



ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Partitioning

Big Data Analysis with Scala and Spark

Heather Miller

“Partitioning”?

In the last session, we were looking at an example involving `groupByKey`, before we discovered that this operation causes data to be *shuffled* over the network.

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.

We concluded the last session asking ourselves,

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

Before we try to optimize that example any further, let's first take a quick detour into what partitioning is...

Partitions

The data within an RDD is split into several *partitions*.

Properties of partitions:

- ▶ Partitions never span multiple machines, i.e., tuples in the same partition are guaranteed to be on the same machine.
- ▶ Each machine in the cluster contains one or more partitions.
- ▶ The number of partitions to use is configurable. By default, it equals the *total number of cores on all executor nodes*.

Two kinds of partitioning available in Spark:

- ▶ Hash partitioning
- ▶ Range partitioning

Customizing a partitioning is only possible on Pair RDDs.

Hash partitioning

Back to our example. Given a Pair RDD that should be grouped:

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

Hash partitioning

Back to our example. Given a Pair RDD that should be grouped:

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

groupByKey first computes per tuple (k, v) its partition p:

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

Then, all tuples in the same partition p are sent to the machine hosting p.

Intuition: hash partitioning attempts to spread data evenly across partitions *based on the key*.

Range partitioning

Pair RDDs may contain keys that have an *ordering* defined.

- ▶ Examples: Int, Char, String, ...

For such RDDs, *range partitioning* may be more efficient.

Using a range partitioner, keys are partitioned according to:

1. an *ordering* for keys
2. a set of *sorted ranges* of keys

Property: tuples with keys in the same range appear on the same machine.

Hash Partitioning: Example

Consider a Pair RDD, with keys [8, 96, 240, 400, 401, 800], and a desired number of partitions of 4.

Hash Partitioning: Example

Consider a Pair RDD, with keys [8, 96, 240, 400, 401, 800], and a desired number of partitions of 4.

Furthermore, suppose that hashCode() is the identity ($n.hashCode() == n$).

$$\begin{aligned} p &= K \bmod \text{numPartitions} \\ &= K \% 4 \end{aligned}$$

Hash Partitioning: Example

Consider a Pair RDD, with keys [8, 96, 240, 400, 401, 800], and a desired number of partitions of 4.

Furthermore, suppose that hashCode() is the identity ($n.hashCode() == n$).

In this case, hash partitioning distributes the keys as follows among the partitions:

- ▶ partition 0: [8, 96, 240, 400, 800]
- ▶ partition 1: [401]
- ▶ partition 2: []
- ▶ partition 3: []

$$p = K \% P$$

The result is a very unbalanced distribution which hurts performance.

Range Partitioning: Example

Using *range partitioning* the distribution can be improved significantly:

- ▶ Assumptions: (a) keys non-negative, (b) 800 is biggest key in the RDD.
- ▶ Set of ranges: [1, 200], [201, 400], [401, 600], [601, 800]

Range Partitioning: Example

Using *range partitioning* the distribution can be improved significantly:

- ▶ Assumptions: (a) keys non-negative, (b) 800 is biggest key in the RDD.
- ▶ Set of ranges: [1, 200], [201, 400], [401, 600], [601, 800]

In this case, range partitioning distributes the keys as follows among the partitions:

- ▶ partition 0: [8, 96]
- ▶ partition 1: [240, 400]
- ▶ partition 2: [401]
- ▶ partition 3: [800]

The resulting partitioning is much more balanced.

Partitioning Data

How do we set a partitioning for our data?

Partitioning Data

How do we set a partitioning for our data?

There are two ways to create RDDs with specific partitionings:

1. Call `partitionBy` on an RDD, providing an explicit Partitioner.
2. Using transformations that return RDDs with specific partitioners.

Partitioning Data: `partitionBy`

Invoking `partitionBy` creates an RDD with a specified partitioner.

Partitioning Data: `partitionBy`

Invoking `partitionBy` creates an RDD with a specified partitioner.

Example:

```
val pairs = purchasesRdd.map(p => (p.customerId, p.price))
```

Partitioning Data: `partitionBy`

Invoking `partitionBy` creates an RDD with a specified partitioner.

Example:

```
val pairs = purchasesRdd.map(p => (p.customerId, p.price))
```

```
val tunedPartitioner = new RangePartitioner(8, pairs)
```

```
val partitioned = pairs.partitionBy(tunedPartitioner).persist()
```



Partitioning Data: `partitionBy`

Invoking `partitionBy` creates an RDD with a specified partitioner.

Example:

```
val pairs = purchasesRdd.map(p => (p.customerId, p.price))
```

```
val tunedPartitioner = new RangePartitioner(8, pairs)
```

```
val partitioned = pairs.partitionBy(tunedPartitioner).persist()
```

Creating a `RangePartitioner` requires:

1. Specifying the desired number of partitions.
2. Providing a Pair RDD with *ordered keys*. This RDD is *sampled* to create a suitable set of *sorted ranges*.

Partitioning Data: `partitionBy`

Invoking `partitionBy` creates an RDD with a specified partitioner.

Example:

```
val pairs = purchasesRdd.map(p => (p.customerId, p.price))
```

```
val tunedPartitioner = new RangePartitioner(8, pairs)
```

```
val partitioned = pairs.partitionBy(tunedPartitioner).persist()
```

Creating a RangePartitioner requires:

1. Specifying the desired number of partitions.
2. Providing a Pair RDD with *ordered keys*. This RDD is *sampled* to create a suitable set of *sorted ranges*.

Important: the result of `partitionBy` should be persisted. Otherwise, the partitioning is repeatedly applied (involving shuffling!) each time the partitioned RDD is used.

Partitioning Data Using Transformations

Partitioner from parent RDD:

Pair RDDs that are the result of a transformation on a *partitioned* Pair RDD typically is configured to use the hash partitioner that was used to construct it.

Automatically-set partitioners:

Some operations on RDDs automatically result in an RDD with a known partitioner – for when it makes sense.

For example, by default, when using `sortByKey`, a `RangePartitioner` is used. Further, the default partitioner when using `groupByKey`, is a `HashPartitioner`, as we saw earlier.

Partitioning Data Using Transformations

Operations on Pair RDDs that hold to (and propagate) a partitioner:

- ▶ cogroup
- ▶ groupWith
- ▶ join
- ▶ leftOuterJoin
- ▶ rightOuterJoin
- ▶ groupByKey
- ▶ reduceByKey
- ▶ foldByKey
- ▶ combineByKey
- ▶ partitionBy
- ▶ sort
- ▶ mapValues (if parent has a partitioner)
- ▶ flatMapValues (if parent has a partitioner)
- ▶ filter (if parent has a partitioner)

All other operations will produce a result without a partitioner.

Partitioning Data Using Transformations

...All other operations will produce a result without a partitioner.

Why?

Partitioning Data Using Transformations

...All other operations will produce a result without a partitioner.

Why?

Consider the map transformation. Given that we have a hash partitioned Pair RDD, why would it make sense for map to lose the partitioner in its result RDD?

Partitioning Data Using Transformations

...All other operations will produce a result without a partitioner.

Why?

Consider the map transformation. Given that we have a hash partitioned Pair RDD, why would it make sense for map to lose the partitioner in its result RDD?

Because it's possible for map to change the key . *E.g.,:*



Partitioning Data Using Transformations

...All other operations will produce a result without a partitioner.

Why?

Consider the map transformation. Given that we have a hash partitioned Pair RDD, why would it make sense for map to lose the partitioner in its result RDD?

Because it's possible for map to change the key . *E.g.,:*

```
rdd.map((k: String, v: Int) => ("doh!", v))
```



In this case, if the map transformation preserved the partitioner in the result RDD, it no longer make sense, as now the keys are all different.

Hence mapValues. It enables us to still do map transformations without changing the keys, thereby preserving the partitioner.

