Strata+ Hadoop WORLD

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#StrataHadoop

for Big Data

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RStudio, Inc.

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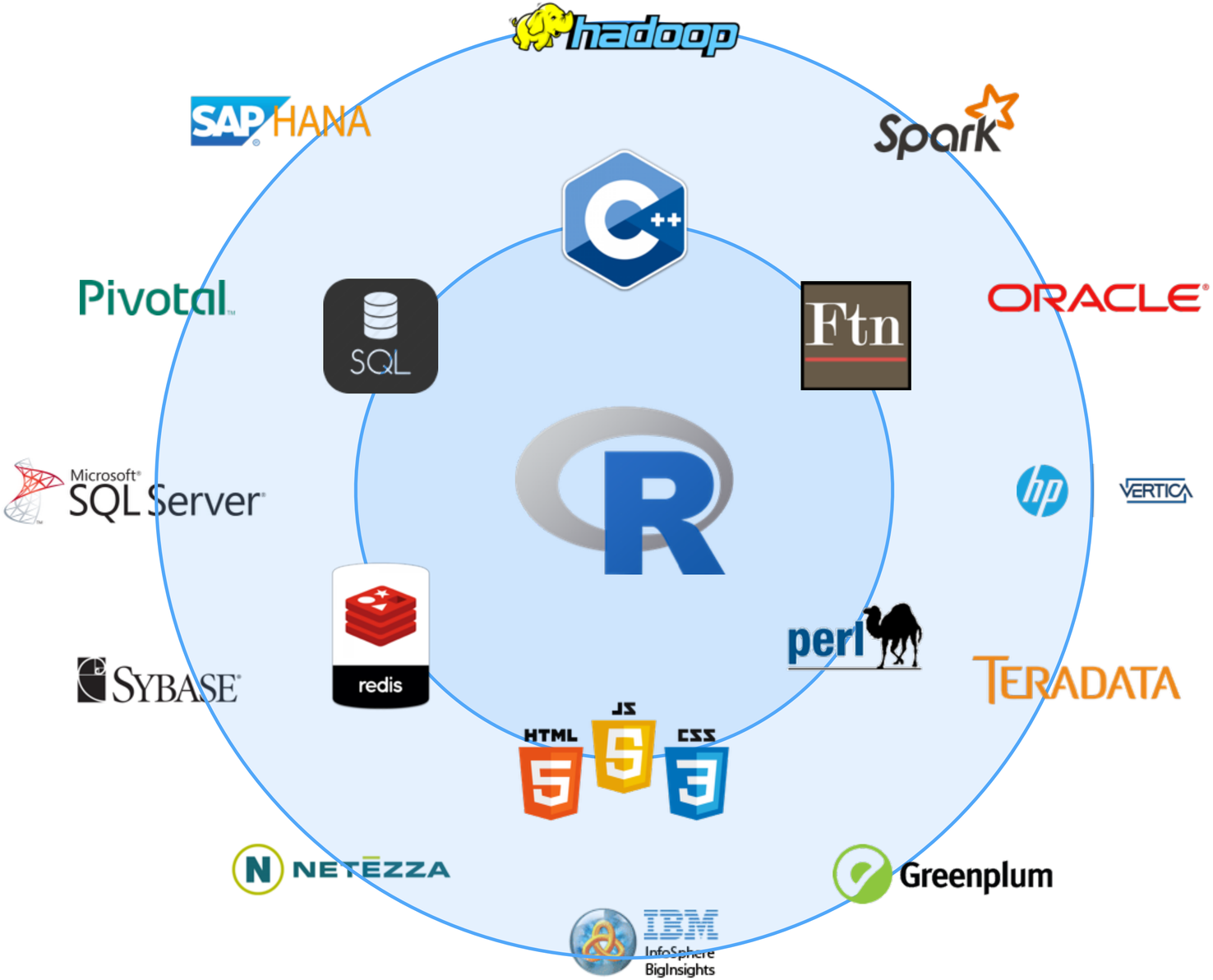
@StatGarrett

@nwstephens

Warm up

Introduce yourself to your table

- Name
- What do you do with data?
- For how long have you been using R?


hadoop
SAP HANA
Spark
C++
Pivotal
SQL
Ftn
ORACLE
Microsoft SQL Server
R
hp
VERTICA
redis
perl
SYBASE
TERADATA
HTML
JS
CSS
NETEZZA
Greenplum
IBM
InfoSphere
BigInsights

Velocity

Volume

Value

Variety

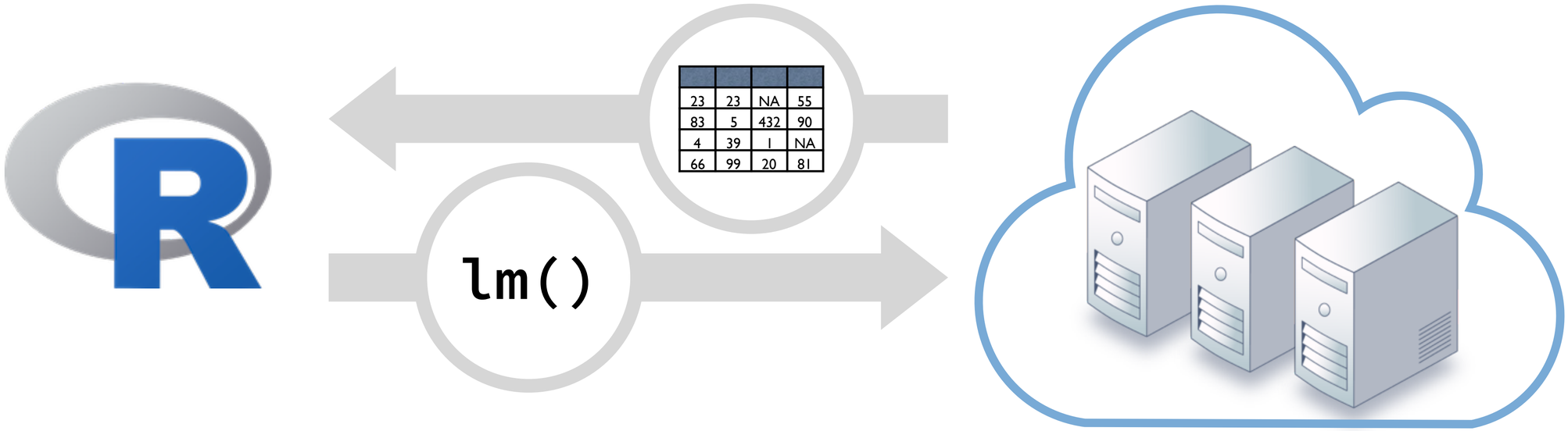
Veracity

Big Data > 1/3 RAM

General Strategy

Store big data in a data warehouse

1. Pass subsets of data from warehouse to R
2. Transform R code, pass to warehouse.



General Strategy

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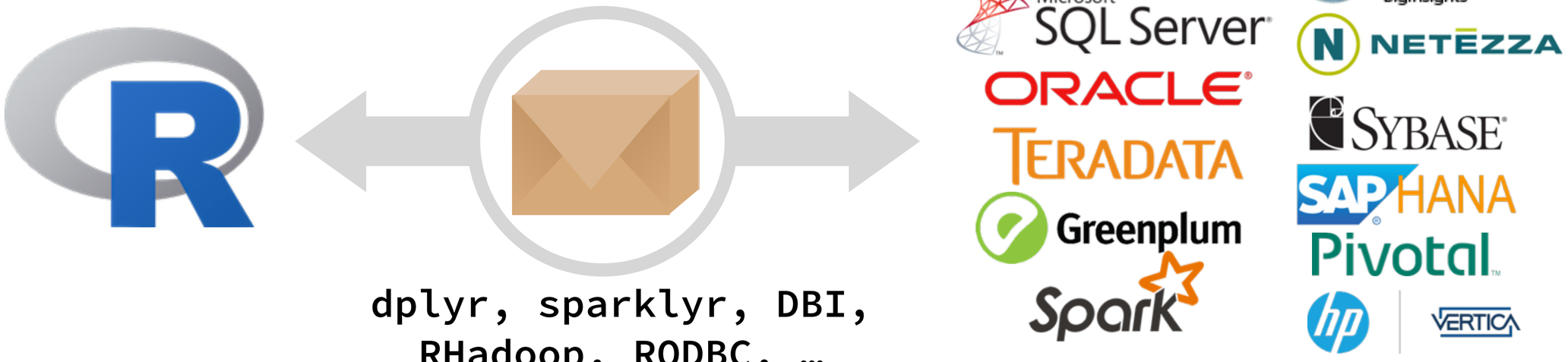
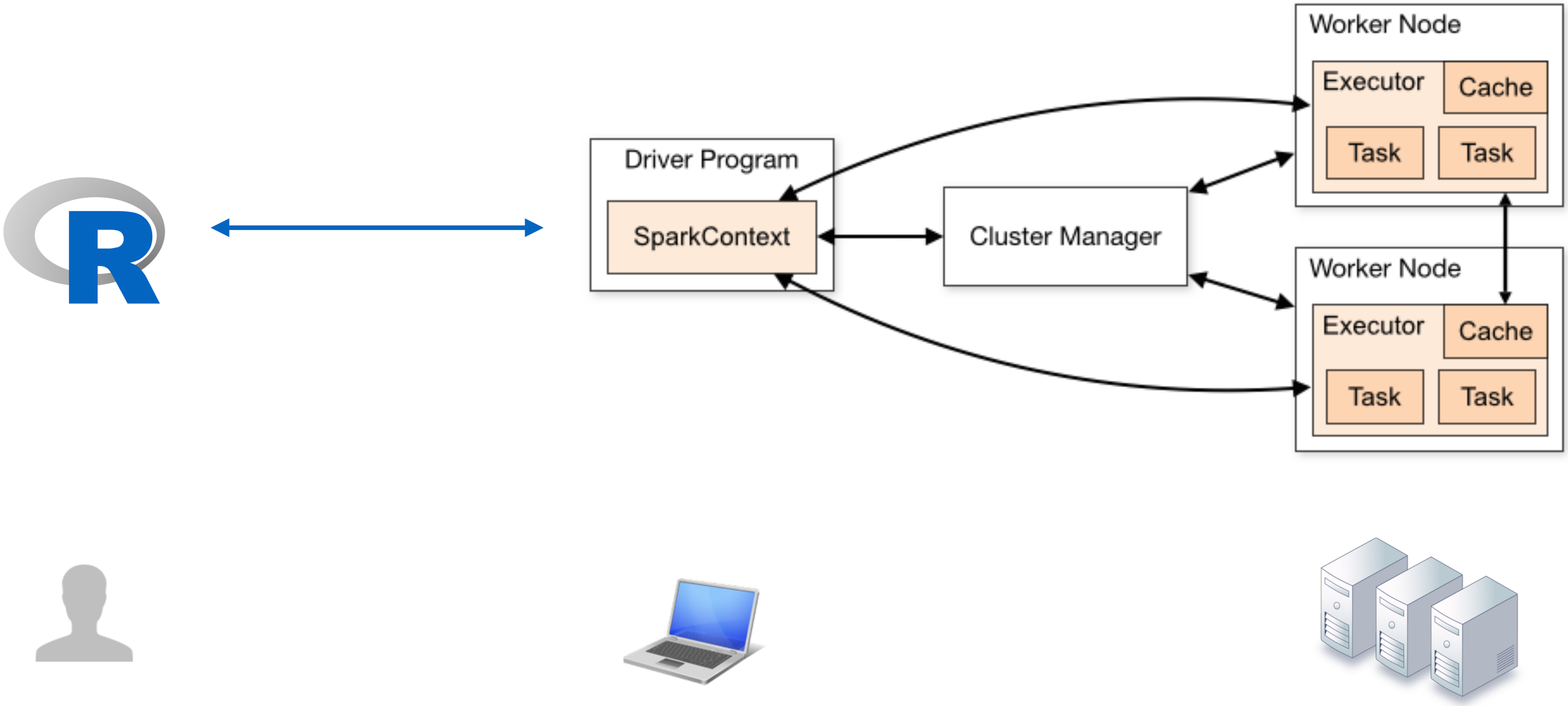
2. Transform R code, pass to warehouse.



`dplyr, sparklyr, DBI,`
`RHadoop, RODBC, …`



graphic from http://spark.apache.org/docs/latest/img/cluster-overview.png

Demo

Outline

1. **dplyr**
   The basic, universal commands

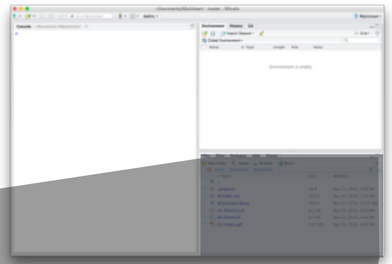
2. **Databases**
   A quick aside, using dplyr with DBMS

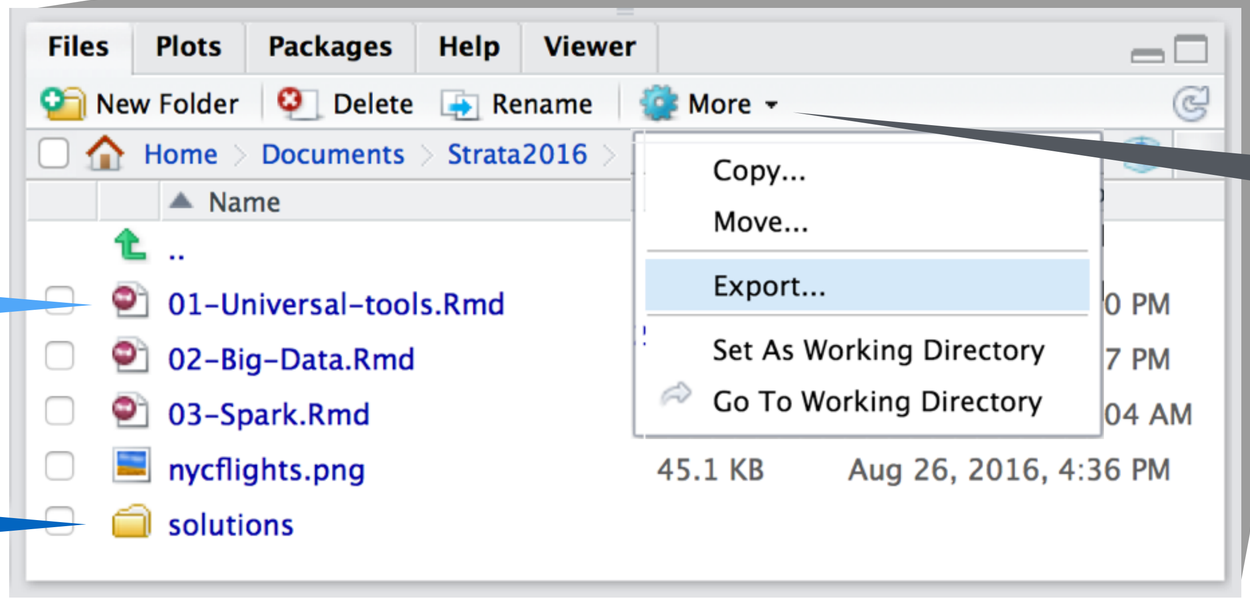
3. **sparklyr**
   Using dplyr and sparklyr with Spark

Class Materials

In the **Files** pane, you will find

`01-Universal-tools.Rmd`
`02-Big-Data.Rmd`
`03-Spark-SQL.Rmd`
`04-Spark-ML.Rmd`





Exercises

Solutions

To Downlo

What is R Markdown?

Exercise 1

Open 01-Universal-tools.Rmd.

Read through the Notebook Logistics section and try out the features described.

Stop when you get to the first horizontal rule (`***`)

dplyr

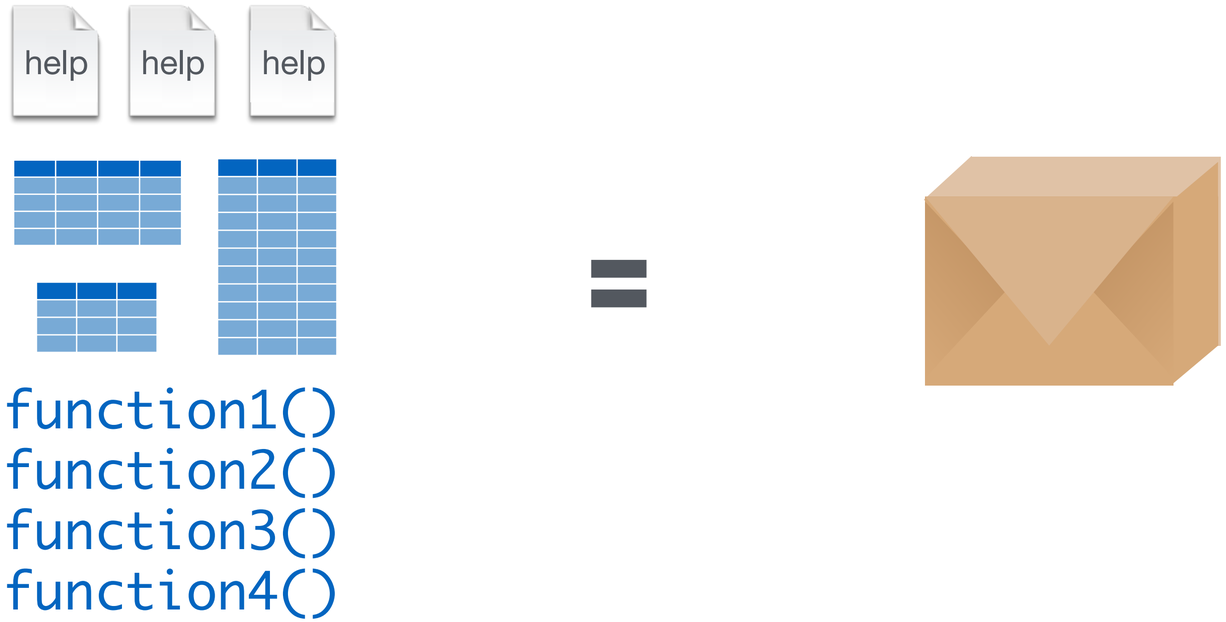
R tools for data manipulation

Packages

A bundle of functions, data sets, and help pages that you install in addition to the base R installation, e.g.

```
install.packages("dplyr")
```

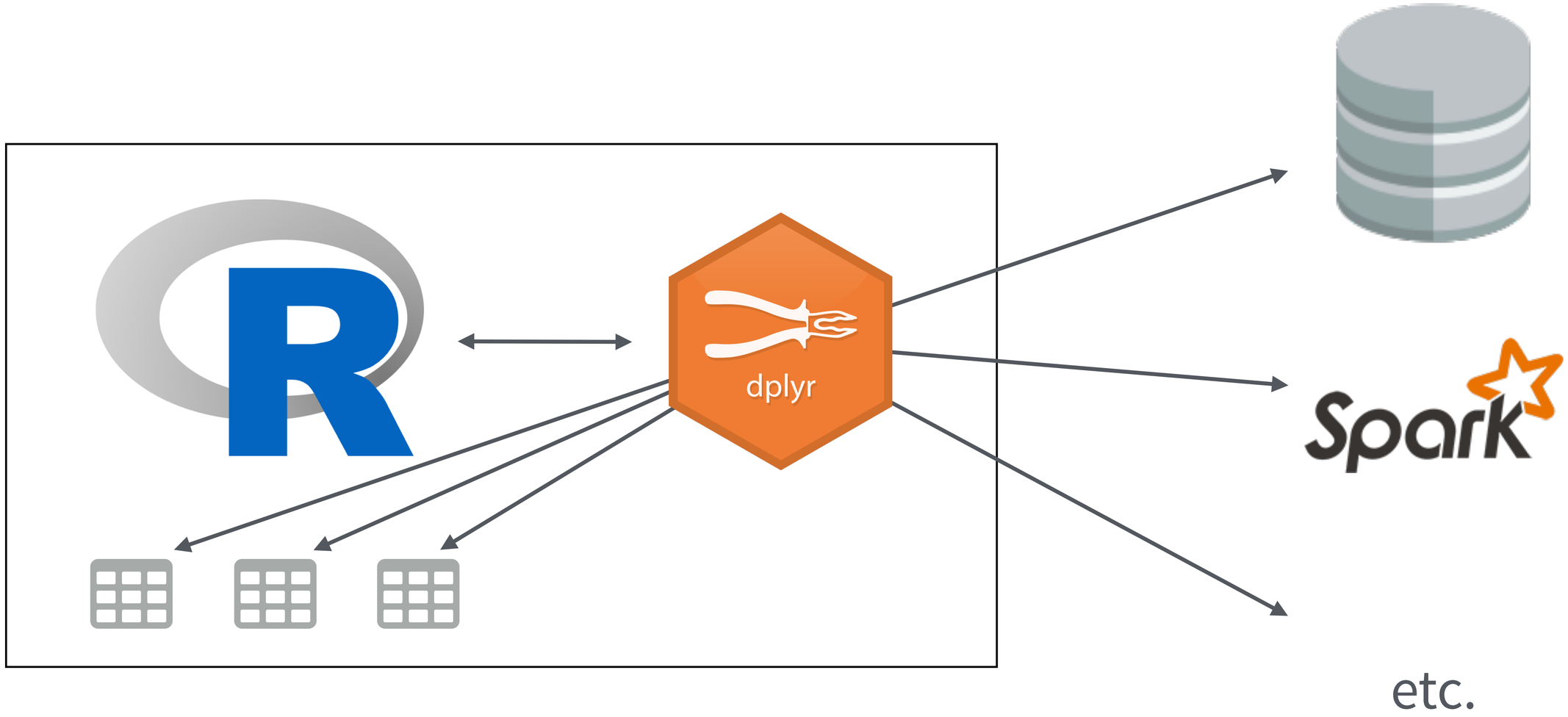
To use a package, you must load it with `library()`



dplyr

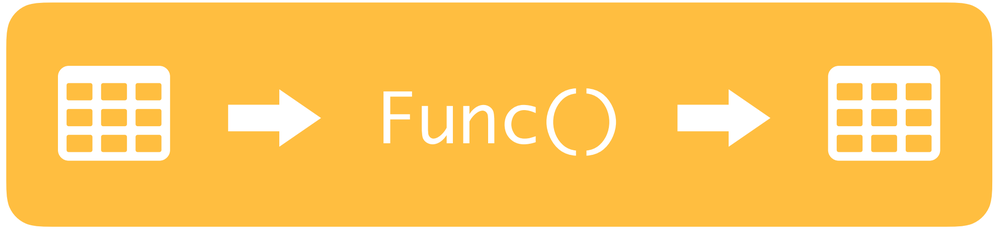
A grammar of data manipulation

`select`	`left_join`	`bind_cols`
`filter`	`right_join`	`bind_rows`
`arrange`	`inner_join`	`union`
`mutate`	`full_join`	`intersect`
`summarise`	`semi_join`	`setdiff`
`group_by`	`anti_join`	`` `%>%` ``


dplyr
Spark
etc.

Single Table Verbs

Manipulate tabular data



`select` `filter` `summarise`

`mutate` `arrange` `group_by`

Two Table Verbs

Join together relational data

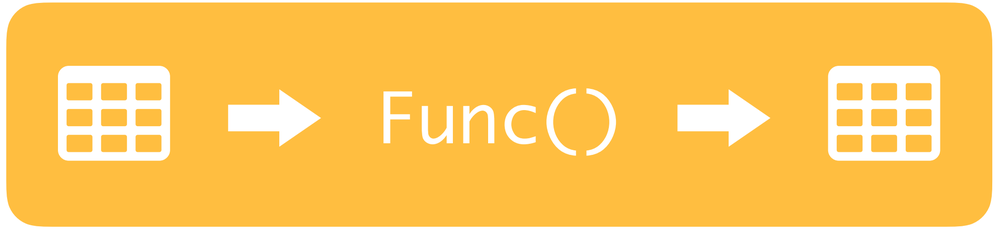
`left_join` `full_join` `union` `bind_cols`

`right_join` `semi_join` `intersect` `bind_rows`

`inner_join` `anti_join` `setdiff`

Single Table Verbs

Manipulate tabular data



`select` `filter` `summarise`

`mutate` `arrange` `group_by`

Two Table Verbs

Join together relational data

`left_join` `full_join` `union` `bind_cols`

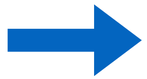
`right_join` `semi_join` `intersect` `bind_rows`

`inner_join` `anti_join` `setdiff`

select()

storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



storm	pressure
Alberto	1007
Alex	1009
Allison	1005
Ana	1013
Arlene	1010
Arthur	1010

```
select(storms, storm, pressure)
```

* These data sets are in the EDAWR package

mutate()

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storm	wind	pressure	date	ratio
Alberto	110	1007	2000-08-12	9.15
Alex	45	1009	1998-07-30	22.42
Allison	65	1005	1995-06-04	15.46
Ana	40	1013	1997-07-01	25.32
Arlene	50	1010	1999-06-13	20.20
Arthur	45	1010	1996-06-21	22.44

```
mutate(storms, ratio = pressure / wind)
```

* These data sets are in the EDAWR package

filter()

storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storm	wind	pressure	date
Alberto	110	1007	2000-08-12

```
filter(storms, wind == max(wind))
```

* These data sets are in the EDAWR package

logical tests in R

?Comparison

<	Less than
>	Greater than
==	Equal to
<=	Less than or equal to
>=	Greater than or equal to
!=	Not equal to
%in%	Group membership
is.na	Is NA
!is.na	Is not NA

?base::Logic

&	boolean and
|	boolean or
xor	exactly or
!	not
any	any true
all	all true

filter()

storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Allison	65	1005	1995-06-04
Arlene	50	1010	1999-06-13

```
filter(storms, wind >= 50)
```

* These data sets are in the EDAWR package

filter()

storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storm	wind	pressure	date
Alex	45	1009	1998-07-30
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

```
filter(storms, wind < 60, wind >= 40)
```

* These data sets are in the EDAWR package

arrange()

storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storm	wind	pressure	date
Ana	40	1013	1997-07-01
Alex	45	1009	1998-07-30
Arthur	45	1010	1996-06-21
Arlene	50	1010	1999-06-13
Allison	65	1005	1995-06-04
Alberto	110	1007	2000-08-12

```
arrange(storms, wind)
```

* These data sets are in the EDAWR package

arrange()

storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storm	wind	pressure	date
Ana	40	1013	1997-07-01
Alex	45	1009	1998-07-30
Arthur	45	1010	1996-06-21
Arlene	50	1010	1999-06-13
Allison	65	1005	1995-06-04
Alberto	110	1007	2000-08-12

```
arrange(storms, wind)
```

* These data sets are in the EDAWR package

arrange()

storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Allison	65	1005	1995-06-04
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21
Alex	45	1009	1998-07-30
Ana	40	1013	1997-07-01

```
arrange(storms, desc(wind))
```

* These data sets are in the EDAWR package

summarise()

city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

median
22.5

```
summarise(pollution, median = median(amount))
```

* These data sets are in the EDAWR package

summarise()

city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

mean	sum	n
42	252	6

```
summarise(pollution, mean = mean(amount), sum = sum(amount), n = n())
```

* These data sets are in the EDAWR package

city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

mean	sum	n
42	252	6

* These data sets are in the EDAWR package

city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14
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London	small	16
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Beijing	small	56

mean	sum	n
42	252	6

* These data sets are in the EDAWR package

city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

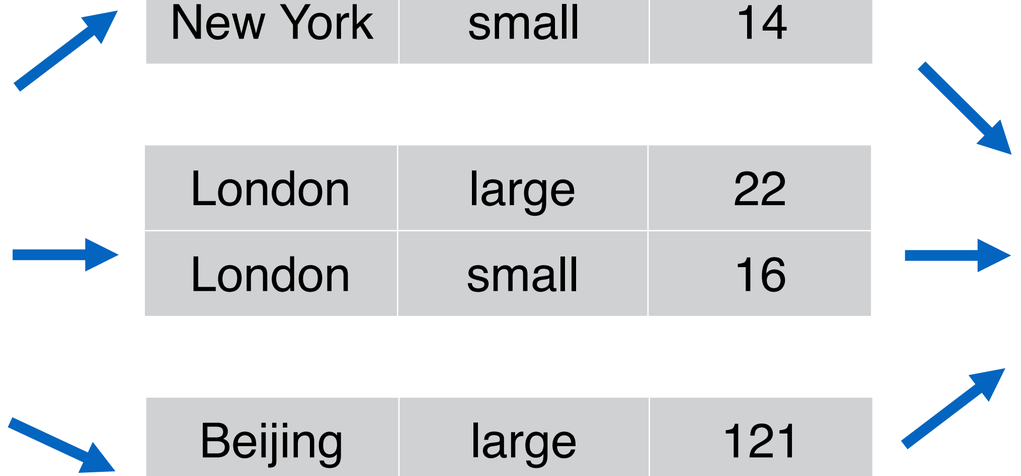
mean	sum	n
18.5	37	2
19.0	38	2
88.5	177	2

group_by() + summarise()

* These data sets are in the EDAWR package

group_by()

city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56



city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14

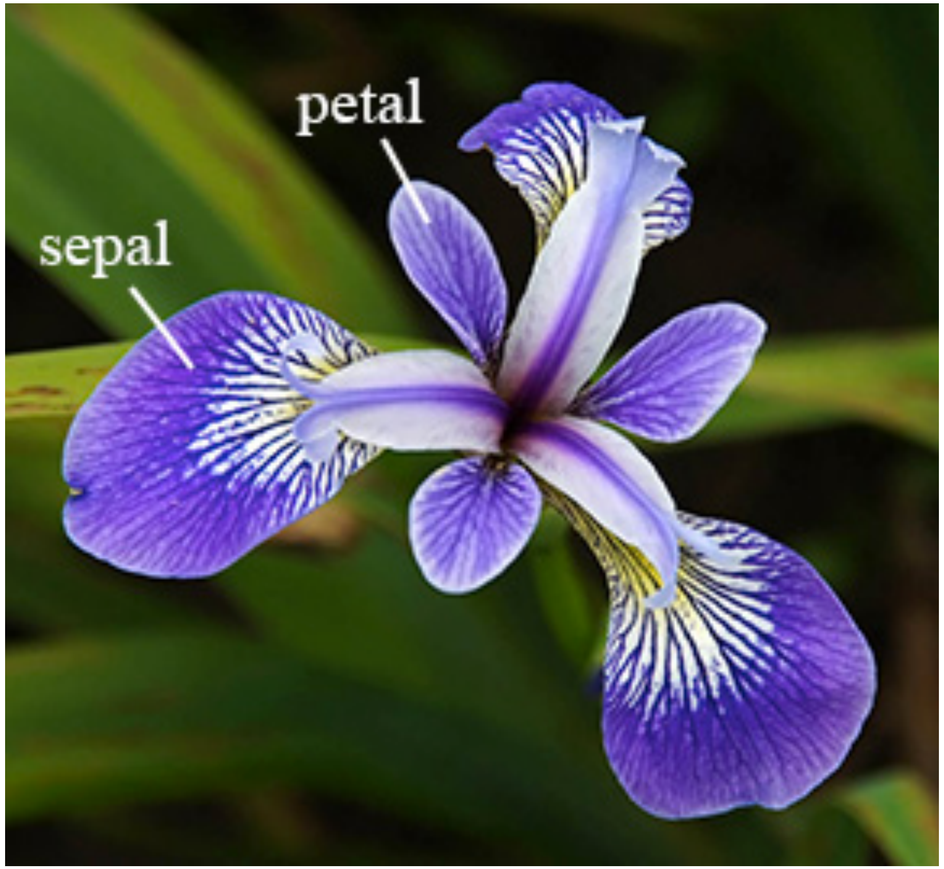
city	particle size	amount ($\mu g/m^3$)
London	large	22
London	small	16

city	particle size	amount ($\mu g/m^3$)
Beijing	large	121
Beijing	small	56

mean	sum	n
18.5	37	2
19.0	38	2
88.5	177	2

```
p <- group_by(pollution, city)
summarise(p, mean = mean(amount), sum = sum(amount), n = n())
```

iris

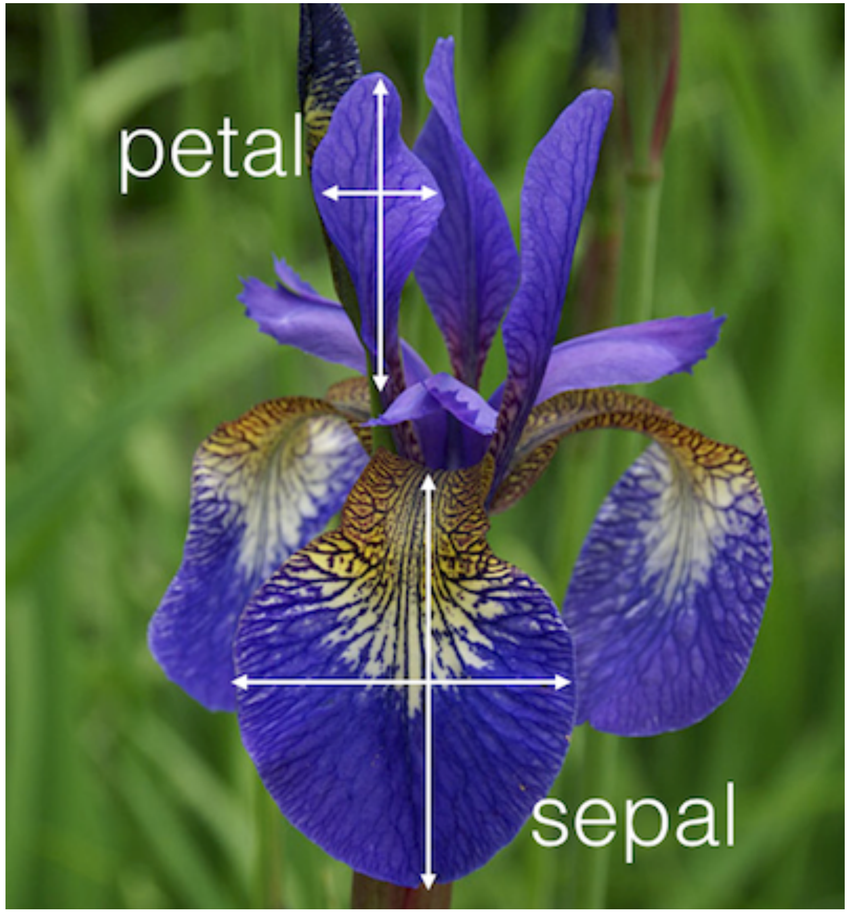


iris

Sepal.Length	Sepal.Width	Petal. length	Petal.Width	Species
5.1	3.5	1.4	0.2	setosa
4.9	3.0	1.4	0.2	setosa
…	…	…	…	…
6.5	3.0	5.2	2.0	virginica
6.2	3.4	5.4	2.3	virginica
5.9	3.0	5.1	1.8	virginica

iris

On average, which species has the greatest difference in *petal width* and *petal length*?



Exercise 2

Species	avg_width	avg_length
?	?	?

1. **Group** iris by Species
2. For each group, return:
    - avg_width = mean Petal.Width
    - avg_length = mean Petal.Length
3. For each row, calculate diff = avg_length - avg_width
4. Return the **row** whose diff == the max diff
5. Return the **columns** above

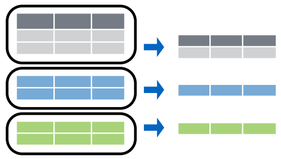
```
iris1 <- group_by(iris, Species)
iris2 <- summarise(iris1,
  avg_width = mean(Petal.Width),
  avg_length = mean(Petal.Length))
iris3 <- mutate(iris2, diff = avg_length - avg_width)
iris4 <- filter(iris3, diff == max(diff))
select(iris4, Species, avg_width, avg_length)
```

Recap: dplyr

Extract columns and rows with **select()** and **filter()**

Arrange rows with **arrange()**.

Make new columns with **mutate()**.



Make groupwise summaries with **group_by()** and **summarise()**.

%>%

Ceci n'est pas une pipe.

```
iris1 <- group_by(iris, Species)
iris2 <- summarise(iris1,
  avg_width = mean(Petal.Width),
  avg_length = mean(Petal.Length))
iris3 <- mutate(iris2, diff = avg_length - avg_width)
iris4 <- filter(iris3, diff == max(diff))
select(iris4, Species, avg_width, avg_length)
```

The pipe operator %>%

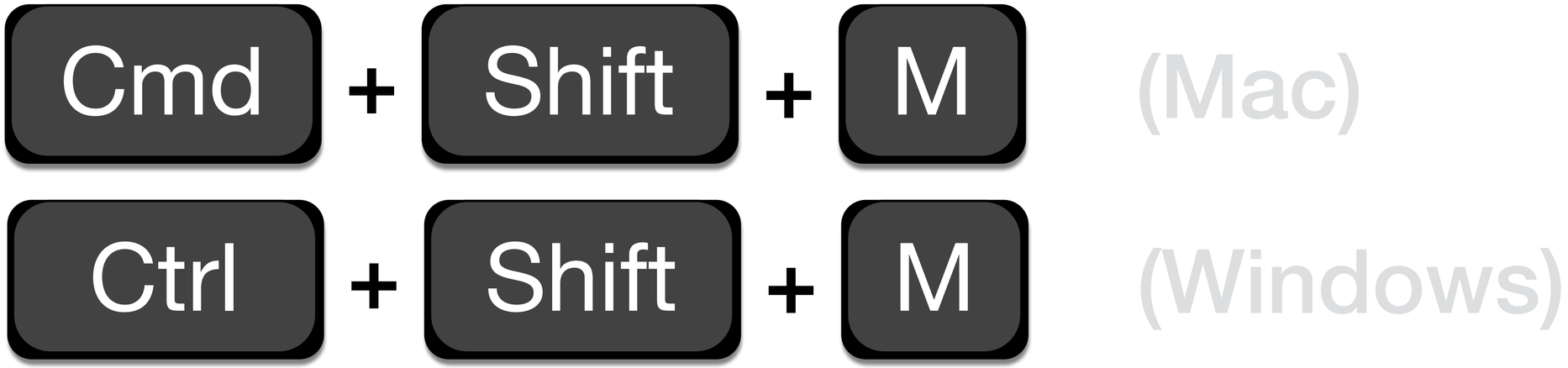
These do the same thing

Try it!

```
filter(iris, Sepal.Length == max(Sepal.Length))
iris %>% filter(Sepal.Length == max(Sepal.Length))
```


```
iris        filter(_____, Sepal.Length == max(Sepal.Length))
```

Shortcut to type %>%



A pipe

```
iris %>%
  filter(Sepal.Length == max(Sepal.Length)) %>%
  mutate(total = Sepal.Length + Sepal.Width) %>%
  select(Species, total) %>%
  …
```

Exercise 3

Use %>% to turn your code from Exercise 3 into a single long pipe.

```
iris1 <- group_by(iris, Species)
iris2 <- summarise(iris1,
  avg_width = mean(Petal.Width),
  avg_length = mean(Petal.Length))
iris3 <- mutate(iris2, diff = avg_length - avg_width)
iris4 <- filter(iris3, diff == max(diff))
select(iris4, Species, avg_width, avg_length)
```

```
iris %>%
  group_by(Species) %>%
  summarise(
    avg_width = mean(Petal.Width),
    avg_length = mean(Petal.Length)) %>%
  mutate(diff = avg_length - avg_width) %>%
  filter(diff == max(diff)) %>%
  select(Species, avg_width, avg_length)
```

Single Table Verbs

Manipulate tabular data

`select` `filter` `summarise`

`mutate` `arrange` `group_by`

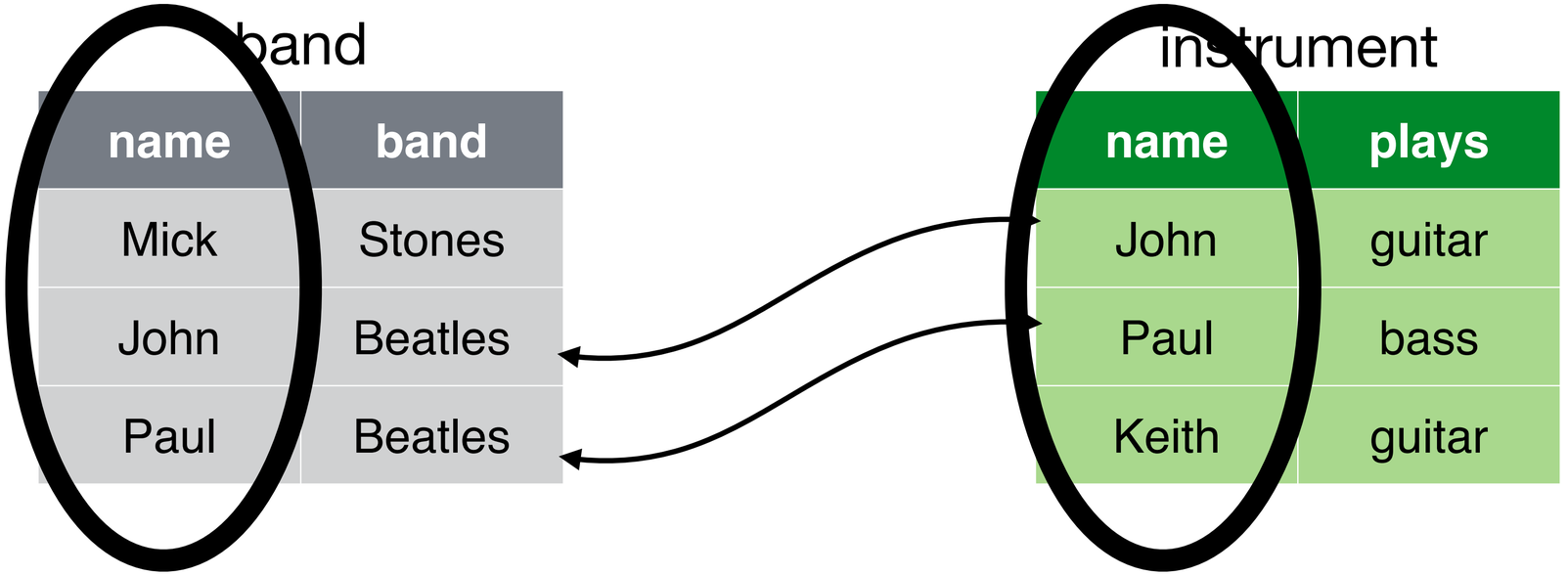
Two Table Verbs

Join together relational data

`left_join` `full_join` `union` `bind_cols`

`right_join` `semi_join` `intersect` `bind_rows`

`inner_join` `anti_join` `setdiff`


band
name
band
Mick
Stones
John
Beatles
Paul
Beatles
instrument
name
plays
John
guitar
Paul
bass
Keith
guitar

left_join()

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
Mick	Stones	<NA>
John	Beatles	guitar
Paul	Beatles	bass

```
left_join(band, instrument, by = "name")
```

left_join()

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
Mick	Stones	<NA>
John	Beatles	guitar
Paul	Beatles	bass

```
left_join(band, instrument, by = "name")
```

Exercise 4

Recreate bands and instruments in your notebook.

Use them to test each join function and to complete the join definitions.

left_join()

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
Mick	Stones	<NA>
John	Beatles	guitar
Paul	Beatles	bass

```
left_join(band, instrument, by = "name")
```

right_join()

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
John	Beatles	guitar
Paul	Beatles	bass
Keith	<NA>	guitar

```
right_join(band, instrument, by = "name")
```

inner_join()

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
John	Beatles	guitar
Paul	Beatles	bass

```
inner_join(band, instrument, by = "name")
```

full_join()

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
Mick	Stones	<NA>
John	Beatles	guitar
Paul	Beatles	bass
Keith	<NA>	guitar

```
full_join(band, instrument, by = "name")
```

semi_join()

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band
John	Beatles
Paul	Beatles

```
semi_join(band, instrument, by = "name")
```

anti_join()

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

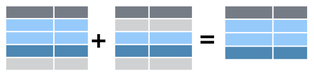
=

name	band
Mick	Stones

```
anti_join(band, instrument, by = "name")
```

Recap: Two table verbs

Join together observations with **left_join()**, **right_join()**, **inner_join()**, and **full_join()**



Filter one data set based on another with **semi_join()** and **anti_join()**

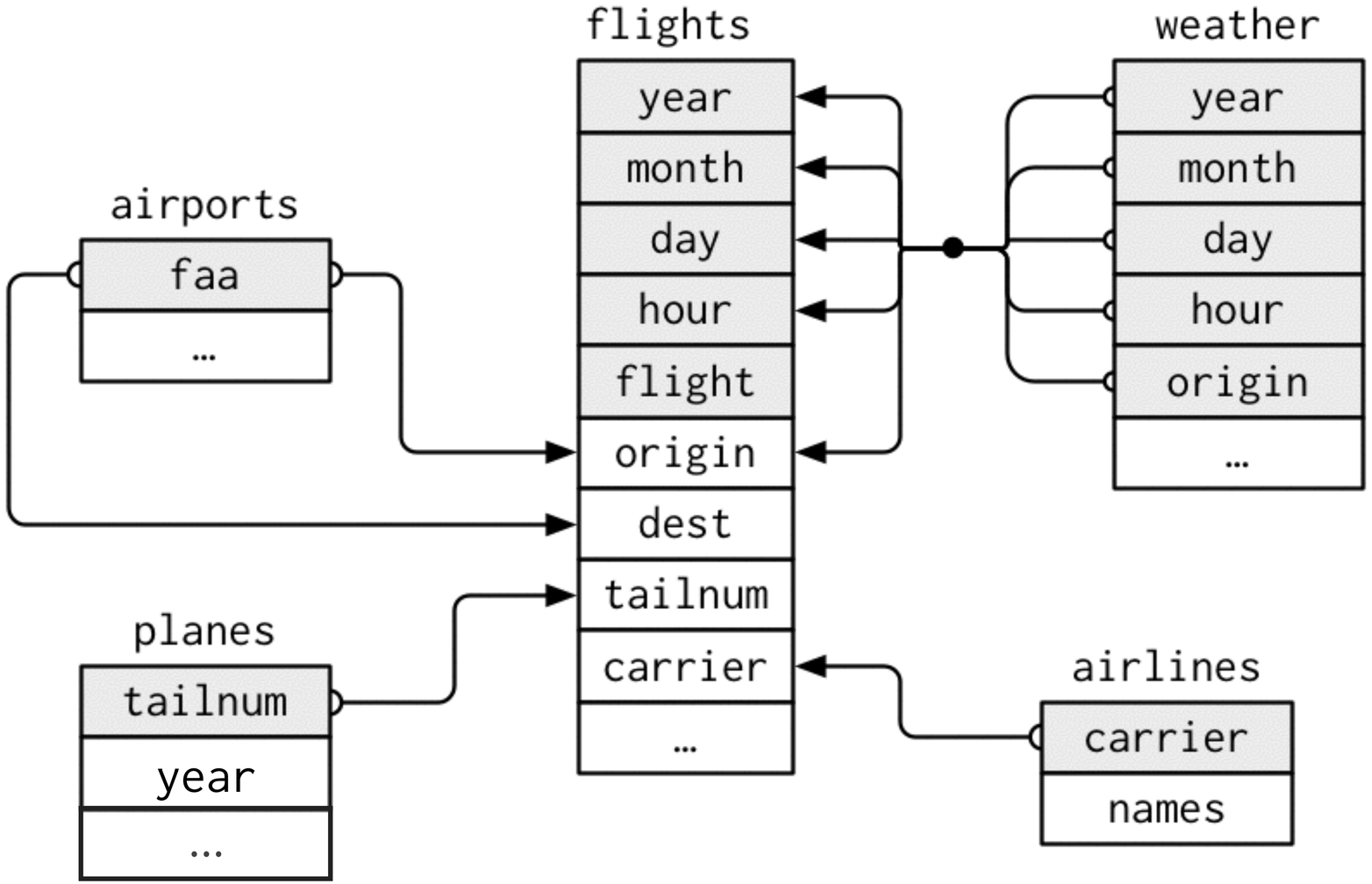
Bind data sets together with **bind_rows()** and **bind_cols()**

Do set operations on rows with dplyr's **union()**, **intersect()**, and **setdiff()**

nycflights13

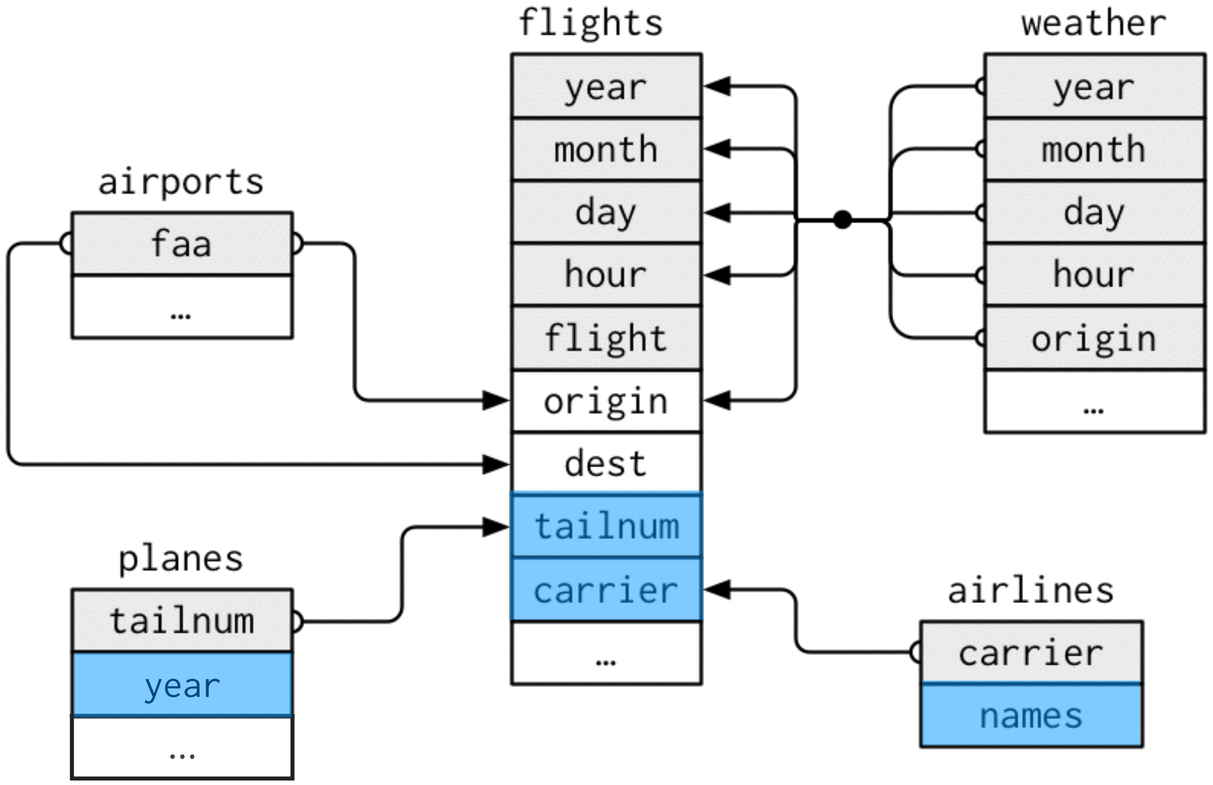
Data about every flight that departed La Guardia, JFK, or Newark airports in 2013

nycflights13



nycflights13

On average, which airline has the newest planes (assigned to the NYC area)?



```
flights %>%
  distinct(carrier, tailnum) %>%
  _____________________________ %>%
  _____________________________ %>%
  _____________________________ %>%
  _____________________________ %>%
  _____________________________ %>%
  _____________________________
```

Exercise 6

Determine which airline has the newest planes. Start with the code in the notebook.

```
flights %>%
  distinct(carrier, tailnum) %>%
  left_join(planes, by = "tailnum") %>%
  group_by(carrier) %>%
  summarise(avg = mean(year, na.rm = TRUE),
            n = n(), nas = sum(is.na(year))) %>%
  left_join(airlines, by = "carrier") %>%
  select(name, avg, n, nas) %>%
  arrange(desc(avg))
```

name	avg	n	nas
Hawaiian Airlines Inc.	2011.769	14	1
Virgin America	2008.712	53	1
Frontier Airlines Inc.	2008.000	26	3
Alaska Airlines Inc.	2007.843	84	6
JetBlue Airways	2006.503	193	0
…	…	…	…

Airlines Data Set

Arrival and departure details for all commercial flights in US between October 1987 and April 2008. 120,000,000 records. **12 GB**

stat-computing.org/dataexpo/2009/

Data does not fit in memory

Airlines database

database: **airontime**

host: **sol-eng-sparklyr.cyii7eabibhu.us-east-1.redshift.amazonaws.com**

port: **5439**

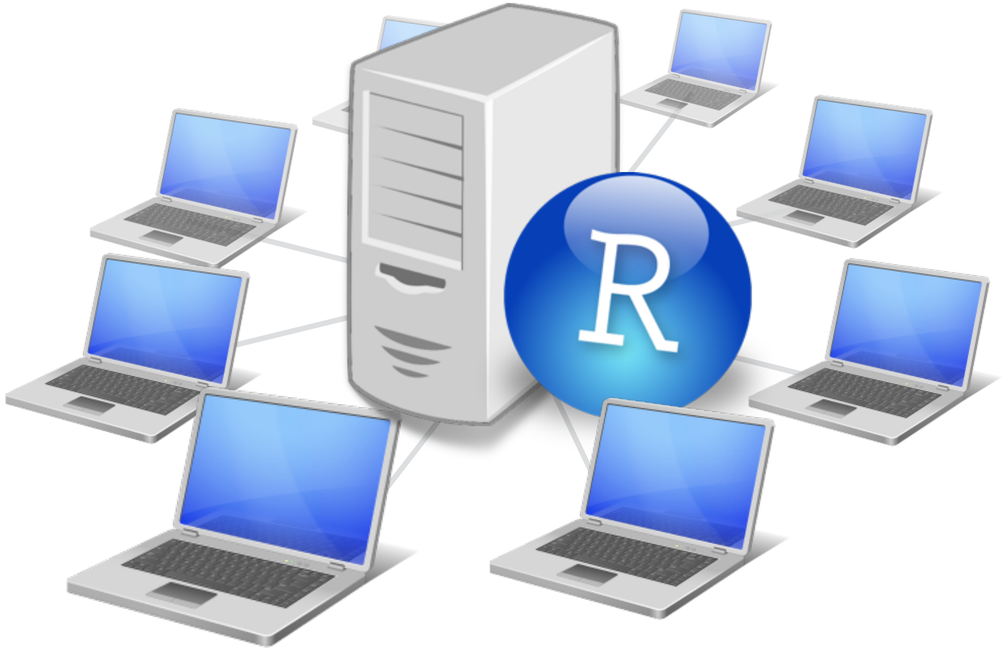
user: **redshift_user**

password: **ABCd4321**

databases

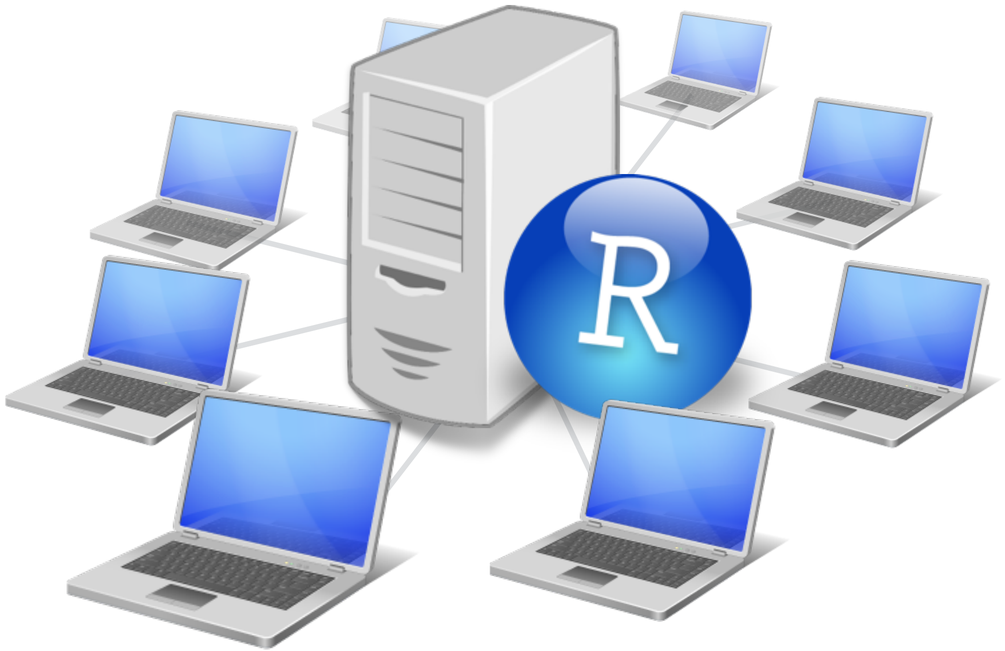
manipulating big data with R

RStudio
Desktop IDE



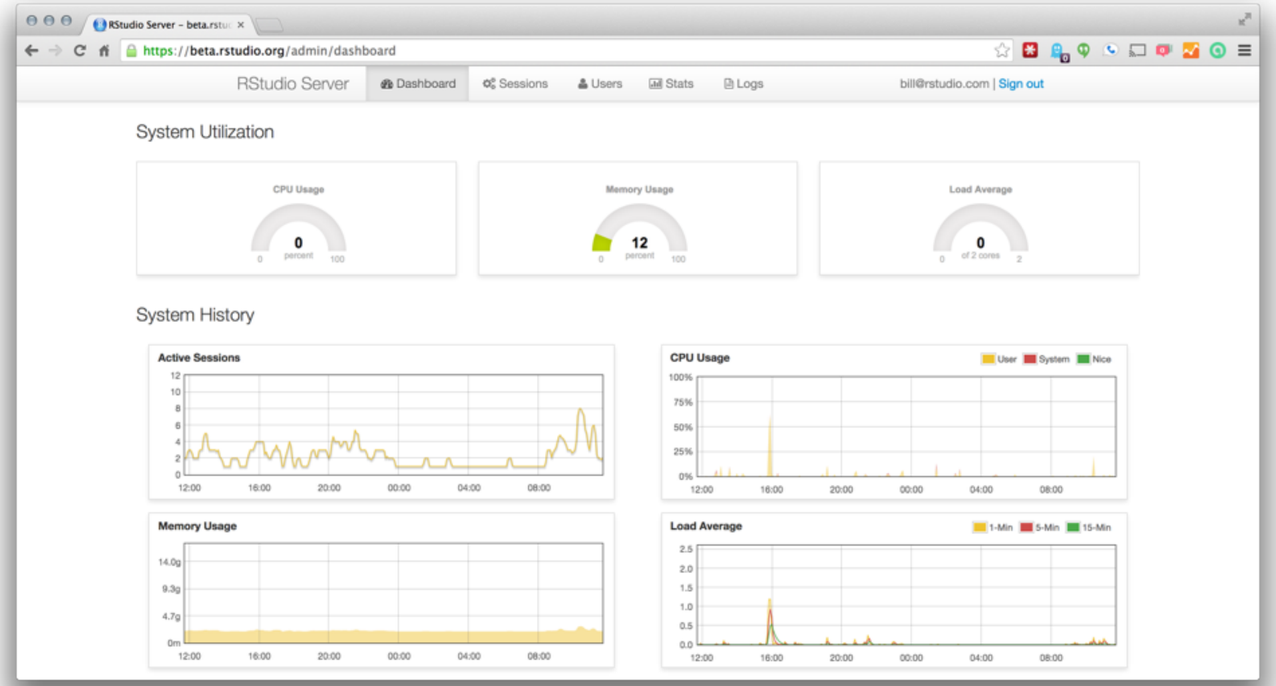
RStudio Server Pro

- Security
- Load balancing
- Administrative tools
- Resource management
- Metrics and monitoring
- Multiple sessions
- Collaborative editing
- Easy R versioning
- Audit history

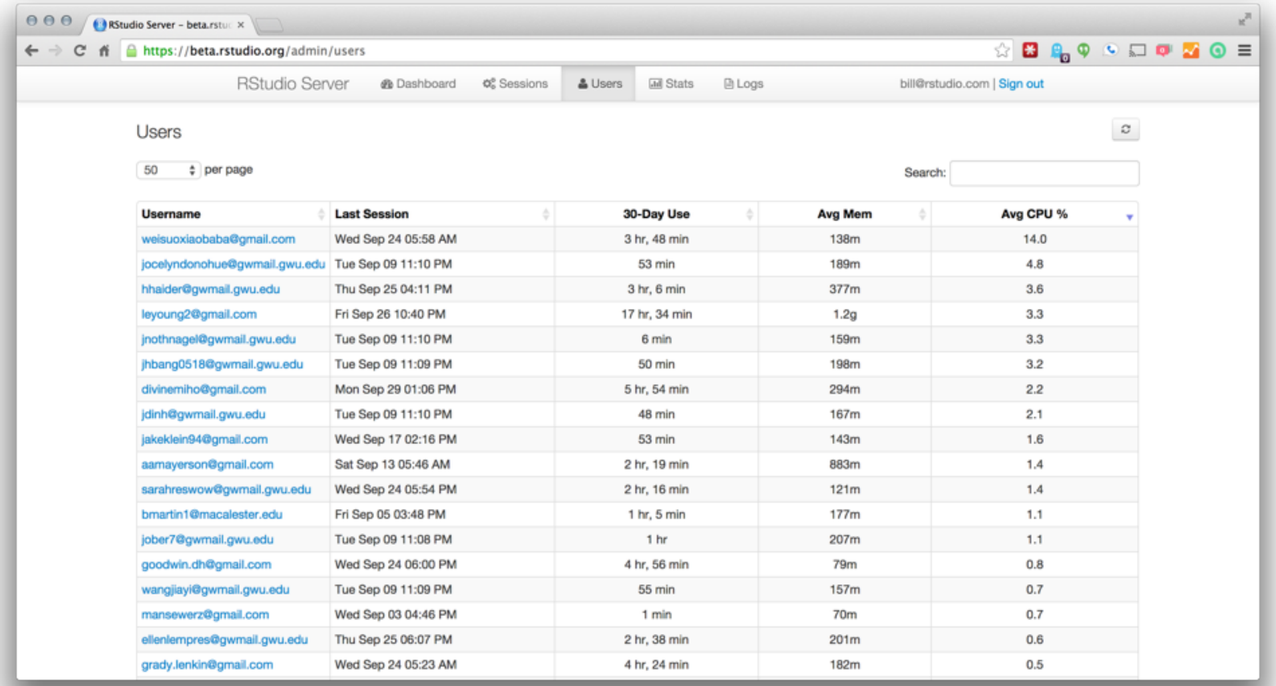


RStudio Server Pro

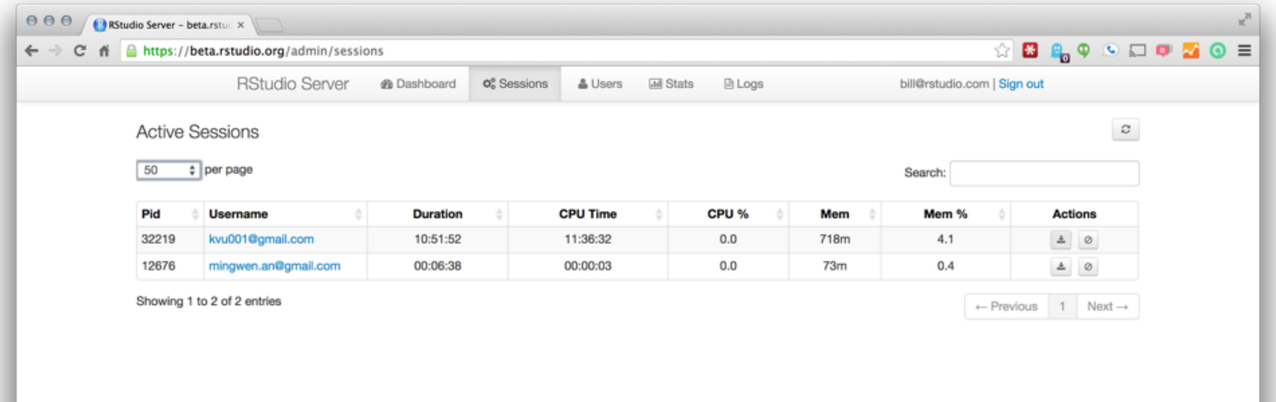
Administrative Dashboard



View and manage resource utilization



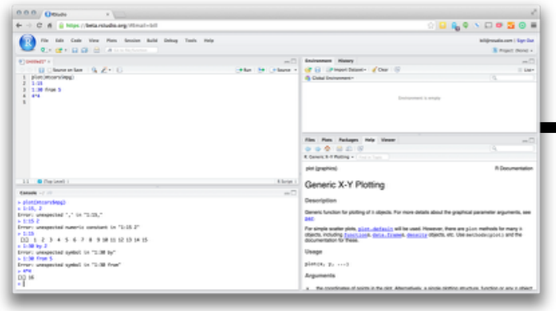
View and manage active sessions



RStudio®

User Browser

Server

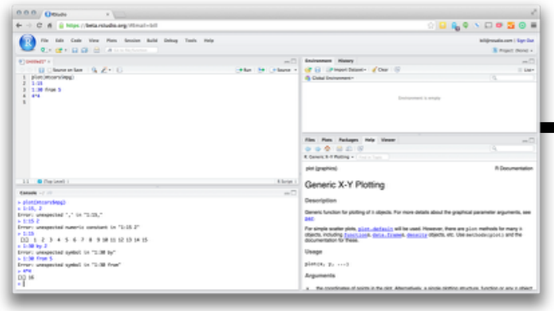


RStudio Server Pro

User Browser

Server

Database



RStudio Server Pro

Redshift

dplyr

Airlines

1. **Create a connection**

```
con   <-   src_postgres(dbname = 'DATABASE_NAME',
                        host = 'HOST',
                        port = 5432,
                        user = 'USERNAME',
                        password = 'PASSWORD')
```

Save to use

src_ driver function

driver specific args

Lists tables in DB

```
src_tbls(con)
## "iris"   "iris2"   "iris3"
```

dplyr driver functions

Package	DBMS
src_sqlite()	SQLite
src_mysql()	MySQL, MariaDB
src_postgres()	PostgreSQL
library(bigrquery) src_bigquery()	Google BigQuery

https://cran.r-project.org/web/packages/dplyr/vignettes/databases.html

Exercise 1

Open 2-Big-Data.Rmd in the class materials. Use the information in the Airlines Database section to create a dplyr connection to the database.

```
air <- src_postgres(
         dbname = 'DATABASE_NAME',
         host = 'HOST',
         port = 5432,
         user = 'USERNAME',
         password = 'PASSWORD')
```

```
air <- src_postgres(
  dbname = 'airontime',
  host='sol-eng-sparklyr.cyii7eabibhu.us-east-1.redshift.amazonaws.com',
  port = '5439',
  user = 'redshift_user',
  password = 'ABCd4321')
```

2. **Create a table reference**


```
tab <- tbl(con, "table_name")
```

Use `tbl()` to create objects that refer to tables in the database

3. **Manipulate the reference**

Treat the reference as if it were a table in R. dplyr will translate your code to SQL and execute it in the DBMS.*

```
flights <- tbl(air, "flights")
flights %>%
  distinct(uniquecarrier, tailnum) %>%
  …
```

Exercise 1

1. Open 2-Big-Data.Rmd in the class materials. Run the first code chunk to connect to the database.

2. The second code chunk applies your nycflights13 analysis to the new data sets. Create table references named:

    1. flights for the flights table
    2. planes for the planes table
    3. airlines for the airlines table

Then re-run the analysis to see which airline used the newest planes.

```
flights <- tbl(air, "flights")
airlines <- tbl(air, "carriers")
planes <- tbl(air, "planes")

flights %>%
  distinct(uniquecarrier, tailnum) %>%
  mutate(tailnum = substring(tailnum, 1L, 5L)) %>%
  left_join(planes, by = "tailnum") %>%
  group_by(uniquecarrier) %>%
  summarise(avg = mean(year, na.rm = TRUE),
            n = n(), nas = sum(is.na(year))) %>%
  left_join(airlines, by = "uniquecarrier") %>%
  select(name, avg, n, nas) %>%
  arrange(desc(avg))
```

show_query

To see the SQL that dplyr will run.

```
clean <- flights %>%
  filter(!is.na(arrdelay), !is.na(depdelay)) %>%
  filter(depdelay > 15, depdelay < 240) %>%
  filter(year >= 2002 & year <= 2007) %>%
  select(year, arrdelay, depdelay, distance, uniquecarrier)

show_query(clean)
```

```
show_query(clean)
##  <SQL>
##  SELECT "year" AS "year",
##    "arrdelay" AS "arrdelay",
##    "depdelay" AS "depdelay",
##    "distance" AS "distance",
##    "uniquecarrier" AS "uniquecarrier"
##  FROM "flights"
##  WHERE NOT("arrdelay"IS NULL) AND NOT("depdelay"IS NULL)
##    AND "depdelay" > 15.0 AND "depdelay" < 240.0
##    AND "year" >= 2002.0 AND "year" <= 2007.0
```

** dplyr can convert all of the following to SQL*
*** other functions will be passed as is into SQL*

dplyr functions	`arrange, filter, group_by. mutate, select, summarize, %>%, left_join, etc.`
Operators	`+, -, *, /, %%, ^`
Math functions	`abs, acos, cosh, sin, asinh, atan, atan2, atanh, ceiling, cos, cosh, cot, coth, exp, floor, log, log10, round, sign, sin, sinh, sqrt, tan, tanh`
Comparisons	`<, <=, !=, >=, >, ==, %in%`
Booleans	`&, &&, |, ||, !, xor`
Aggregations	`mean, sum, min, max, sd, var`

Lazy Execution 1

```
q1 <- filter(flights, year < 2007)
q2 <- filter(q1, depdelay > 15)
q3 <- filter(q2, depdelay < 240)
q4 <- select(q3, arrdelay, depdelay, yea
q4
```

When should dplyr query the database?

Lazy Execution 1

```
q1 <- filter(flights, year < 2007)
q2 <- filter(q1, depdelay > 15)
q3 <- filter(q2, depdelay < 240)
q4 <- select(q3, arrdelay, depdelay, year)
q4
```

dplyr will not retrieve data until last possible moment. It combines all necessary work into a single optimized query.

```
show_query(q4)
##   <SQL>
##   SELECT "arrdelay" AS "arrdelay",
##     "depdelay" AS "depdelay",
##     "year" AS "year"
##   FROM "flights"
##   WHERE "year" > 2007.0
##     AND "depdelay" > 15.0
##     AND "depdelay" < 240.0
```

collapse()

Forces execution in DBMS

```
q5 <- flights %>%
    mutate(adjdelay = depdelay - 15) %>%
    collapse() %>%
    filter(adjdelay > 0)
```

collapse() turns the preceding queries into a table expression

remaining queries are run against the table described in the collapsed expression

Lazy Execution 2

dplyr will only retrieve the **first 10 rows** of a query when you look at the output.

```
clean
## Source: postgres 8.0.2 […]
## From: flights [6,517,621 x 4]
## Filter: !is.na(arrdelay), !is.na(depdelay), …

##     year arrdelay depdelay uniquecarrier
##    (int)    (int)    (int)         (chr)
## 1   2007       42       40            9E
## 2   2007       90       94            9E
## 3   2007       19       20            9E
## 4   2007      184      167            9E
## 5   2007       21       30            9E
## 6   2007      178      179            9E
## 7   2007       56       59            9E
## 8   2007       21       21            9E
## 9   2007       50       57            9E
## 10  2007       56       23            9E
## ..   ...      ...      ...           ...
```

4. **Collect the results**

Use `collect()` to import the entire set of results into R.

```
q6 <- flights %>%
    filter(year > 2007, depdelay > 15) %>%
    filter(depdelay == 240) %>%
    collect()
```

5. **Close the connection**

```
rm(air)
gc()
```

dplyr automatically closes connections when you remove the connection object *and then run the garbage collector,* `gc()`*.*

dplyr database workflow

1. **Create a connection**

```
con <- src_postgres(dbname, host, port, user, pass,...)
```

2. **Create a reference**

```
tab <- tbl(con, "tablename")
```

3. **Manipulate the reference**

```
query <- tab %>% filter(x > 1) %>% select(x, y, z)
```

4. **Collect the results**

```
results <- collect(query)
```

5. **Close the connection**

```
rm(con); gc()
```

sparklyr

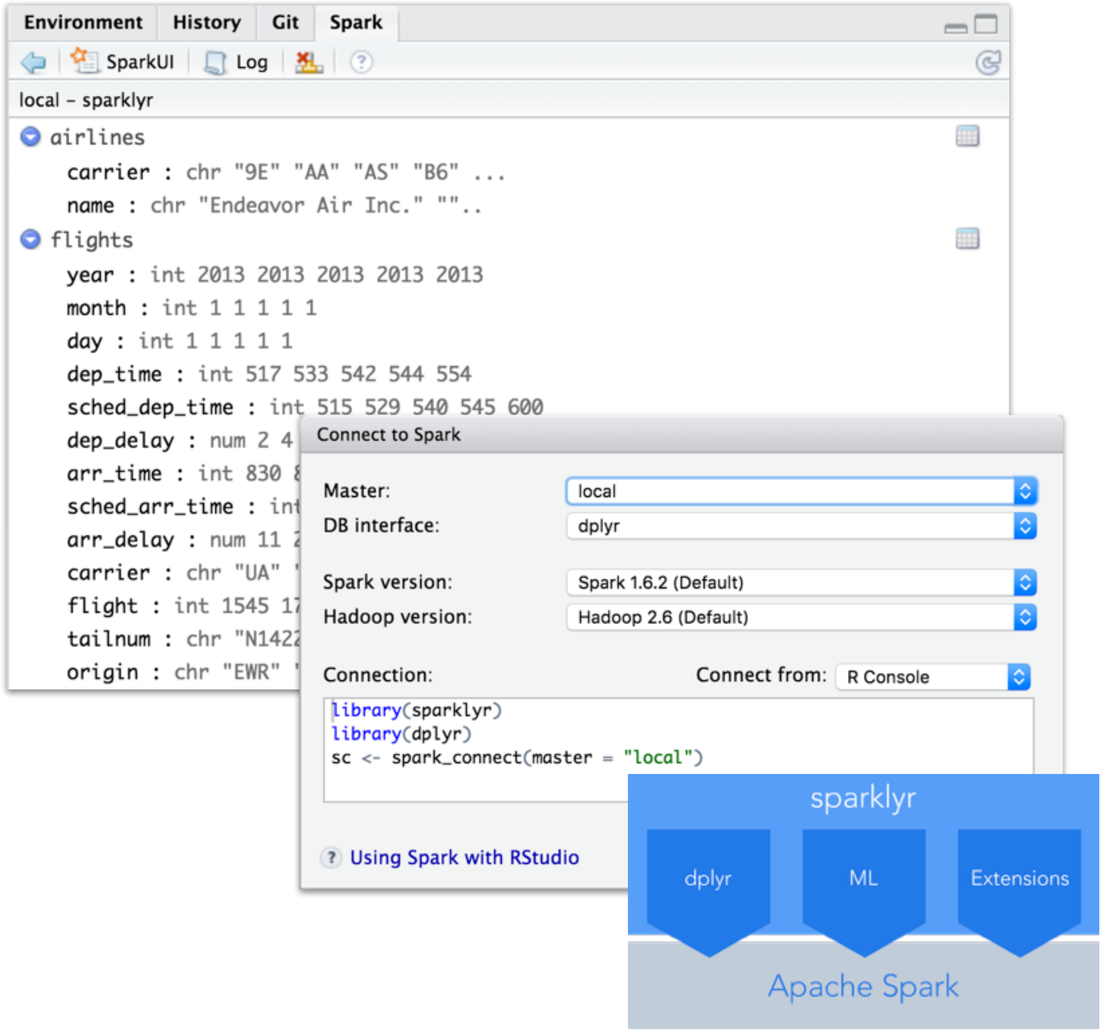
manipulating big data with Apache Spark

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

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



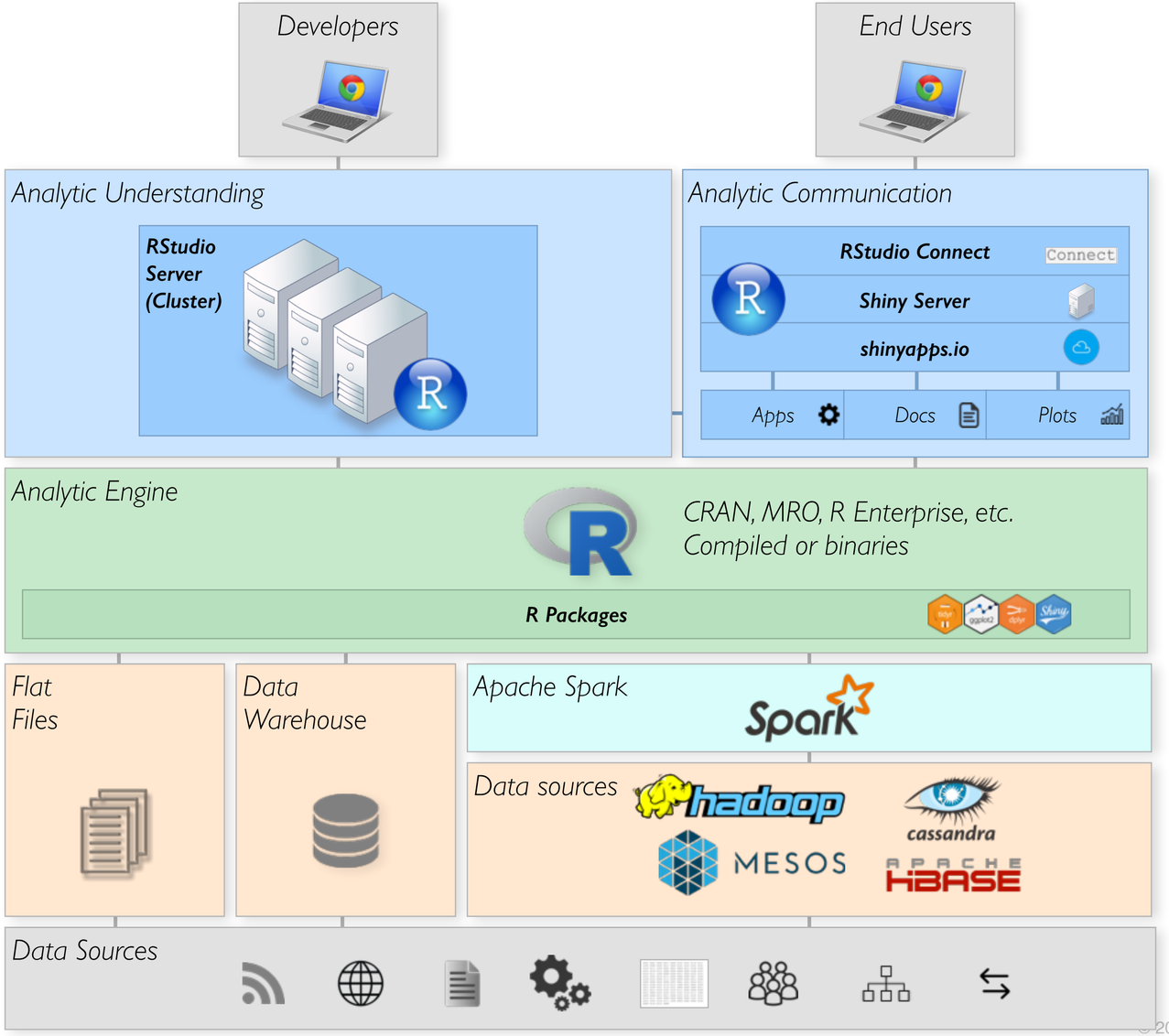
Use dplyr to write spark sql

```
library(dplyr)

# use standard verbs to filter and aggregate
select(
 filter(my_tbl, Petal_Width < 0.3),
 Petal_Length, Petal_Width
)

# use magrittr pipes for a cleaner syntax
my_tbl %>%
 filter(Petal_Width < 0.3) %>%
 select(Petal_Length, Petal_Width)
```

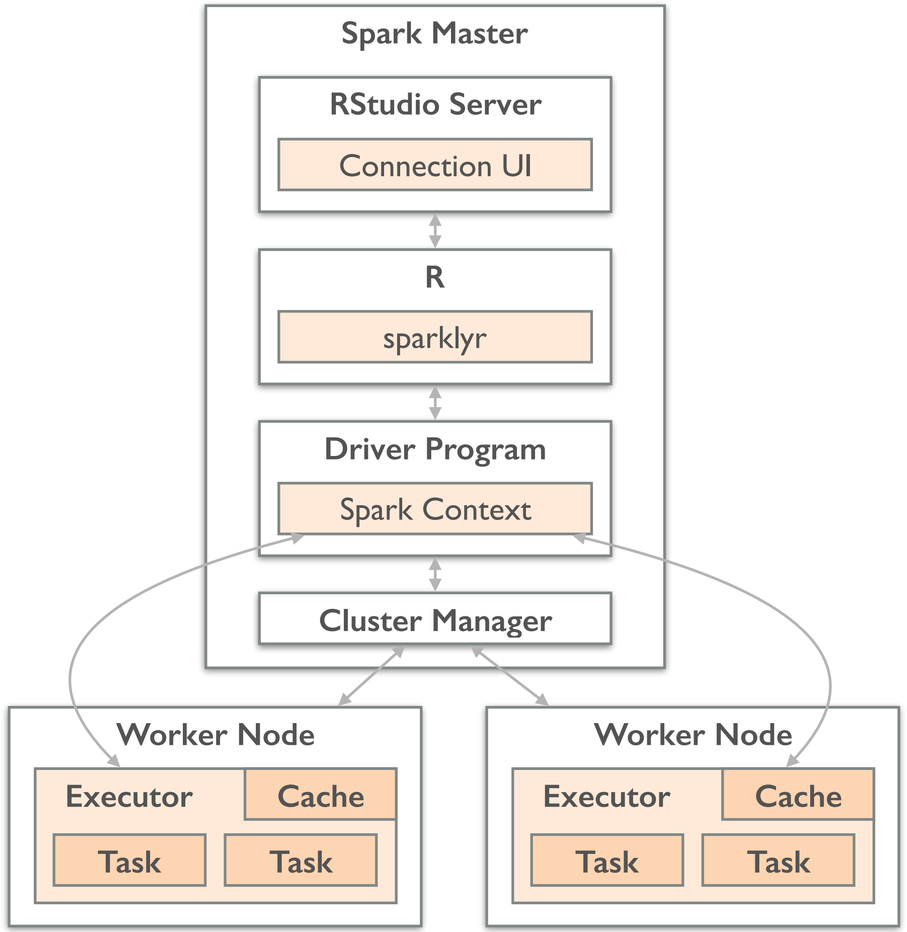
Setup



Cluster Mode

Use RStudio Server on the Spark cluster master node

```
spark_connect("spark://spark.company.org:7077")
my_tbl <- tbl(sc, "tblname")
```



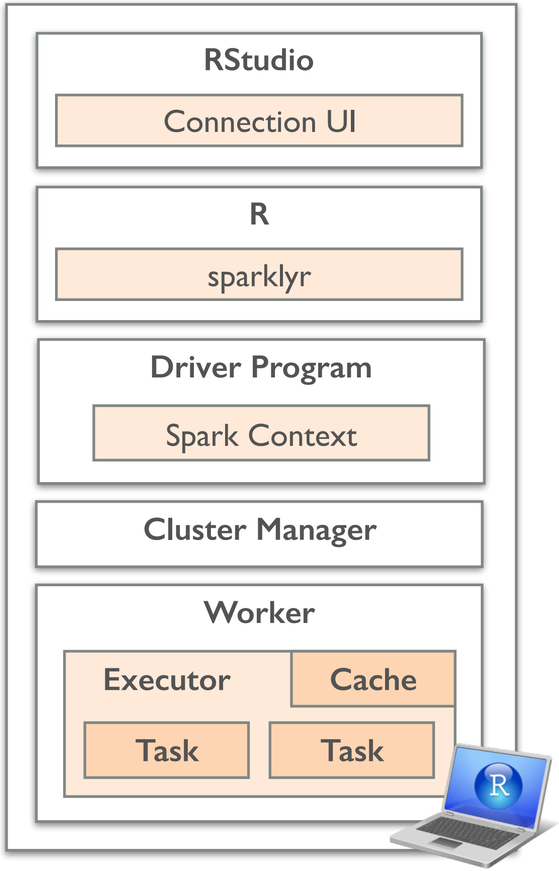
Local Mode

```
library(sparklyr)

spark_install()

sc <- spark_connect("local")

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



Relationship to SparkR

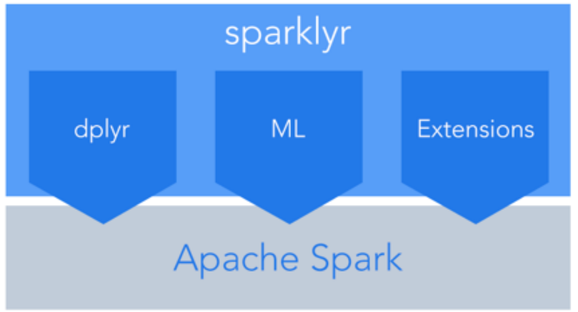
- Some differences in approach:
  - CRAN distribution
  - dplyr compatibility

- Working together to establish a common extension API

sparklyr.rstudio.com

sparklyr — R interface for Apache Spark

- 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 **sparklyr** using the **devtools** package as follows:

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

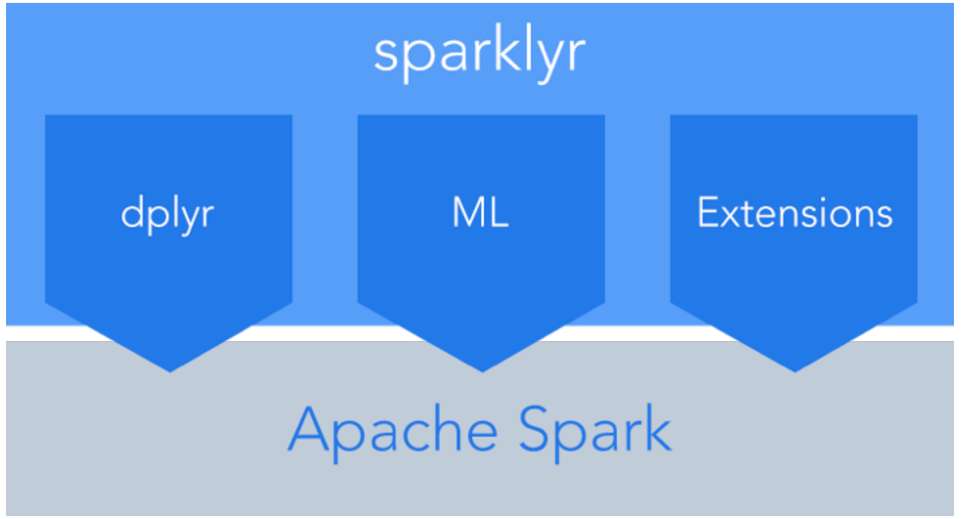
You should also install a local version of Spark for development purposes:

```
library(sparklyr)
spark_install(version = "1.6.1")
```

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

sparklyr Interface for Apache Spark



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
```

Spark SQL

Open 03-Spark-SQL.Rmd for notes and exercises.

Spark ML

Execute analytic commands inside Spark

- **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

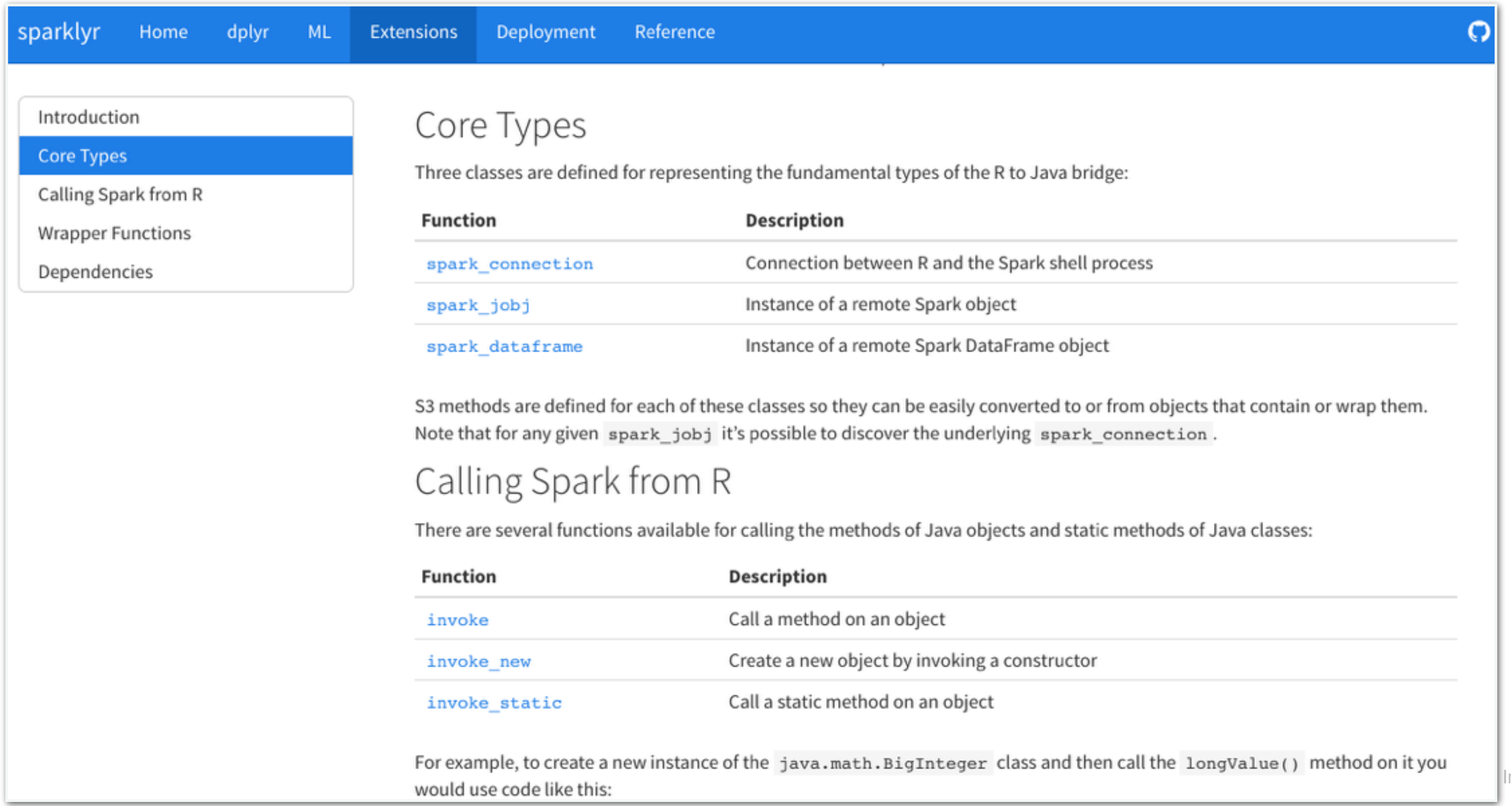
- **ml**. Use machine learning algorithms (ml_*) to train models.
  Examples: ml_kmeans, ml_logistic_regression, ml_pca

Spark ML

Open 04-Spark-ML.Rmd for notes and exercises.

Spark Extensions

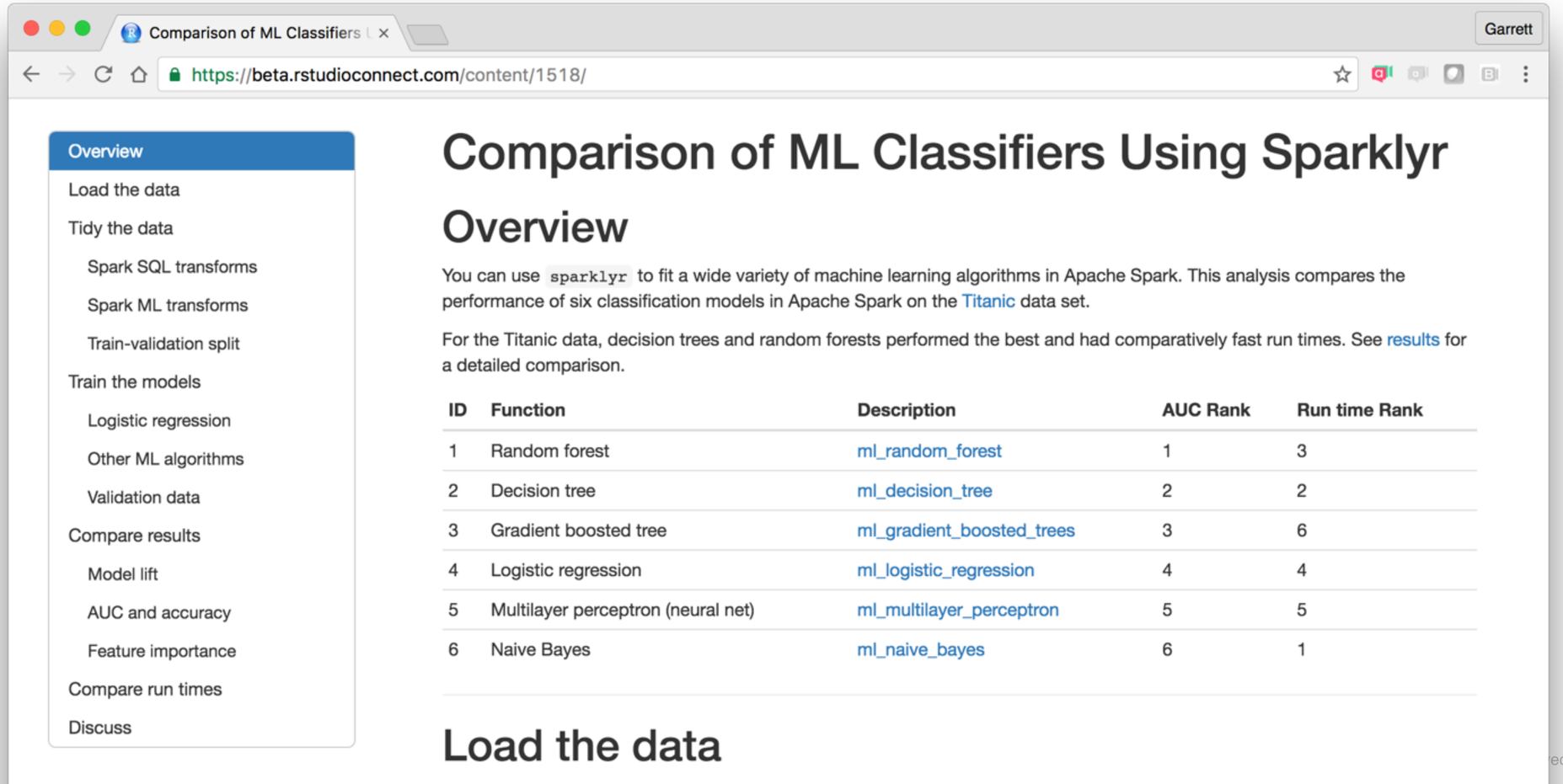
Write your own Spark extensions in R. Use extensions in Spark much like you use CRAN packages in R.



sparklyr examples

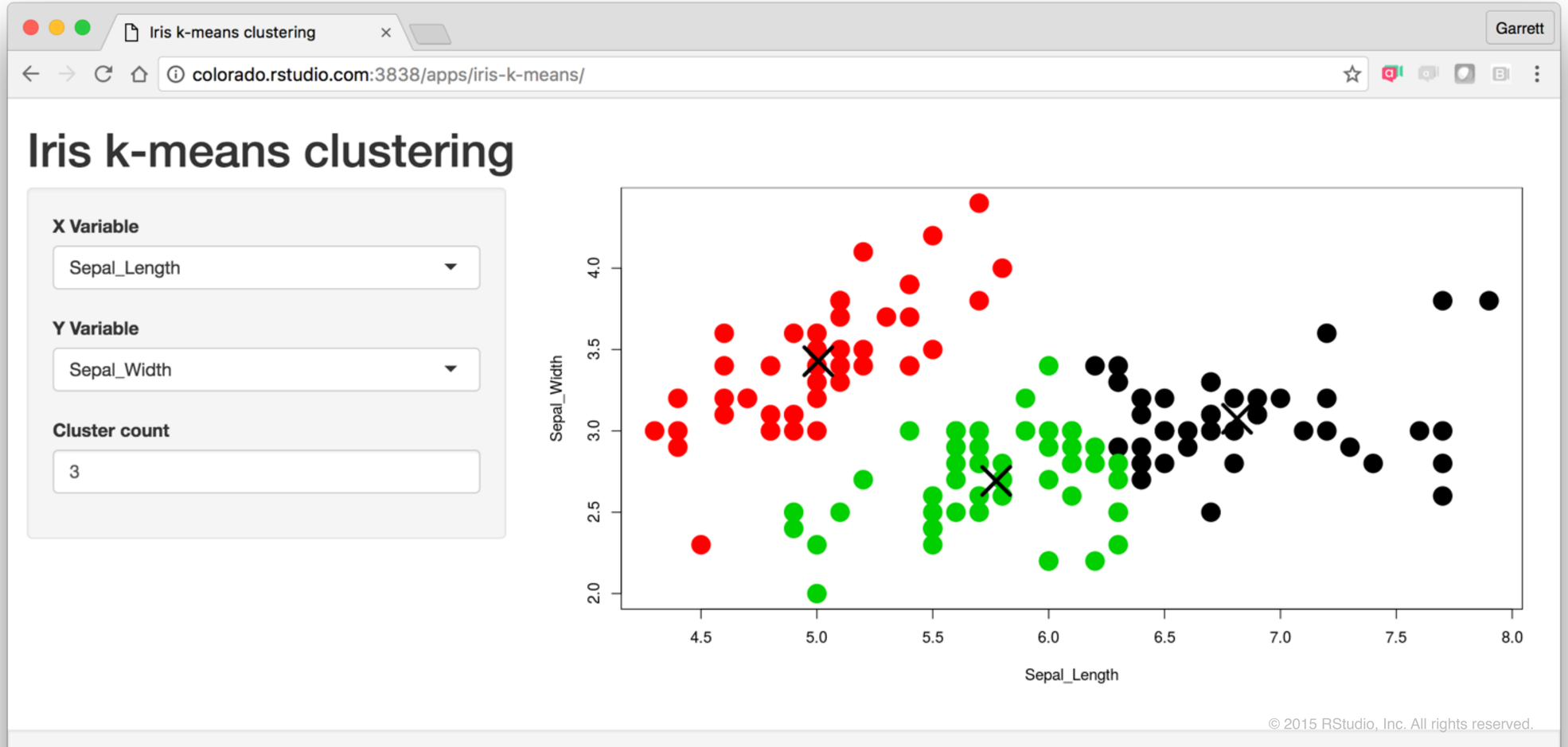
Titanic Machine Learning

https://beta.rstudioconnect.com/content/1518/



Iris K Means Clustering

http://sparkdemo.rstudio.com/apps/iris-k-means/



Diamonds Dashboard

sparkdemo.rstudio.com/dashboards/diamonds-explorer/