Spark RDD

DS 5110: Big Data Systems

Spring 2025

Lecture 8

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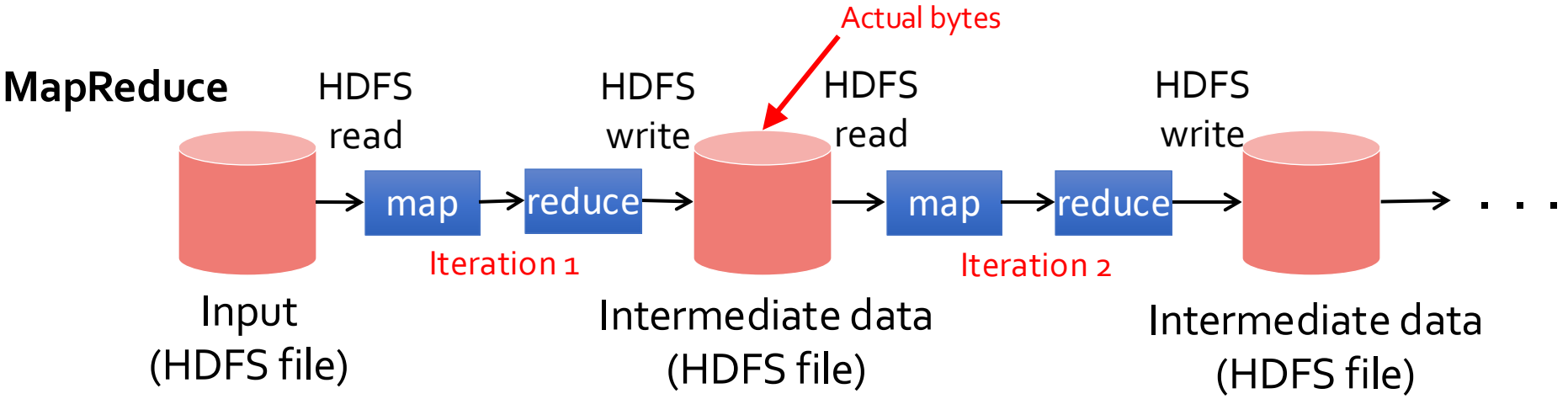
Some material taken/derived from:
- Wisconsin CS 320 by Tyler Caraza-Harter.

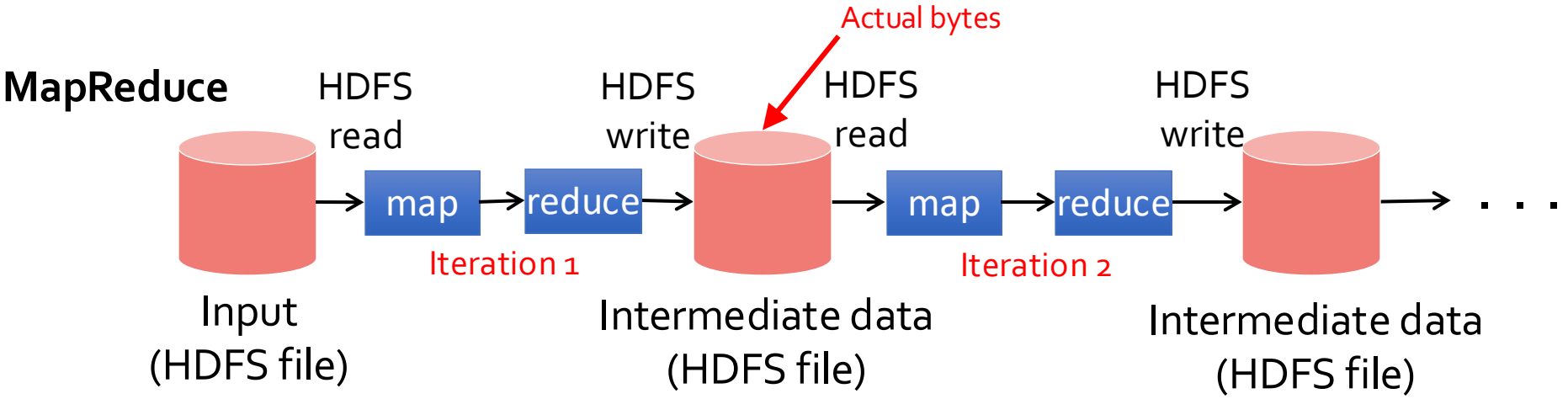
Learning objectives

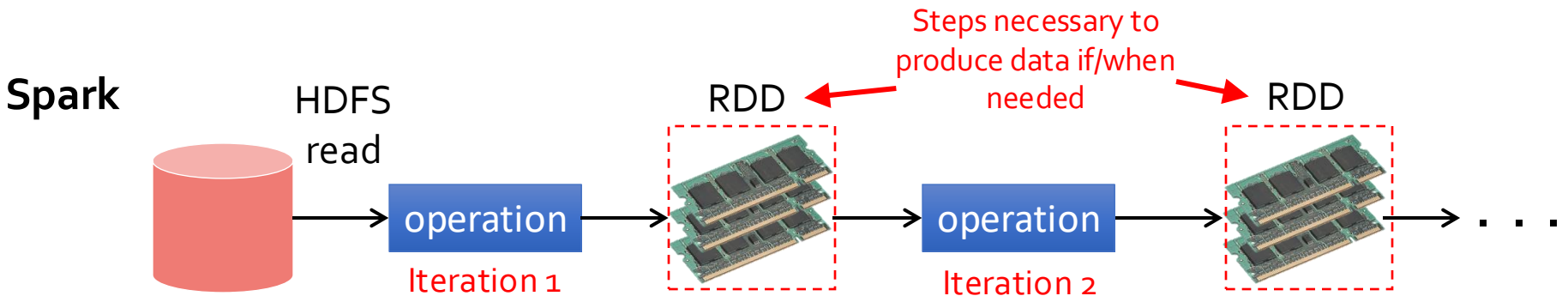
- The motivation of Spark RDD
- The difference between RDD transformations and actions
- The benefits of the RDD abstraction

Intermediate data: MapReduce



Intermediate data: MapReduce vs. Spark





Resilient Distributed Datasets (RDD)

- **Data lineage:** Record series of operations on the data necessary to obtain results
- **Lazy evaluation:** Computation only done when results needed (to write file, make plot, etc.)
- **Immutability:** You can't change an RDD, but you can define a new one in terms of another

Data lineage: Transformations & Actions

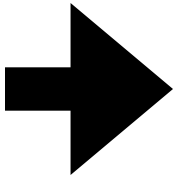
```
data = [
    (“A”, 1),
    (“B”, 2),
    (“A”, 3),
    (“B”, 4)
]
```

```
def mult2(row):
    return (row[0], row[1]*2)

def onlyA(row):
    return row[0] == “A”
```

Goal: Get 2 times the second column wherever the first column is “A”

```
table = sc.parallelize(data)
double = table.map(mult2)
doubleA = double.filter(onlyA)
doubleA.collect()
```



```
[(‘A’, 2),
 (‘A’, 6)]
```

The computation is a sequence of 4 operations. Operations come in two types:

- Transformation: Create a new RDD (lazy, so no execution yet). Here: `parallelize`, `map`, and `filter`.
- Action: Perform all operations in the graph to get an actual result. Here: `collect`.

Data lineage: Transformations & Actions

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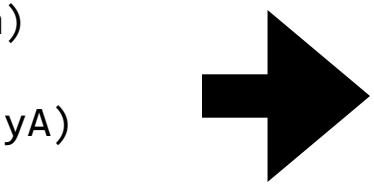

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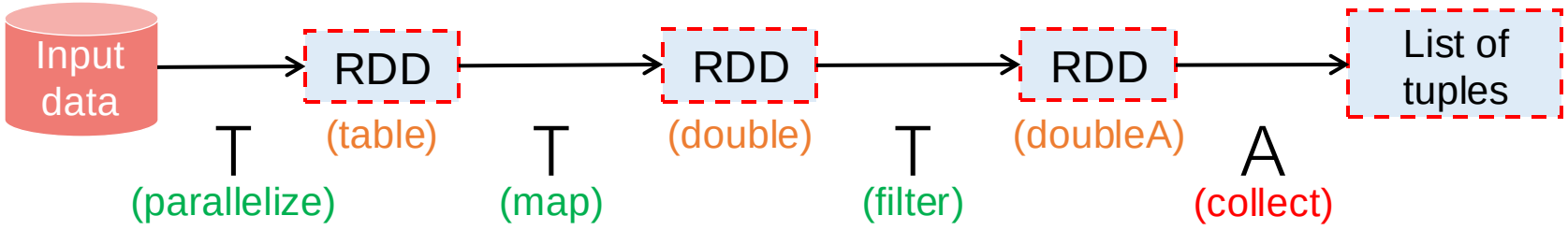

Q: Are there alternative paths you could create from the start to end node?

Optimization

Transformation vs. action:

- Transformation: intermediate results (means to an end)
- Action: Final results we care about
- This distinction creates opportunities for optimize (choosing a more efficient sequence of transformations to get the same result + pipelining the compute)

Goal: Get 2 times the second column wherever the first column is "A"

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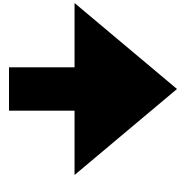

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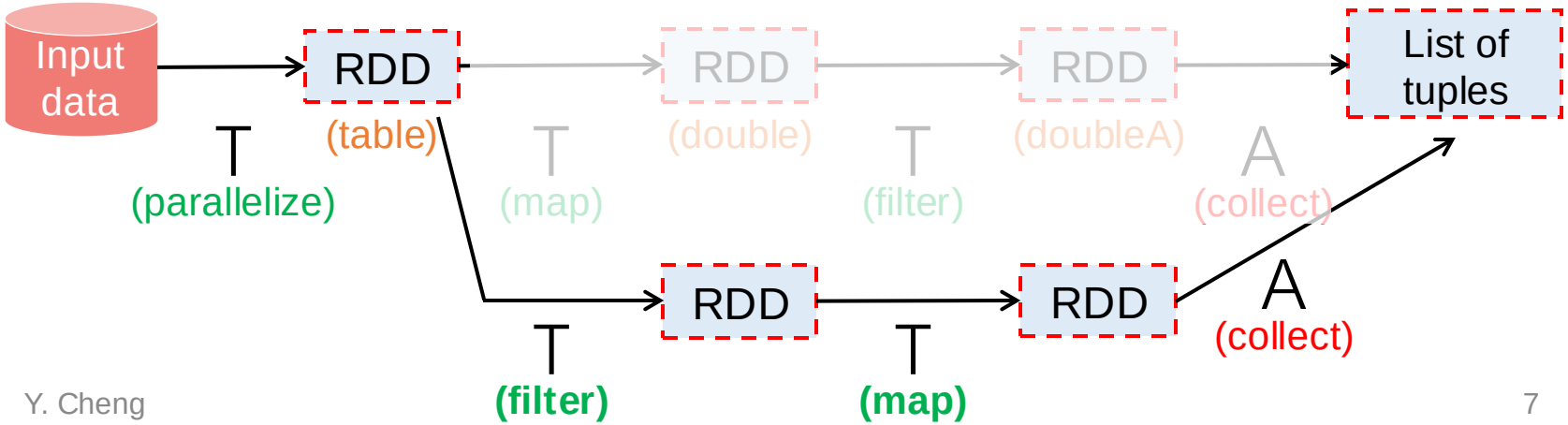
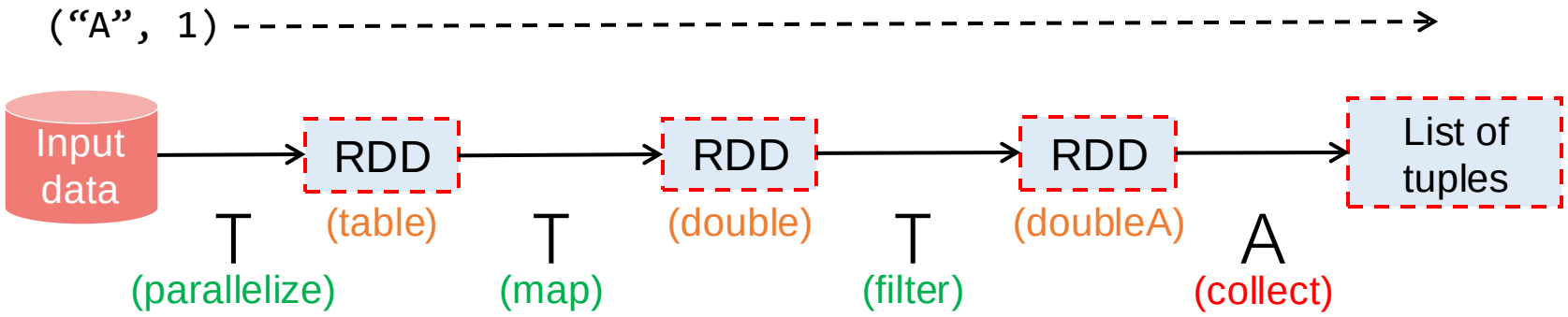


Partitions



At what granularity should data flow through the transformation?

- **Whole dataset:** It could all proceed through, one transformation at a time, but might not fit in memory
- **Row:** In this pipeline, nothing prevents each row from passing through independently, but probably slower than computing in bulk
- **Partition:** Spark users can specify the number of partitions for an RDD

```
sc.parallelize(data, 1)
    data = [
        ("A", 1),
        ("B", 2),
        ("A", 3),
        ("B", 4)
    ]
```

partition

```
sc.parallelize(data, 2)
    data = [
        ("A", 1),
        ("B", 2),
        ("A", 3),
        ("B", 4)
    ]
```

partition

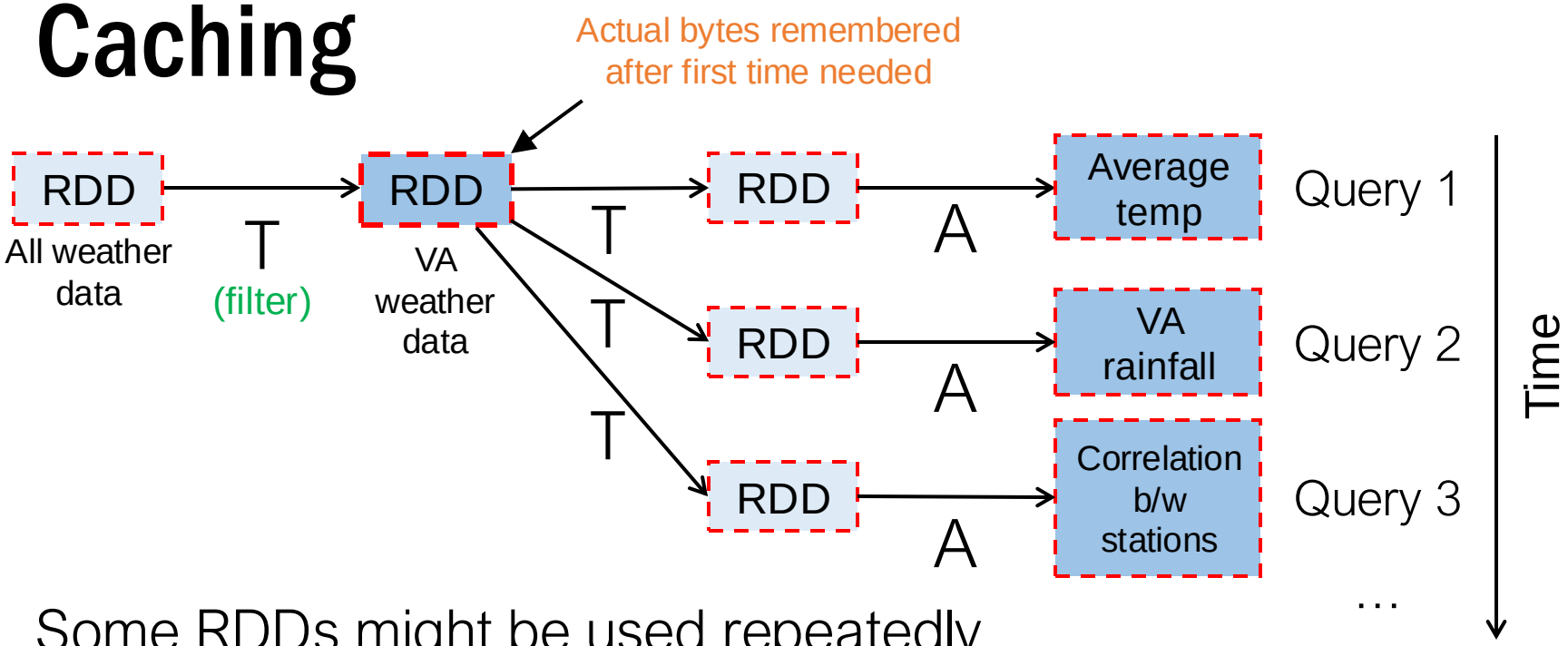
partition

Tasks

- Spark work
  - Spark code is converted to jobs, which consist of stages, which consist of tasks
  - Tasks:
    - Run on a single CPU core
    - Operate on a single partition, which is loaded entirely to memory
- Choosing a partition count directly affects the number of tasks necessary to do a job.

- Advantages of large partitions
  - Less overhead in starting tasks
- Disadvantages of large partitions
  - Might not expose enough parallelism to use all cores available
  - Harder to balance work evenly
  - Uses more memory

Caching



Some RDDs might be used repeatedly

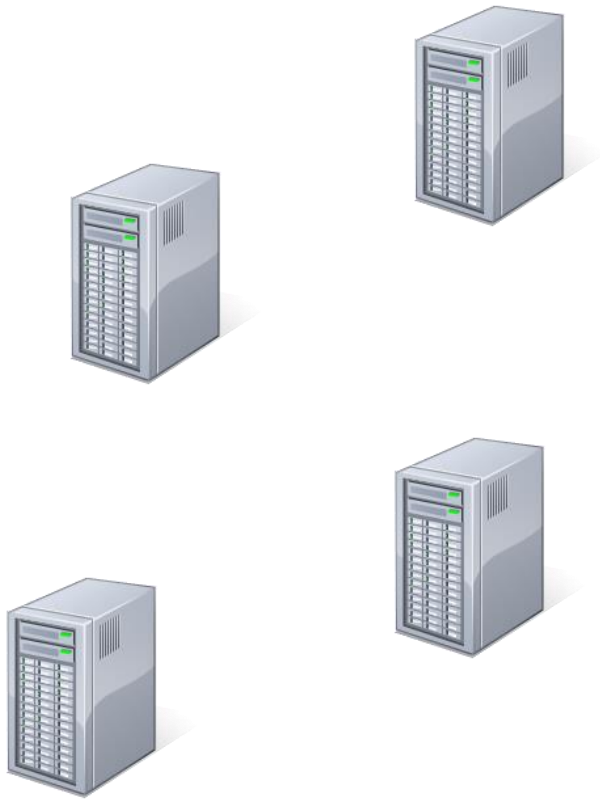
- Spark might cache a copy of the computed results
- OR we can tell it to

```
all_weather = ...
va_weather = all_weather.filter(...)
va_weather.cache()
...
va_weather.unpersist()   # stop caching
```

Putting it all together…

Interactive debugging (control & data flow)

Load input data from an HDFS file into memory, then interactively search for various patterns



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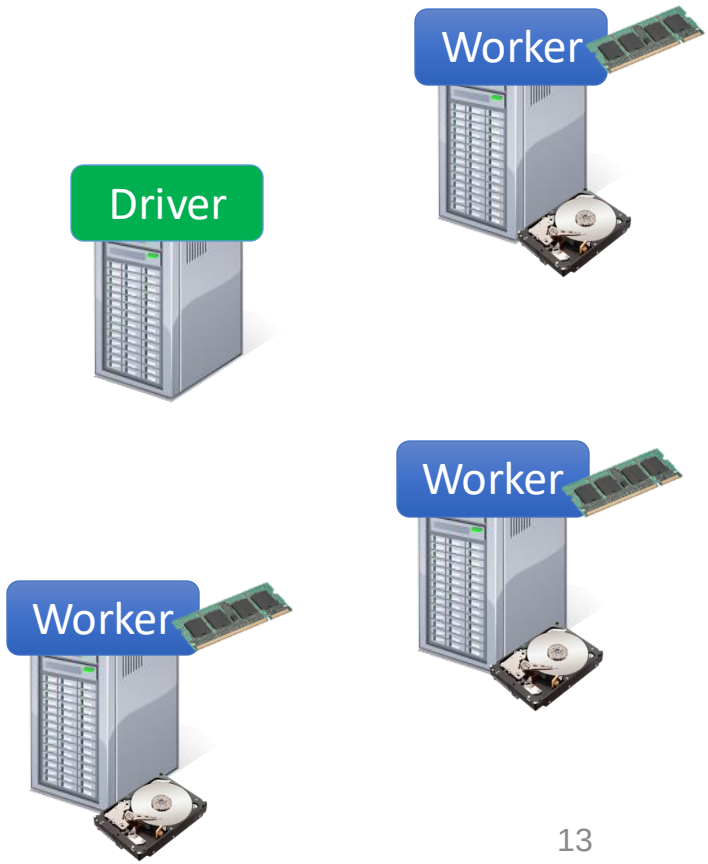

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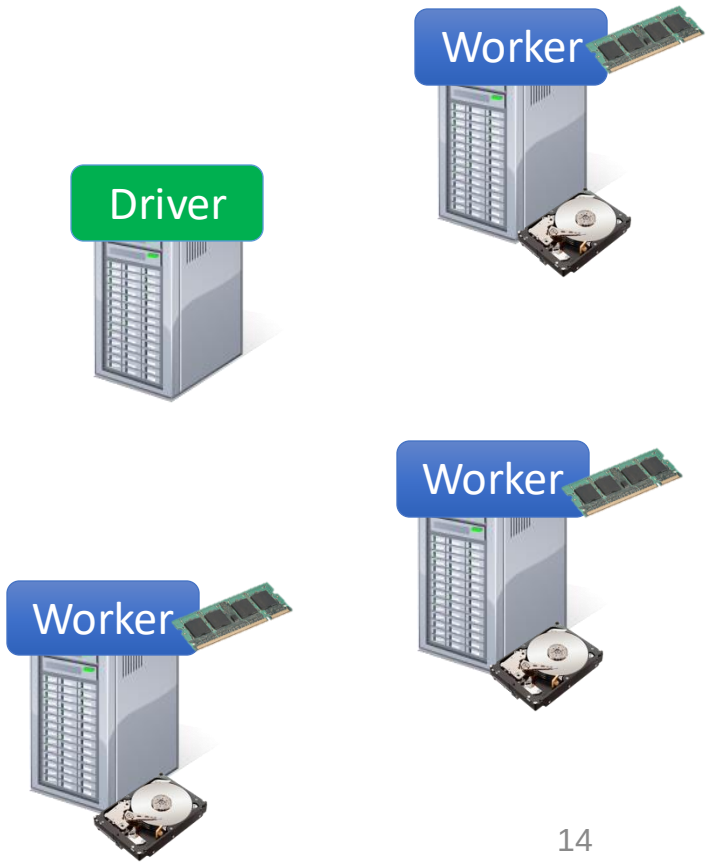

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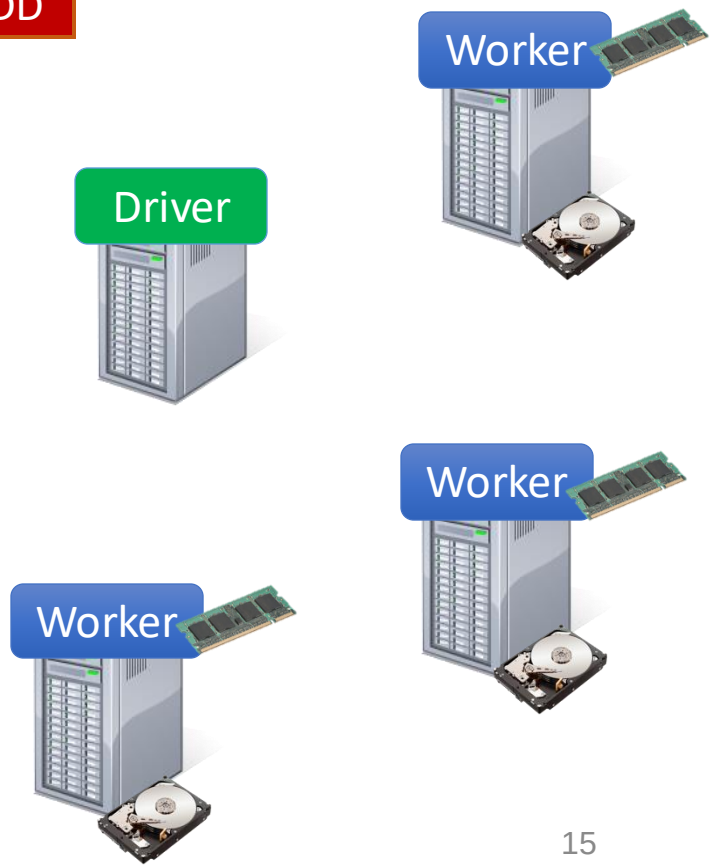
Base RDD



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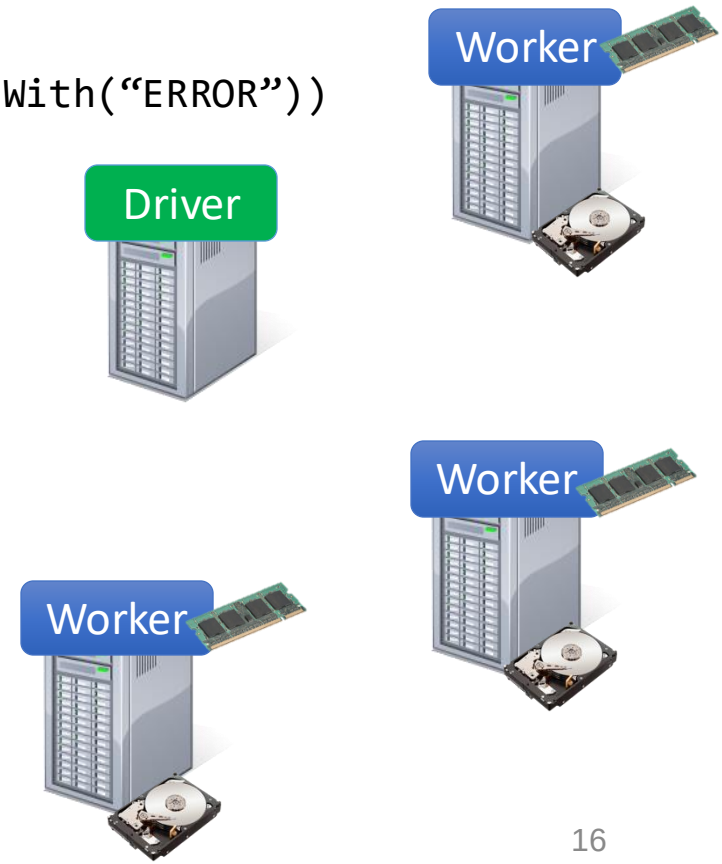

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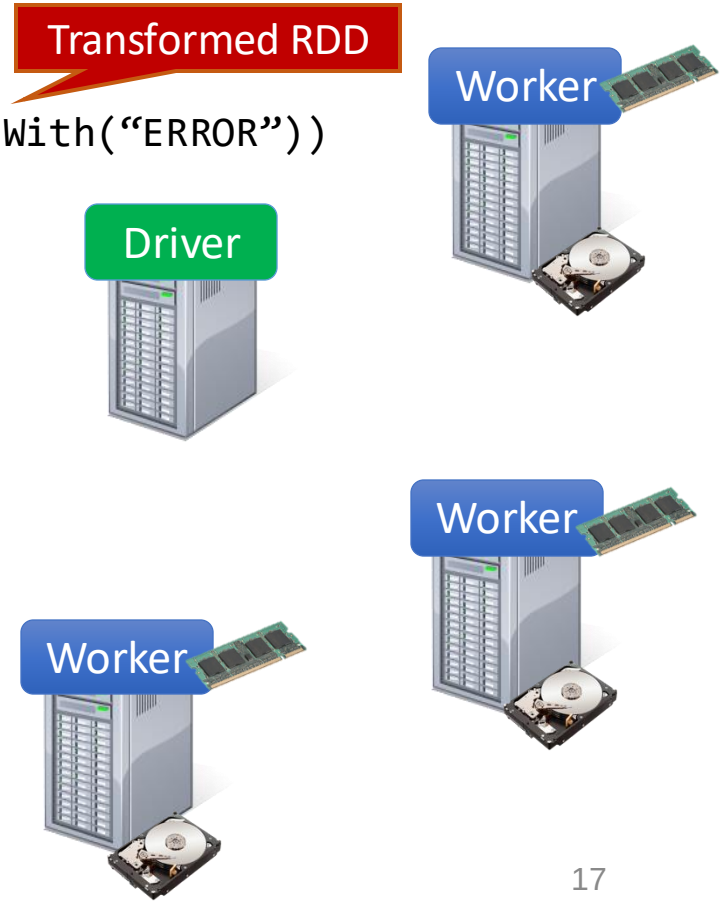

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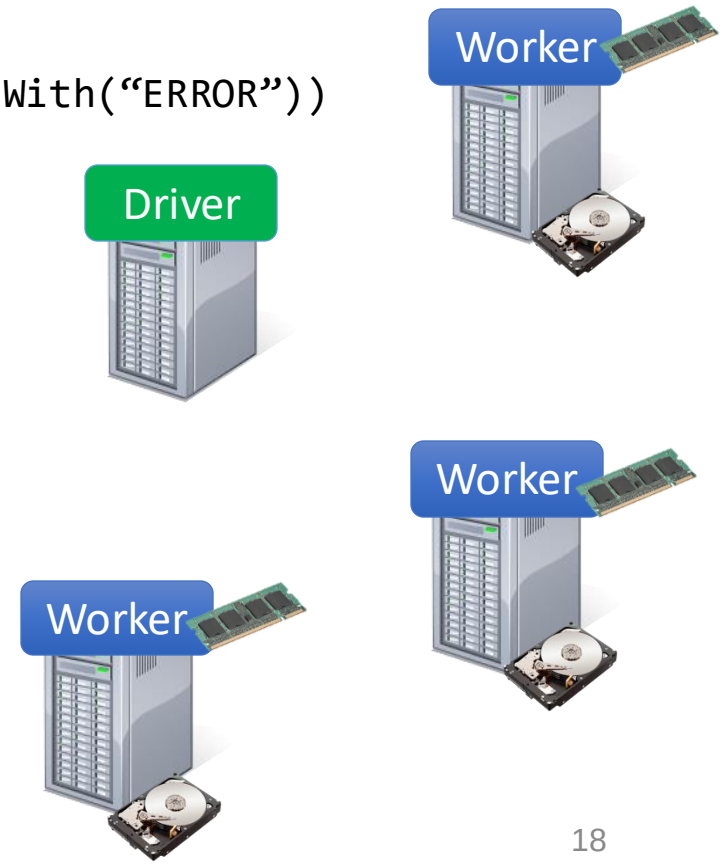

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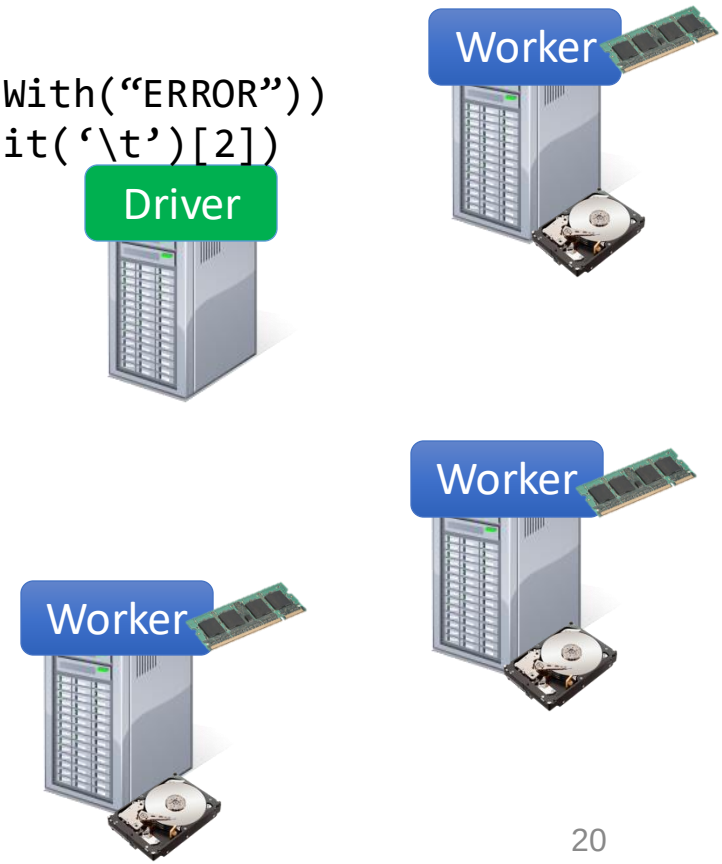
Another Transformed RDD



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messages.cache()
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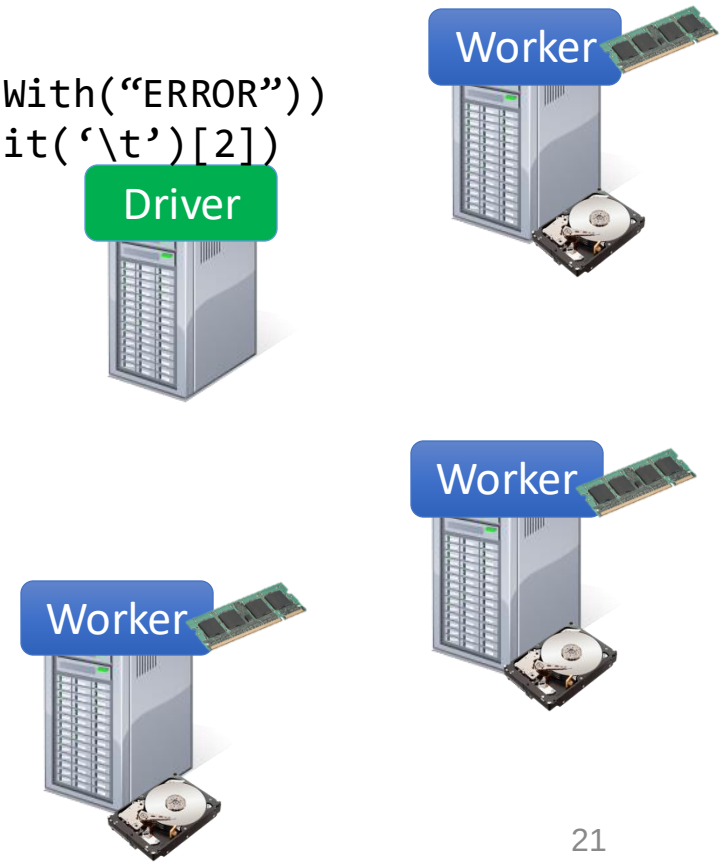

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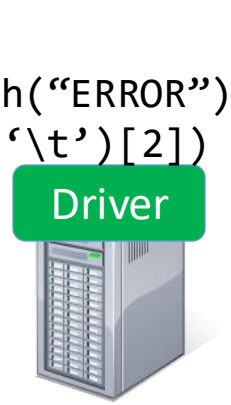
Cache it to memory for reuse



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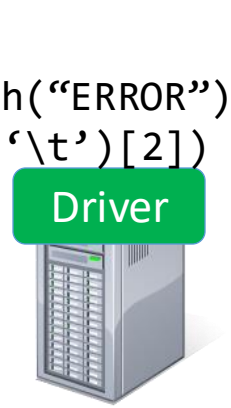

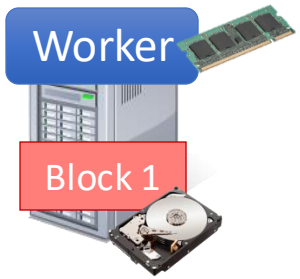

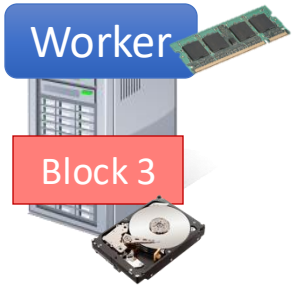

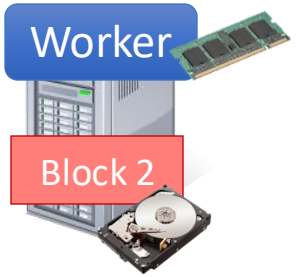

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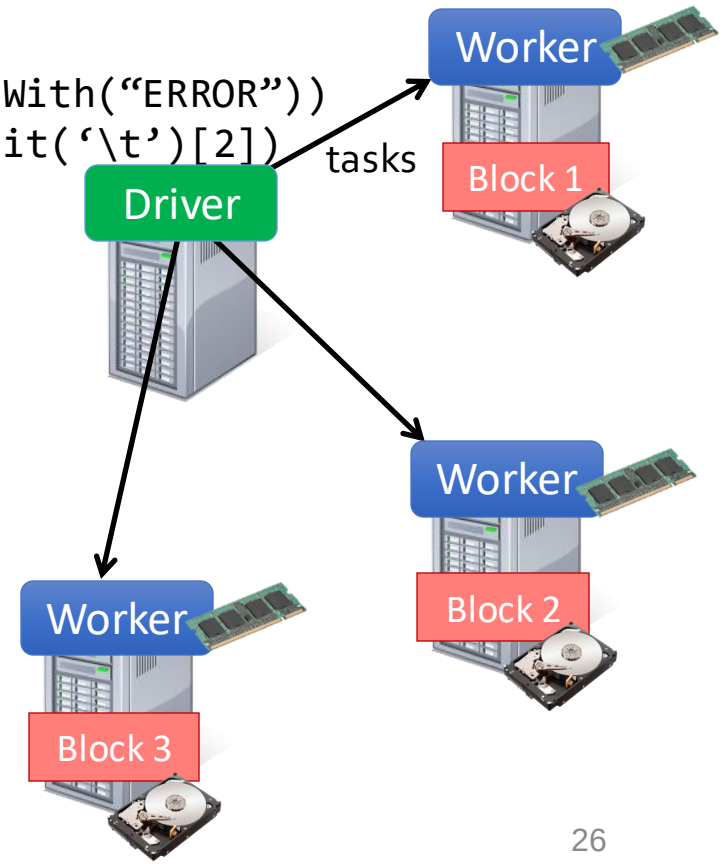

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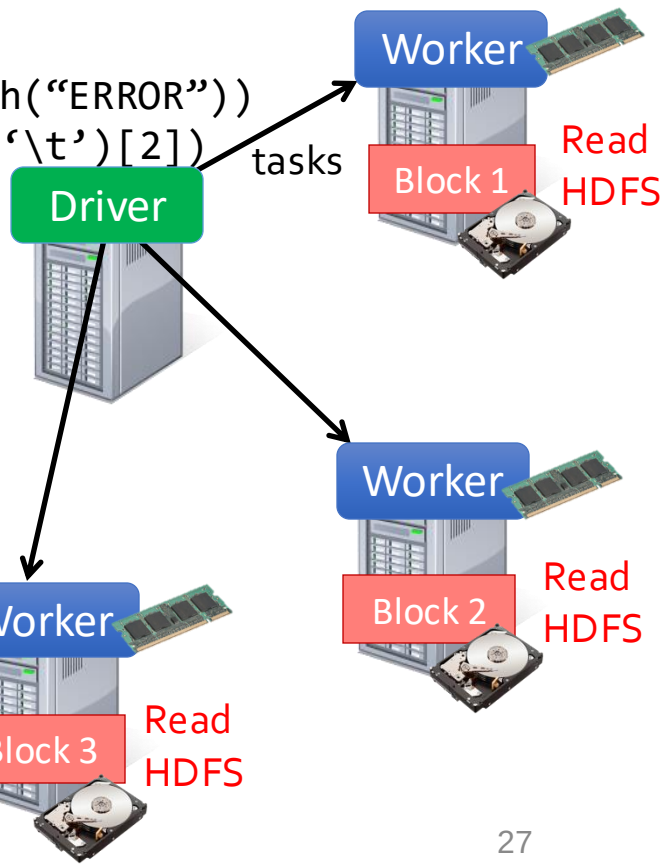

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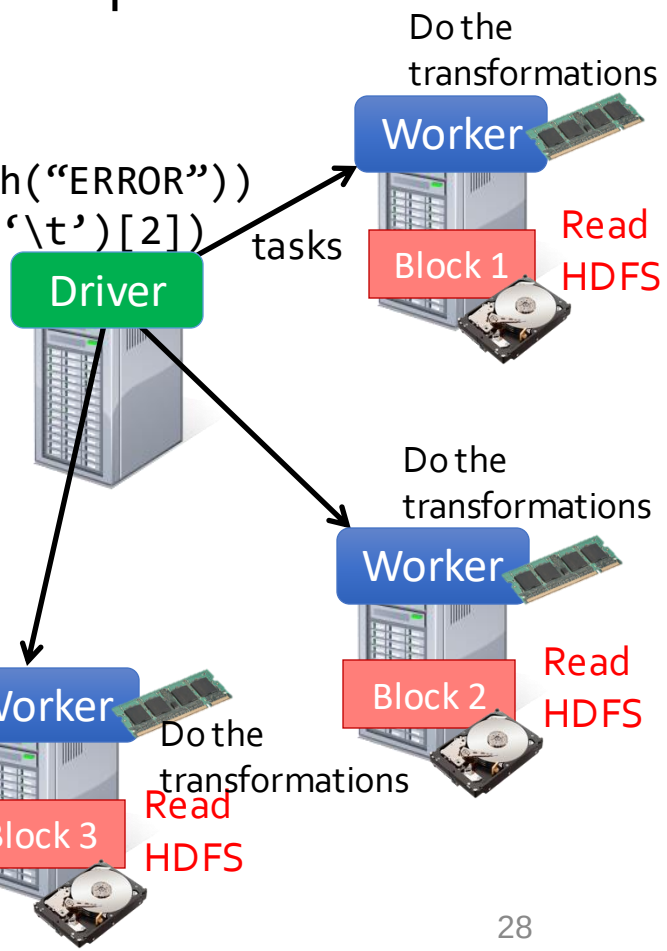

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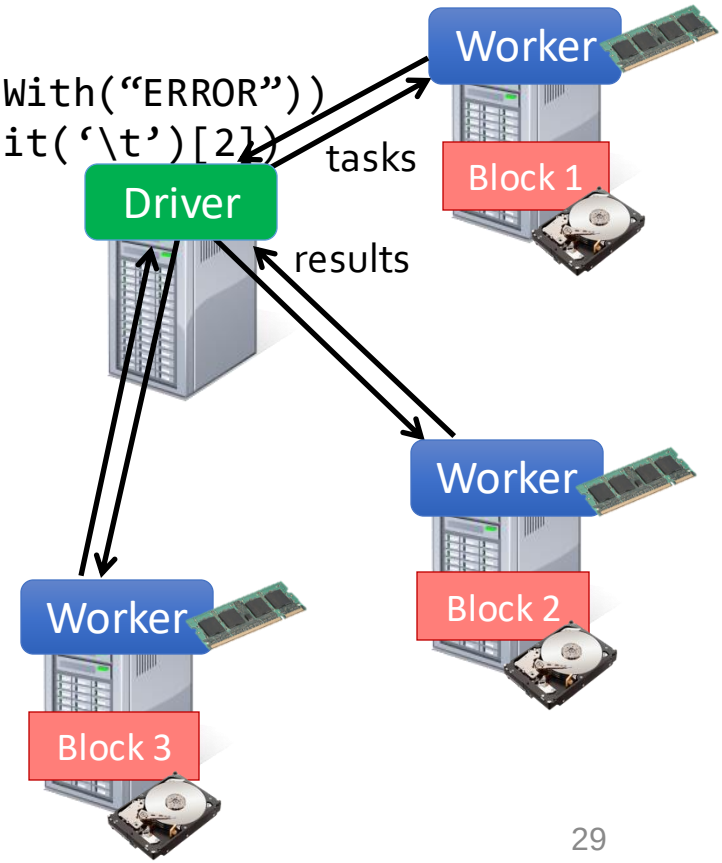

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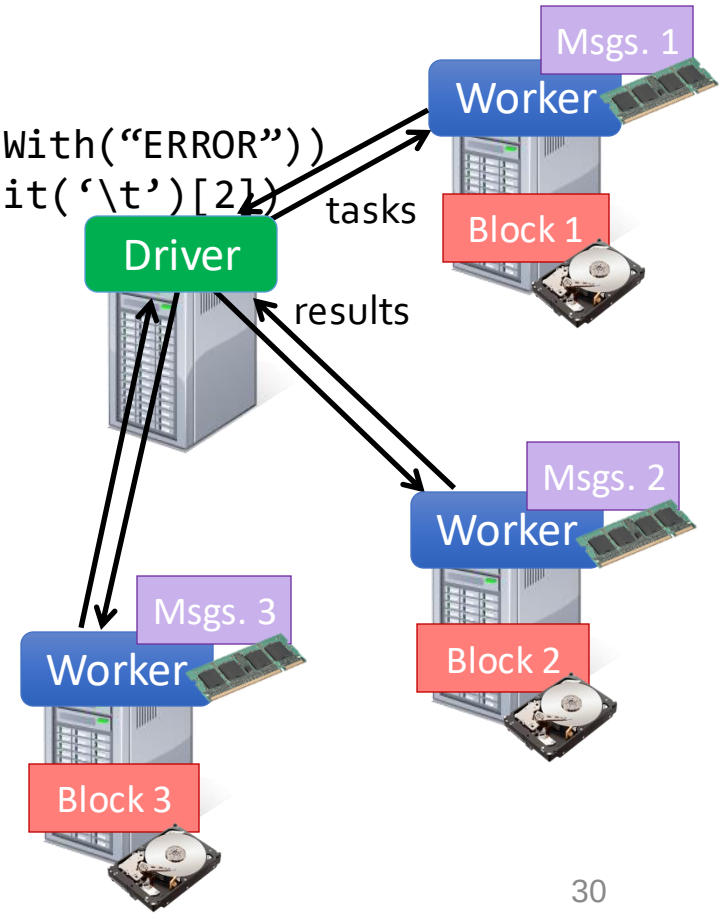

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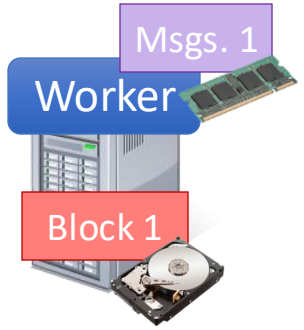

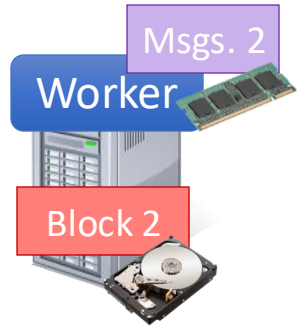

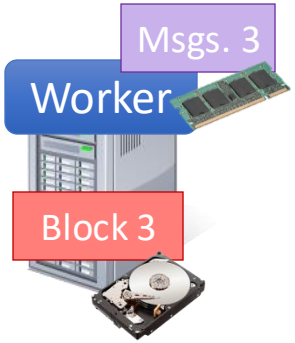

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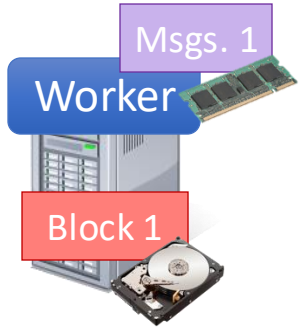

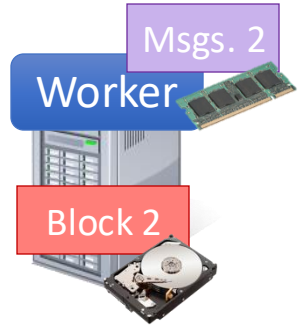

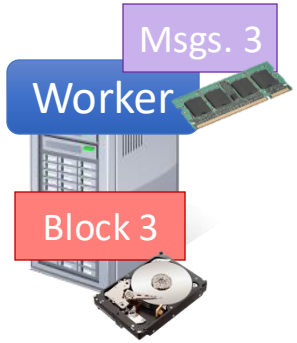

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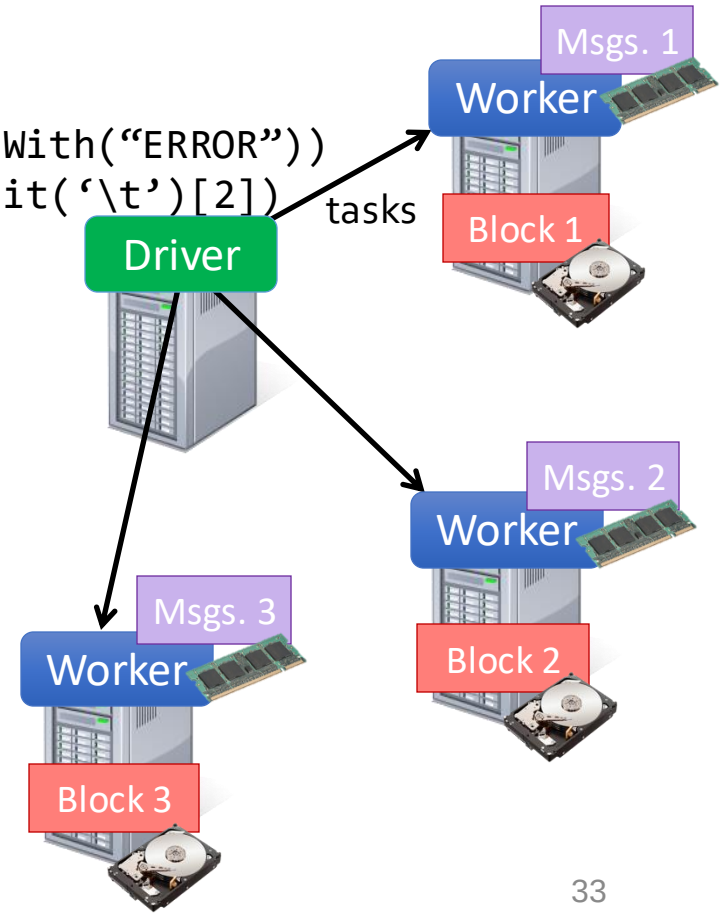
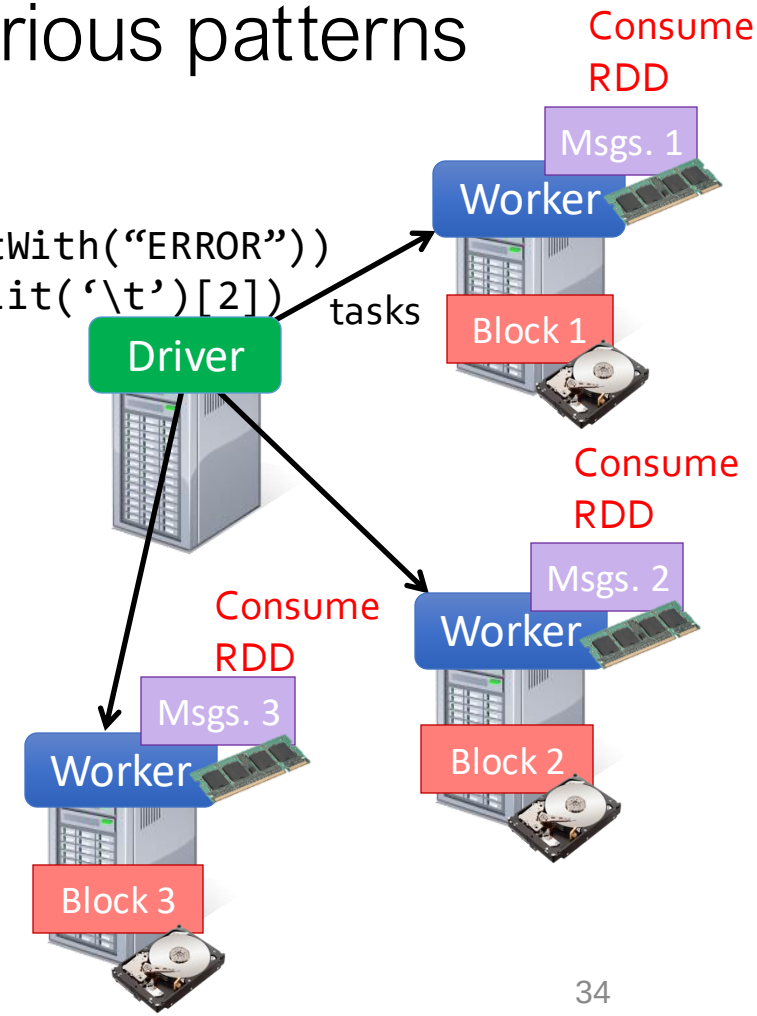


Interactive debugging (control & data flow)

Load input data from an HDFS file into memory, then interactively search for various patterns

```
lines = sc.textFile(“hdfs://...”)
errors = lines.filter(lambda line: line.startWith(“ERROR”))
messages = errors.map(lambda error: error.split(‘\t’)[2])
messages.cache()


messages.filter(lambda line: “MySQL” in line)
                    .count()
messages.filter(lambda line: “HDFS” in line)
                    .count()
```



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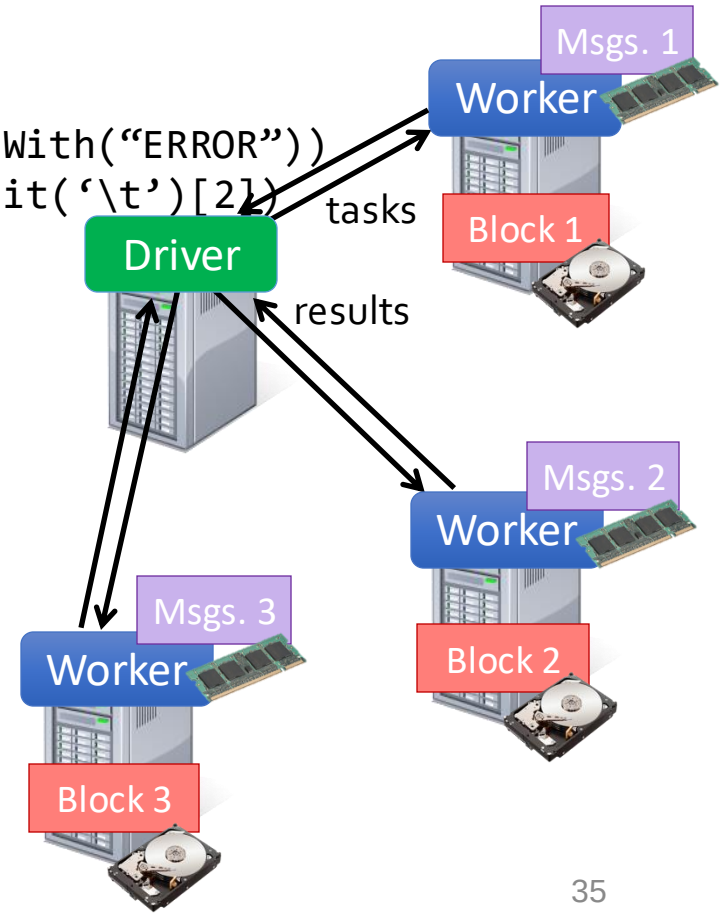

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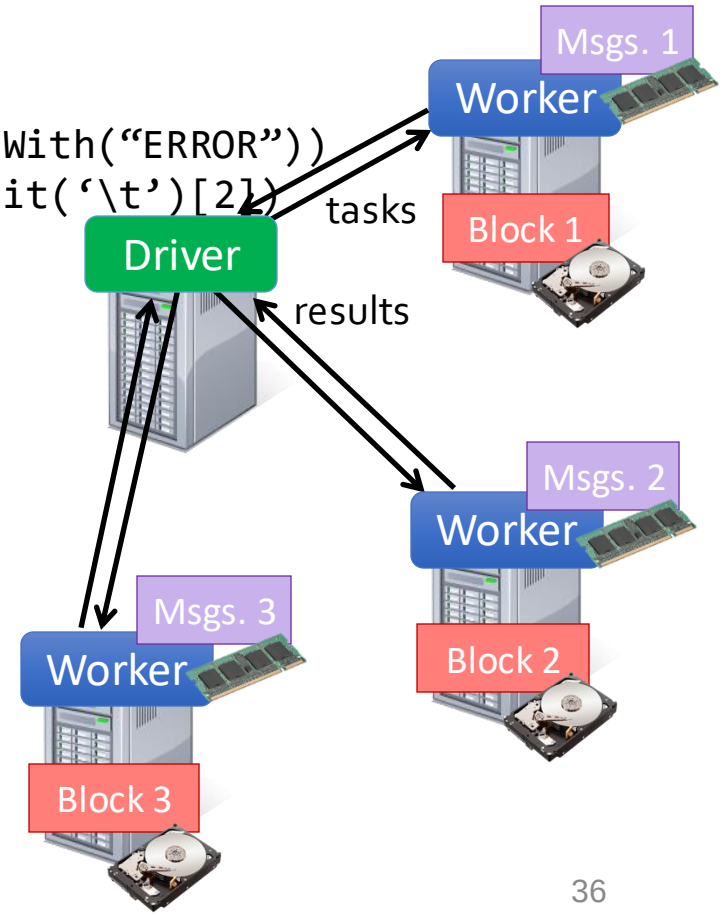

Result: full-text search of Wikipedia in <1 sec (vs. 20 sec for on-disk data)

Interactive debugging (control & data flow)

Load input data from an HDFS file into memory, then interactively search for various patterns

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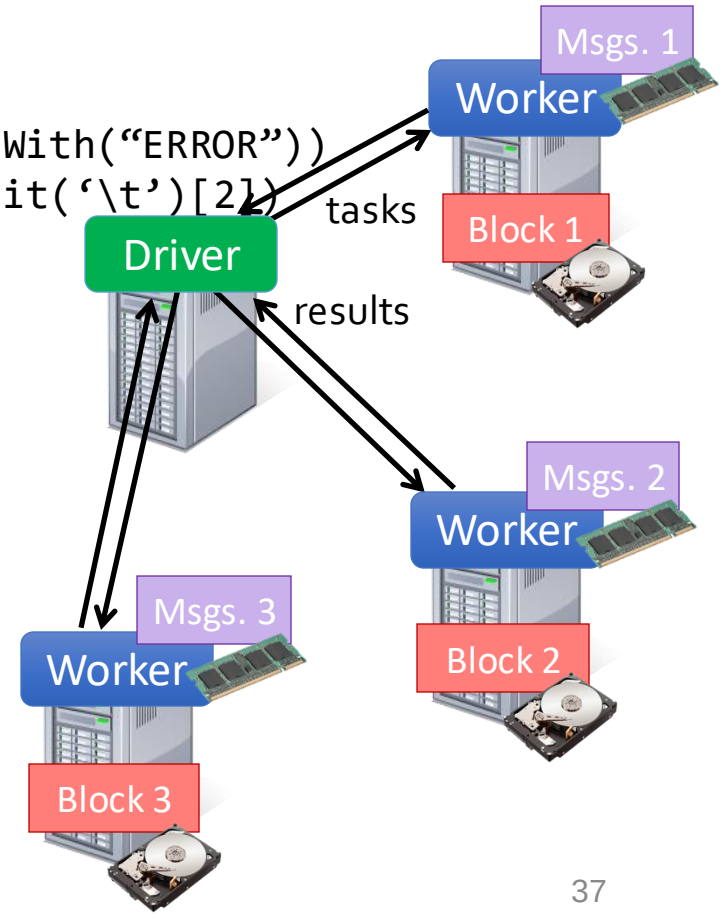
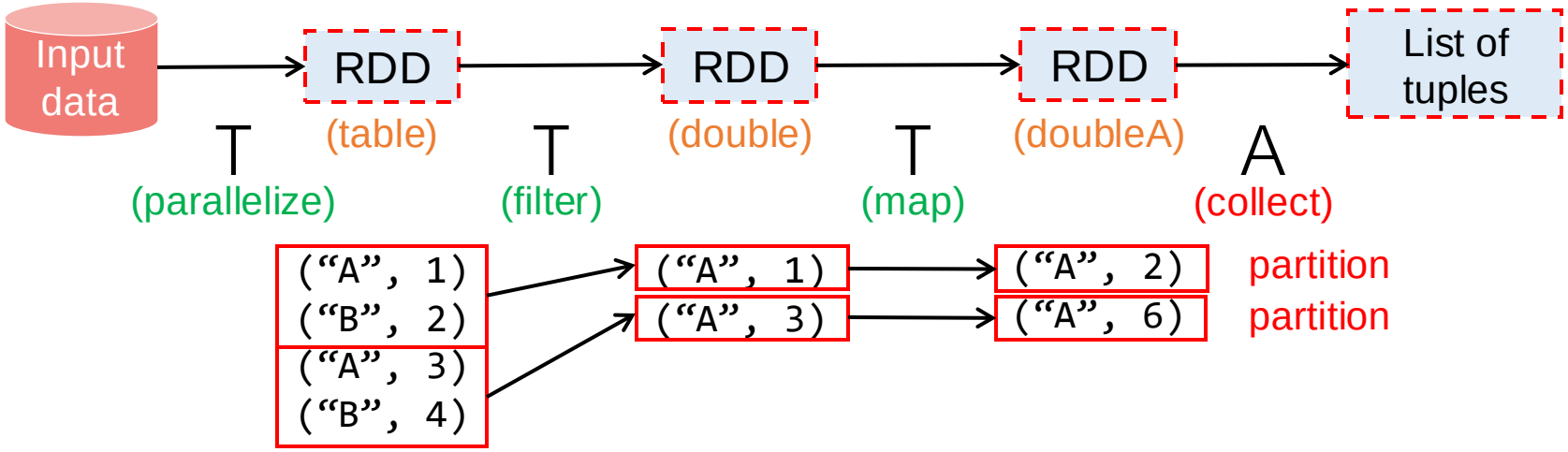


Result: scaled to 1 TB data in 5-7 sec
(vs. 170 sec for on-disk data)

Repartitioning



Many operations (like `filter` and `map`) output the same number of partitions as they receive

- If data is growing/shrinking a lot after transformation, you might want to change the partition count
- `rdd.getNumPartitions()` `# check how many`
- `rdd2 = rdd.repartition(10)` `# change how many`

Examples:

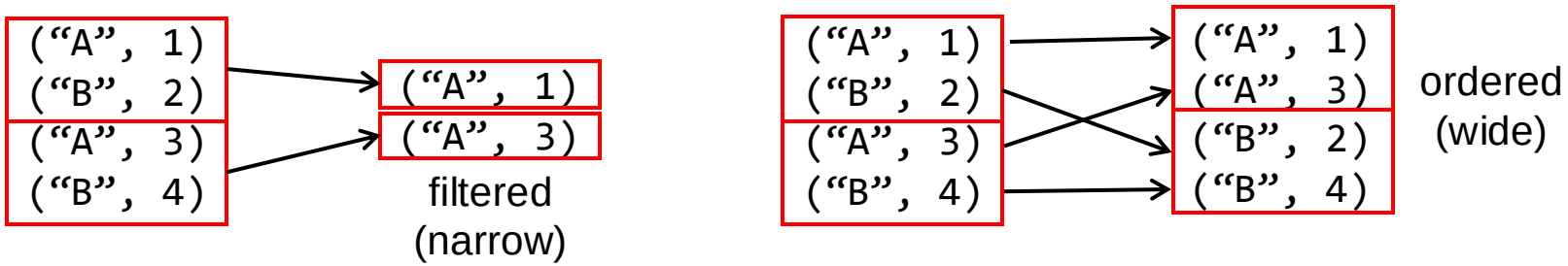
```
table.filter(onlyA).map(mult2).collect()

table.filter(onlyA).repartition(1).map(mult2).collect()
```

Transformations: Narrow vs. Wide

- Any transformation where a single output partition can be computed from a single input partition is a narrow transformation.

- Others are wide transformations.

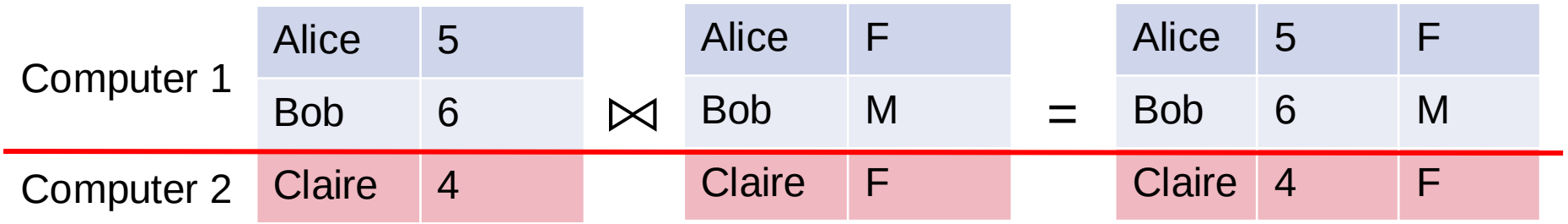
```
data = [("A", 1), ("B", 2), ("A", 3), ("B", 4),]
table = sc.parallelize(data, 2)
filtered = table.filter(lambda row: row[0] == "A")
ordered = table.sortBy(lambda row: row[0])
```



- Wide transformations often require network resources. Unless all input partitions are on the same machine, some will need to be transferred.

More on join and partitioning

Join and partitioning (best case)



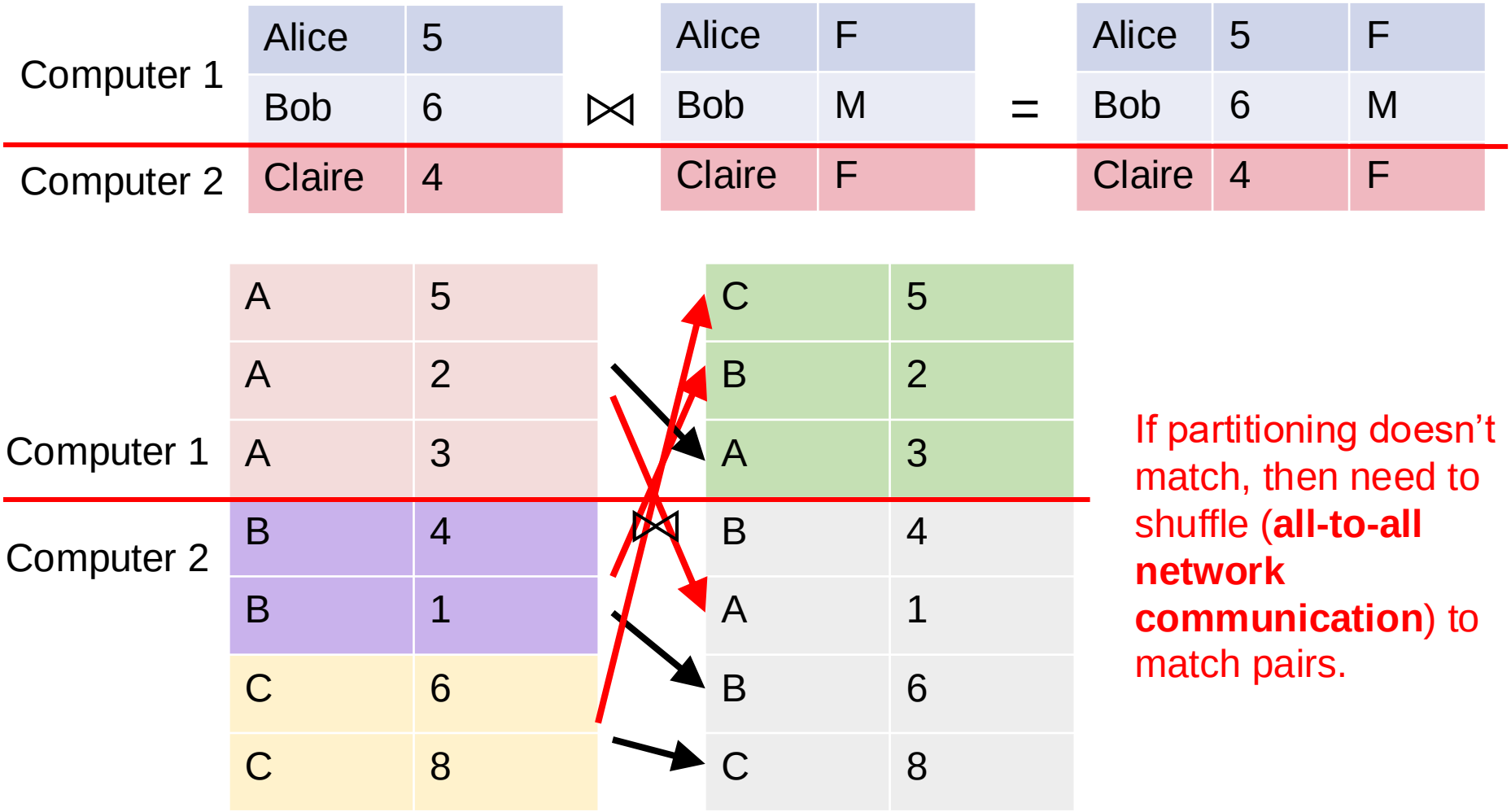
Join and partitioning (worst case)

Computer 1	Alice	5	⋈	Alice	F	=	Alice	5	F
	Bob	6		Bob	M		Bob	6	M
Computer 2	Claire	4		Claire	F		Claire	4	F

Computer 1	A	5		C	5
	A	2		B	2
	A	3		A	3
Computer 2	B	4	⋈	B	4
	B	1		A	1
	C	6		B	6
	C	8		C	8

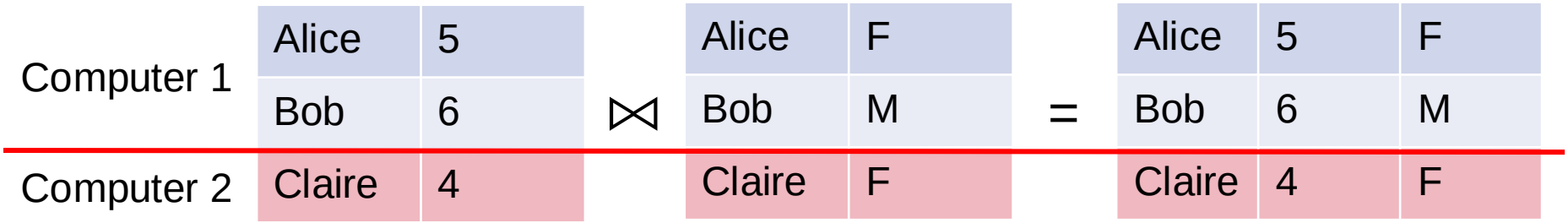
If partitioning doesn't match, then need to shuffle (**all-to-all network communication**) to match pairs.

Join and partitioning (worst case)

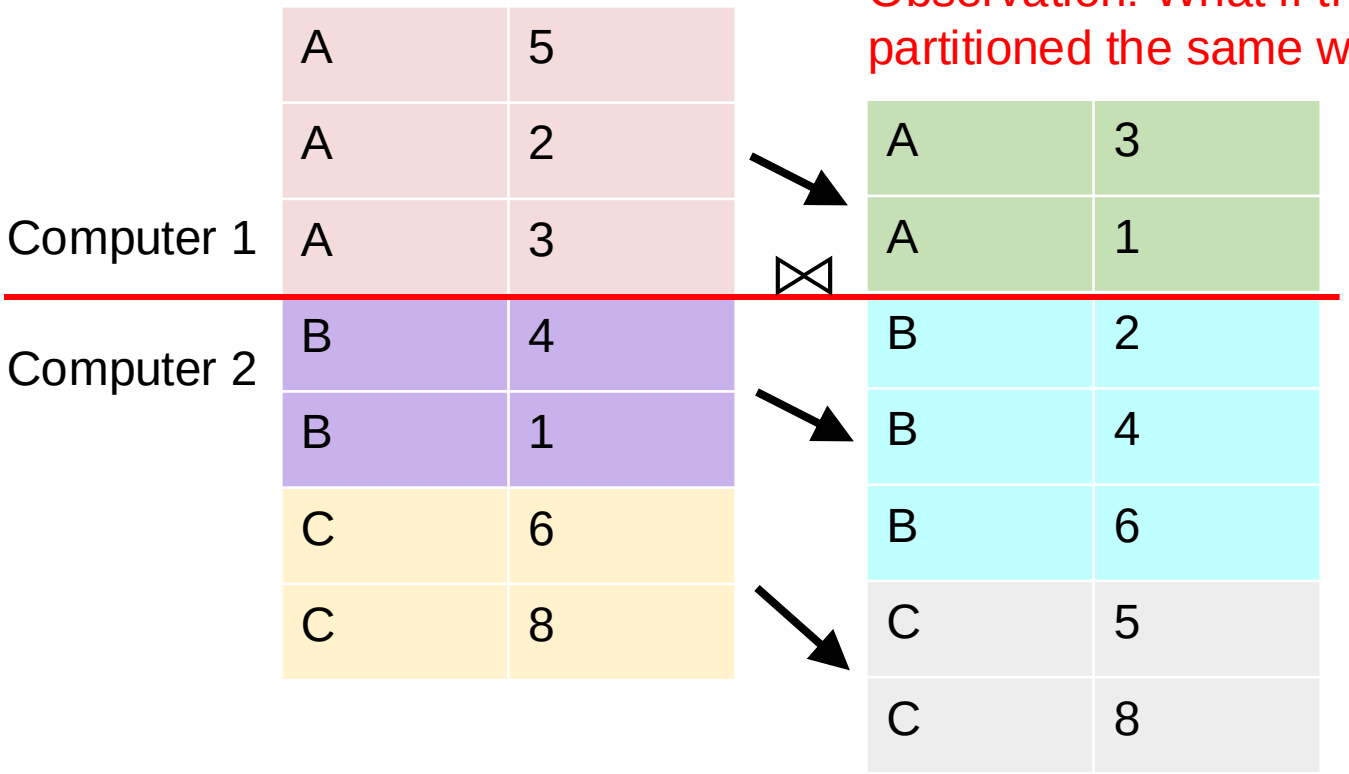


If partitioning doesn't match, then need to shuffle (**all-to-all network communication**) to match pairs.

Join and partitioning (optimization)



Observation: What if the two tables are partitioned the same way?



`partitionBy()` is specific to key-value pair RDDs. It is used to partition RDDs based on keys, by default using a **hash partitioner**.

Example: PageRank

Example: PageRank

1. Start each page with a rank of 1
2. On each iteration, update each dest page's rank to $\Sigma_{i \in neighbors} rank_{neighbor\_i} / |neighbors_i|$

```
links = // RDD of (url, neighbors) pairs
ranks = // RDD of (url, rank) pairs

for (i <- 1 to ITERATIONS) {
  ranks = links.join(ranks).flatMap {
    (url, (links, rank)) =>
      links.map(dest => (dest, rank/links.size))
  }.reduceByKey(_ + _)
}
```

Example: PageRank

1. Start each page with a rank of 1
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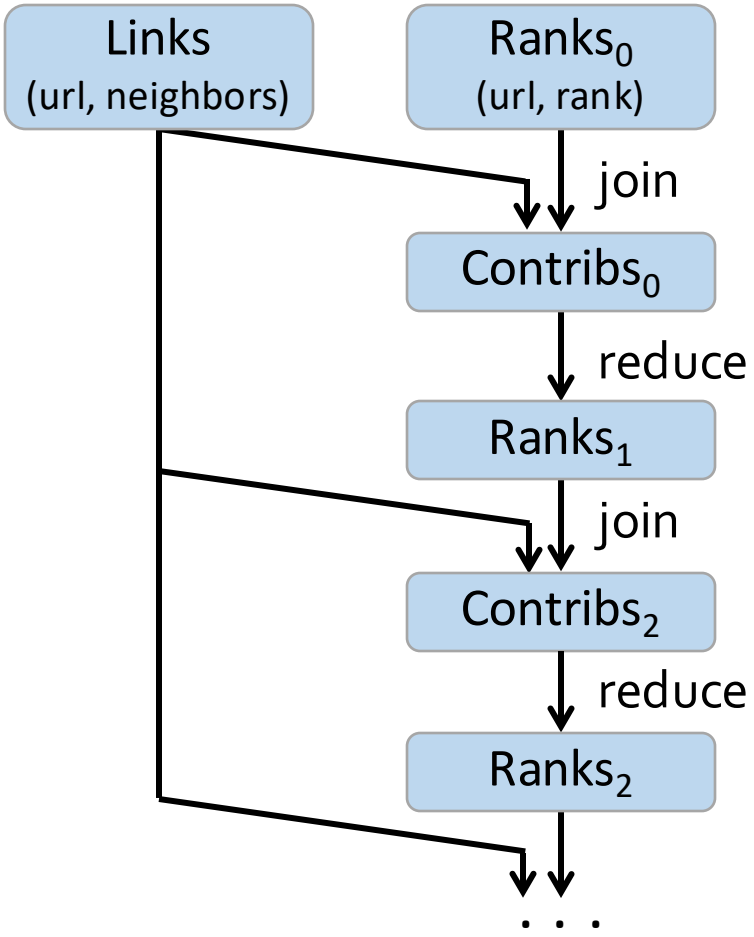
```
RDD[(URL, Seq[URL])]

links = // RDD of (url, neighbors) pairs
ranks = // RDD of (url, rank) pairs        <- RDD[(URL, Rank)]

for (i <- 1 to ITERATIONS) {               <- RDD[(URL, (Seq[URL],Rank))]
  ranks = links.join(ranks).flatMap {
    (url, (links, rank)) =>
      links.map(dest => (dest, rank/links.size))
  }.reduceByKey(_ + _)
}
```

For each neighbor in links emits **(URL, RankContrib)**

Reduce to **RDD[(URL, Rank)]**

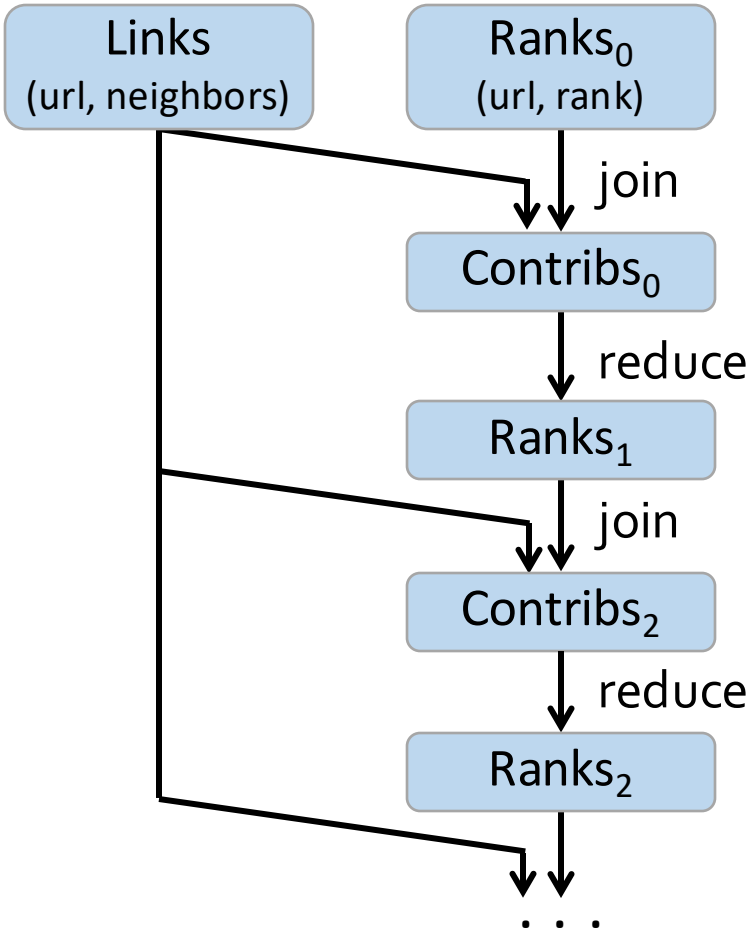
Optimizing placement



- `links` & `ranks` repeated joined
- Can co-partition them (e.g., hash both on source URLs) to avoid shuffles

```
links = links.partitionBy(N)
ranks = ranks.partitionBy(N)
```

Optimizing placement



- `links` & `ranks` repeated joined
- Can co-partition them (e.g., hash both on source URLs) to avoid shuffles

```
links = links.partitionBy(N)
ranks = ranks.partitionBy(N)
```

Q1: Should we apply `.persist(DISK_ONLY)` to `links` or `ranks`?

Q2: Where might we have placed `.persist(DISK_ONLY)`?