



ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Reduction Operations

Big Data Analysis with Scala and Spark

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What we've seen so far

- ▶ we defined *Distributed Data Parallelism*
- ▶ we saw that Apache Spark implements this model
- ▶ we got a feel for what latency means to distributed systems

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Spark's Programming Model

- ▶ We saw that, at a glance, Spark looks like Scala collections
- ▶ However, internally, Spark behaves 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

Transformations to Actions

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But what about actions? In particular, how are common reduce-like actions distributed in Spark?

Reduction Operations, Generally

First, what do we mean by “reduction operations”?

Recall operations such as `fold`, `reduce`, and `aggregate` from Scala sequential collections. All of these operations and their variants (such as `foldLeft`, `reduceRight`, etc) have something in common.

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Example:

```
case class Taco(kind: String, price: Double)
```

```
val tacoOrder =  
  List(  
    Taco("Carnitas", 2.25),  
    Taco("Corn", 1.75),  
    Taco("Barbacoa", 2.50),  
    Taco("Chicken", 2.00))
```

```
val cost = tacoOrder.foldLeft(0.0)((sum, taco) => sum + taco.price)
```


Parallel Reduction Operations

Recall what we learned in the course Parallel Programming course about foldLeft vs fold.

Which of these two were parallelizable?

Parallel Reduction Operations

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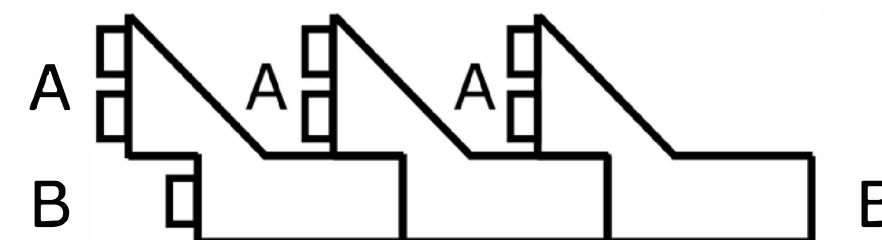
Which of these two were parallelizable?

`foldLeft` is not parallelizable.

```
def foldLeft[B](z: B)(f: (B, A) => B): B
```

Applies a binary operator to a start value and all elements of this collection or iterator, going left to right.

— Scala API documentation



Parallel Reduction Operations: FoldLeft

foldLeft is not parallelizable.

```
def foldLeft[B](z: B)(f: (B, A) => B): B
```

Being able to change the result type from A to B forces us to have to execute foldLeft sequentially from left to right.

Concretely, given:

"1234"

```
val xs = List(1, 2, 3, 4)
```

```
val res = xs.foldLeft("")(str: String, i: Int) => str + i)
```

What happens if we try to break this collection in two and parallelize?

Parallel Reduction Operations: FoldLeft

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```

List(1, 2)

" " + 1 → "1"
"1" + 2 → "12"
string

List(3, 4)

" " + 3 → "3"
"3" + 4 → "34"
String

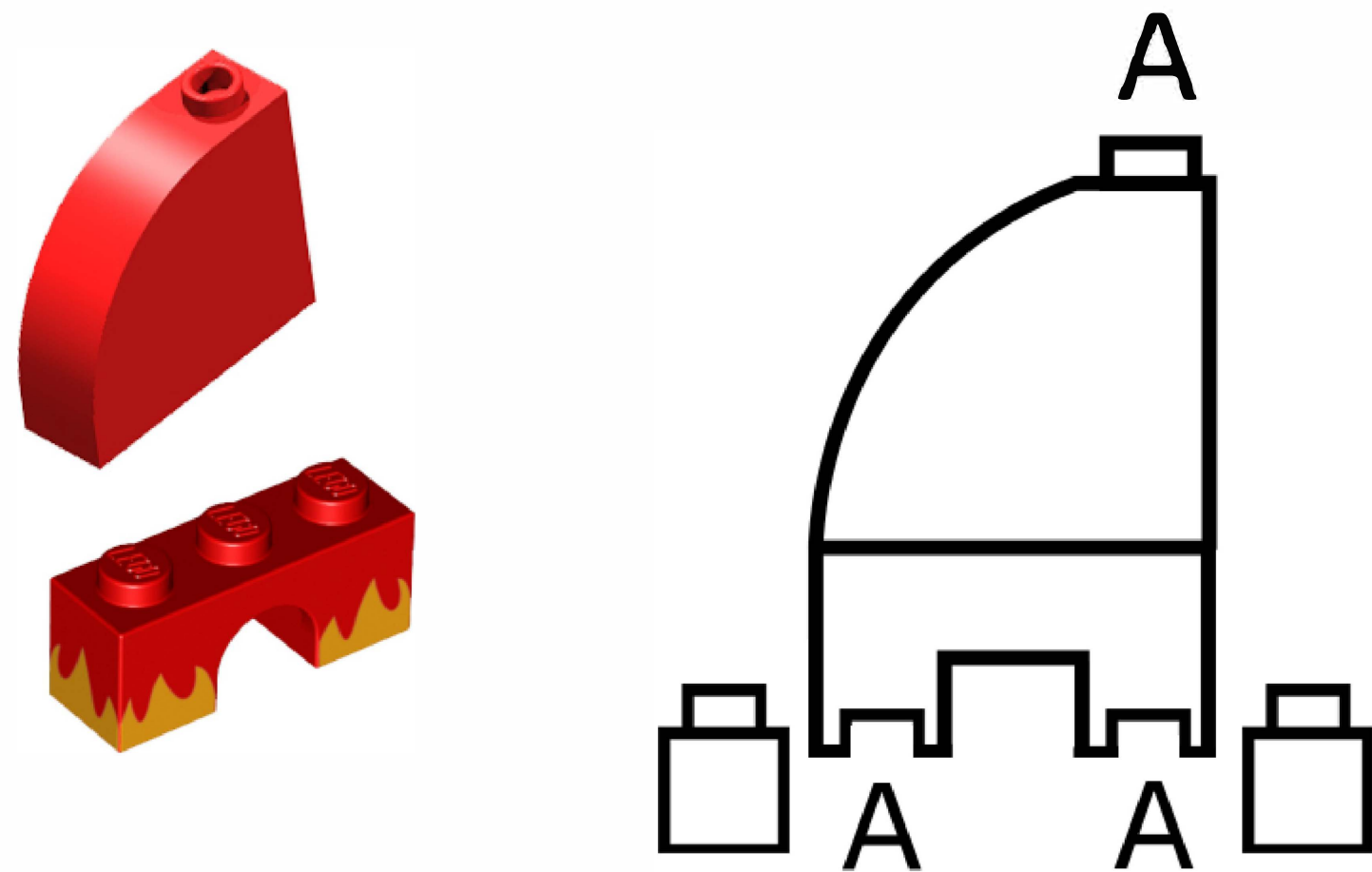
!!! type error !!!

can't apply
(str: String, i: Int) => str + i !!!

Parallel Reduction Operations: Fold

fold enables us to parallelize things, but it restricts us to always returning the same type.

```
def fold(z: A)(f: (A, A) => A): A
```

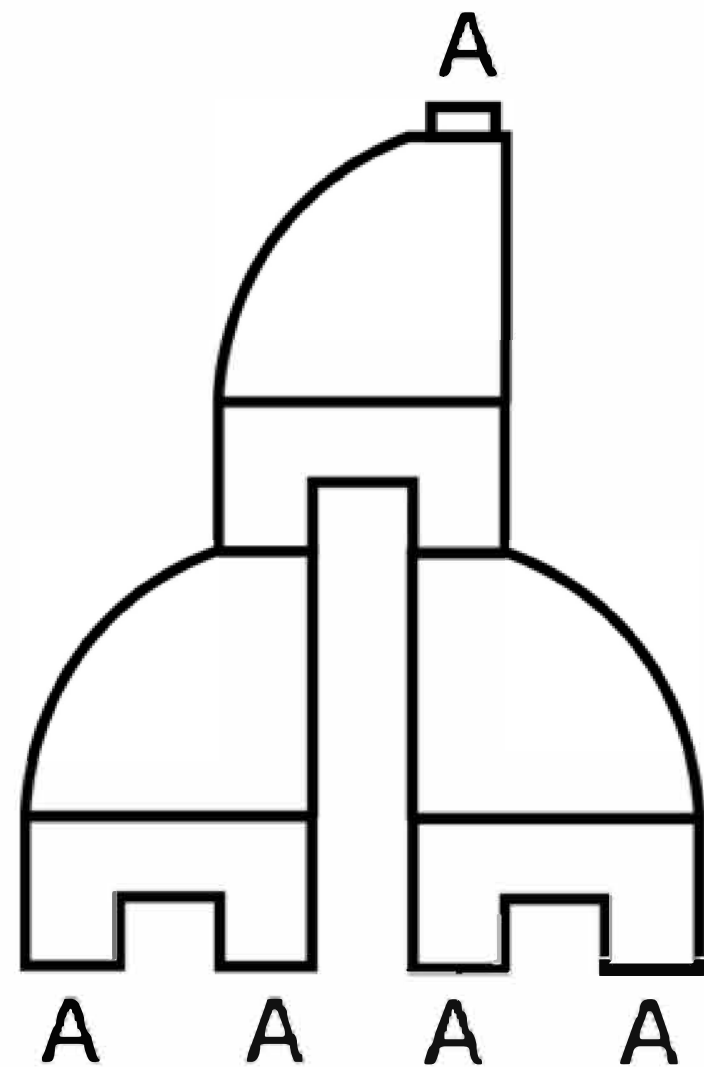
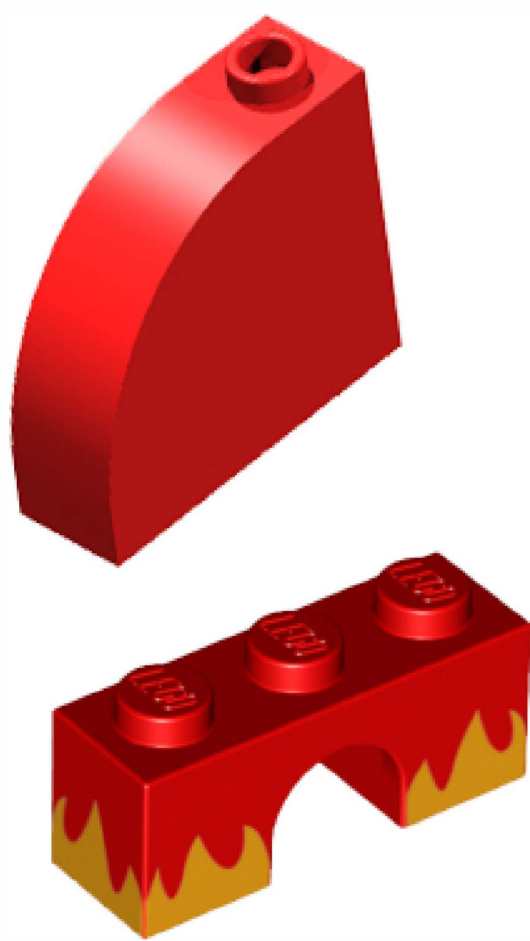


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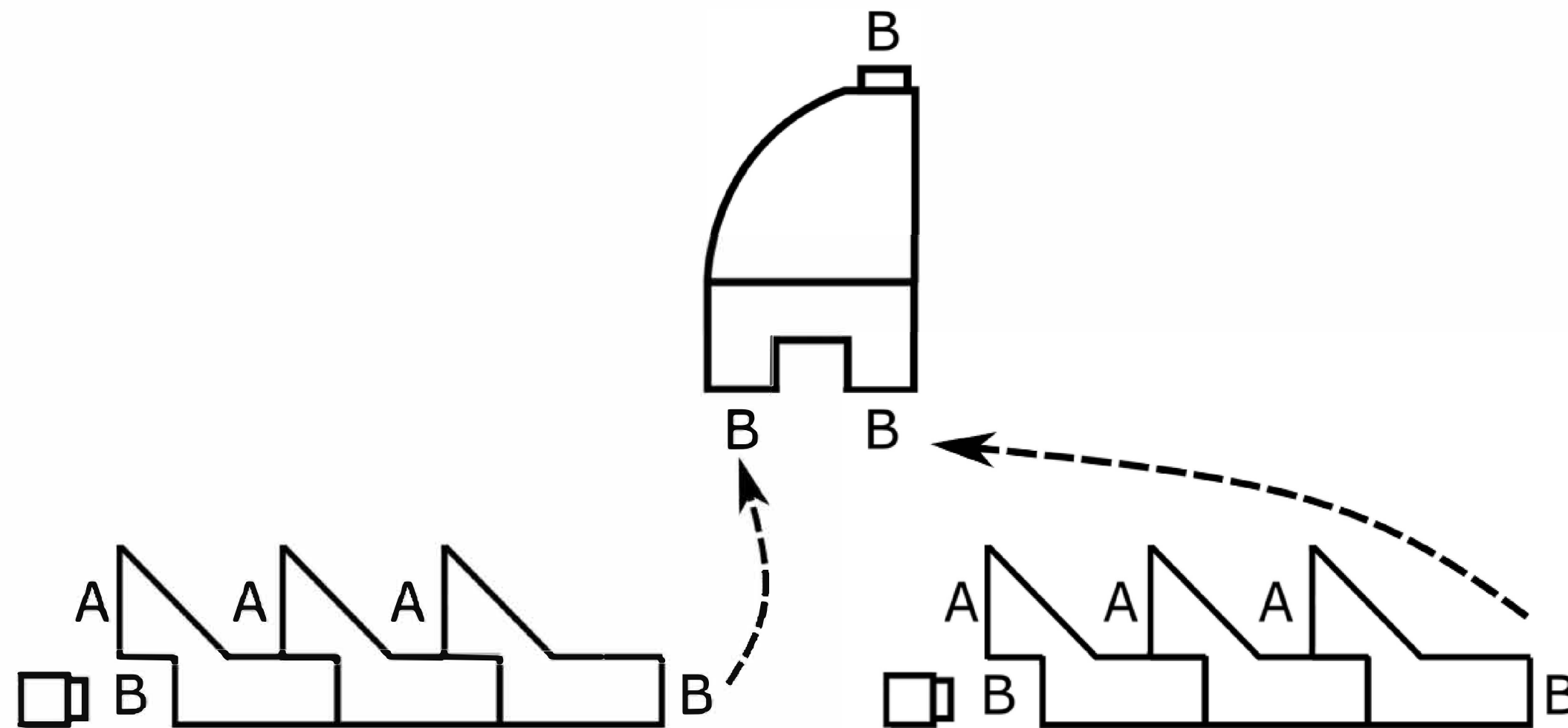
aggregate is said to be general because it gets you the best of both worlds.

Properties of aggregate

1. Parallelizable.
2. Possible to change the return type.

Parallel Reduction Operations: Aggregate

`aggregate[B](z: => B)(seqop: (B, A) => B, combop: (B, B) => B): B`



Aggregate lets you still do sequential-style folds *in chunks* which change the result type. Additionally requiring the combop function enables building one of these nice reduce trees that we saw is possible with fold to *combine these chunks* in parallel.

Reduction Operations on RDDs

Scala collections:

fold

foldLeft/foldRight

reduce

aggregate

Spark:

fold

~~foldLeft/foldRight~~

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***Question:** Why not still have a serial foldLeft/foldRight on Spark?*

Doing things serially across a cluster is actually difficult. Lots of synchronization. Doesn't make a lot of sense.

RDD Reduction Operations: Aggregate

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As you will realize from experimenting with our Spark ^{assignments}~~cluster~~, much of the time when working with large-scale data, our goal is to ***project down from larger/more complex data types.***


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In Spark, aggregate is a more desirable reduction operator a majority of the time. Why do you think that's the case?

As you will realize from experimenting with our Spark cluster, much of the time when working with large-scale data, our goal is to ***project down from larger/more complex data types.***

Example:

```
case class WikipediaPage(  
  title: String,  
  redirectTitle: String,  
  timestamp: String,  
  lastContributorUsername: String,  
  text: String)
```



RDD Reduction Operations: Aggregate

As you will realize after experimenting with Spark a bit, much of the time when working with large-scale data, your goal is to ***project down from larger/more complex data types***.

Example:

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case class WikipediaPage(  
  title: String,  
  redirectTitle: String,  
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```

I might only care about title and timestamp, for example. In this case, it'd save a lot of time/memory to not have to carry around the full-text of each article (text) in our accumulator!

Hence, why accumulate is often more desirable in Spark than in Scala collections!