

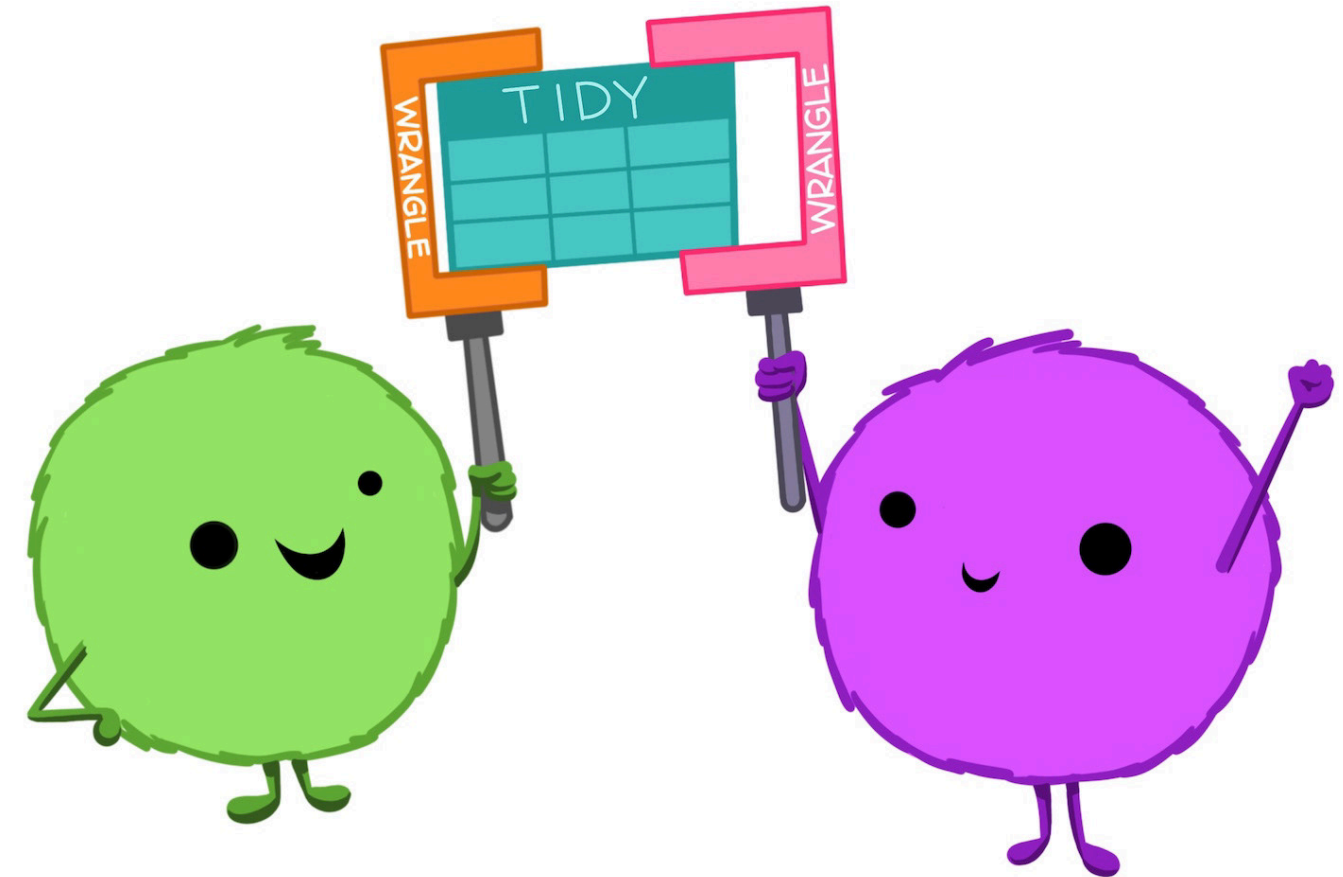
Effective Data Wrangling

Data Exploration and Visualisation

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What is Data Wrangling?

- You have raw data, now what?
- Subset, summarise, create, merge...
- wrangling = manipulation = munging
- Fly-by tour, focusing on common operations



Source: Openscapes blog by J Lowndes and A Horst.

Example Data Sets



```
1 library(palmerpenguins)
2 penguins <- palmerpenguins::penguins
3 cars <- datasets::mtcars
```

Viewing Your Data

View()

```
1 View(penguins)
```

~/Work/quarto-website - main - RStudio

index.qmd x penguins x

Filter

	species	island	bill_length_mm	bill_depth_mm	flipper_length_mm	body_mass_g	sex	year
1	Adelie	Torgersen	39.1	18.7	181	3750	male	2007
2	Adelie	Torgersen	39.5	17.4	186	3800	female	2007
3	Adelie	Torgersen	40.3	18.0	195	3250	female	2007
4	Adelie	Torgersen	NA	NA	NA	NA	NA	2007
5	Adelie	Torgersen	36.7	19.3	193	3450	female	2007
6	Adelie	Torgersen	36.7	20.6	190	3650	male	2007
7	Adelie	Torgersen	38.9	17.8	181	3625	female	2007
8	Adelie	Torgersen	39.2	19.6	195	4675	male	2007
9	Adelie	Torgersen	34.1	18.1	193	3475	NA	2007
10	Adelie	Torgersen	42.0	20.2	190	4250	NA	2007
11	Adelie	Torgersen	37.8	17.1	186	3300	NA	2007
12	Adelie	Torgersen	37.8	17.3	180	3700	NA	2007
13	Adelie	Torgersen	41.1	17.6	182	3200	female	2007
14	Adelie	Torgersen	38.6	21.2	191	3800	male	2007
15	Adelie	Torgersen	34.6	21.1	198	4400	male	2007
16	Adelie	Torgersen	36.6	17.8	185	3700	female	2007
17	Adelie	Torgersen	38.7	19.0	195	3450	female	2007
18	Adelie	Torgersen	42.5	20.7	197	4500	male	2007
19	Adelie	Torgersen	34.4	18.4	184	3325	female	2007
20	Adelie	Torgersen	46.0	21.5	194	4200	male	2007
21	Adelie	Biscoe	37.8	18.3	174	3400	female	2007

Showing 1 to 21 of 344 entries, 8 total columns

head()

```
1 head(x = penguins, n = 7)
```

A tibble: 7 × 8

	species	island	bill_length_mm	bill_depth_mm	flipper_length_mm	body_mass_g
	<fct>	<fct>	<dbl>	<dbl>	<int>	<int>
1	Adelie	Torgersen	39.1	18.7	181	3750
2	Adelie	Torgersen	39.5	17.4	186	3800
3	Adelie	Torgersen	40.3	18	195	3250
4	Adelie	Torgersen	NA	NA	NA	NA
5	Adelie	Torgersen	36.7	19.3	193	3450
6	Adelie	Torgersen	39.3	20.6	190	3650
7	Adelie	Torgersen	38.9	17.8	181	3625

i 2 more variables: sex <fct>, year <int>

str()

```
1 str(penguins)
```

```
tibble [344 × 8] (S3: tbl_df/tbl/data.frame)
 $ species      : Factor w/ 3 levels "Adelie","Chinstrap",...: 1 1 1 1 1 1 1 1 1 1 1 ...
 $ island       : Factor w/ 3 levels "Biscoe","Dream",...: 3 3 3 3 3 3 3 3 3 3 3 ...
 $ bill_length_mm : num [1:344] 39.1 39.5 40.3 NA 36.7 39.3 38.9 39.2 34.1 42 ...
 $ bill_depth_mm  : num [1:344] 18.7 17.4 18 NA 19.3 20.6 17.8 19.6 18.1 20.2 ...
 $ flipper_length_mm: int [1:344] 181 186 195 NA 193 190 181 195 193 190 ...
 $ body_mass_g    : int [1:344] 3750 3800 3250 NA 3450 3650 3625 4675 3475 4250 ...
 $ sex           : Factor w/ 2 levels "female","male": 2 1 1 NA 1 2 1 2 NA NA ...
 $ year          : int [1:344] 2007 2007 2007 2007 2007 2007 2007 2007 2007 2007 ...
```

names()

```
1 names(penguins)
```

```
[1] "species"      "island"        "bill_length_mm"
[4] "bill_depth_mm" "flipper_length_mm" "body_mass_g"
[7] "sex"          "year"
```

```
1 colnames(cars)
```

```
[1] "mpg"  "cyl"  "disp" "hp"   "drat" "wt"   "qsec" "vs"   "am"   "gear"
[11] "carb"
```

```
1 rownames(cars)
```

```
[1] "Mazda RX4"      "Mazda RX4 Wag"    "Datsun 710"
[4] "Hornet 4 Drive" "Hornet Sportabout" "Valiant"
[7] "Duster 360"     "Merc 240D"        "Merc 230"
[10] "Merc 280"       "Merc 280C"        "Merc 450SE"
[13] "Merc 450SL"     "Merc 450SLC"      "Cadillac Fleetwood"
[16] "Lincoln Continental" "Chrysler Imperial" "Fiat 128"
[19] "Honda Civic"    "Toyota Corolla"   "Toyota Corona"
[22] "Dodge Challenger" "AMC Javelin"      "Camaro Z28"
[25] "Pontiac Firebird" "Fiat X1-9"        "Porsche 914-2"
[28] "Lotus Europa"   "Ford Pantera L"   "Ferrari Dino"
[31] "Maserati Bora"   "Volvo 142E"
```


Renaming Variables

colnames()

```
1 cars_renamed <- cars
2 colnames(cars_renamed)[1] <- "miles_per_gallon"
3 colnames(cars_renamed)
```

```
[1] "miles_per_gallon" "cyl"           "disp"           "hp"
[5] "drat"             "wt"            "qsec"           "vs"
[9] "am"               "gear"          "carb"
```

dplyr::rename()

```
1 library(dplyr)
2 cars_renamed <- rename(.data = cars_renamed, cylinders = cyl)
3 colnames(cars_renamed)
```

```
[1] "miles_per_gallon" "cylinders"      "disp"           "hp"
[5] "drat"             "wt"             "qsec"           "vs"
[9] "am"               "gear"           "carb"
```

```
1 cars_renamed <- cars_renamed %>%
2   rename(displacement = disp) %>%
3   rename(horse_power = hp) %>%
4   rename(rear_axel_ratio = drat)
5
6 colnames(cars_renamed)
```

```
[1] "miles_per_gallon" "cylinders"      "displacement"   "horse_power"
[5] "rear_axel_ratio"  "wt"             "qsec"           "vs"
[9] "am"               "gear"           "carb"
```

Subsetting

Subsetting with Base R (1)

Subsetting by index

```
1 # First row
2 penguins[1, ]
3
4 # First Column
5 penguins[ , 1]
6
7 # Rows 2-3 of columns 1, 2 and 4
8 penguins[2:3, c(1, 2, 4)]
```

Drop rows or columns with negative indices

```
1 # Drop all but first row
2 penguins[-(2:344), ]
3
4 # Drop all but first column
5 penguins[ , -(2:8)]
```

Subsetting with Base R (2)

Subset using logical vector

```
1 is_bill_long <- penguins$bill_length_mm > 70
2 penguins[is_bill_long, ]
```

Subset using names (note different objects)

```
1 penguins[ , "species"] # tibble
2 penguins$species       # vector
```

Subsetting with {dplyr} (1)

```
1 penguins %>%
2   select(species, island, body_mass_g) %>%
3   print(n = 4)
```

```
# A tibble: 344 × 3
  species island    body_mass_g
  <fct>    <fct>        <int>
1 Adelie  Torgersen        3750
2 Adelie  Torgersen        3800
3 Adelie  Torgersen        3250
4 Adelie  Torgersen         NA
# i 340 more rows
```

```
1 penguins %>%
2   select(species, island, body_mass_g) %>%
3   filter(body_mass_g > 6000)
```

```
# A tibble: 2 × 3
  species island    body_mass_g
  <fct>    <fct>        <int>
1 Gentoo  Biscoe         6300
2 Gentoo  Biscoe         6050
```

Subsetting with {dplyr} (2)

```
1 penguins %>%
2   select(species, island, body_mass_g) %>%
3   filter(!(body_mass_g > 6000)) %>%
4   print(n = 4)
```

```
# A tibble: 340 × 3
  species island    body_mass_g
  <fct>    <fct>        <int>
1 Adelie  Torgersen        3750
2 Adelie  Torgersen        3800
3 Adelie  Torgersen        3250
4 Adelie  Torgersen        3450
# i 336 more rows
```

```
1 penguins %>%
2   select(species, island, body_mass_g) %>%
3   filter(!(body_mass_g > 6000)) %>%
4   select(!c(species, island)) %>%
5   print(n = 4)
```

```
# A tibble: 340 × 1
  body_mass_g
  <int>
1      3750
2      3800
3      3250
4      3450
# i 336 more rows
```


Creating new variables

New Variables with Base R

```
1 # add weight column
2 cars_renamed$weight <- cars_renamed$wt
```

```
1 # remove wt column
2 cars_renamed <- cars_renamed[ , -which(names(cars_renamed) == "wt")]
3 head(cars_renamed, n = 3)
```

	miles_per_gallon	cylinders	displacement	horse_power
Mazda RX4	21.0	6	160	110
Mazda RX4 Wag	21.0	6	160	110
Datsun 710	22.8	4	108	93

	rear_axel_ratio	qsec	vs	am	gear	carb	weight
Mazda RX4	3.90	16.46	0	1	4	4	2.620
Mazda RX4 Wag	3.90	17.02	0	1	4	4	2.875
Datsun 710	3.85	18.61	1	1	4	1	2.320

New Variables with `dplyr::mutate()`

```
1 cars_renamed <- cars_renamed %>%
2   mutate(weight_kg = weight * 1000)
3
4 cars_renamed %>%
5   select(weight, weight_kg) %>%
6   head(n = 3)
```

	weight	weight_kg
Mazda RX4	2.620	2620
Mazda RX4 Wag	2.875	2875
Datsun 710	2.320	2320

```
1 cars_renamed <- cars_renamed %>%
2   mutate(cylinder_adjusted_mpg = miles_per_gallon / cylinders)
```

Row names / id to column

```
1 cars %>%
2   tibble::rownames_to_column(var = "model") %>%
3   head(n = 3)
```

	model	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
1	Mazda RX4	21.0	6	160	110	3.90	2.620	16.46	0	1	4	4
2	Mazda RX4 Wag	21.0	6	160	110	3.90	2.875	17.02	0	1	4	4
3	Datsun 710	22.8	4	108	93	3.85	2.320	18.61	1	1	4	1

```
1 cars %>%
2   tibble::rowid_to_column(var = "row_id") %>%
3   head(n = 3)
```

	row_id	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
1	1	21.0	6	160	110	3.90	2.620	16.46	0	1	4	4
2	2	21.0	6	160	110	3.90	2.875	17.02	0	1	4	4
3	3	22.8	4	108	93	3.85	2.320	18.61	1	1	4	1

Summaries

```
1 penguins %>%
2 summarise(average_bill_length_mm = mean(bill_length_mm, na.rm = TRUE))
```

A tibble: 1 × 1

	average_bill_length_mm
1	43.9

```
1 bill_length_mm_summary <- penguins %>%
2   summarise(
3     mean = mean(bill_length_mm, na.rm = TRUE),
4     median = median(bill_length_mm, na.rm = TRUE),
5     min = min(bill_length_mm, na.rm = TRUE),
6     q_0 = min(bill_length_mm, na.rm = TRUE),
7     q_1 = quantile(bill_length_mm, prob = 0.25, na.rm = TRUE),
8     q_2 = median(bill_length_mm, na.rm = TRUE),
9     q_3 = quantile(bill_length_mm, prob = 0.25, na.rm = TRUE),
10    q_4 = max(bill_length_mm, na.rm = TRUE))
11
12 bill_length_mm_summary
```

A tibble: 1 × 8

	mean	median	min	q_0	q_1	q_2	q_3	q_4
1	43.9	44.4	59.6	32.1	39.2	44.4	39.2	59.6

Grouped Operations

Grouped Operations

```

1 penguins %>%
2   group_by(species) %>%
3   summarise(
4     mean = mean(bill_length_mm, na.rm = TRUE),
5     median = median(bill_length_mm, na.rm = TRUE),
6     min = min(bill_length_mm, na.rm = TRUE),
7     q_0 = min(bill_length_mm, na.rm = TRUE),
8     q_1 = quantile(bill_length_mm, prob = 0.25, na.rm = TRUE),
9     q_2 = median(bill_length_mm, na.rm = TRUE),
10    q_3 = quantile(bill_length_mm, prob = 0.25, na.rm = TRUE),
11    q_4 = max(bill_length_mm, na.rm = TRUE))

```

A tibble: 3 × 9

	species	mean	median	min	q_0	q_1	q_2	q_3	q_4
	<fct>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	Adelie	38.8	38.8	46	32.1	36.8	38.8	36.8	46
2	Chinstrap	48.8	49.6	58	40.9	46.3	49.6	46.3	58
3	Gentoo	47.5	47.3	59.6	40.9	45.3	47.3	45.3	59.6

Multiple Groups

```

1 penguin_summary_stats <- penguins %>%
2   group_by(species, island) %>%
3   summarise(
4     mean = mean(bill_length_mm, na.rm = TRUE),
5     median = median(bill_length_mm, na.rm = TRUE),
6     min = min(bill_length_mm, na.rm = TRUE),
7     q_0 = min(bill_length_mm, na.rm = TRUE),
8     q_1 = quantile(bill_length_mm, prob = 0.25, na.rm = TRUE),
9     q_2 = median(bill_length_mm, na.rm = TRUE),
10    q_3 = quantile(bill_length_mm, prob = 0.25, na.rm = TRUE),
11    q_4 = max(bill_length_mm, na.rm = TRUE))
12
13 penguin_summary_stats

```

A tibble: 5 × 10

Groups: species [3]

	species	island	mean	median	min	q_0	q_1	q_2	q_3	q_4
	<fct>	<fct>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	Adelie	Biscoe	39.0	38.7	45.6	34.5	37.7	38.7	37.7	45.6
2	Adelie	Dream	38.5	38.6	44.1	32.1	36.8	38.6	36.8	44.1
3	Adelie	Torgersen	39.0	38.9	46	33.5	36.7	38.9	36.7	46
4	Chinstrap	Dream	48.8	49.6	58	40.9	46.3	49.6	46.3	58
5	Gentoo	Biscoe	47.5	47.3	59.6	40.9	45.3	47.3	45.3	59.6

Ungrouping

By default each `summarise()` will undo one level of grouping.

```
1 class(penguin_summary_stats)
[1] "grouped_df" "tbl_df"      "tbl"        "data.frame"
```

Use an appropriate number of calls or `ungroup()`.

```
1 penguin_summary_stats %>%
2   summarise_all(mean, na.rm = TRUE)
```

A tibble: 3 × 10

	species <fct>	island <dbl>	mean <dbl>	median <dbl>	min <dbl>	q_0 <dbl>	q_1 <dbl>	q_2 <dbl>	q_3 <dbl>	q_4 <dbl>
1	Adelie	NA	38.8	38.7	45.2	33.4	37.0	38.7	37.0	45.2
2	Chinstrap	NA	48.8	49.6	58	40.9	46.3	49.6	46.3	58
3	Gentoo	NA	47.5	47.3	59.6	40.9	45.3	47.3	45.3	59.6

```
1 ungroup(penguin_summary_stats)
```

A tibble: 5 × 10

	species <fct>	island <fct>	mean <dbl>	median <dbl>	min <dbl>	q_0 <dbl>	q_1 <dbl>	q_2 <dbl>	q_3 <dbl>	q_4 <dbl>
1	Adelie	Biscoe	39.0	38.7	45.6	34.5	37.7	38.7	37.7	45.6
2	Adelie	Dream	38.5	38.6	44.1	32.1	36.8	38.6	36.8	44.1
3	Adelie	Torgersen	39.0	38.9	46	33.5	36.7	38.9	36.7	46
4	Chinstrap	Dream	48.8	49.6	58	40.9	46.3	49.6	46.3	58
5	Gentoo	Biscoe	47.5	47.3	59.6	40.9	45.3	47.3	45.3	59.6

Reordering Factors (1)

- Factors are stored as integers, ordering can make tables and plots confusing.

```
1 tshirts <- tibble::tibble(
2   id = 1:12,
3   size = as.factor(c("L", NA, "M", "S", "XS", "M", "XXL", "L", "XS", "M", "L", "S"))
4 )
5
6 tshirts %>% group_by(size) %>% summarise(count = n())
```

A tibble: 6 × 2

	size	count
	<fct>	<int>
1	L	3
2	M	3
3	S	2
4	XS	2
5	XXL	1
6	<NA>	1

Reordering Factors (2)

- create new variable with the factor in the correct order.

```
1 tidy_tshirt_levels <- c("XS", "S", "M", "L", "XL", "XXL", NA)
2
3 tshirts %>%
4   mutate(size_tidy = factor(size, levels = tidy_tshirt_levels)) %>%
5   group_by(size_tidy, .drop = FALSE ) %>%
6   summarise(count = n())
```

```
# A tibble: 7 × 2
  size_tidy count
  <fct>      <int>
1 XS          2
2 S           2
3 M           3
4 L           3
5 XL          0
6 XXL         1
7 <NA>        1
```

Be Aware!

Be Aware: Factors



Useful `{forcats}` functions:

- `fct_reorder()`: Reordering a factor by another variable.
- `fct_infreq()`: Reordering a factor by the frequency of values.
- `fct_relevel()`: Changing the order of a factor by hand.
- `fct_lump()`: Collapsing the least/most frequent values of a factor into “other”.

Check out the [forcats vignette](#) or the [factors chapter](#) of R4DS.

Be Aware: Strings

- Working with text data is it's own skill.
- Requires some knowledge of **regular expressions**.
- **{stringr}** simplifies this, somewhat.
- Learn as you need it: **strings** section of R4DS.



Be Aware: Dates and Times

Recall ISO standard and proceed with caution

YYYY – MM – DD

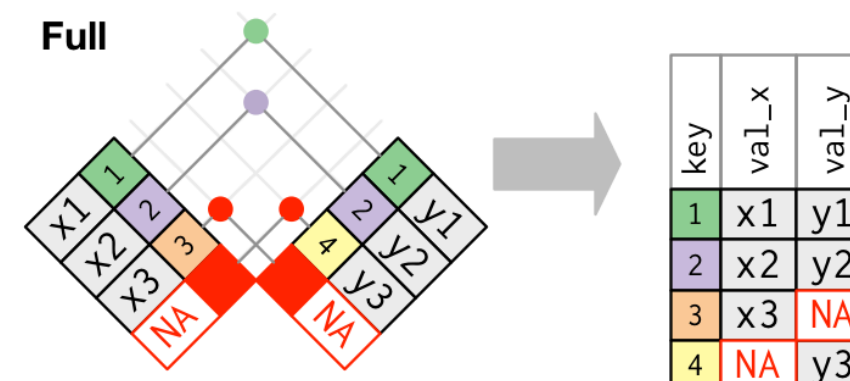
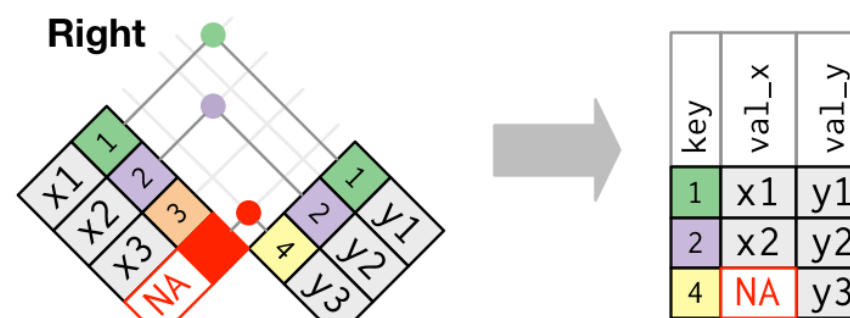
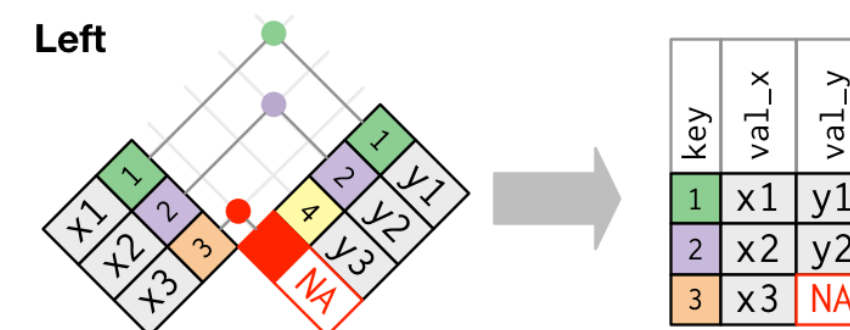
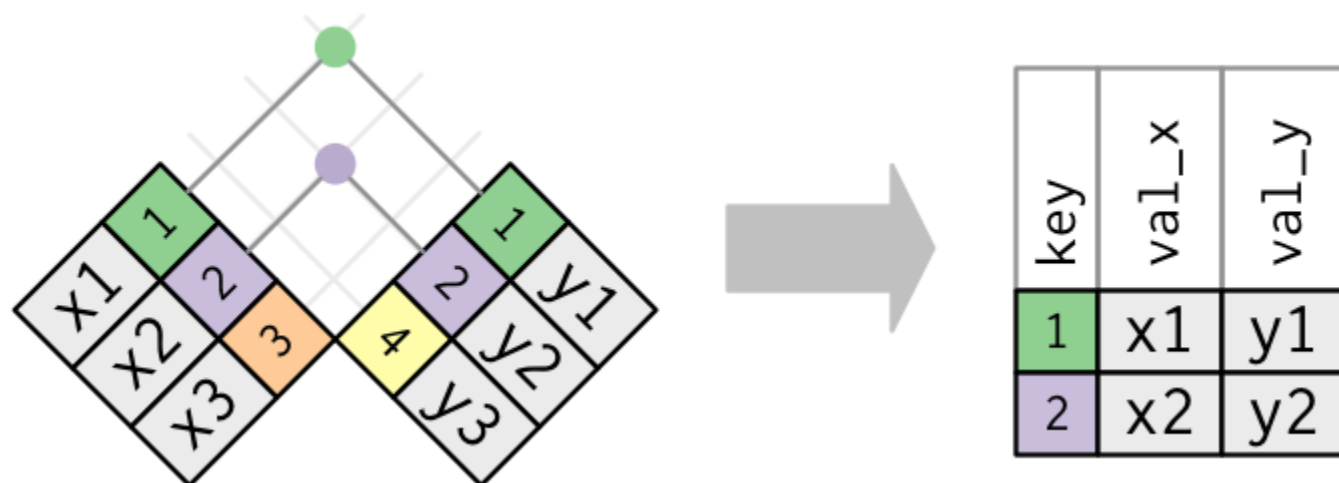
- How many days are there in a year / month? How many hours are there in a day?
- How many seconds are there in a minute?
- What calendar are you using? When does the year begin and how many months?

`{lubridate}` makes this easier, see [dates and times](#) examples from R4DS.

Be Aware: Relational Data

- Data on the same observational units stored across two or more tables.
- [Relational data](#) chapter of R4DS.

Inner Join



Ubiquity of Relational Data

- Relational data base management systems used across data science,
 - More efficient and fewer privacy concerns.
- SQL as a database management language
 - Inspiration for `{dplyr}`, translate with `{dbplyr}`
- More data base theory and efficient queries - big data or introductory SQL books.

Wrapping up

- Learned how to wrangle tabular data in R with base R and `{dplyr}`
- Met the idea of relational data and `{dplyr}`'s relationship to SQL
- Become aware of some tricky data types and packages that can help.

