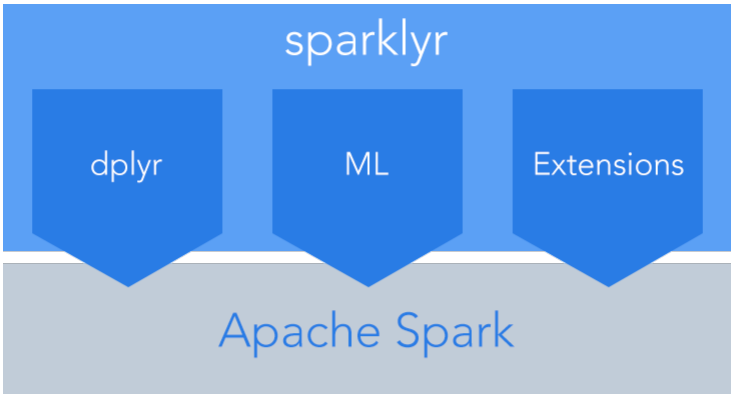
sparklyr: R interface for Apache Spark

build passing CRAN 0.6.4 codecov 64% chat on gitter



- Connect to Spark from R. The sparklyr package provides a complete dplyr backend.
- Filter and aggregate Spark datasets then bring them into R for analysis and visualization.
- Use Spark's distributed machine learning library from R.
- Create extensions that call the full Spark API and provide interfaces to Spark packages.

Installation

You can install the **sparklyr** package from CRAN as follows:

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

You should also install a local version of Spark for development purposes:

```
library(sparklyr)
spark_install(version = "2.1.0")
```

To upgrade to the latest version of sparklyr, run the following command and restart your r session:

```
devtools::install_github("rstudio/sparklyr")
```

If you use the RStudio IDE, you should also download the latest preview release of the IDE which includes several enhancements for interacting with Spark (see the RStudio IDE section below for more details).

Connecting to Spark

You can connect to both local instances of Spark as well as remote Spark clusters. Here we'll connect to a local instance of Spark via the spark_connect function:

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

The returned Spark connection (`sc`) provides a remote dplyr data source to the Spark cluster.

For more information on connecting to remote Spark clusters see the Deployment section of the sparklyr website.

Using dplyr

We can now use all of the available dplyr verbs against the tables within the cluster.

We'll start by copying some datasets from R into the Spark cluster (note that you may need to install the nycflights13 and Lahman packages in order to execute this code):

```
install.packages(c("nycflights13", "Lahman"))
```

```
library(dplyr)
iris_tbl <- copy_to(sc, iris)
flights_tbl <- copy_to(sc, nycflights13::flights, "flights")
batting_tbl <- copy_to(sc, Lahman::Batting, "batting")
src_tbls(sc)
```

```
## [1] "batting" "flights" "iris"
```

To start with here's a simple filtering example:

```
# filter by departure delay and print the first few records
flights_tbl %>% filter(dep_delay == 2)
```

```
## # Source:   lazy query [?? x 19]
## # Database: spark_connection
```

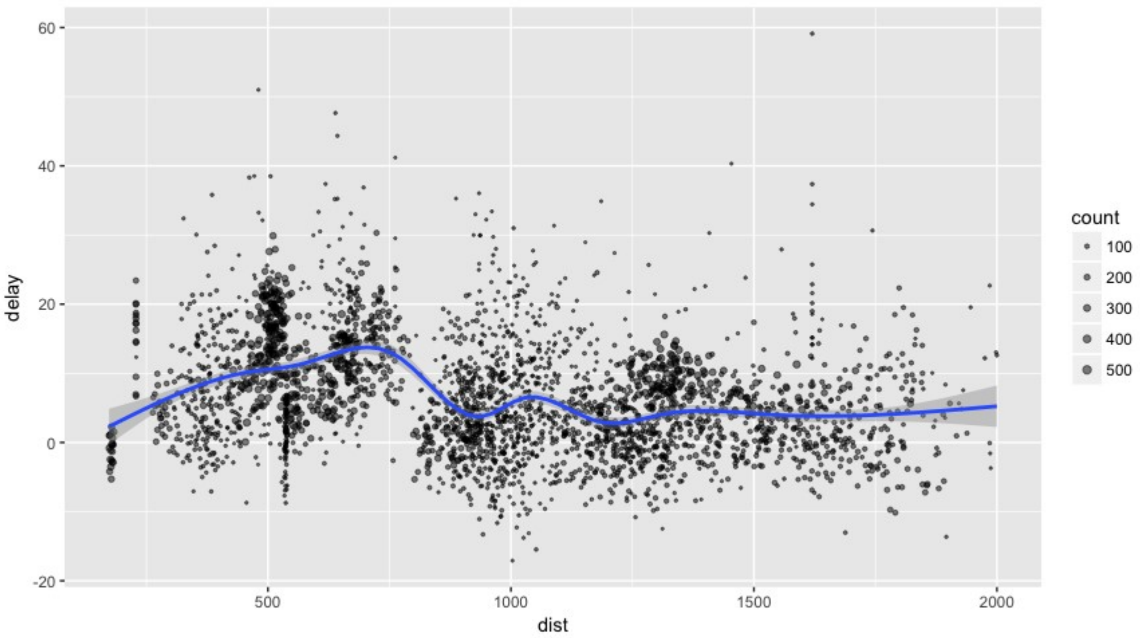
```
##      year month   day dep_time sched_dep_time dep_delay arr_time
##     <int> <int> <int>    <int>          <int>     <dbl>    <int>
##  1  2013     1     1      517            515         2      830
##  2  2013     1     1      542            540         2      923
##  3  2013     1     1      702            700         2     1058
##  4  2013     1     1      715            713         2      911
##  5  2013     1     1      752            750         2     1025
##  6  2013     1     1      917            915         2     1206
##  7  2013     1     1      932            930         2     1219
##  8  2013     1     1     1028           1026         2     1350
##  9  2013     1     1     1042           1040         2     1325
## 10  2013     1     1     1231           1229         2     1523
## # ... with more rows, and 12 more variables: sched_arr_time <int>
## #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
## #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>, hou
## #   minute <dbl>, time_hour <dbl>
```

Introduction to dplyr provides additional dplyr examples you can try. For example, consider the last example from the tutorial which plots data on flight delays:

```
delay <- flights_tbl %>%
  group_by(tailnum) %>%
  summarise(count = n(), dist = mean(distance), delay = mean(arr_del
  filter(count > 20, dist < 2000, !is.na(delay)) %>%
  collect

# plot delays
library(ggplot2)
ggplot(delay, aes(dist, delay)) +
  geom_point(aes(size = count), alpha = 1/2) +
  geom_smooth() +
  scale_size_area(max_size = 2)
```

```
## `geom_smooth()` using method = 'gam'
```



WINDOW FUNCTIONS

dplyr window functions are also supported, for example:

```
batting_tbl %>%
  select(playerID, yearID, teamID, G, AB:H) %>%
  arrange(playerID, yearID, teamID) %>%
  group_by(playerID) %>%
  filter(min_rank(desc(H)) <= 2 & H > 0)
```

```
## # Source:     lazy query [?? x 7]
## # Database:   spark_connection
## # Groups:     playerID
## # Ordered by: playerID, yearID, teamID
##     playerID yearID teamID     G    AB     R     H
##        <chr>  <int>  <chr> <int> <int> <int> <int>
##  1 aaronha01   1959    ML1   154   629   116   223
##  2 aaronha01   1963    ML1   161   631   121   201
##  3 abbotji01   1999    MIL    20    21     0     2
##  4 abnersh01   1992    CHA    97   208    21    58
##  5 abnersh01   1990    SDN    91   184    17    45
##  6 acklefr01   1963    CHA     2     5     0     1
##  7 acklefr01   1964    CHA     3     1     0     1
##  8 adamecr01   2016    COL   121   225    25    49
##  9 adamecr01   2015    COL    26    53     4    13
## 10 adamsac01   1943    NY1    70    32     3     4
## # ... with more rows
```

For additional documentation on using dplyr with Spark see the dplyr section of the sparklyr website.

Using SQL

It's also possible to execute SQL queries directly against tables within a Spark cluster. The `spark_connection` object implements a DBI interface for Spark, so you can use `dbGetQuery` to execute SQL and return the result as an R data frame:

```
library(DBI)
iris_preview <- dbGetQuery(sc, "SELECT * FROM iris LIMIT 10")
iris_preview
```

```
##    Sepal_Length Sepal_Width Petal_Length Petal_Width Species
## 1           5.1         3.5          1.4         0.2  setosa
## 2           4.9         3.0          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           5.0         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           5.0         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
```

Machine Learning

You can orchestrate machine learning algorithms in a Spark cluster via the machine learning functions within **sparklyr**. These functions connect to a set of high-level APIs built on top of DataFrames that help you create and tune machine learning workflows.

Here's an example where we use ml_linear_regression to fit a linear regression model. We'll use the built-in `mtcars` dataset, and see if we can predict a car's fuel consumption (`mpg`) based on its weight (`wt`), and the number of cylinders the engine contains (`cyl`). We'll assume in each case that the relationship between `mpg` and each of our features is linear.

```
# copy mtcars into spark
mtcars_tbl <- copy_to(sc, mtcars)

# transform our data set, and then partition into 'training', 'tes
partitions <- mtcars_tbl %>%
  filter(hp >= 100) %>%
```

```
  sdf_partition(training = 0.5, test = 0.5, seed = 1099)

# fit a linear model to the training dataset
fit <- partitions$training %>%
  ml_linear_regression(response = "mpg", features = c("wt", "cyl"))
fit
```

```
## Call: ml_linear_regression.tbl_spark(., response = "mpg", feature
##
## Formula: mpg ~ wt + cyl
##
## Coefficients:
## (Intercept)          wt         cyl
##   33.499452   -2.818463   -0.923187
```

For linear regression models produced by Spark, we can use `summary()` to learn a bit more about the quality of our fit, and the statistical significance of each of our predictors.

```
summary(fit)
```

```
## Call: ml_linear_regression.tbl_spark(., response = "mpg", feature
##
## Deviance Residuals:
##    Min     1Q Median     3Q    Max
## -1.752 -1.134 -0.499  1.296  2.282
##
## Coefficients:
## (Intercept)          wt         cyl
##   33.499452   -2.818463   -0.923187
##
## R-Squared: 0.8274
## Root Mean Squared Error: 1.422
```

Spark machine learning supports a wide array of algorithms and feature transformations and as illustrated above it's easy to chain these functions together with dplyr pipelines. To learn more see the machine learning section.

Reading and Writing Data

You can read and write data in CSV, JSON, and Parquet formats. Data can be stored in HDFS, S3, or on the local filesystem of cluster nodes.

```
temp_csv <- tempfile(fileext = ".csv")
temp_parquet <- tempfile(fileext = ".parquet")
```

```
temp_json <- tempfile(fileext = ".json")

spark_write_csv(iris_tbl, temp_csv)
iris_csv_tbl <- spark_read_csv(sc, "iris_csv", temp_csv)

spark_write_parquet(iris_tbl, temp_parquet)
iris_parquet_tbl <- spark_read_parquet(sc, "iris_parquet", temp_parc

spark_write_json(iris_tbl, temp_json)
iris_json_tbl <- spark_read_json(sc, "iris_json", temp_json)

src_tbls(sc)
```

```
## [1] "batting"      "flights"      "iris"         "iris_csv"
## [5] "iris_json"    "iris_parquet" "mtcars"
```

Distributed R

You can execute arbitrary r code across your cluster using `spark_apply`. For example, we can apply `rgamma` over `iris` as follows:

```
spark_apply(iris_tbl, function(data) {
  data[1:4] + rgamma(1,2)
})
```

```
## # Source:   table<sparklyr_tmp_115c74acb6510> [?? x 4]
## # Database: spark_connection
##    Sepal_Length Sepal_Width Petal_Length Petal_Width
##           <dbl>       <dbl>        <dbl>       <dbl>
##  1     5.336757    3.736757     1.636757   0.4367573
##  2     5.136757    3.236757     1.636757   0.4367573
##  3     4.936757    3.436757     1.536757   0.4367573
##  4     4.836757    3.336757     1.736757   0.4367573
##  5     5.236757    3.836757     1.636757   0.4367573
##  6     5.636757    4.136757     1.936757   0.6367573
##  7     4.836757    3.636757     1.636757   0.5367573
##  8     5.236757    3.636757     1.736757   0.4367573
##  9     4.636757    3.136757     1.636757   0.4367573
## 10     5.136757    3.336757     1.736757   0.3367573
## # ... with more rows
```

You can also group by columns to perform an operation over each group of rows and make use of any package within the closure:

```
spark_apply(
  iris_tbl,
  function(e) broom::tidy(lm(Petal_Width ~ Petal_Length, e))
```

```
  names = c("term", "estimate", "std.error", "statistic", "p.value")
  group_by = "Species"
)
```

```
## # Source:   table<sparklyr_tmp_115c73965f30> [?? x 6]
## # Database: spark_connection
##      Species         term    estimate  std.error  statistic
##        <chr>        <chr>       <dbl>      <dbl>      <dbl>
## 1 versicolor  (Intercept) -0.08428835 0.16070140 -0.5245029 6.023
## 2 versicolor Petal_Length  0.33105360 0.03750041  8.8279995 1.271
## 3  virginica  (Intercept)  1.13603130 0.37936622  2.9945505 4.336
## 4  virginica Petal_Length  0.16029696 0.06800119  2.3572668 2.253
## 5     setosa  (Intercept) -0.04822033 0.12164115 -0.3964146 6.935
## 6     setosa Petal_Length  0.20124509 0.08263253  2.4354220 1.863
```

Extensions

The facilities used internally by sparklyr for its dplyr and machine learning interfaces are available to extension packages. Since Spark is a general purpose cluster computing system there are many potential applications for extensions (e.g. interfaces to custom machine learning pipelines, interfaces to 3rd party Spark packages, etc.).

Here's a simple example that wraps a Spark text file line counting function with an R function:

```
# write a CSV
tempfile <- tempfile(fileext = ".csv")
write.csv(nycflights13::flights, tempfile, row.names = FALSE, na = '

# define an R interface to Spark line counting
count_lines <- function(sc, path) {
  spark_context(sc) %>%
    invoke("textFile", path, 1L) %>%
      invoke("count")
}

# call spark to count the lines of the CSV
count_lines(sc, tempfile)
```

```
## [1] 336777
```

To learn more about creating extensions see the Extensions section of the sparklyr website.

Table Utilities

You can cache a table into memory with:

```
tbl_cache(sc, "batting")
```

and unload from memory using:

```
tbl_uncache(sc, "batting")
```

Connection Utilities

You can view the Spark web console using the `spark_web` function:

```
spark_web(sc)
```

You can show the log using the `spark_log` function:

```
spark_log(sc, n = 10)
```

```
## 17/11/09 15:55:18 INFO DAGScheduler: Submitting 1 missing tasks f
## 17/11/09 15:55:18 INFO TaskSchedulerImpl: Adding task set 69.0 wi
## 17/11/09 15:55:18 INFO TaskSetManager: Starting task 0.0 in stage
## 17/11/09 15:55:18 INFO Executor: Running task 0.0 in stage 69.0 (
## 17/11/09 15:55:18 INFO HadoopRDD: Input split: file:/var/folders/
## 17/11/09 15:55:18 INFO Executor: Finished task 0.0 in stage 69.0 
## 17/11/09 15:55:18 INFO TaskSetManager: Finished task 0.0 in stage
## 17/11/09 15:55:18 INFO TaskSchedulerImpl: Removed TaskSet 69.0, w
## 17/11/09 15:55:18 INFO DAGScheduler: ResultStage 69 (count at Nat
## 17/11/09 15:55:18 INFO DAGScheduler: Job 47 finished: count at Na
```

Finally, we disconnect from Spark:

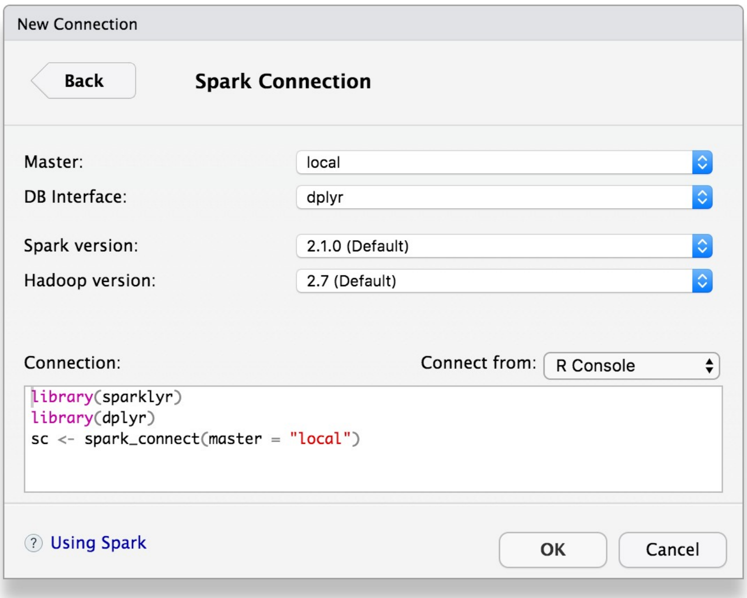
```
spark_disconnect(sc)
```

RStudio IDE

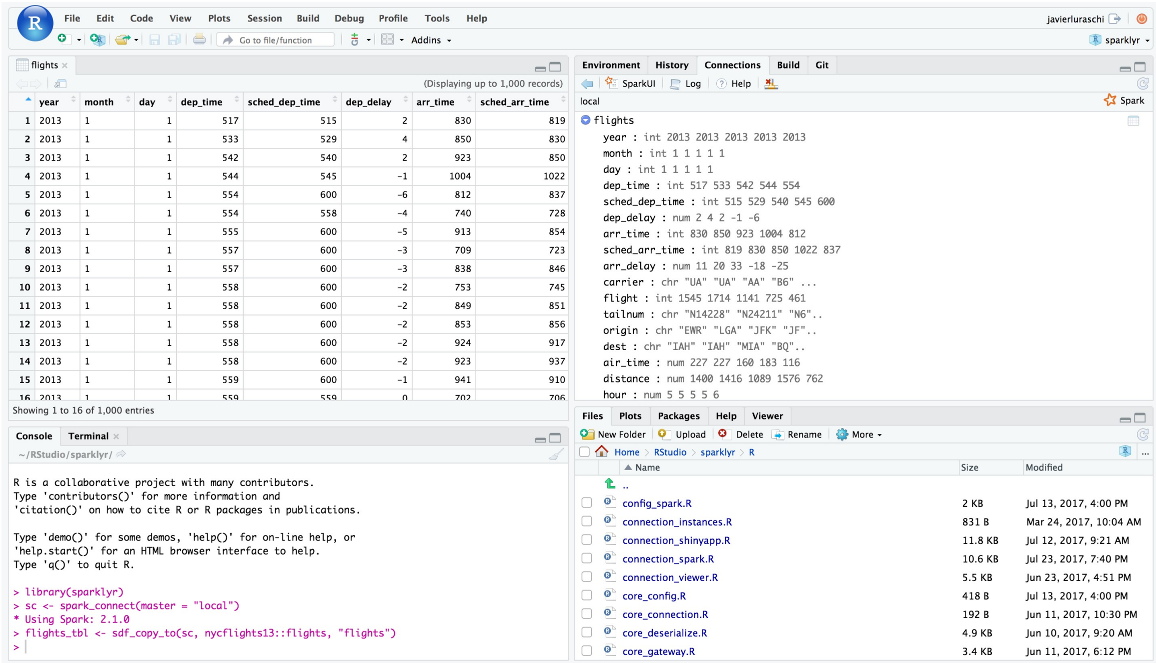
The latest RStudio Preview Release of the RStudio IDE includes integrated support for Spark and the sparklyr package, including tools for:

- Creating and managing Spark connections
- Browsing the tables and columns of Spark DataFrames
- Previewing the first 1,000 rows of Spark DataFrames

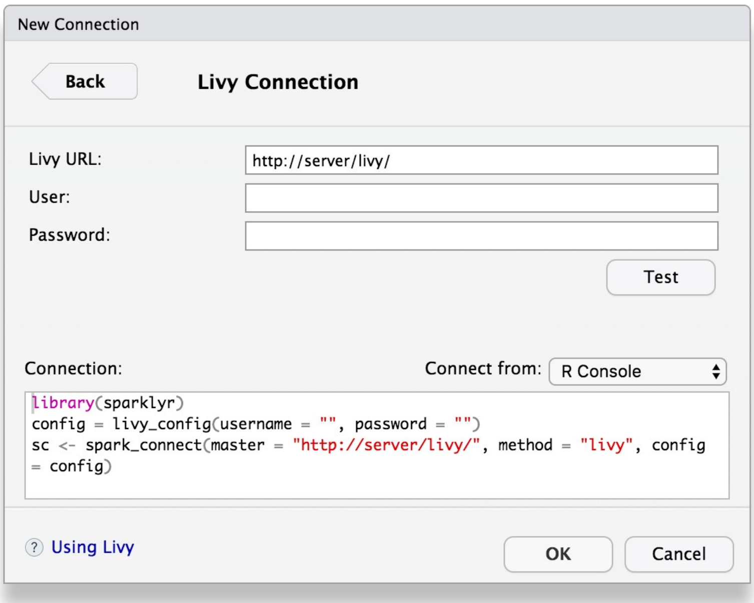
Once you've installed the sparklyr package, you should find a new **Spark** pane within the IDE. This pane includes a **New Connection** dialog which can be used to make connections to local or remote Spark instances:



Once you've connected to Spark you'll be able to browse the tables contained within the Spark cluster and preview Spark DataFrames using the standard RStudio data viewer:



You can also connect to Spark through [Livy](#) through a new connection dialog:



The RStudio IDE features for sparklyr are available now as part of the RStudio Preview Release.

Using H2O

rsparkling is a CRAN package from H2O that extends sparklyr to provide an interface into Sparkling Water. For instance, the following example installs, configures and runs h2o.glm:

```
options(rsparkling.sparklingwater.version = "2.1.14")

library(rsparkling)
library(sparklyr)
library(dplyr)
library(h2o)

sc <- spark_connect(master = "local", version = "2.1.0")
mtcars_tbl <- copy_to(sc, mtcars, "mtcars")

mtcars_h2o <- as_h2o_frame(sc, mtcars_tbl, strict_version_check = FA

mtcars_glm <- h2o.glm(x = c("wt", "cyl"),
                      y = "mpg",
                      training_frame = mtcars_h2o,
                      lambda_search = TRUE)
```

```
mtcars_glm
```

```
## Model Details:
## ==============
##
## H2ORegressionModel: glm
## Model ID:  GLM_model_R_1510271749678_1
## GLM Model: summary
##     family     link                              regularization
## 1 gaussian identity Elastic Net (alpha = 0.5, lambda = 0.1013 )
##                                                                la
## 1 nlambda = 100, lambda.max = 10.132, lambda.min = 0.1013, lambda
##   number_of_predictors_total number_of_active_predictors
## 1                          2                           2
##   number_of_iterations                                training_fr
## 1                  100 frame_rdd_29_b907d4915799eac74fb1ea60ad594
##
## Coefficients: glm coefficients
##       names coefficients standardized_coefficients
## 1 Intercept    38.941654                 20.090625
## 2       cyl    -1.468783                 -2.623132
## 3        wt    -3.034558                 -2.969186
##
## H2ORegressionMetrics: glm
## ** Reported on training data. **
##
## MSE:  6.017684
## RMSE:  2.453097
## MAE:  1.940985
## RMSLE:  0.1114801
## Mean Residual Deviance :  6.017684
## R^2 :  0.8289895
```

```
## Null Deviance :1126.047
## Null D.o.F. :31
## Residual Deviance :192.5659
## Residual D.o.F. :29
## AIC :156.2425
```

```
spark_disconnect(sc)
```

Connecting through Livy

Livy enables remote connections to Apache Spark clusters. Connecting to Spark clusters through Livy is **under experimental development** in `sparklyr`. Please post any feedback or questions as a GitHub issue as needed.

Before connecting to Livy, you will need the connection information to an existing service running Livy. Otherwise, to test `livy` in your local environment, you can install it and run it locally as follows:

```
livy_install()
```

```
livy_service_start()
```

To connect, use the Livy service address as `master` and `method = "livy"` in `spark_connect`. Once connection completes, use `sparklyr` as usual, for instance:

```
sc <- spark_connect(master = "http://localhost:8998", method = "livy
copy_to(sc, iris)
```

```
## # 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         3.0          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          5.0         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          5.0         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
```

```
spark_disconnect(sc)
```

Once you are done using `livy` locally, you should stop this service with:

```
livy_service_stop()
```

To connect to remote `livy` clusters that support basic authentication connect as:

```
config <- livy_config_auth("<username>", "<password">)
sc <- spark_connect(master = "<address>", method = "livy", config =
spark_disconnect(sc)
```