a shell command, e.g. a Perl or bash script
➢ **coalesce**(numPartitions)	Decrease the number of partitions in the RDD to *numPartitions*; useful for running operations more efficiently after filtering down a large dataset
➢ **repartition**(numPartitions)	Reshuffle the data in the RDD randomly to create either more or fewer partitions and balance it across them; **this always shuffles all data over the network**
➢ **repartitionAndSortWithinPartitions**(partitioner)	Repartition the RDD according to the given *partitioner* and, within each resulting partition, sort records by their keys

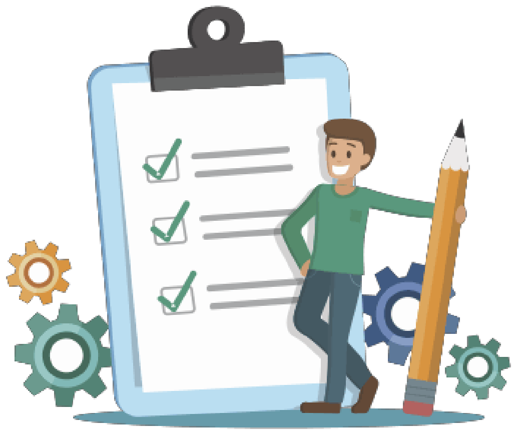
Resilient Distributed Dataset (RDD)

Action	Meaning
➢ **reduce**(func)	Aggregate the elements of the RDD using a function *func* (which takes two arguments and returns one)
➢ **collect**()	Return all the elements of the RDD as an array at the driver program
➢ **count**()	Return the number of elements in the RDD
➢ **first**()	Return the first element of the RDD (similar to *take(1)*)
➢ **take**(n)	Return an array with the first *n* elements of the RDD
➢ **takeSample**(withReplace ment, num, [seed])	Return an array with a random sample of *num* elements of the RDD, with or without *replacement*, optionally pre-specifying a random number generator *seed*
➢ **takeOrdered**(n, [ordering])	Return the first *n* elements of the RDD using either their natural order or a custom comparator

Resilient Distributed Dataset (RDD)

Action	Meaning
➢ **saveAsTextFile**(path)	Write the elements of the RDD as a text file (or set of text files) in a given directory in the local filesystem, HDFS or any other Hadoop-supported file system **Note**: Spark will call toString on each element to convert it to a line of text in the file
➢ **saveAsSequenceFile**(path) (Java and Scala)	Write the elements of the RDD as a Hadoop SequenceFile in a given path in the local filesystem, HDFS or any other Hadoop-supported file system
➢ **saveAsObjectFile**(path) (Java and Scala)	Write the elements of the RDD in a simple format using Java serialization, which can then be loaded using ***SparkContext.objectFile()***
➢ **countByKey**()	Returns a hashmap of *(K, Int)* pairs with the count of each key **Note**: Only available on RDDs of type *(K, V)*
➢ **foreach**(func)	Run a function *func* on each element of the RDD

Hands-on



- Open “Exercises_00_Introduction.ipynb” in Google Colab:
  - Execute examples 3, 4 and 5
  - Try exercise 3 and 4

RDD – When to use

- Use RDDs as we saw in the examples could be hard. However, there are some scenarios where you'll want to consider using RDDs, such as when you:

  - Are using a third-party package that's written using RDDs
  - Can forgo the code optimization, efficient space utilization, and performance benefits available with DataFrames and Datasets
  - Want to precisely instruct Spark how to do a query

Key/Value Pairs RDD

- Spark provides special operations on RDDs containing **(key, value)** pairs
- They expose operations that allow you to act on each key in parallel, regroup or agregate data across the network.
- Creating pair RDD:
  - Many formats loading return pair RDDs for key/value data (e.g. Avro,Json)
  - Parallelize (for testing and PoCs)

```
val pairs = sc.parallelize (List((1,"a"),(2,"b"),(3,"c")))
```

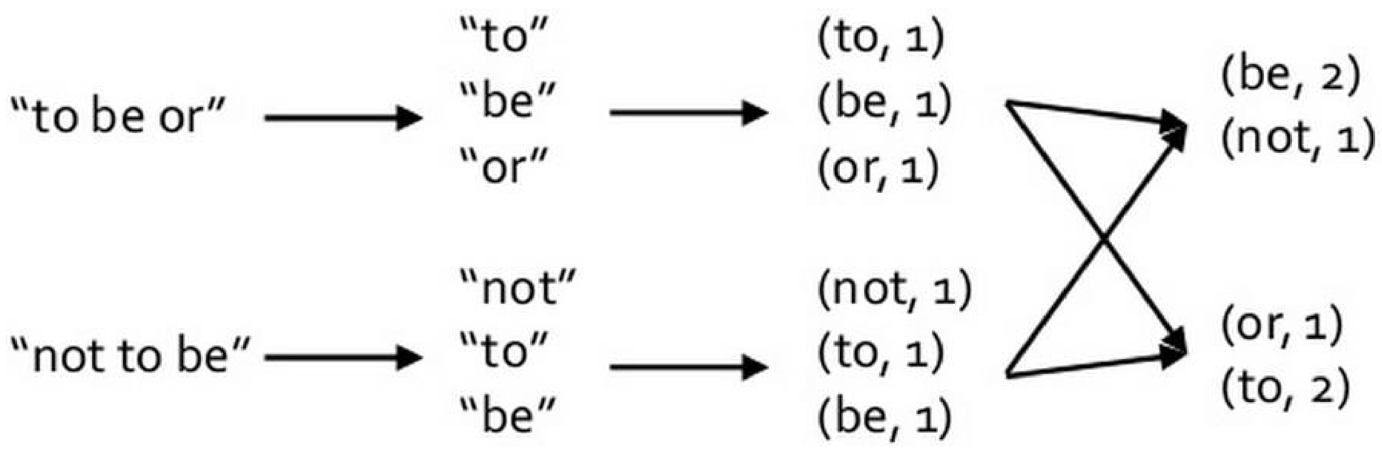
  - Running transformations over regular RDDs

```
  //pair RDD using the first word as the key
val pairs = lines.map(linea => (linea.split(" ")(0), linea))
```

Key/Value Pairs RDD

- Word count example

```
text_file = sc.textFile("hamlet.txt")
counts = text_file.flatMap(lambda line: line.split(" ")) \
                  .map(lambda word: (word, 1)) \
                  .reduceByKey(lambda a, b: a + b) \
                  .counts.saveAsTextFile("hdfs://...")
```



Key/Value Pairs RDD

- Join and Cogroup examples

```
>   visits = sc.parallelize([ (“index.html”, “1.2.3.4”),
                              (“about.html”, “3.4.5.6”),
                              (“index.html”, “1.3.3.1”) ])

>   pageNames = sc.parallelize([ (“index.html”, “Home”),
                                 (“about.html”, “About”) ])

>   visits.join(pageNames)
    # (“index.html”, (“1.2.3.4”, “Home”))
    # (“index.html”, (“1.3.3.1”, “Home”))
    # (“about.html”, (“3.4.5.6”, “About”))

>   visits.cogroup(pageNames)
    # (“index.html”, ([“1.2.3.4”, “1.3.3.1”], [“Home”]))
    # (“about.html”, ([“3.4.5.6”], [“About”]))
```

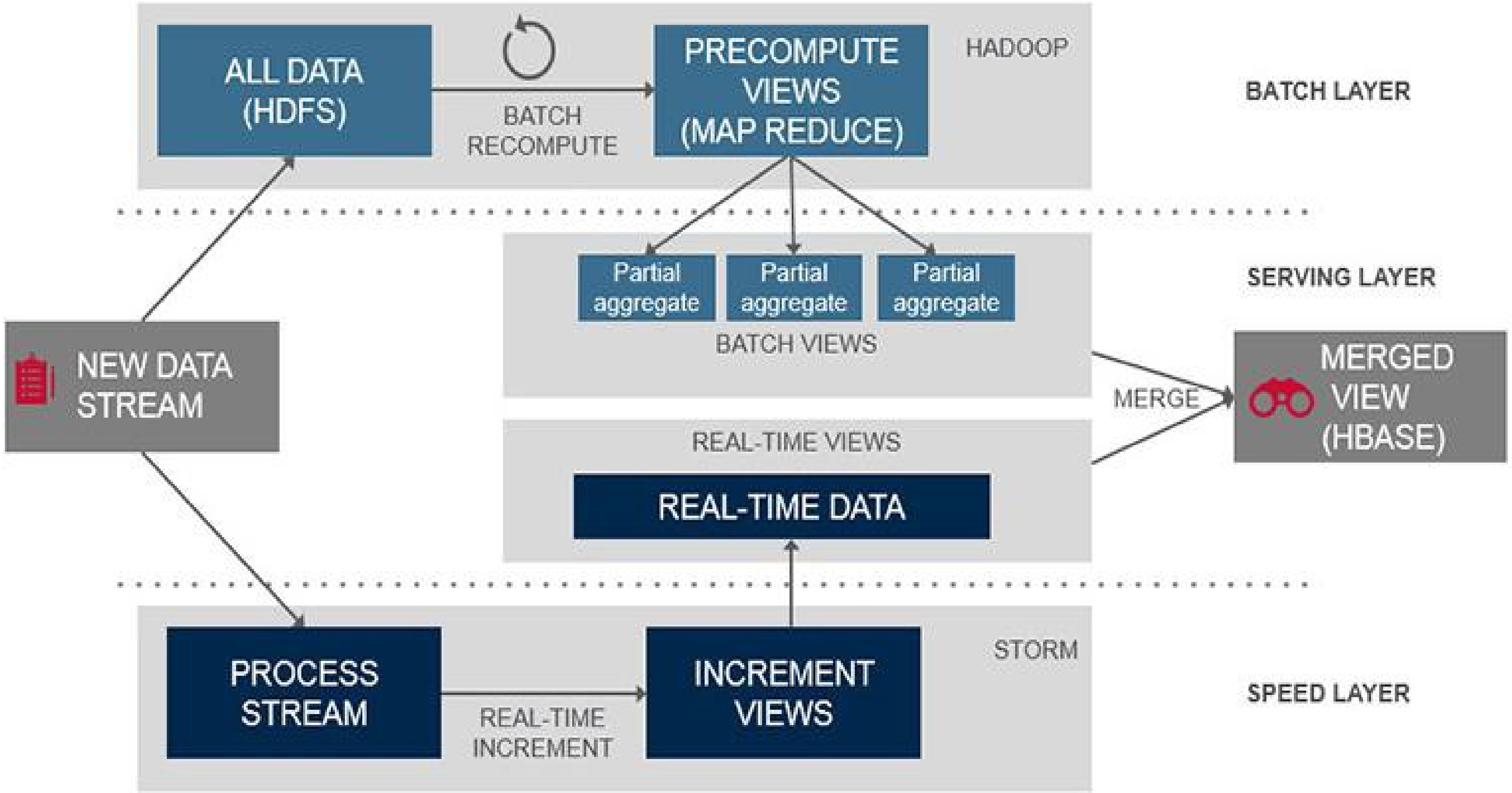
Executing Spark out of Notebook

- **Spark-submit** is the command to launch Spark in a cluster/single machine
- Example:

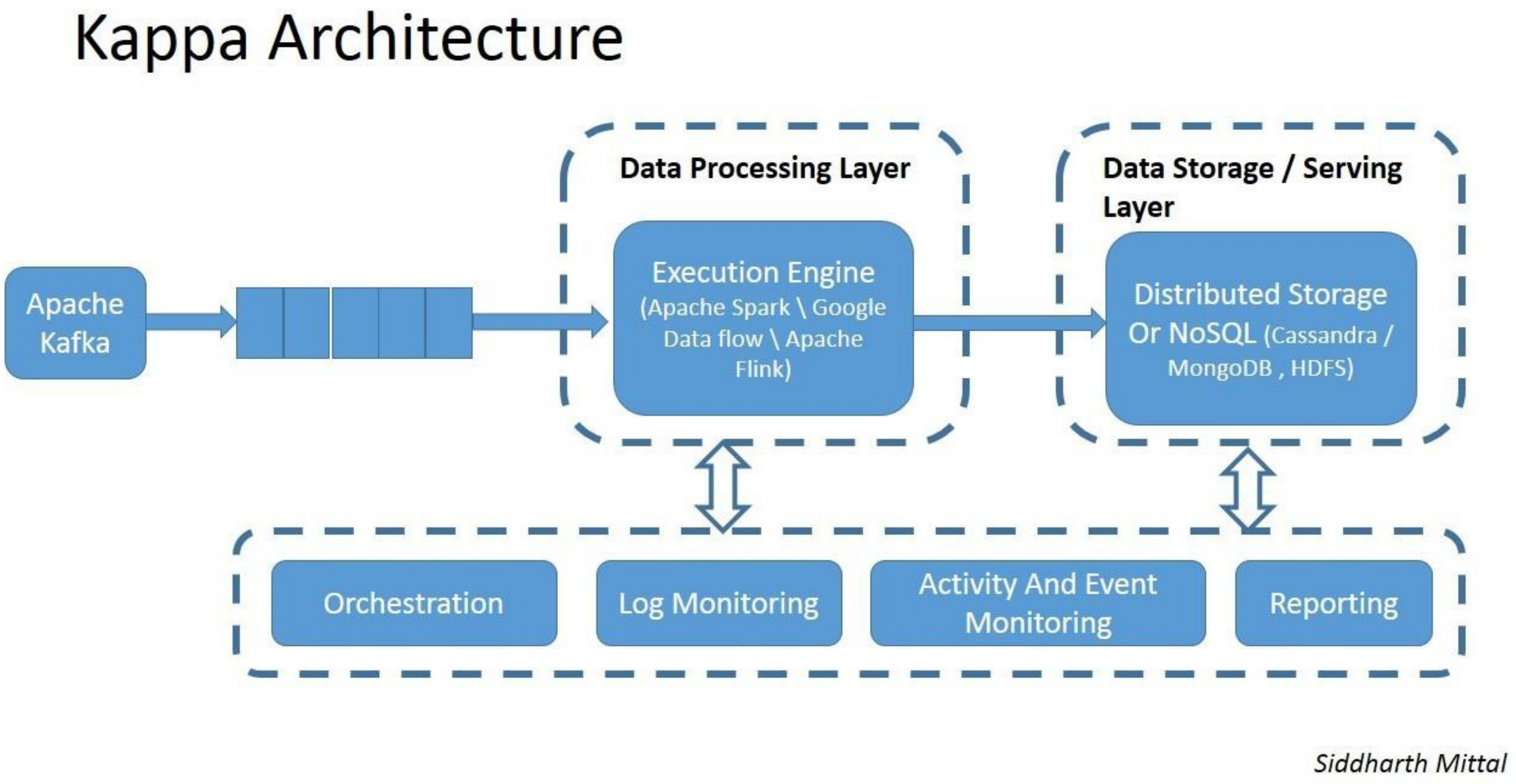
  $ bin/spark-submit --master yarn --deploy-mode cluster --py-files otralib.zip,otrofich.py --num-executors 10 --executor-cores 2 mi-script.py script-options

- Spark-submit options
  - master: cluster manager a usar (opciones: yarn, mesos://host:port, spark://host:port, local[n])
  - deploy-mode: dos modos de despliegue (client: local // cluster: cluster)
  - class: clase a ejecutar (Java o Scala)
  - name: nombre de la aplicación (se muestra en el Spark web)
  - jars: ficheros jar a añadir al classpath (Java o Scala)
  - py-files: archivos a añadir al PYTHONPATH (.py,.zip,.egg)
  - files: ficheros de datos para la aplicación
  - executor-memory: memoria total de cada ejecutor
  - driver-memory: memoria del proceso driver

Lambda Architecture



Kappa Architecture



Modern Streaming Architecture