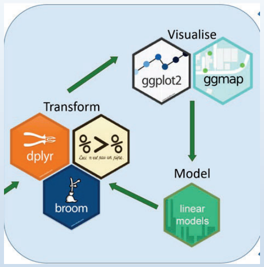
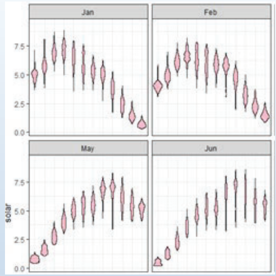
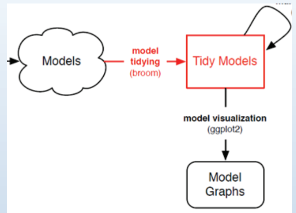






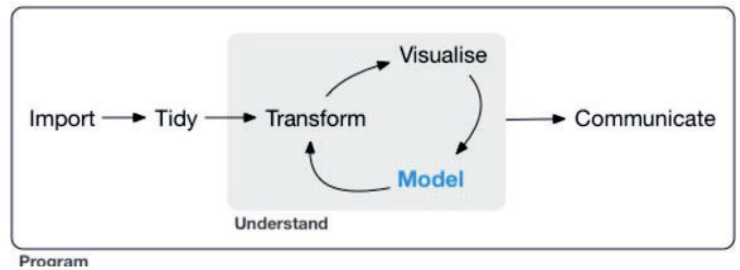
ggplot2: Going further in the tidyverse

Michael Friendly
Psych 6135

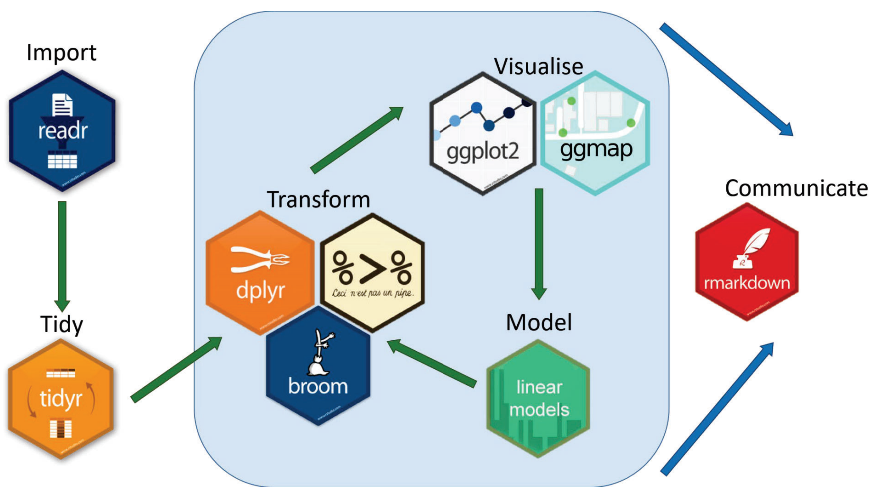
https://friendly.github.io/6135/

A larger view: Data science

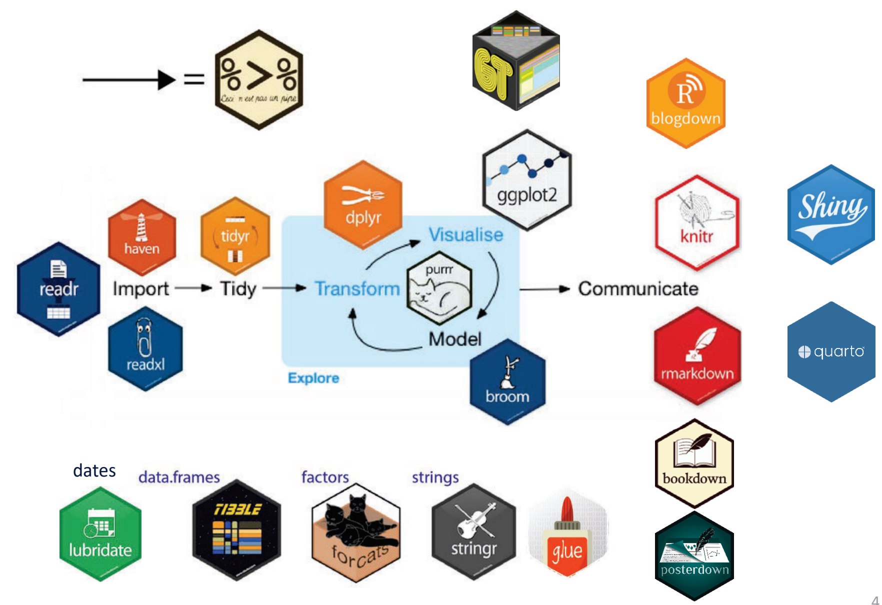
- Data science treats statistics & data visualization as parts of a larger process
  - Data import: text files, data bases, web scraping, …
  - Data cleaning → "tidy data"
  - Model building & visualization
  - Reproducible report writing



The tidyverse of R packages

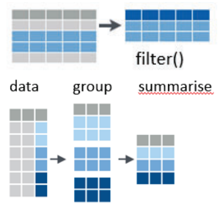


The tidyverse expands



Topics for today

- Data import / export
- Data wrangling: getting your data into shape
  - dplyr & tidyr
  - pipes: %>%, now: |>
  - grouping & summarizing
  - Example: NASA data on solar radiation
- Working with models: broom
  - Example: gapminder data
- Nice tables in R
- Writing & publishing



Ready for some heavy lifting?

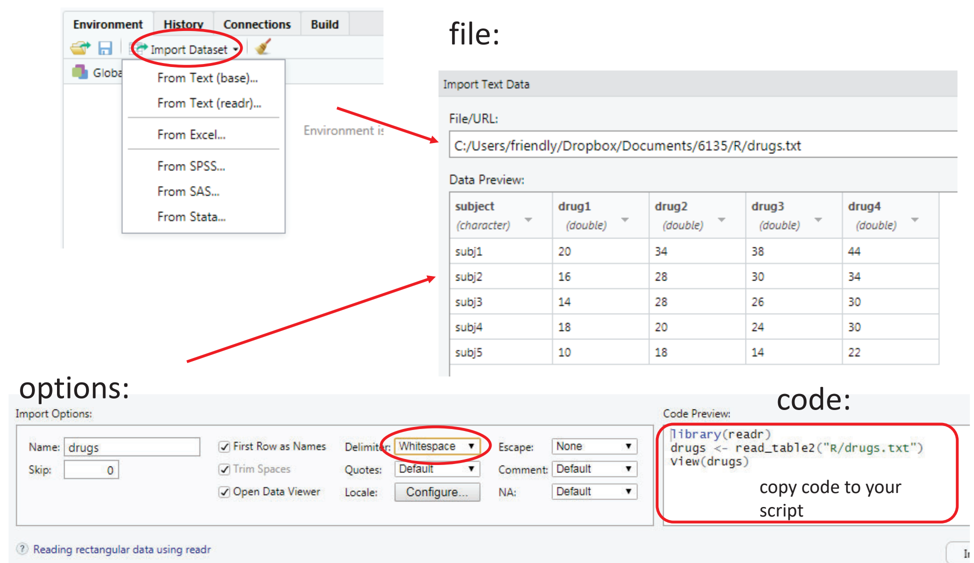
New ideas, ways of thinking & working are on the table!

Data Import / Export

- The `readr` package is the modern, tidy way to import and export data
  - Tabular data:
    - comma delimited (read.csv)
    - any other delimiters (";" = read.csv2; <tab> = read_tsv)
  - Data types:
    - specify column types or let functions guess
- Other data formats

package	Data types
haven	SAS, SPSS, Stata
readxl	Excel files (.xls and xlsx)
DBI	Databases (SQL, …)
rvest	HTML (web scraping)

Data Import: RStudio



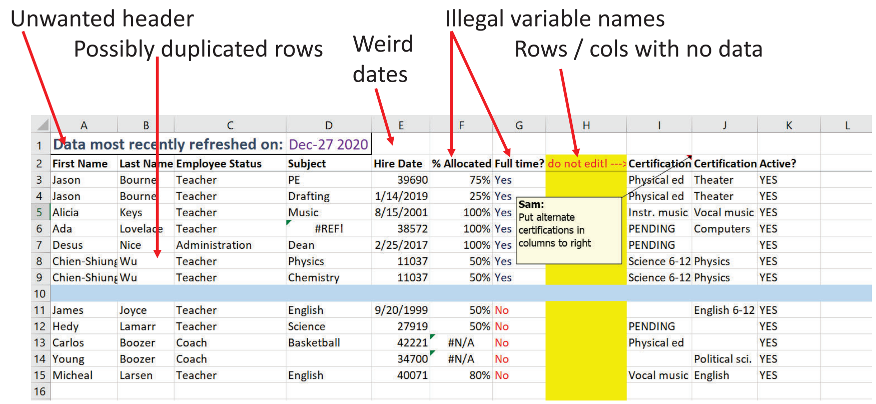
subject (character)	drug1 (double)	drug2 (double)	drug3 (double)	drug4 (double)
subj1	20	34	38	44
subj2	16	28	30	34
subj3	14	28	26	30
subj4	18	20	24	30
subj5	10	18	14	22

Data transformation tools

Some common data types can be messy when imported. Tidy tools are there to help

dates/times	lubridate	read dates/times in various formats; extract components
factors	forcats	Change order of levels, drop levels, combine levels
strings	stringr glue	detect matches, subset, replace interpolate values into strings
Clean-up	janitor	Clean up variable names, find duplicate records

Janitor



	A	B	C	D	E	F	G	H	I	J	K	L
1	Data most recently refreshed on:			Dec-27 2020								
2	First Name	Last Name	Employee Status	Subject	Hire Date	% Allocated	Full time?	do not edit! --->	Certification	Certification	Active?	
3	Jason	Bourne	Teacher	PE	39690	75%	Yes		Physical ed	Theater	YES	
4	Jason	Bourne	Teacher	Drafting	1/14/2019	25%	Yes		Physical ed	Theater	YES	
5	Alicia	Keys	Teacher	Music	8/15/2001	100%	Yes		Instr. music	Vocal music	YES	
6	Ada	Lovelace	Teacher	#REF!	38572	100%	Yes		PENDING	Computers	YES	
7	Desus	Nice	Administration	Dean	2/25/2017	100%	Yes		PENDING		YES	
8	Chien-Shiung	Wu	Teacher	Physics	11037	50%	Yes		Science 6-12	Physics	YES	
9	Chien-Shiung	Wu	Teacher	Chemistry	11037	50%	Yes		Science 6-12	Physics	YES	
10												
11	James	Joyce	Teacher	English	9/20/1999	50%	No			English 6-12	YES	
12	Hedy	Lamarr	Teacher	Science	27919	50%	No		PENDING		YES	
13	Carlos	Boozer	Coach	Basketball	42221	#N/A	No		Physical ed		YES	
14	Young	Boozer	Coach		34700	#N/A	No			Political sci.	YES	
15	Micheal	Larsen	Teacher	English	40071	80%	No		Vocal music	English	YES	
16												

```
library(janitor)
Data <- read_excel(dirty.xlsx) |> clean_names() |> remove_empty() |> …
```

Documentation: https://sfirke.github.io/janitor/

lubridate: Dates & times

PARSE DATE-TIMES (Convert strings or numbers to date-times)

1. Identify the order of the year (**y**), month (**m**), day (**d**), hour (**h**), minute (**m**) and second (**s**) elements in your data.
2. Use the function below whose name replicates the order. Each accepts a wide variety of input formats.

2017-11-28T14:02:00	**ymd_hms**(), **ymd_hm**(), **ymd_h**(). *ymd_hms("2017-11-28T14:02:00")*
2017-22-12 10:00:00	**ydm_hms**(), **ydm_hm**(), **ydm_h**(). *ydm_hms("2017-22-12 10:00:00")*
11/28/2017 1:02:03	**mdy_hms**(), **mdy_hm**(), **mdy_h**(). *mdy_hms("11/28/2017 1:02:03")*
1 Jan 2017 23:59:59	**dmy_hms**(), **dmy_hm**(), **dmy_h**(). *dmy_hms("1 Jan 2017 23:59:59")*
20170131	**ymd**(), **ydm**(). *ymd(20170131)*
July 4th, 2000	**mdy**(), **myd**(). *mdy("July 4th, 2000")*
4th of July '99	**dmy**(), **dym**(). *dmy("4th of July '99")*
2001: Q3	**yq**() Q for quarter. *yq("2001: Q3")*
2:01	hms::**hms**() Also lubridate::**hms**(), **hm**() and **ms**(), which return periods.* *hms::hms(sec = 0, min= 1, hours = 2)*

Dates & times come in so many forms!

```
# parse dates in various formats
ymd("20210604")
#> [1] "2021-06-04"
mdy("06-04-2021")
#> [1] "2021-06-04"
dmy("04/06/2021")
#> [1] "2021-06-04"

# extract date components
minard_bday <- ymd("1781-03-27")
year(minard_bday)
#> [1] 1781
month.name[month(minard_bday)]
#> [1] "March"

# date arithmetic: how old is Minard?
year(today()) - year(minard_bday)
#> [1] 244
```

Learn more at: http://lubridate.tidyverse.org

stringr: Manipulating strings

Detect Matches

str_detect(string, pattern) Detect the presence of a pattern match in a string. *str_detect(fruit, "a")*

str_which(string, pattern) Find the indexes of strings that contain a pattern match. *str_which(fruit, "a")*

str_count(string, pattern) Count the number of matches in a string. *str_count(fruit, "a")*

str_locate(string, pattern) Locate the positions of pattern matches in a string. Also **str_locate_all**. *str_locate(fruit, "a")*

Subset Strings

str_sub(string, start = 1L, end = -1L) Extract substrings from a character vector. *str_sub(fruit, 1, 3); str_sub(fruit, -2)*

str_subset(string, pattern) Return only the strings that contain a pattern match. *str_subset(fruit, "b")*

str_extract(string, pattern) Return the first pattern match found in each string, as a vector. Also **str_extract_all** to return every pattern match. *str_extract(fruit, "[aeiou]")*

str_match(string, pattern) Return the first pattern match found in each string, as a matrix with a column for each ( ) group in pattern. Also **str_match_all**. *str_match(sentences, "(a|the) ([^]+)")*

Mutate Strings

str_sub() <- value. Replace substrings by identifying the substrings with str_sub() and assigning into the results. *str_sub(fruit, 1, 3) <- "str"*

str_replace(string, pattern, replacement) Replace the first matched pattern in each string. *str_replace(fruit, "a", "-")*

str_replace_all(string, pattern, replacement) Replace all matched patterns in each string. *str_replace_all(fruit, "a", "-")*

str_to_lower(string, locale = "en")[1] Convert strings to lower case. *str_to_lower(sentences)*

str_to_upper(string, locale = "en")[1] Convert strings to upper case. *str_to_upper(sentences)*

Join and Split

str_c(..., sep = "", collapse = NULL) Join multiple strings into a single string. *str_c(letters, LETTERS)*

str_c(..., sep = "", **collapse = ""**) Collapse a vector of strings into a single string. *str_c(letters, collapse = "")*

str_dup(string, times) Repeat strings times times. *str_dup(fruit, times = 2)*

str_split_fixed(string, pattern, n) Split a vector of strings into a matrix of substrings (splitting at occurrences of a pattern match). Also **str_split** to return a list of substrings. *str_split_fixed(fruit, " ", n=2)*

str_glue(…, .sep = "", .envir = parent.frame()) Create a string from strings and {expressions} to evaluate. *str_glue("Pi is {pi}")*

Learn more at: http://stringr.tidyverse.org

```
> library(stringr)
> x <- c("house", "car", "plant", "telephone", "arm chair")
> print(x)
[1] "house"    "car"      "plant"    "telephone" "arm chair"

> # how many letters?
> str_length(x)
[1] 5 3 5 9 9

> # detecting characters
> str_detect(x, "ar")
[1] FALSE  TRUE FALSE FALSE  TRUE

> # which ones match?
> x[str_detect(x, "ar")]
[1] "car"      "arm chair"

> # replacing characters
> str_replace(x, "ar", "**")
[1] "house"    "c**"      "plant"    "telephone" "**m chair"
> x |> str_replace("ar", "**")
[1] "house"    "c**"      "plant"    "telephone" "**m chair"

> # regular expressions: find vowels [aeiou]
> str_replace_all(x, "[aeiou]", "_")
[1] "h__s_"    "c_r"      "pl_nt"    "t_l_ph_n_" "_rm ch__r"
```

Changing case

```
> str_to_upper(x)
[1] "HOUSE"    "CAR"      "PLANT"    "TELEPHONE" "ARM CHAIR"
> str_to_sentence(x)
[1] "House"    "Car"      "Plant"    "Telephone" "Arm chair"
> str_to_title(x)
[1] "House"    "Car"      "Plant"    "Telephone" "Arm Chair"
```


glue: Interpolating strings

A common problem: Interpolating the values of variables into a text string.
glue does this by embedding R expressions in {curly braces} which are evaluated and inserted into the argument string.

```
library(glue)
name <- "Michael"; food <- "pizza"
glue('My name is {name}. I like {food}.')
#> My name is Michael. I like pizza.
```

glue is vectorized

```
> food <- c("pizza", "burgers")
> glue('My name is {name}. I like {food}.')
My name is Michael. I like pizza.
My name is Michael. I like burgers.
```

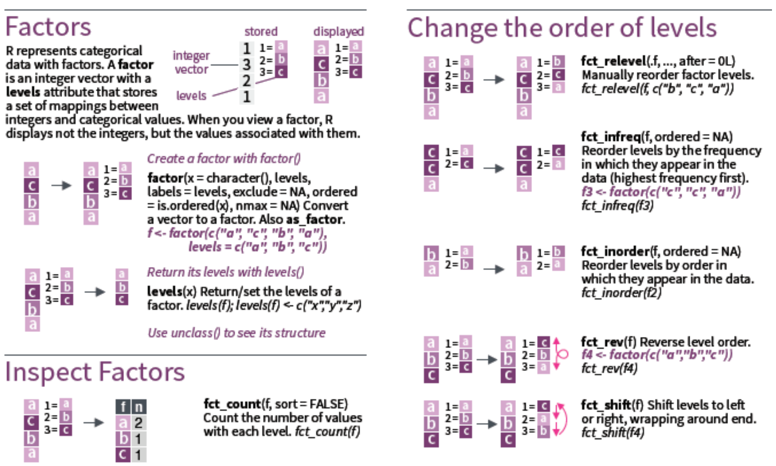
glue_data() is useful with pipes and data frames

```
head(mtcars,4) |>
        glue_data("{rownames(.)} has {hp} hp & {cyl} cylinders")
#> Mazda RX4 has 110 hp & 6 cylinders
#> Mazda RX4 Wag has 110 hp & 6 cylinders
#> Datsun 710 has 93 hp & 4 cylinders
#> Hornet 4 Drive has 110 hp & 6 cylinders
```

NB: paste() is the base-R version. glue() is much more powerful

forcats: Working with factors

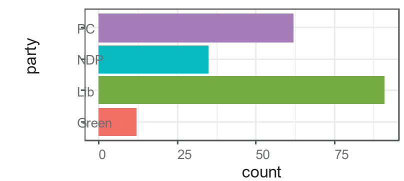
R represents categorical variables as factors, useful for analysis (e.g., ANOVA)
In graphics, we often want to recode levels or reorder them



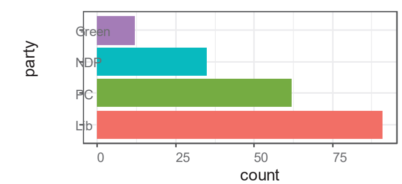
Learn more at: http://forcats.tidyverse.org


```
> str(survey)
'data.frame':        200 obs. of  3 variables:
 $ marital: Factor w/ 5 levels "divorced","married",..: 2 4 2 2 2 ...
 $ party  : Factor w/ 4 levels "Green","Lib",..: 3 4 2 2 4 ...
 $ age    : num  33.5 24 31 ...
```

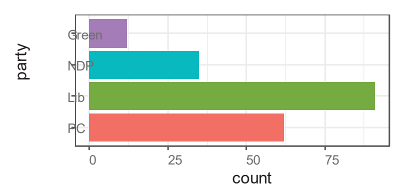
```
# default: Alpha order
ggplot(survey, aes(x= party, fill = party)) +
  geom_bar() + coord_flip()
```



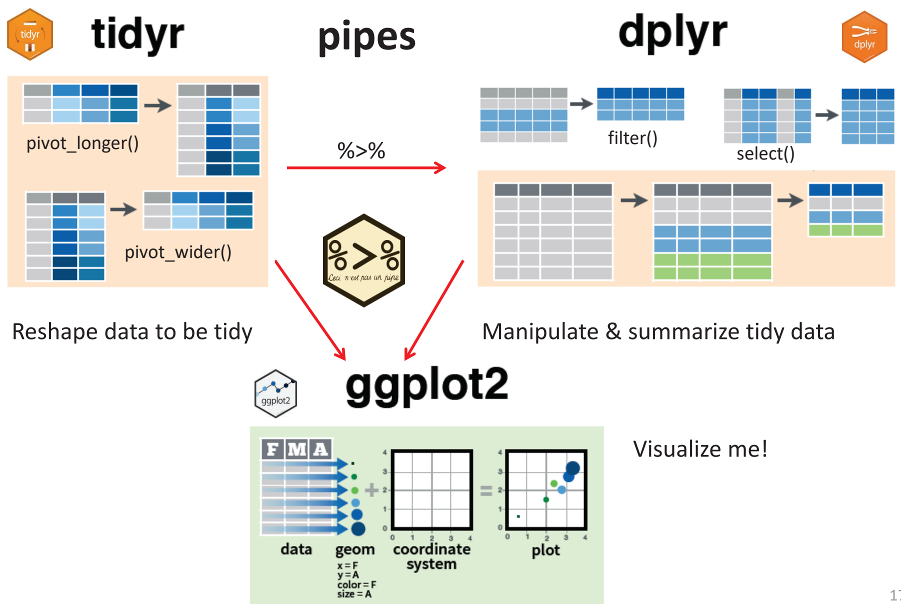

```
# reorder by frequency
survey |> mutate(party=fct_infreq(party)) |>
  ggplot(aes(x= party, fill = party)) +
    geom_bar() + coord_flip()
```




```
# reorder by right - left
survey |>
  mutate(party = fct_relevel(party,
                          c("PC", "Lib",
                           "NDP", "Green"))) |>
  ggplot(aes(x= party, fill = party)) +
    geom_bar() + coord_flip()
```



Tidy tools: overview

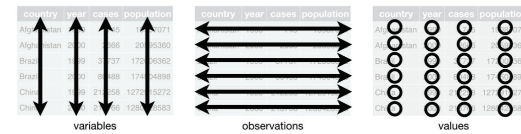


Data wrangling with dplyr & tidyr

What is Tidy Data?

A dataset is said to be tidy if:

- observations are in rows
- variables are in columns
- each value is in its own cell.



A "messy" dataset: Survey of income by religion from Pew Research

- Values of income are in separate columns, not one variable
- Column headers are values, not variable names
- Cell values are frequencies--- implicit, not explicit

religion	<$10k	$10-20k	$20-30k	$30-40k	$40-50k	$50-75k
Agnostic	27	34	60	81	76	137
Atheist	12	27	37	52	35	70
Buddhist	27	21	30	34	33	58
Catholic	418	617	732	670	638	1116

This organization is easy in Excel

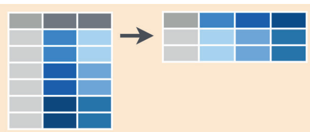
But, this makes data analysis and graphing hard

Tidy operations

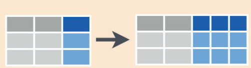
gather(): Reshape wide to long
synonym: **tidyr::pivot_longer()**

spread(): Reshape long to wide
synonym: **tidyr::pivot_wider()**

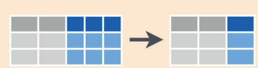
tidyr::**gather(cases, "year", "n", 2:4)**
Gather columns into rows.



tidyr::**spread(pollution, size, amount)**
Spread rows into columns.



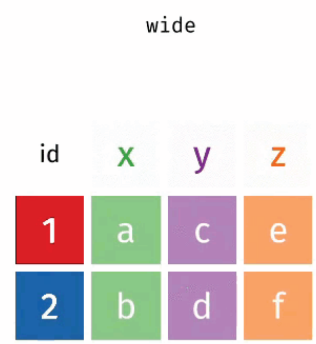
tidyr::**separate(storms, date, c("y", "m", "d"))**
Separate one column into several.



tidyr::**unite(data, col, ..., sep)**
Unite several columns into one.

Separate parts of a value into several variables

Join related variables into one



Wide → Long

```
pivot_longer(wide,
   cols = x:z,
   names_to = “key”,
   values_to = “val”)
```

Long → Wide

```
pivot_wider(long,
   names_from = key,
   values_from = val)
```

Image from:
https://www.garrickadenbuie.com/project/tidyexplain/

Tidying: reshaping wide to long

We can tidy the data by reshaping from wide to long format using **tidyr::gather()** or **pivot_longer()**

```
> pew <- read.delim(
  file = "http://stat405.had.co.nz/data/pew.txt",
  header = TRUE,
  stringsAsFactors = FALSE, check.names = FALSE)

> (pew1 <- pew[1:4, 1:6])  # small subset

  religion <$10k $10-20k $20-30k $30-40k $40-50k
1 Agnostic    27      34      60      81      76
2  Atheist    12      27      37      52      35
3 Buddhist    27      21      30      34      33
4 Catholic   418     617     732     670     638
```

key value columns

```
>library(tidyr)
> gather(pew1, "income", "frequency", 2:6)
   religion  income frequency
1  Agnostic   <$10k        27
2   Atheist   <$10k        12
3  Buddhist   <$10k        27
4  Catholic   <$10k       418
5  Agnostic $10-20k        34
6   Atheist $10-20k        27
7  Buddhist $10-20k        21
8  Catholic $10-20k       617
9  Agnostic $20-30k        60
10  Atheist $20-30k        37
11 Buddhist $20-30k        30
12 Catholic $20-30k       732
13 Agnostic $30-40k        81
14  Atheist $30-40k        52
15 Buddhist $30-40k        34
16 Catholic $30-40k       670
…  …        …             …
```

Another solution, using reshape2::melt()

```
> library(reshape2)
> pew_tidy <- melt(
    data = pew1,
    id = "religion",
    variable.name = "income",
    value.name = "frequency"
)
```

NB: income is a character variable; we might want to create an ordered factor or numeric version

Using pipes: %>%, |>

- R is a functional language
  - This means that f(x) returns a value, as in y <- f(x)
  - → That value can be passed to another function: g(f(x))
  - → And so on: h(g(f(x)))
  - E.g., calculate: $e^{[\log(x_i) - \log(x_{i-1})]}$

```
> x <- c(0.109, 0.359, 0.63, 0.996, 0.515, 0.142)
> exp(diff(log(x)))
[1] 3.29 1.75 1.58 0.52 0.28
```

  - This gets messy and hard to read, unless you break it down step by step

```
> # Compute the logarithm of `x`, calculate lagged differences,
> # return the exponential function of the result
> log(x)
[1] -2.216 -1.024 -0.462 -0.004 -0.664 -1.952
> diff(log(x))              #calculate lagged diffs
[1]  1.19  0.56  0.46 -0.66 -1.29
> exp(diff(log(x)))         # convert back to original scale
[1] 3.29 1.75 1.58 0.52 0.28
```


Using pipes: %>%, |>

- Pipes (|>) change the syntax to make this easier

```
> # use pipes
> x |> log() |> diff() |> exp()
[1] 3.29 1.75 1.58 0.52 0.28
```

- Basic rules
  - `x |> f()` passes object on left hand side as first argument (or . argument) of function on right hand side
    - `x |> f()` is the same as `f(x)`
    - `x |> f(y)` is the same as `f(x, y)`
    - `y %>% f(x, ., z)` is the same as `f(x, y, z)`
  - `x %<>% f()` does the same, but assigns the result to x
    - Shortcut for `x <- x %>% f()`

NB: pipes (%>%) originally in magrittr pkg; native pipe (|>) introduced in R 4.1
Some things, like the "." work only with %>%

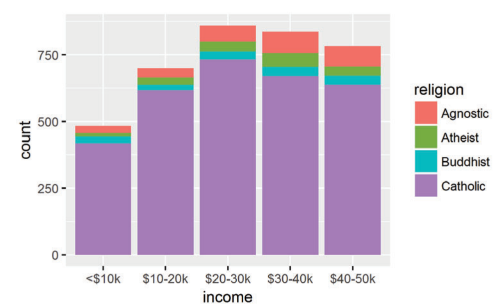
Using pipes: |> ggplot()

For the Pew data, mutate income → ordered factor and |> to ggplot

```
pew1 |>
  gather("income", "frequency", 2:6) |>                            # reshape
  mutate(income = ordered(income, levels=unique(income))) |>       # make ordered
  ggplot(aes(x=income, fill=religion)) +                           # plot
    geom_bar(aes(weight=frequency))                                # as freq bars
```

mutate() calculates or transforms column variables
ordered(income) levels are now ordered appropriately.

The result is piped to ggplot()



Tidying: separate() and unite()

It sometimes happens that several variables are crammed into one column, or parts of one variable are split across multiple columns

tidyr::**separate(storms, date, c("y", "m", "d"))**
Separate one column into several.

tidyr::**unite(data, col, ..., sep)**
Unite several columns into one.

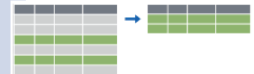
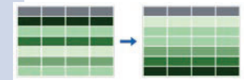
For example, for the pew data, we might want separate income into low & high

```
pew_long |>
  mutate(inc = gsub("[\\$k]", "", income)) |>
  mutate(inc = gsub("<", "0-", inc)) |>
  separate(inc, c("low", "high"), "-") |>
  head()
```

```
  religion   income frequency low high
1 Agnostic    <$10k        27   0   10
2  Atheist    <$10k        12   0   10
3 Buddhist    <$10k        27   0   10
4 Catholic    <$10k       418   0   10
5 Agnostic $10-20k         34  10   20
6  Atheist $10-20k         27  10   20
```

NB: tidyr::separate() now superceded by **separate_wider_{delim, position}()**

dplyr: verbs for manipulating data

verb	What it does	
`filter()`	extract rows	
`select()`	extract columns	
`arrange()`	sort rows	
`mutate()`	make new columns	
`group_by() |> summarize()`	calculate group summaries	

dplyr: Subset observations (rows)

dplyr implements a variety of verbs to select a subset of observations from a dataset

dplyr::**filter(iris, Sepal.Length > 7)**
Extract rows that meet logical criteria.

dplyr::**distinct(iris)**
Remove duplicate rows.

dplyr::**sample_frac(iris, 0.5, replace = TRUE)**
Randomly select fraction of rows.

dplyr::**sample_n(iris, 10, replace = TRUE)**
Randomly select n rows.

dplyr::**slice(iris, 10:15)**
Select rows by position.

dplyr::**top_n(storms, 2, date)**
Select and order top n entries (by group if grouped data).

In a pipe expression, omit the dataset name

```
iris |> filter(Sepal.Length >7)
iris |> filter(Species=="setosa")

iris |> sample_n(10)
iris |> slice(1:50)   # setosa

iris |> group_by(Species) |>
   slice_max(Sepal.Width, n=2)
```

After group_by() does operations w/in each group

dplyr: Subset variables (columns)

dplyr::**select(iris, Sepal.Width, Petal.Length, Species)**
Select columns by name or helper function.

Many helper functions in dplyr allow selection by a function of variable names:

select(iris, **contains**("."))
Select columns whose name contains a character string.

select(iris, **ends_with**("Length"))
Select columns whose name ends with a character string.

select(iris, **everything**())
Select every column.

select(iris, **matches**(".t."))
Select columns whose name matches a regular expression.

select(iris, **num_range**("x", 1:5))
Select columns named x1, x2, x3, x4, x5.

select(iris, **one_of**(c("Species", "Genus")))
Select columns whose names are in a group of names.

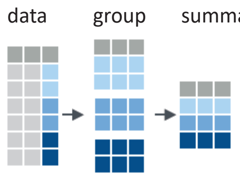
select(iris, **starts_with**("Sepal"))
Select columns whose name starts with a character string.

select(iris, Sepal.Length**:**Petal.Width)
Select all columns between Sepal.Length and Petal.Width (inclusive).

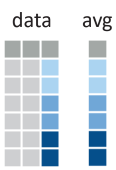
select(iris, **-**Species)
Select all columns except Species.

dplyr: group_by() and summarise()

- Fundamental operations in data munging are:
  - grouping a dataset by one or more variables
  - calculating one or more summary measures
  - ungrouping: expand to an ungrouped copy, if needed

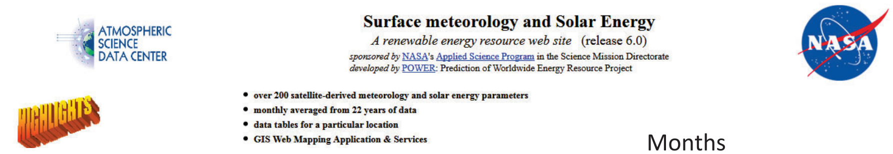



```
mtcars |>
  group_by(cyl) |>
  summarise(avg=mean(mpg))
```




```
mtcars |>
  group_by(cyl) |>
  summarise(avg=mean(mpg)) |>
  ungroup()
```


Example: NASA data on solar radiation

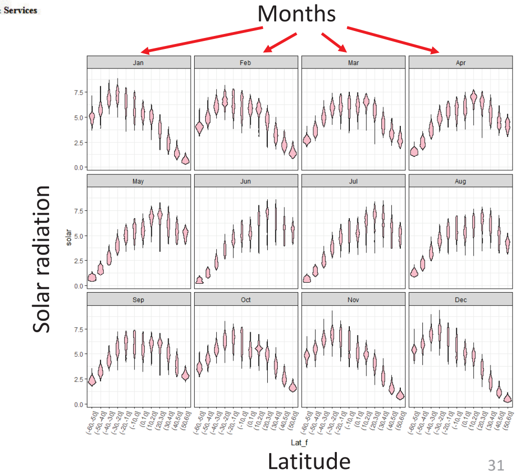


How does solar radiation vary with latitude, over months of the year?

How to make this plot?

Q:
what are the basic plot elements?

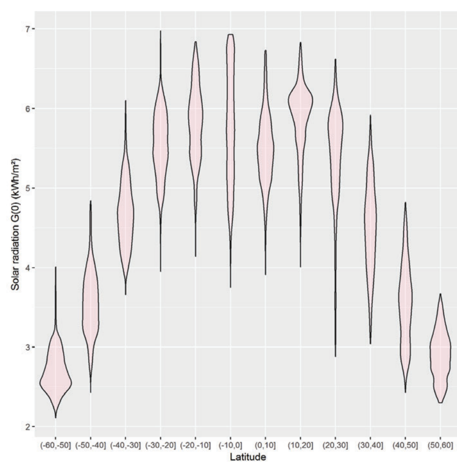
A:
- x = Latitude, y= solar
- geom_violin()
- panels: month



NASA data: solar radiation

This is easy to do for the total Annual solar radiation, a column in the data

```
> str(nasa)
'data.frame':   64800 obs. of  15 variables:
 $ Lat: int  -90 -90 -90 -90 -90 -90 -90 -90 -90 -90 ...
 $ Lon: int  -180 -179 -178 -177 -176 -175 -174 -173 -172 -171 ...
 $ Jan: num  9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 ...
 $ Feb: num  5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 ...
 $ Mar: num  0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 ...
 $ Apr: num  0 0 0 0 0 0 0 0 0 0 ...
 $ May: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Jun: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Jul: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Aug: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Sep: num  0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 ...
 $ Oct: num  3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 ...
 $ Nov: num  8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 ...
 $ Dec: num  11 11 11 11 11 ...
 $ Ann: num  3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 ...
```




```
nasa |>
  filter(abs(Lat) < 60) |>
  mutate(Latf = cut(Lat, pretty(Lat, n=12))) |>
  ggplot(aes(x=Latf, y=Ann)) +
    geom_violin(fill="pink", alpha=0.3) +
    labs(x="Latitude", y="Solar radiation G(0) (kWh/m²)")
```

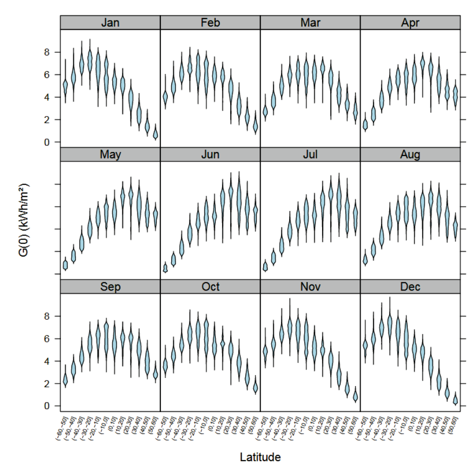
restrict latitude to [-60, 60]
bin Lat into ordered levels, using cut()

violin plot for each

Faceting & tidy data

This is complicated to do for the separate months, because the data structure is **untidy**--- months were in separate variables (wide format)

```
> str(nasa)
'data.frame':   64800 obs. of  15 variables:
 $ Lat: int  -90 -90 -90 -90 -90 -90 -90 -90 -90 -90 ...
 $ Lon: int  -180 -179 -178 -177 -176 -175 -174 -173 -172 -171 ...
 $ Jan: num  9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 9.63 ...
 $ Feb: num  5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 5.28 ...
 $ Mar: num  0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 0.75 ...
 $ Apr: num  0 0 0 0 0 0 0 0 0 0 ...
 $ May: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Jun: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Jul: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Aug: num  0 0 0 0 0 0 0 0 0 0 ...
 $ Sep: num  0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1 ...
 $ Oct: num  3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 3.24 ...
 $ Nov: num  8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 8.28 ...
 $ Dec: num  11 11 11 11 11 ...
 $ Ann: num  3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 3.19 ...
```



tidying the data

To plot solar radiation against latitude by month (separate panels), we need to:

- remove the Ann column
- reshape the data for Jan:Dec to long format, so solar is all in one column
- restrict latitude to [-60, 60]
- bin Lat into ordered levels, using cut()

```
library(tidyr)
library(dplyr)
library(ggplot2)

nasa_long <- nasa |>
   select(-Ann) |>
   gather(month, solar, Jan:Dec, factor_key=TRUE) |>
   filter( abs(Lat) < 60 ) |>
   mutate( Lat_f = cut(Lat, pretty(Lat, 12)))
```

|> “pipes” data to the next stage

select() extracts or drops columns

gather() collapses columns into key-value pairs

filter() subsets observations

mutate() creates new variables

tidying the data

```
> str(nasa_long)
'data.frame':   514080 obs. of  5 variables:
 $ Lat  : int  -59 -59 -59 -59 -59 -59 -59 -59 -59 -59 ...
 $ Lon  : int  -180 -179 -178 -177 -176 -175 -174 -173 -172 -171 ...
 $ month: Factor w/ 12 levels "Jan","Feb","Mar",..: 1 1 1 1 1 1 1 1 1 1 ...
 $ solar: num  5.19 5.19 5.25 5.25 5.17 5.17 5.15 5.15 5.15 5.15 ...
 $ Lat_f: Factor w/ 12 levels "(-60,-50]","(-50,-40]",..: 1 1 1 1 1 1 1 1 1 1 ...

> head(nasa_long)
  Lat  Lon month solar     Lat_f
1 -59 -180   Jan  5.19 (-60,-50]
2 -59 -179   Jan  5.19 (-60,-50]
3 -59 -178   Jan  5.25 (-60,-50]
4 -59 -177   Jan  5.25 (-60,-50]
5 -59 -176   Jan  5.17 (-60,-50]
6 -59 -175   Jan  5.17 (-60,-50]
```

For ease of plotting, I created a factor version of Lat with 12 levels

The data are now in a form where I can plot solar against Lat or Lat_f and facet by month

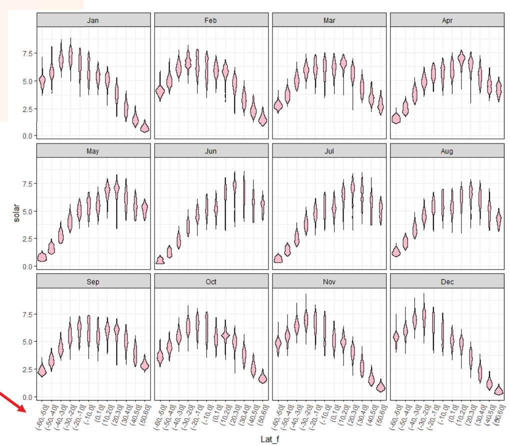
plotting the tidy data

Using geom_violin() shows the shapes of the distributions for levels of Lat_f

```
ggplot(nasa_long, aes(x=Lat_f, y=solar)) +
   geom_violin(fill="pink") +
   facet_wrap(~ month) +
   theme_bw() +
   theme(axis.text.x =
         element_text(angle = 70,
                      hjust = 1))
```

facet_wrap(~month) does the right thing: 12 months $\rightarrow$ 3x4 grid

I had to rotate the x-axis labels for Lat_f to avoid overplotting



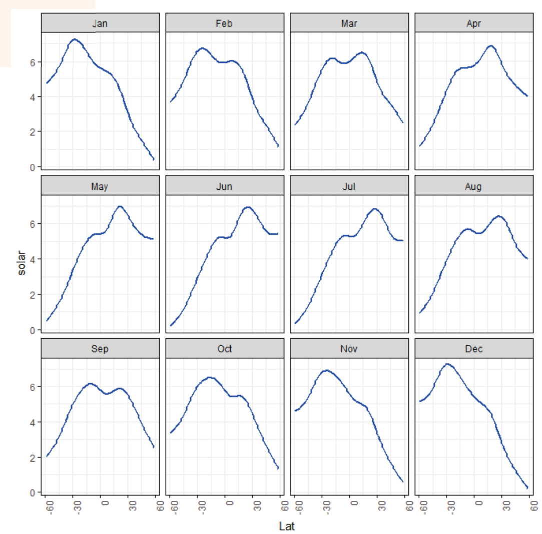
plotting the tidy data: smoothing

```
ggplot(nasa_long, aes(x=Lat, y=solar)) +
   geom_smooth(color="blue" ) +
   facet_wrap(~ month) +
   theme_bw()
```

Here we treat Lat as quantitative. geom_smooth() uses method = “gam” here because of large *n*

The variation in the smoothed trends over the year suggest quite lawful behavior, shifting over the year

Can we express this as a statistical model ?



Build a model

What we saw in the plot suggests a generalized additive model, with a smooth, **s(Lat).**
Similar to loess in spirit, but this is a statistical model that can be tested.

```
library(mgcv)
nasa.gam <- gam(solar ~ Lon + month + s(Lat), data=nasa_long)
summary(nasa.gam)
```

```
Family: gaussian
Link function: identity

Formula:
solar ~ Lon + month + s(Lat)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 4.691e+00  6.833e-03 686.409  < 2e-16 ***
Lon        -1.713e-04  1.898e-05  -9.022  < 2e-16 ***
monthFeb    1.195e-01  9.664e-03  12.364  < 2e-16 ***
  ...          ...
monthDec   -8.046e-02  9.664e-03  -8.326  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The violin plots suggest that variance is not constant. I'm ignoring this here by using the default gaussian model.

Model terms:

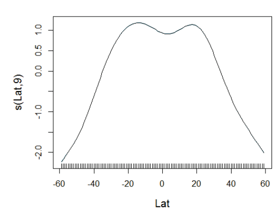
- Lon wasn't included before
- month is a factor, for the plots
- s(Lat) fits a smoothed term in latitude, averaged over other factors

There are other model choices, but it is useful to visualize what we have done so far

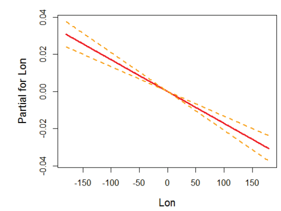
Visualize the model

Effect plots show the fitted relationship between the response and model terms, averaged over other predictors.
The {mgcv} package has its own versions of these: termplot()

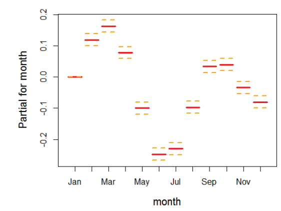
```
plot(nasa.gam, cex.lab=1.25)
termplot(nasa.gam, terms="month", se=TRUE, lwd.term=3, lwd.se=2, cex.lab=1.25)
termplot(nasa.gam, terms="Lon", se=TRUE, lwd.term=3, lwd.se=2, cex.lab=1.25)
```



why the dip at the equator?
s(Lat, 9): gam used 9 df



effect of longitude is very small, but signif. & maybe interpretable



month should be modeled as a cyclic time variable

Visualizing models

- R modeling functions [lm(), glm(), ...] return model objects, but these are "messy"
  - extracting coefficients takes several steps: data.frame(coef(mymod))
  - some info (R^2, F, p.value) is computed in print() method, not stored
  - can't easily combine models
- Some have associated plotting functions
  - plot(model): diagnostic plots
  - car package: many model plot methods
  - effects package: plot effects for model terms
- But what if you want to:
  - make a table of model summary statistics
  - fit a collection of models, compare, summarize or visualize them?

broom: manipulating models

- The broom package turns model objects into tidy data frames
  - **glance**(models) extracts model-level summary statistics (R^2, df, AIC, BIC)
  - **tidy**(models) extracts coefficients, SE, p-values
  - **augment**(models) extracts observation-level info (residuals, ...)

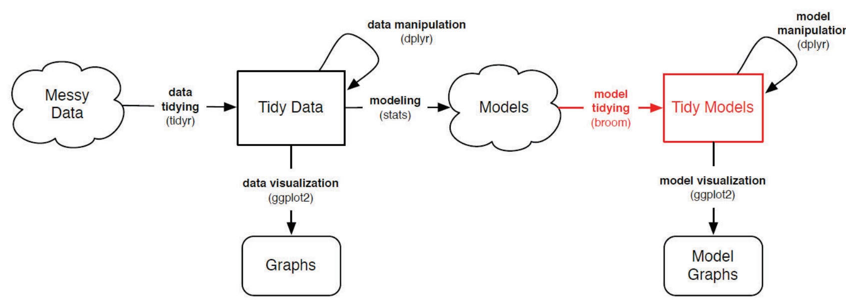


Image from: https://opr.princeton.edu/workshops/Downloads/2016Jan_BroomRobinson.pdf

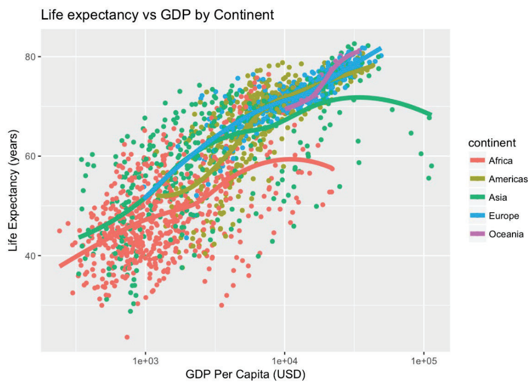
Example: gapminder data

```
ggplot(aes(x = log(gdpPercap), y=lifeExp, color=continent), data=gapminder) +
        geom_point() +
        geom_smooth(method = "loess")
```

How to model this?

How to extract & plot model statistics?

How to fit & display multiple models for subsets?



Example: gapminder data

Predict life expectancy from year, population, GDP and continent:

```
gapmod <- lm(lifeExp ~ year + pop + log(gdpPercap) + continent, data=gapminder)
summary(gapmod)
```

```
Call:
lm(formula = lifeExp ~ year + pop + log(gdpPercap) + continent, data = gapminder)

Residuals:
    Min      1Q  Median      3Q     Max
-24.928  -3.285   0.314   3.699  15.221

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)       -4.58e+02   1.67e+01  -27.43  < 2e-16 ***
year               2.38e-01   8.61e-03   27.58  < 2e-16 ***
pop                5.40e-09   1.38e-09    3.91  9.5e-05 ***
log(gdpPercap)     5.10e+00   1.60e-01   31.88  < 2e-16 ***
continentAmericas  8.74e+00   4.63e-01   18.86  < 2e-16 ***
continentAsia      6.64e+00   4.09e-01   16.22  < 2e-16 ***
continentEurope    1.23e+01   5.10e-01   24.11  < 2e-16 ***
continentOceania   1.26e+01   1.27e+00    9.88  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.79 on 1696 degrees of freedom
Multiple R-squared:    0.8,      Adjusted R-squared:  0.799
F-statistic:  969 on 7 and 1696 DF,  p-value: <2e-16
```

observation level

component level (coefficients)

model level

glance() gives the model level summary statistics

```
> glance(gapmod)
  r.squared adj.r.squared sigma statistic p.value df logLik   AIC   BIC deviance df.residual
1       0.8        0.7992 5.789       969       0  8  -5406 10830 10879    56835        1696
```

tidy() gives the model component (term) statistics

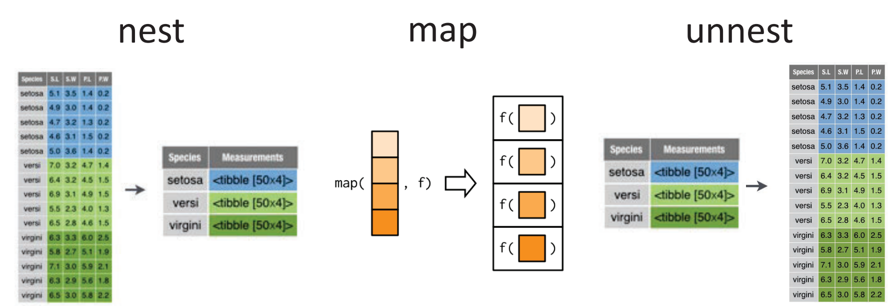
```
> tidy(gapmod)
                term   estimate std.error statistic   p.value
1        (Intercept) -4.585e+02 1.671e+01   -27.433 1.982e-137
2               year  2.376e-01 8.613e-03    27.584 1.122e-138
3                pop  5.403e-09 1.381e-09     3.912  9.496e-05
4     log(gdpPercap)  5.103e+00 1.601e-01    31.876 4.096e-175
5  continentAmericas  8.739e+00 4.635e-01    18.856  3.758e-72
6      continentAsia  6.635e+00 4.091e-01    16.219  4.167e-55
7    continentEurope  1.230e+01 5.102e-01    24.113 1.044e-110
8   continentOceania  1.256e+01 1.270e+00     9.884  1.943e-22
```

augment() gives the observation level statistics

```
> augment(gapmod) |> slice(1:5)
# A tibble: 5 x 12
  lifeExp  year      pop log.gdpPercap. continent .fitted .se.fit .resid    .hat .sigma
    <dbl> <int>    <int>          <dbl> <fct>       <dbl>   <dbl>  <dbl>   <dbl>  <dbl>
1    28.8  1952  8425333           6.66 Asia         46.0   0.408  -17.1 0.00496   5.78
2    30.3  1957  9240934           6.71 Asia         47.4   0.390  -17.1 0.00454   5.78
3    32.0  1962 10267083           6.75 Asia         48.8   0.376  -16.8 0.00423   5.78
4    34.0  1967 11537966           6.73 Asia         49.9   0.372  -15.9 0.00413   5.78
5    36.1  1972 13079460           6.61 Asia         50.5   0.382  -14.4 0.00435   5.78
# ... with 2 more variables: .cooksd <dbl>, .std.resid <dbl>
```

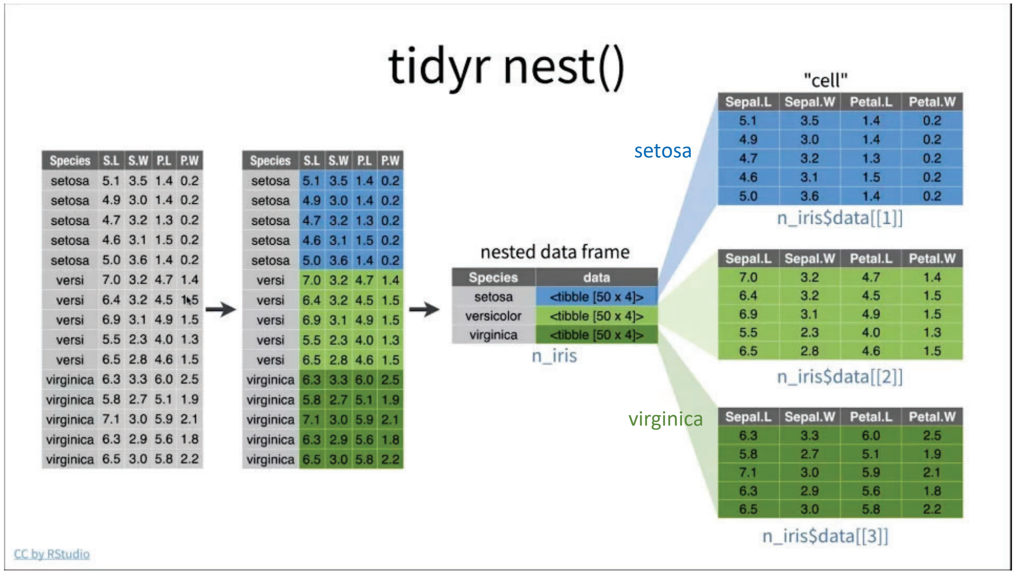

tidyr:: "nest – map – unnest" trick

- In many cases, we want to perform analysis for each subset of a dataset defined by one or more variables
  - dplyr::group_by(), summarise(), ungroup() is one way
- tidyr::nest(), purrr::map(), tidyr::unnest() is more general



See: https://cran.r-project.org/web/packages/broom/vignettes/broom_and_dplyr.html

```
n_iris <- iris |> group_by(Species) |> nest()       # group by Species, then nest
n_iris <- iris |> nest(-Species)                    # nest all other cols
```

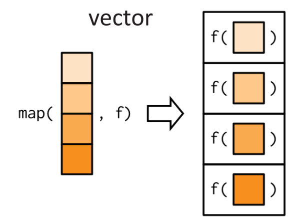


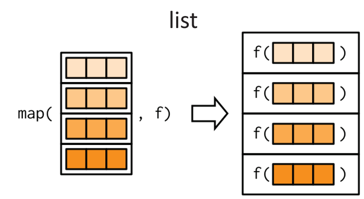
purrr::map() & friends

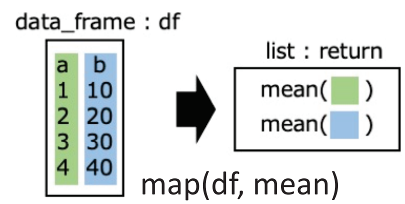
A fundamental operation is doing something, f(), to each element of a vector, list, or column of a data.frame

map(1:3, log) ⟵⟶ list(log(1), log(2), log(3))

`map(x, f)` returns a list of f() applied to each of x
Other variants, map_{dbl, int, chr} return vectors







Fitting multiple models

There may be different effects by continent (GDP x continent interaction)

- What if want to fit (and visualize) a separate model for each continent?
- → nest by continent, then {fit, tidy, glance, augment}

```
models <- gapminder |>
  filter(continent != "Oceania") |>       # only two countries
  nest(data = -continent) |>
  mutate(
    fit = map(data, ~ lm(lifeExp ~ year + pop + log(gdpPercap), data = .x)),
    tidied = map(fit, tidy),
    glanced = map(fit, glance),
    augmented = map(fit, augment)
  )
```

What's in this object?

```
names(models)

[1] "continent" "data"      "fit"       "tidied"     "glanced"    "augmented"
```



```
# view model summaries
models |>
  select(continent, glanced) |>
  unnest(glanced)
```

Model summary statistics

```
# A tibble: 4 x 13
  continent r.squared adj.r.squared sigma statistic   p.value    df logLik   AIC
  <fct>         <dbl>         <dbl> <dbl>     <dbl>     <dbl> <dbl>  <dbl> <dbl>
1 Asia          0.696         0.694  6.56      299. 5.27e-101     3 -1305. 2620.
2 Europe        0.797         0.795  2.46      466. 7.42e-123     3  -833. 1675.
3 Africa        0.500         0.498  6.48      207. 5.90e- 93     3 -2050. 4110.
4 Americas      0.720         0.718  4.97      254. 1.39e- 81     3  -904. 1819.
# ... with 4 more variables: BIC <dbl>, deviance <dbl>, df.residual <int>,
```

```
# model coefficients & tests
models |>
  select(continent, tidied) |>
  unnest(tidied)
```

Coefficients

```
# A tibble: 16 x 6
   continent term           estimate std.error statistic  p.value
   <fct>     <chr>             <dbl>     <dbl>     <dbl>    <dbl>
 1 Asia      (Intercept)    -6.20e+2   4.00e+1    -15.5  1.34e-42
 2 Asia      year            3.23e-1   2.06e-2     15.7  2.41e-43
 3 Asia      pop             5.13e-9   1.66e-9      3.09 2.15e- 3
 4 Asia      log(gdpPercap)  5.04e+0   2.76e-1     18.3  2.25e-54
 5 Europe    (Intercept)    -1.72e+2   1.72e+1    -10.0  4.51e-21
# ...
```

Observations

```
# observation-level statistics
models |>
  select(continent, augmented) |>
  unnest(augmented)
```

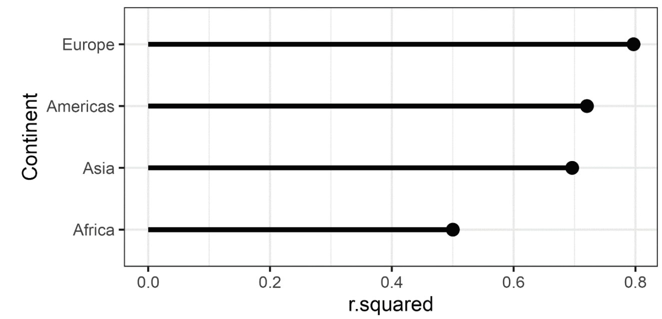
```
# A tibble: 1,680 x 10
   continent lifeExp  year      pop `log(gdpPercap)` .fitted     .hat .sigma .cooksd
   <fct>       <dbl> <int>    <int>            <dbl>   <dbl>    <dbl>  <dbl>   <dbl>
 1 Asia         28.8  1952  8425333             6.66    43.7 0.0101     6.53 0.0133
 2 Asia         30.3  1957  9240934             6.71    45.6 0.00822    6.53 0.0113
 3 Asia         32.0  1962 10267083             6.75    47.4 0.00685    6.53 0.00957
 4 Asia         34.0  1967 11537966             6.73    48.9 0.00616    6.53 0.00805
 5 Asia         36.1  1972 13079460             6.61    49.9 0.00645    6.54 0.00727
 6 Asia         38.4  1977 14880372             6.67    51.9 0.00640    6.54 0.00678
 7 Asia         39.9  1982 12881816             6.89    54.6 0.00607    6.53 0.00771
 8 Asia         40.8  1987 13867957             6.75    55.5 0.00795    6.53 0.0101
 9 Asia         41.7  1992 16317921             6.48    55.8 0.0114     6.53 0.0134
10 Asia         41.8  1997 22227415             6.45    57.3 0.0138     6.53 0.0198
# ... with 1,670 more rows, and 1 more variable: .std.resid <dbl>
```

y $\underbrace{\qquad\qquad}_{\text{predictors}}$ $\hat{y}$ $\underbrace{\qquad\qquad}_{\text{diagnostics}}$

Visualizing multiple models

One visual summary might be a plot of R^2 values, ordered by continent

```
models |>
     select(continent, glanced) |> unnest(glanced) |>
     ggplot(aes(r.squared, reorder(continent, r.squared))) +
        geom_point(size=4) +
        geom_segment(aes(xend = 0, yend = ..y..)) +
        ylab("Continent")
```



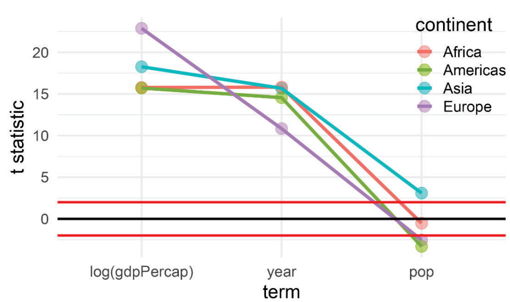
Visualizing coefficients

Coefficient plots are often useful, but these are on different scales.

```
models |> select(continent, tidied) |> unnest(tidied)                     # get model stats
   filter(term != "(Intercept)") |>                                        # ignore the intercept
   mutate(term=factor(term, levels=c("log(gdpPercap)", "year", "pop"))) |>  #  reorder terms sensibly
   ggplot(aes(x=term, y=statistic, color=continent, group=continent)) +
      geom_point(size=5, alpha=0.5) +
      geom_line(size=1.5) +
      geom_hline(yintercept=c(-2, 0, 2),  color = c("red", "black", "red")) +     # hlines for non-significance
      ylab("t statistic") +
      theme_minimal() + theme(legend.position=c(0.9, 0.8))
```

Here, I plot the *t*-statistics, $t=b_{ij}/se(b_{ij})$ for all terms in all models.

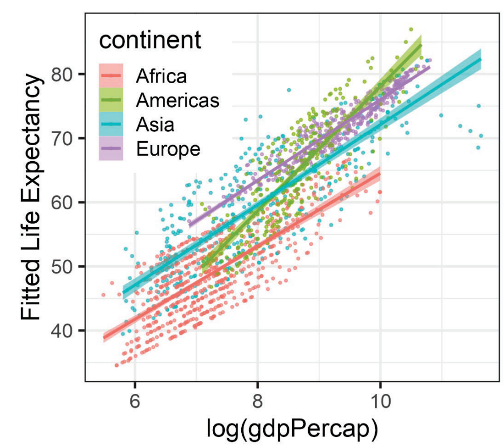
Any values outside ~ ±2 are significant, p < 0.5!



Visualizing model fits

```
models |> select(continent, augmented) |> unnest(augmented) |>
  ggplot(aes(x=`log(gdpPercap)`, y=.fitted, color=continent, fill=continent)) +
  geom_point(size = 0.8, alpha=0.5) +
  geom_smooth(method = "lm", alpha=0.5) +
  ylab("Fitted Life Expectancy")
```

The slope for the Americas is noticeably larger than for other continents



Nice tables in R

- Not a ggplot topic, but it is useful to know how you can produce beautiful tables in R
- There are many packages for this: See the [CRAN Task View on Reproducible Research]
  - xtable: Exports tables to LaTeX or HTML, with lots of control
  - gt: the ggplot of tables!
  - flextable: similar to gt, but with themes
  - stargazer: Well-formatted model summary tables, side-by-side
  - apaStyle: Generate APA Tables for MS Word
  - tinytable: Simple yet powerful tables for HTML, LaTeX, Word, Markdown

Tables in R: xtable

Just a few examples, stolen from xtable: vignette("xtableGallery.pdf")

```
fm1 <- aov(tlimth ~ sex + ethnicty + grade + disadvg, data = tli)
xtable(fm1)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
sex	1	75.37	75.37	0.38	0.5417
ethnicty	3	2572.15	857.38	4.27	0.0072
grade	1	36.31	36.31	0.18	0.6717
disadvg	1	59.30	59.30	0.30	0.5882
Residuals	93	18682.87	200.89		

```
fm3 <- glm(disadvg ~ ethnicty*grade, data = tli, family = binomial)
xtable(fm3)
```

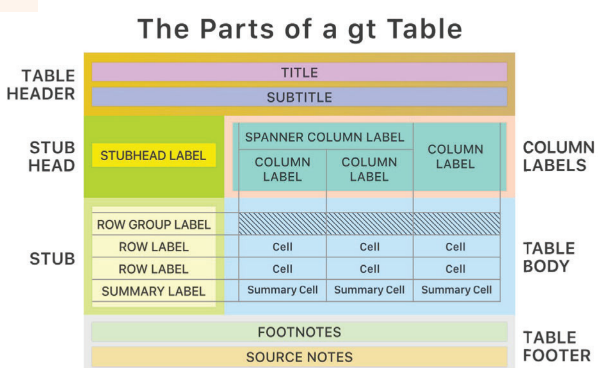
	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	3.1888	1.5966	2.00	0.0458
ethnictyHISPANIC	-0.2848	2.4808	-0.11	0.9086
ethnictyOTHER	212.1701	22122.7093	0.01	0.9923
ethnictyWHITE	-8.8150	3.3355	-2.64	0.0082
grade	-0.5308	0.2892	-1.84	0.0665
ethnictyHISPANIC:grade	0.2448	0.4357	0.56	0.5742
ethnictyOTHER:grade	-32.6014	3393.4687	-0.01	0.9923
ethnictyWHITE:grade	1.0171	0.5185	1.96	0.0498

Too many decimals are used here, but you can control all that

Tables with {gt}

- The {gt} package aims to provide a grammar of tables just as ggplot2 does for graphs
  - Designed to be simple to use, yet powerful

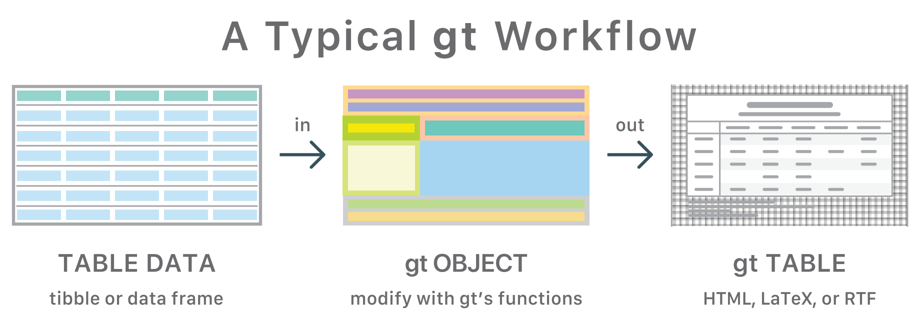
```
iris |> gt()
```



{gt} workflow

- Data table -> gt_tbl object

```
iris |> gt() |>
        tab_header(...) |>
                tab_options(...) |> gtsave()
```



See: https://gt.rstudio.com/

```
iris_tab <-
iris |>
  slice(1:5) |>
  gt() |>
  tab_header(
    title = "Anderson's Iris Data",
    subtitle = "(Collected in ...)")
```

Sample 5 rows
pipe to gt()

add header

Anderson's Iris Data
(Collected in the Gaspe Penninsula)

Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
6.4	3.1	5.5	1.8	virginica
6.9	3.1	5.4	2.1	virginica
4.4	3.2	1.3	0.2	setosa
7.7	2.8	6.7	2.0	virginica
5.0	2.3	3.3	1.0	versicolor


```
iris_tab <-
iris |>
  slice(1:5) |>
  gt() |>
  tab_header(
    title = "Anderson's Iris Data",
    subtitle = "(Collected in ...)")
```

```
iris_tab <-
  iris_tab |>
  tab_spanner(
    label = "Sepal",
    columns = c(Sepal.Length,
                Sepal.Width))    |>
  tab_spanner(
    label = "Petal",
    columns = c(Petal.Length,
                Petal.Width))    |>
```

Add table column spanning headers

Anderson's Iris Data
(Collected in the Gaspe Penninsula)

Sepal		Petal		
Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
6.4	3.1	5.5	1.8	virginica
6.9	3.1	5.4	2.1	virginica
4.4	3.2	1.3	0.2	setosa
7.7	2.8	6.7	2.0	virginica
5.0	2.3	3.3	1.0	versicolor


```
iris_tab <-
iris |>
  slice(1:5) |>
  gt() |>
  tab_header(
    title = "Anderson's Iris Data",
    subtitle = "(Collected in ...)")
```

```
iris_tab <-
  iris_tab |>
  tab_spanner(
    label = "Sepal",
    columns = c(Sepal.Length,
                Sepal.Width))    |>
  tab_spanner(
    label = "Petal",
    columns = c(Petal.Length,
                Petal.Width))    |>
```

```
iris_tab <- iris_tab |>
 cols_label(
  Sepal.Length = "Length",
  Sepal.Width = "Width",
  Petal.Length = "Length",
  Petal.Width = "Width") |>
 tab_options(
  heading.background.color = "#c6dbef",
  column_labels.background.color = "#edf8fb")
```

Re-label columns

Colorize headings

Anderson's Iris Data
(Collected in the Gaspe Penninsula)

Sepal		Petal		
Length	Width	Length	Width	Species
6.4	3.1	5.5	1.8	virginica
6.9	3.1	5.4	2.1	virginica
4.4	3.2	1.3	0.2	setosa
7.7	2.8	6.7	2.0	virginica
5.0	2.3	3.3	1.0	versicolor

tinytable

tinytable is a lightweight but full-featured table generator

- simple interface, easy to learn
- flexible output for all formats


```
library(tinytable)
x <- mtcars[1:5, 1:5]
tt(x)
```

mpg	cyl	disp	hp	drat
21.0	6	160	110	3.90
21.0	6	160	110	3.90
22.8	4	108	93	3.85
21.4	6	258	110	3.08
18.7	8	360	175	3.15

See: https://vincentarelbundock.github.io/tinytable/

tinytable

A few simple functions for constructing nice tables:

```
data |> tt() |>          # basic table
   format_tt() |>        # format columns: significant digits, decimal points, …
   style_tt() |>         # align, colors, …
   theme_tt() |>         # themes for LaTeX, HTML, …
   group_tt()            # spanning labels for groups of rows/ columns

save_tt(x, filename)  # save to  .docx, .html, .png, .pdf, .tex, or render in Rmarkdown
```


Writing & publishing

A variety of R packages make it easy to write and publish research reports, slide presentations in various formats (HTML, Word, LaTeX, …), all within R Studio

knitr rmarkdown — Write R scripts or documents comprising reproducible code and text

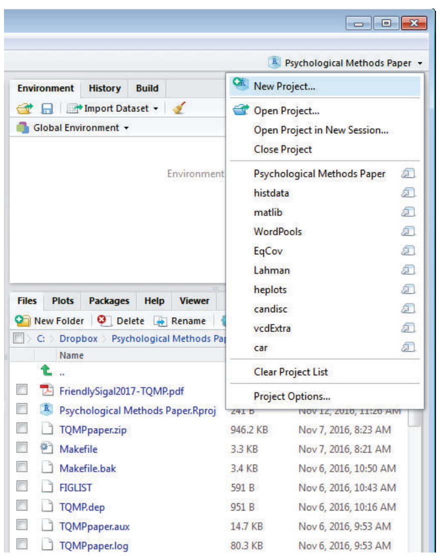
bookdown blogdown quarto — Special format for books, blogs, websites, …

Organize your work with:

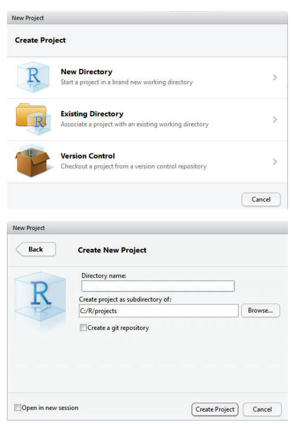
- R Studio projects
- Github for version control & collaboration

Publish online with github-pages, Netlify, …

R Studio projects



R Studio projects are a handy way to organize your work

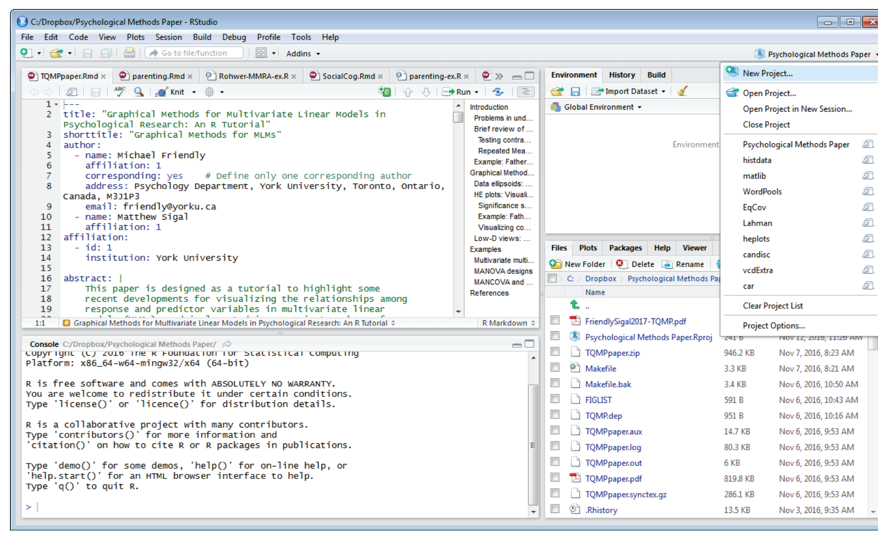


Lahman.Rproj

The .Rproj item opens the project in R Studio

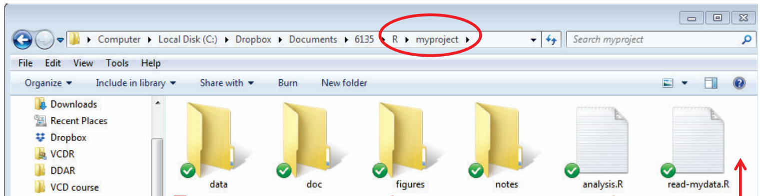
R Studio projects

An R Studio project for a research paper: R files (scripts), Rmd files (text, R “chunks”)



Organizing an R project

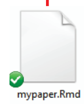
- Use a separate folder for each project
- Use sub-folders for various parts



data files:
- raw data (.csv)
- saved R data (.Rdata)

figures:
- diagrams
- analysis plots

R files:
- data import
- analysis



Write up files will go here (.Rmd, .docx, .pdf)

This project, saved in a Dropbox folder automatically syncs with all my computers & collaborators. I use Git & GitHub for more serious work.

Organizing an R project

- Use separate R files for different steps:
  - Data import, data cleaning, … → save as an RData file
  - Analysis: load RData, …

read-mydata.R

```
# read the data; better yet: use RStudio File -> Import Dataset ...
mydata <- read.csv("data/mydata.csv")

# data cleaning:
#       filter missing, make factors, transform variables, ....

# save the current state
save("data/mydata.RData")
```


Organizing an R project

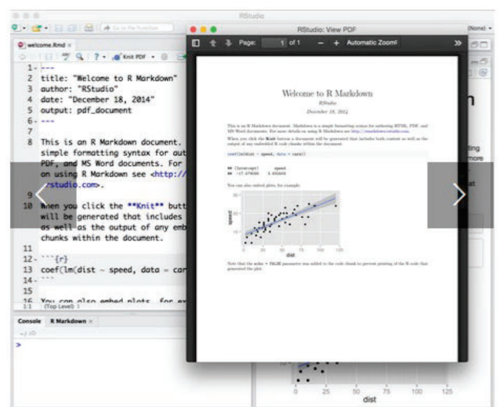
- Use separate R files for different steps:
  - Data import, data cleaning, … → save as an RData file
  - Analysis: load RData, …

analyse.R

```
#' ## load the data
load("data/mydata.RData")

#' ## do the analysis – exploratory plots
plot(mydata)

#' ## fit models
mymod.1 <- lm(y ~ X1 + X2 + X3, data=mydata)

#' ## plot models, extract model summaries
plot(mymod.1)
summary(mymod.1)
```

NB: #' ## is a special R comment for a H2 heading in an R "notebook" script

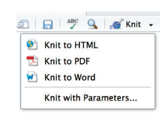
Reproducible analysis & reporting



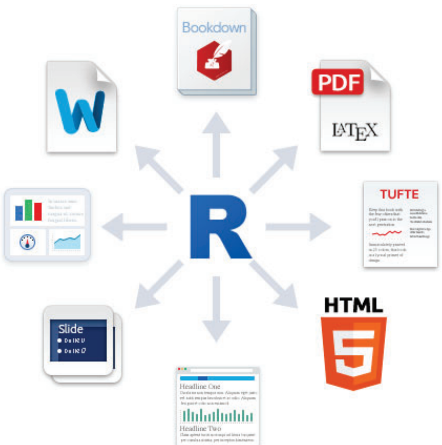
R Studio, together with the knitr and rmarkdown packages provide an easy way to combine writing, analysis, and R output into complete documents

.Rmd files are just text files, using rmarkdown markup and knitr to run R on "code chunks"

A given document can be rendered in different output formats:

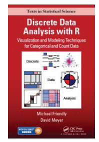


Output formats and templates



Templates are available for APA papers, slides, handouts, entire web sites, etc.

The integration of R, R Studio, knitr, rmarkdown and other tools is now highly advanced.



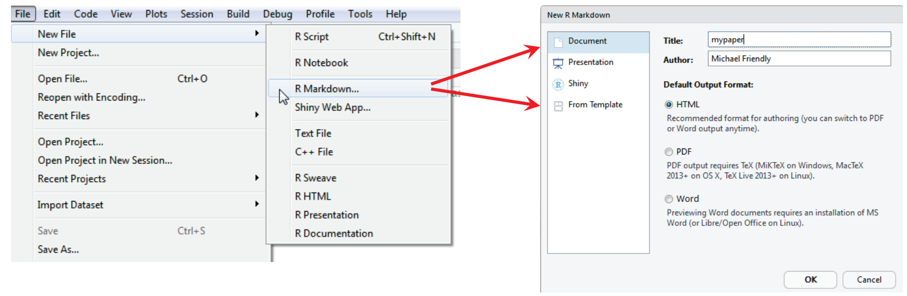
My 2nd last book was written entirely in R Studio, using .Rnw syntax ⟶ LaTeX ⟶ PDF ⟶ camera ready copy

The ggplot2 book was written using .Rmd format.

The bookdown package makes it easier to manage a book-length project – TOC, fig/table #s, cross-references, etc.
Also: blogdown, posterdown, …

Writing it up

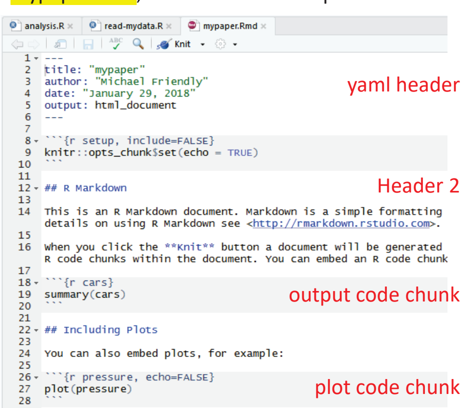
- In R Studio, create a .Rmd file to use R Markdown for your write-up
  - lots of options: HTML, Word, PDF (needs LaTeX)
  - templates for various pub types



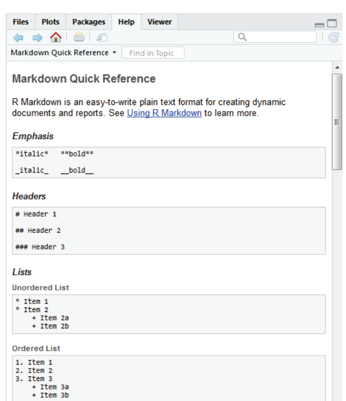
Writing it up

- Use simple Markdown to write text
- Include code chunks for analysis & graphs

mypaper.Rmd, created from a template

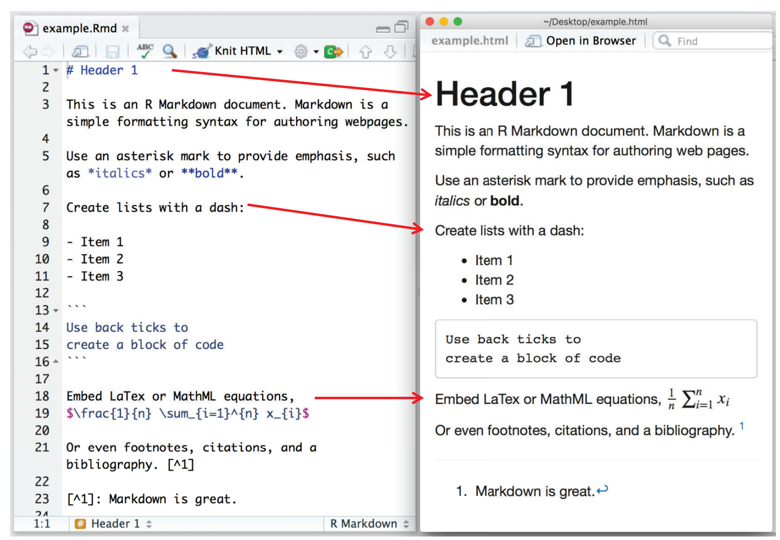


Help -> Markdown quick reference



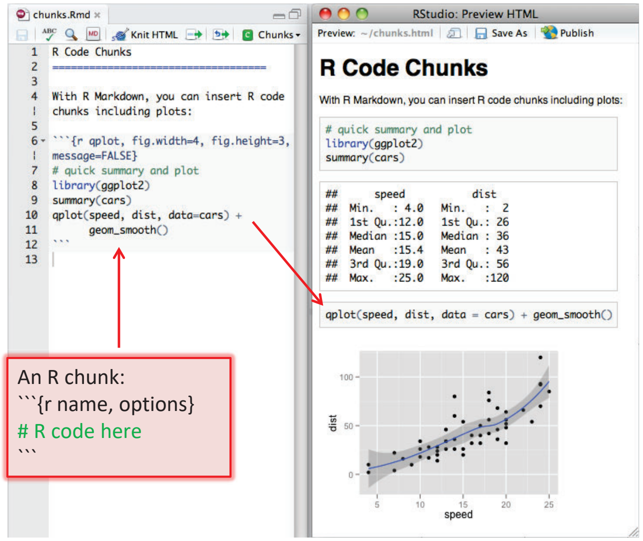
Rmarkdown basics

Rmarkdown uses simple formatting for all standard document elements



R code chunks

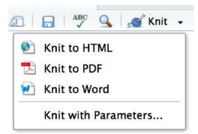
R code chunks are run by knitr, and the results are inserted in the output document



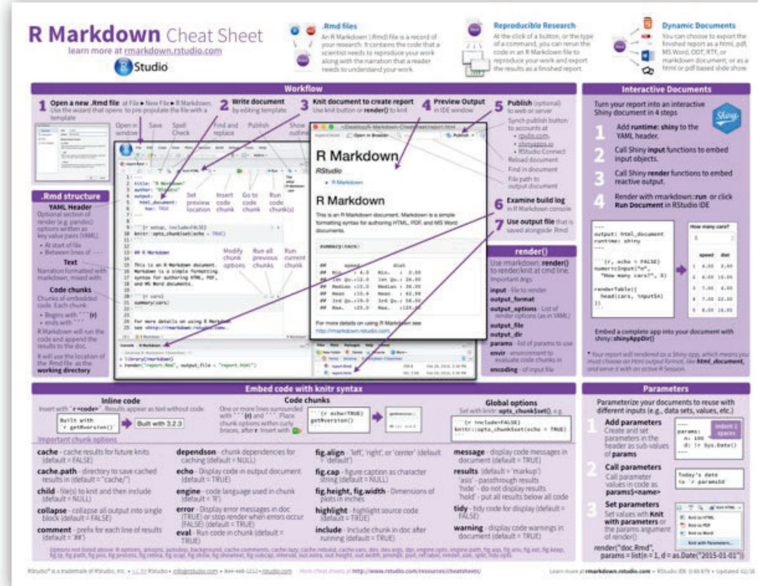
An R chunk:
```{r name, options}
# R code here
```

There are many options for controlling the details of chunk output – numbers, tables, graphs

Choose the output format:

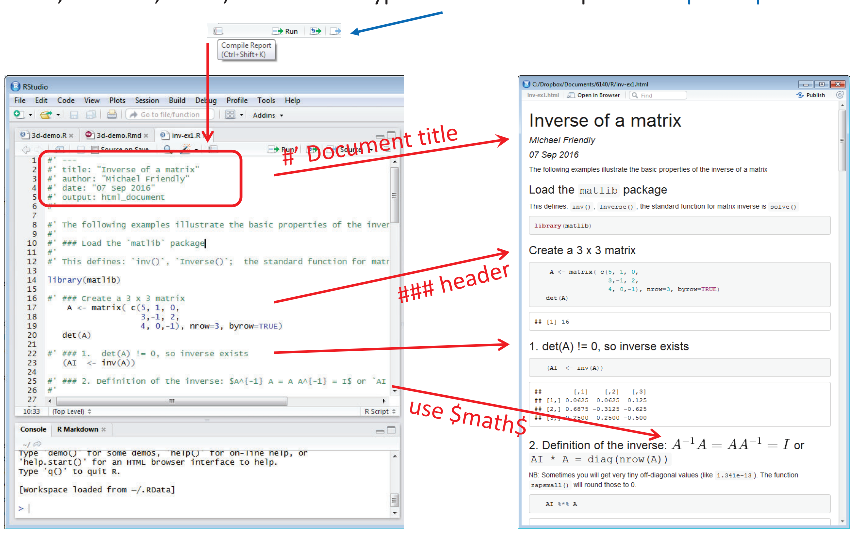


The R Markdown Cheat Sheet provides most of the details
https://www.rstudio.com/wp-content/uploads/2016/03/rmarkdown-cheatsheet-2.0.pdf



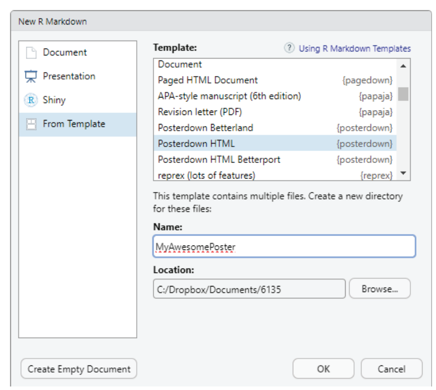
R notebooks

Often, you just want to "compile" an R script, and get the output embedded in the result, in HTML, Word, or PDF. Just type Ctrl-Shift-K or tap the Compile Report button



Posters with posterdown

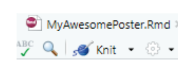
File → New file → R markdown…



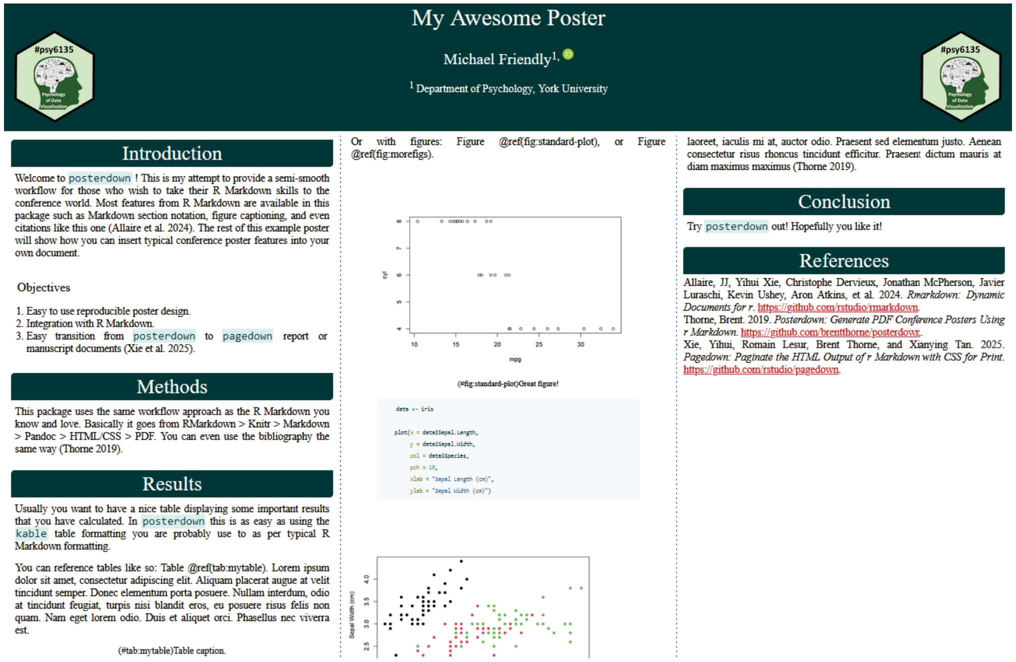
YAML header:

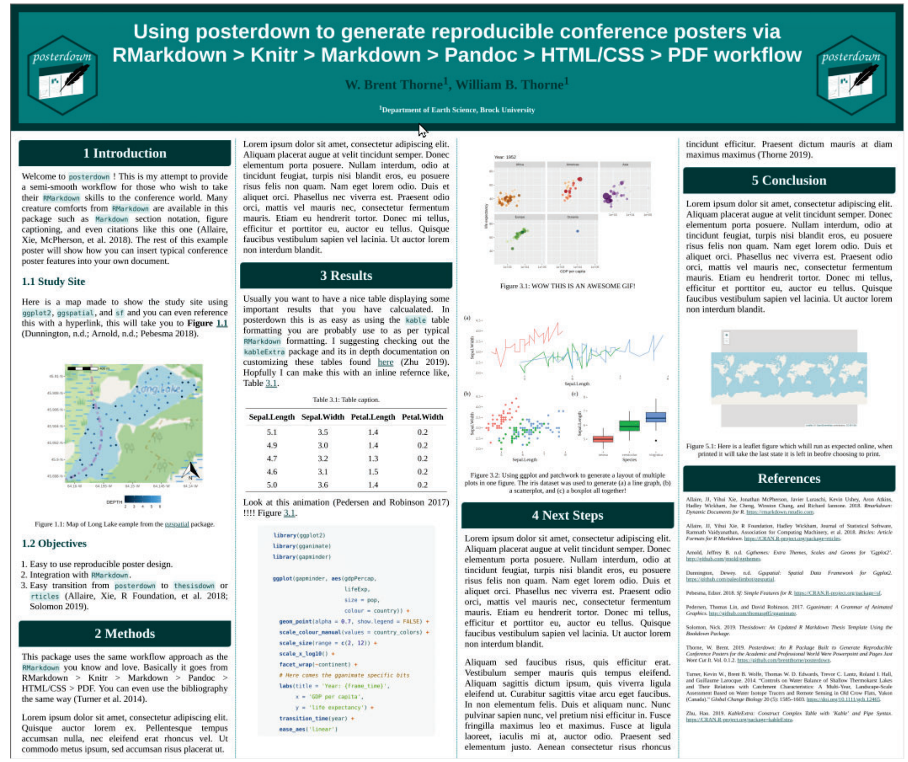
```
---
title: My Awesome Poster
author:
  - name: Michael Friendly
    affil: 1
    orcid: '0000-0002-3237-0941'
affiliation:
  - num: 1
    address: Psychology Dept, York University
column_numbers: 3
logoright_name: psy6135-hex.png
logoleft_name: psy6135-hex.png
output:
  posterdown::posterdown_html:
  self_contained: false
bibliography: packages.bib
---
```

Render: `rmarkdown::render("MyAwesomePoster.Rmd")`



Wiki: https://github.com/brentthorne/posterdown/wiki





Summary

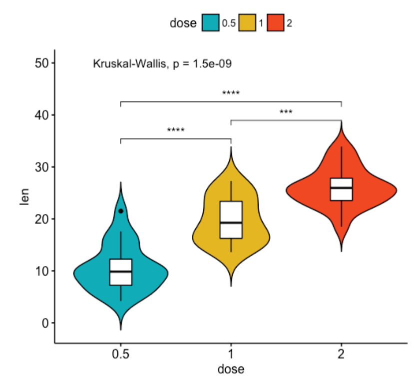
- tidyverse thinking
  - data import → clean → make tidy
  - often need to reshape, wide ↔ long
  - tools for dates, factors, strings
- Models:
  - broom to extract tidy results
  - nest – map trick to fit/plot multiple models
- Writing it up
  - Learn to use table tools
  - Use Rstudio projects
  - Learn to use reproducible reporting (.Rmd)

ggpubr

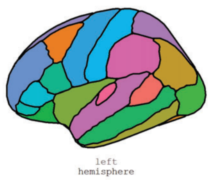
The ggpubr package provides some easy-to-use functions for creating and customizing publication ready plots.

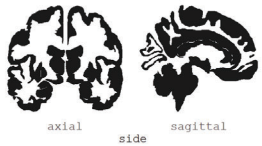
```
ggviolin(df, x = "dose", y = "len", fill = "dose",
       palette = c("#00AFBB", "#E7B800", "#FC4E07"),
       add = "boxplot", add.params = list(fill = "white"))  +
  stat_compare_means(comparisons = my_comparisons, label = "p.signif") +
  stat_compare_means(label.y = 50)
```

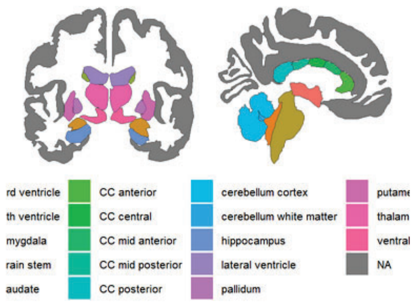
see the examples at
http://www.sthda.com/english/rpkgs/ggpubr/



ggseg: plotting brain atlases








```r
# install.packages("remotes")
# remotes::install_github("LCBC-UiO/ggseg")
library(ggseg)
# install.packages("ggplot2")
library(ggplot2)

ggplot() +
  geom_brain(atlas = aseg) +
  theme_void() +
  theme(legend.position = "bottom",
        legend.text = element_text(size = 8)) +
  guides(fill = guide_legend(ncol = 4))
```