RDD Execution Steps

1. **Data Loading** – Read data from HDFS, S3, or databases.
2. **Partitioning** – Data is split into **smaller chunks (partitions).**
3. **Execution** – Spark processes each partition **in parallel**.

RDD Properties

Property	Description
Immutable	Cannot be modified after creation.
Partitioned	Distributed across nodes for parallel processing.
Fault-Tolerant	Can recover data from lineage.
Lazily Evaluated	Execution is delayed until an action is called.

1. Lazy Evaluation in Spark

Why Lazy Evaluation?

- Optimizes execution by **building a DAG (Directed Acyclic Graph).**
- **Only executes transformations when an action is triggered**.

Transformations (Lazy) vs Actions (Triggers Execution)

Operation Type	Description	Examples
Transformations	Creates a new RDD	`map()` , `filter()` , `flatMap()`
Actions	Executes all transformations	`collect()` , `count()` , `reduce()`

2. Transformations & Actions in RDD

Narrow Transformations (No Shuffling)

- Each output partition **depends on a single input partition**.
- **Faster execution.**
- **Examples:** `map()` , `filter()` , `flatMap()` .

Wide Transformations (Shuffling Required)

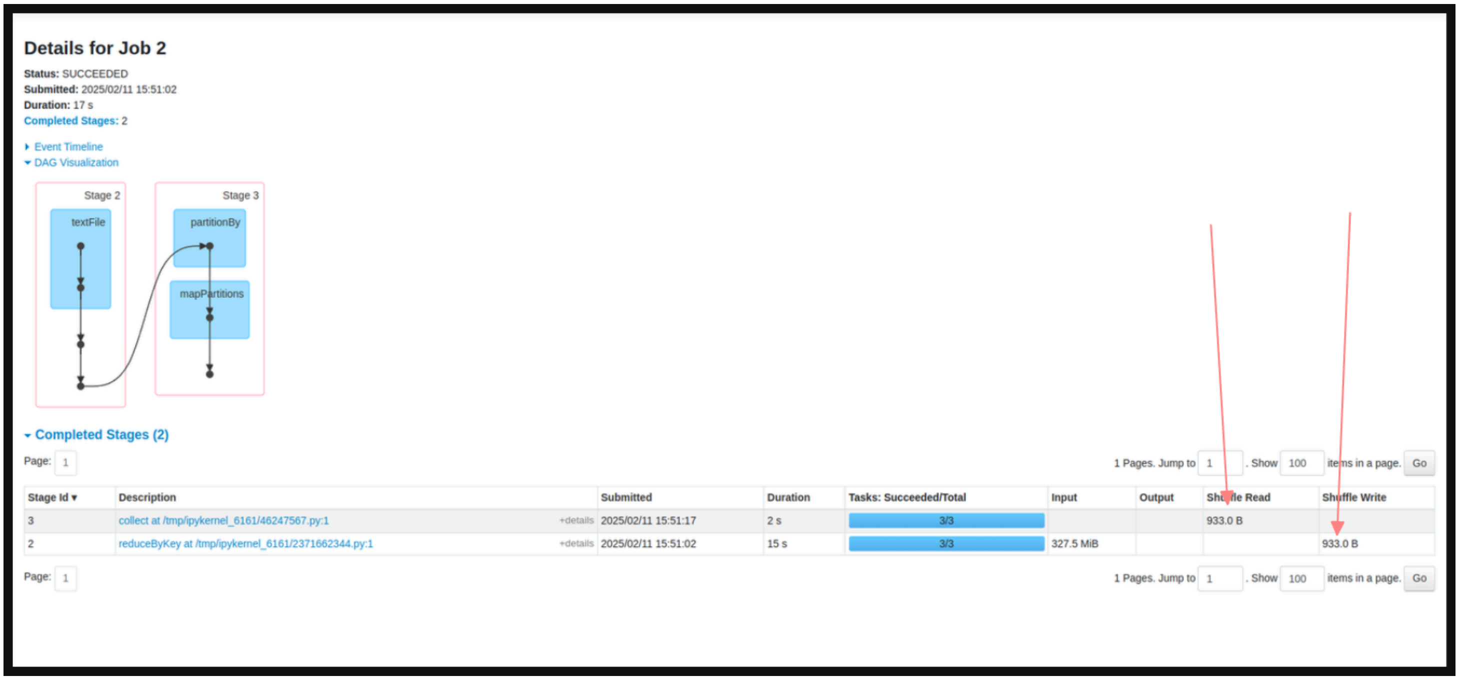
- Data is **redistributed across partitions**.
- **Slower due to network communication.**
- **Examples:** `reduceByKey()` , `groupByKey()` , `sortByKey()` .

Example

ReduceByKey vs GroupByKey in Spark

1. ReduceByKey

- **Type:** Wide Transformation
- **Definition:**
  - Aggregates values for each key using a **specified associative and commutative reduce function**.
  - **Combiner Optimization:** Combines the values **locally within each partition** before shuffling data across the network.
  - **Result:** Produces a single output value per key.
- **Example Function:**
  - `lambda x, y: x + y`
- **Key Points:**
  - Reduces the amount of data shuffled over the network.
  - More efficient for large datasets.
- **Output:**
  - RDD of `(key, aggregated_value)` pairs.
- **Example:**
  Input: `[(a, 1), (b, 2), (a, 3), (b, 4)]`
  Output: `[(a, 4), (b, 6)]`

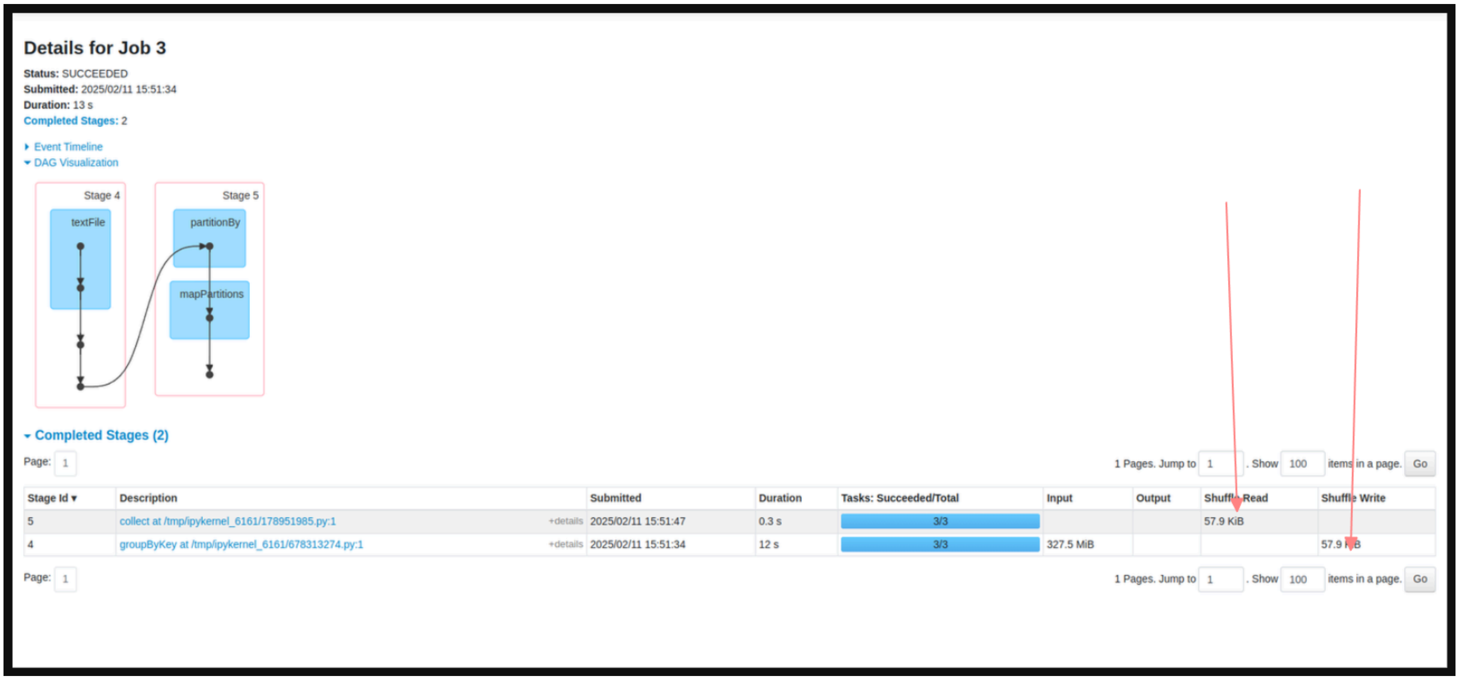


2. GroupByKey

- **Type:** Wide Transformation
- **Definition:**
  - Groups all values associated with each key into a **single iterable collection**.
  - **No Aggregation:** Only groups data, does not perform aggregation.
- **Key Points:**
  - Shuffles all data across the network, which can be expensive for large datasets.
  - Suitable when aggregation is not required and all values per key are needed.
- **Output:**
  - RDD of `(key, Iterable[values])` pairs.
- **Example:**

  Input: `[(a, 1), (b, 2), (a, 3), (b, 4)]`

  Output: `[(a, [1, 3]), (b, [2, 4])]`



Differences Between ReduceByKey and GroupByKey

Feature	ReduceByKey	GroupByKey
Operation Type	Aggregates values per key.	Groups values into an iterable per key.
Shuffling	Combines values locally before shuffling.	Shuffles all data directly.
Efficiency	More efficient for large datasets.	Less efficient due to higher shuffle cost.
Use Case	When aggregation is needed.	When all values for a key are required.
Output	`(key, aggregated_value)` pairs.	`(key, Iterable[values])` pairs.

Shuffle in Wide Transformations

- **Shuffle** involves **redistributing data** across the cluster.
- It is triggered when:
  - Data needs to be grouped or aggregated across partitions.
- Shuffling is **resource-intensive** and **time-consuming**, as it involves:
  - Writing intermediate data to disk.
  - Network communication between nodes.

Optimization Tip

- Try to minimize **wide transformations** (e.g., shuffles) to improve performance.
- Use **narrow transformations** whenever possible to avoid the overhead of data shuffling.