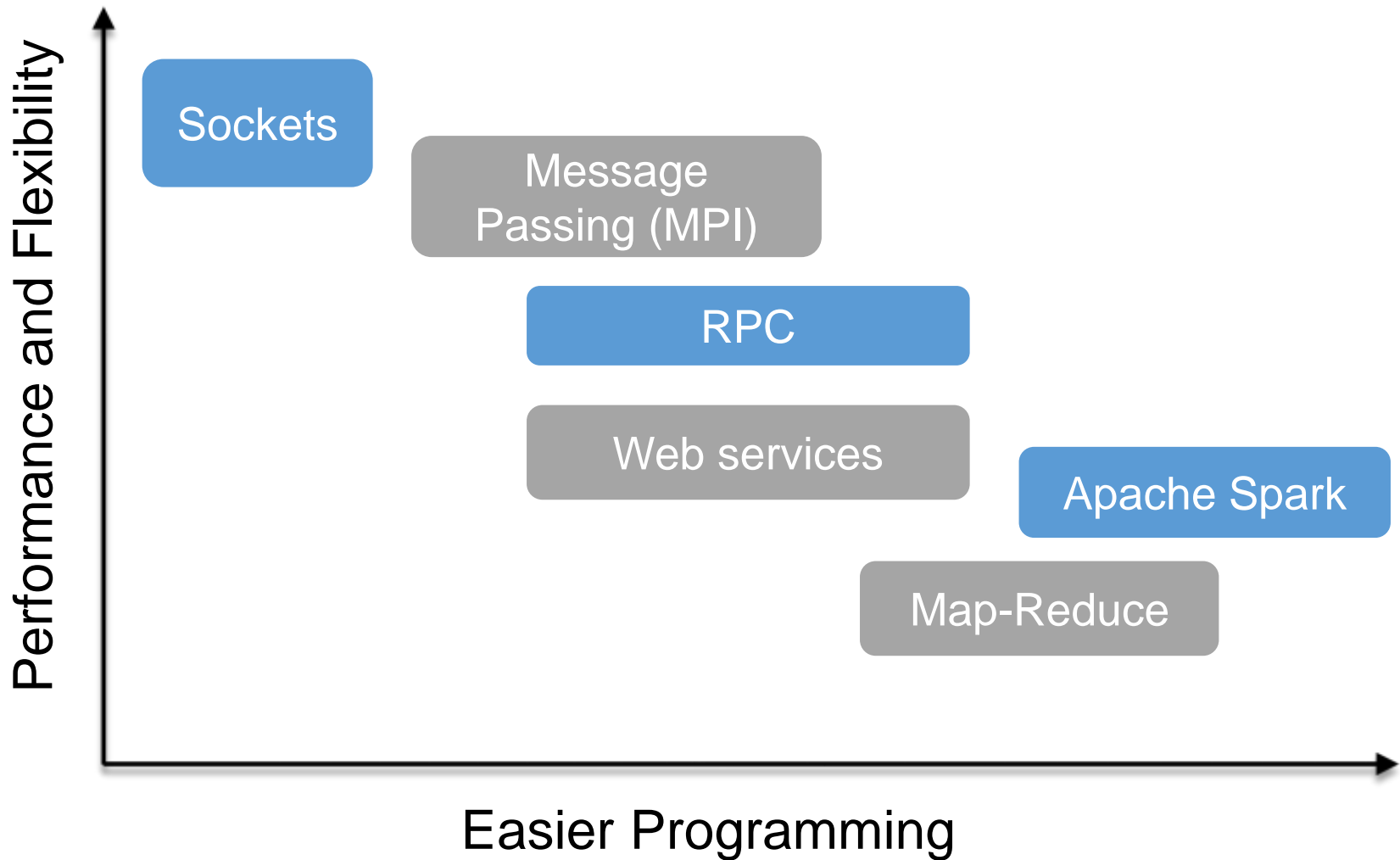


Verteilte Systeme/ Distributed Systems

Artur Andrzejak

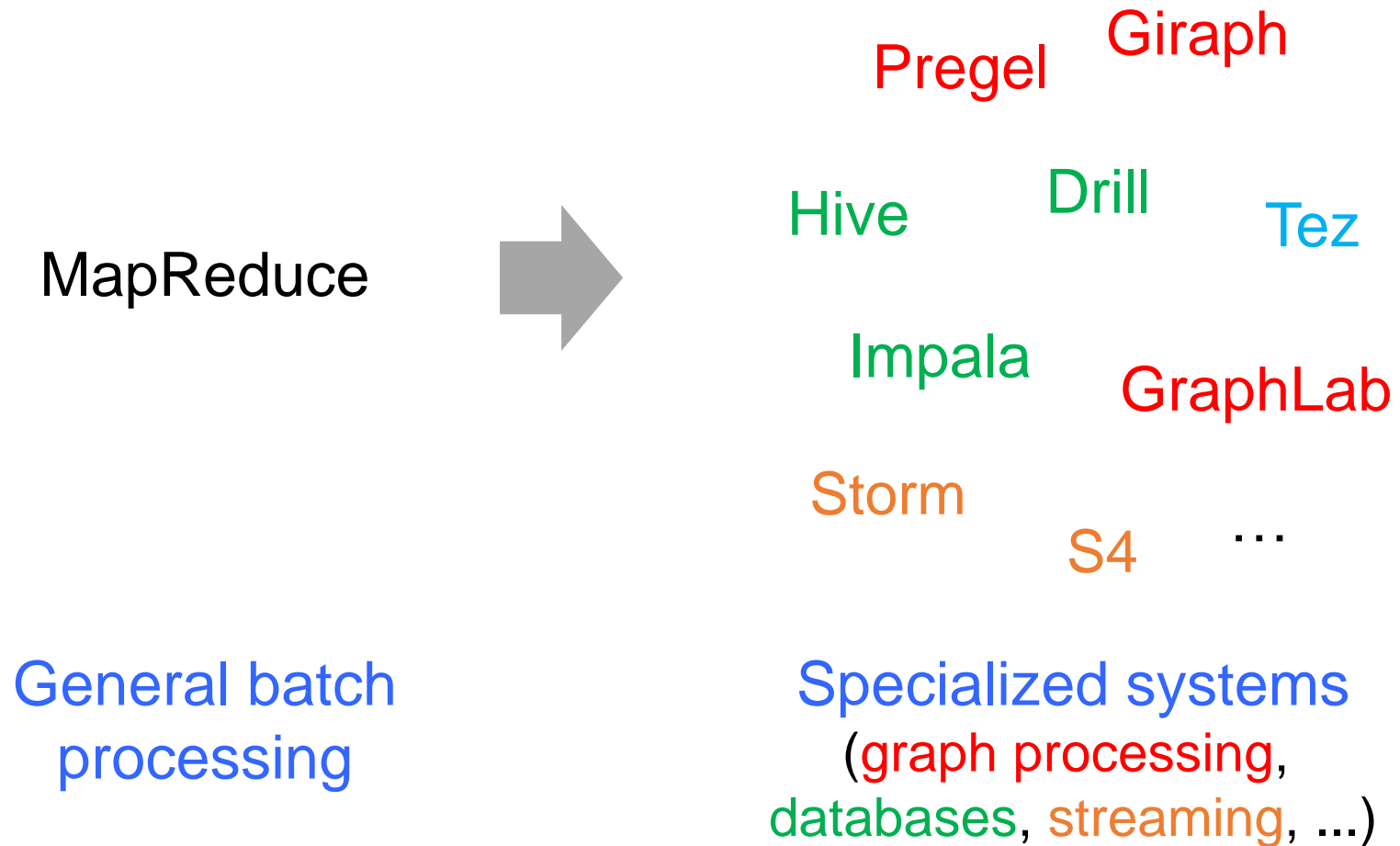
4

Trade-offs Distributed Programming



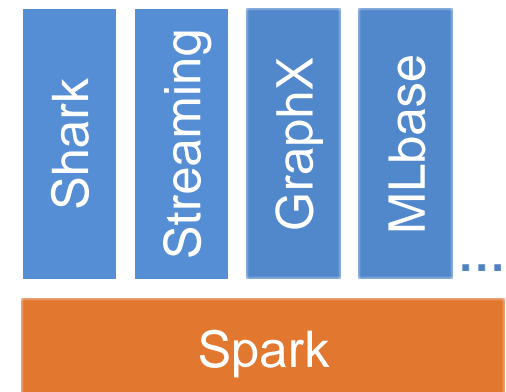
Apache Spark: Basics

MapReduce Problems



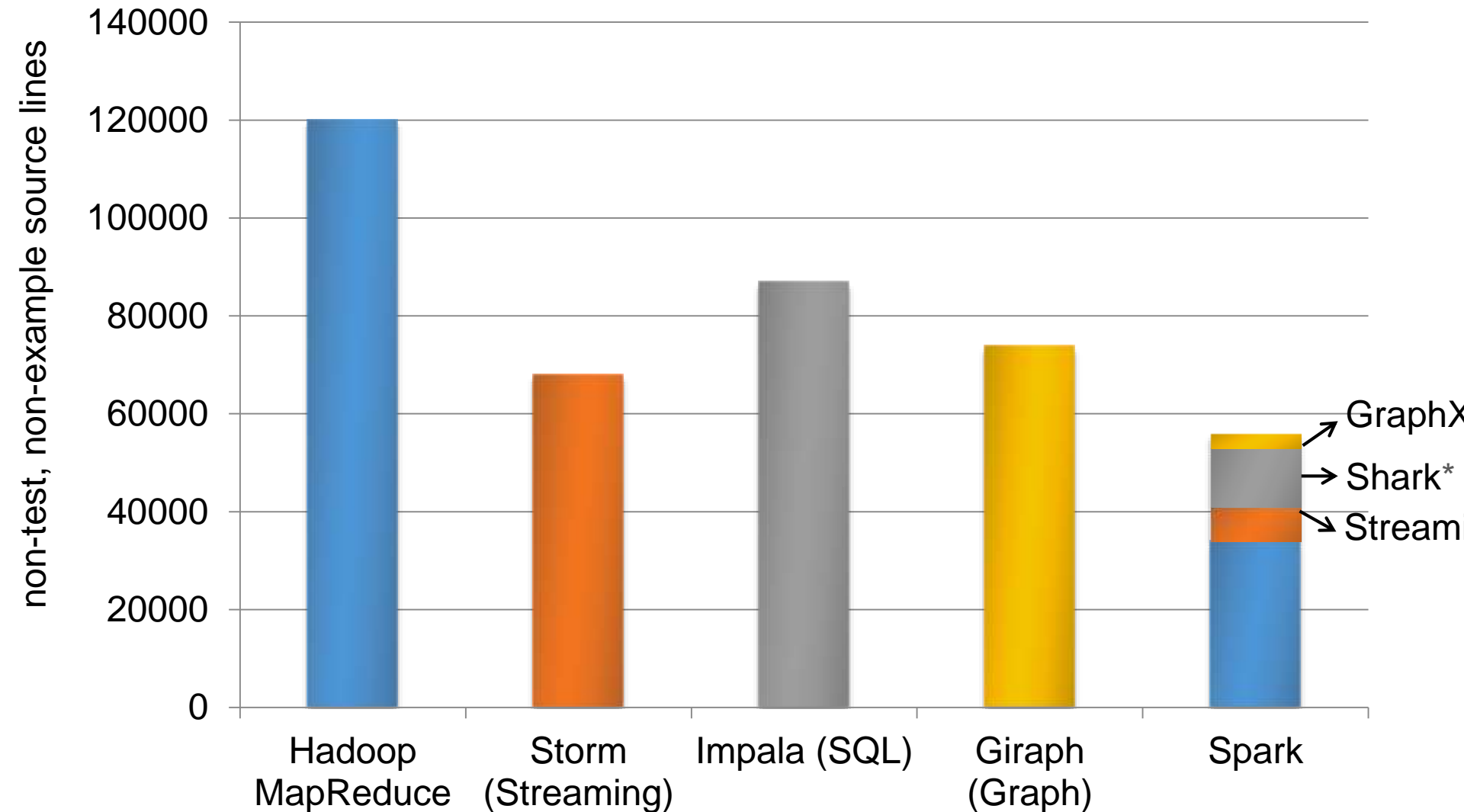
Spark's Approach

- ▶ Instead of specializing, *generalize* MapReduce to support new apps in same engine
- ▶ Two changes (general task DAG & data sharing) are enough to express previous models!
- ▶ Unification has big benefits
 - ▶ For the engine
 - ▶ For users



From: The State of Spark, and Where We're Going Next
Matei Zaharia, Spark Summit (2013)

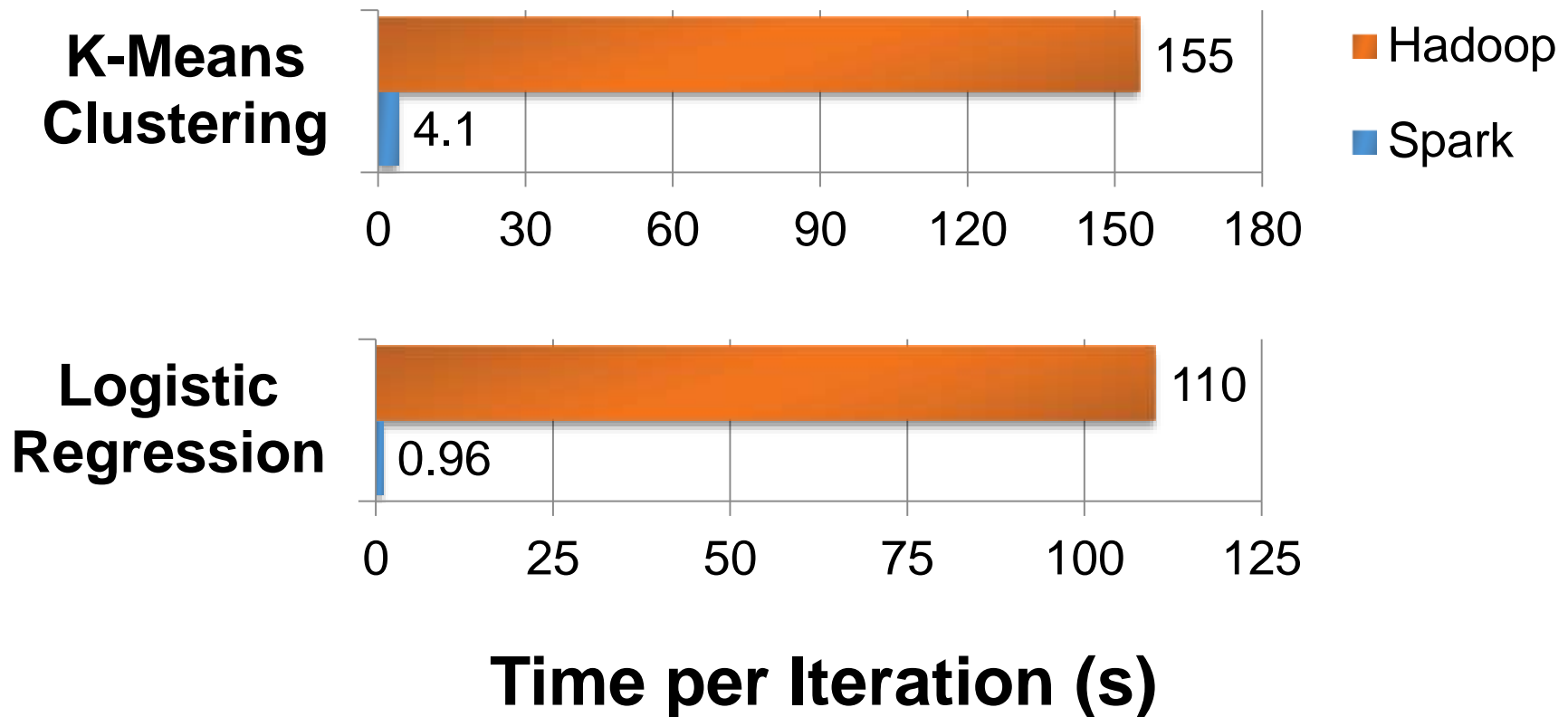
Code Size: Spark vs. Others



From: *The State of Spark, and Where We're Going Next*
Matei Zaharia, Spark Summit (2013)

* also calls into Hive

Performance: Iterative Algorithms

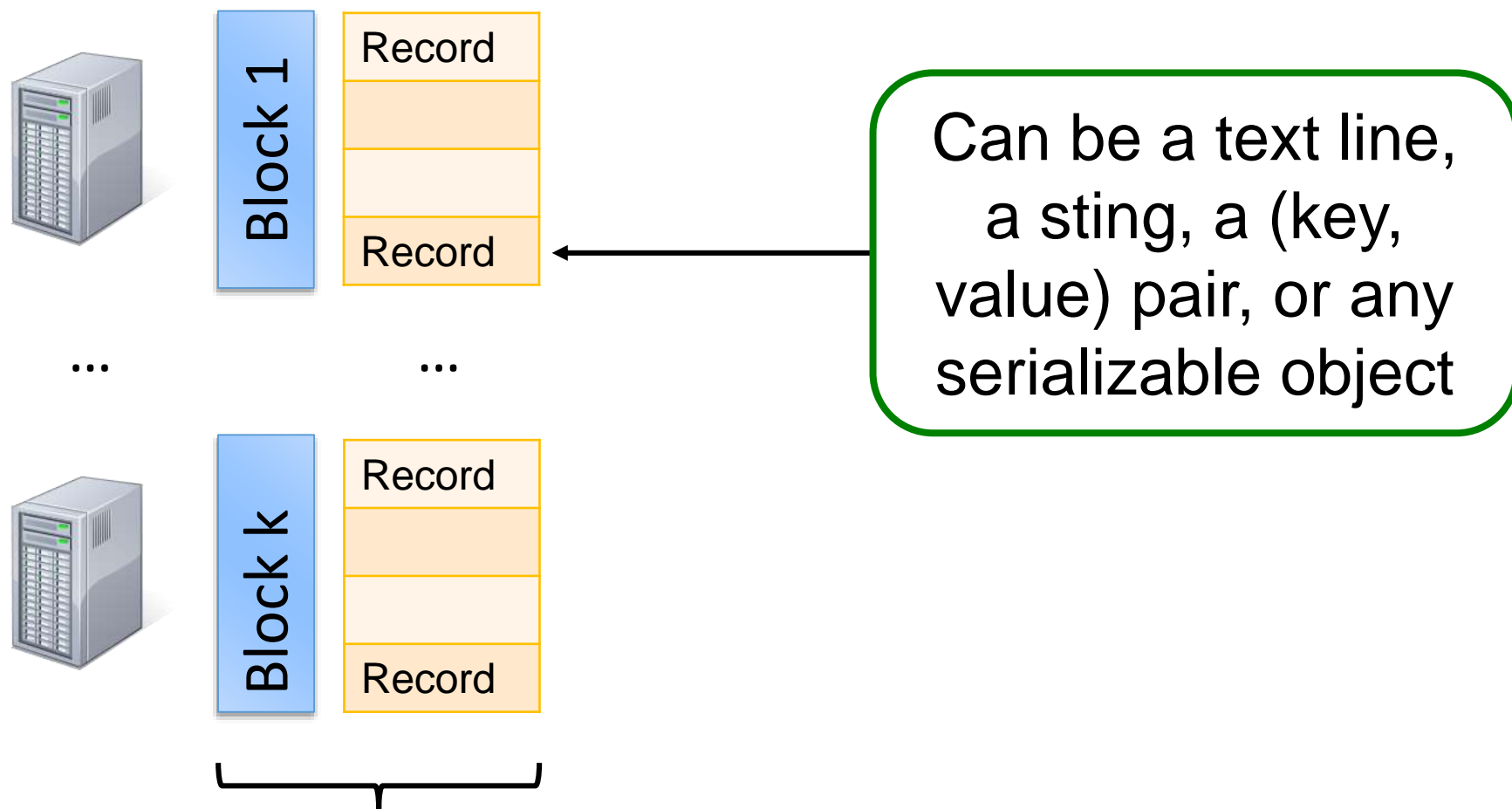


Spark: Key Ideas and Data Structure

- ▶ Write programs in terms of **transformations on distributed datasets**
- ▶ Main data structure: **resilient distributed dataset (RDD)**
 - ▶ Collections of **records** spread across a cluster



Resilient Distributed Dataset (RDD)

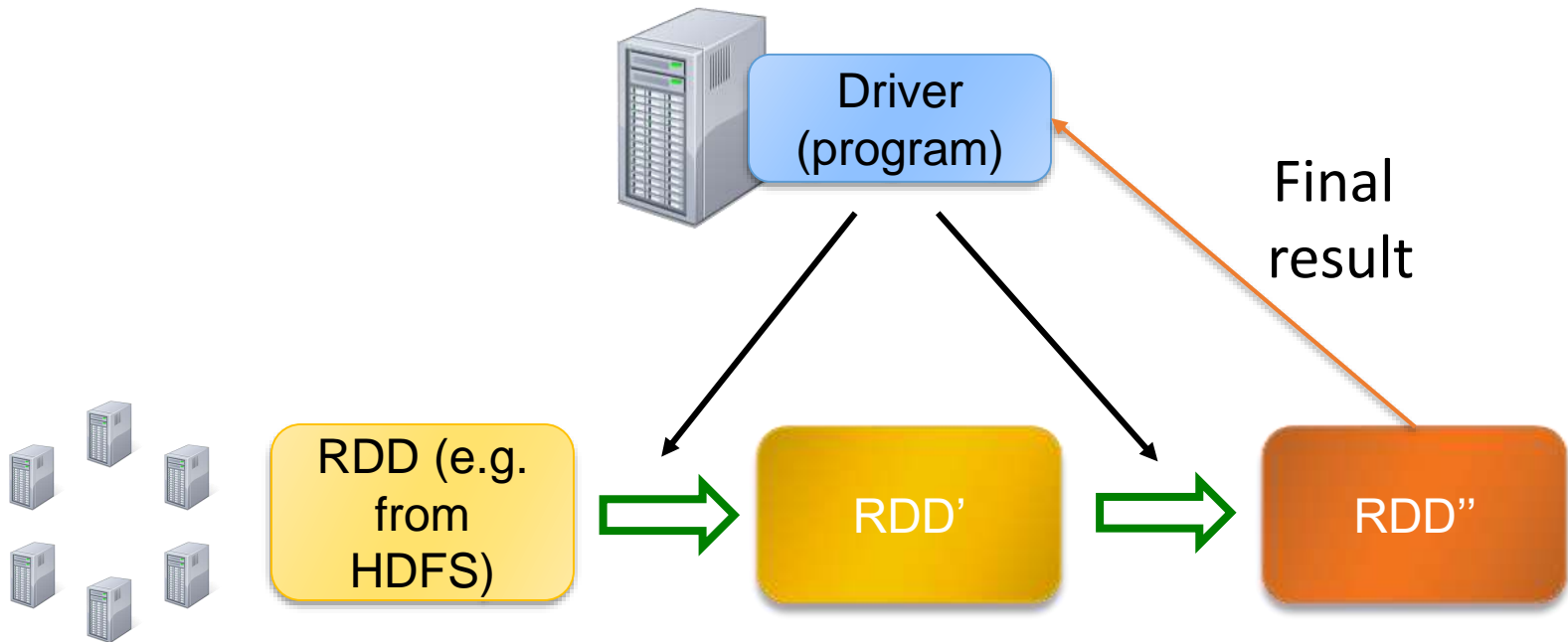


A RDD; accessible in code via a single “variable”

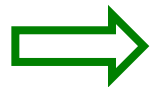
Operations

- ▶ **Transformations** (e.g. map, filter, groupBy)
 - ▶ Lazy operations to build RDDs from other RDDs
- ▶ **Actions** (e.g. count, collect, save)
 - ▶ Return a result or write it to storage

Computations with RDDs



Cluster of
workers



“transformation”



“action”



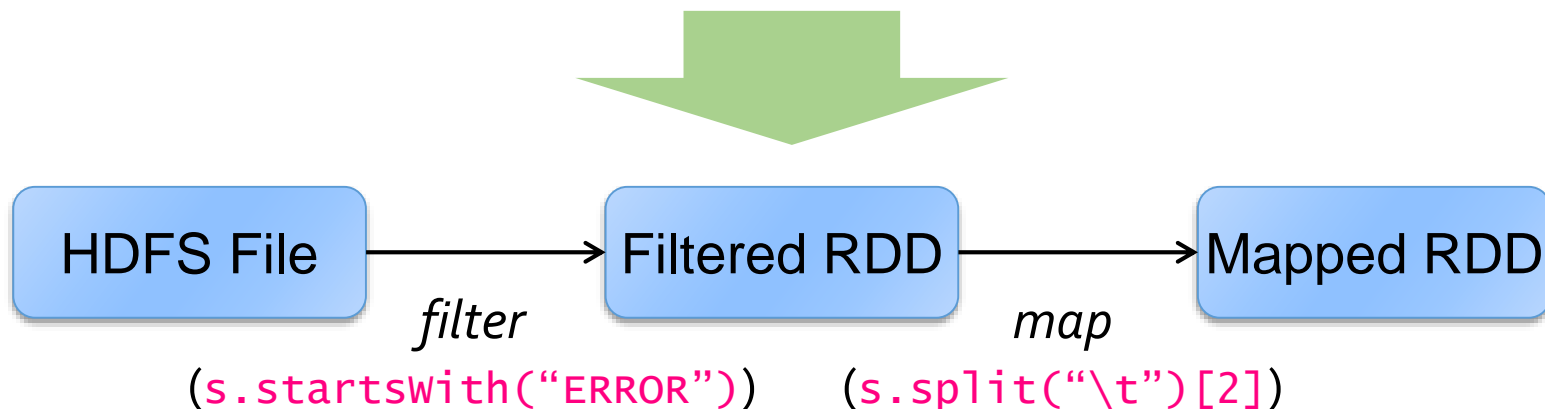
Code and variables for Ts and As

Fault Recovery

RDDs track *lineage* information that can be used to efficiently recompute lost data

Ex:

```
msgs = textFile.filter(lambda s: s.startsWith("ERROR"))  
               .map(lambda s: s.split("\t")[2])
```



Creating RDDs (Python)

SparkContext is the “entry point” to Spark functionality, here referenced by variable `sc`

- ▶ `# Turn a Python list [1, 2, 3] into an RDD`
- ▶ `sc.parallelize([1, 2, 3])`
- ▶ `# Load text file from local FS (file/dir) or HDFS`
- ▶ `sc.textFile("file.txt")`
- ▶ `sc.textFile("directory/*.txt")`
- ▶ `sc.textFile("hdfs://namenode:9000/path/file")`

Interlude: Lambdas in Python

- ▶ We need to pass code to Ts and As
 - ▶ Handle code like variables
- ▶ Convenient: **anonymous functions**, or inline functions; in Python: **lambda functions**
- ▶ Syntax:

lambda <params> : expression
- ▶ Example – computing x^2
 - ▶ `g = lambda x: $x^{**}2$` ; same as `def g(x): return $x^{**}2$`
- ▶ What is this doing?
 - ▶ `lambda x, y: $x^{**}2 + y^{**}2 \leq 1.0$`

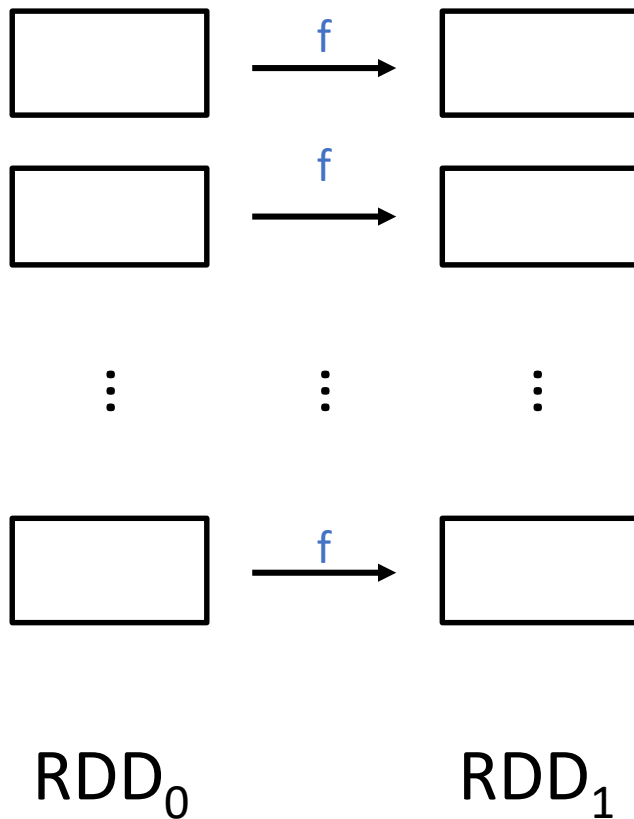
Basic Transformations

- ▶ `nums = sc.parallelize([1, 2, 3])`
- ▶ `# Pass each element through a function`
- ▶ `squares = nums.map(lambda x: x*x) // {1, 4, 9}`
- ▶ `# Keep elements passing a predicate`
- ▶ `even = squares.filter(lambda x: x % 2 == 0) // {4}`
- ▶ `# Map each element to zero or more others`
- ▶ `flats = nums.flatMap(lambda x: [x, -x, x*x])`
`# => {1, -1, 1, 2, -2, 4, 3, -3, 9}`

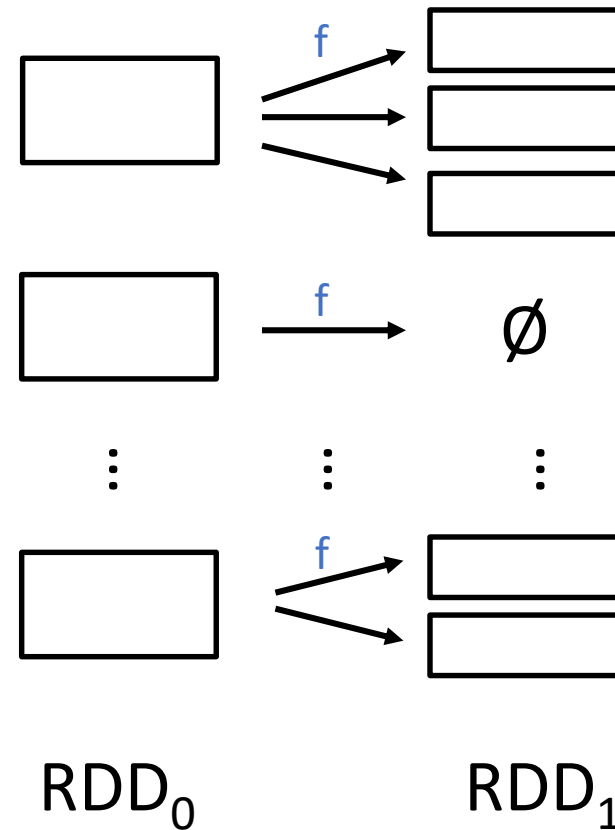


Essential Transformations

map with $f: \text{val} \rightarrow \text{val}$

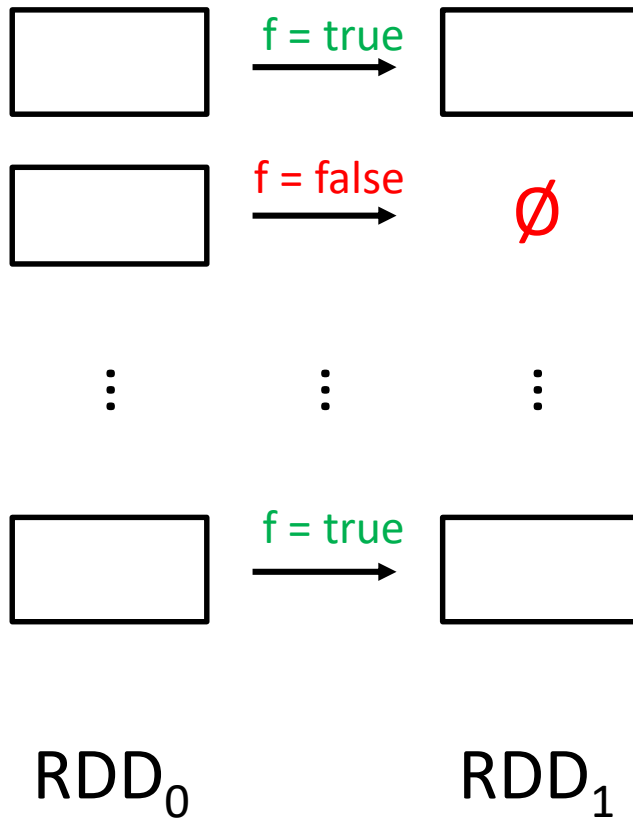


flatMap with
 $f: \text{val} \rightarrow [\text{val}, \dots, \text{val}]$



Essential Transformations

filter with `f:val -> boolean`



Others (useful):

- union
- distinct
- join
- groupByKey ...

Basic Actions

- ▶ `nums = sc.parallelize([1, 2, 3])`
- ▶ `# Retrieve RDD contents as a local collection`
- ▶ `nums.collect() # => [1, 2, 3]`
- ▶ `# Return first K elements`
- ▶ `nums.take(2) # => [1, 2]`
- ▶ `# Count number of elements`
- ▶ `nums.count() # => 3`
- ▶ `# Merge elements with an associative function`
`nums.reduce(lambda x, y: x + y) # => 6`
- ▶ `# Write elements to a text file`
`nums.saveAsTextFile("hdfs://file.txt")`



„Reduce“-Action

reduce with f: **val**, **val** -> **val**

⋮

Working with Key-Value Pairs

- ▶ Spark's “distributed reduce” transformations operate on RDDs of **key-value pairs**

- ▶ Python:

```
pair = (a, b)
pair[0] # => a
pair[1] # => b
```

- ▶ Scala:

```
val pair = (a, b)
pair._1 // => a
pair._2 // => b
```

- ▶ Java:

```
Tuple2 pair = new Tuple2(a, b);
pair._1 // => a
pair._2 // => b
```



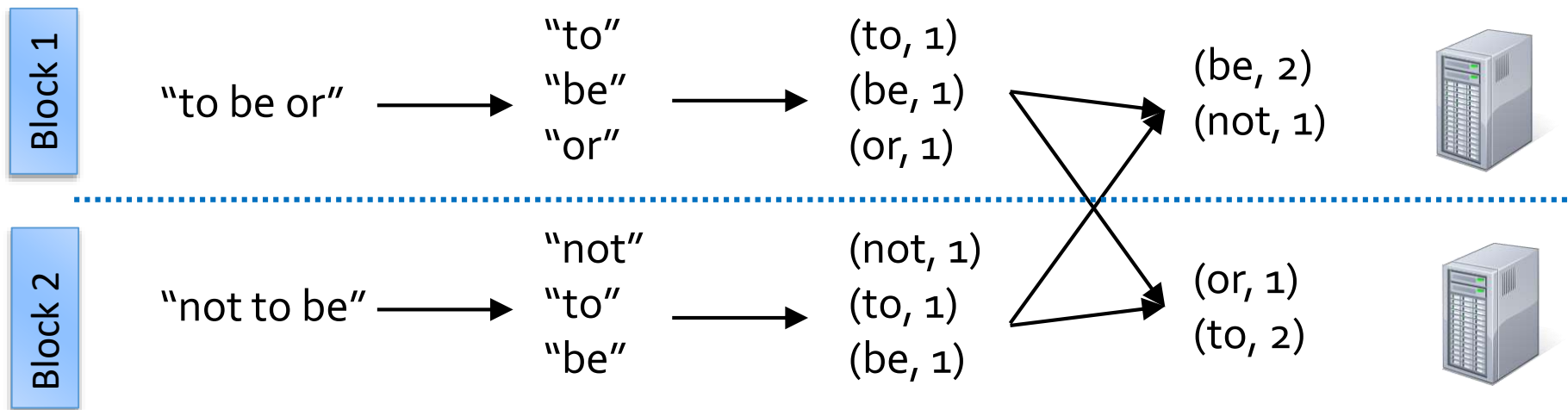
Some Key-Value Operations

- ▶ `pets = sc.parallelize([("cat", 1), ("dog", 1), ("cat", 2)])`
- ▶ `pets.reduceByKey(lambda x, y: x + y)`
=> {(cat, 3), (dog, 1)}
- ▶ `pets.groupByKey() # => {(cat, [1, 2]), (dog, [1])}`
- ▶ `pets.sortByKey() # => {(cat, 1), (cat, 2), (dog, 1)}`



Example: Word Count

- ▶ `lines = sc.textFile("hamlet.txt")`
- ▶ `counts = lines.flatMap(lambda line: line.split(" ")).map(lambda word : (word, 1)).reduceByKey(lambda x, y: x + y)`



Other Key-Value Operations

- ▶ `visits = sc.parallelize([("index.html", "1.2.3.4"),
("about.html", "3.4.5.6"),
("index.html", "1.3.3.1")])`
- ▶ `pageNames = sc.parallelize([("index.html", "Home"),
("about.html", "About")])`
- ▶ `visits.join(pageNames)`
`("index.html", ("1.2.3.4", "Home"))`
`("index.html", ("1.3.3.1", "Home"))`
`("about.html", ("3.4.5.6", "About"))`
- ▶ `visits.cogroup(pageNames)`
`("index.html", (["1.2.3.4", "1.3.3.1"], ["Home"]))`
`("about.html", (["3.4.5.6"], ["About"]))`



Setting the Level of Parallelism

- ▶ All the pair RDD operations take an optional second parameter **p** for number of tasks
- ▶ `words.reduceByKey(lambda x, y: x + y, 5)`
- ▶ `words.groupByKey(5)`



Using Local Variables

Essentially, piece of code executed by a transformation or action

- ▶ Any external variables you use in a **closure** will automatically be shipped to the cluster:
- ▶ `query = sys.stdin.readline()`
`pages.filter(lambda x: query in x).count()`
- ▶ Some caveats:
 - ▶ Each task gets a new copy (no updates sent back)
 - ▶ Variable must be Serializable / Pickle-able
 - ▶ Don't use fields of an outer object (ships all of it!)

There are also shared variables:
broadcasts, accumulators



Passing Values to/from Functions

- ▶ Functions in transformations/actions are **closures**: they have read-only access to all driver variables visible at closure definition
 - ▶ Related: **broadcast** variables
- ▶ Transformations
 - ▶ NOT possible to return values to driver process
 - ▶ NO exchange of values between code executing on different records of a RDD

Other RDD Operators

- ▶ map
- ▶ filter
- ▶ groupBy
- ▶ sort
- ▶ union
- ▶ join
- ▶ leftOuterJoin
- ▶ rightOuterJoin
- ▶ sample
- ▶ count
- ▶ first
- ▶ reduceByKey
- ▶ groupByKey
- ▶ collect
- ▶ save
- ▶ zip..

More details: spark-project.org/docs/latest/



Installing PySpark Natively

- ▶ PySpark: Spark with Python bindings: [info](#), [APIs](#)
- ▶ Linux
 - ▶ See e.g. tutorial [here](#)
 - ▶ Or just do: `pip3 install pyspark` (see [here](#))
- ▶ Windows 10: Windows Subsystem for Linux ([WSL](#))
 - ▶ Install Spark under linux as above
 - ▶ You can even install/run PyCharm etc. under WSL, with X11 server (see previous slides for details)
- ▶ Windows “native”
 - ▶ You could try to install Spark directly ([tutorial](#)), but ...
 - ▶ Tell me if this really works! 😊

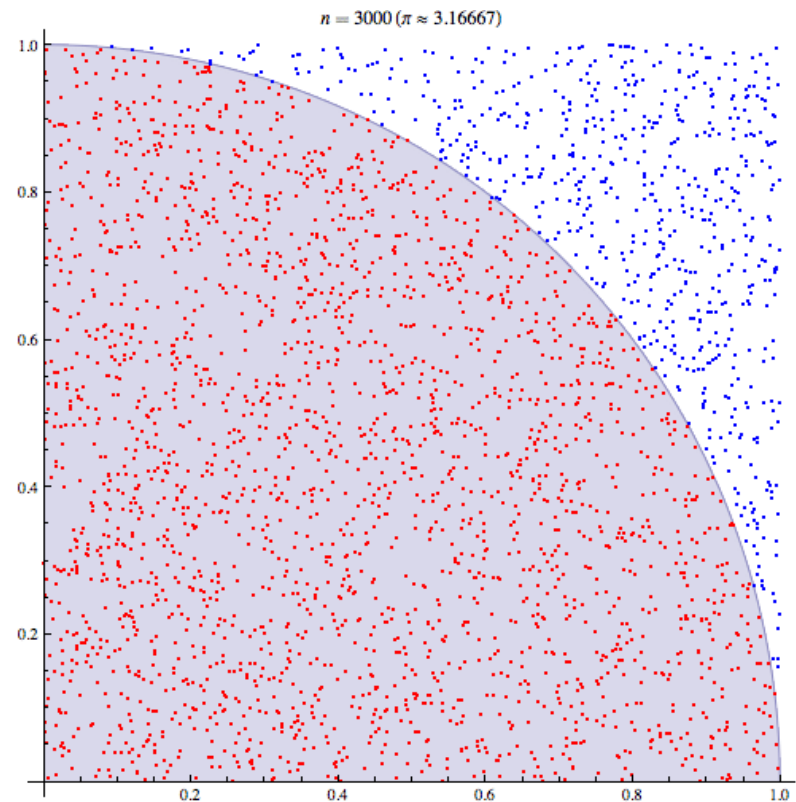
Virtual Machine with Spark

- ▶ We have prepared a virtual machine with Spark (under Oracle VirtualBox):
 - ▶ <https://heibox.uni-heidelberg.de/d/2a001bb696/>
- ▶ Using Spark:
 - ▶ Most convenient: included IntelliJ IDEA IDE with a starter project in Python
 - ▶ For freaks via a Spark shell:
 - ▶ Python: `pyspark`, Scala: `spark-shell`
- ▶ Spark 2.2.0 from July 2017, but ok for exercises

Apache Spark: Example

Estimating π

- ▶ We use a Monte Carlo method to estimate the value of Pi (π)
- ▶ Idea: Count the share of random points (x, y) whose distance to $(0,0)$ is 1 or less
- ▶ Naturally parallelizable



Source: Wikipedia

Estimating Pi/4

N = 1000000

```
def inCircle(p):  
    x, y = random(), random()  
    return 1 if  $x^2 + y^2 < 1$  else 0
```

Generates two pseudo-random
numbers in [0.0, 1.0)

True iff distance of
(x,y) to origin is < 1

```
myplus = lambda a, b: a + b
```

Generates an iterable
("lazy list") from 0 to N-1

```
rawDataRDD = sc.parallelize(xrange(0,N))  
inCircleRDD = rawDataRDD.map(inCircle)  
count = inCircleRDD.reduce(myplus)
```

```
print "Pi is roughly %f" % (4.0 * count / N)
```


A Stand-Alone Program

```
import sys
from random import random
from operator import add
from pyspark import SparkContext
```

```
if __name__ == "__main__":
    """Usage: pi [partitions]"""
```

```
sc = SparkContext (appName="PythonPi")
partitions = int(sys.argv[1]) if len(sys.argv) > 1 else 2
N = 500000 * partitions
```

```
... [code as above, without N = 1000000] ...
```

```
sc.stop()
```

Execution Example

- ▶ Open terminal window
- ▶ `cd spark/examples/src/main/python`
- ▶ `spark-submit pi.py 1`
 - ▶ => Pi is roughly 3.139168
- ▶ `spark-submit pi.py 2`
 - ▶ => Pi is roughly 3.142220
- ▶ `spark-submit pi.py 2`
 - ▶ => Pi is roughly 3.138352
- ▶ `spark-submit pi.py 4`
 - ▶ => Pi is roughly 3.142624

Recommended Videos on Spark

▶ Introduction tutorials on Spark

- ▶ Parallel programming with Spark Presented by Matei Zaharia UC Berkeley AmpLab 2013
- ▶ <https://www.youtube.com/watch?v=e-56inQL5hQ&t=30s>
- ▶ Parallel Programming with Spark (Part 1 & 2) by Matei Zaharia (2012)
- ▶ <https://www.youtube.com/watch?v=7k4yDKBYOcw>

▶ Coursera

- ▶ Big Data Analysis with Scala and Spark
- ▶ <https://www.coursera.org/learn/scala-spark-big-data>
- ▶ Enroll -> Audit, then for free!

Reading Materials on Spark

▶ Free Materials:

- ▶ Spark Programming Guide
 - ▶ <https://spark.apache.org/docs/latest/rdd-programming-guide.html>
- ▶ Apache Spark Tutorial: ML with PySpark
 - ▶ <https://goo.gl/u4RjeB>
- ▶ Cheat Sheet PySpark-RDD Basics, <https://goo.gl/UF5zVr>
- ▶ Jacek Laskowski, Mastering Apache Spark 2, GitBook.com, <https://goo.gl/yFYRYm>

▶ Books

- ▶ Matthew Rathbone: 10+ Great Books for Apache Spark
 - ▶ <https://blog.matthewrathbone.com/2017/01/13/spark-books.html>

Thank you.