POLITECNICO
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Apache Spark

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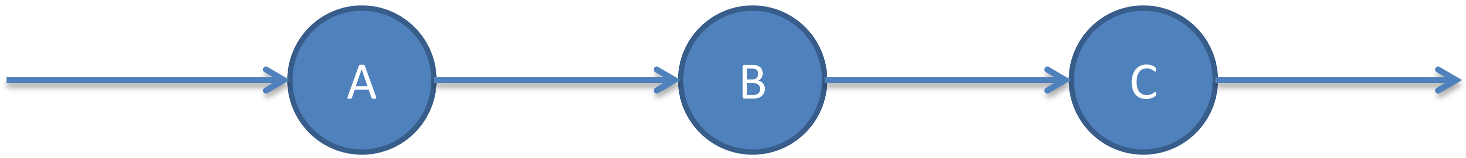
Big Data processing

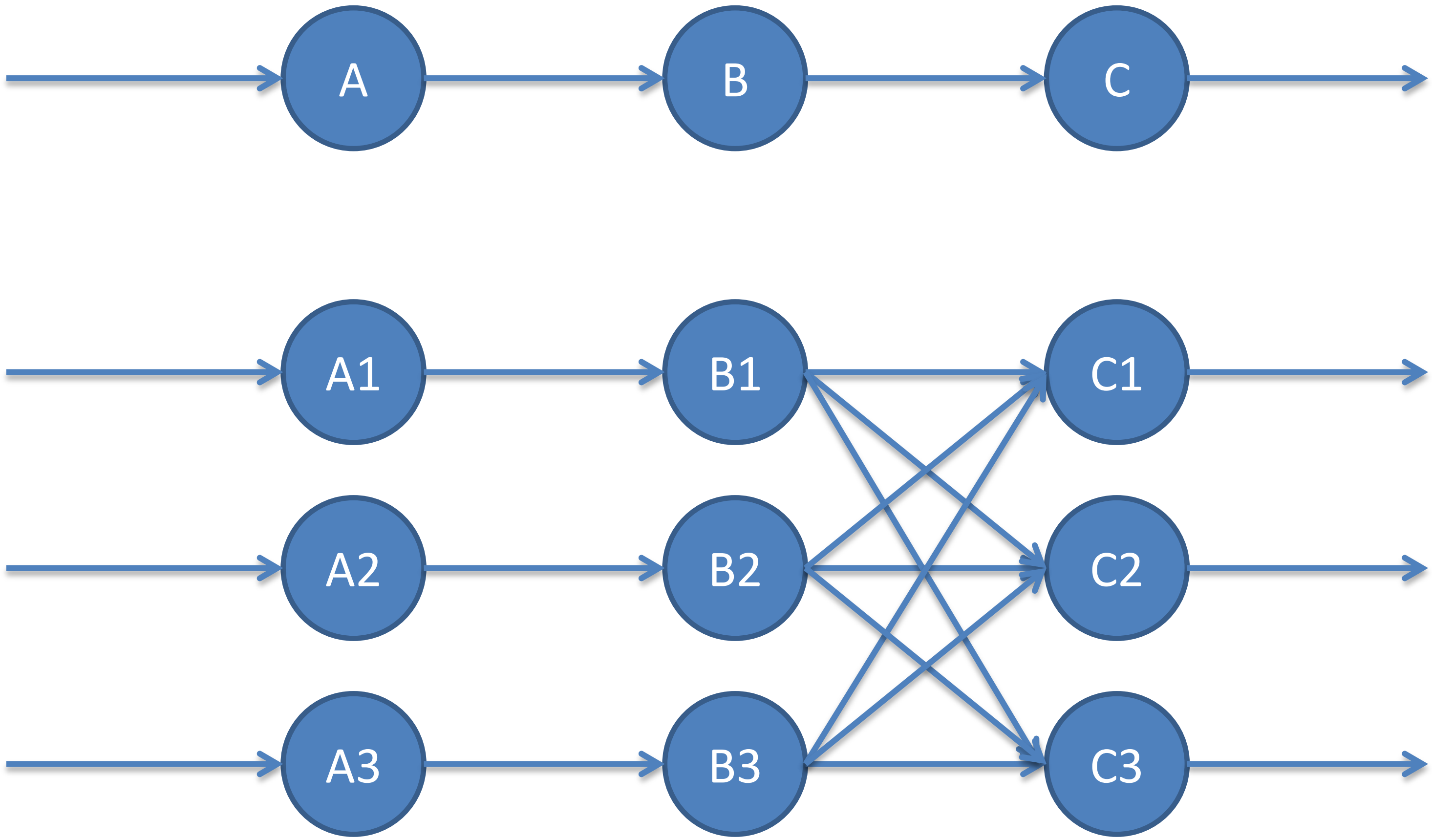
- Technologies to enable large-scale data analytics
  - Extract knowledge from large volumes of data
  - Example: study user behaviors to customize advertisements

- Pioneered in the early 2000s by the Google MapReduce framework
  - Computations on cluster computing infrastructures
  - Simple programming API
  - The framework abstracts away most distribution concerns
    - Data distribution
    - Scheduling of computation
    - Fault tolerance
    - Stragglers

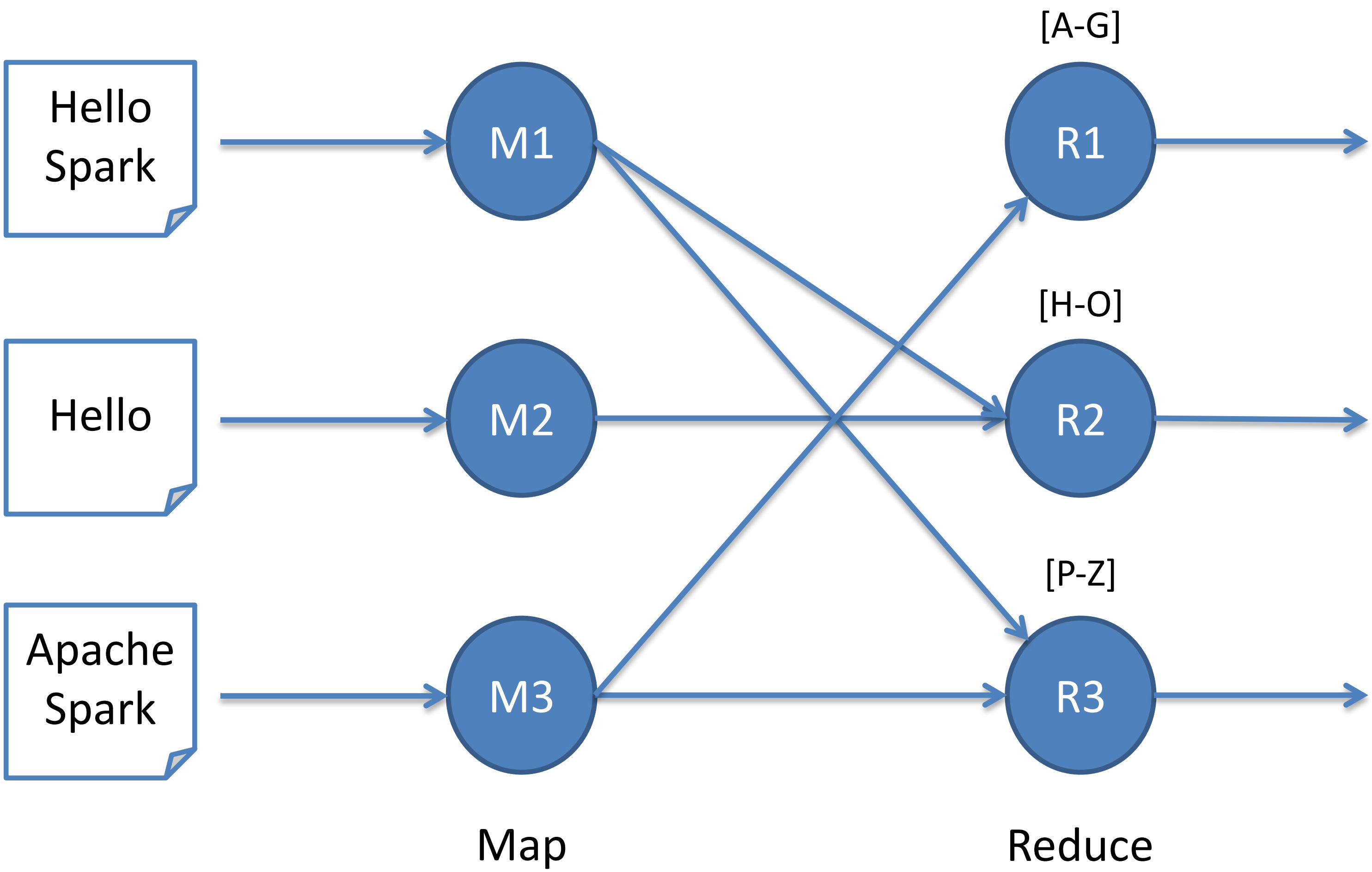
Dataflow programming model



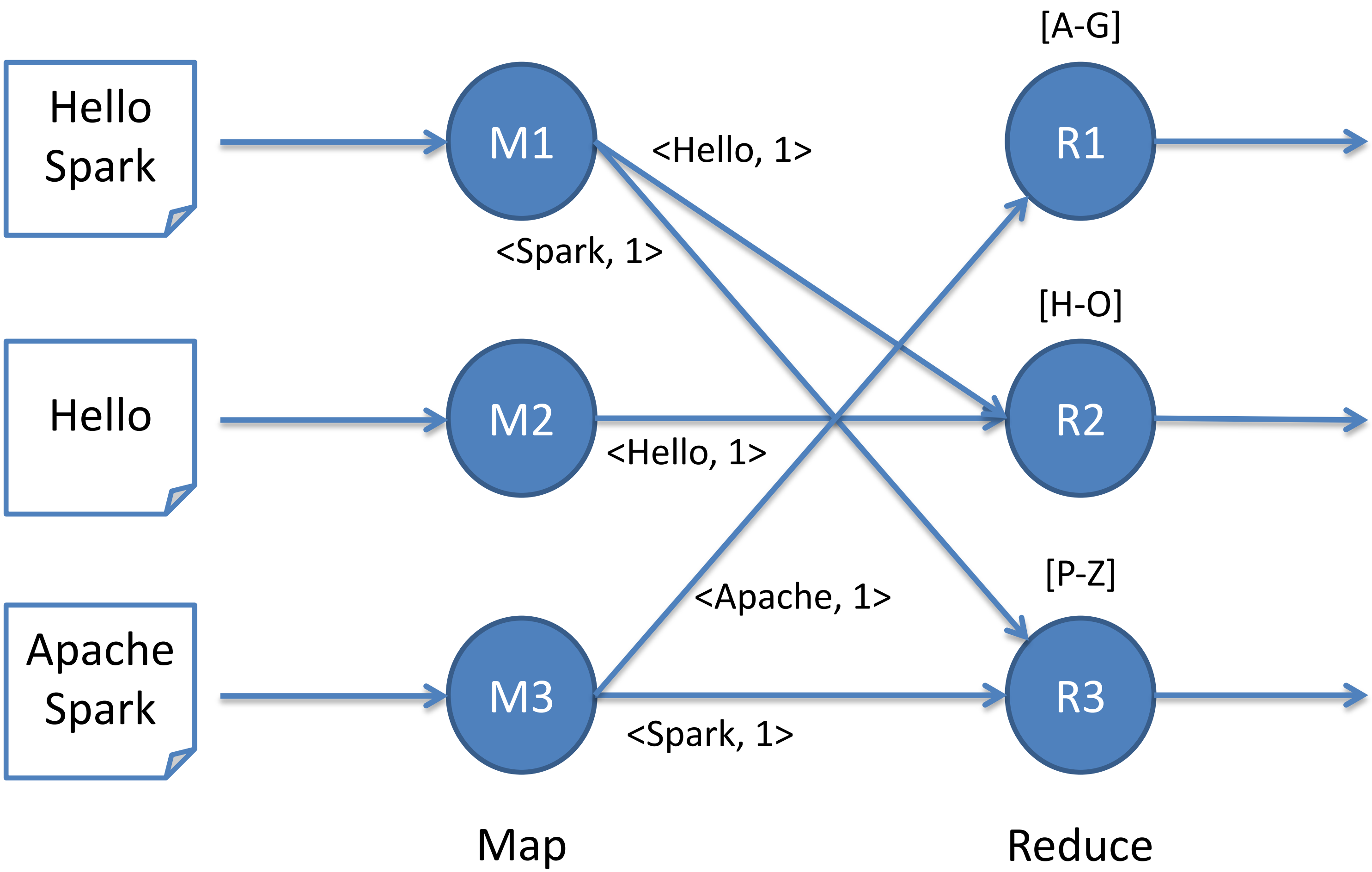
Dataflow programming model



Example: word count



Example: word count



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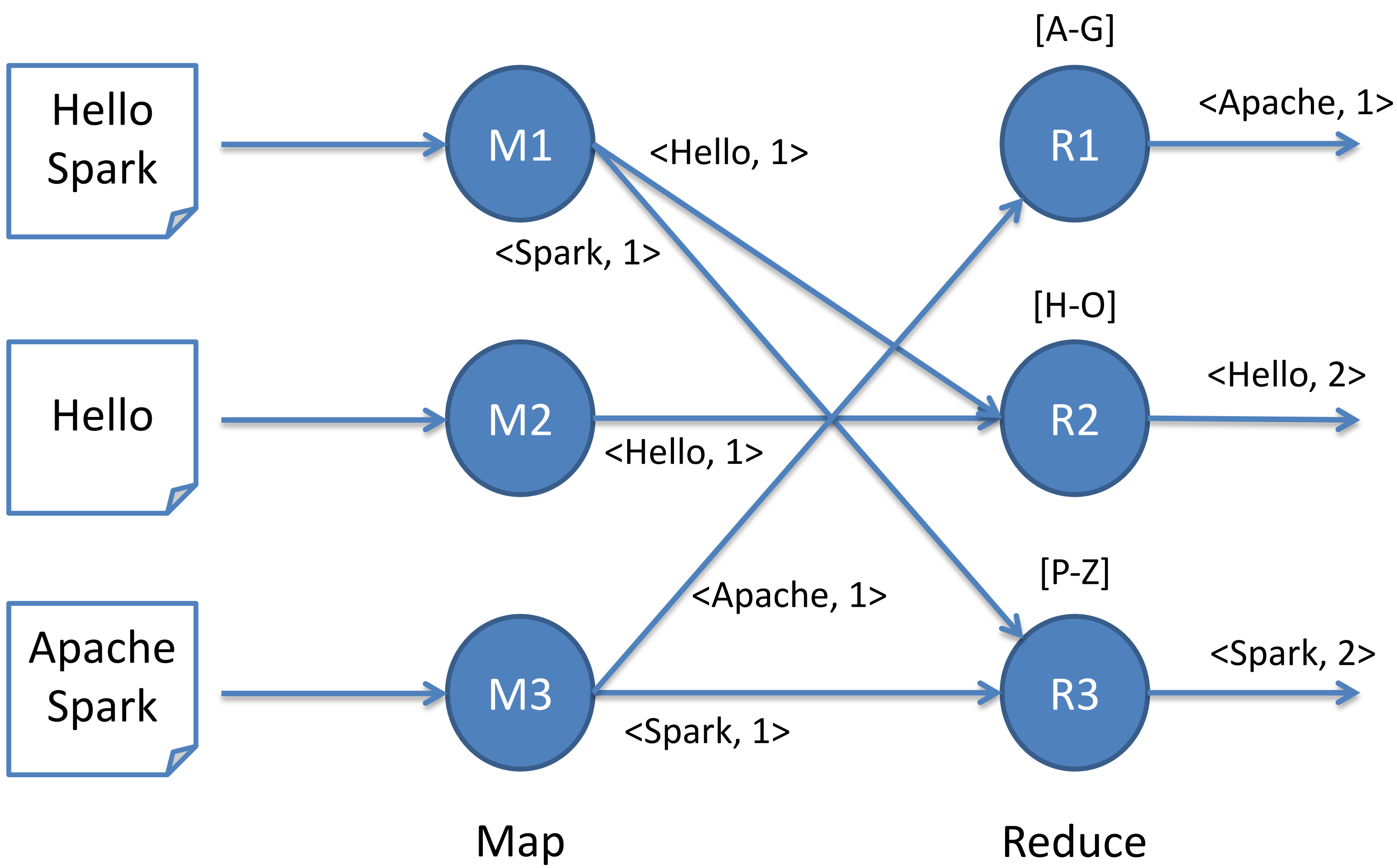


MapReduce: programming model

- The original MapReduce framework was restricted to these two stages
  - Map and Reduce

- Any computation requiring more stages needed to be translated into multiple invocations of the framework
  - Input and output results were written on disk
  - Distributed filesystem: data partitioning and replication

MapReduce: programming model

- Developers write programs from the perspective of individual elements
- Map: given an input document, how to output the occurrences of its words?
- Reducers: given a word and a list of occurrences, how to sum up all occurrences?

MapReduce: execution

- A scheduler instantiates Map workers
  - They save their (intermediate) results on disk
  - Distributed filesystem designed to efficiently handle sequential read of large data blocks

- The scheduler instantiates Reduce workers
  - Data locality: Reduce workers instantiated close to their input data
    - Possibly, same machine: read from local disk

MapReduce: execution

- Benefit of the programming model
  - Operators are independent and stateless
  - Their output only depends on their input

stateless = result doesn't depend on ar

- This simplifies scheduling and fault-tolerance
  - Operators do not need to synchronize with each other
  - In the case of failures, individual operators can simply be re-executed
    - They will produce the same output

MapReduce: execution

- Parallelism
  - Run the same computation in parallel on multiple input elements
- Communication
  - The framework takes care of writing intermediate results
- Scheduling
  - Based on data locality to speed-up computation
  - Tasks are scheduled as close as possible to the input data they consume
- Fault-tolerance / stragglers
  - In the case of failure or slow nodes …
  - … reschedule failed or slow nodes and recompute their results

Apache Spark

Programming model overview

unified == it offers many domain specific API for different types of applications that

Apache Spark

- Unified analytics engine for large-scale data processing
  - Batch, streaming, structured, machine learning, graph processing, …

- Based on the dataflow programming model
- Same execution strategy as MapReduce …
  - Stages are scheduled
- … but more expressive …
  - Not limited to two stages
  - Support for iterative computations

it supports every graph and iterative computation

- … and more efficient
  - E.g., by caching data in main memory

Apache Spark

- A Spark cluster consists of a *master* and one or more workers
  - Typical configuration: one worker per host, using as many cores as available in the host

- The master
  - Accepts jobs from *driver* programs, and
  - Splits jobs into stages and then into elementary tasks
  - Schedules tasks on available workers

Apache Spark

- We will write *driver programs* that submit jobs to the cluster
  - Each job consists of various *parallel operations*

- The main abstraction that Spark provides is the RDD (resilient distributed dataset)
  - Collection of elements
  - Partitioned across the nodes of the cluster
  - Can be processed in parallel
  - Fault tolerant

Apache Spark

- A Spark program accesses the Spark cluster through a SparkContext object

- Contains relevant parameters
  - Name of the Spark application / job
  - Address of the master
  - …

- Only one context can be active per JVM
  - close() closes a context and enables starting a new one

Initializing Spark

```
SparkConf conf = new SparkConf()
      .setAppName(appName)
      .setMaster(master);
JavaSparkContext sc = new JavaSparkContext(conf);

…

sc.close();
```

Initializing Spark

- When running in a real cluster
  - The application is packaged in a jar file
  - The jar is submitted to the cluster with a provided script

- Local mode

both driver programs and the workers run on the same JVM

  - Run the driver and the workers in the same JVM
  - For testing and debugging
  - Setting the master to local[n] requests Spark to use n cores to run the workers

RDDs: initialization

- RDDs can be created from
  - Existing collections in the driver program
  - External datasets
    - Local filesystem
    - HDFS
    - Kafka topics
    - Several DBMSs
    - …

RDDs: initialization

- RDD from local collection

```
List<String> data = Lists.newArrayList("A", "B", "C", "D");
JavaRDD<String> dataRDD = sc.parallelize(data);
```

- RDD from file

```
JavaRDD<String> dataRDD = sc.textFile("filename.txt");
```

RDDs: operations

- RDDs support two types of operations
  - *Transformations* create a new RDD from an existing one
  - *Actions* return a value to the driver program after running a computation on the dataset

- All transformations are lazy
  - They do not compute the results when invoked
  - They remember the computation to be implemented, …
  - … and execute the computation when an action requires a result to be returned to the driver program

RDDs: operations

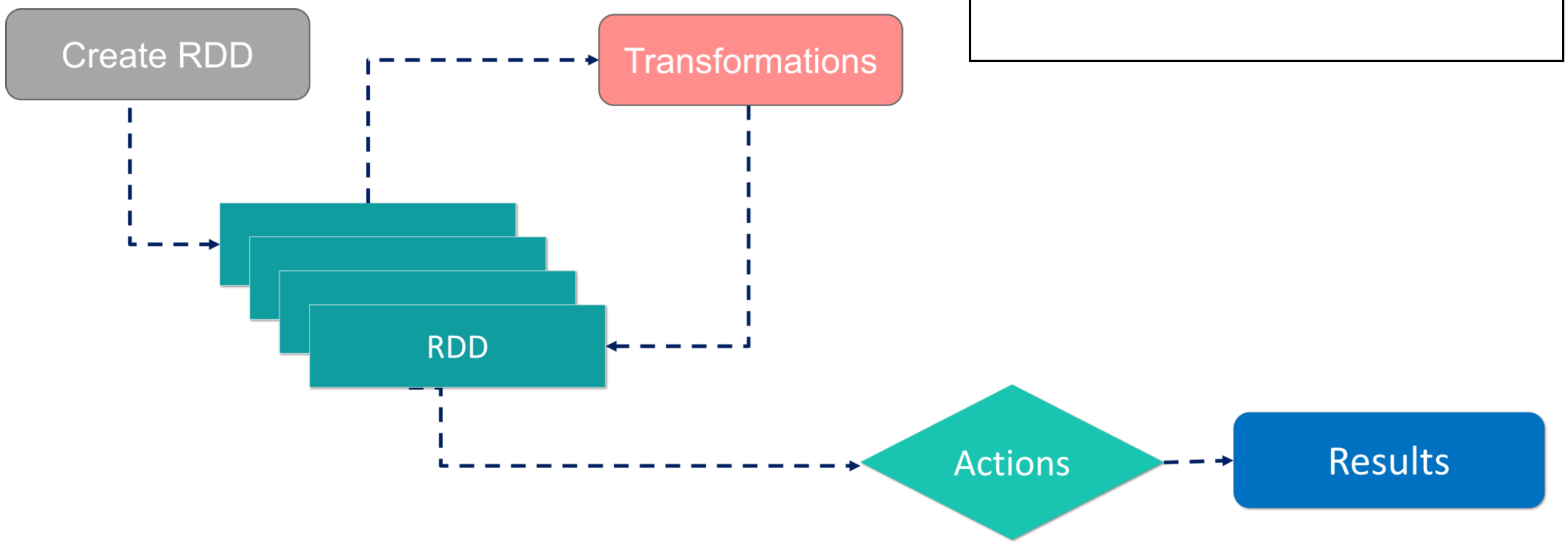
- By default, each transformed RDD is recomputed each time the driver runs (directly or indirectly) an action on it

- The programmer can also persist/cache an RDD in memory (in the workers) for faster access in subsequent queries

- Various storage levels available
  - In-memory objects
  - In-memory serialized objects
  - In-memory + on disk serialized objects
  - On disk serialized objects
  - …

RDD: operations

in spark you create RDD from a source, then you apply trasnfor



RDDs: simple example

computes the sum of the length of all the lines in a file

```
/* Creates an RDD. The number of partitions is decided
based on the available workers */
JavaRDD<String> lines = sc.textFile("data.txt");

/* Transformation. Map applies a function to each and every
element of the original RDD. In this case, it transforms
each string (line) into a number (the length of the line)
*/
JavaRDD<Integer> linesLen = lines.map(s -> s.length());

/* Action. Reduce aggregates all the values in a single
element and returns the result to the driver. In this case,
it returns the sum of all the length of all the lines) */
int totLen = linesLen.reduce((a, b) -> a + b);
```

Apache Spark

Architecture and execution model

Spark execution model

- A driver program can run on any machine
  - In cluster mode, it is typically executed in the master

- Whenever encountering an action in the driver program, Spark creates a new data processing job

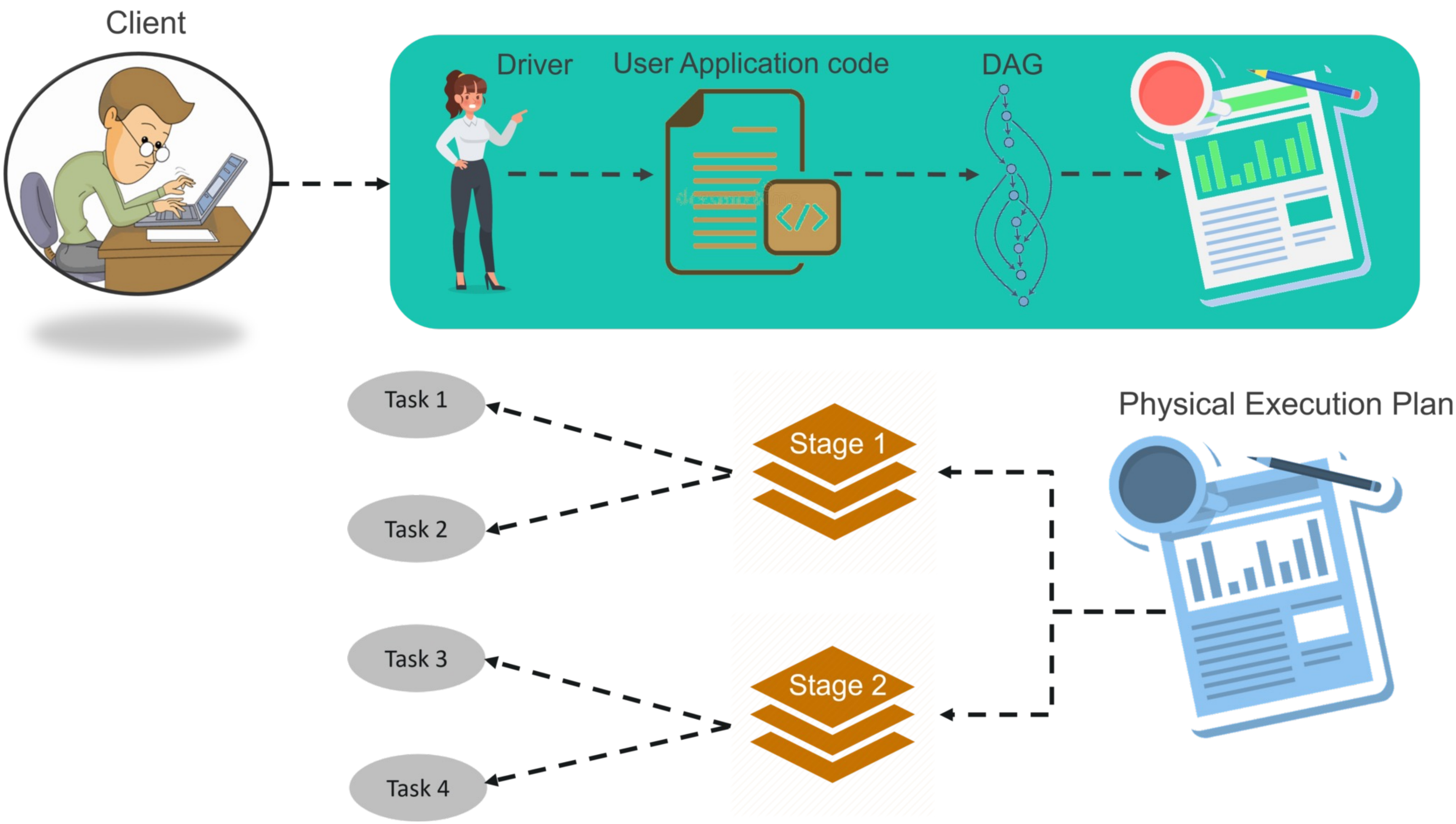
- The job consists of a directed acyclic graph (DAG) of operators
  - Dataflow model
  - Intermediate nodes are transformations, and the final node is the action

Spark execution model

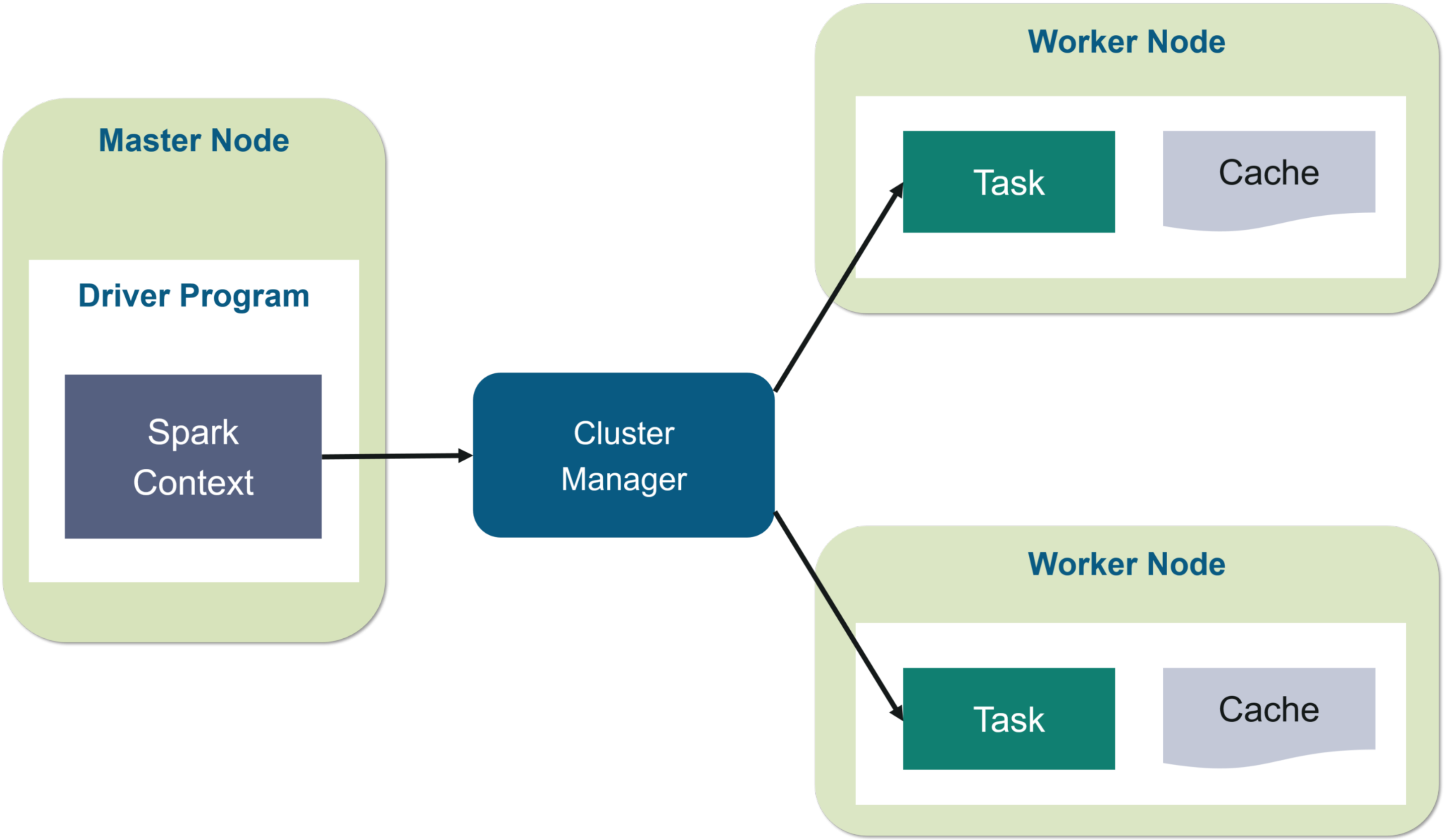
Creating a job

1. The Spark context determines the topology of the DAG
2. The logical DAG is transformed into a physical execution plan
   - Multiple *stages*: each stage contains a sequence of operations with no intermediate data shuffle
3. Each stage is split into tasks (one for each partition)
4. Tasks are scheduled on the cluster
   - Where / close to the data they consume
   - Considering the dependencies between tasks

Spark execution model



Spark architecture



Spark architecture

- When persisted, RDDs are stored in the cache of worker nodes
  - Memory or disk

- RDDs are partitioned across workers according to the specified key

- Tasks are scheduled where the data they consume is located

Fault tolerance

- Fault tolerance based on lineage
  - If an RDD is lost due to a failure just recompute it starting from its input RDDs
  - If any of its input RDDs is lost just recompute it starting from its input RDDs
  - …
  - Apply recursively until some available RDD is found

- In the worst case, recompute the RDD starting from the source

- Important: since RDDs are partitioned, only lost partitions are recomputed when needed, not the entire dataset