The R in Spark: Learning Apache Spark with R

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Contents

Preface

In this book you will learn how to use Apache Spark with R using the sparklyr R package. The book intends to take someone unfamiliar with Spark or R and help them become intermediate users by teaching a set of tools, skills and practices applicable to data science.

Chapter 1

Introduction

This chapter covers the historical background that lead to the development of Apache Spark, introduces R in the context of Spark and sparklyr as a project bridging Spark and R.

1.1 Background

Humans have been storing, retrieving, manipulating, and communicating information since the Sumerians in Mesopotamia developed writing in about 3000 BC. Based on the storage and processing technologies employed, it is possible to distinguish four distinct phases of development: pre-mechanical (3000 BC – 1450 AD), mechanical (1450–1840), electromechanical (1840–1940), and electronic (1940–present) (Kenneth C. Laudon, 1996).

During this last phase, humanity is moving from traditional industries to an economy based on information technology and our footprint of digital information has kept growing at exponential rates (dat, 2016):

With the ambition to provide a searchable tool to all this new digital information, many companies attempted to provide such functionality with what we know today as web search or search engines. Given the vast amount of digital information, managing information at this scale was a challenging problem that companies had to tackle. Search engines were unble to store all the web page information required to support web searches in a single computer. This meant that they had to split information across many machines, which was accomlished by splitting this data and storing it as many files across many machines, this approach became known as the Google File System from a research paper published in 2003 by Google (Ghemawat et al., 2003).

One year later, in 2004, Google published a new paper describing how to perform operations across the Google File System, this approach came to be known as **MapReduce** (Dean and Ghemawat, 2008). As you would expect, there are two operations in MapReduce: Map and Reduce. The **map operation** provides an arbitrary way to transform each file into a new file, usually defined by arbitrary code that scans the file and outputs a different file. The **reduce operation** combines two files into a new one. These two operations are sufficient to process data at the scale of the data available in the web. For instance, one could define a mapping operation that splits each word in a text file and outputs a new file counting occurrence of words; the reduce operation can be defined to take two word-counting files and combine them by aggregating the total occurrences for each worf. Once defined, a cluster implementing MapReduce can perform this operation several times across many machines to process data at the scale of the entire web. Counting words is often the most basic example, but MapReduce can be also used to rank web pages efficietly and many other much more interesting applications.

After these papers were released by Google, a team in Yahoo worked on implementing the Google File System and MapReduce as a single open source project. This project was released in 2006 as **Hadoop** implementing

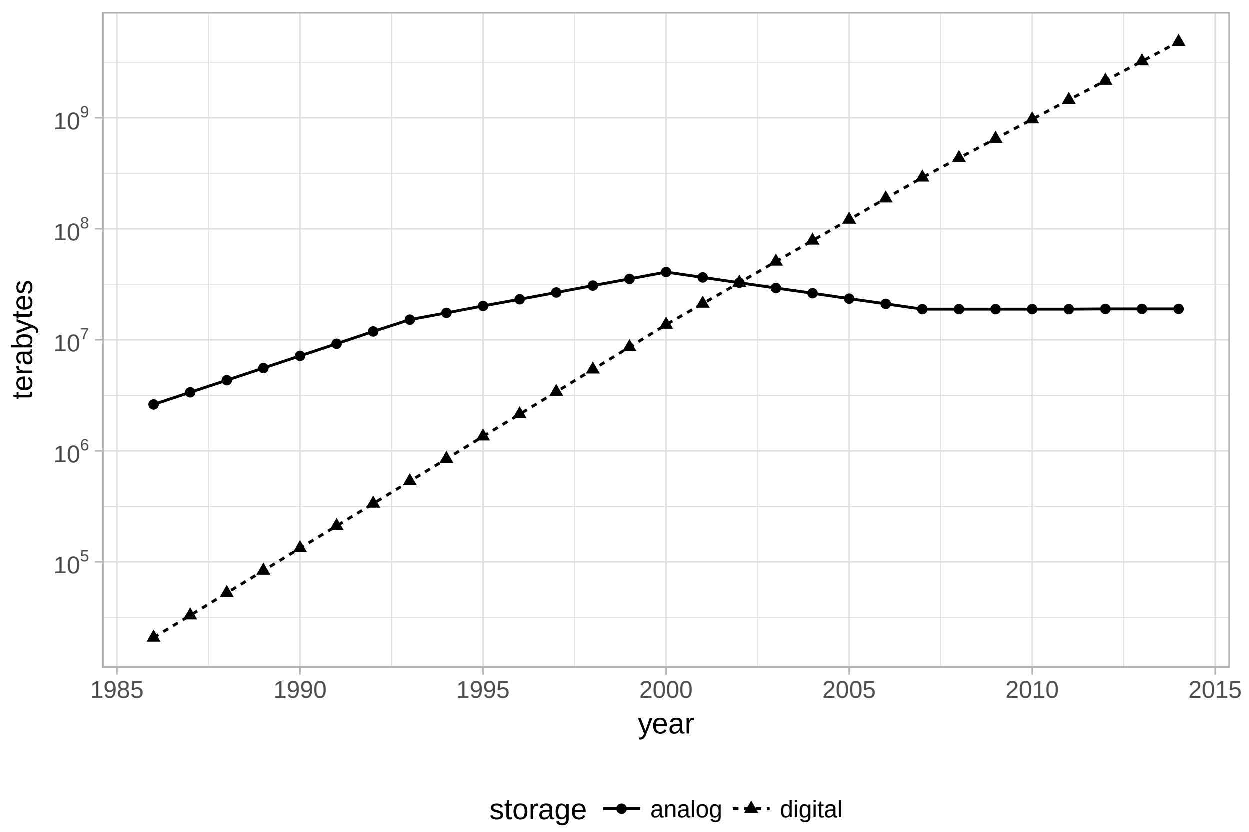


Figure 1.1: World's capacity to store information.

MapReduce and the Google File System implemented as the Hadoop File System, or **HDFS** for short. The Hadoop project made distributed file-based computing accessible to a wider range of users and organizations that made use of MapReduce beyond web data processing.

While Hadoop provided support to perform map/reduce operations over a distributed file system, it still required each map/reduce operation to be written with code every time a data analysys was run. The **Hive** project, released in 2008 by Facebook, brought Structured Query Language (SQL) support to Hadoop. This meant that data analysis could now be performed at large-scale without the need to write code for each map/reduce operation, but instead, one could write generic data analysis statements that are much easier to understand and write.

1.2 Spark

While Hadoop with Hive was a powerful tool, it was still working over a distributed file system and was dependent on map/reduce operations. This meant that it was running using disk drives which tend to be significantly slower than using a computer's memory. In 2009, the **Apache Spark** projects starts in Berkeley to improve over Hadoop. Specifically, by making use of memory (instead of disk drives) and by providing a richer set of verbs beyond map/reduce, this allowed it to be much faster and generic than its predecessor. For instance, one can sort 100TB of data in 72min and 2100 computers using Hadoop, but only 206 computers in 23min using Spark. Spark was build using the Scala programming language, but interfaces to other programming languages are also provided today. Spark was released as an open source project in 2010 with the scope of the project defined as follows:

> "Apache Spark is a fast and general engine for large-scale data processing."
>
> — spark.apache.org

meaning that Spark is a tool designed to support:

- **Data Processing**: Data processing is the collection and manipulation of items of data to produce meaningful information (French, 1996).
- **Large-Scale**: What *large* means is hard to quantify, but one can interpret this as cluster-scale instead, which represents a set of connected computers that work together.
- **General**: Spark optimizes and executes parallel generic code, as in, there is no restriction as to what type of code one can write in Spark.
- **Fast**: Spark is much faster than its predecessor by making efficient use of memory to speed data access while running algorithms at scale.

Spark is good at tackling large-scale data processing problems, this usually known as **big data** (data sets that are more voluminous and complex that traditional ones), but also is good at tackling large-scale computation problems, known as **big compute** (tools and approaches using a large amount of CPU and memory resources in a coordinated way). There is a third problem space where data nor compute are necessarily large scale and yet, there are significant benefits from using the same tools.

Big data and big compute problems are usually easy to spot, if the data does not fit into a single machine, you might have a big data problem; if the data fits into a single machine but a process over the data takes days, weeks or months to compute, you might have a big compute problem.

For the third problem space, there are a few use cases this breaks to:

1. **Velocity**: One can have a dataset of 10GB in size and a process that takes 30min to run over this data, this is by no means big-compute nor big-data; however, if a data scientist is researching ways to improve accuracy for their models, reducing the runtime down to 3min it's a 10X improvement, this improvement can lead to significant advances and productivity gains by increasing the velocity at which one can analyze data.

2. **Variety**: One can have an efficient process to collect data from many sources into a single location, usually a database, this process could be already running efficiently and close to realtime. Such processes are known at ETL (Extract-Transform-Load); data is extracted from multiple sources, transformed to the required format and loaded in a single data store. While this has worked for years, the tradeoff from this system is that adding a new data source is expensive, the system is centralized and tightly controlled. Since making changes to this type of systems could cause the entire process to come to a halt, adding new data sources usually takes long to be implemented. Instead, one can store all data its natural format and process it as needed using cluster computing, this architecture is currently known as a data lake.

Some people refer to some of these benefits as the four 'V's of big data: Velocity, Variety, Volume and Veracity (which asserts that data can vary greatly in quality which require analysis methods to improve accuracy across a variety of sources). Others have gone as far as expending this to five or even as the 10 Vs of Big Data. Mnemonics set aside, cluster computing is being used today in more innovative ways and and is not uncommon to see organizations experimenting with new workflows and a variety of tasks that were traditionally uncommon for cluster computing. Much of the hype attributed to big data falls into this space, where some will argue that everything should be considered big data and where others will argue than nothing should. My hope is that this book will help you understand the opportunities and limitations of Apache Spark with R.

1.3 R

R is a computing language with it's inception dating back to Bell Laboratories. John Chambers explained in useR 2016 that at the time, computing was done by calling Fortran subroutines which, apparently, were not pleasant to deal with. The S computing language was designed as an interface language to support higher abstractions to perform statistical computing over existing subroutines:

R is a modern and free implementation of S, specifically:

> R is a programming language and free software environment for statistical computing and graphics.
>
> — The R Project for Statistical Computing

There are two strong arguments for choosing R over other computing languages while working with data:

- The **R Language** was designed by statisticians for statisticians, meaning, this is one of the few successful languages designed for non-programmers; so learning R will probably feel more natural. Additionally, since the R language was designed to be an interface to other tools and languages, R allows you to focus more on modeling and less on the peculiarities of computer science and engineering.
- The **R Community** provides a rich package archive provided by CRAN (The Comprehensive R Archive Network) which allows you to install ready-to-use packages to perform many tasks, most notably, high-quality statistic models with many only available in R. In addition, the R community is a welcoming and active group of talented individuals motivated to help you succeed. Many packages provided by the R community make R, by far, the place to do statistical computing. To mention some of the popular packages: dplyr to manipulate data, cluster to analyze clusters and ggplot2 to visualize data.

One can argue to what degree other fields, like machine learning, overlap with statistics; so far, most people will argue that the overlap is non-trivial. Similar arguments can be made for data science, big data, deep learning and beyond. With the continuous rise of popularity of R, I can only expect R's influence and scope to keep growing over time; we can take a look at the historic downloads of R packages in CRAN to get some sense of R's recent growth:

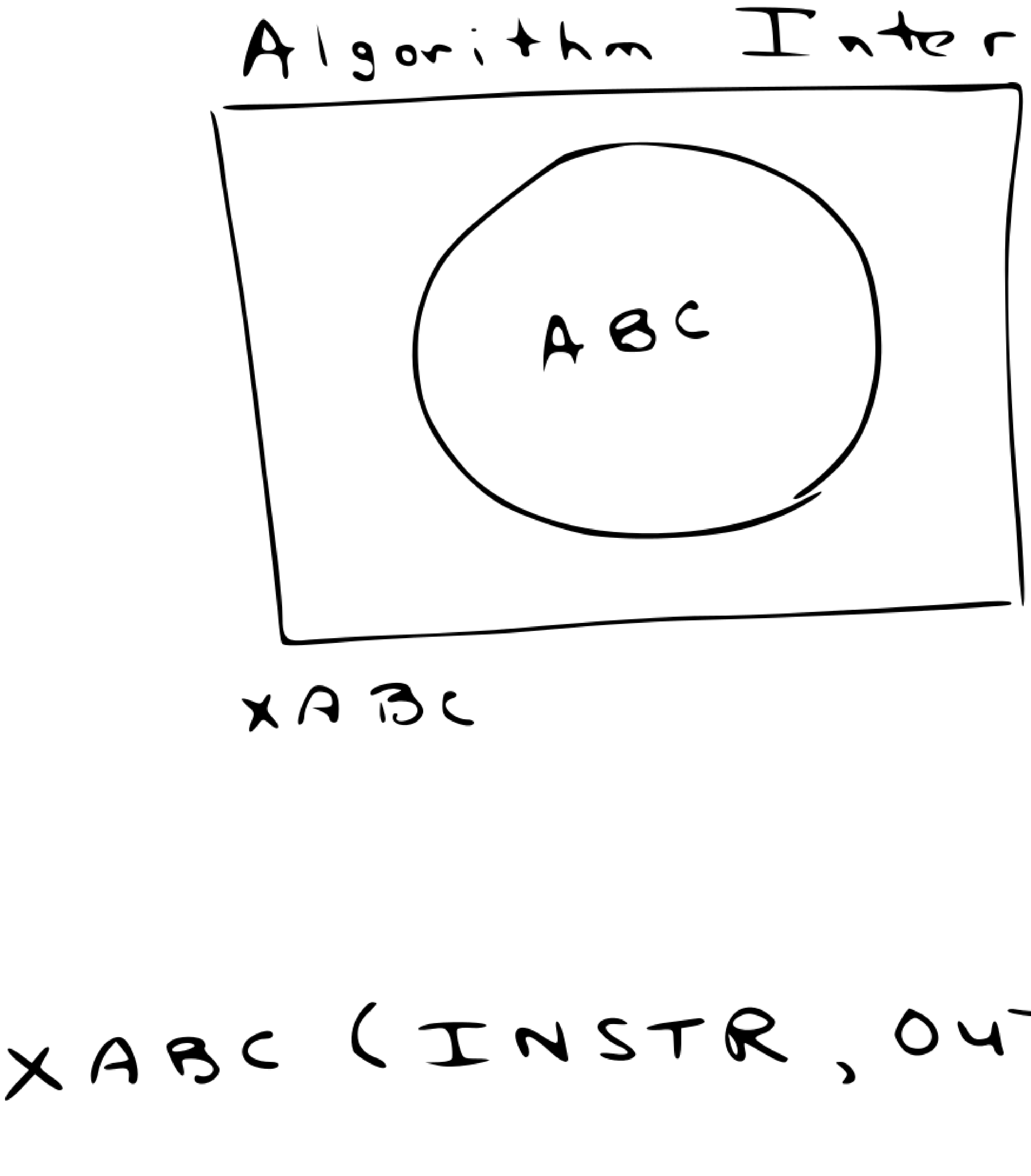


Figure 1.2: Interface language diagram by John Chambers from useR 2016.

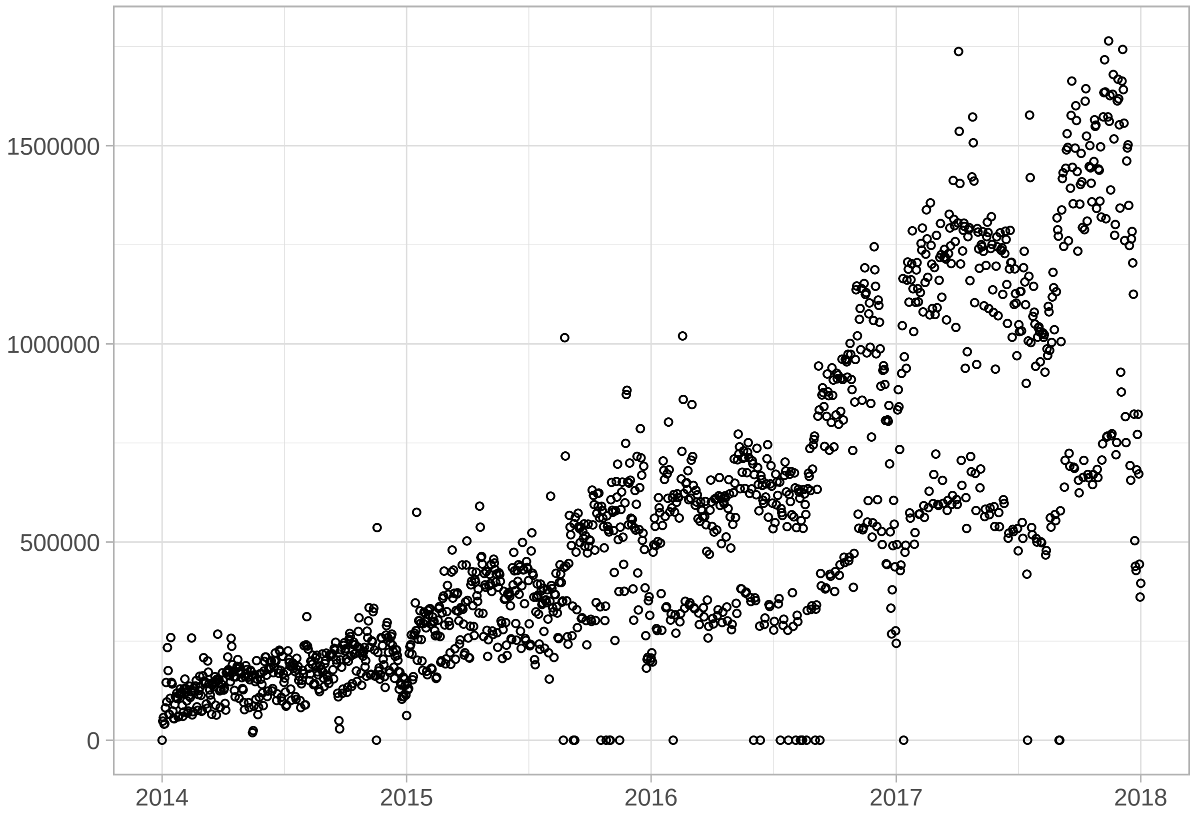


Figure 1.3: Daily downloads of CRAN packages.

1.4 sparklyr

Back in 2016, there was a need in the R community to support Spark through an interface compatible with other R packages, easy to use and available in CRAN. To this end, development of `sparklyr` started in 2016 by RStudio under JJ Allaire, Kevin Ushey and Javier Luraschi, version 0.4 was released in summer during the *useR!* conference, this first version added support for `dplyr`, `DBI`, modeling with `MLlib` and an extensible API that enabled extensions like H2O's rsparkling package. Since then, many new features and improvements have been made available through sparklyr 0.5, 0.6, 0.7 and 0.8.

Officially,

> `sparklyr` is an R interface for Apache Spark.
>
> —github.com/rstudio/sparklyr

It's available in CRAN and works like any other CRAN package, meaning that: it's agnostic to Spark versions, it's easy to install, it serves the R community, it embraces other packages and practices from the R community and so on. It's hosted in GitHub under github.com/rstudio/sparklyr and licensed under Apache 2.0 which is allows you to clone, modify and contribute back to this project.

While thinking of who and why should use `sparklyr`, the following roles come to mind:

- **New Users**: For new users, `sparklyr` provides the easiest way to get started with Spark. My hope is that the first chapters of this book will get you up running with ease and set you up for long term success.
- **Data Scientists**: For data scientists that already use and love R, `sparklyr` integrates with many other R practices and packages like `dplyr`, `magrittr`, `broom`, `DBI`, `tibble` and many others that will make you feel at home while working with Spark. For those new to R and Spark, the combination of high-level workflows available in `sparklyr` and low-level extensibility mechanisms make it a productive environment to match the needs and skills of every data scientist.
- **Expert Users**: For those users that are already immersed in Spark and can write code natively in Scala, consider making your libraries available as an `sparklyr` extension to the R community, a diverse and skilled community that can put your contributions to good use while moving open science forward.

This book is titled "The R in Spark" as a way to describe and teach that area of overlap between Spark and R. The R package that represents this overlap is `sparklyr`; however, the overlap goes beyond a package. It's an overlap of communities, expectations, future directions, packages and package extensions as well. Naming this book `sparklyr` or "Introduction to sparklyr" would have left behind a much more exciting opportunity, an opportunity to present this book as an intersection of the R and Spark communities. Both are solving very similar problems with a set of different skills and backgrounds; therefore, it is my hope that `sparklyr` can be a fertile ground for innovation, a welcoming place to newcomers, a productive place for experienced data scientists and an open community where cluster computing and modeling can come together.

Here are some resources to help you get involved:

- **Documentation**: This should be your entry point to learn more about sparklyr, the documentation is kept up to date with examples, reference functions and many more relevant resources, https://spark.rstudio.com.
- **Github**: If you believe something needs to get fixed, open a GitHub issue or send us a pull request, https://github.com/rstudio/sparklyr.
- **Stack Overflow**: For general questions, Stack Overflow is a good place to start, stackoverflow.com/tags/sparklyr.
- **Gitter**: For urgent issues or to keep in touch you can chat with us in Gitter, https://gitter.im/rstudio/sparklyr.

Chapter 2

Installation

From R, installing and launching a local Spark cluster using `sparklyr` is as easy as running:

```
spark_install()
sc <- spark_connect(master = "local")
```

However, to make sure we can all run the code above and understand it, this chapter will walk you through installing the prerequisites, installing Spark and connecting to a local Spark cluster.

2.1 Prerequisites

As briefly mentioned in the Introduction chapter, R is a programming language that can run in many platforms and environments. Most people making use of a programming language also choose tools to make them more productive in it; for R, RStudio would be such tool. Strictly speaking, RStudio is an Integrated Development Environment or IDE for short, which also happens to support many platforms and environments. R and RStudio are the free software tools this book will make use of and therefore, I strongly recommend you get those installed if you haven't done so already.

Additionally, since Spark is build in the Scala programming language which is run by the Java Virtual Machine, you also need to install Java 7 or newer in your system. It is likely that your system already has Java installed, but is probably worth updating with the steps bellow.

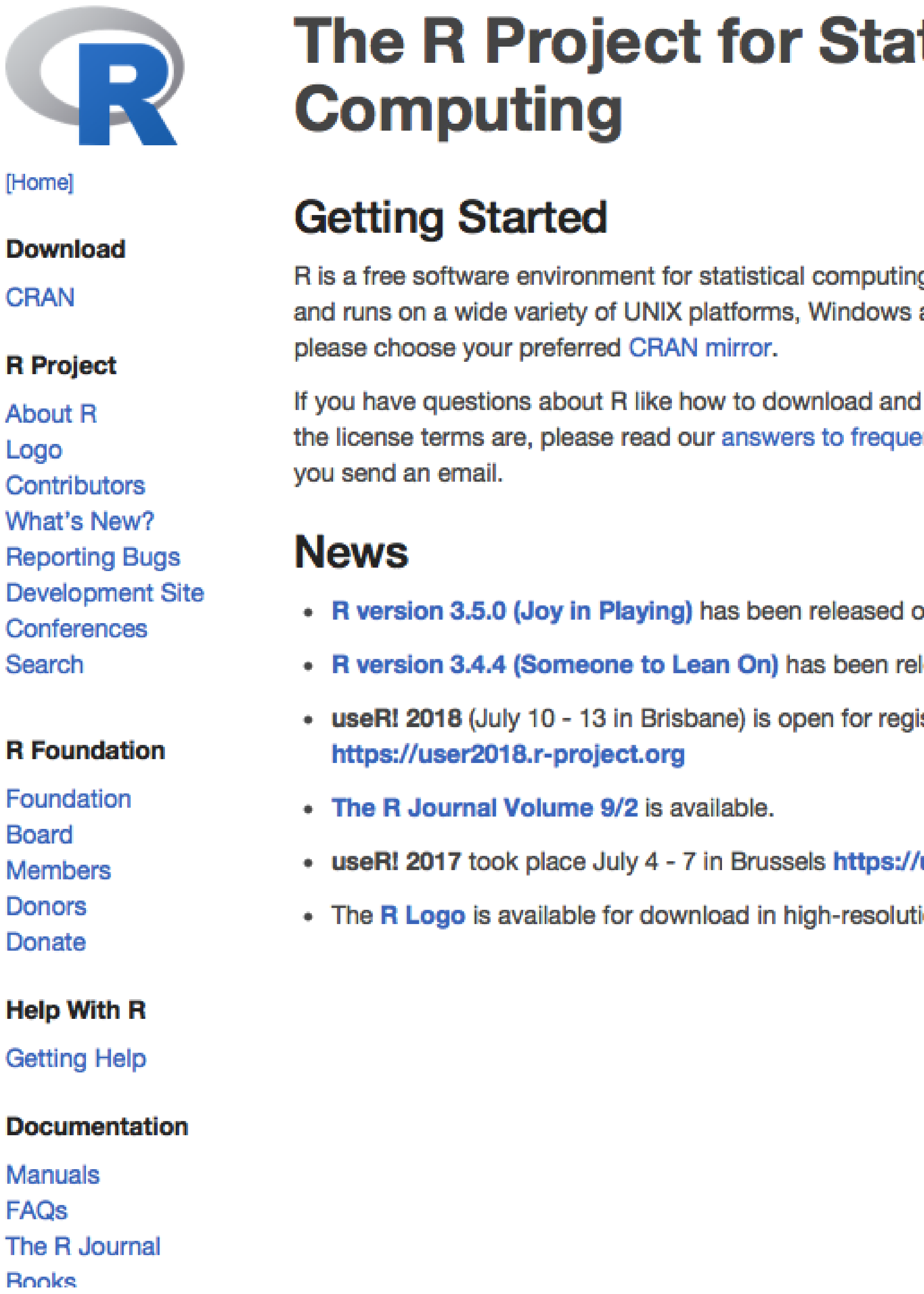
2.1.1 Install R

From r-project.org, download and launch the installer for your platform, Windows, Macs or Linux available.

2.1.2 Install Java

From oracle.com/technetwork/java/javase/downloads/jdk8-downloads-2133151.html, download and launch the installer for your platform, Windows, Macs or Linux available. While installing the JRE (Java Runtime Environment) is sufficient for most operations, in order to build extensions you will need the JDK (Java Developer Kit); therefore, I rather recommend installing the JDK in the first place.

Starting with Spark 2.1, Java 8 is required; however, previous versions of Spark support Java 7. Regardless, we recommend installing Java 8 as described in this chapter



The R Project for Stat
Computing

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Getting Started

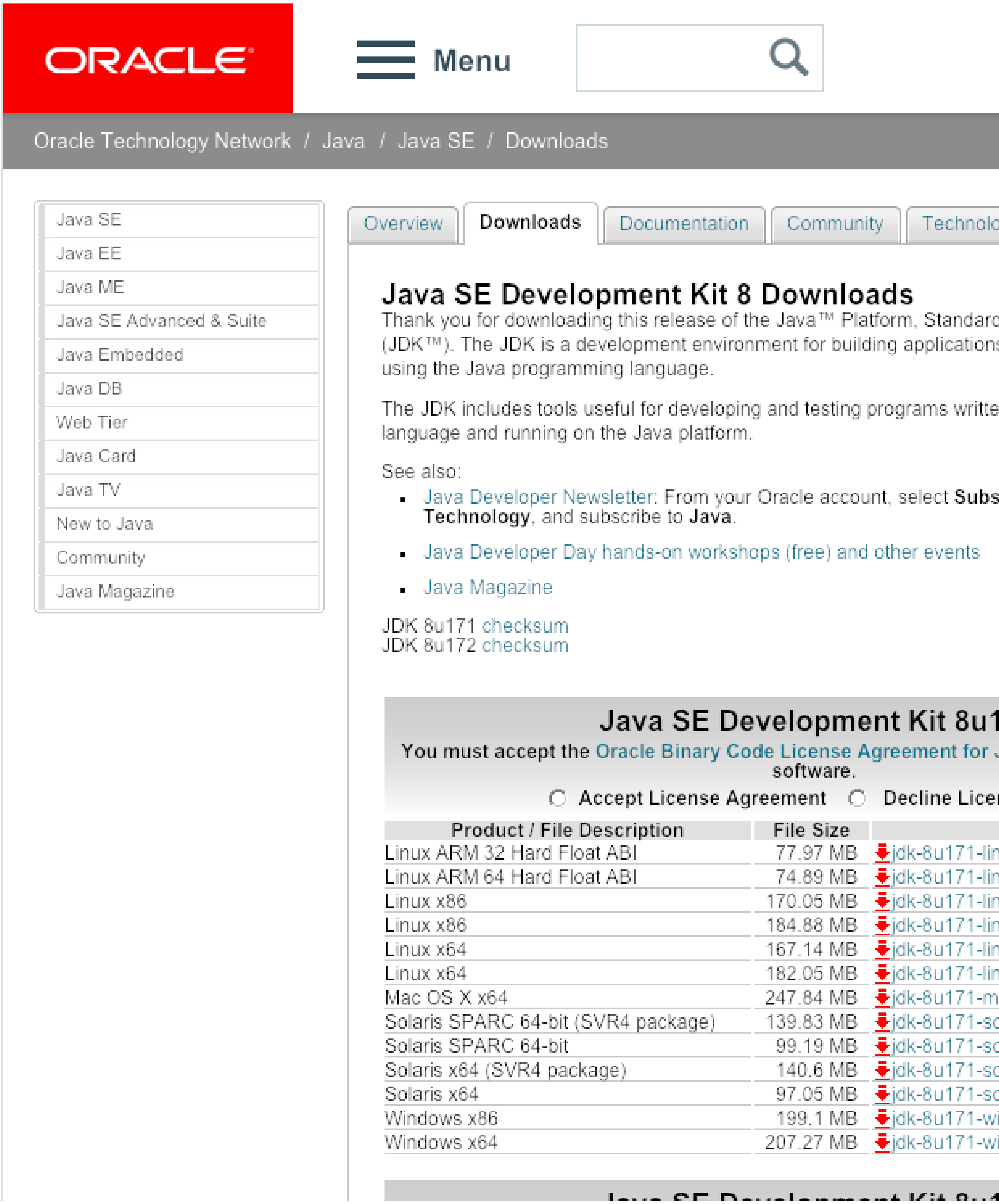
R is a free software environment for statistical computing
and runs on a wide variety of UNIX platforms, Windows
please choose your preferred CRAN mirror.

If you have questions about R like how to download and
the license terms are, please read our answers to freque
you send an email.

News

- **R version 3.5.0 (Joy in Playing)** has been released o
- **R version 3.4.4 (Someone to Lean On)** has been rel
- **useR! 2018** (July 10 - 13 in Brisbane) is open for regis
  https://user2018.r-project.org
- **The R Journal Volume 9/2** is available.
- **useR! 2017** took place July 4 - 7 in Brussels **https://**
- The **R Logo** is available for download in high-resoluti

Figure 2.1: The R Project for Statistical Computing.



Java SE Development Kit 8 Downloads

Thank you for downloading this release of the Java™ Platform, Standard
(JDK™). The JDK is a development environment for building application
using the Java programming language.

The JDK includes tools useful for developing and testing programs writte
language and running on the Java platform.

See also:

- Java Developer Newsletter: From your Oracle account, select **Subs** **Technology**, and subscribe to **Java**.
- Java Developer Day hands-on workshops (free) and other events
- Java Magazine

JDK 8u171 checksum
JDK 8u172 checksum

Java SE Development Kit 8u1

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Product / File Description	File Size	
Linux ARM 32 Hard Float ABI	77.97 MB	jdk-8u171-lin
Linux ARM 64 Hard Float ABI	74.89 MB	jdk-8u171-lin
Linux x86	170.05 MB	jdk-8u171-lin
Linux x86	184.88 MB	jdk-8u171-lin
Linux x64	167.14 MB	jdk-8u171-lin
Linux x64	182.05 MB	jdk-8u171-lin
Mac OS X x64	247.84 MB	jdk-8u171-m
Solaris SPARC 64-bit (SVR4 package)	139.83 MB	jdk-8u171-so
Solaris SPARC 64-bit	99.19 MB	jdk-8u171-so
Solaris x64 (SVR4 package)	140.6 MB	jdk-8u171-so
Solaris x64	97.05 MB	jdk-8u171-so
Windows x86	199.1 MB	jdk-8u171-wi
Windows x64	207.27 MB	jdk-8u171-wi

Figure 2.2: Java Download.

2.1.3 Install RStudio

While installing RStudio is not strictly required to work with `sparklyr` in R, it will make you much more productive and therefore, I would recommend you take the time to install RStudio from rstudio.com/products/rstudio/download/, then download and launch the installer for your platform: Windows, Macs or Linux.

After launching RStudio, identify the Console panel since this is where most of the code will be executed in this book. For additional learning resources on R and RStudio consider visiting: rstudio.com/online-learning/.

2.1.4 Install sparklyr

First of all, we would want to install `sparkylr`. As many other R packages, `sparklyr` is available in CRAN and can be easily installed as follows:

```
install.packages("sparklyr")
```

The CRAN release of `sparklyr` contains the most stable version and it's the recommended version to use; however, for those that need or might want to try newer features being developed in `sparklyr` you can install directly from GitHub using the `devtools` package. First install the `devtools` package and then `sparklyr` as follows:

```
install.packages("devtools")
devtools::install_github("rstudio/sparklyr")
```

2.2 Installing Spark

Start by loading `sparklyr`,

```
library(sparklyr)
```

This will makes all `sparklyr` functions available in R, which is really helpful; otherwise, we would have to run each `sparklyr` command prefixed with `sparklyr::`.

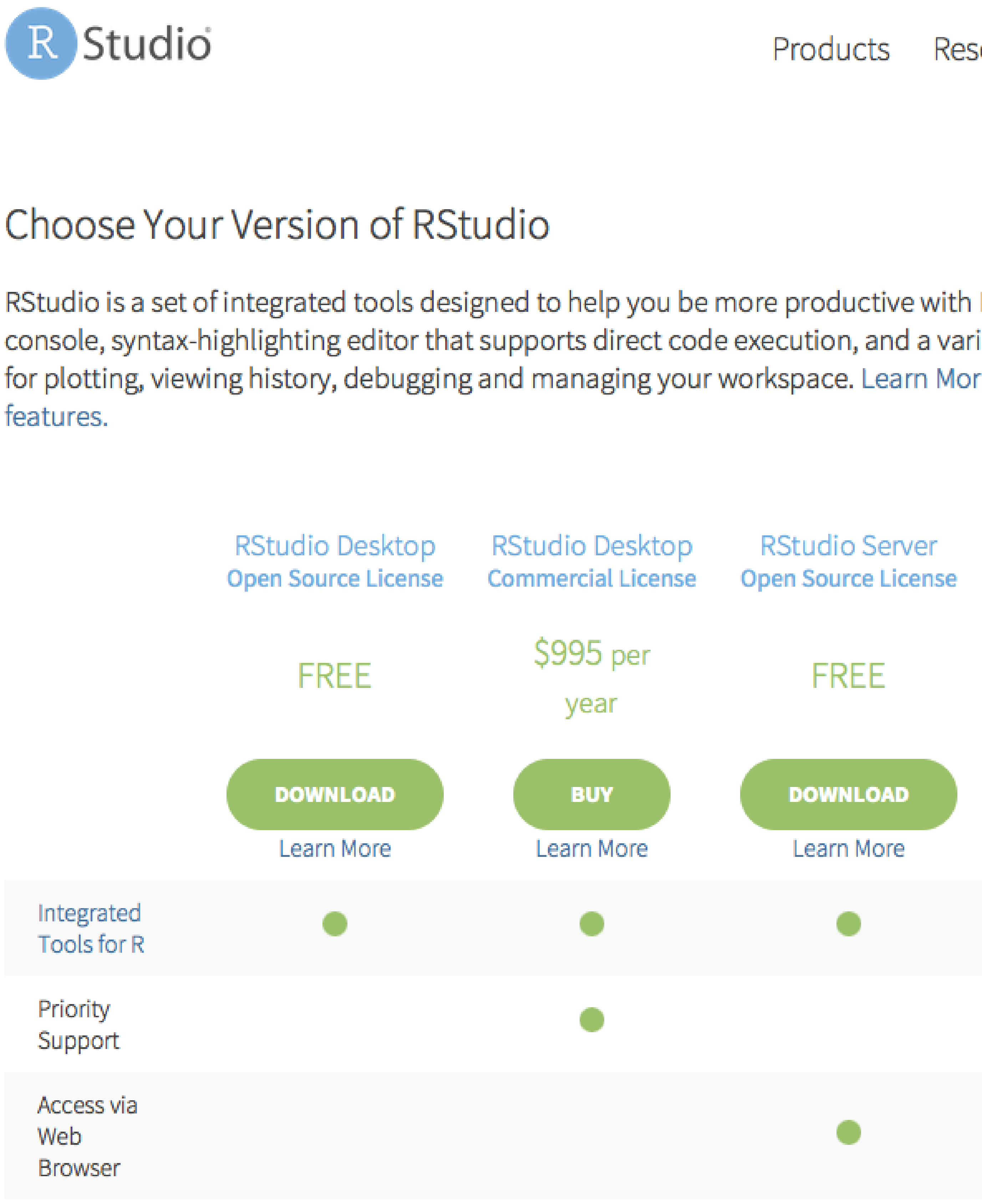
As mentioned, Spark can be easily installed by running `spark_install()`; this will install the latest version of Spark locally in your computer, go ahead and run `spark_install()`. Notice that this command requires internet connectivity to download Spark.

```
spark_install()
```

All the versions of Spark that are available for installation can be displayed with `spark_available_versions()`:

```
spark_available_versions()
```

```
##    spark
## 1  1.6.3
## 2  1.6.2
## 3  1.6.1
## 4  1.6.0
## 5  2.0.0
## 6  2.0.1
## 7  2.0.2
## 8  2.1.0
## 9  2.1.1
## 10 2.2.0
```



Choose Your Version of RStudio

RStudio is a set of integrated tools designed to help you be more productive with
console, syntax-highlighting editor that supports direct code execution, and a vari
for plotting, viewing history, debugging and managing your workspace. Learn Mor
features.

	RStudio Desktop Open Source License	RStudio Desktop Commercial License	RStudio Server Open Source License
	FREE	$995 per year	FREE
	DOWNLOAD Learn More	BUY Learn More	DOWNLOAD Learn More
Integrated Tools for R	●	●	●
Priority Support		●	
Access via Web Browser			●

Figure 2.3: RStudio Downloads.

```
## 11 2.2.1
## 12 2.3.0
```

A specific version can be installed using the Spark version and, optionally, by also specifying the Hadoop version. For instance, to install Spark 1.6.3, we would run `spark_install("1.6.3")`.

You can also check which versions are installed by running:

```r
spark_installed_versions()
```

Finally, in order to uninstall an specific version of Spark you can run `spark_uninstall()` by specifying the Spark and Hadoop versions, for instance:

```r
spark_uninstall(version = "1.6.0", hadoop = "2.6")
```

2.3 Connecting to Spark

It's important to mention that, so far, we've only installed a local Spark cluster. A local cluster is really helpful to get started, test code and troubleshoot with ease; further chapters will explain where to find, install and connect to real Spark clusters with many machines; but for the first few chapters, we will focus on using local clusters.

Threfore, to connect to this local cluster we simple run:

```r
sc <- spark_connect(master = "local")
```

The `master` parameter helps `sparklyr` find which is the "main" machine from the Spark cluster, this machine is often call the driver node. While working with real clusters using many machines, most machines will be worker machines and one will be the master. Since we only have a local cluster with only one machine, we will default to use `"local"` for now.

2.4 Using Spark

Now that you are connected, we can run a simple commands. For instance, let's start by loading some text.

First, lets create a text file by running:

```r
write("Hello World!", "hello.txt")
```

Which we can read back in Spark by running:

```r
spark_read_text(sc, "hello", "hello.txt")
```

```
## # Source:   table<hello> [?? x 1]
## # Database: spark_connection
##   line
##   <chr>
## 1 Hello World!
```

2.4.1 Web Interface

Most of the Spark commands will get started from the R console; however, it is often the case that monitoring and analizing execution is done through Spark's web interface. This interface is a web page provided by the driver node which can be accessed from `sparklyr` by running:

```
spark_web(sc)
```

2.4.2 Logs

Another common tool is to read through the Spark logs, a log is just a text file where Spark will append information relevant to the execution of tasks in the cluster. For local clusters, we can retrieve the `sparklyr` related log entries by running:

```
spark_log(sc, filter = "sparklyr", n = 5)
```

```
## 18/07/16 10:21:20 INFO SparkContext: Submitted application: sparklyr
## 18/07/16 10:21:20 INFO SparkContext: Added JAR file:/Library/Frameworks/R.framework/Versions/3.5/Resour
## 18/07/16 10:21:24 INFO Executor: Fetching spark://localhost:55314/jars/sparklyr-2.3-2.11.jar with times
## 18/07/16 10:21:24 INFO Utils: Fetching spark://localhost:55314/jars/sparklyr-2.3-2.11.jar to /private/v
## 18/07/16 10:21:24 INFO Executor: Adding file:/private/var/folders/fz/v6wfsg2x1fb1rw4f6r0x4jwm0000gn/T/
```

2.4.3 RStudio

TODO: Explain and show a couple integration points for those using `sparklyr` from RStudio.

2.5 Disconnecting

For local clusters and, really, any cluster; once you are done processing data you should disconnect by running:

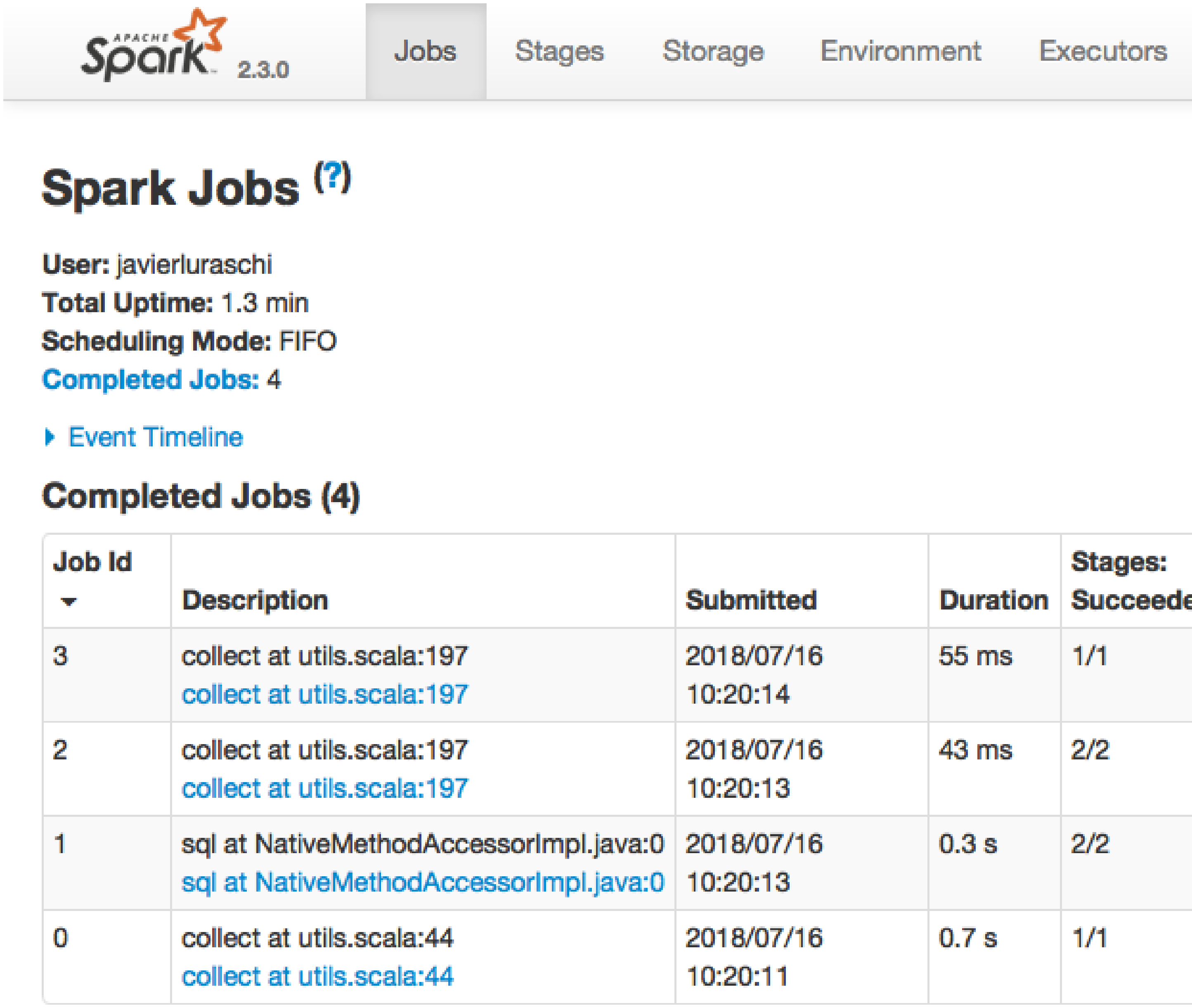
```
spark_disconnect(sc)
```

this will terminate the connection to the cluster but also terminate the cluster tasks as well. If multiple Spark connections are active, or if the conneciton instance `sc` is no longer available, you can also disconnect all your Spark connections by running `spark_disconnect_all()`.

2.6 Recap

This chapter walked you through installing R, Java, RStudio and `sparklyr` as the main tools required to use Spark from R. We covered installing local Spark clusters using `spark_install()` and learned how to launch the web interface using `spark_web(sc)` and view logs using `spark_log(sc)`.

It is my hope that this chapter will help anyone interested in learning cluster computing using Spark and R to get you started, ready to experiment on your own and ready to tackle actual data analysis and modeling tasks without any makor blockers. However, if you hit any installation or connection issues, start by browsing online for the error message or open a GitHub issue under https://github.com/rstudio/sparklyr/issues to help you get going.



Spark Jobs (?)

User: javierluraschi
Total Uptime: 1.3 min
Scheduling Mode: FIFO
Completed Jobs: 4

Completed Jobs (4)

Job Id	Description	Submitted	Duration	Stages: Succeede
3	collect at utils.scala:197 collect at utils.scala:197	2018/07/16 10:20:14	55 ms	1/1
2	collect at utils.scala:197 collect at utils.scala:197	2018/07/16 10:20:13	43 ms	2/2
1	sql at NativeMethodAccessorImpl.java:0 sql at NativeMethodAccessorImpl.java:0	2018/07/16 10:20:13	0.3 s	2/2
0	collect at utils.scala:44 collect at utils.scala:44	2018/07/16 10:20:11	0.7 s	1/1

Figure 2.4: Apache Spark Web Interface.

Chapter 3

Analysis

While **this chatper has not been written**, a few resources and basic examples were made available to help out until this chapter is written.

3.1 dplyr

Using `sparklyr`, you can apply the same data analysis techniques described in Chapter 5 - Data transformation - R for Data Science by Garrett Grolemund and Hadley Wickham.

Once you understand `dplyr`, you can make use of `dplyr` and `sparklyr` as follows:

```r
library(sparklyr)
library(dplyr)

# Connect to Spark
sc <- spark_connect(master = "local")

# Use dplyr's copy_to() to copy the iris dataset to Spark
iris_tbl <- copy_to(sc, iris, overwrite = TRUE)

# The iris_tbl is a Spark data frame compatible with dplyr
iris_tbl
```

```
## # Source:   table<iris> [?? x 5]
## # Database: spark_connection
##    Sepal_Length Sepal_Width Petal_Length Petal_Width Species
##           <dbl>       <dbl>        <dbl>       <dbl> <chr>
##  1          5.1         3.5          1.4         0.2 setosa
##  2          4.9         3            1.4         0.2 setosa
##  3          4.7         3.2          1.3         0.2 setosa
##  4          4.6         3.1          1.5         0.2 setosa
##  5          5           3.6          1.4         0.2 setosa
##  6          5.4         3.9          1.7         0.4 setosa
##  7          4.6         3.4          1.4         0.3 setosa
##  8          5           3.4          1.5         0.2 setosa
##  9          4.4         2.9          1.4         0.2 setosa
## 10          4.9         3.1          1.5         0.1 setosa
## # ... with more rows
```

```
# Transform iris_tbl with dplyr as usual
iris_tbl %>%
  group_by(Species) %>%
  summarise_all(funs(mean))
```

```
## # Source:   lazy query [?? x 5]
## # Database: spark_connection
##   Species    Sepal_Length Sepal_Width Petal_Length Petal_Width
##   <chr>             <dbl>       <dbl>        <dbl>       <dbl>
## 1 versicolor         5.94        2.77         4.26       1.33
## 2 virginica          6.59        2.97         5.55       2.03
## 3 setosa             5.01        3.43         1.46       0.246
```

To understand `dplyr` further, I would recommend taking a look at the following vignettes:

- Introduction to dplyr
- Two-table verbs
- Window functions
- Programming with dplyr

3.2 DBI

The `DBI` provides an database interface for R, meaning, if you are familiar with SQL, you can make use of `DBI` to perform SQL queries in Spark using `sparklyr`. To learn more about `DBI`, I would recommend reading first A Common Database Interface (DBI). Once you are familiar with `DBI`, you can use this package with `sparklyr` as follows:

```
library(DBI)

dbGetQuery(sc,
  "SELECT mean(Sepal_Length), mean(Sepal_Width),
          mean(Petal_Length), mean(Petal_Width)
   FROM iris
   GROUP BY Species")
```

```
##   avg(Sepal_Length) avg(Sepal_Width) avg(Petal_Length) avg(Petal_Width)
## 1             5.936            2.770             4.260            1.326
## 2             6.588            2.974             5.552            2.026
## 3             5.006            3.428             1.462            0.246
```

More advanced `DBI` resources are available in the following vignettes:

- A Common Interface to Relational Databases from R and S – A Proposal
- Implementing a new backend
- DBI specification

Chapter 4

Modeling

While **this chatper has not been written**, a few resources and basic examples were made available to help out until this chapter is written.

4.1 Overview

MLlib is Apache Spark's scalable machine learning library and is available through `sparklyr`, mostly, with functions prefixed with `ml_`. The following table describes some of the modeling algorithms supported:

Algorithm	Function
Accelerated Failure Time Survival Regression	ml_aft_survival_regression
Alternating Least Squares Factorization	ml_als
Correlation Matrix	ml_corr
Decision Trees	ml_decision_tree
Generalized Linear Regression	ml_generalized_linear_regression
Gradient-Boosted Trees	ml_gradient_boosted_trees
Isotonic Regression	ml_isotonic_regression
K-Means Clustering	ml_kmeans
Latent Dirichlet Allocation	ml_lda
Linear Regression	ml_linear_regression
Linear Support Vector Machines	ml_linear_svc
Logistic Regression	ml_logistic_regression
Multilayer Perceptron	ml_multilayer_perceptron
Naive-Bayes	ml_naive_bayes
One vs Rest	ml_one_vs_rest
Principal Components Analysis	ml_pca
Random Forests	ml_random_forest
Survival Regression	ml_survival_regression

Here is an example to get you started with K-Means:

```r
library(sparklyr)

# Connect to Spark in local mode
sc <- spark_connect(master = "local")
```

```r
# Copy iris to Spark
iris_tbl <- sdf_copy_to(sc, iris, overwrite = TRUE)

# Run K-Means for Species using only Petal_Width and Petal_Length as features
iris_tbl %>%
  ml_kmeans(centers = 3, Species ~ Petal_Width + Petal_Length)
```

```
## K-means clustering with 3 clusters
##
## Cluster centers:
##   Petal_Width Petal_Length
## 1    1.359259     4.292593
## 2    0.246000     1.462000
## 3    2.047826     5.626087
##
## Within Set Sum of Squared Errors =  31.41289
```

More examples are reosurces are available in spark.rstudio.com/mlib.

4.2 Pipelines

Spark's ML Pipelines provide a way to easily combine multiple transformations and algorithms into a single workflow, or pipeline.

Take a look at spark.rstudio.com/guides/pipelines to learn about their purpose and functionality.

Chapter 5

Clusters

Previous chapters focused on using Spark over a single computing instance, your personal computer. In this chapter we will introduce techniques to run Spark over multiple computing instances, also known as a computing cluster, to analyze data at scale.

If you already have a Spark cluster in your organization, you could consider skipping to the next chapter, Connections, which will teach you how to connect to an existing cluster.

If don't have a cluster or are considering improvements to your existing infrastructure, this chapter will introduce some of the cluster trends, managers and providers available today.

5.1 Overview

There are three major trends in cluster computing worth discussing: **on-premise**, **cloud computing** and **kubernetes**. Framing these trends over time will help us understand how they came to be, what they are and what their future might be:

For **on-premise** clusters, someone, either yourself or someone in your organiation purchased physical computers that are intended to be used for cluster computing. The computers in this cluster can made of *off-the-shelf* hardware, meaning that someone placed an order to purchase computers usually found in stores shelves or, *high-performance* hardware, meaning that a computing vendor provided highly customized computing hardware which also comes optimized for high-performance network connectivity, power consumption, etc. When purchasing hundreds or thousands of computing instances, it doesn't make sense to keep them in the usual computing case that we are all familiar with, but rather, it makes sense to stack them as efficient as possible on top of each other to minimize room space. This group of efficiently stacked computing instances is known as a rack. Once a cluster grows to thousands of computers, you will also need to host hundreds of racks of computing devices, at this scale, you would also need significant physical space to hosts those racks. A building that provides racks of computing instances is usually known as a *data-center*. At the scale of a data center, optimizing the building that holds them, their heating system, power suply, network connectivity, etc. becomes also relevant to optimize. In 2011, Facebook announced the Open Compute Project inniciative which provides a set of data center blueprints free for anyone to use.

There is nothing preventing us from building our own data centers and in fact, many organizations have followed this path. For instance, Amazon started as an online book store, over the years Amazon grew to sell much more than just books and, with it's online store growth, their data centers also grew in size. In 2002, Amazon considered selling access to virtual servers, in their data centers to the public and, in 2004, Amazon Web Services launched as a way to let anyone rent a subset of their datacenters on-demand, meaning that one did not have to purchase, configure, maintain nor teardown it's own clusters but could rather rent them from Amazon directly.

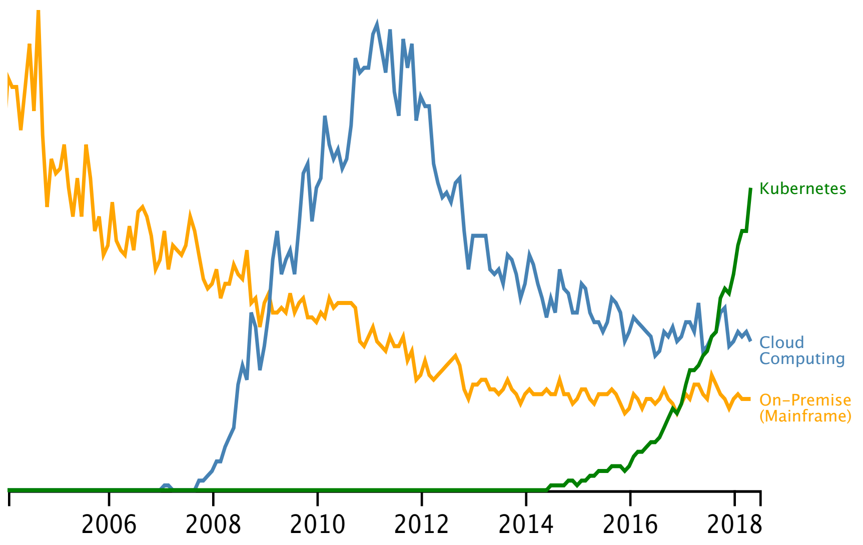


Figure 5.1: Google trends for on-premise (mainframe), cloud computing and kubernetes.

The on-demand compute model is what we know today as **Cloud Computing**. It's a concept that evolved from Amazon Web Services providing their data centers as a service. In the cloud, the cluster you use is not owned by you and is neither in your physical building, but rather, it's a data center owned and managed by someone else. Today, there are many cloud providers in this space ranging from Amazon, Microsoft, Google, IBM and many others. Most cloud computing platforms provide a user interface either through a web applciation and command line to request and manage resources.

While the bennefits of processing data in the *cloud* were obvious for many years, picking a cloud provider had the unintended side-effect of locking organizations with one particular provider, making it hard to switch between provideers or back to on-premise clusters. **Kubernetes**, announced by Google in 2014, is an open source system for managing containerized applications across multiple hosts. In practice, it provides common infrastructure otherwise proprietary to cloud providers making it much easier to deploy across multiple cloud providers and on-premise as well. However, being a much newer paradigm than on-premise or cloud computing, it is still in it's adoption phase but, nevertheless, promising for cluster computing in general and, specifically, for Apache Spark.

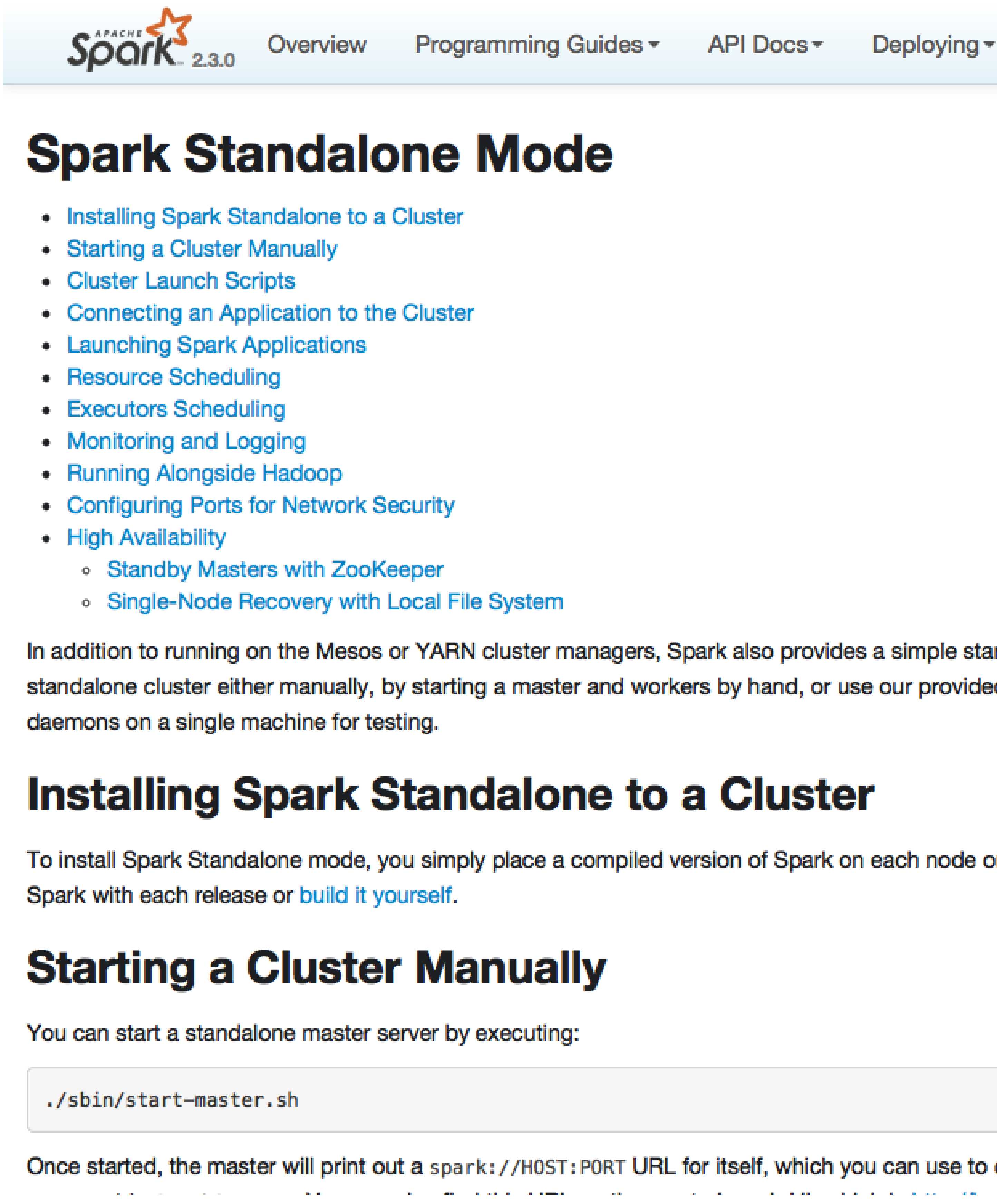
5.2 Managers

In order to run Spark within a computing cluster, one needs to run something capable of initializing Spark over each compute instance, this is known as a cluster manager. The available cluster managers in Spark are: **Spark Standalone**, **YARN**, **Mesos** and **Kubernetes**.

5.2.1 Standalone

In **Spark Standalone**, Spark works on it's own without additional software requirements since it provides it's own cluster manager as part of the Spark installation.

By completing the Installation chapter, you should have a local Spark installation available, which we can use to initialize a local stanalone Spark cluster. First, retrieve the `SPARK_HOME` directory by running `sparklyr::spark_home_dir()` from R and then, from a terminal or R, use `start-master.sh` and `start-slave.sh` as follows:



Spark Standalone Mode

- Installing Spark Standalone to a Cluster
- Starting a Cluster Manually
- Cluster Launch Scripts
- Connecting an Application to the Cluster
- Launching Spark Applications
- Resource Scheduling
- Executors Scheduling
- Monitoring and Logging
- Running Alongside Hadoop
- Configuring Ports for Network Security
- High Availability
  - Standby Masters with ZooKeeper
  - Single-Node Recovery with Local File System

In addition to running on the Mesos or YARN cluster managers, Spark also provides a simple sta
standalone cluster either manually, by starting a master and workers by hand, or use our provide
daemons on a single machine for testing.

Installing Spark Standalone to a Cluster

To install Spark Standalone mode, you simply place a compiled version of Spark on each node o
Spark with each release or build it yourself.

Starting a Cluster Manually

You can start a standalone master server by executing:

```
./sbin/start-master.sh
```

Once started, the master will print out a `spark://HOST:PORT` URL for itself, which you can use to

Figure 5.2: Spark Standalone Site.

```
# Retrieve the Spark installation directory
spark_home <- sparklyr::spark_home_dir()

# Build path to start-master.sh
start_master <- file.path(spark_home, "sbin", "start-master.sh")

# Execute start-master.sh to start the cluster manager master node
system2(start_master)

# Build path to start-slave
start_slave <- file.path(spark_home, "sbin", "start-slave.sh")

# Execute start-slave.sh to start a worker and register in master node
system2(start_slave, paste0("spark://", system2("hostname", stdout = TRUE), ":7077"))
```

The previous command initialized the master node and a worker node, the master node interface can be accessed under localhost:8080 and looks like the following:

Notice that there is one worker register in Spark standalone, you can follow the link to this worker node to see additional information:

Once data analysis is complete, one can simply stop all the running nodes in this local cluster by running:

```
stop_all <- file.path(spark_home, "sbin", "stop-all.sh")
system2(stop_all)
```

A similar approach can be followed to configure a cluster by running each `start-slave.sh` command over each machine in the cluster.

Further reading: Spark Standalone Mode

5.2.2 Yarn

YARN for short, or Hadoop YARN, is the resource manager introduced in 2012 to the Hadoop project. As mentioned in in the Introduction chapter, Spark was built initially to speed up computation over Hadoop; then, when Hadoop 2 was launched, it introduced YARN as a component to manage resources in the cluster, to this date, using Hadoop YARN with Apache Spark is still very common.

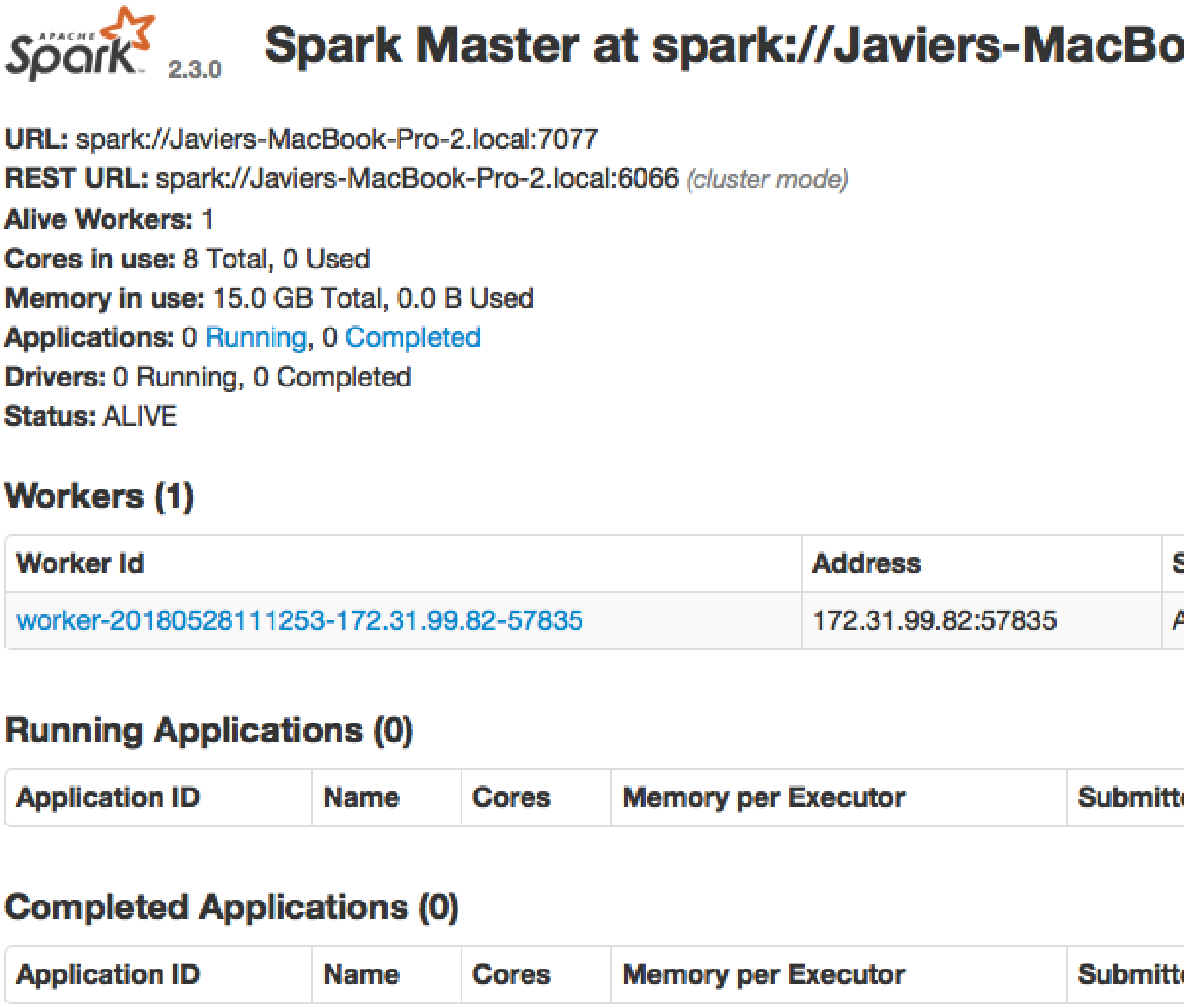
YARN applications can be submitted in two modes: **yarn-client** and **yarn-cluster**. In yarn-cluster mode the driver is running remotely, while in yarn-client mode, the driver is on the machine that started the job, `sparklyr` supports both modes.

Further reading: Running Spark on YARN

5.2.3 Mesos

Apache Mesos is an open-source project to manage computer clusters. Mesos began as a research project in the UC Berkeley RAD Lab by then PhD students Benjamin Hindman, Andy Konwinski, and Matei Zaharia, as well as professor Ion Stoica. Mesos uses Linux Cgroups to provide isolation for CPU, memory, I/O and file system.

Further reading: Running Spark on Mesos



Spark Master at spark://Javiers-MacBo

URL: spark://Javiers-MacBook-Pro-2.local:7077
REST URL: spark://Javiers-MacBook-Pro-2.local:6066 *(cluster mode)*
Alive Workers: 1
Cores in use: 8 Total, 0 Used
Memory in use: 15.0 GB Total, 0.0 B Used
Applications: 0 Running, 0 Completed
Drivers: 0 Running, 0 Completed
Status: ALIVE

Workers (1)

Worker Id	Address	S
worker-20180528111253-172.31.99.82-57835	172.31.99.82:57835	A

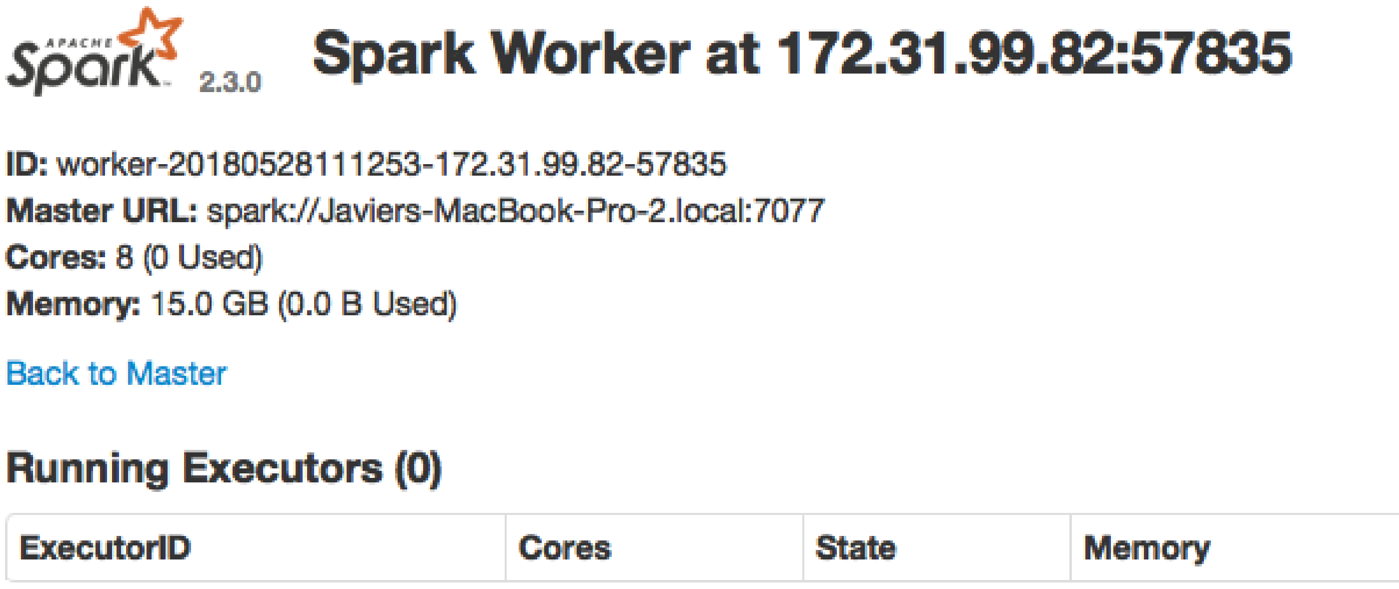
Running Applications (0)

Application ID	Name	Cores	Memory per Executor	Submitt

Completed Applications (0)

Application ID	Name	Cores	Memory per Executor	Submitt

Figure 5.3: Spark Standalone Web Interface.



Spark Worker at 172.31.99.82:57835

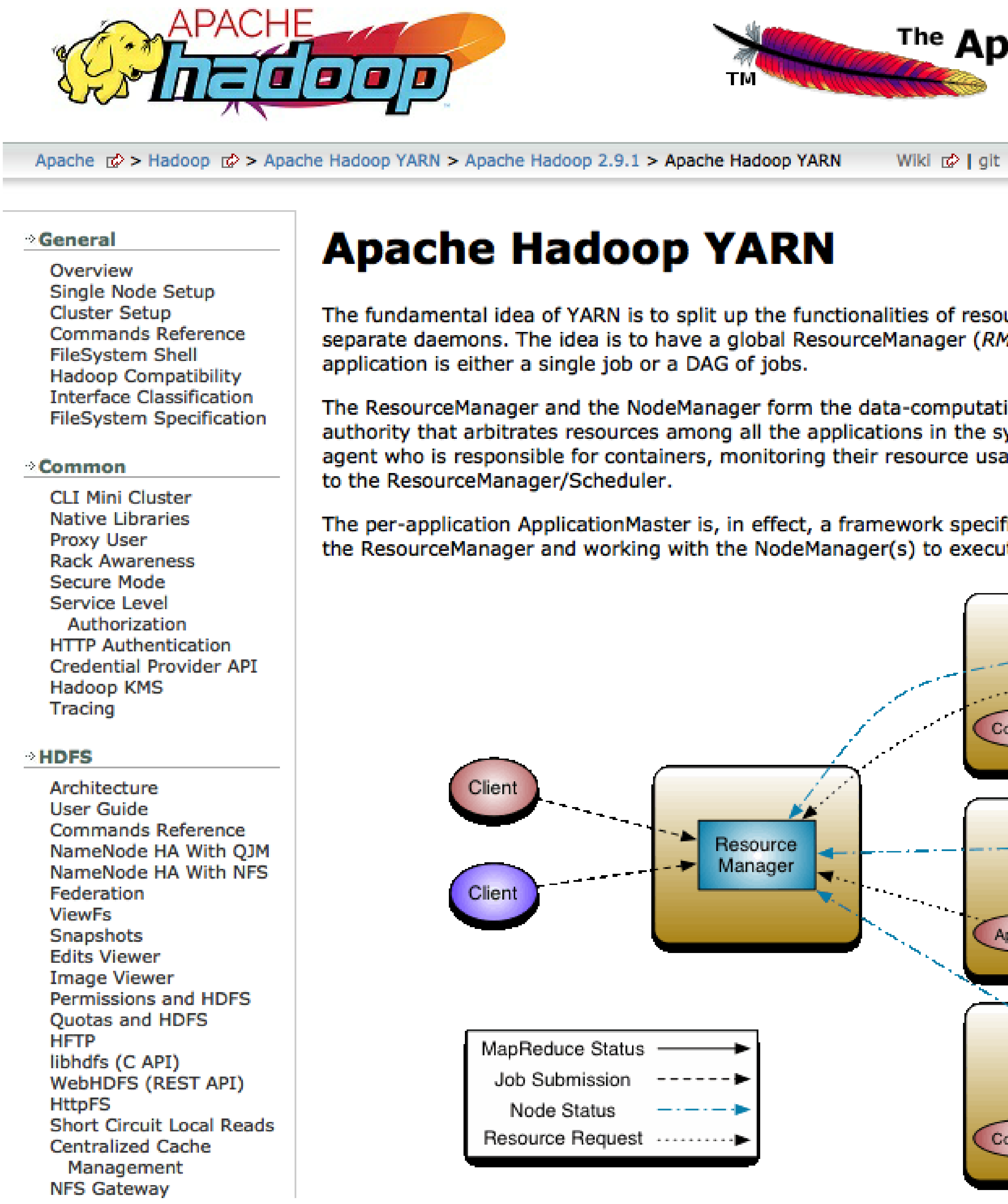
ID: worker-20180528111253-172.31.99.82-57835
Master URL: spark://Javiers-MacBook-Pro-2.local:7077
Cores: 8 (0 Used)
Memory: 15.0 GB (0.0 B Used)

Back to Master

Running Executors (0)

ExecutorID	Cores	State	Memory

Figure 5.4: Spark Standalone Worker Web Interface.



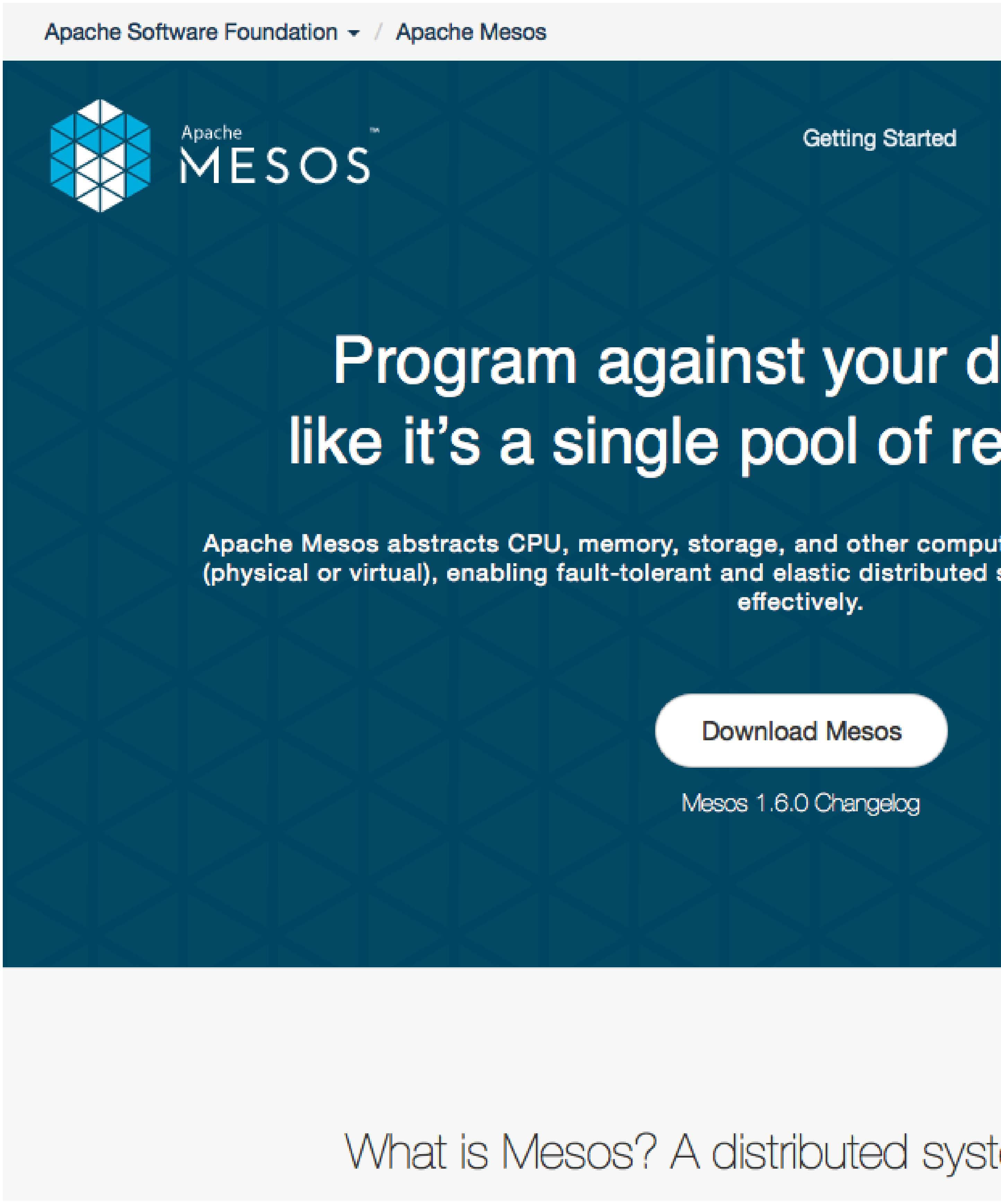
Apache Hadoop YARN

The fundamental idea of YARN is to split up the functionalities of resou
separate daemons. The idea is to have a global ResourceManager (*RM*
application is either a single job or a DAG of jobs.

The ResourceManager and the NodeManager form the data-computati
authority that arbitrates resources among all the applications in the sy
agent who is responsible for containers, monitoring their resource usa
to the ResourceManager/Scheduler.

The per-application ApplicationMaster is, in effect, a framework specif
the ResourceManager and working with the NodeManager(s) to execu

Figure 5.5: Hadoop YARN Site



Program against your d
like it's a single pool of re

Apache Mesos abstracts CPU, memory, storage, and other comput
(physical or virtual), enabling fault-tolerant and elastic distributed s
effectively.

What is Mesos? A distributed syst

Figure 5.6: Mesos Landing Site

5.2.4 Kubernetes

Kubernetes is an open-source container-orchestration system for automating deployment, scaling and management of containerized applications that was originally designed by Google and now maintained by the Cloud Native Computing Foundation.

Further reading: Running Spark on Kubernetes

5.3 On-Premise

As mentioned in the overview section, on-premise clusters represent a set of computing instances procured, colocated and managed by staff members from your organization. These clusters can be highly customized and controlled; however, they can also inccur significant initial expenses and maintenance costs.

One can use a cluster manager in on-premise clusters as described in the previous section; however, many organizations choose to partner with companies providing additional management software, services and resources to manage software in their cluster including, but not limited to, Apache Spark. Some of the on-premise cluster providers include: Cloudera, Hortonworks and MapR to mention a few which will be briefly introduced.

5.3.1 Cloudera

Cloudera, Inc. is a United States-based software company that provides Apache Hadoop and Apache Spark-based software, support and services, and training to business customers.

Cloudera's hybrid open-source Apache Hadoop distribution, CDH (Cloudera Distribution Including Apache Hadoop), targets enterprise-class deployments of that technology. Cloudera says that more than 50% of its engineering output is donated upstream to the various Apache-licensed open source projects (Apache Hive, Apache Avro, Apache HBase, and so on) that combine to form the Apache Hadoop platform. Cloudera is also a sponsor of the Apache Software Foundation.

5.3.2 Hortonworks

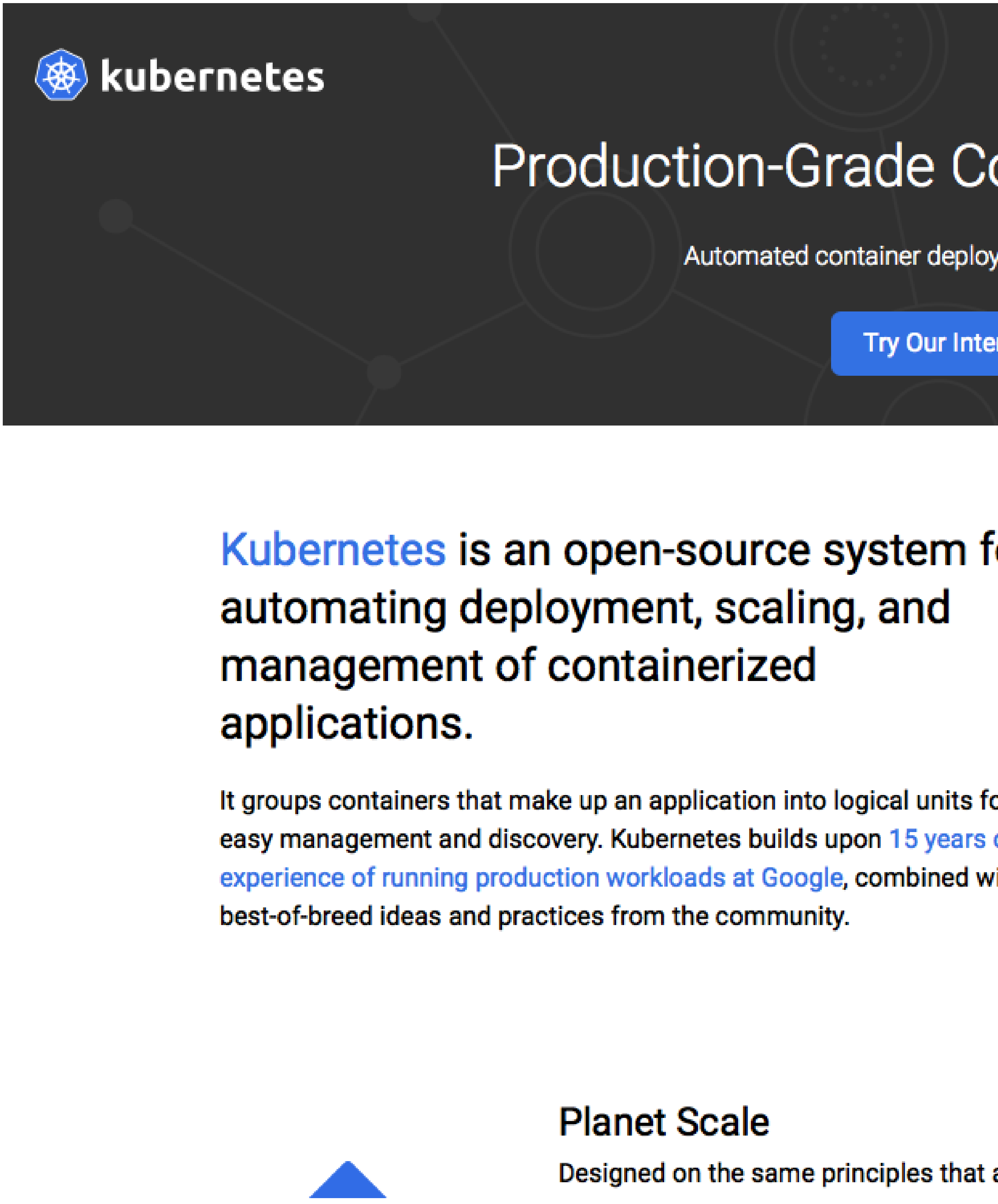
Hortonworks is a big data software company based in Santa Clara, California. The company develops, supports, and provides expertise on an expansive set of entirely open source software designed to manage data and processing for everything from IOT, to advanced analytics and machine learning. Hortonworks believes it is a data management company bridging the cloud and the datacenter.

5.3.3 MapR

MapR is a business software company headquartered in Santa Clara, California. MapR provides access to a variety of data sources from a single computer cluster, including big data workloads such as Apache Hadoop and Apache Spark, a distributed file system, a multi-model database management system, and event stream processing, combining analytics in real-time with operational applications. Its technology runs on both commodity hardware and public cloud computing services.

5.4 Cloud

For those readers that don't have a cluster yet, it is likely that you will want to choose a cloud cluster, this section will briefly mention some of the major cloud infrastructure providers as a starting point to choose



Production-Grade Co

Automated container deploy

Kubernetes is an open-source system fo
automating deployment, scaling, and
management of containerized
applications.

It groups containers that make up an application into logical units fo
easy management and discovery. Kubernetes builds upon 15 years o
experience of running production workloads at Google, combined wi
best-of-breed ideas and practices from the community.

Planet Scale

Designed on the same principles that a

Figure 5.7: Kubernetes Landing Site.

Apache Spark™

An integrated part of CDH and supported with Cloudera Enterprise, Apache Spark is the open standard for flexible in-memory data processing that enables batch, real-time, and advanced analytics on the Apache Hadoop platform. Via the One Platform initiative, Cloudera is committed to helping the ecosystem adopt Spark as the default data execution engine for analytic workloads.

Try now >

Learn why Spark is the heir to MapReduce >

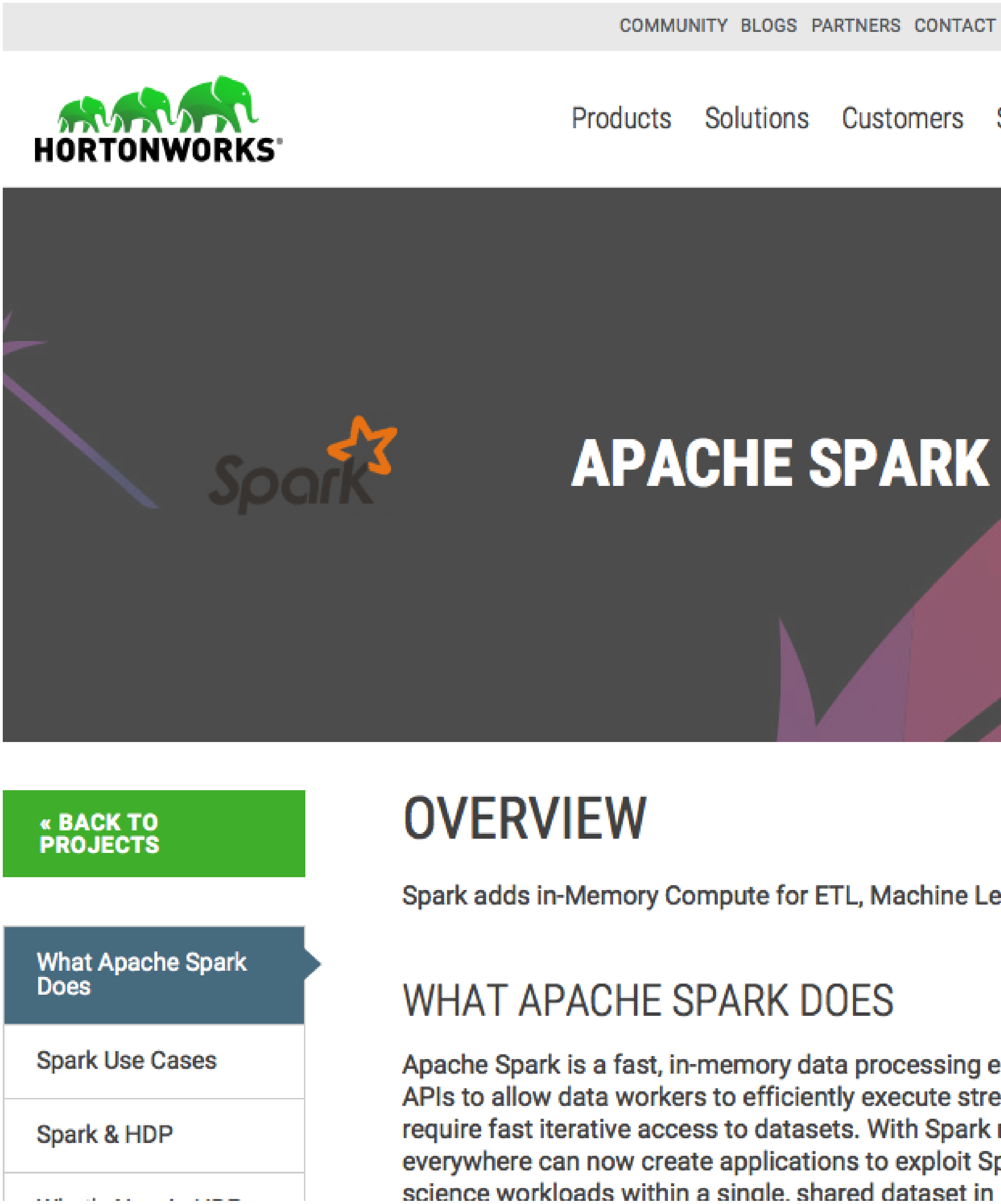
CON1737 Intro to Apache Spark for Java and Scala Dev...

Your browser does not currently recognize any of the video formats

Easy, F
Develo

Simple, yet rich
data for interac

Figure 5.8: Cloudera Landing Site.



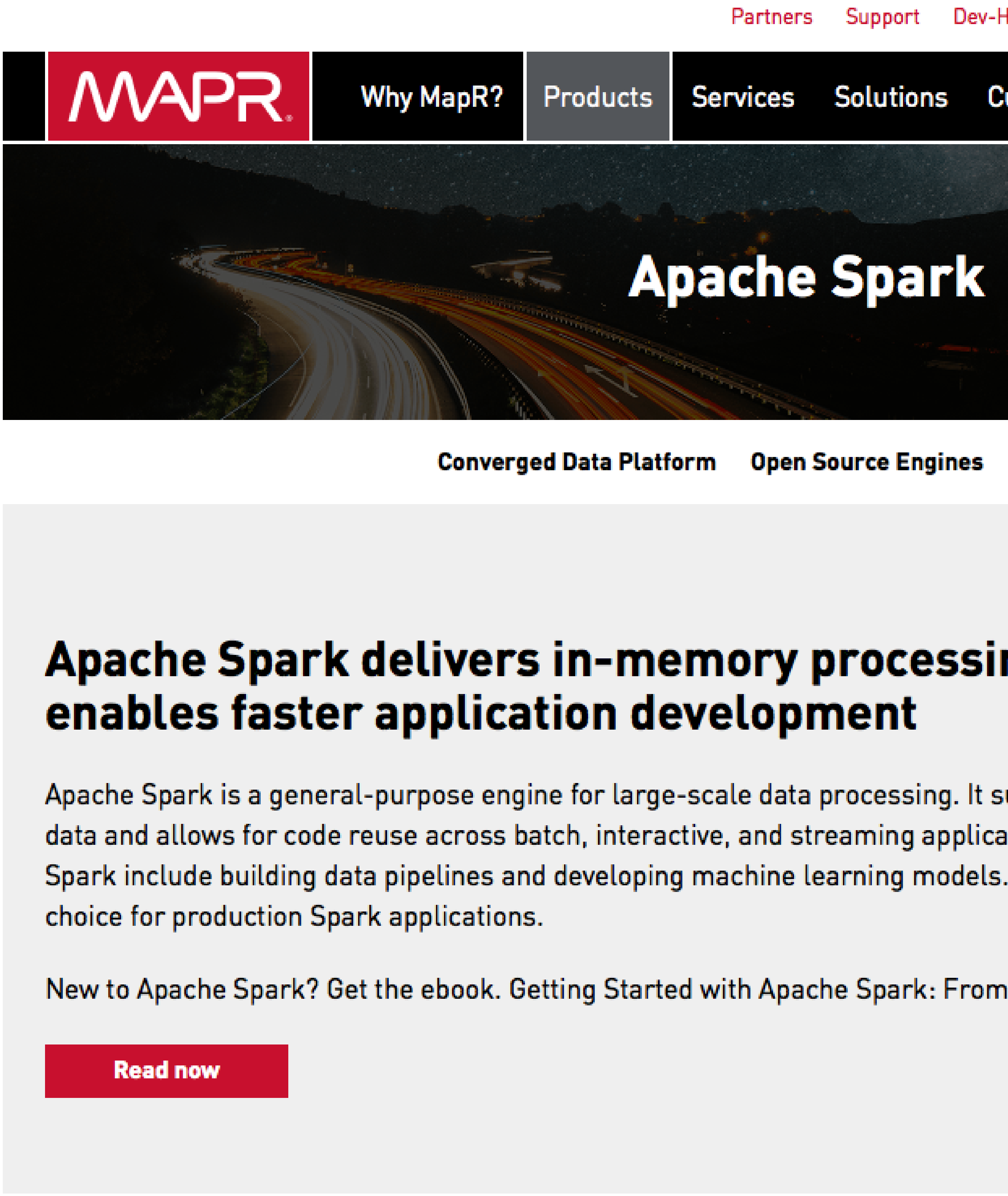
OVERVIEW

Spark adds in-Memory Compute for ETL, Machine Le

WHAT APACHE SPARK DOES

Apache Spark is a fast, in-memory data processing e
APIs to allow data workers to efficiently execute stre
require fast iterative access to datasets. With Spark
everywhere can now create applications to exploit Sp
science workloads within a single, shared dataset in

Figure 5.9: Hortonworks Landing Site.



Apache Spark delivers in-memory processi
enables faster application development

Apache Spark is a general-purpose engine for large-scale data processing. It s
data and allows for code reuse across batch, interactive, and streaming applica
Spark include building data pipelines and developing machine learning models.
choice for production Spark applications.

New to Apache Spark? Get the ebook. Getting Started with Apache Spark: From

Figure 5.10: MapR Landing Site.

the right one for you.

It is worth mentioning that in a cloud service model, the compute instances are charged by the hour and times the number of instances reserved for your cluster. Since the cluster size is flexible, it is a good practice to start with small clusters and scale compute resources as needed. Even if you know in advance that a cluster of significant size will be required, starting small provides an opportunity to troubleshoot issues at a lower cost since it's unlikely that your data analysis will run at scale flawlessly on the first try.

The major providers of cloud computing infrastructure are: Amazon, Google and Microsoft that this section will briefly introduce.

5.4.1 Amazon

Amazon provides cloud services through Amazon Web Services; more specifically, they provide an on-demand Spark cluster through Amazon Elastic Map Reduce or EMR for short.

5.4.2 Google

Google provides their on-demand computing services through their Google Cloud, on-demand Spark cluster are provided by Google Dataproc.

5.4.3 Microsoft

Microsoft provides cloud services thorugh Microsft Azure and Spark clusters through Azure HDInsight.

5.5 Tools

While using only R and Spark can be sufficient for some clusters, it is common to install complementary tools in your cluster to improve: monitoring, sql analysis, workflow coordination, etc. with applications like Ganglia, Hue and Oozie respectevly. This secton is not meant to cover all, but rather mention two that are relevant to R and `sparklyr`.

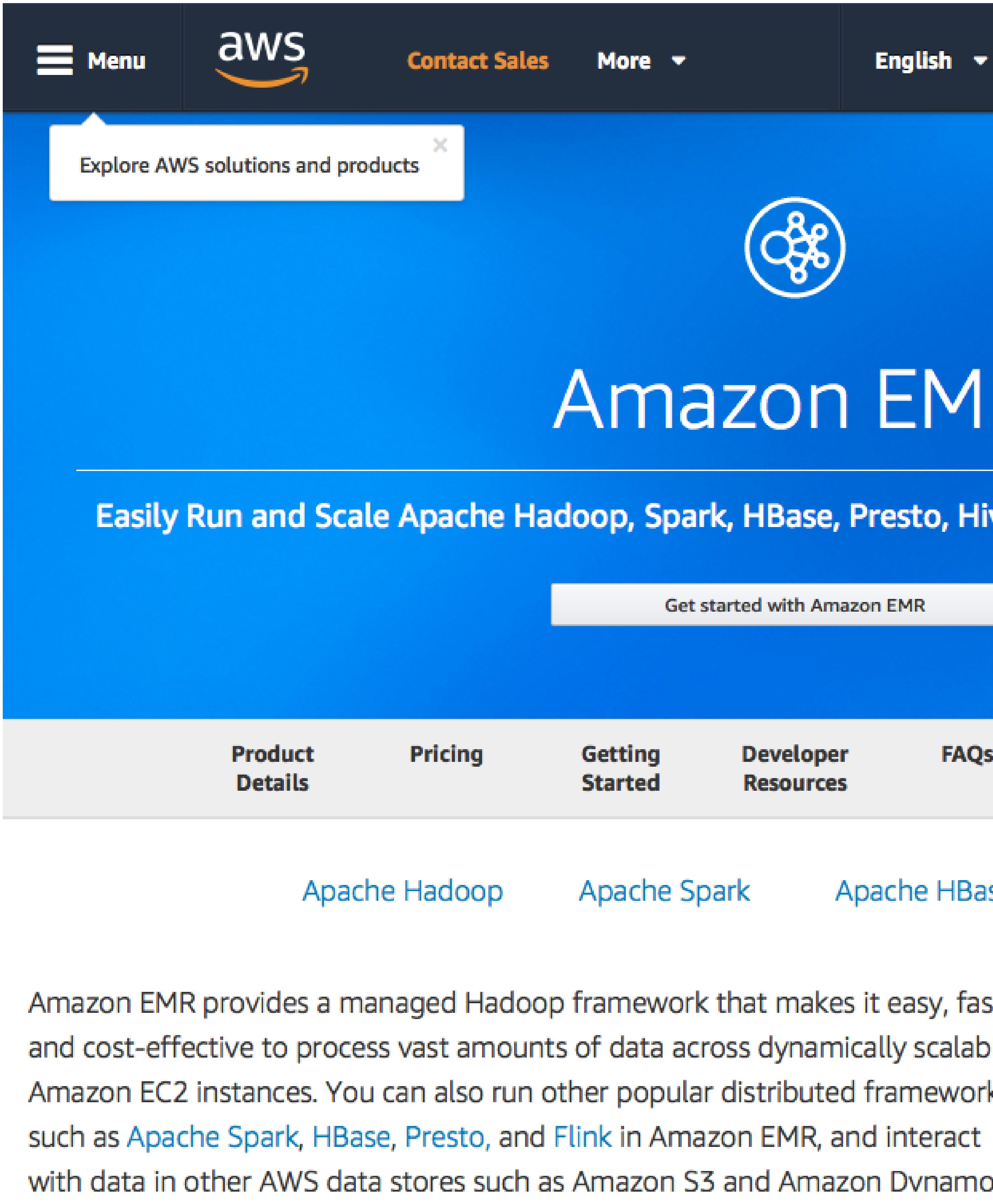
5.5.1 RStudio

RStudio's open source and professional products, like: RStudio Server, RStudio Server Pro, Shiny Server, Shiny Server Pro, or RStudio Connect; can be installed within the cluster to support many R workflows, while `sparklyr` does not require any additional tools, they provide significant productivity gains worth considering.

5.5.2 Livy

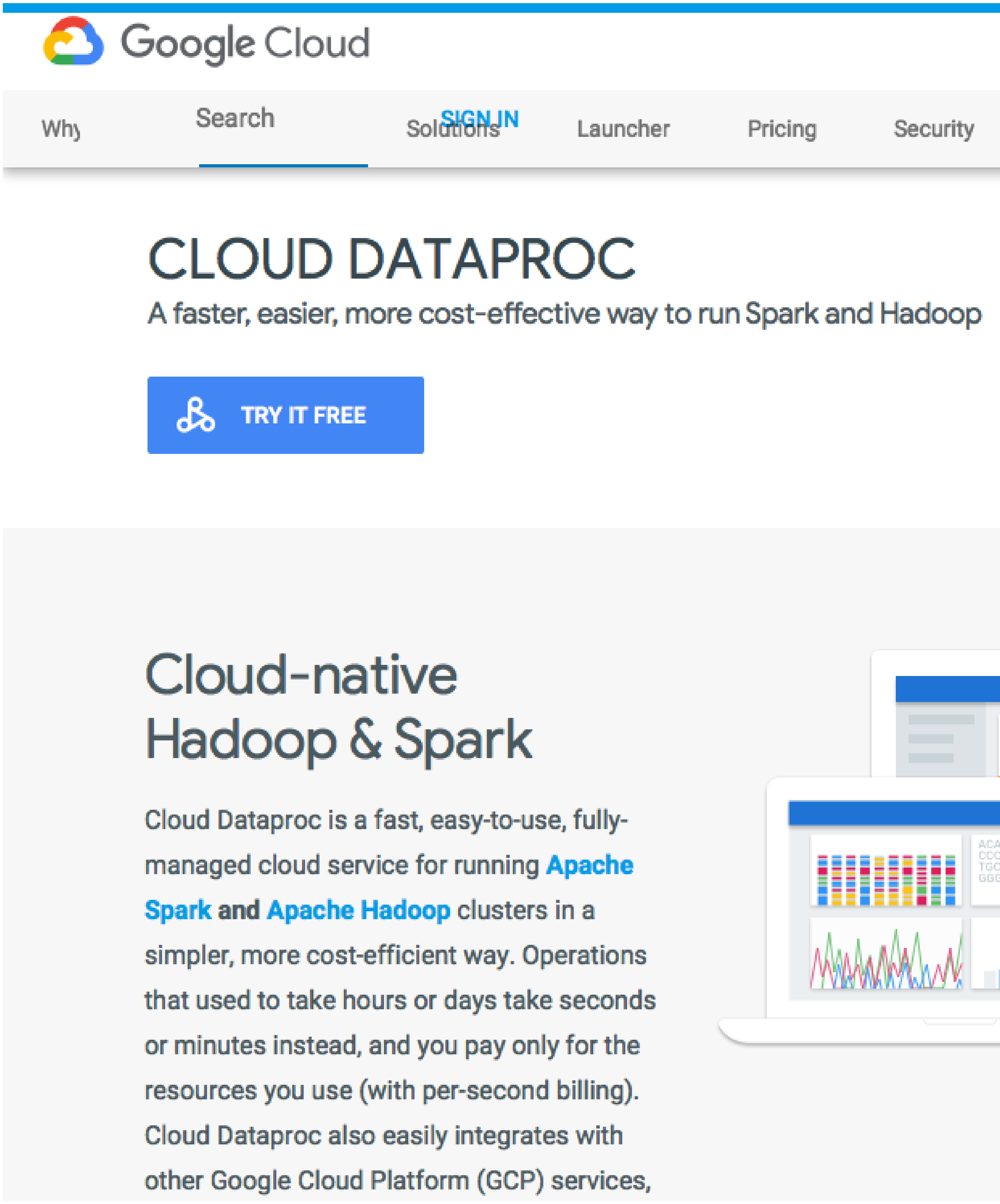
Apapche Livy is an incubation project in Apache providing support to use Spark clusters remotely through a web interface. It is ideal to connect directly into the Spark cluster; however, there are times where connecting directly to the cluster is not feasible. When facing those constraints, one can consider installing Livy in their cluster and secure it properly to enable remote use over web protocols.

However, there is a significant performance overhead from using Livy in `sparklyr` for experimentation, meaning that, executing many client comamnds over Livy has a significant overhead; however, running a few commands to generate complex analysis is usually performant since the performance overhead of starting computation can be insignificant compared to the actual cluster computation.



Amazon EMR provides a managed Hadoop framework that makes it easy, fas
and cost-effective to process vast amounts of data across dynamically scalab
Amazon EC2 instances. You can also run other popular distributed framework
such as Apache Spark, HBase, Presto, and Flink in Amazon EMR, and interact
with data in other AWS data stores such as Amazon S3 and Amazon Dynamo

Figure 5.11: Amazon EMR Landing Site.



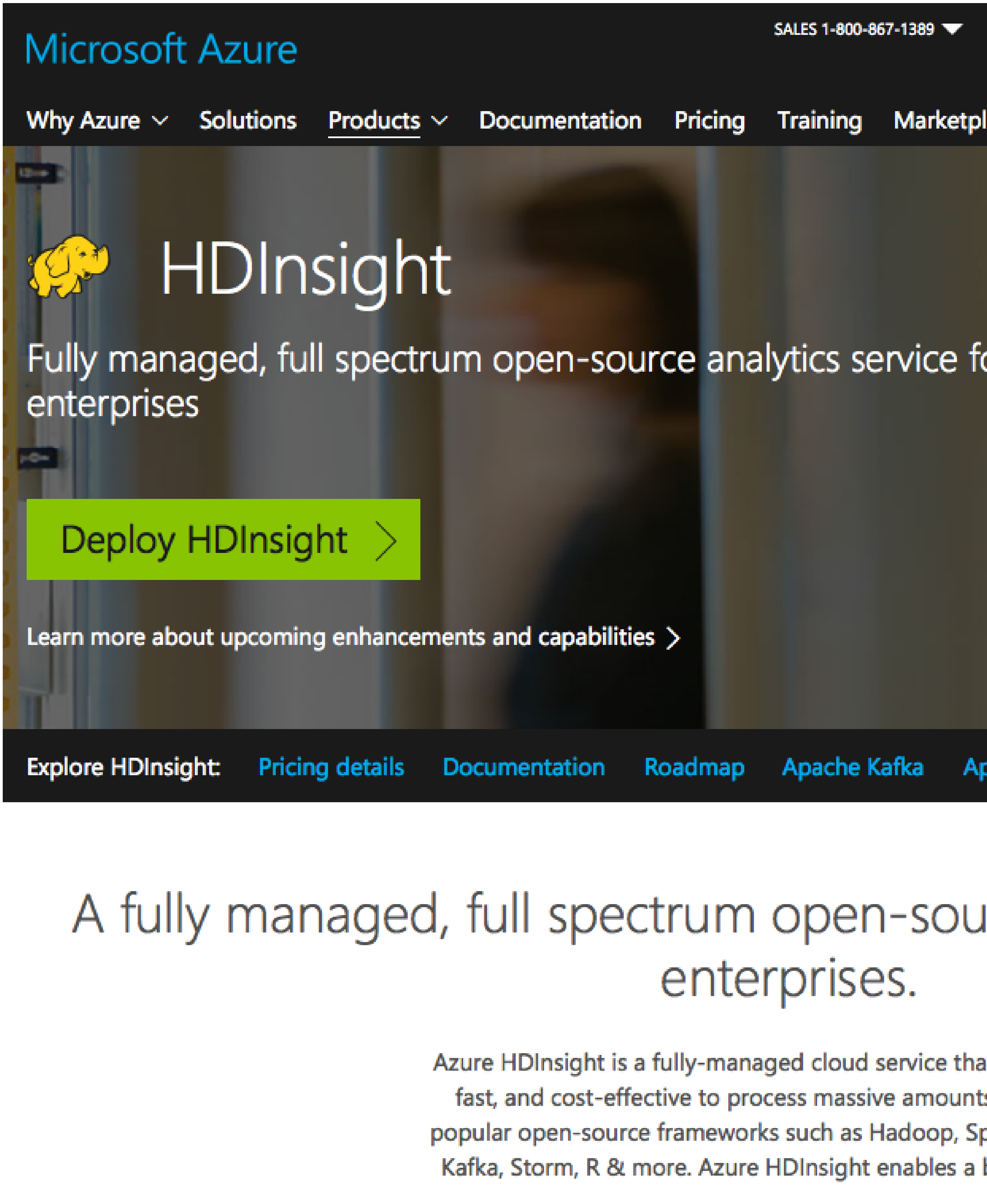
CLOUD DATAPROC

A faster, easier, more cost-effective way to run Spark and Hadoop

Cloud-native Hadoop & Spark

Cloud Dataproc is a fast, easy-to-use, fully-managed cloud service for running Apache Spark and Apache Hadoop clusters in a simpler, more cost-efficient way. Operations that used to take hours or days take seconds or minutes instead, and you pay only for the resources you use (with per-second billing). Cloud Dataproc also easily integrates with other Google Cloud Platform (GCP) services,

Figure 5.12: Google Dataprox Landing Site.

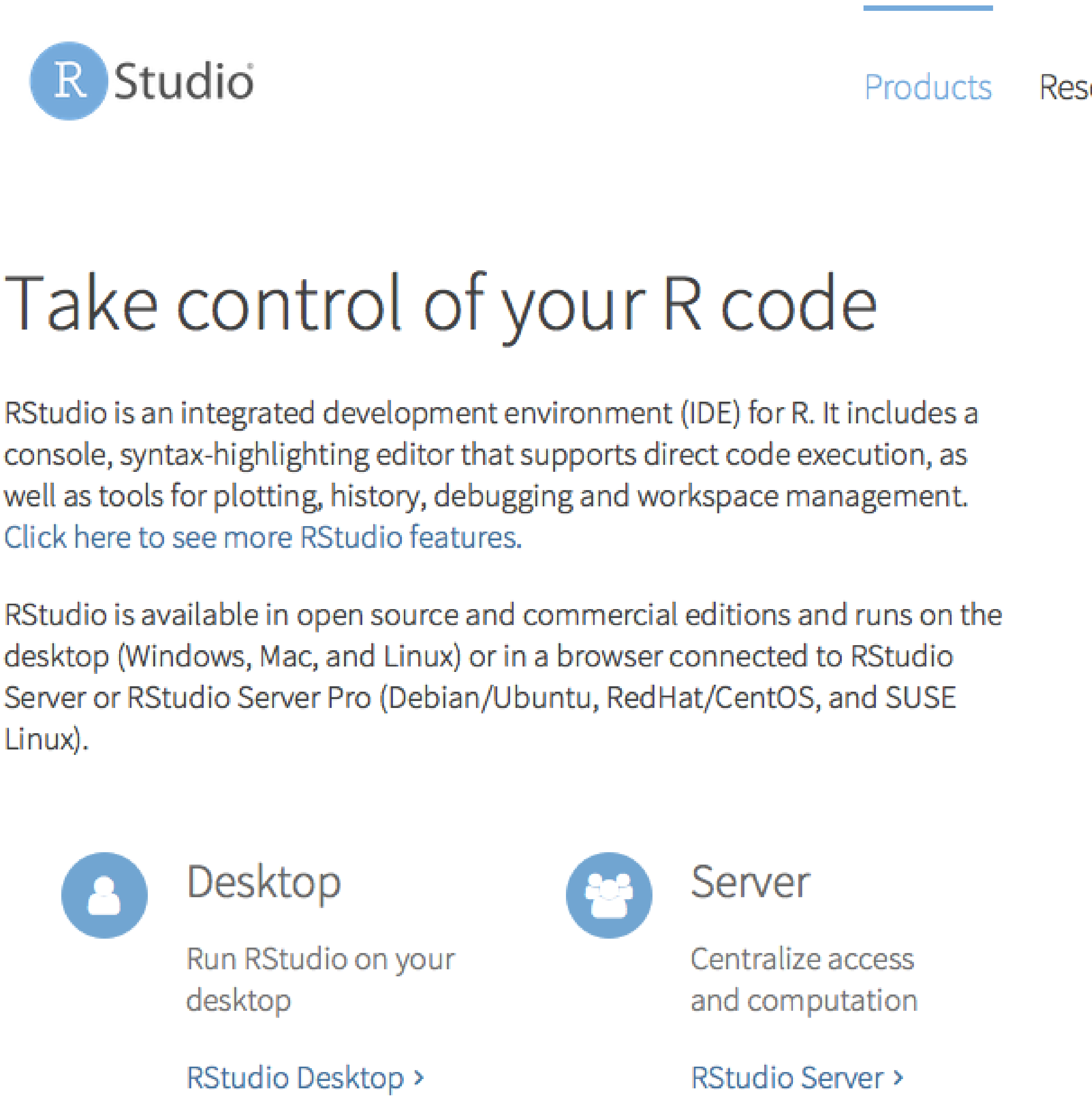


Fully managed, full spectrum open-source analytics service fo
enterprises

A fully managed, full spectrum open-sou
enterprises.

Azure HDInsight is a fully-managed cloud service tha
fast, and cost-effective to process massive amount
popular open-source frameworks such as Hadoop, Sp
Kafka, Storm, R & more. Azure HDInsight enables a b

Figure 5.13: Azure HDInsight Landing Site.



Take control of your R code

RStudio is an integrated development environment (IDE) for R. It includes a console, syntax-highlighting editor that supports direct code execution, as well as tools for plotting, history, debugging and workspace management. Click here to see more RStudio features.

RStudio is available in open source and commercial editions and runs on the desktop (Windows, Mac, and Linux) or in a browser connected to RStudio Server or RStudio Server Pro (Debian/Ubuntu, RedHat/CentOS, and SUSE Linux).

Desktop

Run RStudio on your desktop

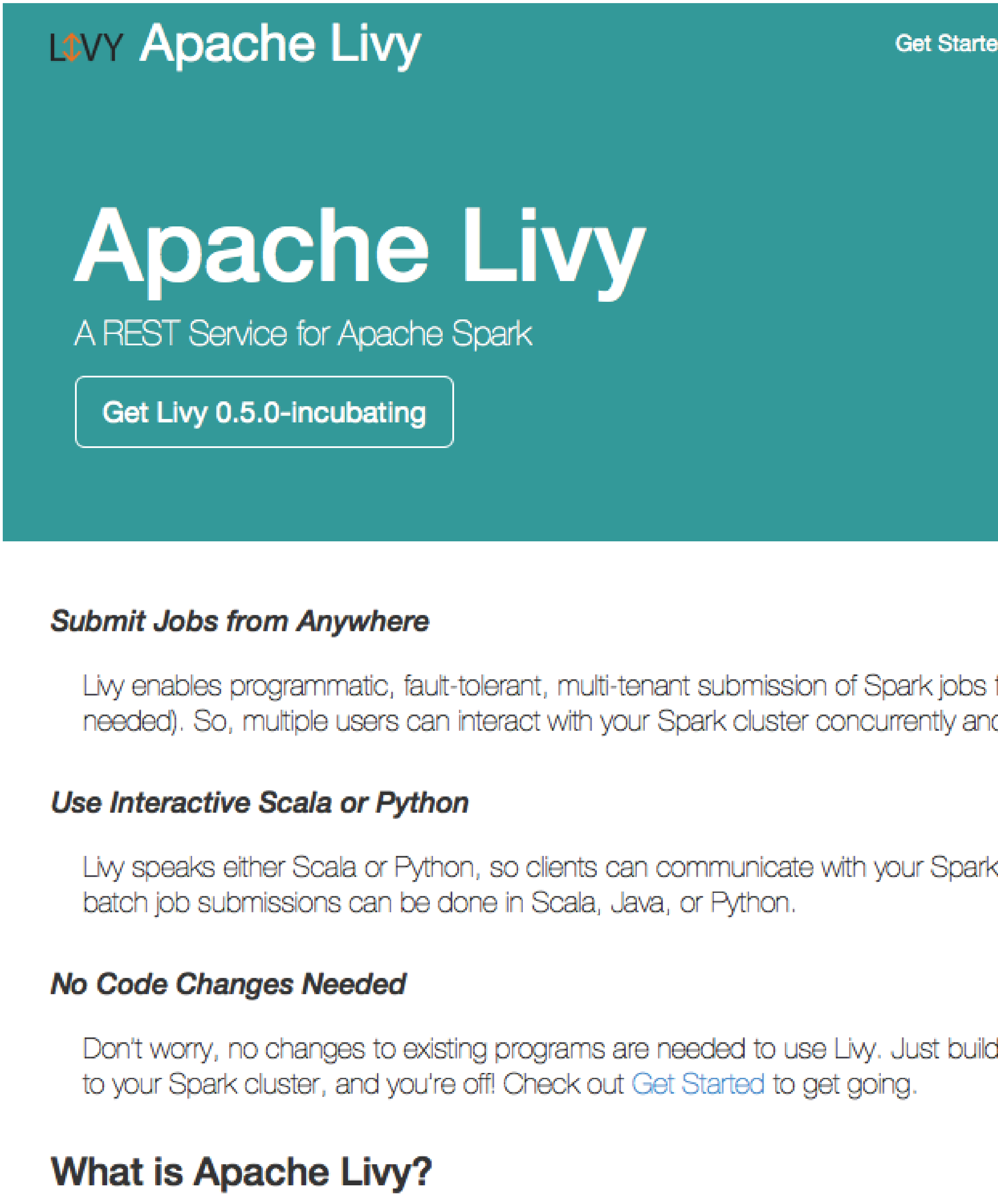
RStudio Desktop ›

Server

Centralize access and computation

RStudio Server ›

Figure 5.14: Rstudio Server



Apache Livy

A REST Service for Apache Spark

Submit Jobs from Anywhere

Livy enables programmatic, fault-tolerant, multi-tenant submission of Spark jobs f
needed). So, multiple users can interact with your Spark cluster concurrently anc

Use Interactive Scala or Python

Livy speaks either Scala or Python, so clients can communicate with your Spark
batch job submissions can be done in Scala, Java, or Python.

No Code Changes Needed

Don't worry, no changes to existing programs are needed to use Livy. Just build
to your Spark cluster, and you're off! Check out Get Started to get going.

What is Apache Livy?

Figure 5.15: Apache Livy Landing Site.

To help test Livy locally, `sparklyr` provides support to list, install, start and stop a local Livy instance by executing:

```
# List versions of Livy available to install
livy_available_versions()
```

```
##    livy
## 1 0.2.0
## 2 0.3.0
## 3 0.4.0
## 4 0.5.0
```

```
# Install default Livy version
livy_install()

# List installed Livy services
livy_installed_versions()

# Start the Livy service
livy_service_start()

# Stops the Livy service
livy_service_stop()
```

The default address for this local Livy service is http://localhost:8998

5.6 Recap

This chapter explained the history and tradeoffs of on-premise, cloud computing and presented Kubernetes as a promising framework to provide flexibility across on-premise and cloud providers. It also introduced cluster managers (Spark Standalone, YARN, Mesos and Kubernetes) as the software needed to run Spark as a cluster application. This chapter briefly mentioned on-premise cluster providers like Cloudera, Hortonworks and MapR as well as the major cloud providers: Amazon, Google and Microsoft.

While this chapter provided a solid foundation to understand current computing trends, cluster tools and providers useful to perform data science; it falls short to help those tasked with deliberately choosing a cluster manager, service provider or architecture. If you have this task assigned to you, use this chapter as a starting point to reach to many more resources to complete your understanding of the platform your organization needs.

The next chapter, Connections, assumes a Spark cluster is already available to you and will focus on understanding how to connect to it from sparklyr.

Chapter 6

Connections

The previous chapter, Clusters, presented the major cluster computing paradigms, cluster managers and cluster providers; this section explains the internal components of a Spark cluster and the how to perform connections to any cluster running Apache Spark.

6.1 Overview

Before explaining how to connect to Spark clusters, it is worth discussing the components of a Spark cluster and how they interact, this is often known as the cluster architecture of Apache Spark.

First, lets go over a couple definitions. As you know form previous chapters, a cluster is a collection of machines to perform analysis beyond a single computer. However, in distributed systems and clusters literature, we often reffer to each physical machine as a compute instance, compute node, or simply instance or node for short. It is helpful to remind this while reading through this chapter and making use of external resource.

In a Spark cluster, there are three types of compute instances that are relevant to Spark: The **driver node**, the **worker nodes** and the **cluster manager**. A cluster manager is a service that allos Spark to be executed in the clsuter and was explained in the Cluster Managers section. The driver node is tasked with delegating work to the worker nodes, but also for aggregating their results and iterating further if needed. For the most part, aggregation happens in the worker nodes; however, even after the nodes aggregate data, it is often the case that the driver node would have to aggregate the worker results. Therefore, the driver node has at least, but often, much more compute resources (read RAM, CPU, Local Storage, etc.) then the worker node.

Strictly speaking, the driver node and worker nodes are just names assigned to machines with particular roles, while the actual computation in the driver node is performed by the **spark context**. The Spark context is a Spark component tasked with scheduling tasks, managing data and so on. In the worker nodes, the actual computation is performed under a **spark executor**, which is also a Spark component tasked with executing subtasks against a data partition.

If you already have an Spark cluster in their organization, you should ask your cluster administrator to provide connection information for this cluster and read carefully their usage policies and constraints. A cluster is usually shared among many users so you want to be respectful of others time and resources while using a shared cluster environment. Your system administrator will describe if it's an **on-premise** vs **cloud** cluster, the **cluster manager** being used, supported **connections** and supported **tools**. You can use this information to jump directly to Local, Standalone, Yarn, Mesos, Livy or Kubernetes based on the information provided to you.

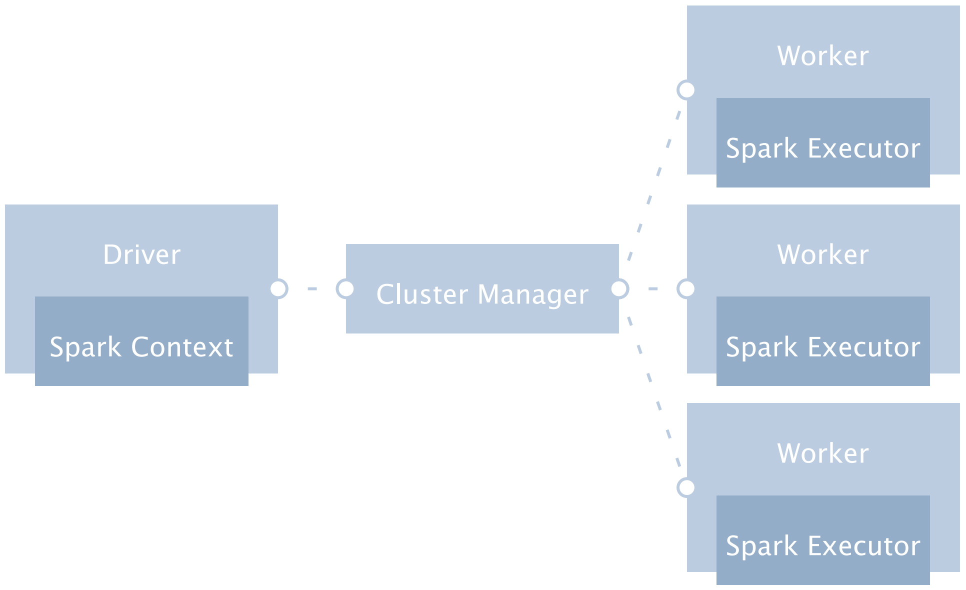


Figure 6.1: Apache Spark Architecture

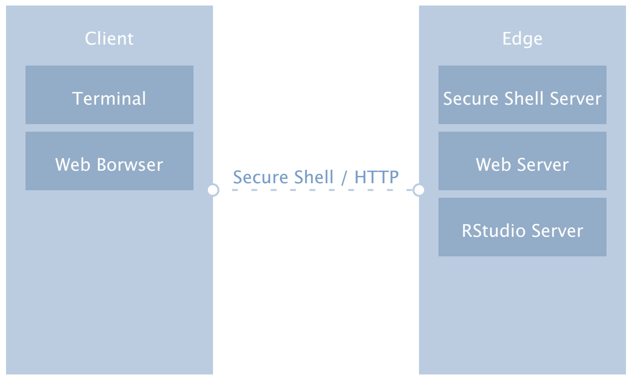


Figure 6.2: Using a Spark Cluster from an Edge Node

6.1.1 Edge Nodes

Before connecting to Apache Spark, you will first have to connect to the cluster. Usually, by connecting to an edge node within the cluster. An edge node, is a machine that can accessed from outside the cluster but which is also part of the cluster. There are two methods to connect to this edge instance:

- **Terminal**: Using a computer terminal applicaiton, one can use a secure shell to establish a remote connection into the cluster, once you connect into the cluster, you can launch R and then use `sparklyr`.
- **Web Browser**: While using `sparklyr` from a terminal is possible, it is usually more producty to install a **web server** in an edge node that provides more tools and functionality to run R with `sparklyr`. Most likely, you will want to consider using RStudio Server rather than connecting from the terminal.

6.1.2 Spark Home

It is important to mention that, while connecting to a Spark cluster, you will need to find out the correct `SPARK_HOME` path which contains the installation of Spark in the given instance. The `SPARK_HOME` path must

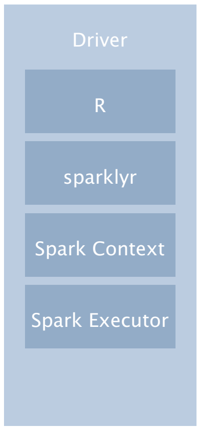


Figure 6.3: Local Connection Diagram

be set as an environment variable before connecting or explicitly specified in `spark_connect()` using the `spark_home` parameter.

For system administrators, we recommend you set `SPARK_HOME` for all the users in your cluster; however, if this is not set in your cluster you can also specify `SPARK_HOME` while using `spark_connect()` as follows:

```
sc <- spark_connect(master = "cluster-master", spark_home = "local/path/to/spark")
```

Where `cluster-master` is set to the correct cluster manager master for Spark Standalone, YARN, Mesos, etc.

6.2 Types

6.2.1 Local

When connecting to Spark in local mode, Spark starts as a single application simulating a cluster with a single node, this is not a proper computing cluster but is ideal to perform work offline and troubleshoot issues. A local connection to Spark is represented in the following diagram:

Notice that in the local connections diagram, there is no cluster manager nor worker process since, in local mode, everything runs inside the driver application. It's also worth pointing out that `sparklyr` starts the Spark Context through `spark-submit`, a script available in every Spark installation to enable users to submit custom application to Spark which `sparklyr` makes use of to submit itself to Spark. For the curious reader, the Contributing chapter explains the internal processes that take place in `sparklyr` to submit this application and connect properly from R.

To perform this local connection, we can connect with the following familiar code used in previous chapters:

```
# Connect to local Spark instance
sc <- spark_connect(master = "local")
```

By default, `sparklyr`, will connect using as many CPU cores are available in your compute instance; however, this can be customized by connecting using `master="local[n]"`, where `n` is the desired number of cores to use. For example, we can connect using only 2 CPU cores as follows:

```
# Connect to local Spark instance using 2 cores
sc <- spark_connect(master = "local[2]")
```

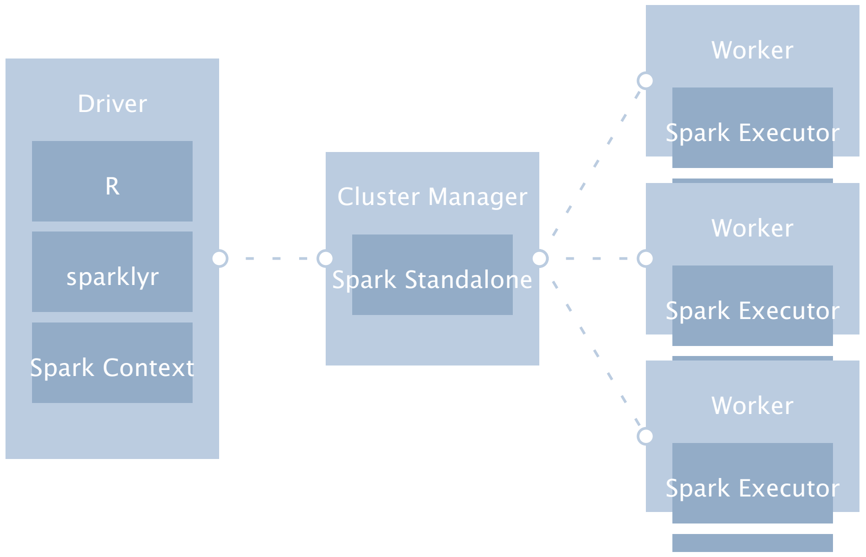


Figure 6.4: Spark Standalone Connection Diagram

6.2.2 Standalone

Connecting to a Spark Standalone cluster requires the location of the cluster manager's master instance, this location can be found in the cluster manager web interface as described in the clusters-standalone section, you can find this location by looking for a URL starting with `spark://`.

A connection in standalone mode starts from `sparklyr` launching `spark-submit` to submit the `sparklyr` application and creating the Spark Context, which requests executors to Spark's standalone cluster manager in the `master` location:

In order to connect, use `master="spark://hostname:port"` in `spark_connect()` as follows:

```r
sc <- spark_connect(master = "spark://hostname:port")
```

6.2.3 Yarn

Hadoop YARN supports two connection modes: YARN Client and YARN Cluster. However, YARN Client mode is much more common that YARN Cluster since it's more efficient and easier to set up.

6.2.3.1 Yarn Client

When connecting in YARN Client mode, the driver instance runs R, sparklyr and the Spark Context which requests worker nodes from YARN to run Spark executors as follows:

To connect, one can simply run with `master = "yarn"` as follows:

```r
sc <- spark_connect(master = "yarn-client")
```

Once connected, you can use all techniques described in previous chapters using the `sc` connection; for instances, you can do data analysis or modeling.

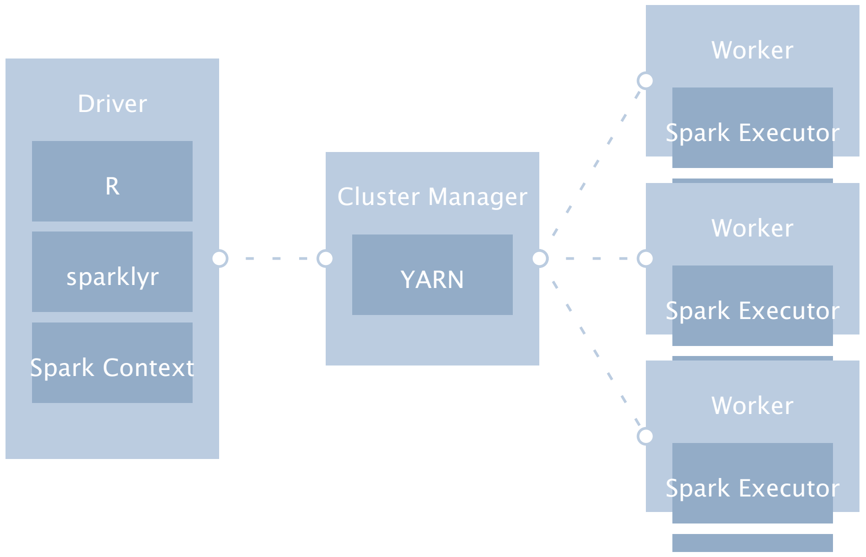


Figure 6.5: YARN Client Connection Diagram

6.2.3.2 Yarn Cluster

The main difference between YARN Cluster mode and YARN Client mode is that in YARN Cluster mode, the driver node is not required to be the node where R and sparklyr get started; instead, the driver node remains the designated driver node which is usually a different node than the edge node where R is running. It can be helpful to consider using YARN Cluster when the edge node has too many concurrent users, is lacking computing resources or where tools (like RStudio) need to be managed independently of other clsuter resources.

To connect in YARN Cluster mode, we can simple run:

```
sc <- spark_connect(master = "yarn-cluster")
```

This connection assumes that the node running `spark_connect()` is properly configured, meaning that, `yarn-site.xml` exists and the `YARN_CONF_DIR` environment variable is properly set. When using Hadoop as a file system, one would also need the `HADOOP_CONF_DIR` environment variable properly configured. This configuration is usually provided by your system administrator and is not something that you would have to manually configure.

6.2.4 Livy

As opposed to other connection methods which require using an edge node in the cluster, Livy Livy provides a **Web API** that makes the Spark cluster accessible from outside the cluster and neither requires a local installation in the client. Once connected through the Web API, the **Livy Service** starts the Spark context by requesting reosources from the cluster manager and distributing work as usual.

Conencting through Livy requires the URL to the Livy service which should be similar to `https://hostname:port/livy`. Since remote connections are allowed, connections usually requires, at the very least, basic authentication:

```
sc <- spark_connect(master = "https://hostname:port/livy", method = "livy", config = livy_config(
  username="<username>",
  password="<password>"
))
```

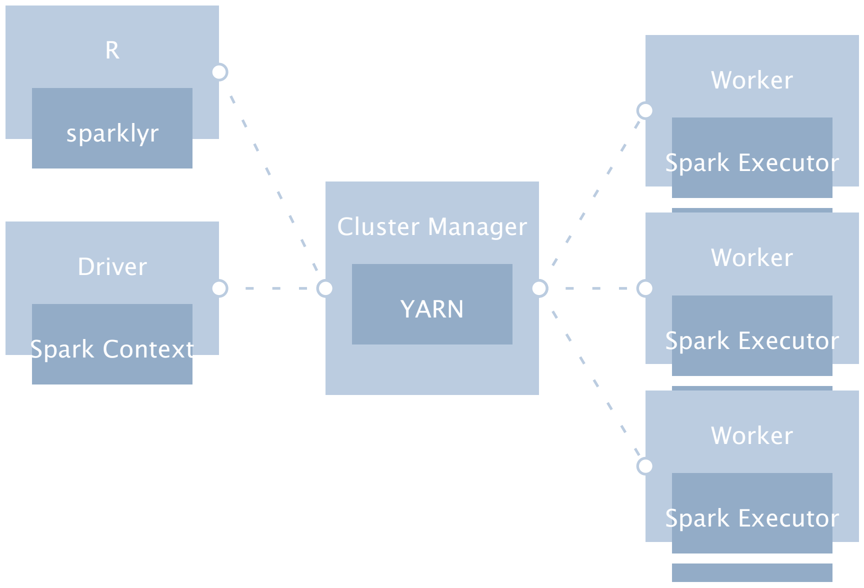


Figure 6.6: YARN Cluster Connection Diagram

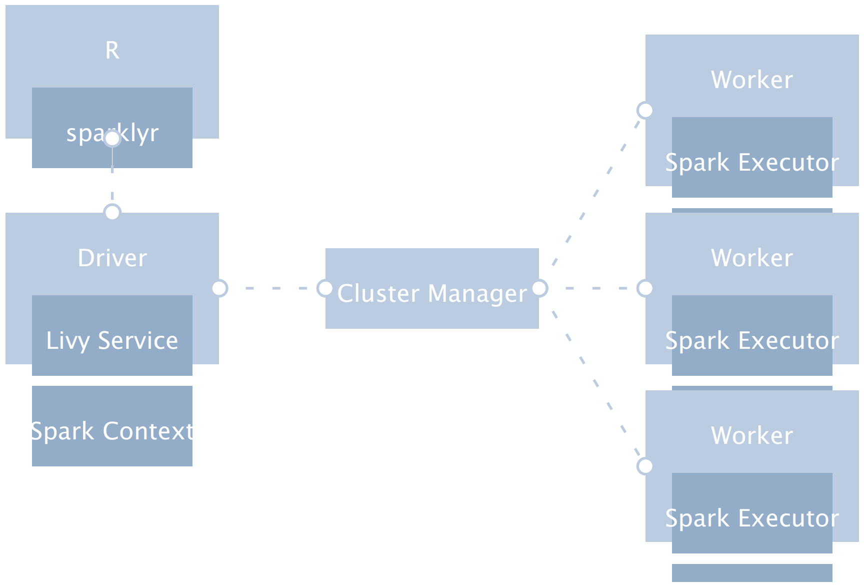


Figure 6.7: Livy Connection Diagram

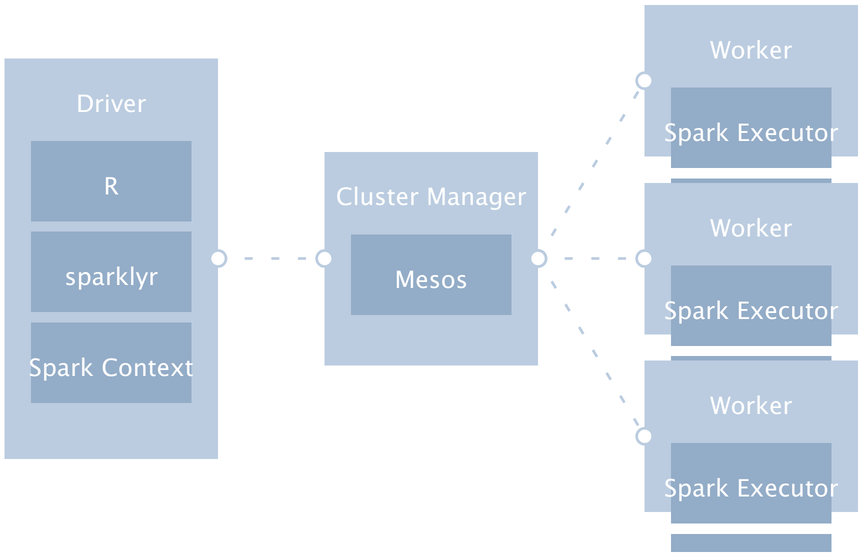


Figure 6.8: Mesos Connection Diagram

Once connected through Livy, operations you can make use of an other `sparklyr` feature; however, Livy is not suitable for experimental data analysis, since executing commands have a significant delay; that said, while running long running computations, this overhead could be considered irrelevant. In general, it is preffered to avoid using Livy and work directly within an edge node in the cluster; if this is not feasible, using Livy could be a reasonable approach.

6.2.5 Mesos

Similar to YARN, Mesos supports client mode and a cluster mode. However, `sparklyr` currently only supports client mode for Mesos.

Connecting requires the address to the Mesos master node, usually in the form of `mesos://host:port` or `mesos://zk://host1:2181,host2:2181,host3:2181/mesos` for Mesos using ZooKeeper.

```
sc <- spark_connect(master = "mesos://host:port")
```

6.2.6 Kubernetes

Kubernetes cluster do not support client modes similar to Mesos or YARN, instead, the connection model is similar to YARN Cluster, where the driver node is assigned by Kubernetes.

Kubernetes support is scheduled to be added to `sparklyr` with sparklyr/issues/1525, please follow progress for this feature directly in github. Once Kubernetes becomes supported in `sparklyr`, connecting to Kubernetes will work as follows:

```
sc <- spark_connect(
  master = "k8s://https://<apiserver-host>:<apiserver-port>"
  config = list(
    spark.executor.instances = 2,
    spark.kubernetes.container.image = "spark-image"
  )
)
```

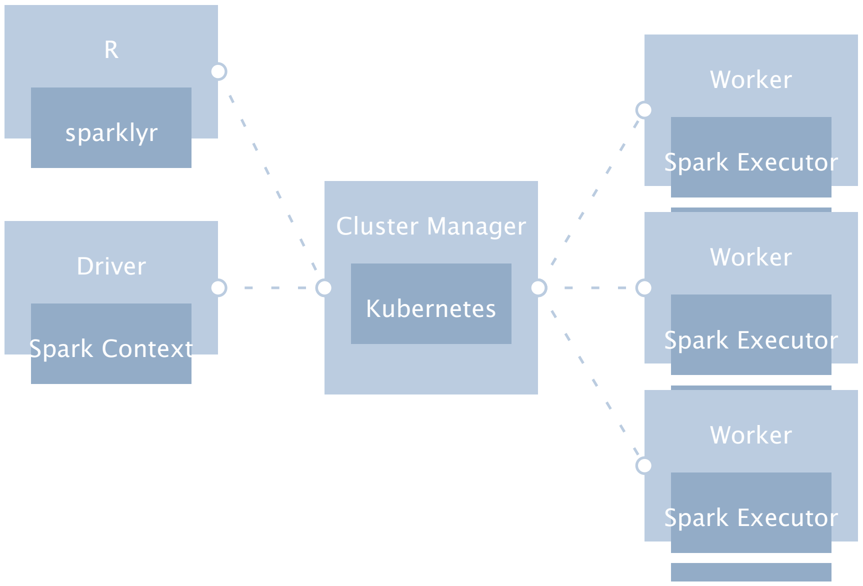


Figure 6.9: Kubernetes Connection Diagram

If your computer is already configured to use a Kubernetes cluster, you can use the following commmand to find the `apiserver-host` and `apiserver-port`:

```r
system2("kubectl", "cluster-info")
```

6.3 Troubleshooting

6.3.1 Logging

One first step is to troubleshoot connections is to run in verbose to print directly to the console additional error messages:

```r
sc <- spark_connect(master = "local", log = "console")
```

6.3.2 Spark Submit

If connections fail in `sparklyr`, first troubleshoot if this issue is specific to `sparklyr` or Spark in general. This can be accomplished by running an example `spark-submit` job and validating that no errors are thrown:

```r
# Find the spark directory using an environment variable
Sys.getenv("SPARK_HOME")

# Or by getting the local spark installation
sparklyr::spark_home_dir()
```

From the terminal run:

```
cd path/to/spark/
bin/spark-submit
```

6.3.3 Multiple

It is common to connect once, and only once, to Spark. However, you can also open multiple connections to Spark by connecting to different clusters or by specifying the `app_name` parameter, this can be helpful to compare Spark versions or validate you analysis before submitting to the cluster. The following example opens connections to Spark 1.6.3, 2.3.0 and Spark Standalone:

```
# Connect to local Spark 1.6.3
sc_1_6_3 <- spark_connect(master = "local", version = "1.6.3")

# Connect to local Spark 2.3.0
sc_2_3_0 <- spark_connect(master = "local", version = "2.3.0", appName = "Spark23")

# Connect to local Spark Standalone
sc_standalone <- spark_connect(master = "spark://host:port")
```

Finally, we can disconnect from each connection:

```
spark_disconnect(sc_1_6_3)
spark_disconnect(sc_2_3_0)
spark_disconnect(sc_standalone)
```

Alternatevely, you can disconnect from all connections at once:

```
spark_disconnect_all()
```

6.3.4 Windows

Connecting from Windows is, in most cases, as straightforward as connecting from Linux or OS X; however, there are a few common connection issues you might hit t

- Firewalls and atni-viruse software might block ports for your connection. The default port used by `sparklyr` is 8880, double check this port is not being blocked.
- Long path names can cause issues in, specially, older Windows systems like Windows 7. When using these systems, try connecting with Spark installed with all folders using 8 characters or less.

6.3.5 Submit Manually

To troubleshoot Windows connections in detail, you can use a 2-step initialization that is often very helpful to diagnose connection issues.

This 2-step initialization os performed by launching `sparklyr` through `spark-submit` followed by connecting with `sparklyr` from R.

First, identify the Spark installation directory. Second, identify the path to the correct `sparklyr*.jar`, you can find this path by running;

```
dir(system.file("java", package = "sparklyr"), pattern = "sparklyr", full.names = T)
```

```
## [1] "/Library/Frameworks/R.framework/Versions/3.5/Resources/library/sparklyr/java/sparklyr-1.5-2.10.j
## [2] "/Library/Frameworks/R.framework/Versions/3.5/Resources/library/sparklyr/java/sparklyr-1.6-2.10.j
## [3] "/Library/Frameworks/R.framework/Versions/3.5/Resources/library/sparklyr/java/sparklyr-2.0-2.11.j
## [4] "/Library/Frameworks/R.framework/Versions/3.5/Resources/library/sparklyr/java/sparklyr-2.1-2.11.j
## [5] "/Library/Frameworks/R.framework/Versions/3.5/Resources/library/sparklyr/java/sparklyr-2.2-2.11.j
## [6] "/Library/Frameworks/R.framework/Versions/3.5/Resources/library/sparklyr/java/sparklyr-2.3-2.11.j
```

Make sure you identify the correct version that matches your Spark cluster, for isntance `sparklyr-2.1-2.11.jar` for Spark 2.1.

Third, from the terminal run:

```
$SPARK_HOME/bin/spark-submit --class sparklyr.Shell $PATH_TO_SPARKLYR_JAR 8880 12345
```

```
18/06/11 12:13:53 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using bui
18/06/11 12:13:53 INFO sparklyr: Session (12345) is starting under 127.0.0.1 port 8880
18/06/11 12:13:53 INFO sparklyr: Session (12345) found port 8880 is available
18/06/11 12:13:53 INFO sparklyr: Gateway (12345) is waiting for sparklyr client to connect to port 8880
```

The parameter `8880` represents the default port to use in `sparklyr` while `12345` is the session number, this is a cryptographically secure number generated by `sparklyr`, but for troubleshooting purpuses can be as simple as `12345`.

Then, from R, connect as follows, notice that there is a 60 seconds timeout, so you'll have to run the R command immediately after running the terminal command:

```
library(sparklyr)
sc <- spark_connect(master = "sparklyr://localhost:8880/12345", version = "2.3")
```

6.4 Recap

This chapter presented an overview of Spark's architecture and detailed connections concepts and examples to connect in local mode, standalone, YARN, Mesos, Kubernetes and Livy. It also presented edge nodes and their role while connecting to Spark clusters. This information should give you enough information to effectevely connect to any cluster with Apache Spark enabled.

To troubleshoot connection problems, it is recommended to search for the connection problem in StackOverflow, the sparklyr github issues and, if needed, open a new GitHub issue in sparklyr to assist further.

In the next chapter, Tuning, you will learn in-detail how Spark works and use this knowledge to optimize it's resource usage and performance.

Chapter 7

Tuning

This chatper has not been written.

7.1 Overview

```r
sc <- spark_connect(master = "local", memory = "4g", cores = 8)

entries <- 100000000
sort_r <- system.time(runif(entries, 0, 100) %>% sort())["elapsed"]
sort_spark <- system.time(sdf_len(sc, entries) %>% dplyr::mutate(x = rand()) %>% dplyr::arrange() %>% d

lapply(expt(1:10))
```

7.2 Configuration

```r
config <- spark_config()
sc <- spark_connect(master = "local")

spark_context_config(sc)

spark_session_config(sc)

# Previous versions
spark_hive_config(sc)
```

https://spark.apache.org/docs/latest/configuration.html

7.3 Caching

Most sparklyr operations that retrieve a Spark data frame, cache the results in-memory, for instance, running `spark_read_parquet()` or `sdf_copy_to()` will provide a Spark dataframe that is already cached in-memory. As a Spark data frame, this object can be used in most sparklyr functions, including data analysis with dplyr or machine learning.

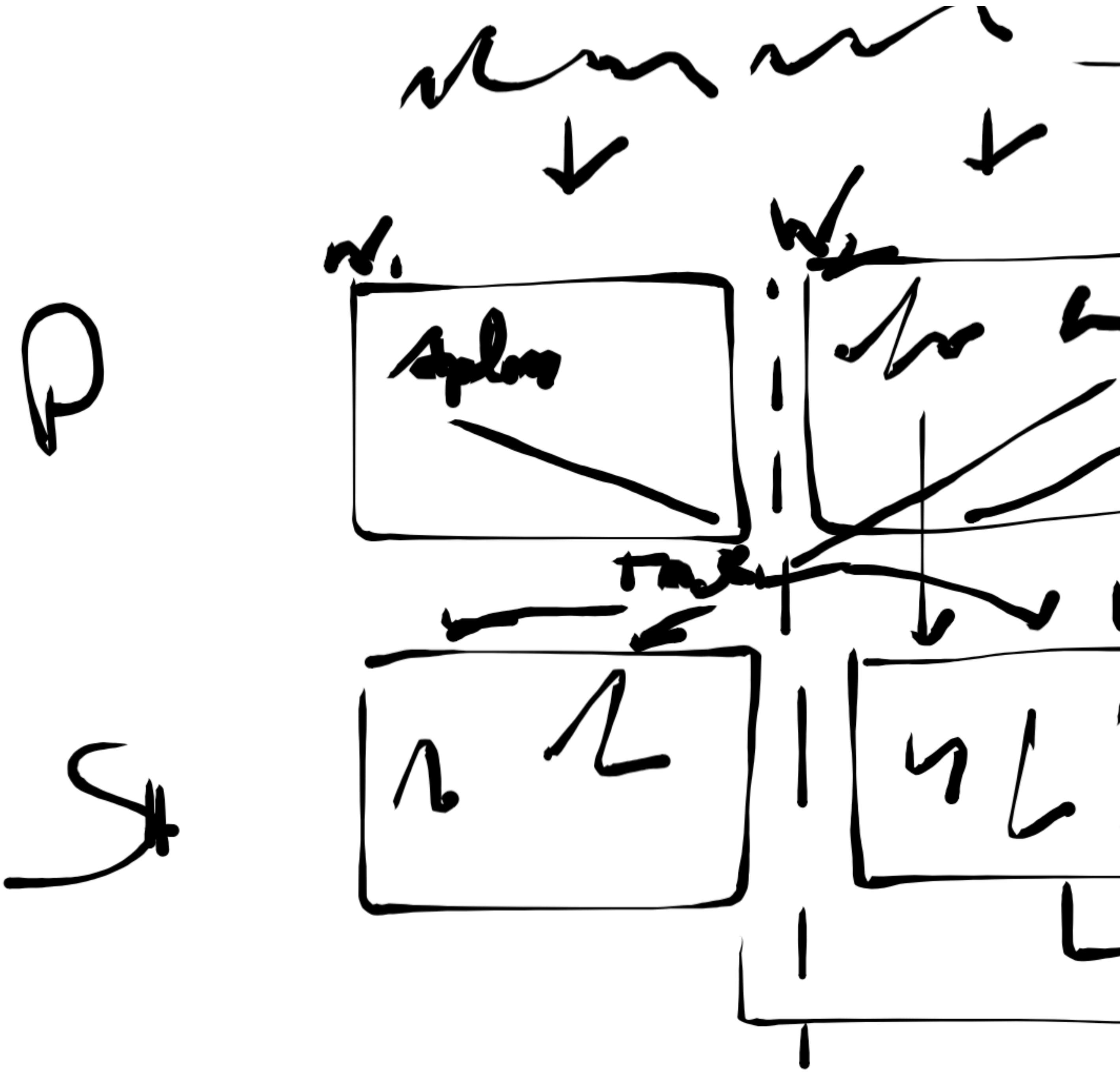


Figure 7.1: Spark RDDs

```r
library(sparklyr)
sc <- spark_connect(master = "local")
```

```r
iris_tbl <- sdf_copy_to(sc, iris, overwrite = TRUE)
```

You can inspect which tables are cached by navigating to the Spark UI using `spark_web(sc)`, opening the storage tab, and clicking on a given RDD:

Data loaded in memory will be released when the R session terminates either explicitly or implicitly with a restart or disconnection; however, to free up resources, you can use `tbl_uncache()`:

```r
tbl_uncache(sc, "iris")
```

7.4 Partitions

7.5 Shuffling

7.6 Checkpointing

7.7 Troubleshooting

7.7.1 Graph Visualization

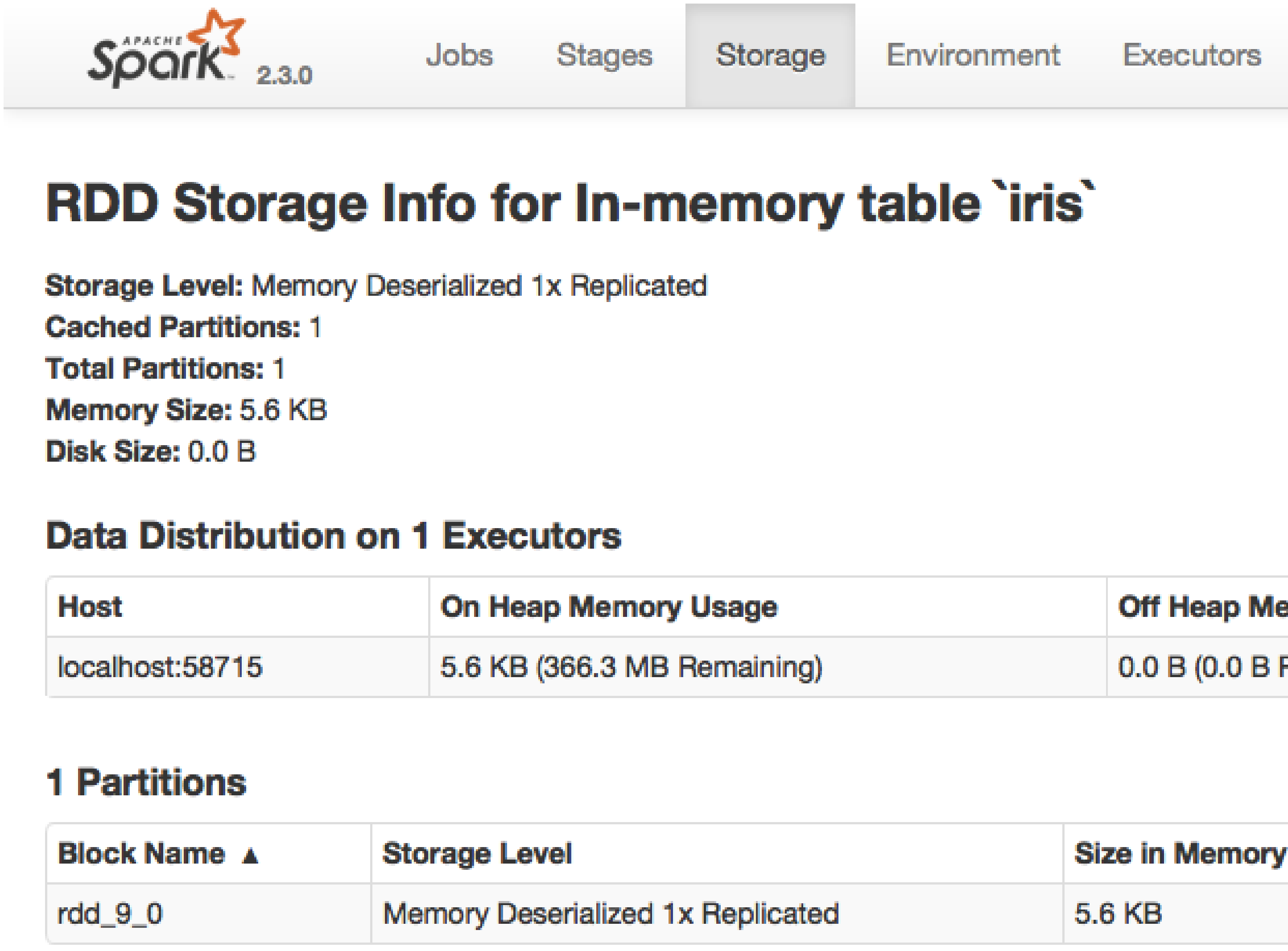
7.7.2 Event Timeline

One of the best ways to tune your Spark jobs is to use the Spark's web interface, click on the job being diagnosed, then the stage and then expand the **event timeline**.

Lets the take a look at the event timeline for the ordering a data frame by a given column using three partitions:

```r
spark_connect(master = "local") %>%
  copy_to(iris, repartition = 3) %>%
  arrange(Sepal_Width)
```

7.8 Recap



RDD Storage Info for In-memory table `iris`

Storage Level: Memory Deserialized 1x Replicated
Cached Partitions: 1
Total Partitions: 1
Memory Size: 5.6 KB
Disk Size: 0.0 B

Data Distribution on 1 Executors

Host	On Heap Memory Usage	Off Heap Me
localhost:58715	5.6 KB (366.3 MB Remaining)	0.0 B (0.0 B F

1 Partitions

Block Name ▲	Storage Level	Size in Memory
rdd_9_0	Memory Deserialized 1x Replicated	5.6 KB

Figure 7.2: Cached RDD in Spark Web Interface.

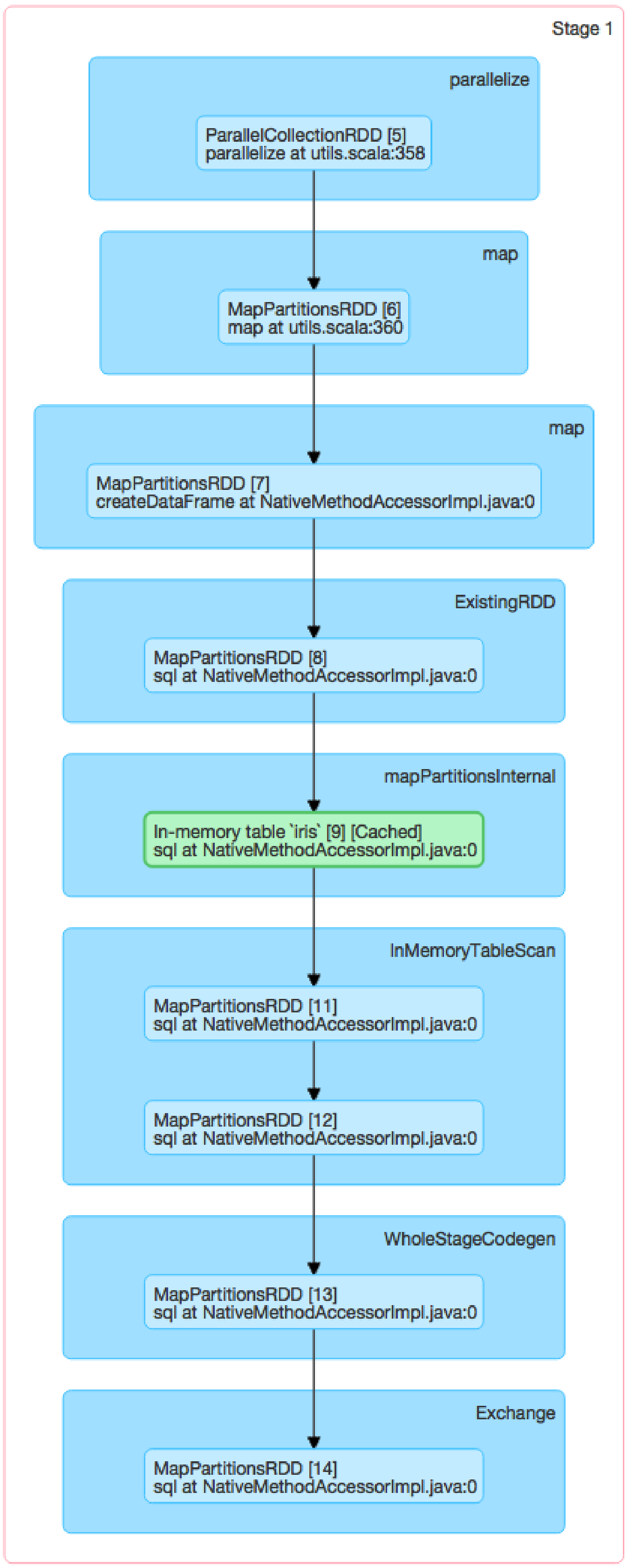

Stage 1
parallelize
ParallelCollectionRDD [5]
parallelize at utils.scala:358
map
MapPartitionsRDD [6]
map at utils.scala:360
map
MapPartitionsRDD [7]
createDataFrame at NativeMethodAccessorImpl.java:0
ExistingRDD
MapPartitionsRDD [8]
sql at NativeMethodAccessorImpl.java:0
mapPartitionsInternal
In-memory table `iris` [9] [Cached]
sql at NativeMethodAccessorImpl.java:0
InMemoryTableScan
MapPartitionsRDD [11]
sql at NativeMethodAccessorImpl.java:0
MapPartitionsRDD [12]
sql at NativeMethodAccessorImpl.java:0
WholeStageCodegen
MapPartitionsRDD [13]
sql at NativeMethodAccessorImpl.java:0
Exchange
MapPartitionsRDD [14]
sql at NativeMethodAccessorImpl.java:0

Figure 7.3: Spark Graph Visualization

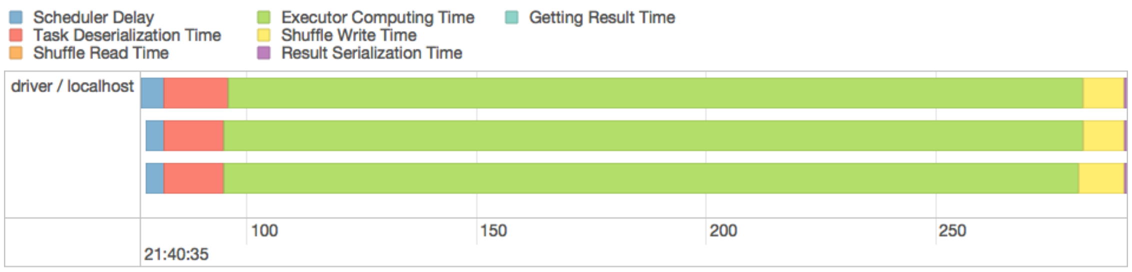


Figure 7.4: Spark Event Timeline

Chapter 8

Extensions

While **this chatper has not been written.**, a few resources are available to help explore these topics until this chapter gets written.

8.1 Using Extensions

8.1.1 GraphFrames

See spark.rstudio.com/graphframes.

8.1.2 Mleap

See spark.rstudio.com/guides/mleap.

8.1.3 H2O

See spark.rstudio.com/guides/h2o.

8.2 Writting Extensions

See spark.rstudio.com/extensions.

8.2.1 RStudio Projects

Chapter 9

Distributed R

While **this chatper has not been written.**, use spark.rstudio.com/guides/distributed-r to learn how to use R directly over each worker node.

9.1 Use Cases

9.2 Grouping

9.3 Packages

9.4 Restrictions

9.5 Troubleshooting

Chapter 10

Streaming

10.1 Overview

One can understand a stream as an unbounded data frame, meaning, a data frame with finite columns but infinite rows. Streams are most relevant when processing real time data; for example, when analyzing a Twitter feed or stock prices. Both examples have well defined columns, like 'tweet' or 'price', but there are always new rows of data to be analyzed.

Spark provided initial support for streams with Spark's DStreams; however, a more versatile and efficient replacement is available through Spark structured streams. Structured streams provide scalable and fault-torerant data processing over streams of data. That means, one can use many machines to process multiple streaming sources, perform joins with other streams or static sources, and recover from failures with at-least-once guarantees (where each message is certain to be delivered, but may do so multiple times).

In order to use structured streams in `sparklyr`, one needs to define the **sources**, **transformations** and a **destination**:

- The **sources** are defined using any of the `stream_read_*()` functions to read streams of data from various data sources.
- The **transformations** can be specified using `dplyr`, `SQL`, scoring pipelines or R code through `spark_apply()`.
- The **destination** is defined with the `stream_write_*()` functions, it often also referenced as a sink.

Since the transformation step is optional, the simplest stream we can define is to continuously process files, which would effectively copy text files between source and destination. We can define this copy-stream in `sparklyr` as follows:

```r
library(sparklyr)
sc <- spark_connect(master = "local")
stream <- stream_read_text(sc, "source/") %>% stream_write_text("destination/")
```

The streams starts running with `stream_write_*()`; once executed, the stream will monitor the `source` path and process data into the `destination/` path as it arrives. We can use `view_stream()` to track the **rows per second (rps)** being processed in the source, destination and their latest values over time:

```r
stream_view(stream)
```

Notice that the rows-per-second in the destination stream are higher than the rows-per-second in the source stream; this is expected and desireable since Spark measures incoming rates from the source, but actual row processing times in the destination stream.

Use `stream_stop()` to properly stop processing data from this stream:

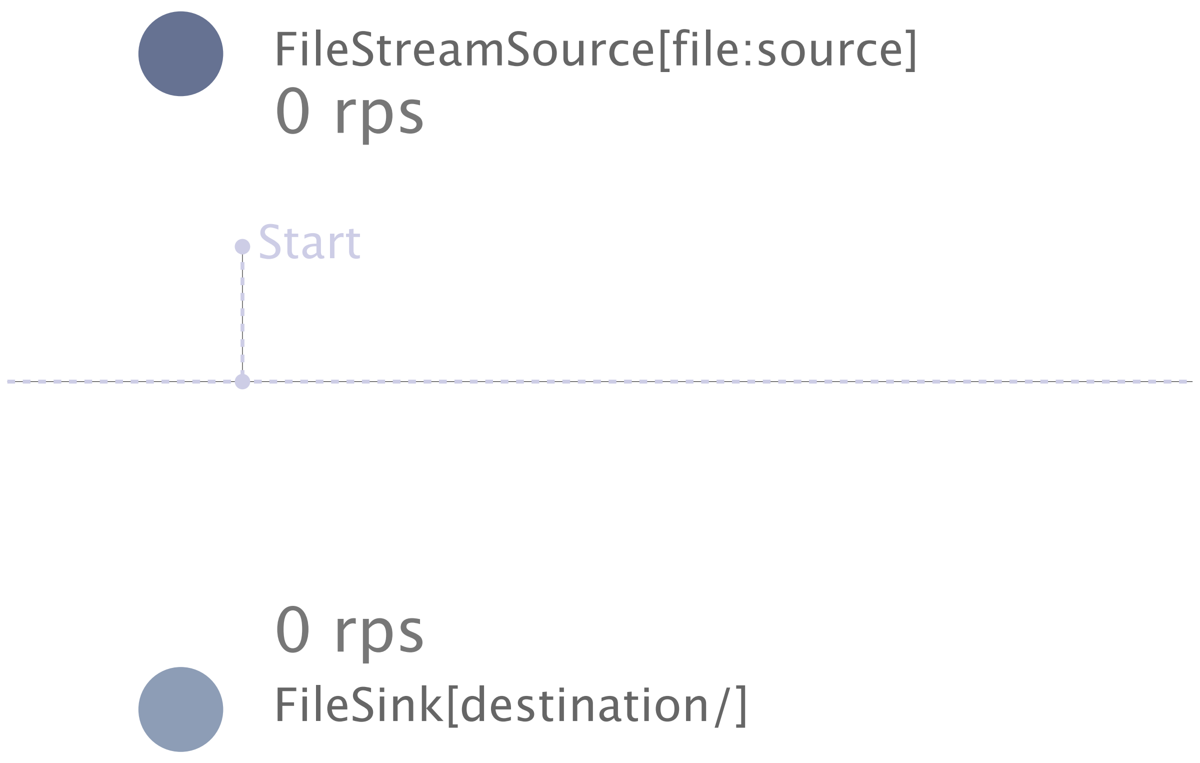


Figure 10.1: Viewing a Spark Stream with sparklyr

```
stream_stop(stream)
```

In order to reproduce the above example, one needs to feed streaming data into the `source/` path. This was accomplished by running, before `stream_view(stream)`, the following script to produce a file every second containing lines of text that follow two overlapping binomial distributions. In practice, you would connect to existing sources without having to generate data artificially.

```
unlink(c("source/", "destination/"), recursive = TRUE)
dir.create("source")
callr::r_bg(function() {
  dist <- floor(10 + 1e5 * (dbinom(1:50, 50, 0.7) + dbinom(1:50, 50, 0.3)))
  for (i in seq_len(10)) {
    writeLines(paste("Row", 1:dist[i]), paste0("source/hello_", i, ".txt"))
    Sys.sleep(1)
  }
})
```

For the subsequent examples, a stream with one hundred rows of text will be used:

```
writeLines(paste("Row", 1:100), "source/rows.txt")
```

10.2 Transformations

Streams can be transformed using `dplyr`, SQL, pipelines or R code. We can use as many transformations as needed in the same way that Spark data frames can be transformed with `sparklyr`. The transformation source can be streams or data frames but the output is always a stream. If needed, one can always take a

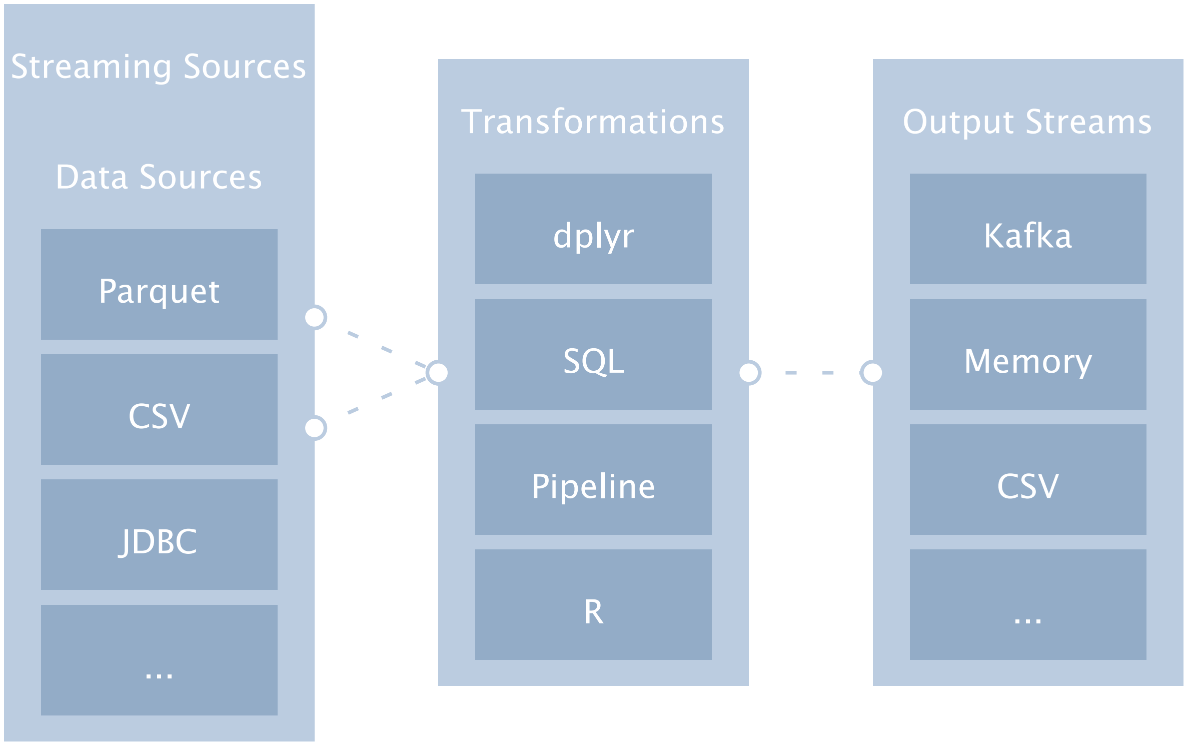


Figure 10.2: Streams Transformation Diagram

snapshot from the destination stream and save the output as a data frame, which is what `sparklyr` will do for you if a destination stream is not specified. Conceptually, this looks as follows:

10.2.1 dplyr

Using `dplyr`, we can process each row of the stream; for example, we can filter the stream to only the rows containing a number one:

```r
library(dplyr, warn.conflicts = FALSE)

stream_read_text(sc, "source/") %>%
  filter(text %like% "%1%")
```

```
## # Source:   lazy query [?? x 1]
## # Database: spark_connection
##    text
##    <chr>
##  1 Row 1
##  2 Row 10
##  3 Row 11
##  4 Row 12
##  5 Row 13
##  6 Row 14
##  7 Row 15
##  8 Row 16
##  9 Row 17
## 10 Row 18
## # ... with more rows
```

Since the destination was not specified, `sparklyr` creates a temporary memory stream and previews the contents of a stream by capturing a few seconds of streaming data.

We can also aggregate data with `dplyr`,

```r
stream_read_text(sc, "source/") %>%
  summarise(n = n())
```

```
## # Source:   lazy query [?? x 1]
## # Database: spark_connection
##       n
##   <dbl>
## 1   100
```

and even join across many concurrent streams:

```r
left_join(
  stream_read_text(sc, "source/") %>% stream_watermark(),
  stream_read_text(sc, "source/") %>% stream_watermark() %>% mutate(random = rand()),
)
```

```
## Joining, by = c("text", "timestamp")
```

```
## # Source:   lazy query [?? x 3]
## # Database: spark_connection
##    text   timestamp           random
##    <chr>  <dttm>               <dbl>
##  1 Row 8  2018-07-16 17:23:05  0.108
##  2 Row 15 2018-07-16 17:23:05  0.965
##  3 Row 16 2018-07-16 17:23:05  0.171
##  4 Row 20 2018-07-16 17:23:05  0.282
##  5 Row 22 2018-07-16 17:23:05  0.868
##  6 Row 27 2018-07-16 17:23:05  0.660
##  7 Row 35 2018-07-16 17:23:05  0.492
##  8 Row 38 2018-07-16 17:23:05  0.609
##  9 Row 39 2018-07-16 17:23:05  0.461
## 10 Row 48 2018-07-16 17:23:05  0.342
## # ... with more rows
```

However, some operations, require watermarks to define when to stop waiting for late data. You can specify watermarks in `sparklyr` using `stream_watermak()`, see also handling late data in Spark's documentation.

10.2.2 Pipelines

Spark pipelines can be used for scoring streams, but not to train over streaming data. The former is fully supported while the latter is a feature under active development by the Spark community.

To use a pipeline for scoring a stream, first train a Spark pipeline over a static dataset. Once trained, save the pipeline, then reload and score over a stream as follows:

```r
fitted_pipeline <- ml_load(sc, "iris-fitted/")

stream_read_csv(sc, "iris-in") %>%
  sdf_transform(fitted_pipeline) %>%
  stream_write_csv("iris-out")
```

10.2.3 R Code

Arbitrary R code can also be used to transform a stream with the use of `spark_apply()`. Following the same principles from executing R code over Spark data frames, for structured streams, `spark_apply()` runs R code over each executor in the cluster where data is available, this enables processing high-throughput streams and fullfill low-latency requirements.

The following example splits a stream of `Row #` line entries and adds jitter using R code:

```r
stream_read_text(sc, "source/") %>%
  spark_apply(function(df) {
    data.frame(
      data = jitter(as.numeric(gsub("Row ", "", df$text)))
    )
  })
```

```
## # Source:   table<sparklyr_tmp_781e6cb21c24> [?? x 1]
## # Database: spark_connection
##      data
##     <dbl>
##  1  0.866
##  2  1.95
##  3  2.92
##  4  3.92
##  5  5.09
##  6  6.16
##  7  6.94
##  8  8.15
##  9  8.81
## 10 10.1
## # ... with more rows
```

10.3 Shiny

Streams can be used with Shiny by making use of the `reactiveSpark()` to retrieve the stream as a reactive data source. Internally, `reactiveSpark()` makes use of reactivePoll() to check the stream's timestamp and collect the stream contents when needed.

The following Shiny application makes use of `reactiveSpark()` to view a Spark stream summarized with `dplyr`:

```r
library(shiny)
library(sparklyr)
library(dplyr)

sc <- spark_connect(master = "local")

ui <- fluidPage(
  sidebarLayout(
    mainPanel(
      tableOutput("table")
    )
  )
)
```

```r
server <- function(input, output, session) {
  pollData <- stream_read_text(sc, "source/") %>%
    summarise(n = n()) %>%
    reactiveSpark(session = session)

  output$table <- renderTable({
    pollData()
  })
}

shinyApp(ui = ui, server = server)
```

10.4 Formats

The following formats are available to read and write streaming data:

Format	Read	Write
CSV	stream_read_csv	stream_write_csv
JDBC	stream_read_jdbc	stream_write_jdbc
JSON	stream_read_json	stream_write_json
Kafka	stream_read_kafka	stream_write_kafka
ORC	stream_read_orc	stream_write_orc
Parquet	stream_read_parquet	stream_write_parquet
Text	stream_read_text	stream_write_text
Memory		stream_write_memory

Chapter 11

Contributing

This chatper has not been written.

While there are many ways to contribute to `sparklyr` from helping community members to opening github issues, this chapter focuses on those readers interested in contributing fixes and features to `sparklyr` but will also help those who want to understand how `sparklyr` works internally.

11.1 Overview

(architecture overview)

11.2 Serialization

11.3 Invocations

11.4 R Packages

(dbi, dplyr, broom, etc)

11.5 Connections

11.6 Distributed R

Appendix

11.7 Worlds Store Capacity

```r
library(tidyverse)
read_csv("data/01-worlds-capacity-to-store-information.csv", skip = 8) %>%
  gather(key = storage, value = capacity, analog, digital) %>%
  mutate(year = X1, terabytes = capacity / 1e+12) %>%
  ggplot(aes(x = year, y = terabytes, group = storage)) +
    geom_line(aes(linetype = storage)) +
    geom_point(aes(shape = storage)) +
    scale_y_log10(
      breaks = scales::trans_breaks("log10", function(x) 10^x),
      labels = scales::trans_format("log10", scales::math_format(10^x))
    ) +
    theme_light() +
    theme(legend.position = "bottom")
```

11.8 Daily downloads of CRAN packages

```r
downloads_csv <- "data/01-intro-r-cran-downloads.csv"
if (!file.exists(downloads_csv)) {
  downloads <- cranlogs::cran_downloads(from = "2014-01-01", to = "2018-01-01")
  readr::write_csv(downloads, downloads_csv)
}

cran_downloads <- readr::read_csv(downloads_csv)

ggplot(cran_downloads, aes(date, count)) +
  geom_point(colour="black", pch = 21, size = 1) +
  scale_x_date() +
  xlab("") +
  ylab("") +
  theme_light()
```

11.9 Google trends for mainframes, cloud computing and kubernetes

```r
library(r2d3)

read.csv("data/05-cluster-trends.csv") %>%
  mutate(month = as.Date(paste(month, "-01", sep = ""))) %>%
  r2d3(script="images/05-clusters-trends.js")
```

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