Strata+Hadoop WORLD

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RStudio

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#StrataHadoop

Modeling big data with R, sparklyr, and Apache Spark

1:30pm–5:00pm Tuesday, March 14, 2017
Data science & advanced analytics
Location: LL21 C/D
Level: Intermediate
Secondary topics: R

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Steve Nolen *(RStudio)*
Edgar Ruiz *(RStudio)*

url: https://github.com/WinVector/BigDataRStrata2017

3 levels of “big data”

1. Need to build summaries or simple predictive models from a large amount of data.
   - Can sample data and run in memory.
2. Need to apply a model or transformation to a lot of data.
   - Can distribute work to a cluster.
3. Need to compute something involving all the relations between the data.
   - Need big data systems and algorithms.

Not teaching OPS/ENG

- We are loaning you single cluster accounts that are non-durable
    - temp tables disappear when you disconnect
- This means we (hopefully) don't end up running "a consulting clinic for installation bugs" (thanks Garrett Grolemund).
- It also means we are not discussing issues such as lifetime of data inside Spark and h2o, starting and stopping the cluster, pinning items into memory, or organization of storage.
- It isn't that OPS isn't important, it is just too big to be in this workshop (and varies depending on where you end up working with big data).

Configuration conflict

Big data systems have a cost

- Big data systems usually trade high throughput for some combination of:
  - High latency
  - Limited state
  - Limited communication patterns
  - Inconvenience
- In fact they can prohibit some superior algorithms

“Scalability! But at what COST?” McSherry, Isard, Murray

- Define COST as cluster size (in machines) needed to be as fast as a good in-ram (single machine, multiple CPU) implementation.
- Typical COST of “best of breed” systems in article:
    - 10
    - 100
    - 256
    - infinity

Redefine “big data”

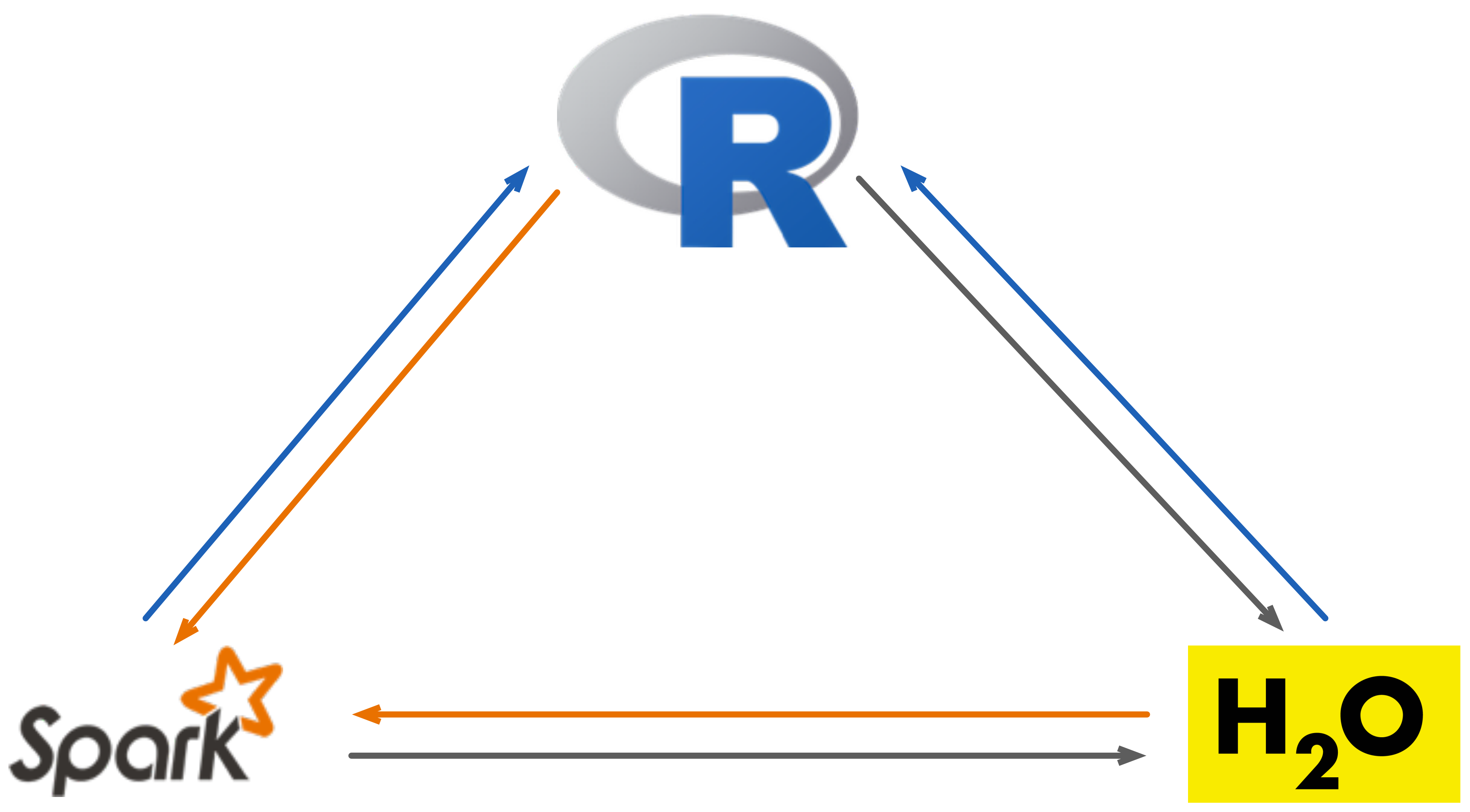
Big Data > 1/3 RAM

What is Spark?

- Open-source Apache computing engine
- Bigger-than-memory data, low-latency distributed computing
- Can integrate with the Hadoop ecosystem
- Built-in machine learning

Architecture choices

SparklyR



SparkR

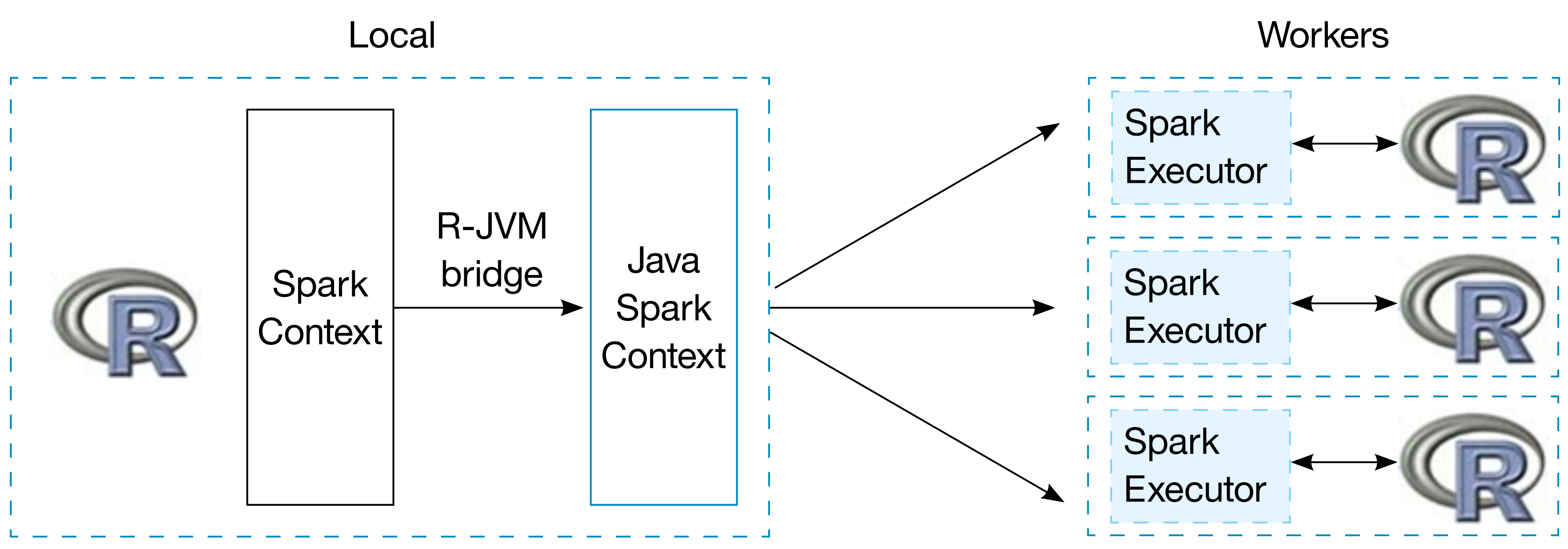


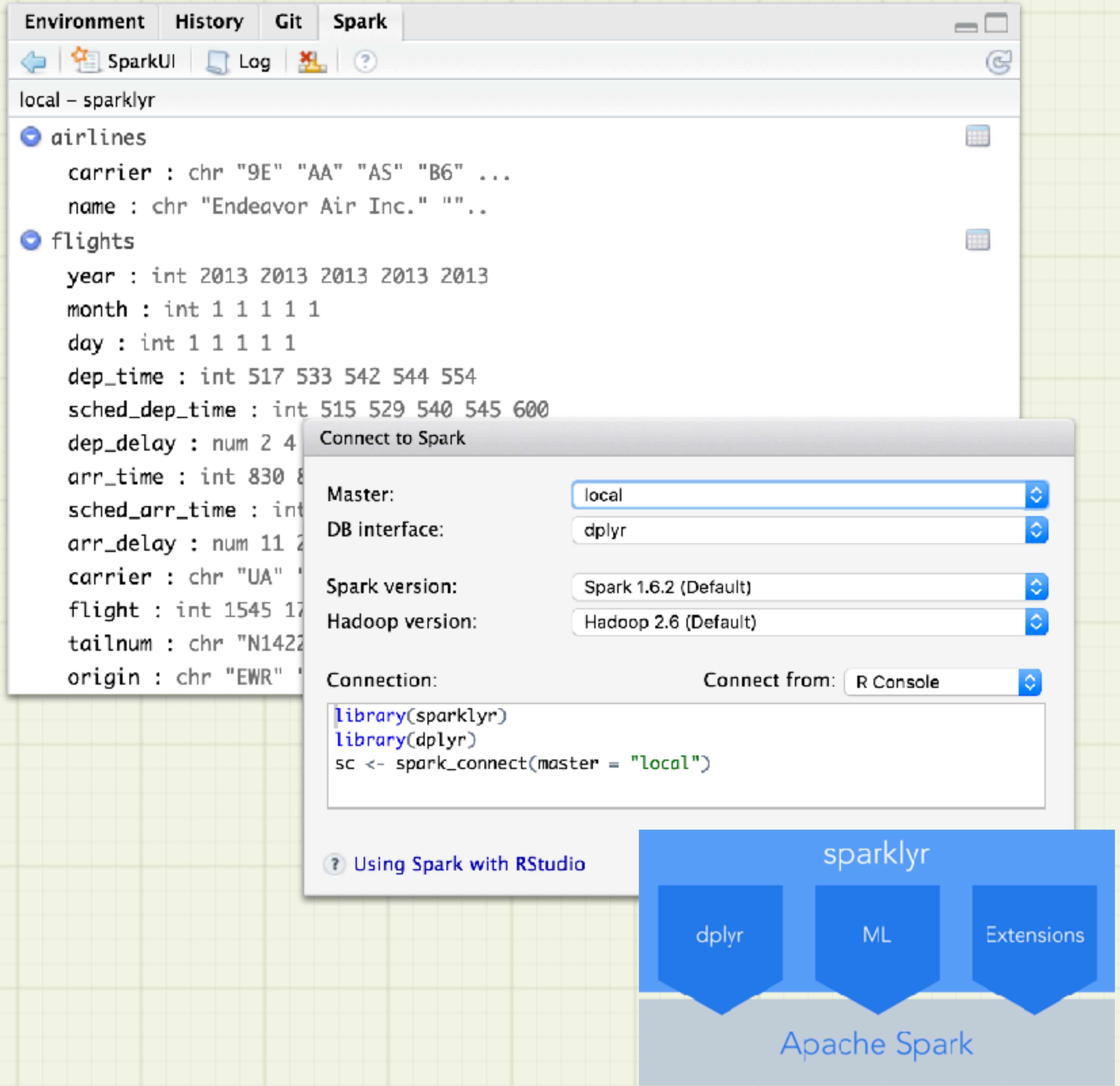
Figure: “SparkR Transforming into a tool for big data analytics” IBM white-paper.

Comparison

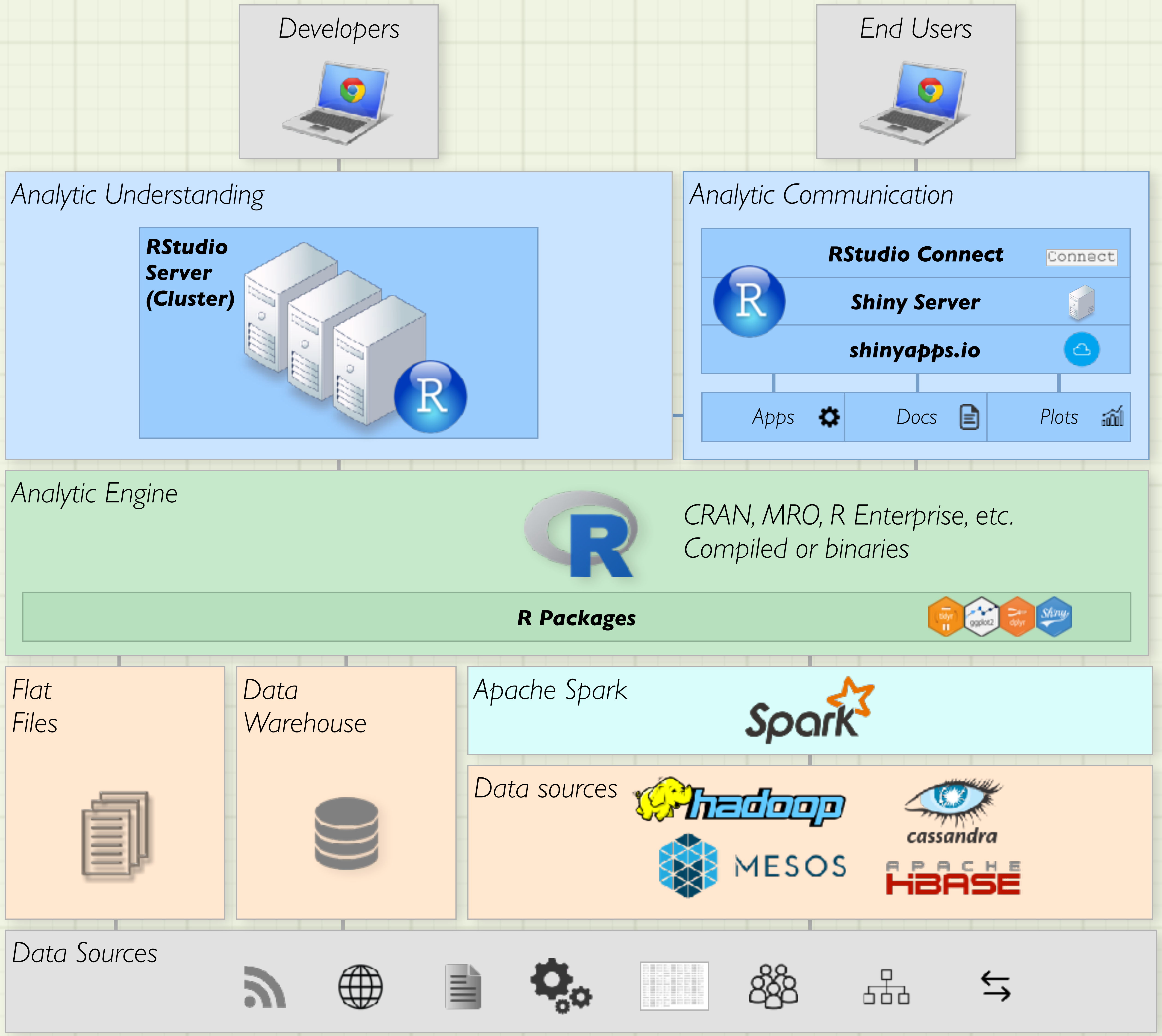
- `SparklyR` / `h2o`
  - Command remote native Spark using adapted `dplyr` notation to allow workflows *as if* you were working in `R`.
  - Use native `SparkML`, and `h2o` methods to do the work.
- `SparkR`
  - Use `R` to command copies of distributed `R` across a cluster.
    - Allows `R` user defined functions.
  - Not currently a `dplyr` backend.
- Which is “better”?
  - It depends on your data, infrastructure, tasks, and legacy code.
  - Also depends *a lot* on the current state of each adapter, and both are under rapid development.
  - Expect to see both going forward.
- We are going to concentrate on `SparklyR`.

sparklyr

- **R package**. New, open-source package from RStudio
- **dplyr**. Complete dplyr back-end for Spark
- **IDE**. Integrated with the RStudio IDE
- **Extensible**. Extensible foundation for Spark and R



Typical setup



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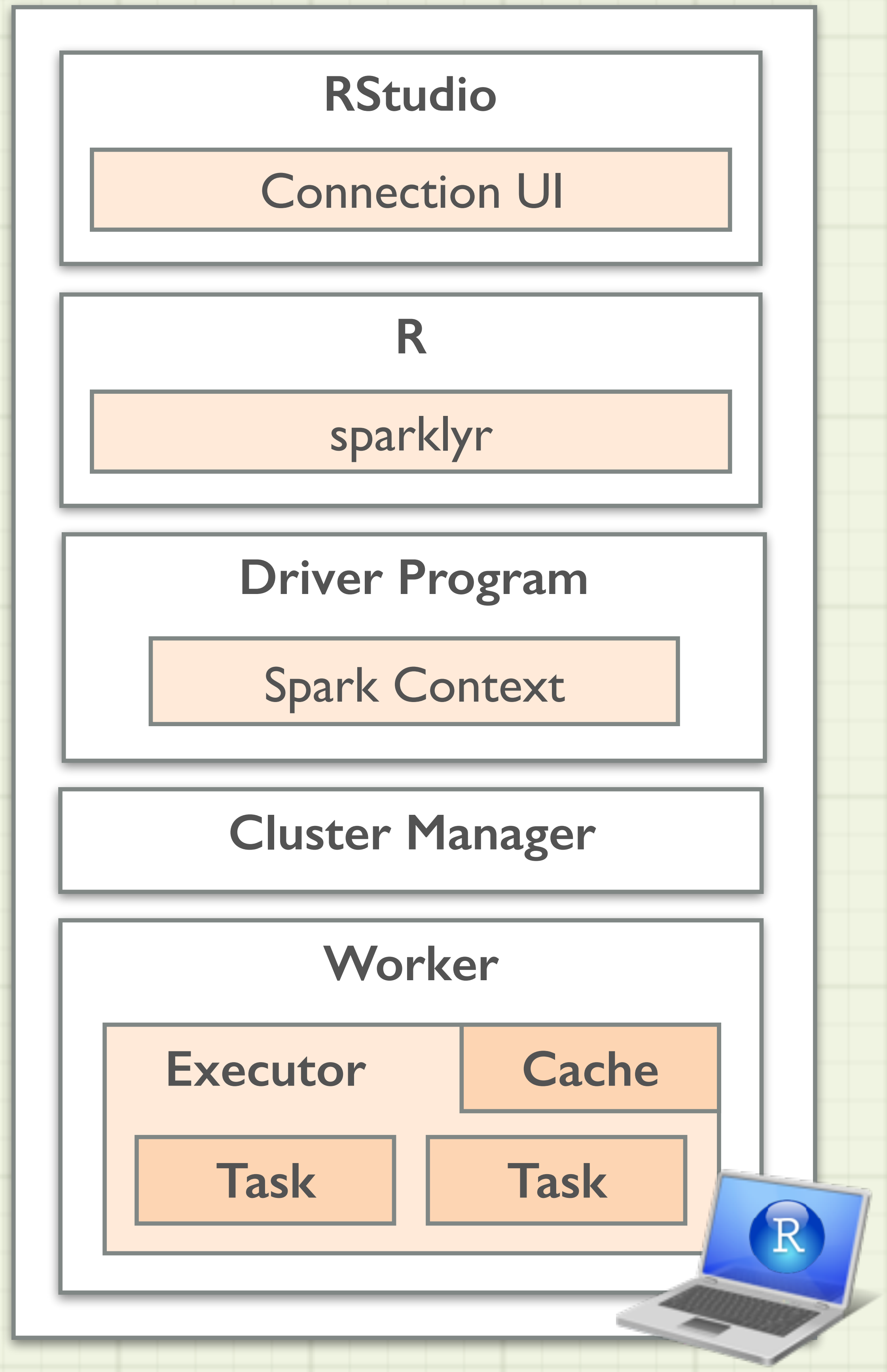
Local Mode

```
library(sparklyr)
library(dplyr)

spark_install()

sc <- spark_connect("local")

my_tbl <- copy_to(sc, iris)
```



Spark SQL

Use dplyr syntax to translate R code
into Spark SQL (HiveQL)

DPLYR

```
my_tbl %>%
  filter(Petal_Width < 0.3) %>%
  select(Petal_Length, Petal_Width) %>%
  arrange(Petal_Length)
```

SPARK SQL

```
select Petal_Length, Petal_Width
from iris
where Petal_Width < 0.3
order by Petal_Length
```

Nota bene

- Remote data services (intentionally) look a lot like local data.
- But there are differences.

Examples

```
library("sparklyr")
library("dplyr")
sc <- spark_connect(master = "local",
                    version = "2.0.0",
                    hadoop_version="2.7")
iris_tbl <- copy_to(sc, iris, "iris",
                    overwrite= TRUE)
```

`iris_tbl` is a handle, not data

```
> str(iris)

'data.frame':	150 obs. of  5 variables:
 $ Sepal.Length: num  5.1 4.9 4.7 4.6 5 5.4 4.6 5 4.4 4.9 ...
 $ Sepal.Width : num  3.5 3 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 ...
 $ Petal.Length: num  1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 ...
 $ Petal.Width : num  0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 ...
 $ Species     : Factor w/ 3 levels "setosa","versicolor",..: 1 1 1 1 1 1 1 1 1 1 ...
```

```
> str(iris_tbl)

List of 2
 $ src:List of 1
  ..$ con:List of 11
  .. ..$ master          : chr "local[4]"
  .. ..$ method          : chr "shell"
  .. ..$ app_name        : chr "sparklyr"
  .. ..$ config          :List of 5
  .. .. ..$ sparklyr.cores.local                 : int 4
…
```

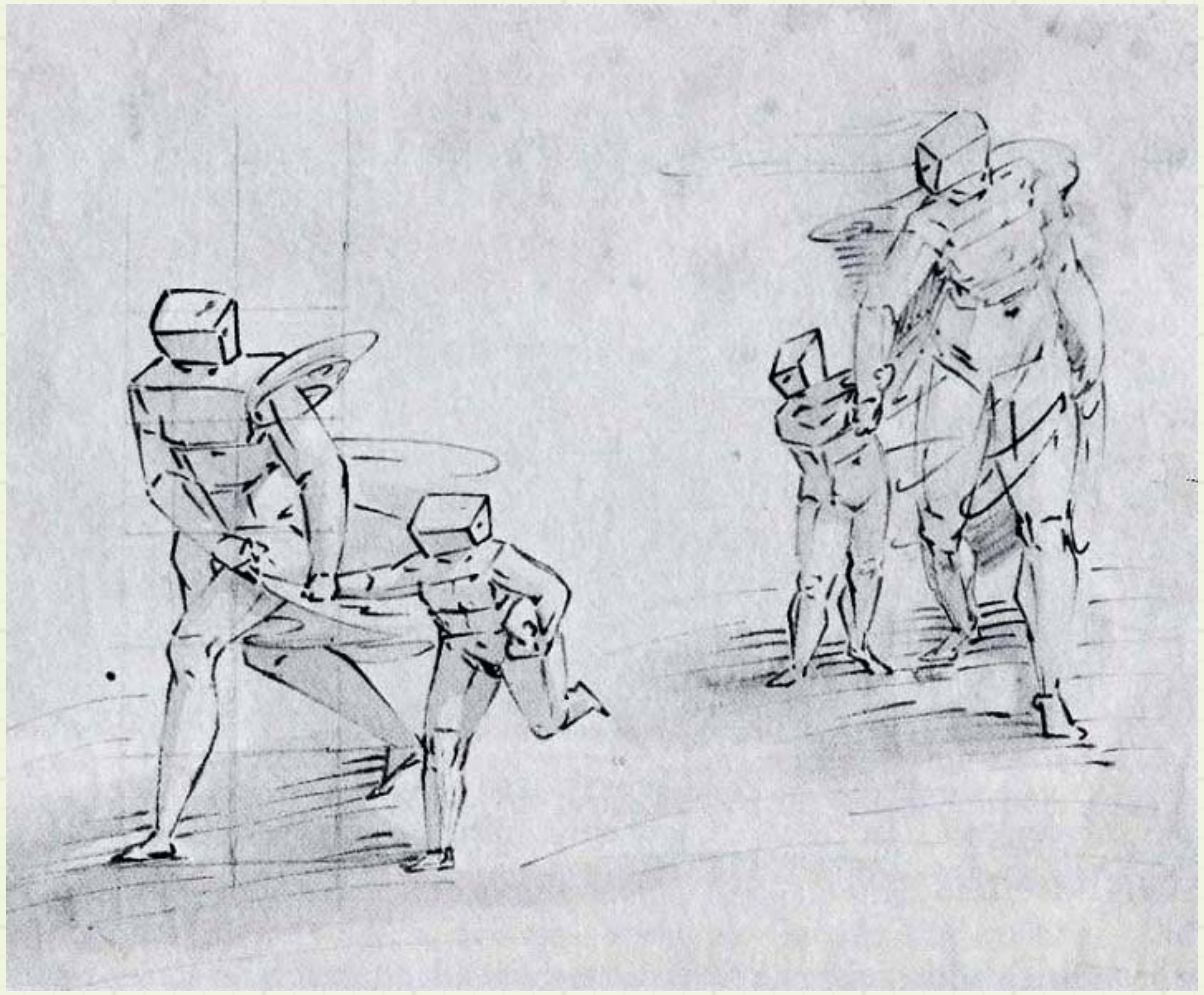
fix: dplyr::glimpse()

```
> glimpse(iris_tbl)

Observations: 150
Variables: 5
$ Sepal_Length <dbl> 5.1, 4.9, 4.7, 4.6, 5.0, 5.4, 4.6, 5.0, 4.4, 4.9, 5.4, 4.8, 4.8, 4.3, 5.8, 5.7,...
$ Sepal_Width  <dbl> 3.5, 3.0, 3.2, 3.1, 3.6, 3.9, 3.4, 3.4, 2.9, 3.1, 3.7, 3.4, 3.0, 3.0, 4.0, 4.4,...
$ Petal_Length <dbl> 1.4, 1.4, 1.3, 1.5, 1.4, 1.7, 1.4, 1.5, 1.4, 1.5, 1.5, 1.6, 1.4, 1.1, 1.2, 1.5,...
$ Petal_Width  <dbl> 0.2, 0.2, 0.2, 0.2, 0.2, 0.4, 0.3, 0.2, 0.2, 0.1, 0.2, 0.2, 0.1, 0.1, 0.2, 0.4,...
$ Species      <chr> "setosa", "setosa", "setosa", "setosa", "setosa", "setosa", "setosa", "setosa",...
```

Mnemonic

In standard R operations are wrestling in with your data

With handles you send operations out to your data

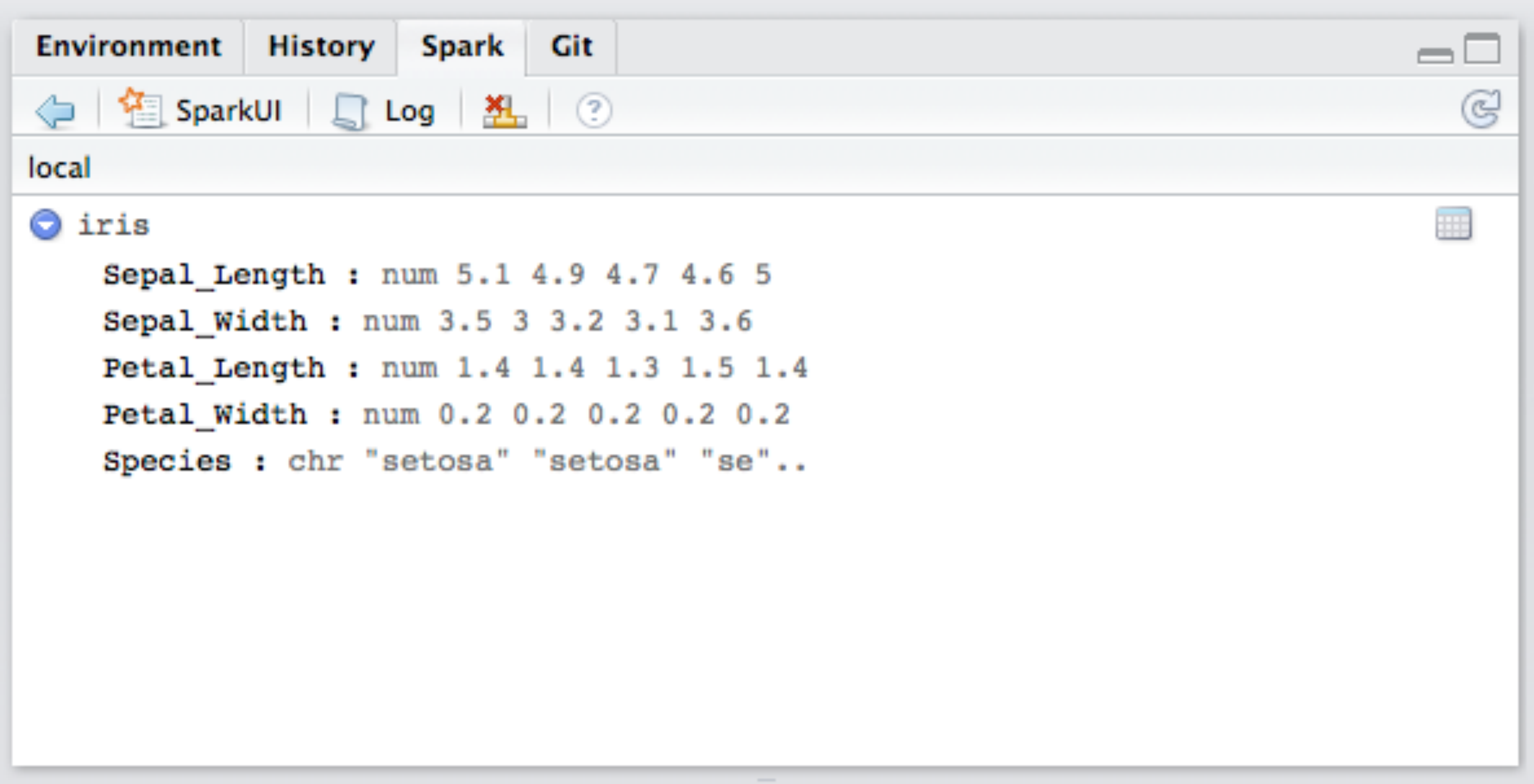


Handles (def: abstract reference to a resource) necessarily have reference semantics. Though we can make objects in the data pool express value semantics.

again: *handles*

```
> summary(iris)

  Sepal.Length    Sepal.Width     Petal.Length    Petal.Width          Species
 Min.   :4.300   Min.   :2.000   Min.   :1.000   Min.   :0.100   setosa    :50
 1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300   versicolor:50
 Median :5.800   Median :3.000   Median :4.350   Median :1.300   virginica :50
 Mean   :5.843   Mean   :3.057   Mean   :3.758   Mean   :1.199
 3rd Qu.:6.400   3rd Qu.:3.300   3rd Qu.:5.100   3rd Qu.:1.800
 Max.   :7.900   Max.   :4.400   Max.   :6.900   Max.   :2.500

> summary(iris_tbl)
    Length Class          Mode
src 1      src_spark      list
ops 3      op_base_remote list

> broom::glance(iris_tbl)

 Error: glance doesn't know how to deal with data
  of class tbl_sparktbl_sqltbl_lazytbl
```

fix: RStudio Spark browser



optional (experimental/expensive) fix:

`replyr::replyr_summary()`

```
> library("replyr")
> replyr_summary(iris_tbl, countUniqueNonNum= TRUE)

        column index     class nrows nna nunique min max     mean        sd lexmin    lexmax
1 Sepal_Length     1   numeric   150   0      NA 4.3 7.9 5.843333 0.8280661   <NA>      <NA>
2  Sepal_Width     2   numeric   150   0      NA 2.0 4.4 3.057333 0.4358663   <NA>      <NA>
3 Petal_Length     3   numeric   150   0      NA 1.0 6.9 3.758000 1.7652982   <NA>      <NA>
4  Petal_Width     4   numeric   150   0      NA 0.1 2.5 1.199333 0.7622377   <NA>      <NA>
5      Species     5 character   150   0       3  NA  NA       NA        NA setosa virginica
```

REPLYR

GET A GRIP ON BIG DATA IN R

Remote data is not “in the tidyverse”

```
> library("tidyr")
> iris %>% nest(-Species)

# A tibble: 3 × 2
Species                    data
<fctr>                   <list>
  1      setosa <tibble [50 × 4]>
  2 versicolor <tibble [50 × 4]>
  3  virginica <tibble [50 × 4]>

> iris_tbl %>% nest(-Species)

Error in UseMethod("nest_") :
  no applicable method for 'nest_' applied to an object
   of class "c('tbl_spark', 'tbl_sql', 'tbl_lazy', 'tbl')"
```

To use the “The Split-Apply-Combine Strategy for Data Analysis”

- You must use `dplyr::group_by()`
- And restrict yourself to operators that are “group aware.”

```
> iris_tbl %>%
   group_by(Species) %>%
   summarize_all(funs(typical=mean))

Source:   query [3 x 5]
Database: spark connection master=local[4] app=sparklyr local=TRUE

     Species Sepal_Length_typical Sepal_Width_typical Petal_Length_typical Petal_Width_typical
       <chr>                <dbl>               <dbl>                <dbl>               <dbl>
1 versicolor                5.936               2.770                4.260               1.326
2  virginica                6.588               2.974                5.552               2.026
3     setosa                5.006               3.428                1.462               0.246
```

How is all this implemented?

- `dplyr` uses `sparklyr` to translate each `dplyr`-verb into `SparkSQL`.
- `dplyr` collects a compound query representing arbitrarily long sequences of operations on the remote (Spark) data.
- The query is lazy, and only run if and when the data is actually used in an eager calculation (such as printing).

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Query examples

```
> iris_tbl %>%
      group_by(Species) %>%
      summarize_all(funs(typical=mean)) %>%
      show_query

<SQL>
SELECT `Species`, AVG(`Sepal_Length`) AS `Sepal_Length_typical`, AVG(`Sepal_Width`) AS
`Sepal_Width_typical`, AVG(`Petal_Length`) AS `Petal_Length_typical`, AVG(`Petal_Width`) AS
`Petal_Width_typical`
FROM `iris`
GROUP BY `Species`

> iris_tbl %>%
      head %>%
      show_query

<SQL>
SELECT *
FROM `iris`
LIMIT 6
```

Being eager

- dplyr::collapse()
  - Try and simplify the the accumulated query.
- dplyr::compute()
  - Force computation, materialize result of query into a new table.
- dplyr::collect()
  - Force computation, materialize result of query into a local `tbl`.

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Lazy eval: nothing done until something triggers `compute()`

```
res <- iris_tbl %>%
  group_by(zpecies) %>%       #OOOPS!
  summarize_all(funs(typical=mean))
# no error!

print(res)
Error:
org.apache.spark.sql.AnalysisException:
cannot resolve '`zpecies`' given
```

```
res <- iris_tbl %>%
  group_by(zpecies) %>%
  summarize_all(funs(typical=mean)) %>%
  compute()
Error:
org.apache.spark.sql.AnalysisException:
cannot resolve '`zpecies`' given
```

```
res <- iris_tbl %>%
  group_by(Species) %>%
  summarize_all(funs(typical=mean)) %>%
  show_query
<SQL>
SELECT `Species`, AVG(`Sepal_Length`) …
```

```
res <- iris_tbl %>%
  group_by(Species) %>%
  summarize_all(funs(typical=mean)) %>%
  compute(name= 'summarizedIris') %>%
  show_query
<SQL>
SELECT *
FROM `summarizedIris`
```

Be cautious with remote data

- Semantics may be different than `R` conventions.
- May have limited ability to represent NA/NULL.
- Will not be able to represent factors other than as strings.
- May have different integer and floating point arithmetic rounding and rules.
- May have different column names and quoting/escaping conventions.
- Do not accept arbitrary `R` user define functions.
    - Will substitute many common `R` functions by name.
- May not have easy to access ranking and other window functions.

The biggest difference

- Most remote data sources do not:
  - Guarantee row order
  - Support row-names
- These are deliberately *not* included as relational concepts.
- R local data frames guarantee row order
  - Many calculations depend on this
  - These calculations will not be correct on remote data sources.

dplyr::mutate example

```
> iris_tbl %>%
    summarize(mx = mean(Sepal_Length))

Source:   query [1 x 1]
Database: spark connection master=local[4] app=sparklyr local=TRUE

        mx
     <dbl>
1 5.843333


> iris %>%
    summarize(mx = median(Sepal.Length))

   mx
1 5.8

> iris_tbl %>%
    summarize(mx = median(Sepal_Length))

Error: org.apache.spark.sql.AnalysisException: Undefined function: 'MEDIAN'. This func
neither a registered temporary function nor a permanent function registered in the d
'default'.; line 1 pos 7
```

Spark `union` example

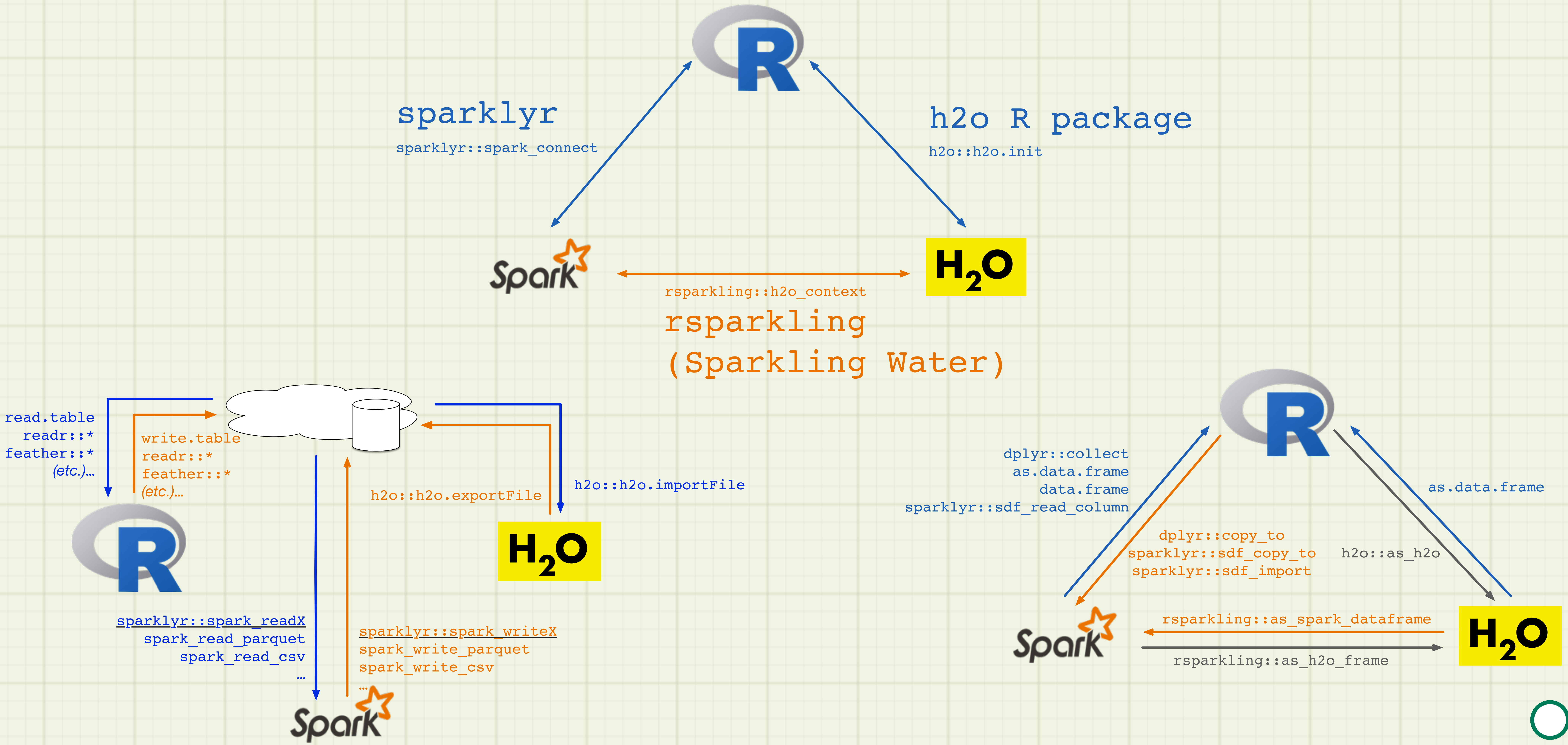
```
> d1 <- data_frame(x= 1, y= 'a')
> d2 <- data_frame(y= 'b', x= 2)

> bind_rows(d1, d2)

# A tibble: 2 × 2
      x     y
  <dbl> <chr>
1     1     a
2     2     b


> union(d1, d2)

# A tibble: 2 × 2
      x     y
  <dbl> <chr>
1     2     b
2     1     a
```

```
> d1s <- copy_to(sc, d1)
> d2s <- copy_to(sc, d2)

> bind_rows(d1s, d2s)

Error: incompatible sizes (1 != 2)


> union(d1s, d2s)

Source:   query [2 x 2]
Database: spark connection
master=local[4] app=sparklyr local=TRUE

      x     y
  <chr> <chr>
1     b   2.0
2   1.0     a
```

Some commands to remember

Command	What it does
`DBI::dbListTables(sc)`	Lists data items in `Spark`
`dplyr::tbl(sc, 'iris')`	Build a handle pointing to the `Spark` object with the given name
dplyr::copy_to(sc, iris, "iris")	Copy data from `R` to `Spark` and choose name of result
dplyr::collect(iris_tbl)	Copy data from `Spark` to `R`
dplyr::db_drop_table(sc, 'iris')	Drop object by name

Please keep the “three island slides” as a handy reference



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Quality of implementation varies by service provider

Service provider	R package	Quality of the experience
SQLite	RSQLite	excellent
PostgreSQL	RPostgreSQL	excellent
Spark2.x.x	SparklyR	excellent
Spark1.6.2	SparklyR	passable
MySQL	RMySQL	low

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Also consider using Spark-specific commands

- **`sdf_*`:** Use spark data frame commands to manipulate data frames.
  - Examples: `sdf_partition`, `sdf_predict`, `sdf_sample`
- **`ft_*`:** Use feature transforms to manipulate features.
  - Examples: `ft_bucketizer`, `ft_index_to_string`
- **`ml_*`:** Use machine learning algorithms to train models.
  - Examples: `ml_kmeans`, `ml_logistic_regression`, `ml_pca`

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Break: please be back by 3:30 pm.

Then we work through some `Spark` exercises together