OPEN DATA SCIENCE CONFERENCE

Burlingame | November 2nd 2017

@ODSC

@WinVectorLLC

@RStudio

Nov 02
2:00 PM
Room T2

Modeling big data with R, sparklyr, and Apache Spark

BIG DATAINTERMEDIATE

Dr. John Mount
Consulting Algorithmist/Researcher/Principal at Win-Vector LLC and
Co-author of Practical Data Science with R

Part 1: lecture `R` and `dplyr`

Win-Vector LLC

- Data science and analytics training and consulting.
- We distribute a number of open source R packages
    - Most importantly the `vtreat` variable preparation package.

Warm up

Introduce yourself to your table

Name

What do you do with data?

For how long have you been using R?

03:00

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The goal

- Help `R` users confidently work with data in `Spark` and `h2o`
    - Go over data manipulation
    - Try some basic supervised machine learning
    - Look at native commands and `Spark` extensions

The plan

- We will alternate
    - Lecture segments
        - All slides are being shared.
    - Hands-on exercises/ walk-throughs
- Using RStudio Server Pro accounts we are supplying.
    - All packages, code, and examples already loaded into each account.
    - We are practicing only with small data to learn the systems.
- All materials (slides, data, code, and solved exercise) are here at this public GitHub repository: https://github.com/WinVector/BigDataRStrata2017

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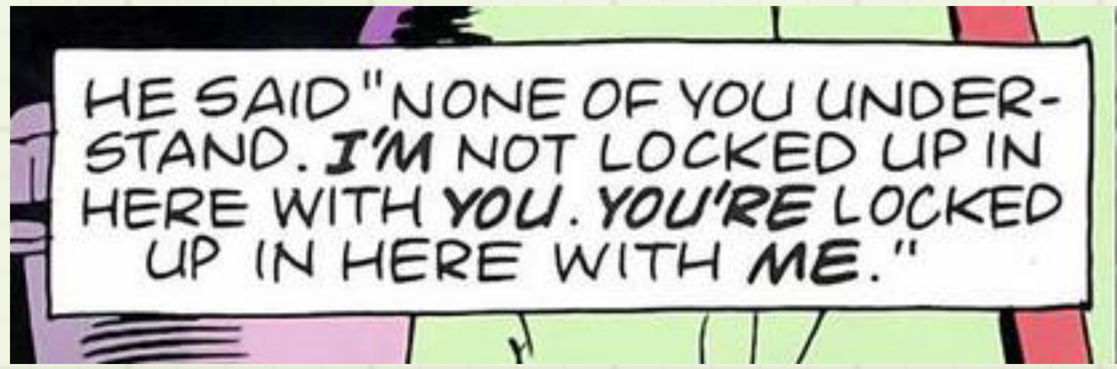
Workshop outline

1. Lecture: R and `dplyr`.
2. Exercises: manipulating data locally.
3. Lecture: `Spark` and `sparklyr`.
4. Exercises: Using `dplyr` to control `Spark` through `sparklyr`.
5. Lecture: Machine learning concepts review.
6. Exercises: Machine learning in `SparkML` and `h2o`.
7. Lecture: Advanced topics.

Break around here

Possibly 5 pounds of sugar in the 3.5 pound bag.



Course developers

- Garrett Grolemund (RStudio)
- Nathan Stevens (RStudio)
- Nina Zumel (Win-Vector)
- John Mount (Win-Vector)

My strategy

- We will cover organizing data and performing supervised machine learning
    - `R`
    - `dplyr`
    - `Spark`
    - `SparkML` / `h2o` machine learning
- Going to (hopefully) avoid an installation debug fest by lending you ready to go RStudio Server Pro environments.
- We are going to go over everything
    - Guarantees I'll hit that 20% you wanted to hear more about.
    - Great chance to see data manipulation tools as a coherent whole.

We will use a warning symbol on some slides

- Doesn’t mean “avoid.”
- Just indicates: “be careful and you will get good results.”

Let's define our terms

- `R`: The analysis language and platform we are using, descended from `S`.
- RStudio Server Pro: a remote `R` service and user interface.
- `Spark`: a fast and general engine for large-scale data processing.
- `h2o`: a large scale machine learning platform from h2o.ai

Apache Spark

- Prefers distributed in-memory operations.
- Can talk to Java, Scala, Python, R.
- Many data operations organized in terms of SQL.
- Runs in many configurations (standalone cluster mode, on EC2, on Hadoop YARN, or on Apache Mesos. Access data in HDFS, Cassandra, HBase, Hive, Tachyon).

Connecting using R

- Will use R as the control system.
    - Data scientist programs in R.
    - R issues commands to remote large data systems to work on remote data.
- For Spark
    - Use sparklyr and dplyr.
- For h2o
    - Use h2o R package and rsparkling.

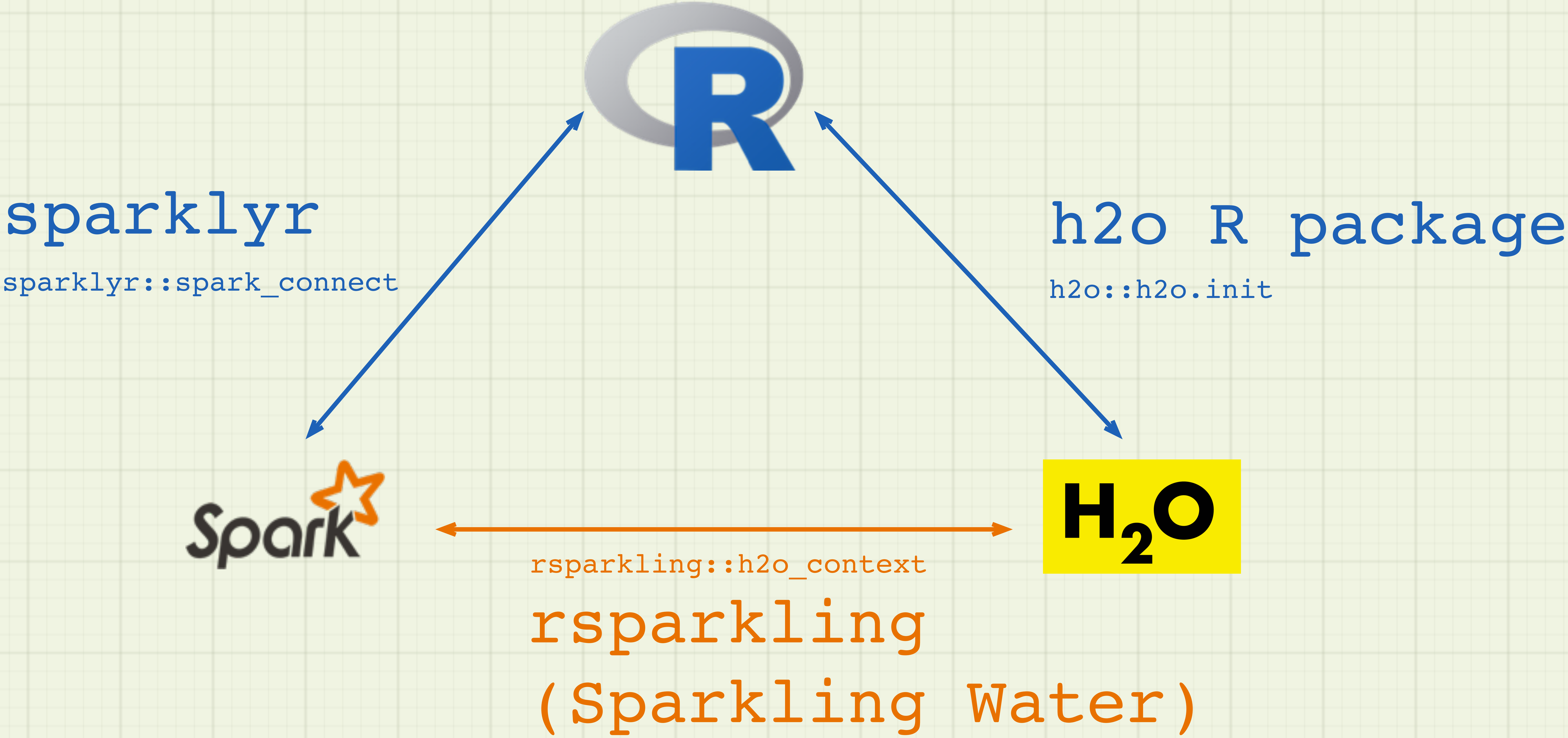
The three island view

```
ls()
<objectname>
```

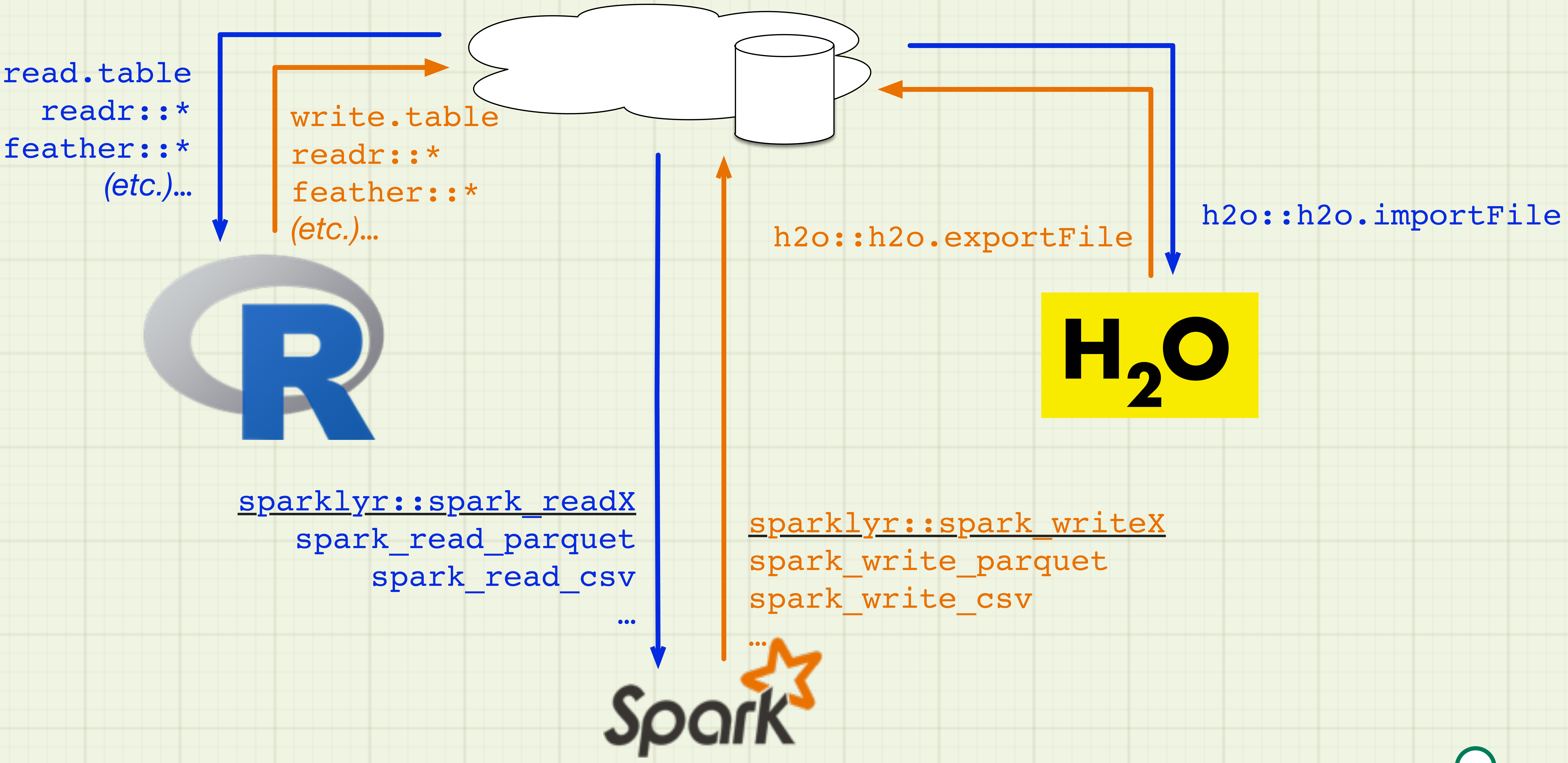
```
DBI::dbListTables(sc)
dplyr::tbl(sc, <objectname>)
```

```
h2o::h2o.ls()
h2o::h2o.getFrame(<keyid>)
```

Bridging islands



Importing/Exporting data



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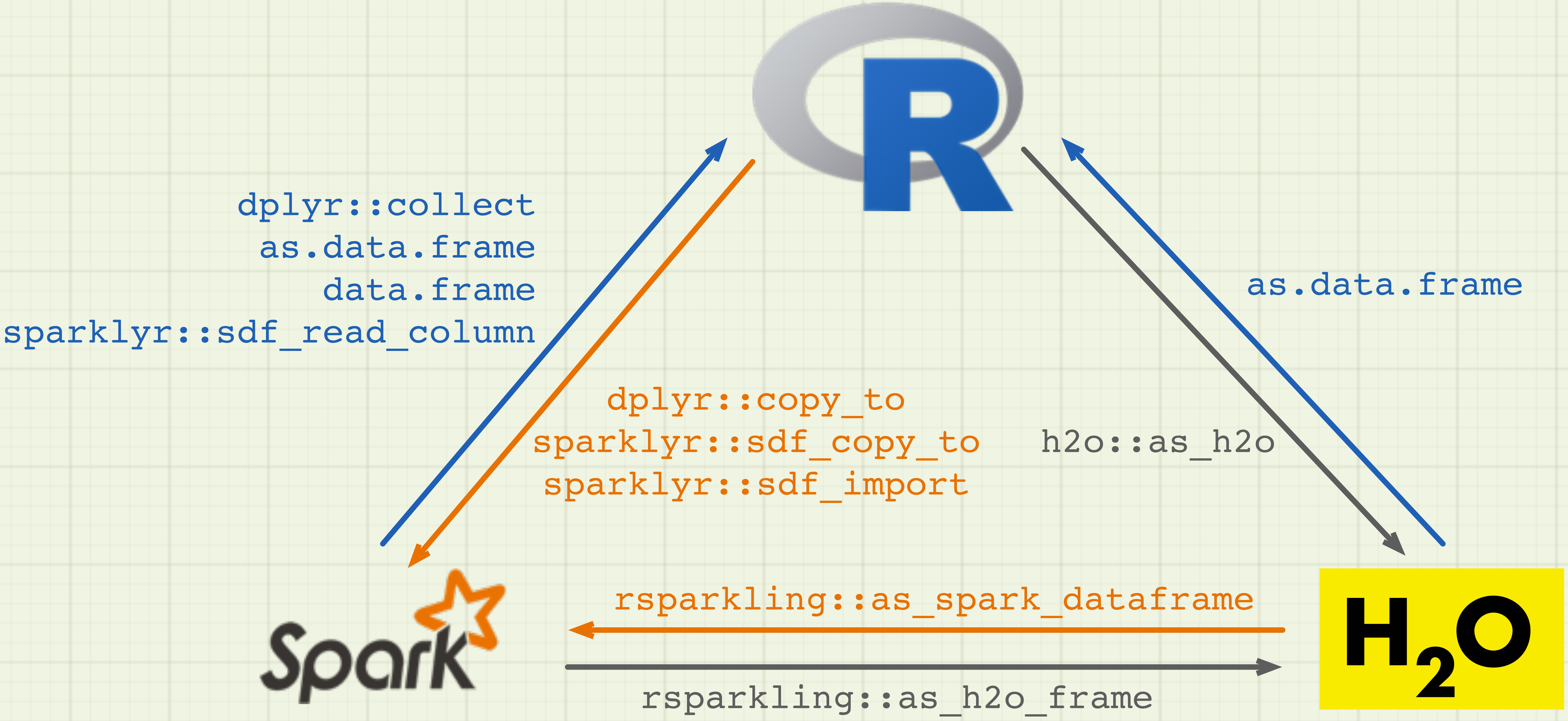
Moving data between islands



First: `R` and `dplyr`

Why data manipulation?

- Supervised machine learning uses structured data in a very regular and explicit form called "denormalized":
  - Every row is an event or observation.
  - Each column is homogeneous facts or variables.
  - Every fact or variable is already landed in a column.
- We need good tools to get from wild recorded forms or efficient *normalized forms* into the above form.

Schematized

Denormalized

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R and dplyr

"No matter how complex and polished the individual operations are, it is often the quality of the glue that most directly determines the power of the system."

— Hal Abelson

dplyr

A grammar of data manipulation

select
filter
arrange
mutate
summarise
group_by

left_join
right_join
inner_join
full_join
semi_join
anti_join

bind_cols
bind_rows
union
intersect
setdiff
`%>%`

dplyr formula components

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, n(), rank, rank_min, sum, min, max, sd, var

example

```
> d <- data.frame(x= 1:4)
> d$y <- 2*d$x
> print(d)

  x y
1 1 2
2 2 4
3 3 6
4 4 8
```

```
> library("dplyr")
> d <- data_frame(x= 1:4)
> d <- mutate(d, y = 2*x)
> print(d)

# A tibble: 4 × 2
      x     y
  <int> <dbl>
1     1     2
2     2     4
3     3     6
4     4     8
```

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Why `dplyr`?

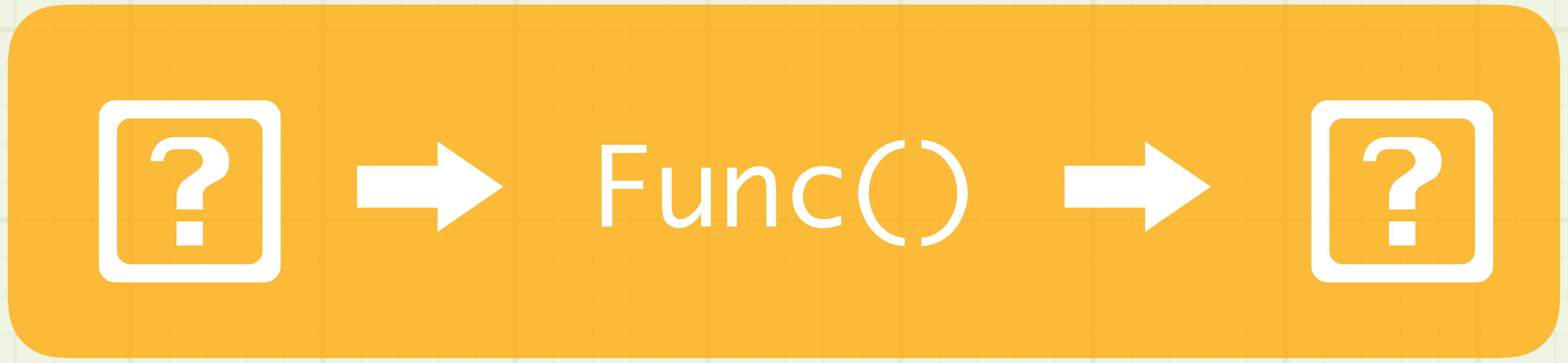
- `dplyr` is a collection of transforms you can decompose your task into.
- There are multiple `dplyr` “data service” implementations.
    - Tasks written as a sequence of `dplyr` operations can be moved from service to service.
        - Local `data.frame` / `tbl`
        - `Spark` / `Sparklyr`

Why review `dplyr`?

To make sure we are all *really familiar* with `dplyr` operations before trying to use them on `Spark`.

Single Table Verbs

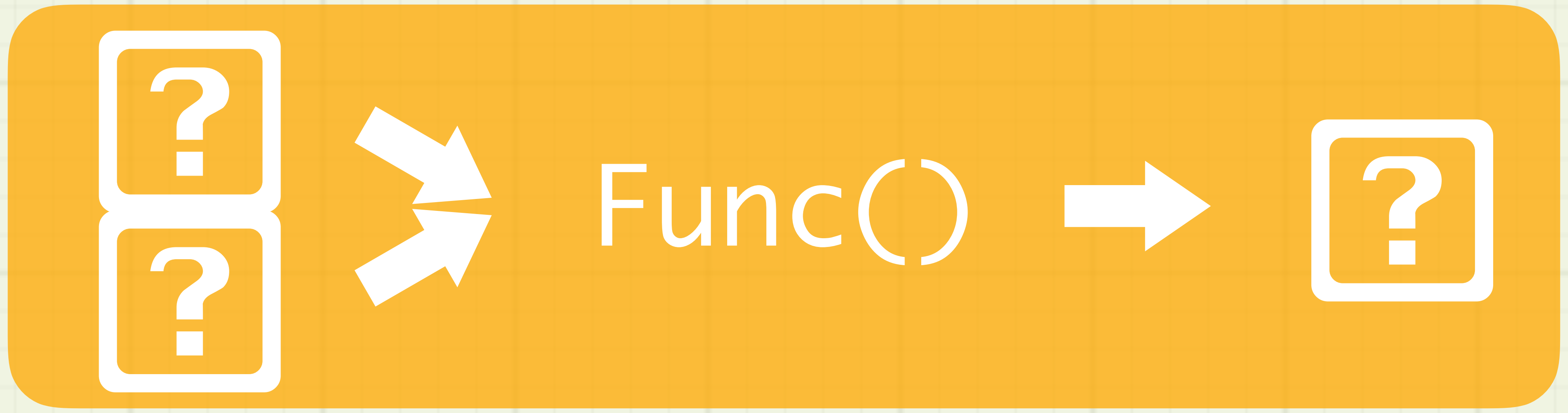
Manipulate tabular data



`select`	`filter`	`summarise`
`mutate`	`arrange`	`group_by`

Two Table Verbs

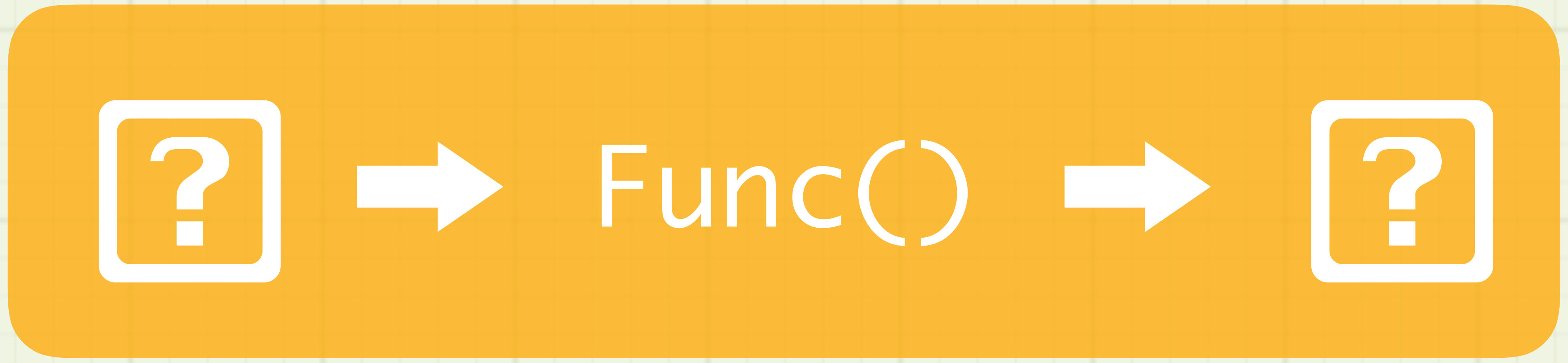
Join together relational data



`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

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

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

* These data sets are in the EDAWR package

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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

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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

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summarise()

city	particle size	amount (μg/m³)
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

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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 (μg/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
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

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group_by()

city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	particle size	amount (µg/m³)
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

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

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Single Table Verbs

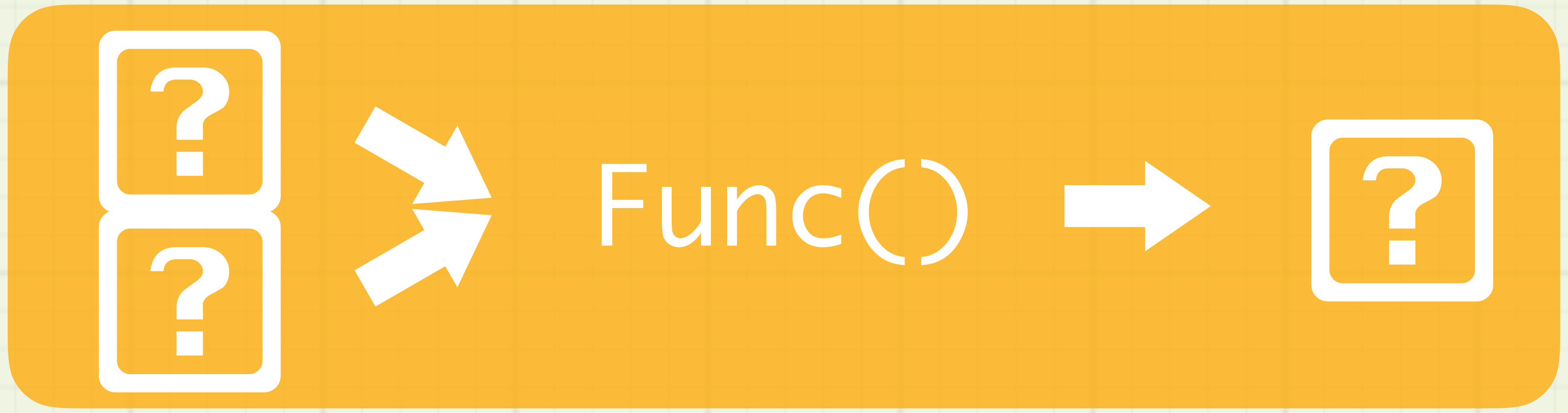
Manipulate tabular data

`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`

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Joins

- The core of relational data processing.
- Most important data transforms can be written in terms of a sequence of joins:
    - intersection
    - cross-product
    - lookup
    - lapply / list comprehensions
- Master these and you have mastered data manipulation

Joins: the math

- Joins are implemented *as if:*
  - Each row in each table is paired with every other row in the other table and once more with an extra “no match” row.
    - Two tables with `m` rows and `n` rows respectively could generate as many as (m+1)*(n+1) notional rows.
    - Rows contain columns from both tables. Duplicate column names are disambiguated by appending extra names to the columns.
  - The result is winnowed down to only rows matching the join conditions, and only columns named in the statement.
- Join implementations are *much* more efficient than the above specification.
  - The database implementation examines to join conditions to only generate rows the user wants. Filtering is implicit, unwanted rows and duplicate columns are not generated.

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joins: first example

- Task: For each band member look up what, if any instrument they play.
- The right tool:
  - “left join by name” (also called “left join on name”).
    - “left” means keep records from left table
    - “by name” means names must match
- This join can be implemented in time proportional to the smallest of the two tables!
  - *Very* fast.

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

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left_join(): result

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(): theory

band

name	band
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

Smaller example, so we can illustrate all the notional steps.

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

left_join(): theory

band

name	band
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

Augment each table with a no-match or empty row.

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

left_join(): theory

band

name	band
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	name	plays
Paul	Beatles	John	guitar
Paul	Beatles	Paul	bass
Paul	Beatles	Keith	guitar
Paul	Beatles		
		John	guitar
		Paul	bass
		Keith	guitar

Form the cross product.

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

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left_join(): theory

band

name	band
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	name	plays
~~Paul~~	~~Beatles~~	~~John~~	~~guitar~~
Paul	**Beatles**	**Paul**	**bass**
~~Paul~~	~~Beatles~~	~~Keith~~	~~guitar~~
~~Paul~~	~~Beatles~~		
		~~John~~	~~guitar~~
		~~Paul~~	~~bass~~
		~~Keith~~	~~guitar~~

Cross out rows that don't match specified conditions.

killed by "left" specification

killed by "by = "name"" specification

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

ProTip

- *Always* inspect your intermediate results after joins.
- In particular ***count rows*** and groups of rows to make sure you haven't missed a join condition.
  - Missing a join condition can cause some rows to be duplicated.

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")
```

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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")
```

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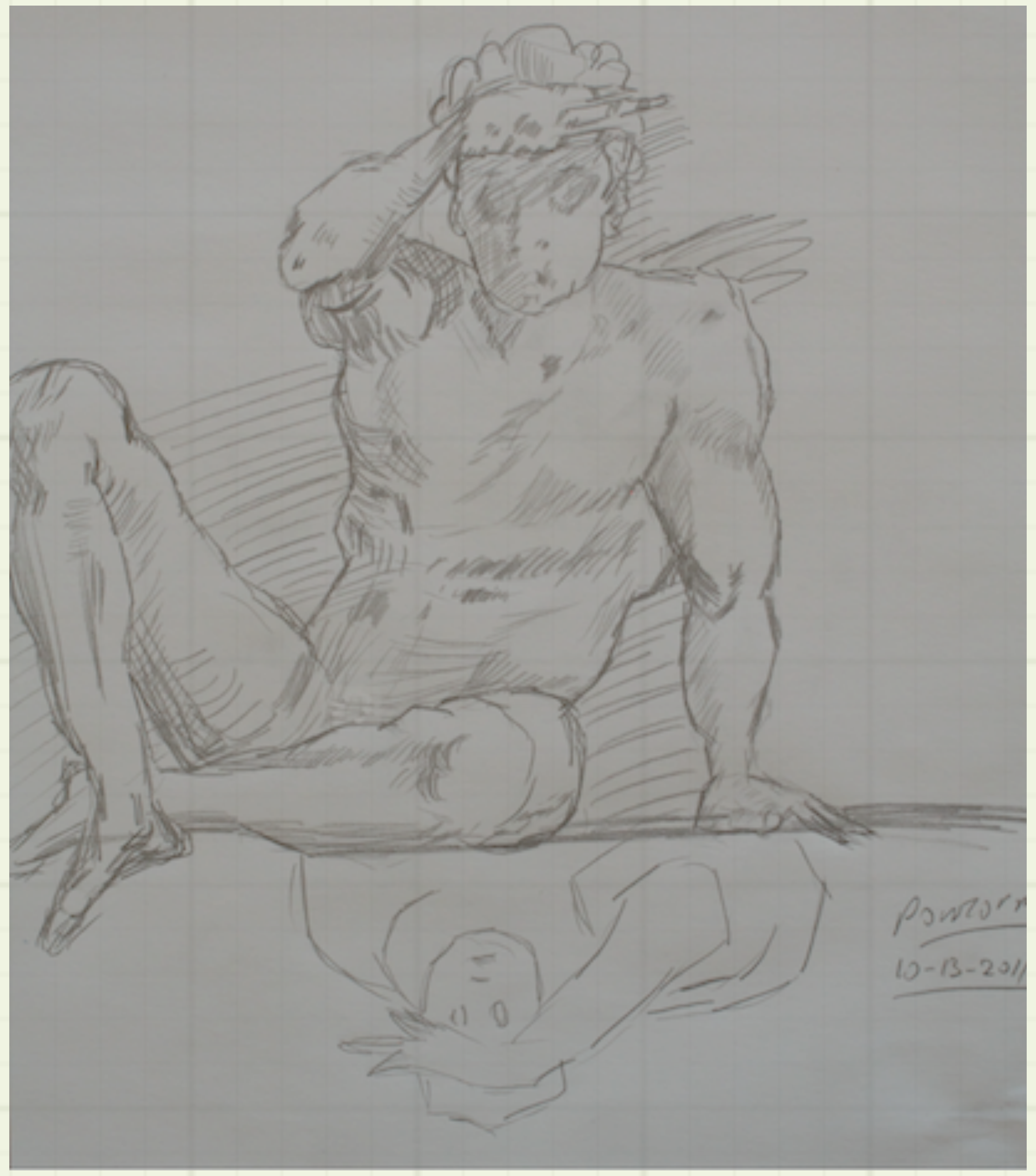
Relational Thinking

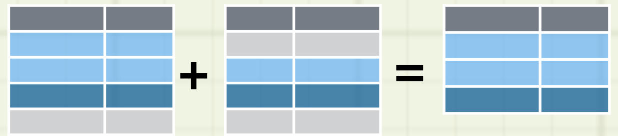
- To think relationally (in terms of joins) you must simultaneously hold three conflicting ideas in your head:
  - join sequences can be made comprehensible
  - joins are powerful
  - joins can be fast.



“Theory versus practice” (after Pontromo).

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()**

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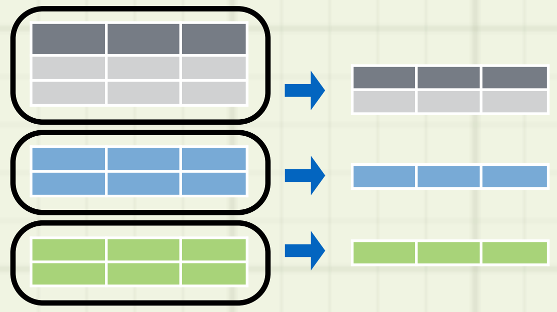
Recap: dplyr one table verbs

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()**.

Next:

`dplyr` exercises