Shuffling, Partitioning, and Closures

Parallel Programming and Data Analysis

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What we've learned so far

Spark's Basic Programming Model

- We saw that, at a glance, Spark looks like Scala collections
- However, Spark behaves **very differently** than Scala collections
  - Spark uses ***laziness*** to save time and memory
- We saw *transformations* and *actions*
- We saw caching and persistence (*i.e.*, cache in memory, save time!)
- We saw how the cluster topology comes into the programming model
- We learned in detail about reduction operations in Spark vs Scala collections

What we've learned so far

Distributed Key-Value Pairs (Pair RDDs)

- We got a sampling of Spark's key-value pairs (Pair RDDs)
- We saw all of the different sorts of joins
- We learned other important operations on just Pair RDDs
- We got a glimpse of "shuffling"

Today...

Now that we understand Spark's programming model, and a majority of Spark's key operations, we'll now see how we can optimize what we do with Spark to keep it practical.

It's very easy to write clear code that takes tens of minutes to compute when it could be computed in only tends of seconds.

1. **Shuffling**

- What is it and why is it important?
- How do I know when it happens?
- How can I optimize an operation that requires a shuffle?

2. **Partitioning**
3. **Closures and Capturing**
4. **Shared Variables**

Grouping and Reducing, Example

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

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

// Returns: Array[(Int, (Int, Double))]
val purchasesPerMonth =
  purchasesRdd.map(p => (p.customerId, p.price)) // Pair RDD
              .groupByKey() // groupByKey returns RDD[K, Iterable[V]]
              .map(p => (p._1, (p._2.size, p._2.sum)))
              .collect()
```

Grouping and Reducing, Example – What's Happening?

Let's start with an example dataset:

```
val purchases = List(CFFPurchase(100, "Geneva", 22.25),
                     CFFPurchase(300, "Zurich", 42.10),
                     CFFPurchase(100, "Fribourg", 12.40),
                     CFFPurchase(200, "St. Gallen", 8.20),
                     CFFPurchase(100, "Lucerne", 31.60),
                     CFFPurchase(300, "Basel", 16.20))
```

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

Grouping and Reducing, Example – What's Happening?

What might this look like on the cluster?

Grouping and Reducing, Example

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

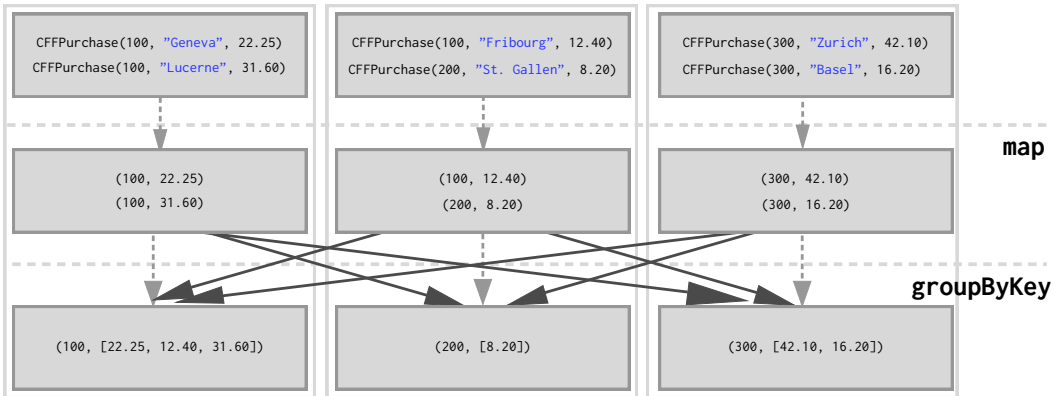
```
val purchasesRdd: RDD[CFFPurchase] = sc.textFile(...)


val purchasesPerMonth =
  purchasesRdd.map(p => (p.customerId, p.price)) // Pair RDD
              .groupByKey() // groupByKey returns RDD[K, Iterable[V]]
```

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

Grouping and Reducing, Example – What's Happening?

What might this look like on the cluster?



Grouping and Reducing, Example – What's Happening?

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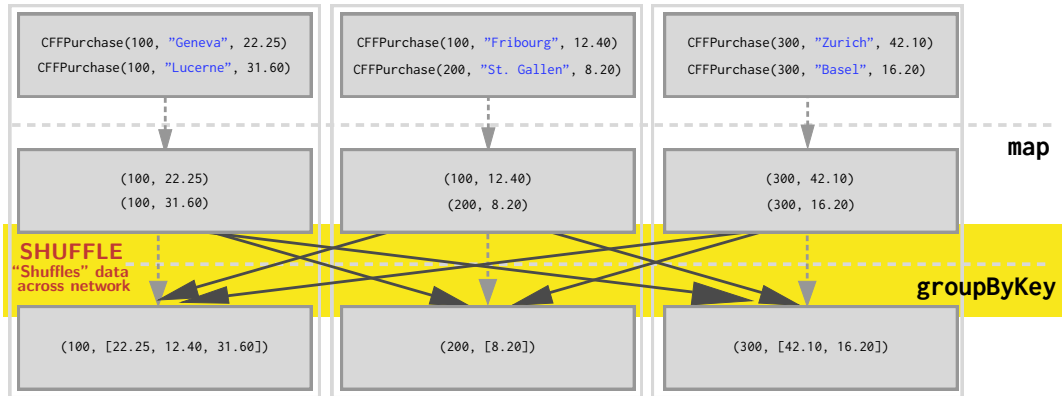
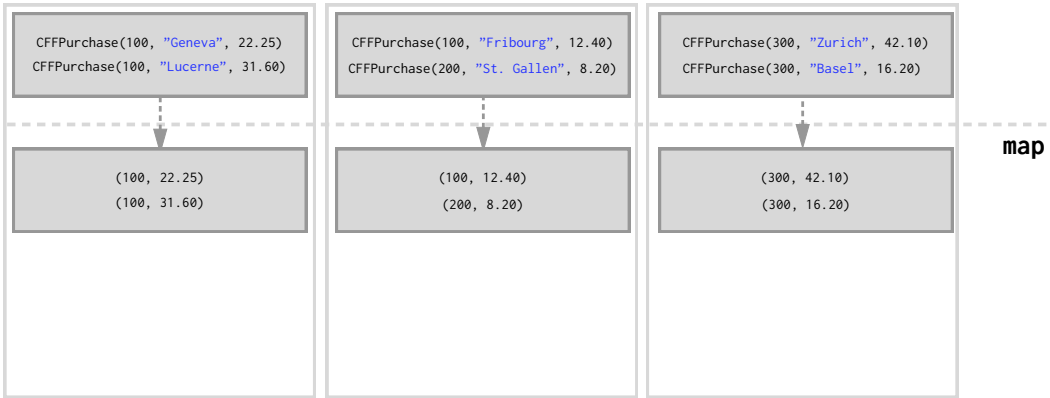


Can we do a better job?

Perhaps we don't need to send all pairs over the network.



Can we do a better job?

Perhaps we don't need to send all pairs over the network.

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

Grouping and Reducing, Example – Optimized

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)]
```

Grouping and Reducing, Example – Optimized

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

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

val purchasesPerMonth =
  purchasesRdd.map(p => (p.customerId, (1, p.price))) // Pair RDD
              .reduceByKey(...) // ?
```

Grouping and Reducing, Example – Optimized

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

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

val purchasesPerMonth =
  purchasesRdd.map(p => (p.customerId, (1, p.price))) // Pair RDD
              .reduceByKey(...) // ?
```

Notice that the function passed to `map` *has changed. It's now* `p => (p.customerId, (1, p.price))`.

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

Grouping and Reducing, Example – Optimized

```
val purchasesPerMonth =
  purchasesRdd.map(p => (p.customerId, (1, p.price))) // Pair RDD
              .reduceByKey((v1, v2) => (v1._1 + v2._1, v1._2 + v2._2))
              .collect()
```

Grouping and Reducing, Example – Optimized

```
val purchasesPerMonth =
  purchasesRdd.map(p => (p.customerId, (1, p.price))) // Pair RDD
              .reduceByKey((v1, v2) => (v1._1 + v2._1, v1._2 + v2._2))
              .collect()
```

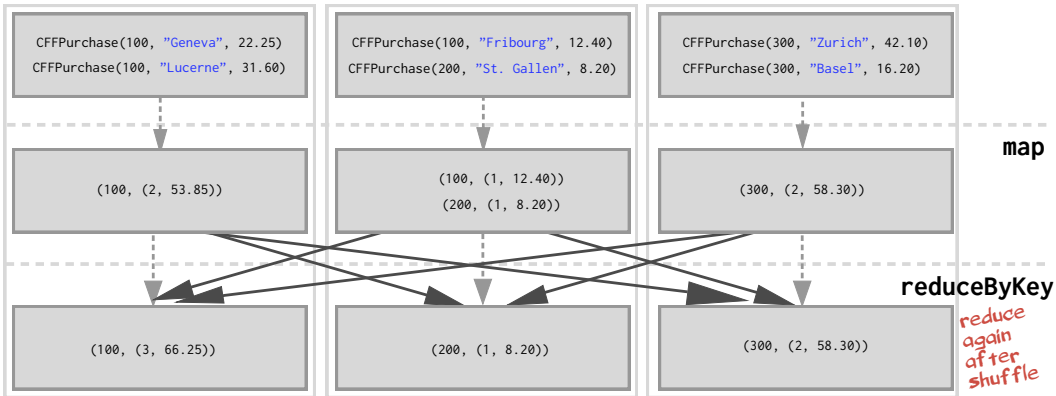
What might this look like on the cluster?

Grouping and Reducing, Example – Optimized

What might this look like on the cluster?

Grouping and Reducing, Example – Optimized

What might this look like on the cluster?



Grouping and Reducing, Example – Optimized

What are the benefits of this approach?

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

This can result in non-trival gains in performance!

Let's benchmark on a real cluster.

groupByKey and reduceByKey Running Times

```
> val purchasesPerMonthSlowLarge = purchasesRddLarge.map(p => (p.customerId, p.price))
                                                    .groupByKey()
                                                    .map(p => (p._1, (p._2.size, p._2.sum)))
                                                    .count()

  purchasesPerMonthSlowLarge: Long = 100000

  Command took 15.48s
```

```
> val purchasesPerMonthFastLarge = purchasesRddLarge.map(p => (p.customerId, (1, p.price)))
                                                    .reduceByKey((v1, v2) => (v1._1 + v2._1, v1._2 + v2._2))
                                                    .count()

  purchasesPerMonthFastLarge: Long = 100000

  Command took 4.65s
```

Full example with 20 million element RDD can be found in the lecture2-apr2 notebook on our Databricks Cloud installation.

Shuffling

Recall our example using `groupByKey`:

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

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?

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

“Partitioning”?

First, a quick detour into partitioning...

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()
```

`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*.

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: `[]`

The result is a very unbalanced distribution which hurts performance.

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.

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?

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.

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?

Consider the `map` transformation. Given 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 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.

Optimization using range partitioning

Using range partitioners we can optimize our earlier use of `reduceByKey` so that it does not involve any shuffling over the network at all!

```
val pairs = purchasesRdd.map(p => (p.customerId, p.price))
val tunedPartitioner = new RangePartitioner(8, pairs)

val partitioned = pairs.partitionBy(tunedPartitioner)

val purchasesPerCust =
  partitioned.map(p => (p._1, (1, p._2)))

val purchasesPerMonth = purchasesPerCust
      .reduceByKey((v1, v2) => (v1._1 + v2._1, v1._2 + v2._2))
      .collect()
```

Optimization using range partitioning

```
> val purchasesPerMonthSlowLarge = purchasesRddLarge.map(p => (p.customerId, p.price))
                                                    .groupByKey()
                                                    .map(p => (p._1, (p._2.size, p._2.sum)))
                                                    .count()

  purchasesPerMonthSlowLarge: Long = 100000

  Command took 15.48s
```

```
> val purchasesPerMonthFastLarge = purchasesRddLarge.map(p => (p.customerId, (1, p.price)))
                                                    .reduceByKey((v1, v2) => (v1._1 + v2._1, v1._2 + v2._2))
                                                    .count()

  purchasesPerMonthFastLarge: Long = 100000

  Command took 4.65s
```

On the range partitioned data:

```
> val purchasesPerMonthFasterLarge = partitioned.map(x => x)
                                                .reduceByKey((v1, v2) => (v1._1 + v2._1, v1._2 + v2._2))
                                                .count()

  purchasesPerMonthFasterLarge: Long = 100000

  Command took 1.79s
```

almost a 9x speedup over purchasePerMonthSlowLarge!

Back to shuffling

Recall our example using `groupByKey`:

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

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.

Grouping is done using a hash partitioner with default parameters.

The result RDD, `purchasesPerCust`, is configured to use the hash partitioner that was used to construct it.

How do I know a shuffle will occur?

Rule of thumb: a shuffle *can* occur when the resulting RDD depends on other elements from the same RDD or another RDD.

Note: sometimes one can be clever and avoid much or all network communication while still using an operation like `join` *via smart partitioning*

How do I know a shuffle will occur?

You can also figure out whether a shuffle has been planned/executed via:

1. The return type of certain transformations, *e.g.*,

```
org.apache.spark.rdd.RDD[(String, Int)] = ShuffledRDD[366]
```

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

```
partitioned.reduceByKey((v1, v2) => (v1._1 + v2._1, v1._2 + v2._2))
           .toDebugString
res9: String =
(8) MapPartitionsRDD[622] at reduceByKey at <console>:49 []
 |  ShuffledRDD[615] at partitionBy at <console>:48 []
 |      CachedPartitions: 8; MemorySize: 1754.8 MB; DiskSize: 0.0 B
```

Operations that *might* cause a shuffle

- `cogroup`
- `groupWith`
- `join`
- `leftOuterJoin`
- `rightOuterJoin`
- `groupByKey`
- `reduceByKey`
- `combineByKey`
- `distinct`
- `intersection`
- `repartition`
- `coalesce`

Avoiding a Network Shuffle By Partitioning

There are a few ways to use operations that *might* cause a shuffle and to still avoid much or all network shuffling.

Can you think of an example?

2 Examples:

1. `reduceByKey` running on a pre-partitioned RDD will cause the values to be computed *locally*, requiring only the final reduced value has to be sent from the worker to the driver.
2. `join` called on two RDDs that are pre-partitioned with the same partitioner and cached on the same machine will cause the join to be computed *locally*, with no shuffling across the network.

Closures

Closures are central to RDDs.

- Passed to most transformations.
- Passed to *some* actions (like `reduce` and `foreach`).

However, they can also cause issues that are *specific to distribution* (but would not be problematic with parallel collections, say)

Two main issues:

1. Serialization exceptions at run time when closures are not serializable.
2. **Closures that are "too large."**

Closure Troubles: Example

```
class MyCoolApp {
  val repos: RDD[Repository] = ... // repositories on GitHub (many!)
  val team: Map[String, List[String]] = ... // maps username to skills
  // GitHub repos that users in "team" map contribute to
  def projects(): Array[Repository] = {
    val filtered = repos.filter { repo =>
      team.exists(user => repo.contributors.contains(user))
    }
    filtered.collect()
  }
}
```

What happens when you run this?

Closure Troubles: Example

What happens when you run this?

java.io.NotSerializableException

Why?

Closure Troubles: Example

What happens when you run this?

java.io.NotSerializableException

Why?

Let's have a look at the closure passed to the RDD:

```
val filtered = repos.filter { repo =>
  team.exists(user => repo.contributors.contains(user))
}
```

Closure Troubles: Example

What happens when you run this?

java.io.NotSerializableException

Why?

Let's have a look at the closure passed to the RDD:

```
val filtered = repos.filter { repo =>
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}
```

Is this closure serializable?

Closure Troubles: Example

What happens when you run this?

java.io.NotSerializableException

Why?

Let's have a look at the closure passed to the RDD:

```
val filtered = repos.filter { repo =>
  team.exists(user => repo.contributors.contains(user))
}
```

Is this closure serializable?

It should be: it only captures the "team" map. `Map[String, List[String]]` is serializable in Scala.

Closure Troubles: Example

What happens when you run this?

java.io.NotSerializableException

Why?

Let's have a look at the closure passed to the RDD:

```
val filtered = repos.filter { repo =>
  team.exists(user => repo.contributors.contains(user))
}
```

Is this closure serializable?

It should be: it only captures the "team" map. `Map[String, List[String]]` is serializable in Scala.

In reality: closure is **not serializable!**

Closures: Variable Capture

A closure is serializable if...

...all captured variables are serializable.

```
val filtered = repos.filter { repo =>
  team.exists(user => repo.contributors.contains(user))
}
```

What are the captured variables?

Just `team`.

Closures: Variable Capture

A closure is serializable if...

...all captured variables are serializable.

```
val filtered = repos.filter { repo =>
  team.exists(user => repo.contributors.contains(user))
}
```

What are the captured variables?

Just `team`.

Wrong!

Closures: Variable Capture

A closure is serializable if...

...all captured variables are serializable.

Instead of `team`, it is `this` (of type `MyCoolApp`) which is captured:

```
val filtered = repos.filter { repo =>
  this.team.exists(user => repo.contributors.contains(user))
}
```

However, `this` is not serializable. `MyCoolApp` does not extend the marker interface `Serializable`.

Closure Trouble: Solution 1

Make a local copy of `team`. No more accidental capturing of `MyCoolApp`.

It should be written like this:

```
val localTeam = team
val filtered = repos.filter { repo =>
  localTeam.keys.exists(user => repo.contributors.contains(user))
}
```

With `localTeam`, `this` is no longer captured. **Now it's serializable**.

Closure Trouble: Big Closures

Let's assume that `this` and everything within it (`MyCoolApp`) is serializable.

Problem:

It could be silently capturing, serializing, and sending over the network, some huge pieces of captured data. Typically the only hint of this occurring is high memory usage and long run times.

Note: this is a real problem which could appear in your programming assignments! If you're using too much memory, and if performance is slow, make sure you're not accidentally capturing large enclosing objects!

Shared Variables

Normally, when a function passed to a Spark operation (such as map or reduce) is executed on a remote cluster node, it works on separate copies of all the variables used in the function.

These variables are copied to each machine, and no updates to the variables on the remote machine are propagated back to the driver program.

However, Spark does provide two limited types of shared variables for two common usage patterns:

1. **Broadcast variables**
2. **Accumulators**

Broadcast Variables

Let's revisit the closure from a few slides ago:

```
val localTeam = team
val filtered = repos.filter { repo =>
  localTeam.keys.exists(user => repo.contributors.contains(user))
}
```

1. What if `localTeam`/`team` is a `Map` of thousands of elements?
2. What if several operations require it?

Broadcast Variables

Let's revisit the closure from a few slides ago:

```
val localTeam = team
val filtered = repos.filter { repo =>
  localTeam.keys.exists(user => repo.contributors.contains(user))
}
```

1. What if `localTeam`/`team` is a `Map` of thousands of elements?
2. What if several operations require it?

This is the ideal use-case for *broadcast variables*.

Broadcast Variables

Broadcast variables:

- allow the programmer to keep a read-only variable cached on each machine rather than shipping a copy of it with tasks.

They can be used, for example, to give every node a copy of a large input dataset in an efficient manner.

Spark also distributes broadcast variables using efficient broadcast algorithms to reduce communication cost.

Broadcast Variables

To make `localTeam`/`team` a broadcast variable, all we have to do is:

```
val broadcastTeam = sc.broadcast(team)
```

We can then use it in our closures without having to ship it over the network multiple times!

(Its value can be accessed by calling the `value` *method)*

```
val filtered = repos.filter { repo =>
  broadcastTeam.value.keys.exists(user => repo.contributors.contains(user))
}
```

Accumulators

Accumulators:

- are variables that are only "added" to through an associative operation and can therefore be efficiently supported across nodes in parallel.
- provide a simple syntax for aggregating values from worker nodes back to the driver program.

They can be used to implement counters (as in MapReduce) or sums.

Out of the box, only numeric accumulators are supported in Spark. But it's possible to add support for your own types with a bit of effort.

Accumulators: Example

val badRecords = sc.accumulator(0) val badBytes = sc.accumulator(0.0)

```
records.filter(r => {
  if (isBad(r)) {
    badRecords += 1
    badBytes += r.size
    false
  } else {
    true
  }
}).save(...)

printf("Total bad records: %d, avg size: %f\n",
 badRecords.value, badBytes.value / badRecords.value)
```

Accumulators

Accumulators can appear both in transformations and actions.

What about fault tolerance? What happens to an accumulator when a node dies and must be restarted?

Accumulators and fault tolerance:

- **Actions:** Each tasks' update is applied to each accumulator only once.
- **Transformations:** An accumulator update within a transformation can occur more than once. E.g., when an RDD is recomputed from its lineage, it can update the accumulator. *Should only be used for debugging in transformations*.