

# Shuffling: What it is and why it's important

Big Data Analysis with Scala and Spark

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#### **Shuffles Happen**

Shuffles can be an enormous hit to because it means that Spark must send data from one node to another. Why? **Latency!** 

Let's start with an example. Given:

```
case class CFFPurchase(customerId: Int, destination: String, price: Double)
```

Assume we have an RDD of the purchases that users of the Swiss train company's, the CFF's, mobile app have made in the past month.

```
val purchasesRdd: RDD[CFFPurchase] = sc.textFile(...)
```

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val purchasesPerMonth = ...
```

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val purchasesRdd: RDD[CFFPurchase] = sc.textFile(...)

val purchasesPerMonth =
  purchasesRdd.map(p => (p.customerId, p.price)) // Pair RDD
```

Let's start with an example dataset:

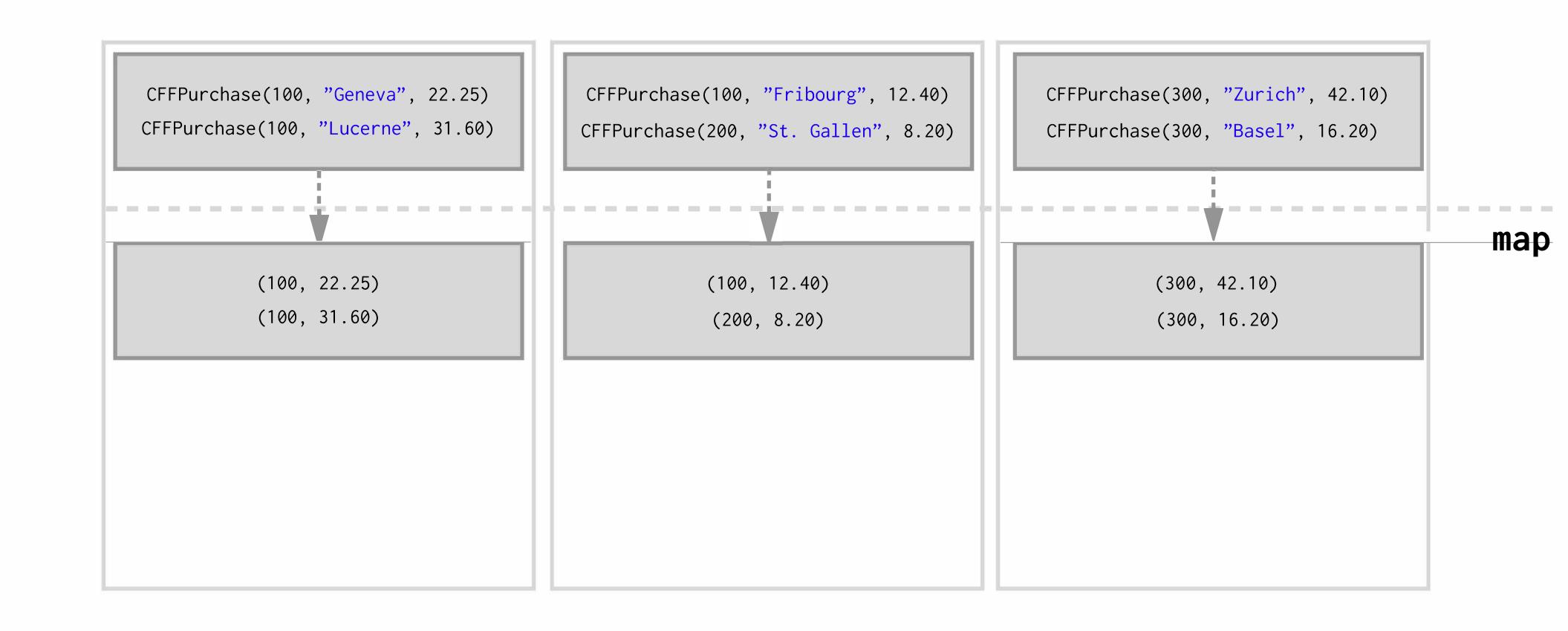
What might the cluster look like with this data distributed over it?

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```
CFFPurchase(100, "Geneva", 22.25)
CFFPurchase(100, "Lucerne", 31.60)
```

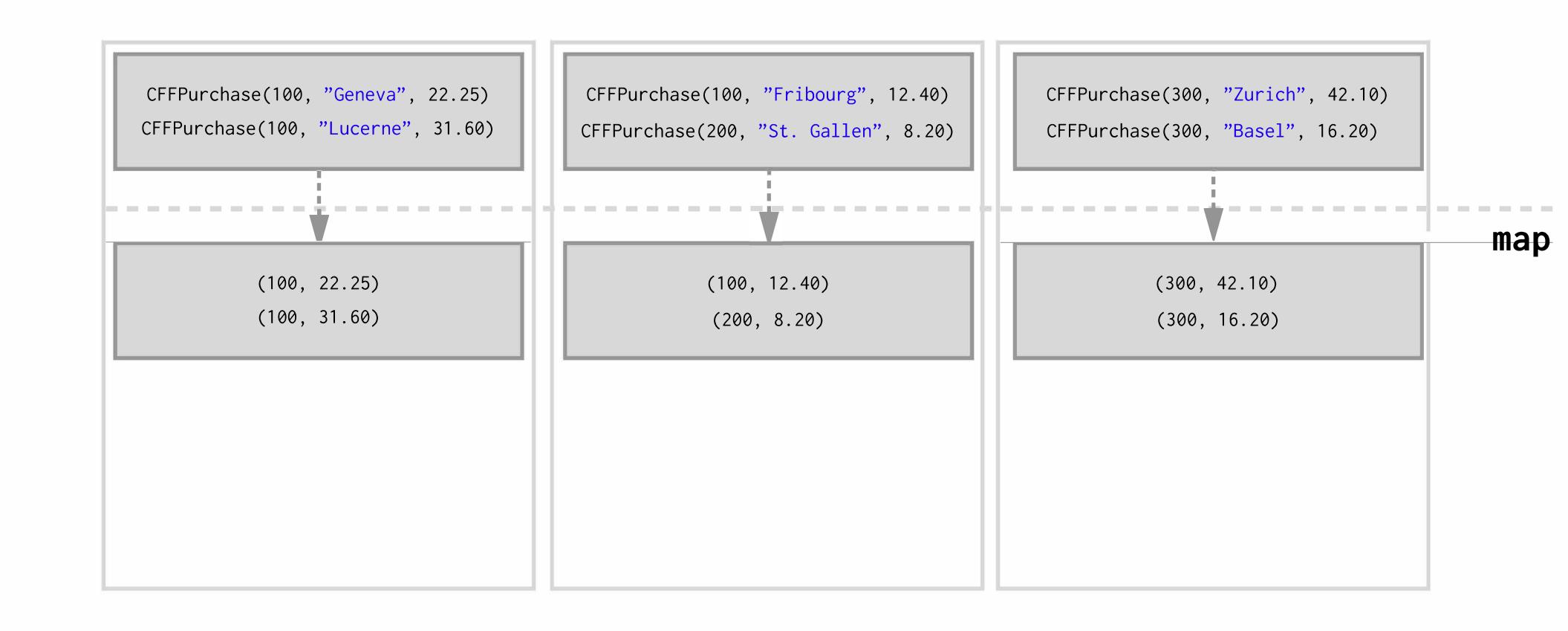
```
CFFPurchase(100, "Fribourg", 12.40)
CFFPurchase(200, "St. Gallen", 8.20)
```

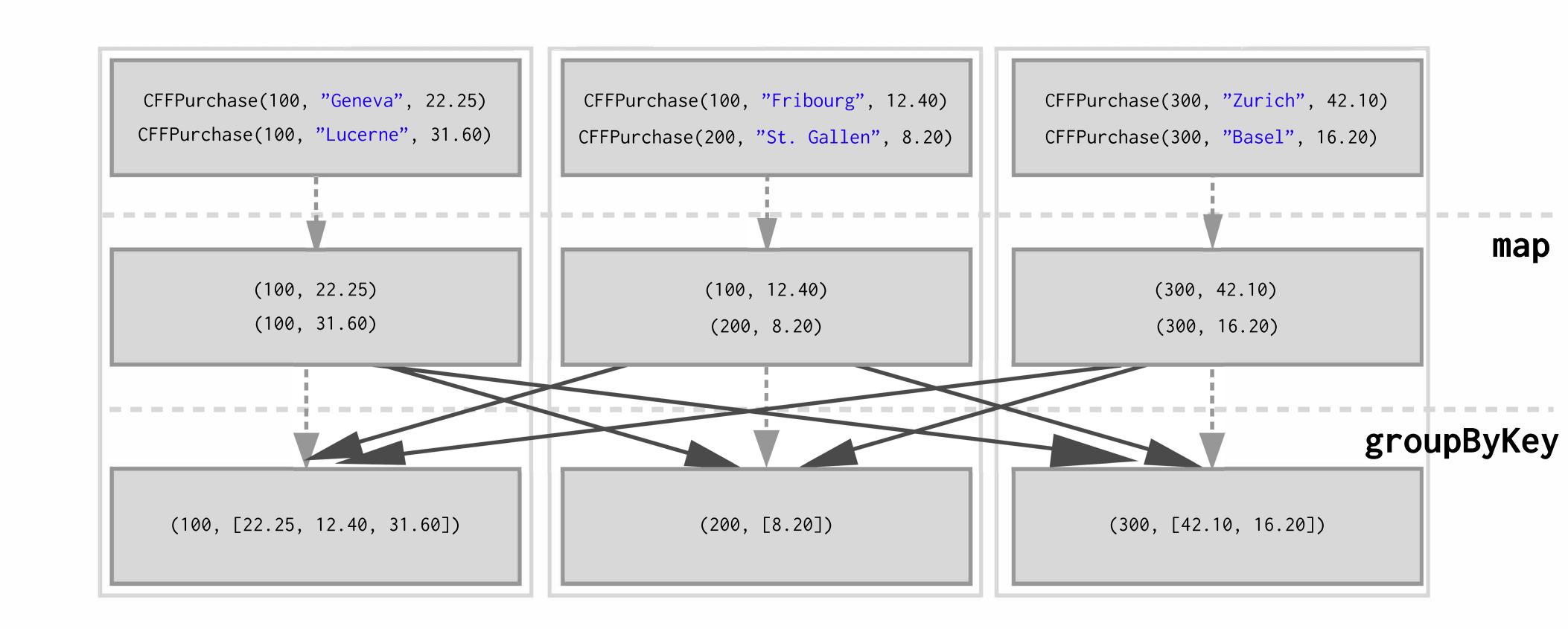
```
CFFPurchase(300, "Zurich", 42.10)
CFFPurchase(300, "Basel", 16.20)
```

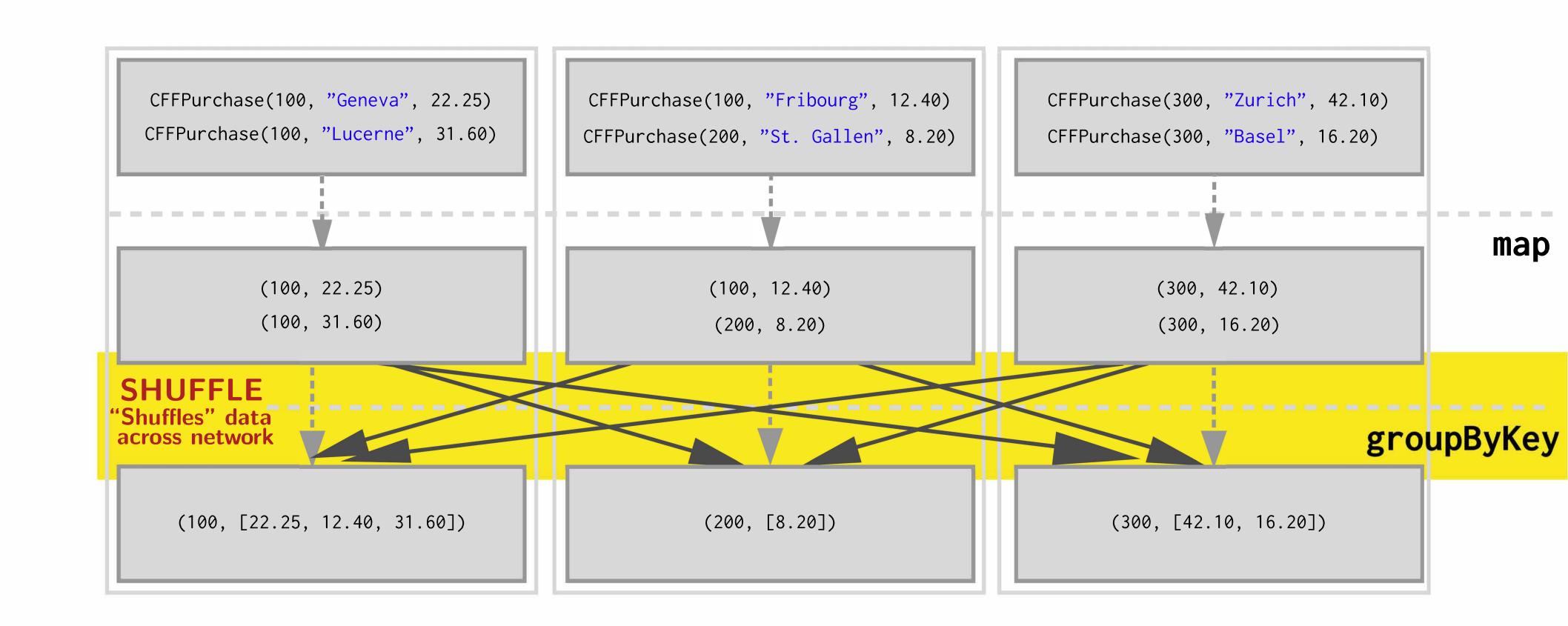


Goal: calculate how many trips, and how much money was spent by each individual customer over the course of the month.

Note: groupByKey results in one key-value pair per key. And this single key-value pair cannot span across multiple worker nodes.







#### Reminder: Latency Matters (Humanized)

#### **Shared Memory**

#### Seconds

L1 cache reference......0.5s

L2 cache reference......7s

Mutex lock/unlock......25s

#### **Minutes**

Main memory reference....1m 40s

#### **Distributed**

#### Days

Roundtrip within same datacenter.....5.8 days

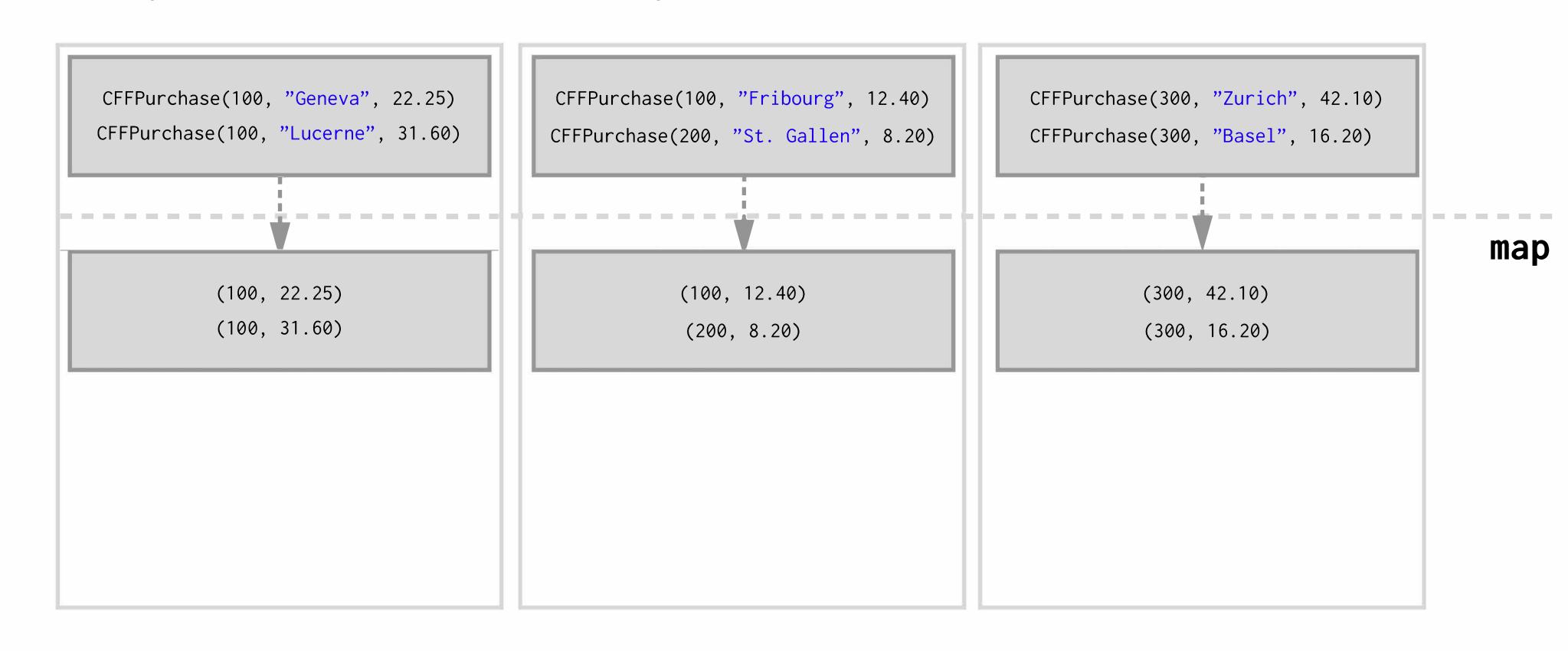
#### **Years**

Send packet CA->Netherlands->CA....4.8 years

We don't want to be sending all of our data over the network if it's not absolutely required. Too much network communication kills performance.

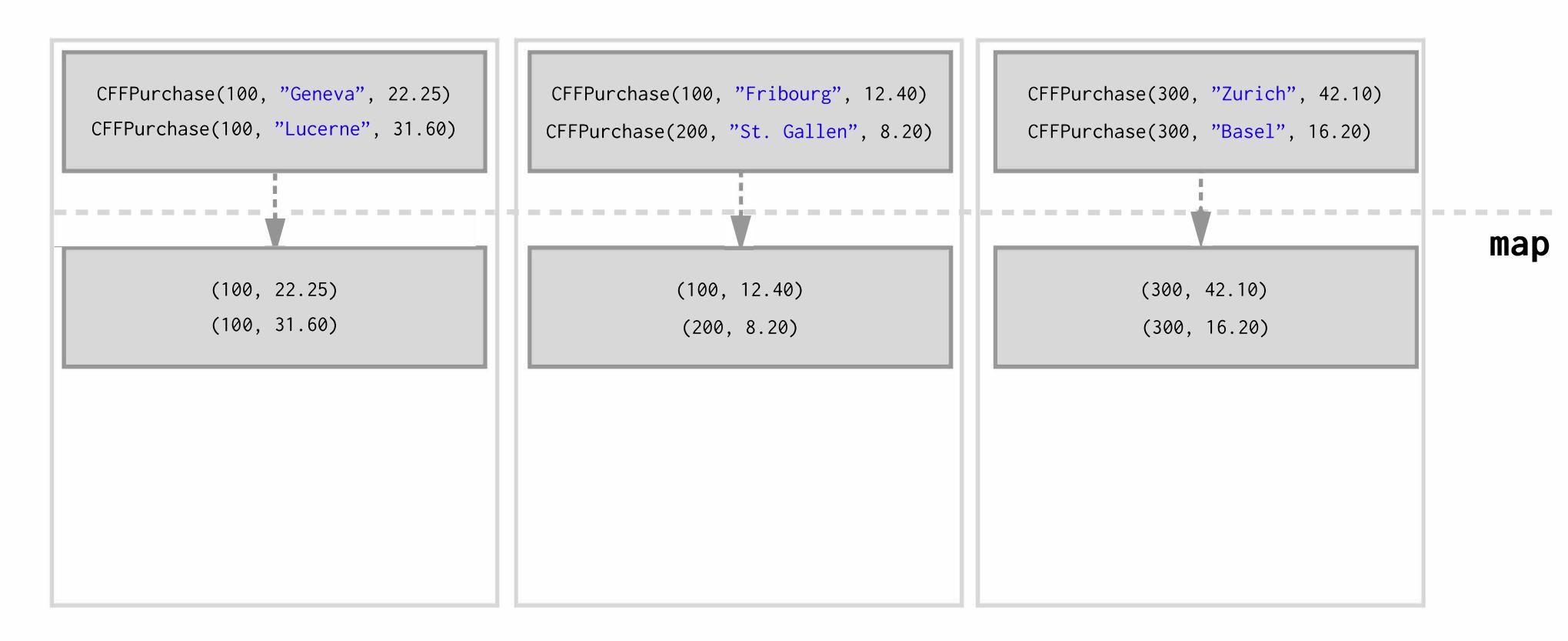
#### Can we do a better job?

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Perhaps we can reduce before we shuffle. This could greatly reduce the amount of data we have to send over the network.

We can use reduceByKey.

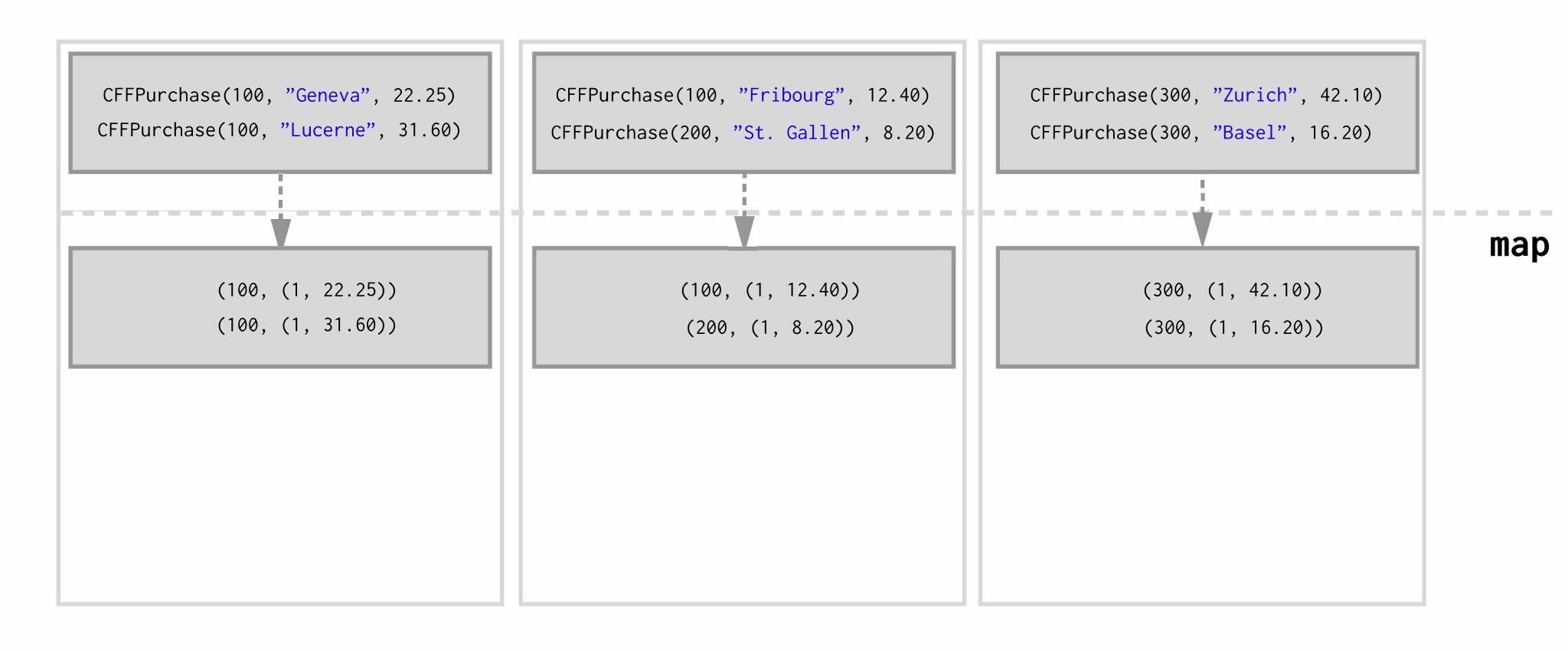
Conceptually, reduceByKey can be thought of as a combination of first doing groupByKey and then reduce-ing on all the values grouped per key. It's more efficient though, than using each separately. We'll see how in the following example.

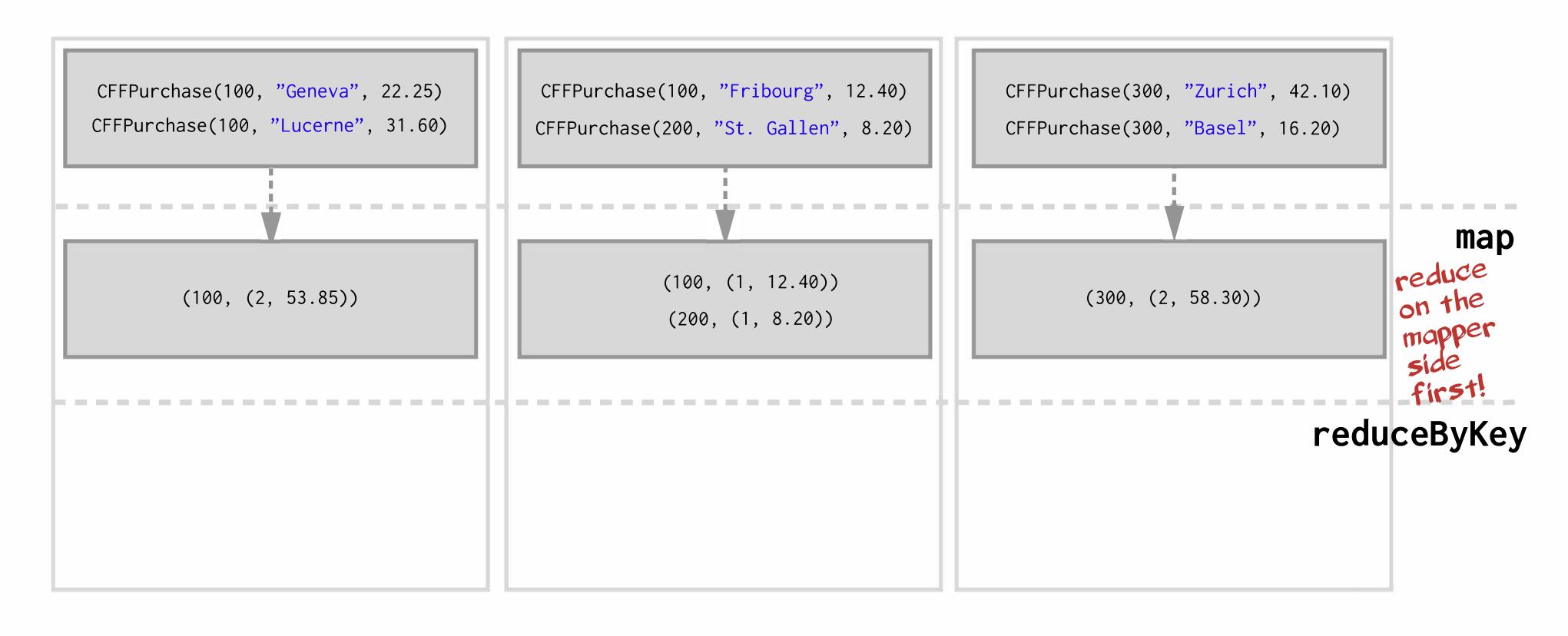
#### Signature:

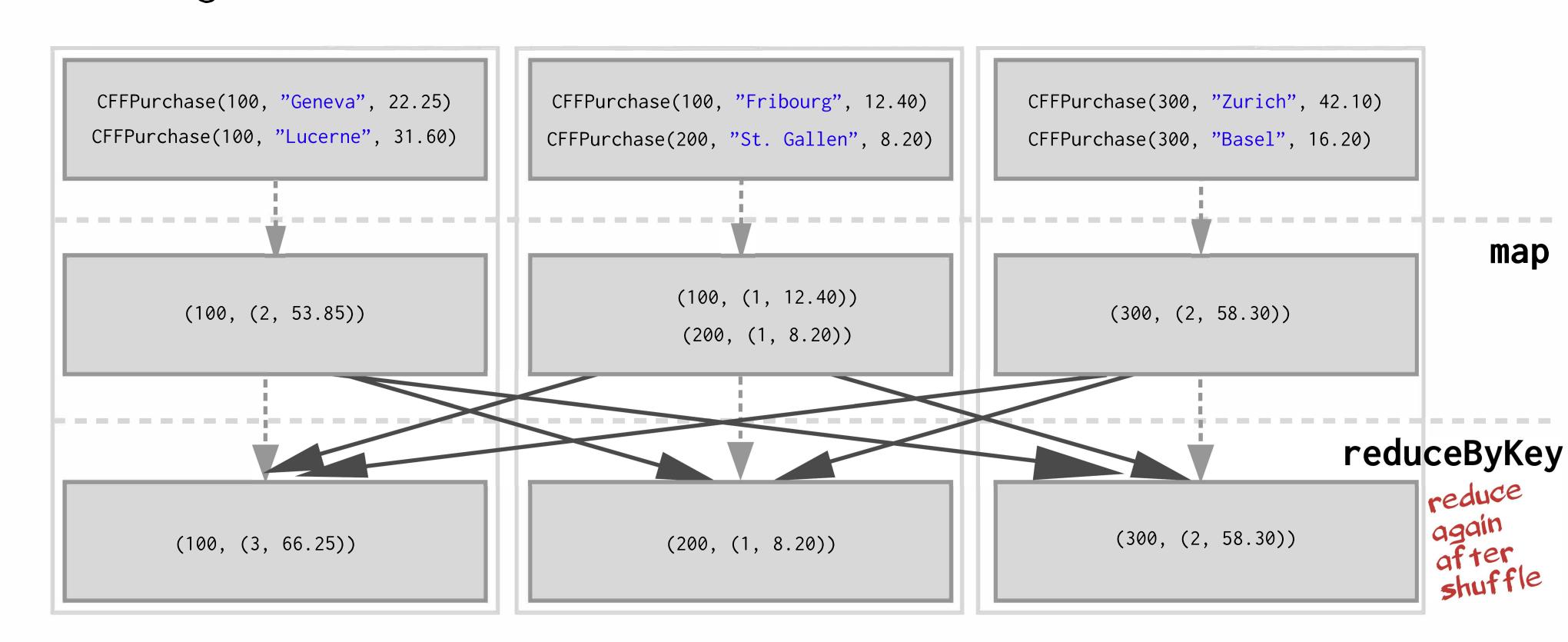
```
def reduceByKey(func: (V, V) => V): RDD[(K, V)]
```

**Goal:** calculate how many trips, and how much money was spent by each individual customer over the course of the month.

What function do we pass to reduceByKey in order to get a result that looks like: (customerId, (numTrips, totalSpent)) returned?







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Let's benchmark on a real cluster.

#### groupByKey and reduceByKey Running Times

## Shuffling

Recall our example using groupByKey:

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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?

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

▶ By default, Spark uses *hash partitioning* to determine which key-value pair should be sent to which machine.