

# How Spark RDD Operations Work

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# Objectives

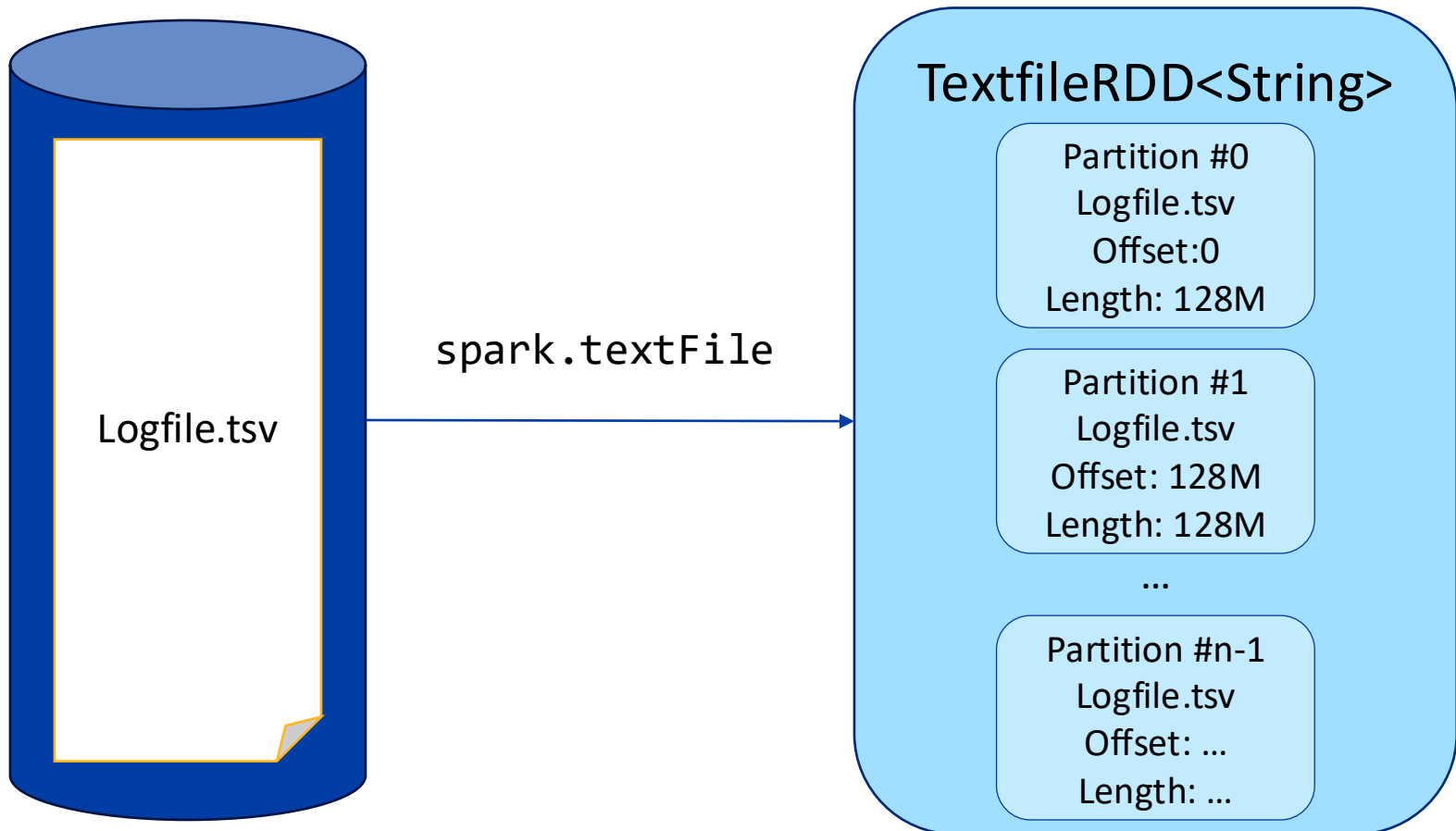
- Understand how several RDD operations internally work
- Map RDD operations to MapReduce
- Compare narrow dependency to wide dependency transformations implementation
- Assess the memory overhead of RDD functions

# Spark Operations

- Data loader/creator. Creates the first RDD
- Transformation. Converts one RDD to another.
  - Narrow dependency
  - Wide dependency
- Action. Executes the application.

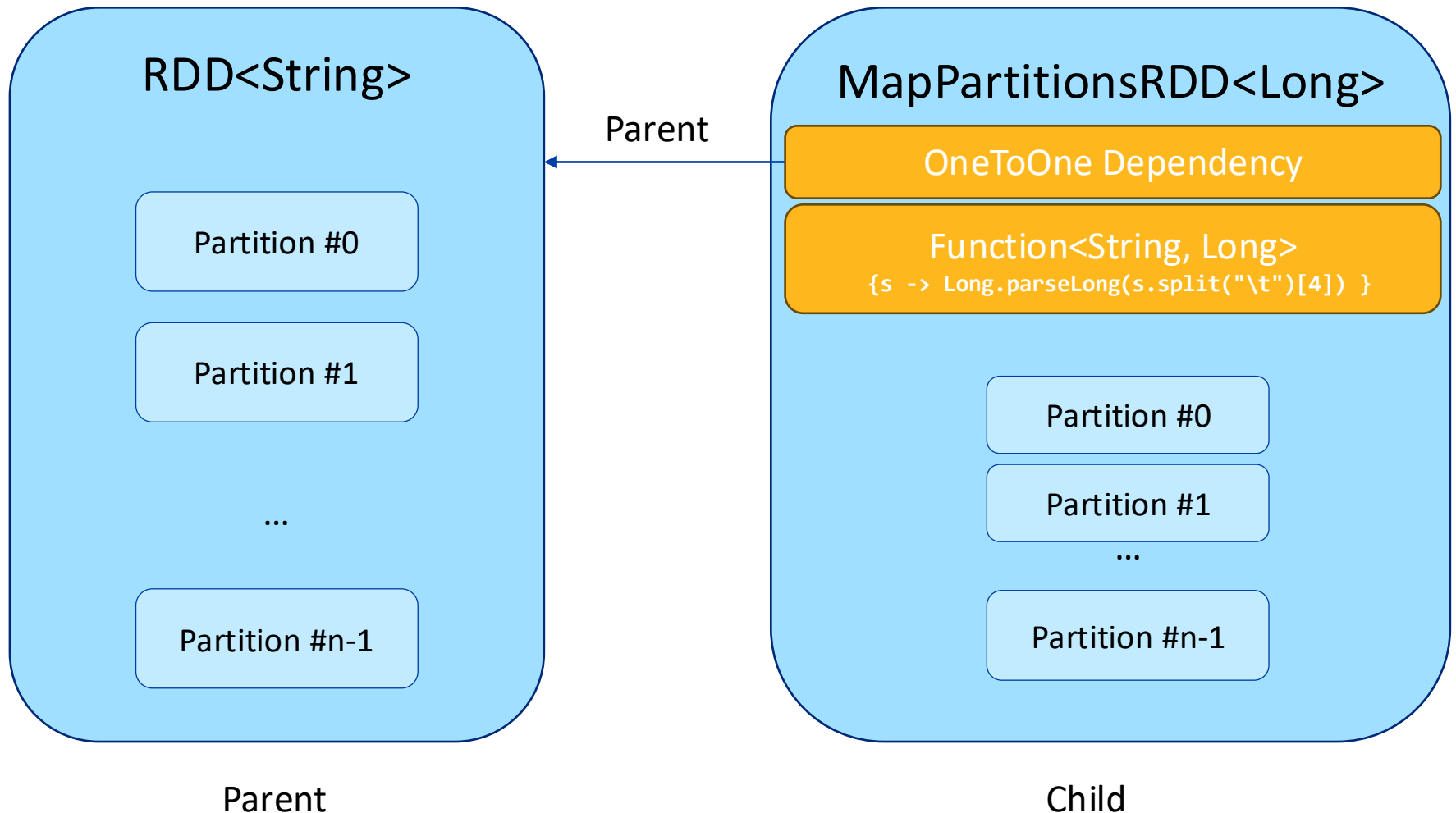
# Data Loader

```
JavaRDD<String> textFileRDD =  
    spark.textFile("Logfile.tsv");
```



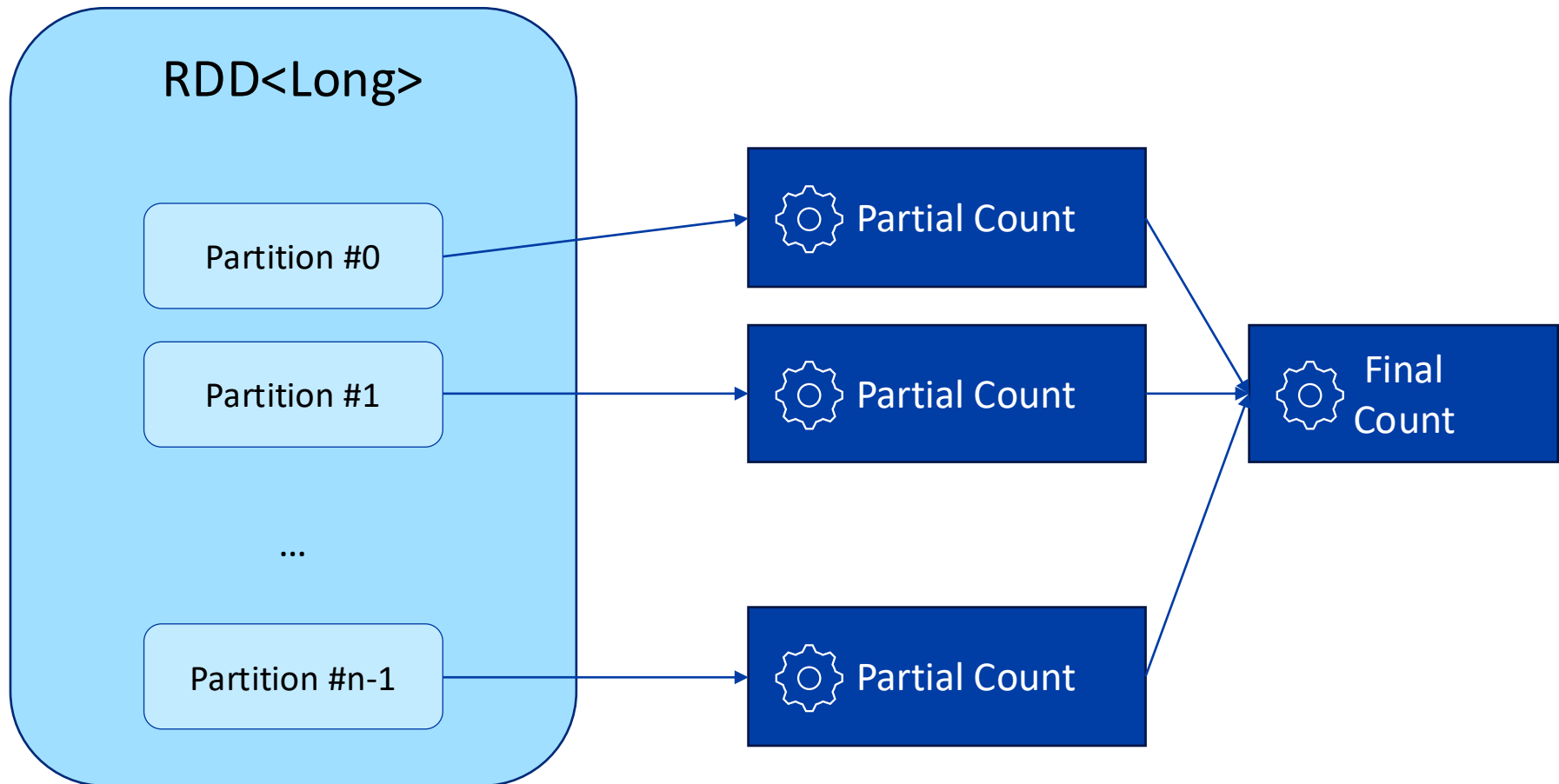
# Map Operation

```
JavaRDD<Long> sizes = textFileRDD.map(s ->  
    Long.parseLong(s.split("\t")[4]));
```

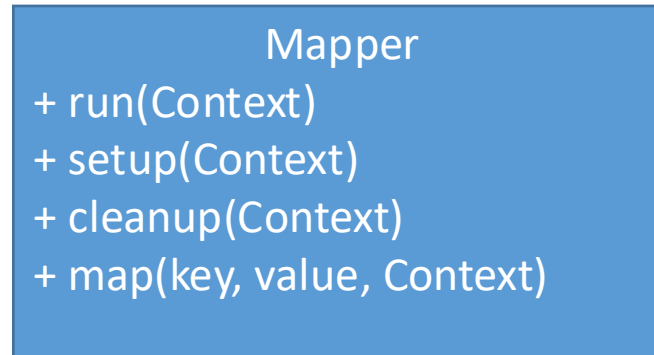
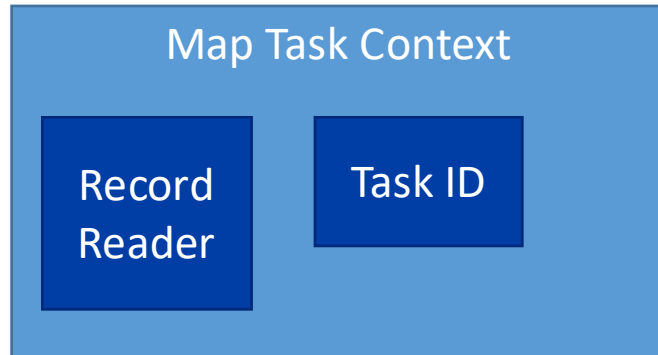


# Reduce Action

```
Long size = codes.reduce((a, b) -> a + b);
```



# Hadoop Mapper (under the hood)



```
public void run(Context context) throws IOException, InterruptedException {
    setup(context);
    try {
        while (context.nextKeyValue()) {
            map(context.getCurrentKey(), context.getCurrentValue(), context);
        }
    } finally {
        cleanup(context);
    }
}
```

# RDD Operation Notation

`RDD<T>#operation(params, func): RDD<U>`

- The operation is applied on an **RDD** with records of type **T**
- The output is an **RDD** with records of type **U**
- Types **T** and **U** can be any Java classes
- The **operation** can take additional **parameters** or **functions**
- The **parameters** can be any constant values
- **func**:  $\{T \rightarrow U\}$ 
  - indicates a user-defined function that takes an input of type **T** and return an output of type **U**



# **RDD<T>#filter(pred:{T→Boolean}): RDD<T>**

- Applies the predicate function on each record and produces that tuple only of the predicate returns true
- Result RDD<T> with same or fewer records than the input
- Narrow dependency
- In Hadoop:
  - ```
map(T value) {  
    if (pred.apply(value))  
        context.write(value)  
}
```

# **`RDD<T>#map(func: {T→U}): RDD<U>`**

- Applies the map function to each record in the input to produce one record
- Results in `RDD<U>` with the same number of records as the input
- Narrow dependency
- In Hadoop:
  - `map(T value) {  
 context.write(func.apply(value));  
}`

## **RDD<T>#flatMap(func: {T→Iter<U>}): RDD<U>**

- Applies the map function to each record and add all resulting values to the output RDD
- Result: RDD<U>
- This is the closest function to the Hadoop map function
- Narrow dependency
- In Hadoop:
  - map(T value) {  
    Iterator<U> results = func.apply(value);  
    for (U result : results)  
        context.write(result)  
}

# **RDD<T>#mapPartition(func): RDD<U>**

- func:  $\text{Iterator}\langle T \rangle \rightarrow \text{Iterator}\langle U \rangle$
- Applies the map function to a list of records in one partition in the input and adds all resulting values to the output RDD
- Narrow dependency
- Can be helpful in two situations
  - If there is a costly initialization step in the function
  - If many records can result in one record
- Result: RDD<U>

# RDD<T>#mapPartition(func): RDD<U>

- In Hadoop, the mapPartition function can be implemented by overriding the run() method in the Mapper, rather than the map() function
  - ```
run(context) {  
    // Initialize  
    Array<T> values;  
    for (T value : context)  
        values.add(value);  
    Iterator<U> results = func(values.iterator());  
    for (U value : results)  
        context.write(value);  
    // Cleanup  
}
```

## **RDD<T>#mapPartitionWithIndex(func): RDD<U>**

- func: {(Integer, Iterator<T>) → Iterator<U>}
- Similar to mapPartition but provides a unique index for each partition
- Narrow dependency
- In Hadoop, you can achieve a similar functionality by retrieving the InputSplit or taskID from the context.

## **RDD<T>#sample(r: Boolean, f: Float, s: Long): RDD<T>**

- r: Boolean: With replacement (true/false)
- f: Float: Fraction [0,1]
- s: Long: Seed for random number generation
- Returns RDD<T> with a sample of the records in the input RDD
- Narrow dependency
- Can be implemented using `mapPartitionWithIndex` as follows
  - Initialize the random number generator based on seed and partition index
  - Select a subset of records as desired
  - Return the sampled records

# **RDD<T>#reduce(func: {(T,T)→T}): T**

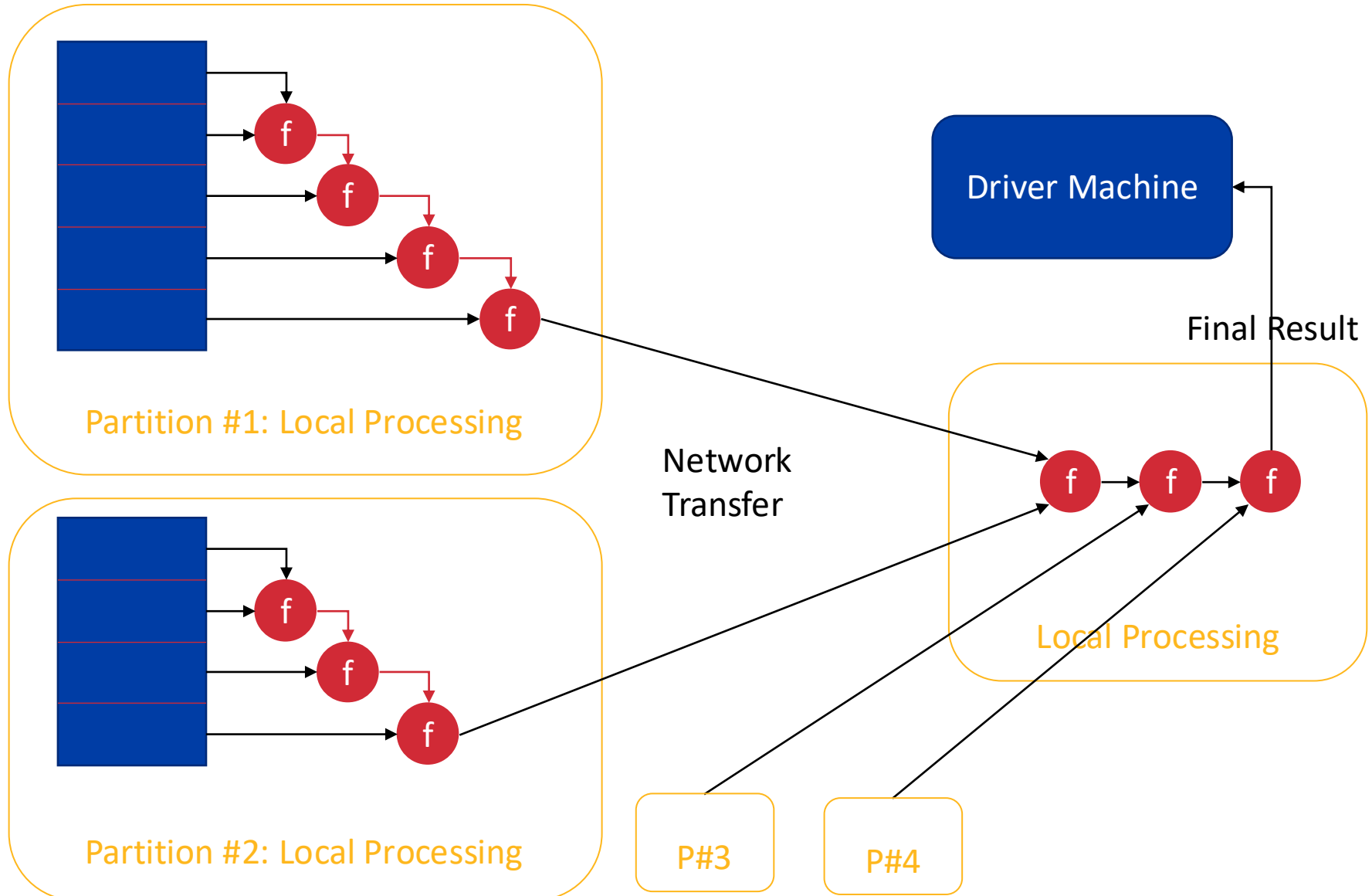
- This is not the same as the reduce function of Hadoop even though it has the same name
- Reduces all the records to a single value by repeatedly applying the given function
- Result: T
- This is an action



# **RDD<T>#reduce(func: {(T,T)→T})**

- In Hadoop
  - `map(T value) {  
    context.write(NullWritable.get(), value);  
}`
  - `combine, reduce(key, Iterator<T> values)  
{  
    T result = values.next();  
    while (values.hasNext())  
        result = func(result, values.next());  
    context.write(result);  
}`

# $\text{RDD}\langle T \rangle \# \text{reduce}(\text{func}: \{(T, T) \rightarrow T\})$



## **RDD<K,V>#reduceByKey(func: (V, V) → V): RDD<K,V>**

- Similar to reduce but applies the given function to each group separately
- Since there could be so many groups, this operation is a transformation that can be followed by further transformations and actions
- Wide dependency
- Result: RDD<K,V>
- By default, number of reducers is equal to number of input partitions but can be overridden

# RDD<K,V>#reduceByKey(func)

- In Hadoop:
  - `map(K key, V value) {  
    context.write(key, value);  
}`
  - `combine, reduce(K key, Iterator<V>  
values) {  
    V result = values.next();  
    while (values.hasNext())  
        result = func(result, values.next());  
    context.write(key, result);  
}`

# **RDD<T>#distinct(): RDD<T>**

- Removes duplicate values in the input RDD
- Returns RDD<T>
- Implemented as follows  
map(x => (x, null)).  
reduceByKey((a, b) => a, numPartitions).  
map(\_.\_1)
- Note: Both a and b are null in the reduceByKey function above
- Question: Is this a narrow or wide dependency transformation

# Limitation of reduce methods

- Both reduce methods have a limitation is that they have to return a value of the same type as the input.
- Let us say we want to implement a program that operates on an `RDD<Integer>` and returns one of the following values
  - 0: Input is empty
  - 1: Input contains only odd values
  - 2: Input contains only even values
  - 3: Input contains a mix of even and odd values

## **RDD<T>#aggregate(zero, seqOp, combOp): U**

- zero: U - Zero value of type U
  - seqOp: (U, T)  $\rightarrow$  U – Combines the aggregate value with an input value
  - combOp: (U, U)  $\rightarrow$  U – Combines two aggregate values
  - Returns U, hence, an action
- 
- Similarly, aggregateByKey operates on RDD<K,V> and returns RDD<K,U>

## **RDD<T>#aggregate(zero, seqOp, combOp)**

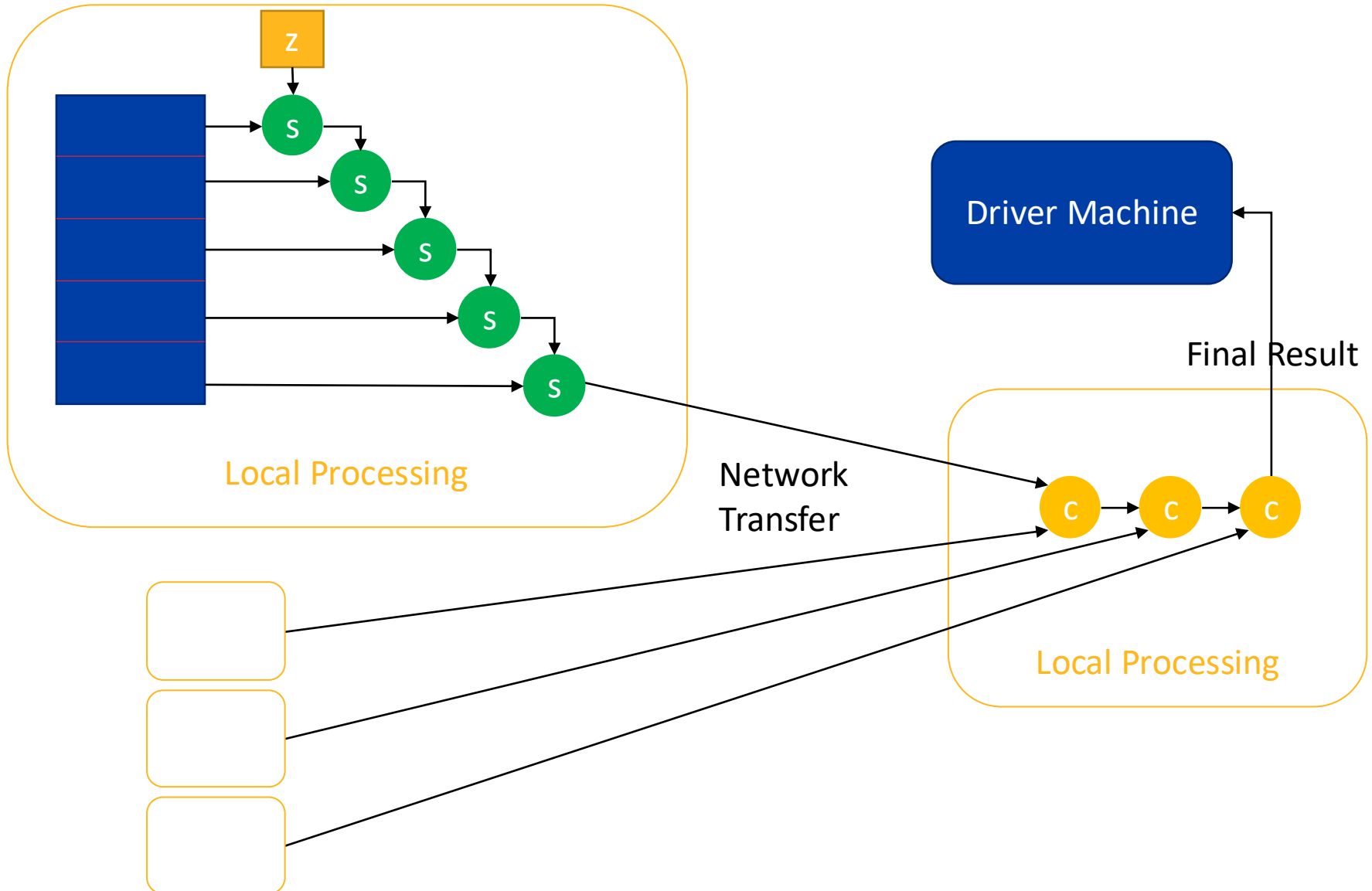
- In Hadoop:
  - `run(context) {`  
    `U result = zero;`  
    `for (T value : context)`  
        `result = seqOp(result, value);`  
    `context.write(NullWritable.get(), result);`  
    `}`
  - `combine,reduce(key, Iterator<U> values) {`  
    `U result = values.next();`  
    `while (values.hasNext())`  
        `result = combOp(result, values.next());`  
    `context.write(result);`  
    `}`



## `RDD<T>#aggregate(zero, seqOp, combOp)`

- Example:
- `RDD<Integer>` values
- `Byte marker = values.aggregate( (Byte)0, (result: Byte, x: Integer) => { if (x % 2 == 0) // Even return result | 2; else return result | 1; }, (result1: Byte, result2: Byte) => result1 | result2 );`

# RDD<T>#aggregate(zero, seqOp, combOp)



## **RDD<K,V>#groupByKey(): RDD<K, Iterator<V>>**

- Groups all values with the same key into the same partition
- Closest to the shuffle operation in Hadoop
- Returns RDD<K, Iterator<V>>
- Wide dependency
- **ⓘ Performance notice:** By default, all values are kept in memory so this method can have a very high memory consumption.
- Unlike the reduce and aggregate methods, this method does not run a combiner step, i.e., all records get shuffled over network

# **RDD<T>#foreach(func: {T→None})**

- An action that iterates over all records in parallel and applies a function on each one
- Notice: This given function runs in parallel on the worker nodes
- You cannot use this function to iterate over records on the local node

# RDD<T>#collect(): Array[T]

- Returns the set of records in the RDD as an array
- This should only be used with very small datasets
- Spark has a default limit of 1GB for the total result size (`spark.driver.maxResultSize`)
- Related actions:
  - RDD<T>#take(n): Array[T]
  - RDD<T>#takeSample(n): Array[T]
  - RDD<T>#takeOrdered(n): Array[T]

# Running a complex DAG

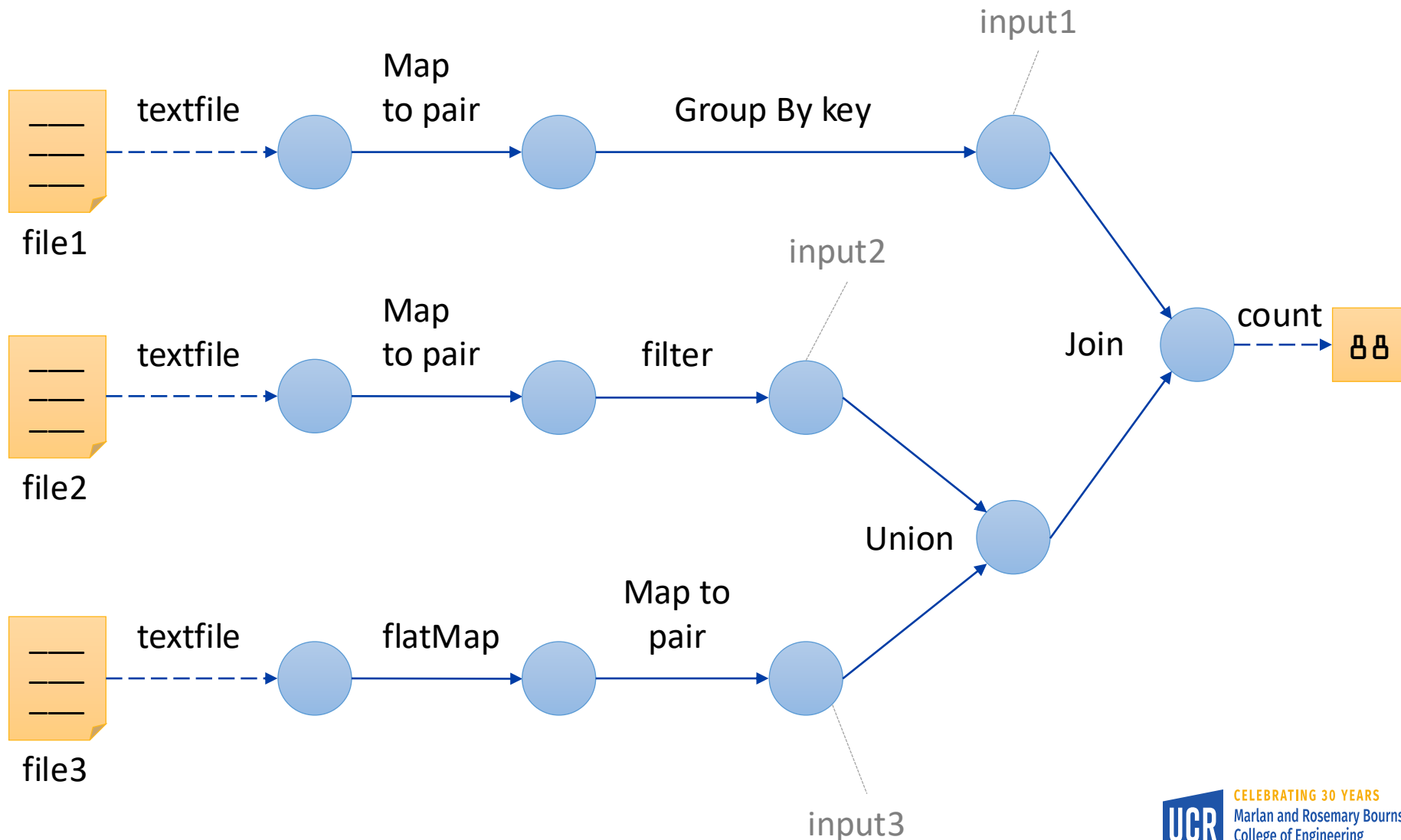
```
PairFunction<String, String, String> lineParser =  
    (PairFunction<String, String, String>) line -> {  
        String[] parts = line.split(",");  
        return new Tuple2<>(parts[0], parts[1]);  
    };  
JavaPairRDD<String, Iterable<String>> input1 =  
    sc.textFile("file1")  
        .mapToPair(lineParser)  
        .groupByKey();  
  
JavaPairRDD<String, String> input2 = sc.textFile("file2")  
    .mapToPair(lineParser)  
    .filter(record -> record._1.equals("200"));  
  
JavaPairRDD<String, String> input3 = sc.textFile("file3")  
    .flatMap(line -> Arrays.asList(line.split(";")).iterator())  
    .mapToPair(lineParser);  
  
long count = input2.union(input3).join(input1).count();
```



# Practice Questions

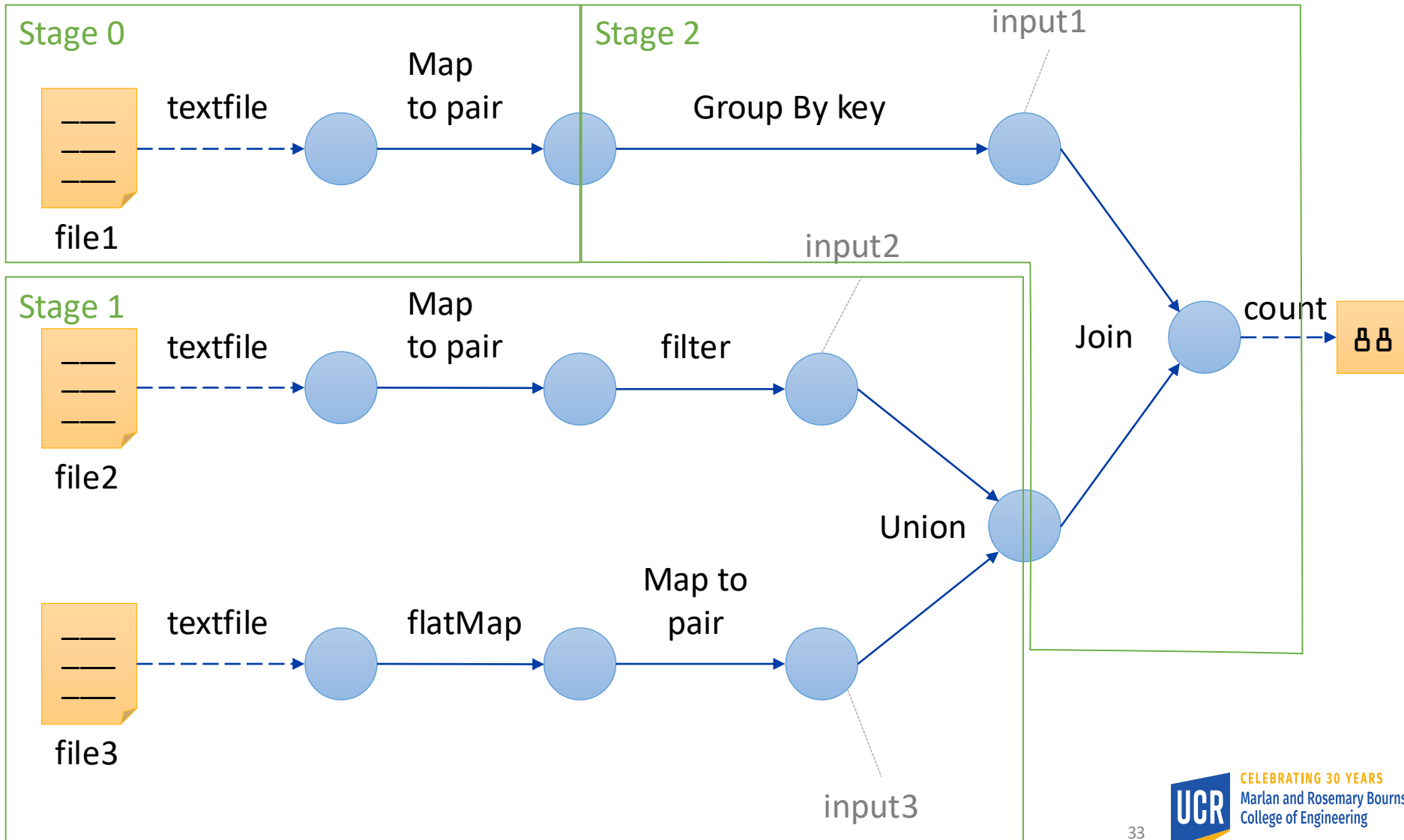
- Convert the short program provided earlier into a DAG.
- Break down the DAG into stages. How many stages will this program have?

# Answer - Overall DAG





# Answer - Overall DAG



# Answer – Overall DAG



Jobs

Stages

Storage

Environment

Executors

Beast Example application UI

## Details for Job 0

Status: SUCCEEDED

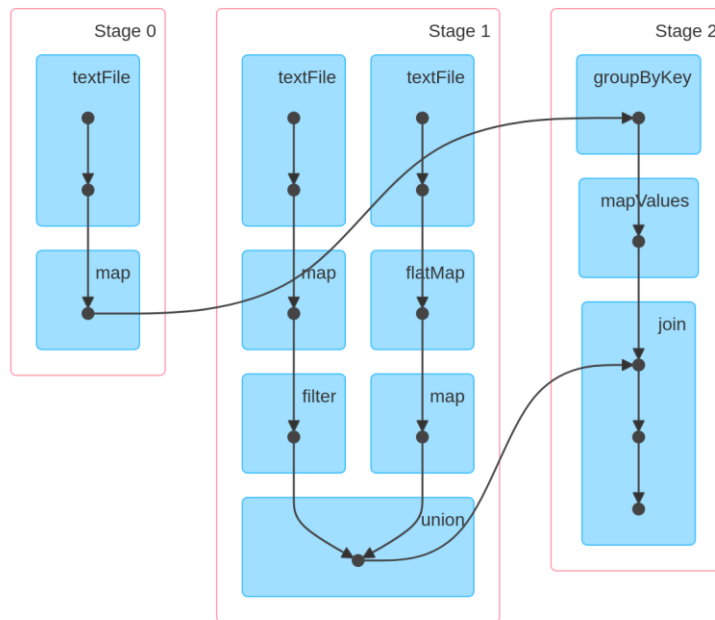
Submitted: 2021/11/22 12:32:37

Duration: 8 s

Completed Stages: 3

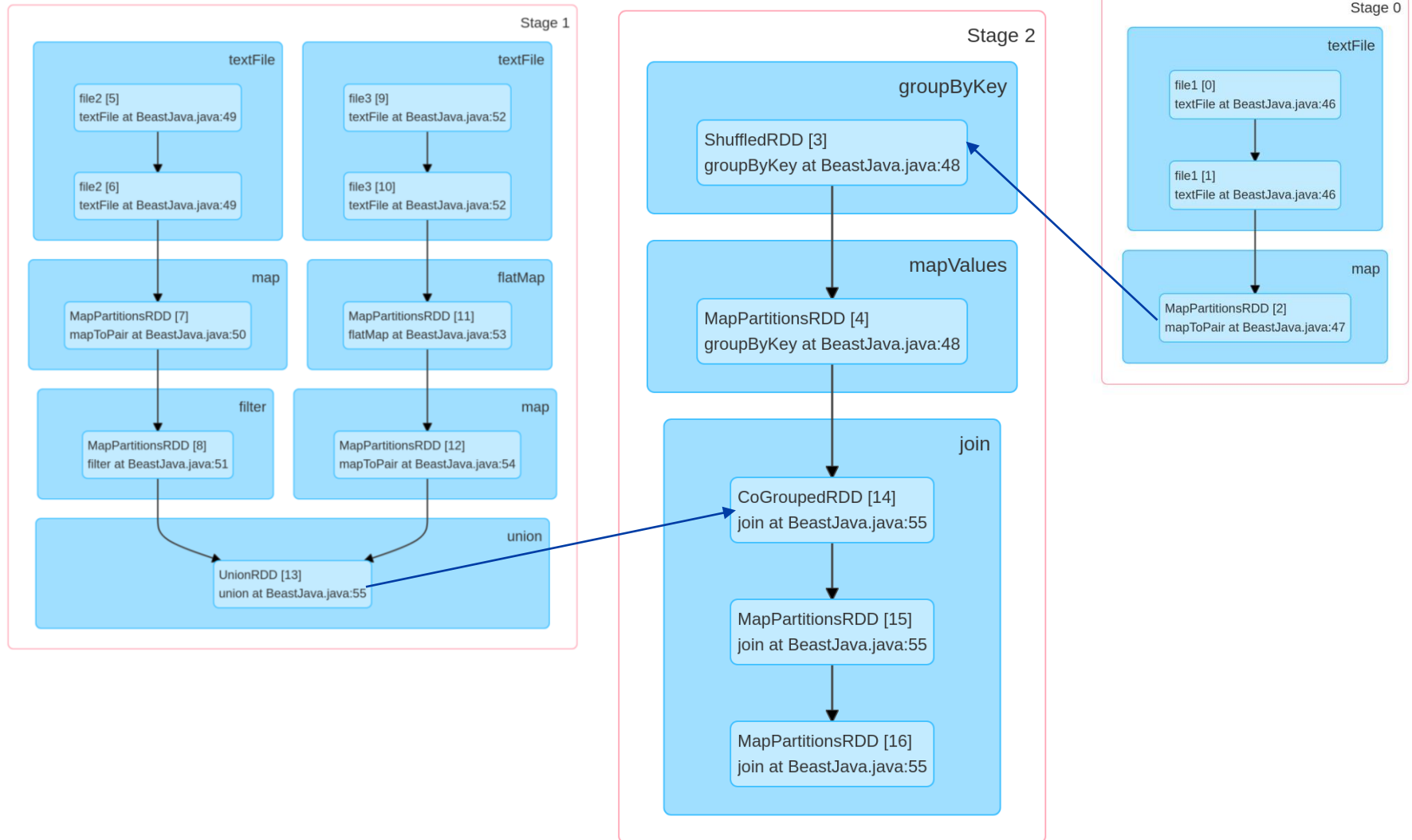
▶ Event Timeline

▼ DAG Visualization



▼ Completed Stages (3)

# Answer – Stages



# Further Readings

- List of common transformations and actions
  - <http://spark.apache.org/docs/latest/rdd-programming-guide.html#transformations>
- Spark RDD Scala API
  - <http://spark.apache.org/docs/latest/api/scala/index.html#org.apache.spark.rdd.RDD>