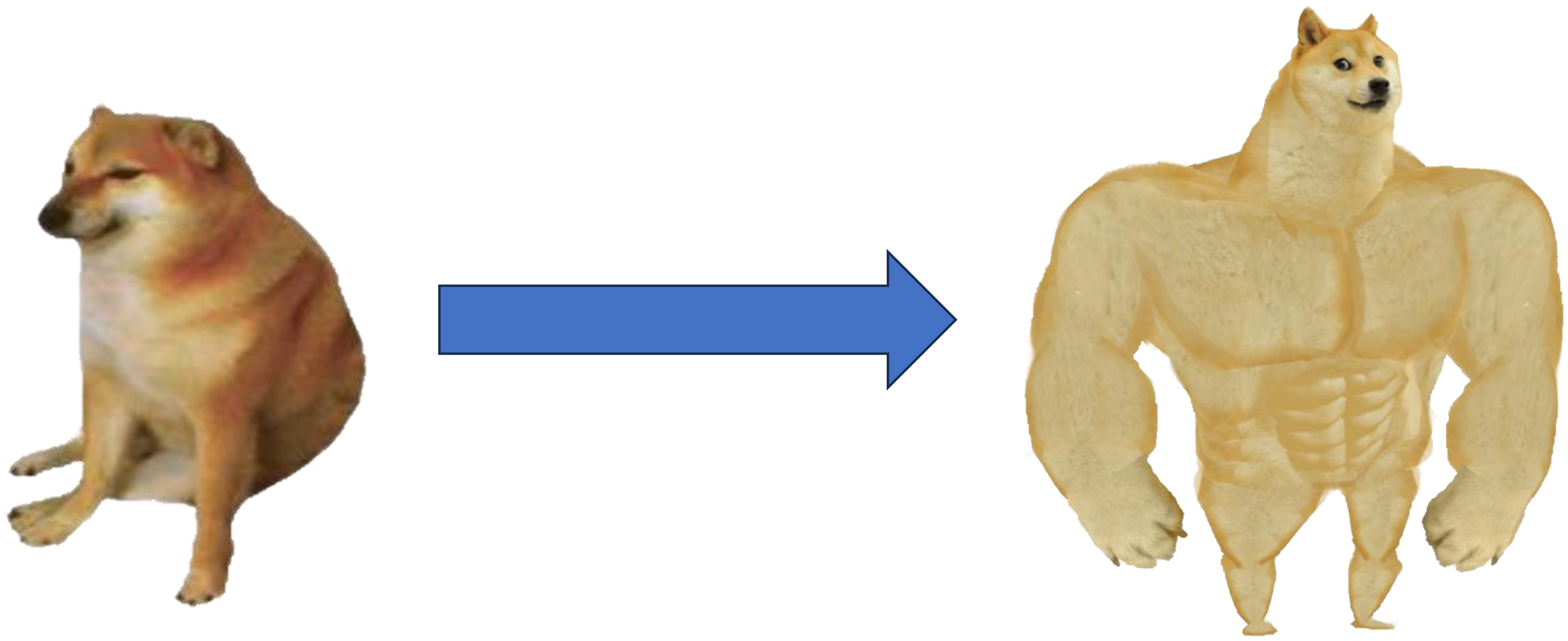
PySpark Zero-Hero



Prerequisites

- Familiar with Python and Python OOP, pip, virtual environments (Non-Negotiable)
- Familiar with Jupyter Notebooks (Negotiable)
- **STRONG SQL Fundamentals (Non-Negotiable)**
- Familiar with file formats like, *.csv, *.parquet, *.json, *.xlsx
- Familiar with RDBMS like MYSQL, MSSQL etc.
- Familiar with setting up Python and PIP Environment
- Familiar with Virtualization (Good to know)

Overview

- PySpark is the **Python API for Apache Spark**. It enables you to perform real-time, large-scale data processing in a distributed environment using Python. It also provides a PySpark shell for interactively analyzing your data.
- PySpark supports all of Spark's features such as **Spark SQL, Data Frames, Structured Streaming, Machine Learning (MLlib) and Spark Core**.

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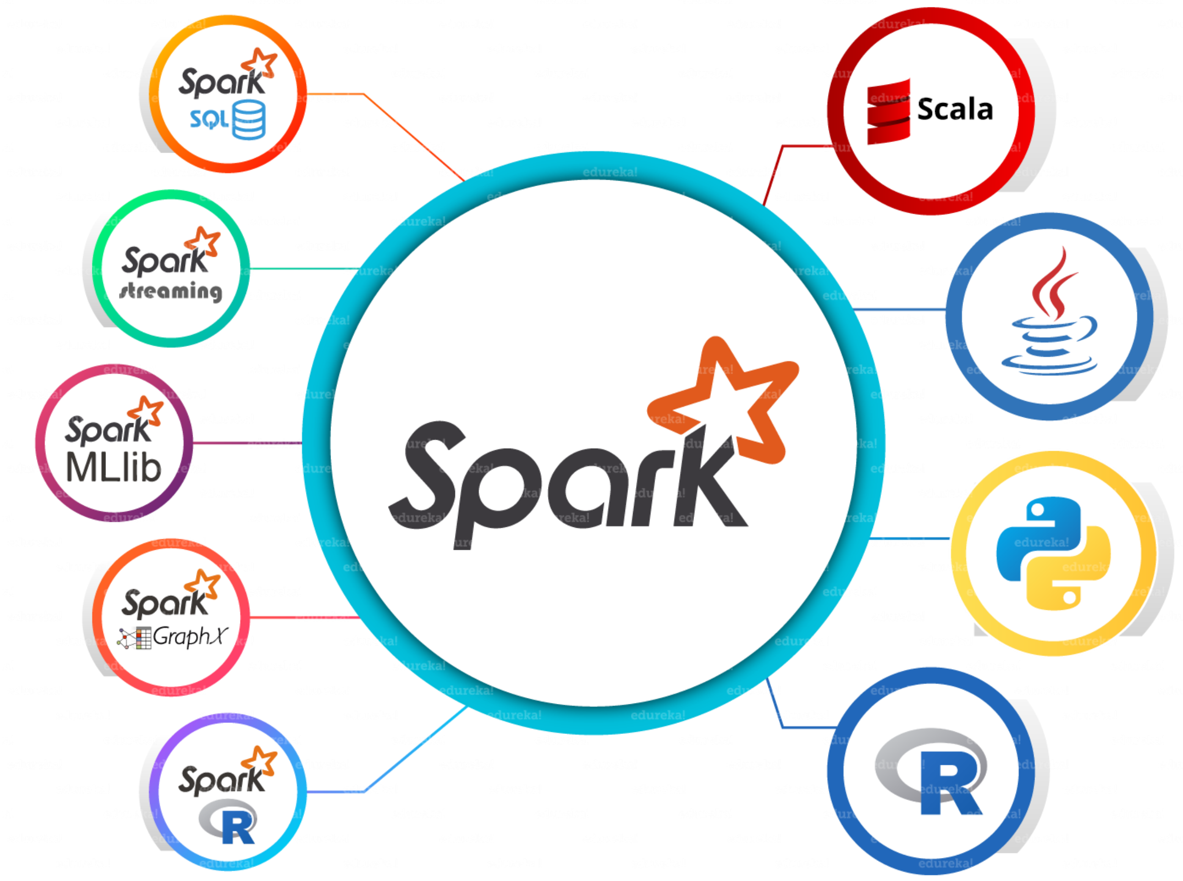
Spark
PySpark

Spark Ecosystem



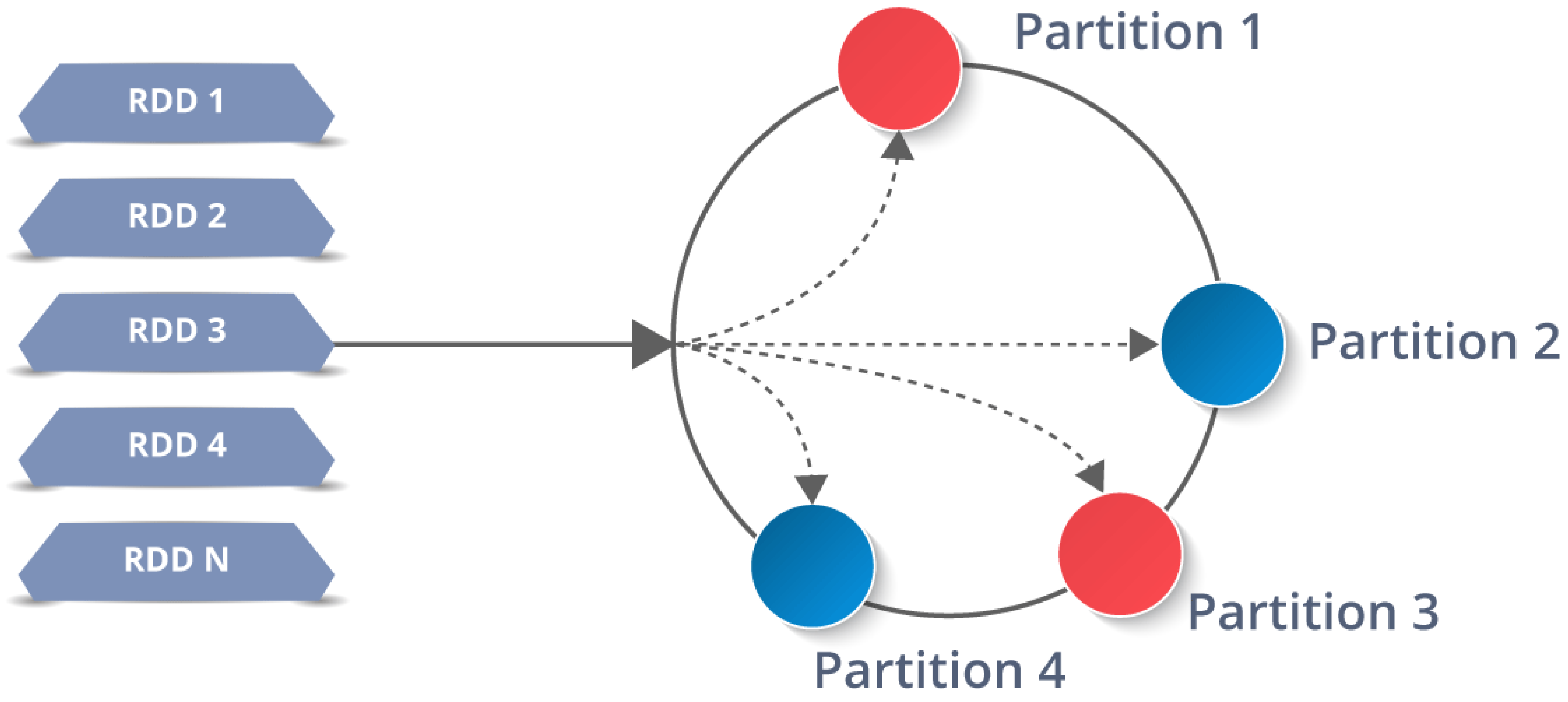
PySpark Components

- **Spark Core:** Spark Core is the base engine for large-scale parallel and distributed data processing. Further, additional libraries which are built on the top of the core allows diverse workloads for streaming, SQL, and machine learning. It is responsible for memory management and fault recovery, scheduling, distributing and monitoring jobs on a cluster & interacting with storage systems.
- **Spark Streaming:** Spark Streaming is the component of Spark which is used to process real-time streaming data. Thus, it is a useful addition to the core Spark API. It enables high-throughput and fault-tolerant stream processing of live data streams.
- **Spark SQL:** Spark SQL is a new module in Spark which integrates relational processing with Spark's functional programming API. It supports querying data either via SQL or via the Hive Query Language. For those of you familiar with RDBMS, Spark SQL will be an easy transition from your earlier tools where you can extend the boundaries of traditional relational data processing.
- **GraphX:** GraphX is the Spark API for graphs and graph-parallel computation. Thus, it extends the Spark RDD with a Resilient Distributed Property Graph. At a high-level, GraphX extends the Spark RDD abstraction by introducing the Resilient Distributed Property Graph (a directed multigraph with properties attached to each vertex and edge).
- **MLlib (Machine Learning):** MLlib stands for Machine Learning Library. Spark MLlib is used to perform machine learning in Apache Spark.
- **SparkR:** It is an R package that provides a distributed data frame implementation. It also supports operations like selection, filtering, aggregation but on large data-sets.

Resilient Distributed Dataset(RDD)

- RDDs are the building blocks of any Spark application. RDDs Stands for:
  - ***Resilient:*** Fault tolerant and is capable of rebuilding data on failure.
  - ***Distributed:*** Distributed data among the multiple nodes in a cluster.
  - ***Dataset:*** Collection of partitioned data with values.
- It is a layer of abstracted data over the distributed collection. It is immutable in nature and follows lazy transformations.

Resilient Distributed Dataset(RDD)



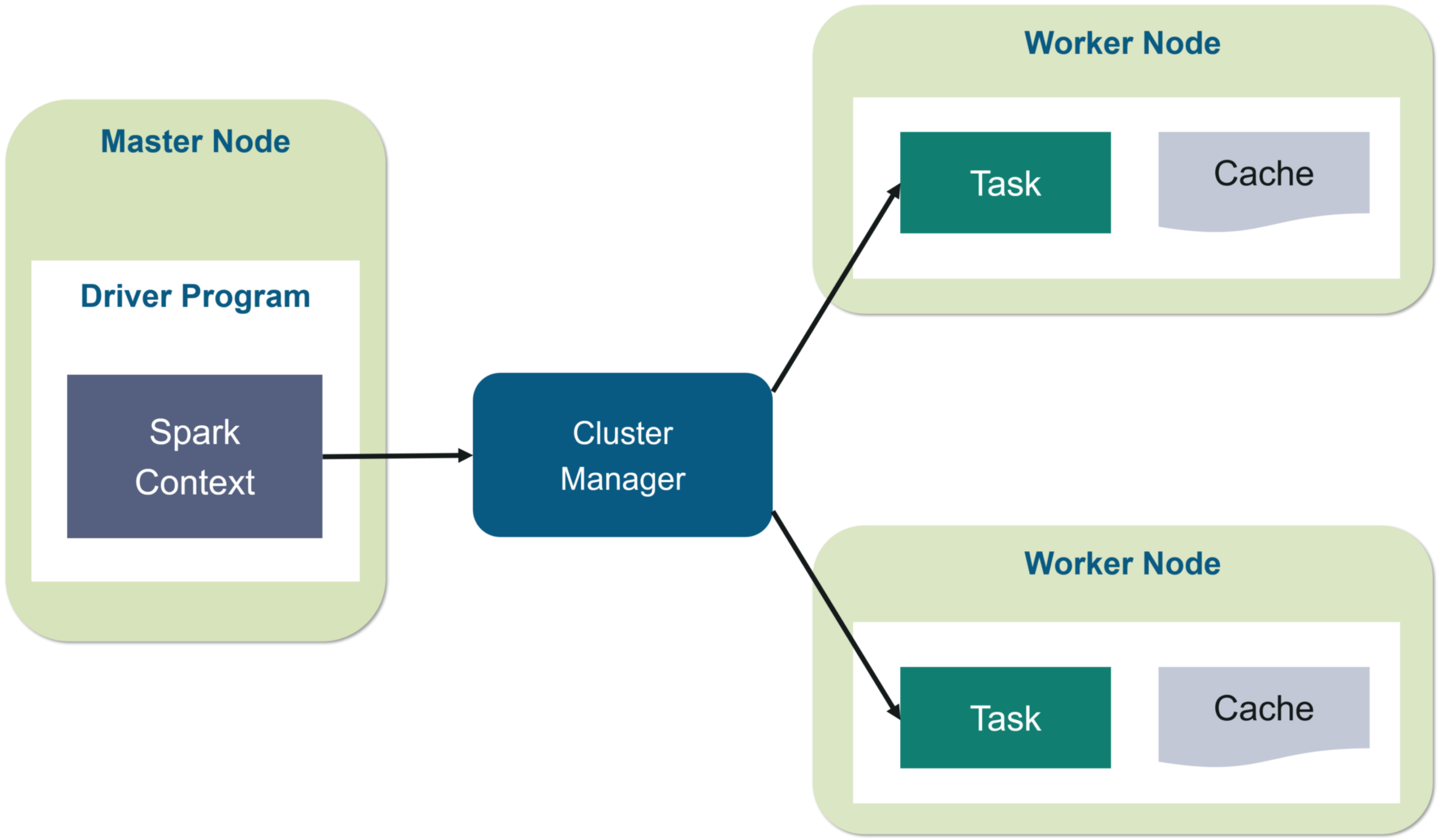
Working of RDD

- The data in an RDD is split into chunks based on a key.
- RDDs are highly resilient, i.e., they are able to recover quickly from any issues as the same data chunks are replicated across multiple executor nodes.
- Even if one executor node fails, another will still process the data. This allows you to perform your functional calculations against your dataset very quickly by **harnessing the power of multiple nodes**.
- Once you create an RDD it becomes immutable. By immutable I mean, an object whose state cannot be modified after it is created, but they can surely be transformed.

Creating an RDD

- There are two ways to create RDDs –
  - parallelizing an existing collection in your driver program
  - by referencing a dataset in an external storage system, such as a shared file system, HDFS, HBase, etc.
- With RDDs, you can perform two types of operations:
  - Transformations: They are the operations that are applied to create a new RDD.
  - Actions: They are applied on an RDD to instruct Apache Spark to apply computation and pass the result back to the driver.

Working of Spark

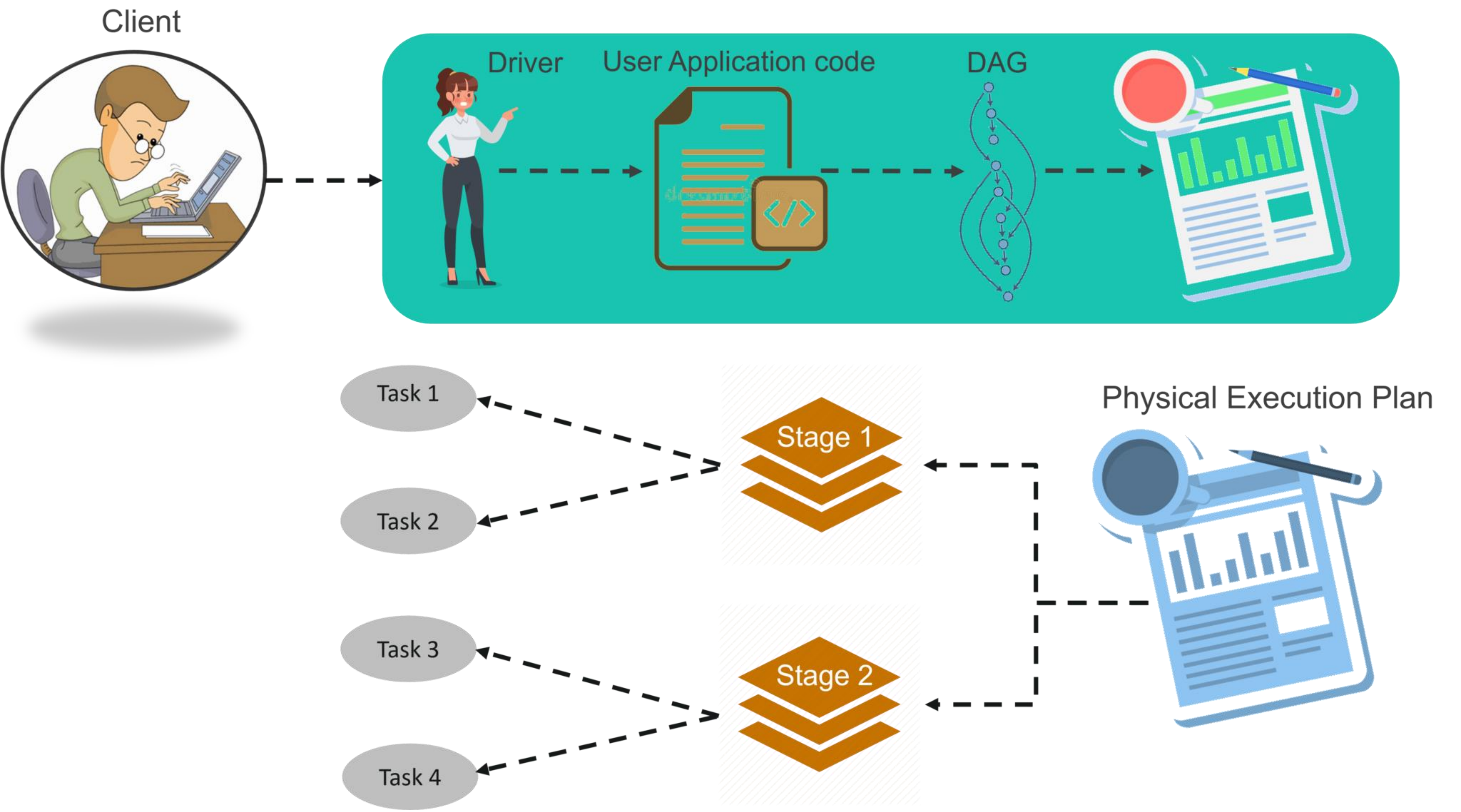


Working of Spark

- In your master node, you have the driver program, which drives your application. The code you are writing behaves as a driver program or if you are using the interactive shell, the shell acts as the driver program.
- Inside the driver program, the first thing you do is, you create a Spark Context. Assume that the **Spark context is a gateway to all the Spark functionalities**. It is similar to your database connection. Any command you execute in your database goes through the database connection. Likewise, anything you do on Spark goes through Spark context.

Working of Spark

- Now, this **Spark context works with the cluster manager to manage various jobs**. The driver program & Spark context takes care of the job execution within the cluster. **A job is split into multiple tasks which are distributed over the worker node**. **Anytime an RDD is created in Spark context, it can be distributed across various nodes and can be cached there.**
- Worker nodes are the slave nodes whose job is to basically execute the tasks. These tasks are then executed on the partitioned RDDs in the worker node and hence returns back the result to the Spark Context.
- Spark Context takes the job, breaks the job in tasks and distribute them to the worker nodes. These tasks work on the partitioned RDD, perform operations, collect the results and return to the main Spark Context.
- If you increase the number of workers, then you can divide jobs into more partitions and execute them parallelly over multiple systems. It will be a lot faster.
- With the increase in the number of workers, memory size will also increase & you can cache the jobs to execute it faster.


Client
Driver
User Application code
DAG
Physical Execution Plan
Task 1
Task 2
Task 3
Task 4
Stage 1
Stage 2

Working Example

- STEP 1: The client submits spark user application code. When an application code is submitted, the driver implicitly converts user code that contains transformations and actions into a logically directed acyclic graph called DAG. At this stage, it also performs optimizations such as pipelining transformations.
- STEP 2: After that, it converts the logical graph called DAG into physical execution plan with many stages. After converting into a physical execution plan, it creates physical execution units called tasks under each stage. Then the tasks are bundled and sent to the cluster.
- STEP 3: Now the driver talks to the cluster manager and negotiates the resources. Cluster manager launches executors in worker nodes on behalf of the driver. At this point, the driver will send the tasks to the executors based on data placement. When executors start, they register themselves with drivers. So, the driver will have a complete view of executors that are executing the task.
- STEP 4: During the course of execution of tasks, driver program will monitor the set of executors that runs. Driver node also schedules future tasks based on data placement.

References

- https://www.edureka.co/blog/spark-architecture/
- https://spark.apache.org/docs/latest/api/python/index.html