

DATA ENGINEERING BOOTCAMP

Spark - Performance



PERSISTENCE (CACHING)

```
rdd = sc.textFile(???) .filter(???) .map(???) .groupBy(???)
```

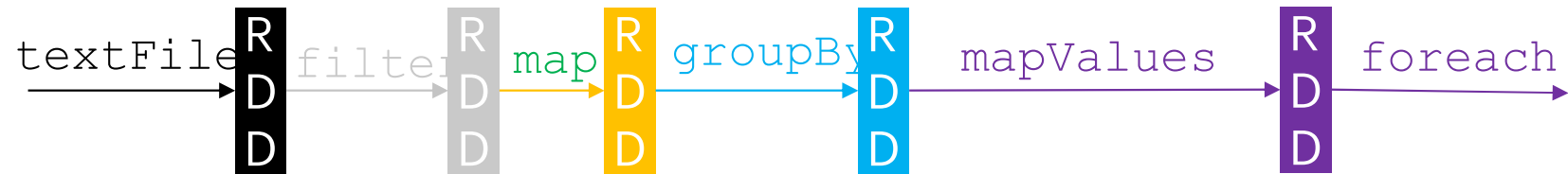
```
rdd.mapValues(???) .foreach(???)
```

```
println(rdd.filter(???) .count())
```

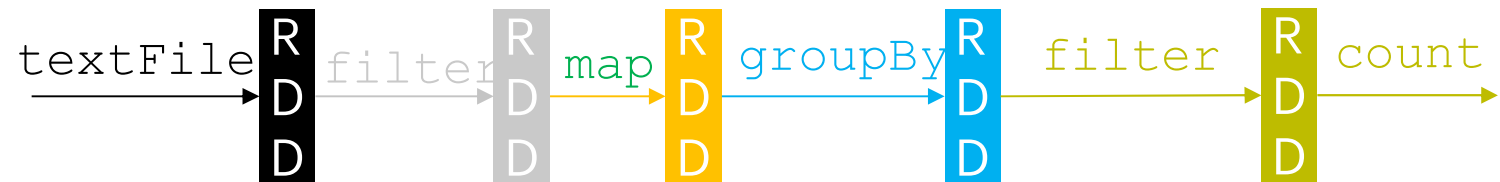
PERSISTENCE (CACHING)

```
rdd = sc.textFile(???) .filter(???) .map(???) .groupBy(???)
```

```
rdd.mapValues(???) .foreach(???)
```



```
println(rdd.filter(???) .count())
```



PERSISTENCE (CACHING)

Caching or persistence are optimization techniques for (iterative and interactive) Spark computations.

Main point to remember:

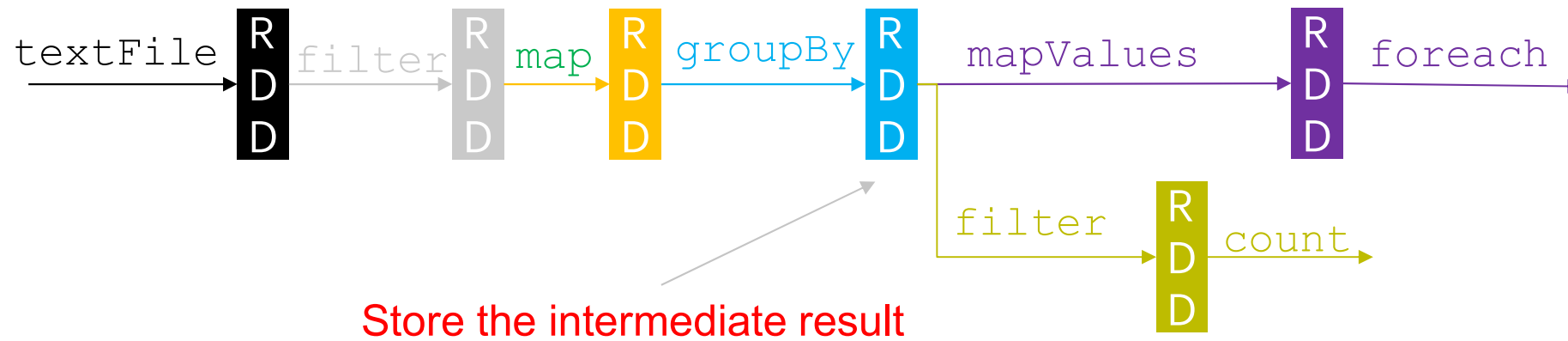
Transformations does not trigger calculations (only actions do).

That means:

Transformation can be executed multiple times!

PERSISTENCE (CACHING)

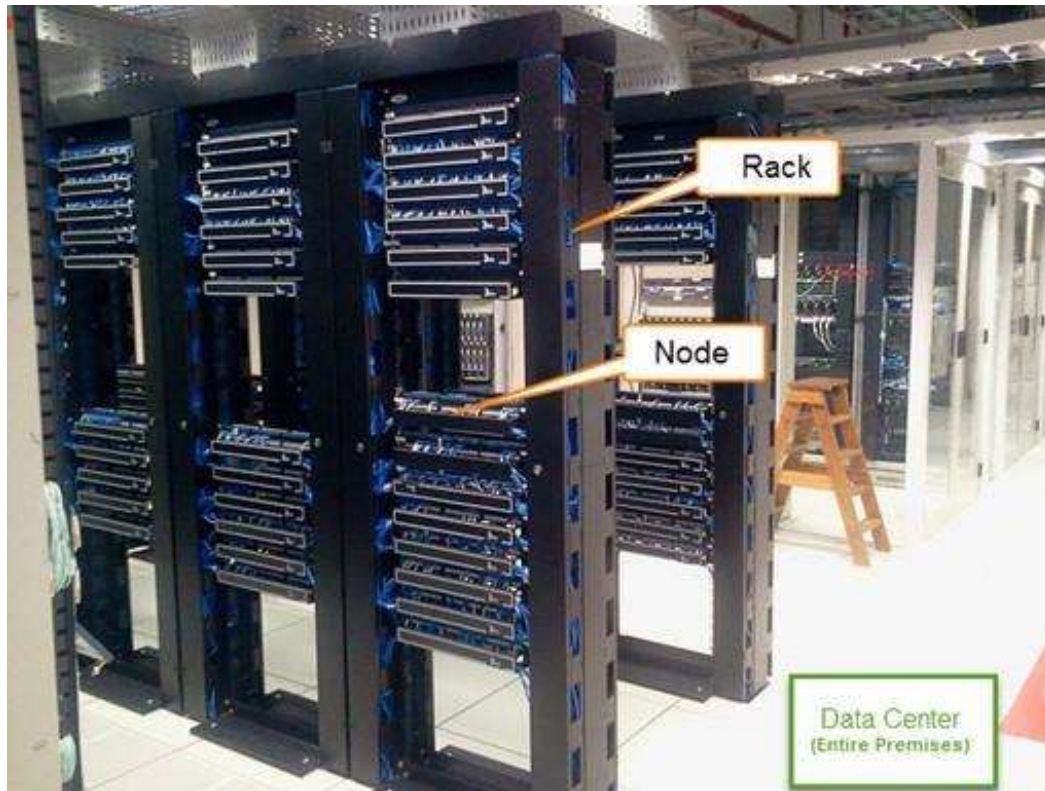
```
rdd = sc.textFile(???) .filter(???) .map(???)  
    .groupBy(???) .cache()    // .persist(<type>)  
  
rdd.mapValues(???) .foreach(???)  
  
println(rdd.filter(???) .count())  
  
rdd.unpersist()           // release persistence
```



PERSISTENCE TYPES

- MEMORY_ONLY
 - MEMORY_AND_DISK
 - DISK_ONLY
 - ...
-
- `.cache()` same as `.persist(MEMORY_ONLY)`

CLUSTER TOPOLOGY



PARTITIONING

- Partition cannot span multiple nodes
- Single concurrent task for every partition
 - More partitions – more parallelism
- By default number of partitions is number of cores
- Number of partitions is configurable
- By default data is read from nodes that are close



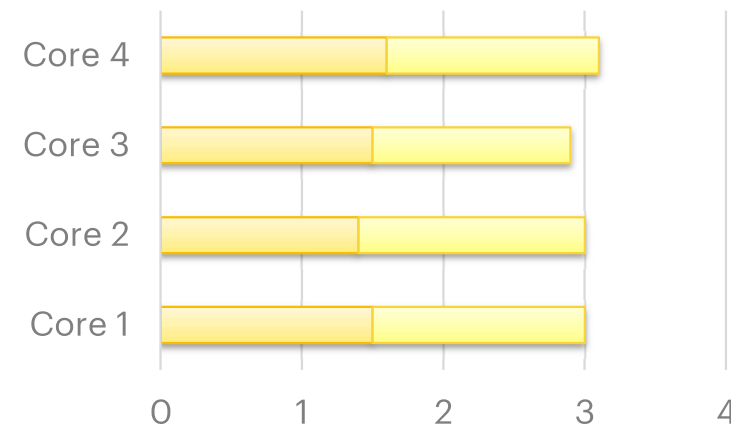
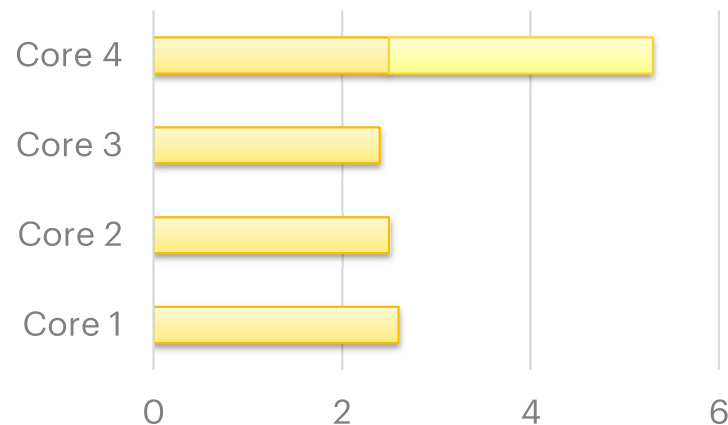
WHY PARTITIONING?

- Increase parallelism
- More equally spread the data
 - e.g. after `filter` operations
- To reduce network traffic
 - More about that later



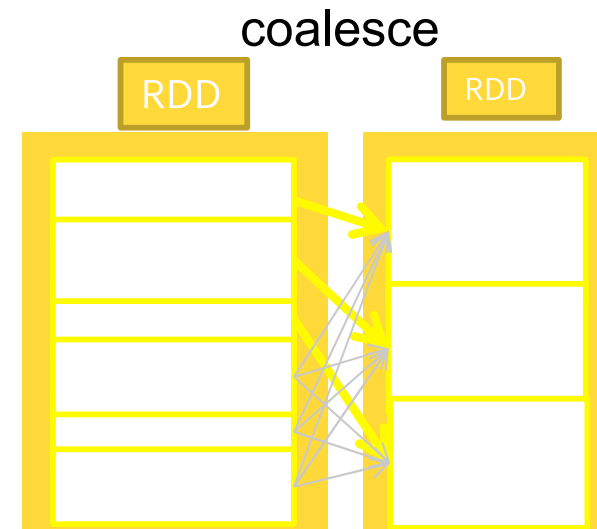
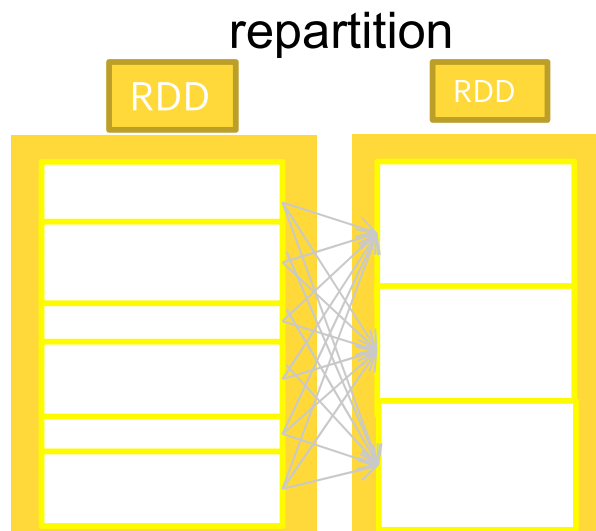
PARTITIONING: OPTIMAL NUMBER OF PARTITIONS

- $N * c$
 - Where c is number of cores in whole cluster
 - N – natural number (No fanaticism!!!)
- This way data will be equally spread for processing



HOW TO SET NUMBER OF PARTITIONS

- `repartition(numPartitions: Int)`
- `coalesce(numPartitions: Int, shuffle: Boolean = false, ...)`



HOW TO SET NUMBER OF PARTITIONS

- `repartition(numPartitions: int)`
- `coalesce(numPartitions: int, shuffle: Boolean = false, ...)`
- Optional parameter to transformations:
 - `textFile(path: String, minPartitions: int)`
 - `distinct(numPartitions: int)`
 - `groupBy(f: Callable[[T], K], numPartitions: int)`
 - `join(other: RDD[Tuple[K, U]], numPartitions: int)`

TYPES OF CUSTOM PARTITIONING

- Hash Partitioning
 - `key.hashCode() % numPartitions`
 - Does not ensure equal spread of data
- Range Partitioning
 - For keys with particular ordering
 - Split keys by ranges depending on number of partitions

HOW TO SET PARTITIONING

- `partitionBy` method on an RDD
- Specific transformations. Examples:
 - `(reduce|fold|combine|group)ByKey` – `HashPartitioner`
 - `sortByKey` – `RangePartitioner`
 - `filter`, `mapValues`, `flatMapValues` – keep parent RDD's partitioner
 - `cogroup`, `join` – `HashPartitioner`
- **NOTE:** some transformations (like `map`) resets the partitioner!

PARTITIONER NOTES

```
rdd.partitionBy(new RangePartitioner(8,  
rdd)).persist()
```

NB! Always persist after partitioning

```
pairRDD.mapValues // preserved partitioner
```

```
pairRDD.map // lost partitioner
```

PARTITIONS: SPECIAL OPERATIONS

```
RDD.mapPartitions(f: Callable[[Iterable[T]], Iterable[U]], preservesPartitioning: bool = False)
```

```
RDD.mapPartitionsWithIndex(f: Callable[[int, Iterable[T]], Iterable[U]], preservesPartitioning: bool = False)
```

```
RDD.foreachPartition(f: Callable[[Iterable[T]], None])
```

```
def foreachPartitionDemo(iterator):  
    // Open connection to storage system (e.g. a database connection)  
    for x in iterator:  
        foreach (x)  
            // Use connection to push item to system  
// Close connection  
def foreachDemo(x): print(x)  
sc.parallelize([1, 2, 3, 4, 5]).foreachPartition(foreachPartitionDemo)
```


USEFUL FUNCTIONS

// Check number of partitions

```
rdd.getNumPartitions
```

// Get array of partitions

```
rdd.partitions
```

// Get current partitioner

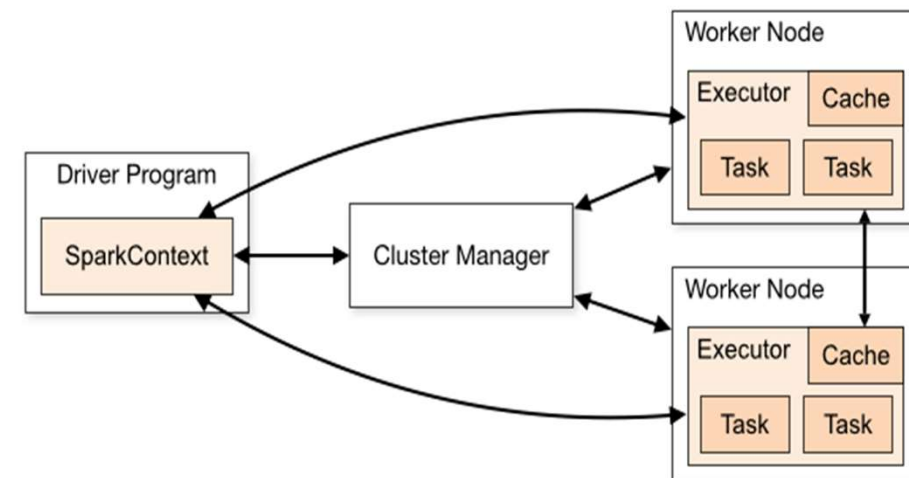
```
rdd.partitioner
```

TAKEAWAYS (PARTITIONING AND PERSISTENCE)

- Number of partitions defines parallelism
- Number of partitions can be set programmatically
- RDD can be persisted (cached) for re-use without re-calculation
 - Especially useful after “heavy” transformations
- By default Spark decides how to split data, but
- Some transformation apply default partitioners and
- Custom partitioners can be created and applied to RDDs
- Transformation which may change keys (like `map`) will reset partitioner

SPARK APPLICATION EXECUTION STEPS

1. `spark-submit` launches the driver program and invokes the `main()` method
2. The driver program contacts the cluster manager to launch executors.
3. The cluster manager launches executors on behalf of the driver program.
4. Based on the RDD actions and transformations, the driver sends work to executors in the form of tasks.
5. Tasks are run on executor processes to compute and save results.
6. If the driver's `main()` method exits or it calls `SparkContext.stop()`, it will terminate the executors.



SPARK APPLICATION ARCHITECTURE

```
conf = ...
```

```
sc = ...
```

```
textFile = sc.textFile("hdfs://...")
```

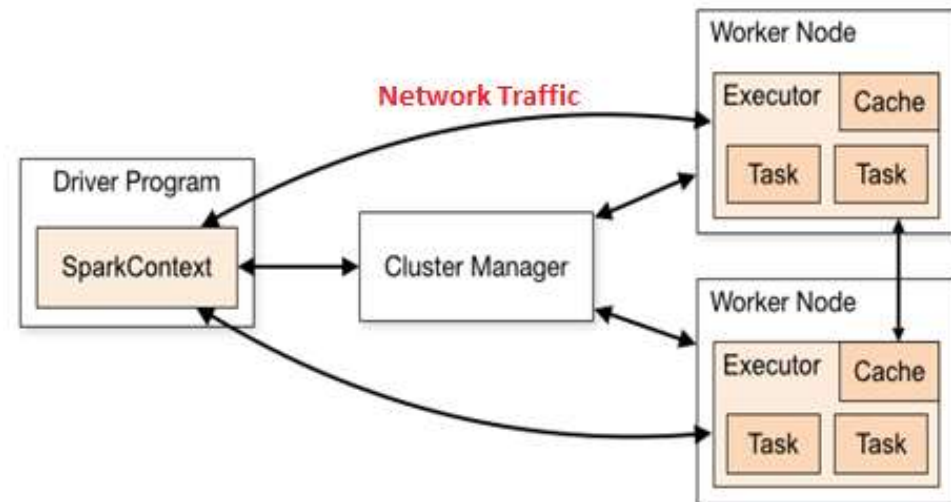
```
counts = textFile
```

```
.flatMap(lambda x: x.split(" "))
```

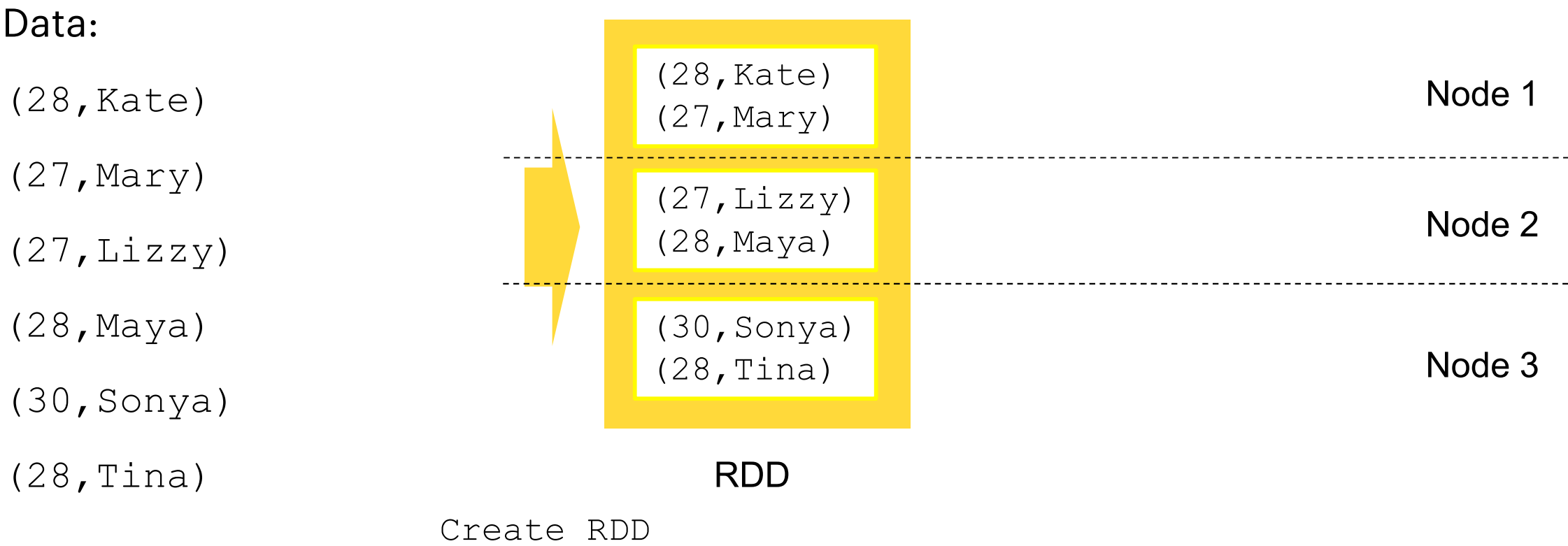
```
.map(lambda word: (word, 1))
```

```
.reduceByKey(lambda x, y: x + y)
```

```
.collect()
```



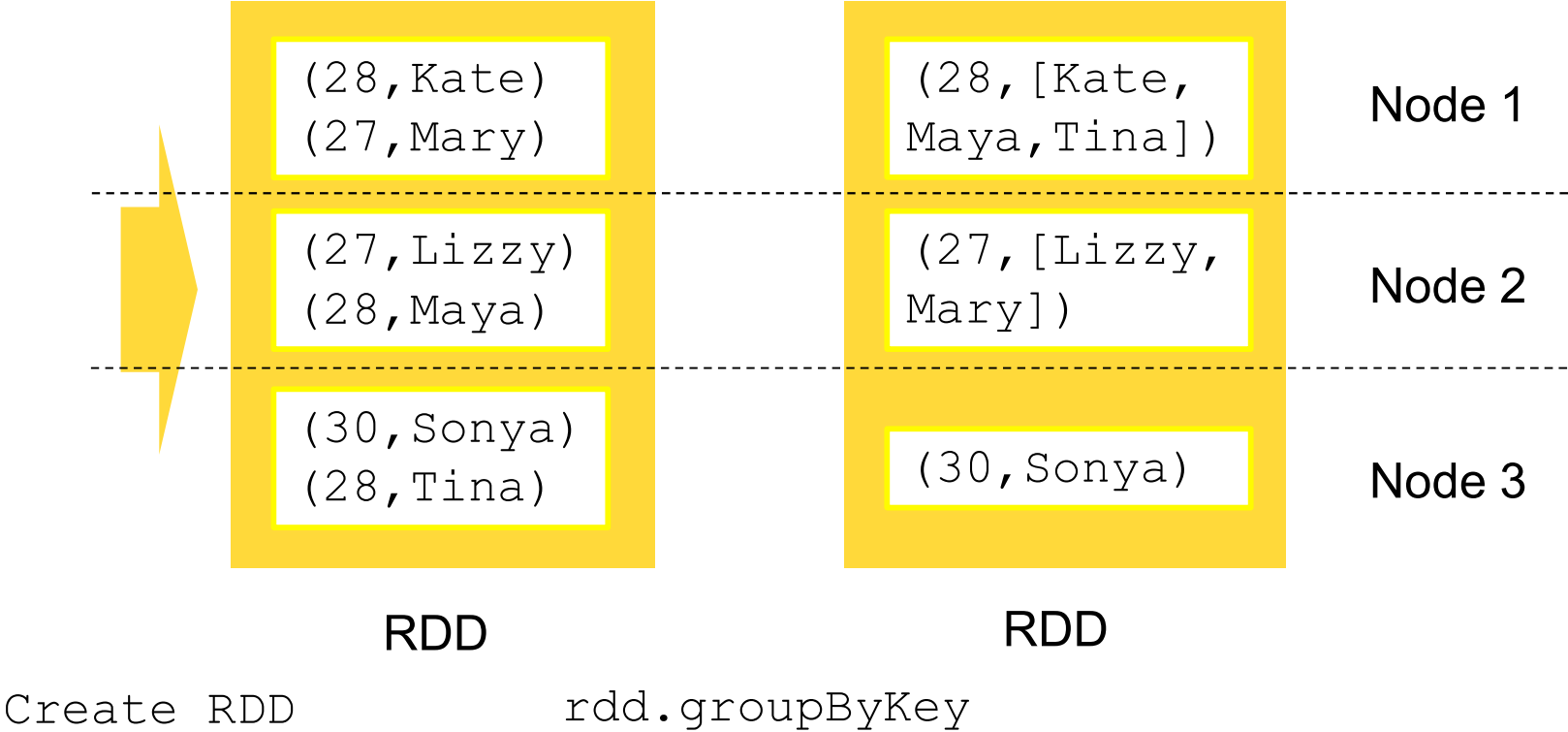
SHUFFLING



SHUFFLING

Data:

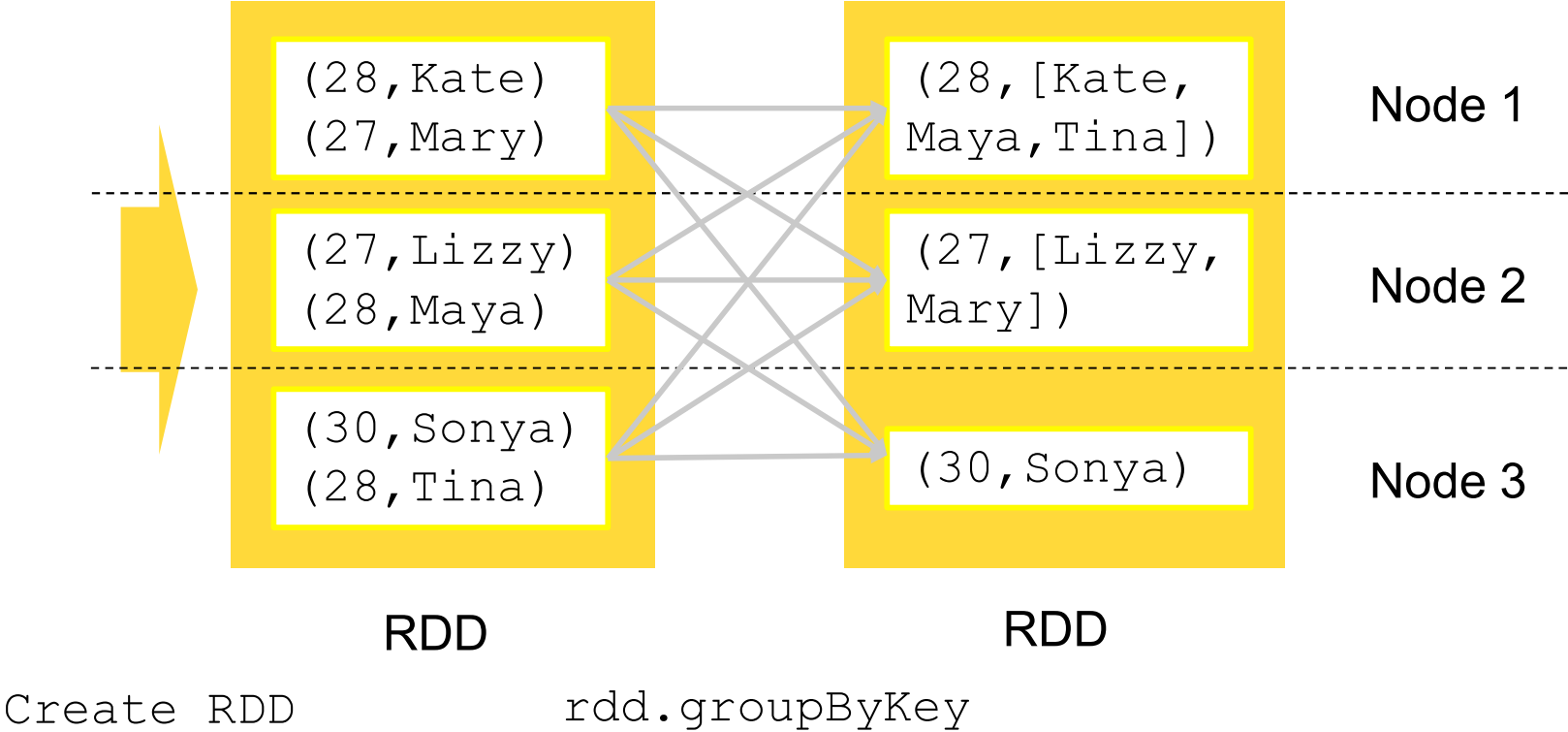
(28, Kate)
(27, Mary)
(27, Lizzy)
(28, Maya)
(30, Sonya)
(28, Tina)



SHUFFLING

Data:

(28, Kate)
(27, Mary)
(27, Lizzy)
(28, Maya)
(30, Sonya)
(28, Tina)



WHAT CAUSES SHUFFLE?

- groupBy
- ...byKey
 - **Except** countByKey
- join
- ...
- **RULE:** When elements in RDD depends on elements in other RDD or other elements in same RDD

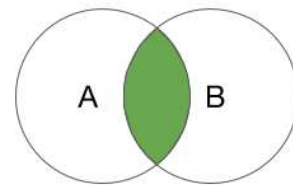
HOW TO MINIMIZE SHUFFLE IMPACT

Minimize data to be shuffled

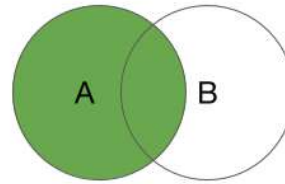
- Filter unneeded data as early as possible
 - `personRDD.filter(lambda p: p.age > 21).groupBy(???)`
- Use map to discard redundant data
 - `personRDD.map(lambda p: (p.age, p.salary)).groupByKey`

HOW TO MINIMIZE SHUFFLE IMPACT: JOINS

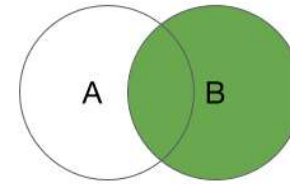
What does joins do?



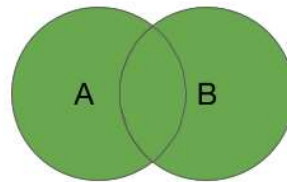
INNER JOIN



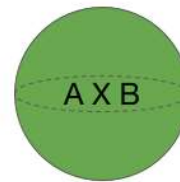
LEFT OUTER JOIN



RIGHT OUTER
JOIN



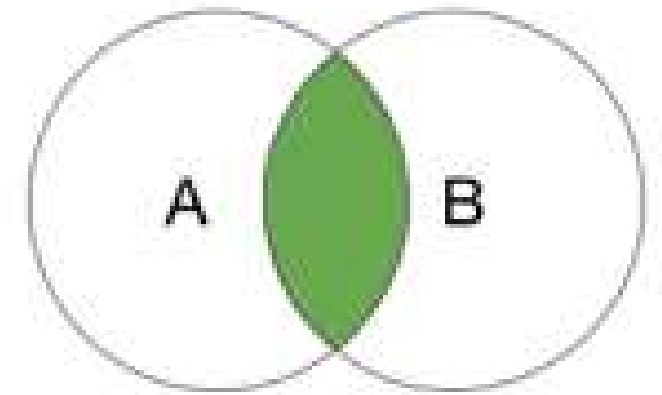
FULL OUTER
JOIN



CARTESIAN
(CROSS) JOIN

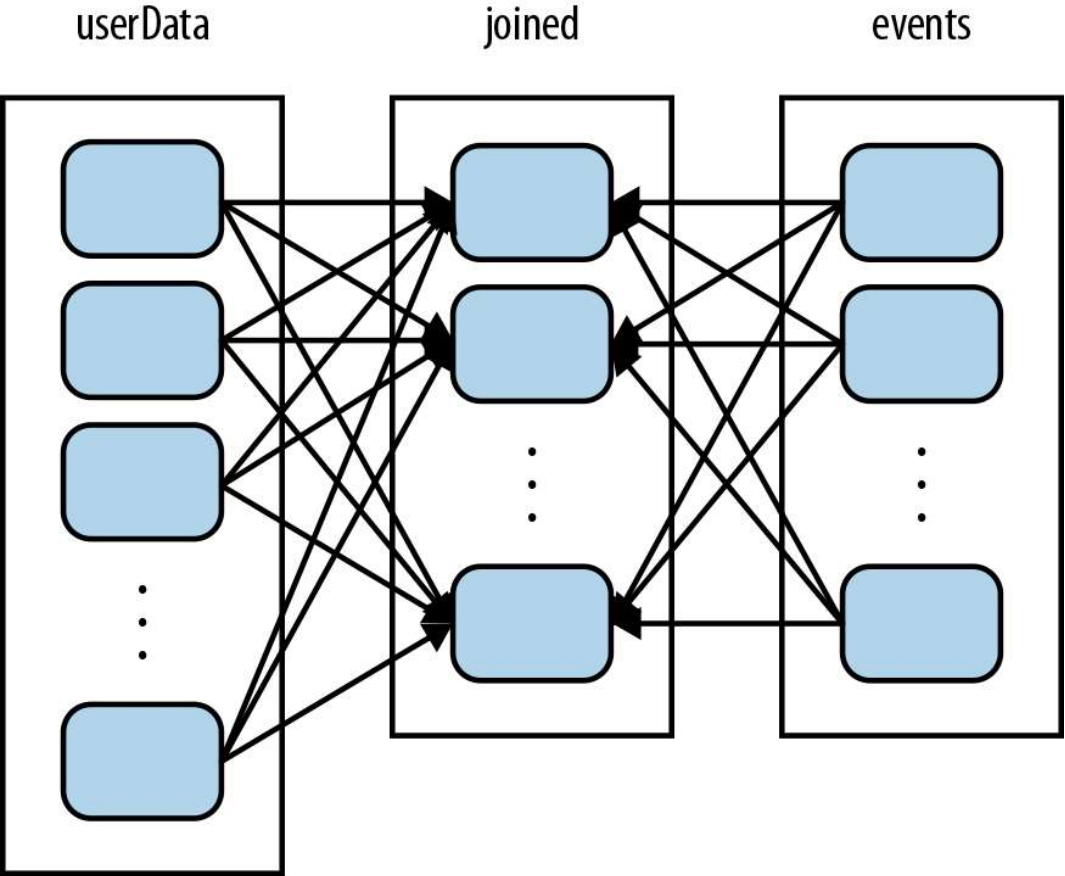
JOIN EXAMPLE USE CASE

- One large dataset – userData (A)
 - changes once per day
- Small datasets – events (B)
 - Comes every minute
- Question:
 - For each event get user information for analysis

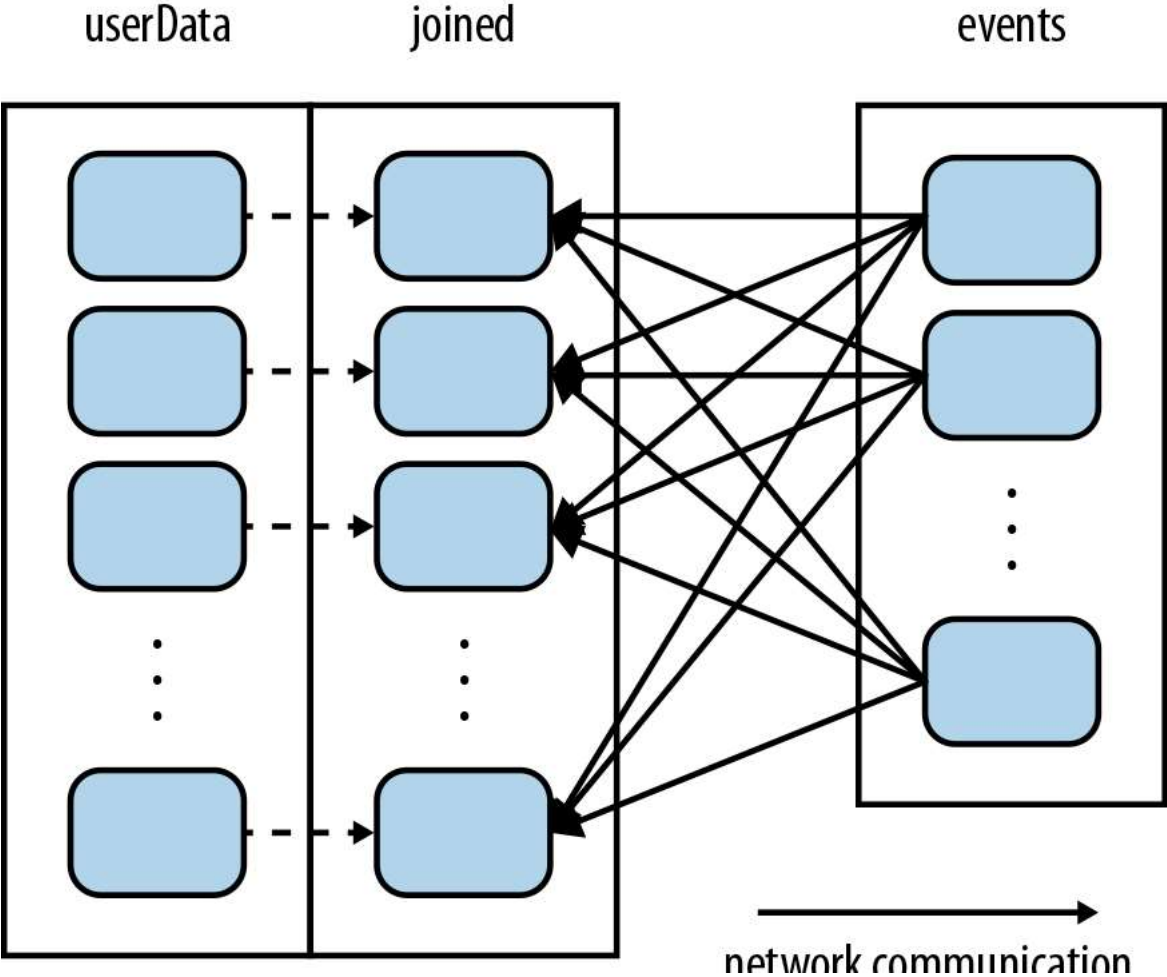


INNER JOIN

JOIN EXAMPLE (BAD CASE)



JOIN EXAMPLE (GOOD CASE)



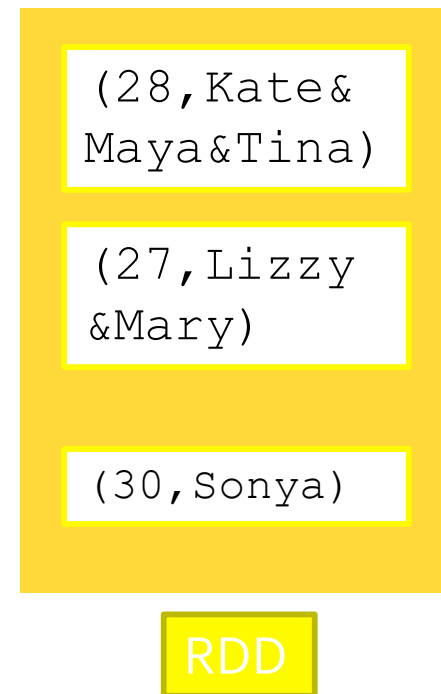
HOW TO MINIMIZE SHUFFLE IMPACT: JOINS

Careful with joins

- Already partitioned data will not be shuffled again
 - `rdd.groupBy(...).join(rdd2)` // only `rdd2` is shuffled
- Use same **partitioner** (co-grouped joins does not cause shuffle)

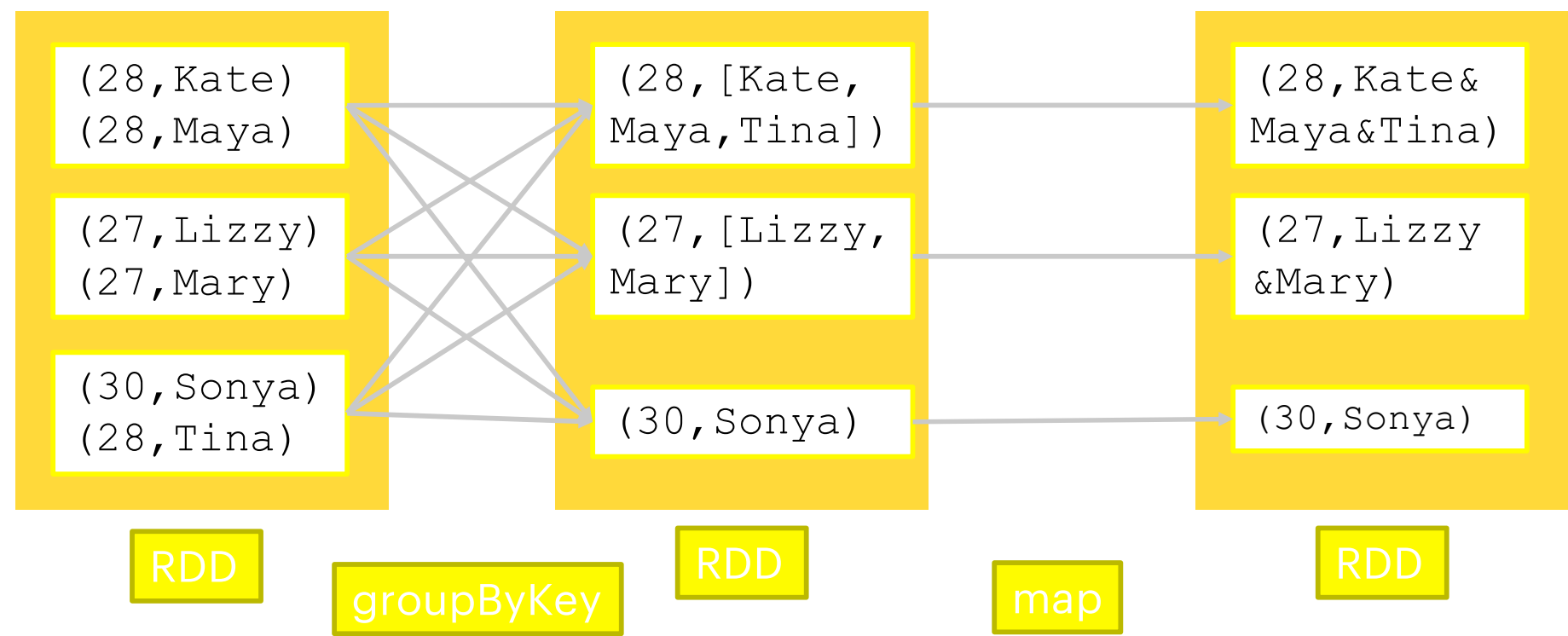
HOW TO MINIMIZE SHUFFLE IMPACT: API

Use reduction API when applicable



HOW TO MINIMIZE SHUFFLE IMPACT: API

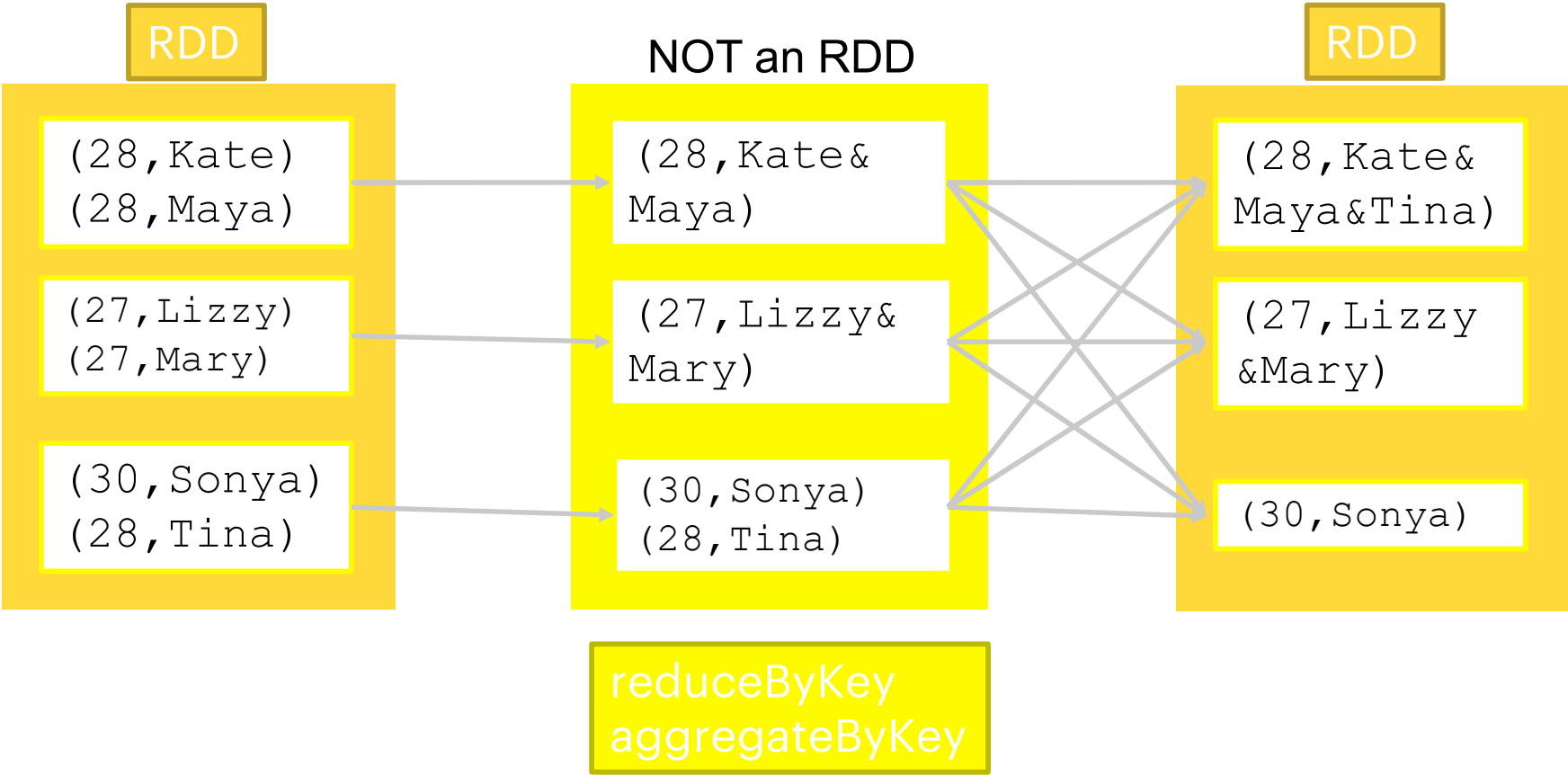
Use reduction API when applicable



HOW TO MINIMIZE SHUFFLE IMPACT: API

Use reduction API when applicable

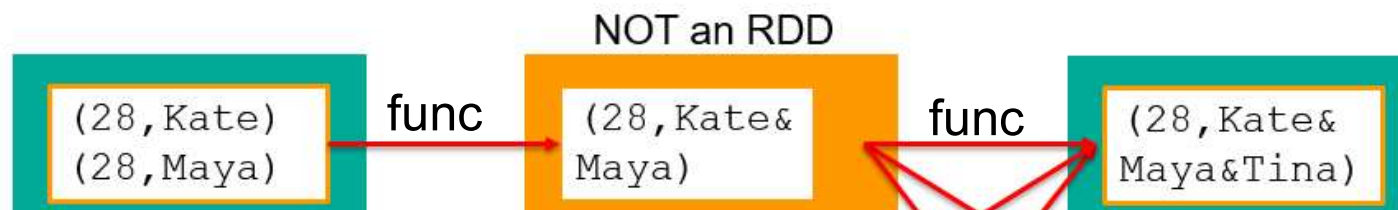
- `reduceByKey` or `aggregateByKey` is a better solution



REDUCBYKEY VS AGGREGATEBYKEY

- `reduceByKey(func: (V, V) => V) => RDD[(K, V)]`
 - **Value type change is impossible**

```
rdd.reduceByKey(lambda v1, v2: v1 + "&" + v2)
```

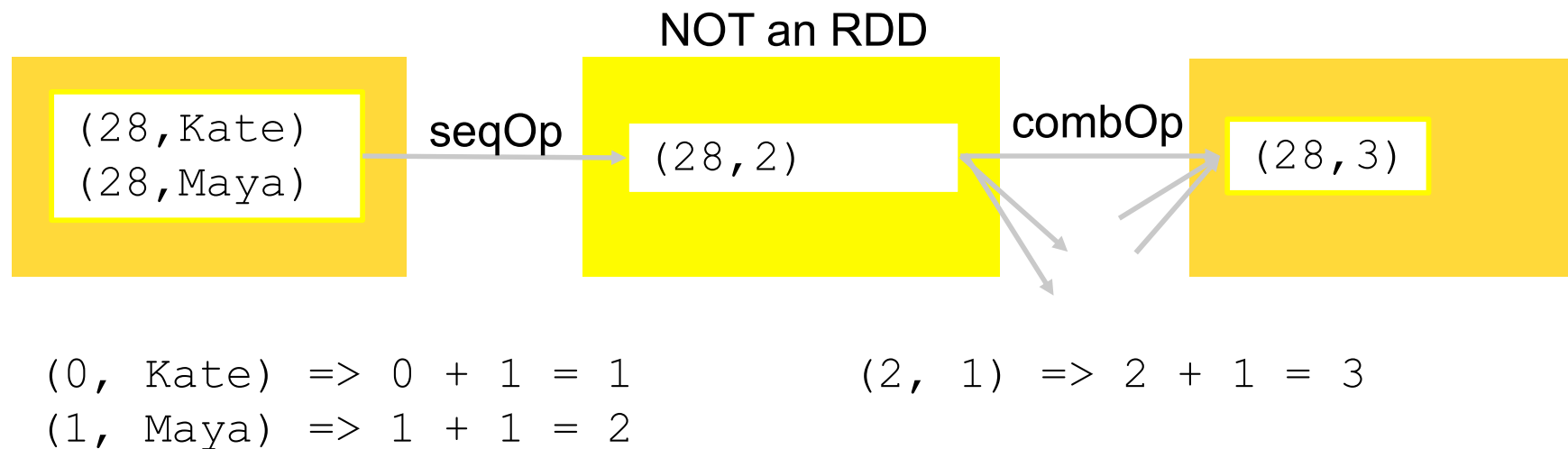


`(Kate, Maya)`
`=>`
`Kate&Maya`

`(Kate&Maya, Tina)`
`=>`
`Kate&Maya&Tina`

REDUCBYKEY VS AGGREGATEBYKEY

- `aggregateByKey(zero:U) (seqOp: (U,V) => U, combOp: (U,U) => U)`
=> `RDD[(K, U)]`
 - **Type of value can be changed**
- `rdd.aggregateByKey(0) ((acc,v) => acc + 1, (v1,v2) => v1 + v2)`



USEFUL FUNCTIONS

```
/** A description of this RDD and its recursive  
dependencies for debugging. */
```

```
rdd.toDebugString
```

```
(8) MapPartitionsRDD[11] at join at <console>:23 [] |  
MapPartitionsRDD[10] at join at <console>:23 [] |  
CoGroupedRDD[9] at join at <console>:23 []
```

```
+-(8) ParallelCollectionRDD[8] at parallelize at  
<console>:21 []
```

```
+-(8) ParallelCollectionRDD[8] at parallelize at  
<console>:21 []
```

TAKEAWAYS (SHUFFLING)

- Shuffle can occur, when elements in RDD depends on:
 - Elements in another RDD
 - Other elements in same RDD
- Shuffle can dramatically impact performance
- Shuffle can be controlled (optimized) by:
 - Caching and persistence
 - Partitioning
 - Reduction API
 - Reduction of shuffled data size

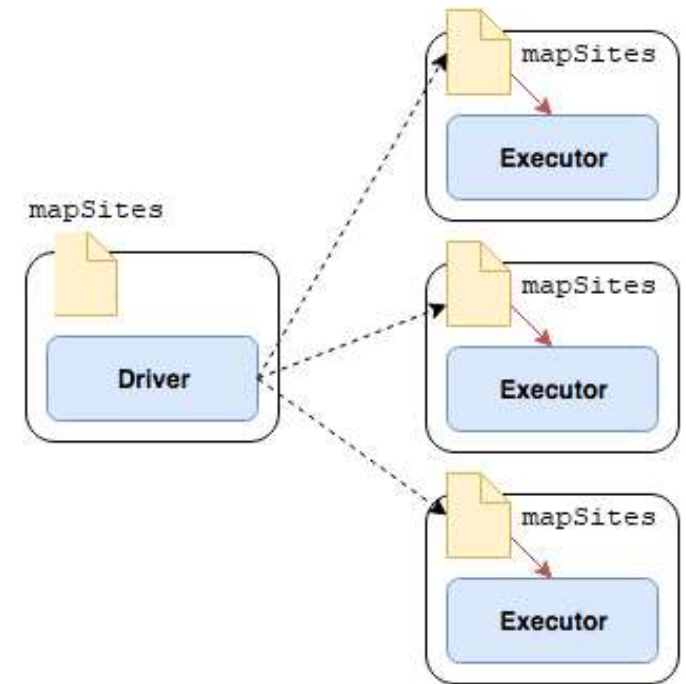
BROADCAST VARIABLES

```
# Define the mapSites dictionary
```

```
mapSites = ???
```

```
# Use the map transformation
```

```
mapped_rdd = rdd.map(lambda v: mapSites[v])
```



BROADCAST VARIABLES

```
# Define the mapSites dictionary
```

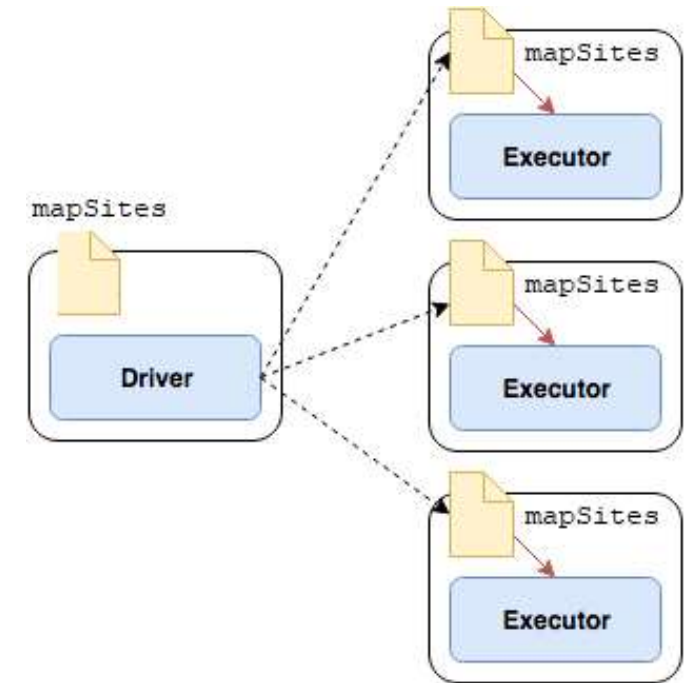
```
mapSites = ???
```

```
# Use the map transformation
```

```
mapped_rdd = rdd.map(lambda v: mapSites[v])
```

```
# Use the filter transformation with contains
```

```
filtered_rdd1 = rdd1.filter(lambda v: v in  
mapSites)
```



x2 times

BROADCAST VARIABLES

- Read-only
 - Once broadcasted values can't be changed
- Efficient distribution for large variables
 - BitTorrent-like data distribution
- When same data is used multiple times

SHARED VARIABLES

```
# Define the mapSites dictionary
```

```
mapSites = ???
```

```
# Broadcast the mapSites dictionary
```

```
broadcastMapSites = sc.broadcast(mapSites)
```

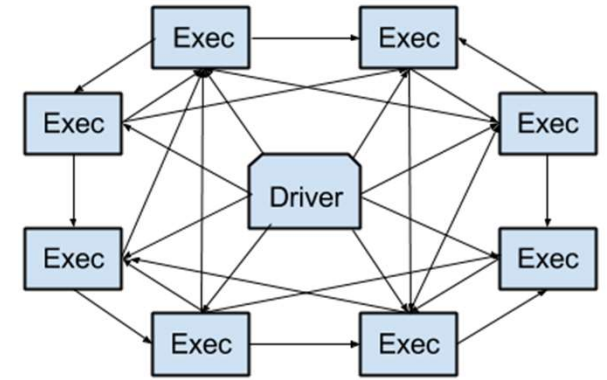
```
# Use the map transformation with broadcasted value
```

```
mapped_rdd = rdd.map(lambda v: broadcastMapSites.value[v])
```

```
# Use the filter transformation with broadcasted value
```

```
filtered_rdd1 = rdd1.filter(lambda v: v in broadcastMapSites.value)
```

```
broadcastMapSites.unpersist()
```



ACCUMULATOR VARIABLES

```
// How to count filtered lines  
sc.textFile(???).filter(???).map(???)
```

How to know how much lines were filtered out?

How to know which lines were filtered out?

ACCUMULATOR VARIABLES

- Can be only “added” to
- Nodes can’t read the value
 - Only driver can
- Can be either *named* or *unnamed*
- Can be custom
 - Subclass AccumulatorParam (Spark 1.6)
 - Subclass AccumulatorV2 (Spark 2.0)
- **NB!** In transformations - might add multiple times

ACCUMULATOR VARIABLES

// In Spark 1.6

```
acc = sc.accumulator(0)
```

```
sc.textFile(???) .filter { v =>
```

```
    if (???) {
```

```
        acc += 1
```

```
        false
```

```
    }
```

```
    true
```

```
}.map(???)
```

```
acc.value
```

// In Spark 2.0

```
acc = sc.longAccumulator
```

TAKEAWAYS

- Optimize data processing with:
 - Persistence
 - Partitioning
 - Avoiding or lessen impact from shuffles
 - Broadcast reusable or large data
 - Use accumulators to avoid re-calculations