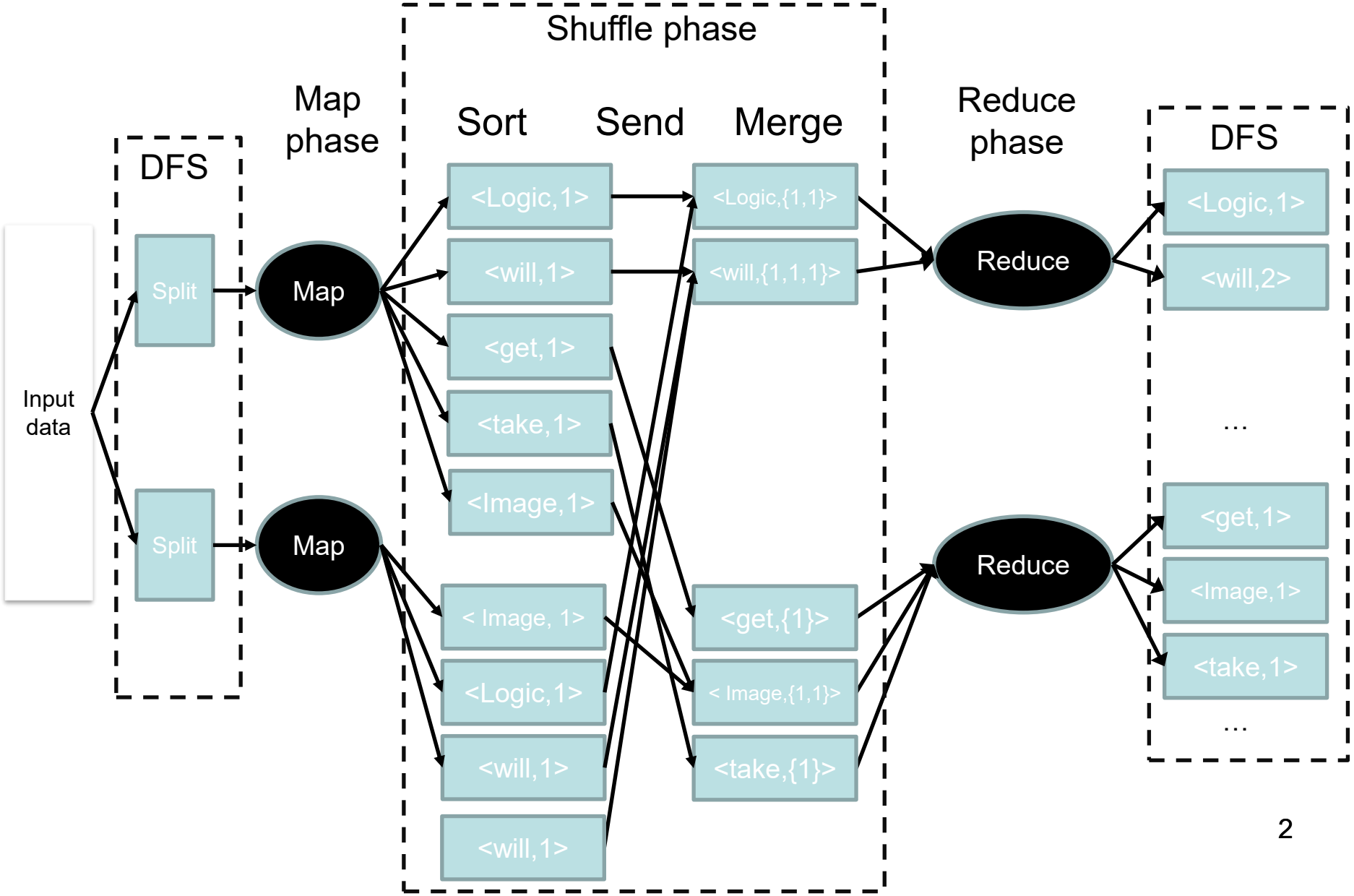
Programming for Data Science at Scale

Optimising Distributed Data Processing

THE UNIVERSITY *of* EDINBURGH

Amir Noohi, Fall 2025

MapReduce – under the hood



What is shuffling?

What happens when you do a `groupBy` or a `groupByKey`?

```scala
// Create an RDD of (Grade, Student) pairs
val students = sc.parallelize(List(
  ("A", "Alice"),
  ("B", "Bob"),
  ("A", "Adam"),
  ("C", "Charlie"),
  ("B", "Ben")
))

// Group students by their grade
val groupedStudents = students.groupByKey()

// The output of groupByKey is a ShuffledRDD
// Type of groupedStudents: RDD[(String, Iterable[String])] =
ShuffledRDD[4] at groupByKey at <console>:24
```

move data from one node to another to be "grouped with" its key.

Shuffling is **expensive** because:

- Network I/O (moving data between nodes).
- Disk I/O when data is too large to fit in memory.
- Serialisation and deserialisation of data.

Example of Shuffling

We have a list of three ATMs from which customers withdraw money. Now, we want to calculate how much each customer has withdrawn in total.

```
// Define a case class for ATM withdrawals
case class ATMWithdrawal(customerId: Int, atmId: Int, amount: Double)

// Create an RDD of customer withdrawals from different ATMs, distributed across 3
partitions
val withdrawals = sc.parallelize(List(
  ATMWithdrawal(1, 101, 200.0),  // Partition 1
  ATMWithdrawal(2, 102, 150.0),  // Partition 1
  ATMWithdrawal(3, 103, 300.0),  // Partition 2
  ATMWithdrawal(1, 101, 100.0),  // Partition 2
  ATMWithdrawal(2, 102, 50.0),   // Partition 3
  ATMWithdrawal(3, 103, 400.0)   // Partition 3
), 3)  // The data is split across 3 partitions
```

Example of Shuffling

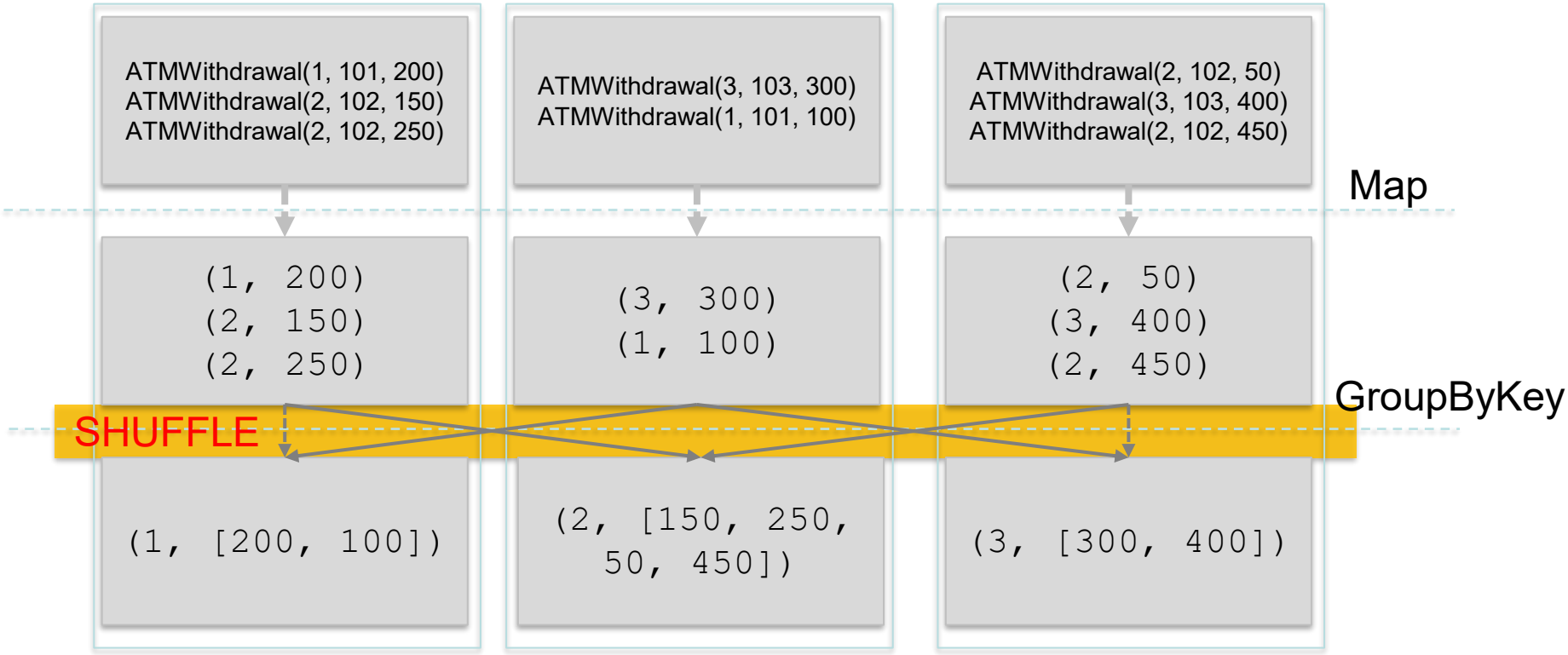
What is the solution?

```
// Group withdrawals by customerId and calculate the total amount per customer
val totalWithdrawalsPerCustomer = withdrawals
  .map(w ⇒ (w.customerId, w.amount))    // Convert to (customerId, amount) tuples
  .groupByKey()                         // Group by customerId (Shuffle occurs here)
  .mapValues(amounts ⇒ amounts.sum)      // Sum all amounts for each customer
```

What might the cluster look like with this data distributed over it?

Which data needs to be moved between nodes?

Example of Shuffling



Can we make it better?

`reduceByKey` combines the steps of `groupByKey` and reduction into one operation

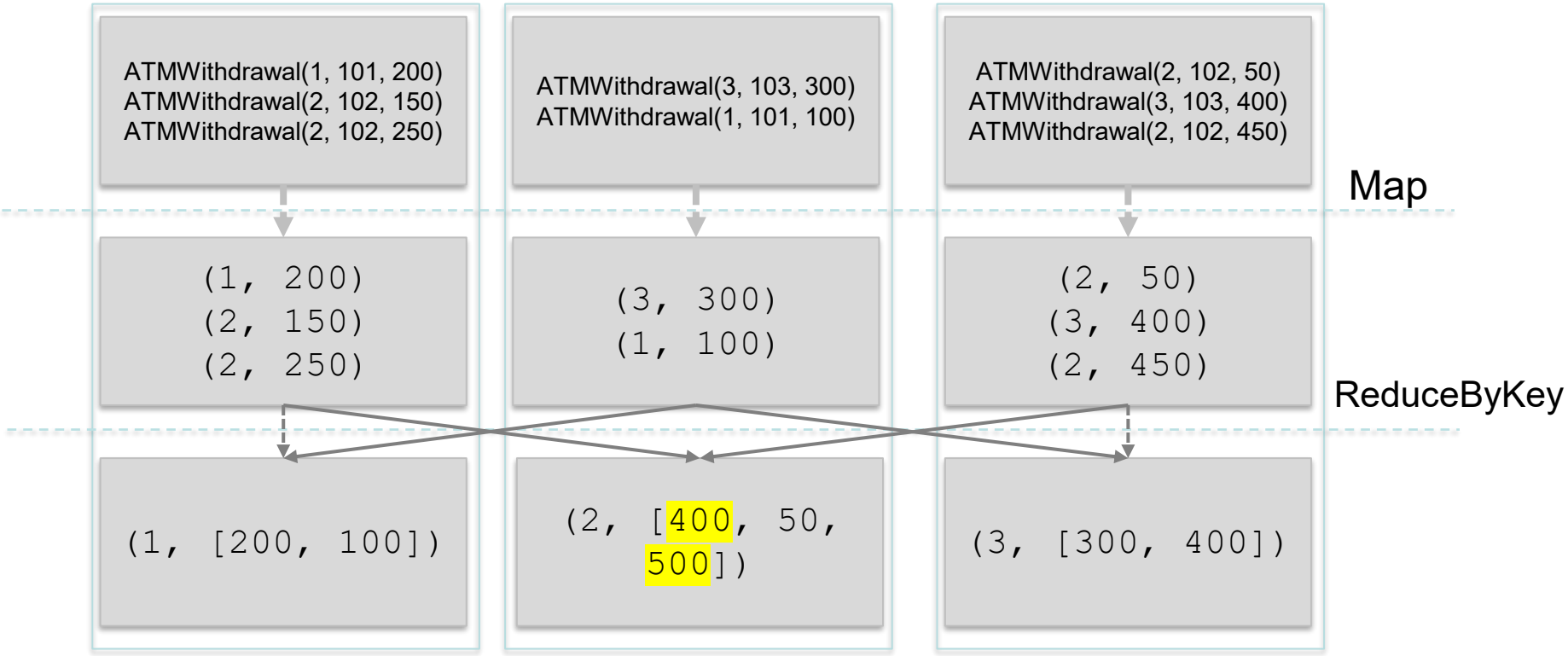
Key Advantage: It performs **local aggregation**

```
val totalWithdrawalsPerCustomer = withdrawals
  .map(w ⇒ (w.customerId, w.amount))  // (customerId, amount)
  .reduceByKey(_ + _)                 // Sum amounts per customer
```

By reducing the dataset first, the amount of data sent over the network during the shuffle is greatly reduced.

This can result in non-trivial gains in performance!

Example of Shuffling



When will shuffle occur?

1. The return type of certain transformations:

```
org.apache.spark.rdd.RDD[(String, Int)]= ShuffledRDD[1104]
```

2. Using the function `toDebugString` to see its execution plan:

```
partitioned.reduceByKey((v1, v2) ⇒ (v1 ._1 + v2._1, v1 ._2 + v2._2))
           .toDebugString

res9: String=
(8) MapPartitionsRDD[1104] at reduceByKey at <console>:49 []
                     | ShuffledRDD[l6151J at partitionBy at <console>:48 []
                     | CachedPartitions: 8; MemorySize: 1754.8 MB; DiskSize: 0.0 B
```

Where else shuffling?

1. `groupByKey()`:
   - Spark needs to move all records with the same key to the same partition.

2. `reduceByKey()`:
   - Shuffling occurs **after local aggregation** when Spark needs to move partial sums between partitions to calculate the final result.

3. `join()`:
   - Spark must align keys from two RDDs.

4. `distinct()`:
   - ensure that duplicate records across partitions are compared and removed.

5. `sortByKey()`:
   - Spark needs to globally sort data across all partitions.

6. `repartition()`:
   - redistributing data into a different number of partitions.

What is Partition?

Grouping all values of key-value pairs with the same key requires collecting all key-value pairs with the same key on the same machine.

But how does Spark know which key to put on which machine?

Key Properties of Partitions:

- Partitions **never span multiple machines**; all data in a partition stays on one machine.
- Each machine in the cluster contains **one or more partitions**.
- The **number of partitions** is configurable (default = total number of cores across executor nodes).

Types of Partitioning:

1. Hash Partitioning
2. Range Partitioning

Hash Partitioning

How It Works:

- **Hashing** customerId: Spark applies a hash function to customerId (e.g., 1, 2, 3) to determine the partition.

```
p = k.hashCode() % numPartitions
```

- **Partitioning**: Data with the same hash value goes to the same partition. Different customerIds go to different partitions based on their hash.
- **Result**: All records for a specific key are grouped into a single partition based on the hash function, ensuring **efficient distribution**

Range Partitioning

How It Works:

- Spark **sorts the keys** and divides them into ranges.
- Each partition holds a **specific range of keys** (e.g., 1-100 in one partition, 101-200 in another).
- **Efficient for ordered data** or when you need to process data within specific key ranges.

Example:
Withdrawals Data: If customerIds range from 1-1000, Spark splits this into partitions like:

- **Partition 1**: customerId 1-100
- **Partition 2**: customerId 101-200
- **Partition 3**: customerId 201-300

BREAK

Partitioning Data

There are two ways to create RDDs with specific partitionings:

1. Call *partitionBy* on an RDD, providing an explicit Partitioner.
   - Apply partitionBy() and provide an explicit **Partitioner** (e.g., Hash or Range).

```
// Example with HashPartitioner
val partitionedRDD = rdd.partitionBy(new HashPartitioner(numPartitions))

// Example with RangePartitioner
val rangePartitionedRDD = rdd.partitionBy(new RangePartitioner(numPartitions, rdd))
```

2. Using transformations that return RDDs with specific partitioners

```
val reducedRDD = rdd.reduceByKey(_ + _) // Automatically hash partitioned
```

Persisting Partitioned Data

Problem:

- After `partitionBy()`, Spark **re-shuffles and recomputes** the entire RDD every time you perform an action (e.g., count(), collect()).

Solution: Persist!

- `Persist()` stores the RDD in memory (or disk) after the first computation.

```
// Without persist - recomputes partitioning every time
val partitionedRdd = rdd.partitionBy(new HashPartitioner(100))
partitionedRdd.count()   // Recomputes partitionBy and counts
partitionedRdd.collect() // Recomputes partitionBy again

// With persist - avoids recomputation
partitionedRdd.persist()
partitionedRdd.count()   // Computes partitionBy and persists
partitionedRdd.collect() // Reuses the persisted data, no recomputation
```

Partitioner Inheritance

1. **Partitioner from Parent RDD**
   - Pair RDDs resulting from transformations on a partitioned RDD **inherit the partitioner** (usually Hash) from the parent RDD.

```
val transformedRDD = parentRDD.mapValues( ... ) // Uses the same partitioner as parentRDD
```

2. **Automatically-set Partitioners**

   Some operations **automatically apply partitioners** when it makes sense:
   - `sortByKey`: Uses a **RangePartitioner** by default.
   - `groupByKey`: Uses a **HashPartitioner** by default.

```
val sortedRDD = rdd.sortByKey()    // RangePartitioner is used
val groupedRDD = rdd.groupByKey() // HashPartitioner is used
```

Automatic Partitioners

Certain operations on Pair RDDs **retain and propagate** the partitioner from the parent RDD:

1. **Cogroup**
2. **groupWith**
3. **Join, leftOuterJoin,** r**ightOuterJoin**
4. **groupByKey**
5. **reduceByKey**, **foldByKey**,**combineByKey**
6. **partitionBy**
7. **sortmapValues** (if parent has a partitioner)
8. **flatMapValues** (if parent has a partitioner)
9. **filter** (if parent has a partitioner)

All other operations will produce a result without a partitioner.

Partitioning Example

Partitioning can bring substantial performance gains, especially in the face of shuffles.

Consider an application that keeps a large table of user information in memory:

- *userData* - BIG, containing (User ID, User Info) pairs, where User Info contains a list of topics the user is subscribed to

The application periodically combines this big table with a smaller file representing events that happened in the past five minutes

- *events* - small, containing (UserID, LinkInfo) pairs for users who have clicked a link on a website in those five minutes:

For example, we can count how many users visited a link that was not to one of their subscribed topics. We can perform this combination with Spark's join operation, which can be used to group the UserInfo and LinkInfo pairs for each UserID by key.

Partitioning Example

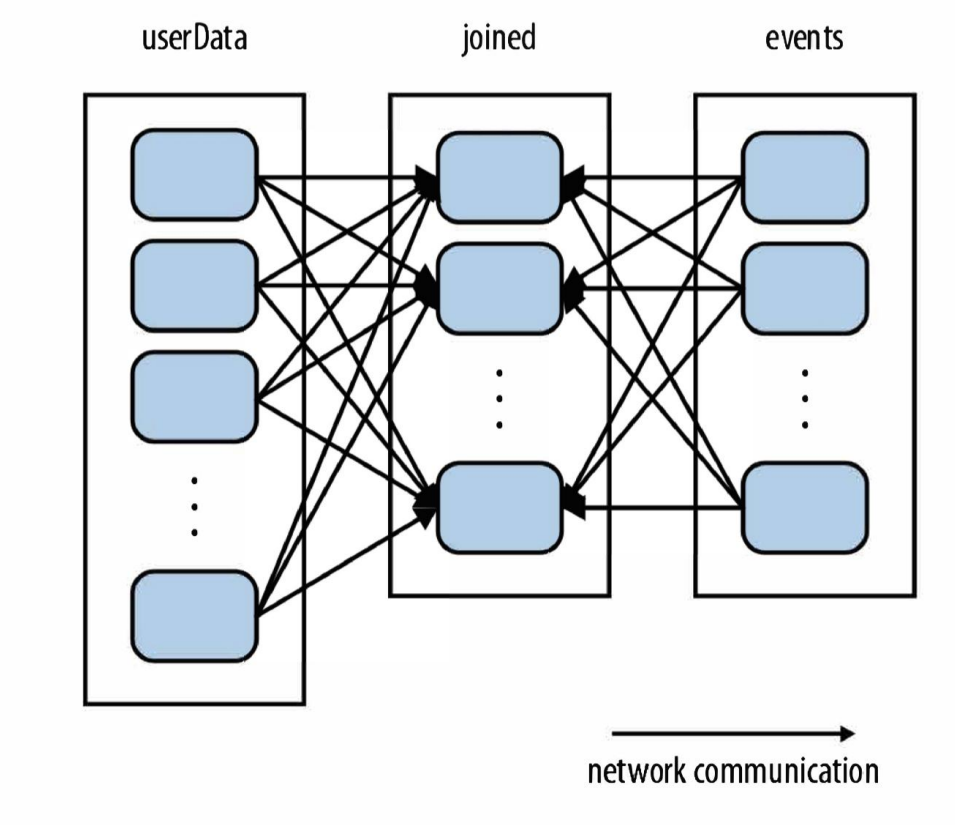
```
val sc = new SparkContext( ... )
val userData = sc.sequenceFile[UserID, Userlnfo]("hdfs:// ... ").persist()


def processNewlogs(logFileName: String) {
  val events = sc.sequenceFile[UserID, Linklnfo](logFileName)
  val joined = userData.join(events) //ROD of (UserID, (Userlnfo, Linklnfo))
  val offTopicVisits = joined.filter {
    case (userId, (userlnfo, linklnfo)) ⇒ //Expand the tuple
        !userlnfo.topics.contains(linklnfo.topic)
  }.count()
  println(''Number of visits to non-subscribed topics: '' + offTopicVisi ts)
}
```

Is this OK?

Partitioning Example

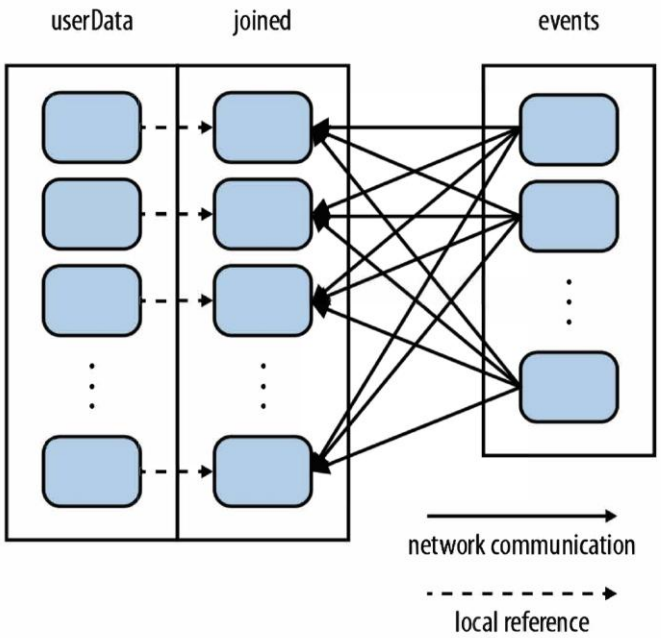
It will be very inefficient!

Why? The join operation, called each time processNewLogs is invoked, does not know anything about how the keys are partitioned in the datasets



Partitioning Example

```
val userData = sc.sequenceFile[UserID, UserInfo]("hdfs://  ...  ")
                 .partitionBy(new HashPartitioner(100)) // Create 100 partitions
                 .persist()
```



QUESTIONS?