



PRESENTED BY



strataconf.com

#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

John Mount (Win-Vector LLC)

Steve Nolen (RStudio)

Edgar Ruiz (RStudio)

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

HELLO

my name is

John



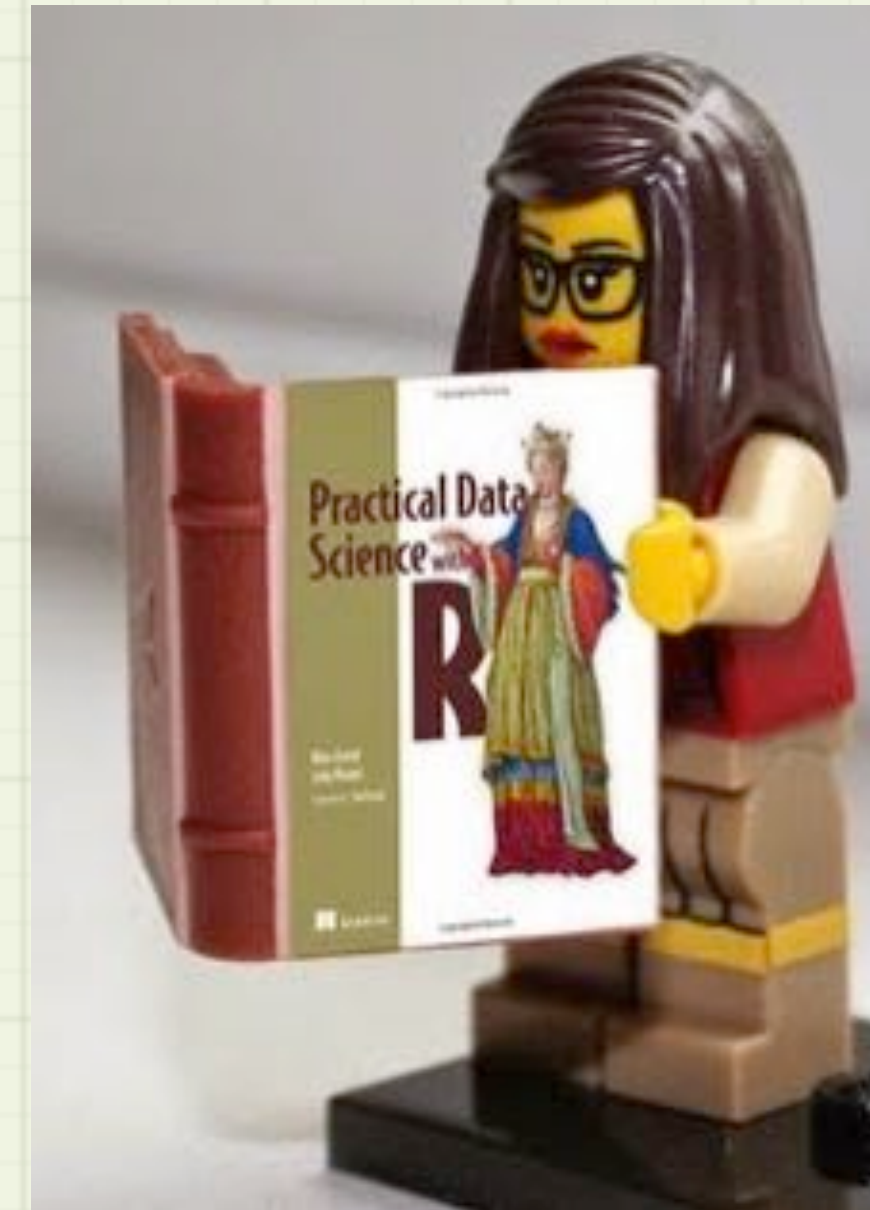
Data science consulting
<http://www.win-vector.com/>

John Mount

@Win-Vector LLC

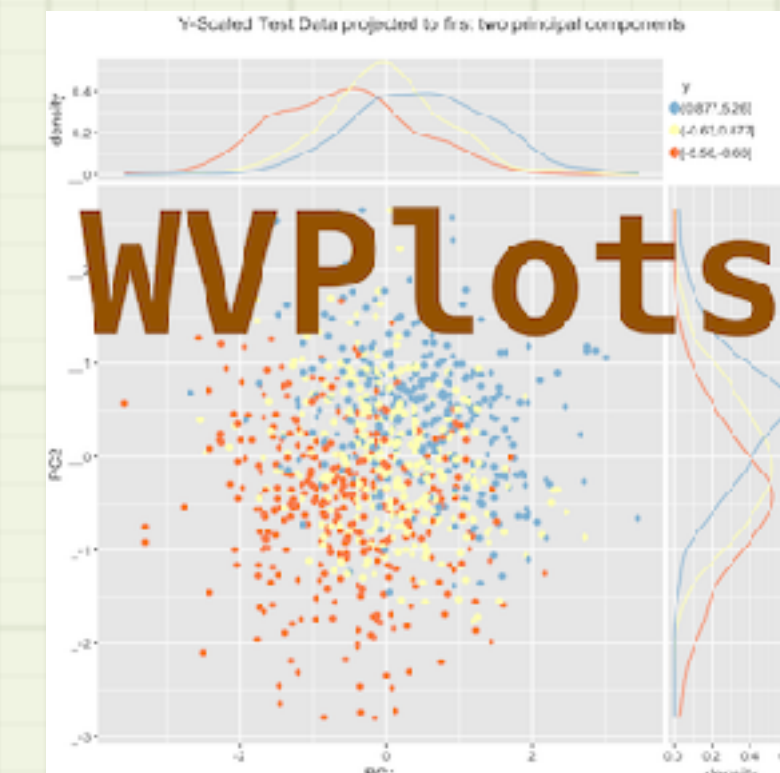
<http://win-vector.com/>

jmount@win-vector.com



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.
- Please reach out to us for partnerships
 - Myself or Dr. Lin Chase of Big Tech Strategy (who is working with us).



HELLO

my name is

Steve



Steve Nolen



HELLO

my name is

Edgar



2:40pm–3:20pm Wednesday, March 15, 2017

Sparklyr: An R interface for Apache Spark

Edgar Ruiz (RStudio)

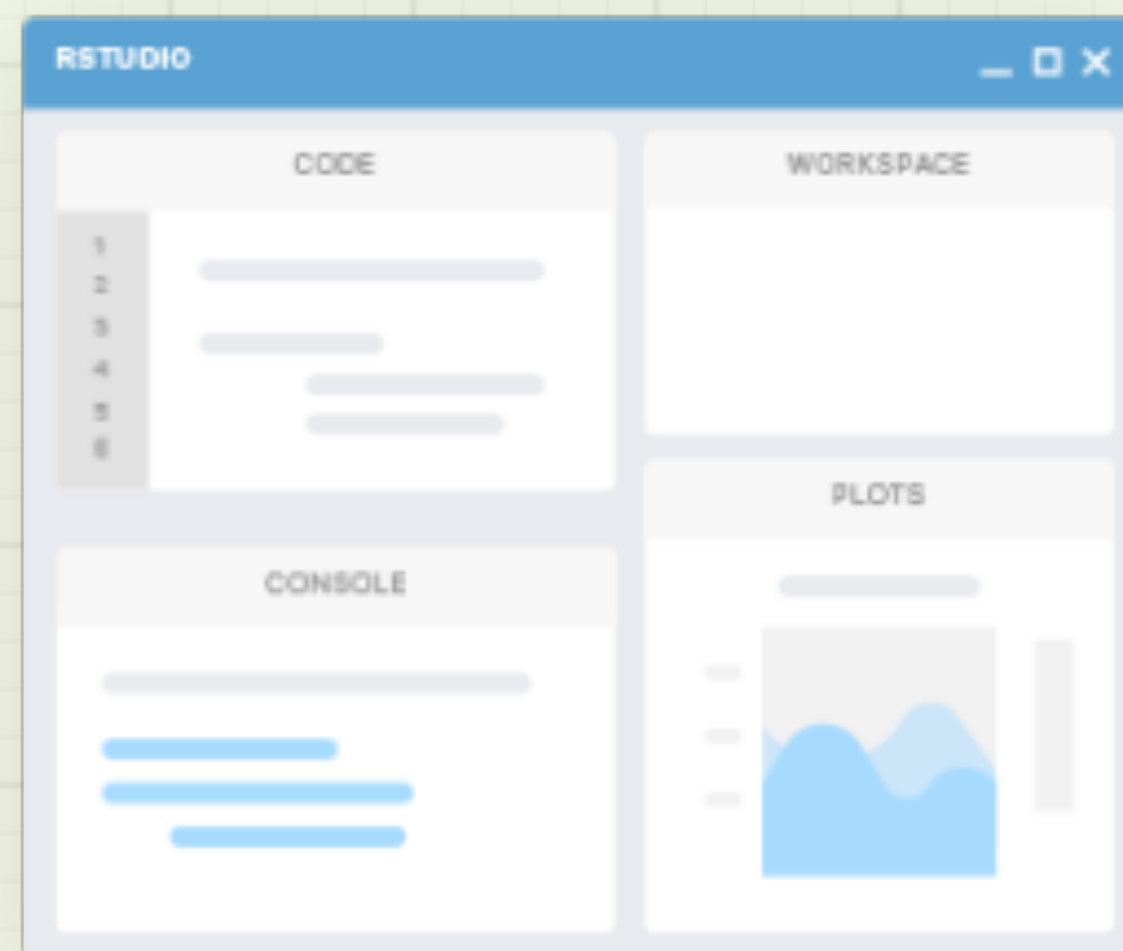
Primary topic: Spark & beyond

Location: LL21 C/D

Level: Beginner



RStudio



RStudio asked us to produce and present this workshop, and is supplying the free accounts.

Warm up

Introduce yourself to your table

Name

What do you do with data?

For how long have you been using R?

03:00

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

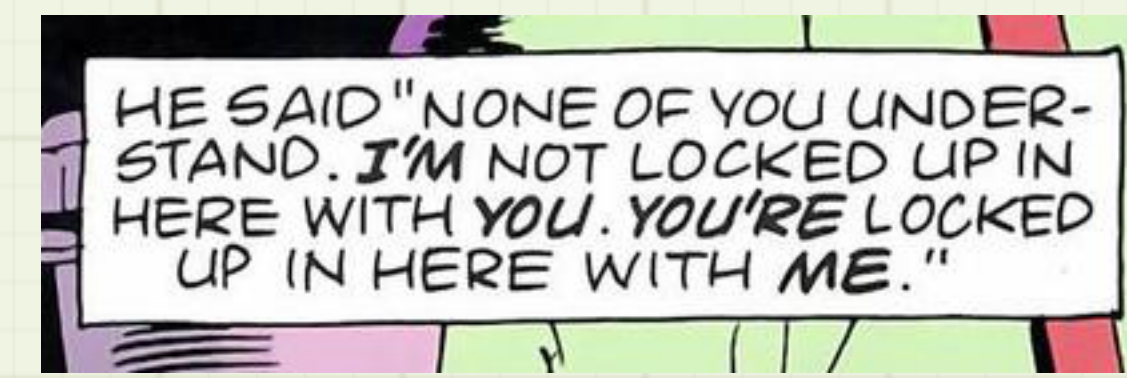
- We will alternate
 - Lecture segments
 - All slides are being shared.
 - Hands-on exercises/ walk-throughs
- Using RStudio Server Pro accounts we are supplying.
 - All packages, code, and examples already loaded into each account.
 - We are practicing only with small data to learn the systems.
- All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

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.

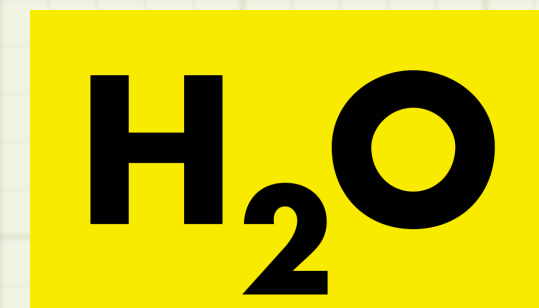
The three island view



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

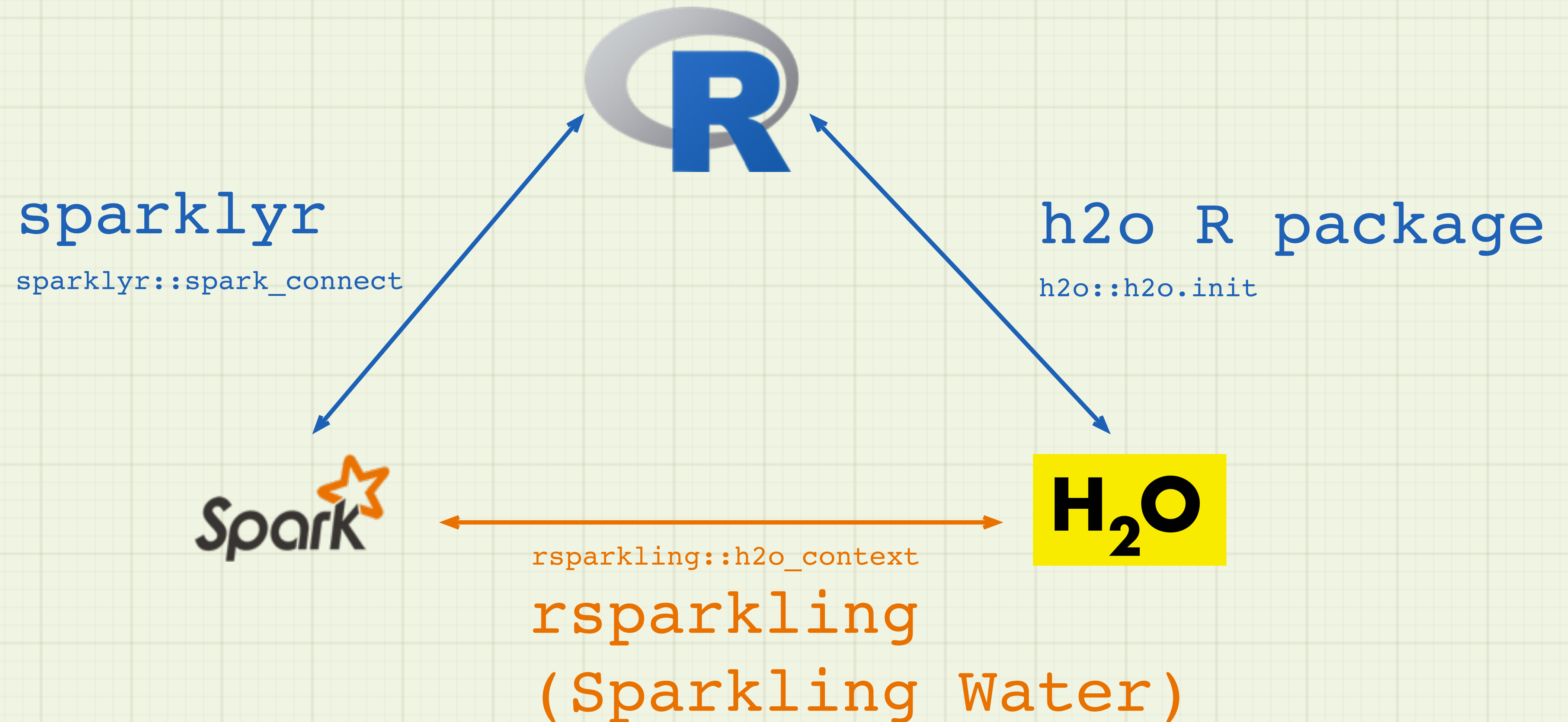


```
DBI::dbListTables(sc)  
dplyr::tbl(sc, <objectname>)
```

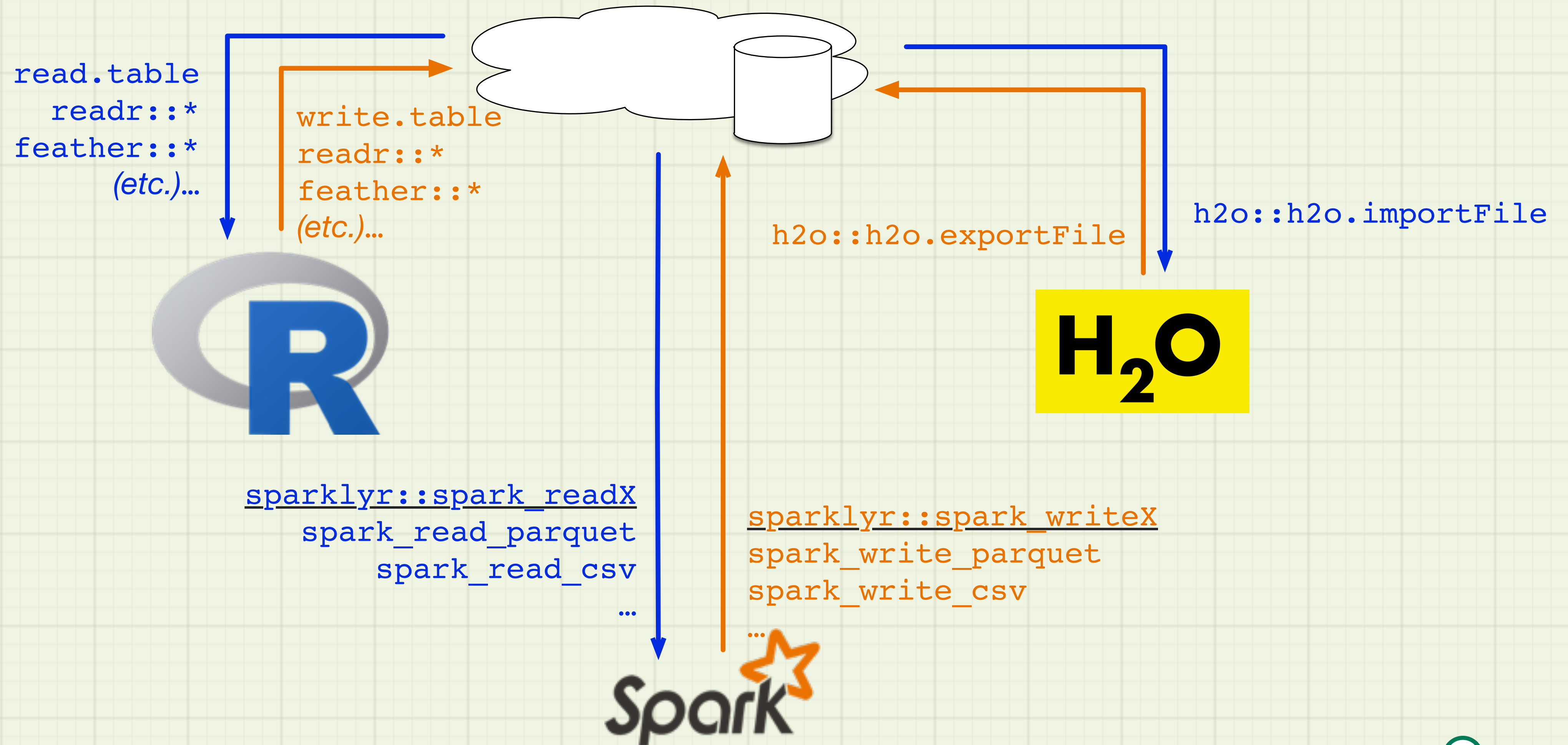


```
h2o::h2o.ls()  
h2o::h2o.getFrame(<keyid>)
```

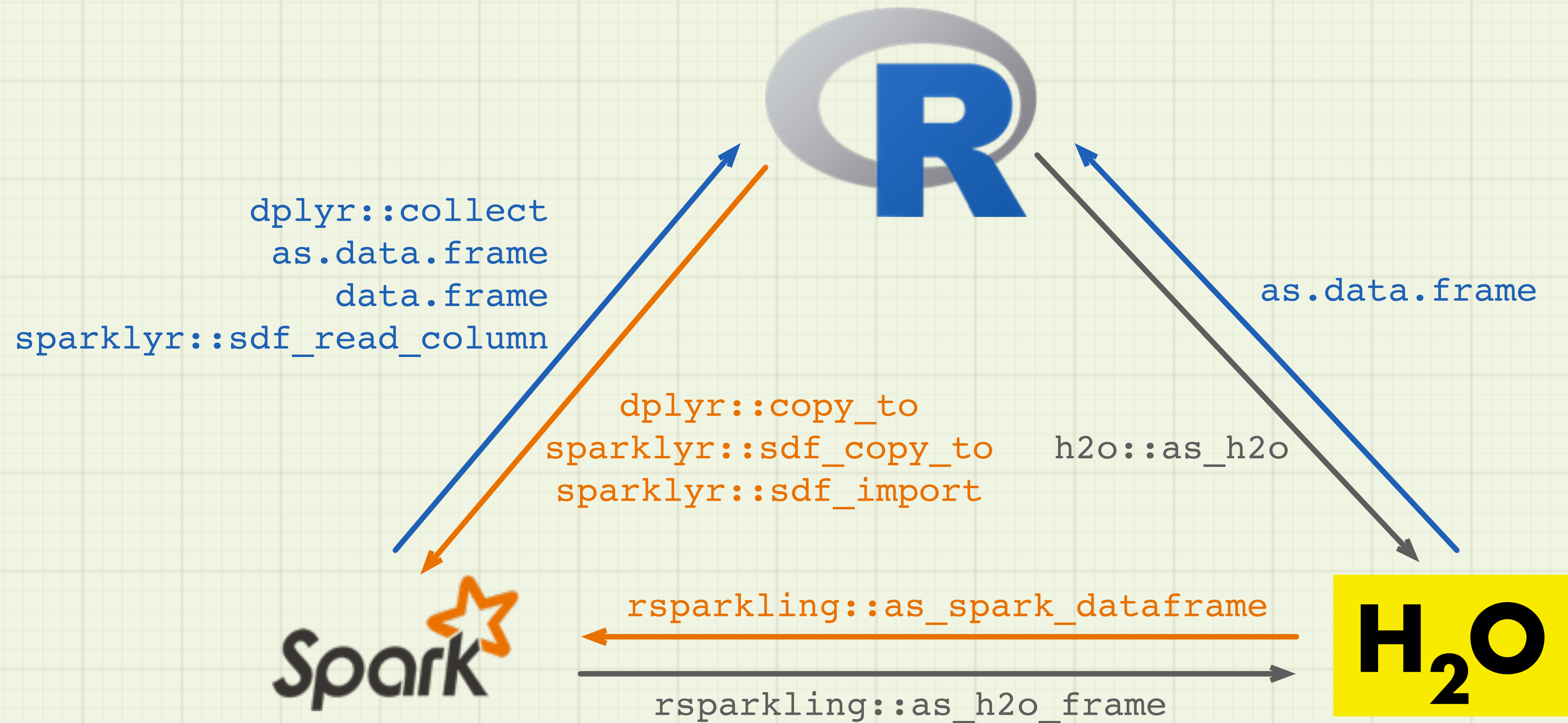
Bridging islands



Importing/Exporting data



Moving data between islands

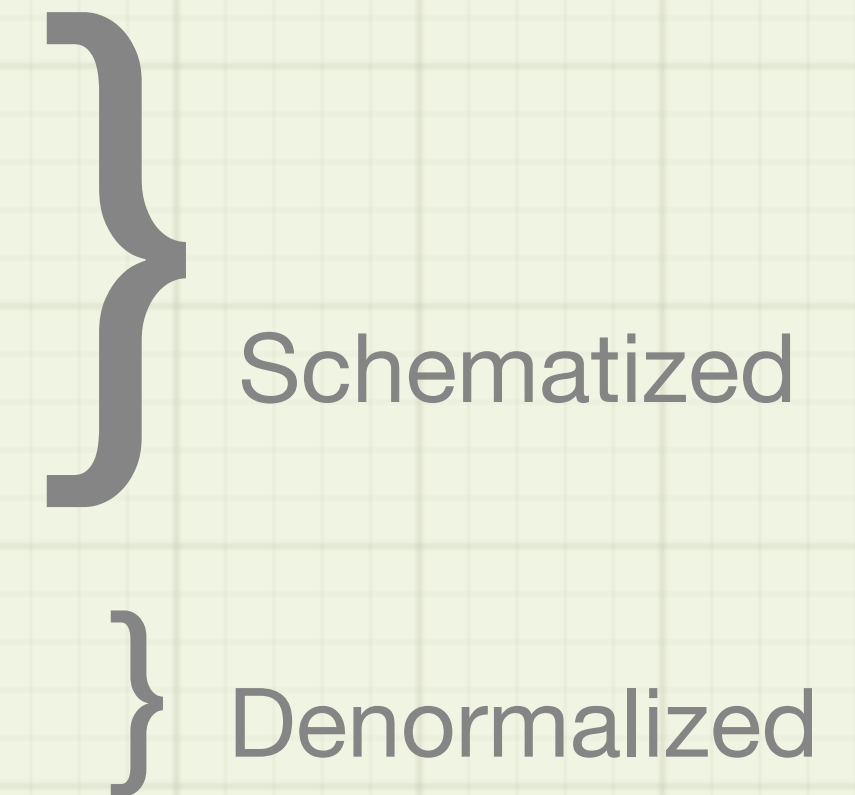


First: R and dplyr



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.



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
```

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

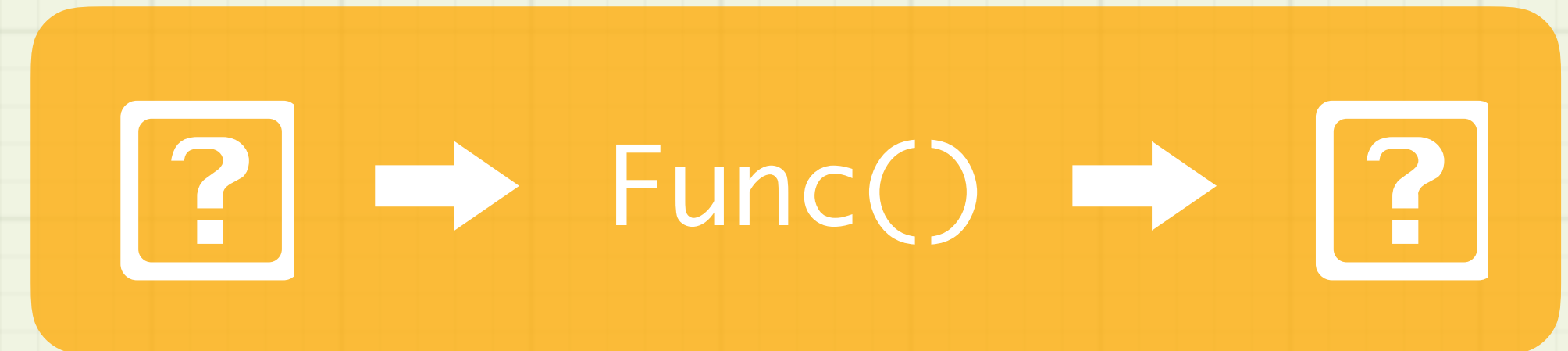
Manipulate tabular data

select

mutate

filter

arrange



summarise

group_by

Two Table Verbs

Join together relational data

left_join

right_join

inner_join

full_join

semi_join

anti_join



union

intersect

setdiff

bind_cols

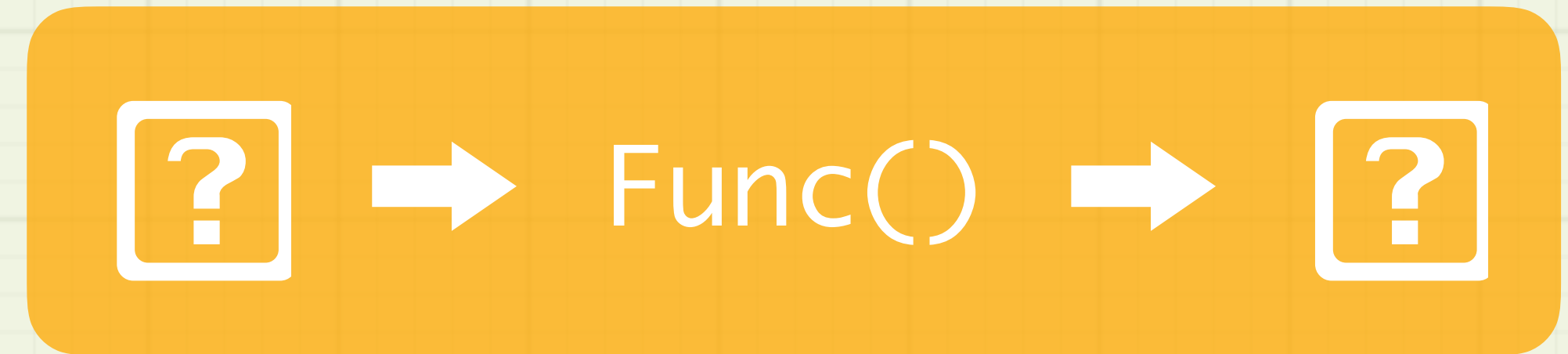
bind_rows

Single Table Verbs

Manipulate tabular data

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Two Table Verbs

Join together relational data

left_join
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anti_join



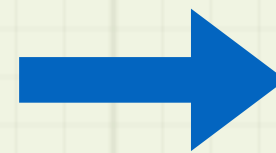
union
intersect
setdiff

bind_cols
bind_rows

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



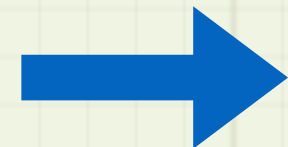
storm	pressure
Alberto	1007
Alex	1009
Allison	1005
Ana	1013
Arlene	1010
Arthur	1010

`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

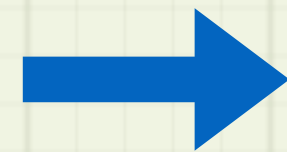
?base::Logic

&	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

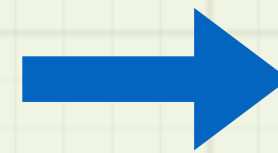
```
filter(storms, wind == max(wind))
```

* These data sets are in the EDAWR package

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

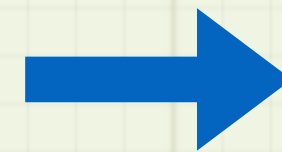
`filter(storms, wind >= 50)`

* 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

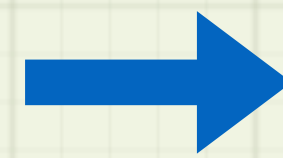
```
filter(storms, wind < 60, wind >= 40)
```

* 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

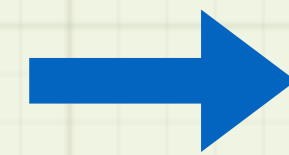
arrange(storms, **wind**)

* 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

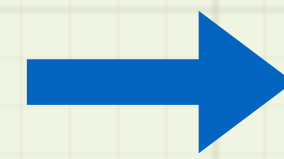
arrange(storms, **wind**)

* 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



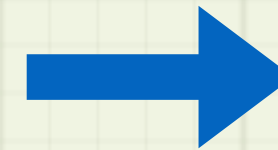
storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Allison	65	1005	1995-06-04
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21
Alex	45	1009	1998-07-30
Ana	40	1013	1997-07-01

`arrange(storms, desc(wind))`

* These data sets are in the EDAWR package

summarise()

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



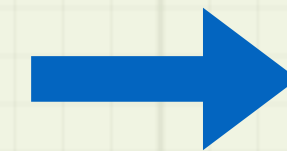
median
22.5

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

* These data sets are in the EDAWR package

summarise()

city	particle size	amount ($\mu\text{g}/\text{m}^3$)
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 ($\mu\text{g}/\text{m}^3$)
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 ($\mu\text{g}/\text{m}^3$)
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

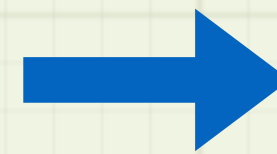
* These data sets are in the EDAWR package

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



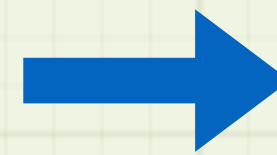
mean	sum	n
18.5	37	2

London	large	22
London	small	16



19.0	38	2
------	----	---

Beijing	large	121
Beijing	small	56



88.5	177	2
------	-----	---

`group_by() + summarise()`

* These data sets are in the EDAWR package

group_by()

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

city	particle size	amount ($\mu\text{g}/\text{m}^3$)
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

```
p <- group_by(pollution, city)
```

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

Single Table Verbs

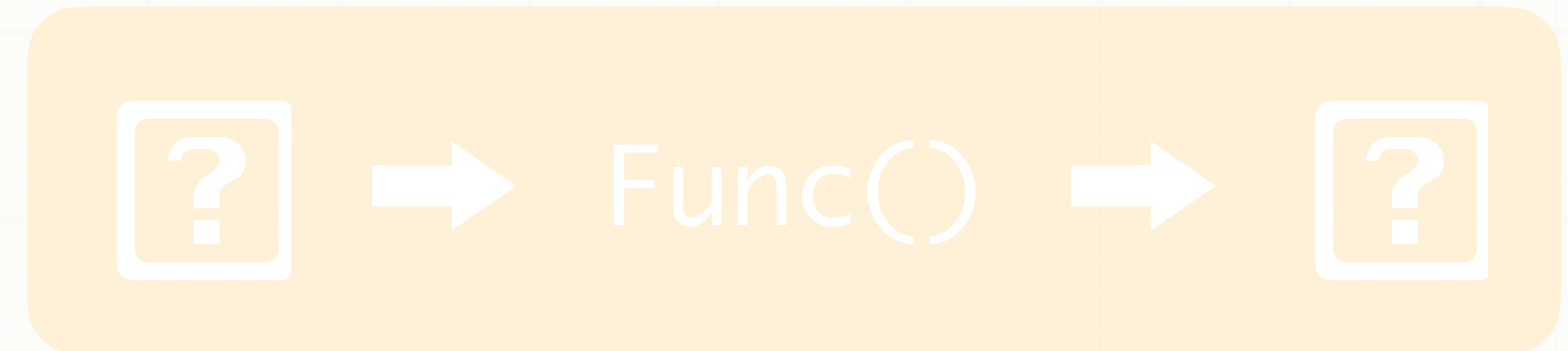
Manipulate tabular data

select

mutate

filter

arrange



summarise

group_by

Two Table Verbs

Join together relational data

left_join

right_join

inner_join

full_join

semi_join

anti_join



union

intersect

setdiff

bind_cols

bind_rows

Joins

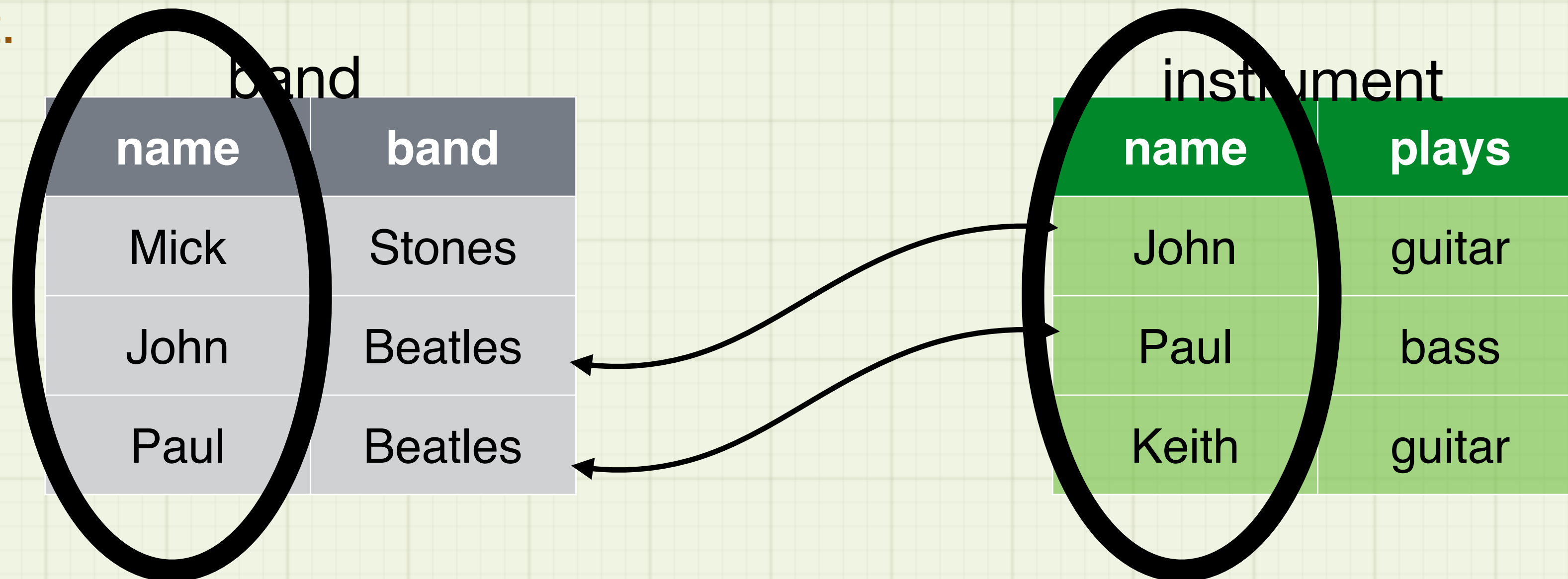
- The core of relational data processing.
- Most important data transforms can be written in terms of a sequence of joins:
 - intersection
 - cross-product
 - lookup
 - lapply / list comprehensions
- Master these and you have mastered class data manipulation

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.

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.*



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

+

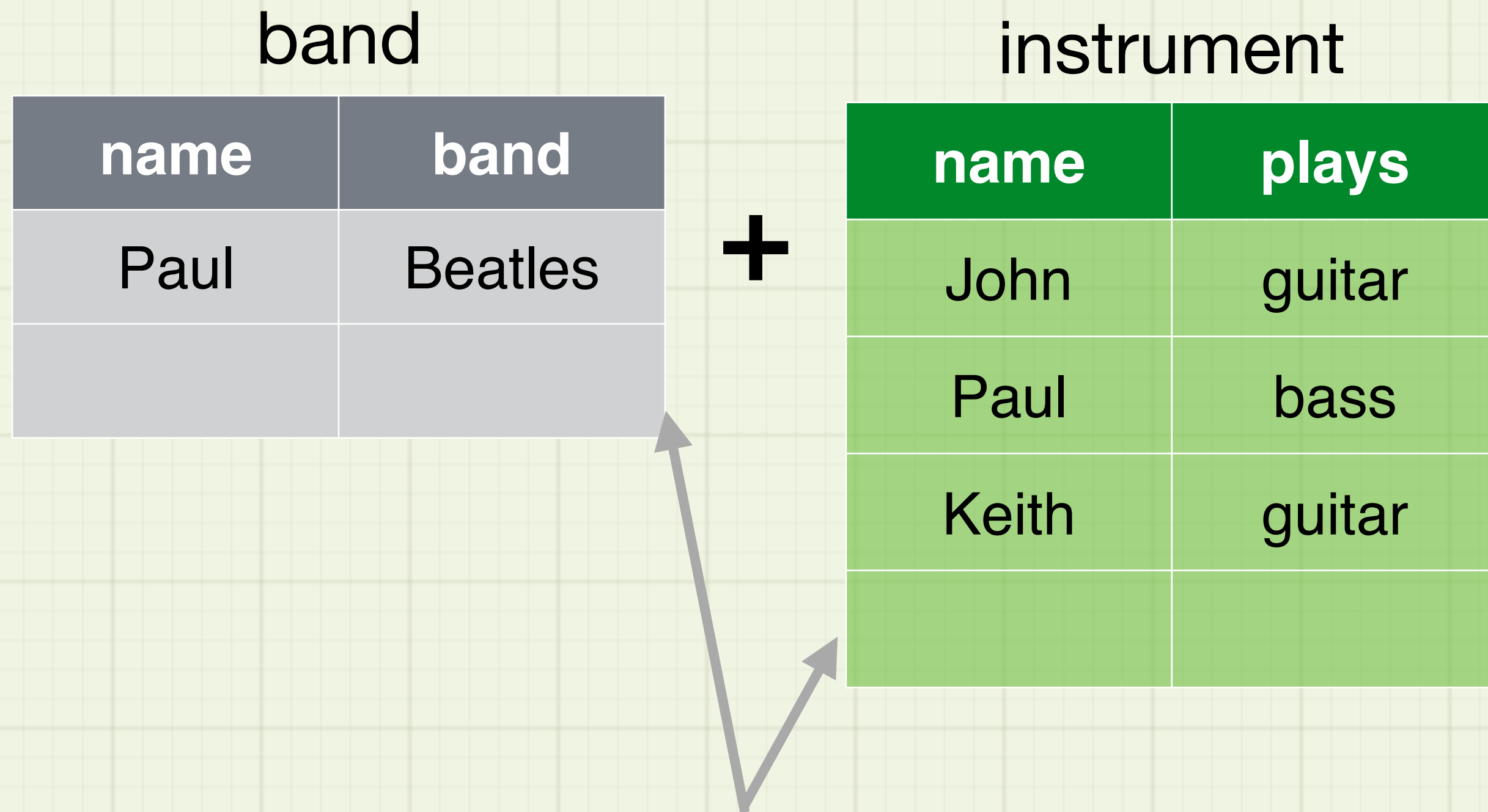
instrument

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



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

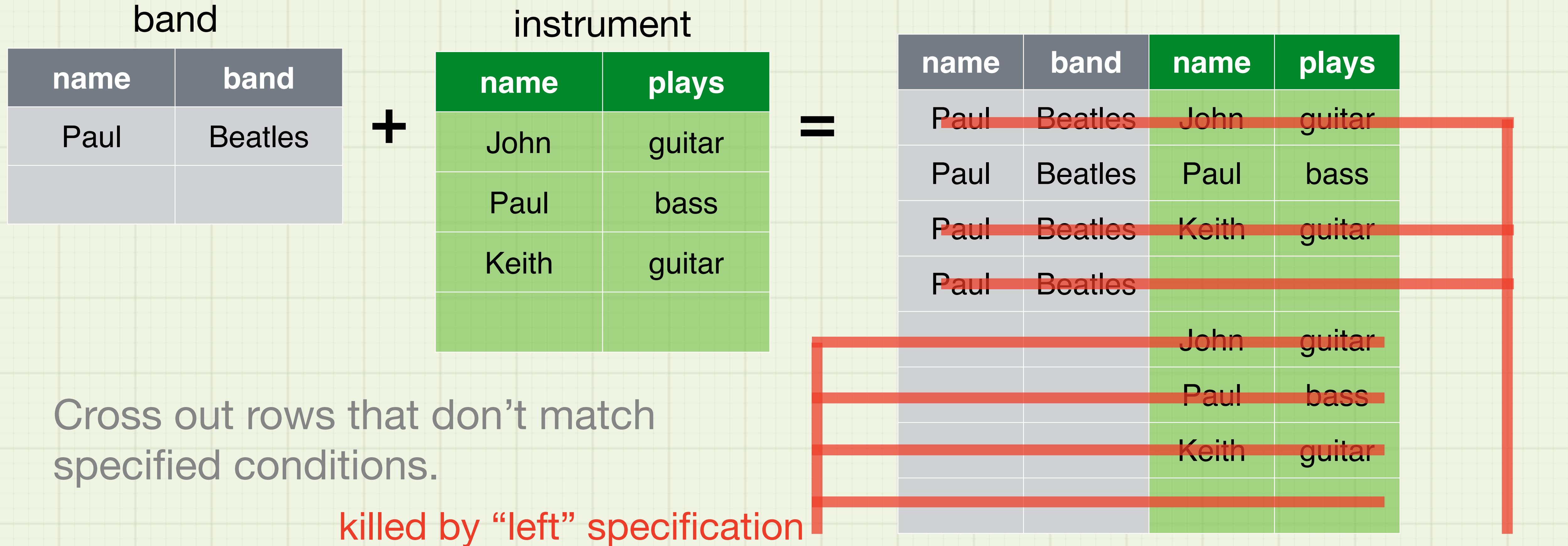
=

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")
```

left_join(): theory



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

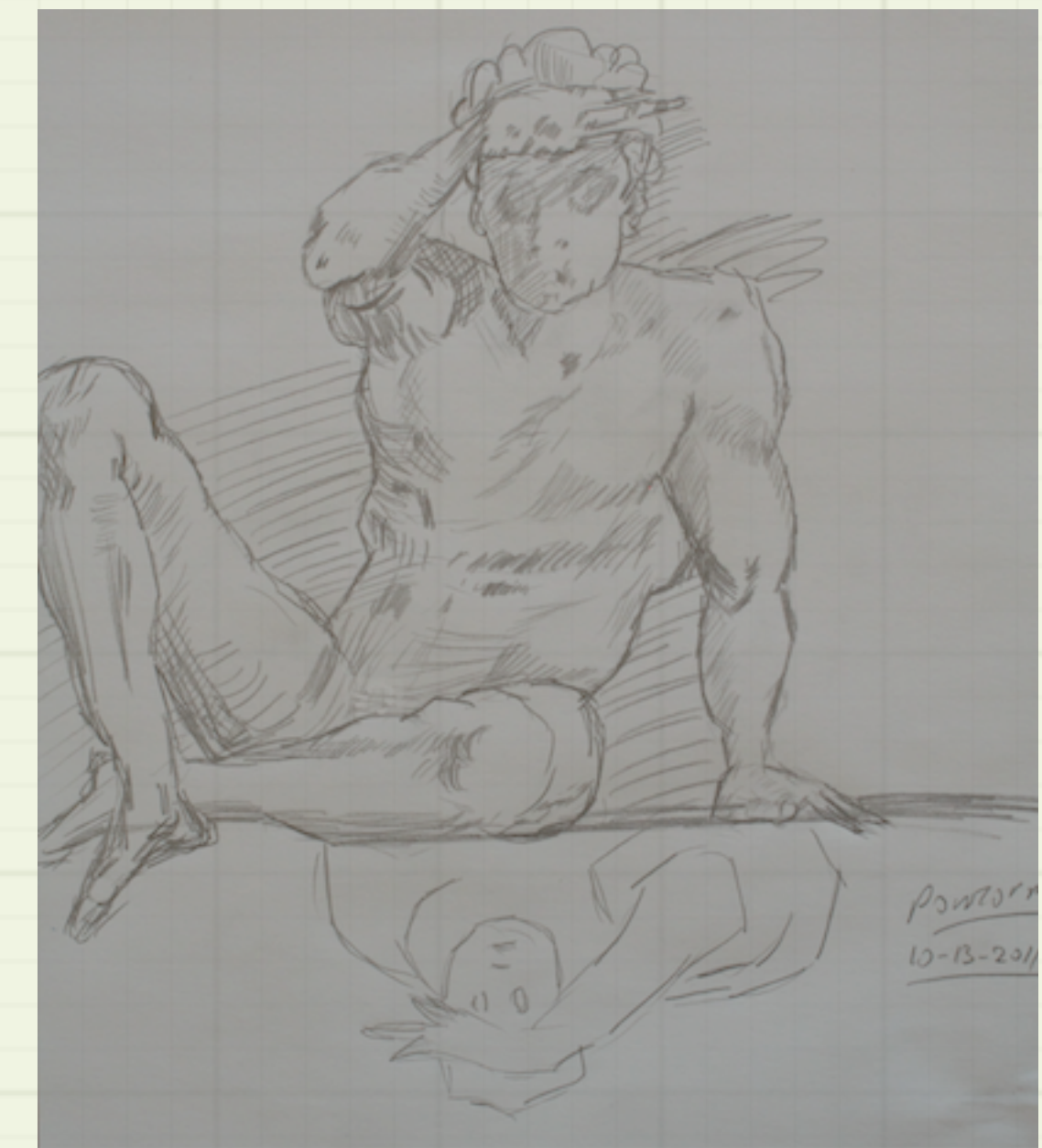
=

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

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

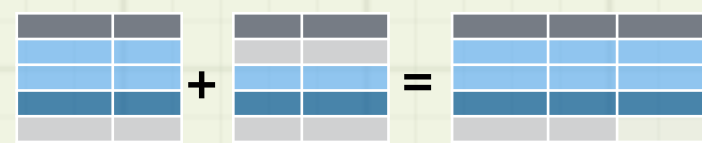
Relational Thinking

- 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.

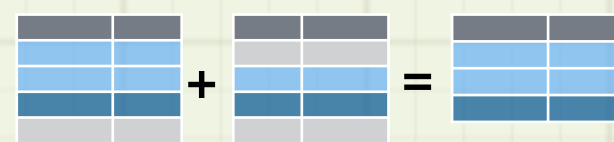


“Theory versus practice”
(after Pontromo).

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()**

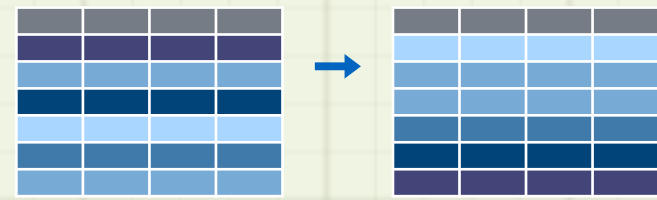


Do set operations on rows with dplyr's **union()**, **intersect()**, and **setdiff()**

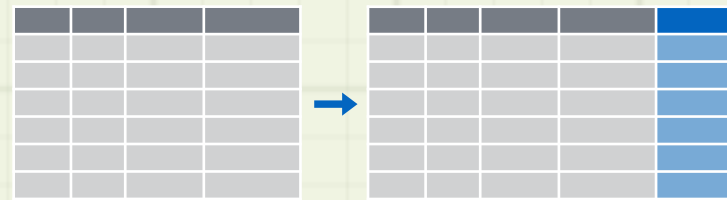
Recap: dplyr one table verbs



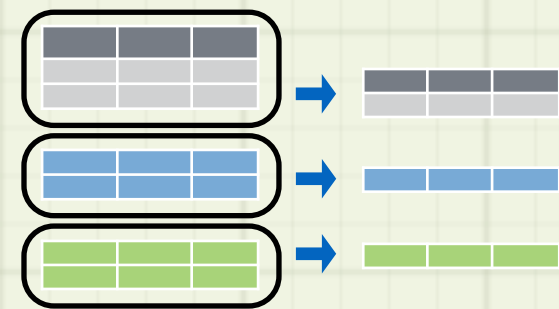
Extract columns and rows with **select()** and **filter()**



Arrange rows with **arrange()**.



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



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

Next:
dplyr exercises